Generation of Look-Up Tables for Dynamic Job Shop Scheduling Decision Support Tool

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Abstract. Majority of existing scheduling techniques are based on static demand and deterministic processing time, while most job shop scheduling problem are concerned with dynamic demand and stochastic processing time. As a consequence, the solutions obtained from the traditional scheduling technique are ineffective wherever changes occur to the system. Therefore, this research intends to develop a decision support tool (DST) based on promising artificial intelligent that is able to accommodate the dynamics that regularly occur in job shop scheduling problem. The DST was designed through three phases, i.e. (i) the look-up table generation, (ii) inverse model development and (iii) integration of DST components. This paper reports the generation of look-up tables for various scenarios as a part in development of the DST. A discrete event simulation model was used to compare the performance among SPT, EDD, FCFS, S/OPN and Slack rules; the best performances measures (mean flow time, mean tardiness and mean lateness) and the job order requirement (inter-arrival time, due dates tightness and setup time ratio) which were compiled into look-up tables. The well-known 6/6/J/Cmax Problem from Muth and Thompson (1963) was used as a case study. In the future, the performance measure of various scheduling scenarios and the job order requirement will be mapped using ANN inverse model.

1. Introduction

In order to remain competitive in the global marketplace, job shop manufacturing companies need to improve their operational practice. One of the methods to increase competitiveness in such manufacturing environment is by implementing proper job scheduling system to achieve minimum production lead time, reduce work-in-process and improve machine utilization. Although most of the job shops scheduling problems are considered dynamic and stochastic, majority of existing scheduling are based on static and deterministic techniques. The dynamics of real manufacturing system are very complex especially with unscheduled changes in demand and capacity \cite{1}. Schedule prepared based on deterministic algorithms is no longer effective when facing unexpected disruptions such as rush job, job cancellation, changes in master production schedule, machine breakdowns, and absenteeism.

Scheduling is a decision-making process dealing with the allocation of resources to tasks over given time periods, and its goal is to optimize one or more objectives \cite{1}. A decision support system is a system that is intended to support managerial decision making in semi-structured or unstructured situations \cite{2}. A decision support system can be either a model-based or a knowledge-based system...
intended to support operational decision making. Such systems normally provide user interface module to facilitate interaction between user and the system. Researchers in [3] noted that an ideal a
decision support system should have flexibility and adaptability features to accommodate various scheduling problem domains.

Researchers such as [3, 4, 5, 6, 7, 8 and 9] have reported works related to development of a decision support system for scheduling. Specifically, [3, 8, 9] studied the job shop manufacturing environments, [4, 6] studied the single machine, while [7] studied the flexible job shop. Some researchers focus on static demand [6, 8], while some researchers investigated on dynamic demand [3, 4, 7, 9].

The standard decision support system proposed by Turban and Aronson [10] contains three basic sub systems: data management, model management and dialog management. Some works [4, 8, 9] follow this standard form, while other works [3, 6, 7] expand the standard form by adding rule base on the system. In this research, the standard decision support system was extended by employing look-up tables as a rule base.

From the strategy of rescheduling, some works are based on current shop performance [7], while the other used event-driven for their rescheduling strategy [3, 4]. Based on the rescheduling policy, [3, 4, 7] applied predicative-reactive policy in their study. In this research, event driven strategy was adopted.

Mahdavi et al [7] combined a discrete-event simulation based and decision support system for controlling stochastic flexible job shop manufacturing system. In their model, the simulator would evaluate the current shop performance and accordingly adjusts the simulation model when appropriate. Such modelling approach has also been used by some other researchers [11, 12, 13, 14, 15, 16]. It seems that this approach is time consuming since it requires simulation re-run whenever changes occurs in the system.

This research intends to develop a decision support tool (DST) based on promising artificial intelligent that is able to accommodate the dynamics that regularly occur in job shop scheduling problem. The DST was designed through three phases, i.e. (i) the look-up table generation, (ii) inverse model development and (iii) integration of DST components. It provides alternative recommended schedules to be selected by practitioners with minimum knowledge in job shop scheduling. This paper reports the generation of look-up tables for various scenarios as a component in development of the DST.

