A Genetic Algorithm Approach for Minimization of Mean Flow Time in Job Shop Scheduling

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Abstract— This dissertation is motivated by a scheduling problem that is commonly observed in today's manufacturing world. It contributes to the theoretical and practical aspects of scheduling research. It is dedicated to the analysis of scheduling a set of jobs on multiple machines when the jobs have uncertain processing times and conformance to the due date is the performance objective. Efficient scheduling can improve productivity through reduced work-in-process and finished goods inventories. The objective of the research is to efficiently solve the adaptive job shop scheduling problem and to determine best job schedule for the problem using genetic algorithm that minimizes the mean flow time and mean tardiness. In this research, we are developing a method to optimize the scheduling process that improves the customer satisfaction through better adherence to deliver dates and simultaneously minimizing the resource usage.

Key words: Job Shop Scheduling, Genetic Algorithm Approach

I. Introduction

Scheduling is the science of assigning a group of different tasks to available resources for a specific period of time. The result of allocation is specified in a schedule. An Effective scheduling activity imparts a key of success in today's competitive manufacturing world. Performance criteria of any job shop such as customer satisfaction, quality of products, inventory costs, machine utilization, meeting due dates and manufacturing lead times are all dependent upon the efficiency of scheduling operation.

A schedule is feasible if it does not violate any accompanying constraints. Sometimes, finding a single feasible schedule is enough. However, under many circumstances, the goal is to find the best schedule from among all feasible schedules to achieve certain objective(s), such as the shortest schedule length or the maximum number of tasks completed before the due dates. Hence, it becomes increasingly important to develop effective scheduling approaches that help in achieving the desired objectives. Scheduling may be considered as an optimization process.

Literature survey revealed that ample of research work has been done on scheduling Nasr and Elsayed [1] presented two efficient heuristic to minimize the mean flow time in a general job shop type machining system with alternative machine tool routings. Their methods were based on decomposing a big problem into multiple sub-problems and solving them individually. Moon and Lee [2] developed a heuristic to solve the job shop scheduling problem with alternate routings by dividing the problem into two problems; allocation and sequencing problem. They presented two different approaches to solve the two problems. Aldakhilallah and Ramesh [3] developed cyclic scheduling heuristics for the reentrant job shop scheduling environments. Their approach considered a repetitive production re-entrant job shop with a predetermined operations sequence on a particular single product. Their objective was to minimize both cycle time and flow time simultaneously. Anderson and Nyirenda [4] developed an effective heuristic that minimizes the total tardiness of jobs combining two different dispatching rules. Braun [5] developed a genetic algorithm based traveling salesman problem with purely two mutation strategies. Chakroborthy and Mandal [6] developed a GA for the general single vehicle routing problem. Their algorithm was mutation based and could handle various types of vehicle routing problems. Kubiak [7] proved that there is an optimal job schedule with the shortest processing time (SPT) job order. They derived a dynamic programming algorithm to find the optimal schedule under the bottleneck assumption and the hereditary order assumption. Aldakhilallah and Ramesh [8] developed cyclic scheduling heuristics for the reentrant job shop scheduling environments. Their approach considered a repetitive production re-entrant job shop with a predetermined operations sequence on a particular single product. Their objective was to minimize both cycle time and flow time simultaneously.

II. Methodology

This chapter focuses on the methodology used for multi objective scheduling in a job shop environment. A brief description of the operation of the job shop system is also provided in this chapter.

A. Description of Job Shop Scheduling Problem

To formally define the problem using scheduling terminology, we have a set of n jobs to be processed on m different machines, where in each job has its own machining sequence. The problem is denoted by eq. 2.1.1

$$J_m \mid prec \mid \sum_{j=1}^{n}(Cj/n), \sum_{j=1}^{n}(Tj/n) \qquad (2.1.1)$$

Where;

- J_m denotes a job shop with m machines,
- prec denotes precedence constrains on jobs
- C_j denotes the completion time of job j
- T_j denotes the tardiness of job j

III. Experimentation

This chapter presents the details of the experimentations conducted on the Adaptive Multi Objective Genetic Algorithm (AMOGA). Experimentation was conducted in two stages. In the first stage, single day (first day) experimentation is conducted. In the second stage, the multiple day experimentation is performed. The details of the problems tested are given below.

