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Research Article

Improving the Steel Household Appliances Production Through Simulation and Gray Proximity Indexed Value

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ABSTRACT

Improving the efficiency of the production process is one of the most critical goals for manufacturing companies to reduce costs and compete in the market. Identifying and resolving process bottlenecks is essential to enhance efficiency. This issue is particularly significant in the steel products industry due to the complexity and large scale of production lines. This research investigated the efficiency improvement of the sink production process at Alborz Steel Company using Discrete event simulation and gray multi-criteria decision-making. Through simulation, the current conditions of the production line and process bottlenecks were identified, and five suggested scenarios were examined for their improvement. These scenarios are designed based on preventive maintenance, adding operators, outsourcing part of the process, adding a new device, and combining the previous four scenarios. The results show that the combined four scenarios would improve production productivity by 6.08% and reduce waste by 27.13%, with a 6.66% increase in the number of personnel in the production process. However, the criteria of cost, improvement in the company's technical capabilities, and ease of execution should also be considered in order to prioritize the scenarios. Hence, the Proximity Indexed Value approach was used in multi-criteria decision-making to prioritize the scenarios. Given the probabilistic nature of the simulation results and the uncertainty of experts' opinions, the gray Proximity Indexed Value method was developed. The prioritization of the scenarios based on simulation results and expert criteria was preventive maintenance, adding operators, adding a new device, and outsourcing part of the process.

1. Introduction

Nowadays, companies seek to improve the performance of their production systems to compete efficiently and increase their market share [1]. They strive to enhance quality [2] and reduce production time to meet customer demands [3] while addressing the challenge of reducing the gap between costs and revenues [4, 5]. In the current market, price is not the only competitive factor; other factors such as increasing quality [6], shorter delivery times [7, 8], and meeting customer needs are crucial, and weaknesses in these areas can lead to loss of market share [9]. Therefore, companies seek ways to identify and deal with these issues [10], with one of their key goals being time reduction and optimization in the production process [11].

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Bottlenecks are a concerning issue affecting productivity and production time [12]. Manufacturing companies must identify bottlenecks [13] and implement appropriate solutions to address them [14, 15]. Discrete Event Simulation (DES) effectively identifies and resolves process bottlenecks [16]. Simulation in production processes involves using a computer model to answer how a production system responds to different conditions [17]. Another critical issue for organizations is waste reduction. DES can help organizations identify ways to reduce waste by implementing different scenarios [18]. Making changes in the production process or redesigning the process is also one of the issues investigated by DES that can effectively contribute to design cost reduction [19].

Finally, DES can play the role of a decision support system for the organization [20], contributing to planning and scheduling [21], capacity management [22], and performance evaluation of production and service activities [23].

In most industries, major or even minor changes to production lines are not feasible due to the potential for disruptions and negative impacts on line efficiency [24]. However, a model of the assembly steps can enable any changes without affecting the real assembly line, provide greater understanding and control of the assembly process [25], and ultimately enhance efficiency with lower costs and higher productivity.

As production processes become more complex and larger in scale, the importance of simulating improvement scenarios before implementation increases. The steel products industry is often part of large and complex industries. The size and complexity of the production system in the steel industry pose various challenges, including the sensitivity and costliness of changes and improvements [26].

Therefore, this research focuses on enhancing efficiency in the production process of steel home appliances using DES. This study simulates the sink production and assembly process at Alborz Steel Company, identifies production bottlenecks, and examines improvement scenarios. Given the practical challenges of implementing all scenarios simultaneously in an organization, the gray multi-criteria decision-making approach has been used to prioritize the scenarios.

2. Literature Review

Due to its case-study nature, simulation is a widely used tool in various studies, including production systems, transportation, emergency services, and other service systems. Research articles in production system simulation are reviewed here.

Some studies have examined the production and assembly process of various products using DES and hybrid approaches. Improving and optimizing production planning, machine scheduling, implementing lean production systems, and enhancing the production supply chain are the goals considered in these papers. Zandiyeh and Motlabi (2018) presented customer order separation points and production planning optimization using DES. The paper focuses on improving production planning to reduce production costs and time in a dairy factory [27]. Vieira et al. (2017) used simulation for job shop scheduling, which could be applied in the automotive industry. This paper presented a model combining DES and genetic algorithms for complex scheduling problems [28]. Afifi et al. (2022) combined lean integrated concepts with DES to improve productivity in the assembly line of residential building doors. DES was used to identify bottlenecks and accumulation points on the assembly line while examining scenarios for updating equipment at automated stations and adding parallel stations [29]. Detty and Yingling (2000) used DES for lean production principles in assembly systems. In addition to the assembly processes, the related warehousing, inventory, and transportation were included in the model to illustrate lean production impacts on the system [30]. Yuan et al. (2020) used DES for lean planning and optimization of the production of prefabricated components. The results showed that this method could minimize differences in processing times across workstations to avoid bottlenecks as much as possible [31]. Zupan and Herakovic (2015) combined balancing and simulation for production and assembly line optimization. The combined line balancing and further process optimization enhanced the process's production rate significantly [32]. Gonçalves et al. (2019) used DES to design an optimal process for the reverse supply chain and standard burial of scrapped vehicle tires, leading to a 15% cost reduction and a 71% reduction in pollutant gas emissions [33].

