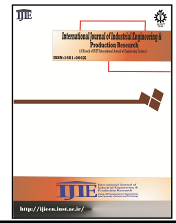
International Journal of Industrial Engineering & Production Research (2018)

September 2018, Volume 29, Number 3
pp. 343- 357

DOI: 10.22068/ijiepr.29. 3.343 http://IJIEPR.iust.ac.ir/



Bi-Criteria Robotic Cell Scheduling and Operation Allocation in the Presence of Break-downs

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KEYWORDS

Robotic manufacturing cell;
Scheduling;
Breakdowns;
Weighted sum method;
∊-constraint method.

ABSTRACT

This paper focused on scheduling problems arising in a two-machine, identical parts robotic cell, which was configured in a flow shop. Through the current research, a mathematical programming model on minimizing cycle time as well as operational cost, considering the availability of a robotic cell as a constraint, was proposed to search for the optimum allocation and schedule of operations for both two machines. Two solution procedures, including weighted sum method and ∊-constraint method, were provided. Based on the weighted sum method, like some previous studies, sensitivity analysis on model parameters was done, and the optimum solutions were compared with previous results, while ∊-constraint method could find the Pareto optimal solutions to problems with up to 18 operations in a reasonable time.

1. Introduction

The most common flexible manufacturing system (FMS) often consists of robots, computer numerical controlled machines (CNC), instrumentation devices, computers, sensors, and other stand-alone systems such as inspection machines. Herein, a robot is responsible for pick-up products, loading & unloading machines, and also material handling operations within the cell.
Extensive mechanization and automation reduces the number of production employees, yet increases investment in production equipment.
In order to promote system productivity, several researchers have focused on sequencing of machine feedings and robot movements in robotic cells. In this context, the optimization method is adopted as a common method of analyzing the system; however, most researches focused on scheduling problems using one criterion; however, considering more than one criterion is privileged. In addition, the effects of machine failures and repair times on the scheduling and sequencing process have been relaxed thus far and are maintained on research basket.
A survey of the most important results on multi-criteria scheduling appeared in [1]. To minimize the cycle time and total manufacturing cost in a robotic cell, a Bi-criteria scheduling model was presented by Gultekin et al. [2]. The robotic cell consists of two identical CNC machines and produces identical parts. Instead of assuming the processing times to be fixed on each machine, they assumed the allocations of the operations as

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Received 29 January 2018; revised 9 May 2018; accepted 12 June 2018

well as their processing times to be decision variables. The authors claimed that manufacturing costs as an objective function are being considered for the first time in robotic cell scheduling problems. A bi-objective mixed integer programming model with valid inequalities for a robotic manufacturing cell scheduling problem was developed by Feng et al. They tried to minimize the cycle time and total robot travel distance simultaneously. Thus, they proposed ε-constraint approach to solve the model that could find the complete Pareto front[3]. The reader is referred to [4], [5], [6], [7] for studying other papers regarding bi-objective problems in the field of robotic manufacturing cell scheduling.

In most of the previous researches conducted in the field of robotic cells, scheduling is done based on a single criterion. The most important objective functions used in previous studies have minimized cycle time or maximized the output rate of the cell (see papers [8], [9], [10], [11], [12], [13], [14]). The first analytic study of the robotic cell's operations, in which one process has a stochastic processing time, was presented by Geismar and Pinedo [15]. Finding the operation processing times, job assignment, and robot movements considering minimum make span was the problem raised by Al-Salem et al. [16]. Their challenging problem arises in a robotic manufacturing cell consisting of m consecutive machines as well as a material handling robot. They presented a novel genetic algorithm for the problem. A dynamic scheduling problem in robotic manufacturing cells was addressed by [17], where more than one new job arrives at the system and needs to be scheduled immediately, which leads to uncertainty. By achieving an optimal new schedule, the problem is formulated as a mixed integer programming model with the objective that minimizes the total completion time of the new jobs; then, a hybrid discrete differential evolution (DDE) algorithm is proposed to search for a near-optimal solution. In another new paper, scheduling machines and mobile robots in the FMS to minimize the make span were considered by Dang and Nguyen [18]. Genetic algorithm-based heuristic was presented to solve the problem.

In most industrial environments, it is required to perform different tasks during a specific time interval; corrosion and stoppage between these tasks may incur massive costs, thus the importance of considering maintenance. The objective of condition-based maintenance (CBM) is typically to determine an optimal maintenance policy to minimize the overall maintenance cost based on condition monitoring information. In a study, Tian and Liao [19] reported that determining the optimal condition-based maintenance policy previously has done for single unit systems; they proposed a multi-component system condition-based maintenance policy based on proportional hazards model. Recently, in a study, a new CBM model was considered for the minimization of the average long-run maintenance cost rate in multi-component systems with continuous stochastic deteriorations proposed by Zhu et al. [20].

