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GLOSSARY OF NOTATION

Sets

$\mathcal{M}$	Set of resources
$\mathcal{J}$	Set of jobs
$\mathcal{O}$	Set of operations
$\mathcal{O}_j$	Set of operations of j^{th} job
$\sharp$	Cardinality of a set
f	Set of Objectives
$\mathcal{C}$	Set of Constraints
$\mathcal{J}_j$	j^{th} job
$\mathcal{M}_k$	k^{th} machine
$\mathcal{O}_{jk}$	An operation of j^{th} job to be processed on k^{th} machine
$\mathcal{O}_{j(i)}$	i^{th} operation of job $\mathcal{J}_j$

Indices

j	Index for job, j^{th} job
k	Index for machine, k^{th}machine
i	Index for operation, i^{th} operation of a given job
j,j	Indexes for jobs
u,v	Indexes for operations

Job Attributes

r_j	Ready time, Ready time of j^{th} job
s_j	Start time of j^{th} job
p_j	Total processing time of j^{th} job
d_j	Due date of j^{th} job.
$\tilde{d}_j$	Dead-line of j^{th} job
C_j	Completion time of j^{th} job
o_j	Total number of operations of j^{th} job.
L_j	Lateness of j^{th} job
T_j	Tardiness of j^{th} job
ϱ_j	Remaining processing time of j^{th} job
ς_j	Slack of j^{th} job
W_j	Expected waiting time for j^{th} job

Operation Attributes

$p_{j(i)}$	Processing time of i^{th} operation of j^{th} job
$d_{j(i)}$	Due date of i^{th} operation of j^{th} job
$s_{j(i)}$	Service start time of i^{th} operation of j^{th} job
$C_{j(i)}$	Completion time of i^{th} operation of j^{th} job
p_{jk}	Processing time of an operation of j^{th} job to be processed on k^{th} machine
d_{jk}	Due date of an operation of j^{th} job to be processed on k^{th} machine
$s_{j(i)}$	Service start time of an operation of j^{th} job to be processed on k^{th} machine
C_{jk}	Completion time of an operation of j^{th} job to be processed on k^{th} machine
$W_{j(i)}$	Expected waiting time for i^{th} operation of j^{th} job

System parameters/Variables

t	Current time
π	A processing sequence
σ	A schedule
τ	Due-date tightness factor
ρ	Due-date range
m	Number of machines
n	Number of jobs
n_t	Number of jobs in system at time t
μ_x	Mean of x
$E(x)$	Expectation of x
$Var(x)$	Variance of x
$(x)^+$	max(x,0)
X	set of input features.

Introduction

Over the last fifty years, scheduling theory has evolved as a major active area of research attracting a wide spectrum of researchers ranging from computer and management scientists to production engineers. There exist a significant amount of literature on a wide variety of methods to solve different scheduling problems. These methods range from industry-standard dispatching rules to state-of-the-art meta-heuristics and sophisticated optimization algorithms.

Scheduling is concerned with solving a Constraint Optimization Problem (an optimization problem with finite solution space for each of its instance (Colorni *et al.*, 1996)).

The job shop problem is considered as one of the most general and well developed scheduling problems with much practical significance. The problem is generally NP-hard (Non-deterministic Polynomial-time hard) except for a very few special cases. Conway *et al.* (1967) describes the problem as a fascinating challenge that is extremely hard to solve despite its quite simple structure. The reason for computational intractability of job shop scheduling problem is mainly its combinatorial nature besides many conflicting factors that must be taken into account (Zobolas *et al.*, 2008).

The history of solving job shop scheduling problem encompasses a wide spectrum of approaches. Initially, the focus of researchers remained on the exact approaches. These include the earlier efficient methods, mathematical methods and enumerative techniques. Branch and bound are considered among the most successful exact methods, however they demand phenomenal computing time to obtain an optimal solution (Zobolas *et al.*, 2008). Later on, an era of heuristic methodologies is observed, although simple dispatching rules were already in use. Various bottleneck-based heuristics are developed during this period. Thereafter, with the emergence of more sophisticated meta-heuristics and tech-

niques based on artificial intelligence, substantial progress is made in late 80s and early 90s (Jain and Meeran, 1998). Powerful meta-heuristics coupled with the computational power of modern computer systems enabled to make use of these approaches on relatively larger problems. However, Lawrence and Sewell (1997) found that the performance of these solution methodologies deteriorates due to processing time uncertainty when compared to dynamically updated heuristic schedules.

In dynamic scheduling, jobs are continually revealed during the process of schedule execution. Dynamic scheduling is closely related to real-time control, as decisions are to be made based on the current state of the system. This on-line aspect greatly influences the scheduling decisions as the schedule creation and schedule execution no longer remain two different processes. Scheduling decisions are to be made in a very short time as the time required to generate a schedule becomes relatively more important factor than merely finding a best quality schedule in an extended period of time. Moreover, schedule is required to be highly reactive to cope with unanticipated circumstances. Priority dispatching rules are considered as the best choice in such an environment mainly due to their ease of implementation and intuitive appeal despite their poor performance in most of the scheduling problems.

The priority dispatching rules based approach is the simplest and most used approach in practice for dispatching jobs in real-time for processing on machines. Numerous studies have been made on the nature, effectiveness and performance of different priority dispatching rules under varying scheduling conditions. Panwalker and Iskander (1977) has reviewed 113 priority dispatching rules while new rules are continuously emerging. However, there is still a lack of satisfactory results in literature on the performance of priority dispatching rules that would have lead to extensive real-world applications. Unfortunately, the superiority of one scheduling rule to the other is not obvious and often conflicting results have been reported possibly due to different conditions and parameter-settings used for the scheduling environment. Moreover, the performance of priority dispatching rules is dependent on the performance criterion. An apparently highly efficient rule in regards with one performance criteria may give very poor results for some other performance criterion even under the same conditions. Even for the pragmatic priority scheduling approach, the overall performance of priority dispatching rules diminishes due to the dynamic and stochastic nature of the system.

Under the general title of Artificial Intelligence (AI), a series of new techniques emerged in early 80s to solve the job shop scheduling problem (Jones and Rabelo, 1998). They include expert/knowledge-based systems, artificial neural networks and inductive learning. These techniques generally employ both the quantitative and qualitative knowledge spe-

cific to problem domain as well as procedural knowledge of the solving methods. These approaches are assumed to capture complex relationships and transform them into elegant data structures for subsequent generation of heuristics. The heuristics obtained however, are quite complex in most of the cases, as compared to priority dispatching rules. Moreover, systems based on these techniques are too time-consuming to build and quite complex to maintain.

Knowledge acquisition is the basic step in developing the knowledge-base. The knowledge source is usually a human expert, the simulation data or the historical data. A machine learning technique employs this data as a set of training examples. These training examples are used to train the machine-learning algorithm to acquire knowledge about the manufacturing system (Michalski *et al.*, 1986, 1998). Intelligent decisions are then made (such as selecting the best rule for each possible system state) in real time, based on this knowledge (Nakasuka and Yoshida, 1992; Shaw *et al.*, 1992; Yeong-Dae, 1994; Min and Yih, 2003).

The major drawbacks of priority dispatching rules include their performance-dependence on the state of the system and non-existence of any single rule, superior to all the others for all possible states the system might be in (Geiger *et al.*, 2006). Meta-heuristics (*e.g.* simulated annealing and tabu search) have an advantage over the priority dispatching rules in terms of solution quality and robustness, however these are usually more difficult to implement and tune, and computationally too complex to be used in a real time system. Robust and better-quality solutions provided by meta-heuristics contain useful knowledge about the problem domain and solution space explored. Such a set of solutions represents a wealth of scheduling knowledge to the domain that can be transformed in a form of decision tree or a rule-set. In this work, we propose an approach to exploit this scheduling knowledge.

The proposed data mining-based approach discovers previously unknown dispatching rules for job shop scheduling problem. An efficient meta-heuristic such as tabu search can provide robust and better-quality solutions for a job shop scheduling problem that contains useful knowledge about the problem domain and solution space explored. A set of such solutions for different instances of a job shop scheduling problem represents a wealth of scheduling knowledge to the domain. The idea is to exploit this scheduling knowledge and to transform it in a form of decision tree or a rule-set. The rule-set may then be used as a standard dispatching rule at the waiting lines of a job shop in an on-line manner.

Thesis Organization

This thesis report is composed of five chapters. The first chapter presents the scheduling problem and the basic concepts in the field of scheduling. The key elements, of which of shop scheduling problem is composed as well as the notations used to characterize the problem are recalled. Thereafter, we present different classes of schedules. Classification of scheduling problems are then presented in order to distinguish different combinations of scheduling environments, conditions and objectives. This follows with a formal definition of job shop scheduling problem. Then the schedule visualization by Gantt diagram and the scheduling problem representation using disjunctive graph formulation is described. Finally, a general introduction to different methods used in solving job shop scheduling problems are discussed.

The second chapter provides a state-of-the-art review on priority dispatching rules in context with job shop scheduling environment. Frequently used classification schemes for these pdrs found in literature are reviewed. This follows with a detailed discussion on the structure and characteristics of most frequently used pdrs in literature.

In the third chapter, a simulation based analysis of tardiness based performance measures for a set of frequently used pdrs is made in order to highlight the similarities/dissimilarities in the behavior of pdrs. Tardiness based performance measures focus on different aspects of a very important class of objectives in a manufacturing system. The first part of the chapter presents these different tardiness based performance measures. These performance measures are not independent of each other. Moreover, the relation among these performance measures is generally not obvious even for simple scheduling strategies such as priority dispatching rules. Based upon the behavior of different priority dispatching rules in regards with these performance measures, we identify two sets of pdrs using the distribution of the maximum tardiness (*i.e.* $T_{\max}$), a very important measure representing the worst case behavior. The worst-case behavior in regards with tardiness is very difficult to identify due to its value at a single-point only. However, it is possible to establish some guidelines in predicting this worst-case behavior in regards with tardiness as well as the width of the tardiness by evaluating root mean square tardiness (T_{rms}). Results showing the correlation among two very important measures, maximum tardiness ($T_{\max}$) and root mean square tardiness (T_{rms}) are presented along-with discussion on these results.

In chapter 4, a state-of-the-art survey on the application of learning based approaches in the field of job shop scheduling is given. It provides an effective overview of the challenges and benefits related to the application of learning algorithms in solving scheduling problems. The survey reveals that their is a lack of systematic use of the scheduling know-

ledge despite the fact that the approach has been acknowledged by most of the authors as promising in scheduling domain. Moreover, it is generally not obvious how much a certain set of scheduling data is relevant to the scheduling environment for desired objectives. The emergence of data mining has invoked the academic interest in analyzing the complex problems like this in a more methodical way. A brief review of the factors affecting the performance of inductive learning algorithm, for example feature selection and discretization is given in the last part.

A data mining based approach to discover previously unknown priority dispatching rules for job shop scheduling problem is presented in chapter 5. In the beginning, a brief description of some necessary background areas such as tabu search and data mining is given. Then the proposed framework is presented along with the structure and functional details of the different modules. The approach is based upon seeking the knowledge that is assumed to be embedded in the efficient solutions provided by the optimization module, built using tabu search. The objective is to discover the scheduling concepts using data mining and hence to obtain a set of rules capable of approximating the efficient solutions for a job shop scheduling problem (JSSP). The data mining based scheduling framework is implemented for a job shop problem with mean tardiness and maximum lateness as the scheduling objectives. The results indicate the superior performance of the proposed system relative to a number of priority dispatching rules and hence proves to be promising approach.

1 Scheduling: A General Introduction

This chapter presents an overview of the scheduling domain and related concepts. The key elements of shop scheduling problem and notations are presented. Different shop scheduling environments along with classification of shop scheduling problems is given. A

formal definition of job shop scheduling problem (JSSP) and its representation are given. Then a general introduction to different approaches used in solving JSSP are discussed.

1.1 Introduction

Scheduling is a decision-making process that is extensively encountered in a large variety of systems. However it is widely used in manufacturing systems where it is generally referred as machine scheduling. Machine scheduling is one of the most important issues in the planning and operation of manufacturing systems. It is aimed at efficiently allocating the available machines to jobs, or operations within jobs and subsequent time-phasing of these jobs on individual machines (Shaw *et al.*, 1992).

A solution to a scheduling problem represents a schedule (σ) that satisfies all the constraints of the problem. A schedule is composed of following three major processes:

assignment : It is a process of allocating a machine to each task to be executed.

sequencing : It is the process of assigning an order of execution of the tasks on each machine.

timetabling : It is the process of assigning a start time and finish time to each task.

However, these three processes may be dealt as separate problems, known as assignment problem, sequencing problem and timetabling problem respectively (French, 1982).

Scheduling problems are generally very complex in nature due to their combinatorial nature. However these problems are extensively studied in literature as benchmark problems for the optimization methods apart from their own practical applications. Traditional approaches to solve scheduling problems use simulation, analytical models, heuristics or combination of these methods.

Different components of a scheduling problem are the tasks, constraints, resources and the objective functions. In the following, these key elements of a scheduling problem are presented.

1.2 Elements of a Scheduling Problem

A scheduling problem is a typical representative of a combinatorial optimization class of problems consisting of a set of jobs $\mathcal{J}$, a set of resources $\mathcal{M}$, a set of objectives f and a set of constraints $\mathcal{C}$.

1.2.1 Jobs

A job $\mathcal{J}_j$ is a fundamental entity described in time domain by a start time and finish time, that is executed for a processing time on one or more resources/machines (Esquirol and Lopez, 1999).

Each job $\mathcal{J}_j$ consists of o_j number of operations, $\{\mathcal{O}_{j(1)},\mathcal{O}_{j(2)},...,\mathcal{O}_{j(o_j)}\}$ with each operation, $\mathcal{O}_{j(i)}$ (or $\mathcal{O}_{jk}$) to be processed on a machine $\mathcal{M}_k$ during a processing time p_{jk}. A job is associated with a release date, r_j, specifying the time before which no operation of the job can be processed, a processing time, $p_j(=\sum_{j=1}^{n} p_{j(i)})$, the time for which the job executes on machine(s) and a due date, d_j, the date at which job is promised to be completed. The completion time of a job, C_j, is by which all the operations of the job complete its execution on corresponding machines. Number of jobs in the problem is denoted as n $(=\sharp\mathcal{J})$ while number of jobs available for processing at any instant t, is denoted as n_t.

Total number of operations, $\sum_{j=1}^{n} o_j$ $(=\sharp\mathcal{O})$ in a scheduling problem generally reflect the problem size.

1.2.2 Resources

A resource, $\mathcal{M}_k$ is any physical or virtual entity of limited capacity and/or availability, allocated to the execution of jobs competing for it.

The term machine is generally used instead of resource in shop scheduling literature.

There are different types of resources. A resource can be classified as renewable and consumable. Renewable resources become available again after use with the same capacity, while consumable resources lose their capacity or disappear after use (Kind't and Billaut, 2006).

Resources can also be classified as cumulative or disjunctive. Cumulative resources are capable of processing more than one task in parallel while disjunctive resources can process only one task at a time. Usually a limit on the capacity of the resources is the major constraint besides others.

In this study, only renewable disjunctive resources are taken into account. Number of machines denoted as m $(= \sharp\mathcal{M})$, also reflect the size of a scheduling problem.

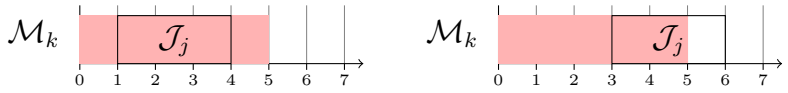
1.2.3 Constraints

A constraint represents a restricted set of value that can be taken by a decision variable involved in the problem. A solution of a scheduling problem must always satisfy the given constraints. A solution that violates any of the constraints is not a feasible solution.

Constraints can be classified as temporal constraints and resource-capacity constraints.

Temporal Constraints

Temporal constraints are generally related to execution window of a job (or operations) in time horizon. These constraints specify absolute position, relative position or structure of this execution window.



(a) Feasible schedule (b) Infeasible schedule

Figure 1.1 – *Temporal constraint: Absolute position and size of execution window*

Temporal constraints specify absolute position of the execution window for a job in time horizon. This means that a job $\mathcal{J}_j$ can not start its execution before r_j and must finish its processing before $\tilde{d_j}$. It may be specified as

$$r_j \leqslant s_j, C_j \leqslant \tilde{d_j},$$

where s_j is the time at which j^{th} job starts its execution. Figure 1.1 illustrates the execution of a job $\mathcal{J}_j$ with ready time $r_j = 0$ and dead-line $\tilde{d_j} = 5$. Figure 1.1(a) shows a feasible schedule with respect to this constraint whereas an infeasible schedule is shown in Figure 1.1(b).

■

Temporal constraints may also specify the relative positions of execution windows of different jobs on the same machine (known as precedence constraints), *e.g.* for the constraint that $\mathcal{O}_{gk}$ must precede job $\mathcal{O}_{hk}$ (*i.e.* $\mathcal{O}_{gk} \rightarrow \mathcal{O}_{hk}$) can be expressed as

$$C_{gk} \leqslant s_{hk}.$$

Temporal constraints specify the structure of this execution window *i.e.* whether it must be in an integral form for an operation or may be split (preemption) on time scale.

Resource Constraints

These constraints specify the capacity and/or availability of a resources. They are also referred as disjunctive constraints in the case of renewable resources. This means, for example, that no more than one operation can be executed at the same time on a resource of unit capacity. This type of constraint is expressed as

$$\forall u,v \in \mathcal{O},\ \mathcal{M}(u) = \mathcal{M}(v) \Rightarrow C_u \leqslant s_v \text{ or } C_v \leqslant s_u.$$

1.2.4 Objectives

An objective reflects the desired characteristics in the solution to find, for a scheduling problem by executing a given set of tasks on the machines in a certain sequence.

Generally, there are more than one possible solution to a problem. Each solution of the problem has its own characteristics. The objectives take into account these characteristics, for preferring one solution to the other. In some cases it is not possible to find all the required characteristics in a single solution. However, in such cases some of the preferences may be relaxed to find the solution of the problem with relatively more important characteristics, reflecting the objectives.

The objectives reflect the characteristics desired in the final schedule. Different performance measures may be used for the evaluation of schedules in regards with the objectives under consideration. These may be based upon completion times, due dates or inventory, utilization costs *etc.*. Performance measures specify the extent to which the desired objectives are achieved. Two performance measures are equivalent if a schedule which is

optimal with respect to one is always optimal with respect to the other as well and vice versa (French, 1982).

The two large families of objectives are:

- minimax, which represent the maximum value of a set of functions to be minimized, and
- mini-sum, which represent a sum of functions to be minimized.

The most studied objective related to completion times is minimizing the completion time of the entire schedule, known as makespan and denoted as $C_{\max}$. It is defined as

$$C_{\max} = \max_{1 \leqslant j \leqslant n} C_j.$$

$C_{\max}$ is one of the flow time based objectives where flow time of a job $\mathcal{J}_j$ is defined to be the time that the job spends in the shop (French, 1982), and is represented as F_j. Mean flow time ($\bar{F}$) and maximum flow time ($F_{\max}$) are among other flow time based performance measures that are often used in scheduling problems. These measures are defined respectively as follows:

$$\bar{F} = \frac{\Sigma_j F_j}{n},$$

$$F_{\max} = \max_{1 \leqslant j \leqslant n} F_j.$$

An objective may also be a function of the due dates. One of the basic functions involving due dates is lateness. The lateness of job j is defined as $L_j = C_j - d_j$, which is positive when job j is completed late and negative when it is completed early. An important example of performance measure using lateness is maximum lateness, $L_{\max}$. It is defined as

$$L_{\max} = \max_{1 \leqslant j \leqslant n} L_j.$$

Another very important function of due dates is tardiness, which can be measured through several performance measures. The tardiness of a job is computed as

$$T_j = \max(0, L_j).$$

The most used performance measure to evaluate the tardiness is the mean tardiness ($\bar{T}$).

It is defined as

$$\bar{T} = \frac{\Sigma_j T_j}{n}.$$

Maximum tardiness, $T_{\max}$ is another very important tardiness based measure that is equivalent to $L_{\max}$ and defined as

$$T_{\max} = \max_{1 \leqslant j \leqslant n} T_j.$$

It can be of great interest for the decision-maker in the shop as an indication of the worst case behavior during a particular experiment.

The number of tardy jobs is defined as,

$$U_j = \begin{cases} 1 & \text{if } L_j > 0 \\ 0 & \text{otherwise} \end{cases}$$

There is a unit penalty for each tardy job. It does not consider the amount of tardiness involved for any job. An equivalent measure namely percentage tardiness ($\%T = \Sigma U_j/n \times 100$) is also used extensively in literature.

The conditional mean tardiness described as

$$CMT = \frac{\Sigma_j T_j}{\Sigma U_j}.$$

measures the average amount of tardiness for the completed jobs which are found to be tardy.

Name	**Notation**	**Regular**	**Type**
Makespan	$C_{\max}$	yes	minimax
Maximum tardiness	$T_{\max}$	yes	minimax
Total tardiness	$\Sigma_j T_j$	yes	mini-sum
Mean tardiness	$\bar{T}$	yes	mini-sum
Conditional mean tardiness	CMT	no	mini-sum
Total weighted tardiness	$\sum_j w_j T_j$	yes	mini-sum

Table 1.1 – *Some Performance Measures*

Performance measures can be classified into regular ones and those that are not. A regular measure of performance is one that is non-decreasing in the completion times C_1,...,C_n. Thus R is the function C_1,C_2, ...,C_n such that

$$C_1 \leqslant C'_1, C_2 \leqslant C'_2, \ldots, C_n \leqslant C'_n, \text{ together}$$

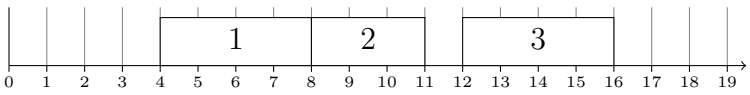
$$\Rightarrow R\{C_1, C_2, \ldots, C_n\} \leqslant R\{C'_1, C'_2, \ldots, C'_n\}.$$

Maximum completion time ($C_{\max}$) and mean tardiness ($\bar{T}$) are examples of regular measure whereas CMT is not a regular one. Table 1.1 lists a few performance measures.

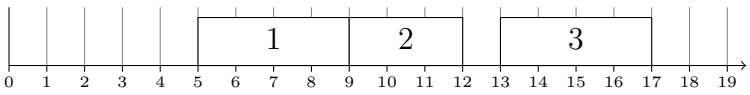
Two different solutions are illustrated in Figure 1.2 for problem of Table 1.3. If we compare, for example, the σ_1 and σ_2 schedules, although $C_{\max}$ is higher for the σ_2 schedule, the CMT obtained is less for this schedule, *i.e.* $C_{\max}(\sigma_1) \leqslant C_{\max}(\sigma_2)$ does not imply $CMT(\sigma_1) \leqslant CMT(\sigma_2)$. Hence CMT is a non-regular measure.

j	r_j	p_j	d_j
1	0	4	8
2	2	3	8
3	4	4	12

Table 1.2 – *An example problem to illustrate Regular measure*



(a) σ_1: $C_{\max}$= 16, CMT= 3.5



(b) σ_2: $C_{\max}$= 17, CMT= 3.33

Figure 1.2 – *Schedules for problem in Table 1.2 illustrating performance measures*

Single Objective Optimization

In a single objective scheduling problem, it is desired to find a feasible schedule with the best possible quality of only one objective. Majority of the literature on scheduling tackles

the problems with a single objective.

Multi-objective Optimization

Generally, single objective scheduling problems make the major part of the literature in machine scheduling domain. However, it is often desired to have multiple preferences for a solution to find. These preferences may lead to conflicting objectives. Thus maximizing one objective may degrade the other objectives to an unacceptable level. It is required to find a compromise solution, satisfying all given objectives simultaneously, although may not be optimal with respect to a single objective.

Multi-objective (MO) optimization is the process of simultaneously optimizing two or more objectives subject to certain constraints. A multi-objective optimization problem is defined by (Ehrgott and Gandibleux, 2000) as

$$\min f(x),\ x \in X, \qquad \text{where } f(x) = [f_1(x), f_2(x), ..., f_p(x)]^T$$

with each $f(x) \in Y$, p being the number of objectives, X is the set of all possible solutions and Y is the objective space.

We speak of dominance of solutions as the way to compare the solutions of a multi-objective problem. If $x_1, x_2 \in X$ and $\forall k, f_k(x_1) \leqslant f_k(x_2)$, with at least one strict inequality, we say x_1 dominates x_2 ($x_1 \succ x_2$) and $f(x_1)$ dominates $f(x_2)$. A feasible solution $\hat{x} \in X$ is efficient or Pareto optimal if there is no other $x \in X$ such that $\forall k, f_k(x) \leqslant f_k(\hat{x})$ with at least one strict inequality, *i.e.* there is no solution at least as good as x. As $\hat{x}$ is efficient then $f(\hat{x})$ is called non-dominated point (Ehrgott and Gandibleux, 2000). It is generally required to generate a set of efficient solutions. The set of all efficient solutions is denoted by X_E, the representation of X_E in objective space is called the efficient frontier or Pareto front, and the set of all non-dominated points $\hat{y} = f(\hat{x}) \in Y$ by Y_E. Figure 1.3 illustrates the difference between dominated and non-dominated solutions in a bi-objective space.

There are different approaches, found in literature to solve multi-objective optimization problem.

- **Weighted sum approach:** In this approach, a multi-objective problem is transformed into single objective problem by aggregating all the objectives. This single objective problem is then solved repeatedly with different parameter values. This is the most commonly used technique to find X_E. X_E can be partitioned into supported efficient solutions and non-supported efficient solutions, X_{SE} and X_{NE} respectively.

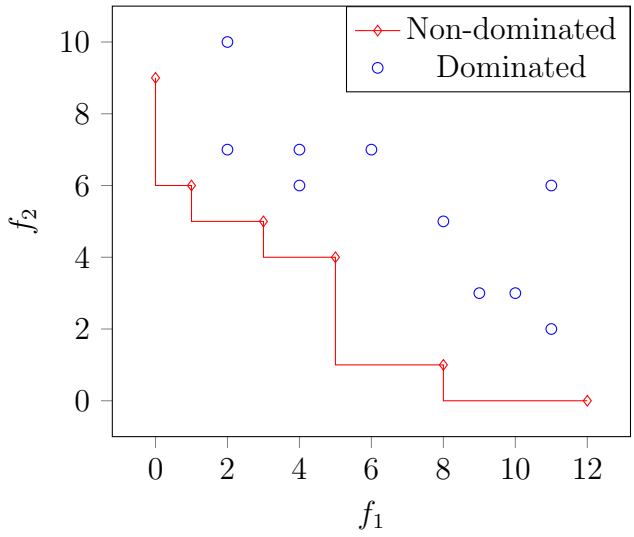


Figure 1.3 – *A bi-objective space with dominated and non-dominated solutions*

$x \in X_{SE}$ is an optimal solution of the following parameterized single objective problem for some non-negative $\lambda = (\lambda_1,\lambda_2,...,\lambda_p), \forall k$

$$\min_{x \in X} \sum_{k=1}^{p} \lambda_k f_k(x).$$

- **ϵ-constraint approach:** The ϵ-constraint method is another technique to solve multi-objective optimization problems that consists of minimizing one of the objectives with an upper bound constraints on the other objectives.
- **Lexicographic approach:** In this approach, the objectives are ranked in a certain priority order and then optimized in that order without degrading the already optimized objectives.
- **Pareto approach:** This approach is aimed at generating the complete set of efficient solutions.

1.3 Classes of Schedules

Assumptions have to be made with regard to what the scheduler may or may not require when he generates a schedule. For example, it may be the case that a schedule must not have any unforced idleness on any of the machines or vice versa.

The schedule space can be partitioned into subclasses on the basis of how different operations are executed on the time horizon. These classes help to rank different schedules

according to some regular performance measure. Figure 1.4 illustrates the schedule space of these classes as a Venn diagram for a regular performance measure.

1.3.1 Feasible schedule

A schedule is feasible if the execution order of all the jobs respect all the specified constraints of the scheduling problem.

1.3.2 Semi-active schedule

A semi-active schedule is a left-aligned feasible schedule where no task can be shifted to its left without changing the order of operations and without delaying any other operation. Hence it is not possible to finish an operation earlier on a machine without reordering tasks. In such a schedule the only way to improve the makespan is by reordering the sequence of operations on the machines. For each processing sequence, there exists a unique semi-active schedule (French, 1982). On the Gantt diagram, such a schedule may be seen as a schedule where no sliding of a block to its left is possible.

1.3.3 Active schedule

A feasible schedule is active if no operation can be processed earlier without delaying the starting date of another operation. This means that the schedule is left-shift and there in not enough room available between any two jobs where some other job may be inserted without violating any of the constraints. An active schedule is necessarily a semi-active schedule as well. To minimize a regular measure of performance it is sufficient to consider active schedules only.

On Gantt diagram, it may be seen as schedule where there is neither the possibility of sliding a block to its left, nor the leap frogging of a block to its left is possible. Of course, generating an active schedule for a given processing sequence may alter the sequence of operations, if there is possibility of leap-frogging.

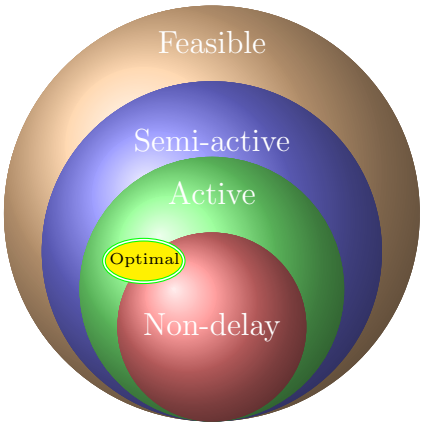


Figure 1.4 – *Classes of Schedules*

1.3.4 Non-delay schedule

A schedule is called non-delay if no machine is kept idle while an operation is waiting for being processed on that machine. A non-delay schedule is necessarily an active schedule and hence semi-active as well.

1.3.5 Optimal schedule

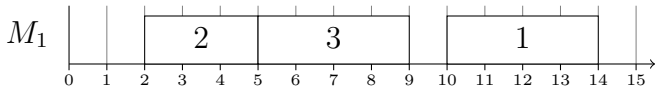
An optimal schedule is a schedule that gives the best possible value for some given performance measure. There may be more than one optimal schedules for the same performance measure. For more than one objective, the sense of optimality is quite different as explained in § 1.2.4. Note that at least one optimal schedule is active, however there need not be an optimal schedule, which is non-delay.

Consider an example of a single machine problem with three single-operation jobs as given in Table 1.3. Figure 1.5 illustrates these classes of schedules for this simple problem.

