Multi-Objective Optimal Model for Task Scheduling and Allocation in a Two Machines Robotic Cell Considering Breakdowns

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Abstract: - This paper aimed to demonstrate a metaheuristic as a solution procedure to schedule a two-machine, identical parts robotic cell under breakdown. The proposed previous model enabled one to determine optimal allocation of operations to the machines and corresponding processing times of each machine. For the proposed mathematical model to minimize cycle time and operational cost, multi-objective particle swarm optimization (MOPSO) algorithm was provided. Through some numerical examples, the optimal solutions were compared with the previous results. MOPSO algorithm could find the solutions for problems embeds up to 50 operations in a rationale time.

Key-Words: - Robotic manufacturing cell, Scheduling, Breakdowns, multi-objective particle swarm optimization algorithm.

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1 Introduction
Almost all flexible manufacturing systems are comprised of robots, CNC machines and other relevant stand-alone systems such as inspection machines, instrumentation devices, computers and sensors. The responsibility of robot is to pick-up products, load/unload machines and also material transposition inside the robotic cell.

To improve the system’s productivity, there are several researches about the sequencing of machine feedings and robot movements in robotic cells. Machine breakdowns and transportation times so far have been relaxed while they may result in changing the solutions.

Although in most of the previous researches conducted in the field of robotic manufacturing cells such as [28], [29], [17], [30], [7], [15], [6], [16], [10], [8] and [3], scheduling is done based on a single criterion, the most important results of multi criteria scheduling were surveyed in [14]. Bi-criteria scheduling model in a two-machine robotic cell which produces identical parts was presented by Gultekin et al. [11]. They assumed that, the allocations of operations and their processing times are decision variables. Bi-objective mixed integer programming scheduling model in a cyclic robotic cell with processing time windows and non-Euclidean travel times was developed in [9]. ε-constraint method was proposed to solve the model. For studying other bi objective robotic cell scheduling papers, the reader is referred to [21], [2], [18], [12], [4], [33] and [24].

In a new paper a dynamic scheduling problem was addressed by Ma et al. [23]. In their robotic cell, more than one new jobs were arrived and should be scheduled immediately. The problem was formulated as a mixed integer programming model then a hybrid algorithm was proposed to search for a near-optimal solution.

One of the basic assumptions in aforementioned studies was that, there isn’t any need for maintenance because robots and machines never experience failure. Moreover, in none of the previous studies, availability of robotic cell was recommended as a constraint, because in all of them machine/robot were assumed to be available. But in real world it is impossible, so to make the robotic cell scheduling issue more practical, no failure assumption for the machines was relaxed (see papers [26], [27] and [13]).

In this study, we developed a stochastic model for an unreliable robotic cell under different operational conditions comprising failures and preventive maintenance. The system was served by a single gripper robot for load/load identical parts as well displacements. Considering condition-based maintenance and its impact on the processing time of operations in a two-machine robotic cell, the focus of study is on S2 as the most commonly used robot’s move cycle. Additionally, robotic cell’s availability was considered as a constraint. As availability improvement will increase the output of the robotic cell, making an appropriate balance between cycle time and total operational cost,
considering breakdowns, are our objective in this study.

This paper is presented as follows: in section 2 the problem definition is demonstrated. In section 3 MOPSO as a solution procedure for the S2 cycle is given and through numerical examples sensitivity analysis about results and discussion based on the previous proposed model is revealed in section 4. Finally, conclusion is presented in section 5.

2 Problem Statement
Decreasing production cost and rising quality is manageable by applying a flexible system. Such systems, consist of one or more machines, supported by a robot for load/load of parts. A typical in-line two-machine robotic cell based on [11] is shown in Fig.1.

Fig.1. A typical layout for a 2-machine in-line robotic cell

In the production system there are two identical CNC machines that each of which has no priority in operation. Typically, in a 2-machine cell, three cycles, S1, S2 and S12S21, is being applied to part displacements. As mentioned before, we focused on the S2 cycle because it is a commonly used cycle with more complexity rather than the others. As a well-known rule, the activity sequence of S2 cycle is coded by \( A_{23}A_{12} [1] \). Where \( A_{pq} \) denotes the robot activity sequence from station \( p \), to station \( q \).

