Data Envelopment Analysis-based Scenario Selection for Sequencing Pattern in a Simulated Robotic Cell

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***Abstract*—In this study, the performance of suggested scenarios for part input sequences in a 3-machine robotic cell producing different parts is determined through the application of data envelopment analysis (DEA) and the Banker–Charnes–Cooper model. A single gripper robot supports the manufacturing process by loading and unloading products and moving them inside the system. This study addresses random machine failures and repairs to minimize cycle time based on two robot move cycles in a three-machine robotic cell and overall production costs. Here, simulation assists in the modeling of uncertainty and a simulation-based optimization approach is applied to find the best scenarios for sequencing patterns in the cell through several numerical examples using DEA. The results displayed that, efficient scenarios satisfying minimum time and cost, are those, in which the percentages of operations assigned to the machines are close to each other. This enables decision-makers in manufacturing systems to make precise selections of the optimal part sequencing pattern with the lowest production cost and cycle time for robotic cells.**

***Index Terms*—Data envelopment analysis, Part sequencing, Robotic cell, Scenario design, Simulation**.

I. Introduction

The dominance of robotic systems has arisen as a pivotal point of both academic and industrial consideration, obtaining considerable attention (Ali, 2024). A robotic manufacturing cell consists of computer numerical control (CNC) machines with at least one robot (to pick up products and load/unload the machines). Consideration is given to the problem of part sequencing in a robotic cell served by a single gripper robot and three machines that produce different parts. We are interested in minimizing cycle time and production costs. Cycle time is the average time required to process a component in a system. In the majority of published studies, cycle time minimization has served as the objective function for part sequencing problems. (Vaisi, Farughi and Raissi, 2022) Surveyed recent developments in the problems of robotic manufacturing systems between 2005 and 2021, including the problem of determining optimal part sequencing in robotic manufacturing cells.

Simultaneous optimization of the robotic move sequence and part input sequence was studied by (Zhao and Guo, 2018), and an effective chemical reaction optimization (ECRO) was proposed as an encoding solution method. How to incorporate machine breakdowns into robotic manufacturing cells is an unanswered question in the part sequencing problem. By using a simulation-based optimization strategy, (Vaisi, Farughi, and Raissi, 2018) demonstrated that it is possible to determine the optimal part input sequence in an unreliable two-machine robotic cell. In another study, the performance of different layouts in two-machine robotic cells that produce non-identical parts was compared (Foumani and Tavakkoli Moghaddam, 2019). (Vaisi, Farughi and Raissi, 2020) demonstrated the robustness of three-machine robotic cells using simulation-based optimization and multi-criteria decision-making techniques. In a recent study, (Vaisi, Farughi and Raissi, 2021) simulated the sequencing problem of a three-machine robotic cell under S_6 cycle, where it produces different parts to obtain minimum cycle time/operational cost and maximum throughput. Then, response surface methodology and goal programming approach were utilized on the simulation results to optimize the sequencing problem. In a different study, a robotic cell was simulated to improve the reliability of the cell. By means of a supervised machine learning model, the faulty behavior of the critical component was classified (Mourtzis, Tsoubou and Angelopoulos, 2023). To find the optimal cycle time in two-machine circular robotic cells with swap ability to maximize the output, a study has recently been conducted by (Khebouche and Boudhar, 2024). However, optimal sequencing of parts in the case of an existing unreliable robotic cell with three machines through data envelopment analysis (DEA) is also on appeal.

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Unreliable robotic cells are those that are subject to random failure and maintenance.

Complex decisions regarding sequencing issues in robotic manufacturing cells, as a result of uncertainty, can be supported by computer simulation models. The development of simulation techniques dates back to the early 1960s, and simulation may be the most widely used analytical tool (Pidd, 1986). Although simulation methods are commonly referred to as descriptive modeling techniques, it has been demonstrated that computer simulation is an effective interface between operations research and computer science (Fu, 2002). The use of simulation in manufacturing from 2002 to 2013 was examined by (Negahban and Smith, 2014). The major milestones in the development of simulation tools were analyzed by (Mourtzis, Doukas and Bernidaki 2014) through a comprehensive study. In the context of the manufacturing system, they examined recent industrial simulation practices, their evolution, advances, and future trends. Using computer simulation in manufacturing systems has been considered by a number of researchers, such as the simulation of a chain store as a service sector by (Vaisi, Raissi and Vaisi, 2015); the simulation of a flexible manufacturing system by (Florescu, Barabaş and Sârbu, 2017); the simulation of an assembly line by (Yang, Chen and Lin, 2017); the simulation of capacitated assembly systems by (Woerner, Laumanns and Wagner, 2018); the simulation of a material handling system by (Leung and Lau, 2019), and so on. Furthermore, to support the strategic maintenance development in a production system, simulation-based optimization was done by (Linnéusson, Ng and Aslam, 2020). Simulation was also applied to train operators in a study done by (Karagiannis et al., 2021). The furniture manufacturing and assembly process in a furniture company were recently simulated through Arena software by (Kolny, Kaczmar-Kolny and Dulina, 2023). One more fresh study was done to simulate an automobile assembly manufacturing line and analyze bottlenecks in the manufacturing system, (Mohammed, Abdulghafour and AL-Enzi, 2024).

