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Evaluation of Feedback among Multiple Scheduler Profiles in Fuzzy Genetic Scheduling

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Abstract

This paper extends the earlier studies conducted on multiple scheduler profile in fuzzy genetic scheduling. Multiple schedulers can set up individual fuzzy membership bounds which results in different evaluation of multi-objective problem of single machine scheduling. A new software application enables feedback among schedulers by applying seeding of individual scheduler's population by best chromosomes from other scheduler's population. Few experiments are performed on the aforementioned software application to evaluate the performance of the multi objective single machine scheduling problem by varying the level and frequency of feedback. More improvement is observed as the frequency of the feedback is increased but no significant improvement is observed when the level is increased.
Keywords: Genetic algorithm, multi-person scheduling, multiple objective, single machine, fuzzy systems

1. Problem studied:

Modern manufacturing is highly automated and the production lines consist of interdependent processes which are performed by several groups of machines. It is always expected for any manufacturing system to use minimum amount of resource for highest production. It is necessary to reduce the waste and use all resources available as efficiently as possible. Machines can be calibrated for high throughput but it is extremely necessary to schedule the tasks to be performed in these machines or group of machines so that one of many performance measures is optimized. It is interesting to note that as different scheduling of same chain of tasks are necessary to achieve optimization in different performance measures like throughput, processing time, tardiness etc., production needs to implement different scheduling strategy according to its requirement. Sometimes it is necessary to implement a scheduling algorithm which optimizes more than one performance measures.

There have been many research work done in the past two decades on optimizing competing performance measures. The problem of multi-objective performance optimization is not linear in nature and when we consider non-zero ready time, the problem cannot be solved in polynomial time. For this reason genetic algorithm became immensely popular in solving this type of problem. Fonseca and Fleming [1] implemented genetic algorithm to obtain a set of non-dominated Pareto solutions. Other researchers also implemented Pareto optimal strategy to solve multi-criteria GA; such as, vector evaluated genetic algorithm(VEGA) by Schaffer[2], strength Pareto evolutionary algorithm by Sbalzarini[3] etc. Suer et al. [4] proposed a mixer strategy where populations from different GA optimizer dedicated to optimize different performance measures are mixed and fed back for further evolution.

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Fuzzy modelling to deal with the uncertainty of real world scheduling has been investigated in the past. Vlach [5] showed how fuzzy membership functions can be used to model this type of scheduling problems. In past research conducted by Suer and Allard [6] [7] fuzzy membership function is used to achieve harmonized fitness values of different GA optimizers. In this study, different GA optimizers are configured by different schedulers and results of their recommendations are evaluated against the fuzzy fitness values obtained from different membership functions. Later Suer, *et al*. [8] extended this concept with more experiments by applying a secondary operator considering different schedulers profile.

It is not unusual for large corporations to employ more than one scheduler for achieving optimization in multiple performance criteria. In that situation each scheduler will aim for their individual satisfaction level for any performance measure. In 1959, a structural communication method, called Delphi, is developed for achieving consensus among experts on a forecast. This particular method lets individual expert to receive feedback from other experts and modify their earlier decision on basis of the feedback. It is thus necessary to create feedback channels among different schedulers and make them able to review each other's results after a certain number of evolutions of GA optimization.

In this paper, different GA optimizers are configured by different schedulers. Each of the scheduler defines their fuzzy membership bounds for multiple performance measures. However as an extension of the earlier work, new software is built to allow the schedulers to perform the following two extra tasks.

- Schedulers are allowed to review results after certain number of generations and are allowed to modify their configurations by changing fuzzy membership bounds.
- Schedulers are also allowed to seed their own population by best chromosomes from other scheduler's population.

Different experiments are performed on this software to evaluate how choices of different schedulers can affect the overall improvement of solution. Moreover special observations are made to evaluate how quickly the different schedulers can reach to optimal solution when they borrow each other's best population to seed their own population.

