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

Muchamad Oktaviandri[1,3], **Adnan Hassan**[2], **Awaluddin Mohd. Shaharoun**[2]

[1]Faculty of Manufacturing Engineering, Universiti Malaysia Pahang, 26600, Malaysia.
[2]Faculty of Mechanical Engineering, Universiti Teknologi Malaysia, 81300, Malaysia.
[3]Fakultas Teknologi Industri, Universitas Bung Hatta, Padang, 25143, Indonesia.

E-mail: muchamad_oktaviandri@yahoo.com

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 [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 [1]. A decision support system is a system that is intended to support managerial decision making in semi-structured or unstructured situations [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.

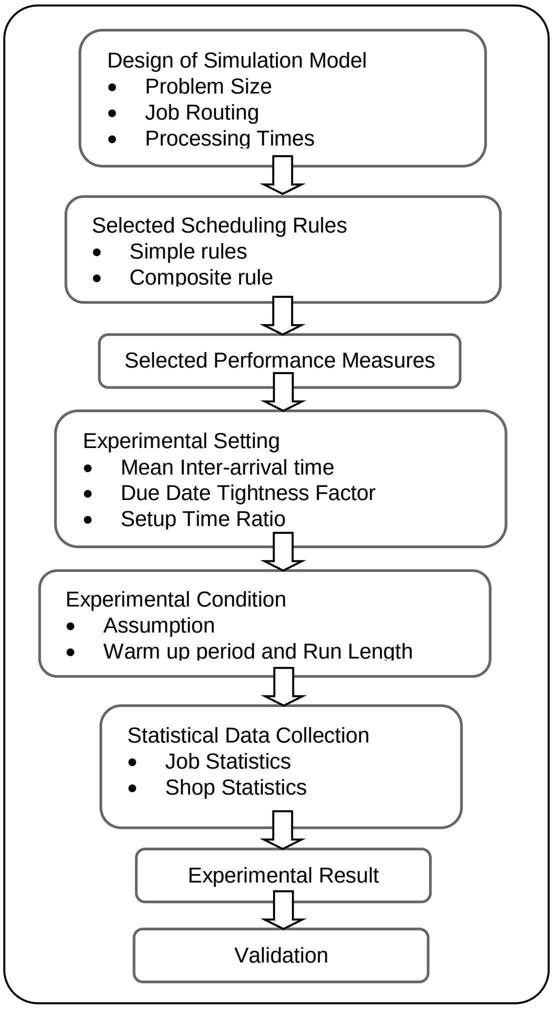


Figure 1. Simulation procedures.

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	Experimental Setting		
	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	Inter-arrival								
		34			51			68		
		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	1094.3	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.

Due date	Rule	Inter-arrival								
		34			51			68		
		F	**L**	**T**	**F**	**L**	**T**	**F**	**L**	**T**
0.25	SPT	276.4	-263.4	32.6	548.7	-50.9	231.4	594.4	489.0	550.4
	S/OPN	309.7	-230.0	35.2	644.9	45.2	496.6	921.3	769.9	769.5
	FCFS	341.5	-198.2	15.5	790.2	118.6	211.3	1098.1	1032.2	1032.2
	EDD	329.3	-210.5	6.3	669.8	70.1	156.6	870.0	803.9	803.9
	SLACK	369.2	-224.5	38.5	845.1	113.5	519.8	1147.5	1077.7	1075.1
0.50	SPT	266.1	-273.2	31.7	482.0	-117.5	183.6	605.1	404.1	402.9
	S/OPN	302.8	-236.5	33.0	616.1	16.5	231.1	998.8	746.0	456.1
	FCFS	340.0	-199.3	15.9	700.4	100.9	195.3	1321.2	1255.5	1255.5
	EDD	327.8	-211.5	6.8	656.8	57.3	143.7	1042.1	976.2	976.1
	SLACK	366.6	-226.6	36.1	748.6	89.1	249.5	1217.7	1217.2	1217.2
0.75	SPT	268.1	-271.6	32.2	496.7	-104.5	190.3	585.2	450.6	400.9
	S/OPN	310.8	-228.9	34.4	704.1	102.7	298.7	910.2	687.3	367.2
	FCFS	342.2	-197.5	16.3	762.5	161.2	242.7	1261.4	1195.7	1195.7
	EDD	329.5	-210.2	6.3	709.8	108.5	182.7	1010.8	944.9	951.2
	SLACK	369.0	-224.7	37.6	812.2	150.8	317.7	1290.0	1217.7	1217.7

