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# Solving the Workshop Production Planning Problem Using the Meta-Heuristic Algorithm

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***Abstract*—** Workshop (cellular) production systems are one of the applications of group technology in industry, the purpose of which is to benefit from the physical or operational similarity of products in various aspects of manufacturing and design. Today, the use of workshop production systems and the use of its benefits as one of the ways to increase the speed of the organization's response to rapid market changes, has received much attention. In this paper, a meta-heuristic algorithm based on a composition of genetic and greedy algorithms is used to optimize and evaluate the performance indicators of workshop production planning systems. To improve the effectiveness of the genetic algorithm, the initial population is generated by a greedy algorithm and several elite operators are used to improve the solutions. The greedy approach to improving the create an initial population prioritizes the cells and tasks in each cell and produces quality solutions accordingly. In order to evaluate performance quality of the proposed method, the P-FJSP dataset and quality, scatter, distance and time indices in a multi-objective function have been used. The experimental results show better performance of the proposed approach compared to NRGA and NSGA-II algorithms.

***Keywords*—** Workshop Production Planning, Meta-Heuristic, Genetic Algorithm, Greedy Algorithm.

## I. INTRODUCTION

The problem of workshop production planning is to find sequence optimization solutions of performing different operations related to each machine in the cells and also to determine the optimal sequence of the cells themselves. These issues are usually addressed with the aim of minimizing the length of the schedule, in which the timing of operations is fixed and predetermined. The issue of cell production planning is one of the NP-Hard issues [1, 2]. Based on the challenges of hybrid optimization problems and especially the problem of scheduling cell production, the use of innovative and meta-innovative algorithms to solve such problems creates effective improvements in the production of acceptable solutions, because by increasing the dimensions Problem: In practice, traditional algorithms for determining the optimal answer lose their efficiency due to time consuming [3].

In order to be able to meet the needs of different industries in today's competitive world, production systems with higher efficiency must be used. In this regard, not only the automation and flexibility of machines is sufficient, but also systems with appropriate scheduling must be created [4]. The problem of cell production system planning is one of the hybrid optimization problems that due to the applicability of this problems mode, extensive investigation has been done to solve the problems of cell production system [5, 6]. In many researches, artificial intelligence optimization algorithms such as genetics have been used to solve this type of problems [7-9]. In this research, the use of a hybrid meta-heuristic method in multi-objective type for solving this problem is considered. Since in all optimization problems, Meanwhile, a main components in decision making is time, in the problem of cell production system, it also has objective functions such as minimizing time completed, minimizing the delay, minimizing the early works will be used.

The workshop production planning issue consists of two scheduling stages. In first step, the cells sequence is determined and then in second step, the sequence of fragments is determined. The main goal in this issue is to minimize the maximum time of completion of works. In this case, there is a $P$ (work) that must be applied to $M$ machines. Machines are located in separate $C$ cells that allow time for parts to move between cells. In addition, $t_{ij}$ is the processing time of $i$-th part on the $j$-th machine, and $a_{ij}$ binarily indicates that. If part $i$ needs machine $j$ for processing, $a_{ij} = 1$, otherwise $a_{ij} = 0$.

The remaining of the paper is organized as follows: Section II is dedicated to background research. The details of the proposed approach are given in Section III and the discussion and simulation results are given in Section IV. Finally, Section V contains conclusions and future work.

## II. LITERATURE REVIEW

Written work on the workshop scheduling problem was first done by Johnson (1954) and he is believed to have been one of the founders of scheduling theory [10]. He proposed an optimal algorithm for a workshop workflow problem with two machines and extended this algorithm to the workshop work scheduling problem. Akers (1956) then used a Boolean algebra algorithm to show the processing sequence. There are various definitions and interpretations of group technology, the scientific principles of which were founded by Epitz in Germany in 1958 [11]. In 1998, Lpez considered it a new production philosophy that eliminated the disadvantages of the two philosophies of custom production and mass production and gathered their advantages [12].

