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# Novel Approaches for Determining Exogenous Weights in Dynamic Networks DEA

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## ABSTRACT

Most analysts believe that the network-based dynamic data envelopment analysis needs to define a set of endogenous/exogenous weights to evaluate the performance scores of stages and periods. Against this background, the general aim of this study is to introduce heuristic novel approaches based on fuzzy interpretive structural modeling along with the historical value of periods to obtain such weights. In this context, a closer look is taken at how to perfect the model established by Kalantary and its shortcomings. The models are initially developed here in both weighted and unweighted forms, in which a company's current performance can be influenced by its past socio-environmental performance. In the next step, heuristic methods for finding weights for stages and periods are described, and depending on the specific conditions of the models, two alternatives are proposed to combine and formulate the calculated weights. This method is then applied to data from a company, Nirou Moharekeh Industrial Group, to demonstrate the capabilities of the proposed models. The results of probing 12 suppliers show the power of the developed models in the differentiation of the decision-making units since there are no two units with the same ranks. In sum, the results can provide rich information for decision-makers. However, analysts must decide which characteristics to prioritize for evaluation purposes to achieve the best results for each situation.

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## 1. Introduction

So far, as a non-parametric technique, Data Envelopment Analysis (DEA) has been used in numerous studies, both within organizations and supply chains, to the extent that the related literature is rich enough in this line of work. Although previous research has contributed to the understanding of the evaluation process in this regard, there have been some shortcomings. In this way, no models for supply chain sustainability have attention to the socio-environmental backgrounds of organizations in their assessments but are only concerned with the economic ones. Despite numerous studies on the significance of weights for stages and periods in assessment models, until now, no standard approach for determining these weights has been developed. Besides, it is unclear which subsection of a station causes inefficiency at each stage. Therefore, it seems essential to provide an approach and subsequently develop a model to address these shortcomings.

In today's competitive business environment, supply chain performance has also become a critical issue in a wide variety of industries [1]. Many businesses have faced challenges resulting from accelerated globalization, outsourcing, technological advances, lowered geographical borders, and customer expectations regarding sustainable development. Consequently, organizations are now rigorously evaluating their suppliers to ensure they meet their sustainability goals, missions, and requirements [2]. As has already been indicated, the DEA method has been extensively exploited in numerous studies to date to assess the relative performance of various structures. Over the years, researchers have further developed it by proposing a wide variety of DEA-based models, each with its benefits and drawbacks [3]. Given the supply chain's multi-stage structure and the shortcomings of the classical, network-based, and dynamic DEA models alone, this study attempts to develop the so-called Dynamic Network DEA (DNDEA) model.

There are several issues to consider when implementing the DNDEA models, including the need for assigning endogenous/exogenous weights to the efficiency scores of periods or stages [4]. However, many DNDEA-based studies that have fulfilled this purpose over time have either completely ignored this requirement or simply assigned the same weight to all components or periods during the process, regardless of whether the efficiency of the evaluated units has been important. Another concern regarding the supply-chain sustainability assessment is the emphasis on short-term profits from a purely cost-oriented perspective, which favors one aspect of sustainability over others. Sustainability can be viewed as the extent to which an organization's current decisions will impact its future socioeconomic and environmental status [5,6]. It is reasonable to conclude that the current state of organizations is generally influenced by the socio-environmental and economic decisions made in the past. Thus, in the models developed here, the current performance of a business is affected by prior socio-environmental actions as the main key aspect of sustainability, and results from the implementation of the heuristic methods can be controlled. In particular, in addition to presenting an equation to measure the historical value weights of periods, a Common Set of Weights (CSWs) is extracted using a new heuristic method based on fuzzy interpretive structural modeling (FISM) for the first time. As a result, two strategies -centralized and decentralized- are provided for calculating efficiency based on the data conditions. The first strategy is centralized, which directly calculates the weighted efficiency scores based on CSWs. Depending on the data type, this strategy can have its own restrictions, such as requiring each decision-making unit (DMU) to have at least one input greater than or equal to one; otherwise, it is almost impossible to use this strategy. In these cases, a second strategy, called decentralization, should be used, where each stage is weighted individually by the CSW for each supplier. In addition, two alternatives presenting to formulate the weights obtained with the DNDEA models. The first is to directly introduce them to the model if it meets the requirements to do so. If this is not possible, the overall efficiency can then be improved by combining component efficiency with a weighted harmonic mean. Based on our knowledge:

- Developing hybrid models for the first time to assess sustainable supply chains and giving a case study to demonstrate the model's use.
- For the first time, the fuzzy-ISM-based heuristic method for determining a set of weights for process components is proposed.
- For the first time, we propose a relation termed the historical value of periods to evaluate the periodic performance weight of DMUs, which provides more weight to recent years' efficiency.

Given the foregoing, this research aims to create DNDEA models based on the Range-Adjusted Measure (RAM) model proposed by Kalantary et al., (2018) and to present heuristic approaches for identifying a set of exogenous weights in DNDEA models. This methodology provides more insight into how processes should be weighted and the performance of DNDEA models should be improved, allowing us to not only measure supplier performance but also track dynamic changes over time. Additionally, the proposed method broadens the field of ISM's use. The remainder of this study is structured as follows: Part two examines the research literature. Part three develops the proposed models and includes a numerical example to demonstrate their capacity and application. The final section presents the conclusions.

## 2. Literature Review

The literature on the techniques utilized in the article is briefly reviewed in this part.

### 2.1 Dynamic Network Data Envelopment Analysis

In early DEA models, such as CCR [8] and BCC [9], inputs and outputs of independent DMUs were considered contemporaneously. However, these models consider a DMU as a black box and ignore its inner workings[10]. Following an earlier study by Färe (1991) and subsequent expansions by Chen et al. (2009); Fukuyama & Weber (2010), researchers created DEA models that can assess both the overall and partial DMU efficiencies within a single structure. This approach is called Network DEA (NDEA). However, these models do not consider time because they are static. Later, Nemoto & Goto ( 2003) introduced the Dynamic DEA (DDEA) model to solve this problem, but this model completely ignored the internal structures, so a model that considered both the internal structure and time was required. Ratio and non-ratio are the two main approaches proposed in the existing literature to develop DEA models with dynamic network structures[4]. To generate possibility sets, Fare and Groskopf [18] used the non-ratio approach. Using the ratio approach, Tone and Tsutsui (2014) developed an NDEA model for dynamic structures followed by a Slack-based measurement (SBM) DNDEA model. In addition, taking another ratio approach to DNDEA, Avkiran & McCrystal (2014) developed two models: Dynamic Network Range-Adjusted Measure (DNRAM) and Dynamic Network Slacks-Based Measures (DNSBM). They showed that DNRAM is more resilient to data perturbations and has translation invariance properties, unlike DNSBM. However, like DNDEA, DNRAM requires endogenous or exogenous weight assignment to the efficiency of periods/stages. So far, many studies have emphasized the importance of weighting methods, but researchers have yet to agree on the use of specific weighting methods. Therefore, more advanced and efficient algorithms and approaches are needed to find new methods. The present study proposes a heuristic approach based on Fuzzy ISM for weight calculation and integration into DNDEA.