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

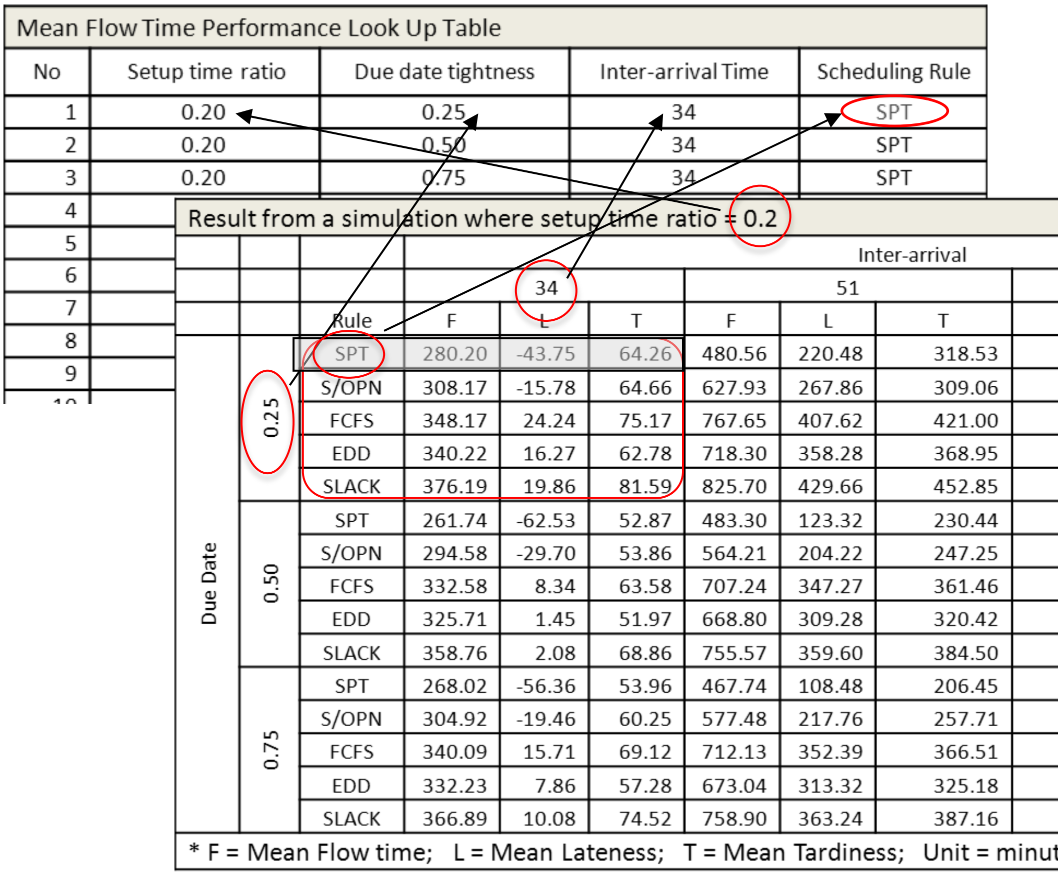
Table 4. Summary of results from a simulation where setup time ratio = 0.40.