A preferred look-up table is a collection of selected scheduling rule for each scheduling scenario that is generated through discrete event simulation. It is an associative array of data structure. Look-up tables are used to map input values (inter-arrival time, due date, and set up time) against a list of pre-determined scheduling rules. In other words, it provides the matching “criteria-response” functions. The rest of this paper is organized as follows; the methodology outlined, followed by result, discussion, and conclusions.

2. Methodology
Look-up table was generated through discrete event simulation. Discrete event simulation is a strategic evaluation technique which uses an abstract representation of reality (a model) and studies its behavior through time. The behavior may be influenced by certain or uncertain factors. For model which considers uncertainties, the simulation methodology involves the following steps:

a. Describe system to study.
b. Formulate simplifying assumption about the system.
c. Under the set of assumption, identify:
c.1 Parameters. System attributes which are held constant during the period that the system is being studied.

c.2 Variables. System attributes which are subject to random variations through time. The variations are represented by appropriate probability distribution.

d. Develop a model which embodies the interrelationships among the parameters and the variables.

e. Use a random number generator to generate a set of inter-temporal events based on the random variation of the variables.

f. Run the model and
g. Collect statistics on the resulting values of the variables

Figure 1 shows the simulation procedures for dynamic job shop scheduling in this study.

![Simulation procedures](image)

**Figure 1. Simulation procedures.**

The first experiment (scenario 1) involved the following settings: Mean inter-arrival time of jobs, $a = 51$; due date tightness, $d = 0.5$; setup time ratio, $s = 0.3$; five scheduling rules and three performance measures were studied. The experimentation settings for other scenarios are summarized in table 1.
For every simulation setting (due date tightness, Inter-arrival time and setup time ratio), it will select the best value of each performance measures resulting from different scheduling rules. The best value of mean flow time and percentage of number late job is the smallest value, while the best value of mean tardiness is the biggest.

Table 1. Summary of experiment setting.

| Scenario | Inter-arrival time, (a) | Due date tightness, (d) | Setup time ratio, (s) |
|----------|--------------------------|-------------------------|-----------------------|
| 1        | 51                       | 0.5                     | 0.3                   |
| 2        | 51                       | 0.5                     | 0.2, 0.4              |
| 3        | 51                       | 0.25, 0.75              | 0.3                   |
| 4        | 34, 68                   | 0.5                     | 0.3                   |

3. Result and Discussions
Simulation experiments should be run multiple times to minimize random variation and to obtain more statistically significant results. Most researchers [18, 19, 20, 21, 22] reported they used between 5 to 20 replications. As such, this study used 20 replications for each trial to minimize the random variation. The experimental settings for simulation are as follows: mean inter-arrival times of jobs are 34, 51 and 68; mean due date tightness are 0.25, 0.50 and 0.75; mean setups up time ratio are 0.2, 0.3 and 0.4. The results from 20 replications were averaged. Tables 2 to 4 give the summary of the simulation results.

Table 2. Summary of results from a simulation where setup time ratio = 0.20.