In [13], the comparison of cell production system design algorithms has been investigated. This research focuses on designing a cell production system and minimizing the number of cells. The results show that meta-heuristic algorithms are more effective to most designs due to the average flow time and inventory under construction. Yazi et al. Investigated the issue of cell production scheduling by considering cell sequence-dependent preparation times, based on the aim of minimizing the average all flow-time for all delays [14]. The algorithm of this research is based on a mathematical technique and the harmonic hybrid search algorithm is proposed. In another study, Kia et al. Presented a mathematical model for evaluating the effects of feature segmentation in a dynamic cell production system [15]. In this research, a dual-purpose model and Pareto archive have been used.

The NRGA algorithm was proposed by Jadan et al., Which is a recessive order genetic algorithm to solve the workshop production problem [16]. This algorithm uses a parametric penalty algorithm to search for the Pareto archive best solutions. The NSGA-II method was suggested by Ahmadi et al., Which is an extended version of the NRGA algorithm [17]. Important difference among NSGA-II and NRGA algorithms is the selection process, in NSGA-II algorithm it uses the match selection algorithm, while NRGA algorithm uses the roulette wheel. Also in NSGA-II, simultaneous improvement of makespan and stability goals through Pareto archive is considered.

## III. THE PROPOSED APPROACH

In this paper, a combination of genetic and greedy algorithms is used to provide a meta-heuristic method for solving the workshop production planning problem. The combination of these two algorithms to achieve quality initial answers, accelerates the finding of the range of answers, and thus ensures the speed of problem solving and the appropriate quality of the final answers. The details of the proposed meta-heuristic algorithm are described below.

### *A. Initial Population Based on the Greedy Algorithm*

This paper uses a vector of the total number of tasks ($P$) to represent chromosomes in a genetic algorithm. In this structure, the sequence of tasks shows the schedule of doing it in the production system. Due to the simultaneous optimization of the sequence of cells and tasks, the timing of the cells is automatically determined according to the position of the tasks. This simple structure makes it possible to increase the design capabilities of different operators and reduces the complexity of the proposed approach. Also, by considering only the number of jobs in the proposed structure, it is possible to easily move jobs between cells. To increase genetic diversity and reduce the likelihood of getting caught up in local optimism, a greedy method is used to create the initial population. The proposed greedy method makes the most optimal choice at each stage based on the current state of the system and the prioritization of cells and tasks. Fig. 1 shows the stages of the initial population.

| **Generate the initial population with a greedy algorithm** |
|---|
| 1. Start |
| 2. Calculate the number of displacements for each cell. |
| 3. The probability of selecting each cell is calculated based on a smaller number of displacements. |
| 4. Select the next cell in the chromosome based on the roulette wheel operator. |
| 5. Identify parts of the selected cell that are not present on the chromosome. |
| 6. The probability of selecting each part should be calculated based on the criterion of less “the product of the displacement of the part multiplied by the processing time of the part”. |
| 7. Select the next piece in the chromosome based on the roulette wheel operator. |
| 8. If all the current cell components are not selected, go to step 5. |
| 9. If not all cells are selected, go to step 4. |
| 10. End |

Figure 1. Generate initial population with greedy algorithm

In this algorithm, the minimum number of intercellular displacements is calculated according to the parts attributed to the machines inside that cell. For example, suppose a piece needs machines $\{m_1, m_2, m_3\}$ to complete, so that machines $m_1$ and $m_3$ are in cell $c_1$ and machine $m_2$ is in cell $c_2$. In this case, the minimum number of displacements for this piece is 2. Because after applying the $m_1$ machine in cell $c_1$, it has to go to the $m_2$ machine in cell $c_2$, which is a move case. In the next step, when the $m_2$ machine process is complete, the piece must go from cell $c_2$ to cell $c_1$ to use machine $m_3$ . This step also imposes an intercellular displacement on the fragment. To consider the intercellular translocations for each particular cell, the translocations for the transfected cell are taken into sample. In here, in the example above, for cells $c_1$ and $c_2$ , the number of displacements is equal to 1 .