Following the aforementioned literature review, solution methods for the part sequencing problem primarily consisted of the Gilmore and Gomory algorithm, heuristics, and formulations based on the traveling salesman problem. A review of the relevant literature reveals that scenario design and scenario evaluation in three-machine robotic cells using DEA have not been previously conducted. Therefore, a scenario concept is being developed to bridge this gap. Two cycles are considered robot move cycles in 3-machine robotic manufacturing cells, which contributes to the novelty of the present study. The cycles are compared to determine the optimal sequencing pattern for the parts, in which each of the move cycles simultaneously minimizes cycle time and total production cost. It should be noted that there are six cycles for robot movements in three-machine robotic cells, and in "Table I", all the cycles will be presented. In the current study, two of the cycles are selected because few researches have been focused on them as their complexity is high.

Table I
Robot Activity Sequences in Three-Machine Robotic Cells

Cycles	Encoding of robot activity sequences
S_1	$A_{01}\, A_{12}\, A_{23}\, A_{34}$
S_2	$A_{01}\, A_{12}\, A_{23}\, A_{34}$
S_3	$A_{01}\, A_{12}\, A_{23}\, A_{34}$
S_4	$A_{01}\, A_{12}\, A_{23}\, A_{34}$
S_5	$A_{01}\, A_{12}\, A_{23}\, A_{34}$
S_6	$A_{01}\, A_{12}\, A_{23}\, A_{34}$

DEA as a nonparametric mathematical programming technique has been evaluated as one of the most notable methods for measuring the performance of homogeneous units, i.e., decision-making units (DMUs) that transform inputs into outputs. A study of DEA applications from 1978 to August 2010 by (Liu et al., 2013) revealed that DEA is applicable in a variety of contexts for measuring efficiency. Furthermore, in another paper, (Emrouznejad and Yang, 2018) conducted a survey related to the theory and applications of DEA, reporting published papers from 1978 to 2017. Here are some recent studies demonstrating the practical applications of DEA in various industries: (Vaisi and Raissi, 2014) in Pride's spare parts manufacturing system; (Banker et al., 2017) in electric distribution firms; (Pjevcevic et al., 2017) in a port container terminal; (Vaisi, 2017) in a production system; (Vaisi et al., 2018) in a two-machine robotic cell; (Solgi et al., 2019) in complex product systems; (Wen et al., 2020) in the construction sector; (Zhu, Zhu and Emrouznejad, 2020) in manufacturing companies; (Vaisi, 2023) in a manufacturing system with a transport robot; and (Sinha, Vaisi and Edalatpanah, 2024) in the banking industry. With the exception of (Vaisi et al., 2018; Vaisi et al., 2023), there are no known published studies on the part sequencing problem utilizing DEA, which were done for a two-machine robotic cell. The current study seeks to fill this gap by considering a three-machine robotic manufacturing cell. It should be highlighted that the use of DEA to select the best sequencing patterns in robotic cells has been unparalleled in its field, and the current study is entirely distinct from our previous work due to the differences in terms of the nature of complexity for movement cycles in the two-machine and three-machine robotic cells.

Thus, the contribution of the current study is summarized as:

a. Application of a simulation-based optimization approach to solve the part input sequencing problem in unreliable three-machine robotic cells.
b. Presenting the DEA-based performance measurement of S_2 and S_6 cycles as two movement cycles for robots in three-machine robotic cells.

The structure of the paper is as follows: In the following section, the problem is defined, and assumptions and numerical examples are provided. In section III, the problem is modeled using a computer simulation technique. For the purpose of solving the problem, proposed scenarios are presented and DEA is utilized to determine the optimal part entrance sequence to the cell in section IV. In section V, the conclusion is presented.

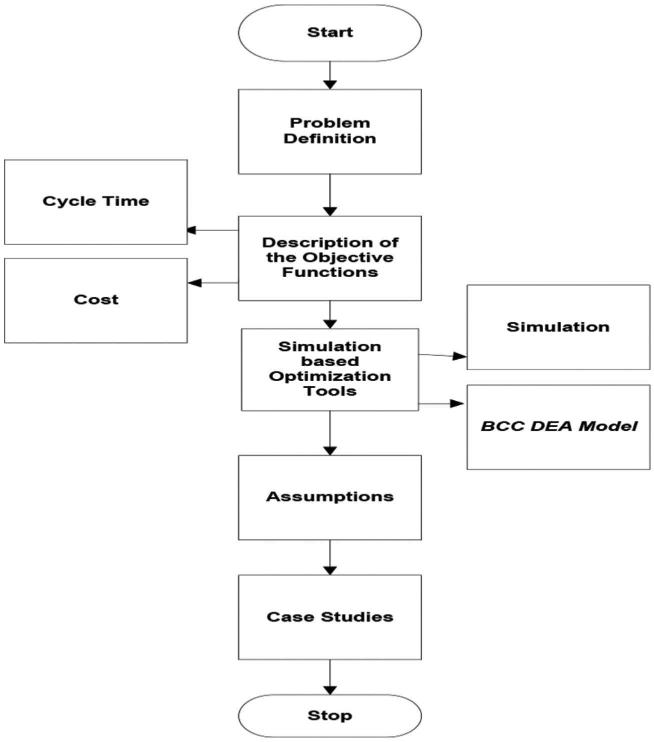

Fig. 1. Flowchart for the problem statement and optimization tools presentation.