Some research has focused on improving maintenance and repair systems, seeking to improve operations planning, reducing shortages and delays in the supply of spare parts, and enhancing human resource planning. Zandieh and Motallebi (2019) proposed a simulation model to boost business performance by improving the productivity and profitability of a production line. This model examined the performance of just-in-time production systems considering diverse operational conditions and maintenance policies. The results revealed that the application of condition-based maintenance and repairs for production and assembly machinery would improve the productivity and profitability of the production line [34]. Corrotea et al. (2024) investigated the maintenance and repair system of a port company. Shortages of spare parts, delays in sending parts, and queues for repairing machines were introduced as some factors leading to increased production time and reduced production numbers. The study also referred to rearranging the distribution of workload among employees as a solution to improve the maintenance and repair process [35]. Mwans et al. (2023) presented an optimization simulation model for the maintenance and repair process optimization in healthcare systems with a DES and refrigeration simulation approach. Although there are many papers with a DES approach in healthcare systems, there is scant research examining their maintenance and repair systems [36].

Some studies have also addressed the inspection and quality control system improvement. Martinez and Ahmed (2021) used DES to improve inspection processes in production lines, offering flexibility for custom production and task and system diversity in inspections [37]. Pena et al. (2022) used DES for mining production control with machine learning capabilities in gold processing. The study was based on a simulated processing plant exposed to mineralogical feed variations, revealing that the proposed framework would provide a valuable tool for the potential risk assessment and mitigation of gold processing performance [14].

Due to the continuous nature of the system, a few studies have focused on simulation in metal industries or integrating continuous and discrete simulation approaches. In particular, scant research has been conducted in the steel products industry. Solding et al. (2009) used simulation to reduce energy consumption in an iron casting production system in Sweden, seeking to reduce energy consumption due to rising energy prices. Their study revealed that DES could effectively reduce energy consumption [38]. Huynh et al. (2020) used DES for performance management and optimization in industrial gearbox production, where the simulated data were stored in a production database accessible via an IoT platform for calculating key production performance indicators. These simulated indicators could serve as a basis for production performance management [39]. Navarra (2023) presented a model for the integrated management simulation of mining and metallurgical systems. The results of the paper showed that with integrated management, productivity could be increased while paying attention to environmental criteria [40]. Navarra et al. (2017) presented a combined system dynamics model and DES for a copper smelting plant. The output of the discrete simulation served as the input to the system dynamics model for evaluating copper smelting units [41].

According to the literature review, discrete event simulation has rarely been used in the steel products industry, especially in sink production. Given the nature of the simulation case study, this paper examines the simulation of the sink production line of Alborz Steel Company. It is also worth noting that in addition to the better scenario results, other performance criteria should also be considered to select the best scenario in the simulation. This paper has used a multi-criteria decision-making approach to select the best scenario. Also, the Gray Proximity Index Value method has been developed given the probabilistic nature of the simulation results.

3. Research Methodology

The tool used in this study is simulation, specifically creating a DES model. The simulation was conducted using Arena software version 14 and historical data from Alborz Steel Company. For this purpose, an 8-step framework was designed to conduct the research, as presented in Fig. 1.

Initially, the overall production and assembly processes at Alborz Steel Company were identified, followed by their review and validation based on expert opinion. Then, the conceptual model was completed for each production phase, and the final model was validated based on expert opinion.

The production process consists of 11 phases, each generally executed as shown in Fig. 2. Each part in each phase undergoes three operations, including preparation (separation, initial cleaning, removing the part from packaging, and transferring it to the relevant station), assembly (installing parts on each other), and inspection (checking parts for defects). A decision is made after inspecting the parts based on their condition (sound or defective). Approved parts proceed to the next stage, while defective parts are temporarily removed for rework or replacement, returning to the production line within an average of 30 minutes after inspection and defect correction by the operator. At the end of phase 11, the assembled product is packaged and the complete and tested product exits the line. The total production and assembly operations are carried out by 15 people.

In the next step, the simulation model was created in Arena software. Then, the required data were collected, and the data distribution function was identified if necessary.