A. First Day Experimentations

Testing is performed on three different test problems. The purpose of this single day testing was to validate the effectiveness of the AMOGA in finding effective solutions to optimize the selected objectives.

1) Initial Testing Parameters

Several test cases were generated to test the performance of AMOGA. Table 1 shows the input parameters considered for the testing all the problems.

Index	Parameters	Values
1	Population Size	10
		20
		30
2	Number of Generation	50
		100
		200
3	Mutation 1 Rate	20
		40
		60
		80
4	Mutation 2 Rate	2
		5
		10

Table 1: Input Parameter

Three different strategies were considered for selection as described earlier. Table 2 explains the three selection strategies.

Strategy	Description
S1	Select the best among all the Parents and Off-springs pairs
S2	Select the best among (Parents + Off-springs) pairs
S3	A combination of S1 & S2

Table 2: Selection Strategy

The objective of AMOGA is to minimize the mean flow time and mean tardiness. Since this is a multi-objective problem, several weight combinations for the individual objectives are tested. Table 3 explains the weights used for testing.

Mean Flow Time	Mean Tardiness
0	1
0.2	0.8
0.4	0.6
0.6	0.4
0.8	0.2
1	0

Table 3: Weight for Objective

B. Test Problems

The three problems are presented in the following section. Details for each problem are provided separately.

1) Test Problems 1

The problem involves a set of 6 jobs to be processed on 6 different machines where every job has its own machining sequence. The due dates for this problem are given. Table 4 shows the processing times (min) and due dates (min) for the problem.

Jobs	Processing Time (Min) *						Due Dates (Min)
1	3(001)	1(003)	2(006)	4(007)	6(003)	5(006)	52
2	2(008)	3(005)	5(010)	6(010)	1(010)	4(004)	94
3	3(005)	4(004)	6(008)	1(009)	2(001)	5(007)	68
4	2(005	1(005)	3(005)	4(003)	5(008)	6(009)	70
5	3(009)	2(003)	5(005)	6(004)	1(003)	4(001)	25
6	2(003)	4(003)	6(009)	1(010)	5(004)	3(001)	45
* Note :- 3(001) = First operation is on machine 3, Processing time 1 min							

Table 4: Test problem 1

The problem is extensively tested. The initial parameters are already provided in previous tables. All possible combinations of the parameters were tested on this problem. Each parameter set is run for 100 trials for a specified weight set 2 (0.2, 0.8). The objective of this extensive experimentation is to identify the best parameter set which produces minimum weighed fitness value. Those parameters can then be used for the subsequen

a) Results

This section presents the results for all the experimentations conducted for the adaptive job shop problem. We tested on a single test problem for 3 successive days. The adaptability of the developed GA to the assigned priority was observed during these experimentations. All the results are summarized separately under each section.

b) First Day Results

The results for first day of the multiple day problems are provided below. Similar to the previous experimentation, each combination of weights with best parameter set is run for 100 trials and the best result is recorded. Tables 5 shows the best mean flow time and mean tardiness values obtained from each weight combination.

Objective Weight		Best Result	
Mean flow time	Mean Tardiness	Mean flow Time (min)	Mean Tardiness (min)
0	1	973.33	3.33
0.2	0.8	866.67	16.67
0.4	0.6	866.67	16.67
0.6	0.4	866.67	16.67
0.8	0.2	866.67	16.67
1	0	866.67	16.67

Tables 5: First day result

Fig. 1: shows the Pareto Front plot for the above results.