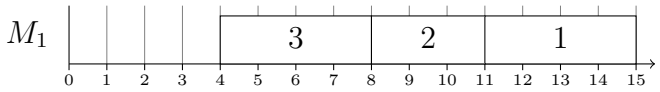
Schedule σ_1 (Figure 1.5(a)) is not a semi-active schedule, because job 1 starts at $t = 10$,

j	r_j	p_j
1	0	4
2	2	3
3	4	4

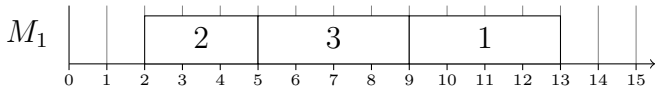
Table 1.3 – *An example problem to illustrate classes of schedules*



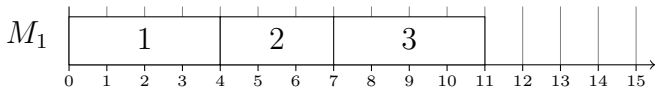
(a) σ_1: Non Semi-active schedule



(b) σ_2: Semi-active schedule



(c) σ_3: Active schedule



(d) σ_4: Non-Delay schedule

Figure 1.5 – *Schedules of the problem described in Table 1.3*

that could have started at $t = 9$ without violating any constraint, and without changing the execution order of jobs on the machine. Since this ordering is not semi-active, it is neither active nor non-delay.

Schedule σ_2 (Figure 1.5(b)) is a semi-active schedule as no job can be slid towards its left without reordering the tasks. It is not an active schedule. In fact, if job 3 is at first position, the schedule can never be active as there will always be a room for job 1 before job 3. As it is not active, so it is also not non-delay.

Schedule σ_3 (Figure 1.5(c)) is an active schedule (and a semi-active as well) because no job can be shifted towards its left without delaying other tasks. It is however, not a non delay schedule as job 1 could have been processed on machine at $t = 0$, but machine is kept idle.

Schedule σ_4 (Figure 1.5(d)) is a non-delay (as well as active and semi-active) as machine is never kept idle when a job was available.

■

1.4 Classification and Notations of Scheduling Problem

Based on the job arrival process, scheduling problems in which number of jobs are known and fixed with all jobs having the same ready times are referred as static problems in contrast to the dynamic problems in which jobs are continually revealed during the execution process (French, 1982).

Scheduling problems with all the variables describing the problem data (*e.g.* process times) are known a priori are termed as deterministic problems in contrast to stochastic scheduling problems where these variables are probabilistic in nature.

Scheduling problems can have single stage and multi-stage environments. In a single stage environment, each operation goes through one machine only. In a multi-stage environment, an operation can be executed by one of the machines of the same stage, so a machine has to be selected first to perform the operation (Pinedo and Chao, 1999).

There are different notations used to classify scheduling problems. (Conway *et al.*, 1967) formulated a four field notation, A/B/C/D which is suitable for basic scheduling problems. In this notation, the field A represents number of jobs, B represents number of machines, C represents the shop environment and D represents the scheduling objective. MacCarthy and Liu (1993) improved this notation by proposing several modifications to C descriptor. Graham *et al.* (1979) proposed a three field notation α, β and γ. This is the most used descriptive method to represent a scheduling problem.

1.4.1 α field:

The α field describes the machine environment. It consists of α_1 and α_2 where α_1 is the type of shop and α_2 is the number of machines in the problem and is optional. If this field is empty, then the number of machines is the data of the problem. Some notations of α field are given in Table 1.4.

Machine environments can be classified in two categories. In the first category, each job requires one and only one machine. Single machine, identical parallel and unrelated parallel machine environments fall into this category. In the second category, there are m different work-centers with each work-center consisting of one or many parallel machines. Each job $\mathcal{J}_j \in \mathcal{J}$ consists of a set of operations $\mathcal{O}_j$. Depending upon the routing policy of

Table 1.4 – *Some examples for the field* α

α	**Description**
ϕ	Single machine, the value for the field α is "1"
Pm	m Identical parallel machines
Qm	m Parallel machines with different speeds
Rm	m Unrelated parallel machines
Fm	m machine flow shop
FFc	c stages in series as a flow shop with each stage as Pm or Qm
$F_\pi m$	Permutation flow shop of m machines
Jm	m machine job shop
FJc	c work-centers with each work center as Pm or Qm
Om	m machine open shop

these operations on the machines, three different classes of machine environments can be identified.

Flow shop

All jobs are to be processed sequentially on multiple machines where each job has to follow the same route. Figure 1.6 demonstrates a three machine flow shop. A generalization of flow shop is the flexible flow shop that consists of a number of stages in series with a number of machines in parallel at each stage. There exist many variants of the flow shop *e.g.* zero-buffer flow shop, flow shop with blocking, no-wait flow shop and the hybrid flow shop. Academic research, however is more focused on a simplified version of flow shop, the permutation flow shop where jobs are to to be processed in the same sequence by each of the machine. A permutation flow shop is illustrated in Figure 1.7.

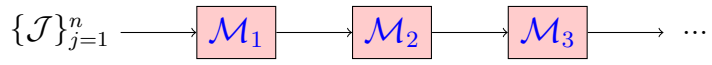


Figure 1.6 – *A three machine flow shop,* $F3$

Job shop

In a job shop, each job has its own predetermined route to follow. It is a generalization of a flow shop (A flow shop is a job shop in which each job has the same route). Job shop

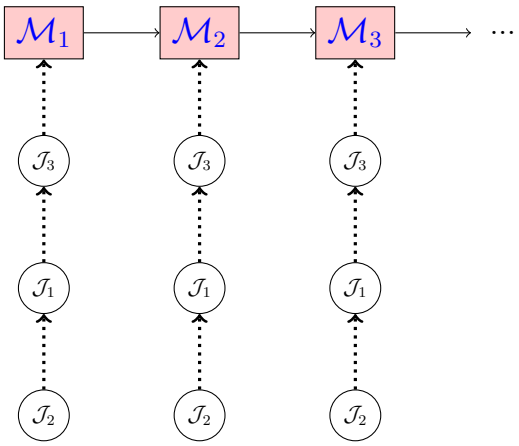


Figure 1.7 – *A three machine permutation flow shop,*$F3|prmu|-$

has a special precedence relation of the form $\mathcal{O}_{j1} \rightarrow \mathcal{O}_{j2} \rightarrow \mathcal{O}_{j3} \rightarrow \ldots \mathcal{O}_{jo_j}, \forall j \in \mathcal{J}$. A generalization of the job shop is the flexible job shop with work-centers that have multiple machines in parallel. Each job visits each machine at most once, however in a variant of job shop, called recirculation job shop, a route may not go through all machines however a job may have multiple visits on a machine for execution of its operations. The latter case is represented by a *rcrc* entry in the β-field. A flexible job shop with recirculation is considered the most complex machine environment from combinatorial point of view, and is very common in semiconductor industry (Pinedo and Chao, 1999). Figure 1.8 illustrates a simple job shop with three machines.

$$\begin{array}{lccc} \mathcal{J}_1: & \mathcal{M}_1 & \mathcal{M}_2 & \mathcal{M}_3 \\ \mathcal{J}_2: & \mathcal{M}_2 & \mathcal{M}_1 & \mathcal{M}_3 \\ \mathcal{J}_3: & \mathcal{M}_3 & \mathcal{M}_2 & \end{array}$$

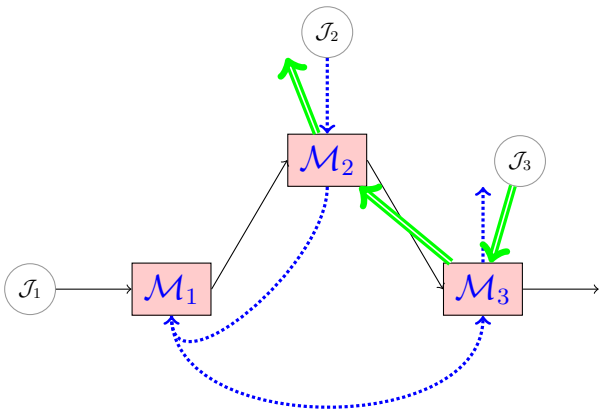


Figure 1.8 – *A three machine job shop, J*3

As in this study we focus on job shop problem, a detailed description of the job shop is

given in § 1.6.

Open shop

In an open shop, there is no predefined sequence of operations among jobs *i.e.* jobs do not have a predefined routing, instead it is established during the scheduling.

In a mixed shop, the machine routes of jobs can either be fixed or unrestricted. It can be regarded as a mix of aforementioned shops.

1.4.2 β field:

The β field describes the constraints and particularities of the problem. For example:

Deadline These are imperative due-dates. A deadline is a due date for which tardiness is not allowed.

Preemption Processing of a job on a machine may be interrupted and resumed at a later time even on a different machine and already processed amount is not lost.

Precedence One or more jobs have to be completed before another job is allowed to start.

Release Date The release date of job $\mathcal{J}_j$, is the time when a job is arrived at the system to be processed and the job cannot start its processing before release date.

Some possible entries of β field and their notations are given in Table 1.5.

Any other entry that may appear in the β field is self-explanatory. For example, $p_j = p$ implies that all processing times are equal and $d_j = d$ implies that all due dates are equal. Due dates, in contrast to release dates, are usually not explicitly specified in this field; the type of objective function gives sufficient indication whether or not the jobs have due dates.

1.4.3 γ field:

The $\gamma \in \{f_{max}, \sum f\}$ field describes the objective function and is similar to the D descriptor of the notation of Conway *et al.* (1967).

■

Table 1.5 – *Some examples for the field β*

β	**Value**	**Description**
β_1	pmtn, ϕ	pmtn: preemption is allowed
		ϕ: preemption is not allowed
β_2	res♯, ϕ	res♯: ♯ limited number of resources
		ϕ: no resource limitation
β_3	prec, tree, ϕ	prec: a precedence relation between jobs is specified
		tree: a tree like precedence relation between jobs is specified
		ϕ: no precedence relation
β_4	r_j, ϕ	r_j: release dates are specified
		ϕ: $\forall j$, $r_j = 0$
β_5	$\mathcal{J} \leqslant p$, ϕ	$\mathcal{J} \leqslant p$: all jobs have at most p operations
		ϕ: no restrictions on size of jobs
β_6	$p_{jk} = 1$, $a \leqslant p_{jk} \leqslant b$, ϕ	$p_{jk} = 1$: each operation has a unit processing time
		$a \leqslant p_{jk} \leqslant b$: processing time of each operation has a lower bound a and an upper bound b
		ϕ: no restriction on processing times

Table 1.6a – *Some examples for the field γ*

γ	**Description**
$C_{\max}$	Makespan
$T_{\max}$	Maximum tardiness
$\Sigma_j T_j$	Total tardiness
$\bar{T}$	Mean tardiness

Some are given in Table 1.6a. For multi-objective problems, list of objectives separated by comma are used in γ field. For instance, a single machine problem with $C_{\max}$ and $\bar{T}$ can be noted as $1||C_{\max},\bar{T}$. Moreover, based on the method to compute Pareto optimum, different values for the γ field can be introduced, as shown in Table 1.6b.

Table 1.6b – *Some MO examples for the field* γ

γ	**Description**
$\sharp(f_1,...,f_K)$	Enumeration of non-dominated solutions
$Lex(f_1,...,f_K)$	Lexicographic optimisation of K objectives
$F_l(f_1,...,f_K)$	Convex combination of K objectives
$\epsilon(f_1,...,f_K)$	ϵ-constraint method of K objectives

1.5 Scheduling Phases

1.5.1 Predictive Phase

The phase of a scheduling method that takes place before the actual execution of the schedule is referred as predictive phase. This phase of the scheduling method is generally not time constrained in terms of finding the solution and is applied to the model of the real system as an off line method.

1.5.2 Reactive Phase

The reactive phase of a scheduling method takes place during the execution of the schedule. The scheduling method during this phase, therefore can observe the occurrence of actual events of the system. However the scheduling method during this phase must not be too time consuming.

1.6 Job Shop Scheduling Problem

Our focus in this study is on a specific scheduling environment, namely job shop. Here we shall describe the formal definition of a job shop scheduling problem (JSSP), graphical representation, its complexity, different benchmark problems and a brief overview of resolution approaches for JSSP.

1.6.1 Formal definition of JSSP

The job shop scheduling problem with multiple precedence constraints is a combinatorial optimization problem composed of a finite set $\mathcal{J}$ of n jobs $\{\mathcal{J}_j\}_{j=1}^{n}$ to be processed on a finite set $\mathcal{M}$ of m resources $\{\mathcal{M}_k\}_{k=1}^{m}$. A job $\mathcal{J}_j$ consists of a sequence $\mathcal{O}_j = (\mathcal{O}_{j1},\mathcal{O}_{j2},...\mathcal{O}_{jo_j})$ of o_j operations with each operation $\mathcal{O}_{jk}$ as part of exactly one job $\mathcal{J}_j$ to be processed during a processing time $p_{jk} > 0$ on a resource $\mathcal{M}_k$. A resource can execute only one operation at a time. Solving a job shop problem is the task of assigning each operation, a specific position on the time scale of specified machine while optimizing a set of given performance measures (Conway, 1965b).

Generally size of the JSSP is given as $m \times n$. An instance of a JSSP is given in table Table 1.7.

Job	r_j	machine sequence	p_{jk}
$\mathcal{J}_1$	0	$\mathcal{M}_1$, $\mathcal{M}_2$, $\mathcal{M}_3$	p_{11}=10, p_{12}=8, p_{13}=4
$\mathcal{J}_2$	0	$\mathcal{M}_2$, $\mathcal{M}_1$, $\mathcal{M}_4$, $\mathcal{M}_3$	p_{22}=8, p_{21}=3, p_{24}=5, p_{13}=6
$\mathcal{J}_3$	0	$\mathcal{M}_1$, $\mathcal{M}_2$, $\mathcal{M}_4$	p_{31}=4, p_{32}=7, p_{34}=3

Table 1.7 – *An instance of a JSSP*

1.6.2 Graphical Representation

1.6.2.1 Gantt Diagram

Gantt diagram is a very simple and extensively used tool to graphically present the execution order and timings of tasks on the machines throughout the time horizon. Gantt diagram can be machine-oriented or job-oriented. In this study, all the Gantt diagrams will be machine-oriented. An example of a machine-oriented Gantt diagram is shown in Figure 1.9 for an arbitrary feasible solution for the problem instance given in Table 1.7.

1.6.2.2 Disjunctive Graph

Although Gantt diagram is an excellent monitoring tool of a schedule, it is incapable of representing the problem itself. Disjunctive graph representation proposed by (Roy and Vincke, 1981) is able to effectively represent a scheduling problem.

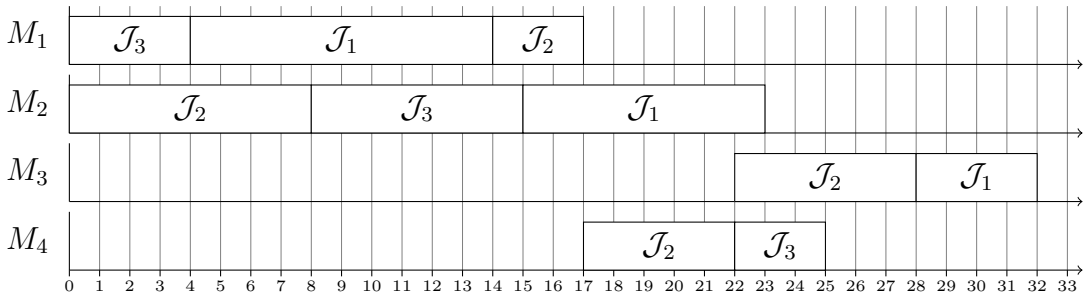


Figure 1.9 – *Gantt diagram for a schedule for the problem in Table 1.7.*

A disjunctive graph is a 3-tuple G=(V,C,D) with V as set of vertices representing the set of operations $\mathcal{O}$ and two special vertices as a source node and a terminal node, C as set of conjunctive arcs representing the given precedence constraints between the operations of the same job, and set of disjunctive arcs by D=$\{\{u,v\}|u,v \in \mathcal{O}, u \neq v, \mathcal{M}(u) = \mathcal{M}(v)\}$ represent the machine capacity constraints. Each arc has a weight, equal to the processing time of the operation corresponding the vertex from which the arc emits. Figure 1.10 illustrates a disjunctive graph for a job shop problem with four machines and three jobs as given in Table 1.7. For even a slightly larger problem, the disjunctive graph representation gets too complicated to visualize. A relatively simplified version the disjunctive graph, where instead of inter-connecting all the operations of the same machine by disjunctive arcs, only one disjunctive arc is drawn, may be used (as shown in Figure 1.11). By setting the direction of each arc such that there are no cycles in the disjunctive graph, a solution to the problem is represented, as shown Figure 1.12.

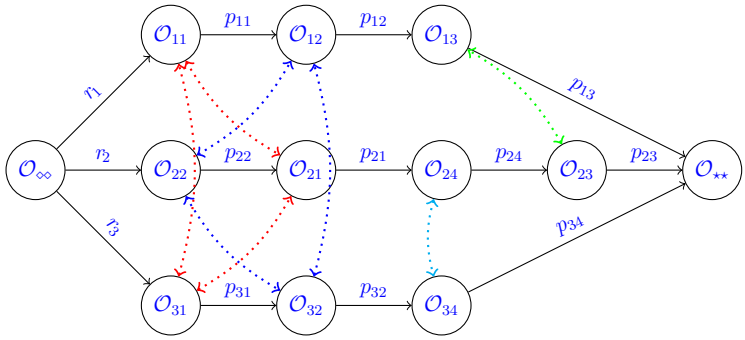


Figure 1.10 – *Disjunctive graph representation of problem in Table 1.7*

1.7 Solving Methods

There has been extensive research in a plethora of methods to solve JSSP. These methods can be classified in three broad classes of exact, heuristic and AI based methods. An excellent survey on these methods is presented by (Jain and Meeran, 1998). A brief review

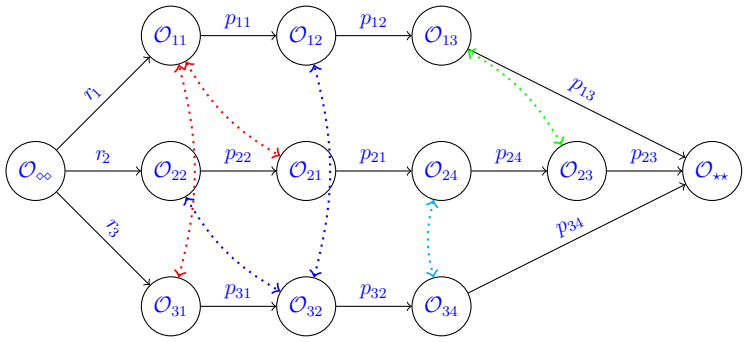


Figure 1.11 – *Simplified Disjunctive graph representation of problem in Table 1.7*

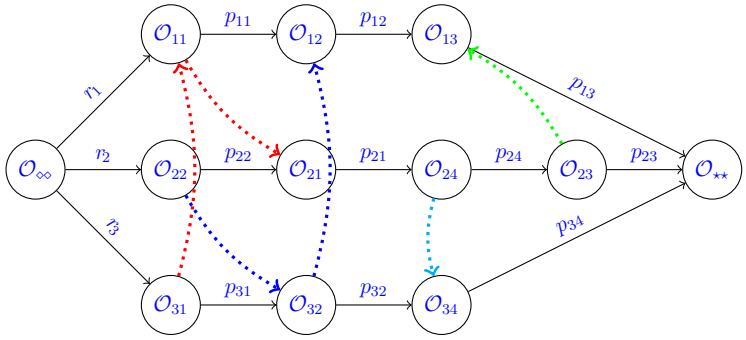


Figure 1.12 – *Disjunctive graph representation of solution*

of different methods is presented in this section.

1.7.1 Exact methods

Exact methods are guaranteed to find an optimal solution for a finite size instance of a combinatorial optimization problem in a bounded time. However, for a typical combinatorial optimization problem like JSSP, no algorithms exist to solve these problem in polynomial time (Conway *et al.*, 1967; French, 1982). Enumerative methods such as branch and bound algorithms, mathematical programming (Integer Linear Programming (ILP) and Mixed Integer Linear Programming (MILP)) are the most well-known methods to solve scheduling problems like JSSP. Branch and bound methods are very sensitive to individual instances and the initial bounds used. They are found to be unsuitable for larger instances.

1.7.2 Approximation methods

The computational complexities required by exact methods lead the research to approximation methods. Solutions by such methods are obtained in reasonable computational

times, however these are not guaranteed to be optimal. These can be divided into constructive and iterative methods.

1.7.2.1 Constructive methods

In these methods, the schedule is generated gradually by adding schedulable operations to an initially empty schedule. Priority dispatching rules (pdrs), such as First In First Out (FIFO) and Earliest Due Date (EDD) *etc.* are among the most widely used constructive heuristics for shop scheduling problems due to their ease of implementation and substantially lower computational requirements. They give inferior quality schedules in general, however some pdrs generate optimum schedules for some simple problems. There does not exist a single rule that can be applied to all shop problem with a satisfying performance. Moreover, it is not possible to estimate the performance of a pdr for a specific instance a priori (Zobolas *et al.*, 2008).

Shifting Bottleneck (SB) heuristic have been a very effective heuristic in job shop scheduling. In SB heuristic, several single machine problems are solved to optimality. Bottleneck machine is selected first for the optimization, where bottleneck machine is defined as the machine having longest makespan as its optimum. The algorithm continues until all machines are scheduled.

1.7.2.2 Iterative Methods

Iterative methods such as meta-heuristics efficiently and effectively explore the search space driven by logical moves and knowledge of the effect of the move facilitating the escape from locally optimum solutions (Blum and Roli, 2003). Two important ways to classify the meta-heuristics are population based vs single point search and memory based vs memory-less meta-heuristics (Jain and Meeran, 1998).

Most known meta-heuristic algorithms applied to JSSP include evolutionary algorithms (EA), particle swarm optimization (PSO), ant colony optimization (ACO), scatter search, exploratory local search, neural networks, simulated annealing (SA) and tabu search (TS).

Population based meta-heuristics work simultaneously on a set of solutions. Genetic algorithms are the most important representatives of this class among others concerning the literature on JSSP. However, Genetic algorithms are not found to be suitable for fine-tuning of solutions close to optimal (Zobolas *et al.*, 2008). PSO and ACO did not find any significant success as well in this domain, except when hybridized with other methods.

Simulated annealing (SA) is one of the earliest proposed meta-heuristic. However, it is unable to quickly achieve good solutions to JSSP. This is generally attributed to its generic nature and memory-less functionality.

Tabu search has been shown to be a very powerful meta-heuristic for JSSP (Nowicki and Smutnicki, 1996; Jain and Meeran, 1998; Watson *et al.*, 2006; Zobolas *et al.*, 2008; Zhang *et al.*, 2008). The main characteristic of tabu search is its memory-usage which is an indication of intelligence employed during the search process.

1.8 Conclusions

In this chapter, the basic notions of the scheduling domain are presented. More specifically, the problem of job-shop is presented with its variants and representation schemes. Like most of the real-world scheduling problems, job shop problem is $\mathcal{NP}$-hard with a very few exceptions. To solve job shop problems, numerous techniques have been applied belonging to the category of either exact methods or approximate methods and in nature either constructive or iterative. However, none of these methods is capable to show its supremacy over others in all desired aspects of solving the problem. On one side, some of them are too time-consuming to be adopted or very specific to the environment while on the other hand, some of the methods perform very poorly despite being fast and/or generic. In the next chapter, we present a review of a very important class of methods, called priority dispatching rules, that gained much attraction of the researchers due to their extensive use in real-time systems and ease of implementation.

2 A State of the Art Survey of Priority Dispatching Rules

For real-time management of waiting-lines in manufacturing system, priority dispatching rules appear to be the most frequently used method. Over the years, numerous dispatching rules have been proposed by the researchers. This chapter provides a survey of priority dispatching rules that have been extensively used by researchers and practitioners. All the rules presented in this chapter are described in Annex A.

2.1 Introduction

Although approximation methods to solve job shop scheduling problem do not guarantee achieving optimal solutions, they are able to attain acceptable solutions within moderate computing times and are therefore more suitable for larger problems. Koulamas (1994)

states that there is abundant of optimization procedures available for a variety of standard scheduling environments such as single-machine, flow shop and job shop settings. However, these procedures are generally limited to static problems of relatively smaller in size (Panwalker and Iskander, 1977). Hence, more scheduling research introducing efficient heuristics has been called for especially for large-size dynamic problems. According to (Jain and Meeran, 1998), approximation procedures applied to job shop scheduling problem were first developed on the basis of priority dispatching rules (pdrs). Many different terms such as priority rule, dispatch heuristic, and scheduling rule are used to refer to the principles that determine the relative importance of a job among all waiting jobs when selecting the next one for processing without inserting idle time. However, it is possible in practice that some idle time is inserted in the schedules while waiting for a soon-to-arrive urgent job instead of prioritizing back-logged jobs.

In the dispatching approach, each machine is loaded as soon as there is at least one job awaiting service in front of the queue, eliminating any unnecessary idle time of the resources. At each successive step all the operations which are available to be scheduled are assigned a priority index and the operation with the highest priority index is chosen to be sequenced. In most of the cases, this is referred as implicit scheduling decision based approach, where the impact of each dispatching decision on the completion times of other jobs is not monitored (Kemppainen, 2005).

The general approach for a dispatching rule, according to (Montana, 2005), is to define a score associated with assigning a given task to a given resource and select the eligible task that minimizes (or maximizes) that score for the chosen resource. (Haupt, 1989) defines it as a policy with a specific sequencing decision, applied each time a resource gets idle. According to him, priority rule-based scheduling approach considers the sequencing decision as a set of independent decentralized one-machine problems.

A priority dispatching rule (pdr) determines a value of priority index, κ_j, for any job $\mathcal{J}_j$ in a given scheduling situation, and of a ranking procedure using the priority indices for selecting one of the schedulable jobs waiting on an idle machine to be started next (Baker, 1974; Panwalker and Iskander, 1977).

Dynamic scheduling uses dispatching rules to prioritize jobs waiting for processing at a resource (Vieira *et al.*, 2003). Due to their ease of implementation and their substantially reduced computational requirement they remained a very popular technique despite of their poor performance in the long run (Baker, 1974; French, 1982; Morton and Pentico, 1993). This approach is best when there is on-line scheduling (*i.e.* tasks being revealed during execution), the fundamental time scale of the problem is short, and the future is very uncertain (Montana, 2005).

This chapter provides a state-of-the-art review on priority dispatching rules in context with job shop scheduling environment. In § 2.2, we present frequently used classification schemes for pdrs found in literature. In § 2.2, different pdrs have been discussed. In the next section a comparative analysis of these pdrs is made. In the last section we draw some concluding remarks.

2.2 Classification of Priority Dispatching Rules

For identifying the characteristics and making a comparative study of the behavior of different priority dispatching rules, it is important to classify the priority dispatching rules. A number of classifications of pdrs have been presented in the literature that help to improve the understanding of the status of research in this area. Generally, structural based, information based or performance measure based classifications of pdrs are found in literature. However, the classification is not unique as some pdrs may fall in multiple classes.

2.2.1 Structure Based Classification

A structure based classification (Panwalker and Iskander, 1977) divides the pdrs in three broad classes namely, basic rules, heuristic scheduling rules and other rules. Basic rules are further categorized as simple, composite and weighted priority rules. Simple rules typically use job-specific information like processing times, due dates or the queue length at next machine for the job. The composite rules apply different pdrs to certain groups of jobs or use different pdrs depending on the shop status and circumstances. The weighted priority rules combine different simple or composite rules by assigning parameterized weight to each rule. The heuristic scheduling rules, such as CEXSPT, (although not considered as pdrs by (Panwalker and Iskander, 1977)) involve a relatively complex consideration of situations such as anticipated waiting times on subsequent machines and the effect of alternate job routing etc. They may also include non-mathematical aspects such as inserting a job in an idle time slot by visual inspection (Kemppainen, 2005). Other rules include rules designed for specific shop, combination of priority indexes based on mathematical functions of job parameters or those that are not categorized earlier.

2.2.2 Information Based Classification

Information based classification divides the pdrs in three classes based on information content (Blackstone *et al.*, 1982), scope and detail of information and time dependency.

Based on the Information Content

Pdrs based on individual piece of information related to job, queue or resource may be grouped in the information content based class.

Based on the Scope and Detail

Scope and detail based classification groups the pdrs in local and global pdrs (Hausman and Scudder, 1982). The rule is local, if the priority index is based on the information of the current machine, queue and/or the attributes of the jobs in the queue of current machine only. On the other hand, a global rule uses information concerning the status of the shop, such as the length of the current queue relative to the average queue length in the shop or system load etc. A global rule may further be sub-divided as indirect global and direct global, based on how the global information is obtained (Vepsalainen, 1984). For indirect global pdrs, the information is derived from aggregate system indicators (*e.g.* distribution of processing times) without any explicit reference to the attributes of the specific jobs to be scheduled on subsequent machines. In contrast, direct global rules use explicit, observable or anticipated global information pertaining to specific jobs (*e.g.* queue length on the next machine).

Based on the the Horizon of Information

Based on the horizon of information, a pdr can be static or dynamic. For a static pdr, priority index is fixed when the job is introduced and hence it is based on the initial data only. So for a static rule, the information on which the priority index is assigned, is not changing over time and for on-going scheduling process, it may be seen as information from past. Dynamic priority index depends on the actual evolution of the system and cannot be computed in advance (Moser and Engell, 1992). So for dynamic pdrs (some of) the information content used to assign priority index is changing over time. However, this information is from observable status of the shop only without any forecasting (hence referred as myopic dynamic pdrs).

The concept can be extended to take future information by forecasting as well and then providing a feedback for current scheduling decision to be made. On the basis of type of

information feedback, (Vepsalainen, 1984) divided the dynamic pdrs as anticipated status feedback and performance feedback.

Anticipated status feedback The anticipated status of the shop in the future is used as feedback, for example average queue lengths estimated through aggregate forecasts or detailed forward simulation.

Performance feedback The anticipated performance of the rule over some forecasting horizon is used as feedback to adjust its parameters .

Moser and Engell (1992) have classified the rules as being a-priori and a-posteriori, where in a-priori rules the priority index is computed from j^{th} operation alone in contrast to a-posteriori rule which considers the situation which would arise if j^{th} operation is scheduled as the next operation. A-posteriori rules can be seen as general dynamic pdrs with feedback (usually obtained by repeated forward simulations) .

Kutanoglu and Sabuncuoglu (1999) have classified pdrs into two categories: (1) single-pass and (2) multi-pass. In single-pass heuristics, a single complete solution is built up one step at a time. Most priority dispatching rules proposed in the literature can be considered in this category. In multi-pass heuristics, an initial schedule is generated in the first pass, and then the consecutive passes search, for improvement in performance *e.g.* iterative dispatching.

The generic rules, that are not specific to a particular manufacturing facility, are classified using a matrix form by (Kemppainen, 2005) where it is assumed that the positioning of a rule within the classification predicts its performance as a coordinative mechanism, shown in Figure 2.1. These categories are briefly described below.