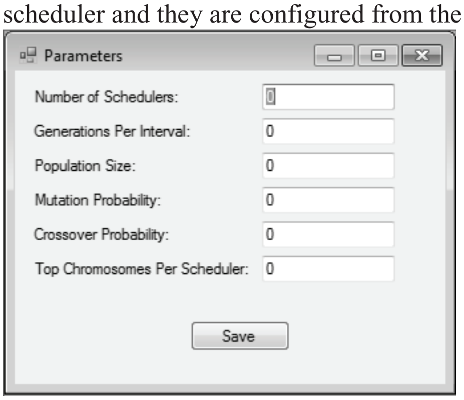
In this particular study single machine scheduling is performed for different performance measures.

2. Methodology

In this section, the GA methodology is discussed in brief.

2.1. Genetic algorithm features

The chromosomes are represented as array of job number each of which correspond to one job with its processing time and due date. The software is capable of loading the job information from a tab delimited file. Initial population is generated randomly for each of the scheduler. In this software the parameters for GA is same for every scheduler and they are configured from the screen below.



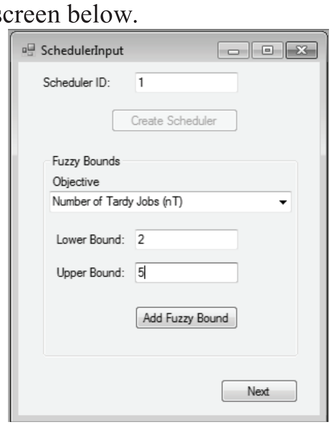


Fig 1: Parameter selection and scheduler input screen

In this software basic crossover strategy with double cut points is used. For mutation, two job ids are selected randomly and their positions are swapped in the array. Fitness function of the chromosome is calculated by computing the performance measure chosen and the selection probability of the chromosome is determined by the following formula

$$P_i = \frac{FF_i}{\sum_{i=1}^{M} FF_i}$$

Where,

p_i reproduction probability for chromosome *i*

FF_i fitness function for chromosome *i*

M population size

2.2. Fuzzy features

The fitness function is formed using the fuzzy membership functions on each performance measure. In this study only linear fuzzy membership function is used. The linear fuzzy membership function determines the membership of a solution based on a linear relationship as shown in figure 1. In the software the lower and upper bound of the function is configured by individual in the scheduler input screen in figure 1.

In the linear relationship shown in the figure (min type problem) the lower bound is the 'most desirable' value of the performance measure and vice versa. As for example if the scheduler determines that having only two tardy jobs in the above scenario is ideal and five is unacceptable then he must choose the lower and upper bounds as 2 and 5 respectively. So any chromosome having number of tardy jobs between 2 to 5 will be linearly scaled and return a fractional value between 0 and 1. Any chromosome with number of tardy jobs greater than 5 or less than 2 will have fuzzy membership value as 1 and 0 respectively. The general formula below is used to determine the fuzzy membership value for performance measure of any chromosome.

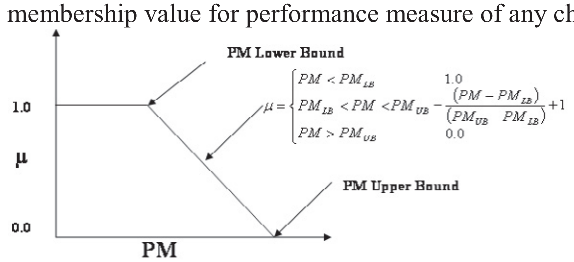


Figure 2: Linear membership function

$\mu = 1$ *if* $PM \leq PM_{LB}$,

$\mu = 0$ *if* $PM \geq PM_{UB}$ *and*

$\mu = 1 - ((PM - PM_{LB})/(PM_{UB} - PM_{LB}))$ *if* $PM_{LB} < PM < PM_{UB}$

2.3. Schedulers

Each scheduler chooses individual sets of the fuzzy membership bounds for their own performance measures. It is to be noted that different schedulers can choose different combinations of the performance measures. Naturally a chromosome can have different fitness value depending on the bounds chosen by the scheduler. Total satisfaction value is determined in the following way.