Due date	Rule	Inter-arrival								
		34			51			68		
		F	**L**	**T**	**F**	**L**	**T**	**F**	**L**	**T**
0.25	SPT	275.3	-589.0	15.5	552.7	-407.0	180.8	690.3	649.6	718.7
	S/OPN	308.7	-555.6	16.0	652.8	-306.8	192.8	817.9	588.1	606.9
	FCFS	340.6	-523.7	1.2	741.1	-218.8	86.2	1184.0	1079.0	1079.0
	EDD	323.8	-540.5	0.0	685.1	-274.8	40.0	937.3	832.0	832.0
	SLACK	368.1	-582.6	17.5	796.3	-259.5	210.9	1230.9	1115.5	1121.0
0.50	SPT	264.2	-600.4	14.4	495.1	-465.0	153.0	754.7	726.4	709.8
	S/OPN	299.4	-565.0	14.1	621.0	339.4	175.3	840.4	622.7	622.7
	FCFS	337.6	-527.1	1.3	725.1	-235.0	84.4	1180.2	1075.1	1075.1
	EDD	322.1	-542.5	0.0	666.5	-293.6	37.8	938.9	833.5	833.5
	SLACK	364.0	-587.1	15.8	774.7	-281.5	190.6	1217.7	1102.1	1108.4
0.75	SPT	264.2	-599.8	15.7	472.8	-485.4	132.9	760.7	723.0	734.4
	S/OPN	302.1	-561.9	13.2	642.7	-315.7	179.0	864.7	543.8	719.3
	FCFS	332.8	-531.2	1.3	791.6	-239.5	79.0	1180.16	1075.0	1075.0
	EDD	316.0	-548.0	0.0	662.9	-295.4	35.4	955.2	849.9	849.9
	SLACK	359.2	-591.2	17.3	838.9	-288.0	192.3	1101.4	1075.0	1101.4

* 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.



Mean Flow Time Performance Look Up Table

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				
5				
6				
7				
8				
9				

Result from a simulation where setup time ratio = 0.2

			Inter-arrival					
			34			51		
		Rule	F	L	T	F	L	T
Due Date	0.25	SPT	280.20	-43.75	64.26	480.56	220.48	318.53
		S/OPN	308.17	-15.78	64.66	627.93	267.86	309.06
		FCFS	348.17	24.24	75.17	767.65	407.62	421.00
		EDD	340.22	16.27	62.78	718.30	358.28	368.95
		SLACK	376.19	19.86	81.59	825.70	429.66	452.85
	0.50	SPT	261.74	-62.53	52.87	483.30	123.32	230.44
		S/OPN	294.58	-29.70	53.86	564.21	204.22	247.25
		FCFS	332.58	8.34	63.58	707.24	347.27	361.46
		EDD	325.71	1.45	51.97	668.80	309.28	320.42
		SLACK	358.76	2.08	68.86	755.57	359.60	384.50
	0.75	SPT	268.02	-56.36	53.96	467.74	108.48	206.45
		S/OPN	304.92	-19.46	60.25	577.48	217.76	257.71
		FCFS	340.09	15.71	69.12	712.13	352.39	366.51
		EDD	332.23	7.86	57.28	673.04	313.32	325.18
		SLACK	366.89	10.08	74.52	758.90	363.24	387.16

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

Figure 2. Illustration of selection of entries in development the 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 intelligent 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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References

[1] Pinedo M 2008 *Scheduling: Theory, Algorithms, and Systems* (New York: Springer).

[2] Pol A and Ahuja R 2007 *Developing Web-Enabled Decision Support Systems using Access, VB.Net, and ASP.Net.* (Massachusetts: Dynamic Ideas)

[3] Abdallah M H 1995 A knowledge-based simulation model for job shop scheduling. *International Journal of Operations & Production Management* **15**(10) 89-102.

[4] Jahangirian M and Conroy G V 2000 Intelligent Dynamic Scheduling System: The Application of Genetic Algorithms *Int. J. of Manufacturing Technology Management* **11**(4) 247-257.

