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Sustainable Supplier Selection: A New Integrated Approach of Fuzzy Interpretive Structural Modeling and Dynamic Network Data Envelopment Analysis

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Data envelopment analysis (DEA), as a well-established nonparametric method, is used to meet efficiency evaluation purposes in many businesses, organizations, and decision units. This paper aims to present a novel integrated approach to fuzzy interpretive structural modeling (FISM) and dynamic network data envelopment analysis (DNDEA) for the selection and ranking of sustainable suppliers. First, suppliers' efficiency values in a supply chain are determined, using the dynamic network data envelopment analysis (DNDEA) model developed for this purpose. Then, a heuristic method is presented based on the fuzzy interpretive structural modeling (FISM) to find a common set of weights (CSWs) for the variables involved. Depending on the data conditions, two approaches, viz. centralized and decentralized, are proposed for efficiency measurement. To illustrate the model's capability, the proposed methodology is further applied to the real data of a company, named Nirou Moharekeh Industries (NMI). The results of a study on 12 suppliers within the DNDEA model accordingly reveal that one unit (i.e. KARAN) obtains an efficient value, but an inefficient score is observed in 11 units, whose technical efficiency value is in the range of 0.6409 to 0.9983. After utilizing the weights gained from the heuristic method, the efficiency value of the most inefficient supplier (that is, SIRINS.N.) dwindles from 0.6409 to 0.6319.

Keywords: *data envelopment analysis, sustainable supply chain, Fuzzy Interpretive Structural Modeling.*

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1. Introduction

The efficiency evaluation of businesses and organizations is known as one of the most important processes in managerial decision-making (Zhou & Zhan, [54]). This process has become now strategic since businesses rarely try to change their suppliers, but suppliers do their best to stay and cement their place in supply chains. This is even more significant once it is realized that suppliers' conditions may vary over time, and their outputs may be shaped by such changes (Krishnan, [28]). Meanwhile, the fluctuations in the markets and customers' expectations in relation to sustainable development can pose some new challenges to businesses (Alimohammadlou & Khoshsepehr,[2]), as sustainability has a multidisciplinary essence and is mostly defended as the relationship between economy, society, and the environment (Andarkhora et al.[5]; Caiado et al. [8]; Hashim et al. [23]).

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To ensure compliance with sustainability requirements, numerous businesses are currently evaluating their suppliers in a rigorous manner (Amiri et al. [4]), so a wide variety of methods have been developed for this purpose. Data envelopment analysis (DEA) is accordingly one of the most common methods to benchmark and assess the relative performance of various structures (Li et al. [31]; Parashkouh et al, [40]). In this nonparametric approach, there is no need to determine the mathematical structure of production functions, and the relative efficiency of businesses can be merely analyzed by applying any input/output measurement (Milenković et al, [35]) . Over the years, this method has been expanded by many researchers, proposing various DEA-based models, with their drawbacks and strengths. Given the multi-stage nature of the supply chain, considered in this study, and the flaws of the classical DEA, network DEA, and dynamic DEA models in analyzing such chains, this study developed a model, called dynamic network data envelopment analysis (DNDEA), with the capability to measure network efficiency during multiple periods (del Barrio-Tellado & Herrero-Prieto, [14]). This structure allows analysts to address the management of potentially complex entities involving interconnected processes (Álvarez-Rodríguez et al. [3]).

On the other hand, DEA models allow each DMU to choose an individual CSWs freely in order to put itself in the best possible light (Afsharian et al. [1]). According to Liu et al. [33], the DNDEA model fails to obtain the optimal input and output weights. Hence, each DMU is assigned the best CSWs with values varying from one DMU to another (Goker et al.[21]). This flexibility in selecting the weights can maximize the efficiency score, and even deter comparisons among DMUs on a common and identical basis. In addition, various DMUs tend to give very different weights to similar inputs and outputs, which may lead to unreliable and inaccurate estimation. Implementing weights in DEA models is usually done through elements (viz. variables), time terms, or divisions in line with decision-maker preferences from the standpoint of company managers, environmental policy-makers, or the local community (Álvarez-Rodríguez et al. [3]). In this paper, first, the CSWs are extracted, exploiting a novel heuristic method based on the fuzzy ISM. Afterward, depending on the data conditions, two approaches, i.e. centralized and decentralized, are proposed for efficiency measurement. The first approach is called "centralized" since it applies CSWs to all DMUs, and the efficiency values are obtained directly via such weights. Considering the type of data, this approach can have some limitations, including the fact that each DMU must have at least one input greater than or equal to one; otherwise, it is practically impossible to implement this approach. In the face of these conditions, the second approach termed "decentralized" is recommended. Here, utilizing CSWs, each station can be weighted separately for each supplier. Accordingly, the efficiency values are modeled as a weighted harmonic mean. In addition to dealing with the limitations of the centralized approach, this approach solves one of the problems in previous studies. That is, the efficiency score of a process is the arithmetic mean of the efficiency value of its components or stages. One of the problems encountering this approach is that all divisions may have the same weight during efficiency calculations regardless of how much important they are for the process. Thus, this issue is addressed in the present study. To the best of our knowledge:

- Proposing, for the first time, a heuristic method based on fuzzy-ISM for finding a set of weights for the components of processes.
- This is the first time fuzzy-ISM is integrated into DEA.
- Presenting, for the first time, a weighted approach for DEA models when data are not standard.

Accordingly, this paper aims to present a heuristic method for determining a set of weights in the DNDEA models. This method provides better insights into the way processes should be weighted, and is expected to improve the results of the DNDEA models. The method also allows for not only quantifying the efficiency of suppliers, but also monitoring dynamic changes over certain periods. Furthermore, the proposed method expands the scope of the interpretive structural modeling (ISM) applications. Practical cases are further applied to clarify and validate the method concerned. In section two, the research literature is reviewed. In section three, the proposed model is formulated and a numerical example is provided to showcase its capability and application. The final section presents the conclusions.

2. Theoretical framework

In this section, we briefly review the literature on the methods used in the article.

2.1. Dynamic Network Data Envelopment Analysis

The early DEA models, like Charnes, Cooper, and Rhodes (CCR) [9], Banker, Charnes, and Cooper (BCC) [6], which take account of the inputs and outputs of independent decision-making units (DMUs) simultaneously (Pourmahmoud & Sharak, [41]), are very good tools for relative efficiency evaluations (Ge, [19]), but they suffer from some drawbacks, such as ignoring the internal mechanisms of activities and DMUs (Shieh et al. [42]). Following the initial studies by Farrell [15] and the subsequent expansions in Chen et al. [10]; Fare et al. [17]; Färe et al. [16]; Fukuyama & Weber, [18]; Tone & Tsutsui, [47], researchers developed DEA models, capable of measuring not only the total efficiency, but also the divisional efficiency of DMUs within an integrated framework. This approach, known as the network data envelopment analysis (NDEA), is static and does not consider time (Lu et al. [34]), which can induce misleading results based on short-term analyses (Tone et al. [46]). Later, [38] introduced the dynamic data envelopment analysis (DDEA) model to address this issue, but the given model could simply treat DMUs as black boxes, completely overlooking their internal structure. Therefore, a model reflecting on time as well as the internal structure of DMUs was a necessity. Several reviews of the NDEA and DDEA models (Fukuyama & Weber, [18]; Hashimoto & Fukuyama, [24]; Johnson & Pope,[26]) have thus far highlighted the need for extending a dynamic DEA to network structures. Among of the first studies in this line was that completed by Tone & Tsutsui,[48], wherein a dynamic NDEA model was considered, and then a DNDEA model was developed based on the slacks-based measure (SBM).