II. Problem Statement

In this section, the problem and solution tools are defined as they come in Fig. 1. Hence, the problem is defined in A, objective functions are described in B and C, the simulation-based optimization approach and its tools are represented in D and E, assumptions are summarized in F, and numerical examples are denoted in sub-section G of the existing section.

A. Robotic Cell

In this study, an in-line robotic cell encompasses three similar CNC machines with no priority in operation, and a single gripper robot is assumed. A robotic cell is a manufacturing system composed of a number of CNC machines, a material-handling robot, and other relevant systems. The processing of each component begins in the input buffer and concludes in the output buffer (Vaisi et al., 2020; Vaisi et al., 2023). “Fig. 2” depicts an in-line three-machine robotic cell. It should be noted that different colors for the parts in “Fig. 2” represents that the cell produces different parts.

In-line robotic cells are a type of robotic cell layout. Based on this layout, robot movement between machines and buffers is linear. All machines are capable of performing the operations simultaneously. In addition, a single gripper robot is responsible for loading and unloading parts to and from the selected machine. In the current study, the output of this system consists of various part types and operates continuously. Each component requires processing by the machines, and there is no buffer storage between the machines. For the production of each part, multiple types of operations must be performed on the machines; by percentage, some of these operations are performed on machine one, while the remaining ones are performed on machines two and three, respectively.

The primary objective of this study is to determine the sequence of entering parts into an unreliable three-machine robotic cell that experiences random failure and repair times while minimizing cycle time (S_2/$S6$ cycles) and total production cost.

B. Cycle time

Six cycles, designated S_1, S_2, S_3, S_4, S_5 and S_6 cycles, may be utilized for part displacements in a 3-machine robotic cell. Here, we focused on the S_2 and S_6 cycles because they are well-known and commonly used cycles, but they have received less modeling attention than the other robot move cycles since they are more complicated. The move cycles S_2 and S_6 are described in the following paragraphs.

Based on the S_6 cycle, the robot begins following operations sequentially from the input buffer. (1) picking part *i,* (2) proceeding to the first machine, (3) loading the first machine, (4) transferring to the third machine, (5) Waiting for the completion of the process on part (i–2) (if required), (6) unloading the part from the third machine, (7) transferring the item to the output buffer, (8) loading the output buffer, (9) moving to the second machine, (10) If necessary, waiting for the completion of the process on the part (*i*-1), (11) unloading the part from the second machine, (12) moves the part to the third machine, (13) loads the part onto the third machine, (14) transferring to the first machine, 15) if necessary, waiting until the part *i* ‘s process is complete, (16) unloading the initial machine, (17) transferring the part from the first machine to the second machine, (18) loading the part on the second machine, and (19) returning to the input buffer. The activity sequence of the S_6 cycle is encoded by A_{01} A_{34} A_{23} A_{12} and it is a one-unit cycle, as shown by (Sethi et al., 1992; Gultekin, Akturk and Karasan, 2007).

Equation (1) could be used to calculate the S_6 cycle time based on Table II’s key cycle time calculation parameters and according to (Gultekin, Akturk and Karasan, 2008).

$$T_{S6}=\max\{8\epsilon+12\delta, t(1)+4\epsilon+4\delta, t(2)+4\epsilon+4\delta, t(3)+4\epsilon+4\delta\} \quad (1)$$

The general process of S_2 cycle in a three-machine cell is as follows. Once more, the input buffer is the initial location of the robot. Then, the robot performs the subsequent operations in succession. (1) The robot picks up part *i,* (2) moves to the first machine, (3) loads part *i* onto the first machine, (4) moves to the second machine, (5) Waits for the completion of the process on part (*i*-1) (if necessary), (6) unloads the component from the second machine (*i*-1), (7) moves the part (*i*-1) to the third machine, (8) loads the part onto the third machine, (9) returns to the first machine, (10) If necessary, wait until the process on part *i* is complete, (11) unload the part from the first machine, (12) transfer it to the second machine, (13) load the part *i* onto the second machine, (14) proceeds to the third machine, (15) if necessary, waits until the third machine’s process is complete, (16) unloads the part (*i*–1) from the third machine,