Priority index fixed on entry based on job-specific information The pdrs relying on static data typically use information on job attributes only. Examples of such rules include earliest due date(EDD), number of operations (NOP), and first come first served (FCFS). Some composite rules like average processing time AVPRO also fall in this category.

Priority index fixed on entry using operations detail information SI, FIFO and operational due date (ODD) rules fall in this category. Also there are other rules, which can be implemented with operation-specific information.

Priority index fixed on entry using load and resource information Priority dispatching rules that use information about the machine for which the dispatching decision is done fall in this category. For example, the value of the shortest setup (SST) rule depends on both the machine and imminent operation.

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Priority index updated by stage using job-specific information Many of the generic dispatch priority rules are stage-update-able, *i.e.* priority index values are time-dependent. Examples include the modified due date (MDD) rule and SLACK rule.

Priority index updated by stage using operations detail information This category includes several composite rules such as the process time plus process wait (PT+PW) rule, CR/SI , S/RPT+SPT (Anderson and Nyirenda, 1990) and the different versions of the SLACK rule *e.g.* slack per number of operations (S/OPN), slack per time allowable (S/RAT), and slack per remaining processing time (S/RPT).

Priority index updated by stage using load and resource information Examples of dispatch priority rules that use information about the entire production system in the calculation of job-specific priority values are the work in the next queue (WINQ) and the number of jobs in the next queue (NINQ) rules. The PT+WINQ rule introduced by (Holthaus, 1997) prioritizes jobs with the least work in the current operation and lowest expected load in the next operation.

Priority index adapted by probing and job attribute information None of the generic dispatch priority rules fall in this category. There are, however, modifications of the conventional dispatching rules such as the high response ratio (HRN) rule by (Selladurai *et al.*, 1995) and the shortest expected processing time (SEPT) rule by (Wein and Chevalier, 1992) that anticipate the processing and waiting times of jobs.

Priority index adapted by probing and operations detail data By controlling the scheduling of jobs with long processing times and by employing both job-based and operation-based due date information to expedite late jobs the CEXSPT rule decreases the undesirable property of SPT that results in some very late jobs (Schultz, 1989).

Priority index adapted by probing and load and resource information The classification of two integrated trade-off heuristics COVERT and ATC rules, depends on the lead time estimation method used. If job-specific lead times are estimated using a multiple of processing time, the rules can be positioned to category of pdrs that are updated by stage using operations detail information. With lead time iteration these methods should be classified into this category.

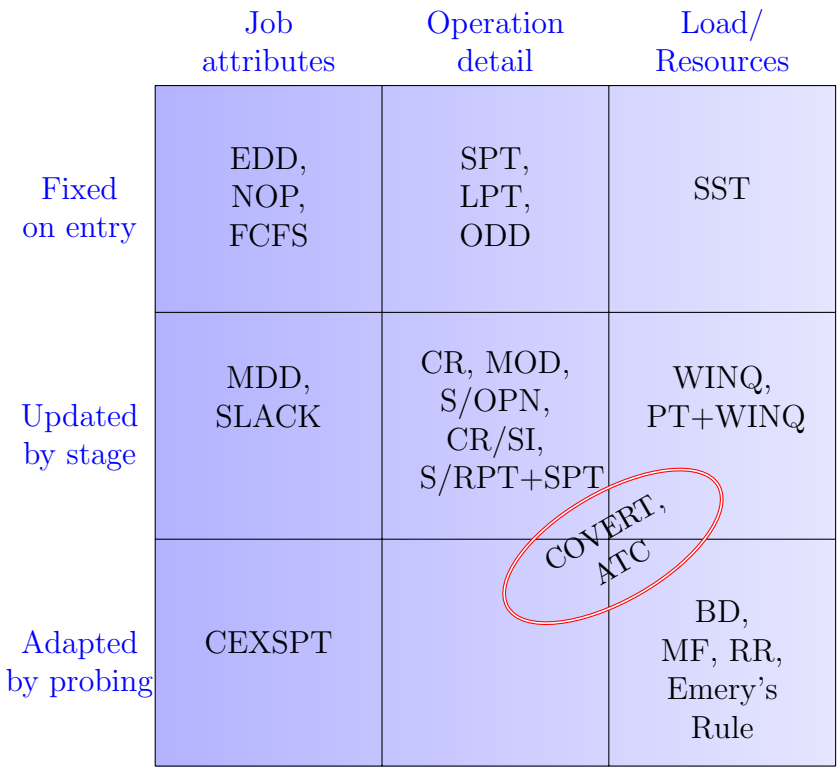


Figure 2.1 – *Classification Matrix of PDRs, adapted from (Kemppainen, 2005)*

2.3 Literature Reviews on Priority Dispatching Rules

The earliest work on pdrs was done by (Jackson, 1955, 1957; Smith, 1956; Rowe and Jackson, 1956; Sisson, 1959; Giffler and Thompson, 1960; Baker and Dzielinski, 1960; Gere Jr, 1966). The algorithm of Giffler and Thompson (1960) is the common basis of all pdrs and its importance is derived from the fact that it generates active schedules. In active schedule, the processing sequence is such that no task can be started any earlier without delaying some other task or violating the technological constraints. The procedure commences by choosing a yet to be sequenced operation, $\mathcal{O}_{jk}$, with the earliest completion time, then it finds all the other operations that use the same machine $\mathcal{M}_k$ and which start earlier than the completion time of $\mathcal{O}_{jk}$. These operations are placed in a conflict set. An operation is then selected from the conflict set and sequenced as early as possible. The procedure is repeated until all operations have been sequenced. Pdrs are characterized by the method applied to select operations from the conflict set where a random choice is the simplest priority assignment.

Jackson (1955); Moore (1968) have presented the earliest reviews on the simulation of job shop, discussing the use of priority dispatching rules.

Table 2.1 – *Relevant Literature Review on PDRs*

Reference	Conditions	Performance measures	Pdrs tested [a]
Schultz (1989)	Job Shop, TWK [b], η [c]=80%,90%	$\bar{T}$, CMT, $\%T$	CEXSPT, MOD, COVERT, SPT, ODD, S/OPN, OCR
Moser and Engell (1992)		$\bar{T}$, T_{rms}, $T_{\max}$	WLS, ODD, CR, SL/OPN, CR+SPT, SPT-T, COVERT, WINQ
Raghu and Rajendran (1993)	Open shop TWK with allowance factor of 4,5,6 η=85%,95%	$\bar{T}$, T_{rms}, $\%T$	RR, SPT, EDD, MOD, ATC , S/RPT + SPT, CR+SPT
Chang *et al.* (1995)			
Holthaus (1997)	TWK with allowance factor of 2,4,6,8 η=85%, 90%, 95%	$\bar{T}$, $T_{\max}$, $\%T$, σ_T^2	AT, AT-RPT, FIFO, SPT, WINQ, RR, RAN(SPT,WINQ), PT+WINQ, PT+WINQ+SL ,(PT+WINQ)/TIS
Kutanoglu and Sabuncuoglu (1999)	Job shop RATWK with 6,9,12 η=60%, 80%, 90%	$\bar{T}$	FCFS, WSPT, WLWKR,EDD, MDD, SLACK, CD, S/OPN, MDSPRO, ODD, OSLACK,OCR, MOD, CEXSPT, W(CR+ SPT),W(S/RPT+ SPT), COVERT
Horng and Chou (2002)	η=80%, 90% TWK with 4, 6	$\bar{T}$, $T_{\max}$, $\%T$, σ_T^2	SPT, RR ,PT+WINQ, AT-RPT, PT+WIND+AT, PT+WINQ+AT+SL, PT+WIND+SL
Dominic *et al.* (2005)			MF, SPT, EDD, Weighted COVERT, ATC
Kemppainen (2005)	Job shop RANSLK(0-6) η=85 %, 95%	$\bar{T}$, $T_{\max}$, $\%T$	EDD, CR, ODD AVPRO, SPT SLACK, S/OPN, S/RPT AT-RPT, OPSLK/PT, ODD, PT+PW ATC, COVERT, CR+SPT, PT+WINQ, PT+WINQ+SL, RR, S/RPT+SPT
Weng and Ren (2006)	Job shop TWK with 6,12 η=80%, 85%, 90%, 95%, 97%	$\bar{T}$	WR, FCFS, EDD, SPT, COVERT, ATC
Chiang and Fu (2007)		$\bar{T}$, $T_{\max}$, $\%T$	SPT, SRPT, LTWK, SPT/TWK, SLACK, EDD, MDD, ODD, MOD, COVERT, ATC, CR,PT+PW, PT+PW+ODD, WINQ, PT+WINQ+SLACK

[a] see § 2.4 and Annex A
[b] see § 2.6.3
[c] Shop Utilization

Later on, (Conway *et al.*, 1967; Jones, 1973; Holloway and Nelson, 1974; Baker, 1974) provided thorough reviews of various dispatching rules and their performance in different

circumstances. However, (Panwalker and Iskander, 1977) has provided a most comprehensive survey of scheduling heuristics presenting 113 pdrs. They reviewed and classified these pdrs along-with information about the scheduling environment and performance measures used in earlier surveys. They concluded that in many cases, the results were found conflicting due to difference in operating conditions and the underlying assumptions. They also observed that there are many rules that assign the same priority to two or more jobs waiting to be processed, requiring their use in conjunction with other rules, possibly as tie-breaking rules.

Blackstone *et al.* (1982) provide an extended discussion and summary of 34 pdrs, mostly used in literature and industrial practice. They discussed various factors that influence the performance of pdrs as well. In addition, a brief review of the "'secondary dispatching heuristics"'- procedures that may be used to identify circumstances under which the job selected by a dispatching rule should not be processed first.

Haupt (1989) reviewed 26 different pdrs (and a few pdrs for extended job shop environments), while classifying them based on the scope and time horizon. They also described two standard procedures of combining the simple pdrs, namely additive and alternative combinations, with a particular importance to the appraach proposed by (O'Grady and Harrison, 1985).

Chan *et al.* (2002) provides a state-of-the art on different scheduling strategies using simulation. They reviewed a number of publications on the use of pdrs, specifying the job configurations used by the authors.

In the next section, we present some of the most used pdrs in practice as well as in literature.

2.4 Priority Dispatching Rules

In this section, a few well-known pdrs - that have been extensively used in experimental or analytical studies on scheduling- are discussed. The names of the rules may not be the same as the names used by many researchers.

The FIFO (First In First Out) rule is considered to be a fair priority rule, especially in service operations and extensively used as a benchmark rule in literature. It is expressed as $\min_j(C_{j(i-1)})$. Job based version of the rule is FCFS (First Come First Served) and is expressed as $(\min_j(r_j))$.

SI[1] (Shortest Imminent) rule is probably the most widely tested pdr in literature. Conway (1965a) was the first to summarize that it should be considered as the standard benchmark for all dispatching studies, even though in his experiments the rule did not exhibit the minimum value for any of the performance measures including average queue length and average work-in-process measured with total work. The rule is expressed as, $\min_j(p_{jk})$. Obviously it requires a single, yet the most important piece of information, the processing time from the local queue only.

In case of a single machine static problem, it minimizes the mean flow-time (maximizes throughput), mean lateness (Conway, 1965a; French, 1982; Blackstone *et al.*, 1982) and for all due-dates to be equal or all jobs are to be inevitably finished late, this rule minimizes $\bar{T}$ as well (Moser and Engell, 1992).

This rule performs well with externally set due dates in general. For internally set due dates using TWK method (see § 2.6.3), it is found to be better than due date based rules if due dates are set at less than seven times total processing time (Elvers, 1973). The rule is found to be least sensitive to the due-date assignment method (Conway, 1965a) and forecasting errors in due dates as well (Eilon and Hodgson, 1967). The major drawback of this rule is that some jobs become very late. This results in a very high value for maximum tardiness, $T_{\max}$ and variation of the tardiness.

Eilon and Cotterill (1968); Eilon and Choudury (1975) proposed a modification of the SI rule called the SI^x rule, in order to alleviate the disadvantage of holding some jobs quite long in the queue by SI. Two separate queues with one having priority over the other are formed with both queues ranked by SI rule. Jobs with slack less than a control parameter, Q (same for all jobs) are placed in the priority queue. Although the rule reduces the variance of missed due-dates as compared to SI, the authors do not report testing the rule against other tardiness-orientated rules, nor do they provide guidance for selecting Q based on factors such as due-date tightness, shop utilization or the method of assigning due-dates.

Oral and Malouin (1973) developed a similar rule, known as the SPT-T rule. The rule combines the SI and S/OPN (defined later) rules in such a way as to retain the advantages of both while avoiding their disadvantages. Specifically, a job's priority is given by the minimum of its imminent operation time plus a control parameter, γ, and its S/OPN (*i.e.* $\min(SI+\gamma, S/OPN)$). Thus as γ is increased, the rule effectively becomes the S/OPN rule. Although the authors suggest a way to select γ, the procedure is extremely cumbersome and makes the practical implementation of the rule unappealing.

1. Some authors (Haupt, 1989) used the acronym SPT (Shortest Processing Time)to represent SI rule, while other acronyms like TWORK or TWK (Total Work Content) are used by them for SPT

Schultz (1989) proposed an expediting heuristic (CEXSPT) which attempts to lessen the undesirable properties of SI by controlling the jobs with long processing times. Job-based and operation-based due date information is employed to expedite the late jobs. CEXSPT partitions the waiting jobs into three queues according to whether a job is late (queue 1), behind schedule (queue 2) or ahead of schedule (queue 3). The job with the smallest processing time in queue 1 is processed next unless doing so creates at least one new late job, in which case, the job with the smallest processing time in queue 2 goes next provided it does not create a new operationally late job. If it does, the job with the smallest processing time in queue 3 is processed next.

EDD (Earliest Due Date) is one of the most important simple rule that formalizes a natural, intuitive due-date behavior of everyday life. It is expressed as $\min_j(d_j)$. This rule produces a lower variance for job lateness than FIFO and SI regardless of the due date assignment method (Conway, 1965a). The performance of due date based rules such as the EDD rule is excellent when there is enough production capacity. The EDD rule finds a non-tardy schedule, if feasible. It minimizes the maximum tardiness in case of a single machine (French, 1982). The performance of this rule is poor in regards with mean tardiness except in lightly loaded conditions (Weng and Ren, 2006). In the next, we discuss some rules based on due-dates.

Slack[2] (ς_j) is defined as the time until the job is due less its remaining processing time and is negative if the due date of the job has already passed.

The SLACK rule (or Minimum Slack Time (MST)) assigns the highest priority to the job with the least slack. If the dynamic slack of a job $\mathcal{J}_j$ at some instant t is negative (zero), $\mathcal{J}_j$ will definitely (most likely) be tardy. On the other hand, if the dynamic slack is positive, the job may or may not be tardy, depending on how long the job will wait at the remaining operations. If the dynamic slack exceeds some generous estimate of the waiting time, job $\mathcal{J}_j$ is expected to complete on time. This rule is expressed as,

$$SLACK = \min_j(d_j - t - \sum_{i=l}^{o_j} p_{j(i)})$$

where l is the operation number being executed at time t, for the job for which slack value is being computed. This rule is designed for due-date-related objectives. Although (Jones and Rabelo, 1998) found the basic SLACK rule to be superior to the SI rule in general, however it is outperformed by SI for congested shops and tight due dates. One reason for this behavior may be that when the slacks of all jobs are negative (*i.e.* all jobs are late), SI performs very well, but SLACK still selects to first process the least dynamic

2. Sometimes static slack is defined as well, where instead of current time, the ready time, r_j is used.

slack job, which may have a very long remaining processing time.

CR (Critical Ratio) rule gives priority to the job with the smallest remaining processing time to total processing time ratio. It is expressed as,

$$CR = \min_j \left(\frac{d_j - t}{\sum_{i=l}^{o_j} p_{j(i)}}\right).$$

Note that S/RPT is similar to CR rule, using the ratio of remaining slack to remaining work (Anderson and Nyirenda, 1990). While both SLACK and CR tend to reflect a job's urgency in a more appropriate manner than this is done by the simple allowance, they modify EDD in their own ways, SLACK referring to the difference and CR referring to the fraction of a job's allowance and its remaining work. CR might possibly be more appealing version, because a "critical" job is defined as one with CR<1 (Haupt, 1989).

S/OPN is another ratio based rule, quite similar to the S/RPT. It is expressed as,

$$S/OPN = \min_j \left(\frac{d_j - t - \sum_{i=l}^{o_j} p_{j(i)}}{o_j - i - 1}\right).$$

For ratio-based priority rules (like S/RPT, S/OPN), since a negative ratio is difficult to interpret, they have the drawback that when the remaining allowance or slack is negative, these rules behave contrary to their intent. For example, the intent of the S/OPN rule is to give relatively higher priorities to the jobs which have more remaining operations because they may encounter more queuing delay. However, when the slack becomes negative it shows an undesired behavior as a result of assigning higher priorities to the jobs with fewer remaining operations. Kanet (1982) resolved this anomaly by proposing the rule called modified dynamic slack per remaining operation (MDSPRO).

Some rules utilize operation due dates. Among several ways of assigning operation due dates, the work content method is generally suggested for mean tardiness (Baker 1984). According to this method, the initial flow allowance of a job is allocated to the operations proportional to their processing times. The rules such as EDD, SLACK and CR have their operation due date versions (ODD, OSLACK and OCR). Kutanoglu and Sabuncuoglu (1999) compared 17 priority rules concluding that the use of operational information such as operation due dates and operation processing times instead of job-based counterparts improves the performance of dispatching rules.

Several researchers have attempted to develop new rules by combining the simple rules to benefit the useful characteristics of individual rules. The basic idea is to develop rules which combine the processing time and due date information. Generally, combined rules

work by applying different pdrs to some specified groups of jobs or use different pdrs depending on the shop status. These rules include MDD, CR/SI rule, COVERT, ATC and MF etc.

In modified due date (MDD), the job's original due date serves as the due date until the job's slack becomes zero, and then its earliest finish time acts as the modified due date (Baker and Bertrand, 1982). It is expressed as,

$$\min_j \left(\max(d_j, t + p_j)\right).$$

Operation based version of MDD rule is the Modified Operation Due date (MOD) rule. In MOD rule, priority is defined as its original operation due date or its earliest finish time, whichever is larger. It is expressed as,

$$\min_j \left(\max(d_{jk}, t + p_{jk})\right).$$

where d_{jk} is the due date of operation $\mathcal{O}_{jk}$ to be processed on machine $\mathcal{M}_k$. Thus when all jobs are operationally late, MOD will dispatch on the basis of SI, and when all jobs are 'ahead of schedule' (*i.e.*, operation slack time greater than zero), MOD will dispatch using ODD (operation due date). Since the former situation occurs more frequently when due-dates are tight, the desired SI sequencing dominates. When due-dates are loose, the majority of jobs are ahead of schedule and an effective tardiness-based rule, ODD, predominates. (Baker and Kanet, 1983) demonstrated that the MOD rule compares very favorably with other dispatching rules and, as expected, is more robust to changes in due-date tightness than other tardiness-orientated rules.

Anderson and Nyirenda (1990) composed new extensions of the MOD rule, namely CR+SPT and S/RPT+SPT (we refer to them as CR/SI and S/RPT+SI, respectively). CR/SI rule sets the operational date as a multiple of the processing time of the imminent operation and the critical ratio of that job. Thus, the CR/SI rule can be expressed as,

$$\min_j \left(\max\left(d_j, p_{jk} \times CR\right)\right)$$

They showed that these rules performs better than the MOD rule in various conditions. Both the rules have been found very competitive and have similar performance characteristics, with the S/RPT +SI being more efficient in minimizing the number of tardy jobs while the CR/SI rule being more efficient in minimizing mean tardiness (Jain and Meeran, 1998; Raghu and Rajendran, 1993; Kutanoglu and Sabuncuoglu, 1999). The CR/SI rule functions similarly as the MOD rule, when jobs are on schedule (Kemppainen, 2005).

Carroll (1965) introduced the cost over time (COVERT) rule especially for the mean tardiness problem. The COVERT rule calculates priority indices on the basis of the slack and the expected waiting time of a job on subsequent machines. Expected waiting time for a remaining operation $\mathcal{O}_{jk}$ is given as $W_{jk} = b \times p_{jk}$, where b is a lead time estimation parameter. The COVERT priority index represents the expected incremental tardiness per unit of imminent processing time. The expected tardiness is a relative measure of how much tardiness a job might experience if it is delayed by one time unit. This rule is expressed as

$$\max_j \left(\frac{1}{p_{j(i)}} \left(1 - \frac{(d_j - t - \sum_{i=l}^{o_j} p_{j(i)})^+}{h_1 \sum_{l=i}^{o_j} W_{j(l)}} \right)^+ \right).$$

Expected waiting time, $\sum_{l=i}^{o_j} W_{j(l)}$ needs look-ahead multiplier h_1 as well as a lead time estimation parameter, b for its computation in COVERT rule. (Russell *et al.*, 1987) found that the overall performance of the COVERT rule is best when it uses dynamic average waiting times with a small look-ahead parameter ($h_1 = 1$) Its success has been delayed by the fact that only a minority of scheduling researchers has used it as a benchmark rule claiming the difficulty of choosing an appropriate value for the parameter, even though it outperforms many dispatching priority rules in most of the performance measures (Russell *et al.*, 1987). The rule has been found superior in mean tardiness and number of tardy jobs under both tight and loose due date conditions by (Chen and Lin, 1999).

Vepsalainen and Morton (1987) proposed the apparent tardiness cost (ATC) rule, which uses an exponential function of operational slack. In the ATC rule, $\bar{p}_{[k]}$ is the average operation processing time of all the jobs currently waiting for machine k. As opposed to the COVERT rule, the slack component $(d_j - t - h_3 \sum_{i=l}^{o_j} p_{j(i)})$ in the ATC rule has already included a waiting time estimate (*i.e.* $h_3 \sum_{i=l}^{o_j} p_{j(i)}$). Consequently, a job with less slack may be expected to complete on time. This rule assigns job $\mathcal{J}_j$ a priority that is equal to $1/p_j$ if the job slack is negative or zero, and is exponentially reduced to zero from $1/p_j$ as the job slack increases from zero. In other words, the job priority is reduced more dramatically as the slack becomes positive but the priority reduction levels off as the slack further increases. This rule is expressed as

$$\max_j \left(\frac{1}{p_{j(i)}} \exp\left(-\frac{(d_j - t - p_{j(i)} - h_2 \sum_{i=l+1}^{o_j} p_{j(i)})}{h_3 \sum_{i=l}^{o_j} p_{j(i)}} \right)^+ \right)$$

where l is the current operation of j^{th} job. The quantities h_2 and h_3 in the ATC rule are user-defined constants. As in the COVERT rule, the ATC rule is also reduced to the SPT rule if no job in a queue has a strictly positive slack. (Vepsalainen and Morton, 1987).

■

Chen and Lin (1999) proposed a rule, called MF (Multi-factor) rule inspired of COVERT, with a more comprehensive way of calculating the expected waiting time that take into account the job routings alongwith processing times. The expected waiting time is calculate as,

$$W_{j(q)} = \sum_{i=k}^{n(\neq k)} \sum_{j=1}^{q} p_{j(i)} - \sum_{j=1}^{q-1} p_{j(i)}$$

Using this expected waiting time, MF rule can be expressed as,

$$\max_{j}\left(\frac{1}{p_{j(i)}}(W_{j(i)} - (d_j - t - \sum_{i=l}^{o_j} p_{j(i)})\right)$$

This rule does not depend on any multipliers like COVERT and ATC.

The weighted-loss-of-slack rule (WLS) proposed by (Moser and Engell, 1992) compares the situation of all other operations in the queue if operation i would be scheduled. This decision will cause a loss of slack for all other operations considered. This, however is only critical if an operation would have negative slack afterwards. The queue is again divided into two sub-queues. The high-priority queue contains those operations for which $\varsigma_j < \max_{j\neq i}(p_j)$ *i.e.* the operations which have negative slack or might get negative slack due to the scheduling of some other operation before operation i. These critical operations are ordered according to the WLS formula. The uncritical operations are scheduled according to the ODD rule.

Raghu and Rajendran (1993) proposed a new rule referred as RR, that is based upon the combination of processing time and slack per remaining processing time with weights as a function of the utilization level of the shop. Under tight load conditions, the process time component will be dominant, while the due date or slack component will be dominant under light load conditions. The negative exponential term in the due date component also serves to reduce the magnitude of the slack and thus reduces the disparity in the magnitude of the process time and due date terms. In addition, the coefficients for the process time and due date components are influenced by the shop utilization level, rendering the coefficients dynamic in nature. Yet another indication of the utilization level of the shop is the waiting time at the subsequent machines. The expected waiting time beyond the next immediate machine W_{jk} is computed as follows: Assume that a job, $\mathcal{J}_j$, is taken up for processing on the current machine at the time instant t, then it joins the queue on the next machine at $t + p_{j(i)}$. Let t_{nxt} be the time at which the next machine becomes free. The time at which the scheduling decision involving this job is made on the next machine is at t_{nxt}. The priority indices of all the jobs in the queue are calculated at

this time t_{nxt}. Thus the expected waiting time of the j^{th} job, at the next machine, is the sum of the processing times of all the jobs which have a higher priority than j. This rule is expressed as

$$\left(\frac{d_j - t - \sum_{i=l}^{o_j} p_{j(i)}}{o_j} \exp(-\eta)\, p_{j(i)} + \exp(\eta)\, p_{j(i)} + W_{nxt} \right).$$

Weng and Ren (2006) proposed a composite rule by combining SI, SLACK and SQNO rules. In both the COVERT and ATC rules, if the slack of a job is less than or equal to zero, a positive priority proportional to the absolute slack is assigned to the job and, on the other hand, if the slack of a job is greater than zero, a priority of zero is used. One problem with this is that if the slack of a job is slightly smaller than zero, the job will definitely be tardy but its priority may be too small to recognize this fact. The rule proposed by (Weng and Ren, 2006) rectifies this problem by modifying the slack-related portion of priority assignment. Using relative queue size for the next queue instead of absolute queue size (as in SQNO) amplifies the relative priority assigned to a short queue, gives a better load balance on machines and improves the performance when queue size differences are smaller compared to queue sizes (Weng and Ren, 2006).

In fact, the idea to combine simple priority terms to more complex rules opens a field of great heuristic variety (Haupt, 1989). It might be reasonable to link any of the introduced basic expressions, which would produce an immense number of possible priority functions. (Haupt, 1989) characterizes two basic combination mechanisms. The additives and the alternative combination. Ratios or products of rules are classified under simple rules. As individual rules perform so poorly, and provide no clear conclusion with respect to the criterion under study, more involved heuristics have been formulated. For example, Viviers algorithm (Viviers, 1983) incorporates three levels of priority classes within the SPT heuristic. The most common method of improving solution performance is to have a probabilistic combination of individual pdrs. The earliest examples of such a strategy are by (Crowston *et al.*, 1963) and (Fisher and Thompson, 1963) . (Lawrence, 1984) compares the performance of ten individual priority dispatch rules with a randomized combination of these rules and shows that the combined method provides far superior results but requires substantially more computing time. Other more sophisticated methods used to control the choice of which rule to apply includes a genetic algorithm (Dorndorf and Pesch, 1995) and fuzzy logic (Grabot *et al.*, 1994).

2.5 Comparative Studies and Important Factors

There are numerous studies, that have discussed different pdrs, while making a comparison among them, developing a new dispatching rule, modifying an existing rule or studying the behavior of different pdrs under various operating conditions. Panwalker and Iskander (1977) have listed 36 studies, describing the environment and conditions in which pdrs have been tested. We shall present a review of some recent comparative studies in the first subsection. After this, some of important factors that possibly influence the performance of pdrs are discussed.

2.5.1 A Review of Comparative Studies on PDRs

Schultz (1989) compared his proposed rule, CEXSPT with SI, ODD, MOD, S/OPN, COVERT and OCR in a dynamic job shop environment of four machines. He tested the pdrs for $\bar{F}$, $\bar{T}$, $\%T$ and CMT under four level of due date tightness using TWK method and two levels of shop load. The results for CEXSPT and COVERT were reported as the best for all measures, with CEXSPT having an advantage of not requiring any parameter. The results reported by him indicate that CEXSPT, COVERT and MOD were more robust than other rules in regards with due date tightness, particularly for $\bar{T}$ and $\%T$.

Anderson and Nyirenda (1990) presented two rules, CR/SI and S/RPT+SI and compared the performance of these new rules with MOD, CEXSPT, COVERT and SI for the $\bar{F}$, $\bar{T}$, $\%T$ and CMT in job shop environment. They performed their experiments for seven settings for due-date tightness parameter using TWK method and a single level for shop utilization. For $\%T$, S/RPT+SI is reported to be more effective than CR/SI, while for CMT, CR/SI performed significantly better. Their proposed rules outperformed all the other rules for $\bar{T}$, exhibiting similar behavior.

Moser and Engell (1992) have discussed the results of comprehensive evaluations of pdrs and have also presented a new rule based on the effect that a hypothetical selection of a job has, on the other jobs waiting in the queue.

Using the data envelopment analysis, (Chang *et al.*, 1996) assessed the efficiency of 42 dispatching rules that they had categorized into six groups based on information content. They conclude that scheduling the shortest operation first increases the flexibility of a resource for the further operations, and thereby improves its utilization. Scheduling the earliest or the least slack operation first increases the possibility of finishing more jobs on time.

Holthaus (1997) tested the relative performance of 10 pdrs, while proposing two new rules, under three shop load levels and four different setting for due date tightness using TWK method. They used $\bar{F}$, $\bar{T}$ and $\%T$ as the performance measures.

Kutanoglu and Sabuncuoglu (1999) compared 17 priority rules concluding that the use of operational information such as operation due dates and operation processing times instead of job-based counterparts improves the performance of dispatching rules. Composite rules integrating, for example, the SPT rule and the CR rule can be very effective especially in reducing weighted tardiness (Kutanoglu and Sabuncuoglu, 1999)

Dominic *et al.* (2004) used five performance measures ($\bar{T}$, $\bar{F}$, $F_{\max}$, ΣU_j and $Var(T)$) to test the performance of 9 simple pdrs in a six machine dynamic job shop environment. They made use of TWK method for assigning due-dates with four levels for due date tightness and two levels of shop-load.

Weng and Ren (2006) compared FIFO, EDD, SI, SLACK, S/RPT, SQNO (Shortest Queue Next Operation), COVERT and ATC for $\bar{T}$ and $\bar{F}$ in a dynamic job shop environment with ten machines. Five levels of shop load and two levels of due date tightness using Random TWK method. Reporting their proposed rule as the best performing rule (especially in congested shops), they noticed, however that ATC performed poorly than COVERT for $\bar{T}$. The performance of these three rules improved in tight due-date conditions for both performance measures.

