

## Flexible Job-shop Scheduling Using NSGA-II Algorithm

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**Abstract** Flexible job-shop scheduling is the general model for classic problem of job-shop scheduling. Whenever substitute paths are possible, we ran into this problem. However the production scheduling problem is getting more complicated with more jobs, operations, parts and machines. Scheduling problem was considered with deterministic number of all parameters, until recently. Actually, this assumption ignores unpredictable events. In this paper we solve deterministic flexible job-shop scheduling by meta-heuristic algorithms and then in order to find stable scheduling, we change the method by entering random stops. The genetic algorithm applied in this paper which is a meta-heuristic algorithm, contains two stages. The first one is for one objective job-shop scheduling problem and has been designed in a way that all parameters are deterministic. Afterwards, in order to obtain a scheduling which is stable with random breakdowns of machines, the multi-objective genetic algorithm has been applied in second stage. NSGA-II has been used in second stage.

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**Keywords:** Flexible scheduling, Genetic algorithm, NSGA-II algorithm

### 1. Introduction

Programming is one of the important daily subjects in industrial and production environments. There are too many questions which should be answered in programming process, such as scheduling problem. Scheduling may be defined as resource allocation to implement a set of activities in a period of time. In job-shop scheduling, n jobs should be done on m machines with special priorities. Jobs in this case consist of several operations and their path of implementation. The relation between operations and machines means that any operation should be done on one machine and any machine should do one type of operation. It should be noted that machines in this model in its basic case are accessible from time zero, operations are done on machines without cut and any machine is able to do just one operation simultaneously. Considering these assumptions, the goal of job-shop scheduling is to determine the scheduling for a set of machines to optimize one or more performance objectives. Machines getting flexible and multi-job and increasing their capability in processing, a anew and applied version of the

problem was arisen which is called flexible job-shop scheduling. In this new model, the assumption of single purpose machines was generalized and any operation can be done on a set of machines which are able to do it (Rahmati, 2011). Due to inevitable stops in a real system, the rescheduling is necessary which imposes too many extra costs to the system. Therefore, achieving a stable scheduling is necessary due to non-deterministic situation (Leon, et al. 1994). Stable scheduling is a program which is less costly, encountering stops and shifting right as a rescheduling algorithm, in compare with other scheduling (Jensen, 2003). Now it is clear that this problem consists of two sub problems, i.e. besides sub problem of determining jobs sequence which arises in JSP problem, the sub problem of operation allocation is also proposed. In the first sub problem order of several operations on machines are determined, while in the second one it is cleared that which machine is assigned to process an operation among the set of capable machines.

Now the model of the problem can be written as follows (Frutos, et al. 2010):

$$\text{Min } C_{\text{max}} = \max (t_{j|k} \mid p_{j|k}) \quad (1 - 1)$$

Subject to:

$$t_{j|k} - t_{s|h} \geq p_{s|h} : \text{if } O_{s|h} \text{ precedes } O_{j|k} \quad \forall i \in J, \forall \{h, k\} \in M \quad (1 - 2)$$

$$t_{j|k} - t_{s|g} \geq p_{s|g} : \text{if } O_{s|g} \text{ precedes } O_{j|k} \quad \forall \{i, g\} \in J, \forall k \in M \quad (1 - 3)$$

$$\sum_k^M x_{jik} = 1; \forall i \in J, \forall j \in n_i \quad (1-4)$$

Where:

$$t_{jik} = \max\{t_{(j-1)ik} + p_{(j-1)ik}, t_{sgk} + p_{sgk}, 0\}, t_{jik} \geq 0, \forall i \in J, \forall j \in n_i, \forall k \in M \quad (1-5)$$

$$\begin{cases} x_{jik} = 0 & \forall i \in J, j \in n_i, k \in M_{ij} \\ x_{jik} \in \{0,1\} & \forall i \in J, j \in n_i, k \in M_{ij} \end{cases} \quad (1-6)$$

$$\forall \{s, j\} \in n_i, \forall \{k, h\} \in M, \forall \{g, i\} \in J$$

## 2. Proposed Algorithm

Concept of MTTR and MTBF are necessary for simulation algorithm. Machines are not always accessible and have random breakdowns. MTBF is the average time between two breakdowns and MTTR is the average time for repair and both of the have exponential distribution (Zandie, Gholami, 2009). Heltas (1999) showed that the selected number for MTTR is equal to  $0.1 \times \bar{P}$ ,  $0.1 \times \bar{P}$  and  $5 \times \bar{P}$  where  $\bar{P}$  is the total average of processing time for a job. The value of MTBF is determined based on several values of Ag in a breakdown.  $Ag = MTTR / (MTTR + MTBF)$  is showing the level of breakdown in job-shop or the percent of time in which a machine does not work. For example if MTTR=60 unit of  $\bar{P}$  and MTBF=140 unit of  $\bar{P}$ , then  $Ag=60/(60+140)=0.05$ . So in 5% of time machine breaks down. Range of variation of Ag is from 0.026% to 20.833%.