 

The use of the roulette wheel technique is due to the population diversity and the lack of duplicate chromosomes. In addition, the parts associated with a cell are determined by the first machine needed to complete that part. For example, if machines $\{m_1, m_2, m_3\}$ are needed to complete a piece and these machines are in cells $\{c_1, c_2, c_1\}$, respectively, then with respect to machine $m_1$ which Cell belongs to $c_1$, the fragment is part of cell $c_1$. This is because the first machine marks the beginning of the part-making process.

This algorithm will largely maintain the distribution of tasks between machines and cells based on their priority, and will also reduce the number of displacements between cells.

*B. Calculate the Fitness and Create the Pareto Archive*

Various studies have shown that meta-heuristic algorithms are much more effective in solving multi-objective optimization problems than traditional tools. Since in solving multi-objective problems due to the existence of contradiction between goals, there is no single answer in which all goals are optimal, finally a set of dominant answers will be presented as optimal answers to which The archive of Pareto answers says [18].

In this paper, four objective functions "reduction of total parts manufacturing time", "reduction of intercellular motions", "reduction of cost of parts delay" and "reduction of cost of parts delay" are used to calculate the suitability of solutions. Be. The purpose of the proposed algorithm is to minimize these functions to improve the quality of the production scheduling. Object functions are shown in Eq. (1) to (4).

$$F_1 = C_{max} \tag{1}$$

$$F_2 = C_{Move} \tag{2}$$

$$F_3 = \sum_{i=1}^{P} E_i . max\{0, d_i - C_i\} \tag{3}$$

$$F_4 = \sum_{i=1}^{P} L_i . max\{0, C_i - d_i\} \tag{4}$$

The value attributed to $F_1$ is the period of making the last piece ($C_{max}$). The function $F_2$ is to indicate the number of displacements made between cells in the construction of components. If a piece requires several machines to make and these machines are in different cells, the piece must be moved between the cells and this displacement is proportional to the distance between Two cells cost the system (increase period ). Therefore, the sequence of cells and components must be such that it creates the least amount of $C_{Move}$ in the solution. In $F_3$, $E_i$ is the expeditious cost for part $i$, $d_i$ is the delivery period of part $i$, and $C_i$ is the completion period of part $i$. The cost of acceleration of parts is equal to the total cost of acceleration for all $P$ parts. The positive difference among the delivery period of the part and the period of completion of the part indicates the period that the part is prepared ahead of period and creates the maintenance cost ($E$). Finally, $F_4$ calculates the total delay cost for all $P$ parts. In this regard, $L_i$ is the delay cost for part $i$. The positive difference between the completion period of the part and the delivery period of the part indicates the period when the part is prepared late and leads to the cost of delay ($L$).

*C. Genetic Operators*

**Selection Operator:** From both parents used for reproduction, one is selected from the Pareto list by elitism and the other from the current generation population. The selection policy used in both algorithms is based on the roulette wheel.

**Combination Operator:** In this paper, two combination operators are used, one to improve cell sequence and the other to improve task scheduling. In the cell-based combination operator, cells are first identified in the parents and then one cell from each parent is randomly selected and copied into the child chromosome with a non-replication limit. If there is one or more tasks on the child chromosome that are in the cell selected for copying on the child chromosome, these tasks are removed from the cell and then copied. In the task-based combination operator, a task is selected randomly from each parent and then copied into the child chromosome with a non-duplication limit. The order in which tasks are selected indicates the sequence of tasks in the scheduling system. To increase performance of this operator, the selected tasks are selected from each cell in each step. In fact, when a task is selected from cell $c$ from the first parent, it is also selected from cell $c$ from the second parent if there is a task. This strategy prevents sequential shifts in the child's chromosome.

**Mutation Operator:** In this paper, two mutation operators are used, one to improve cell sequence and the other to improve task scheduling. In a cell-based mutation operator, first all the non-adjacent cells in the chromosome are identified, then randomly selected and moved for each other cell. In the task-based mutation operator, first all the non-adjacent cells in the chromosome are identified, then for each task, another task in the same cell is randomly selected and displaced with the possibility of $MR$.