### 2.2 Fuzzy Form of Interpretive Structural Modeling

Warfield introduced ISM in 1974 [22], the methodology for identifying relationships among specific items [23]. Based on a binary spectrum, classical ISM only discusses the connections between components [24] and the idea that the system's more effective components are always more crucial [25]. It is possible that the classical ISM does not accurately represents reality [26], and binary values may also lead to undesirable relationships between certain elements in the final model. Generally, the amplitude and magnitude of the interaction between the factors are not taken into account by the classical ISM .This issue can be overcome by extending ISM with a fuzzy form [27,28]. As shown in Table , Fuzzy ISM utilizes a linguistic scale to construct contextual relationships based on group judgment by experts [27]. The remainder of the Fuzzy ISM process resembles the classical ISM. To the best of the authors' knowledge, while Fuzzy ISM has great potential, no algorithm has been developed to compute weights using this method, making this study the first attempt to extract weight for DNDEA using Fuzzy ISM.

### 2.3 Background and Research gap

In this study, the model presented by Kalantary et al. (2018) as a null model is initially described and then extended. Afterward, the gap in the research literature and the reasons for its development are described. Using the RAM model designed by Cooper, Park, and Pastor (1999) as the foundation, Kalantary et al. (2018) extended the input-oriented model into a DNDEA one. In this model, there is no surplus, shortages are also allowed across the supply chain, and no preference had assumed for the stages, inputs, and periods. Moreover, the intermediate and carry-over variables, as defined in Tone and Tsutsui's (2014) classification, are treated as the constants and outputs, respectively. The objective function of this model focuses entirely on the input variables representing economic and financial aspects of sustainability. Although these are precious works that lay the groundwork for better sustainability assessment and provide a better understanding of this process, it needs to be further developed for the following reasons:

1. This model simply focuses on short-term profits from a purely cost-oriented perspective, which makes it ignore the socio-environmental background of an organization during evaluations, despite the fact that socio-environmental sustainability is turning into one of the key competitive priorities for many businesses [30]. According to Sy (2016), All three sustainability pillars - economic, social, and environmental - can have significant impacts on the performance and efficiency of businesses.
2. This model ignores previous research on sustainability. With reference to the studies by Paul et al. (2021); Elmsalmi et al. (2021), sustainability can be defined as the extent to which current decisions in organizations will impact the socio-economic and environmental status of the organization in the future. From this definition, it is reasonable to conclude that the current state of organizations is often inspired by the socio-environmental decisions made in the past.
3. According to Kou et al. (2015), the DNRAM, like the DNDEA, requires endogenous or exogenous weight assignment to the efficiency of stages or periods. While this model has defined weights for this purpose, these match the component's efficiency arithmetic mean values, and also the source of the inefficiency in each period is unknown.

Therefore, the proposed models offer several innovations to achieve a higher degree of practicality compared to the existing ones for supplier selection in supply chains.

## 3. The Proposed Methods

### 3.1 Dynamic Network Data Envelopment Analysis

In the present study, Kalantary's (2018) model is developed in two phases. In both phases, developed models provide an integrated platform for calculating overall, partial, periodic, and periodic-partial efficiency scores. Provided that the following is a description of the variables and parameters used in these models:

| | |
|---|---|
| $x_{ija}^{t}$ : | The $i_{th}$ input of the $j_{th}$ DMU in the $a_{th}$ stage in time t. |
| $y_{rja}^{t}$ : | The $r_{th}$ output of the $j_{th}$ DMU in the $a_{th}$ stage in time t. |
| $C_{uja}^{t,t+1}$ : | The $u_{th}(u=1,...,U)$ carry-over of the $j_{th}$ DMU in the $a_{th}$ stage from time t to time t+1. |
| $C_{uja}^{t-1,t}$ : | The $u_{t-1h}(u=1,...,U)$ carry-over of the $j_{th}$ DMU in the $a_{th}$ stage from time t-1 to time t. |
| $l_{qj(a-z)}^{t}$ : | The $w_{th}(u=1,...,W)$ intermediate measure of the $j_{th}$ DMU which sent from $a_{th}$ stage to $z_{th}$ stage in time t. |
| $R_{ioa}^{t}$ : | The range of inputs in time t; $R_{ioa}^{t}=\max(x_{ija}^{t})-\min(x_{ija}^{t})$ . |
| $R_{uoa}^{t-1}$ : | The range of carry-over variables in time t-1; $R_{uoa}^{t-1}=\max(C_{uja}^{t-1,t})-\min(C_{uja}^{t-1,t})$ . |
| $s_{ioa}^{t}$ : | Input slack for stage a in time t. |
| $s_{uoa}^{t-1,t}$ : | The bad carryover's slack for stage a, from time t-1 to t. |
| $w_{a}$ : | Relative exogenous weight of stage a, $\sum_{a}^{A} w_{a}=1,\ w_{a}\geq 0$ |
| $w_{t}$: | Relative exogenous weight of period t, $\sum_{t}^{T} w_{t}=1,\ w_{t}\geq 0$ |
| $\lambda_{jk}^{t}$ : | Intensity vector of $j_{th}$ DMU in the $a_{th}$ stage in time t. |

### 3.2 Model Formulation

To address the issues stated in notes 1 and 2 in the research background, the model developed by Kalantary et al. (2018) expanded at the first phase in such a way as to avoid over-focusing on short-term profits from a purely cost-oriented perspective and ensure that the socio-environmental effects of supply chain activities are appropriately represented in the model. This helps lay the foundation for making supply chain activities much more sustainable by addressing the factors that influence the environment surrounding the chain. This model also incorporates variables taking value from previous periods t-1 (t=2, 3, …, T) that could affect the current performance. Therefore, Constraint 6 is introduced to the formulation as follows:

$$
\begin{aligned}
\min e = 1-\frac{1}{T}\sum_{t=1}^{T}\frac{1}{A}\sum_{a=1}^{A}\frac{1}{m+r}\sum_{i=1}^{m}\sum_{r=1}^{R}\frac{S_{ioa}^{t}}{R_{ioa}^{t}}+\frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}& \\
\text{s.t.}\quad \sum_{j}^{n} x_{ija}^{t}\lambda_{ja}^{t}+s_{ioa}^{t}=x_{ioa}^{t}, &\quad i=1,\cdots,m,\ \forall A,T \\
\sum_{j}^{n} y_{rja}^{t}\lambda_{ja}^{t}\ge y_{roa}^{t}, &\quad r=1,\cdots,R,\ \forall A,T \\
\sum_{j}^{n} l_{qj(a-z)}^{t}\lambda_{jk}^{t}=\sum_{j}^{n} l_{qj(a-z)}^{t}\lambda_{jh}^{t}, &\quad q=1,\cdots,Q,\ a=1,\cdots,A-1,\ \forall T \\
\sum_{j}^{n} C_{uja}^{t,t+1}\lambda_{ja}^{t}=\sum_{j}^{n} C_{uja}^{t,t+1}\lambda_{ja}^{t+1}, &\quad u=1,\cdots,U,\ t=1,\cdots,T-1, \forall A \\
\sum_{j}^{n} C_{uja}^{t,t+1}\lambda_{ja}^{t}\ge C_{uoa}^{t,t+1}, &\quad u=1,\cdots,U,\ t=1,\cdots,T-1, \forall A \\
\sum_{j}^{n} C_{uja}^{t-1,t}\lambda_{ja}^{t}+s_{uoa}^{t-1,t}=C_{uoa}^{t-1,t}, &\quad u=1,\cdots,U, t=2,\cdots,T-1, \forall A \\
\sum_{j}^{n}\lambda_{ja}^{t}=1,\ \forall A,T,& \\
\lambda_{ja}^{t}, s_{ioa}^{t}, s_{uoa}^{t-1,t}\ge 0,\ \forall i,j,r&
\end{aligned}
\tag{1}
$$

In the second phase, the DNDEA model is assigned to work with the exogenous weights, resulting in a weighted version of the DNDEA model, to tackle the problem indicated in note 3 of section 2.3. For the first time, the stages of each process are further assigned a set of weights ($w_a$) determined by a heuristic model based on the FISM, which reflects on the expert's knowledge of the relative significance of each stage for process efficiency. A set of weights ($w_t$) is then assigned to the periods, reflecting the historical value of periods for efficient assessment.

$$
\min e = 1-\sum_{t=1}^{T} w_t\left[\sum_{a=1}^{A}\frac{w_a}{m+r}\sum_{i=1}^{m}\sum_{r=1}^{R}\frac{S_{ioa}^{t}}{R_{ioa}^{t}}+\frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right] \tag{2}
$$

Subject to the constraints of (1).