Based on the identified process and obtained information, the simulation model was constructed in Arena software, comprising 11 phases, each with a minimum of one and a maximum of three operations. Fig. 3. shows the schematic representation of the created model.

Data on process parameters such as product type, required time for each workstation, number of products produced per shift, number of operators, and equipment breakdown rates were collected. The identified relationships were incorporated into the model after data collection and obtaining statistical distribution functions. For example, the average preparation, assembly, and inspection times and the defect rates in various phases of the production line at Alborz Steel Company are presented in Table 1. comprising an important part of the collected data. The data were obtained based on sampling at 40 different times (6 hours each time).

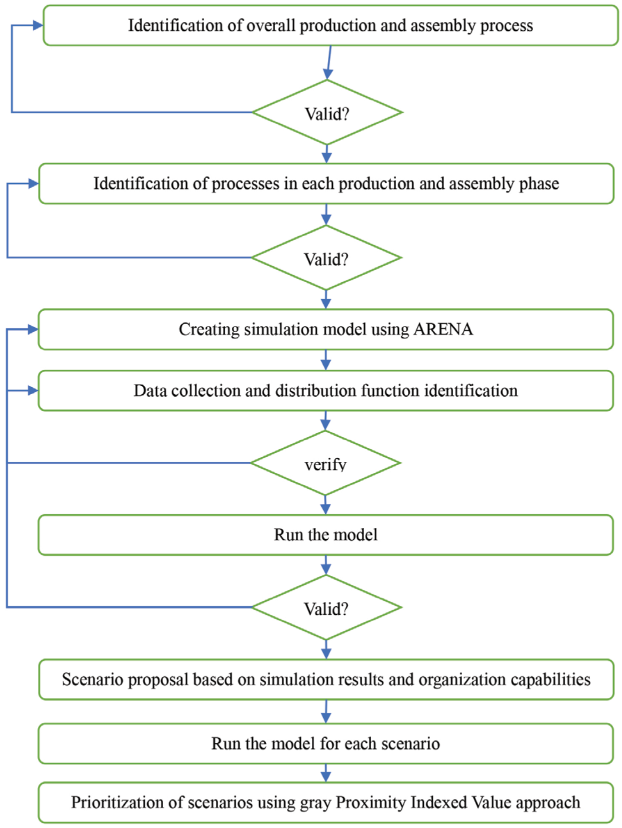

Fig. 1. Research steps.

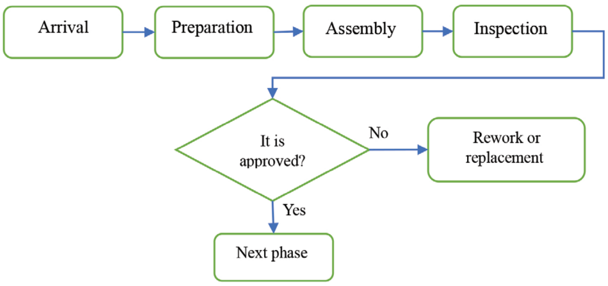

Fig. 2. Production Process Steps.

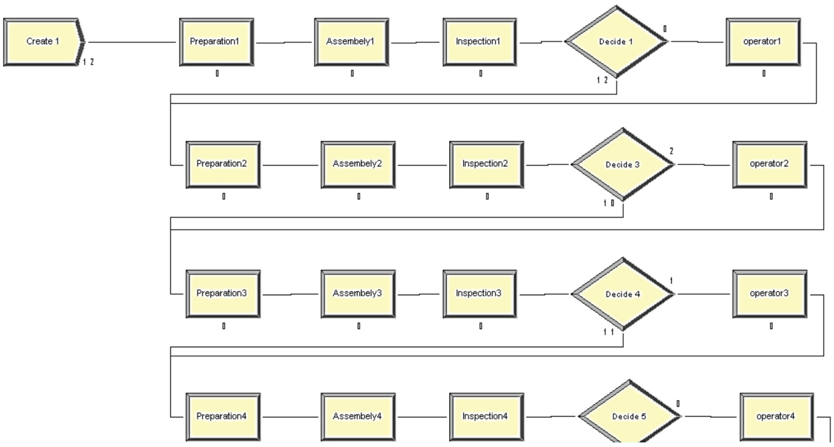

Fig. 3. Schematic of the Model in Arena Software.

Table 1. Average Operation Times and Defect Rates in the Production Line (in seconds).

