Concurrent Optimization of Reliability, Maintainability and Total Cost in a Job Shop Production System with Multiple Fuzzy Parameters

Ali Bonyadi Naeini[*1], Hossien Gholizadeh[2]

[1,*] Corresponding author: Department of the Business, Iran University of Science and Technology, Tehran, Iran

Address: Department of Progress Engineering at Iran University of Science and Technology (IUST), Narmak, Tehran, Iran, Tel. : +982173228056 , Mob. :+98 9121056721, E-mail: bonyadi@iust.ac.ir

(https://orcid.org/0000-0003-3119-551X)

[2] Department of Progress Engineering, Iran University of Science and Technology, Tehran, Iran

Address: Department of Progress Engineering at Iran University of Science and Technology (IUST), Narmak, Tehran, Iran, Tel.: +982123576350 , Mob. :+98 9127091799, E-mail: hossein_gholizadeh@ind.iust.ac.ir

(https://orcid.org/0000-0001-7549-6846)

Abstract

An integrated intelligent algorithm is proposed to optimize the reliability, maintainability, and total cost in the job shop production system. The algorithm consists of three basic modules of computer simulation. each comprising three phases of Algorithm, simulation, and Experiments/robustness validation. In the design phase, different scenarios are determined by changing parameters affecting the reliability, maintainability, and total cost. The job shop production system is simulated in the simulation phase. Then, a fuzzy simulation approach is implemented to run the simulation model for each scenario with ambiguous inputs. Accordingly, the investment cost, maintenance cost, mean time to repair (MTTR), and mean time to failure (MTTF) are obtained. Finally, the performance of different scenarios is assessed in the third module. ANN and DEA are separately used in this module and the preferred method is selected based on the robustness test and extensive sensitivity analysis. DEA and ANN are then employed to rank the design alternatives concerning the initial inputs and outputs. To show the applicability and superiority of the proposed integrated algorithm, it is applied to optimize the design of a fuzzy job shop production system consisting of five workstations.

Keywords: Maintainability; Reliability; Fuzzy Parameters; Artificial Neural Network; Data Envelopment Analysis; Fuzzy Simulation

1. Introduction

Quality factors such as availability, maintainability, and reliability have turned into important issues in production systems [1, 2]. Increasing the maintainability in the design phase will lead to fewer failures while decreasing the maintenance cost [3, 4]. Increasing the reliability in the design phase also decreases the repair time and consequently the corrective maintenance cost of the system [5].

Therefore, the design phase should be emphasized more than other phases of the system life cycle. In the other words, different scenarios can be defined in this phase. Then, the optimum design scenario can be chosen by performance assessment. On the one hand, one of the best ways to minimize the failures in the production systems is to increase both of reliability and maintainability parameters. On the other hand, these parameters are highly related to cost. Therefore, in order to generate different scenarios, reliability, maintainability and cost of the system should be concurrently changed. In the design phase, there are two general ways of increasing production systems reliability:

- Using machines with higher level of reliability. For example, the machines with greater Mean Time to Failure (MTTF).
- Allocating redundant machines to workstations.

Optimization scheduling with regard to the reliability, maintainability and cost is difficult in job shop production system because of its complexity [6, 7]. So, there is a scarcity in articles about optimization job shop production systems with the reliability, maintainability and cost, simultaneously.

In this paper, an integrated algorithm has been proposed to optimize design of a fuzzy job shop production system. The proposed algorithm has three basic modules. In the first module (design phase), different scenarios are generated by changing the parameters which are the number of identical redundant machines in each workstation and their MTTFs. In the second module (simulation phase), job shop production system is simulated. After that, the fuzzy simulation approach is implemented to run the simulation model for each scenario. Mean time to repair (MTTR), MTTF, investment cost and maintenance cost are obtained by the fuzzy simulation. The investment and maintenance costs are considered as the inputs of third module whereas MTTR and MTTF are its outputs. Finally, the performances of each scenario are assessed in the third module (the performance assessment phase). The performance assessment is about determination of overall performance score of probable scenarios considering both consumed inputs and generated outputs. In this paper, artificial neural network (ANN) and data envelopment analysis (DEA) methods are separately used in this module and the preferred method is selected based on robustness test.

1.1. Research contribution

An integrated algorithm is proposed in this paper to optimize the design of a fuzzy job shop production system (FJSP). A fuzzy job shop production system consisting of five workstations is studied to show the applicability and superiority of the proposed algorithm. Each workstation is composed of at most three identical redundant machines. The MTTFs of machines are fuzzy parameters. The corrective maintenance restores failed machines into the operational mode. Standby redundancy is used in the system where each component has one of three states of standby, operation, or repair. When the component under operation fails, one of the standby components starts its operational mode. The components can fail only when they are in the operation or standby modes.

1.2. Research steps

The rest of this paper is organized as follows. The literature on analyzing, modeling, and optimizing production systems based on the cost, reliability, and other quality factors is reviewed in Section 2. The methodology (the main concepts and the proposed algorithm) is described in Section 3. A case study is presented in Section 4 to illustrate the proposed algorithm. The results and analyses (the sensitivity analysis, robustness test, verification, and validation of results) are presented in Section 5. Finally, concluding remarks are presented in Section 6.