Now according to the above discussions, we are going to explain simulation algorithm:

Step 0. Initialization

Start

For NB times do following steps:

For all chromosome genes do following step:

Step 1. Initialize FEL for all machines with random values obtained by exponential distribution with mean of MTBF.

FEL (machine) =exp-rand (MTBF), for all machines

Step 2. Time of processing jth operation of ith job assigned to kth machine is added to variable Life of that machine:

Life (K) =Life (K) +process time (I, J)

Step 3. If Life (K)>FEL (K, got to step 4, else go to step 7.

Step 4. A breakdown has occurred, do the following steps:

Generate a random number with mean of MTTR.

This value is considered as repair time:

Repair time = exp-rand (MTTR)

Add repair time to correspondence completion time on that stage:

Completion time (I) = Completion time (I) +Repair time

Reinitialize FEL for corresponding machine. According to this, determine the next time of breakdown for this machine:

FEL (K) = exp-rand (MTBF)

LIFE variable for corresponding machine is set to zero:

Life (K) = 0

Step 5. If steps 1 to 4 are done for all chromosome genes, calculate completion time and stability factor for that chromosome. Otherwise go to step 1.

Step 6. Calculate the average stability factor and completion time, after executing the algorithm for NB times and consider them as objective value of the corresponding chromosome.

Step 7. Go to original algorithm.

End.

## 3. Data Analysis

The applied parameters in two stage algorithm are as following: Popularity size (pop-size) 200, number of iteration of the first stage (max-it) 100, total number of generation in two stages (ngeneraion) 1600, conjunction probability (Pc) 0.95 and mutation probability (Pm) 0.01. 0.14 of the best chromosome in any generation is transferred to the next generation. In break down simulation algorithm, there are 3 different levels for MTTR and 3 levels for MTBF and values for Ag are set as 0.05, 0.1 and 0.15. NSGA-II algorithm is run 5 times for each level of MTTR and MTBF and the results are saved. BR data set is used to analyze the results. This data set consists of 10 problems which is provided by Prandimat (1993) and is generated randomly using uniform distribution between definite bounds. Number of jobs is between 10 and 20, number of machines is between 14 and 15 and number of operations for each job is between 5 and 15 and also number of operations for all jobs is between 55 and 240.

### 3.1 The analysis of the distance from the ideal point

Figure 1 shows the result of variance analysis test:

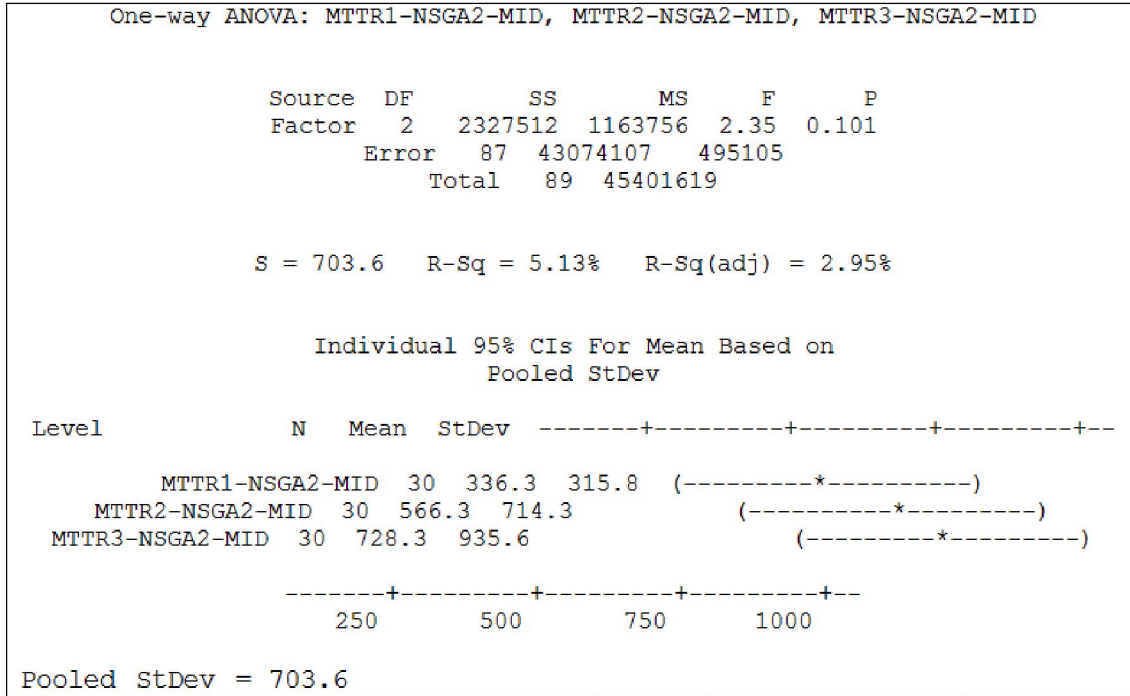


Fig 1. Output form variance analysis for comparing MID based on MTTR levels of NSGA-II algorithm

According to figure 1, the obtained P-value from variance analysis is equal to 0.101 which means that about this criterion of NSGA-II algorithm, different

levels of MTTR do not have significant difference. Figure 2 shows the 95% confidence level for mean by the criterion of distance from the ideal point.

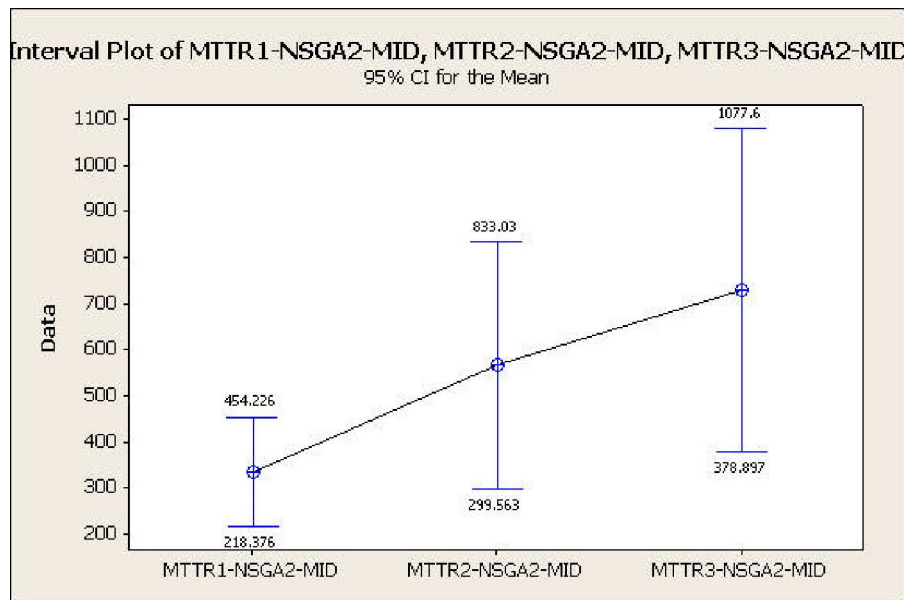


Fig 2: 95% confidence level for mean by the criterion of distance from the ideal point.

Figure 2 shows that although values of Mid in different levels do not report significant difference, but MID is increasing by increase of MTTR and hence achieves its optimal value in MTTR=0.1<sup>F</sup>. In

other words the less average repair time is, the less distance from ideal point.

**3.2 Most development analysis**

Figure 3 shows results of variance analysis test:

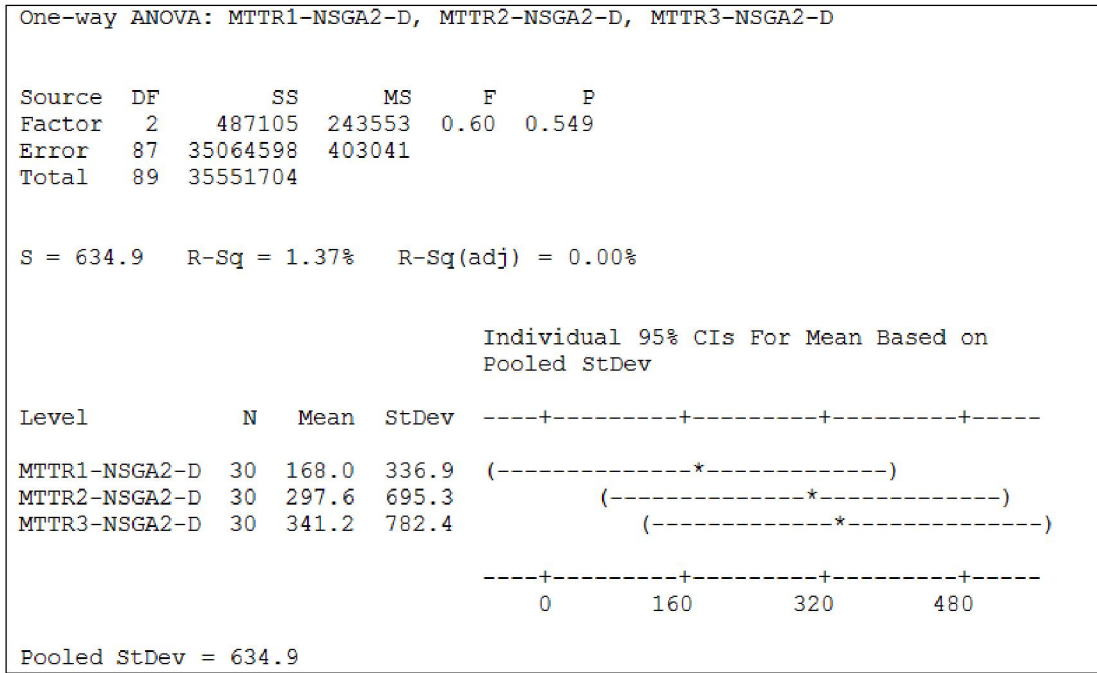


Fig 3: Output form variance analysis for comparing MD based on MTTR levels of NSGA-II algorithm

According to figure 3, the obtained P-value from one-way variance analysis is equal to 0.549 which means that about this criterion of NSGA-II algorithm,

different levels of MTTR do not have significant difference. Figure 4 shows the 95% confidence level for mean by the criterion of most extension.

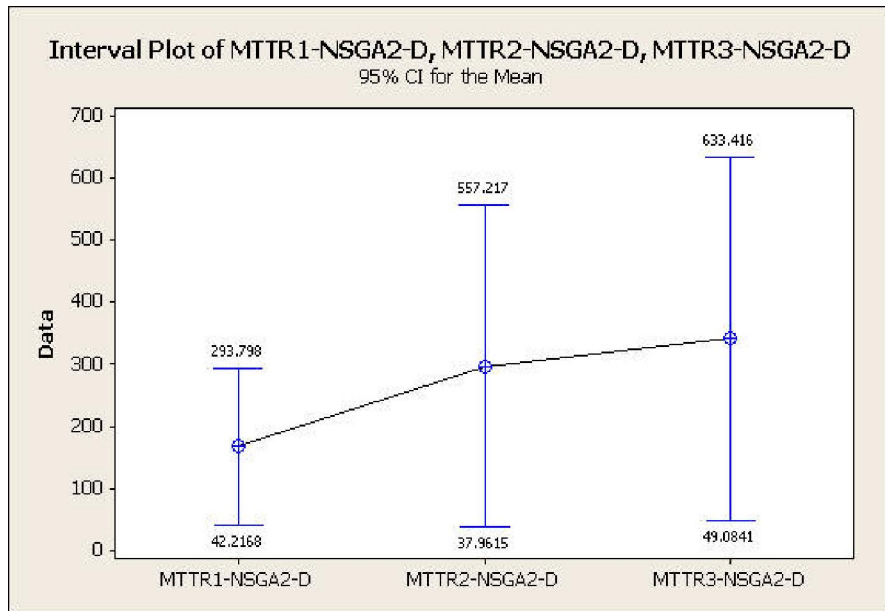


Fig 4: 95% confidence level for mean by the criterion of most extension.