2.2. Fuzzy Interpretive Structural Modeling

First introduced by Warfield in 1974 [49], ISM is a well-established method for identifying the relationships between variables (Kumar et al. [29]; Mohammadian et al.[36]). The classical ISM only discusses the relationships between elements (viz. the absence of a relationship, the presence of a one-sided relationship, or the presence of a two-sided relationship) (Sindhu, [43]), based on a binary spectrum, with the logic that more effective elements of a system are always more important (Yadav & Sharma, [52]). It can be argued that the classical ISM may not fully manifest reality (Jamwal et al. [25]). Moreover, using binary values to rate the relationships can lead to unwanted relationships between some elements in the final model. In other words, the classical ISM fails to factor in the magnitude and intensity of the relationships between elements. To avoid this problem, the fuzzy variant of ISM (FISM) is used in this paper to develop a novel logical framework for extracting a set of weights.

2.3. Background

In this section, we will briefly review the research background in supply chain performance evaluation and combined approach with DEA, At the end, the research gap will be explained.

Table1. Background

Author's	Method	objectives	description

(Stević et al. [44])	DEA + PCA+ CRITIC + entropy + MARCOS	development of an integrated model for determining the efficiency of representative transport companies	the efficiency analysis of transport companies was performed by using an integrated PCA–DEA model. then CRITIC and Entropy were used to determine the weight values of defined input and output parameters and finally to precisely determine the ranking was performed MARCOS method.
(Han & Gu, [22])	DEA + AHP	Evaluating the effectiveness of the combined method (DEA-AHP) and extending the boundaries of the research	estimated criteria weights with AHP and then applied the calculated weights in a DEA model .an efficiency evaluation system for the knowledge supply chain was constructed, which was used to measure the efficiency of high-tech enterprises in four provinces and cities in the Yangtze River Delta.
(Goker et al. [21])	DEA + FWA+ HOQ	proposes a fuzzy multiple criteria group decision-making procedure combining quality function deployment and DEA.	The developed approach enables to include the interactions among country evaluation criteria via forming a HOQ. The lower and upper bounds on country evaluation criteria are determined by utilizing the FWA technique. A common-weight DEA-based modeling framework, which uses the weights of country attributes calculated by FWA with the data from HOQ, was employed for identifying Latin American countries' rankings.
(Ghasemi et al. [20])	DEA + Quadratic Programming	presenting stochastic Efficiency Based on a Common Set of Weights in Data Envelopment Analysis	utilizing the concept of chance-constrained programming, first introduced a stochastic CSW model along with probability restrictions. Then, transformed the stochastic CSW model into a deterministic model, and following that, the deterministic model was transformed into a quadratic programming model, and the efficiency obtained using stochastic data
(Omrani et al. [39])	DEA + BWM	Presenting an integrated DEA-BWM which considers DMs' preferences in DEA and reduces flexibility in weights of inputs and outputs.	First, the preferences vectors are designed using BWM, and then, a multi-objective DEA-BWM model was introduced. The proposed DEA-BWM model simultaneously maximizes the efficiency scores of DMUs and considers DMs' preferences about the weights of inputs and outputs. Finally, a goal programming model was suggested for extending the DEA-BWM model and finding common weights of inputs and outputs based on the DMs' judgments.
(Davoudabadi et al. [13])	DEA + PCA + entropy	suggesting an integrated model for solving resilient supplier selection problems based on fuzzy set theory and a combination of DEA, PCA, and entropy	the DEA was utilized to determine the criteria's importance and to calculate the relative efficiency of suppliers. To eliminate the dependency between the data and to reduce problem dimensions, the PCA approach was applied and finally, Weights of the criteria were established using the entropy, and judgments of decision-makers simultaneously.
(Yazdani et al. [53})	DEA + R-FUCOM + R-CoCoSo	Development of a two-stage decision model to select the establishment of logistics centers in the autonomous communities of Spain	In the first stage, the considered communities were compared based on five evaluation criteria using DEA to identify the efficient and inefficient alternatives. In the second stage, the R-FUCOM method is utilized to obtain the optimal weights of the criteria, while the R-CoCoSo method was finally used to rank the efficient communities.
(Blagojevic et al. [7])	Entropy-Fuzzy PIPRECIA + DEA	Development of a new integrated Entropy-Fuzzy PIPRECIA and DEA model for determining the state of safety in B&H under particular conditions of uncertainty	The Entropy model was used to determine the weight values of the inputs and the Fuzzy PIPRECIA was used to evaluate the weight values of the outputs. After the application of the two methods, the way of averaging their values was defined. The DEA model, which implies an input- and output-oriented model, was applied to determine which railway sections have satisfactory performance in terms of safety.
(Cheng & Wei, [11])	DEA + AHP	Evaluating the effectiveness of the combined method (DEA-AHP) and extending the boundaries of the research	estimated criteria weights with AHP and then applied the calculated weights in a DEA model to evaluate and determine the optimal bike-sharing parking points.

2.4. Research gap

There are several research gaps. A review of the issues in the field of supply chain performance evaluation and a combined approach with DEA shows that weight control has been often investigated in classical models, which may show a black-box unit as efficient, while containing some inefficient sub-processes. Given the importance of sustainability, weight control is examined in the DNDEA models developed in this paper, unlike previous studies on CSWs, in which each input of the DMU must have had at least one input greater than or equal to one $(x_i \geq 1)$, so efficiency could be measured by the typical method of the weighted output to weighted input ratio. Otherwise, when $x_i = 0$, this method could no longer be implemented. To deal with this situation and its limitations, a solution is provided in this paper. Although many studies have thus far highlighted the importance of using CSWs, researchers are yet to reach a consensus on utilizing a specific weighting method. Therefore, there is room for developing new methods, and even better and more effective algorithms for this purpose. For the first time in the related literature, the weights for criteria were thus simultaneously established using the heuristic method based on the fuzzy ISM and decision-makers judgments. Generally, no study had previously evaluated supply chain sustainability via the DNDEA models with weight control, especially the fuzzy ISM, to the best of the authors' knowledge. Thus, this paper bridges the gap in the literature. Considering its innovation, this study can be the basis for future research.

3. Materials and Methods

3.1. Dynamic Network Data Envelopment Analysis (DNDEA)

In this paper, a development DNDEA model based on the RAM model is used to evaluate the sustainability of supply chains (Moradi et al.[37]). In this model, the impact of economic, social, and environmental variables on the efficiency of decision-making units would be considered directly rather than indirectly through other variables. In other words, in addition to input variables, carry-over variables also have a direct effect on the objective function. Table (2) shows the Tone and Tsutsui [48] classification of intermediate and carry-over variables.

