Simulation-Based Optimization using DEA and DOE in Production System

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Abstract

Production System (PS) is the process of planning, organizing, directing and controlling the tactical and strategic planning of the different components of the company, to transform inputs into finished products which must be effectively managed. Important parts of PS that always face major challenges in manufacturing systems include production strategy, resource allocation, logistics and production planning. Because of the importance of examining the various components of PS and evaluating its performance on key indicators of organization, it is necessary to evaluate the impact of any changes in these elements to the system prior to its creation. In this regard, the present study aimed to increasing the efficiency and determining the useful methods to evaluate and optimize the performance in different part of PS. To this end, an integrated Discrete-Event Simulation (DES), Design of Experiments (DOE), Data Envelopment Analysis (DEA), and Multi-Attribute Decision Making (MADM) models were implemented to analyze and optimize the real PS process. In the case study of the automobile manufacturing industry in Iran, the accurate analysis was applied to the proposed approach and its different aspects were considered as well. The results indicated that the proposed approach is a practical way for evaluating and optimizing the performance of different part of PS, compared to previous models and helps the manufacturing companies to make efficient decisions regarding increasing productivity while decreasing the essential problems.

Keywords: Production System, Simulation, DOE, DEA, SWARA

1. Introduction

Production System (PS) is the process of planning, organizing, directing, and controlling production activities in an organization, to transform inputs into finished products in line with the strategic goals of the organization. It is a function that is responsible for the tactical and strategic planning of the components of the company, consisting of many elements that must effectively manage. Essential parts of a PS that always face significant challenges in manufacturing systems include production strategies, resource allocation, logistics, production planning, flow of products. Each of these departments independently performs tasks in the system that contribute to the organization's short- and long-term goals and that is why today, in industrial businesses, optimizing the performance of PS in different manufacturing sectors is one of the most critical issues in order to achieve the goals of the organization. Further, PS with the aims to plan, organize, direct, and control the activities of the production process, performs a substantial role in promoting productivity and controlling the factors which influence the organization. Moreover, the systematic PS leads to an efficient and optimal production chain and thus increases the return of capital by promoting the quality of the intense global

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competitive markets of manufacturing industries and respond quickly and accurately to the needs of customers. It also causes to overcome the biggest challenges in manufacturing, which is the growing complexity of manufacturing systems for dealing with the challenges imposed by variability, uncertainty and randomness [1]. Furthermore, an increase in the efficiency of PS needs for operational and detailed planning in a different part of PS concerning the strategic objectives of the organization, production flow planning while minimizing the costs, as well as the rational and continuous utilization of the workforce, materials, and processing equipment. The performance optimization in PS by useful methods can help each manufacturer to solve the problems such as reduce transportation costs, optimize production lines, ensure the continuity of processes from supply to sales, and finally, evade shocking variations in the production systems. Therefore, the performance evaluation in PS regarded as an important means for achieving the intended goals.

Performance Evaluation in PS taking into account all its essential parts leads to maximum efficiency in a PS. Previous studies have modeled and simulated different processes of PS with validated results over the past years. For instance, Abdulaziz et al. proposed a combined model of Discrete-Event Simulation (DES) with System Dynamics (SD) and mainly aimed to assess the green logistics practices in the automotive industry [2]. They did not take into account the effects of the proposed model on the PS and the flow of products, thus affecting the rate of production and profitability of the products. Dumetz et al. presented a simulation framework for evaluating and comparing different production planning, as well as order management strategies [3]. Vieira et al. considered simulation analysis for complex production scheduling problems with the stochastic behavior [5], and Müller et al. proposed a method to set up a system for simulation based online production planning system [6]. Production planning alone without applying it to different parts of the system and considering its impact on other components cannot provide a clear picture of the production process and system performance. Zahraee et al. suggested an integrated computer simulation, response surface methodology, and Design of Experiments (DOE) model in a continuous production line due to the need for an impact of essential factors on the paint manufacturing system [7]. Caterino et al. implemented DES to verify the improvement adopted on existing production lines or the design solution adopted for a new line, optimizing the process [8]. Moreover, Pawlewski presented a simulation modeling in a PS, aiming at flow of materials [9]. Motlagh et al. further applied the simulation optimization methodology to improve the performance in production lines. Before and after the production lines, they are of particular importance as they may increase productivity by some modifying in the Production line under investigation but reduce the efficiency and productivity of other components of the system [10]. Further, Vaisi and Ebrahimi introduced a hybrid computer simulation, Data Envelopment Analysis Goal Programming (DEAGP), and DOE model in automobile spare part manufacturers. They aimed to extend a simulation model based on a real system in order to improve the performance of the PS [11].

In manufacturing industries, increasing the efficiency of the production halls does not necessarily increase the overall system productivity and improve the strategic goal indices. Therefore, in addition to improving the performance of the PS, external factors of a production hall such as logistics and the effects of system changes on critical indicators such as production rate of the whole system and benefits of the organization should be considered. Therefore as discussed in the preceding paragraph, the consideration of the different components of PS in a production process is of great importance in enhancing the efficiency and productivity. Besides, it has not been considered the simultaneous effects of the different components on each other and its impact on the strategic indicators of the whole system. Consequently, this research has attempted to fill this gap. Although this integration is necessary for decision making, the methods used in this evaluation are also of particular importance.

In this research a combination of DES, DOE, Multi-Attribute Decision Making (MADM), and Data Envelopment Analysis (DEA) approaches used. First, the DES method used to model the production processes by considering different parts of PS. Then, according to the organization's essential indices, the DOE method was applied to produce the scenarios. Afterward using MADM, the weight of indicators was determined, and finally, with the DEA method, the performance of scenarios evaluated, and the optimal scenario obtained.

Simulation modeling is a useful method for all managers, researchers, and practitioners to analyze the dynamic systems without interrupting their operations [12]. In real complex systems, computer simulation can used to mimic the behavior of the system over time and to access data similar to the real system. Furthermore, DES
method is beneficial at the operational level of the projects. Additionally, the simulation of operational processes sheds light on the project condition by considering different discrete variables such as process duration, resource utilization, cycle time, throughputs, and entity arrival rate [13]. Kayhani and Atieh proposed a simulation approach to enhance production scheduling procedures. Their results for potential changes may not be valid unless they optimize the simulation model with optimization tools [14]. Gyulai et al. applied a simulation approach based on production planning in the automotive industry. The model did not consider a proper method for designing and analyzing the scenarios of the simulation approach [16]. In the large scale simulation, a sophisticated computer experiment frequently requires permutation among hundreds or even thousands of input variables and takes a long time to run each excursion [17]. Thus, performance evaluation in PS can utilized through Optimization via Simulation (OVS), which is based on DES principles and considered as one of the most essential techniques.

The DEA method regarded as an effective non-parametric evaluation method for measuring the relative efficiency of a set of Decision-Making Units (DMUs) that use multiple inputs to produce multiple outputs [18]. Also, it is a nonparametric approach that requires no assumption about the functional form of production [19, 38]. So DEA could be beneficial for every industry or organization in which a logically homogeneous set of DMUs use a similar set of inputs in order to produce a certain range of outputs [20, 21]. Further, the impact of experts’ preferences in DEA models makes the results more precise. For this purpose, the Multi-attribute Decision-Making method, as the impact of the experts’ preferences, can be considered for weighting the input and output indicators of the DEA model. Park et al. used the hybrid stochastic DES and DEA model for vendor selection [22]. In another study, Ebrahiminejad et al. proposed an integrated DEA and simulation approach to group consensus ranking [23]. Additionally, Azadeh et al. applied an integrated simulation and stochastic DEA in facility layout design problem [24]. In these studies, the weight of DEA indicators did not recognize, and simulation scenarios designed with experts’ opinions, which may not be precise enough.