Operator No	Defective percentage	inspection	assembly	preparation	Part No	Operation	The order of arrival of parts	Phases
1	2	60	124.6	75	1	Drawing 735	1	1
					1	Drawing 814	2	
					1	Drawing 120	3	
1	4	45	393.12	45	1	Ironing 735	4	2
					1	Ironing 814	5	
					1	Ironing 120	6	
2	23	60	498.2	80	1	Bending	7	3
					1	Basin polishing	8	
					1	Puncher	9	
2	3	90	663.426	75	1	Robot	8	4
					1	Tray polishing	9	
1	2	30	445.513	20	1	Beach	10	5
					1	Wash	11	
2	7	45	185.02	30	1	Shaving	12	6
					1	Check waste	13	
					1	Send to warehouse	14	
1	2	-	-	15	1	Laboratory test	15	7
1	-	-	-	120	1	Welding	16	8
2	3	-	-	60	1	Re-polishing	17	9
					1	Labeling	18	
1	3	-	-	30	1	Inspection	19	10
1	10	45	257.8	30	1	Packing	20	11

The distribution functions of the production line data were identified through the input analyzer feature of the software, and the model simulation modules were completed accordingly. For this purpose, the recorded data were entered into the software to identify the best distribution that fitted the data.

The Create module inserted entities into the simulation model, with one part entering the production process every 200 seconds. The Preparation, Assembly, and Inspection modules performed operations with normal distribution functions mostly. Beta and gamma distributions were also used in three out of 25 modules. The parameters of these functions were determined based on the data entered into the software. The adjusted averages for the functions are shown in Table 1. The Decide module separated sound parts from defective ones, with the separation percentage based on results obtained from Table 1. Finally, the Operator module fixed defects in defective goods and reintroduced them into the production flow.

By completing the information, the model was run and the model was verified by examining the connections between the modules and the input data. Two steps were taken to validate the model. First, the model was explained to the experts, and their approval was obtained to confirm that the constructed model matched the actual operations process. In the second step, the output data from the actual Alborz Steel Company assembly line in 40 different times (each time 6 hours of operation) were compared with the simulation outputs as shown in Table 2. A statistical hypothesis test was used to compare the average output of the simulation model and the actual system.

To begin with, the hypothesis of equal variances between two populations was tested. The test statistic was calculated as $= \frac{s_1^2}{s_2^2}$. In this test, the statistic value was 1.589, and the acceptance interval for the test ranged from 0.5319 to 1.88, assuming a 5% error rate. This reflected the validity of the obtained data, as there was no significant difference between the dispersion of the actual and simulated systems. Accordingly, a t-test with the assumption of equal variances was used to examine the hypothesis of equal means between the two systems. The null hypothesis for the test is expressed in Eq. (1).

$$H_0: \mu_1 - \mu_2 = 0 \qquad \text{Eq.(1)}$$

Eq. (1) calculates the numerical value of the statistic based on the information in Table 2. and Eq. (2). Since the sample size is >30, the t statistic is used. The critical value for a two-tailed test at a 95% confidence level is 1.99085. Therefore, the null hypothesis cannot be rejected. In other words, there is no noticeable heterogeneity between the system responses and the model predictions in terms of the number of outputs, implying that the simulation model is sufficiently valid.

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{sp\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} = \qquad \text{Eq.(2)}$$

$$\frac{77.1 - 78.2}{\sqrt{\frac{39 * 2.9^2 + 39 * 2.3^2}{40 + 40 - 2}} * \sqrt{\frac{1}{40} + \frac{1}{40}}}$$

$$= -1.8795$$

Table 2. Outputs of the System and Model in 6 Hours of Operation.

Input data	System output	Model output
1	77	75
2	81	81
3	74	76
4	79	80
5	73	78
…	…	…
40	76	77
	$\overline{x_1} = 77.1$	$\overline{x_2} = 78.2$
	$s_1 = 2.9$	$s_2 = 2.3$

As the model is validated, scenario building for process improvement, model running for scenarios, and finally their prioritization will be presented in the findings section.

3.1. Gray Proximity Indexed Value for Minimizing Rank Reversal

One issue with multi-criteria decision-making methods is rank reversal. This means that a solution might initially be ranked the best, but upon adding another option and re-ranking, the best option might change to the worst or one of the worst, which is identified as rank reversal [40]. The gray Proximity Indexed Value method is proposed to minimize rank reversal [41]. This advantage is crucial when ranking simulation scenarios so that if a new simulation scenario is added, the ranking structure of the scenarios does not change.