2. Literature Review

Van der Duyn Schouten and Vanneste [8] presented an optimal preventive maintenance policy for a production system. The presented production system was equipped with an installation to be supplied with and a buffer to prevent interruptions in the production process when the installation randomly fails. Their maintenance policy was based on the age of the installation and the content of the buffer. Levitin and Meizin [9] Used redundant machines and in-process buffers to obtain an acceptable level of reliability. Kodama and Sawa [10] Obtained the availability and reliability function of a series-parallel system where its components were subject to failure, and a general distribution function was considered for repair times. Boschian, Rezg [11] Presented two maintenance strategies to optimize a production system composed of two in-parallel machines. Tsarouhas, Arvanitoyannis [12] Analyzed a cheese production line based on the reliability, availability, and maintainability (RAM) to investigate and solve problems in the cheese manufacturing process. They found some parameters in the system such as the system availability, dominant failure modes, MTTF, and MTTR. Simulation has been extensively used in various types of production systems [8, 13-17]. Rajpal, Shishodia [18] Used an ANN to model the reliability, availability, and maintainability in a helicopter transportation facility. Optimization algorithms and several reliability approaches have also been used in recent studies [19]. Taking the advantages of fuzzy sets theory in various applications, it is one of the topics of interest to both scientists and managers, and several studies have been recently conducted in this area (*e.g.*,Jamrus, Chien [20], Wen, Yan [21]). Mettas [22] Presented a model to estimate the minimum required reliability for each component that satisfies the reliability value for the multi-component system. Simulated-annealing and genetic algorithms have also been used to optimize reliability in complex systems [23, 24]. Optimization algorithms have received more attention since information technology played a more prominent role in the production process [25, 26]. These algorithms will be more important in the decision-making process, especially in cases where "cost" is one of the key factors [27]. By reviewing the thematic literature on the flexible job-shop scheduling problem, we can distinguish three categories in previous research. In the following, we will explain the main reason for using the hybrid method (a combination of optimization methods). First, we describe the advantages and features of different optimization methods, and finally, we will compare these methods with the hybrid ones used in new studies.

2.1.multi-objective optimization

Initial studies in the field of optimization were single-objective functions and therefore it was not possible to evaluate and compare several different indicators simultaneously. Hence, optimization using multi-objective functions was proposed. For example, Gen, Zhang [28] in their study expressed the optimization of consumption and total surplus resources using a multi-objective algorithm. The research of Qin, Fan et al (2019) was indeed the design of a multi-objective function to optimize production volume, total production cost, and delivery delay time [29]. Gong, Deng (2018) in a scheduling study, by designing a model, entered the variables "machine flexibility" and "worker flexibility" simultaneously into evaluation functions and proposed a magnetic algorithm to solve the optimization function [30, 31]. The purpose of this function was to minimize the amount of production, the workload of the machines, and the total work of all machines. So, it is obvious that as the number of factors influencing decision-making increases, we will have to use new methods to be able to optimize multiple goals simultaneously. In the present study, that three basic factors play an important role in the final decision, we must use the multi-objective optimization method. Fazlollahtabar and Niaki[32] described a comprehensive fault tree analysis based on the critical components of industrial robots [33]. Karimi, Niaki [34] presented A complete classification of the subject literature in this field.

2.2. multi-constraint optimization

Given different configurations for various types of production scheduling programs, different types of FJSSPs with additional constraints were placed in the background. For instance, Gao and Pan[35] analyzed the necessary FJSSP resources for operations. Wu and Sun[36] Chaudhry and Khan (2016) conducted a study by reviewing the FJSP thematic literature [37]. They have found that most research on FJSP has looked at simple FJSP instead of looking at different scenarios. But in recent years, the trend towards the FJSP method has increased intending to evaluate different scenarios. Lu, Li et al (2017) examined FJSP with controllable processing time [28]. developed an FJSSP in which machines could operate at different levels of speed. Lu, Li[38] focused on an FJSSP with controlled processing times, in which additional resources could be allocated to control the processing time. El Khoukhi, Boukachour [39] analyzed an FJSSP with constraints on the unavailability of machines with respect to preventive maintenance activities. Sun, Lin [40], Lin, Zhu[41] modeled the FJSSP processing time on a fuzzy triangular number to resolve the uncertainty caused by volatility in production environments. However, Xie and Chen[42] defined the indefinite processing time as an interval gray number. Considering consecutive events in production scheduling, some researchers addressed the flexible job shop rescheduling problem of the dynamic FJSSP. Shahgholi Zadeh, Katebi[43] analyzed a dynamic FJSSP with variable processing times by considering certain constraints. For instance, they predicted that machines could change due to the nature of production processes or different configurations. Given the job priority constraints, most studies of the FJSSP assume jobs to be independent. Nevertheless, some researchers considered assembly operations and concentrated on dependent jobs. This type of an FJSSP with constraints on job priorities usually emerges in the assembly job shop scheduling problem (AJSSP). Generally, an AJSSP can be classified as a two-step AJSSP and a composite AJSSP. In the two-step AJSSP, the first step is called manufacturing in which usual operations are performed, whereas the second step is called assembly in which assembly operations are implemented [44]. Basically, the first step of a conventional FJSSP includes constraints on the priority of serial operations, whereas the second step includes only constraints on the hierarchical priority. Therefore, two types of constraints called the linear structure and the tree structure can be analyzed in two separate steps. By contrast, the composite AJSSP combines usual operations and assembly operations and leads to a combination of constraints on hierarchical priority and serial priority. As a result of growing complexity, a few papers have analyzed the AJSSP. Dileeplal and Narayanan[45] developed a multi-objective genetic algorithm based on a permutation scheme and invented evolutionary operators to solve the multi-objective AJSSP. However, they allocated each operation to one fixed machine and excluded the machine flexibility. To solve the single-objective AJSSP, Zou, Rajora [46] developed a level-based method for generating initial solutions level by level in the priority tree and implementing crossover and mutation operators based on the level obstacle for the evolutionary optimization of the single-objective AJSSP. Nonetheless, the level-based method is completely complicated because an encrypted solution should be decomposed into several levels. In Zhu, Zhou[47] , a Neo4j-based semantic diagram method was proposed for modeling the scheduling problem and developed an ant colony optimization algorithm that would directly manipulate the job shop data on diagrams. However, the proposed method focused on the single-objective FJSSP–JPC, and the non-encryption graph method can only be executed on the ant colony optimization algorithm.