The DOE method is utilized for designing and evaluating the scenarios of the simulation modeling. Furthermore, the applications of experimental designs and simulation for improving productivity play a leading role in projects, which implemented within time and budget limits. Thus, the result is more credible and reliable since all possible combinations of factors evaluated using the methods as mentioned earlier [7]. Marlin and Sohn presented a hybrid analytical process that combined simulation, DOE, and DEA in the Afghan educational system. In this study, the importance of DEA indicators did not determine [17].

The DES, DOE, and DEA methods are considered as some suitable methods for evaluating the behavior of a system [12]. Previous evaluations in this field indicated that the simulation results could apply as an input to DOE or DEA techniques for analyzing a system. With DEA, designing the scenarios is not possible precisely, and they are often designing based on experts’ opinions and empirical experiments. Also, in DOE, after performing simulation experiments, it is not possible to carefully examine the efficient scenarios and improve the performance of the scenarios close to efficiency based on the organization situation. Additionally, MADM approaches can help the DEA to keep the calculations more accurate. Thus, this research with combining these four techniques attempt to propose a comprehensive and practical approach which can use in any industrial company.

In the current study, a real sample with complexity and variety of products in Iran’s automobile manufacturing industry for six months was investigated, and the accurate analysis was performed on the model accordingly. Compared to the other recent studies, the present study attempted to fill the gap in the literature by optimization the different parts of PS such as Logistic, production strategies, production planning and productivity of production halls, and thus presenting a novel approach. In this regard, we identified bottlenecks, the components that most demanded change, key organizational indicators, and the different parts of the real-world PS process simulated, and the impact of different parts on each other evaluated. Then the model outputs were used as the raw data of the designed scenarios were evaluated by the Ratio Efficiency of DOE, and the factorial design 2^k Dominance (RED) and the Step-wise Weight Assessment Ratio Analysis (SWARA) techniques. Finally, the study aimed to assist the managers to manage their enterprise efficiently and to deal with the bottleneck problems related to the Irankhodro Industrial Plant, which, to the best of our knowledge, has never been addressed before.
The remaining parts of the present study organized as follows. The proposed approach described in Section 2. Besides, Section 3 provides a case study used to demonstrate how the framework can used. Section 4 represents a discussion about the effects of combined methods in the proposed approach, and finally, the concluding remarks summarized in Section 5.

2. Proposed Approach

Examining the various components of PS and evaluating their performance on key indicators of the organization is significant. Therefore it is necessary to evaluate the impact of any changes to the system before its creation. In this regard, the present study aimed to optimize the performance of different parts of PS on a system in uncertainty conditions via simulation. To this end, the current state of the manufacturing system at first modeled using a DES, and the decisive factors, and the decision variables were characterized accordingly. The main reason of choosing this method is mostly because OVS is based on discrete event simulation principles, and this is crucial both in the application of this technique and in the recognition of the system by analysts. That means there is at least one random event to be sampled in the actual model, the state of the system changes at discrete time intervals, and the number of decision variables is numerous.

In real world, there is no clear mathematical relationship between controllable decision variables and objective (response) variables. The second step after modeling the system via simulation is therefore using Meta-model Based Methods, meaning that they seeking to establish a clear mathematical relationship between response variables on the one hand and controllable decision variables on the other; hence, based on designing of an experiment and determining possible levels for each decision variable, structured data is collected and for each scenario, simulation software model is ran in determined numbers and consequently the amount of decision variables and response variables are recorded each time. In this regard, the scenarios designed utilizing the DOE model, followed by determining the optimal value of decision variables using DES.

A next step to provide a precise analysis regarding to each decision variable and response variable is determine the weight and priority of them, and this can be done with MADM methods which use a common set of weights that express a decision maker's preferences. The MADM method of this study is SWARA which is a rational technique for dispute resolution and allows the assessment of differences of attribute significance that characterize the decision alternatives. The main feature of SWARA method is the possibility to estimate experts or interest groups opinion about significance ratio of the attributes in the process of their weights determination, and experts have an important role in calculating the weight and evaluating the indicators. Furthermore, this method has features such as compensatory as well as independence of indicators. At the same time, in this method, qualitative indicators should be converted into quantitative ones [32].

Afterwards, the performance of the scenarios should be evaluated in comparison to each other. DEA is a non-parametric method of calculating the efficiency and separating the efficient scenarios from the inefficient ones as well as identifying the causes of the inefficiency of the inefficient scenarios. In this regard, the efficiency of the scenarios as a DMU is determined by applying the RED model. The efficiency score which is based on the initial definition of efficiency dominance and ratio efficiency is calculated for each DMU using all the DMUs’ input and output. Instead of using LP to optimize efficiency of a DMU with respect to the other DMUs, in this method, the efficiency score of a DMU is compared with other DMUs using a weight value calculated using normalization function to determine its ranking. The RED method addressed both the issues of computation time and accuracy in efficiency evaluations of DMUs specifically for large data sets [36].

The proposed approach keeps the calculation more precise because without a combination of DOE and DEA approaches, we may not be able to design scenarios and analyze the efficiency of each of them at the same time. These two methods complement each other and make the results more realistic and accurate. Furthermore, DEA cannot take into account expert opinions, and with SWARA, we surely access a superior analysis. Figure 1 illustrates a schematic view of the proposed approach.
2.1. DES

In recent years, the technological advancements in computer simulation as an appropriate approach have guaranteed the feasibility and effectiveness of the designed process plan in a variety of engineering issues [25]. The use of simulation for real-time decision making directly in the manufacturing process is commonly employed before launching a new production [26]. A DES model enables the analysis of the dynamic of the stochastic system. Also, it can verify the functioning of a new element in the process and allow for evaluating both the operations and resources of the system and the mechanical efforts of a new device inserted in the plant of a process [27]. In DES, the state of the system changes only during specific time instants, which defined as the events. Further, the simulation can considered as a list of events that are ordered by a timestamp where an event can edit the status of the system, add new future events, or remove the already scheduled events [28, 29]. In the current study, the Enterprise Dynamics (ED) used, which is a DES simulation software platform developed by INCONTROL Simulation Solutions. The following seven steps provide the best practice in the job of simulation in order to achieve better results regarding the expected goals [27]:

**Step 1:** Defining the goals: In the first step, the aims should be determined since they suggest which areas should be emphasized on the process. In the present study, the objectives were characterized by the expert opinions of the manufacturing system.

**Step 2:** Providing conceptual description: Conceptual definition is the crucial step for developing a simulation model. In this study, a conceptual description was performed in the manufacturing factory by observing the production lines, production flows, logistic paths, and warehouses.

**Step 3:** Collecting the required data: In this step, analyzing the actual system in order to evaluate what information is relevant for building the model is essential. The required data were collected by designing the production processes and production flows of the manufacturing plant such as the number of the conveyor, queues, logistic paths, the number of the truck loader, cycle times, travel times between the sequential halls, conveyer speeds, and the like.

**Step 4:** Building the simulation model: In this step, ED simulation software was used for building the current state of the manufacturing system.

**Step 5:** Verifying and validating the model: Before collecting the results, investigating the verification and validation of the simulation model is necessary. In the present study, the verification of the model was determined using ED software abilities and the validation was performed utilizing the paired t-test.

**Step 6:** Simulating: In this phase, a simulation experiment is defined and run on an acceptable time horizon. Finally, a time horizon for this model was determined 100 times in 24 hours.

**Step 7:** Analyzing the results: In the final step, the results should be critically analyzed to decide whether to represent valid information for the goals. A negative answer could force the simulation process to restart from step 2.