### 3.3 Proposed Weight Extraction Algorithm

Consider the hypothetical multistage structure illustrated in Figure 1. Each stage has its inputs and outputs. One of the merits of Figure 1 is that it can be simultaneously defined as network analysis in DEA and, given time, as dynamic network analysis in DEA.

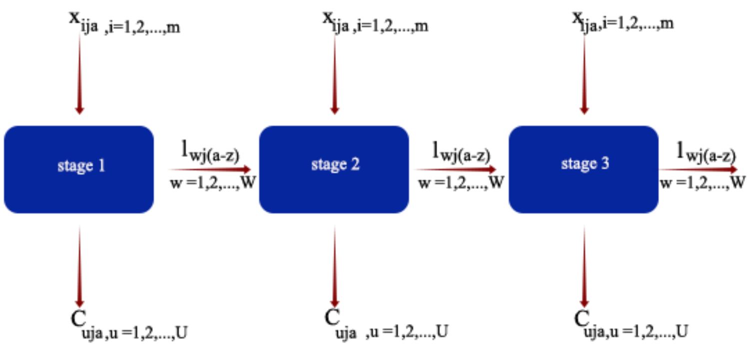


**Figure 1.** Assumed multistage structure

Where:

$X_{ija}$: The $i_{th}$ input of DMU j at stage a.
$C_{uja}$: The $u_{th}$ output of DMU j at stage a.
$l_{wj(a-z)}$: The $w_{th}$ intermediate variable of DMU j which sent from stage a to stage z.

The input, output, and intermediate variables are represented by the non-negative coefficients $V_{ija}$, $u_{ija}$, and $\eta_{wj(a-z)}$, respectively. Using fuzzy-ISM, we can derive criteria weights by following these ten steps:

1- **Pairwise comparison matrix formation:** Once the indicators have been identified and selected, a pairwise comparison between each pair of variables should be performed.

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

In this case, $C_r$ represents the pairwise comparison matrix filled by the $r_{th}$ expert. The linguistic scale utilized in fuzzy-ISM is shown in Table 1.

**Table 1.** Fuzzy linguistic scale

| Linguistic description | Notation | Triangular fuzzy number |
|---|---|---|
| Very low influence | VL | $(0 \quad 0 \quad 0.25)$ |
| low influence | L | $(0 \quad 0.25 \quad 0.5)$ |
| Mediocre | M | $(0.25 \quad 0.5 \quad 0.75)$ |
| High influence | H | $(0.5 \quad 0.75 \quad 1)$ |
| Very high influence | VH | $(0.75 \quad 1 \quad 1)$ |

Source:[28]

To check the consistency of responses, it is necessary to calculate the rate of inconsistency after completing the questionnaire. It can be said that the response matrix is completely consistent if the rate of inconsistency is less than 5%.

$$IR = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j}^{n} \left| \frac{t_{ij}^{n} - t_{ij}^{n-1}}{t_{ij}^{n}} \right| *100\% \tag{3}$$

where:

n: The number of variables.
IR: The rate of inconsistency.
$t_{ij}^{n}$: Experts' mean score given to the i-th variable compared to the j-th variable for $1 \le i \le n$, and $1 \le j \le n$.

2- **Aggregating expert opinions:** To aggregate expert opinions, several methods have been developed. In the present study, the geometric mean ($G_{ij}$) formulated below is used [35].

$$G_{ij} = (l_{ij}, m_{ij}, u_{ij}), \quad l_{ij} = \left(\prod_{k=1}^{n} l_{ij}\right)^{1/n}, \ m_{ij} = \left(\prod_{k=1}^{n} m_{ij}\right)^{1/n}, u_{ij} = \left(\prod_{k=1}^{n} u_{ij}\right)^{1/n} \tag{4}$$

where:

$(l_{ij}, m_{ij}, u_{ij})$: The $k_{th}$ expert opinion on the relative importance of variables i, j.
n: The rate of inconsistency.

**3- Normalized matrix formation:** This, $\mu$ must first be determined from Equation 5 then the normalized matrix (N) can be obtained by Equation (6).

$$\mu = \max_{1 \le i \le n} \sum_{j=1}^{n} u_{ij} \quad (5) \qquad N = G/\mu \tag{5}$$

where:

$u_{ij}$: The maximum value for each row's fuzzy numbers in the decision matrix.
N: The normalized matrix.

**4 - Normalized matrix defuzzification:** Different methods can be used to de-fuzziness the fuzzy number. In this investigation, the most widely defuzzification technique is employed (7).

$$\pi_{ij} = \frac{u_{ij} - l_{ij} + m_{ij} - l_{ij}}{3} + l_{ij} \tag{7}$$

**5 – Threshold limit calculation:** The arithmetic mean formula must be used to compute the threshold limit (Equation 8).

$$T = \frac{\sum_{j=1}^{n}\sum_{i=1}^{n} a_{ij}}{n^2} \tag{8}$$

where:

$a_{ij}$ : Result of de-fuzzifying the normalized matrix, $1 \le i \le n$ and $1 \le j \le n$

n: A number of elements.

T: Threshold limit's value.

The incidence matrix (R) can then be obtained by using Equation (9).

$$\begin{aligned} &\text{if } \pi_{ij} \ge T \rightarrow \pi_{ij} = 1,\ \pi_{ij} = 0 \\ &\text{if } \pi_{ij} < T \rightarrow \pi_{ij} = 0,\ \pi_{ij} = 1 \end{aligned} \tag{9}$$

**6 - The initial matrix of reachability:** The incidence and identity matrices are combined to create the initial reachability matrix, as shown in the following formula.

$$M = R + I \tag{10}$$

**7 - The final matrix of reachability:** After checking and modifying the initial matrix for transitivity, the final reachability matrix is obtained, so that, such that:

$$M^* = M^p = M^{p+1} \quad , p > 1 \tag{11}$$

where p and M represent natural numbers and the final reachability matrix, respectively.