Kemppainen (2005) demonstrated that a few dispatching rules consistently work best in the common types of job shop problems in priority scheduling research. Based on the analysis of the simulation results, ATC, COVERT, and CR+SPT rules were found with dominating performance (note that CR+SPT does not necessitate any parameter), especially with high load and tight due dates, while RR rule works well with medium system load. The EDD rule gives low maximum tardiness in any problem instance, as expected. Also the slack-based rules reduce very late orders, a relevant concern in practice whereas processing time based rules (*e.g.* AVPRO(Average Processing time) and SPT) cut down the portion of tardy jobs.

Table 2.1 lists the relevant reviewed literature on comparative analysis of pdrs for tardiness based performance measures.

In practice, there is generally a lack of knowledge on the impact of making a a particular scheduling decision, by applying a dispatching rule, on the desired objectives. The coordination among different scheduling decisions and the effect of this coordination on the performance measures is dependent on the fact that how much relevant to desired objec-

tives and consistent the priority index values are. Of course, this has a strong relation with the scheduling environment and constraints. However, it is not a trivial task to predict these coordinating factors except the identification of few guidelines. For example, a basic level of coordination is by using an attribute such as due-date, consistently replicating the same sequence of execution on a machine, compared to RANDOM rule. Or as a higher level of coordination, adapting the priority index values using the information obtained by probing the downstream queues over certain forecasting horizon (Kemppainen, 2005). The question of relevance of a scheduling rule in regards with desired objectives is not simple as well. However, local efficiency of the rule for a queue (*e.g.* SI minimizing flow-time in one machine case), capability of the rule to trade-off against other objectives (like COVERT) and use of lead time estimation methods to anticipate expected performance.

2.6 Factors Affecting Performance of PDRs

In this section, factors affecting the performance of pdrs are discussed. These include load variation (LV), due date variation (DDV) and method of due date assignment.

2.6.1 Load Variation

The combined effects of job arrival distribution, job routing and processing times determine the system load. System load affects the queue lengths in job shop systems. If the average queue length is too small, alternative pdrs become indiscriminate towards job selection decision. On the other hand, too long queue lengths extend the transient conditions over long time period. Many researchers have employed different load setting for the experiments (Lejmi and Sabuncuoglu, 2002). In literature, commonly found values for system load ranges from 60% to 95%. Results from Elvers and Taube (1983) indicate that relative performance of pdrs is dependent on load level. Lejmi and Sabuncuoglu (2002) conclude that LV has generally a negative impact on the performance measure of pdrs in regards with tardiness (the degree of impact depends on LV pattern and magnitude) although relative performance of pdrs is unaffected except MOD, MDD and ODD.

2.6.2 Due Date Variation

Lejmi and Sabuncuoglu (2002) characterizes two types of effects on MT due to due date variation (DDV). Type-I effect is due to changes in corresponding completion times be-

cause of the possible change in the relative priority index of the job, while Type-II effect is the due date itself (as tardiness is a function of due dates). Non due date based rules are insensitive to type-I effect. For due date based rules, type-I effect has a negative impact on tardiness based performance measures such as $\bar{T}$, which gets even more severe in higher load levels (Lejmi and Sabuncuoglu, 2002).

2.6.3 Method of Assigning Due Dates

Due dates are usually treated as given information and taken as input to a scheduling problem. However, in actual practice, the due date can be a decision variable within the domain of the scheduling problem (Cheng and Gupta, 1989). A variety of decision rules has been suggested to assign due dates. The concern of some of the past research on due-date assignment has been that of indicating the effects of varying degrees of tightness as opposed to establishing procedures and measuring the effects of realistic or attainable due-dates (Ovacik and Uzsoy, 1994). The due date assignment procedures can be discussed under the following categories.

Exogenous Methods Due dates are set by some independent external agency and are announced upon arrival of the job. Two types of due-date assignment methods have been studied in this category:

1. Constant (CON): All jobs are given exactly the same flow allowance.
2. Random (RAN): The flow allowance for a job is randomly assigned. Clearly, these two methods entirely ignore any information about the arriving job, jobs already in the system, future jobs, or the structure of the shop itself.

Endogenous Methods In this case, the due dates are set internally by the scheduler as each job arrives on the basis of job characteristics, shop status information and an estimate of the job flow time. Following are some due date assignment methods which fall into this category:

1. TWK: Due dates are based on total work content.
2. SLK: Jobs are given flow allowances that reflect equal waiting times or equal slacks.
3. NOP: Due dates are determined on the basis of number of operations to be performed on the job.
4. RATWK: Random Total Work Content is a more general and somewhat random due date setting method that incorporates TWK, NOP and RAN.

(Conway, 1965a) demonstrated in his study that due-date assignment methods based on job characteristics, such as processing time and number of operations, leads to poorer performance than external due-date assignment methods which are not related to job characteristics. In their study, (Eilon and Choudury, 1975) indicated that due-date procedures that take into account the shop congestion information produce less mean tardiness than procedures based only on job content. They also concluded that due-date priority rules may perform better than non-due-date priority rules in terms of missed due-dates. TWK and NOP methods perform better when combined together (Cheng and Gupta, 1989).

This study is not aimed at the exhaustive survey of due date setting methods, however relative effects on the performance measures of selected pdrs has been discussed.

2.7 Conclusions

The chapter summarizes the prior research on priority dispatching rules with a focus to job shop scheduling. The review of the literature reveals that different researchers have used different experimental conditions to study the performance of the different pdrs. This may account for apparently conflicting conclusions that are reported in the literature. Therefore there is a need for a systematic study under a common set of conditions so that a common basis of comparison is available to evaluate the research results.

Overall, based on the evidence of the extensive comparisons of pdrs in literature, there is an opportunity to agree on a family of pdrs recommendable for a dynamic job shop. Nevertheless, further research is needed in order to assess according to what constraints these pdrs could be employed as the core for a standard job shop scheduling protocol. One of the primary goals of this study is the identification of different families of pdrs that perform well and robustly for tardiness based performance measures.

On the basis of the published results, no single pdr, in general, has been found superior in dynamic job shop problems with tardiness-based criteria. Yet, some promising alternatives as well as conflicting results published in prestigious journals are found. These observations alone motivate the re-examination of the performance of different priority index rules in relevant job shop test settings and to look for possible performance enhancement in these efficient rules via minor modifications/combinations of pdrs or by use of heuristics.

For implementation purposes, it is also important to test what are the tolerances of different pdrs to the detail and scope of information available. Additionally, sensitivity

of selected pdrs to different due date setting methods (and hence potentially different types of usage) in a dynamic job shop environment would be investigated. It would be interesting to investigate the predictability of on-time progress of jobs through the shop by classifying the jobs and hence to assess, to what extent the system performance is linked to the type of priority rules used (*i.e.* the effect of keeping operational due dates on overall system performance in regards with selected pdrs).

3 Correlation Among Tardiness Based Measures For PDRs

One of the most important class of objectives to deal with in a manufacturing system is related to the tardiness of jobs in relation to their due-dates. This can be measured through several performance measures. These performance measures focus different aspects of this objective. However, it is not necessary that these performance measures are independent of each other. Moreover, the relation among these performance measures is generally not obvious even for simple scheduling strategies such as priority dispatching rules (pdrs). It is desired to distinguish the behavior of different pdrs in regards with tardiness based performance measures. We identify two sets of pdrs based upon the distribution of the maximum tardiness (*i.e.* $T_{\max}$), a very important measure representing the worst case behavior. Experiments have shown that maximum tardiness and root mean square tardiness of the system are positively correlated. This provides an opportunity to predict the worst-case behavior of the manufacturing system in regards with tardiness as well as the width of the tardiness by evaluating root mean square tardiness.

Part of this chapter was presented in the 13^{th} IFAC Symposium on Information Control Problems in Manufacturing (INCOM'09) (Shahzad and Mebarki, 2009)

3.1 Introduction

Priority dispatching rules are widely used to dynamically schedule the operations in a shop. However, their efficiency depends on the performance criteria of interest. Tardiness is an important criteria in real systems which can be measured through several performance measures. These measures are used to rank different scheduling strategies under different conditions. However, the superiority of one strategy over the other is not obvious in general, for a mix of performance measures and conditions. Usually certain guidelines are adopted from the expertise of the scheduler, literature and/or historic scheduling data.

In this chapter a simulation based analysis of tardiness based performance measures for a set of frequently used pdrs is made in order to highlight the similarities/dissimilarities in the behavior of these pdrs. The worst-case behavior in regards with tardiness is very difficult to identify due to its value at a single-point only. However, it is possible to establish some guidelines in predicting this worst-case behavior. We use the properties of root mean square tardiness to identify two different sets of rules.

The rest of the chapter is organized as follows. We will first discuss different tardiness based performance measures frequently used in literature on job shop scheduling problem. This follows with a description of experimental setup and the simulation procedure used. In § 3.4, results showing the correlation among two very important measures, maximum tardiness ($T_{\max}$) and root mean square tardiness (T_{rms}) are presented along-with discussion on these results. Finally, some conclusions are drawn which are presented in the last section.

3.2 Tardiness Based Measures

Dynamic scheduling of manufacturing systems for due date based objectives has received considerable attention from practitioners and researchers due to the importance of meeting due dates in most industries (Raman *et al.*, 1989). Unfortunately, the study of due date based objectives is much more complicated than the flow-time based objectives (Baker and Bertrand, 1982). To what extent the goal of keeping the due-dates is achieved, is judged by tardiness based measures (French, 1982). However, there is no single universally accepted measure on this dimension.

The tardiness of a job is computed as $T_j = \max(0, C_j - d_j)$. It causes potential losses in terms of bad reputation, higher stock-holdings, rush shipping costs and possibly contrac-

tual penalties. To measure the effective performance of the system in regards with the tardiness, there are several performance measures of interest. Generally it is not sufficient to assess the performance of a schedule with a single tardiness based performance measure alone.

The most used performance measure to evaluate the tardiness is the total tardiness (*i.e.*, $\Sigma_j T_j$). While using simulation to compare two different scheduling strategies, the number of completed jobs is usually fixed. Thus, in that case, the mean tardiness (*i.e.*, $\bar{T}$) is equivalent to the total tardiness. This measure represents an average level of customer satisfaction in terms of delivery performance (Lejmi and Sabuncuoglu, 2002).

The number of tardy jobs (ΣU_j) or an equivalent measure namely percentage tardiness ($\%T = \Sigma U_j/n \times 100$), is also extensively used in literature on comparative study of pdrs. However this measure is risky as standalone measure due to its discrete nature and resulting instability (Kemppainen, 2005).

The conditional mean tardiness (*i.e.*, $CMT = \frac{\Sigma_j T_j}{\Sigma U_j}$) measures the average amount of tardiness for the completed jobs which are found to be tardy. This performance measure is, however, not regular. It means that it can decrease while the completion times are not decreasing (French, 1982).

For the judgment of relative performance of pdrs in regards with tardiness, the shape of the tardiness distribution must be considered. Overall performance of the system will be disturbed heavily due to a very large delay for a job in comparison with a small constant (or varying very little) tardiness values among several jobs (Moser and Engell, 1992). In this case, the maximum tardiness, (*i.e.*, $T_{\max} = \max_j T_j$) can be of great interest for the decision-maker in the shop. It is an indication of a worst case behavior of a rule during a particular experiment.

The root mean square tardiness, defined as,

$$T_{rms} = \sqrt{\frac{1}{n}\Sigma_j T_j^2}$$

permits to differentiate a system which presents a little number of tardy jobs with higher tardiness from a system which presents a lot of tardy jobs with low tardiness. This performance measure exhibits higher values for the first kind of systems (Moser and Engell, 1992).

Finally, the variance of the distribution of the tardiness is defined as,

$$\sigma_T^2 = E(T_j - \bar{T})$$

With stochastic models, tardiness (T) being a real-valued random variable, its expectancy is the first central moment and its variance is the second central moment. For the computational purpose, the variance of tardiness is equal to the mean of the squared tardiness minus the square of the mean tardiness. Thus, we have

$$\begin{aligned} Var(T) &= E(T^2) - (E(T))^2 \\ &= \frac{1}{n}\Sigma_j T_j^2 - \bar{T}^2 \\ &= T_{rms}^2 - \bar{T}^2. \end{aligned}$$

This is used to measure the statistical dispersion of tardiness values.

Research investigations have focused primarily on the relative effectiveness of various dispatching rules in job shops. For due date based objectives, the relative performance is affected by the the quality of the due date assignment methods (Sha and Liu, 2005), the due date tightness and due date variations (Lejmi and Sabuncuoglu, 2002). For example, tighter due dates tend to produce larger values for $\bar{T}$ and $\%T$, while keeping other conditions unchanged (Carroll, 1965). The relative ranking of pdrs is thus affected by such varying conditions for some specified tardiness based measure. It is the structure of the pdr-the constituent attributes making the pdr- that reflects its behavior for a particular performance measure.

We want to distinguish the behavior of different pdrs in regards with tardiness based performance measures. In the next section, we present a set of experiments conducted on a set of pdrs for $T_{\max}$ and T_{rms} in a job shop scheduling environment, in order to identify two distinct behaviors that relate to $\%T$ and $\bar{T}$.

3.3 Experiments

We consider the model of an unweighted job shop that is frequently used in the literature to evaluate the performance of pdrs (Eilon and Cotterill, 1968; Baker and Kanet, 1983; Baker, 1984; Russell *et al.*, 1987; Schultz, 1989; Pierreval and Mebarki, 1997; Mebarki and Shahzad, 2008).

Table 3.1 summarize the parameter settings used in the simulation model. The system

is a four machine job-shop. Each machine can perform only one operation at a time. The number of operations of the jobs processed in the system follows a discrete uniform distribution between 2 and 6. The routing of each job is fixed and assigned randomly with limited revisits policy. More precisely, when a job leaves a machine and needs another machine for the execution of subsequent operation, each machine has the same probability to be the next, except the one just released, which cannot be chosen. The processing times of operations on machines follow a negative exponentially distributed with a mean of one.

The arrival of jobs in the system is modeled as a Poisson process and are simulated over long time periods. Since shop utilization, η is given as,

$$\eta = \frac{\lambda}{\mu}$$

where λ is the job arrival rate and μ is the service rate of jobs, given as

$$\mu = \frac{1}{\bar{p}} = 1$$

We have the shop utilization rate equal to the arrival rate for this particular model, *i.e.* the job release dates are used to control the desired level of job load. Due dates of jobs are determined using the Total Work Content (TWK) method (Baker, 1984). Operation due dates are set in proportion to the operation processing times. From the review made in Chapter 2, we have selected 12 rules which are either extensively used (such as FIFO, EDD, SLACK) or which perform very well for tardiness based measures (see Table 3.1 for a list of these rules).

There are $2 \times 3 = 6$ configurations to be simulated (see Table 3.2) for each pdr. Two levels of shop load were defined. A moderate shop load level, which corresponds to a utilization rate of 80% for the resources, and a high level of shop load, which corresponds to utilization rate of 90%. For each load level, three different levels of due-date were established. Each given due date tightness (*e.g.*, tight, moderate or loose) is computed in a proportion depending on the utilization rate of the resources (Schultz, 1989; Pierreval and Mebarki, 1997).

Firstly, the performance measures for the set of pdrs were collected for 5,000 jobs over 100 replications with a warm-up period of 1,000 time units (corresponding approximately to 500 jobs) under given operating conditions. Then one long simulation for 500,000 jobs is carried out to obtain the distributions of tardiness values for these pdrs under the same operating conditions.

Table 3.1 – *Simulation model parameters*

Parameter	Value
Number of machines	4
Number of completed jobs	5,000 and 5,00,000
Number of operations	U[2,6]
Warm-up period	1,000 time units
Number of replications	100 and 1
Job routings	random with limited revisiting
Release dates	EXP[$\frac{1}{\eta}$]
Operation processing times	EXP[1]
Tie-breaking rule	First in Queue
Due date assignment method	TWK

3.4 Results

Figure 3.1-3.6 present the boxplots of $T_{\max}$ for the set of pdrs under different operating conditions for 100 replications. For each rule, there are 6 boxplots, each one corresponding to a particular operating condition, *e.g.* the boxplot of Figure 3.1 represents high level of shop load (*i.e.* =90%) and tight due dates, Figure 3.2 represents high level of shop load and moderate due dates and so on.

From these box-plots, we can identify two sets of rules based on their behavior in regards with $T_{\max}$.

- FIFO, EDD, SLACK, CR noted as set 1 for which $T_{\max}$ is quite low with less degree of dispersion and there are very few outliers.
- SI, SPT, MOD, MF noted as set 2 for which there is a much higher degree of dispersion for $T_{\max}$ with larger number of extreme outliers.

For example, in the case of SI rule under high load and tight due date conditions, inter-quartile range (IQR is the range within which the middle 50% of the ranked data is found) is 301.5 (=744.3-442.5) with two extreme outliers at 2369.3 and 2446.5. On the other hand, for SLACK rule under similar conditions, IQR is merely 19.8 with only one mild outlier at 97.6.

Table 3.2 – *Operating conditions tested.*

Factor	Levels	Number of levels
Utilization rate of the resources (η)	80%, 90%	2
Due date tightness (τ)	**tight due dates** (7.5 for η=90% and 5 for η=80%) **moderate due dates** (12.5 for η=90% and 7.5 for η=80%) **loose due dates** (9.5 for η=90% and 8.75 for η=80%)	3
Pdrs tested	FIFO, SI, SPT, EDD, SLACK, CR, CRSI, COVERT, MOD, CEXSPT, ATC, MF	12

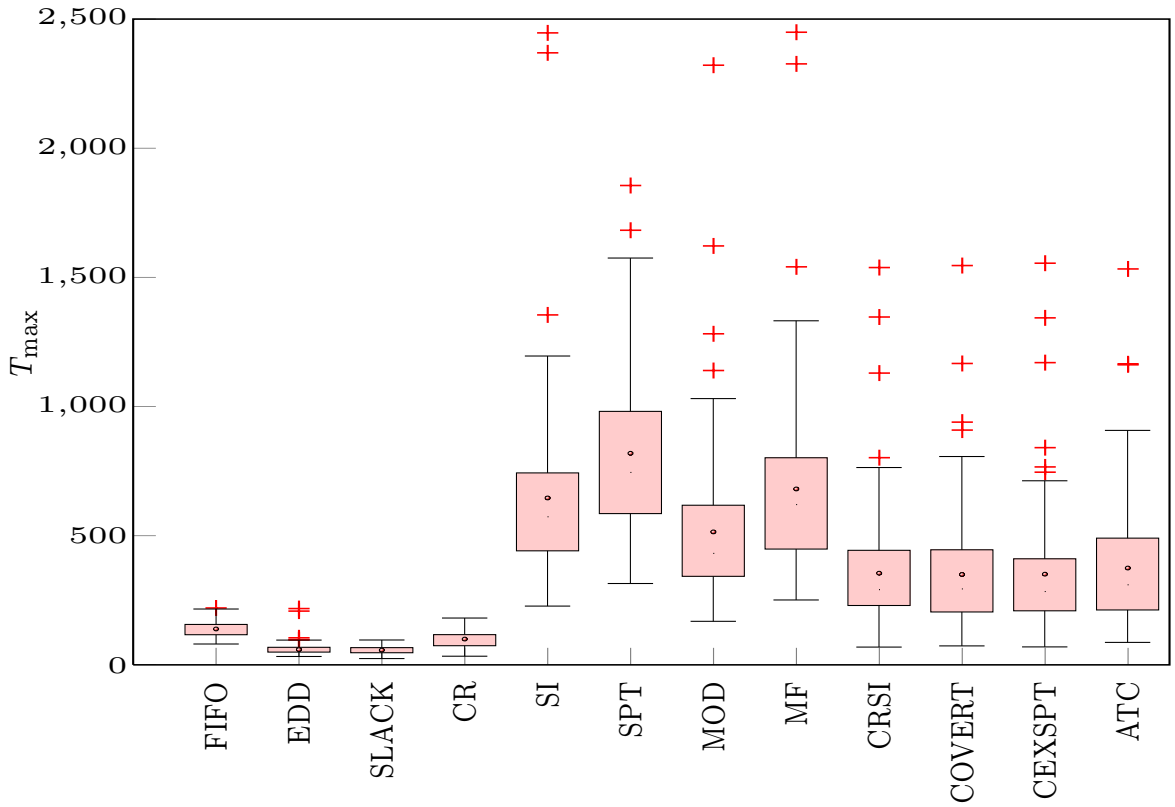


Figure 3.1 – *Box plot of* $T_{\max}$ *with* $(\tau,\eta) = (7.5,90\%)$

For the other rules (CR/SI, COVERT, CEXSPT, ATC) it can be observed that these rules change their behavior in regards with the varying conditions of load and due date tightness. For tight due date settings, the behavior of these rules compares to rules of set

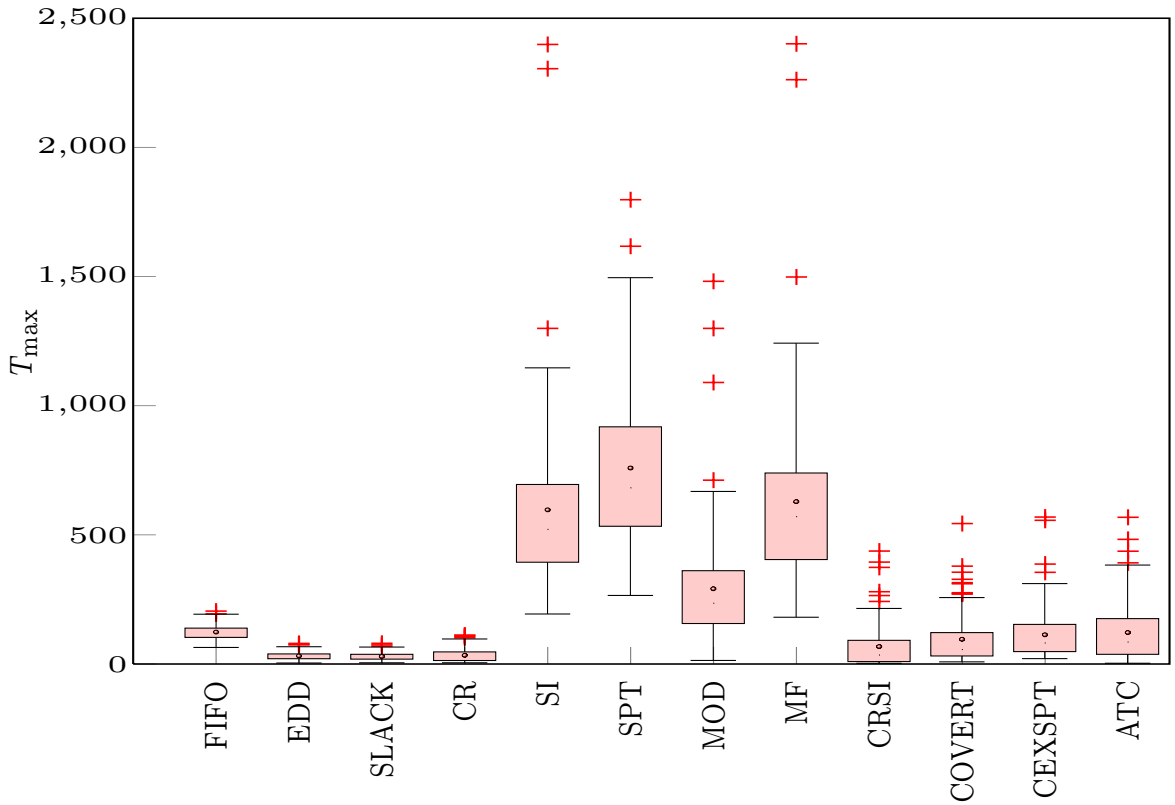


Figure 3.2 – *Box plot of* $T_{\max}$ *with* $(\tau,\eta) = (12.5,90\%)$

1. However, as the due date dates get looser, these rules tend to behave like rules of set 2. This behavior is inherent to the structure of these rules (and hence generally referred as trade-off heuristics). For example CR/SI does not take into account the amount of relative lateness and it has two different behaviors for late jobs and non-late jobs.

Under higher loading conditions, the performance of the pdrs deteriorate however, there is no significant impact on the relative ranking of the pdrs.

The corresponding distribution plots of the tardiness values, obtained through single long simulation run, for these two sets of rules are shown in Figure 3.7 and Figure 3.8. These distribution plots for a single long simulation run clearly show two different kinds of behaviors for rules of set 1 and rules of set 2. Our measures show that for rules of set 1, the tardiness values are quite evenly distributed in contrast to the rules of set 2 where the concentration of tardiness is only on a few jobs, that are very tardy, justifying the high value of maximum tardiness for rules of set 2. This is a typical behavior that is measured by T_{rms}, as mentioned earlier. In order to check if the two sets of rules previously identified in regards with the $T_{\max}$, can also be discriminated by using the T_{rms}, it is decided to measure the relative performance of these benchmark pdrs in regards with the T_{rms}.

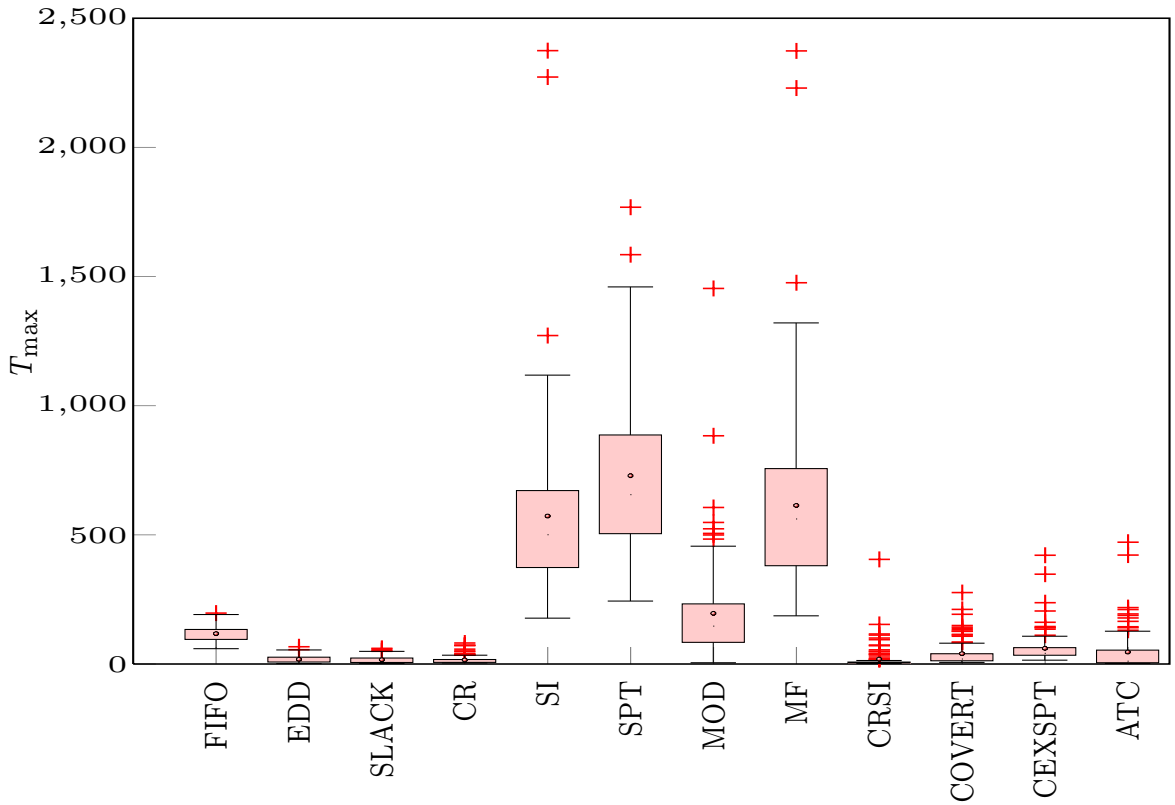


Figure 3.3 – *Box plot of* $T_{\max}$ *with* $(\tau,\eta) = (15,90\%)$

Figure 3.9-3.11 present a comparison of $T_{\max}$ and T_{rms} under different operating conditions within the two sets of rules previously identified and other rules. Rules of set 1 perform significantly well for $T_{\max}$, with SLACK rule as always the best performing rule. For rules of set 1, EDD and SLACK exhibit quite a similar behavior, however for FIFO, $T_{\max}$ and T_{rms} are not as strongly correlated as the other two pdrs of this set. Probably, this is due to the fact that, in FIFO there is neither the involvement of due date factor nor the processing times resulting in higher values for tardiness (as compared to other two rules of set 1).

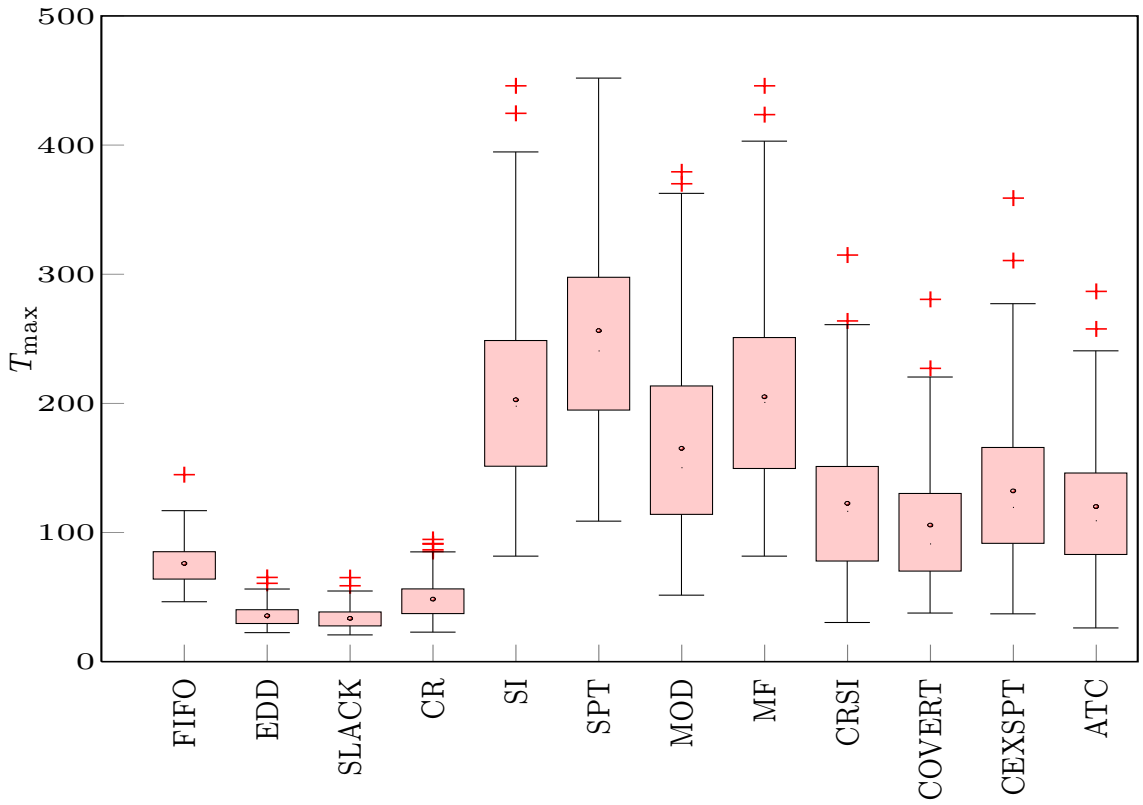


Figure 3.4 – *Box plot of* $T_{\max}$ *with* $(\tau,\eta) = (5,80\%)$

For stochastic models, it is required to construct a confidence interval for a parameter estimate in statistical inferences. Bootstrapping procedure is used to obtain 95% confidence intervals for the correlation coefficients between $T_{\max}$ and T_{rms}, which are presented in Table 3.3. For SI rule, for example, under moderate load and tight due date conditions, the confidence limits for the correlation coefficient is 0.814 (lower limit) and 0.918 (upper limit). Table 3.3 presents strong quantitative evidence that $T_{\max}$ and T_{rms} are positively correlated. Moreover, this evidence does not require any strong assumptions about the probability distribution of the correlation coefficient. It is also observed that this correlation is stronger under High load and loose due date settings for all the rules.