2.2. DOE

Factorial designs widely applied in experiments involving several factors which studying the joint effect of the factors on a response is a matter of importance. \( k \) factors, each at only two levels, are considered as the most important and special cases, which presented in the current study. The process of the \( 2^k \) factorial design is summarized in the following steps [30]:

**Step 1:** Choosing the effective factor, levels, and response variables: The response variable of experiments was determined in this step. Then, effective factors and their levels, which can affect the substantiate outputs, were generated with respect to decision experts.

**Step 2:** Forming the initial model: The \( 2^k \) factorial design with respect to effective factors and response variables were applied in step 2. In the present study, \( 2^4 \) factorial design was used based on four factors.
Step 3: Performing the experiments: In this step, the simulation model was developed and the results were extracted for each experiment (scenario).

Step 4: Interpreting the results: Finally, the response variables were interpreted after developing the simulation model for each experiment.

2.3. SWARA

Decision making approaches act as a boon for the person who has to reach some conclusions by keeping all the favorable and unfavorable conditions in their mind [37, 39]. Multi-criteria Decision Making (MCDM) paradigm considered as the most famous wing of decision-making theory. Each MCDM technique has its advantages and disadvantages [31] and can be classified into two categories. Based on the number of alternatives under consideration, differences can cater between MADM and Multi-objective Decision Making (MODM) [33]. The SWARA method, as one of the new MADM methods, was developed by Kersuliene, Zavadskas, and Turskis in 2010. In the present study, the compelling factor (input) and response variable (output) weights calculated using the SWARA method.

The input of SWARA, as a relative importance value \( S_j \), is provided by the decision-makers, and this technique involves five steps [32]:

**Step 1:** Initially, indicators are prioritized according to the importance given by decision-makers.

**Step 2:** Beginning with the second attribute, the relative importance indicates the attribute \( j^{th} \) in relation to the previous attribute \((j-1)\), and this process is performed for each attribute. This ratio is called “average relative importance” \( S_j \).

**Step 3:** The coefficient \( K_j \) is calculated from Eq. (1).

\[
K_j = \begin{cases} 
1 & j = 1 \\
S_j + 1 & j > 1
\end{cases}
\]

(1)

Where \( j \) is an attribute number and \( S_j \) is a comparative importance of average value.

**Step 4:** The initial weight is derived from Eq. (2).

\[
q_j = \begin{cases} 
1 & j = 1 \\
q_j - 1 & j > 1
\end{cases}
\]

(2)

Where \( j \) is an attribute number, \( K_j \) is a coefficient of each attribute, and \( q_j \) is a recalculated weight.

**Step 5:** The weights of attributes are determined through the Eq. (3).
\[ W_j = \frac{q_j}{\sum_{j=1}^{n} q_j} ; j = 1, \ldots, n \]  

(3)

Where \( q_j \) is a recalculated weight and \( W_j \) is a weight of each attribute.

2.4. RED

DEA is a methodology based upon an interesting application of linear programming. It has been successfully employed for assessing the relative performances of a set of firms, usually called DMUs, which use a variety of identical inputs to produce a variety of identical outputs [34]. The Charnes, Cooper, Rhodes (CCR) model as the most popular DEA model, at first was introduced by Charnes et al. in 1978. They idea is to define the efficiency measure by assigning to each unit the most favorable weights as long as the efficiency scores of all DMUs calculated from the same set of weights do not exceed one [35]. Let \( X_{ij}, j = 1, \ldots, m \) and \( Y_{rj}, r = 1, \ldots, s \) denote the \( i \)th input and \( r \)th output, respectively, of the \( j \)th DMU, \( j = 1, \ldots, n \). The relative efficiency of DMU \( k \) under an assumption of constant returns to scale (CRS) is formulated via the following DEA model [35]:

\[
E_k = \max \sum_{r=1}^{s} u_r Y_{rk}
\]

s.t.

\[
\sum_{i=1}^{m} v_i X_{ik} = 1
\]

(5)

\[
\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1,2,3,\ldots,n
\]

(6)

\[
u_r \geq \varepsilon, r = 1,\ldots,s, i = 1,\ldots,m
\]

(7)

Where \( E_k \) is the efficiency of DMU \( k \), \( v_i \) and \( u_r \) are the virtual multipliers associated with the \( i \)th input and \( r \)th output, respectively, and \( \varepsilon \) is a small non-Archimedean number. This model is commonly denoted by the ratio-form DEA model because the constraint \( \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \) has a ratio form of \( \sum_{r=1}^{s} u_r Y_{rj}/\sum_{i=1}^{m} v_i X_{ij} \leq 1 \), which is just efficiency of DMU \( k \) for \( j = k \) [35].

In the current study, the RED model utilized to compute the efficiency of DMUs (scenarios). Farahmand and Desa introduced this model in 2017. The speed of computing is highly essential due to a considerable amount of data and the number of DMUs. Additionally, the time of computation obtained for dual and primal simplex around 36 and 136 h for 100,000 DMUs, respectively. Also, this model can help evaluate the efficiency of DMUs in small, large, and substantial problems within a limited time. The RED model includes seven steps [36]:
Step 1: Suppose $DMU_j = (X_1, X_2, ..., X_m, Y_1, Y_2, ..., Y_s)$, where $X_j = (x_{1j}, x_{2j}, ..., x_{mj})$ and $Y_j = (y_{1j}, y_{2j}, ..., y_{sj})$ are input consumption and output production vectors, respectively, and $x_{ij} > 0$, $y_{ij} > 0$, $j \in \{1, 2, ..., n\}$.

Step 2: If $x_{ip} = 0$, then $x_{ip} = \min\{x_{ij}\} - \varepsilon$, where $\varepsilon = \frac{1}{n} \max_j \{x_{ij}\}$ and $j \in \{1, 2, ..., n\}$.

Step 3: The weighted normalized values of inputs and outputs are determined from Eqs. (8) and (9).

$$\omega_{ij} = \mu_{ij} w_{ij}, \; i = 1, ..., m, \; r = 1, ..., s \; j = 1, ..., n \tag{8}$$

$$\omega_{rj} = \mu_{rj} w_{rj}, \; i = 1, ..., m, \; r = 1, ..., s \; j = 1, ..., n \tag{9}$$

Where $i = 1, ..., m, \; r = 1, ..., s$ and $j = 1, ..., n$ are inputs, outputs, and DMUs, respectively. $w_{ij}$ and $w_{rj}$ are calculated by the SWARA method, which respectively based on the weight of the input and the output indicators. Also the normalized values of the inputs ($\mu_{ij}$) and outputs ($\mu_{rj}$) are computed from Eqs. (10) and (11) for each DMU.

$$\mu_{ij} = \frac{x_{ij}}{\max_j \{x_{ij}\}}; \; x_{ij} > 0, \; i = 1, ..., m, \; r = 1, ..., s \; j = 1, ..., n \tag{10}$$

$$\mu_{rj} = \frac{y_{rj}}{\max_j \{y_{rj}\}}; \; y_{rj} > 0, \; i = 1, ..., m, \; r = 1, ..., s \; j = 1, ..., n \tag{11}$$

Where $x_{ij}, i = 1, ..., m$ and $y_{rj}, r = 1, ..., s$ denote the $i$th input and $r$th output, respectively, of the $j$th DMU, $j = 1, ..., n$.

Step 4: The relative score of $DMU_j$ is computed from Eq. (12).

$$SODI^+_j = \sum_{i=1}^{m} \sum_{r=1}^{s} \omega_{ij} \omega_{rj}, \; i = 1, ..., m, \; r = 1, ..., s, \; j = 1, ..., n \tag{12}$$

Where $SODI^+_j$ is the relative score of $DMU_j, j = 1, ..., n$. $\omega_{ij}$ and $\omega_{rj}$ are weighted normalized values of inputs and outputs, respectively.