There are very few studies in the field of reliability of robotic manufacturing systems, and none of them is definitely connected with the robotic manufacturing cell, such as Fazlollahtabar & Saidi-Mehrabad [21]. Savsar and Aldaihani [22] developed a model to analyze performance measures of a flexible manufacturing cell (FMC), consisting of two machines served by a robot, under different operational conditions including machine failures and repairs. The model was based on the Markov processes and closed-form solutions were determined for the probabilities of system states. In a similar study conducted by Hamasha et al. [23], the Markov chain model was constructed for one-machine and two-machine FMCs, after which the model was generalized to an FMC with n machines. In a new study, Gultekin et al. [24], through a mathematical model, tried to overlap unavailability periods with tool changes periods in a fully automated robotic spot welding line.

In this study, a stochastic model was developed for an unreliable robotic manufacturing cell with two machines under different operational conditions including failures and preventive maintenance (PM) activities, served by a single gripper robot for loading and unloading identical parts. This study considered condition-based maintenance and studied the impact of these items on the processing time of operations in a two-machine robotic cell based on S_2 robot's move cycle. Moreover, unlike previous studies that perceived reliable robotic cells, the availability of robotic cell was considered as a constraint. Since raising availability will increase the output of the robotic cell, regarding availability as a constraint and making an appropriate balance between cycle time and total operational cost, considering breakdowns, are our target in this study.

The rest of the paper is organized as follows and illustrated as a flowchart in Figure 1. In Section 2, the problem definition and assumptions are presented, and a mathematical model for solving the problem is developed. In Section 3, solution procedures for S_2 cycle through numerical examples were presented to evaluate the validity of the proposed model. Sensitivity analysis of results and discussion is revealed in Section 4. Finally, conclusion is presented in Section 5.

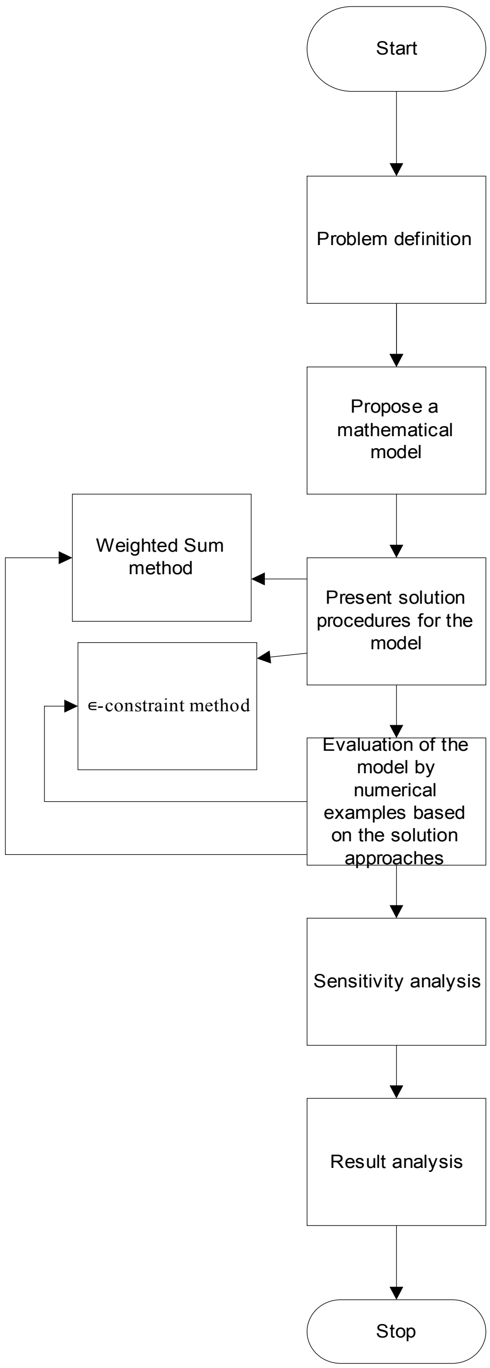


Fig. 1. Flowchart for the paper and approaches presentation

2. The Problem Statement

A flexible manufacturing cell consists of one or more machines, served by a robot for parts loading/unloading. A robotic cell as a FMC is normally used in the industry to accomplish high productivity in production with rapidly changing product configurations and customer demand [22]. Applying a flexible system could decrease production cost and increase quality of the system.

The robotic cell configures in a flow shop and like all classical flow shops, a set of operations should be processed on a number of consecutive machines. The order of processing the operations is fixed [25].

In a 2-machine cell, three cycles labeled as S_1, S_2 and $S_{12}S_{21}$ cycles may be applied for part movements. Herein, we focused on S_2 cycle, because this cycle is well known and more complex than the others.