### 3.3 Analysis of spacing results

Figure 5 shows results of variance analysis test



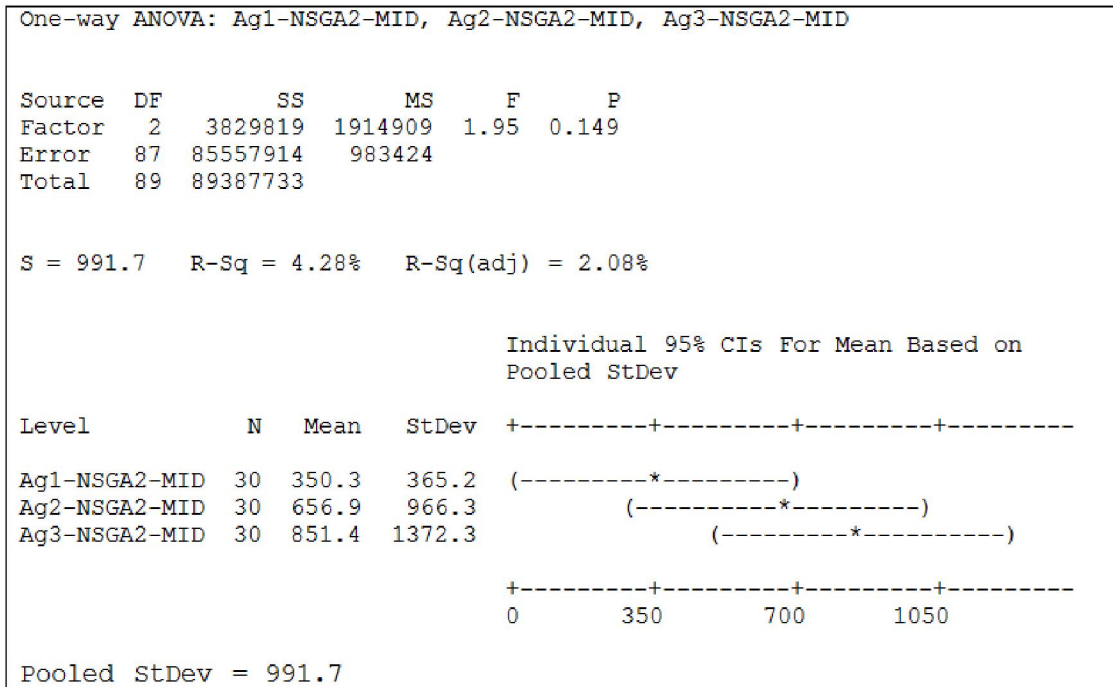


Fig 7: Output form variance analysis for comparing MID criterion based on Ag levels of NSGA-II algorithm

According to Figure 7, the obtained P-value from one-way variance analysis is equal to 0.149 which means values of this criterion of NSGA-II algorithm do not have significant difference at different levels of

Ag at 95% confidence level, i.e. hypothesis H0 is confirmed. Figure 8 shows the 95% confidence level for mean by the criterion of distance form ideal point.

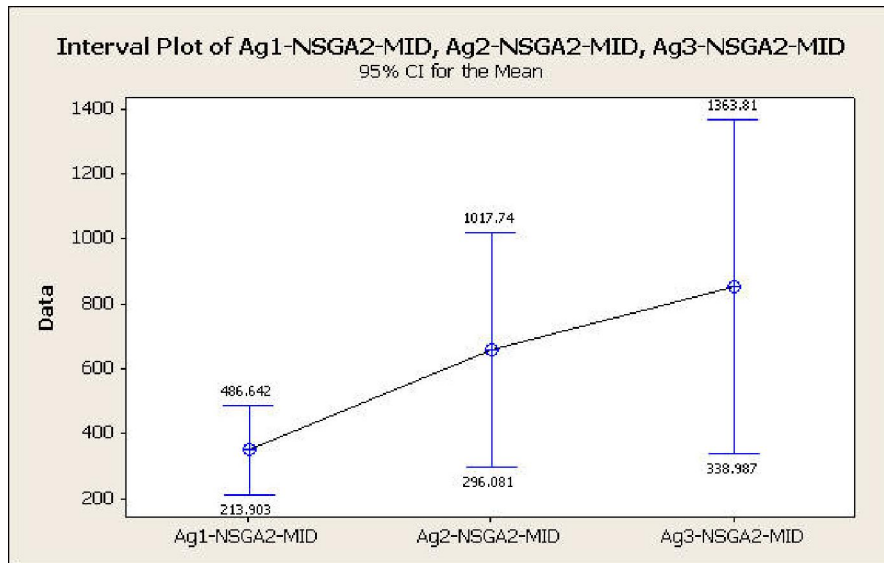


Fig 8: 95% confidence level for mean by the criterion of distance from ideal point

**Analysis of the most extension**

Figure 9 shows the results of variance analysis test.