| Due date | Rule | F  | L  | T  | F  | L  | T  | F  | L  | T  |
|----------|------|----|----|----|----|----|----|----|----|----|
| 0.25     | SPT  | 280.2 | -43.8 | 64.3 | 480.5 | 220.4 | 318.5 | 572.5 | 933.0 | 592.7 |
|          | S/OPN | 308.8 | -15.8 | 64.7 | 627.9 | 267.8 | 309.0 | 945.8 | 448.7 | 552.7 |
|          | FCFS  | 348.8 | 24.2 | 75.2 | 767.6 | 407.6 | 421.0 | 1133.8 | 1048.3 | 1094.3 |
|          | EDD   | 340.2 | 16.2 | 62.8 | 718.3 | 358.2 | 368.9 | 899.2 | 859.6 | 859.6 |
|          | SLACK | 376.2 | 19.9 | 81.6 | 825.7 | 429.6 | 452.8 | 1181.0 | 1137.7 | 1138.6 |
| 0.50     | SPT  | 261.7 | -62.5 | 52.9 | 483.3 | 123.3 | 230.4 | 595.6 | 558.3 | 566.1 |
|          | S/OPN | 294.6 | -29.7 | 53.9 | 564.2 | 204.2 | 247.2 | 755.4 | 459.4 | 463.4 |
|          | FCFS  | 332.6 | 8.3 | 63.6 | 707.2 | 347.2 | 361.4 | 1191.1 | 1151.6 | 1151.6 |
|          | EDD   | 325.7 | 1.5 | 51.9 | 668.8 | 309.2 | 320.4 | 935.0 | 895.4 | 895.4 |
|          | SLACK | 358.8 | 2.1 | 68.8 | 755.5 | 359.6 | 384.5 | 1230.6 | 1188.2 | 1187.2 |
| 0.75     | SPT  | 268.0 | -56.4 | 53.9 | 467.7 | 108.4 | 206.4 | 594.2 | 539.6 | 569.6 |
|          | S/OPN | 304.9 | -19.5 | 60.2 | 577.4 | 217.7 | 257.7 | 917.5 | 498.8 | 498.8 |
|          | FCFS  | 340.1 | 15.7 | 69.1 | 712.1 | 352.3 | 366.5 | 1136.8 | 1097.4 | 1097.4 |
|          | EDD   | 332.2 | 7.9 | 57.2 | 673.0 | 313.3 | 325.1 | 907.7 | 868.1 | 868.1 |
|          | SLACK | 367.0 | 10.1 | 74.5 | 758.9 | 363.2 | 387.1 | 1166.3 | 1123.8 | 1123.8 |

* F = Mean Flow time;  L = Mean Lateness;  T = Mean Tardiness;  Unit = minute
Table 3. Summary of results from a simulation where setup time ratio = 0.30.

| Rule  | 34   | 51   | 68   |
|-------|------|------|------|
|       | F    | L    | T    | F    | L    | T    | F    | L    | T    |
| S/OPN | 276.4| -263.4|32.6| 548.7| -50.9|231.4| 594.4| 489.0| 550.4|
| FCFS  | 309.7| -230.0|35.2| 644.9| -45.2|496.6| 921.3| 769.9| 769.5|
| EDD   | 341.5| -198.2|15.5| 790.2| -118.6|211.3| 1098.1| 1032.2| 1032.2|
| SLACK | 329.3| -210.5|6.3 | 669.8| 70.1 |156.6| 870.0| 803.9| 803.9|
|       | 369.2| -224.5|38.5| 845.1| 113.5|519.8|1147.5|1077.7|1075.1|

Table 4. Summary of results from a simulation where setup time ratio = 0.40.

| Rule  | 34   | 51   | 68   |
|-------|------|------|------|
|       | F    | L    | T    | F    | L    | T    | F    | L    | T    |
| S/OPN | 266.1| -273.2|31.7| 482.0| -117.5|183.6| 605.1| 404.1| 402.9|
| FCFS  | 302.8| -236.5|33.0| 616.1| -16.5|231.1| 998.8| 746.0| 456.1|
| EDD   | 340.0| -199.3|15.9| 700.4| 100.9|195.3|1321.2|1255.5|1255.5|
| SLACK | 327.8| -211.5|6.8 | 656.8| 57.3 |143.7|1042.1| 976.2| 976.1|
|       | 366.6| -226.6|36.1| 748.6| 89.1 |249.5|1217.7|1217.2|1217.2|

* F = Mean Flow time; L = Mean Lateness; T = Mean Tardiness; Unit = minute

Finally, the best result for each unique simulated condition was selected. Selection was made based on; which rules are best for mean flow time? which rules are best for mean tardiness? which rules are best for mean lateness?

The best among the five scheduling rules for a certain simulation condition was selected and compiled to produce the Preferred Look-Up Tables. For example; when setup time ratio (s) = 0.2; due date tightness (k) = 0.25; and inter-arrival time (a) = 34; then, the best scheduling rule for mean flow time performance is the SPT. Figure 2 illustrates the selection process of entries in development of a look-up table.
Table 5 shows the preferred look-up table for mean flow time; table 6 shows the preferred look-up table for mean lateness; and table 7 shows the preferred look-up table for mean tardiness performance. The table will be used as a component of DST in the next study.