Therefore, we considered a linear robotic cell consisting of two identical CNC machines producing identical parts. Each of the identical parts has a number of operations to be performed, and both machines are capable of performing all of the operations, and processing time of the operations on each machine is equal. Consistent with most of the previous studies, we assumed the loading/unloading of parts and travel between machines is done by a single gripper robot. The loading/unloading times and travel time of the robot between two consecutive machines or stations are all assumed to be constant, and there is no buffer between the machines. In S_2 cycle, initially, only the second machine is loaded and the robot is in front of the input buffer. Then, the robot picks up a part, moves to the first machine, loads the part on the first machine, and moves to the second machine. If necessary, it waits until the previous part has been processed, unloads the previous part and loads output buffer for the previous part, and then moves to the first machine; if necessary, waits until the part has been processed, unloads it, moves to the second machine, and loads the part on the second machine. Lastly, robot moves to the input buffer. Similar to flow shop models, the capacity of buffers is unlimited [26]. As a well-known rule, the activity sequence of S_2 cycle is coded as A_{01} A_{23} A_{12} and is a one-unit cycle [27].

Different definitions of the concept of CBM exist. According to the British Standard, CBM is defined as the maintenance policy carried out in response to a significant deterioration in a machine as indicated by a change in a monitored parameter of the machine condition. To implement the CBM, it is required to install and use monitoring equipment. The CBM can be done by (1) gathering product status data and monitoring; (2) making a diagnosis of a product status in a real-time way; (3) estimating the deterioration level of the product, its repairing cost which depends on the deterioration level, or its replacement cost, and so on; (4) predicting the time of products abnormality; (5) executing appropriate actions such as repair, replace, left to use as it is, and disposal [28].

In this study, by specifying the maintenance interval based on degrading components, maintenance is executed before failures occur in the products.

Therefore, a static maintenance interval based on degrading level of machines is presented to reduce the costs by specifying the control limits. By exceeding the physical conditions in a component over the specified control limits, the component will be maintained at the next upcoming time point. Due to the convenience of implementation, maintenance policies with a fixed interval are commonly adopted in practice. We consider such a policy with a static maintenance interval τ; accordingly, it could be possible to set up maintenance activities at time points $n\tau$, $n \in N$. For each machine j, $X_j(t)$ is the degradation path over time $t \in [0, \infty)$.

In order to avoid a high corrective maintenance cost, when $X_j(t)$ exceeds H_j, failure threshold, it is economically beneficial to take maintenance actions with a lower cost. Thus, for each machine, a control limit C_j to trigger preventive maintenance (PM) actions is introduced at the next closest maintenance point, before its degradation exceeds H_j (C_j<H_j). When the stochastic degradation increases fast and exceeds both C_j and H_j at the next closest maintenance point $n\tau$, a corrective maintenance (CM) action will be taken. Nevertheless, if the stochastic degradation increases slowly and the degradation level is between C_j and H_j at the next closest maintenance point $n\tau$, a preventive maintenance will be taken. After a maintenance action, the condition of the machine is restored to the original degradation level ("Repair-As-New") and the machine continues its operation till taking the next maintenance action. This process will repeat during the infinite time horizon. The period between two consecutive maintenance actions for a machine is defined as a maintenance cycle and the beginning of each cycle is called renewal point. According to renewal theory, the average cost rate over an infinite time horizon is equal to the average cost rate over each maintenance cycle [20]. In this study, by assuming the possibility of gathering machine data and monitoring, the degradation level of each machine could be estimated.

We considered the following parameters as most of other robotic cell problems:

a	The processing time for a part on the 1[st] machine
b	The processing time for a part on the 2[nd] machine
p	Total processing time for a part (in 2-machine problem p= a +b)
ε	Load/unload time
δ	Time taken by a robot to move between two consecutive machines
T_{S2}	Cycle time based on S_2 robot move cycle
W_j	Robot's waiting time in front of machine j
A_{pq}	Robot activity sequence from station, p, to station, q, for p= 0, 1, 2 & q= 1, 2, 3.

Consequently,

$$T_{S2} = 6\varepsilon + 8\delta + Max\{0, W_1, W_2\} \quad (1)$$

$$W_1 = a - (2\varepsilon + 4\delta) \quad (2)$$

$$W_2 = b - (2\varepsilon + 4\delta) \quad (3)$$

Waiting in front of machine may exceed by performing maintenance on them. Regarding possible deterioration and stoppage in the robotic cell, CBM is done. In this paper, breakdowns initiating by machine failures and maintenance activities are considered.

2-1. Assumptions and notations

The literature reveals that although several studies have been done on scheduling FMCs, a common assumption of those studies included certain processing times and machine availability. The availability of the robotic cell was considered in none of the previous researches in the field of robotic cells as a constraint, because machine/robot was supposed to be available. Additionally, in the field of maintenance and the availability of robotic systems, there have been very few studies, none of which has been specifically associated with the robotic cell. Hence, considering availability as a constraint and making a proper balance between cycle time and manufacturing system cost by considering breakdowns resulting from machine failures are contributions of this paper.

A typical layout for a robotic cell is illustrated in Figure 2. As noted earlier, the effect of machine breakdown on cell scheduling needs further research. It is assumed that machines have two states: up and down. Each machine experiences breakdown independent of each other and repair randomly with constant given rates; mean time to failure and repair follows the given exponential distributions. In order to analyze the desired robotic cell, the following model is developed. It is noteworthy that the layout of the assumed robotic manufacturing cell was based on Gultekin et al. [2].