The literature revealed that, scheduling of flexible manufacturing cells commonly was carried out in deterministic conditions and little research has done on this issue under uncertainty. None of published papers has focused on scheduling-allocation optimization in the presence of random failures. For the scheduling-allocation optimization, the assumptions, parameters and proposed mathematical model are equivalent to [34]. In this study, we want to examine another solution method and compare the results.

3 Solution Methodology
In this paper, we applied MOPSO algorithm to generate different sets of non-dominated solutions for the model. Then, results were compared with the results of \( \varepsilon \)-constraint approach in [34].

3.1 MOPSO
The simplicity, low computation cost and increasing popularity of Multi-Objective Particle Swarm Optimization, enhance its efficiency to solve simple as well as complex problems [22]. Before describing MOPSO algorithm, the particle swarm optimization (PSO) needs to be presented, shortly.

PSO is a computational method to optimize a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO is originally attributed to Kennedy, Eberhart and Shi and was first intended for simulating social behavior as a stylized representation of the organisms movements in a bird flock or fish school [19], [31], [20]. The analogy of PSO with evolutionary algorithms makes evident the notion that using a Pareto ranking scheme could be the straightforward way to extend the approach to handle multi objective optimization problems [5]. In PSO, first, some predefined particles are generated incidentally in the solution space. The situation of each particle represents an order of alternatives. Besides, the fitness function value for algorithm is given identically as the determined score for the considered problem. In each iteration, each particle should be moved based on other particles situations. Two types of solutions have to be updated in each iteration of this algorithm. The first variable which is denoted by \( PBest \) is the best permutation experienced by each particle while the second one named as \( GBest \) is the best experienced arrangement by all particles. Particles movement direction and their final position in each iteration will be calculated according to the following equations [32]:

\[
V_i(t + 1) = w.V_i(t) + c_1.r_1.(PBest_i(t) - X_i(t)) + c_2.r_2.(GBest(t) - X_i(t))
\]

\[
X_i(t + 1) = X_i(t) + V_i(t + 1)
\]
4 Test Problems, parameter Tuning and Software Implementation

A set of problems with different sizes from [34] are considered to test the performance of MOPSO method in comparison with $\varepsilon$-Constraint in this section.

Example. Let us consider three different Test Problems including different groups of operations with their processing times in a 2-machine robotic cell for producing identical parts. Values are given in Table 2. The main difference between these test problems is the number of operations (i.e., group size). The parameters and user defined values for the considered robotic cell are presented in Table 1. It should be noted that, the same tool is used for all of these operations and we assumed these parameter values are constant.

Table 1. Characteristics of required parameters

| Parameter       | Value |
|-----------------|-------|
| $C_{PM}$         | 35    |
| $C_{0}$          | 50    |
| $C_{TOOL}$       | 45    |
| $A$              | 40    |
| $t_{LPM}$        | 7     |
| $t_{CM}$         | 10    |
| $B$              | 80    |
| $k$              | 4     |
| $C$              | 7     |
| $\mu$            | 2     |
| $\lambda$        | 3     |
| $\lambda$        | 3     |
| $\delta$         | 2     |
| $\varepsilon$    | 1     |
| $A$              | 40    |
| $H$              | 15    |
| $\delta$         | 2     |
| $t_{1PM}$        | 7     |
| $t_{CM}$         | 10    |
| $t_{1CM}$        | 10    |

4.1 MOPSO Results

To express the performance of the proposed model to solve the problems, we test the proposed MOPSO on a set of instances in Table 2 with MATLAB software and show the results in Table 4. It should be noted that, MOPSO algorithm was run on a portable PC with MS-Windows Vista, 3.0 GB of RAM, and 2.0 GHz Core 2 Duo CPU. Parameter setting for MOPSO algorithm was based on Table 3 and the algorithm procedure is shown in Fig.2. In Fig.3, we represent the best results of feasible region for objective functions in Test Problems based on MOPSO algorithm. Similar to the previous paper [34], as an instance, regarding the machine’s generated degradation level, we demonstrate the allocation of operations to them for the Example Number 9 (see Table 2) in Table 5.