Table2. Classification of carry-over and intermediate variables

Intermediate measures	Carry-overs
Free	Free
Fixed	Fixed
Input intermediate	Good (play role of output)
Output intermediates	Bad (play role of input)

Based on the classification provided in (table 2), in model (1), intermediate variables are considered to be fixed and carry-over variables are considered to be free. so, we have:

$$\min q = 1 - \frac{1}{T}\sum_{t=1}^{T}\frac{1}{K}\sum_{k=1}^{K}\frac{1}{m+u}\sum_{i=1}^{m}\sum_{u=1}^{U}\frac{S_{iok}^{t}}{R_{iok}^{t}} + \frac{S_{uok}^{t-1,t}}{R_{uok}^{t-1}}$$

$$\text{s.t.} \quad \sum_{j}^{n} x_{ijk}^{t}\lambda_{jk}^{t} + s_{iok}^{t} = x_{ijk}^{t}, \qquad i = 1,\cdots,m,\ \forall K,T$$

$$\begin{aligned}
&\sum\nolimits_j^n l_{wj(k-h)}^t \lambda_{jk}^t = \sum\nolimits_j^n l_{wj(k-h)}^t \lambda_{jh}^t, w = 1,\cdots,W, k = 1,\cdots,K-1, \ \forall T \\
&\sum\nolimits_j^n C_{ujk}^{t,t+1} \lambda_{jk}^t = \sum\nolimits_j^n C_{ujk}^{t,t+1} \lambda_{jk}^{t+1}, \quad u = 1,\cdots,U, \ t = 1,\cdots,T-1, \forall K \\
&\sum\nolimits_j^n C_{ujk}^{t,t+1} \lambda_{jk}^t \geq C_{uok}^{t,t+1}, \qquad u = 1,\cdots,U, \ t = 1,\cdots,T-1, \forall K \\
&\sum\nolimits_j^n C_{ujk}^{t-1,t} \lambda_{jk}^t + s_{uok}^{t-1,t} = C_{uok}^{t-1,t}, \quad u = 1,\cdots,U, \ \forall K \\
&\sum\nolimits_j^n \lambda_{jk}^t = 1, \ \forall K, T, \qquad \lambda_{jk}^t, s_{iok}^t, s_{uok}^{t-1,t} \geq 0, \ \forall i, j, r
\end{aligned} \tag{1}$$

Where:

x_{ijk}^t : The i_{th} input of the j_{th} DMU in the k_{th} station in time t

$C_{ujk}^{t,t+1}$: The $u_{th} (u=1,...,U)$ carry-over of the j_{th} DMU in the k_{th} station that is transferred from time t to time t+1.

$C_{ujk}^{t-1,t}$: $C_{ujk}^{t-1,t}$: The $u_{t-1h} (u=1,...,U)$ carry-over of the j_{th} DMU in the k_{th} station that is transferred from time t-1 to time t.

$l_{wj(k-h)}^t$: The $w_{th} (u=1,...,W)$ intermediate of the j_{th} DMU that is transferred from the k_{th} station to the h_{th} station at time t.

R_{iok}^t : Range of inputs in time t; $R_{iok}^t = \max(x_{ijk}^t) - \min(x_{ijk}^t)$.

R_{uok}^{t-1} : Range of carry-over variables in time t-1; $R_{uok}^{t-1} = \max(C_{ujk}^{t-1,t}) - \min(C_{ujk}^{t-1,t})$.

λ_{jk}^t : Intensity vector of the j_{th} DMU in the k_{th} station in time t.

The efficiency (divisional, annual, and total) of each supplier is obtained from the implementation of the model (1). According to Liu et al. [33] and the contents mentioned in section 1, the DNDEA model cannot obtain the optimal input and output weight, To address this issue, in the next section, for the first time, a Novel Method Based on Fuzzy Interpretive Structural Modeling for Determining a Set of Weights for Dynamic Network Data Envelopment Analysis efficiency of suppliers.

3.2. Proposed Weight Extraction Algorithm

The three-stage structure assumed for each supplier is shown in Figure (1).

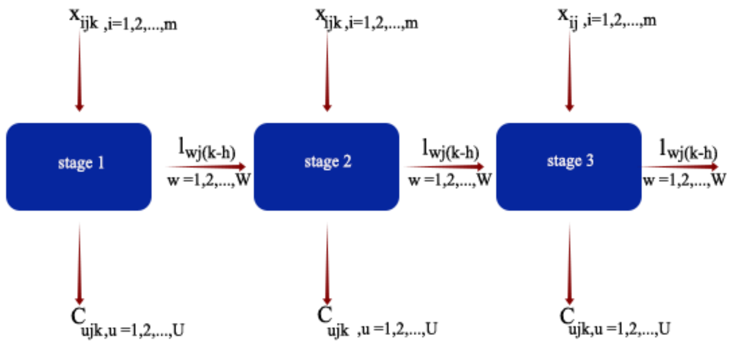

Figure1. Assumed multistage structure

Where:

X_{ijk}	:	the *i*-th input of DMU *j* at station *k*.
C_{ujk}	:	the *u*-th input of DMU *j* at station *k*.
$l_{wj(k-h)}$	:	the *w*-th intermediate variable of DMU *j* that is transferred from station *k* to station *h*.

Here V_{ijk}, u_{ijk} and $\eta_{wj(k-h)}$ are, respectively, the non-negative coefficients of inputs, outputs, and their carry-overs. By following the ten-step guide provided below, we will be able to extract a set of criteria weights using fuzzy-ISM.

Step 1 - Forming the matrix of pairwise comparisons

After identifying and selecting the sustainability indices, pairwise comparisons should be made between each pair of variables using a questionnaire designed for this purpose.

$$D_r = \begin{bmatrix} - & \tilde{p}_{12} & \cdots & \tilde{p}_{1n} \\ \tilde{p}_{21} & - & \cdots & \tilde{p}_{2n} \\ \vdots & \vdots & - & \vdots \\ \tilde{p}_{m1} & \tilde{p}_{m2} & \cdots & - \end{bmatrix}$$

Here, D_r is the pair-wise comparison matrix that is completed by the r-th expert. The effect of the i-th variable on the j-th variable is denoted by the triangular fuzzy number, where is the lower limit, is the mean, and is the upper limit of. When completing the questionnaire, respondents should use the verbal expression codes given in Table (3).

Table 3. Score table

Verbal variable	Symbol	Fuzzy Triangular Scale
Very weak	UN	$(0 \quad 0 \quad 0.25)$
Weak	LR	$(0 \quad 0.25 \quad 0.5)$
Moderate	M	$(0.25 \quad 0.5 \quad 0.75)$
Strong	SR	$(0.5 \quad 0.75 \quad 1)$
Very strong	AR	$(0.75 \quad 1 \quad 1)$

Once the questionnaires are completed, the inconsistency rate needs to be calculated in order to verify the consistency of responses. As long as the inconsistency rate is below 5%, it can be stated that the response matrix is properly consistent.

$$IR = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j}^{n} \left| \frac{t_{ij}^{n} - t_{ij}^{n-1}}{t_{ij}^{n}} \right| *100\% \tag{2}$$

In Equation (2), IR is the inconsistency rate, n is the number of variables, and t_{ij}^{n} is the mean score given by experts to the i-th variable relative to the j-th variable for $1 \le i \le n$ and $1 \le j \le n$.