I. Each satisfaction value obtained from the fuzzy membership function for a particular chromosome is added to get the total satisfaction value for that particular chromosome. This fuzzy-add operator is suggested by Sommer and Pollatscheck (1978) on basis of the fact that chromosomes that are good with all performance measures will have a greater sum of member ship functions and therefore a higher fitness value.

$$FF = \sum_{i=1}^{m} \mu_i$$ Where m = number of schedulers

II. According to the parameter set in the screen of figure 1, certain number of top chromosomes is selected for each scheduler after every generation according to the total satisfaction value.

III. Every top chromosome for one scheduler is also evaluated according to the fuzzy membership bounds chosen by other schedulers. Ion this way, for every chromosome, we obtain different total satisfaction values for each scheduler profiles. These values are aggregated in hybrid fashion and hybrid total satisfaction value is obtained for each chromosome.

IV. In the end the chromosome with the maximum of hybrid total satisfaction value is declared as the best chromosome. For the detail of the concept please refer to the paper [7].

After every round of predetermined number of generations, schedulers are allowed to evaluate their populations. In the compare schedulers screen below they can see the satisfaction levels of their top chromosomes and corresponding satisfaction levels of those top chromosomes according to other schedulers' profile. Every scheduler is allowed to seed their population by other scheduler's best chromosomes. They can also change their own fuzzy membership bounds. Once all schedulers completed their review process the software is ran for another round of evolution.

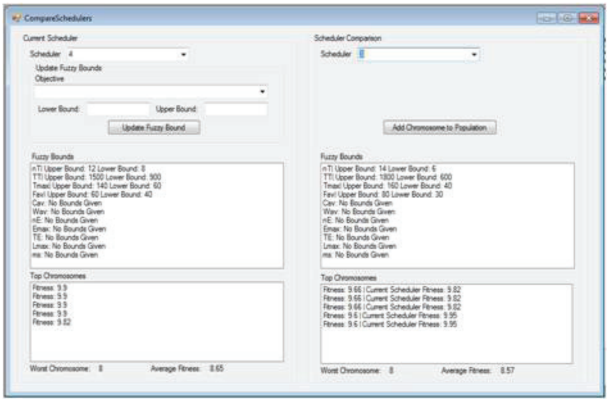
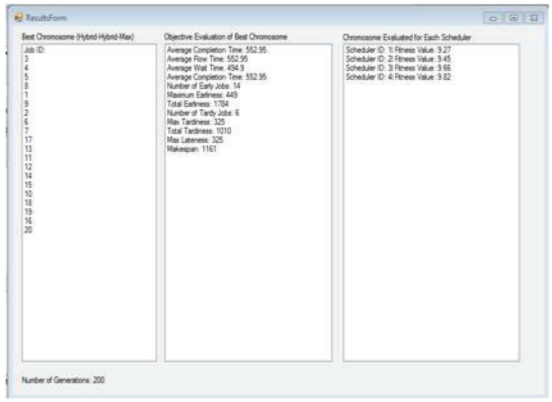



Fig 3: Scheduler comparison screens

3. Results

Two different datasets are used for the experiments. These datasets are borrowed from the earlier experiments from [7]. Each of the datasets has 20 jobs with individual processing time, ready time and due date. For all the experiments, population size, mutation probability and crossover probability are chosen as 50, .7 and .5 respectively.

All of the experiments are carried out by four scheduler profiles with individual fuzzy membership bounds for four different performance measures; such as, number of tardy jobs, total tardiness, maximum tardiness and average flowtime. Two different profile sets IV and V are also borrowed from [7] and used for the experiments below.

3.1. Level of feedback

In this experiment, number of chromosomes seeded from one scheduler to others is varied. The evolution is stopped after every 20 generation and the feedback operation among schedulers is carried out. In two sets of runs, first for one chromosome seeding and second for two chromosomes seeding are carried out. The results are in the table below.