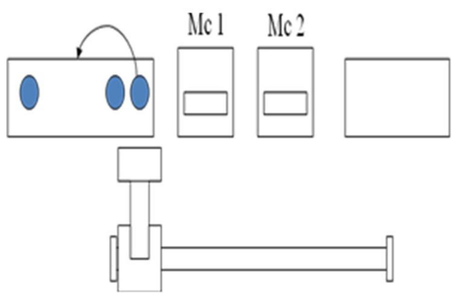


Fig. 2. Two-machine In-line robotic cell layout

First, the assumptions and characteristics of the robotic cell in the present study are summarized as follows.

Parts are always available at the input buffer and an empty place is available at the output buffer.

The robots and machines could not be in possession of more than one part at any time.

The proposed scheduling model is a Bi-criteria one.

There is an In-line robotic cell including two machines and a single gripper robot.

We focus on S_2 cycle in 2-machine robotic manufacturing cell.

Machines experience random failure and require PM or CM.

MTTF and MTTR follow exponential distribution.

Monitoring and estimating the degradation level of machines is probable.

Then, the model parameters are introduced below:

C_0	Machining cost ($/min)
C_{PM}	Cost of a PM visit ($/visit): without setup costs
C_{TOOL}	Cost of tool ($/tool): Tools replacement prohibited in an operating cycle
λ	Failure rate
μ	Repair rate
$AV(\infty)$	Steady state availability
A, B, K	Coefficients and exponents for the proposed PM index function
$t_{j,PM}$	Duration of a PM visit for machine j (min)
$t_{j,CM}$	Duration of a CM visit for machine j (min)
t_i	Processing time of operation i (min)
W_{Rj}	Duration of a maintenance in machine j (min)
W	Robot's waiting time in a cycle (min)
F	Total cost ($/min)
$EPSM$	The epsilon-constraint symbol

At last, decision variables are given as follows.

$O_{ij} = \begin{cases} 1 & \text{if Operation } i \text{ is allocated to machine } j, \\ 0 & \text{Otherwise} \end{cases}$

$R_{j,PM} = \begin{cases} 1 & \text{if PM visit performed for machine } j, \\ 0 & \text{Otherwise} \end{cases}$

$R_{j,CM} = \begin{cases} 1 & \text{if CM visit performed for machine } j, \\ 0 & \text{Otherwise} \end{cases}$

U_{ij} Expected usage rate of machine j for operation i

P_{ij} PM index for operation i when machine j is used

The proposed model is given as follows:

$$MinF = (\sum_{j=1}^{2}\sum_{i=1}^{n} C_0 t_i O_{ij} + C_{PM} P_{ij}) + C_{TOOL} \quad (4)$$

$$MinT_{S2} \quad (5)$$

S.T.

$$AV(\infty) = (\mu^2 + 2\lambda\mu)/(\mu^2 + 2\lambda\mu + 2\lambda^2) \quad (6)$$

$$U_{ij} = (t_i * O_{ij})/((T_{S2})AV(\infty)) \quad (7)$$

$$P_{ij} = [(At_i U_{ij} + AW_{Rj} + B(U_{ij}/t_i^{k-1}) + B(W_{Rj}/t_i^{k}))/T_{S2}C_{PM}]O_{ij} \quad (8)$$

$$a = (\sum_{i=1}^{n} t_i O_{i1}) + W_{R1} \quad (9)$$

$$b = (\sum_{i=1}^{n} t_i O_{i2}) + W_{R2} \quad (10)$$

$$W_{Rj} = (t_{j,PM} R_{j,PM}) + (t_{j,CM} R_{j,CM}) - (t_{j,PM} R_{j,PM})(t_{j,CM} R_{j,CM}) \quad (11)$$

$$R_{j,PM}, R_{j,CM} \varepsilon \{0,1\} \quad (12)$$

$$0 < C < H \quad (13)$$

$$W = Max\{0, a - [2\varepsilon + 4\delta + W_{R1}], (p - a) - [2\varepsilon + 4\delta + W_{R2}]\} \quad (14)$$

$$T_{S2} = 6\varepsilon + 8\delta + W \quad (15)$$

$$O_{i1} + O_{i2} = 1 \quad (16)$$

$$O_{ij} \varepsilon \{0,1\} \quad (17)$$

$$W \geq 0 \quad (18)$$

Objective functions are explained as follows.

In this model, considering Equation (4), according to [29], on a CNC turning machine, for a given operation i using machine j, we have three cost terms: the machining cost, the tooling cost, and the PM cost. We considered tooling cost value constant, because there is no tool replacement in a cycle. One of the basic objectives in robotic cell scheduling problems is to minimize cycle time; that is, in our model, S_2 robot move cycle in a two-machine problem. The second objective is expressed in Equation (5).

The explanations of constraints are as follows.