2.3.Hybrid algorithm

hybrid methods will have high accuracy and fast convergence in search of optimal solutions due to the strengths of the subset of different algorithms. So that's why they have attracted the attention of many researchers. Fathollahi-Fard, Hajiaghaei-Keshteli et al (2018) proposed a three-level decision model intending to optimize a tire supply chain. In this model, four new hybrid algorithms based on metaheuristics have been used and the Keshtel hybrid algorithm was formed to solve this problem [25, 26].

Finally, the simulation showed the best performance. Gen, Zhang, et al (2017) also summarized three hybrid evolutionary algorithms and presented them as five scheduling problems in production systems, proving the possibility of solving hybrid optimization problems [28].

Lin, Zhu (2019) Lin, Zhu (2019) in their study has proposed a hybrid multi-verse optimization (HMVO) which is a heuristic approach. The challenges of flexible planning have plagued many researchers for years. [41] Given the exponential complexity of these problems, swarm intelligence (SI) and evolutionary algorithms (EA) have been used to solve them, and these methods are constantly being developed and improved. Gao, Cao et al. 2019 state that since 2011, algorithms using real-life constraints to solve FJSP problems have evolved. The analysis presented in this study considers the process of using SI and EA to solve FJSP. As a result, two steps can be considered for simulation [48]. Table 1 summarizes some key features of previous studies.

3. Method: The Integrated Intelligent Algorithm

An integrated intelligent algorithm is proposed for concurrent optimization of reliability, maintainability, and total cost of a fuzzy job shop system with multiple outputs and noises. The proposed integrated algorithm consists of three basic modules of algorithm design, simulation, and Experiments/robustness validation of scenarios. These modules are shown in figure1.

3.1. Algorithm design

In this module, different scenarios are determined by changing the number of redundant machines in each workstation and their MTTFs.

3.1.1. Collection of Data

In this step, the data related to the parameters determined in the previous step are collected.

3.1.2. Identification of Scenarios

Possible scenarios are identified in this step. For this purpose, the number of redundant machines in workstations and their MTTFs are concurrently changed. Other parameters of the job shop production system are fixed in different scenarios.

3.2. Simulation

The increasing level of complexity and heterogeneity of modern systems has made the use of advanced tools in reliability problem analysis inevitable. Most current software uses classical methods to solve problems.

These methods can only be used to evaluate traditional criteria at a steady state; for example, to solve problems such as system failure probability, failure rate estimation, MTTF, MTBF, and MTTR. But newer models that have more flexibility will not have such limitations [59]. The job shop production system is simulated in this step. Considering that analytical methods are not capable of calculating the reliability, maintainability, and cost in the job shop production system, the computer simulation model needs to determine the exact values of the parameters of the job shop production system. The simulation model is described in Section 4 where the case study is presented.

3.2.1. Simulate system

In this step, the system is simulated assuming that all of the inputs and outputs are crisp.

p 1: estimate a propriety a-level sets.

p 2: Randomly generate $C_j(MTTF_i) = 95000000/190 \times (MTTF_j - 10) + 10000000; J = 1,2,...,15$ from the a-level sets of fuzzy variables

$\varepsilon, j = 1,2,...,N$.

p 3: Add $M_{\varepsilon' aj}$ into an index I.

p 4: Repeat the second to three steps N times.

p 5: back to I.

Running simulation model: The simulation model must be run three times. Feeding inputs and generated outputs of the simulation model in these three runs are as follows:

- Run 1: all the inputs are set to their lower bounds and the consequent generated outputs take their lower bounds.
- Run 2: all the inputs are set to their medium values and the consequent generated outputs take their medium values.
- Run 3: all the inputs are set to their upper bounds and the consequently generated outputs take their upper bounds.

Identifying fuzzy outputs: Considering that by performing the previous step, the lower, mid and upper bounds of each fuzzy output have been estimated, each output can be determined as a fuzzy triangular number.

Defuzzifying the inputs and outputs: In this step, if we need crisp data, we can defuzzify all of inputs and outputs by one of the proper defuzzifier methods.

3.2.2. Execution of Simulation Model

In this step, the computer simulation model presented in the previous step is run for each scenario. For this purpose, the values of parameters in each scenario are set in the simulation model. The number of redundant machines in each workstation and their MTTFs are changed in each scenario but other parameters are considered fixed. Therefore, the number of redundant machines in each workstation and their MTTFs are inputs to the simulation model whereas the outputs include the investment cost, maintenance cost, MTTR, and MTTF of the system. An important question must be answered before running the simulation model: how long should the simulation model be run? On the other hand, the simulation results should be retrieved from a steady state because of the importance of the system parameters such as the MTTF. Moreover, transient and steady states are identified through trial and error and robust examination.

3.3. Experiments/robustness validation

The efficiency scores of scenarios are measured in this module. ANN and DEA approaches are separately used for this purpose.

3.3.1. Determination of Variables

The maintenance and investment costs are the inputs to the performance assessment approaches. The outputs include the MTTR and MTTF of the system.

3.3.2. ANN Execution

Artificial neural networks (ANNs) are accounted as mathematical approaches to model cultured systems [60]. They can be used for classification [61] and regression problems [62]. These networks are huge complexes of analogous processors named Neuron performing coordinately to solve the problem and transfer data through electromagnetically connections (or synapses). Transferring the input data sets into the meaningful outputs is the purpose of neural networks.