Step 5: The maximum relative score is obtained by Eq. (13).
\[
SODI^+ = \max_j \left( SODI_j^+ \right); j = 1, \ldots, n
\]  
(13)

Where \( SODI^+ \) is the maximum relative score of DMUs.

**Step 6**: The efficiency of \( DMU_j \) that is calculated through the Eq. (14).

\[
SODI_j^+ = \frac{SODI_j^+}{SODI^+}; j = 1, \ldots, n
\]  
(14)

Where \( SODI_j^+ \) is the efficiency of \( DMU_j \), \( j = 1, \ldots, n \) which is obtained by dividing the relative score of \( DMU_j \) (\( SODI_j^+ \)) and the maximum relative score of DMUs (\( SODI^+ \)).

**Step 7**: Classify the efficiency level in descending order, Rank the DMUs according to their scores and analyze the results. The DMU with value 1 is determined as the most efficient DMU.

3. Experiment

3.1. System Description

The producer of automobile products in Tehran, Iran, regarded as a practical case that is related to IranKhodro Company. IranKhodro area contains one of the largest industrial plants in the Middle East. Besides, this company has eight body shops, three paint shops, and four assembler shops independently and produces eight different products. In addition to the high volume of logistics between the production halls, the state of supply, the capacity of production lines, product flow, and the like can provide various complexities and problems for the company in order to achieve its goals. The actual case of this study indicates the efficiency and effectiveness of the proposed approach. Figure 2 displays the existing condition of the company.

Insert Figure 2 Here

The manager of the plant would like to assure that their PS is efficient in the entire production process. In other words, the company would like to know what production scenarios are efficient if the current PS is inefficient. The experience learned from this study is expected to provide the overviews for future PS performance evaluation and optimization.

The following assumptions considered in the proposed approach. With considering the stated assumption, the DES, the DOE, DEA and MADM approach explained as well.

- The material flow initiated from the body shops;
- The manufacturing system is continuous;
- The cycle times are determined based on the probability distribution and the nature of the manufacturing system;
- The loading and offloading of the parts, bodies and the like by the insoles are limited;
- The production planning of each product considered in the body shop halls;
- The body shop stock halls are called WBS (Without paint Body Stock) and the paint shop stock halls are called PBS (Painted Body Stock);
- Several painted body products sent to five different sites, which are far from the central site.

3.2. Data Collection

In this section, the optimization of PS is evaluated in the automobile manufacturing industry in Iran. The productive system produces eight different products totaling 2050 products daily. The structure of the real model under investigation is summarized using the conceptual model (Figure 2).
Based on production planning, the primary components enter the body shops and then receive some services and become the iron bodies. Next, the bodies transported to paint shops utilizing the conveyors or logistic paths and converted into painted bodies. Then, they move to the final circuit and enter the assembler shops. Finally, the products become a complete automobile.

Further, some painted bodies, as a Semi-Knocked-Down (SKD), are sent to several shops such as Assembler shop 5 (Fars), Assembler shop 6 (Kermanshah), Assembler shop 7 (Semnan), Assembler shop 8 (Khazar), and Assembler shop 9 (Tabriz) in different sites. The information of the production flows of each product provided in Table 1. The amount of one indicates the path of manufacturing a product. Take product 4 as an example here. The body of this product is produced in Body shop 4, and then it has the ability to paint in Paint shop 1 and 3 as well as the ability to assemble in Assembler shop 5, 6, 7, and 8, which are all shown in the Table 1 with number 1. It should be noted that based on the product flow and production planning, this product is produced in one or more than one of these Paint shops and assembler shops.

The company is active 24 hours a day in three shifts starting from 7:30 AM to 3:30 PM, 3:30 PM to 11:45 PM, and 11:45 PM to 7:30 AM, respectively. Table 2 presents the cycle time and active shifts of each production hall. The resulting distributions for each production hall were validated by the Kolmogorov-Smirnov test for their goodness of fit. Furthermore, the logistic path between the production halls and the storage space capacities are shown in Tables 3 and 4, respectively.

The present study aimed to optimize the performance of the system. For this aim, some performance measures defined that were necessary for the company. These variables defined as the outputs aiming to collect based on the purpose of the study. It should be noted that these are determined according to two main data sources. Historical data is first of all one of the crucial resource for collecting required information, by which it means databases that contains the process of the last 40 years and information such as profit and loss, number of products produced, logistics processes, etc. Secondly, expert opinions that are in the company are another essential resource. These people manage production processes with expertise in daily basis, and they are experts in various fields of production including planning, organizing, engineering, managing logistics, controlling product flow, and managing resource allocation. Table 5 demonstrates these variables with the current values of the manufacturing system.

Furthermore, Based on historical data and expert opinions, several practical factors are also determined, which had more influence over the response variables of the productive system. The production of product 3 considered the most crucial factor aiming to increase the production value, and thus, the company attempts to increase this product as the most valuable product. Therefore, increasing the production planning of product 3 may have a positive effect on the essential goals of the company. On the other hand, increasing the production of products that fabricate below the sufficient production capacity (e.g., product 6) can be useful in the number of production. According to shift works, production scheduling, and capacity measurements of production lines, minimum and maximum amounts of product 3 and product 6 that can be produced are (200,350) and (60,220), respectively. Moreover, minimizing non-mechanized stocks, including WBS 4 and WBS 7, is regarded as another substantial factor that the company has always sought to improve as well. These stocks are caused by production speed of production halls, work shifts, and differences in capacity of production lines in the origin and destination halls, which can reach to maximum amount of 120 bodies, due to the space allocated for these
bodies. This can be rectified by optimizing the production process, leading to reach to minimum amount of zero. Additionally, reducing the cycle time of the Assembler shop 4 leads to an increase in the production rate without additional cost in this production hall. This factor reduces the logistics between the production halls and capital sleep. As the level of automation in this hall is high and does not depended on human resources for speed changes, its speed can be easily changed and reach to minimum and maximum amount of 92 and 115, respectively. Table 6 summarizes the factors and levels that selected for the experimental design.

Insert Table 6 Here

3.3. Results

The present study used ED in order to build the model and simulate the system. Also, a computer simulation utilized for solving the problem since it provides a systematic plan for evaluating different production scenarios based on the generated and objective data in order to assist the decision-maker [24]. Figure 3 illustrates the simulation model of the manufacturing system.

Insert Figure 3 Here

After developing a computer simulation model, evaluating the validity and accuracy of the simulation model is of considerable significance since the model should have a similar function to the real world in order to extend the results. Therefore, the vast capabilities of the ED software used to verify the model, followed by performing the paired t-test for validation purposes. Further, the warm-up time (i.e., the time it takes for a non-terminate system to reach a relatively stable state) set at 20 hours based on the throughput/hour diagram. Then, the scenarios were created based on Tables 5 and 6, as well as the DOE method. Table 7 indicates the scenario design and the results of simulation modeling. Each scenario simulated for 24 hours, 100 replications, and the average of 100 runs used accordingly.