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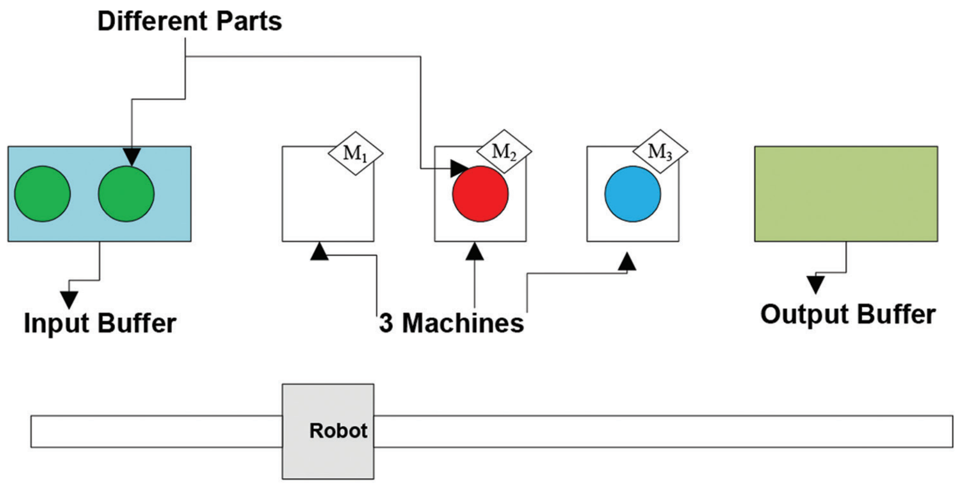

Fig. 2. A typical layout for an in-line robotic manufacturing cell comprising 3 machines.

Table II
Cycle Time Parameters

Parameters	Expression
∊	Loading/unloading time
δ	Robot's movement time between two consecutive locations
T_{S6}	Cycle time based on S_6 robot move cycle
T_{S2}	Cycle time based on S_2 robot move cycle
A_{pq}	Robot activity sequence from station, *p*, to station, *q*, for *p*=0,1,2,3 and *p*=0,1,2,3.
ti (j)	Processing times of part *i*based on the Percentage of operations done by each machine *j*; *i*=1,…., *n*; *j*=1,2,3.

(17) transports the product to the output buffer; (18) deposits the product at the output buffer; and (19) returns to the input buffer. As a general rule, the activity sequence of the S_2 cycle is encoded by A_{01} A_{23} A_{12} A_{34}, and this cycle produces one product in each cycle; see (Sethi et al., 1992). Equation (2) reveals the S_2 cycle time based on "Table II" and in accordance with (Gultekin, Akturk and Karasan, 2008).

$$T_{S2} = max\{8\in +12\delta, t(1)+6\in +8\delta, t(2) +4\in +4\delta, t(3)+6\in +8\delta, \frac{(t(1)+t(2)+t(3))}{2+4\in +4\delta}\} \quad (2)$$

The encoding of the movement cycles for three-machine robotic cells is tabulated in Table I.

C. Total Production Cost

Total production cost is the second objective function of this study. The components of the total cost of production are machining, tooling, and preventive maintenance (Akturk and Gurel, 2007). Although tool switching has been measured in several studies, such as (Kamalabadi, Sadeghi and Maihami, 2012), (Farughi et al., 2017), and (Moradi, Yousefi Nejad Attari and Farughi, 2018), in the present study, it was ignored and the cost of tooling is considered to be a constant value. The following are the main parameters for calculating the total production cost:

CM	Machining cost ($/min)
CPM	Cost of a PM visit ($/visit) without considering any setup cost
CT	Cost of tool ($/tool) Tool replacement prohibited in an operating cycle
DR_j	Expected down rate of machine *j*
OP	Observation period
n	The number of produced parts by type based on the percentage of operations done by each machine during the simulation period
N	Number of throughout products in the simulation period
F	Total cost ($/times unit)
TTF	Time to failure (times unit)
TTR	Time to repair (times unit)
t_i (j)	Processing times of part based on the Percentage of operations done by each machine *j*; *i*=1,…., *n*; *j*=1,2,3

Consequently, the total cost per operating cycle could be calculated by Eq. (3).

$$F = \sum_{i=1}^{n} n\ CM\ t_i(j) + \sum_{j=1}^{3} \mathrm{CPM}\ DR_j\ OP\ + \mathrm{N\ CT}; \quad j=1,2,3 \quad (3)$$

D. Simulation

Simulation-based optimization approaches have become efficient measures for decision-makers to find near-optimal solutions within a reasonable time. In this research, a simulation model of different scenarios for parts sequencing in a three-machine robotic cell is developed using discrete-event simulation software. In the simulation model, each unique sequence of parts entering the robotic cell is considered a scenario, and a simulation model is developed to simulate the scenarios and generate output data for each one.

Simulation builds a real-process model of a system over time and conducts experiments to determine the system's behavior (Shannon, 1998). The procedure for doing a simulation in a robotic cell (as an example) briefly includes formulating the problem and objectives; presenting a conceptual model for the cell or a series of mathematical equations regarding the context of the robotic cell; collecting data; developing the simulated model of the robotic cell; confirming the simulated model; designing experiments;

performing simulation runs; and analyzing and documenting results (Banks, 1998).

After a certain period of simulation run, the system could reach a stable state. This period is known as a warm-up period and is typically set to 10% of the observation period in simulation software configurations. The beginning of the observation period coincides with the conclusion of the warm-up period. The simulation model is developed in Section III.