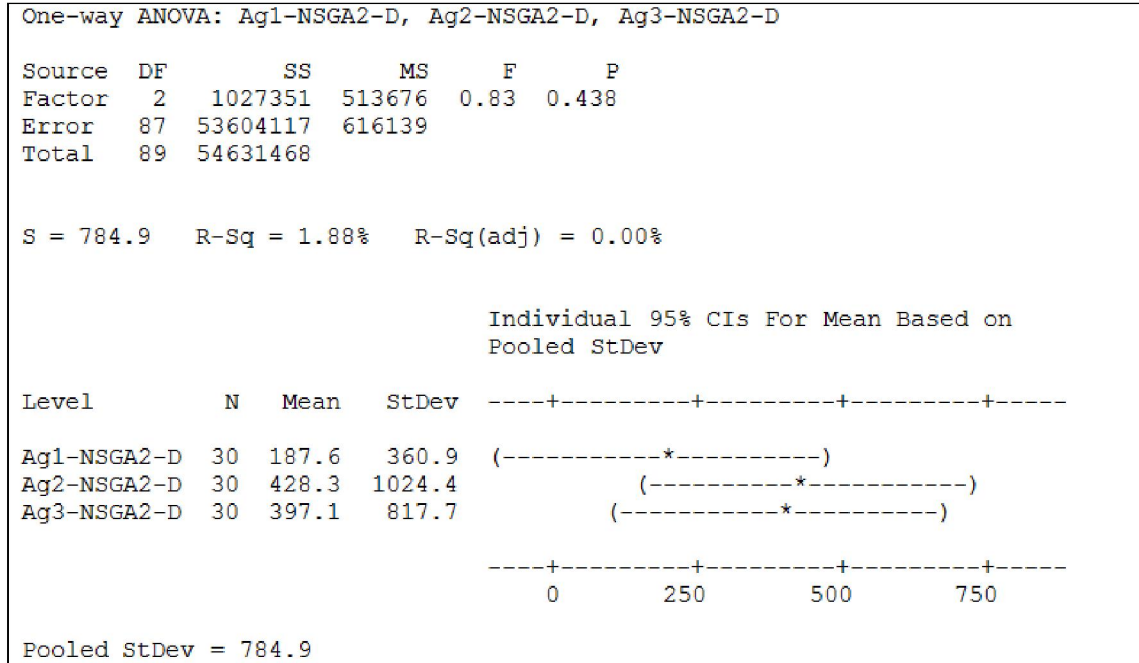


Fig 9: Output form variance analysis for comparing MID criterion based on Ag levels of NSGA-II algorithm

According to Figure 9, the obtained P-value from one-way variance analysis is equal to 0.438 which means that the values of the most extension of NSGA algorithm, do not have significant difference at 95%

confidence level, i.e. hypothesis H0 is not rejected. Figure 10 shows the 95% confidence level for mean by the criterion of the most extension.

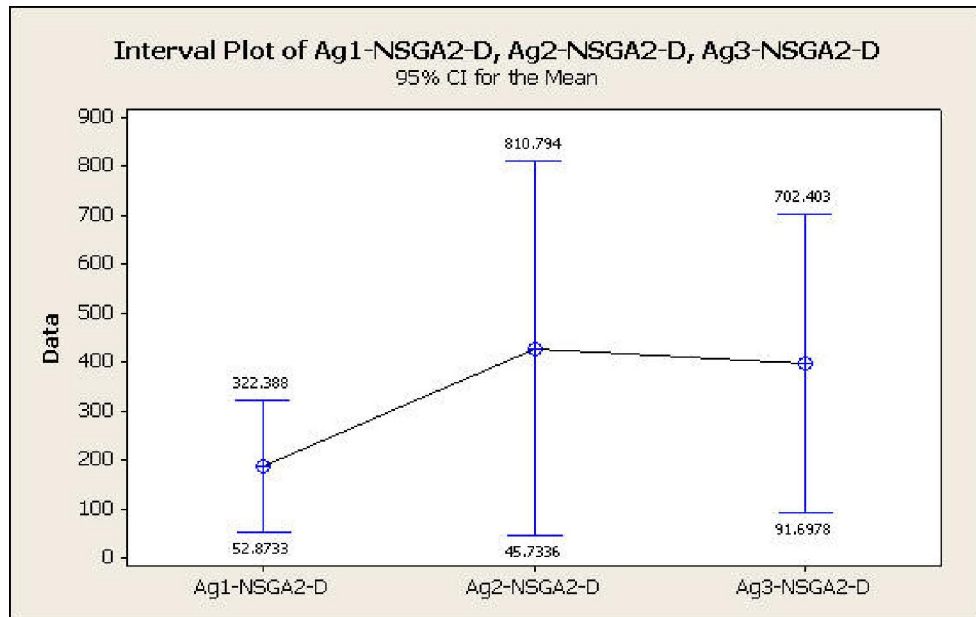


Fig 10: 95% confidence level for mean by the criterion of the most extension

**Analysis of spacing results**

Figure 11 shows the results of variance analysis test.