Gen	Seed	20	40	60	80	100	120	140	160	180	200
scheduler1	1	10.85	10.95	10.98	11	11.02	11.02	11.02	11.03	11.03	11.05
	2	10.84	10.95	10.98	11	11.02	11.02	11.02	11.03	11.03	11.05
scheduler2	1	10.48	10.62	10.65	10.66	10.68	10.68	10.68	10.68	10.68	10.68
	2	10.48	10.59	10.62	10.65	10.68	10.68	10.68	10.68	10.68	10.68
scheduler3	1	10.92	11.1	11.22	11.22	11.32	11.32	11.32	11.32	11.32	11.32
	2	10.91	11.1	11.21	11.21	11.32	11.32	11.32	11.32	11.32	11.32
scheduler4	1	11.14	11.15	11.3	11.33	11.33	11.33	11.33	11.35	11.36	11.36
	2	11.08	11.15	11.3	11.3	11.3	11.3	11.3	11.35	11.36	11.36

Table 1: Level of feedback

It can be observed from the results above that there is no significant difference in the improvement rate between one chromosome feedback and two chromosome feedbacks.

3.2. Frequency of feedback

In this experiment the number of generations after which the feedback is carried out is varied. The same sets of experiment are carried out by two different scheduler profile sets. For each profile set, 200 generations are run for 10, 20, 30, 40 and 50 feedback frequencies.

Profile IV

Feed Freq: 10	**10**	**50**	**100**	**150**	**200**
Sceduler 1	8.74	9.06	9.43	9.68	10.31
Sceduler 2	8.83	8.93	9.67	9.86	10.41
Sceduler 3	9	9	9.91	10	10.61
Sceduler 4	9.13	9.27	9.6	9.75	10.46

Best					
Sceduler 1	8.6	8.8	9.36	9.44	9.7
Sceduler 2	8.67	8.79	9.54	9.63	10
Sceduler 3	8.75	8.88	9.91	9.88	10
Sceduler 4	9.13	9.26	9.6	9.69	9.76

Feed Freq: 20	**20**	**60**	**100**	**140**	**200**
Sceduler 1	8.7	8.8	8.86	8.86	9.29
Sceduler 2	8.75	8.86	8.91	8.92	9.39
Sceduler 3	9	9	9	9	9.27
Sceduler 4	9.19	9.29	9.29	9.33	9.56

Best					
Sceduler 1	8.66	8.66	8.88	8.91	9.21
Sceduler 2	8.67	8.67	8.91	8.92	9.39
Sceduler 3	8.75	8.75	9	8.88	9.27
Sceduler 4	9.19	9.19	9.28	9.33	9.44

Feed Freq: 30	**30**	**60**	**90**	**150**	**210**
Sceduler 1	8.7	8.75	8.89	8.89	9.29
Sceduler 2	8.83	8.83	9	9	9.19
Sceduler 3	9	9	9	9.07	9.75
Sceduler 4	9	9.03	9.2	9.48	9.48

Best					
Sceduler 1	8.6	8.6	8.77	9.08	9.03
Sceduler 2	8.67	8.67	8.83	9.15	9.07
Sceduler 3	8.75	8.75	9	9.18	9.07
Sceduler 4	9	9.03	9.2	9.44	9.45

Feed Freq: 40	**40**	**80**	**120**	**160**	**200**
Sceduler 1	8.82	8.82	8.82	9.15	9.15
Sceduler 2	8.83	8.83	9.08	9.25	9.27
Sceduler 3	9	9	9	9.37	9.37
Sceduler 4	9	9.49	9.49	9.49	9.71

Best					
Sceduler 1	8.6	9.15	9.15	9.15	9.52
Sceduler 2	8.67	9.25	9.25	9.25	9.76
Sceduler 3	8.75	9.37	9.37	9.37	10
Sceduler 4	9	9.49	9.49	9.49	9.71