The root mean square tardiness (T_{rms}) is a very interesting measure as it permits to differentiate a system with a little number of tardy jobs having higher values for tardiness from a system with a lot of tardy jobs having low tardiness. It can also be used along with mean tardiness to compute the variance of the tardiness. Moreover, it gives an indication of the relative performance of the rules for $T_{\max}$ as T_{rms} is found to be strongly correlated with the maximum tardiness.

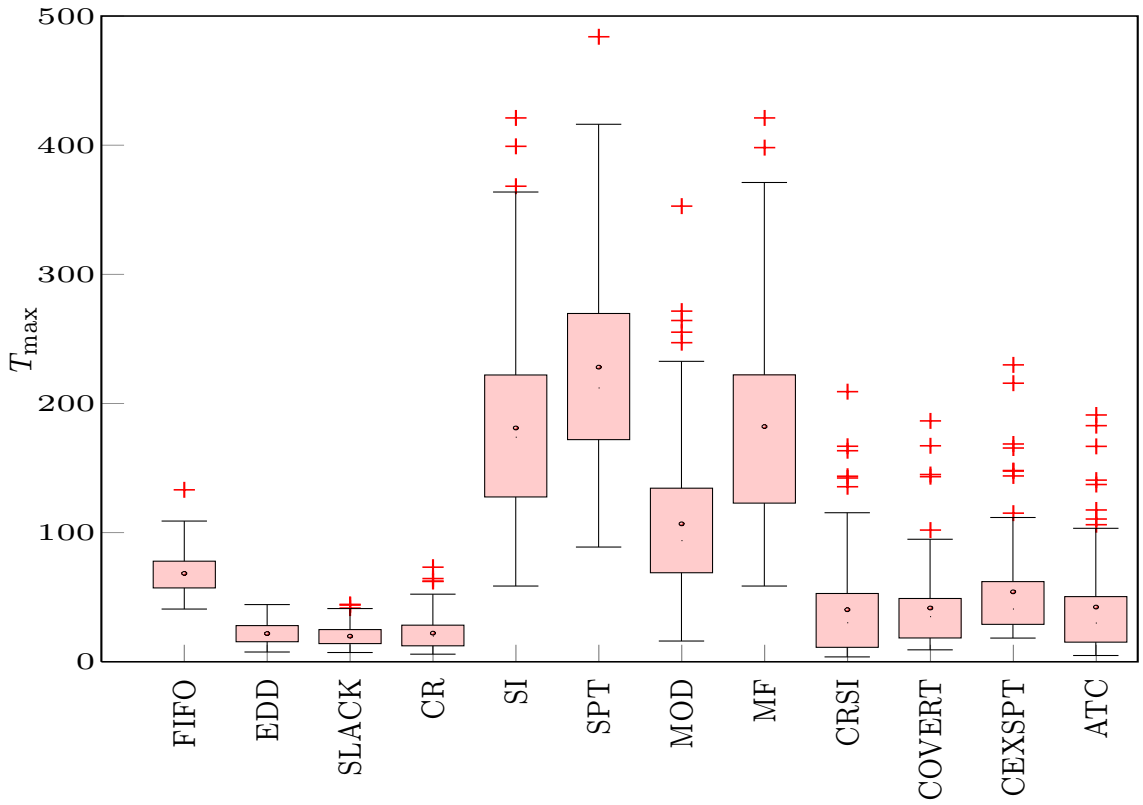


Figure 3.5 – *Box plot of* $T_{\max}$ *with* $(\tau,\eta) = (7.5,80\%)$

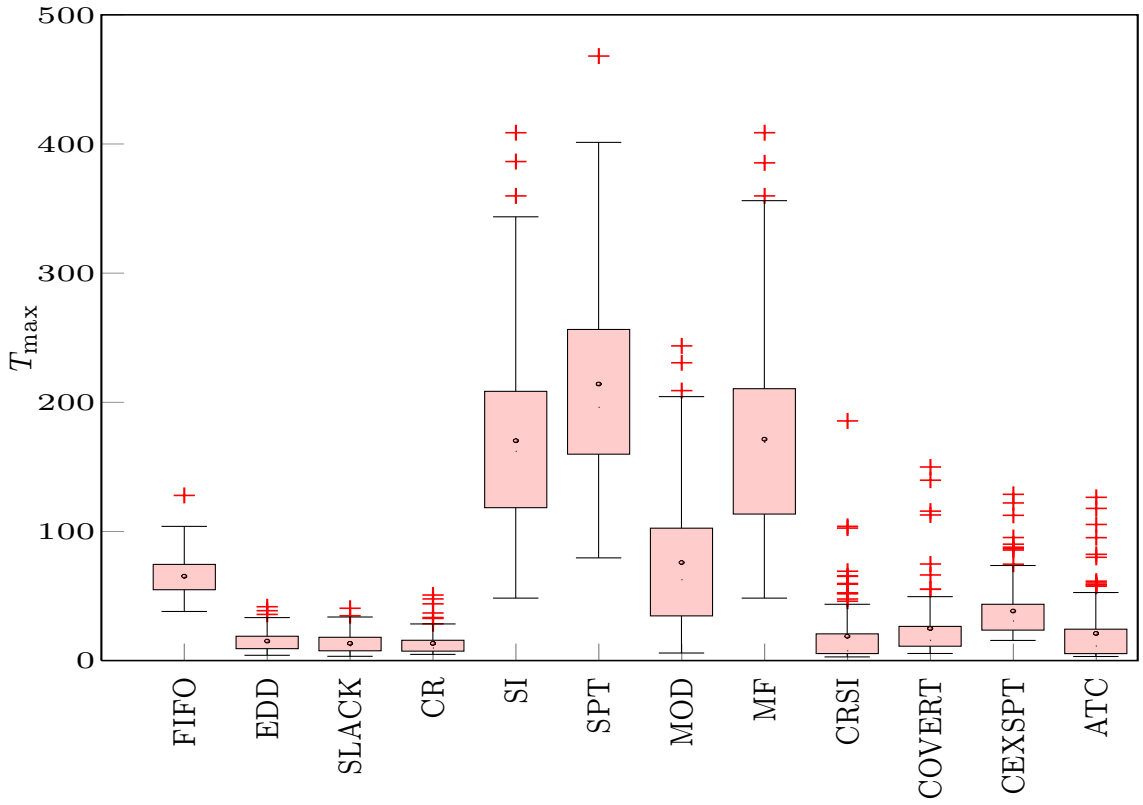


Figure 3.6 – *Box plot of* $T_{\max}$ *with* $(\tau,\eta) = (8.75,80\%)$

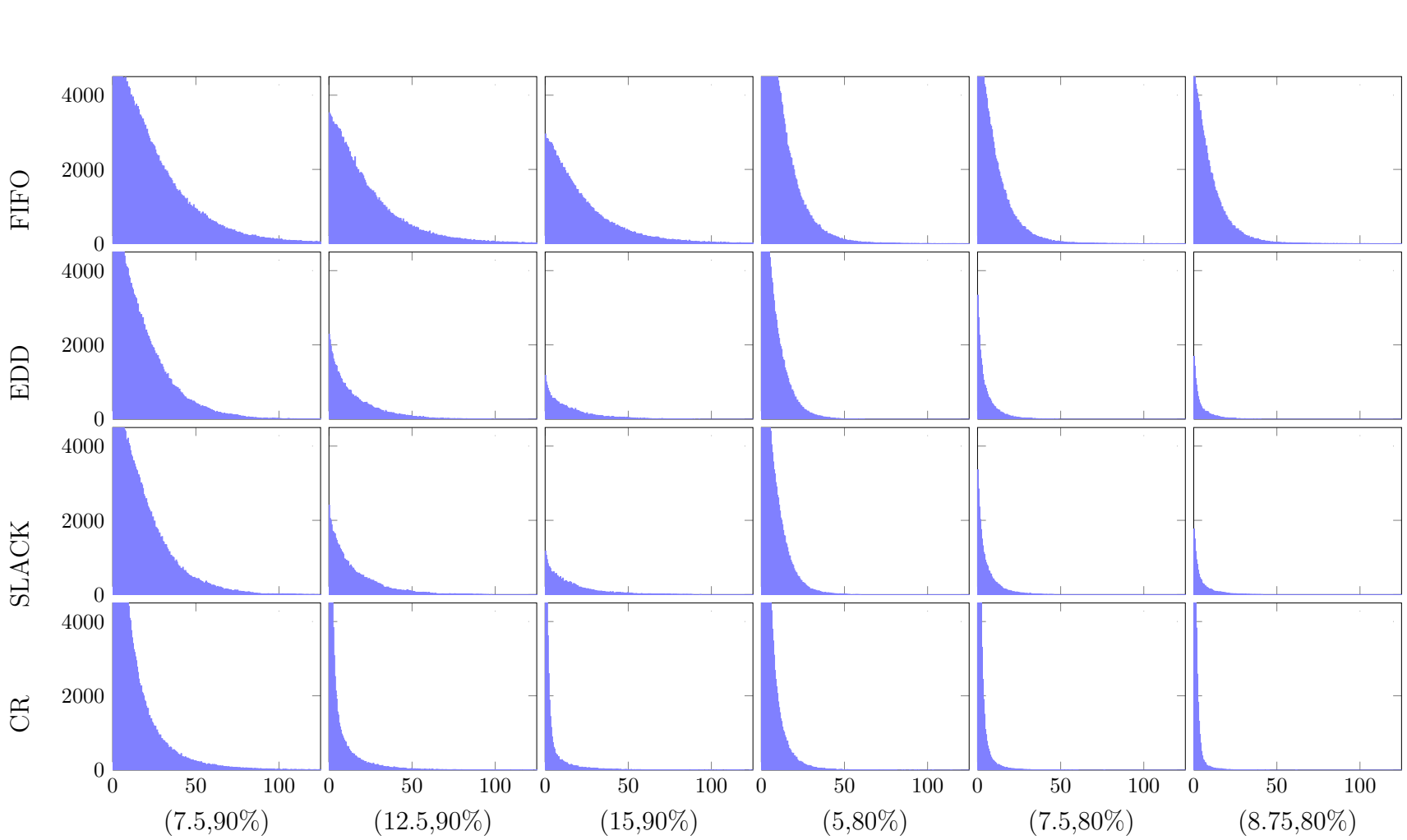


Figure 3.7 – *Tardiness distribution for rules of set 1 with corresponding (τ,η)*

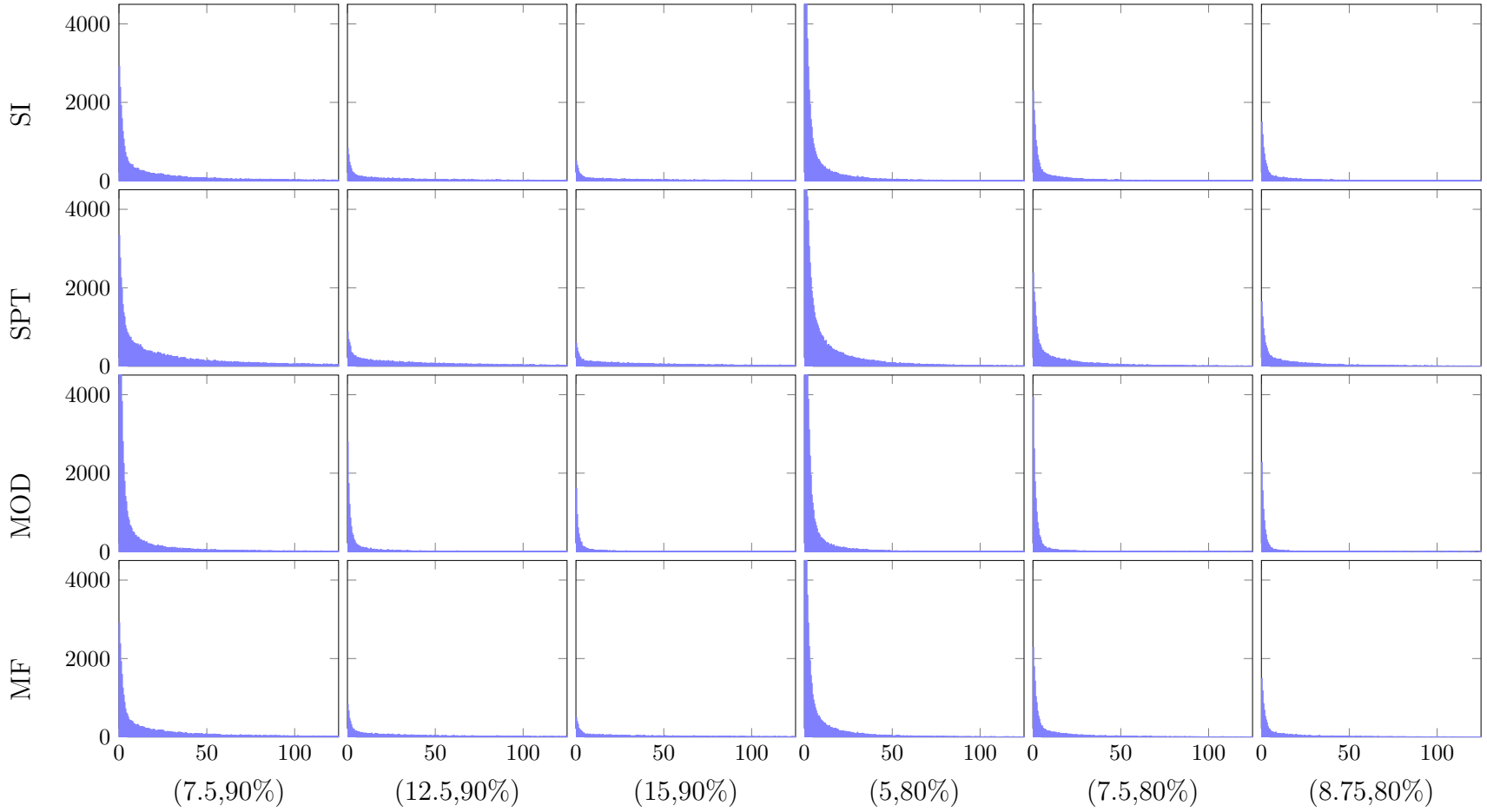


Figure 3.8 – *Tardiness distribution for rules of set 2 with corresponding (τ,η)*

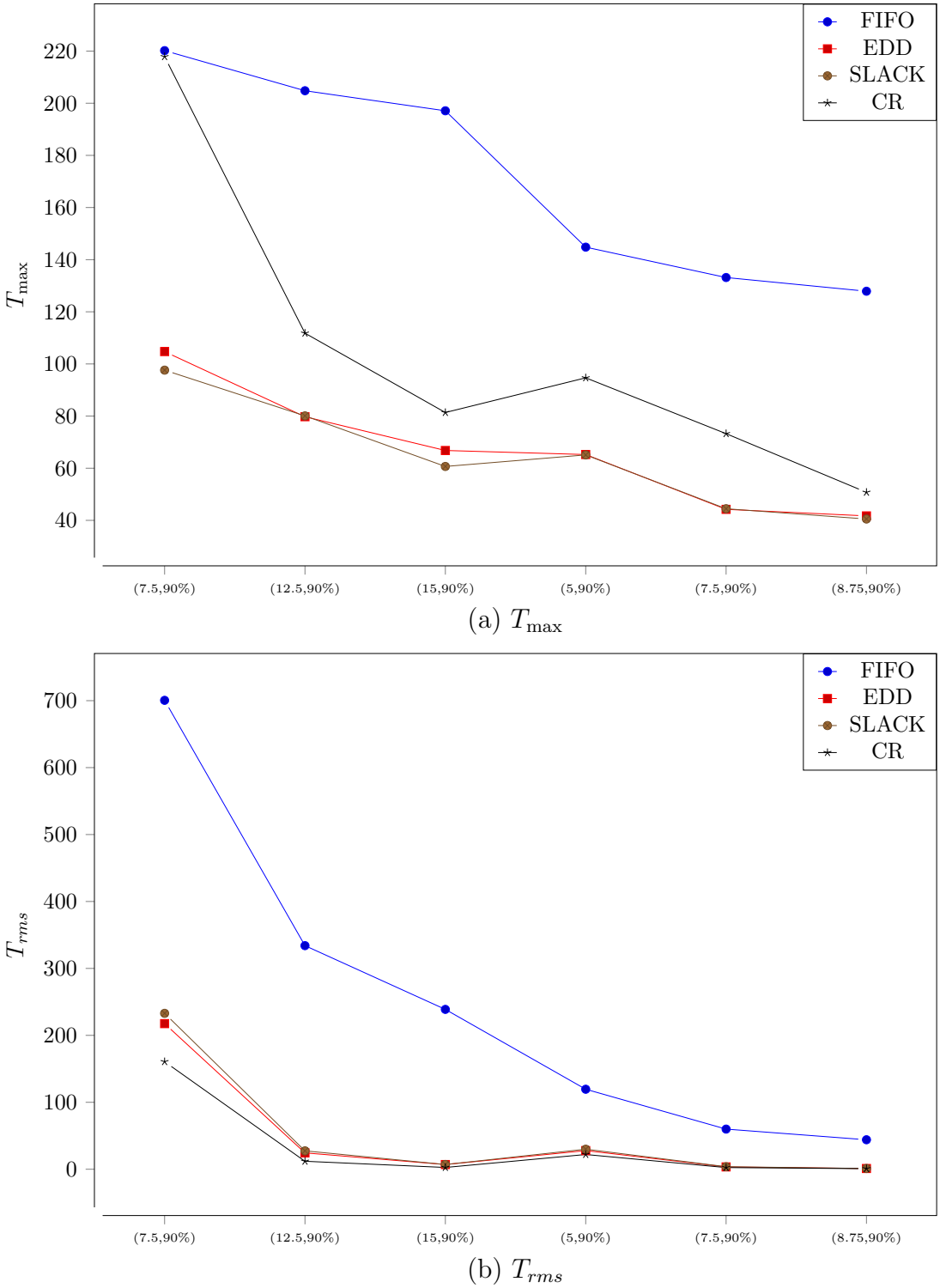


Figure 3.9 – *Comparison of* $T_{\max}$ *and* T_{rms} *for rules of set 1*

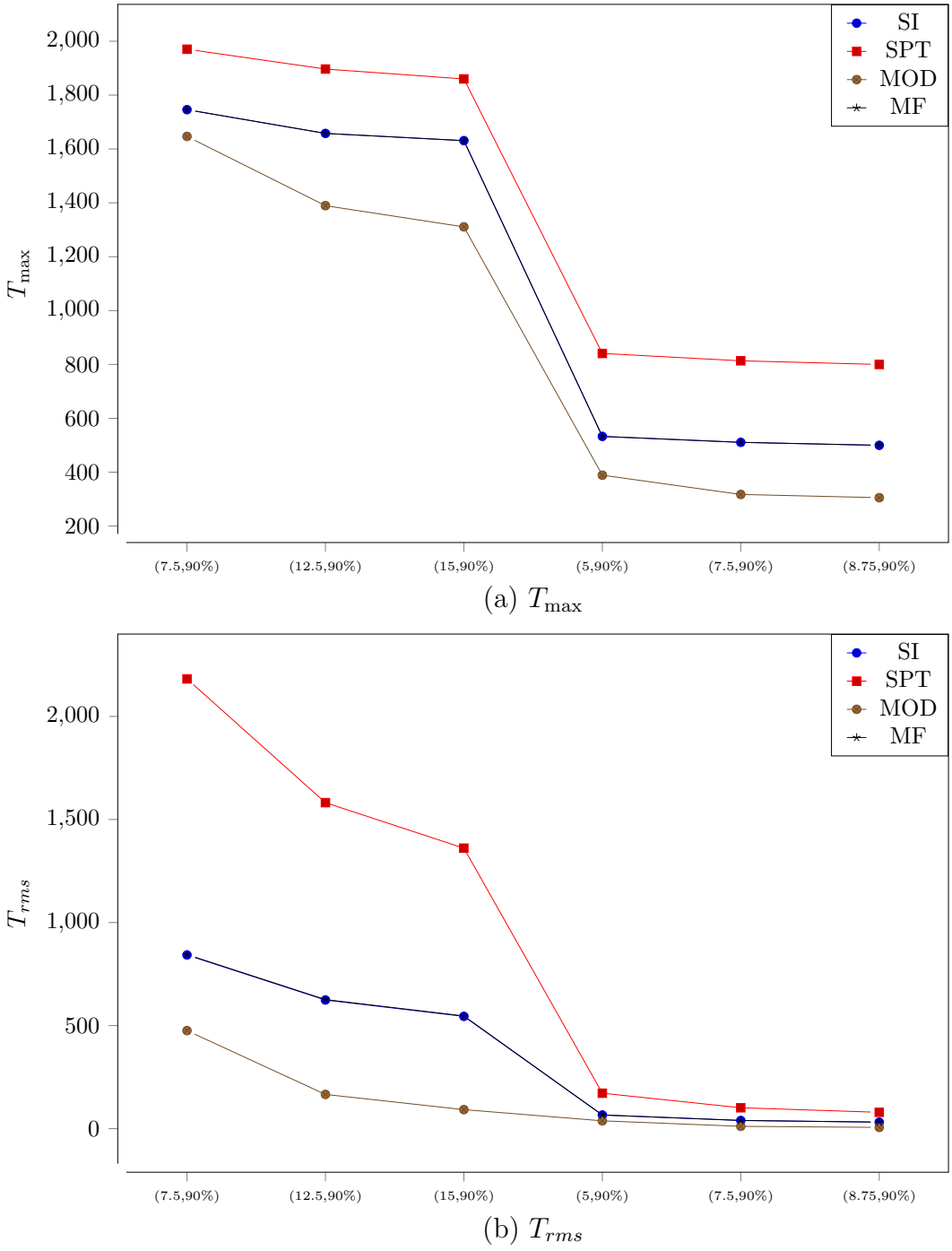
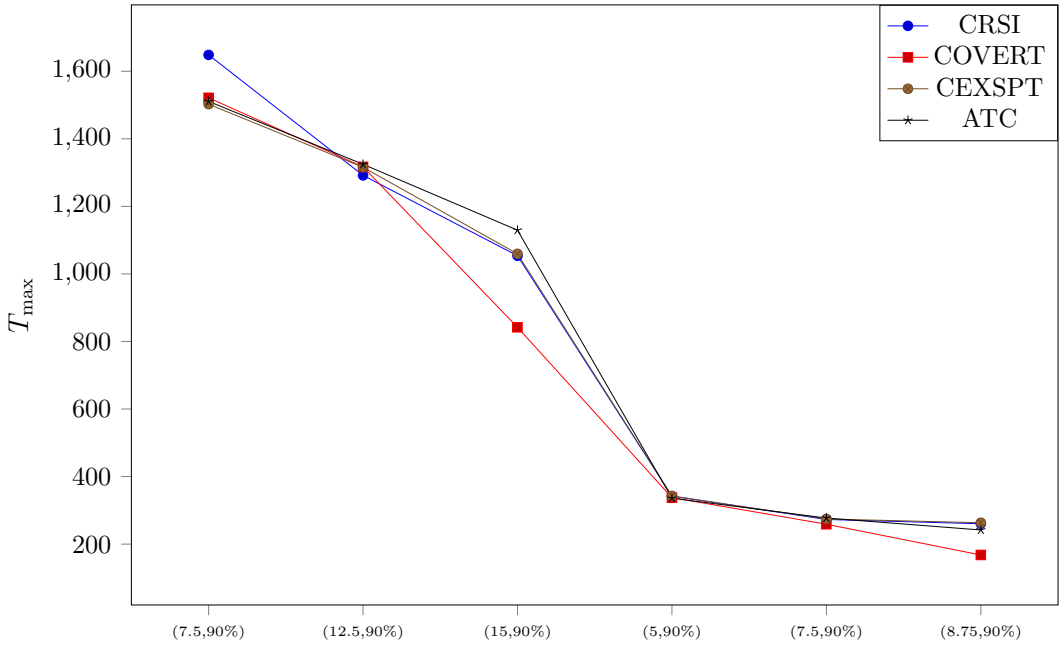
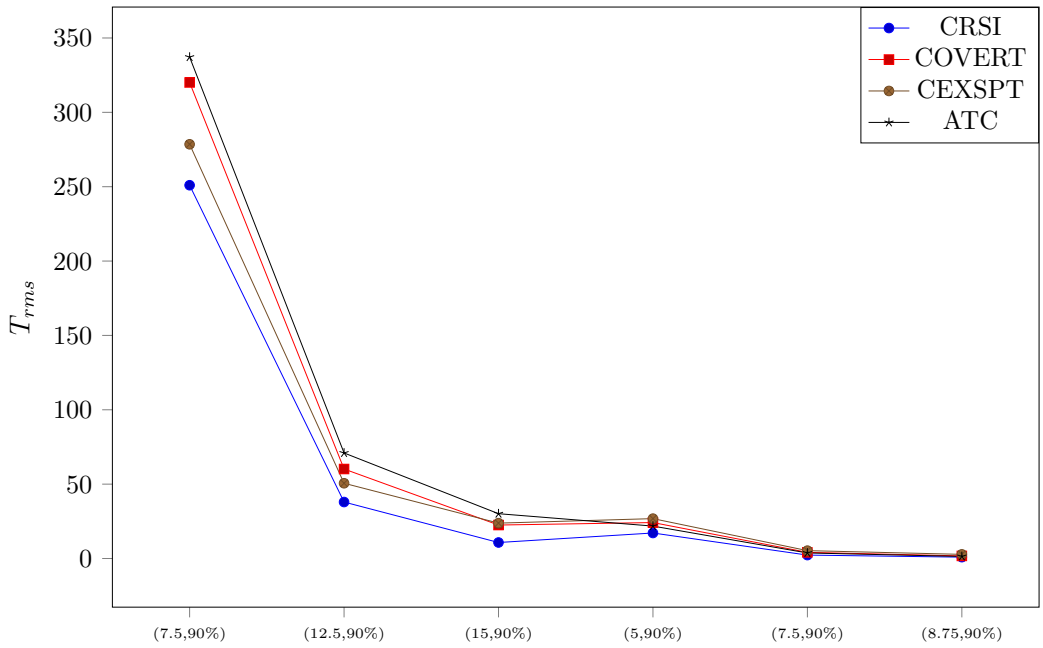


Figure 3.10 – *Comparison of* $T_{\max}$ *and* T_{rms} *for rules of set 2*



(a) $T_{\max}$



(b) T_{rms}

Figure 3.11 – *Comparison of* $T_{\max}$ *and* T_{rms} *for other rules*

Table 3.3 – *Confidence Interval for Correlation between* $T_{\max}$ *and* T_{rms}

	(7.5,90%)	(12.5,90%)	(15,90%)	(5,80%)	(7.5,80%)	(8.75,80%)
FIFO	0.85529	0.85963	0.85604	0.74663	0.75248	0.75248
	[0.7926,0.89986]	[0.79261,0.90482]	[0.78931,0.90291]	[0.64096,0.84518]	[0.64177,0.86386]	[0.64177,0.86386]
SI	0.89076	0.90969	0.91798	0.82116	0.85957	0.85957
	[0.81299,0.94655]	[0.84568,0.95843]	[0.85023,0.96146]	[0.73265,0.89054]	[0.7919,0.91477]	[0.7919,0.91477]
SPT	0.87495	0.88438	0.88884	0.77426	0.80669	0.80669
	[0.81709,0.91214]	[0.83268,0.91846]	[0.84133,0.92192]	[0.68927,0.83444]	[0.73219,0.86285]	[0.73219,0.86285]
EDD	0.87681	0.91346	0.89915	0.82829	0.88431	0.88431
	[0.80323,0.92411]	[0.87314,0.93581]	[0.85284,0.92789]	[0.73672,0.89456]	[0.84067,0.91658]	[0.84067,0.91658]
SLACK	0.87442	0.92353	0.9143	0.82894	0.92511	0.92511
	[0.80542,0.91772]	[0.89158,0.9479]	[0.88377,0.94044]	[0.74006,0.89895]	[0.89416,0.94954]	[0.89416,0.94954]
CR	0.88691	0.94371	0.94926	0.80228	0.92711	0.92711
	[0.81835,0.92796]	[0.91115,0.96202]	[0.91001,0.96929]	[0.71576,0.86626]	[0.88473,0.959]	[0.88473,0.959]
CR/SI	0.92886	0.95837	0.98692	0.87255	0.95654	0.95654
	[0.88921,0.96166]	[0.91968,0.97568]	[0.96101,0.99877]	[0.80903,0.91708]	[0.93018,0.97198]	[0.93018,0.97198]
CoverT	0.91365	0.9529	0.93416	0.85643	0.90983	0.90983
	[0.8615,0.94638]	[0.92114,0.97366]	[0.88398,0.97113]	[0.77751,0.91454]	[0.83947,0.95133]	[0.83947,0.95133]
MOD	0.88924	0.93424	0.95677	0.86473	0.89796	0.89796
	[0.83239,0.93016]	[0.89132,0.96964]	[0.93001,0.96886]	[0.80519,0.90954]	[0.85873,0.92713]	[0.85873,0.92713]
CEXSPT	0.92407	0.95033	0.95927	0.83688	0.90615	0.90615
	[0.88205,0.96247]	[0.90848,0.97623]	[0.91218,0.98616]	[0.7736,0.88755]	[0.8533,0.93747]	[0.8533,0.93747]
ATC	0.92855	0.95065	0.9859	0.8715	0.94496	0.94496
	[0.89352,0.95382]	[0.91384,0.96863]	[0.9693,0.99507]	[0.81272,0.91484]	[0.91124,0.96844]	[0.91124,0.96844]
MF	0.9091	0.92447	0.925	0.80034	0.83919	0.83919
	[0.84872,0.95256]	[0.86551,0.96275]	[0.86443,0.96358]	[0.70001,0.87661]	[0.75322,0.90042]	[0.75322,0.90042]

3.5 Conclusions

In this chapter, we have discussed tardiness based performance measures using a set of pdrs that are extensively used in the literature on scheduling. From their relative performance for the maximum tardiness, two sets of rules have been identified, FIFO, EDD, SLACK and CR from one side and SI, SPT, MOD and MF on the other side. The behavior for the rules of the first set is to exhibit a large number of tardy jobs with low tardiness, which is exactly opposite to that for the rules of the second set. There are some rules (CRSI, COVERT, CEXSPT and ATC) exhibiting these two behaviors under different conditions. For tight due date setting, these rules behave more like the rules of set 1 while under loose due date setting, their behavior tends towards rules of set 2. This kind of discrimination is typically found through the T_{rms}.