E. Banker–Charnes–Cooper (BCC) DEA model

As mentioned earlier, the use of simulation in connection with optimization may assist decision-makers in developing efficient scenarios. Using DEA as the optimization tool to evaluate and classify the scenarios is a distinctive aspect of three-machine robotic cells that have not been done yet. DEA is one of the most distinguished methods for measuring the performance of homogeneous DMUs. A DMU is an entity responsible for converting inputs into outputs. This method's strengths are that it permits the use of multiple inputs and outputs, and the dimensions of input/output do not need to be converted. However, this method's weakness is that outliers may affect the results.

In this study, one of the classical DEA models is used to evaluate the designed scenarios. Scenarios are treated as DMUs due to their output and input characteristics. We obtain DMU data through scenario execution. Here, DEA utilizes the BCC model to select the most effective scenarios.

The BCC DEA model can be described as follows (Banker et al., 1984): suppose there are "*n*" DMUs to be measured with "*m*" different inputs and "*s*" different outputs. DMU_0 consumes the input value x_{i0} and produces the output value y_{r0}. Under the assumption $x_{i0}\geq 0$, $y_{r0}\geq 0$, the efficiency formula is $\frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}}$. Equation (4) represents the efficiency of DMU_0 as a fractional linear program based on the BCC Ratio Model (Input Orientation). "u_r", and "v_i" are the assigned output and input weights, while "*W*" is a free variable. In this study, the inputs/outputs will be determined, explained in detail, and implemented in sections III and IV.

$$\max E_0 = \frac{\sum_{r=1}^{s} u_r y_{r0} + W}{\sum_{i=1}^{m} v_i x_{i0}} \tag{4}$$

S.t.

$$\frac{\sum_{r=1}^{s} u_r y_{rj} + W}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad j=1,2,\ldots,n$$

$$W;\ \text{free variable}$$
$$u_r \geq 0$$
$$v_i \geq 0$$
$$r=1,2,\ldots,s$$
$$i=1,2,\ldots,m$$

F. Assumptions

Assume that machines in this robotic cell have two independent states: active and inactive. Failure and repair rates may be constant or time-dependent; λ(t) and μ(t) separately. The study's basic assumptions are summarized:

1. The availability of components at the input buffer and an empty position at the output buffer are both true.
2. The processing time for parts on the machines has been specified, despite breakdowns, etc.
3. The machines are subject to random failures and require maintenance.
4. The statistical density functions of TTF and TTR have accepted reliable parameters.
5. Setup times are insignificant.
6. Pre-emption in the processing of any operation is prohibited.

G. Cases

The issue is investigated using an example derived from prior work (Batur, Karasan and Akturk, 2012). In the following examples, each color corresponds to a distinct type of part.

Example 1. A three-machine robotic cell produces three different products separately, including Blue (B): 57, Red (R): 84, and Purple (P): 87, with their respective process times (in minutes), ∈=1 and δ=2 time units, see (Batur, Karasan and Akturk, 2012).

Example 2. A three-machine robotic cell is assumed to produce a product in 57 minutes (a Blue colored product). ∈ and δ separately are 1 and 2 min; see (Batur, Karasan and Akturk, 2012).

Table III contains the cost parameters and their corresponding values for these three-machine robotic cells (Examples 1 and 2). These parameter values are assumed to be constant.

III. Developing Simulation Model

For the purpose of analyzing the existing robotic cell, the integration of computer simulation and linear programming optimization is used to control different sources of uncertainty. Enterprise dynamics (ED) is used to model the sequence of components in the presented robotic cell for simulation purposes. This simulation tool employs drag-and-drop technology and has a user-friendly interface to facilitate the modeling of anticipatory layouts.

"Fig. 3" illustrates the system's simulation model. In this model, three dissimilar products flow through the system based first on the move the cycle of the robot and then on the S_2 move cycle, utilizing the ED special elements.

To obtain unbiased estimates, simulation models were run for long periods of time (>10000 h) following a 50-h warm-up period. In addition, the definition of performance measures (PFM) is as follows. The desired input and output variables of the DEA method are comprised PFMs.

Y_1: The average time for each S_6 (S_2) cycle in the simulation period

Y_2: The average operating cost per part in the simulation period

Table III
Characteristics Of Cost Parameters

Characteristics of Cost Parameters	CM=50	CT=45
TTF=NegExp (10)	TTR=NegExp (2)	