## IV. RESULTS AND DISCUSSION

In this paper, extensive simulations are presented to show the superiority of the proposed approach. For the simulation work, the P-FJSP dataset uses the UCI machine learning repository, and an average of 15 distinct performances is reported to ensure results. The results are compared with NRGA [16] and NSGA-II [17] algorithms according to Quality, Dispersion, Distance and Run-time indices. All simulations and comparisons are done with the 3.0 GHz

Intel Core i7 processor and 16 GB of RAM. Meanwhile, MATLAB software R2019a is used for simulations.

The value of the parameters used in the simulation of the proposed algorithm is as follows; Population size: 50, Combination operator rate: 0.85, Mutant operator rate: 0.15, Pareto archive size: 10, Number of generations: 500.

### A. *Evaluation Criteria*

In order to evaluate performance quality of the proposed method with four-objective function, quality, dispersion, distance and period indices are used. The quality index tests the uniformity of the distribution of Pareto archives obtained at the boundaries of the solutions. This index is defined as Eq. (5).

$$Q = \frac{\sum_{i=1}^{N-1} \left|\bar{d} - d_i\right|}{(N-1) \times \bar{d}} \qquad (5)$$

Where, $d_i$ represents the Euclidean distance between two adjacent non-defeated solutions in the Pareto archive. $\bar{d}$ is the mean of $d_i$, and $N$ represents the number of members in the Pareto archive list. The scatter index shows the amount of variation that exists between the data of a distribution (around the mean). This index is used to determine the amount of unresolved solutions in the Pareto archive on the optimal boundary. This index is defined as Eq. (6).

$$D = \sqrt{\sum_{i=1}^{N} max\left(\left\|x_t^i - y_t^i\right\|\right)} \qquad (6)$$

Where, $\left\|x_t^i - y_t^i\right\|$ Euclidean distance between two adjacent solutions $x_t^i$ and $y_t^i$ on the optimal boundary. The scattering criterion represents the Euclidean distance among solutions of first and last in the Pareto archive, and the superior the variability scores, the bigger the results quality. The distance index is used to show the compatibility of the distance among solutions in the Pareto archive. Less scores of the distance criterion represent that the stability of the distance among the solutions is bigger. This index is defined as Eq. (7).

$$S = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (d_i - \bar{d})^2} \qquad (7)$$

Where, $d_i$ indicates the Euclidean distance among the two non-defeated solutions in the Pareto archive, where makespan is 1 and stability is 2. The last criterion used for comparison is runtime. Whereas all the parameters in the methods are the identical, this criterion is a suitable comparison factor for evaluating the production planning system.

### B. *P-FJSP Dataset*

In this paper, the P-FJSP dataset is used to evaluate the proposed algorithm and perform comparisons. This data set was produced by Brandimart (1993) and includes 10 samples [19, 20]. The parameters of each of the problems in this data set are generated randomly using the uniform distribution among the two measures. The number of machines is defined between 4 and 15, the number of tasks between 10 and 20, the number of operations for each task between 5 and 15 and the number of operations for all tasks between 55 and 240. In addition, it is specified what machines are needed for each job. Table 1 shows the details of the P-FJSP dataset.

Table 1 Details of the p-fjsp dataset

| Instances | No. of jobs | No. of machines | No. of cells | No. of operations range | Processing time range | Size | Total operation time |
|---|---|---|---|---|---|---|---|
| MK01 | 10 | 6 | 3 | 7-5 | 7-1 | 6×10 | 56 |
| MK02 | 10 | 6 | 6 | 7-5 | 7-1 | 6×10 | 58 |
| MK03 | 15 | 8 | 5 | 10-10 | 20-1 | 8×15 | 150 |
| MK04 | 15 | 8 | 3 | 10-3 | 10-1 | 8×15 | 90 |
| MK05 | 15 | 4 | 2 | 10-5 | 10-5 | 4×15 | 106 |
| MK06 | 10 | 15 | 5 | 15-15 | 10-1 | 15×10 | 150 |
| MK07 | 20 | 5 | 5 | 5-5 | 20-1 | 5×20 | 100 |
| MK08 | 20 | 10 | 2 | 10-5 | 10-5 | 10×20 | 225 |
| MK09 | 20 | 10 | 5 | 15-10 | 10-5 | 10×20 | 250 |
| MK10 | 20 | 15 | 5 | 15-10 | 20-5 | 15×20 | 240 |