**8 - Implement proposed weighting logic:** The reachability and antecedent set for each factor are determined from the final reachability matrix. The reachability set includes the factor itself and the other factor that it may influence, whereas the antecedent set includes the factor itself and the other factor that may influence it. Therefore:

$$D_{ij} = (Re_{ij})^2 - (An_{ij})^2 \tag{12}$$

Reachability and antecedent degrees are $Re_{ij}$ and $An_{ij}$, respectively. The exponent causes the variables to be weighted differently. The following will exist since some $D_{ij}$ values will be negative:

$$Z_{ij} = D_{ij} + (\left|\min D_{ij}\right| + 1) \tag{13}$$

Having a weight of "0" is impossible with the presence of "1". As the final step, the variable's weight is calculated based on (14).

$$L_{ij} = z_{ij} \Big/ \sum z_{ij} \qquad \text{where } \sum L_{ij} = 1. \tag{14}$$

$L_{ij}$ is based on the type of the variable equivalent to the non-negative coefficients of the input $(v_{ija})$, output $(u_{uja})$, and intermediate $(\eta_{wj(a-z)})$ variables. In Equation (14) more significant variable is also given greater weight. Based on the dataset, weighted efficiency can be determined using two strategies.

1. Centralized strategy: If the largest and smallest values in the data set do not differ significantly and each DMU has at least one input greater than or equal to 1, Equation (15) can be used to calculate the weighted efficiency score.

$$e_j = \left(\sum_{i=1}^{m} u_{uja} c_{uja} + \sum_{w=1}^{W} \eta_{wj(a-z)} l_{wj(a-z)}\right) \Big/ \left(\sum_{i=1}^{m} v_{ija} x_{ija} + \sum_{w=1}^{W} \eta_{wj(a-z)} l_{wj(a-z)}\right), \tag{15}$$

Here, $u_{uja}$ $\eta_{wj(a-z)}$ and $v_{ija}$ are optimal values of (14). in the above equation, the yield is not necessarily expressed in unit value, so:

$$\theta_j = \theta_j / \max_j(\theta_j) \qquad \forall j. \tag{16}$$

2. Decentralized strategy: If the largest and smallest values in the data set differ significantly, using the extracted weights set, each part is weighted separately for each supplier. The stage weight ($w_a$) is reasonably determined by the ratio of the resources allocated in stage a to all resources consumed in the process[36], so:

$$w_a = \left( \sum_{w=1}^{W} \eta_{wj(a-z)} l_{wj(a-z)} + \sum_{i=1}^{m} v_{ija} x_{ija} \right) \Bigg/ \left\{ \sum_{i=1}^{m} v_{ij1} x_{ij1} + \sum_{a=2}^{A} \left( \sum_{w=1}^{W} \eta_{wj(a-z)} l_{wj(a-z)} + \sum_{i=1}^{m} v_{ija} x_{ija} \right) \right\},\ a > 1 \tag{1}$$

Equation (17) uses different weights depending on the supplier's specific conditions for the different stages of the process. The decentralized strategy provides two alternatives for combining and formulating the weight of the stages calculated using the DMU efficiency scores.

a) When the value of the components is equal or ignored, such as Model (1), the overall efficiency of the multi-stage process is defined as the weighted harmonic mean of the efficiencies of multi-individual stages, therefore:

$$\theta_a = w_1 + \cdots + w_a \Bigg/ \left( \frac{w_1}{\theta_1} + \cdots + \frac{w_a}{\theta_a} \right) = 1 \Bigg/ \left( \frac{w_1}{\theta_1} + \cdots + \frac{w_a}{\theta_a} \right), \quad \text{where} \sum_{a=1}^{A} w_a = 1 \tag{18}$$

where:

$w_a$: The relative contribution of the efficiency of Stage a $(a = 1, \ldots, A)$

$\theta_a$: Efficiency of stage a

b) In weighted models such as Model (2), the weights of stages ($w_a$) are formulated directly in the model. However, in this model, for the first time, the periods are also weighted ($w_t$) based on the historical value of the data belonging to those periods using a novel formulation:

$$q_{Total} = \sum_{t=1}^{n} w_t q_{jt} \rightarrow w_t = \frac{2 \times t}{n^2 + n} \rightarrow q_{Total} = \sum_{t=1}^{n} \frac{2 \times t \times q_{jt}}{n^2 + n} \tag{19}$$

where:

$q_{jt}$: Periodic efficiency of $DMU_j$ at time $t\,(t = 1, \ldots, n)$

$n$: The review period

In Equation (19), as the years get closer to the end of the period under study, the weight increases [19,37]. Figure 2 illustrates the conceptual framework for the Integrated Approach of Fuzzy ISM and DNDEA.

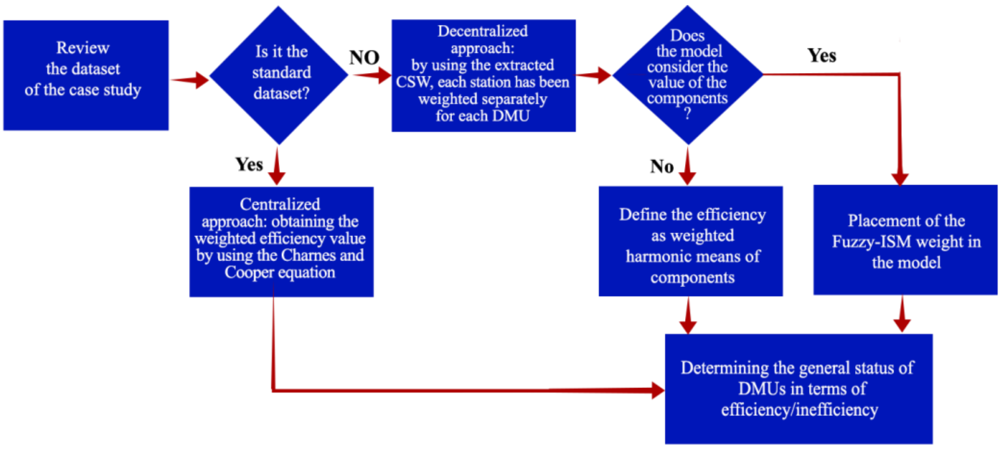


**Figure 2.** Framework for the FISM-DNDEA Integrated Approach

### 3.4 Numerical Illustration

An Iranian company called Nirou Moharekeh Industrial Group (NMI) produces spare components such as gearboxes, splines, and shafts. This study focused on 12 suppliers that provide parts that NMI needs to manufacture gearboxes. Each DMU has three stages, including processing (Stage.1), packing

(Stage.2), and distribution (Stage.3). Apart from the first stage, each stage has three inputs, including the labor costs, energy costs, and material costs (economic factors), two carryovers including environmental initiatives like ISO TS and green programs, and social initiatives like human care programs. Moreover, each stage has one intermediate measure (products). Each NMI supplier's structure is shown in Figure 3.