Learning process is performed in a comparative way, i.e., through the examples the weights of synapses are altered in way that system will give a sensible response in case of new input data set (test data set). The artificial neural networks contain three layers including input, hidden and output. There are several architectonics for the neural networks, however there is a special stress on the most used and well-known one i.e., the multi-layer Perceptron (MLP) in this examination. This type of neural network is Perceptron which exists as the single layer Perceptron and Multi-layer Perceptron. Multilayer Perceptron is a fully connected network since each neuron in a layer is connected to the neurons in other layers. Mathematical representation of multilayer Perceptron is as follows (Relation.1):

$$y_k = f_{outer}\left[\sum_{(j=1)}^{M} w_{kj}^{(2)} f_{inner}\left[\sum_{i=1}^{d} w_{ji}^{(1)} x_i + w_{j0}^{(1)}\right] + w_{0k}^{(2)}\right] \tag{1}$$

Before using ANNs, some important issues should be considered as follows:

- Input and output variables number: input(s) and output(s) of ANN should be determined carefully.
- Hidden layers' number: hidden layers' number and number of neurons in hidden layers can be found by trial-error method.
- Hidden and output activation function: these functions are also determined by trial-error.

- Learning algorithm: The difference between real output and ANN's output shows the error in each neuron. The threshold value and interconnections weight in each neuron is attuned in order to minimize the error [63, 64].

A metaheuristic approach is developed in this step for ANN-based performance assessment.

- Divide S into two subsets: train (S_1) and test (S_2) data set.
- Use the ANN method to estimate the relation between input(s) and output(s).
- Run ANN* for S_C.
- Do the following steps for output $j^{th}:1,...,L$
- Calculate the error between the real output ($P_{real(ij)}$) and estimated output ($P_{ANN*(IJ)}$) in the evaluated scenarios (S_c).

$$E_{ij} = P_{real(ij)} - P_{ANN*(IJ)}; \qquad i = 1,...,n \qquad (2)$$

- Shift frontier function from the neural network for obtaining the effect of the largest positive error which is one of the unique features of this algorithm:

$$E'_{kj} = \max(E'_{ij}); \quad i = 1,...,n \qquad (3)$$

- $Sh_{ij} = E'_{Kj} * P_{ANN*(ij)} / P_{ANN*(Kj)}$ Calculate the efficiency scores for the j^{th} output $(j = 1,...,L)$. The efficiency scores range from 0 to 1. This maximum score is assigned to the unit used for the correction in each cluster.

$$F_{ij} = P_{ij} / (P_{ANN*(ij)} + Sh_{ij}); \qquad (4)$$

- Calculate the final efficiency scores by the following formula:

$$F_i = Average(F_{i1}, F_{i2}, ..., F_{iL}); \quad i = 1,...,n \qquad (5)$$

3.3.3. Running the DEA approach

In this step, the CCR DEA method is used to calculate the efficiency scores of scenarios in S_C.

3.3.4. Robustness Experimentation

The robustness test and sensitivity analysis of the ANN and DEA approaches are performed in this step. In other words, the sensitivity of the above approaches in dealing with small, medium and large noises is compared. The MAPE error between the efficiency scores of non-noisy and noisy scenarios (with noisy inputs) is used to show the robustness of the proposed methods.

4. Experiments: The Case Study

To show the applicability of the proposed algorithm, it is used to optimize design of a fuzzy job shop production system. Moreover, its parameters have been determined by expert judgments.

4.1. Step 1-1

The parameters and characteristics of the studied fuzzy job shop production system are as follows:

- It operates 7 days per week in two shifts (a total of 16 h) per day. It is assumed that there is no interruption between the two shifts.
- It has five workstations; each workstation with one to three inflexible identical redundant machines.
- Machines fail independently and failure happens only when a machine is in the operational or standby modes. The failure distribution functions are presented in Table 2. The MTTFs of machines are triangular fuzzy numbers listed in Table 3.
- The MTTF of each machine in the standby mode is twice that in the operational mode.
- Good-as-new corrective maintenance was used. In this type of corrective maintenance, the failure time distribution of repaired items is identical to that of a new item [65]. Therefore, after the repair, the MTTF of the repaired machine is identical to that of a new machine.
- The distribution functions of corrective maintenance associated with each machine time are presented in Table 2.
- Product demand arrivals follow a Poisson distribution. Inter-arrival times distribute exponentially every two hours. It is assumed that there is no space limit for demand under process and completed products.
- The presented system can produce four types of products. The demands for these four product types are as follows:
  - Type 1: 50%
  - Type 2: 20%
  - Type 3: 15%
  - Type 4: 15%
- The production process grid for each type of product is presented in Figure 2, and the distribution functions for the processing times are presented in Table 4.
- The relation between the cost of a machine and its MTTF is as follows:

  $$C_j(MTTF_i) = 95000000/190 \times (MTTF_j - 10) + 10000000; J = 1, 2, ..., 15. \quad (5)$$

  The cost and MTTF of the machines are respectively presented in dollar and hour in our case study.
- The maintenance cost is considered equal for all the machines with a uniform distribution and lower and upper bounds of 13.328 and 16.664 dollars per time unit, respectively. The annual interest rate of investment in the bank "*r*" is 15%.

4.2. Step 1-2

The required data were collected from experts' judgments as the historical data are not collected properly or are not approved by the management and experts of the system.

4.3. Step 1-3

Possible scenarios are determined by changing the number of redundant machines in each of the five workstations and their MTTFs according to Table 3. The number of possible scenarios is equal to 110084832 $(= 3 \times 11 \times 3 \times 11 \times 3 \times 16 \times 3 \times 18 \times 3 \times 13)$. 120 scenarios were by experts' judgments as of the sample of possible scenarios. The following hypothesis testing is defined to show that the number of scenarios in the sample is statistically sufficient:

H_0: all four indicators of scenarios follow a normal distribution function.

H_1: at least one of four indicators does not follow a normal distribution function.

Hypothesis testing is performed by MATLAB 2009 and the default value for the P-value is equal to 0.05. The null hypothesis is not rejected confirming that the sample of scenarios follows a normal distribution function by the probability of 95%.