Insert Table 7 Here

According to the experts' opinion, four input indicators of the production planning of product 3 (\(x_1\)), the production planning of product 6 (\(x_2\)), the non-mechanized stocks (\(x_3\)), and the Assembler shop 4 cycle time (\(x_4\)) investigated in the scenarios. Furthermore, the five output indicators of the total production profit (\(y_1\)), the number of production (\(y_2\)), the average productivity of production halls (\(y_3\)), the number of trucks carrying the body (\(y_4\)), and the number of semi-finished products during the process (\(y_5\)) determined for performance optimization as the output indicators. In order to investigate the importance of input and output indicators, the statistical population was selected from the experts of Irankhodro Automotive Company according to the expertise conditions. Qualification requirements include three characteristics: high education, high work experience (at least 10 years of work experience) and managerial experience. Therefore, with these conditions, out of 70 experts in this company, 33 qualified experts were selected. Afterwards, SWARA was used to determine the weight of input and output indicators according to expert opinions, in the score range between 0 and 100 via questionnaire. Validity of questionnaire was confirmed by experts, and reliability was calculated with Cronbach's Alpha in SPSS software. The obtained reliability was equal to 0.814, which indicates the acceptability of the questionnaire. According to the average importance of the indicators assigned by the experts, the importance of the input and output indicators are shown in Figures 4 and 5.

Insert Figure 4 Here

Insert Figure 5 Here

According to the importance of input and output indicators, the relative importance between the indicators is determined in pairs. Afterwards, based on the steps expressed in section (2.3), the final weight of each indicator is determined. Tables 8 and 9 present the weights of input and output indicators, and consequently the efficiency values and the rank of DMUs, namely, the scenarios provided in Table 10.
The steady status of the company based on two objectives, including the number of production and the productivity of the equipment. This situation achieved by the repeated changes in production planning and trial-error method over three years. Also, the performance is proved in relation to the current strategy of the organization. Additionally, unpredictable events in Iran’s automobile industry have increased the fixed price of the automobiles and thus changing the goals of the organization regarding producing its products. These goals include increasing the profit of the total production of profitable products, reducing low-efficiency manufacturing sites, moving to green logistics, and reducing semi-finished products during the process alongside maintaining the production numbers. Therefore, to achieve these new goals, the performance optimization of current status and the proposed scenarios were evaluated, and the efficient scenario obtained using previous years of experience, along with the simulation optimization method. Table 7 represented the effect of decreasing and increasing each input indicator on the output indicators of the DMUs.

Based on Table 10, Scenario 13 indicates the current status of the organization, which is ranked tenth. The profitable product is at its maximum level in an efficient scenario. Although the number of productions demonstrates a decrease as compared to Scenario 13, which is still highly rated due to a significant increase in the production profits and is highly essential for the organization. In designing and simulating this scenario, SKD products and Kermanshah site (Assembler shop 6) reduced as a site due to high logistical requirements and meager profits, and thus their supply sources were used to increase the production of profitable products. Another advantage of this scenario is the reduction of road traffic to 526 KM, which is a big step toward social responsibility and green logistics.

In Scenario 10, which is ranked second, the total production profit, the number of semi-finished products during the process, and the logistics factors indicate a significant improvement compared to the current situation while the final product number and the production profit represent a decrease compared to the fourth scenario. Scenario 10 is one of the best scenarios in terms of reducing the semi-finished products during the process. On the other hand, Scenario 16 is at the bottom of the rankings. In this scenario, production performance and the productivity of the equipment decrease while the stock levels increase despite increasing all of the resources.

4. Discussion

In this section, we examine the effect of the combined methods in the proposed approach with other methods in literature for optimization of different parts of PS. One of the crucial preferences of this approach is employing the advantages of DES, DOE, DEA, and MADM methods simultaneously. Although DES is one of the most effective and useful tools in manufacturing industries, the use of this method without utilizing suitable optimization tools causes a lack of comprehensive and accurate analysis in researches.

Previous studies used a DES method to assess the green logistics practices in the automotive industry [2], enhance production scheduling procedures [3], implement a simulation based online production planning system [6], demonstrate the applicability of DES for monitoring the production lines performance [8], construction of simulation models of production systems [9], evaluate and compare different production planning [14], and suggest production planning in the automotive industry [16]. In their study, the results evaluated without a suitable tool for production scenarios.

One of the most widely used tools for producing scenarios is DOE. This method enables us to analyze the simulation models systematically and present an appropriate analysis of the results and finally choose the optimal scenario for the case study. For example, Zahraee et al. suggested an integrated computer simulation and DOE method in a continuous production line [7]. Although this tool helps exceedingly to close the optimal scenario, it cannot be an accurate tool for selecting the optimal scenario. Thus, in order to compare the proposed
approach using only the DOE method in simulation, Table 7 has been solved with $2^k$ factorial design in MINITAB software. Table 11 shows the propriety of the effectiveness of factors for each response variable.

Insert Table 11 Here

According to the Table 11, because $X_1$ (Production planning of product 3) and $X_3$ (Non-mechanized stocks) factors have the most significant effect on response variables, with increasing these factors and decreasing $X_2$ (Production planning of product 6) and $X_4$ (Assembler shop 4 cycle time) the best scenario would have arrived. Thus, scenario 6 is efficient. According to the calculation of the proposed approach, this scenario ranked in the eleventh position. Because it has an extreme difference in $Y_1$ (Total production profit), $Y_2$ (Number of production) and $Y_5$ (Number of semi-finished products during the process) variables, which is very important for the company, compare with an efficient scenario. DOE method is not able to rank the scenarios concerning other output variables and also does not consider the degree of importance of the inputs and outputs in its calculations. Therefore, it can only provide some comparative analysis about the results obtained from the degree of effectiveness of each factor on the response variables and suggest the optimal scenario that may not necessarily be the best.

On the other hand, DEA is one of the most useful methods in the field of performance evaluation and scenario ranking in simulation models. In previous studies, the combination of simulation and DEA methods used for vendor selection [22], group consensus ranking [23], and facility layout design problem [24]. Although DEA is one of the best optimization methods in scenario ranking, it is unable to produce scenarios and can only design scenarios using expert opinions. In order to show the importance of the DOE method in producing scenarios, Table 12 shows sixteen scenarios based on expert opinions, which solved with simulation and DEA methods.

Insert Table 12 Here

According to Table 12, scenario 7 is efficient. Compared to the same scenario in the proposed approach, scenario 3 in Table 7 is close to the scenario which is efficient in Table 12. In this scenario, $X_1$ (Production planning of product 3), $X_3$ (Production planning of product 3), and $X_4$ (Non-mechanized stocks) factors have their lowest value and ranked in the fifth position. Because $Y_1$ (Total production profit) and $Y_2$ (Number of production) variables, which are the most crucial outputs for company, have less value than efficient scenario and DEA is not capable of considering the weights of the inputs and the outputs concerning the opinions of the experts of the company. Also, in these 16 scenarios, not only scenario 4 in Table 7 is not considered, but for the performance results in Table 12, some scenarios are the same. Therefore, the combination of DEA and DOE methods would have avoids these such as problems.

Previous research tried to relieve this weakness and use the benefits of simulation, DEA, and DOE methods simultaneously. The combinations of these methods have used to improve the performance of the PS in the automobile spare parts manufacturer [11] and evaluate the performance of the educational system [17]. Although this combination would have cause improvement in the optimization process, it still has a weakness in considering the input and output weights in calculations. In order to show the importance of this subject, Table 7 calculated regardless of the weight of the inputs and outputs. Besides, the results showed in Table 13.