Table 3. The MOPSO parameter setting

| Parameter                     | Value |
|--------------------------------|-------|
| Population size               | 50    |
| Repository Size                | 50    |
| Personal Learning Coefficient  | 1     |
| Global Learning Coefficient    | 2     |
| Grid Inflation                 | 0.1   |
| Number of Grids                | 5     |
| Leader Selection Pressure      | 2     |
| Repository Member Selection Pressure | 2     |
| Maximum Number of Iterations   | 100   |

Table 4. The MOPSO results (lower bounds) through designated test problems

| Example # | Min cost | $S_2$ Cycle time | Elapsed time in seconds |
|-----------|----------|------------------|-------------------------|
| 1         | 1655.47  | 22               | 20.19                   |
| 2         | 2555.31  | 27               | 23.49                   |
| 3         | 2702.28  | 29               | 22.04                   |
| 4         | 3252.61  | 34               | 20.72                   |
| 5         | 4200.71  | 44               | 23.23                   |
| 6         | 4851.34  | 50               | 21.26                   |
| 7         | 5201.86  | 54               | 19.81                   |
| 8         | 5551.34  | 57               | 25.11                   |
| 9         | 5700.28  | 59               | 25.19                   |
| 10        | 8049.49  | 82               | 24.86                   |
| 11        | 11350.03 | 115              | 27.03                   |
| 12        | 15648.31 | 158              | 31.08                   |

Table 5. Allocation of operations for case 9 in the test problems based on MOPSO algorithm

| Machine # | Allocated operations |
|-----------|----------------------|
| 1         | 1, 5, 8, 10, 12, 13, 14, 18 |
| 2         | 2, 3, 4, 6, 7, 9, 11, 15, 16, 17 |
4.1.1 Comparison Metrics
We used diversity and spacing metrics to provide a basis for assessing the relative performance of MOPSO as a multi-objective optimization algorithm. The metrics definition is being summarized in Table 6:

| Metric       | Definition                                                                 |
|--------------|-----------------------------------------------------------------------------|
| Spacing      | \[ SP = \frac{\sum_{i=1}^{n} (d^i - \bar{d})^2}{n-1} \]                     |
| Diversity    | \[ DM = \sum_{i=1}^{n} \max(||x_i - y_i||) \]                               |

Where \([x_i - y_i]\) is Euclidean distance between two non-dominated solutions \(x_i\) and \(y_i\) [35]. Comparison metrics were calculated for all test problems (see Table 2) over 10 runs of MOPSO algorithm. Table 7 is presented the diversity and spacing metrics obtained for small, large and big size instances.

4.2 Statistical analysis
To compare the outcome of both Pareto optimal solution methods (\(\varepsilon\)-constraint and MOPSO), we define objective functions result and elapsed time required by each method as the criteria. The criteria values have been summarized in Table 8.

4.2.1 Comparison between Solution Methods
To compare the performance of \(\varepsilon\)-constraint method with multi-objective particle swarm optimization algorithm, firstly, \(\varepsilon\)-constraint method’s minimum cost was measured against that of MOPSO algorithm. The first objective function (i.e. cost) in exact solution is consistently less than meta-heuristic solution, regarding Fig.4. In considered Test Problems (see Table 2), the difference between objective function values is at least 15 and at most 122 currencies.

In the second objective function (i.e. S₂ cycle time) a statistical significant difference between these two solution methods is not observed and precisely describing, the test of equality between these solution procedures based upon Test Problems result, is significant at 99.7% significance level with 190 as non-parametric Mann-Whitney statistics and p-value of 0.4728, by applying Minitab™. Consequently, there is no difference between the two solutions method behavior in terms of S₂ cycle time.

From the standpoint of elapsed time, the average elapsed time for running MOPSO algorithm is repeatedly lower than that of \(\varepsilon\)-constraint method, concerning Fig. 5. In the considered Test Problems (see Table 2), the smallest difference between elapsed time amounts is 1 and the maximum difference between elapsed time values is 3569 Seconds.

5 Conclusion
The studied system consists of a two-machine robotic manufacturing cell which produces identical parts and the robot moves cyclic on the basis of S₂ cycle. This robotic cell faces failures and repairs. This study aimed to demonstrate other solution procedure for the previous proposed model for the
defined above system and a generated set of Pareto optimal solutions based on MOPSO was presented. The link between operating conditions decisions in robotic manufacturing cells and maintenance decisions through following up maintenance task, will improve time and operational costs simultaneously.

We believe that, the model and solution procedures could be extended to the robotic cell considering robot breakdowns or to the dual-gripper robot.