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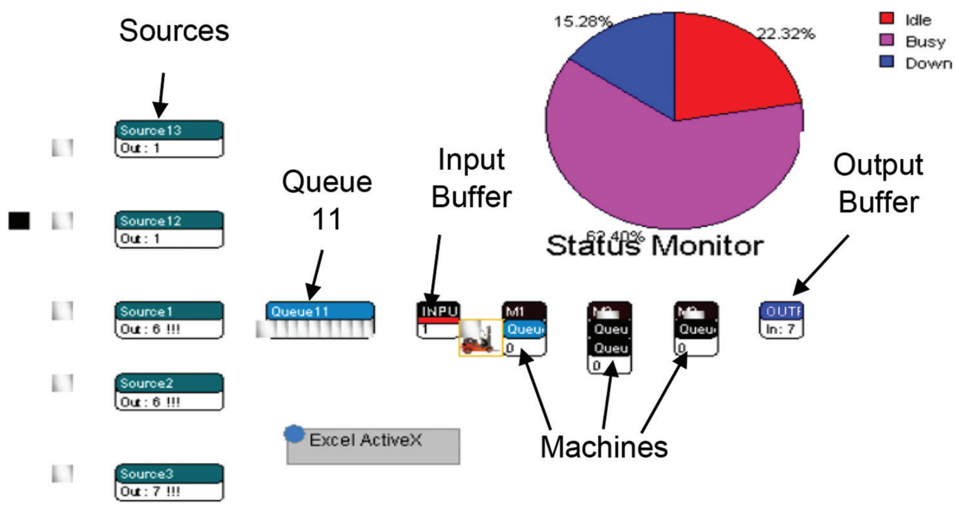

Fig. 3. A simulated model for the 3-machine robotic cell layout using ED.

Y_3: Number of generative throughout the simulation period

To select the inputs/outputs of the system, a fundamental understanding of the production system and data analysis is required. In general, the major resources that enter the manufacturing system are the inputs, and the primary output is the production quantity (Jain, Triantis and Liu, 2011). This is also true for the robotic cell. Therefore, cycle time and cost are the typical inputs, and the operational output of the current robotic cell is the produced throughput.

IV. Results

Simulation-based optimization methods were used to find the best sequencing patterns in a three-machine robotic cell. In this section, first, the validity of the simulation model is evaluated in A. Then, by defining the scenarios in B, DEA as the optimization tool will classify the scenarios in C. Discussion over the results will come in D.

A. Validation of the Simulated Model

Example 2 was simulated as a three-machine robotic cell (machine failures were ignored) based on the S_6 cycle and the S_2 cycle, respectively. After running the simulation model, it was determined with a confidence level of 95% that the average S_6 cycle time and operating cost are 86.719 seconds and 187.5, respectively. ED software also reports that the average S_2 cycle time and operating cost are 68.948 and 187.5, respectively.

Mann–Whitney Hypothesis testing is used to compare the statistical differences between the simulated model dataset and the real dataset. This is performed to validate the simulation model. The results of Equations (1) and (2) are referred to as the real dataset. The simulated model data includes the mean daily production after 25 replications of the simulation model. A P-value >0.85 indicates that there is no significant difference to reject the equality of two means, and the simulation model's validity is confirmed.

In the next step, several scenarios are created to determine the optimal sequence for the part's entrance into the robotic cell.

B. Scenario Design

In this step, various sequencing patterns for the part's entrance to the robotic cell are formed. Each sequence pattern is simulated by ED software as a scenario. Table IV depicts the designed scenarios derived from Example 1. B-P-R and B-R-P are two possible sequences for case study 1 which come in the right part of "Table IV," and the percentage of operations performed by each machine is defined in the left part of the table. Example 1 was simulated twice, once according to the S_6 cycle and the second time according to the S_2 cycle. The results according to the definable PFMs for the S_6 cycle and the S_2 cycle are separately summarized in Tables V and VI. After adjusting the simulation time, it is possible to obtain the average cycle time (S_2/S_6), average cost, and number of generative throughput. The objective is to maximize throughput while minimizing cost and cycle time.

Let us discuss scenario 7 as an example. Consequently, scenario 7 indicates that 60% of the operations are done on Machine1 and Machine3, equally. The rest of the operations to produce a part are performed by Machine2. Meanwhile, the first part to be allocated to machines 2 and 3 is Blue (B) and the sequencing pattern for entering the parts to the cell is B-P-R, meaning Blue-Purple-Red; see (Cases in Section II). Results for this scenario show that based on the S_6 cycle outcomes in "Table V," the cycle time is 48.841, the cost is 15959.735, and the throughput is 40539. Whereas based on the S_2 cycle results in "Table VI," the cycle time is 69.862, the cost is 22782.198, and the robotic cell can produce 28341 parts during the simulation period.

On the dataset, the DEA tool is utilized to identify the optimal scenarios and the results will be displayed in C.

C. DEA Results

The optimal sequence is determined using a simulation-based optimization approach and the DEA method. DMUs in this case have two inputs and one output. As previously mentioned, the inputs consist of average cycle time (S_6/S_2) and average cost, while the output is the number of produced throughput. The DEA method based on the "Equation (4)" is applied to compare the proposed scenarios.