Insert Table 13 Here

In Table 13, the second scenario is efficient. In comparison with the proposed approach that identified the fourth scenario is efficient, shows that this scenario is reduced by 3 % in both $Y_1$ (Total production profit) and $Y_2$ (Number of production) variables. These two variables are crucial for the company, and virtually it will not be the most efficient scenario. Therefore, the use of the MADM method (SWARA) creates at least a 3% improvement, which is a significant percentage in the industry.
In ranking with the proposed approach the maximum amount of Total production profit ($ Y_1 $) and Number of production ($ Y_2 $) with minimum amount of Non-mechanized stocks ($ X_3 $) and Assembler shop 4 cycle time ($ X_4 $) is obtained, which we did not get to these amounts in any scenarios without applying the proposed approach. To recapitulate, various production processes including the capacity of production halls, logistics, resource allocations, production strategies in accordance with the goals of the organization, production planning, and flow of products were considered simultaneously in simulation model, which cannot be found in previous studies. Moreover, the optimization of simulation model is the combination of DOE, DEA, and SWARA methods, which is essential to perform precise analysis. DOE helped to produce different scenarios according to strategic goals of the organization. In addition to this, SWARA provided the weight of input and output indicators, leading to accurate calculation of the efficient scenario in DEA. Some characteristics of the proposed method are also compared with those of the aforementioned methods, as listed in Table 14.

5. Conclusion

In general, increasing the production efficiency and determining the useful methods for optimizing the performance of different parts of PS and measuring the impact of any changes in every element in line with the strategic goals of the organization are the major concerns of the manufacturing companies. Optimization the PS can help each manufacturer to resolve failures, reduce transportation costs, optimize production lines, ensure the continuity of the processes from supply to sales, and eventually, evade the shocking variations in the production systems. In other words, the optimization of different part of a production processes provides a theoretical and practical overview. The present study aimed to investigate the optimization of the different part of PS such as production strategies, resource allocation, logistics and production planning, flow of products, and the proposed approach was evaluated in a case study related to the automobile manufacturing industry in Iran.

As mentioned earlier, the efficiency optimization in PS has received less attention in previous studies. In other words, previous studies focused on some parts of PS including the production line [7], or only used the simulation approach with the DOE or DEA methods [22]. In addition, these studies optimize the process by basic DEA model [31]. However, the algorithm of the present study, which deals with the optimization of performance in different part of PS with integrated new methods for the first time, maximizes the productivity of production process and the total profit while it minimizes the logistic resources and develops the simulation optimization approach. After the scenarios were designed with DOE, the weights of the input and output indicators from the DOE were added to the RED model (to increase the accuracy of the performance evaluation) and the model was improved using the SWARA model taking into account the experts opinions. Finally, the results were analyzed after calculating the efficiency of DMUs, namely, the scenarios which were designed in the automobile industry in Iran.

Further, the impact of variation on performance and output indicators were evaluated by DES and DOE models. Based on the results, the changes in production planning of Product 3 ($ X_1 $), production planning of Product 6 ($ X_2 $), non-mechanized stocks ($ X_3 $), and Assembler shop 4 cycle time ($ X_4 $) indicators played a significant effect on the efficiency of DMUs. Therefore, appropriate decisions should be adopted given the number of changes and the initial efficiency of each DMU. For example, as regards DMU 13, the changes were related to a decrease in Assembler shop 4 cycle time ($ X_4 $) or non-mechanized stocks ($ X_3 $) indices in order to increase the efficiency of the current state. Furthermore, the changes in the production planning of Product 3 ($ X_1 $) indicator had a greater impact on the total production profit ($ Y_1 $) and the number of trucks carrying the body ($ Y_4 $) indicators. Additionally, the amount of the total production profit ($ Y_1 $), and the number of trucks carrying the body ($ Y_4 $) for DMU4 optimized with increasing $ X_1 $ and $ X_2 $. On the other hand, a decrease in the average productivity of production halls ($ Y_3 $) could be observed by reducing $ X_3 $ and $ X_4 $ indicators.
In general, the results indicated that the proposed algorithm is a practical instrument for optimizing the production process and helped the manufacturing companies to make efficient decisions, increase their productivity, and thus decrease the essential problems in every part of PS. In addition, this approach is able to consider the impact of any changes in a whole system, which can find the optimal solution through ranking the DMUs.

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Figure and table captions:

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Figure 1. Schematic view of proposed approach

Note. DES= Discrete-Event Simulation; DOE= Design of Experiments; MADM= Multi-Attribute Decision Making; SWARA= Step-wise Weight Assessment Ratio Analysis; DEA= Data Envelopment Analysis; RED= Ratio Efficiency Dominance.

Figure 2. The existing condition of the company

Note. WBS= Without paint Body Stock; PBS= Painted Body Stock; SKD= Semi-Knocked-Down
Figure 3. The simulation model of the manufacturing system in ED software
Figure 4. The importance of input indicators

Figure 5. The importance of output indicators
**Table 1.** The information of the production flow of each product

| Product | Body shop | Paint shop | Assembler shop |
|---------|-----------|------------|----------------|
|         | 1 2 3 4 5 6 7 8 | 1 2 3 | 1 2 3 4 5 6 7 8 9 |
| 1       | 1 0 0 0 0 0 0 0 0 | 0 0 1 | 0 0 1 0 0 0 0 0 0 |
| 2       | 0 1 0 0 0 0 0 0 0 | 1 1 0 | 0 0 0 0 0 0 0 0 1 |
| 3       | 0 0 1 0 0 0 0 0 0 | 1 1 0 | 0 1 0 0 0 0 0 0 0 |
| 4       | 0 0 0 1 0 0 0 0 0 | 1 0 1 | 0 0 0 1 1 1 1 1 0 |
| 5       | 0 0 0 0 1 0 0 0 0 | 0 1 0 | 0 0 0 1 0 0 0 0 0 |
| 6       | 0 0 0 0 0 1 0 0 0 | 0 1 0 | 0 0 0 1 0 0 0 0 0 |
| 7       | 0 0 0 0 0 0 1 0 0 | 1 0 0 | 1 0 0 0 0 0 0 0 0 |
| 8       | 0 0 0 0 0 0 0 1 0 | 1 0 0 | 1 0 0 0 0 0 0 0 0 |

**Table 2.** The cycle time and active shifts of each production hall

| Production hall | Cycle time | Active shift |
|-----------------|------------|--------------|
| Body shop 1     | Uniform(168.66,171.14) | 1 |
| Body shop 2     | Uniform(148.83,151.87) | 1-3 |
| Body shop 3     | Uniform(259.81,263.09) | 1-2 |
| Body shop 4     | Uniform(176.66,179.14) | 1-2-3 |
| Body shop 5     | Uniform(118.68,122.62) | 1-2-3 |
| Body shop 6     | Uniform(423.35,426.95) | 1 |
| Body shop 7     | Uniform(538.10,542.20) | 1-2 |
| Body shop 8     | Uniform(519.41,523.69) | 1-2 |
| Paint shop 1    | Uniform(94.23,97.87) | 1-2-3 |
| Paint shop 2    | Uniform(84.18,88.12) | 1-2-3 |
| Paint shop 3    | Uniform(142.13,146.27) | 1-2 |
| Assembler shop 1| Uniform(262.99,265.31) | 1-2 |
| Assembler shop 2| Uniform(265.89,267.51) | 1-3 |
| Assembler shop 3| Uniform(168.31,171.59) | 1 |
| Assembler shop 4| Uniform(108.77,112.03) | 1-2-3 |
| Assembler shop 5| Uniform(316.91,319.69) | 1 |
| Assembler shop 6| Uniform(409.86,412.34) | 1-2 |
| Assembler shop 7| Uniform(508.79,511.01) | 1 |
| Assembler shop 8| Uniform(295.76,298.14) | 1-2 |
| Assembler shop 9| Uniform(151.88,154.12) | 1-2 |