Step 2 - Forming the decision matrix (aggregation of expert opinions)

Multiple methods have been developed for aggregating expert opinions. In this paper, we used the geometric mean as formulated below (Lai, [30]).

$$\tilde{g}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right), \quad l_{ij} = \left(\prod_{k=1}^{n} l_{ij}\right)^{1/n}, \; m_{ij} = \left(\prod_{k=1}^{n} m_{ij}\right)^{1/n}, u_{ij} = \left(\prod_{k=1}^{n} u_{ij}\right)^{1/n} \tag{3}$$

Where $\left(l_{ij}, m_{ij}, u_{ij}\right)$ is the opinion of the k-th expert on the relative importance of variables i and j, and n is the number of experts.

Step 3 - Forming the normalized matrix

The normalized matrix is obtained from the decision matrix. For this purpose, first, γ must be determined using Equation (4).

$$\gamma = \max_{1 \le i \le n} \sum_{j=1}^{n} u_{ij} \tag{4}$$

Where u_{ij} is the upper limit of the fuzzy numbers in each row of the decision matrix. Having γ , the normalized matrix is obtained using Equation (5).

$$N = G/\gamma \tag{5}$$

Where N denotes the normalized matrix.

Step 4 - Defuzzification of the normalized matrix

Fuzzy numbers can be defuzzified by a variety of methods, including Mean of Maxima (MOM), centroid, and bp. In this paper, we use a commonly used defuzzification method (6).

$$\pi_{ij} = \frac{u_{ij} - l_{ij} + m_{ij} - l_{ij}}{3} + l_{ij} \tag{6}$$

Step 5 - Calculating the threshold limit

Once the matrix is de-fuzzified, the threshold limit must be calculated using the arithmetic mean formula given in Equation (7).

$$C = \frac{\sum_{j=1}^{n} \sum_{i=1}^{n} a_{ij}}{n^2} \tag{7}$$

In this equation, a_{ij} is the value obtained from the defuzzification of the normalized matrix for $1 \le i \le n$ and $1 \le j \le n$, and n and c are the number of elements and the value of the threshold limit, respectively. Equation (8) is then used to obtain the incidence matrix (R).

$$\begin{aligned} &\text{if } \pi_{ij} \ge C \rightarrow \pi_{ij} = 1,\ \pi_{ij} = 0 \\ &\text{if } \pi_{ij} < C \rightarrow \pi_{ij} = 0,\ \pi_{ij} = 1 \end{aligned} \tag{8}$$

Step 6 - Forming the initial reachability matrix

This matrix is obtained from the sum of the incidence matrix and the identity matrix as formulated below.

$$M = R + 1 \tag{9}$$

Step 7 - Forming the final reachability matrix

The final reachability matrix is obtained by checking for transitivity. The transitivity of relationships is a basic assumption in ISM that indicates if element an impacts element b and element b impacts element c, then element an impacts element c. In order to identify the internal relations between elements, the initial reachability matrix must be raised to a sufficiently high power to reach the following:

$$M^{*} = M^{k} = M^{k+1} \quad , k > 1 \tag{10}$$

Where M^{*} is the final reachability matrix and k, is a natural number.

Step 8 - Applying the proposed weighting logic

In this step, the final reachability matrix is used to obtain input (reachability) and output (antecedent) sets. The input set of an element contains the element itself and all elements that it impacts. The output set of an element includes the element itself and all elements that have an impact on it. Then:

$$g_{ij} = (w_{ij})^2 - (z_{ij})^2 \tag{11}$$

Where (w_{ij}) and (z_{ij}) are the reachability and antecedent degrees. Because of the presence of exponent, if two variables have different reachability and antecedent degrees but with an equal difference, they will not be given the same weight. Since some g_{ij} values will be negative, we will have:

$$s_{ij} = g_{ij} + (\left|\min g_{ij}\right| + 1) \tag{12}$$

The presence of “1” in this equation will prevent having a zero weight. Finally, the weight of variables is extracted using Equation (13).

$$n_{ij} = {s_{ij}}\Big/{\sum s_{ij}} \qquad \text{where } \sum n_{ij} = 1. \tag{13}$$

Depending on the type of variable, n_{ij} in the above equation is the non-negative coefficient of input variables (v_{ijk}), output variables (u_{ijk}), or carry-over variables $\left(\eta_{wj(k-h)}\right)$. Equation 13 assigns greater weights to more impactful variables.

Before calculating the efficiency scores with the weights of all stages, it is necessary to define the standard data in this paper. Here, the standard data represent no large differences between the largest and the smallest values. At least each DMU has one input greater than or equal to one. Therefore, depending on the type of data, two approaches can be provided to determine the weighted efficiency, which are more stable, succinct, and practical:

1. Centralized approach: If the data are standard, the weighted efficiency scores are obtained using the following equation (known as the Charnes and Cooper's equation), taking into account the weight of the variables.

$$e_j = \left(\sum_{i=1}^{m} u_{ujk} c_{ujk} + \sum_{w=1}^{W} \eta_{wj(k-h)} l_{wj(k-h)}\right) \Big/ \left(\sum_{i=1}^{m} v_{ijk} x_{ijk} + \sum_{w=1}^{W} \eta_{wj(k-h)} l_{wj(k-h)}\right), \tag{14}$$

Where u_{ujk} , $\eta_{wj(k-h)}$ and v_{ijk} are optimal values of (13). In cases where none of the DMUs is efficient, all output weights can be increased (and/or input weights decreased) by minimal proportion until an efficient DMU is reached. One way to do the task is the following substitutions:

$$M_{ujk} = u_{ujk} / e,\ O_{wj(k-h)} = \eta_{wj(k-h)} / e \tag{15}$$

Where $e = \max_{1 \le j \le n} \{e_j\}$. The resulted weights M_{ujk} and $O_{wj(k-h)}$ are the outputs proposed CSW. After eliciting the CSW, the efficiencies of DMUs are determined by:

$$e_j = (\sum_{i=1}^{m} M_{ujk} c_{ujk} + \sum_{w=1}^{W} O_{wj(k-h)} l_{wj(k-h)}) \Big/ (\sum_{i=1}^{m} v_{ijk} x_{ijk} + \sum_{w=1}^{W} \eta_{wj(k-h)} l_{wj(k-h)}) \tag{16}$$

i. Decentralized approach: If the data are not standard, it is practically impossible to use Equations (14-16). So, each station is weighted separately for each supplier by using the extracted CSWs. A rational choice for the weight of a station (w_k) is the ratio of resources allocated to stage k to all resources consumed in the process, which reflects its relative magnitude. More precisely, refers to the magnitude or the amount of input spent in the whole process, and w_k indicates the portion of the total input used in stage k (Cook et al.2010). Thus, there are:

$$\begin{aligned}
& w_k = (\text{component k input})/(\text{total input across all components}) \\
& w_1 = (\sum_{i=1}^{m} v_{ij1} x_{ij1}) \Big/ (\sum_{i=1}^{m} v_{ij1} x_{ij1} + \sum_{w=1}^{W} \eta_{wj(1,2)} l_{wj(1,2)} + \sum_{i=1}^{m} v_{ij2} x_{ij2} + \sum_{w=1}^{W} \eta_{wj(2,3)} l_{wj(2,3)} + \sum_{i=1}^{m} v_{ij3} x_{ij3}), \\
& w_2 = (\sum_{w=1}^{W} \eta_{wj(1,2)} l_{wj(1,2)} + \sum_{i=1}^{m} v_{ij2} x_{ij2}) \Big/ (\sum_{i=1}^{m} v_{ij1} x_{ij1} + \sum_{w=1}^{W} \eta_{wj(1,2)} l_{wj(1,2)} + \sum_{i=1}^{m} v_{ij2} x_{ij2} + \sum_{w=1}^{W} \eta_{wj(2,3)} l_{wj(2,3)} + \sum_{i=1}^{m} v_{ij3} x_{ij3}), \\
& w_3 = (\sum_{w=1}^{W} \eta_{wj(2,3)} l_{wj(2,3)} + \sum_{i=1}^{m} v_{ij3} x_{ij3}) \Big/ (\sum_{i=1}^{m} v_{ij1} x_{ij1} + \sum_{w=1}^{W} \eta_{wj(1,2)} l_{wj(1,2)} + \sum_{i=1}^{m} v_{ij2} x_{ij2} + \sum_{w=1}^{W} \eta_{wj(2,3)} l_{wj(2,3)} + \sum_{i=1}^{m} v_{ij3} x_{ij3}),
\end{aligned} \tag{17}$$