Equation (6) is a formula for steady state availability by assuming two components in the system and a maintenance crew based on [30]. Expected machine usage for an operation can be calculated by applying the processing time divided by availability in a cycle (because of cyclic production, steady state is true) and comes in Equation (7). In Equation (8), we assumed that the cost of a PM visit (CPM) is constant for all visits. We determined the contribution of an operation to the PM need of a machine using the ratio of the PM cost of an operation to CPM. This value is between 0 and 1. P_{ij} is calculated for each operation and is used to schedule the required PM visits based on [29].

Equations (9), (10), (15) and (18) are provided based on the definitions of S_2 robot move cycle and redefined in accordance with our assumed problem. Equation (11) shows duration of a maintenance in each machine which considering Equation (13); according to the concepts described in Section 2, for each run of the model, the degradation level of each machine is estimated. Based on the control limits in Section 2, breakdowns in production are predicted; the implementation of appropriate actions which is PM or CM is considered; duration of the actions is calculated based on Equation (11). Equation (12) states that it is not possible to do both PM and CM activities at the same time for the same machine; finally, Equation (14) states robot waiting time in a cycle.

3. Problem Solution

In this section, we apply some classical solution procedures for S_2 cycle. First, by applying Weighted Sum method, a test problem, including some numerical examples with different parameters, was considered and results were compared.

In the process of solving multi-objective problems, rather than optimal points, since non-dominant set points are considered, in order to achieve the set, special procedures should be used. So far, many methods have been introduced to solve these types of issues [1]. One of the popular non-evolutionary methods that converts the problem into a one-dimensional one by reformulating some of the objectives as constraints is ∊-constraint approach [29]. Therefore, ∊-constraint method is proposed to generate a set of non-dominated solutions for the model defined in Section 2.

3-1. Weighted sum method

Although weighted sum method is the simplest approach, it is probably the most widely used classical method. Despite the deficiencies with respect to depiction of Pareto optimal set, the Weighted Sum method for multi-objective optimization problems continues to be used extensively not only to provide multiple solution points by varying the weights consistently, but also to provide a single solution point that reflects preferences presumably incorporated in the selection of a single set of weights [31].

The weighted sum problem for S_2 cycle is formulated as follows:

$$Min G = w_1[(\sum_{j=1}^{2}\sum_{i=1}^{n} C_0 t_i O_{ij} + C_{PM} P_{ij}) + C_{TOOL}] + w_2[T_{S2}] \tag{19}$$

S.T.

$Equation 6$

...

$Equation 18$

where the weights have been normalized to sum to 1, w_1 and w_2 ∈ [0, 1] are the weights of the 1[th] and 2[nd] objective functions, respectively. Through this method, we run Example 1; then, the discussion opens by obtaining the results.

Example1. Let us consider the proposed model for three different groups of operations with their processing times. This example was originated from [2]. Values are given in Table 1.

Tab. 1. Designated examples

Example #	Processing times
A	10, 8, 7, 4, 3
B	7, 4, 8, 10, 3
C	10, 7, 13, 8, 5, 2, 5, 4, 10

The parameters and user-defined values for the considered robotic cell are presented in Table 2. It should be noted that the same tool is used for all of these operations, and we assumed these parameter values are constant.

Tab. 2. Characteristics of required parameters

C_{PM}=35	B=80	μ=2
C_o=50	k=4	λ=3
C_{TOOL}=45	C=7	∊=1
A=40	H=15	δ=2
$t_{j,PM}$ =7	$t_{j,CM}$ =10	

Therefore, an attempt was made to determine how changes in the values of the main parameters, such as loading/unloading time, ∊, travel time, δ, and the coefficient concerning the age of machines, B, affected the objective values. The results are shown in Table 3. Moreover, by increasing repair rate, μ, and keeping failure rate and other parameters constant based on Table 2, while the operational cost diminished, there was an increase in S_2 cycle time or remained unchanged. Table 4 shows this result.

Tab. 3. Sensitivity analysis results of main parameters

Example #	Changes	T_{S2}	F	W
# A (P=32), (∊=1)	δ =0	21	1708.71	15
	δ =2	22	1767.316	0
	δ =4	38	1696.128	0
# B (P=32), (∊=1)	δ =0	21	1756.213	15
	δ =2	22	1778.4	0
	δ =4	38	1702.469	0
# C (P=64), (∊=1)	δ =0	27	3438.942	21
	δ =2	34	3393.196	12
	δ =4	-	-	-
# A(P=32), (δ=2)	∊=1	22	1767.316	0
	∊=2	28	1725.481	0
	∊=4	40	1708.007	0
# B (P=32), (δ=2)	∊=1	22	1778.4	0
	∊=2	29	1698.153	1
	∊=4	41	1657.057	1
# C (P=64), (δ=2)	∊=1	34	3393.196	12
	∊=2	45	3293.124	17
	∊=4	46	3346.697	6
# A, P=32, (∊=1, δ=2)	B=80	22	1767.316	0
	B=800	23	1720.234	1
	B=2000	22	1795.101	0
# B, P=32, (∊=1, δ=2)	B=80	22	1778.4	0
	B=800	22	1761.001	0
	B=2000	22	1768.671	0
# C, P=64, (∊=1, δ=2)	B=80	34	3393.196	12
	B=800	39	3318.331	17
	B=2000	-	-	-