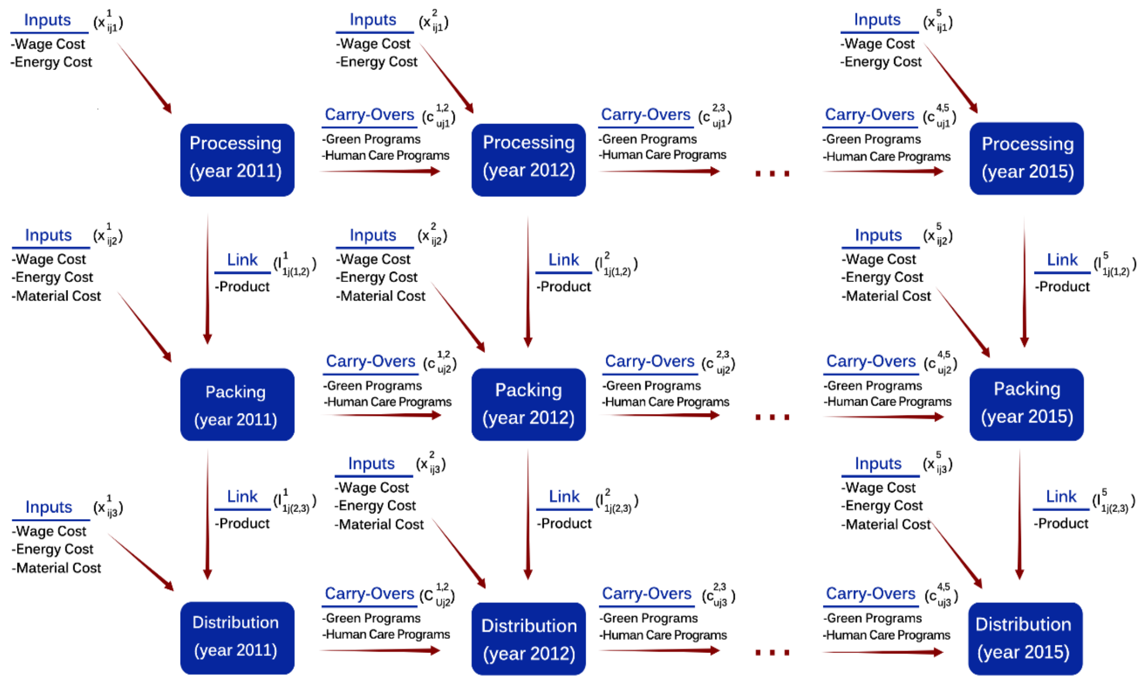

**Figure 3.** Structure of each supplier of NMI

Based on the case study data, the largest and smallest values are significantly different, so the decentralized strategy should be followed. Considering that the present study provides two alternatives to integrate the exogenous stage weight into the DNDEA models in the decentralized strategy, the Fuzzy ISM model is used to calculate stage weights, and the heuristic method is used to calculate period weights. Subsequently, the developed Models (1) and (2) are implemented in the Lingo software, and the results are tabulated. According to Figure 1 and the structure of NMI, suppliers are inputs ($x_{ija}$: cost of labor, energy cost, material cost), outputs ($C_{uja}$: green programming and human care programming), and intermediate link ($l_{wj(a\text{-}z)}$: product). Table 2 shows the symbol of sustainability measures of the suppliers of NMI.

**Table 2.** NMI's suppliers' sustainability measures

| Sustainability variable of NMI | labor Costs | Energy Cost | Material Cost | ISO TS &green program | human care programs | Products |
|---|---|---|---|---|---|---|
| Symbols | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ |

A pairwise comparison questionnaire is designed and distributed to 14 experts and managers. Experts were selected based on their theoretical knowledge, practical experience, and willingness and ability to participate. The respondents filled out the questionnaire using linguistic variables. The linguistic scales utilized in fuzzy-ISM are shown in Table 1. According to experts, the questionnaire showed excellent content validity. The inconsistency rate for each stage of the system confirmed its reliability. Based on the pairwise comparison matrices for the three stages, the inconsistency rate was equal to 0.0328, 0.0345, and 0.0337 (Table 3). Next, we have obtained the decision matrix, normalized, and defuzzification normal matrices.

Then, we calculated the threshold limit and obtained a value of 0.102, 0.083, and 0.123 for stage 1, stage 2, and stage 3, respectively. As shown in Table 4, the incidence and initial reachability matrices were calculated next.

**Table 3.** The defuzzification of normal matrices of stages

| STAGE. 1 | $S_6$ | $S_5$ | $S_4$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|
| $S_1$ | 0. 1540 | 0. 1351 | 0. 0273 | 0. 0315 | - |
| $S_2$ | 0. 1341 | 0. 0319 | 0. 0585 | - | 0. 1521 |
| $S_4$ | 0. 1520 | 0. 1462 | - | 0. 1686 | 0. 0498 |
| $S_5$ | 0. 1318 | - | 0. 1124 | 0. 1422 | 0. 1545 |
| $S_6$ | - | 0. 0273 | 0. 0983 | 0. 0307 | 0. 0559 |

| STAGE. 2 | $S_6$ | $S_5$ | $S_4$ | $S_3$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|---|
| $S_1$ | 0. 0630 | 0. 1261 | 0. 0217 | 0. 0238 | 0. 0233 | – |
| $S_2$ | 0. 0971 | 0. 0289 | 0. 0357 | 0. 0283 | – | 0. 1503 |
| $S_3$ | 0. 1392 | 0. 0265 | 0. 0332 | – | 0. 0245 | 0. 0327 |
| $S_4$ | 0. 1341 | 0. 0866 | – | 0. 1008 | 0. 0995 | 0. 0599 |
| $S_5$ | 0. 1216 | – | 0. 0397 | 0. 0211 | 0. 1216 | 0. 1539 |
| $S_6$ | – | 0. 0245 | 0. 0209 | 0. 0240 | 0. 0172 | 0. 0492 |

| STAGE. 3 | $S_6$ | $S_4$ | $S_3$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|
| $S_1$ | 0. 0726 | 0. 0253 | 0. 0315 | 0. 0334 | – |
| $S_2$ | 0. 0910 | 0. 0351 | 0. 0297 | – | 0. 1464 |
| $S_3$ | 0. 1330 | 0. 0345 | – | 0. 0264 | 0. 0359 |
| $S_4$ | 0. 1271 | – | 0. 0970 | 0. 0962 | 0. 0659 |
| $S_5$ | 0. 1211 | 0. 0459 | 0. 0241 | 0. 1190 | 0. 1543 |

**Table 4.** Matrix of initial reachability

| DIV. 1 | $S_6$ | $S_5$ | $S_4$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|
| $S_1$ | 1 | 1 | 0 | 0 | 1 |
| $S_2$ | 1 | 0 | 0 | 1 | 1 |
| $S_4$ | 1 | 1 | 1 | 1 | 0 |
| $S_5$ | 1 | 1 | 0 | 1 | 1 |
| $S_6$ | 1 | 0 | 0 | 0 | 0 |

| STAGE. 2 | $S_6$ | $S_5$ | $S_4$ | $S_3$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|---|
| $S_1$ | 0 | 1 | 0 | 0 | 0 | 1 |
| $S_2$ | 1 | 0 | 0 | 0 | 1 | 1 |
| $S_3$ | 1 | 0 | 0 | 1 | 0 | 0 |
| $S_4$ | 1 | 1 | 1 | 1 | 1 | 0 |
| $S_5$ | 1 | 1 | 0 | 0 | 1 | 1 |
| $S_6$ | 1 | 0 | 0 | 0 | 0 | 0 |

| STAGE. 3 | $S_6$ | $S_4$ | $S_3$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|
| $S_1$ | 1 | 0 | 0 | 0 | 1 |
| $S_2$ | 0 | 0 | 0 | 1 | 1 |
| $S_3$ | 0 | 0 | 1 | 0 | 0 |
| $S_4$ | 1 | 1 | 1 | 1 | 0 |
| $S_5$ | 1 | 0 | 0 | 1 | 1 |

Equation 11 was used to calculate the final reachability matrices (Table 5).