Based on the preferred look-up tables that have been developed, the following observations can be made:

a. There is not much difference in terms of scheduling rules in the look-up table between matrices of mean lateness and mean flow time. This possibly due to these two performance measures provide the similar information about the job, which is the amount of time a job takes in the system. However, SPT consistently provides the smallest value for both mean lateness and mean flow time in all simulated scenarios.

b. In terms of mean tardiness, it can be seen that EDD is superior in most conditions. This is expected because EDD relies heavily on the information of due date into priority rule. However, SPT and S/PON are found to be good competitors and sometimes gave better results.

c. There are no situations in which one rule that previously performed better than another performs worse as a condition progresses up to a certain point and then somehow shows a better result again. The absence of this phenomena in these results confirm the fundamental concept that if a condition causes a rule to perform worse than another, in a condition of increasing intensity, the relative quality of result provided by these two rules should be the same.
Table 5. Preferred look-up table for mean flow time performance of 6×6 job shop problem.

| No | Setup time ratio | Due date tightness | Inter-arrival Time | Scheduling Rule |
|----|------------------|--------------------|--------------------|-----------------|
| 1  | 0.20             | 0.25               | 34                 | SPT             |
| 2  | 0.20             | 0.50               | 34                 | SPT             |
| 3  | 0.20             | 0.75               | 34                 | SPT             |
| 4  | 0.20             | 0.25               | 51                 | SPT             |
| 5  | 0.20             | 0.50               | 51                 | SPT             |
| 6  | 0.20             | 0.75               | 51                 | SPT             |
| 7  | 0.20             | 0.25               | 68                 | SPT             |
| 8  | 0.20             | 0.50               | 68                 | SPT             |
| 9  | 0.20             | 0.75               | 68                 | SPT             |
| 10 | 0.30             | 0.25               | 34                 | SPT             |
| 11 | 0.30             | 0.50               | 34                 | SPT             |
| 12 | 0.30             | 0.75               | 34                 | SPT             |
| 13 | 0.30             | 0.25               | 51                 | SPT             |
| 14 | 0.30             | 0.50               | 51                 | SPT             |
| 15 | 0.30             | 0.75               | 51                 | SPT             |
| 16 | 0.30             | 0.25               | 68                 | SPT             |
| 17 | 0.30             | 0.50               | 68                 | SPT             |
| 18 | 0.30             | 0.75               | 68                 | SPT             |
| 19 | 0.40             | 0.25               | 34                 | SPT             |
| 20 | 0.40             | 0.50               | 34                 | SPT             |
| 21 | 0.40             | 0.75               | 34                 | SPT             |
| 22 | 0.40             | 0.25               | 51                 | SPT             |
| 23 | 0.40             | 0.50               | 51                 | SPT             |
| 24 | 0.40             | 0.75               | 51                 | SPT             |
| 25 | 0.40             | 0.25               | 68                 | SPT             |
| 26 | 0.40             | 0.50               | 68                 | SPT             |
| 27 | 0.40             | 0.75               | 68                 | SPT             |

Table 6. Preferred look-up table for mean lateness performance of 6×6 job shop problem.