The core DEA of Equation (17) is to use different weights for different stages of the process depending on the specific conditions of the evaluated supplier. Unlike the studies of Cook et al. [12]; Kao & Liu, [27]; Liu et al. [32]; Su & Chen,[45], which the overall efficiency is calculated as the weighted sum of the efficiency of individual stages, in this paper, we define the overall efficiency of the multi-stage process can also be modeled as a weighted harmonic mean of the efficiencies of multi individual stages (Wang & Chin, [50]). Therefore, we have:

$$\theta_k = w_1 + \cdots + w_k \Big/ \left(\frac{w_1}{\theta_1} + \cdots + \frac{w_k}{\theta_k} \right) = 1 \Big/ \left(\frac{w_1}{\theta_1} + \cdots + \frac{w_k}{\theta_k} \right), \quad \text{where } \sum_{k=1}^{K} w_k = 1. \tag{18}$$

Note that weights w_k represents the relative importance of the efficiency of stage k for (or its relative contribution to) the overall efficiency of the process. Here, θ_k is the efficiency of Θ at station k, say, by solving model (1) or any other DEA method, is determined.

4. Case study

To validate the proposed model, it was used to examine the sustainability of a company named Nirou Moharekeh Industries (NMI) from 2011 to 2015. NMI is an Iranian manufacturer of auto spare parts and has 12 suppliers. It is assumed that NMI aims to evaluate the overall, divisional, and annual efficiency of its suppliers. Each supplier has three stations including production, packaging, and distribution. The structure of the input, carry over, and intermediate variables over the five-year period are shown in Figure 1.

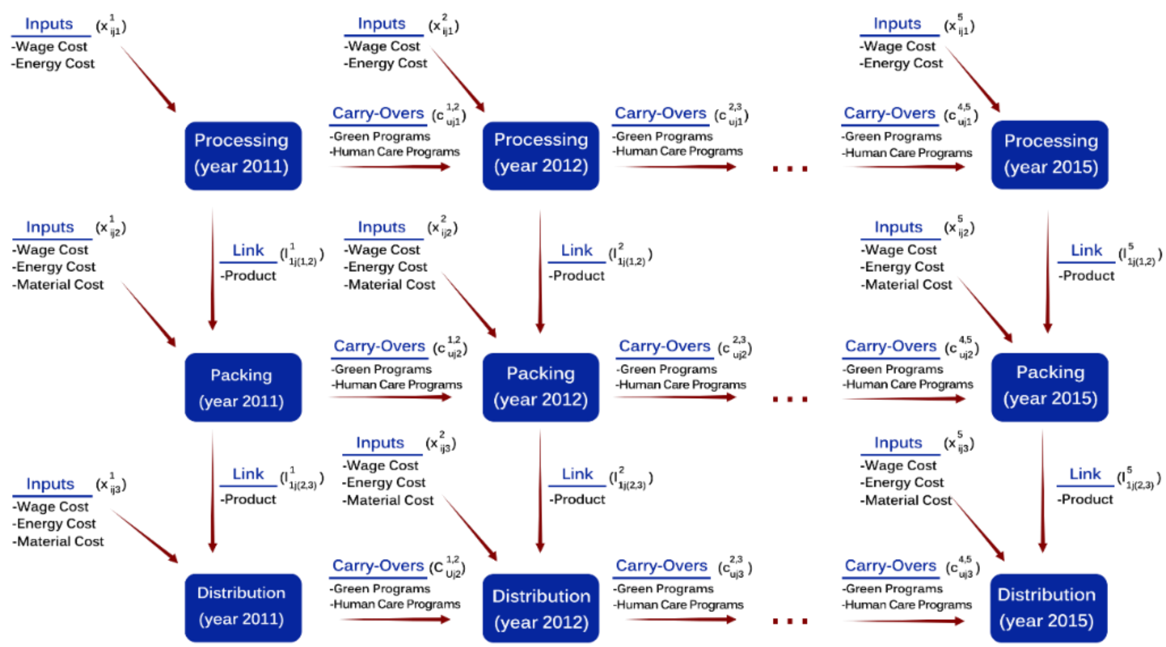

Figure 2. Structure of the suppliers of NMI

Table 4 shows the efficiency (divisional, annual, and overall) of each supplier of NMI based on Model (1).

Table 4. Efficiency values of the supplier of NMI

NO	DMUs	Rank	overall efficiency	Divisional efficiency			Term efficiency														
							2011			2012			2013			2014			2015		
				div.1	div.2	div.3	div1	div2	div3	div1	div2	div3	div1	div2	div3	div1	div2	div3	div1	div2	div3
1	TECH A.T	3	0.9926	1.0000	0.9794	0.9985		1.0000			1.0000			1.0000			1.0000			0.9631	
							1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8971	0.9923
2	STEEL. P	9	0.7910	0.8221	0.7842	0.7667		0.4460			0.6506			0.9690			1.0000			0.8894	
							0.4886	0.4220	0.4273	0.7455	0.6019	0.6046	1.0000	1.0000	0.9071	1.0000	1.0000	1.0000	0.8762	0.8972	0.8948
3	D.L. KARAN	10	0.7682	0.8165	0.7036	0.7845		0.4416			1.0000			1.0000			0.8703			0.5292	
							0.4649	0.4306	0.4293	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.6109	1.0000	0.6176	0.4767	0.4932
4	PARS HAM	11	0.7552	0.7640	0.7500	0.7515		0.5089			0.6867			0.6845			0.9973			0.8984	
							0.4558	0.5357	0.5352	0.7499	0.6554	0.6548	0.7169	0.6668	0.6697	0.9920	1.0000	1.0000	0.9055	0.8920	0.8978
5	FARAZAN	5	0.9865	0.9883	0.9854	0.9857		0.9845			0.9505			1.0000			0.9973			1.0000	
							0.9899	0.9815	0.9820	0.9598	0.9455	0.9462	1.0000	1.0000	1.0000	0.9920	1.0000	1.0000	1.0000	1.0000	1.0000
6	SIRIN S.N.	12	0.6409	0.6182	0.6346	0.6700		0.5939			0.7865			0.5878			0.5981			0.6383	
							0.5418	0.6180	0.6219	0.7918	0.7829	0.7848	0.6351	0.5307	0.5975	0.5121	0.6319	0.6504	0.6102	0.6096	0.6951
7	PIROZ	6	0.9827	0.9827	0.9825	0.9828		1.0000			0.9400			1.0000			1.0000			0.9735	
							1.0000	1.0000	1.0000	0.9409	0.9392	0.9399	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9725	0.9735	0.9742
8	ALSAN	4	0.9910	0.9923	0.9903	0.9903		0.9996			1.0000			1.0000			1.0000			0.9553	
							0.9988	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9627	0.9516	0.9516
9	KARAN	1	1.0000	1.0000	1.0000	1.0000		1.0000			1.0000			1.0000			1.0000			1.0000	
							1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
10	TIR	8	0.8490	0.8615	0.8412	0.8443		0.6640			0.6683			1.0000			1.0000			0.9127	
							0.6350	0.6762	0.6809	0.7638	0.6201	0.6210	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9090	0.9098	0.9194
11	BARAN	7	0.9120	0.9624	0.8550	0.9187		0.7059			0.9256			1.0000			0.9499			0.9787	
							0.8919	0.6128	0.6129	0.9445	0.8324	1.0000	1.0000	1.0000	1.0000	1.0000	0.8496	1.0000	0.9754	0.9803	0.9803
12	HAMRAH	2	0.9994	0.9983	1.0000	1.0000		0.9972			1.0000			1.0000			1.0000			1.0000	
							0.9917	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