Tab. 4. Sensitivity analysis based on changing the repair rate

Examples#	μ=2		μ=3	
	T_{S2}	F	T_{S2}	F
A	22	1767.316	23	1709.982
B	22	1778.4	22	1747.368
C	34	3393.196	34	3384.428

Furthermore, for the first two instances of Examples 1, the model was applied considering no failure and repair situation (based on previous models). Then, we compared the results of these reliable robotic cells without availability function as a constraint with the best results from our random run in terms of being an unreliable cell with availability function as a constraint (based on Table 3). Tables 5 and 6 show the results.

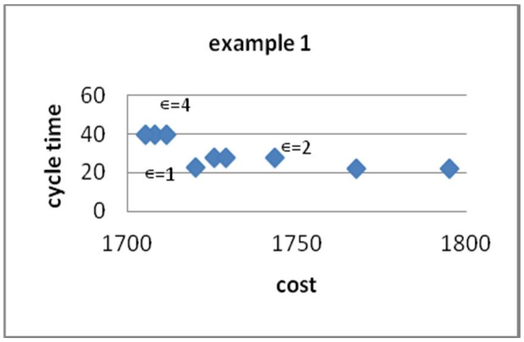
In addition, we depict the effects of simultaneous changing ∈ and B on objective functions in Figure 3.

Tab. 5. The effect of unreliability with availability function as a constraint on allocation of operations to the machines (A.O.M) and objective functions

Example #	A.O.M. based Sensitivity analysis on ∈	Best results of Unreliable 2-machine cell T_{S2}	F
A	∈=1	22	1720.234
	AOM:	M_1:t_4, t_5- M_2:t_1, t_2,t_3	M_1:t_3,t_4-M_2:t_1,t_2,t_5
	∈=2	28	1725.481
	AOM:		M_1: t_3- M_2:t_1,t_2,t_4,t_5
	∈=4	40	1705.233
	AOM:		M_1: t_3,t_4,t_5 - M_2:t_1,t_2
B	∈=1	2 2	1761.001
	AOM:		M_1:t_4 - M_2:t_1,t_2,t_3,t_5
	∈=2	28	1698.153
	AOM:	M_1:t_1, t_5- M_2:t_2, t_3,t_4	M_1:t_4,t_5-M_2:t_1,t_2,t_3
	∈=4	40	1657.057
	AOM:	M_1:t_1, t_2,t_5- M_2:t_3, t_4	M_1: t_2,t_4,t_5-M_2:t_1,t_3

Tab. 6. The effect of reliability without availability function on (A.O.M) and objective functions

Example #	A.O.M. based Sensitivity analysis on ∈	Reliable 2-machines cell without Availability function T_{S2}	F
A	∈=1	29	1645
	AOM:	M_1:t_2,t_3 - M_2:t_1,t_4,t_5	
	∈=2	33	1645
	AOM:	M_1:t_2,t_3- M_2:t_1,t_4,t_5	
	∈=4	41	1645
	AOM:	M_1:t_2,t_3 - M_2:t_1,t_4,t_5	
B	∈=1	29	1645
	AOM:	M_1:t_1,t_3 - M_2:t_2,t_4,t_5	
	∈=2	33	1645
	AOM:	M_1:t_1,t_3 - M_2:t_2,t_4,t_5	
	∈=4	41	1645
	AOM:	M_1:t_1,t_3 - M_2:t_2,t_4,t_5	



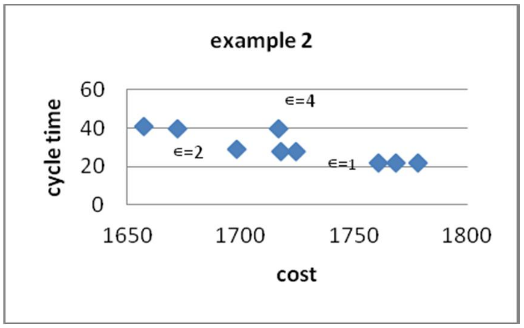


Fig. 3. Effects of simultaneous changing ∊ and B on objective functions

3-2. ∊-constraint solution method

One of the popular non-evolutionary methods is ∊-constraint approach, which converts the problem into a one-dimensional one by keeping only one of the objectives and restricting the rest of the objectives [32]. Consequently, in this study, to produce a representation of the Pareto optimal solutions for the problem, the ∊-constraint approach denoted by ∊ (F\T) for S_2 cycle is used. It is clear from Eq. (15) that the cycle time of S_2 does not depend on the allocation of operations to the machines. Therefore, we get the cycle time as a constraint. As a result, the ∊-constraint problem for S_2 cycle is formulated as follows:

$$\varepsilon(F \setminus T)^{S_2} : Min(\sum_{j=1}^{2}\sum_{i=1}^{n} C_0 t_i O_{ij} + C_{PM} P_{ij}) + C_{TOOL}$$

S.T.

$$T_{S_2} \leq EPSM \tag{20}$$

$$Equation 6$$

...

$$Equation 18$$

This formulation is Mixed Integer Nonlinear Programming model (MINLP) which allocates the operations to the machines and determines processing time values for the machines in view of breakdowns resulting from machine failures.