[5] Sun J and Xue D 2001 A dynamic reactive scheduling mechanism for responding to changes of production orders and manufacturing resources *Computers in Industry* **46**(2) 189-207.
[6] Wang W K 2006 An Intelligent Decision Support System for Performance Evaluation of State-Owned Enterprises of Electronics Industry *DSI 37th Annual Conference*. 1-4 March. Oklahoma, 40-51.
[7] Mahdavi I, Shirazi B and Solimanpur M 2010 Development of a simulation-based decision support system for controlling stochastic flexible job shop manufacturing systems *Simulation Modelling Practice and Theory* **18** 768-786.
[8] Hasan M S K, Sarker R and Essam D 2011 A DSS for Job Shop Scheduling under Process Interruptions *Flex Serv Manuf J*. **23**, 137-155.
[9] Mendes J M 2011 A Genetic Algorithm for the Job Shop Scheduling with a New Local Search using Monte Carlo Method *Proceeding of the 10th WSEAS international conference on AI, knowledge engineering and data base* 20-22 February. Wisconsin, 26-31.
[10] Turban E and Aronson J E 2001 *Decision support systems and intelligent systems* (6th ed.). (New Jersey: Prentice Hall).
[11] Alpay S 2007 Agent Based Dynamic Job Shop Simulation System. *IEA/AIE'07 Proceedings of the 20th international conference on Industrial, engineering, and other applications of applied intelligent systems*. June 26-29. Kyoto-Japan, 364-373.
[12] Arakawa M, Fuyuki M and Inoue I 2003 An Optimization-Oriented Method for Simulation-Based Job Shop Scheduling Incorporating Capacity Adjustment Function *Int. J. Production Economics* **85** 359–369.
[13] Azadeh A and Maghsoud A 2010 Optimization of Production Systems through Integration of Computer Simulation, Design of Experiment, and Tabu search: the case of a large steelmaking workshop *Int J Adv Manuf Technol* **48** 785-800.
[14] Gholami M and Zandieh M 2009 Integrating Simulation and Genetic Algorithm to Schedule a Dynamic Flexible Job Shop *J Intell Manuf* **20** 481-498.
[15] Kanhal T A and Abbod M F 2008 Modelling and Optimisation of Reheat Furnace *EMS '08 Proceedings of the 2008 Second UKSIM European Symposium on Computer Modeling and Simulation* IEEE Computer Society Washington 9-14.
[16] Mahdavi I, Shirazi B and Solimanpur M 2010 Development of a Simulation-Based Decision Support System for Controlling Stochastic Fexible Job Shop Manufacturing Systems *Simulation Modelling Practice and Theory* **18** 768-786.
[17] Muth J F And Thompson G L 1963 *Industrial Scheduling* (New Jersey: Englewood Cliffs).
[18] Huang K L and Liao C C 2008 Ant Colony Optimization Combined with Taboo Search for the Job Shop Scheduling Problem *Computers & Operations Research* **35** 1030-1046.
[19] Pan Q K, Wang L, Tasgetiren M F and Zhao B H 2008 A Hybrid Discrete Particle Swarm Optimization Algorithm for the No-wait Flow Shop Scheduling Problem with Makespan Criterion *Int J Adv Manuf Technol* **38** 337-347.
[20] Azadeh A and Maghsoud A 2010 Optimization of Production Systems through Integration of Computer Simulation, Design of Experiment, and Tabu search: the case of a large steelmaking workshop *Int J Adv Manuf Technol* **48** 785-800.
[21] Rajabinasab A and Mansour S 2011 Dynamic Flexible Job Shop Scheduling with Alternative Process Plans: an agent-based approach *Int J Adv Manuf Technol*. **54** 1091-1107.
[22] Zhang R and Wu C 2011 An Artificial Bee Colony Algorithm for the Job Shop Scheduling Problem with Random Processing Times *Entropy* **13** 1708-1729.