Table 2. Test problems

| Test problem | Group size | Example # | Processing times |
|--------------|------------|-----------|------------------|
| (Small size) | (5-10)     | 1         | 10, 8, 7, 4, 3.  |
|              |            | 2         | 10, 7, 13, 8, 5, 2, 5.|
|              |            | 3         | 7, 4, 3, 7, 4, 8, 10, 3, 7.|

|              | (10-18)    | 4         | 10, 8, 7, 4, 3, 7, 4, 8, 10, 3.|
|              |            | 5         | 10, 8, 7, 4, 3, 7, 4, 8, 10, 3, 7, 4, 8.|
|              |            | 6         | 10, 7, 13, 8, 5, 2, 5, 4, 10, 7, 4, 8, 10, 3.|
|              |            | 7         | 10, 7, 13, 8, 5, 2, 5, 4, 10, 10, 8, 7, 4, 3, 7.|
|              |            | 8         | 10, 7, 13, 8, 5, 2, 5, 4, 10, 10, 8, 7, 4, 3, 7, 5, 2.|

| (Large size) | (18-50)    | 9         | 10, 7, 13, 8, 5, 2, 5, 4, 10, 10, 8, 7, 4, 3, 7, 5, 2, 3.|
|              |            | 10        | 10, 7, 13, 8, 5, 2, 5, 4, 10, 10, 8, 7, 4, 3, 7, 4, 8, 10, 3, 10, 8, 7, 4, 3.|

| (Big size)   | (18-50)    | 11        | 10, 7, 13, 8, 5, 2, 5, 4, 10, 10, 8, 7, 4, 3, 7, 4, 8, 10, 3, 10, 8, 7, 4, 3, 10, 8, 7, 4, 3, 7, 4, 8, 10, 3, 2, 10, 8, 7, 4, 3, 7.|
|              |            | 12        | 10, 7, 13, 8, 5, 2, 5, 4, 10, 10, 8, 7, 4, 3, 7, 4, 8, 10, 3, 2, 10, 8, 7, 4, 3, 7, 4, 8, 10, 3, 2, 10, 8, 7, 4, 3.|

Table 7. Computational results for comparison metrics in test problems

| Test Problem | Example # | DM | SM | Test Problem | Example # | DM | SM |
|--------------|-----------|----|----|-------------|-----------|----|----|
| Small size   | 1         | 153.0380 | 0  | Large size  | 7         | 270.2473 | 0  |
|              | 2         | 190.4197 | 0  |             | 8         | 279.2708 | 0  |
|              | 3         | 195.6059 | 0  | Big size    | 9         | 283.0309 | 0  |
| Large size   | 4         | 214.2844 | 0  |             | 10        | 335.6310 | 0  |
|              | 5         | 243.2365 | 0  |             | 11        | 398.7655 | 0  |
|              | 6         | 260.9949 | 0  |             | 12        | 467.9246 | 0  |

Table 8. Summary of the objective functions result and elapsed time for Pareto optimal solutions

| Example | Min cost | Min S2 Cycle time | Elapsed time (in seconds) |
|---------|----------|-------------------|----------------------------|
| #       | ε-        | ε-                | ε-                         |
|         | constraint| constraint        | constraint                 |
| MOPSO   | MOPSO     | MOPSO             | MOPSO                      |
| 1       | 1683.457  | 1655.4687         | 23                         | 22          | 22          | 20.185975 |
| 2       | 2601.222  | 2555.3125         | 30                         | 27          | 18          | 23.488227 |
| 3       | 2720.021  | 2702.2802         | 35                         | 29          | 68          | 22.036794 |
| 4       | 3267.914  | 3252.6064         | 44                         | 34          | 47          | 20.715749 |
| 5       | 4259.988  | 4200.7082         | 49                         | 44          | 409         | 23.224983 |
| 6       | 4919.679  | 4851.5939         | 60                         | 50          | 824         | 21.258663 |
| 7       | 5223.75   | 5201.8659         | 60                         | 54          | 114         | 19.805676 |
| 8       | 5623.888  | 5551.3398         | 59                         | 57          | 69          | 25.112806 |
| 9       | 5801.277  | 5700.2773         | 59                         | 59          | 3600        | 25.191318 |
| 10      | 8131.095  | 8049.487          | 84                         | 82          | 1211        | 24.857310 |
| 11      | 11373.37  | 11350.0269        | 122                        | 115         | 3600        | 27.025602 |
| 12      | 15770.43  | 15648.3065        | 158                        | 158         | 3600        | 31.076154 |
Fig. 3. Results of feasible region for objective functions in designated Examples based on MOPSO algorithm
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