Considering the probabilistic nature of the scenario results, this article developed the gray Proximity Value method to minimize rank reversal based on gray numbers. The steps of the method are as follows:

Step 1. Create a decision matrix with gray numbers for the options, as shown in Eq. (3).

$$\otimes X = \begin{bmatrix} \otimes x_{11} & \cdots & \otimes x_{1n} \\ \vdots & \ddots & \vdots \\ \otimes x_{1m} & \cdots & \otimes x_{mn} \end{bmatrix} \qquad \text{Eq.(3)}$$

Step 2. Calculate the normalized weighted decision matrix, where the value of each component is obtained from Eq. (4).

$$\otimes r_{ij} = w_j * \frac{\otimes x_{ij}}{\sqrt{\sum \otimes x_{ij}^2}} \qquad \text{Eq.(4)}$$

Step 3. Obtain the proximity value for each option for each criterion based on Eqs. (5) and (6).

$$\otimes u_{ij} = \otimes r_{maxj} - \otimes r_{ij} \qquad \forall j \qquad \text{Eq.(5)}$$

For positive criteria

$$\otimes u_{ij} = \otimes r_{ij} - \otimes r_{minj} \qquad \forall j \qquad \text{Eq.(6)}$$

For negative criteria

Step 4. The final value of each option is obtained from the sum of the proximity values based on Eq. (7). The lower this value, the better.

$$\otimes r_i = \sum \otimes u_{ij} \qquad \forall i \qquad \text{Eq.(7)}$$

Step 5. Rank the options by calculating the probability of one option being smaller than another, based on Eqs. (8) and (9). If two options A and B are equal, the probability is 0.5. If the probability is >0.5, then A < B, and if it is >0.5, then A > B . The parameter l represents the length of the interval for each number, and L is the sum of the interval lengths of the two numbers being compared.

$$p(\otimes A \leq \otimes B) = \frac{\max(0, L - \max(0, \overline{A} - \underline{B})}{L} \qquad \forall i \qquad \text{Eq.(8)}$$

$$L = l(A) + l(b) \qquad \text{Eq.(9)}$$

Eqs. (10) to (16) are used for gray number calculations to derive Eqs. (3) through (9).

$$\otimes A + \otimes B = (\underline{A} + \underline{B}, \overline{A} + \overline{B}) \qquad \text{Eq.(10)}$$

$$\otimes A^n = (\underline{A}^n, \overline{A}^n) \qquad \text{Eq.(11)}$$

$$w * \otimes A = (w * \underline{A}, w * \overline{A}) \qquad \text{Eq.(12)}$$

$$\otimes A / \otimes B = (\underline{A}/\overline{B}, \overline{A}/\underline{B}) \qquad \text{Eq.(13)}$$

$$\otimes A - \otimes B = (\max(0, \underline{A} - \overline{B}), \max(0, \overline{A} - \underline{B})) \qquad \text{Eq.(14)}$$

$$\otimes A_{maxj} = (max\underline{A}_j, max\overline{A}_j) \qquad \text{Eq.(15)}$$

$$\otimes A_{minj} = (min\underline{A}_j, min\overline{A}_j) \qquad \text{Eq.(16)}$$

4. Findings

The simulation model is executed in this stage. The number of simulation iterations is calculated based on the standard deviation obtained from the model outputs in Table 3. and Eq. (17). According to Eq. (3), R is the required number of repetitions in the simulation, and S_0 is the standard deviation calculated in Table 4. The values of α and ε are considered to be 0.05 and 0.15, respectively. The number of repetitions for a 95% confidence interval for the assembly line system at Alborz Steel Company is calculated as follows.

$$R \geq \left(\frac{t_{\frac{\alpha}{2};K-1} S_0}{\varepsilon}\right)^2 \rightarrow R \geq \left(\frac{t_{0.025;39} * 2.3}{0.15}\right)^2 = 960.29 \cong 961 \qquad \text{Eq.(17)}$$

4.1. Execution of Simulation Scenarios

Different scenarios were designed to identify ways to improve production efficiency according to production experts in Alborz company. Each scenario was implemented separately in the simulation model and its results were analyzed to compare the results of the scenarios with the current situation and with other scenarios. Increasing production and reducing waste were considered as two simulation goals to design scenarios. With this in mind, the first scenario was based on reducing waste, and scenarios 2 to 4 were based on increasing production. Also, the simulation results were analyzed in the current situation and the implementation conditions, considering cost and physical limitations to design the scenarios.

4.1.1. Current Scenario

The current scenario was executed 961 times based on the obtained number of repetitions, and the results eere recorded. Based on the analysis of the simulation results of the current state, scenarios for improving the production process performance were created, and changes were made in the model to evaluate the system's performance. Each scenario was also executed 961 times in the software, and the average of these executions was considered the final output of the scenario.

4.1.2. First Scenario

Since the defect rate in phase 3 is 23% (Table 1.), which is the highest defect rate in the system, the first scenario aims to reduce it. The main cause of defects is the equipment in this phase, so preventive maintenance and equipment readjustment are defined for this stage. This scenario reduces equipment availability time since the machines must be stopped for maintenance and readjustment. Based on previous experience and statistics, the defect rate decreases to 15% after maintenance.