The results show that the development of the DNDEA model can help rank the most efficient one. Upon determining the efficiency values and the general condition of the suppliers, it was observed that KARAN earned the highest efficiency score. According to Liu et al.[33], the DNDEA model cannot obtain the optimal input and output weights. To solve this problem, this study utilizes, for the first time, a heuristic method based on FISM, to find a set of weights for variables. The symbols representing the suppliers of NMI are given in Table 5.

Table 5. Sustainability measures of the suppliers of NMI

Sustainability Variable of NMI	**Wage cost**	**Energy Cost**	**Material Cost**	**green program and ISO TS**	**human care programs**	**Products**
Symbols	C_1	C_2	C_3	C_4	C_5	C_6

The questionnaire designed to identify the interrelationships of the variables was thus distributed among 14 experts and managers. The criteria for selecting the experts were theoretical mastery, field experience, along with willingness and ability to participate in the study. The respondents' opinions were thus collected through verbal expressions. This was done using the fuzzy spectrum provided in Table 3, which shows the relationship between verbal expressions, their codes, and triangular fuzzy numbers. The validity of the questionnaire was further confirmed through formal content analysis, and its reliability was assessed by calculating the inconsistency rate. In this regard, the inconsistency rate of the experts’ pairwise comparison matrices for the three stations were calculated to be 0.328, 0.345, and 0.337 (Table 6), confirming the reliability of the questionnaire. Next, the decision matrix and its normalized and defuzzified versions were obtained for all three stations.

Table 6. Defuzzified normalized matrices of stations

DIV. 1	C_6	C_5	C_4	C_2	C_1
C_1	0. 1540	0. 1351	0. 0273	0. 0315	-
C_2	0. 1341	0. 0319	0. 0585	-	0. 1521
C_4	0. 1520	0. 1462	-	0. 1686	0. 0498
C_5	0. 1318	-	0. 1124	0. 1422	0. 1545
C_6	-	0. 0273	0. 0983	0. 0307	0. 0559

DIV. 2	C_6	C_5	C_4	C_3	C_2	C_1
C_1	0. 0630	0. 1261	0. 0217	0. 0238	0. 0233	-
C_2	0. 0971	0. 0289	0. 0357	0. 0283	-	0. 1503
C_3	0. 1392	0. 0265	0. 0332	-	0. 0245	0. 0327
C_4	0. 1341	0. 0866	-	0. 1008	0. 0995	0. 0599
C_5	0. 1216	-	0. 0397	0. 0211	0. 1216	0. 1539
C_5	-	0. 0245	0. 0209	0. 0240	0. 0172	0. 0492

DIV. 3	C_6	C_4	C_3	C_2	C_1
C_1	0. 0726	0. 0253	0. 0315	0. 0334	-
C_2	0. 0910	0. 0351	0. 0297	-	0. 1464
C_3	0. 1330	0. 0345	-	0. 0264	0. 0359
C_4	0. 1271	-	0. 0970	0. 0962	0. 0659
C_5	0. 1211	0. 0459	0. 0241	0. 1190	0. 1543

The threshold limit was then obtained by calculating the arithmetic mean of the defuzzified matrix. This threshold was determined to be 0.102, 0.083, and 0.123 for div 1, div 2, and div 3, respectively. Afterward, the incidence and the initial reachability matrices were achieved, as illustrated in Table 7.

Table 7. The initial reachability matrix obtained for the studied case

DIV. 1	C_6	C_5	C_4	C_2	C_1
C_1	1	1	0	0	1
C_2	1	0	0	1	1
C_3	1	1	1	1	0
C_4	1	1	0	1	1
C_5	1	0	0	0	0

DIV. 2	C_6	C_5	C_4	C_3	C_2	C_1
C_1	0	1	0	0	0	1
C_2	1	0	0	0	1	1
C_3	1	0	0	1	0	0
C_4	1	1	1	1	1	0
C_5	1	1	0	0	1	1
C_6	1	0	0	0	0	0

DIV. 3	C_5	C_4	C_3	C_2	C_1
C_1	1	0	0	0	1
C_2	0	0	0	1	1
C_3	0	0	1	0	0
C_4	1	1	1	1	0
C_5	1	0	0	1	1

The final reachability matrix was then obtained by checking for transitivity (Table 8).

Table 8. The final reachability matrix obtained for the studied case

DIV. 1	C_6	C_5	C_4	C_2	C_1
C_1	1	1	0	1^*	1
C_2	1	1^*	0	1	1
C_3	1	1	1	1	1^*
C_4	1	1	0	1	1
C_5	1	0	0	0	0

DIV. 2	C_6	C_5	C_4	C_3	C_2	C_1
C_1	1^*	1	0	0	1^*	1
C_2	1	1^*	0	0	1	1
C_3	1	0	0	1	0	0
C_4	1	1	1	1	1	1^*
C_5	1	1	0	0	1	1
C_6	1	0	0	0	0	0

DIV. 3	C_5	C_4	C_3	C_2	C_1
C_1	1	0	0	1^*	1
C_2	1^*	0	0	1	1
C_3	0	0	1	0	0
C_4	1	1	1	1	1^*
C_5	1	0	0	1	1

At this stage, the final reachability matrix was used to obtain the input set $\left(w_{ij}\right)$ and the output set $\left(z_{ij}\right)$, which represent reachability and antecedent degrees respectively. Then, the weight of variables was calculated using Equation (13).