One of the critical elements in minimization problems to find the best solution is the quality of lower bound. Sometimes, relaxing some constraints and solving a new easier problem is done [9]. In this work, we begin by finding f_1^{min} and f_2^{min}, the best achievable value of f_1 in the lack of f_2, and the best achievable value of f_2 in the absence of f_1. These values will be the lower bound (lower bounds for the objective functions) for the Bi-criteria scheduling-allocation problem. The Pareto optimal solution will not be better than this solution.

The present work is an effort to perform effectively the ∊-constraint method for producing the Pareto optimal solutions in a Bi-criteria scheduling and allocation problem using commercial software (GAMS). This method generates the exact Pareto front of the Bi-criteria scheduling and allocation problem addressed.

Example 2. 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. The problems are tested and the performance of ∊-constraint method is compared. Values are given in Table 7. 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 2.

Tab. 7. Designated test problems

Test problem	Group size	Example #	Processing times
1 (Small size)	(5-10) operations	1	10, 8, 7, 4, 3.
		2	10, 7, 13, 8, 5, 2, 5.
		3	7, 4, 3, 7, 4, 8, 10, 3, 7.
2 (Large size)	(10-18) operations	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.
		9	10, 7, 13, 8, 5, 2, 5, 4, 10, 10, 8, 7, 4, 3, 7, 5, 2, 3.

4. Result and Discussion

4-1. Results of the weighted sum method

On the basis of Weighted Sum method, in order to discuss how breakdowns affect S_2 cycle in terms of time, cost, and output rate, a mathematical model was proposed and the following results were obtained:

By applying possible breakdowns including random failures and repairs in the machines of the robotic cell, the costs increased (i.e., the first objective function) and S_2 cycle time decreased. It means that unreliability had opposite effect on the second objective function; consequently, the output rate went up. It is worth mentioning that, in this study, we ignored breakdowns in robot, and assumed that the robot is reliable.

Sensitivity analysis of the numerical example produced the following results:

By changing ϵ and keeping other parameters constant, it was revealed that, in accordance with the proof provided by[27],

If $P <= 2\epsilon+4\delta$, thus the cycle time can be obtained by $6\epsilon+8\delta$ formula in our model. However,

If $P>2\epsilon+4\delta$, the results differ. It means that, unlike [27], in this case,

If $P>4\epsilon+8\delta$, thus the cycle time value will be less than $4\epsilon+4\delta+P/2$ and,

If $P<=4\epsilon+8\delta$, thus calculating $6\epsilon+8\delta$ will be a lower bound for cycle time value of S_2.

By changing δ and keeping other parameters constant, the alterations of objective functions had fluctuation and did not follow any specific rule.

By changing B as a coefficient related to the machine's age, where bigger B shows older machine, and keeping other parameters constant, in the numerical examples, minimum cost was achieved by B=800. Of note, all the computations were done by commercial software (GAMS).

4-2. ϵ-constraint results

The minimum cycle time-minimum cost solution was found by solving the coded ϵ-constraint problem with solver GAMS-BARON. The codes were run on a portable PC with MS-Windows Vista, 3.0 GB of RAM, and 2.0 GHz Core 2 Duo CPU. We depicted the first twenty iterations of the ϵ-constraint solution for the designated examples of Table 7 to show a Pareto optimal solution. Figure 4 illustrates the results. Then, in Table 8, the upper and lower bounds of generated solutions for ϵ-constraint method are shown. It should be noted that the ϵ-constraint method was run 10 times and the results of small-size and large-size problems were obtained within 1800s average computation time; for producing parts with more than 18 operations, the computing time will be more than 3600s. It means that the group size has an impact on the model computation time. Thus, considering the average obtained solutions in our computations, the results in Table 8 can be seen. The allocation of operations to the machines based on the proposed model is attainable, too. For instance, concerning the level of generating machines degradation, the allocation of operations to the machines for Example 9 (see Table 7) is demonstrated in Table 9.