4.1.3. Second Scenario

In this scenario, the number of active personnel in the production process is increased. In other words, new operators are added in parts of the process where the workload is high or lack of operator access causes delays, as per the simulation results. Adding new operators reduces human error defects. Thus, one operator is added to phase 5 and one to phase 11.

4.1.4. Third Scenario

In the third scenario, phase 9 is outsourced to a contractor outside the company, removing this phase from the production process. Instead, sending semi-finished goods to the contractor and receiving finished goods is added to the simulation. This reduces the cost of two personnel and the utilization time of the equipment in phase 9 but increases ordering time and cost.

4.1.5. Fourth Scenario

In the fourth scenario, the number of welding machines in phase 8 is increased from one to two. The production line has no space constraints for adding welding equipment, and welding is a bottleneck causing semi-finished goods to accumulate. Adding another welding machine also adds one operator to the system.

4.1.6. Fifth Scenario

Since the defined scenarios do not conflict in nature, the fifth scenario is a combination of these scenarios. All changes from the four scenarios are implemented in the base model.

4.2. Comparison of Scenario Results

The results obtained from each scenario are presented in Table 3. based on three criteria, including the number of personnel, the average total number of faults in all phases per hour, and the average number of products per hour. Also, the percentage of changes in each scenario compared to the current situation is displayed next to the result column.

4.3. Identifying and Weighing Selection Criteria

Next, a multi-criteria decision-making approach was used to select the best scenario. To this end, the best scenario selection criteria were chosen with the cooperation of four experts from the company's production department, and the weights of these criteria were determined using the Analytical Hierarchy Process (AHP). Three criteria were derived from the simulation outputs, including the number of products, the number of defective parts in the production process, and the number of personnel. Three other criteria—scenario execution cost, improvement in the company's technical capabilities following scenario implementation, and ease of execution—were introduced by the experts. Each criterion was then compared in pairs by each expert. After reviewing the inconsistency of comparisons and making necessary adjustments, the results were integrated using the geometric mean, as shown in Table 4.

The inconsistency of the expert opinion integration table was 0.067, which was acceptable. Based on this, the criteria weights were obtained, as shown in Table 4. according to which the weights of the criteria were determined as follows: The number of products, 36.9%; the number of defective parts, 27.7%; improvement in the company's technical capabilities, 16.4%; scenario execution cost, 12.2%; ease of execution, 4.1; and the number of personnel, 2.7%.

Table 3. Comparison of Average Scenario Results.

	Number of personnel	Percentage change compared to the current situation	Average total number of faults in all phases per hour	Percentage change compared to the current situation	Average number of products per hour	Percentage change compared to the current situation
Current Scenario	15	0	45.96	0	77.9	0
Scenario1	15	0	39.72	-13.57	78.95	1.35
Scenario2	17	13.33	42.84	-6.78	78.78	1.14
Scenario3	13	-13.33	43.62	-5.1	78.84	1.21
Scenario4	16	6.66	45.18	-1.69	79.81	2.46
Scenario5	16	6.66	33.49	-27.13	82.63	6.08

Table 4. Final Pairwise Comparison Matrix for Scenario Selection Criteria.

	Number of products	Number of defective parts	Number of personnel	Scenario execution cost	Improvement in the company's technical capabilities	Ease of execution	Weight
Number of products	1	1.817	8.277	3.557	3.107	6.804	0.369
Number of defective parts		1	7	3	2.466	7.114	0.277
Number of personnel			1	0.16	0.147	0.382	0.027
Scenario execution cost				1	0.585	4.217	0.122
Improvement in the company's technical capabilities					1	5.739	0.164
Ease of execution						1	0.041

4.4. Ranking of Scenarios

In this section, the decision matrix for comparing scenarios was first completed. For this purpose, the interval estimates for the number of products produced and the number of defects in the final output of the simulation software were regarded as grey values for these two criteria. The number of personnel was considered a fixed number but is displayed in an interval format. The cost of implementing each scenario was estimated as minimum and maximum by four experts and entered into the decision matrix as grey numbers. Finally, a questionnaire with linguistic variables was completed by a group of experts to evaluate the criteria for improving the company's technical capabilities and the ease of implementing the scenarios. The linguistic variables were converted to grey numbers through Table 5. and their results were aggregated using the geometric mean.

The prioritization steps were then carried out using the proximity value method.

Step 1: Based on the obtained values, a decision matrix with grey numbers was obtained, which is presented in Table 6. The decision matrix results for three criteria, including the number of products, the number of defective parts, and the number of personnel were obtained from the 5% confidence interval of the simulation results. For other three criteria, scenario execution cost, improvement in the company's technical capabilities, and ease of execution were obtained based on expert opinions.