Table IV
Designed Scenarios for the Example 1

Scenario Group (SG)	Sequence			Seq. 1 B-P-R			Seq. 2 B-R-P		
	The Percentage of operations performed by each machine			The first allocated part to the Second and Third machine			The first allocated part to the Second and Third machine		
SG	M_1	M_2	M_3	B	P	R	B	P	R
				Scenario Number					
A	33.3%	33.3%	33.3%	1	2	3	16	17	18
B	20%	40%	40%	4	5	6	19	20	21
C	30%	40%	30%	7	8	9	22	23	24
D	25%	25%	50%	10	11	12	25	26	27
E	60%	20%	20%	13	14	15	28	29	30

Table V
Definable PFM Values Based on the Scenarios of S_6 Cycle in Example 1

PFMs	Scenario Number (SN)					
	1	2	3	4	5	6
Y_1	47.915	43.587	43.586	49.155	58.234	49.154
Y_2	15659.37	15669.16	15668.785	17657.079	20898.394	17657.076
Y_3	41322	41296	41297	36618	30909	36618
SN	7	8	9	10	11	12
Y_1	48.841	44.406	44.367	54.779	54.744	60.157
Y_2	15959.735	15961.3	15947.624	19665.213	19652.724	19632.534
Y_3	40539	40535	40570	32858	32879	32913
SN	13	14	15	16	17	18
Y_1	76.917	69.965	70.047	43.594	59.893	59.872
Y_2	25071.426	25085.985	25115.143	15671.424	21490.558	21482.735
Y_3	25742	25727	25697	41290	30053	30064
SN	19	20	21	22	23	24
Y_1	49.221	49.196	64.08	48.819	44.382	44.365
Y_2	17680.594	17671.95	20905.797	15952.7	15952.7	15946.842
Y_3	36569	36587	30898	40557	40557	40572
SN	25	26	27	28	29	30
Y_1	54.629	54.716	54.695	69.989	70.115	70.04
Y_2	19611.201	19642.028	19635.499	25094.724	25139	25113.195
Y_3	32949	32897	32908	25718	25672	25699

Table VI
Definable PFM Values Based on the Scenarios of S_2 Cycle in Example 1

PFMs	Scenario Number (SN)					
	1	2	3	4	5	6
Y_1	73.967	67.268	67.238	78.605	71.531	78.708
Y_2	24114.609	24123.581	24112.815	25620.482	25645.829	25653.953
Y_3	26768	26758	26770	25188	25163	25155
SN	7	8	9	10	11	12
Y_1	69.862	69.865	69.876	81.572	81.649	89.89
Y_2	22782.198	22783.799	22787	29231.379	29257.8	29282.941
Y_3	28341	28339	28335	22065	22045	22026
SN	13	14	15	16	17	18
Y_1	114.033	92.838	102.153	67.222	67.3	73.919
Y_2	37118.066	33252.545	33262.809	24106.54	24135.253	24099.373
Y_3	17363	19388	19382	26777	26745	26785
SN	19	20	21	22	23	24
Y_1	71.498	78.633	91.69	69.816	69.862	69.881
Y_2	25633.656	25629.602	29866.601	22767.807	22782.199	22788.601
Y_3	25175	25179	21594	28359	28341	28333
SN	25	26	27	28	29	30
Y_1	92.862	89.778	92.878	92.825	92.797	102.132
Y_2	33261.095	29245.905	33266.227	33247.419	33237.167	33255.967
Y_3	19383	22054	19380	19391	19397	19386

Tables VII and VIII summarize the efficiency scores for each scenario, as well as the S_6 and S_2 cycles, in that order. Using the Lingo software, calculations were performed.

According to the results for scenario 7 (as an example), this scenario is more efficient based on the S_2 movement cycle of the robot than S_6. The efficiency scores of this scenario confirm this fact which is a 0.963 score based on the S_6 cycle and 0.999 scores based on the S_2 cycle. However, none of them is efficient, since the efficiency score is one.

V. Discussion

The relative score of an efficient scenario is one, according to DEA logic. Thus, scenarios numbered “1” and “3” will be the most efficient for Example 1 under S_6. Concerning the foregoing, as shown in Example 1, the sequence Blue-Purple-Red is preferred over any other sequence pattern when the Blue or Red part is the first one to be produced on the second and third machines. This applies to three different part types. Scenario “3” with 43.586-time units has a lower average S_6 cycle time score than scenario “1” with 47.915 time units. In contrast, scenario “1” has lower production costs than scenario “3.” During the observation period, the output rate for scenario “1” is 41322 versus 41297 for scenario “3”.

In a three-machine robotic cell operating on the S_2 cycle, the “22” scenario has the optimal part sequence pattern for Example 1. The Blue-Red-Purple sequence when Blue part is the first part on the second and third machines is the optimal part sequence pattern for these three different part types, robotic cell under S_2.

In optimal scenarios, although the average cycle time and cost under S_6 are less than those values under S_2, the number of total products produced during the simulation period under S_6 exceeds that of S_2. Among the efficient scenarios, scenario coded “1” (which is under S_6) has the highest throughput, which is just over 41,300 during the simulation period.

Figs. 4 and 5 compare the average efficiency of each scenario group based on the two candidate sequences for the move cycles (S_6/S_2). Clearly, the efficiency scores of the two sequences based on both cycles follow a nearly identical trend.

Scenario number 7 till 15 and scenario number 22 till 30 for the S_6 movement cycle in both sequence patterns have comparable amounts of efficiency, whereas the trends of both sequence patterns based on the S_2 cycle are volatile, fluctuating between 0.375 and 1. Nevertheless, on average, sequence pattern 1 has more efficient scenarios in both cycles.