Tab. 8. The upper (U) and lower (L) bounds of the generated Pareto front in the test problems

Example #	Cost		S_2 Cycle time	
	L	U	L	U
1	1683.457	1770.861	23	61
2	2601.222	2652.825	30	49
3	2720.021	2760.251	35	48
4	3267.914	3302.313	44	63
5	4259.988	4291.183	49	68
6	4919.679	4961.363	60	71
7	5223.75	5242.855	60	73
8	5623.888	5658.538	59	78
9	5801.277	5840.731	59	78

Tab. 9. Allocation of operations for case 9 in the test problems based on ϵ-constraint method

Machine #	1	2
Generated Degradation Level	35.0157	34.04165
Allocated operations #	2, 6, 7, 10, 12, 13, 16	1, 3, 4, 5, 8, 9, 11, 14, 15, 17, 18

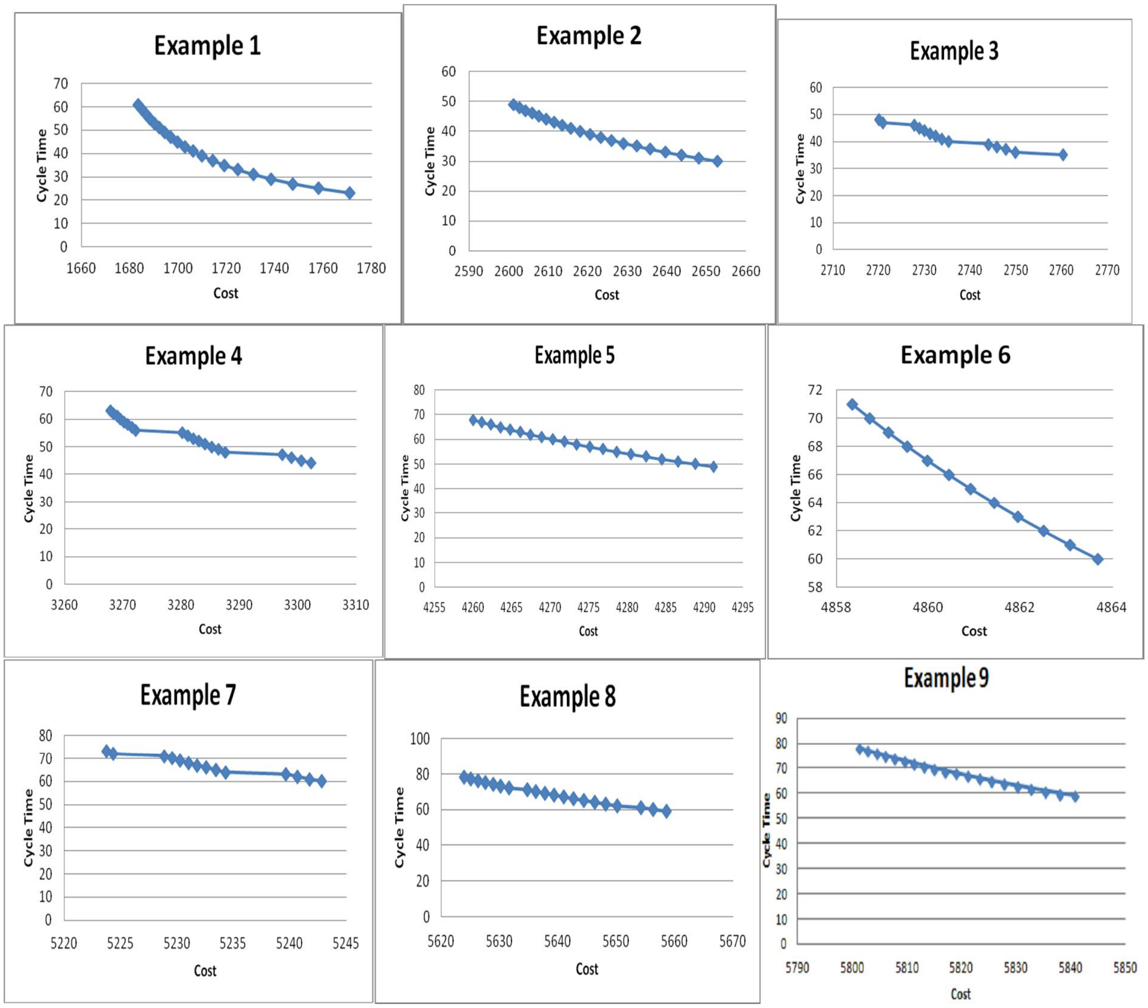


Fig. 4. Results of the first twenty iterations of the ∊-constraint for Test Problems

5. Conclusion and Future Researches

The proposed model was focused basically on minimizing operational cost and S_2 cycle time in a two-machine, identical parts robotic cell, under breakdowns comprising failures and repairs. In this study, we tried to link the operating conditions decisions in robotic manufacturing cells with maintenance decisions through CBM, which will improve cycle time and operational costs concurrently. The problem was formulated as a Mixed Integer Nonlinear Programming model. Exact solution procedures were developed for S_2 cycle including Weighted Sum (Table 3, Table 4, and Figure 3) and ∊-Constraint (Table 8, Table 9, and Figure 4) methods, and a generated set of Pareto optimal solutions was presented.

We believe that the results could be extended to the robotic cell considering robot failures or to the dual-gripper robot instead of single-gripper ones. Excluding flexibility in robotic cell is also considerable for future research studies.

Conversely, we are interested in developing new models with other probability distributions of the time to failure and time to repair for the machines besides the exponential probability distribution. Furthermore, optimal sequencing of parts for different problems, in the robotic manufacturing cell, can be another topic for future research.

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