Table 9. Proposed weighting logic

DIV. 1	w_{ij}	z_{ij}	g_{ij}	s_{ij}	$n_{ij}(div_{total})$	
C_1	4	4	0	25	0.2000	C_1
C_2	4	4	0	25	0.2000	C_2
C4	5	1	24	49	0.3920	C_3
C_5	4	4	0	25	0.2000	C_5
C_6	1	5	-24	1	0.0080	C_6

DIV. 2	w_{ij}	z_{ij}	g_{ij}	s_{ij}	$n_{ij}(div_{total})$	
C_1	4	6	0	36	0.1667	v_{ij2}
C_2	4	4	0	36	0.1667	v_{ij2}
C_3	2	1	0	36	0.1667	v_{ij2}
C_4	6	2	35	71	0.3287	u_{ij2}
C_5	4	4	0	36	0.1667	u_{ij2}
C_6	1	4	-35	1	0.0046	$\eta_{wj(2-3)}$

DIV. 3	w_{ij}	z_{ij}	g_{ij}	s_{ij}	$n_{ij}(div_{total})$	
C_1	3	4	-7	1	0.0250	v_{ij3}
C_2	3	1	-7	1	0.0250	v_{ij3}
C_3	1	2	-3	5	0.1250	v_{ij3}
C_4	5	4	24	32	0.8000	u_{ij3}
C_5	3	4	-7	1	0.0250	u_{ij3}

In Table 9, the fourth and the fifth columns represent the results of Equations 11 and 12, and the sixth column stands for the outcomes of Equation 13, indicating the weight of the variables separately for each station. After reviewing the case study data, the findings revealed that the data are not standard, and it is impossible to use Charnes and Cooper Equation (16), so the decentralized approach described in Section 2.3 was applied. That means each station can be weighted exclusively for each supplier by this set of weights. Using the efficiency values of the stations (Table 4) and the set of weights obtained from the heuristic method (Table 9), the weight of each station was consequently gained from Equation 17.

Table 10. Results of the proposed method (weight of each station)

DMUs	Average of Divisional Weights																		
	div.1	div.2	div.3	2011			2012			2013			2014			2015		
				div1	div2	div3	div1	div2	div3	div1	div2	div3	div1	div2	div3	div1	div2	div3
TECH A.T	0.3583	0.4891	0.1515	0.1868	0.6412	0.172	0.1731	0.6622	0.1647	0.171	0.6652	0.1638	0.1046	0.7647	0.1307	0.0977	0.7757	0.1266
STEEL .P	0.3328	0.4779	0.1357	0.0663	0.8262	0.1075	0.0761	0.8111	0.1128	0.1622	0.6819	0.1559	0.1417	0.7131	0.1452	0.1652	0.6773	0.1575
D.L. KARAN	0.3128	0.4891	0.1123	0.0793	0.8071	0.1136	0.0954	0.783	0.1216	0.1047	0.7688	0.1265	0.116	0.7828	0.1012	0.052	0.8491	0.0989
PARSHAM	0.3070	0.4970	0.1207	0.1185	0.7467	0.1348	0.0914	0.7885	0.1201	0.0951	0.7818	0.1231	0.0849	0.7975	0.1176	0.0677	0.8241	0.1082
FARAZAN	0.3503	0.4817	0.2018	0.0787	0.8073	0.114	0.1241	0.7367	0.1392	0.1673	0.6696	0.1631	0.2513	0.4522	0.2965	0.2513	0.4522	0.2965
SIRIN S.N.	0.4086	0.4657	0.1597	0.1367	0.7178	0.1455	0.1356	0.7194	0.145	0.1446	0.7054	0.15	0.2016	0.6193	0.1791	0.2038	0.6171	0.1791
PIROZ	0.2942	0.5006	0.1087	0.1346	0.7916	0.0738	0.1086	0.7604	0.131	0.1446	0.7071	0.1483	0.0353	0.8743	0.0904	0.0535	0.8462	0.1003
ALSAN	0.2696	0.5007	0.1842	0.1062	0.7659	0.1279	0.2513	0.4522	0.2965	0.2513	0.4522	0.2965	0.1074	0.7634	0.1292	0.0005	0.9282	0.0713
KARAN	0.2022	0.5026	0.0820	0.4637	0.469	0.0673	0.0236	0.8926	0.0838	0.1361	0.7734	0.0905	0.0112	0.9116	0.0772	0.0372	0.8715	0.0913
TIR	0.3463	0.4874	0.1191	0.1204	0.7426	0.137	0.1151	0.7569	0.128	0.0596	0.8369	0.1035	0.1936	0.7289	0.0775	0.1429	0.7073	0.1498
BARAN	0.2167	0.5134	0.1727	0.0197	0.8987	0.0816	0.1198	0.7714	0.1088	0.2512	0.4523	0.2965	0.047	0.8728	0.0802	0.2513	0.4522	0.2965
HAMRAH	0.3259	0.4883	0.1473	0.1946	0.6287	0.1767	0.2512	0.4523	0.2965	0.0572	0.8408	0.102	0.1200	0.8089	0.0711	0.036	0.8734	0.0906

Finally, Equation (18) and data provided in Tables (4) and (10) were used to recalculate the annual and overall efficiency values of the suppliers.

Table 11. Efficiency values of the suppliers of NMI according to the proposed heuristic method

NO	DMU	overall efficiency	Rank	Divisional efficiency			Term efficiency														
				div.1	div.2	div.3	2011			2012			2013			2014			2015		
							div1	div2	div3	div1	div2	div3	div1	div2	div3	div1	div2	div3	div1	div2	div3
1	TECH A.T	0.9896	4	1.000	0.9794	0.9985	1.000			1.000			1.000			1.000			0.9175		
							1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.8971	0.9923
2	STEEL .P	0.7929	9	0.8221	0.7842	0.7667	0.4264			0.6112			0.9843			1.000			0.8933		
							0.4886	0.4220	0.4273	0.7455	0.6019	0.6046	1.000	1.000	0.9071	1.000	1.000	1.000	0.8762	0.8972	0.8948
3	D.L. KARAN	0.7515	11	0.8165	0.7036	0.7845	0.4330			1.000			1.000			0.6673			0.4840		
							0.4649	0.4306	0.4293	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.6109	1.000	0.6176	0.4767	0.4932
4	PARS HAM	0.7545	10	0.7640	0.7500	0.7515	0.5238			0.6630			0.6716			0.9993			0.8935		
							0.4558	0.5357	0.5352	0.7499	0.6554	0.6548	0.7169	0.6668	0.6697	0.9920	1.000	1.000	0.9055	0.8920	0.8978
5	FARAZAN	0.9865	5	0.9883	0.9854	0.9857	0.9822			0.9473			1.000			0.9980			1.000		
							0.9899	0.9815	0.9820	0.9598	0.9455	0.9462	1.000	1.000	1.000	0.9920	1.000	1.000	1.000	1.000	1.000
6	SIRIN S.N.	0.6319	12	0.6182	0.6346	0.6700	0.6069			0.7844			0.5531			0.6064			0.6235		
							0.5418	0.6180	0.6219	0.7918	0.7829	0.7848	0.6351	0.5307	0.5975	0.5121	0.6319	0.6504	0.6102	0.6096	0.6951
7	PIROZ	0.9826	6	0.9827	0.9825	0.9828	1.000			0.9395			1.000			1.000			0.9735		
							1.000	1.000	1.000	0.9409	0.9392	0.9399	1.000	1.000	1.000	1.000	1.000	1.000	0.9725	0.9735	0.9742
8	ALSAN	0.9908	3	0.9923	0.9903	0.9903	0.9999			1.000			1.000			1.000			0.9516		
							0.9988	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.9627	0.9516	0.9516
9	KARAN	1.000	1	1.000	1.000	1.000	1.000			1.000			1.000			1.000			1.000		
							1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
10	TIR	0.8486	8	0.8615	0.8412	0.8443	0.6716			0.6339			1.000			1.000			0.9111		
							0.6350	0.6762	0.6809	0.7638	0.6201	0.6210	1.000	1.000	1.000	1.000	1.000	1.000	0.9090	0.9098	0.9194
11	BARAN	0.8933	7	0.9624	0.8550	0.9187	0.6166			0.8603			1.000			0.8662			0.9791		
							0.8919	0.6128	0.6129	0.9445	0.8324	1.000	1.000	1.000	1.000	1.000	0.8496	1.000	0.9754	0.9803	0.9803
12	HAMRAH	0.9994	2	0.9983	1.000	1.000	0.9984			1.000			1.000			1.000			1.000		
							0.9917	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

As Table (11) shows, using the heuristic method changed the efficiency scores of some suppliers, leading to a change in the ranking, which is discussed next section.