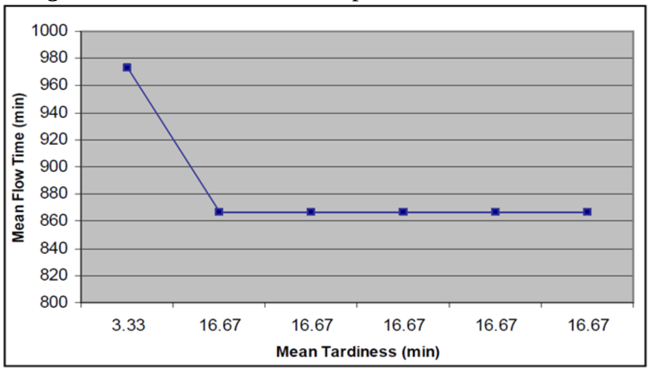


Fig 2: Pareto Chart

In order to obtain the best job schedule the weigh combination of α = 0.2 and β = 0.8 was chosen for further experimentations. The best sequence that minimizes both mean flow time and mean tardiness was 11 – 61 – 51 – 21 - 41 -31. The Gantt chart for the sequence is shown in Figure 4.2.1.3. The jobs are identified based on the job number and the day on which they enter the production plant. All the jobs of a particular day will have the day's index as suffix for proper identification.

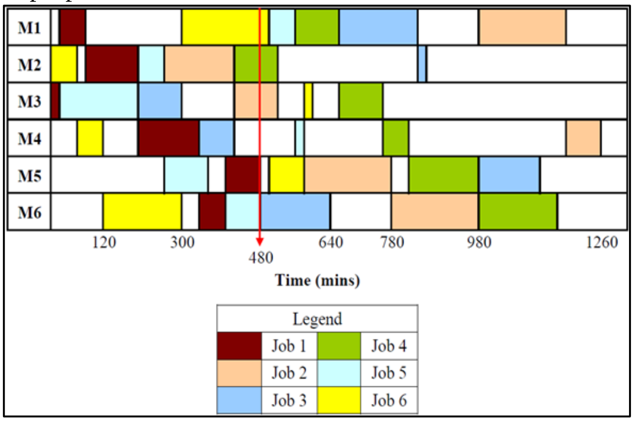


Fig. 3: Gantt chart for 1st day Result

c) End of Day 1

From the Figure it can be clearly observed that only job 1 is finished at the end of the first day (8 hour run). The rest of the jobs 2, 3, 4, 5 and 6 still have some operations to be performed on the machines. All these jobs have to be carried forward to the next day for processing. Jobs carried forward and corresponding processing times at the end of the first day are shown in Table. Since these jobs have already been in the system for a day, their due date is effectively reduced by one day in Table 6. The text in bold indicates operations that are partially completed.

+++J OBS	Processing Time (min)						Due Dates (Days)
11	0	0	0	0	0	0	1
21	0	**3(040)**	5(200)	6(200)	1(200)	4(080)	3
31	0	0	6(160)	1(180)	2(020)	5(140)	2
41	**2(040)**	1(100)	3(100)	4(060)	5(160)	6(180)	2
51	0	0	0	0	1(060)	4(020)	0
61	0	0	0	**1(020)**	5(080)	3(020)	1

Table 6: End of Day 1

The partially completed operations for J21, J41 and J61 are kept unchanged when moving to the following days and are processed first on the corresponding machines. The remaining operations for these jobs are included in the AMOGA for scheduling.

d) Day 2 Results

	Jobs	Processing Time (MIN.)						Due Dates (Days)	Days in System
Carried Forward	21	0	0	5(200)	6(200)	1(200)	4(080)	3	1
	31	0	0	6(160)	1(180)	2(020)	5(140)	2	1
	41	0	1(100)	3(100)	4(060)	5(160)	6(180)	2	1
	51	0	0	0	0	1(060)	4(020)	0	1
	61	0	0	0	0	5(080)	3(020)	1	1
New	**72**	**1(020)**	**3(050)**	**4(050)**	**2(040)**	**5(030)**	**6(060)**	**1**	**0**
	82	**4(090)**	**3(070)**	**1(120)**	**5(250)**	**2(025)**	**6(080)**	**2**	**0**
	92	**5(090)**	**6(015)**	**3(030)**	**2(150)**	**4(025)**	**1(120)**	**3**	**0**

Table 7: Day 2 Results

The same parameter set is used with all sets of weights. The results for the minimum mean flow time and mean tardiness for 100 trials is shown in Table 7. When calculating the mean flow times for the continuous day operations all the jobs that entered the system on the first day and were carried forward, 480 minutes added to their flow time.