**Table 3.** The logistic path between the production halls

| Transportati on Network | Preceding hall | Following hall | Load time (second) | Unload time (second) | Load quantity | Number of truck | Distance (km) | Speed (km/h) |
|-------------------------|----------------|----------------|-------------------|---------------------|---------------|-----------------|---------------|--------------|
| 1                       | WBS 4          | Paintshop1     | 60                | 58                  | 2             | 5               | 1.2           | 20           |
| 2                       | WBS 4          | Paintshop3     | 60                | 58                  | 2             | 8               | 2.7           | 25           |
| 3                       | Bodyshop7      | Paintshop1     | 120               | 130                 | 1             | 5               | 0.1           | 5            |
| 4                       | WBS 8          | Paintshop1     | 60                | 58                  | 2             | 2               | 0.9           | 15           |
| 5                       | PBS 1          | SKD hall       | 90                | 65                  | 2             | 5               | 2.2           | 25           |
| 6                       | PBS 2          | SKD hall       | 75                | 75                  | 2             | 5               | 2             | 20           |
| 7                       | PBS 3          | SKD hall       | 75                | 75                  | 2             | 5               | 3             | 30           |
| 8                       | SKD hall       | Assembler shop 5| 1800              | 1800                | 11            | 30              | 924           | 90           |
| 9                       | SKD hall       | Assembler shop 6| 1740              | 1740                | 11            | 42              | 526           | 85           |
| 10                      | SKD hall       | Assembler shop 7| 1920              | 1820                | 11            | 6               | 236           | 90           |
| 11                      | SKD hall       | Assembler shop 8| 1800              | 1800                | 11            | 24              | 229           | 70           |
| 12                      | SKD hall       | Assembler shop 9| 1860              | 1860                | 11            | 92              | 559           | 90           |

Note. WBS= Without paint Body Stock; PBS= Painted Body Stock; SKD= Semi-Knocked-Down.
Table 4. The storage space capacities

| Hall     | Preceding hall | Following hall | Capacity |
|----------|----------------|---------------|----------|
| WBS 1    | Body shop 1    | Paint shop 3  | 100      |
| WBS 2    | Body shop 2    | Paint shop 1  | 100      |
|          | Body shop 3    | Paint shop 2  | 130      |
|          | Body shop 6    |               |          |
| WBS 5    | Body shop 5    | WBS 2        | 100      |
| WBS 4    | Body shop 4    | Paint shop 1  | 20       |
|          |                | Paint shop 3  |          |
| WBS 8    | Body shop 8    | Paint shop 1  | 100      |
| PBS 1    | Paint shop 1   | Assembler shop 1 | 195 |
|          |                | Assembler shop 2 |    |
|          |                | SKD hall      |          |
| PBS 2    | Paint shop 2   | Assembler shop 2 | 155 |
|          |                | Assembler shop 4 |    |
|          |                | SKD hall      |          |
| PBS 3    | Paint shop 3   | Assembler shop 3 | 135 |
|          |                | SKD hall      |          |
| Conveyor 1 | WBS 1        | Paint shop 3  | 5        |
| Conveyor 2 | PBS 3         | Assembler shop 3 | 15   |
| Conveyor 3 | Body shop 2   | WBS 2        | 17       |
| Conveyor 4 | Body shop 3   | WBS 2        | 17       |
| Conveyor 5 | Body shop 6   | WBS 2        | 15       |
| Conveyor 6 | WBS 5         | WBS 2        | 15       |
| Conveyor 7 | WBS 2         | Paint shop 1  | 40       |
| Conveyor 8 | WBS 2         | Paint shop 2  | 60       |
| Conveyor 9 | PBS 1         | Assembler shop 1 | 2    |
| Conveyor 10 | PBS 1       | Assembler shop 2 | 2    |
| Conveyor 11 | PBS 2        | Assembler shop 2 | 10   |
| Conveyor 12 | PBS 2        | Assembler shop 4 | 60   |

Note. WBS= Without paint Body Stock; PBS= Painted Body Stock; SKD= Semi-Knocked-Down.

Table 5. The Response variables

| Variable | Description                                      | Current state |
|----------|--------------------------------------------------|---------------|
| $y_1$    | Total production profit                         | $2,368,750.00$|
| $y_2$    | Number of production                            | 2045          |
| $y_3$    | Average productivity of production halls         | 97.27%        |
| $y_4$    | Number of trucks carrying the body              | 299           |
| $y_5$    | Number of semi-finished products during the process | 482          |

Table 6. The factors and levels

| Factor | Description                                      | Level |
|--------|--------------------------------------------------|-------|
| $x_1$  | Production planning of product 3                 | 200   | 350  |
| $x_2$  | Production planning of product 6                 | 60    | 220  |
| $x_3$  | Non-mechanized stocks                            | 0     | 120  |
| $x_4$  | Assembler shop 4 cycle time                      | 92    | 115  |
Table 7. The scenario design and the results of simulation modeling

| Scenario | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $y_1$ | $y_2$ | $y_3$ | $y_4$ | $y_5$ |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1        | -     | -     | -     | -     | $2,154,250.00$ | 1652  | %81.52 | 229   | 390   |
| 2        | +     | -     | -     | -     | $2,671,225.00$ | 1792  | %84.25 | 197   | 355   |
| 3        | -     | +     | -     | -     | $2,220,875.00$ | 1662  | %90.71 | 224   | 494   |
| 4        | +     | +     | -     | -     | $2,743,875.00$ | 1832  | %93.47 | 174   | 621   |
| 5        | -     | -     | +     | -     | $2,368,150.00$ | 1954  | %96.63 | 229   | 477   |
| 6        | +     | -     | +     | -     | $2,538,875.00$ | 1760  | %90.30 | 197   | 512   |
| 7        | -     | +     | +     | -     | $2,412,250.00$ | 1908  | %95.05 | 224   | 641   |
| 8        | +     | +     | +     | -     | $2,699,500.00$ | 1770  | %91.95 | 174   | 585   |
| 9        | -     | -     | -     | +     | $2,148,475.00$ | 1634  | %81.02 | 229   | 422   |
| 10       | +     | -     | -     | +     | $2,678,050.00$ | 1802  | %85.45 | 197   | 369   |
| 11       | -     | +     | -     | +     | $2,204,875.00$ | 1515  | %88.10 | 224   | 587   |
| 12       | +     | +     | -     | +     | $2,652,125.00$ | 1663  | %89.44 | 174   | 578   |
| 13       | -     | -     | +     | +     | $2,368,750.00$ | 1989  | %97.27 | 229   | 482   |
| 14       | +     | -     | +     | +     | $2,627,375.00$ | 1818  | %92.25 | 197   | 563   |
| 15       | -     | +     | +     | +     | $2,401,375.00$ | 1836  | %94.87 | 224   | 690   |
| 16       | +     | +     | +     | +     | $2,671,875.00$ | 1763  | %92.13 | 174   | 671   |

Table 8. Weight of input indicators based on the SWARA method

| Indicator | Comparative Importance of average value (S) | Coefficient (K) | Recalculated weight (q) | Weight (W) |
|-----------|---------------------------------------------|-----------------|-------------------------|------------|
| $x_1$     | 0.2433                                      | 1               | 1                       | 0.3704     |
| $x_2$     | 1.2433                                      | 0.8043          | 0.2979                  |
| $x_3$     | 0.1944                                      | 0.5594          | 0.2072                  |
| $x_4$     | 0.2299                                      | 0.3354          | 0.1242                  |

Table 9. Weight of output indicators based on the SWARA method

| Indicator | Comparative Importance of average value (S) | Coefficient (K) | Recalculated weight (q) | Weight (W) |
|-----------|---------------------------------------------|-----------------|-------------------------|------------|
| $y_1$     | 0.2521                                      | 1               | 1                       | 0.3436     |
| $y_2$     | 0.1942                                      | 0.7986          | 0.2744                  |
| $y_3$     | 0.1375                                      | 0.5521          | 0.1897                  |
| $y_4$     | 0.0721                                      | 0.3486          | 0.1198                  |
| $y_5$     | 1.6560                                      | 0.2105          | 0.0723                  |
### Table 10. The efficiency values and the rank of DMUs

| DMU/Scenario | Efficiency | Rank |
|--------------|------------|------|
| DMU₁         | 0.8905     | 7    |
| DMU₂         | 0.9624     | 3    |
| DMU₃         | 0.9159     | 5    |
| DMU₄         | 1          | 1    |
| DMU₅         | 0.0526     | 9    |
| DMU₆         | 0.0476     | 11   |
| DMU₇         | 0.0382     | 13   |
| DMU₈         | 0.0340     | 15   |
| DMU₉         | 0.8869     | 8    |
| DMU₁₀        | 0.9661     | 2    |
| DMU₁₁        | 0.8943     | 6    |
| DMU₁₂        | 0.9466     | 4    |
| DMU₁₃        | 0.0500     | 10   |
| DMU₁₄        | 0.0462     | 12   |
| DMU₁₅        | 0.0349     | 14   |
| DMU₁₆        | 0.0312     | 16   |

Note. DMU = Decision-Making Unit.