| No | Setup time ratio | Due date tightness | Inter-arrival Time | Scheduling Rule |
|----|------------------|--------------------|--------------------|-----------------|
| 1  | 0.20             | 0.25               | 34                 | SPT             |
| 2  | 0.20             | 0.50               | 34                 | SPT             |
| 3  | 0.20             | 0.75               | 34                 | SPT             |
| 4  | 0.20             | 0.25               | 51                 | SPT             |
| 5  | 0.20             | 0.50               | 51                 | SPT             |
| 6  | 0.20             | 0.75               | 51                 | SPT             |
| 7  | 0.20             | 0.25               | 68                 | SPT             |
| 8  | 0.20             | 0.50               | 68                 | SPT             |
| 9  | 0.20             | 0.75               | 68                 | SPT             |
| 10 | 0.30             | 0.25               | 34                 | SPT             |
| 11 | 0.30             | 0.50               | 34                 | SPT             |
| 12 | 0.30             | 0.75               | 34                 | SPT             |
| 13 | 0.30             | 0.25               | 51                 | SPT             |
| 14 | 0.30             | 0.50               | 51                 | SPT             |
| 15 | 0.30             | 0.75               | 51                 | SPT             |
| 16 | 0.30             | 0.25               | 68                 | SPT             |
| 17 | 0.30             | 0.50               | 68                 | SPT             |
| 18 | 0.30             | 0.75               | 68                 | SPT             |
| 19 | 0.40             | 0.25               | 34                 | SPT             |
| 20 | 0.40             | 0.50               | 34                 | SPT             |
| 21 | 0.40             | 0.75               | 34                 | SPT             |
| 22 | 0.40             | 0.25               | 51                 | SPT             |
| 23 | 0.40             | 0.50               | 51                 | SPT             |
| 24 | 0.40             | 0.75               | 51                 | SPT             |
| 25 | 0.40             | 0.25               | 68                 | SPT             |
| 26 | 0.40             | 0.50               | 68                 | SPT             |
| 27 | 0.40             | 0.75               | 68                 | SPT             |
Table 7. Preferred look-up table for mean tardiness performance of 6×6 job shop problem.

| No | Setup time ratio | Due date tightness | Inter-arrival Time | Scheduling Rule |
|----|------------------|--------------------|--------------------|-----------------|
| 1  | 0.20             | 0.25               | 34                 | EDD             |
| 2  | 0.20             | 0.50               | 34                 | EDD             |
| 3  | 0.20             | 0.75               | 34                 | SPT             |
| 4  | 0.20             | 0.25               | 51                 | S/OPN           |
| 5  | 0.20             | 0.50               | 51                 | SPT             |
| 6  | 0.20             | 0.75               | 51                 | SPT             |
| 7  | 0.20             | 0.25               | 68                 | S/OPN           |
| 8  | 0.20             | 0.50               | 68                 | S/OPN           |
| 9  | 0.20             | 0.75               | 68                 | S/OPN           |
| 10 | 0.30             | 0.25               | 34                 | EDD             |
| 11 | 0.30             | 0.50               | 34                 | EDD             |
| 12 | 0.30             | 0.75               | 34                 | EDD             |
| 13 | 0.30             | 0.25               | 51                 | EDD             |
| 14 | 0.30             | 0.50               | 51                 | EDD             |
| 15 | 0.30             | 0.75               | 51                 | EDD             |
| 16 | 0.30             | 0.25               | 68                 | SPT             |
| 17 | 0.30             | 0.50               | 68                 | SPT             |
| 18 | 0.30             | 0.75               | 68                 | S/OPN           |
| 19 | 0.40             | 0.25               | 34                 | EDD             |
| 20 | 0.40             | 0.50               | 34                 | EDD             |
| 21 | 0.40             | 0.75               | 34                 | EDD             |
| 22 | 0.40             | 0.25               | 51                 | EDD             |
| 23 | 0.40             | 0.50               | 51                 | EDD             |
| 24 | 0.40             | 0.75               | 51                 | EDD             |
| 25 | 0.40             | 0.25               | 68                 | SPT             |
| 26 | 0.40             | 0.50               | 68                 | SPT             |
| 27 | 0.40             | 0.75               | 68                 | SPT             |

4. Conclusions
This research intends to develop a decision support tool (DST) based on promising artificial intelligence that is able to accommodate the dynamically that regularly occur in job shop scheduling problem. The DST was designed through three phases, i.e. (i) the look-up table generation, (ii) inverse model development and (iii) integration of DST components. A MT06 job shop scheduling problem from Muth and Thompson [17] was adapted as a case study. A discrete event simulation was used to generate various job shop scheduling scenarios. The simulation experiment was used to find the performance difference among SPT, EDD, FCFS, S/OPN and Slack rules. The best performance among SPT, EDD, FCFS, S/OPN and Slack scheduling priority rules were compiled into look-up tables. The preferred look-up table will be used as one of the key components in the decision support system. In the future, the performance measure of various scheduling scenarios and the job order requirement will be mapped using ANN inverse model.

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