Overall, the comparison demonstrates that the scenarios, as DMUs in the DEA method, are more efficient when the percentage of operations assigned to machines is closer to one another. Moreover, due to the similarity of the machines and their TTF/TTR, the optimal assignment of operations to machines occurs when the number of operations allocated to each machine is close. Consider the characteristics of scenarios 1, 2, 3, 7, 8, 9, 22, 23, and 24 as the near-optimal scenarios in both cycles.

Table VII
Efficiency Scores of Scenarios Based on the BCC Model for S_6 Cycle in Example 1

SN	Scenario Number (SN) Efficiency Scores (ES) (Below comes)					
	1	2	3	4	5	6
ES	**1**	0.999	**1**	0.786	0.56	0.786
SN	7	8	9	10	11	12
ES	0.963	0.963	0.965	0.633	0.634	0.635
SN	13	14	15	16	17	18
ES	0.39	0.388	0.387	0.999	0.529	0.529
SN	19	20	21	22	23	24
ES	0.784	0.785	0.56	0.963	0.964	0.965
SN	25	26	27	28	29	30
ES	0.63656	0.634	0.635	0.388	0.386	0.387

Table VIII
Efficiency Scores of Scenarios Based on the BCC Model for S_2 Cycle in the Example 1

SN	Scenario Number (SN) Efficiency scores (ES) (Below comes)					
	1	2	3	4	5	6
ES	0.891	0.979	0.98	0.789	0.866	0.787
SN	7	8	9	10	11	12
ES	0.999	0.998	0.998	0.666	0.665	0.603
SN	13	14	15	16	17	18
ES	0.375	0.514	0.467	0.981	0.978	0.892
SN	19	20	21	22	23	24
ES	0.867	0.788	0.579	**1**	0.998	0.998
SN	25	26	27	28	29	30
ES	0.514	0.605	0.514	0.514	0.515	0.467

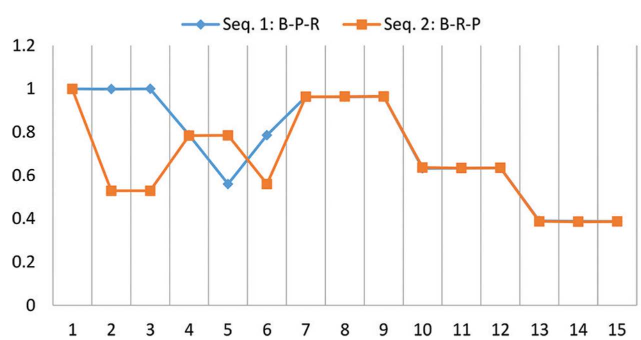

Fig. 4. Comparing the average efficiency of each scenario group based on the two candidate sequence patterns for the S_6 cycle.

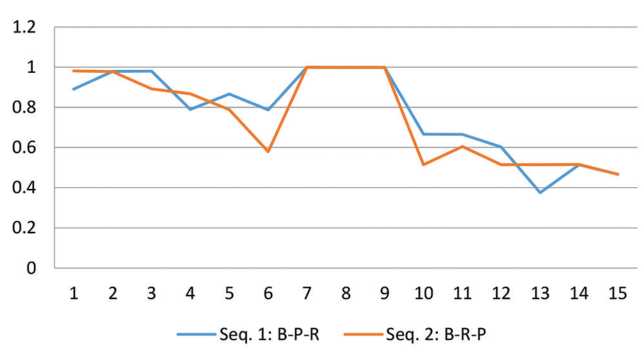

Fig. 5. Comparing the average efficiency of each scenario group based on the two candidate sequence patterns for the S_2 cycle.

V. Conclusion

Simulation-based optimization, as a novel practice, was demonstrated in this study to determine the sequencing pattern of the parts in a robotic cell under breakdowns resulting from random failures. The cell consists of three machines that produce dissimilar parts and follow a S_6 or S_2 cyclic pattern for the robot. For the production of a part, multiple types of operations are performed on the machines. By percentage, some of these operations are done on machine one, while the remainder are performed on machines two and three separately. Optimal scenarios for the part's entrance into the robotic manufacturing cell are evidence of the simultaneous minimization of cycle time and cost. Using the DEA method, the proposed scenarios, which have been designed based on different sequences for entering the parts of the cell, were compared in numerical examples. Furthermore, the comparison reveals that the efficient scenarios are those, in which the percentages of operations assigned to the machines are close to each other, due to the similarity of the machines and their TTF/TTR. The results endorse the practicality of applying the DEA approach in robotic cell problems, which can be a helpful tool for decision-makers in robotic manufacturing systems. There is a range of robotic cells available to any industry, such as the automotive industry, to fabricate, finish, weld, transfer, or assemble parts. This depends on the size, weight, or type of the robots used. It is possible to extend the results of this study to include robotic cells with robot failures or robotic cells with dual gripper robots instead of single ones. Consequently, evaluating parts sequencing in unreliable m-machine robotic cells with the above features using simulation and other DEA models is an excellent practical topic for future study.

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