4.4. Step 2-1

The simulation model is run for each of the scenarios. The model is characterized as follows:

- It has 10 inputs, 5 inputs for the number of identical redundant machines in 5 workstations, and the rest for the MTTFs of machines in workstations.
- The outputs are the investment cost, maintenance cost, MTTR, and MTTF of the system.
- It found 8760-time units of simulation by trial and error, which is equal to one year in the real world and seems appropriate to reach stable conditions.
- There are 5 fuzzy inputs related to the MTTFs of machines in the workstations. Consequently, a fuzzy simulation approach is used to run the simulation model for each of the scenarios. After running the simulation model for each scenario and identifying its fuzzy outputs, the center of gravity (COG) defuzzification method is employed to defuzzify all inputs and generated outputs.

4.5. Step 3-1

The maintenance and investment costs are inputs of performance assessment approaches and the MTTR and MTTF of the system output.

4.6. Step 3-2

This section describes the architecture of the ANN as follows:

- 120 designed scenarios are divided into two subsets: S includes 100 scenarios and the remaining 20 scenarios belong to S_C .
- S_1 and S_2 respectively include 80 and 20 scenarios.
- The preferred ANN architecture is presented in Table 5.
- The preferred ANN (ANN^*) is run for S_C . Table 6 lists the outputs evaluated by ANN^*.
- The results of Steps 6, 7, 8, 9, and 10 of the ANN are presented in Table 7.

4.7. Step 3-3

The efficiency scores of different scenarios in S_c were measured by the CCR DEA approach and presented in Table 8.

4.8. Step 3-4

The robustness test and sensitivity analysis are performed by 60 experiments in Section 6.

5. Result and Discussion

In this article, the primary question is addressed: designing a model covering MTTR, MTTF, investment, and maintenance costs simultaneously. In this case, it can measure the considered scenarios in terms of performance by fuzzy simulation, and finally, select the preferred method. In the actual world likely, what is considered in modeling is not plausible, and therefore, the authenticity test of the case study is conducted. The designed model's assessment and its examination with input data as a real case proved its plausibility. To the best of our knowledge, this is the first study that presents an integrated intelligent algorithm for concurrent optimization of the reliability, maintainability, and total cost in the job shop systems with multiple fuzzy inputs.

ANN and DEA are employed separately in this module, and the preferred technique is chosen according to the resistance test and extensive sensitivity analysis. Perhaps one of the chief drawbacks indicated in this article is that what is the reason for the selection of this method? And whether it is necessary to examine other techniques or not. In response, it should be stated that thanks to its nature, the DEA method can be extremely helpful in optimization. And, this method's advantages is the reason why it is chosen in this article. Therefore, it can be claimed that the quality improvement of this article can be examined from two perspectives. The first perspective is to employ different methods, and the second is to analyze current methods with different and developed tools (for instance employing PIM-DEA Soft, Frontier Analysis). At the beginning of the investigation, none of the two DEA and ANN methods had an advantage over another from the authors' perspective, while it should be noted that most of the investigations conducted in this field have employed the DEA method. Other methods such as the Ant Colony Optimization algorithm or Neural Network methods have also been employed besides the mentioned methods.

In this section, the robustness test and sensitivity analysis are performed by creating noise into the production system. Moreover, 60 distinct noisy experiments are created to test the robustness of the algorithm. Besides, the results are verified and validated by statistical analyses.

5.1. Sensitivity Analysis

To test the capability of the ANN and DEA approaches in handling noisy data, 60 imaginary noisy experiments are utilized. To generate noisy experiments, the noise is introduced in inputs. To execute both the robustness test and sensitivity analysis, three levels of the small, medium and large noises are used. These three levels are as follows:

- Small noises include small changes in variables. To generate this kind of noisy data, the input variables are multiplied by a random number between 1.01 and 1.2.
- Medium noises include medium changes in variables. To generate this kind of noisy data, the input variables are multiplied by a random number between 1.2 and 1.4.
- Large noises include large changes in variables. To generate this kind of noisy data, the input variables are multiplied by a random number between 1.4 and 10.

The following steps are performed to complete the sensitivity analysis and robustness test:

- Create noisy experiments. To this end, 60 noisy experiments are conducted: 20 experiments with small, 20 with medium, and 20 with large noisy data. In each experiment, noise is created in one of the scenarios belonging to S_C.
- Run the ANN to assess the performance of different scenarios in each of the noisy experiments. The MAPE between the measured efficiencies of scenarios belonging to the experiment and those belonging to S_C is then calculated.
- Run the DEA to assess the performance of different scenarios in each of the noisy experiments. The MAPE between the measured efficiencies of scenarios belonging to the related experiment and those belonging to S_C is then calculated.

- Select the preferred approach. To this end, the MAPE error obtained by the sensitivity analysis and the robustness test of ANN and DEA approaches in small, medium, and large noisy data are compared. Table 9 shows the MAPE errors. Considering the relative efficiency of the ANN over the DEA, the ANN results are more robust than the DEA in assessing the performance of design scenarios of the fuzzy job shop production system.

5.2. Verification and Validation of Results

Table 9 includes the results of the robustness test and the sensitivity analysis of the ANN and DEA approaches. As shown, the ANN is much more robust than the DEA in the performance assessment of the case study. Thus, the optimum scenario with the highest efficiency score can be chosen. The parameters (the number of identical redundant machines in workstations and their MTTFs) of the optimum scenario are presented in Table 10. These optimum parameters can be used in the design of the job shop system presented in this study.