5. Findings and managerial implications

Our framework and discussion have several managerial implications. In this paper, a develop sustainable supply chain model is initially used to provide an overview of the multitude of factors and relationships involved in this discussion. The study findings highlight the need for the development and adoption of integrated strategies for supply chains. With some adjustments in the intervals of analyses and simulations of causal relationships, this method to supply chain analysis can thus aid managers predict the risks and threats that may obstruct the transition of a chain toward sustainability and then devise a plan, accordingly. Thus, the method provides managers with a framework for conservative decision-making in this area. Since the proposed model is independent of the criteria utilized in this paper, decision-makers can introduce more criteria to the system or remove those they feel are not appropriate for their specific cases. This enables managers to adjust their supply chain strategies more easily, especially when they feel the chain is exposed to some risks originating from sustainability-related pressures and concerns. Generally, the development model and its complementary approaches (centralized and decentralized) are robust for valid results; however, they can bring about changes in the ranking. In order to select the most appropriate model for each situation, the analyst must decide according to the type of data which approach, he or she prefers to calculate for the assessment. As model (1) quantifies efficiency, while simultaneously considering process structure, process stages, and time (see Table 4), it can be practiced to accurately trace the source of inefficiency of each decision-making unit (DMU: supplier) each year. For example, the supplier TECH. A.T became inefficient with a score of 0.9631 because of inefficiency in stage 2 (packing) and stage 3 (distribution) in 2015 while it had an efficient in the production stage. Thus, in that year, this supplier should have focused on the packing and distribution stages. As the results presented in Table (4) show, the highest efficiency score was obtained for KARAN, and the lowest efficiency score belonged to *SIRIN S. N.*

The use of the heuristic model based on the fuzzy ISM compared to Model 1, makes some changes in the efficiency value. By comparing the results in Tables 4 and 11, it is observed that the efficiency of all suppliers is affected by the set of stage weights. More specifically, after the implementation of the proposed model in 2011-2015, except for 2 suppliers whose annual efficiency had elevated, the efficiency of other suppliers had reduced. For example, the overall efficiency score in DMU3 was 0.7515 compared to 0.8046 in Model 1. Generally, *STEEL. P* had the highest rising trend in 2013 (0.0110) and *D.L. KARAN* had the lowest decline in 2014 (0.1063) in their annual efficiency relative to the results in Model 1. This was attributed to the fact that the choice of weights could introduce some sort of value judgment into the DEA model. This was why the efficiency value of Model 1 in most cases was larger than the heuristic model developed (based on the fuzzy ISM) when $w_1 = w_2 = w_3 = 0.\overline{33}$ in optimality theory. In some other cases (e.g. the efficient DMUs), the efficiency values of the suppliers remained unchanged. These findings were consistent with the reports in Xiao et al.[51], indicating that the assignment of a weight to each stage could have an impact on the annual efficiency and the overall efficiency of DMUs. Nonetheless, *KARAN* remained as the supplier with the highest efficiency score and *SIRIN S. N* was the one with the lowest efficiency value, changing the ranking of five suppliers (*TECH A.T, D.L. KARAN*, *PARSHAM and ALSAN*), and consequently making the ranking more consistent with the factory managers' opinions.

6. Conclusion

In this paper, a DNDEA model was used based on the RAM model to evaluate the sustainability of supply chains. This model (viz. Model 1) was to determine the overall, divisional, and annual efficiency scores of units (Table 4). Upon determining the general condition of the units, a heuristic method based on the fuzzy ISM was employed to extract CSWs for the variables involved, by asking decision-makers and experts to express their opinions on the appropriate weight for each variable (Model 2-13). With this weighting method, the factors having a greater impact on the efficiency of the process were given greater weights. After defining the standard data, two approaches, viz. centralized and decentralized, were proposed for determining the weighted efficiency, wherein the centralized approach was based on the Charnes and Cooper's equation, and the second approach applied the extracted CSWs to determine the weights of all stations (Equation 17). The overall efficiency (Equation 18) was further described as the weighted harmonic mean of the efficiency of the individual stages, with the weights that reflected the importance of the components for the process efficiency. Exploiting this approach, the total efficiency values took account of the potential significance of more (or less) divisional scores.

The most obvious feature of Model 1, developed here, is selecting the best DMU from different DMUs. In other words, this model can be implemented to select the best DMU. Moreover, it is claimed that the present model enjoys high capability and discriminating power in the evaluation of all DMUs, and reflects reality. Compared to the model developed by Moradi (Moradi et al. 2022) and those in previous research, the main contribution and advantages of this paper are the development of an expert-centered heuristic method based on the fuzzy ISM, which helps expand the scope of the application of the fuzzy ISM, provides CSWs on which experts may agree because these weights are extracted through the integration of their subjective preferences. The application of this heuristic method is not limited to the single type of the DEA model, but it can manage the weight of the stages well, even with non-standard data, so it is a great complement to DEA. It also allows researchers to calculate efficiency scores for certain periods as well as overall efficiency only using the efficiency values of individual stages. The utilization of the fuzzy approach also helps consider uncertainty in expert opinions, which makes the data more realistic. In this paper, an alternative solution was suggested for non-standard data. Therefore, the proposed model can always have feasible solutions, as one of the computational advantages concerning previous studies. Although the overall efficiency of the two-stage process had been modeled as a weighted sum of the efficiencies of two individual stages in Chen, Cook, Li, and Zhu [10], this paper looked into the multi-stage DEA and modeled the overall efficiency of the multi-stage process as a weighted harmonic mean of the efficiencies of multi-individual stages. This paper looks into the multi-stage DEA and models the overall efficiency of the multi-stage process as a weighted harmonic mean of the efficiencies of multi-individual stages. In general, since the models presented in this article have independent of the number of criteria and their values, they can be applied to any type of activity in production or service sectors. The findings of this paper have also been expected to assist the managers of NMI in making better decisions for improved management and risk minimization in their supply chain to achieve sustainability. It has hoped that the research conducted can enrich the theory of DEA and provide more alternative ways of measuring the performance of the multi-stage process.

Suggestions

In this article, all experts and decision-makers were given the same weight. However, since different decision-makers/experts may have different levels of knowledge, skill, and experience, because of different capabilities, unequal access to resources, and economic and social issue, future studies are recommended to assign a weight to each expert based on their prominence in the field, work experience, etc. to further improve the accuracy of the results.

Declaration of competing interest

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. This study also does not violate other relevant ethical issues.

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