Objective Weight		Best Result	
Mean flow time	**Mean Tardiness**	**Mean flow Time (min)**	**Mean Tardiness (min)**
0	1	973.75	166.875
0.2	0.8	970	166.875
0.4	0.6	890.625	193.125
0.6	0.4	890.625	193.125
0.8	0.2	890.625	193.125
1	0	890.625	193.125

Table 8: Result

Figure 4 shows the Pareto Front plot for the above results.

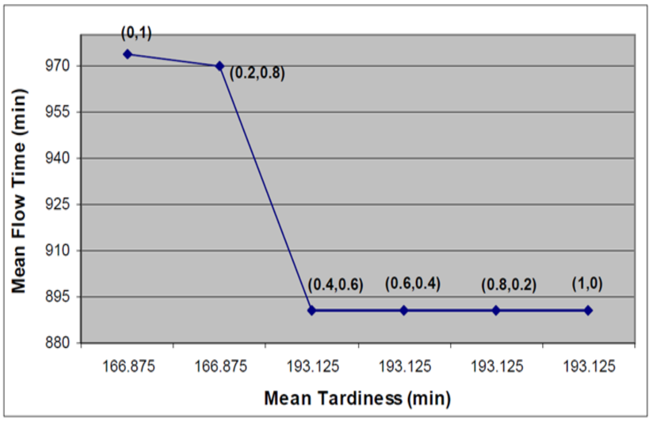


Fig. 4: Pareto Front plot

From the Pareto chart it is noticed the best values for individual objectives and intermediate weights vary considerably. To proceed scheduling operations on the third day the best sequence obtained for objective weights of $\alpha = 0.2$ and $\beta = 0.8$ were considered.

Figure 5 shows the Gantt chart for best sequence obtained through AMOGA. The job sequence obtained for this schedule is 61 – 21 – 72 – 41 – 51 - 31 - 82 – 92. The minimum mean flow time obtained for this best schedule is 970 minutes while the mean tardiness was 166.875 minutes.

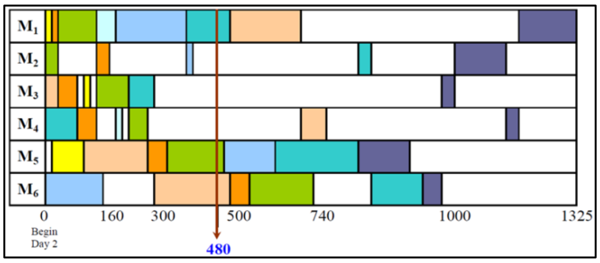


Fig. 5: Gantt chart

e) End of Day 2

From the Figure it can be observed that at the end of day 2 jobs 82, 41, 21, 72, 31 and 92 have partially completed operations. All these jobs must be carried forward to day 3 for processing. Table 9 shows the left over jobs and corresponding processing times at the end of day 2. Text in bold indicates the partially completed operations and remaining processing times.

Jobs	Processing Time (Min.)						Due Dates (Days)
82	0	0	**1(020)**	5(250)	2(025)	6(080)	2
41	0	0	0	0	**5(010)**	6(180)	2
21	0	0	0	**6(020)**	1(200)	4(080)	3
72	0	0	0	0	0	6(060)	1
31	0	0	0	0	0	5(140)	2
92	5(090)	6(015)	3(030)	2(150)	4(025)	1(120)	3

Table 9:

f) Day 3 Continued Operations

The following Figure 10 shows the processing times and due dates interface for the test problem on day 3.

g) Day 3 Results

For the third day of scheduling all the data for carried forward jobs and new jobs are considered. Therefore, the AMOGA determines the best schedule for all these jobs. Table 10 shows data for carried forward jobs with remaining operations and entering on day 3.

Jobs	Processing Time (Min.)						Due Dates (Days)	Days In System (Days)
82	0	0	0	5(250)	2(025)	6(080)	1	1
41	0	0	0	0	0	6(180)	1	2
21	0	0	0	0	1(200)	4(080)	2	2
72	0	0	0	0	0	6(060)	0	1
31	0	0	0	0	0	5(140)	1	2
92	5(090)	6(015)	3(030)	2(150)	4(025)	1(120)	2	1
13	**3(010)**	**2(030)**	**6(040)**	**1(070)**	**4(060)**	**5(050)**	**1**	**0**
53	**2(100)**	**1(080)**	**5(020)**	**3(040)**	**4(050)**	**6(190)**	**2**	**0**

Table 10:

The GA parameters used previously are kept the same. The results for the minimum values of mean flow time and mean tardiness after 100 trials are shown in Table 4.2.1.8.