Step 2: In this step, the weighted normalized decision matrix was obtained based on relation 4, and the maximum value for positive criteria and the minimum value for negative criteria were identified. The results are presented in Table 7.

Table 5. Grey numbers corresponding to linguistic variables.

Linguistic variables	Gray numbers
Very Low	(0,0.2)
Low	(0.1, 0.3)
Medium Low	(0.2, 0.4)
Medium	(0.35, 0.65)
Medium High	(0.6, 0.8)
High	(0.7, 0.9)
Very High	(0.8, 1)
Linguistic variables	Gray numbers
Very Low	(0,0.2)
Low	(0.1, 0.3)
Medium Low	(0.2, 0.4)
Medium	(0.35, 0.65)
Medium High	(0.6, 0.8)
High	(0.7, 0.9)
Very High	(0.8, 1)

Table 6. Decision matrix with grey numbers.

	Number of products	Number of defective parts	Number of personnel	Scenario execution cost	Improvement in the company's technical capabilities	Ease of execution
Scenario1	(77.842, 80.058)	(39.01, 40.43)	(15 ، 15)	(100, 150)	(0.765, 0.965)	(0.231, 0.502)
Scenario2	(77.665, 79.895)	(42.328, 43.352)	(17 ، 17)	(17, 200)	(0.556, 0.807)	(0.58, 0.836)
Scenario3	(77.623, 80.057)	(42.97, 44.27)	(13 ، 13)	(500, 700)	(0.152, 0.388)	(0.07, 0.339)
Scenario4	(78.91, 80.71)	(44.16, 45.18)	(16 ، 16)	(400,700)	(0.441, 0.724)	(0.732, 0.932)
Scenario5	(81.207, 84.053)	(32.41, 33.49)	(16 ، 16)	(1170, 1750)	(1 ، 1)	(0 ، 0)

Table 7. Weighted normalized decision matrix.

	number of products	number of defective parts	number of personnel	scenario execution cost	improvement in the company's technical capabilities	ease of execution
Scenario1	(0.159, 0.168)	(0.116, 0.124)	(0.011, 0.011)	(0.006, 0.013)	(0.069, 0.109)	(0.006, 0.022)
Scenario2	(0.158, 0.167)	(0.126, 0.133)	(0.013, 0.013)	(0.01, 0.018)	(0.05, 0.09)	(0.017, 0.035)
Scenario3	(0.158, 0.168)	(0.128, 0.136)	(0.009, 0.009)	(0.03, 0.063)	(0.013, 0.043)	(0.00, 0.014)
Scenario4	(0.161, 0.169)	(0.131, 0.138)	(0.012, 0.012)	(0.024, 0.063)	(0.04, 0.08)	(0.021, 0.039)
Scenario5	(0.165, 0.176)	(0.0966, 0.103)	(0.012, 0.012)	(0.07, 0.158)	(0.09, 0.11)	(0,0)
max	(0.165, 0.176)				(0.09, 0.11)	(0.021, 0.039)
min		(0.0966, 0.103)	(0.009, 0.009)	(0.006, 0.013)		

Step 3: At this stage, the proximity value for each option relative to the best criterion value was obtained using relations 5 and 6. The results are presented in Table 8.

Step 4: The final score for each option was obtained by summing the proximity values based on relation 7, as shown in Table 9.

Finally, two approaches were used for ranking the options. The first approach took the average of each interval, and the averages were compared. The second approach used formula 8 for ranking, and both approaches provided consistent results.

5. Results and Discussion

As shown in Table 3. the proposed scenarios led to improvements in the system and increased production

Table 8. Proximity value matrix.

	number of products	number of defective parts	number of personnel	scenario execution cost	improvement in the company's technical capabilities	ease of execution
Scenario1	(0, 0.0177)	(0.0136, 0.0274)	(0.001, 0.001)	(0, 0.007)	(0, 0.043)	(0.00, 0.033)
Scenario2	(0, 0.0181)	(0.0235, 0.0364)	(0.003, 0.003)	(0, 0.012)	(0, 0.062)	(0 , 0.022)
Scenario3	(0, 0.0181)	(0.0254, 0.0392)	(0, 0)	(0.016, 0.057)	(0.047, 0.099)	(0.007, 0.037)
Scenario4	(0, 0.0155)	(0.289, 0.419)	(0.0023, 0.0023)	(0.01. 0.057)	(0.009, 0.073)	(0, 0.018)
Scenario5	(0, 0.0108)	(0, 0.006)	(0.0023, 0.0023)	(0.056, 0.152)	(0, 0.022)	(0.039 ، 0.217)

Table 9. Final score for each Scenario.