6. Conclusion

An integrated algorithm based on ANN and DEA was proposed to optimize the design of a fuzzy job shop production system concerning the reliability, maintainability, and total cost. It includes three basic modules of design, simulation, and the performance assessment of scenarios. one of the unique features of the proposed approach was Modeling and simulating the fuzzy job shop production system to calculate the cost, reliability, and maintainability of the system. Furthermore, the sensitivity analysis and robustness test were performed to examine the capability of the presented approaches in dealing with noises.

To show the applicability and superiority of the proposed integrated algorithm, it was applied to optimize the design of a fuzzy job shop production system consisting of five workstations. Each workstation includes at most three identical redundant machines, and the MTTFs of machines were presented in the form of fuzzy numbers. A total of 120 scenarios were designed, simulated, and assessed. To test the robustness and analyze the sensitivity of the mentioned approaches, 60 noisy experiments including the small, medium and large noises in input variables were created. The comparative analysis concerning the robustness test and sensitivity analysis showed that the ANN is more robust to noises than the DEA. The results indicated that the ANN method was much more robust than the DEA method in assessing the performance of the case study. In the previous studies, the DEA method had always performed better, especially in cases with single-row facility layout problems (SRFLP). Moreover, this model has been assumed to be a linear programming method whose fundamental objective is to compare and evaluate the productive efficiency of some identical decision-making units (DMUs) that have various amounts of employed inputs and produced outputs.

As literature shows, the DEA method benefits from two approaches, namely 1. Reducing the extent of inputs without reducing outputs (or input-oriented approach), and 2. Increasing the extent of outputs without increasing inputs (or output-oriented approach). However, as the results of the current study indicates. In previous studies, this method was measured for one parameter and there were not several parameters fuzzy with each other, while in the current study several parameters are considered simultaneity which can justify the change in results. This investigation indicated that other linear programming methods such as Ant colony optimization algorithms, ACO, DSS, and other decision-making methods could be employed. It can be examined that which one of these methods can have higher efficiency. Despite the strengths of the Neural

Network method, network training might be difficult and even impossible due to some weaknesses, such as the lack of certain rules or instructions for designing the network for an optional application, and extreme dependence of results' accuracy on the education setting. And ultimately, the impossibility of predicting future performance can affect the application of this method, which of course, was also observed in this case.

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Appendix

Table 1: The list of important indicators in the performance of production systems by some authors

Study	Fields/Tools	Indicators in the performance of production systems

		R[1]	Cost				A[6]	M[7]
			OP[2]	RP[3]	MN[4]	IV[5]		
Levitin and Lisnianski [49]	For continuous production systems	✓	✓					
Kodama and Sawa [10]	Series-parallel system	✓					✓	
Boschian, Rezg [11]	Production system		✓				✓	
Tsarouhas, Arvanitoyannis [12]	Cheese production line	✓					✓	✓
Tsarouhas, Varzakas [50]	Strudel production line	✓						✓
Rajpal, Shishodia [18]	Helicopter transportation facility /ANN	✓					✓	✓
Koren, Hu [51]	Performance measures	✓	✓					
Mettas [22]	-	✓						
Hosseini, Amidpour [24]	Multi-objective genetic algorithm (MOGA)	✓	✓					
Miodragović, Tanasijević [52]	Service of agricultural machinery	✓						✓
Qin, Hongbin, et al [29]	casting production scheduling	✓	✓			✓	✓	
Liu [53]	workshop production	✓	✓	✓				
Yang [54]	Robust scheduling	✓		✓	✓		✓	✓
Wang [55]	hybrid multi-objective evolutionary algorithm	✓	✓			✓		✓
Mohammadi [56]	furniture manufacturing company	✓	✓					✓
Sun [57]	maintenance and energy scheduling	✓	✓	✓	✓		✓	✓
Gao [58]	steel plant	✓	✓					

R[1]: Reliability; OP[2]: Operation; RP[3]: Repairs; MN[4]: Maintenance; IV[5]: Investment; A[6]: Availability; M[7]: Maintainability

Figure 1: Proposed integrated algorithm including robustness test and sensitivity analysis schemes