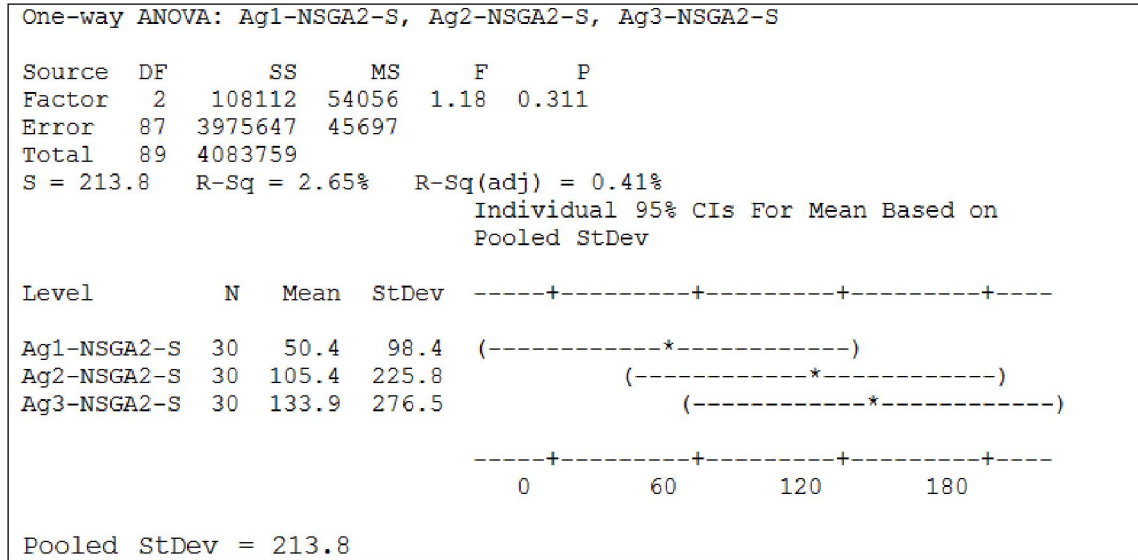


Fig 11: Output form variance analysis for comparing MID criterion based on Ag levels of NSGA-II algorithm

According to Figure 11, the obtained P-value from one-way variance analysis is equal to 0.311 which means that the values of spacing criterion of NPGA algorithm, do not have significant difference

on different levels of Ag at 95% confidence level, i.e. hypothesis H0 is not rejected. Figure 12 shows the 95% confidence level for mean by the criterion of the most extension.

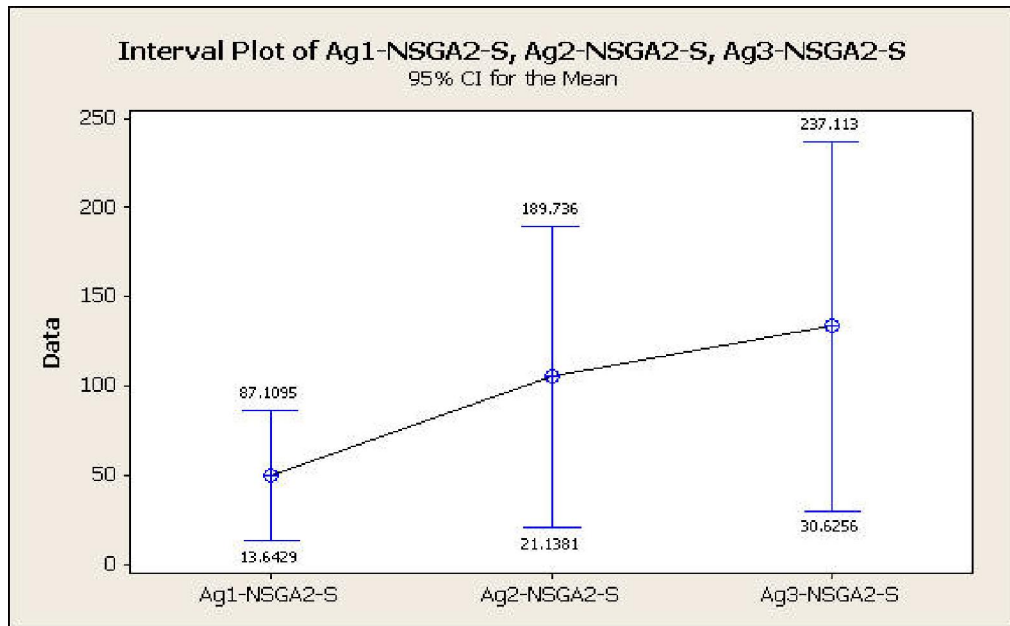


Fig 12: 95% confidence level for mean by the criterion of spacing

#### 4. Conclusion

In classic problem of flexible job-shop, all parameters are assumed to be predetermined but this is not the case in real world. Therefore, scheduling with this deterministic assumption does not result in nice solution. There exist inevitable stops such as machine breakdowns, etc. in scheduling problem.