	Final score	Interval average	Interval length	Final rank
Scenario1	(0.0153, 0.131)	0.073	0.115	1
Scenario2	(0.026, 0.154)	0.091	0.128	2
Scenario3	(0.096, 0.25)	0.17	0.155	5
Scenario4	(0.051, 0.21)	0.13	0.157	3
Scenario5	(0.08, 0.233)	0.157	0.152	4

efficiency. If the company can implement these scenarios simultaneously, as in the fifth scenario, it can increase production by 6.08%. Implementing this scenario requires rescheduling the maintenance tasks, planning and setting up outsourcing contracts, purchasing a new welding machine, adding it to the production line layout, and adding operators to the existing and new welding stations, which can be achieved by rearranging the current operators.

The average total defects column was derived from summing the number of defects in each phase, totaling 45.96 defective products across 11 phases that needed rework. The scenarios demonstrated a reduction in defects due to the use of maintenance programs, outsourcing capacity, and increased personnel. In the fifth scenario, which combined all four proposed scenarios, there was an overall 27.13% reduction in defects compared to the current situation.

However, companies often cannot implement all scenarios simultaneously. Moreover, executing one scenario and observing the improvements under real-world conditions builds trust in the simulation results for implementing other scenarios. Therefore, the scenarios were ranked based on the new criteria of execution cost, improvement of the company's technical capability, and ease of implementation, alongside the three criteria derived from the simulation execution. The proximity value method for minimizing rank reversal was used so that if a new scenario were identified and added to the decision matrix, the reliability of the ranking results would be enhanced. Moreover, given that the simulation results are probabilistic and have confidence intervals, the cost estimation for implementing scenarios is not precise, and the experts' opinions on improving the company's capabilities and ease of implementation are uncertain, grey numbers were used for ranking the scenarios, and the grey proximity value method was developed.

The results show that the criteria for increasing production and reducing defective parts in the simulation results and the criteria for implementation cost and improving capability were the most important for selecting scenarios. The scenarios were ranked in the order of 1, 2, 4, 5, 3. In other words, the organization should first focus on improving maintenance, then recruiting personnel for the production line, purchasing a new welding machine and adding it to the production line, and finally outsourcing part of the production process. Scenarios 3 and 5 occur simultaneously.

In the scenario execution phase, it is recommended to first implement the highest priority scenario, which is improving maintenance, while the other scenarios can be implemented if the process improves as predicted by the model. If there is a discrepancy between the model results and reality, the data or model logic needs to be re-evaluated. The developed simulation model can serve as a basis for evaluating new scenarios to improve the production process, and the proximity value method can serve as a basis for prioritizing scenarios and comparing them with previous ones.

6. Conclusions

This study examined the sink production process at Steel Alborz Company through DES. The constructed model comprised 11 phases, each including preparation, assembly, and inspection operations. The simulation results of the current state were analyzed, and five scenarios were subsequently proposed to improve and enhance the efficiency of the production process. The scenarios were created based on improving maintenance planning, adding personnel, outsourcing part of the process, adding new machinery, and ultimately combining the four previous scenarios.

The results showed that the fourth scenario had the best performance in increasing the number of products, increasing production by an average of 2.46%. The first scenario also had the greatest reduction in the number of defective parts, reducing by an average of 13.57%. The third scenario also reduced the number of personnel by 2 people. The results of the simulation of the scenarios showed an improvement in production efficiency and a reduction in defective parts. The combination of all scenarios in the fifth scenario improved production efficiency by 6.08% and reduced defective parts by 27.13%.

The three criteria of scenario execution cost, ease of execution, and improvement in the company's technical capabilities were also examined, along with the three output criteria from the simulation, to prioritize the implementation of the scenarios. For this purpose, the weights of the six criteria were first determined. The results showed that the number of products (36.9%), the number of defective parts (27.7%), and improvement in the company's technical capabilities (16.4%) were the most significant criteria, making up 80% of the total weight. The Gray Proximity Indexed Value method was used for ranking based on the identified criteria, revealing that scenarios 1, 2, and 4 were the most important for implementation in order of priority.

The simulation results of the scenarios showed an improvement in production efficiency and a waste reduction, with the implementation of all scenarios in the fifth scenario leading to a 6.08% increase in production efficiency and a 27.13% reduction in waste. The scenarios were then ranked using the grey proximity value method. The advantage of the proximity value method lies in reducing the possibility of rank reversal if new scenarios are added to the problem, thus enhancing the reliability of the scenario ranking. Additionally, the grey proximity value method was proposed due to the probabilistic or uncertain nature of the issue. The ranking results indicated that improving the maintenance process, adding personnel to the production line, adding a welding machine, and finally outsourcing part of the process were of higher priority. Finally, the simulation can be applied to other production processes at Steel Alborz Company.

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