Profile V

Feed Freq: 10	**10**	**50**	**100**	**150**	**200**
Sceduler 1	8.65	8.83	8.93	9.15	9.26
Sceduler 2	8.75	8.92	8.95	9.37	9.56
Sceduler 3	9	9	9.06	9.51	9.53
Sceduler 4	9	9	9	9.71	9.71

Best					
Sceduler 1	8.6	8.65	8.92	9.19	9.19
Sceduler 2	8.67	8.75	9.03	9.31	9.31
Sceduler 3	8.75	8.88	9.17	9.46	9.46
Sceduler 4	9	9	9.34	9.67	9.67

Feed Freq: 30	**20**	**60**	**100**	**140**	**200**
Sceduler 1	8.78	9.08	9.18	9.21	9.27
Sceduler 2	8.75	9.14	9.3	9.35	9.52
Sceduler 3	9	9.31	9.5	9.5	9.66
Sceduler 4	9	9.67	9.67	9.8	9.9

Best					
Sceduler 1	8.6	9.17	9.14	9.21	9.27
Sceduler 2	8.67	9.3	9.23	9.35	9.45
Sceduler 3	8.75	9.46	9.33	9.5	9.66
Sceduler 4	9	9.41	9.67	9.75	9.82

Feed Freq: 30	**30**	**60**	**90**	**180**	**210**
Sceduler 1	8.85	8.85	8.85	9.2	9.26
Sceduler 2	8.83	8.92	9.21	9.23	9.34
Sceduler 3	9	9	9	9.35	9.51
Sceduler 4	9	9	9.07	9.57	9.57

Best					
Sceduler 1	8.6	8.6	9	9.21	9.13
Sceduler 2	8.67	8.67	9.01	9.36	9.23
Sceduler 3	8.75	8.75	9.03	9.53	9.35
Sceduler 4	9	9	9.07	9.57	9.45

Feed Freq: 40	**40**	**80**	**120**	**160**	**200**
Sceduler 1	8.75	8.87	8.87	9.09	9.09
Sceduler 2	8.83	8.92	9.17	9.17	9.2
Sceduler 3	9	9	9	9.29	9.29
Sceduler 4	9	9	9	9	9.18

Best					
Sceduler 1	8.6	8.65	8.65	8.65	9.06
Sceduler 2	8.67	8.75	8.75	8.75	9.13
Sceduler 3	8.75	8.88	8.88	8.88	9.22
Sceduler 4	9	9	9	9	9.18

Feed Freq: 50	50	100	150	200
Sceduler 1	8.75	8.75	8.75	8.75
Sceduler 2	8.92	8.92	8.92	9.09
Sceduler 3	9	9	9	9
Sceduler 4	9	9.1	9.11	9.19

Feed Freq: 50	50	100	150	200
Sceduler 1	9.05	9.05	9.12	9.2
Sceduler 2	8.75	9.15	9.27	9.36
Sceduler 3	9	9.22	9.42	9.42
Sceduler 4	9	9	9	9.35

Best				
Sceduler 1	8.65	8.7	8.65	8.65
Sceduler 2	8.75	8.83	8.75	8.67
Sceduler 3	8.88	9	8.88	8.75
Sceduler 4	9	9.1	9.11	9.19

Best				
Sceduler 1	8.6	8.6	8.6	9.2
Sceduler 2	8.67	8.67	8.67	9.36
Sceduler 3	8.75	8.75	8.75	9.42
Sceduler 4	9	9	9	9.35

Table 2: Frequency of feedback

From the result above it can be observed that as the frequency of the feedback is increased the improvement in the satisfaction value is also increased. When feedback is applied after every 10 generations the improvement in the satisfaction value is more rapid. However this is more prominent in profile set IV than profile set V.

4. Future work

In the future more experiments on the software application needs to be carried out. The software application needs to be improved to take care of seeding automatically and experiments will be carried out with feedback after every generation. Moreover, in these initial experiments, no scheduler was allowed to change their fuzzy membership bounds after reviewing other's results. In future experiments, intermittent modification of fuzzy membership bounds for each scheduler profile along with seeding will be applied.

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