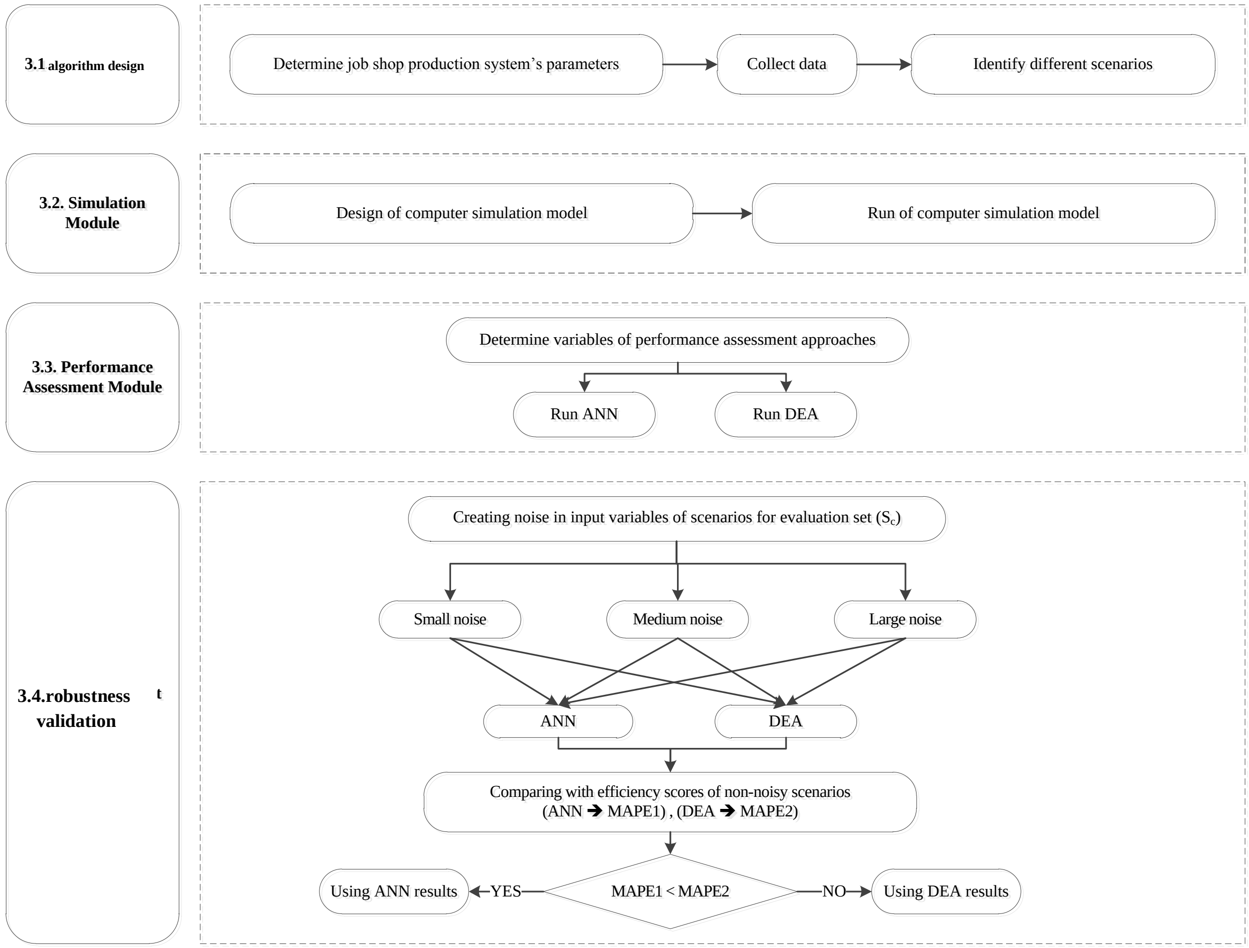

Figure 2: Production process grid of different type of products

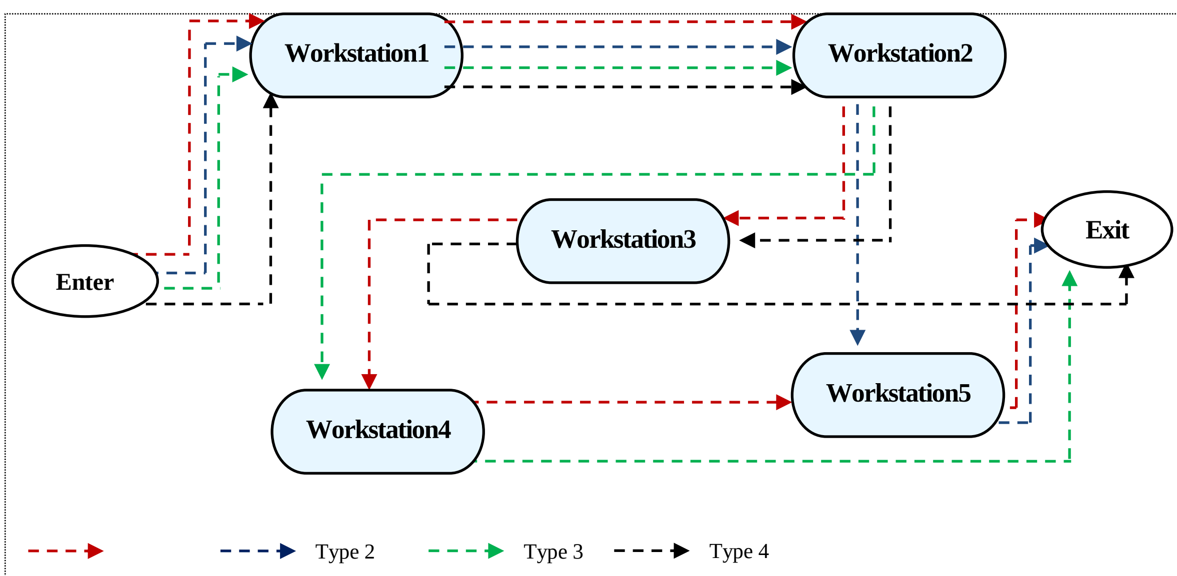

Table 2: Distribution functions of corrective maintenance and failure

Workstation	Failure (Hour)	Corrective maintenance (Hour)
1	Exponential	Erlang (1,3)
2	Exponential	Erlang (1,3)
3	Weibull	Erlang (1,3)
4	Normal	Erlang (1,3)
5	Log-Normal	Erlang (1,3)

Table 3: Available MTTFs of machines

Workstation	Available MTTfs (Fuzzy numbers-hour)
1	*(8/10/12), (16/20/24), (25/30/35), (33/40/47), (42/50/58), (50/60/70), (60/70/80), (70/80/90), (80/90/100), (90/100/110), (100/110/120)*
2	*(25/30/35), (33/40/47), (42/50/58), (50/60/70), (60/70/80), (70/80/90), (80/90/100), (90/100/110), (100/110/120), (110/120/130), (115/130/145)*
3	*(42/50/58), (50/60/70), (60/70/80), (70/80/90), (80/90/100), (90/100/110), (100/110/120), (110/120/130), (115/130/145), (125/140/155), (135/150/165), (145/160/175), (155/170/185), (165/180/195), (175/190/205), (180/200/220)*
4	*(25/30/35), (33/40/47), (42/50/58), (50/60/70), (60/70/80), (70/80/90), (80/90/100), (90/100/110), (100/110/120), (110/120/130), (115/130/145), (125/140/155), (135/150/165), (145/160/175), (155/170/185), (165/180/195), (175/190/205), (180/200/220)*
5	*(16/20/24), (25/30/35), (33/40/47), (42/50/58), (50/60/70), (60/70/80), (70/80/90), (80/90/100), (90/100/110), (100/110/120), (110/120/130), (115/130/145), (125/140/155)*