Objective Weight		Best Result	
Mean flow time	**Mean Tardiness**	**Mean flow Time (min)**	**Mean Tardiness (min)**
0	1	960.625	375.625
0.2	0.8	960.625	375.625
0.4	0.6	960.625	375.625
0.6	0.4	960.625	375.625
0.8	0.2	951.250	396.250
1	0	948.125	397.500

Table 11: Result

Figure 11 shows the Pareto Front plot for the above results.

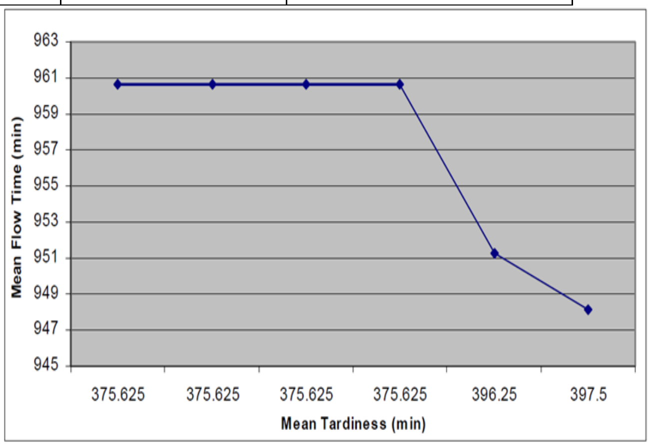
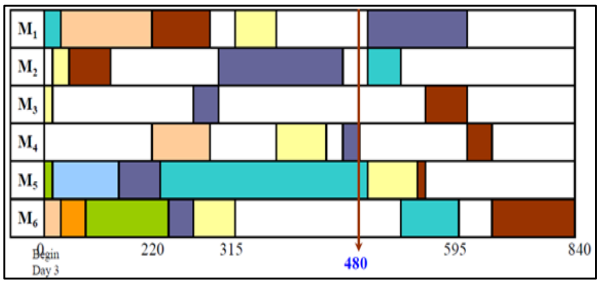


Fig. 11: Pareto chart

Figure 11 shows the Gantt chart for best sequence obtained through AMOGA For α = 0.2, β = 0.8. The job sequence obtained for this schedule is 72 – 31 – 21 – 41 – 92 – 82 – 13 – 53. The minimum mean flow time obtained for this schedule is 960.625 minutes and the mean tardiness is 375.625 minutes.