We found results that show a strong correlation between the $T_{\max}$ and the T_{rms} for a set of pdrs that are extensively used in literature on scheduling. This correlation is found to be relatively stronger in congested shops. The worst case performance in regards with tardiness of a particular priority dispatching rule may therefore be predicted by evaluation of T_{rms} which can be used along with the mean tardiness to compute the variance of the tardiness. So, the T_{rms} can be used to rank the priority dispatching rules in regards with the $T_{\max}$ and the width of the tardiness.

4 Learning based Approach in Scheduling: A Review

This chapter gives a state-of-the-art survey on the use of learning based approaches in the field of job shop scheduling. It provides an effective overview of the challenges and benefits related to the application of learning algorithms in solving scheduling problems. The survey reveals that their is a lack of systematic use of the scheduling knowledge despite the fact that the approach has been acknowledged by most of the authors as promising in scheduling domain. Moreover, it is generally not obvious how much a certain set of scheduling data is relevant to the scheduling environment for desired objectives. The emergence of data mining has invoked the academic interest in analyzing the complex problems like this in a more methodical way.

4.1 Introduction

Scheduling is an important and complex activity in manufacturing that quickly crosses the human cognitive capabilities even by a slight increase in its size. Machine learning

Part of this chapter was presented in the 8^{th} International Conference of Modeling and Simulation (MOSIM'10) (Shahzad and Mebarki, 2010) (has been pre-selected for publication in Engineering Application of Artificial Intelligence, ISSN: 0952-1976, Imprint: ELSEVIER).

simulates the human learning to assist in analyzing complex problems like scheduling. Data mining integrates machine learning and modern database managements systems for the discovery of new knowledge.

In recent years, several studies have focused on use of data mining as one of the approach to understand the scheduling activities in a manufacturing system.

This chapter reviews the literature on the application of inductive learning algorithms and their relative merits in the field of scheduling. The aim is to discuss the major contributions in solving the scheduling problems and to identify their strengths and weaknesses. Case-based reasoning, neural networks and inductive learning are the main approaches that have been adapted to the scheduling problems.

Inductive learning approaches are considered to be more intuitive and hence gained much attraction. Learning algorithms are greatly influenced by a number of parameters including feature extraction, feature selection and discretization. Feature extraction involves the creation of new attributes through transformation or combination of the primitive features. Feature selection is the task of finding the most relevant subset of features for a classifier to seek fewer features and maximum class separability.

The remainder of this chapter is organized as follows. We present a general overview of literature on learning algorithms used in scheduling in § 4.2. A survey of the publications applying inductive learning methods to scheduling problems is given in § 4.3. A brief review of discretization, binning methods and feature selection is presented in § 4.4. In the last section, some concluding remarks on this review are presented.

4.2 A General Overview of Literature on Learning Based Scheduling

As there does not exist a pdr that is globally better than all the others (Lee *et al.*, 1997), numerous techniques based on the approach for dynamic selection of pdrs at the right moment according to the systems' conditions and production objectives were proposed. This approach is referred as multi-pass adaptive scheduling (MPAS) approach (Shiue and Guh, 2006a). Priore *et al.* (2001) categorized MPAS strategies as look-ahead simulation based and knowledge based.

In the simulation based approach, the rule is chosen at the right moment by simulating a set of pre-established dispatching rules and selecting the one that gives the

best performance (see for example, (Wu Richard and David, 1988; Wu and Wysk, 1989; Ishii and Talavage, 1991; Yeong-Dae, 1994; Pierreval and Mebarki, 1997; Jeong and Kim, 1998)). The selected pdr is then used for a scheduling period of shorter length that may be fix or dynamically sized according to system performance.

The second approach, from the field of artificial intelligence, employs a set of earlier system simulations (training examples) to determine what the best rule is for each possible system state. These training examples are used to train a machine-learning algorithm to acquire knowledge about the manufacturing system (Michalski *et al.*, 1986, 1998). Intelligent decisions are then made in real time, based on this knowledge (see for example, (Nakasuka and Yoshida, 1992; Shaw *et al.*, 1992; Yeong-Dae, 1994; Min and Yih, 2003)).

The main algorithm types from the field of machine learning used in scheduling problems include case-based reasoning (CBR), neural networks and inductive learning (Priore *et al.*, 2006). CBR is a kind of analogy-making that exploits the experience gained from the similar problem-solving cases of the past (Watson, 1995). Lamatsch *et al.* (1988) employed the same principle and incorporated reduction digraphs to search for a matching problem. Schmidt (1998) merged case-based reasoning with the theory of scheduling to solve production planning and control problems using an interactive problem-solving framework. However, due to extremely complex nature of scheduling problems, this approach is considered inadequate (Aytug *et al.*, 1994).

Inductive learning is broadly categorized as unsupervised and supervised inductive learning. In an unsupervised inductive learning, the learner is given only unlabeled examples, the observations and it seeks to determine how the data is organized. On the other hand, supervised learning is the machine learning task of inferring a function from supervised training data. The training data consists of a set of training examples. Each example is a pair consisting of an input object (typically a vector) and a desired output value. A supervised learning algorithm analyzes the training data and produces an inferred function, which is called a classifier. The next section gives a state-of-the-art on the use of inductive learning in production scheduling.

4.3 Literature Review on Inductive Learning in Scheduling

Inductive learning in production scheduling has primarily been devoted to issues such as selecting the best dispatching rule using simulation data. (Aytug *et al.*, 1994) presented a

comprehensive review of different machine learning techniques with emphasis on inductive learning methods applied in scheduling.

Pierreval and Ralambondrainy (1988) used the induction algorithm GENREG proposed by (Ralambondrainy, 1988) to obtain a set of rules with best mean tardiness as target concept on simulation data for flow shop environment. They acknowledged that the identified rules may not be strong enough, however it is mentioned that the approach is a promising one especially when there is a lack of knowledge of the problem domain.

Nakasuka and Yoshida (1989) employed a learning algorithm named as Learning Aided Dynamic Scheduler (LADS), capable of automatically generating new useful attributes for on-line rule selection in a production line. The algorithm can handle quantitative as well as qualitative type attributes. Selection of useful attributes is done using a local knowledge-base (of each machine). They concluded that the good switching of rules can effectively draw strong features of each individual rule. They also observed that incorporating a mechanism to identify more informative problem sets increases the learning efficiency.

Shaw *et al.* (1992) developed pattern-directed scheduler (PDS) to monitor the scheduling activity for changes in manufacturing patterns (combinations of various parameters that together represent a given state of the system). Their system performed better than the best dispatching rule considered for mean tardiness, under similar conditions. However for higher number of machines and lower switching frequency of the selected rules, the performance of system degraded.

Piramuthu *et al.* (1994) proposed a mechanism based on same principle to select among a given set of heuristics using a well-known data mining algorithm C4.5, proposed by (Quinlan, 2003) for decision tree generation for a flow shop. They considered both the dispatching at individual machines and releasing jobs into the system. They investigated the performance of PDS over a range of values for coefficient of variation of process time and identified that their results were superior for large process time variations at bottleneck machines. They observed that pattern-directed scheduling based decision trees were not able to significantly improve upon the results. Moreover, these results are not generalized.

Priore *et al.* (2001) used induction learning to select a heuristic through a set of training examples created by using different values of the control attributes and identifying the relevant manufacturing patterns. They observed that on certain occasions, the obtained heuristic was bettered by the SPT or the EDD rule. A major cause of such behavior is identified as the transitory changes of the control attributes. This effect is reduced by assigning a weight function to each selected rule and triggering a rule only when its weight

reaches a certain lower limit.

Later, (Priore *et al.*, 2006) compared inductive learning based on C4.5 algorithm with other machine learning techniques for a selected flexible manufacturing system. They incorporated a generator module to create new control attributes in order to reduce the test error rate.

Li and Olafsson (2005) used decision-tree induction in their proposed approach to discover the key scheduling concepts by applying data mining techniques on historic scheduling data and to generate scheduling rules. Instead of selecting a particular pdr, they used the dominance between two jobs (which job should be dispatched first) as the target concept to be learned. This knowledge is then transformed in a form of dispatching lists. They studied a single machine problem with $C_{\max}$ as scheduling objective and compared the performance with standard benchmark pdrs. They, however did not perform any selection of the subset of data to be used for learning.

The review of the literature on knowledge based approach for MPAS reveals that the usual practice involves the implementation of a pre-defined set consisting of a number of candidate rules in a discrete event simulation model of the system under consideration, and comparing their performance using simulation experiments under varying values of system parameters characterizing the system dynamics. A set of best performing rules under varying conditions are taken as training examples to be input to the learning system. Intelligent decisions are then made in real time based on the knowledge obtained through the learning system. Generally, examination of the simulation results suggests changes to the selected rule-set, requiring repetition of at least a subset of the simulation experiments. This, of course, assumes that all the dispatching rules are known in advance and that the performance of these rules can accurately be simulated. Exception to this usual approach include (Koonce and Tsai, 2000; Geiger *et al.*, 2006; Huyet, 2006). In most of these studies, simulation is not used for the generation of knowledge (although it is employed in intermediate steps).

Lee *et al.* (1997) proposed to combine the strengths of genetic algorithm and induction learning for developing a job shop scheduling system. Genetic algorithm used the heuristic space as the search space. However they limited the learning process only to job release, referring the difficulties to develop dispatching knowledge-bases for the dispatching phase.

Koonce and Tsai (2000) applied data mining on solutions generated by a genetic algorithm (GA) based scheduling and developed a rule set approximating the GA scheduler. The Attribute Oriented Induction approach was used to characterize the relationship between the operations' sequences and their attributes. The approach outperformed SPT, however

the obtained rules were unable to match the performance of GA scheduler.

Dimopoulos and Zalzala (2001) used genetic programming (GP) to evolve sequencing policies that combine known sequencing rules and problem specific information. They studied a single machine scheduling problem with the objective of minimizing the total tardiness. Various sets of problems are used for training the proposed GP-based algorithm for the evolution of a dispatching rule. Nine dispatching rules were evolved with comparable performance to man-made dispatching rules on training and validation problem set. However the approach lacks transparency for a human scheduler in making decisions.

Ho and Tay (2005) made use of genetic programming as well for evolving effective composite dispatching rules for solving a flexible JSSP with recirculation, with the objective of minimizing total tardiness. They generated five pdrs for variable due date settings that are reported to perform marginally well over the EDD in 74% to 85% of problem instances. Their framework had the same drawback of lack of transparency as well as redundancy of parameters in the evolved rules.

Geiger *et al.* (2006) proposed a genetic programming based system, named SCRUPLES that combines an evolutionary learning mechanism with a simulation model to discover new priority dispatching rules. They studied single machine scheduling problem with three different objectives of minimizing $\sum C_i$, $L_{\max}$ and $\sum T_i$. A framework for more complex scheduling environments is also presented. They observed that number of jobs to be scheduled has no significant impact on the performance of the system

Huyet and Paris (2004) proposed a methodology based on synergistic action of evolutionary optimization and induction graph learning method to search for relevant knowledge of manufacturing system. Optimization process provides increasingly efficient solutions during its search. These solutions are then classified by the learning process using certain solution characteristics. These characteristics are highlighted in the learning process to characterize the attractive areas of search space as well. They experimented with an assembly kanban system for its optimal configuration.

Later, (Huyet, 2006) implemented the same approach for configuration of a job shop and compared the results with a classical evolutionary optimization via simulation approach. They generated some profiles for the system that contribute to characterization of high-performance solutions.

As is evident from the prior work, the major contribution of learning in production scheduling is focused on selection of the best dispatching rule for specific conditions. Different learning algorithms are used to extract the desired knowledge, with no algorithm capable

of outperforming others for all system conditions. The major drawback has been to ignore the question of relevance of the solutions considered for the knowledge generation. The contents of the scheduling knowledge play a major role in improving the efficiency of the learning algorithm. However, it is generally not obvious which solutions would be more relevant with respect to defined scheduling objectives in a particular environment. Simulated data, historical data or data generated by some meta-heuristic like GA remained the source of this scheduling knowledge. Huyet and Paris (2004) considered the problem of relevance of scheduling knowledge while using GA to generate it.

A few studies focused on discovering new rules using GP and data mining. The proposed approach relies on the solutions generated by tabu search. However instead of restricting the focus on the pdr-space, dominance relations of competing jobs is identified, making use of a set of pre-defined attributes. This differs from the selection of a pdr, where a selected pdr is known to exist in the pool of candidate rules and is then used for dispatching jobs during a certain length of scheduling period.

4.4 Parameters Influencing the Induction Algorithm

4.4.1 Feature Extraction and Selection

Feature extraction involves the creation of new attributes through transformation or combination of the primitive features. Some of the important observations drawn from literature review (Kwak and Yih, 2004; Metan *et al.*, 2010; Zhao and Liu, 2007; Siedlecki and Sklansky, 1993; Chen and Yih, 1996) are as under:

1. higher number of features is not necessarily beneficial for performance improvement.
2. Transformations or combinations of primitive features do not always guarantee better performance.
3. Each attribute must consider some important information about the system under consideration.
4. Attribute values must be computable at the right time with available information at that time.
5. Generally, there exist feature interaction for a given subset of features, *i.e.* a feature is not directly relevant to the target concept, rather it forms another feature subset that is correlated to the target concept.

High dimensionality poses a challenge to learning tasks. Due to irrelevant features, classification algorithms tend to over-fit training data and degrade the generalization ability (Guyon and Elisseefi, 2003; Shiue and Guh, 2006b). Feature selection is the task of finding the most relevant subset of features for a classifier to seek fewer features and maximum class separability (Kwak and Yih, 2004).The relevant features are those that are predictive of the class whereas redundant features are those that are although predictive of the class but are highly correlated with other predictive features (see (John *et al.*, 1994) for details). Feature selection is an important issue in classification problems that leads to more accurate and parsimonious models making it necessary to carefully examine the effect of each attribute individually and combined with others (Chiu and Yih, 1995; Chen and Yih, 1996).

The two major approaches in feature selection are the filter and wrapper approaches (John *et al.*, 1994). The filter approach selects features independent of the objective function of the problem and ignores the effects of selected features on the performance of the objective function (Kwak and Yih, 2004). The wrapper approach takes into account the

eventual objective function in its feature selection, however this approach may not be computationally feasible with a large number of features (Hen *et al.*, 2002).

4.4.2 Discretization

Some attributes may contain so many values that the mining algorithm cannot easily identify interesting patterns in the data, from which to create a model. In these cases, one can discretize such data to enable the use of the algorithms to develop a mining model. Discretization is the process of dividing a scale variable into a small number of intervals, or bins, where each bin is mapped to a separate category of the discretized variable.

The discretization process can significantly influence the effectiveness of a classification algorithm, however it is virtually ignored in the machine learning literature (Kerber, 1992). There is an extensive amount of literature on the discretization, however most of the algorithms are static in nature, not taking into account the actual values. The interval boundaries, hence may occur in the places that do not facilitate the accurate classification. The simplest of these methods include equal-width-interval and equal-frequency-intervals. Some more involved discretization methods include 1R algorithm (Holte, 1993), ChiMerge (Kerber, 1992), StatDisc (Richeldi and Rossotto, 1995), Minimum Description length principle Cut (MDLPC) (Fayyad and Irani, 1993), CONTRAST (van De Merckt, 1993) and FUSINTER (Rabaséda, 1996). Dougherty *et al.* (1995) provides an excellent review of these discretization methods.

4.5 Conclusions

In this chapter, an overview of application of different approaches from the field of machine learning in scheduling is presented with an emphasis on the inductive learning method.

Generally, in MPAS strategies employing machine learning, the performance of a set of pre-defined pdrs on given objective function(s) is obtained through simulation. Best performing pdrs under different conditions are selected as training examples for the learning algorithm. The selection of training examples, in this case, is merely based on the performance of a pdr relative to the set of pdrs simulated .

Case Based Reasoning (CBR), Artificial Neural Networks (ANN) and Inductive learning are the main techniques among others, that are used for scheduling . CBR and its variants

are found to be inadequate due to very complex nature of scheduling problems and its inability of generalization. ANN (especially Hopefield networks) require excessive computation times despite their inherent parallelism. GA based schemes also suffer from the problem of relevance and generality. The genetic programming (GP) based approaches are found to be extremely sensitive to the selection of parameters and lacking the transparency.

Decision Tree (DT) based inductive learning , on the other hand, is relatively simple yet powerful technique capable of producing good results without compromising the transparency in decision-making process.

Table 4.1 – *Review of Literature*

Reference	Approach	Learning	Performance Measures	Features	Discretization	Application
Pierreval and Ralambondrainy (1988)	Simulation/Learning	GENREG	$\bar{T}$	9	-	Simplified FlowShop
Nakasuka and Yoshida (1989)	Simulation/Learning	LADS	$C_{\max}$,$\Sigma_j T_j$	13	No	FMS with transportation
Piramuthu *et al.* (1994)	Simulation/Learning	C4.5, PDS	$\bar{F}$	5	No	Flow shop with machine failure
Priore *et al.* (2001)	Simulation/Learning	Inductive Learning	$\bar{T}$		4	Flow shop, Job shop
Priore *et al.* (2006)	Simulation/Learning	C4.5,BPNN,CBR	$\bar{T}$, $\bar{F}$	7	No	FMS with transportation
Metan *et al.* (2010)	Simulation/Data Mining	C4.5	$\bar{T}$	26	No	Job Shop
Lee *et al.* (1997)	GA/Learning	C4.5	$\Sigma_j T_j$	4	No	Job shop
Koonce and Tsai (2000)	GA/Data Mining	Attribute Oriented Induction	$T_{\max}$	4	No	Job shop
Dimopoulos and Zalzala (2001)	GP		$\Sigma_j T_j$	5	No	Single Machine
Harrath *et al.* (2002)	GA/Data Mining	C4.5		5	Yes	Job Shop
Kwak and Yih (2004)	Simulation/Data Mining	C4.5	ΣU_j	11	No	FMS
Huyet and Paris (2004)	GA/Learning	C4.5	JIT	22	No	Job shop
Ho and Tay (2005)	GP			7	No	Job Shop
Li and Olafsson (2005)	Simulation/Data Mining	C4.5	$C_{\max}$	4	Yes	Single Machine
Geiger *et al.* (2006)	GP		$\Sigma_j C_j$, $L_{\max}$,$\Sigma_j T_j$	17	No	Single Machine, Flow shop.
Huyet (2006)	GA/Learning	C4.5	JIT	22	No	Job shop
Shiue and Guh (2006a)	GA/Learning	ANN/C4.5	$\bar{F}$,ΣU_j	30	No	FMS

5 Discovering Dispatching Rules For JSSP through Data Mining

A data mining based approach to discover previously unknown priority dispatching rules for job shop scheduling problem is presented in this chapter. This approach is based upon seeking the knowledge that is assumed to be embedded in the efficient solutions provided by the optimization module built using tabu search. The objective is to discover the scheduling concepts using data mining and hence to obtain a set of rules capable of approximating the efficient solutions for a job shop scheduling problem (JSSP). A data mining based scheduling framework is presented and implemented for a job shop problem

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with mean tardiness and maximum lateness as the scheduling objectives. The results indicate the superior performance of the proposed system relative to a number of priority dispatching rules and hence proves to be promising approach.

5.1 Introduction

The major drawbacks of pdrs include their performance-dependence on the state of the system and non-existence of any single rule, superior to all the others for all possible states the system might be in (Geiger *et al.*, 2006). Meta-heuristics (e.g., simulated annealing, tabu search etc) have an advantage over pdrs in terms of solution quality and robustness, however these are usually more difficult to implement and tune, and computationally too complex to be used in a real time system.

Robust and better-quality solutions provided by meta-heuristics contain useful knowledge about the problem domain and solution space explored. Such a set of solutions represents a wealth of scheduling knowledge to the domain that can be transformed in a form of decision tree or a rule-set. Here, we propose an approach to exploit this scheduling knowledge. In our approach, we seek this scheduling knowledge through a data mining module to identify a rule-set by exploring the patterns in the solution set obtained by an optimization module based on tabu search, a very efficient meta-heuristic for JSSP in particular. This rule-set approximates the output of the optimization module when incorporated in a simulation model of the system. This rule-set is subsequently used to make dispatching decisions in an on-line manner.

This chapter is organized as follows. A brief description of some necessary background areas such as tabu search and data mining is given in § 5.2. The proposed framework is presented in § 5.3 along with the details of the different modules. In § 5.4 , the design of experiments for the proposed framework is given. The results and discussions are provided in section § 5.5 . Conclusions and some perspectives of this study are presented in the last section.

5.2 Background

Some background areas must be discussed before presenting the proposed framework. These include Tabu search; one of the most effective metaheuristic to solve JSSP and data mining; a knowledge discovery approach.

5.2.1 Tabu Search

Tabu search (TS) algorithms are among the most effective approaches for solving JSSP (Jain and Meeran, 1998) using a memory function to avoid being trapped in a local optimum (Zhang *et al.*, 2008). Most state-of-the-art algorithms for JSSP include some sort of tabu search functionality (Zobolas *et al.*, 2008). However, neighborhood structures and move evaluation strategies play the central role in the effectiveness and efficiency of the tabu search for the JSSP (Jain *et al.*, 2000). In contrast to myopic nature of PDRs, metaheuristics such as tabu search can attack the problem more rigorously and intelligently due to relatively higher level of domain knowledge. As a consequence, the decisions made by the proposed system reflect the use of this valuable knowledge.

The fundamental element underlying tabu search is the use of flexible memory that acquires domain and search space relevant information and profits from it as well (Laguna, 1994). The basic tabu search procedure is quite simple. A feasible initial solution is used as a starting point and is set as current seed and the best solution. Depending upon the neighborhood structure, a finite number of neighbors of the current seed are found, that represent the candidate solutions. Through the performance evaluation of those candidate solutions that are are not tabu (one that is obtained through a forbidden move) or those that do not satisfy aspiration criteria (to overrule the tabu status), the best one is selected as the new current seed. This selection is called a move added to tabu list, while removing the oldest move from this list. New seed solution assumes the place of current best, if it is better than it. The procedure is iterated until the stop criterion is met.

A huge number of variations in this basic procedure of tabu search can be found in literature. The most common variation include flexible tabu length, neighbor structure, multi-start search, aspiration and stopping criteria etc. Neighborhood structure is the most crucial ingredient of a particular tabu search algorithm. It is a mechanism to obtain a new set of neighbors by applying small perturbations to the current solution (Zhang *et al.*, 2007).

Neighborhood structure is directly effective on the efficiency of TS algorithm (Jain *et al.*, 2000). A neighborhood structure is a mechanism which can obtain a new set of neighboring solutions by applying small perturbations to a given solution. Each neighbor solution is reached immediately from a given solution by a move.

The earliest implementations of tabu search in JSSP include (Taillard, 1994; Dell'Amico and Trubian, 1993; Barnes and Chambers, 1995). The TSAB (Tabu Search Algorithm with Back jump tracing) method Nowicki and Smutnicki (1996) however, in-

troduced a real breakthrough in terms of efficiency and effectiveness for the JSSP. The i-TSAB technique proposed by Nowicki and Smutnicki (1996) improves upon the earlier algorithm and represents the current-state-of the-art for JSSP. Later, (Watson *et al.*, 2005, 2006) analyzed the reasons of effectiveness of tabu search in JSSP. Some hybrid methods are also proposed to further improve the efficiency. These include the work of (Pezzella and Merelli, 2000), who combined tabu search with shifting bottleneck heuristic and (Zhang *et al.*, 2008) proposing a very effective hybrid tabu-search simulated annealing method.

5.2.2 Data Mining

Data mining is an essential step in process of knowledge discovery from data (KDD), however the two terms are often used interchangeably. Data mining is the process of discovering interesting knowledge from large amounts of data stored in databases, data warehouses, or other information repositories (Han and Kamber, 2002). The data mining approach is particularly applicable for large, complex production environments, where the complexity makes it difficult to model the system explicitly.

From the viewpoint of our approach, data mining can specifically be considered as the analysis of a data set, referred as training data set in order to identify previously unknown and potentially useful hidden patterns and to discover relationships among the various elements of this data set. The aim is to classify the cases in another data set, referred as test data set, by mapping the newly discovered relationships on them. The discovery process can be termed as descriptive data mining, while the classification of test data set using the discovered relationships can be viewed as predictive data mining (Choudhary *et al.*, 2009).

We use decision tree based learning as the data mining step as it is simple to understand and interpret, requires little data preparation, able to handle both numerical and categorical data, uses a white box model, possible to validate a model using statistical tests, robust and performs well with large data in a short time. Induction of decision tree, or ID3 (Iterative Dichotomiser 3) (Quinlan, 1986) is one of the most powerful mining algorithm used in machine learning (Koonce and Tsai, 2000; Dudas *et al.*, 2009; Priore *et al.*, 2006). Revised versions of ID3 include GID3 (Generalized ID3), ID4, ID5, C4.5 (Quinlan, 2003) and C5.0 (Quinlan, 2003).

5.3 Proposed Approach

We propose a hybrid simulation-optimization based approach coupled with data mining for job shop scheduling problem. The goal of the proposed system is to generate a set of rules for making dispatching decisions in a job shop scheduling environment.

First of all control module generates number of problem instances relevant to real scheduling system. This may be replaced by historical data of the manufacturing system. These problem instances are stored in an instance database. The optimization module generates solutions for a subset of these instances. This subset of job shop instances is referred as initial training data set. The solutions to these instances generated by an optimization module are in fact a set of good scheduling decisions that may be made for the manufacturing system. However these good decisions are not evident before these are implemented and corresponding performance measures have been computed. In order to identify and extract the characteristics of these good scheduling decisions, a simulation module is employed which associates a performance measure to each decision taken by the optimization module. This refined set of characteristics of scheduling decisions refers to a relevant scheduling knowledge. The scheduling knowledge is stored in a scheduling database and employed by a learning process to construct a decision tree. This decision tree is then used to dispatch the jobs-awaiting service in an on-line manner. The decision tree is dynamically updated, whenever necessary through a control module. The control module transmits the knowledge of good scheduling decisions to the optimization module as well to improve its own performance at subsequent levels.

Figure 5.1 demonstrates the interaction of these modules in the proposed framework. There are two important aspects of the proposed system besides merely providing a schedule,

1. to provide an insight to the scheduling decisions made by the optimization module and
2. to improve upon the efficiency of the optimization module by utilizing the output of learning module.

Scheduling procedures such as pdrs and meta-heuristics do not provide, in general, any justification of the decisions made, no matter how good or bad they are. This lack of transparency is not only undesirable in practice but also a great hindrance to understand the difference between good and bad scheduling decisions. Identifying the characteristics

of good scheduling decisions generated by an optimization process is thus desired. Our proposed system is aimed at providing transparency in its scheduling decisions.

The proposed system takes benefit from this white-box effect, by making use of the relevant scheduling knowledge in optimization process. The meta-heuristics such as tabu search use a neighborhood mechanism to reduce the search space. Optimization process can make use of this knowledge to create more restricted and potentially stronger neighborhoods.

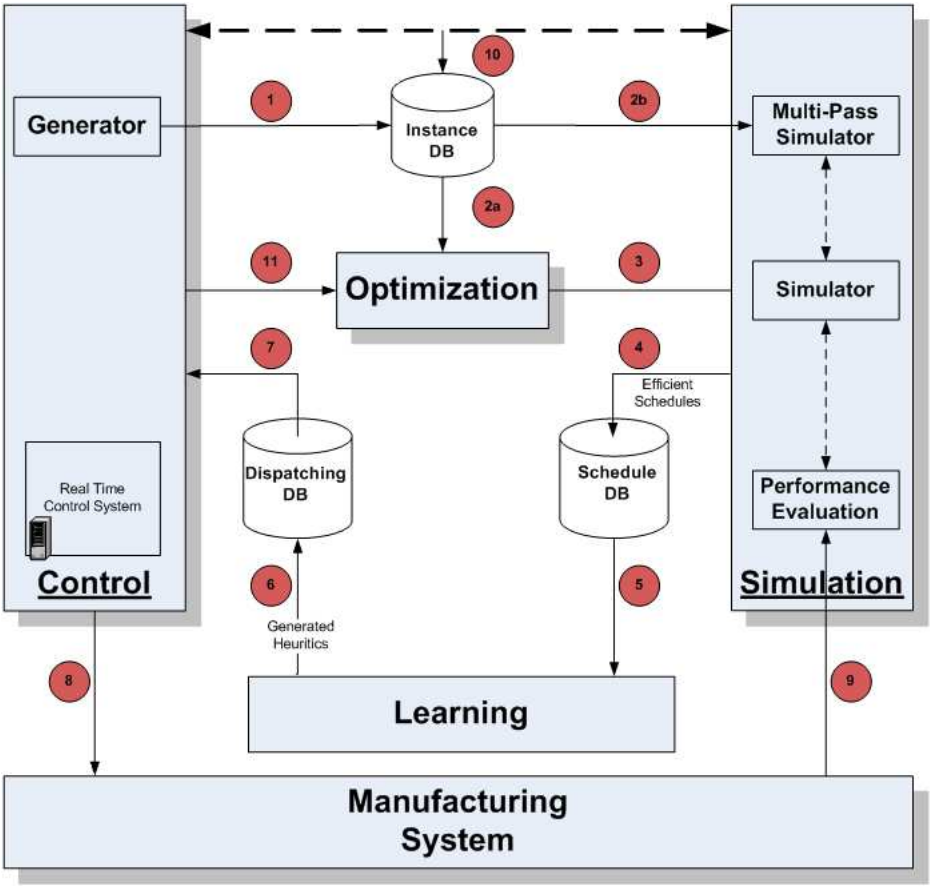


Figure 5.1 – *The proposed framework*

In the following, the structural detail of each module as well as interaction of these modules is explained.

5.3.1 Optimization Module

The optimization module is aimed at providing the most relevant solutions to the scheduling problem. A tabu search, (Nowicki and Smutnicki, 1996) based optimization module generates a set of efficient solutions for a set of problem instances. Since these efficient solutions are obtained through a series of some logical moves of the meta-heuristic, they

have some general characteristics that may describe the relationship between operations and their sequential order in a particular solution. These characteristics are a form of schedule knowledge, like dispatching rules. The aggregation of corresponding set of efficient solutions for each problem instance may then be used as the training data set for the data mining algorithm for discovery of scheduling knowledge. However, it is not expected from this module to identify a priori, the reasons of superiority of one solution to another.