**Table 5.** Matrix of final reachability

| STAGE. 1 | $S_6$ | $S_5$ | $S_4$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|
| $S_1$ | 1 | 1 | 0 | 1* | 1 |
| $S_2$ | 1 | 1* | 0 | 1 | 1 |
| $S_4$ | 1 | 1 | 1 | 1 | 1* |
| $S_5$ | 1 | 1 | 0 | 1 | 1 |
| $S_6$ | 1 | 0 | 0 | 0 | 0 |

| STAGE. 2 | $S_6$ | $S_5$ | $S_4$ | $S_3$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|---|
| $S_1$ | 1* | 1 | 0 | 0 | 1* | 1 |
| $S_2$ | 1 | 1* | 0 | 0 | 1 | 1 |
| $S_3$ | 1 | 0 | 0 | 1 | 0 | 0 |
| $S_4$ | 1 | 1 | 1 | 1 | 1 | 1* |
| $S_5$ | 1 | 1 | 0 | 0 | 1 | 1 |
| $S_6$ | 1 | 0 | 0 | 0 | 0 | 0 |

| STAGE. 3 | $S_6$ | $S_4$ | $S_3$ | $S_2$ | $S_1$ |
|---|---|---|---|---|---|
| $S_1$ | 1 | 0 | 0 | 1* | 1 |
| $S_2$ | 1* | 0 | 0 | 1 | 1 |
| $S_3$ | 0 | 0 | 1 | 0 | 0 |
| $S_4$ | 1 | 1 | 1 | 1 | 1* |
| $S_5$ | 1 | 0 | 0 | 1 | 1 |

Then the weight of the variables was calculated by Equation (14).

Columns 4 and 5 of Table 6 contain the answer to Equations (12) and (13), while column 6 is the answer to Equation (14), showing the variable weights for each stage separately. Based on the weights obtained from the heuristic method (Table 7), the weight for each stage is calculated by Equation (17).

**Table 6.** Proposed weighting logic

| STAGE. 1 | $Re_{ij}$ | $An_{ij}$ | $D_{ij}$ | $Z_{ij}$ | $L_{ij}(Stage_{1total})$ | |
|---|---|---|---|---|---|---|
| $S_1$ | 4 | 4 | 0 | 25 | 0.2000 | $V_{11}$ |
| $S_2$ | 4 | 4 | 0 | 25 | 0.2000 | $V_{12}$ |
| $S_4$ | 5 | 1 | 24 | 49 | 0.3920 | $U_{11}$ |
| $S_5$ | 4 | 4 | 0 | 25 | 0.2000 | $U_{12}$ |
| $S_6$ | 1 | 5 | -24 | 1 | 0.0080 | $\eta_{11}$ |

| STAGE. 2 | $Re_{ij}$ | $An_{ij}$ | $D_{ij}$ | $Z_{ij}$ | $L_{ij}(Stage_{2total})$ | |
|---|---|---|---|---|---|---|
| $S_1$ | 4 | 4 | 0 | 36 | 0.1667 | $V_{21}$ |
| $S_2$ | 4 | 4 | 0 | 36 | 0.1667 | $V_{22}$ |
| $S_3$ | 2 | 2 | 0 | 36 | 0.1667 | $V_{23}$ |
| $S_4$ | 6 | 1 | 35 | 71 | 0.3287 | $U_{21}$ |
| $S_5$ | 4 | 4 | 0 | 36 | 0.1667 | $U_{22}$ |
| $S_6$ | 1 | 6 | -35 | 1 | 0.0046 | $\eta_{22}$ |

| STAGE. 3 | $Re_{ij}$ | $An_{ij}$ | $D_{ij}$ | $Z_{ij}$ | $L_{ij}(Stage_{3total})$ | |
|---|---|---|---|---|---|---|
| $S_1$ | 3 | 4 | -7 | 1 | 0.0250 | $V_{31}$ |
| $S_2$ | 3 | 4 | -7 | 1 | 0.0250 | $V_{32}$ |
| $S_3$ | 1 | 2 | -3 | 5 | 0.1250 | $V_{33}$ |
| $S_4$ | 5 | 1 | 24 | 32 | 0.8000 | $U_{31}$ |
| $S_5$ | 3 | 4 | -7 | 1 | 0.0250 | $U_{32}$ |

**Table 7.** Weight of each stage

| DMU | | | DMU 1 | DMU 2 | DMU 3 | DMU 4 | DMU 5 | DMU 6 | DMU 7 | DMU 8 | DMU 9 | DMU 10 | DMU 11 | DMU 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Partial Weights | | Stage1 | 0. 4107 | 0. 3736 | 0. 3100 | 0. 3770 | 0. 3222 | 0. 4752 | 0. 3673 | 0. 2945 | 0. 1306 | 0. 3647 | 0. 1382 | 0. 1484 |
| | | Stage 2 | 0. 4664 | 0. 4571 | 0. 4901 | 0. 4679 | 0. 4641 | 0. 431 | 0. 4548 | 0. 4833 | 0. 5309 | 0. 4733 | 0. 5304 | 0. 5232 |
| | | Stage 3 | 0. 1268 | 0. 1664 | 0. 1999 | 0. 1551 | 0. 2426 | 0. 1158 | 0. 2061 | 0. 242 | 0. 2879 | 0. 2019 | 0. 2774 | 0. 2674 |
| Term efficiency | 2011 | Stage 1 | 0. 4658 | 0. 2954 | 0. 3145 | 0. 3901 | 0. 2781 | 0. 4051 | 0. 1873 | 0. 3751 | 0. 3274 | 0. 3797 | 0. 1142 | 0. 34674 |
| | | Stage 2 | 0. 4394 | 0. 4953 | 0. 4818 | 0. 4614 | 0. 4841 | 0. 463 | 0. 4765 | 0. 4475 | 0. 4671 | 0. 4725 | 0. 5383 | 0. 51849 |
| | | Stage 3 | 0. 0948 | 0. 2093 | 0. 2037 | 0. 1484 | 0. 2378 | 0. 1319 | 0. 3362 | 0. 1774 | 0. 2055 | 0. 1478 | 0. 3475 | 0. 13477 |
| | 2012 | Stage 1 | 0. 4421 | 0. 3402 | 0. 3661 | 0. 3603 | 0. 2662 | 0. 3075 | 0. 4337 | 0. 4402 | 0. 1655 | 0. 3538 | 0. 2509 | 0. 4402 |
| | | Stage 2 | 0. 4483 | 0. 482 | 0. 4636 | 0. 4700 | 0. 5295 | 0. 5235 | 0. 4498 | 0. 3395 | 0. 517 | 0. 4744 | 0. 4963 | 0. 3395 |
| | | Stage 3 | 0. 1096 | 0. 1778 | 0. 1703 | 0. 1695 | 0. 2043 | 0. 169 | 0. 1165 | 0. 2203 | 0. 3175 | 0. 1718 | 0. 2528 | 0. 2203 |
| | 2013 | Stage 1 | 0. 4448 | 0. 4303 | 0. 4164 | 0. 4130 | 0. 1738 | 0. 4346 | 0. 4567 | 0. 4402 | 0. 273 | 0. 2775 | 0. 4402 | 0. 2076 |
| | | Stage 2 | 0. 4492 | 0. 4304 | 0. 4447 | 0. 4618 | 0. 4976 | 0. 4567 | 0. 3681 | 0. 3395 | 0. 4685 | 0. 4941 | 0. 3395 | 0. 5064 |
| | | Stage 3 | 0. 106 | 0. 1393 | 0. 1389 | 0. 1251 | 0. 3286 | 0. 1087 | 0. 1752 | 0. 2203 | 0. 2586 | 0. 2284 | 0. 2203 | 0. 286 |
| | 2014 | Stage 1 | 0. 3372 | 0. 3874 | 0. 3329 | 0. 3670 | 0. 4402 | 0. 4931 | 0. 3053 | 0. 3303 | 0. 0711 | 0. 1244 | 0. 1137 | 0. 0272 |
| | | Stage 2 | 0. 5075 | 0. 444 | 0. 4806 | 0. 4703 | 0. 3395 | 0. 4221 | 0. 4683 | 0. 4797 | 0. 5516 | 0. 5065 | 0. 5399 | 0. 5579 |
| | | Stage 3 | 0. 1552 | 0. 1686 | 0. 1865 | 0. 1626 | 0. 2203 | 0. 0848 | 0. 2264 | 0. 1900 | 0. 3773 | 0. 3691 | 0. 3464 | 0. 4149 |
| | 2015 | Stage 1 | 0. 3256 | 0. 4371 | 0. 3012 | 0. 3337 | 0. 439 | 0. 5001 | 0. 3627 | 0. 0501 | 0. 216 | 0. 4545 | 0. 4402 | 0. 2093 |
| | | Stage 2 | 0. 5063 | 0. 4261 | 0. 4865 | 0. 4823 | 0. 3386 | 0. 415 | 0. 4611 | 0. 548 | 0. 5037 | 0. 4533 | 0. 3395 | 0. 5096 |
| | | Stage 3 | 0. 1681 | 0. 1368 | 0. 2123 | 0. 1839 | 0. 2223 | 0. 0849 | 0. 1763 | 0. 402 | 0. 2803 | 0. 0922 | 0. 2203 | 0. 2811 |