Thus, we are aimed to obtain a stable timetabling for flexible job-shop system, in which rescheduling have minimum variations in time and operation sequence after stops and impose as less as costs as possible to the system. This scheduling reduces the difference between theoretic and practical problems and provides more applicable results, considering stops. There are



few studies in this field and they are considering balanced sum of criteria or single objective problems which causes inaccurate solutions. In this paper we use two objective algorithms, NSGA-II to overcome this difficulty and we consider 10 sample problems and compare the results obtained by the proposed algorithm. On the other hand, simulation algorithm has been applied to create machine breakdowns, which makes the suggested method more applicable. The efficiency of multi-objective algorithms were evaluated by following criteria: distance from ideal point, the most extension, spacing and set covering. Finally the superiority of the algorithm was determined based on different indices.

### References

1. Rahmati, H. 1390. Efficient meta-heuristic methods for flexible job-shop scheduling multi-objective programming, Master thesis. Islamic Azad University, Qazvin branch [in Persian].
2. Barnes, J.W., and Chambers, J.B. (1996) 'Flexible job shop scheduling by tabu search', Graduate Program in Operations Research and Industrial Engineering, The University of Texas, Austin, Technical Report Series, ORP 96-09.
3. Fattahi, Parviz, Jolai, Fariborz, Arkat, Jamal, (2009). Flexible job shop scheduling with overlapping in operations. *Applied Mathematical Modeling* 33, 3076–3087.
4. Fattahi, Parviz, Saidi Mehrabad, Mohammad, Jolai, Fariborz, (2007). Mathematical modeling and heuristic approaches to flexible job shop scheduling problems, *International Journal of Advance Manufacturing Technology* DOI 10.1007/s10845-007-0026-8, 18:331–342.
5. Frutos, Mariano, Olivera, Ana Carolina, Tohmé, Fernando, (2010). A memetic algorithm based on a NSGAI scheme for the flexible job-shop scheduling problem. *Annual Operation Research*, DOI 10.1007/s10479-010-0751-9.
6. Horn, J., Nafploitis, N., Goldberg, D., 1994. A niched pareto genetic algorithm for multi-objective optimization. In *Proceedings of the First IEEE Conference on Evolutionary Computation*, pp. 82-87.
7. Hurink, E., Jurisch, B., and Thole, M., (1994) 'Tabu search for the job shop scheduling problem with multi-purpose machines', *Operations Research-Spektrum*, Vol. 15, pp.205-215.
8. Jensen, M.T. (2003) 'Generating robust and flexible job shop schedules using genetic algorithms', *IEEE Transactions on Evolutionary Computation*, Vol. 7, No. 3, pp. 275-288.
9. Ling, QI., Jian-dong, Y., Bao, LI., and Han-cheng, YU., (2010) 'Flexible job-shop scheduling problem based on adaptive ant colony algorithm' *Journal of Mechanical and Electrical Engineering*, (doi: CNKI: SUN: JDGC.0.2010-02-016).
10. Zhang H-P, Gen M., 2005. Multistage-based genetic algorithm for flexible job-shop scheduling problem. *Journal of Complexity International*; 11:223–32.
11. Zhang, GH., Shao, XY., Li, PG., and Gao, L., (2009) 'An effective hybrid particle swarm optimization algorithm for multiobjective flexible job-shop scheduling problems', *Computers and Industrial Engineering*, Vol. 56, Issue 4, pp. 1309-1318.
12. Zribi, N., Kacem, I., and Kamel, AE., (2007) 'Assignment and scheduling in flexible job shops by hierarchical optimization', *IEEE Transactions on Systems, Man, and Cybernetics-Part C: Applications and Reviews*, Vol. 37, No. 4, pp. 652-661.
13. Zitzler E., 1999. *Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications*. PhD. Thesis, Dissertation ETH No. 13398, Swiss Federal Institute of Technology (ETH), Zürich.