The optimization module works in an off-line manner, however it continually provides with more and more schedules to the problem instances generated by the control module.

5.3.2 Simulation Module

There are three key functions of the simulation module. Figure 5.2 shows the working of simulation module. The main simulator that is in-loop with learning module, takes the schedule generated by optimization module. This schedule is transformed into a set of decisions, *i.e.* whether a job is dispatched before some other job. Each decision is characterized by a vector of attribute-value pairs, where attributes are the selected attributes and the values are obtained through this simulator. A collection of these vectors is referred as a training block (Chong *et al.*, 2004), (see § 5.3.2.1).

Finally, the simulator associates a relative performance measure to a decision made in the schedule. This is done by considering some alternative decisions at each dispatching decision point. These alternative decisions are taken from a multi-pass simulator, that measures the performance of a pre-defined set of pdrs. Each time a dispatching decision is made, it is compared with the best possible decision by the multi-pass simulator. Based on this comparison, a relative value of performance is associated with the decision. In this way, equivalent schedules are incorporated in the training data set. Both of these simulators take on the same set of problem instances.

5.3.2.1 Training Block

A training block, B_i is a matrix of the form

$$B_i = \begin{bmatrix} \mathrm{x} & \mathrm{z} \end{bmatrix}$$

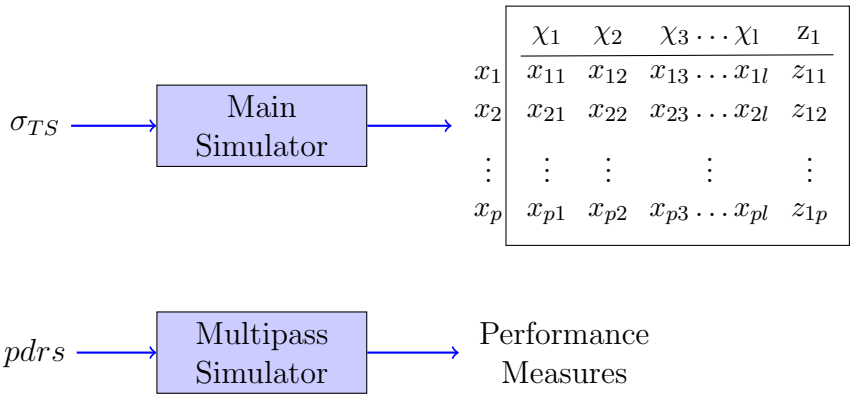


Figure 5.2 – *Simulation Module*

with

$$\mathrm{x} = \begin{bmatrix} \mathrm{x}_1 & \mathrm{x}_2 & \mathrm{x}_3 & \ldots & \mathrm{x}_\mathrm{p} \end{bmatrix}^T$$

and

$$\mathrm{z} = \begin{bmatrix} \mathrm{z}_1 & \mathrm{z}_2 & \mathrm{z}_3 & \ldots & \mathrm{z}_\mathrm{q} \end{bmatrix}^T$$

where p is the number of positive examples in a training block and q is the number of objectives considered. Each row in x is composed of values of the selected attributes at any instant, whereas each z represents the target concept to be learned. The minimum training block is $\{\mathrm{x}_1,\mathrm{z}_1\}^T$. Each element $(\mathrm{x},\mathrm{z}) \in B_i$ represents an example from which we can learn. We refer to each such example or a row in B_i as a positive training example. Each x_k is an l-dimensional row vector, *i.e.*, $\exists k, 1 \leqslant k \leqslant p$,

$$\mathrm{x}_\mathrm{k} = \begin{bmatrix} x_{k1} & x_{k2} & x_{k3} & \ldots & x_{kl} \end{bmatrix}$$

where l is the number of selected attributes with each attribute χ appearing as a column vector in B_i.

For $\mathrm{z} = \mathrm{z}_1$, z becomes a p-dimensional column vector, *i.e.*

$$\begin{bmatrix} z_{11} & z_{21} & z_{13} & \ldots & z_{1p} \end{bmatrix}^T, \forall k, z_k \in \{0,1\}$$

z_k ($z_k := precedes_{u,v,q}$) is a binary variable representing the processing order of two jobs u, v on machine q, *i.e.* $z_k = 1$ represents $u \rightarrow v$ and vice versa.

Each training block, B_i is a chronological sequence of consecutive x's and corresponding

z's, before another sequence of consecutive x's follows. A union of these training blocks is the training data set, B used by the learning module, and is expressed as

$$B = \begin{bmatrix} B_1 & B_2 & B_3 & \dots & B_n \end{bmatrix}^T.$$

There is another simulation model, within the simulation module, that serves the purpose of an observer to the manufacturing system. It records the performance of the system in response to the scheduling decisions taken. This information is used by a controller module for subsequent generation of training data. Since the actual scheduling decisions are taken on the basis of dispatching list generated by learning module, the performance of the system may differ significantly even for the same training data set.

5.3.3 Learning Module

As the solutions in the solution-set used by learning module are restricted to perform above certain threshold, focus remains on the more relevant search space. Figure 5.3 illustrates the working of learning module. The learning module takes the refined relevant scheduling knowledge from the scheduling database. This knowledge constitutes the learning set on which the induction process is built. This process aims at predicting a class of scheduling decisions that may be most accurately generalized.

χ_1	χ_2	χ_3	z_1
v_1	v_5	v_6	0
v_3	v_4	v_6	0
v_2	v_5	v_8	1
v_1	v_5	v_8	0
v_3	v_5	v_7	1
v_3	v_4	v_6	0
v_2	v_4	v_7	1
v_3	v_4	v_8	0

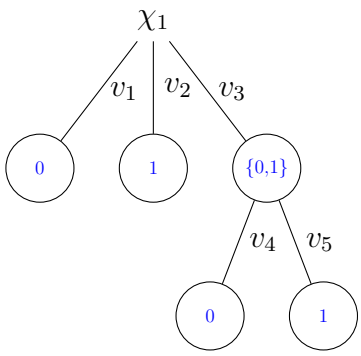


Figure 5.3 – *An Example of Generating Decision Tree from a Simple Training Block*

The learning module deciphers the scheduling data so as to make a particular decision as transparent as possible. It is quite easy to understand the process of classification of scheduling decisions when it is represented as a decision tree. This is the key advantage of the decision tree based learning and the major reason to adopt this method in the proposed

framework. Learning module uses C4.5 algorithm for mining the implicit information in the solutions found by optimization module.

The relevant scheduling knowledge is provided in the form of training blocks from the scheduling database. The collection of these training blocks is used by the learning module as initial training data. However, considerable amount of transformation is required before it is possible to mine any useful knowledge from the data.

Construction of a proper training data set is a very crucial point in the entire Knowledge Discovery from Data (KDD) process. From the data mining perspective in JSSP, the target concept to be learned is to determine which job should be dispatched first within a set of schedulable jobs on the same machine at a particular instant. Extracting this knowledge from the training data set would allow us to dispatch the next job at any given time and thereafter to create dispatching lists for any set of jobs.

Finally, the decision tree induced using the learning algorithm can be applied directly to the same JSSP to validate the explored knowledge and as a predictive model to predict the target concept. A set of scheduling problem instances with similar distribution of processing time is to be used as a test data set for the scheduling knowledge discovered. The overall sequence of operations obtained by these rules is translated to a schedule using a schedule generator. Thus, the tree will, given any two jobs, predict which job should be dispatched first and can be thought of as a new, previously unknown rule. In addition to the prediction, decision trees and decision rules reveal insightful structural knowledge that can be used to further enhance the scheduling decision.

The training blocks provide valuable information about the current status of the system. It is the selection of proper attributes, that can provide with efficient training blocks to help in generating a better quality decision tree. Attribute selection is the task of finding the most reasonable subset of attributes for a classifier to seek fewer attributes and maximum class separability (Kwak and Yih, 2004). This process is also critical for the effectiveness of the subsequent model induction by eliminating certain redundant and irrelevant attributes. It is indeed unlikely that the attributes that are recorded as part of the available data are the attributes that are the most relevant or useful for data mining process. Thus, creation of new attributes must be considered.

There exist a strong relation among the sequencing of operations due to precedence constraints, however, considering only two (operations of the) jobs on the same machine among schedulable jobs (the predecessor (if any) of whom are already dispatched) at any instance for the comparison reduces this dependency effect. Proper selection of attributes plays an important role to reduce this dependency as well.

Both the creation of new attributes and selection of attributes (we call the both process combined as attribute extraction) are primarily linked with the objectives of the JSSP. Tardiness based objectives require different attributes to be taken into account while flow-time based objectives have different requirements. For instance, deadline related statistics and counters are more suited for tardiness based objectives.

Arithmetic combinations of primitive attributes can also be used to generate new useful attributes. However a large set of attributes is not desirable, as the attributes are generally not independent of each other, making the process computationally impractical. Several heuristics such as backward stepwise heuristic, forward stepwise group heuristic have been proposed to limit the selected subset of attributes while maintaining a certain performance level.

5.3.4 Control Module

A control module generates the relevant scheduling problem instances. These instances may represent historical data of the manufacturing system. An on-line controller module takes the relevant dispatching decisions from the dispatching database, to be implemented in actual manufacturing system.

As a scheduling decision is implemented in a manufacturing system, an online performance monitoring is done, to decide whether a new training block is generated for the recent decisions or not. If the actual performance of the system degrades below a certain threshold, controller triggers the learning process for the updating of dispatching database.

A control sub-module is employed for providing feed-back to the optimization module. Feedback to optimization module serves the purpose of improving its own performance at subsequent levels.

5.3.5 Example

In Table 5.1, an instance of a 6×6 problem is given. This instance is taken from training problem set and is solved by the tabu search for mean tardiness ($\bar{T}$). The solution provided by Tabu Search (TS) is illustrated using disjunctive graph representation in Figure 5.4. Corresponding to each disjunctive arc, we get as many examples to learn as there are number of jobs at time t, waiting in the queue corresponding to the machine represented by

disjunctive arc. This forms a training block for this particular instance, to be incorporated in training data set B.

For illustrative purpose, same instance is solved by RS for $\bar{T}$ and shown in Figure 5.4. It is observed that only 14 out of 30 disjunctive arcs coincide in these two graphs, making only 17 out of 36 operations to be processed on the same sequence. However, the earliest non-coincident arc is the first arc on machine 4 ($\mathcal{O}_{34} \rightarrow \mathcal{O}_{64}$ in Figure 5.5). Fixing this arc direction as given by TS and applying an active scheduler immediately gives the same solution as given by TS. This is not true in general, however fixing the earlier arcs for a solution provided by RS results in much closer or identical sequence to the one provided by TS.

Table 5.1 – *An Instance from the Test Data Set*

$\mathcal{J}$	$\mathcal{M}_j,p_j$						
$\mathcal{J}_1$	3,4	1,6	2,8	4,5	6,8	5,7	22
$\mathcal{J}_2$	6,4	2,1	1,10	3,1	4,2	5,3	26
$\mathcal{J}_3$	1,1	2,4	4,2	6,2	3,1	5,1	25
$\mathcal{J}_4$	1,6	2,3	4,9	3,8	5,9	6,8	23
$\mathcal{J}_5$	5,3	2,4	6,6	1,7	3,7	4,3	18
$\mathcal{J}_6$	1,4	2,1	4,2	3,10	5,4	6,5	28

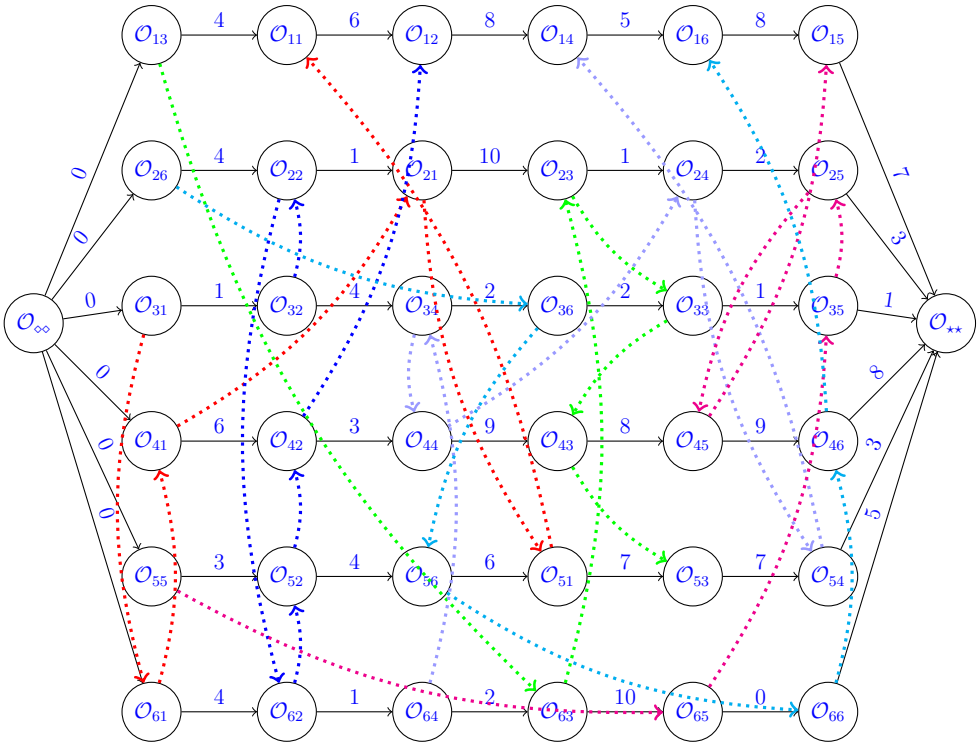


Figure 5.4 – *Disjunctive Graph Solution Given by Tabu Search*

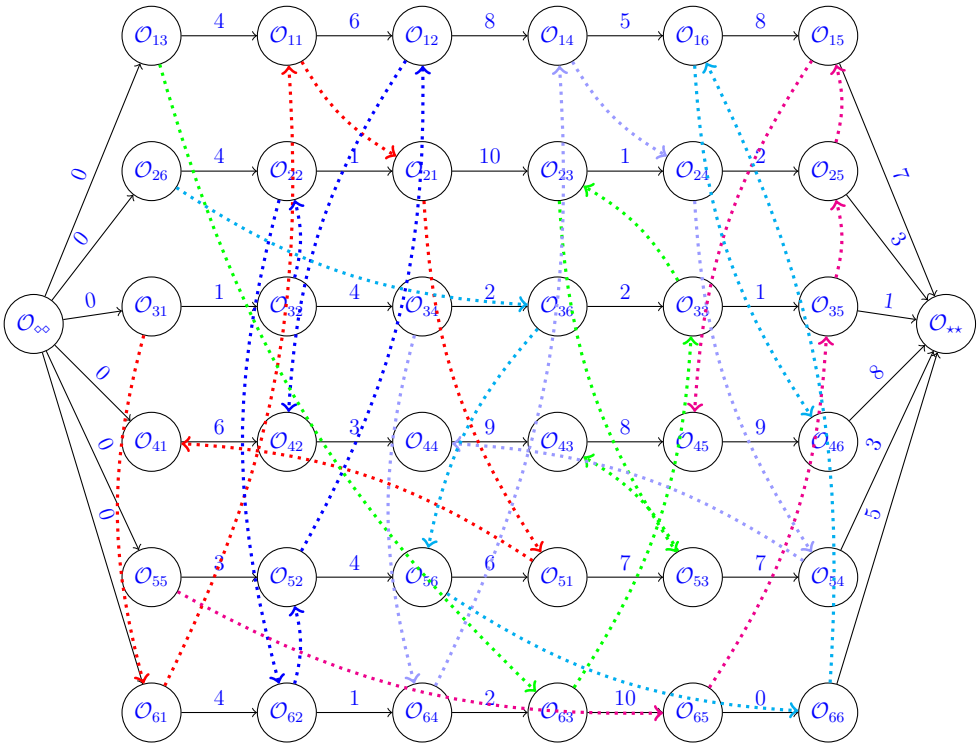


Figure 5.5 – *Disjunctive Graph Solution Given by Rule Set*

5.4 Experiments

Table 5.2 summarizes the experimental setup used. Two sets of 6×6 similarly sized instances of a static job shop problem with different seed values are used as training data-set I and test data-set $\acute{I}$. All jobs are available simultaneously at time zero. Discrete uniform distribution between 1 and 10 is used to generate the operation processing times. The job due dates are determined using two parameters τ and ρ, where τ determines the expected number of tardy jobs (and hence the average tightness of the due dates) and ρ specifies the due date range. Once these parameters have been specified, the job due dates are generated from the discrete uniform distribution given as

$$d_j = UNIFORM(\mu - \frac{\mu\rho}{2}, \mu + \frac{\mu\rho}{2})$$

where $\mu = (1-\tau)E[C_{max}]$ is the mean due date. $E[C_{max}]$ denotes the expected makespan for the problem instance and is calculated by estimating the total processing time required by all operations divided by the number of machines. Note that this assumes no idle time on machines, and hence will be an optimistic estimate of $C_{\max}$. We consider $\tau = 0.3$ and $\rho = 0.5$. $\bar{T}$ (Mean Tardiness) and $T_{\max}$ (Maximum Tardiness) are used as the scheduling objectives.

Table 5.2 – *Experimental Setup*

Parameter	Value
Data Sets	Training Data-set (I), Test Data-set ($\acute{I}$)
Problem size	6×6
Number of training instances, $\sharp I$	100
Number of test instances, $\sharp \acute{I}$	50
Release dates, r_j	0
Operation processing times, $p_{j(i)}$	U[1,10]
Due-dtaes, d_j	$UNIFORM(\mu - \frac{\mu\rho}{2}, \mu + \frac{\mu\rho}{2})$
Objectives, f	$\bar{T}$, $T_{\max}$

5.4.1 System Attributes

Selection of the relevant attributes has a key role in obtaining the appropriate performance level from knowledge-based systems. The selected attributes have the following characteristics:

- The attributes are related to tardiness based performance measures.
- It is preferred to define attributes in relative values instead of absolute values.
- The attributes with high variation are discretized.

Table 5.3 lists the attributes used in the experiments. The selection of these attributes is based on earlier research (see for example, (Kwak and Yih, 2004; Cho and Wysk, 1993; Chen and Yih, 1996)). However, it is acknowledged that a simple model is not capable to generate and guarantee near-optimal subset of attributes. A more rigorous approach for the combinatorial attribute selection may be used at the cost of extra computational complexity(see (Siedlecki and Sklansky, 1989) for review and limitations of other approaches).

Table 5.3 – *Selected Attributes for* $T_{\max}$

Expression	Description
n_t	Number of jobs in the system at any instant t.
$\varrho_{\max} - \overline{\varrho}$	Difference between maximum and average remaining processing times.
$\frac{n_{\acute{p}}}{n_t}$	Percentage of jobs with long processing times.
$\frac{n_{\acute{d}}}{n_t}$	Percentage of jobs with relatively loose due dates.
$\overline{\varrho}$	Average remaining processing time.
$\overline{\varsigma}$	Average remaining time until due-dates.
$\frac{\overline{\varsigma}}{\overline{\varrho}}$	Relative tightness ratio.
$E(f)$	Expected value of $T_{\max}$

Some of the attributes are system related, that are not specifically related to a prticular job or a specif set of jobs. A few attributes are specific only to the jobs considered for the comparison.

For static job shop problems, as we considered in this chapter, $n_t = n$ at r_j for all jobs. Higher the n_t, greater is the size of training block and there are more and more examples

for that instance to learn the target concept.

$\Delta\varrho_j$, $\overline{\varrho}$ and $\varrho_{\max} - \overline{\varrho}$ uses the remaining processing time for direct comparison of two jobs, as an average measure and relative value among all the jobs in system. It is important to note that it is the combined effect of these attributes along-with others, that plays a role in strengthening their relation with the target concept. For example, $\overline{\varrho}$ in relation with n_t and $\varrho_{\max} - \overline{\varrho}$ affects the $\frac{n_{\acute{p}}}{n_t}$. Hence it is very difficult to identify a relationship of an attribute with the target concept. The predicted value of the performance measure is also used as an attribute, however it is again not independent from the other selected attributes.

For this study, we used the binning method, which is an unsupervised discretization method. Based on the values of the mean and standard deviation of the distribution of the specified attribute(s), we generate a field with banded categories. Figure 5.6 illustrates a ± 3 standard deviation based discretization for an attribute to generate seven bins. However, creating banded categories based on standard deviations may result in some bins being defined outside the actual data range and even outside the range of possible data values.

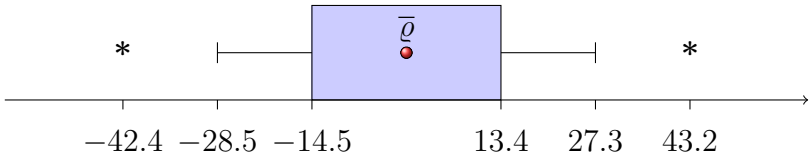


Figure 5.6 – *Standard Deviation based Discretization of* $\overline{\varrho}$ *for* $L_{\max}$

5.5 Results and Discussion

5.5.1 Obtained Rule-sets

A set of 19 rules for the $\bar{T}$ and a set of 57 rules $T_{\max}$ are generated by the proposed system using 100 training blocks of different sizes from the similarly sized problem instances. The differences in the size of the training blocks is due to the fact that the generated training blocks are dependent on the machine precedence constraints of the problem instance as well as the solution method. A partial list of the rules induced is given in Table 5.4 and Table 5.5. The prediction accuracy of these rule sets for $\bar{T}$ and $T_{\max}$ is found to be 79.52% and 69.93% respectively.

Table 5.4 – *A partial list of inferred rules for* $\bar{T}$

No.	Rule
Rule 1 for 0	$\Delta_{\varsigma_j} <= 1 \wedge Bin(\Delta_{p_j})in[1] \wedge \Delta_{\varsigma_j} > -12 \Rightarrow 0$
Rule 2 for 0	$\Delta_{\varsigma_j} <= 1 \wedge Bin(\Delta_{p_j})in[2] \Rightarrow 0$
Rule 3 for 0	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[-1] \wedge \Delta_{\varsigma_j} > 11 \Rightarrow 0$
Rule 4 for 0	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[0] \wedge Bin(\Delta_{\varrho_j})in[-2] \wedge \Delta CR_j = 0.469 \Rightarrow 0$
Rule 5 for 0	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[0] \wedge Bin(\Delta_{\varrho_j})in[-1] \wedge \overline{\varrho} <= 31.333 \Rightarrow 0$
Rule 6 for 0	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[0] \wedge \mathbb{R}Bin(\Delta_{p_j})in[-1] \wedge \overline{\varrho} > 31.333 \wedge \overline{\varrho} <= 218.800 \wedge \Delta_{\varsigma_j} > 8 \Rightarrow 0$
Rule 7 for 0	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[0] \wedge Bin(\Delta_{\varrho_j})in[-1] \wedge \overline{\varrho} > 31.333 \wedge \overline{\varrho} > 218.800 \Rightarrow 0$
Rule 8 for 0	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[0] \wedge Bin(\Delta_{\varrho_j})in[0] \Rightarrow 0$
Rule 9 for 0	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[1\ 2] \Rightarrow 0$
Rule 1 for 1	$\Delta_{\varsigma_j} <= 1 \wedge Bin(\Delta_{p_j})in[-2\ -1\ 0] \Rightarrow 1$
Rule 2 for 1	$\Delta_{\varsigma_j} <= 1 \wedge Bin(\Delta_{p_j})in[1] \wedge \Delta_{\varsigma_j} <= -12 \Rightarrow 1$
Rule 3 for 1	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[-2] \Rightarrow 1$
Rule 4 for 1	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[-1] \wedge \Delta_{\varsigma_j} <= 11 \Rightarrow 1$
Rule 5 for 1	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[0] \wedge Bin(\Delta_{\varrho_j})in[-3] \Rightarrow 1$
Rule 6 for 1	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[0] \wedge Bin(\Delta_{\varrho_j})in[-2] \wedge \Delta CR_j 0.469 \Rightarrow 1$
Rule 7 for 1	$\Delta_{\varsigma_j} > 1 \wedge Bin(\Delta_{p_j})in[0] \wedge Bin(\Delta_{\varrho_j})in[-1] \wedge \overline{\varrho} > 31.333 \wedge \overline{\varrho} <= 218.800 \wedge \Delta_{\varsigma_j} <= 8 \Rightarrow 1$

5.5.2 Performance Metrics

Performance of the proposed system is measured in relative terms and is indicated by two measures namely $\bar{\eta}_1^f$ and $\bar{\eta}_2^f$. η_1 indicates performance of obtained rule-set and the set of pdrs relative to solution provided by tabu search on the objective function f for set of training problem instances (I). Average value of $\bar{\eta}_1^f$ over I is given as,

$$\bar{\eta}_1^f = \begin{cases} \frac{f(r,I) - f(\mathrm{TS},I)}{f(\mathrm{TS},I)} & \text{if } f(r,I) > 0 \\ 0 & \text{otherwise} \end{cases}$$

where

$$r \in \{FIFO,SI,SPT,EDD,SLACK,CR,\\ CR/SI,COVERT,CEXSPT,ATC,MF\}$$

, TS: Tabu Search, RS: Rule-Set obtained and I: set of training problem instances used. For example, $T_{\max}(r,I)$ represents the set of $T_{\max}$ values for all the problem instances of

Table 5.5 – *A partial list of inferred rules for* $T_{\max}$

No.	Rule
Rule 1 for 0	$E(T_{\max}) \leqslant 0 \wedge \overline{\varrho} \leqslant 126.200 \wedge \overline{\varrho} > 102.400 \Rightarrow 0$
Rule 2 for 0	$E(T_{\max}) \leqslant 0 \wedge \overline{\varrho} \leqslant 126.200 \wedge \overline{\varrho} > 102.400 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} > 13.560 \wedge \frac{n_{\acute{p}}}{n_t} \leqslant 0.500 \Rightarrow 0$
Rule 3 for 0	$E(T_{\max}) > 0 \wedge \frac{n_{\acute{p}}}{n_t} \leqslant 0.200 \wedge \overline{\varsigma} \leqslant -25 \wedge \overline{\varrho} \leqslant 1379.200 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} \leqslant -231.360 \Rightarrow 0$
Rule 4 for 0	$E(T_{\max}) > 0 \wedge \frac{n_{\acute{p}}}{n_t} \leqslant 0.200 \wedge \overline{\varsigma} \leqslant -25 \wedge \overline{\varrho} \leqslant 1379.200 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} > -231.360 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} \leqslant -213.600 \wedge \overline{\varsigma} \leqslant -29 \wedge \overline{\varrho} > 1351.200 \Rightarrow 0$
Rule 5 for 0	$E(T_{\max}) > 0 \wedge \frac{n_{\acute{p}}}{n_t} \leqslant 0.200 \wedge \overline{\varsigma} \leqslant -25 \wedge \overline{\varrho} \leqslant 1379.200 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} > -231.360 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} \leqslant -213.600 \wedge \overline{\varsigma} > -29 \wedge E(T_{\max}) > 91 \Rightarrow 0$
Rule 1 for 1	$E(T_{\max}) \leqslant 0 \wedge \overline{\varrho} \leqslant 126.200 \wedge \overline{\varrho} > 102.400 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} \leqslant 13.560 \Rightarrow 1$
Rule 2 for 1	$E(T_{\max}) \leqslant 0 \wedge \overline{\varrho} \leqslant 126.200 \wedge \overline{\varrho} > 102.400 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} > 13.560 \wedge \frac{n_{\acute{p}}}{n_t} > 0.500 \Rightarrow 1$
Rule 3 for 1	$E(T_{\max}) \leqslant 0 \wedge \overline{\varrho} > 126.200 \Rightarrow 1$
Rule 4 for 1	$E(T_{\max}) > 0 \wedge \frac{n_{\acute{p}}}{n_t} \leqslant 0.200 \wedge \overline{\varsigma} \leqslant -25 \wedge \overline{\varrho} \leqslant 1379.200 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} > -231.360 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} \leqslant -213.600 \wedge \overline{\varsigma} \leqslant -29 \wedge \overline{\varrho} \leqslant 1351.200 \Rightarrow 1$
Rule 5 for 1	$E(T_{\max}) > 0 \wedge \frac{n_{\acute{p}}}{n_t} \leqslant 0.200 \wedge \overline{\varsigma} \leqslant -25 \wedge \overline{\varrho} \leqslant 1379.200 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} > -231.360 \wedge \frac{p_{\max}-\overline{\varrho}}{p_{\max}} \leqslant -213.600 \wedge \overline{\varsigma} > -29 \wedge E(T_{\max}) <= 91 \Rightarrow 1$

training set I using the set of pdrs in set r.

Note that $\bar{\eta}_1^f$ is an indication of the average performance of TS algorithm relative to pdrs. On the other hand, $\bar{\eta}_2^f$ refers to the performance of obtained rule-set relative to considered set of pdrs and is given as,

$$\bar{\eta}_2^f = \begin{cases} \frac{f(r,\acute{I})-f(\mathrm{RS},\acute{I})}{f(\mathrm{RS},\acute{I})} & \text{if } f(r,\acute{I}) > 0 \\ 0 & \text{otherwise} \end{cases}$$

Lower value of η_1^f for a pdr given for any problem instance means that solution by that pdr is close to the one provided by TS algorithm. In this case, the performance of the system relative to pdr (given by η_2^f) appears to be degraded however, the fact is that its performance is close to the optimum reached by TS. Consequently, a lower value of η_2^f is observed for that instance despite of obtaining a good schedule. This negatively affects on the average performance. This means that instances with higher value for η_1^f for the pdrs are more representative of the real performance of the proposed system. Higher value for η_2^f, in this case, indicates good performance of the system relative to pdrs and vice versa.