As mentioned earlier, in the decentralized strategy, two alternatives should be considered to combine and formulate the calculated weight of the stages with the efficiency scores of DMUs:

**a:** Based on the fact that Model (1) does not reflect the relative importance of the components, the overall, periodic, partial, and periodic-partial efficiency of the suppliers of the NMI has first been calculated using Model (1). The harmonic weighted mean of the process's components is then used to calculate the overall and periodic efficiency. As shown in Table 8, Model 1 can rank suppliers by overall, periodic, partial, and periodic-partial efficiency and then identify the most efficient options. Regarding the values assigned to the stages and periods, the objective function of Model 1 undergoes some changes. Specifically, the objective function is $\left(\min e = 1 - \frac{1}{T}\sum_{t=1}^{T}\frac{1}{a}\sum_{a=1}^{A}\frac{1}{m+r}\sum_{i=1}^{m}\sum_{r=1}^{R}\frac{S_{ioa}^{t}}{R_{ioa}^{t}} + \frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right)$ for overall efficiency, $\left(\min e = 1 - \frac{1}{A}\sum_{a=1}^{A}\frac{1}{m+r}\sum_{i=1}^{m}\sum_{r=1}^{R}\frac{S_{ioa}^{t}}{R_{ioa}^{t}} + \frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right)$ for periodic efficiency, $\left(\min e = 1 - \frac{1}{T}\sum_{t=1}^{T}\frac{1}{m+r}\sum_{i=1}^{m}\sum_{r=1}^{R}\frac{S_{ioa}^{t}}{R_{ioa}^{t}} + \frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right)$ for partial efficiency, and $\left(\min e = 1 - \frac{1}{m+r}\sum_{i=1}^{m}\sum_{r=1}^{R}\frac{S_{ioa}^{t}}{R_{ioa}^{t}} + \frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right)$ periodic-partial efficiency. It seems easy to rank DMUs using overall efficiency, which helps identify the most efficient supplier in this study. Periodic efficiency can be further utilized to monitor the dynamic state of suppliers in each period, partial efficiency can be applied to identify the impressive stages as well and periodic-partial efficiency can be recruited to identify the source of inefficiency in each period. As pointed out, in section 3.3, the relative importance of the components is not reflected in Model (1). Thus, the proposed heuristic method (FISM) was employed, which gives weight to each stage separately for each supplier. Therefore, the efficiency of the process is defined as the harmonic weighted mean of the efficiency of the constitutive stages of the process. Table 8 shows how the CSWs assigned to stages affect the overall and periodic efficiency scores of all suppliers of the NMI. In both, KARAN earned the highest efficiency score. Other suppliers have also gained efficiency scores between 0.6409-0.9994 and 0.6298-0.9998 from the Model (1) and the weighted model, respectively.

**Table 8.** Efficiency scores of the supplier of NMI according to Model (1) and weighted harmonic mean

| DMUs | Overall efficiently | | Rank | | Partial efficiency | | | Term efficiency | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | 2011 | | | 2012 | | | 2013 | | | 2014 | | | 2015 | | |
| | | | | | | | | Model. Error! Reference source not found. | | Weighted HM | Model. Error! Reference source not found. | | Weighted HM | Model. Error! Reference source not found. | | Weighted HM | Model. Error! Reference source not found. | | Weighted HM | Model. Error! Reference source not found. | | Weighted HM |
| | Reference | Weighted HM | MODEL 1 | Weighted HM | Stage.1 | Stage.2 | Stage.3 | Stage1 | Stage 2 | Stage 3 | Stage 1 | Stage 2 | Stage 3 | Stage 1 | Stage 2 | Stage 3 | Stage 1 | Stage 2 | Stage 3 | Stage 1 | Stage 2 | Stage 3 |
| TECHAT | 0.9926 | 0.9901 | 3 | 4 | 1.0000 | 0.9794 | 0.9985 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 0.9631 | | 0.9439 |
| | | | | | | | | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 0.897 | 0.9923 |
| STEEL P | 0.7910 | 0.7948 | 9 | 9 | 0.8221 | 0.7842 | 0.7667 | 0.4460 | | 0.4409 | 0.6506 | | 0.6447 | 0.9690 | | 0.9859 | 1.0000 | | 1.0000 | 0.8894 | | 0.8876 |
| | | | | | | | | 0.4886 | 0.422 | 0.4273 | 0.7455 | 0.601 | 0.6046 | 1.0000 | 1.000 | 0.9071 | 1.0000 | 1.000 | 1.0000 | 0.8762 | 0.897 | 0.8948 |
| D.L.KARAN | 0.7682 | 0.7513 | 10 | 11 | 0.8165 | 0.7036 | 0.7845 | 0.4416 | | 0.4406 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 0.8703 | | 0.7656 | 0.5292 | | 0.5158 |
| | | | | | | | | 0.4649 | 0.430 | 0.4293 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 0.610 | 1.0000 | 0.6176 | 0.476 | 0.4932 |
| PARSHAM | 0.7552 | 0.7555 | 11 | 10 | 0.764 | 0.7500 | 0.7515 | 0.5089 | | 0.5013 | 0.6867 | | 0.6865 | 0.6845 | | 0.6870 | 0.9973 | | 0.9970 | 0.8984 | | 0..8975 |
| | | | | | | | | 0.4558 | 0.535 | 0.5352 | 0.7499 | 0.655 | 0.6548 | 0.7169 | 0.666 | 0.6697 | 0.9920 | 1.000 | 1.0000 | 0.9055 | 0.892 | 0.8978 |
| FARAZAN | 0.9865 | 0.9864 | 5 | 5 | 0.9883 | 0.9854 | 0.9857 | 0.9845 | | 0.9839 | 0.9505 | | 0.9494 | 1.0000 | | 1.0000 | 0.9973 | | 0.9965 | 1.0000 | | 1.0000 |
| | | | | | | | | 0.9899 | 0.981 | 0.9820 | 0.9598 | 0.945 | 0.9462 | 1.0000 | 1.000 | 1.0000 | 0.9920 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 |
| SIRIN S.N. | 0.6409 | 0.6298 | 12 | 12 | 0.6182 | 0.6346 | 0.6700 | 0.5939 | | 0.5851 | 0.7865 | | 0.7859 | 0.5878 | | 0.5791 | 0.5981 | | 0.5668 | 0.6383 | | 0.6163 |
| | | | | | | | | 0.5418 | 0.618 | 0.6219 | 0.7918 | 0.782 | 0.7848 | 0.6351 | 0.530 | 0.5975 | 0.5121 | 0.631 | 0.6504 | 0.6102 | 0.609 | 0.6951 |
| PIROZ | 0.9827 | 0.9626 | 6 | 6 | 0.9827 | 0.9825 | 0.9828 | 1.0000 | | 1.0000 | 0.9400 | | 0.9400 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 0.9735 | | 0.9732 |
| | | | | | | | | 1.0000 | 1.000 | 1.0000 | 0.9409 | 0.939 | 0.9399 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 0.9725 | 0.973 | 0.9742 |
| ALSAN | 0.9910 | 0.9909 | 4 | 3 | 0.9923 | 0.9903 | 0.9903 | 0.9996 | | 0.9996 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 0.9553 | | 0.9521 |
| | | | | | | | | 0.9988 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 0.9627 | 0.951 | 0.9516 |
| KARAN | 1.0000 | 1.0000 | 1 | 1 | 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 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 |
| TIR | 0.8490 | 0.8490 | 8 | 8 | 0.8615 | 0.8412 | 0.8443 | 0.6640 | | 0.6607 | 0.6683 | | 0.6645 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 0.9127 | | 0.9103 |
| | | | | | | | | 0.6350 | 0.676 | 0.6809 | 0.7638 | 0.620 | 0.6210 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 0.9090 | 0.909 | 0.9194 |
| BARAN | 0.9120 | 0.8891 | 7 | 7 | 0.9624 | 0.8550 | 0.9187 | 0.7059 | | 0.6355 | 0.9256 | | 0.8971 | 1.0000 | | 1.0000 | 0.9499 | | 0.9188 | 0.9787 | | 0.9781 |
| | | | | | | | | 0.8919 | 0.612 | 0.6129 | 0.9445 | 0.832 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 0.849 | 1.0000 | 0.9754 | 0.980 | 0.9803 |
| HAMRAH | 0.9994 | 0.9998 | 2 | 2 | 0.9983 | 1.0000 | 1.0000 | 0.9972 | | 0.9971 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 | 1.0000 | | 1.0000 |
| | | | | | | | | 0.9917 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 | 1.0000 | 1.000 | 1.0000 |