### C. *Results and Comparison*

NRGA and NSGA-II algorithms have been used for comparison work according to the criteria of scatter, distance, quality and execution time (seconds). Comparison of scatter criteria in different algorithms on 10 experimental samples is shown in Fig. 2. The results allegation that the NSGA-II method has a better quality than NRGA method. Meanwhile, the proposed approach with a scatter index of 74.85 has better efficiency than both methods.

Figure 3 shows the comparison results in the distance criterion. Because lower values of distance mean high quality, in the MK09 and MK10 samples the NRGA algorithm performs better than the NSGA-II. However, on average, the distance index in NRGA and NSGA-II algorithms is 19.19 and 12.71, respectively, which indicates the production of better solutions by NSGA-II method.

Despite the superiority of the NSGA-II method over the NSGA, the proposed algorithm with an average distance index of 12.4 performs better than both algorithms.

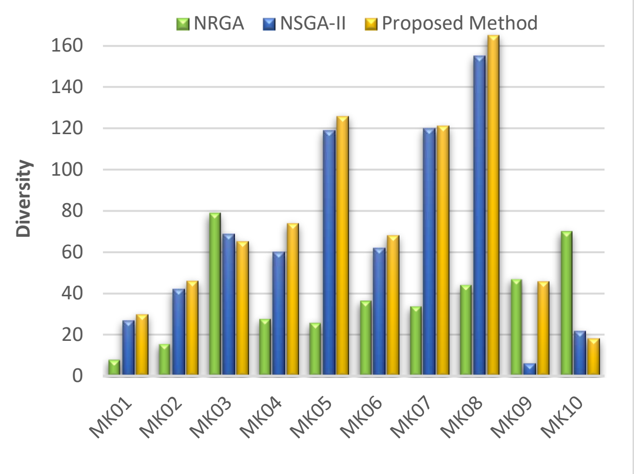


Figure 2. Comparison of different algorithms in the diversity criterion

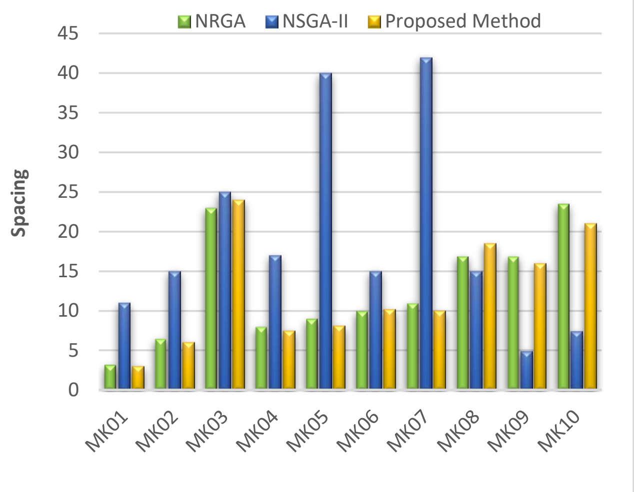


Figure 3. Comparison of different algorithms in the distance criterion

The NSGA-II algorithm is superior to the NRGA algorithm in all samples except MK08 based on the quality index. In this criterion, the superiority of the proposed approach in comparison with the NSGA-II algorithm is present in all samples and as a result, it shows a better quality of performance. Fig. 4 shows the average results of comparing the quality index.