5.5.3 Results for Mean Tardiness ($\bar{T}$)

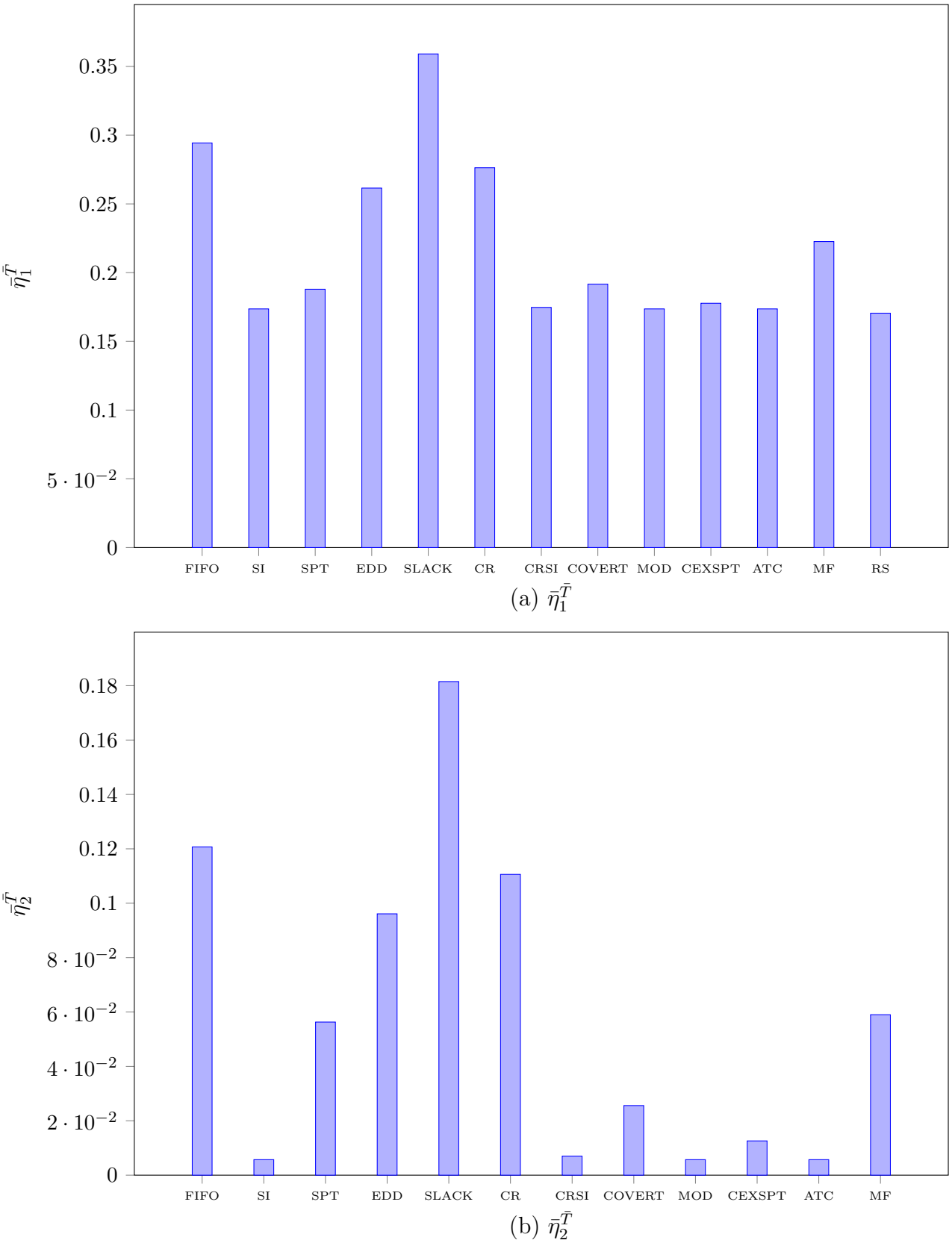
Figure 5.7(a) and Figure 5.7(b) show the plots for $\bar{\eta}_1^{\bar{T}}$ and $\bar{\eta}_2^{\bar{T}}$ respectively. For $\bar{T}$, the RS performs well over all pdrs with SI as the second best performer. However, the SLACK rule is the worst performer for this objective. Figure 5.8 presents the boxplot providing a comparative overview of the $\bar{T}$ values across the test instances. This graphic provides the distribution of actual values of $\bar{T}$ for all pdrs, RS and TS.

For the comparison of performance on individual instances, we found that out of 50 test instances, for only 28 instances, the RS provided better solutions than any other pdr with best solution among pdrs for that instance. On the average, these better solutions were found to be 14% more efficient than the best solution by the best pdrs on those instance. However the computational time to solve all test instances is relatively higher for RS, assuming the time required for each pdr to be the same.

5.5.4 Results for Maximum Tardiness ($T_{\max}$)

In Figure 5.9(a) and Figure 5.9(b) the plots for $\bar{\eta}_1^{T_{\max}}$ and $\bar{\eta}_2^{T_{\max}}$ are presented respectively. It is observed that the results of mined rule-set are superior to the pdrs for the $T_{\max}$ measure.

For a set of fifty test instances, plot of $\bar{\eta}_2$, shown in Figure 5.9(b), reflects the fact that the rule-set is consistently a better performer among all the pdrs used with slack rule as the closest competitor. This is due to the nature of selected attributes used in the algorithm. There is a considerable room of improvement in performance of rule-set, as can be seen from plot of η_1 shown in Figure 5.9(a), that may be obtained through better attribute selection. Figure 5.10 presents the box-plot providing a comparative overview of the $T_{\max}$ values across the test instances, providing the distribution of $T_{\max}$ for all pdrs, RS and TS.



(a) $\bar{\eta}_1^{\bar{T}}$

(b) $\bar{\eta}_2^{\bar{T}}$

Figure 5.7 – *System Performance for* $\bar{T}$

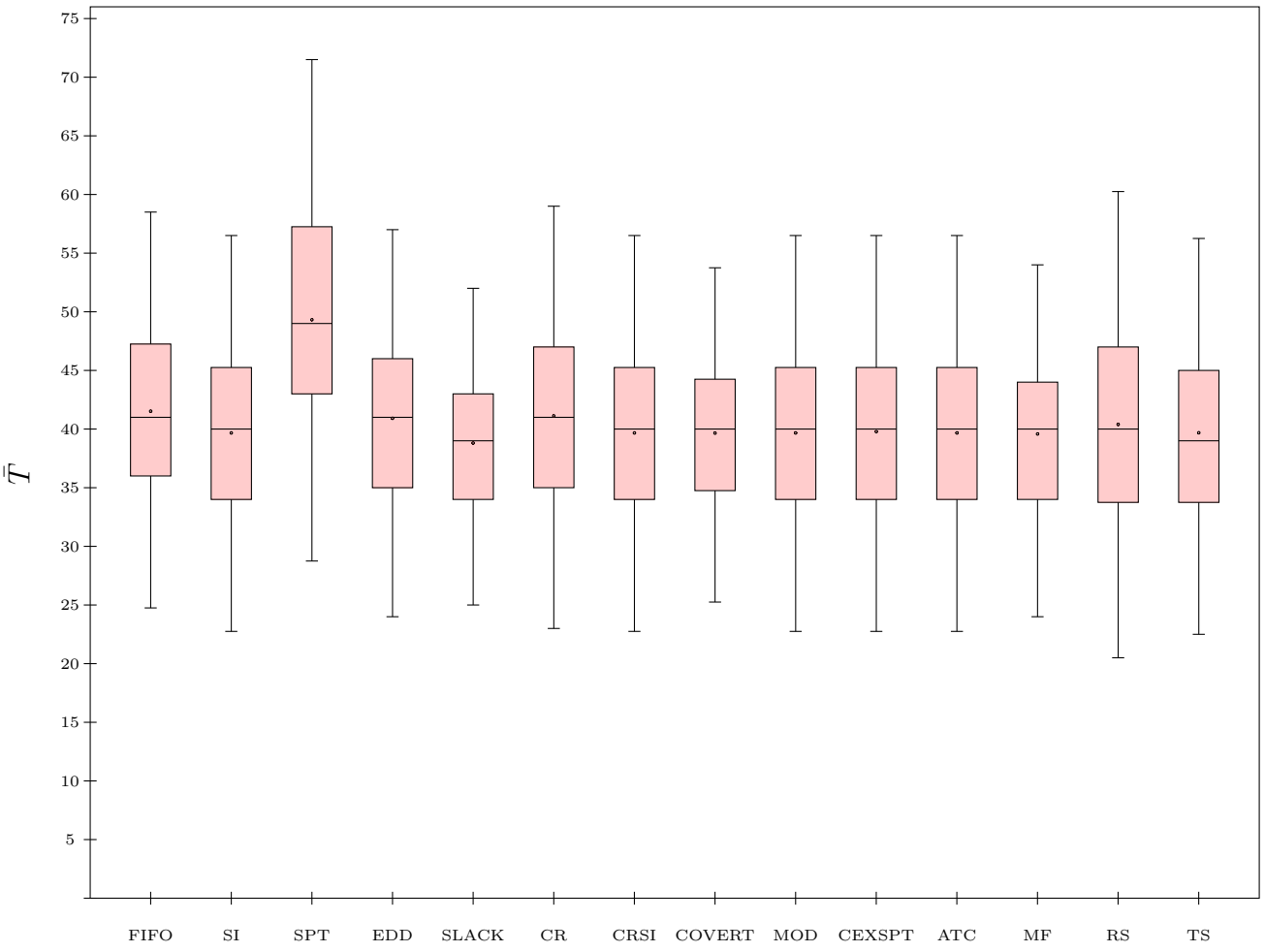
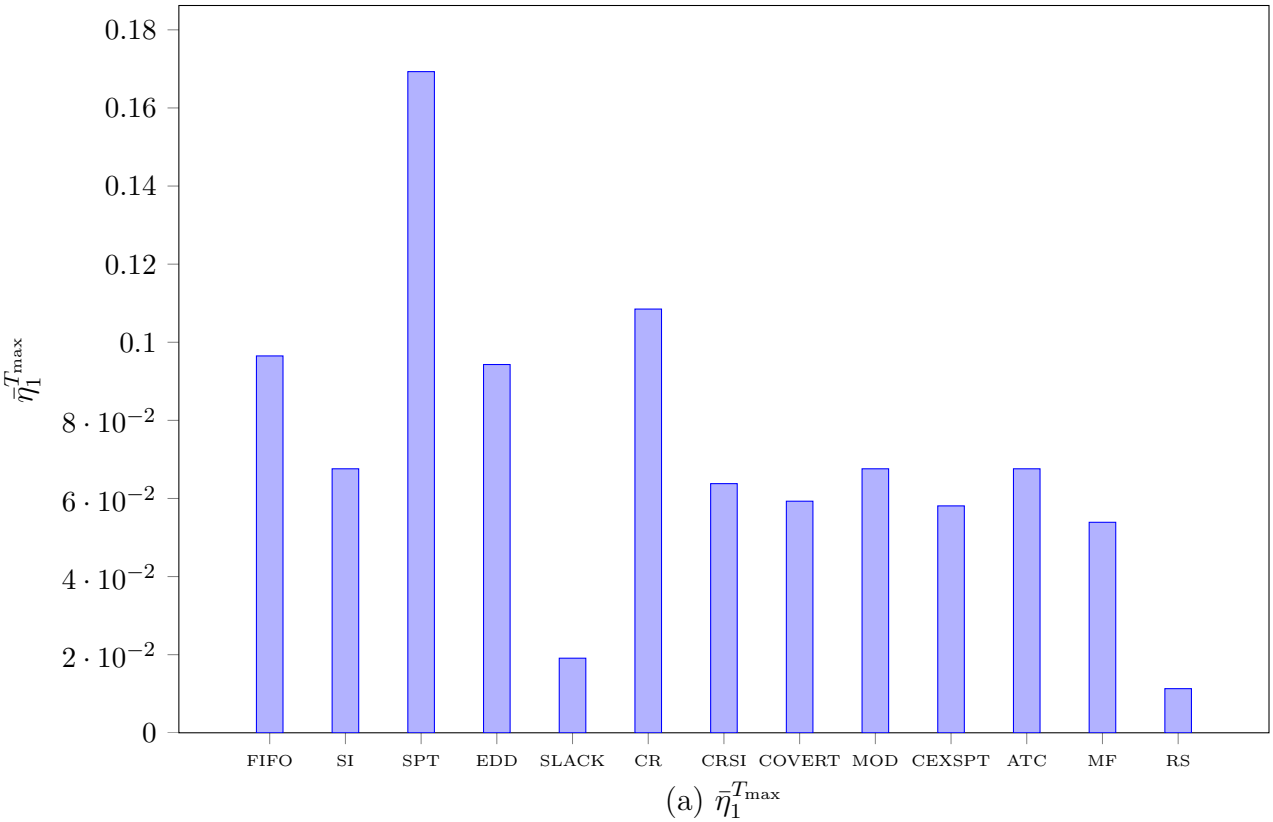
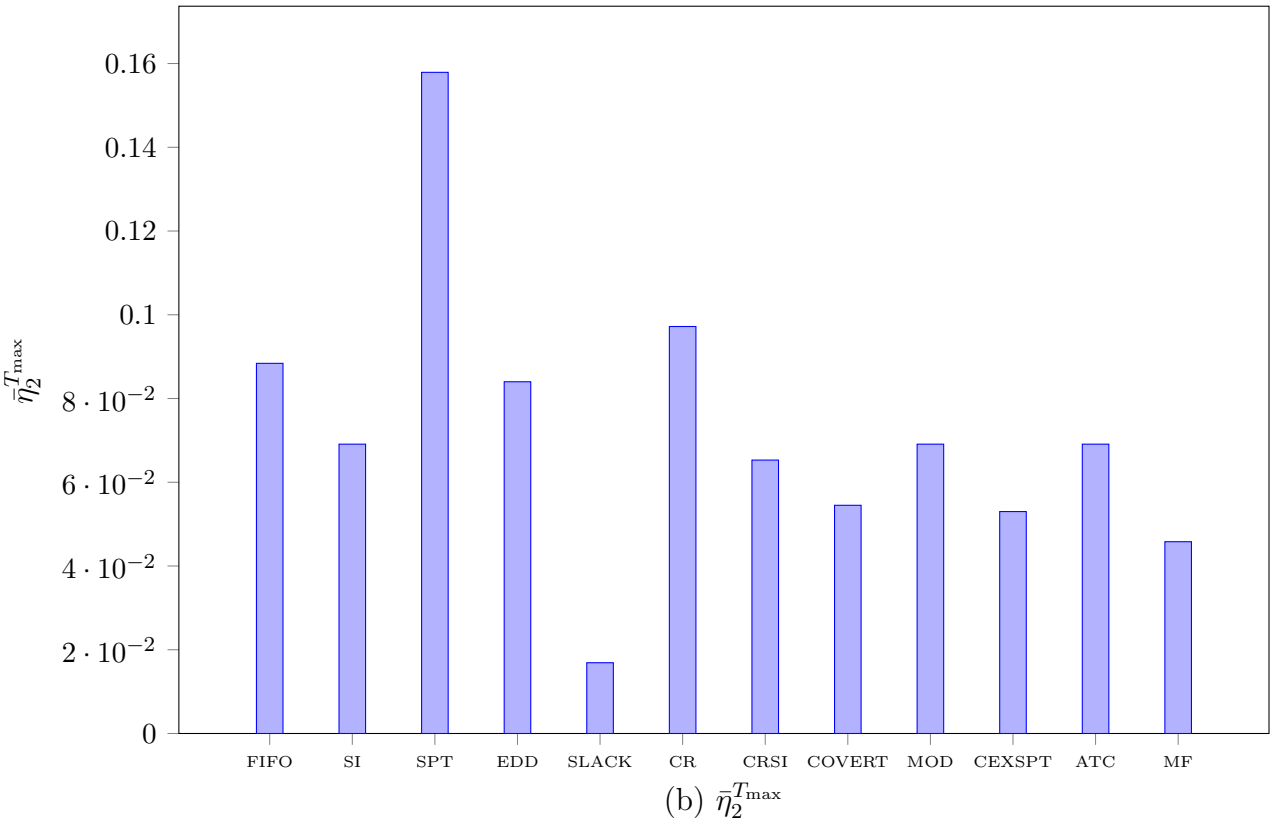


Figure 5.8 – *Box Plot of $\bar{T}$ for Test Instances*



(a) $\bar{\eta}_1^{T_{\max}}$



(b) $\bar{\eta}_2^{T_{\max}}$

Figure 5.9 – *System Performance for* $T_{\max}$

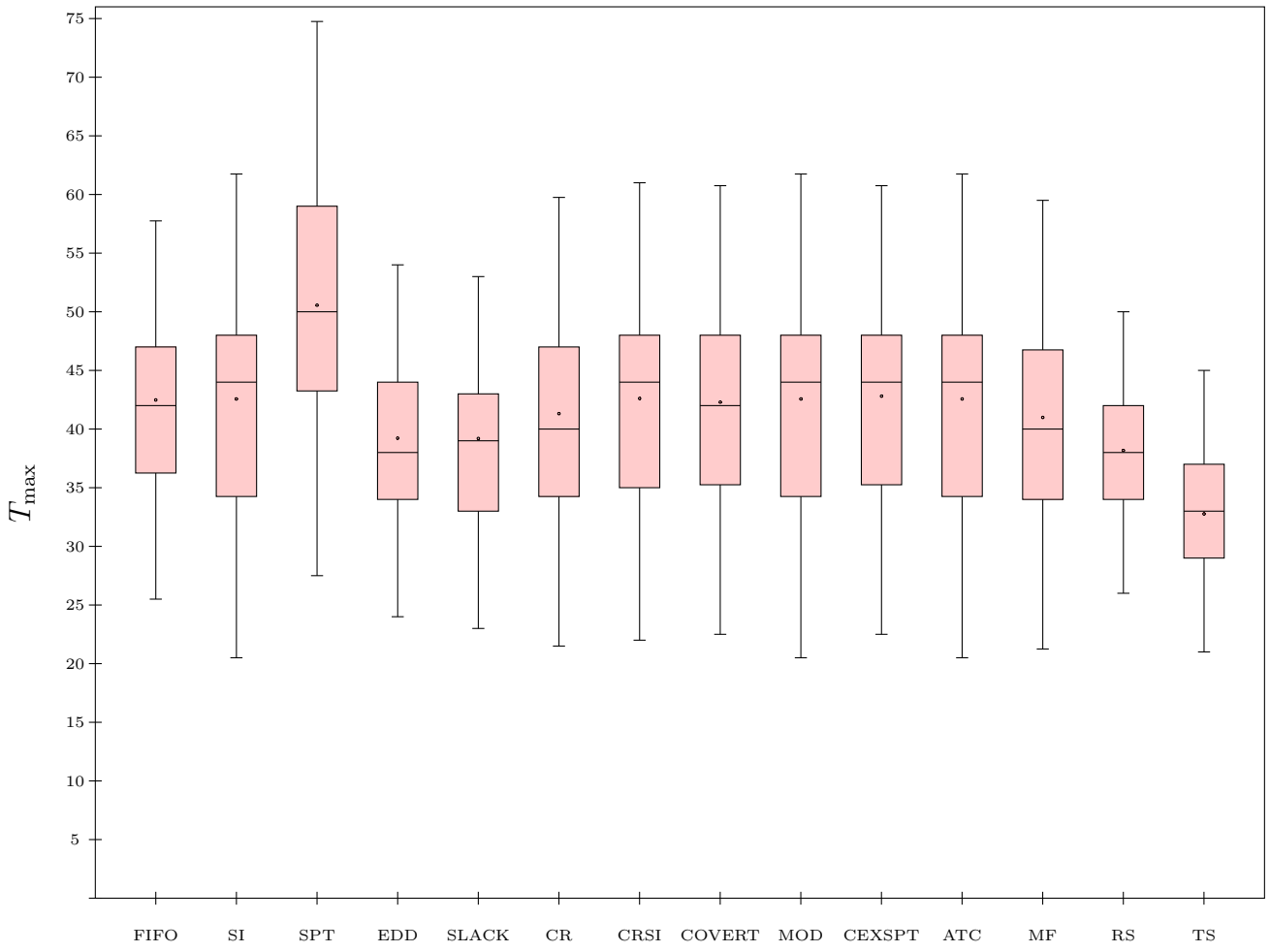


Figure 5.10 – *Box Plot of* $T_{\max}$ *for Test Instances*

5.6 Conclusions

We have proposed a data mining based framework for job shop scheduling problems. The structure as well as functioning of different components of the proposed system are explained. Different modules of the proposed framework are implemented using different software. For the optimization module, we implemented the Tabu Search algorithm in C++. Rockwell ARENA is used to build the simulation module. For the discretization of attributes and the learning algorithm C5.0, SPSS Clementine is used. For some of the routines for the control module, data engineering and integration of different modules, MATLAB programming environment is used. Two rule-sets are obtained for two performance measures namely mean tardiness and maximum lateness. Finally, the results for a test set of job shop instances are presented for these two measures.

The approach focuses on the identification of the critical parameters and states of a particular dynamic scheduling environment that contribute to the construction of some efficient solution. It is not always possible to obtain or to implement the optimal solutions for a complex dynamic real-world sized JSSP due to constantly varying conditions. However, through this approach several alternative solutions could be proposed that are sufficiently efficient. The proposed methodology is based upon the implicit assumption about the ability of tabu search to move intelligently in the solution space while providing the opportunity, at the same time, to learn the embedded knowledge about the thinking lines behind these intelligent moves.

The performance of the rule-set generated are found to be superior to all the dispatching rules considered for both $\bar{T}$ and $T_{\max}$.

The proposed approach is not only quite complicated to develop but an effective implementation of this approach on the real system requires a very careful examination of each and every parameter of the scheduling system. Moreover, for real-time scheduling systems the computational time required is relatively higher than that for pdrs but not prohibiting like meta-heuristics.

It is observed that the performance of the system degrades substantially if the system in unable to perform effectively during the earlier period of scheduling in contrast to later scheduling decisions. This is justified due to the nature of the JSSP problem, as the subsequent scheduling decisions are heavily affected by earlier decisions made.

It is also good to know how the obtained knowledge can be used in-process to reorient the tabu search for some large size instances of the problem. We believe that it is possible

to more effectively benefit from it by making an analysis of long term memory of TS algorithm.

Proper feature selection in regards with scheduling objective under consideration is the key factor for the successful implementation of the proposed framework. Feature selection for different objectives and their combinations has to be rigorously explored to obtain compact and efficient rule set.

The size of the problem used for training as well as test data set plays an important role in the relative performance of the proposed system. As the pdrs are generally used in large dynamic scheduling systems, the true performance of the system relative to pdrs is biased towards pdrs. Using larger problems in optimization modules can reduce this bias, however this comes at extra (rather impractical) computational overhead.

Performance of the proposed system in different loading conditions is to be explored further. Although it is expected to perform relatively better in heavy shop-load conditions. This is due to the fact that more scheduling decisions would be taken by the mined rule-set in heavy shop-load conditions.

General Conclusions

The primary focus of this work is on the scheduling in job-shop environment. Dynamic scheduling imposes rather strict requirements on the selection of the scheduling method to be used. This is primarily due to the constraint on the schedule-generation/repair time. However, the quality of the schedule is required to maintain a certain level as reflected by performance measures for desired objectives. So, there is an inherent trade-off between the response-time and the quality of the schedule in the case of dynamic scheduling.

Dynamic scheduling use priority dispatching rules for their quick reaction to changes in system and for their ease of implementation. Numerous rules have been proposed in literature on scheduling as well as used in practice. In chapter 2, different classifications of the dispatching rules are presented. we have described in detail, some of the dispatching rules that are extensively used. From this review, we have chosen a set of 12 benchmark rules.

As priority dispatching rules are based on some combinations of primitive attributes, their behavior towards the desired objectives may be assessed by analyzing these attribute. Tardiness based measures are no exception to this. These measures strive to valuate the achieved level of the objectives, that are based on due-dates.

Based on the behavior of pdrs on the relative performance on maximum tardiness, two sets of rules have been identified, FIFO, EDD, SLACK and CR from one side and SI, SPT and MOD on the other side. The behavior for the rules of the first set is to exhibit a large number of tardy jobs with low tardiness, which is exactly opposite to that for the rules of the second set. There are some rules (CRSI, COVERT, CEXSPT, ATC, MF) exhibiting these two behaviors under different conditions. For tight due date setting, these rules behave more like the rules of set 1 while under loose due date setting, their behavior

tends towards rules of set 2. This kind of discrimination is typically found through the T_{rms}. Therefore, we gathered the statistics on this measure as well for all the simulations. We found results that show a strong correlation between the $T_{\max}$ and the T_{rms} for the set of pdrs. Moreover, it is observed that, this correlation is relatively stronger in congested shops. This means, that the worst case performance in regards with tardiness of a particular priority dispatching rule may be predicted by evaluation of T_{rms} which can be used along with the mean tardiness to compute the variance of the tardiness. So, for a relative ranking of the priority dispatching rules in regards with the $T_{\max}$, the T_{rms} can be used.

The major problem with priority dispatching rules is their inability to produce high quality schedules due to their myopic nature. Moreover, for a system with high degree of variation in its operating conditions, a set of rules is to be identified and used for dispatching decisions. On the other hand, optimum-seeking off-line approaches like meta-heuristics are able to generate schedules of much better quality than traditional priority dispatching rules at the cost of greater computation times. Further more, meta-heuristics require special information about the problem to be solved. As a consequence, the better-quality solutions provided by meta-heuristics contain useful knowledge about the problem domain and the solution space explored by them. A combined set of solutions to a collection of problem instances, represents a wealth of scheduling knowledge about the problem domain. In our approach, we seek this scheduling knowledge through a data mining module to identify a rule-set by exploring the patterns in the solution set obtained by an optimization module based on tabu search, a very efficient meta-heuristic for JSSP in particular. This rule-set approximates the output of the optimization module when incorporated in a simulation model of the system. This rule-set is subsequently used to make dispatching decisions in an on-line manner. The performance of the rule-set generated are found to be superior to all the dispatching rules considered for both $\bar{T}$ and $T_{\max}$.

The proposed approach is not only quite complicated to develop but an effective implementation of this approach on the real system requires a very careful examination of each and every parameter of the scheduling system. Moreover, for real-time scheduling systems, the computational time required is relatively higher than that for pdrs but not prohibiting like meta-heuristics.

It is observed that the performance of the system degrades substantially if the system in unable to perform effectively during the earlier period of scheduling in contrast to later scheduling decisions. This is justified due to the nature of the JSSP problem, as the subsequent scheduling decisions are heavily affected by earlier decisions made.

A Priority Dispatching Rules

Table A.1 – *Priority Dispatching Rules*

Rule	Definition	Rank	Priority Index
AVPRO	Average processing time	min	$\frac{p_j}{o_j}$
FIFO	First In First Out	min	$C_{j(i-1)}$
FCFS	First Come First Served	min	r_j
SPT	Shortest Processing Time	min	p_j
SI	Shortest Imminent processing time	min	$p_{j(i)}$
EDD	Earliest Due Date	min	d_j
NOP	Number of operations	min	o_j
ODD	Operation due date	min	$d_{j(i)}$
SST	Shortest setup-time	min	$Setup_{jik}$
CR	Critical ratio	min	$\frac{d_j - t}{\sum_{i=l}^{o_j} p_{j(i)}}$
CR/SI		min	$p_{jk} \times \max(\frac{d_j - t}{\sum_{i=l}^{o_j} p_{j(i)}}, 1)$
MDD	Modified due date	min	$\max(d_j, t + p_j)$
MOD	Modified Operation Due date	min	$\max(d_{jk}, t + p_{jk})$
SLACK	Slack	min	$d_j - t - \sum_{i=l}^{o_j} p_{j(i)}$
SI/SLACK/SQNO	Weng and Ren (2006)	max	$\frac{1}{p_{j(i)}}(h_1 \varsigma_j^* + h_2 RQNO_{ji})$
WLS	Weighted loss of slack	min	$d_j - t - \sum_{i=l}^{o_j} p_{j(i)}$
S/OPN	Slack per remaining operation	min	$\frac{d_j - t - \sum_{i=l}^{o_j} p_{j(i)}}{o_j - j + 1}$

Rule	Definition	Rank	Priority Index
S/RAT	Slack per allowable time	min	$\frac{d_j - t - \sum_{i=l}^{o_j} p_{j(i)}}{d_j - t}$
S/RPT	Slack per remaining processing time	min	$\frac{d_j - t - \sum_{i=l}^{o_j} p_{j(i)}}{\sum_{i=l}^{o_j} p_{j(i)}}$
S/RPT+SPT		min	$p_{jk} \times \max(\frac{d_j - t - \sum_{i=l}^{o_j} p_{j(i)}}{\sum_{i=l}^{o_j} p_{j(i)}}, 1)$
ATC	Apparent Tardiness Cost	max	$\frac{1}{p_{j(i)}} \exp\left(-\frac{(d_j - t - p_{j(i)} - h_2 \sum_{i=l+1}^{o_j} p_{j(i)})}{h_3 \sum_{i=l}^{o_j} p_{j(i)}}\right)^+$
CEXSPT	Conditionally Expedited SPT	−	Partition into three queues, late queue, operationally late queue and ahead of schedule queue, with SI as selection criterion within queues. Shifting of job to other queues is not allowed.
COVERT	Cost Over Time	max	$\frac{1}{p_{j(i)}}\left(1 - \frac{(d_j - t - \sum_{i=l}^{o_j} p_{j(i)})^+}{h_1 \sum_{l=i}^{o_j} W_{j(l)}}\right)^+$
MF	Multi-Factor	max	$\frac{1}{p_{j(i)}}\left(W_{j(i)} - (d_j - t - \sum_{i=l}^{o_j} p_{j(i)})\right)$ [a]
RR	Raghu and Rajendran (1993)	min	$\left(\frac{d_j - t - \sum_{i=l}^{o_j} p_{j(i)}}{o_j} \exp(-\eta)\, p_{j(i)} + \exp(\eta)\, p_{j(i)} + W_{nxt}\right)$ [b]

[a] $W_{j(q)} = \sum_{i=k}^{n(\neq k)} \sum_{j=1}^{q} p_{j(i)} - \sum_{j=1}^{q-1} p_{j(i)}$

[b] W_{nxt}=Expected waiting time of job j on next machine

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Une Approche Hybride de Simulation-Optimisation Basée sur la Fouille de Données pour les problèmes d'ordonnancement

Une approche hybride basée sur la fouille de données pour découvrir de nouvelles règles de priorité pour le problème d'ordonnancement job-shop est présentée. Cette approche est basée sur la recherche de connaissances supposées être intégrés dans les solutions efficaces fournies par un module d'optimisation préalablement mis en œuvre et utilisant la recherche tabou. L'objectif est de découvrir les principes directeurs de l'ordonnancement à l'aide de la fouille de données et donc d'obtenir un ensemble de règles capables d'obtenir des solutions efficaces pour un problème d'ordonnancement. Une structure basée sur fouille de données est présentée et mise en œuvre pour un problème de job shop avec comme objectifs le retard maximum et le retard moyen. Les résultats obtenus sont très prometteurs.

Mots clés : Simulation, Optimisation, Ordonnancement, Règles de priorité, Fouille de données, Recherche tabou, Job shop

A Hybrid Simulation/Optimization Approach to Scheduling Control using Data Mining

A data mining based approach to discover previously unknown priority dispatching rules for job shop scheduling problem is presented. This approach is based upon seeking the knowledge that is assumed to be embedded in the efficient solutions provided by the optimization module built using tabu search. The objective is to discover the scheduling concepts using data mining and hence to obtain a set of rules capable of approximating the efficient solutions for a job shop scheduling problem (JSSP). A data mining based scheduling framework is presented and implemented for a job shop problem with maximum lateness and mean tardiness as the scheduling objectives. The results obtained are very promising.

Keywords: Simulation, Optimization, Scheduling, Priority Dispatching Rules, Data Mining, Tabu Search, Job Shop

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