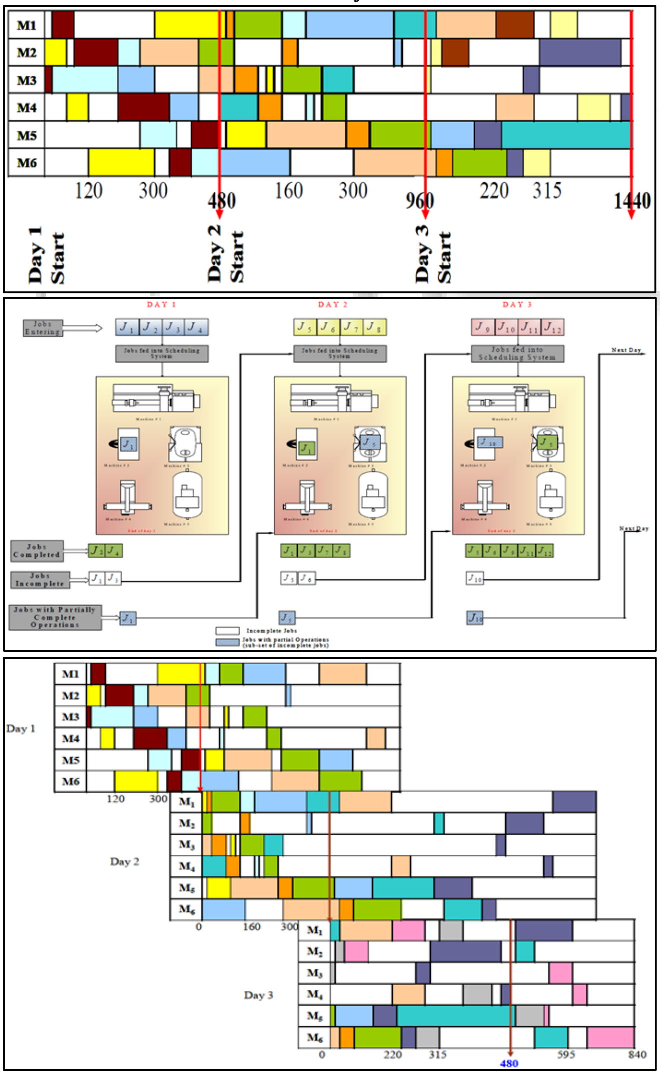


Legend							
	Job 21		Job 41		Job 72		Job 13
	Job 31		Job 82		Job 92		Job 53

Fig. 12: Gantt chart for Mean Flow Time and Mean Tardiness

2) Summary of Results

From the above Gantt schedules we can observe the results generated by the AMOGA. To describe the adaptive scheduling the three days best schedule are considered into a single chart. All the jobs that are not completed on day 1 are carried forward to day 2 and similarly to day 3. Figure 13(b) shows the Gantt chart for the continuous job shop scheduling problem which is based on the integration of Gantt charts for the individual days.



Legend							
	Job 11		Job 41		Job 72		Job 13
	Job 21		Job 51		Job 82		Job 53
	Job 31		Job 61		Job 92		

Fig. 13(b): Summary of Results

As we observe at the end of first day job 11 is finished. As a higher priority is given to minimizing the mean tardiness, jobs with shorter due dates must be completed first. If only tardiness is prioritized job 51 must be processed first. But, the total processing time for this job is greater than 480. Hence among the shorter due date jobs, only job 11 can be completed on day 1. At the end of day 2, we observe that although jobs 21, 31 and 41 are in the system from day 1, jobs with shorter due dates (such as jobs 51 and 61) are finished first. Also since the job 71 coming on day 2 have a shorter due date, the AMOGA finished most of the operations for that job. Hence the AMOGA is delaying jobs with later due dates to finish jobs coming in on following days with shorter due dates.

However, if mean flow time minimization was given a higher priority, the AMOGA should be releasing jobs to minimize the time spent in system.

IV. Conclusion

In this research, adaptive scheduling problem in a real time job shop environment was solved, for the multi-objective optimization of minimizing mean flow time and mean tardiness. The objectives were chosen because minimizing mean flow time minimizes the manufacturing lead time. On the other hand minimizing mean tardiness helps to meet the delivery dates effectively. A genetic algorithm with two mutation strategies was used to solve the adaptive scheduling problem. Adaptive scheduling was considered because in real life manufacturing environments scheduling based on given priorities is very important to achieve desired objectives.

In order to evaluate the effectiveness of the AMOGA developed to solve the adaptive job shop scheduling problem the effectiveness of the model was first tested using a single day dates. For the single day, extensive analyses were conducted on the FT06 benchmark problem and several other problems. The experimentations with these problems confirmed that the AMOGA is able to find good solutions to the problem addressed.

The multiple-day continuous job day's remaining jobs on the following day we followed certain scheduling rules. All the jobs whose last operation is partially completed were scheduled first. For the jobs with partially completed operation that also have other operations to be processed on one or more other machines, the partially completed were unaltered and scheduled first on the following day, the remaining operations were scheduled along with new jobs using GA. All the jobs with no partially completed operations were scheduled along with new jobs. Overall the results indicate that the AMOGA developed for performance of the adaptive shop problem was tested in a similar manner. However, to schedule the previous scheduling of jobs in a job shop environment is able to generate comparable or better results to that formed in literature. The results show considerable adaptability to the

Mean tardiness objective that was considered in this research.

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