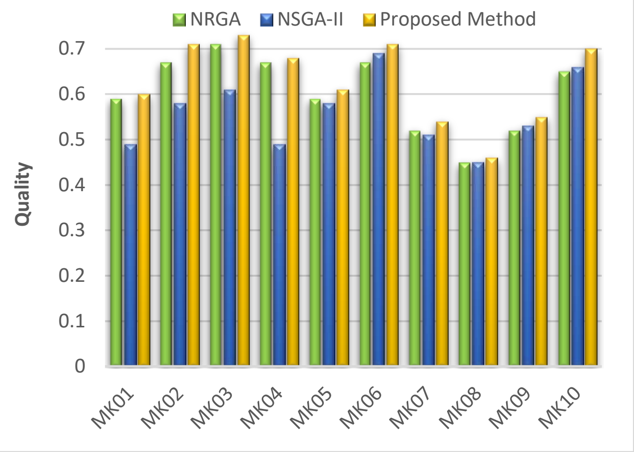


Figure 4. Comparison of different algorithms in the quality criterion

Regarding the runtime index, there is no statistically significant difference among the results of the three compared algorithms. In Fig. 5, the results of the execution time of these methods are reported in 10 samples tested, with slight differences from the results reported.

In general, the proposed approach has a better performance in dispersion index than MKR3, MK09 and MK10 in other samples than NRGA and NSGA-II algorithms, and the dispersion index has an average of 36.19, respectively. And increased by 8.96 points. The reduction of distance index decreased on average in 7 tested samples by 7.05 and 0.57, respectively, against NRGA and NSGA-II algorithms. The results of the proposed approach have a good performance in the quality index and on average, this index has increased by 0.01 and 0.11 compared to the two algorithms compared, respectively. Due to the use of all three algorithms compared to the genetic algorithm, the results in the runtime criterion fluctuate in almost the same range. The average results of this criterion for the proposed approach and the two algorithms NRGA and NSGA-II are 2965, 3015 and 2931 seconds, respectively, which is a relative advantage for the proposed approach.

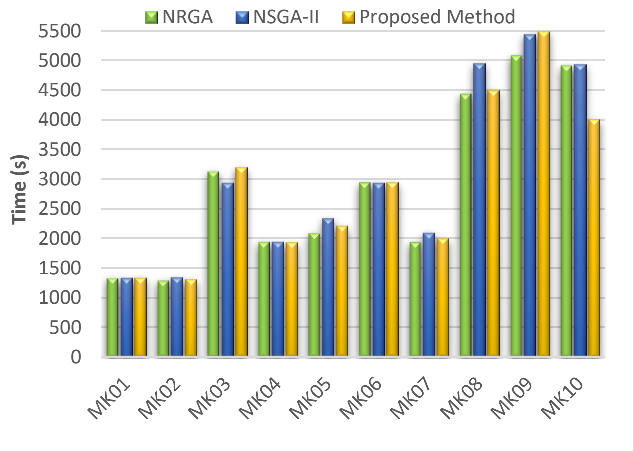


Figure 5. Comparison of different algorithms in the runtime criterion

## V. CONCLUSIONS AND SUGGESTIONS

In the present paper, the multi-objective scheduling of the workshop production system was investigated using a meta-heuristic algorithm. This algorithm is a combination of genetic and greedy algorithms to find the optimal sequence of tasks as well as the sequence of cells. To fit the solutions, four objectives were used to reduce the total manufacturing time of parts, reduce intercellular motions, reduce the cost of early parts and reduce the cost of parts delay. Because creating random solutions reduces the quality of the initial population and increases the duration of convergence, in this study a greedy algorithm was used to create the initial population in a way that preserves genetic diversity. This algorithm makes the best choice at each stage based on the current state of the system and the prioritization of cells and tasks. Hence, the minimum number of intercellular displacements is calculated according to the parts attributed to the machines within that cell. For future work, it is possible to spend time preparing machines as well as examining the problem in a dynamic environment.

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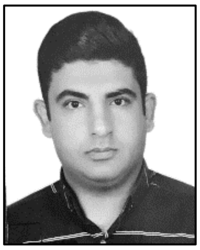

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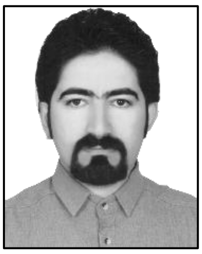

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