Table 4: Processing times of product types

Demand type	Workstation				
	Workstation 1	***Workstation 2***	***Workstation 3***	***Workstation 4***	***Workstation 5***
Type 1	Normal (1,0.2)	Normal (1.2,0.12)	Normal (1.5,0.15)	Normal (0.5,0.1)	Normal (1,0.2)
Type 2	Normal (1.3,0.13)	Normal (1.5,0.15)	-	-	Normal (1.6,0.16)
Type 3	Normal (2,0.4)	Normal (1.3,0.13)	-	Normal (1,0.1)	-
Type 4	Normal (1.2,0.12)	Normal (1,0. 2)	Normal (1,0.1)	-	-

Table 5: Preferred ANN model architecture for each of outputs

Output	Number of neurons in the hidden layer	MAPE
MTTR of the system	43	7%
MTTF of the system	12	7.22%

Table 6: Evaluated outputs of scenarios belonging to S_c by ANN* (pre-processed)

Scenario	MTTR of the system	MTTF of the system
1	1.51	0.669
2	1.692	0.722
3	1.752	0.754
4	1.916	0.707
5	1.859	0.764
6	1.935	0.703
7	1.877	0.724
8	1.97	0.701
9	1.836	0.719
10	1.56	0.744
11	1.967	0.701
12	1.975	0.701
13	1.889	0.706
14	1.857	0.768
15	1.708	0.715
16	1.592	0.748
17	1.661	0.726
18	1.625	0.741
19	1.555	0.752
20	1.571	0.751

Table 7: Efficiency scores of evaluated scenarios by ANN

Scenario	Preal1	Preal2	PANN*1	PANN*2	E1	E2	Sh1	Sh2	F1	F2	F
1	0.7	1.94	0.67	1.51	0.03	0.43	0.24	0.43	0.77	1	0.88
2	0.84	1.83	0.72	1.69	0.11	0.13	0.26	0.49	0.85	0.84	0.85
3	0.87	1.8	0.75	1.75	0.12	0.04	0.27	0.5	0.85	0.8	0.82
4	0.82	1.82	0.71	1.92	0.11	-0.1	0.25	0.55	0.85	0.74	0.79
5	0.85	1.81	0.76	1.86	0.09	-0.05	0.27	0.53	0.82	0.76	0.79
6	0.82	1.81	0.7	1.94	0.12	-0.13	0.25	0.55	0.86	0.73	0.8
7	0.91	1.84	0.72	1.88	0.18	-0.04	0.26	0.54	0.92	0.76	0.84
8	0.7	1.77	0.7	1.97	-0.01	-0.2	0.25	0.56	0.73	0.7	0.72
9	0.83	1.81	0.72	1.84	0.11	-0.03	0.26	0.53	0.85	0.76	0.81
10	0.69	1.8	0.74	1.56	-0.05	0.24	0.27	0.45	0.69	0.9	0.79
11	0.72	1.73	0.7	1.97	0.02	-0.24	0.25	0.56	0.76	0.68	0.72
12	0.73	1.82	0.7	1.98	0.03	-0.15	0.25	0.57	0.77	0.72	0.74
13	0.96	1.77	0.71	1.89	0.25	-0.12	0.25	0.54	1	0.73	0.87
14	0.78	1.72	0.77	1.86	0.02	-0.14	0.27	0.53	0.75	0.72	0.74
15	0.74	1.73	0.72	1.71	0.02	0.02	0.26	0.49	0.76	0.79	0.78
16	0.88	1.71	0.75	1.59	0.13	0.12	0.27	0.46	0.86	0.84	0.85

17	0.74	1.73	0.73	1.66	0.01	0.07	0.26	0.48	0.75	0.81	0.78
18	0.82	1.71	0.74	1.63	0.08	0.09	0.26	0.47	0.82	0.82	0.82
19	0.68	1.67	0.75	1.56	-0.08	0.12	0.27	0.45	0.66	0.84	0.75
20	0.8	1.65	0.75	1.57	0.05	0.08	0.27	0.45	0.78	0.82	0.8

Table 8: Efficiency scores measured by DEA

Scenario	F (Efficiency)
1	1
2	1
3	0.951
4	0.949
5	0.307
6	0.966
7	0.959
8	1
9	0.958
10	0.978
11	0.935
12	0.865
13	1
14	0.629
15	0.912
16	0.769
17	0.914
18	0.279
19	0.978
20	0.92

Table 9: Mean absolute percentage error (MAPE) of sensitivity analysis and robustness test of ANN

Noise	MAPE of ANN	MAPE of DEA	Relative efficiency of ANN over DEA
Small	0.0001	0.004	21
Medium	0.0087	0.1	11
Large	0.0485	0.404	8

Table 10: Optimum design scenarios

Workstation	Number of identical redundant machines	MTTF
1	1	(90/100/110)
2	1	(100/110/120)
3	3	(155/170/185)
4	3	(180/200/220)
5	1	(80/90/100)

Ali Bonyadi Naeini is a Faculty Member at the Business Department of Iran University of Science and Technology (IUST). He has taught a variety of courses such as marketing & innovation management, so far. Furthermore, he has presented several conference papers and scholarly journal papers, mostly focused on quantitative decision-making techniques.

Hossein Gholizadeh received his BSc degree in industrial Engineering from sharif University, Tehran, Iran in 2007, and Master's degree in Management of Technology from Iran University of Science and Technology (IUST), Tehran in 2012. He recently received his PhD degree in Science, Technology and Innovation Policy with the Progress Engineering Department, IUST. His research interests include scientometrics, multi-criteria decision making, Mathematical optimization and Supply chain.