### Table 11. Propriety of effectiveness for Response variables

| Response variable | Propriety of effectiveness |
|-------------------|----------------------------|
|                   | $x_1$ | $x_2$ | $x_3$ | $x_4$ |
| $γ_1$             | 1     | 2     | 3     | 4     |
| $γ_2$             | 1     | 2     | 3     | 4     |
| $γ_3$             | 4     | 3     | 2     | 1     |
| $γ_4$             | 2     | 3     | 1     | 4     |
| $γ_5$             | 2     | 3     | 1     | 4     |
Table 12. The scenario design with expert opinions

| Scenario | Factors | Response | Efficiency | Rank |
|----------|---------|----------|------------|------|
| 1        | 210 60 0 95 | $2,152,200.00 | 1630 | %80.32 | 229 | 390 | 0.95 | 3 |
| 2        | 310 70 0 95 | $2,670,125.00 | 1781 | %83.1 | 197 | 355 | 0.97 | 2 |
| 3        | 210 220 100 95 | $2,410,578.00 | 1912 | %95.15 | 224 | 641 | 0.04 | 13 |
| 4        | 350 220 0 95 | $2,732,754.00 | 1795 | %91.7 | 174 | 621 | 0.81 | 4 |
| 5        | 210 70 100 95 | $2,468,054.00 | 1905 | %95.15 | 224 | 477 | 0.05 | 9 |
| 6        | 350 70 100 95 | $2,549,521.00 | 1912 | %91.7 | 229 | 494 | 0.04 | 13 |
| 7        | 210 220 0 95 | $2,221,073.00 | 1652 | %91.1 | 224 | 494 | 0.03 | 15 |
| 8        | 350 220 100 95 | $2,698,721.00 | 1792 | %92.3 | 174 | 585 | 0.03 | 15 |
| 9        | 210 70 0 115 | $2,152,469.00 | 1638 | %80.02 | 229 | 422 | 0.75 | 8 |
| 10       | 350 70 0 115 | $2,598,254.00 | 1798 | %87.45 | 197 | 369 | 0.76 | 7 |
| 11       | 210 220 0 115 | $2,154,789.00 | 1545 | %89.5 | 224 | 587 | 0.78 | 5 |
| 12       | 350 220 0 115 | $2,635,816.00 | 1697 | %91.1 | 174 | 578 | 0.78 | 6 |
| 13       | 210 70 100 115 | $2,368,212.00 | 1995 | %96.22 | 229 | 482 | 0.05 | 10 |
| 14       | 350 70 100 115 | $2,598,757.00 | 1795 | %92.5 | 197 | 563 | 0.04 | 12 |
| 15       | 210 220 100 115 | $2,458,981.00 | 1846 | %93.65 | 224 | 690 | 0.03 | 14 |
| 16       | 350 220 100 115 | $2,692,541.00 | 1782 | %91.05 | 174 | 671 | 0.03 | 16 |

Table 13. The efficiency values and the rank of DMUs without weights

| DMU/Scenario | Efficiency | Rank |
|--------------|------------|------|
| DMU_1        | 0.93       | 3    |
| DMU_2        | 1.00       | 1    |
| DMU_3        | 0.96       | 2    |
| DMU_4        | 0.82       | 4    |
| DMU_5        | 0.05       | 9    |
| DMU_6        | 0.04       | 11   |
| DMU_7        | 0.04       | 13   |
| DMU_8        | 0.03       | 15   |
| DMU_9        | 0.74       | 7    |
| DMU_10       | 0.80       | 5    |
| DMU_11       | 0.73       | 8    |
| DMU_12       | 0.79       | 6    |
| DMU_13       | 0.05       | 10   |
| DMU_14       | 0.04       | 12   |
| DMU_15       | 0.03       | 14   |
| DMU_16       | 0.03       | 16   |

Note. DMU= Decision-Making Unit.
Table 14. The comparative characteristics of different methods

| Methods                      | Production lines | Logistic process | Resource allocation | Production strategies | Production planning | Flow of products | Whether designing scenarios with regard to the goals of organization | Whether prioritizing the factors by decision-makers | Whether determining the efficiency of production scenarios |
|------------------------------|------------------|------------------|---------------------|-----------------------|--------------------|------------------|-------------------------------------------------------------------|-------------------------------------------------|----------------------------------------------------------|
| Abdulaziz et al. [2]         | ×                | ✓                | ×                   | ×                     | ×                  | ×                | ×                                                                  | ×                                               | ×                                                         |
| Dumetz et al. [3]            | ×                | ×                | ✓                   | ×                     | ×                  | ×                | ✓                                                                  | ×                                               | ×                                                         |
| Vaisi and Ebrahimi [11]      | ✓                | ×                | ×                   | ✓                     | ×                  | ×                | ✓                                                                  | ×                                               | ✓                                                         |
| Azadheh et al. [24]          | ×                | ×                | ✓                   | ×                     | ×                  | ×                | ✓                                                                  | ×                                               | ✓                                                         |
| Kaylani and Atieh [14]       | ✓                | ×                | ×                   | ✓                     | ✓                  | ×                | ✓                                                                  | ×                                               | ×                                                         |
| Gyulai et al. [16]           | ✓                | ×                | ×                   | ✓                     | ×                  | ×                | ✓                                                                  | ×                                               | ×                                                         |
| Ebrahiminejad et al. [23]    | ×                | ×                | ✓                   | ×                     | ×                  | ×                | ✓                                                                  | ×                                               | ✓                                                         |
| Marlin and Sohn [17]         | ×                | ×                | ×                   | ×                     | ×                  | ×                | ✓                                                                  | ×                                               | ✓                                                         |
| Zahraee et al. [7]           | ✓                | ×                | ×                   | ✓                     | ✓                  | ×                | ✓                                                                  | ×                                               | ×                                                         |
| Park et al. [22]             | ×                | ×                | ✓                   | ×                     | ×                  | ×                | ✓                                                                  | ×                                               | ×                                                         |
| Müller et al. [6]            | ✓                | ×                | ×                   | ✓                     | ✓                  | ×                | ✓                                                                  | ×                                               | ×                                                         |
| Caterino et al. [8]          | ✓                | ×                | ×                   | ✓                     | ×                  | ×                | ✓                                                                  | ×                                               | ×                                                         |
| Pawlewski [9]                | ×                | ×                | ×                   | ×                     | ✓                  | ×                | ✓                                                                  | ×                                               | ×                                                         |
| The proposed approach        | ✓                | ✓                | ✓                   | ✓                     | ✓                  | ✓                | ✓                                                                  | ✓                                               | ✓                                                         |

Note. DES= Discrete-Event Simulation.