**b:** The $W_a$ values obtained from the Fuzzy ISM-based heuristic method and the $W_t$ values based on historical periods' values were directly formulated in Model (2), and implemented in the Lingo software. The results are as follows:

**Table 9.** Efficiency scores of the suppliers of NMI according to the Model (2)

| DMUs | Rank | overall efficiency | Partial efficiency | | | Term efficiency | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 2011 ($W_t$=0.0667) | | | | 2012 ($W_t$=0.1334) | | | | 2013 ($W_t$=0.2000) | | | | 2014 ($W_t$=0.2667) | | | | 2015 ($W_t$=0.3333) | | | |
| | | | Stage1 | Stage2 | Stage3 | Term | Stage1 | Stage2 | Stage3 | Term | Stage1 | Stage2 | Stage3 | Term | Stage1 | Stage2 | Stage3 | Term | Stage1 | Stage2 | Stage3 | Term | Stage1 | Stage2 | Stage3 |
| TECH. A. T | 6 | 0.9822 | 1.0000 | 0.9657 | 0.9974 | 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 | 0.9466 | 1.0000 | 0.8971 | 0.9923 |
| STEEL. P | 9 | 0.8763 | 0.8907 | 0.8741 | 0.8555 | 0.4428 | 0.4886 | 0.4220 | 0.4273 | 0.6512 | 0.7455 | 0.6019 | 0.6046 | 0.9871 | 1.0000 | 1.0000 | 0.9971 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.8876 | 0.8762 | 0.8972 | 0.8948 |
| D. L. KARAN | 11 | 0.7537 | 0.8369 | 0.6838 | 0.7930 | 0.4411 | 0.4649 | 0.4306 | 0.4293 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.8130 | 1.0000 | 0.6109 | 1.0000 | 0.5226 | 0.6176 | 0.4767 | 0.4932 |
| PARSHAM | 10 | 0.8278 | 0.8401 | 0.8205 | 0.8229 | 0.5045 | 0.4558 | 0.5357 | 0.5352 | 0.6865 | 0.7499 | 0.6554 | 0.6548 | 0.6879 | 0.7169 | 0.6668 | 0.6697 | 0.9971 | 0.9920 | 1.0000 | 1.0000 | 0.8975 | 0.9055 | 0.8920 | 0.8978 |
| FARAZAN | 3 | 0.9912 | 0.9918 | 0.9915 | 0.9916 | 0.9840 | 0.9899 | 0.9815 | 0.9820 | 0.9494 | 0.9598 | 0.9455 | 0.9462 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9964 | 0.9920 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| SIRIN. S.N. | 12 | 0.6195 | 0.6087 | 0.6234 | 0.6707 | 0.5876 | 0.5418 | 0.6180 | 0.6219 | 0.7860 | 0.7918 | 0.7829 | 0.7848 | 0.5832 | 0.6351 | 0.5307 | 0.5975 | 0.5744 | 0.5121 | 0.6319 | 0.6504 | 0.6172 | 0.6102 | 0.6096 | 0.6951 |
| PIROZ | 5 | 0.9831 | 0.9830 | 0.9831 | 0.9834 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9400 | 0.9409 | 0.9392 | 0.9399 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9733 | 0.9725 | 0.9735 | 0.9742 |
| ALSAN | 4 | 0.9840 | 0.9875 | 0.9839 | 0.9839 | 0.9995 | 0.9988 | 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 | 0.9522 | 0.9627 | 0.9516 | 0.9516 |
| 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 |
| TIR | 8 | 0.9037 | 0.9138 | 0.8977 | 0.9013 | 0.6613 | 0.6350 | 0.6762 | 0.6809 | 0.6711 | 0.7638 | 0.6201 | 0.6210 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9103 | 0.9090 | 0.9098 | 0.9194 |
| BARAN | 7 | 0.9344 | 0.9772 | 0.9052 | 0.9676 | 0.6447 | 0.8819 | 0.6128 | 0.6129 | 0.9029 | 0.9445 | 0.8324 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9188 | 1.0000 | 0.8496 | 1.0000 | 0.9781 | 0.9754 | 0.9803 | 0.9803 |
| HAMRAH | 2 | 0.9998 | 0.9994 | 1.0000 | 1.0000 | 0.9969 | 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 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |

Table 9 also depicts the rate of the changes in the weighted periodic efficiency, resulting from the Model 2 implementation, compared to the harmonic efficiency scores in Table 8 that have augmented in 0.13 cases, dwindled in 0.41 cases, and remained unchanged in 0.45 cases. Compared to the results of the implementation Model 1 (Table 8), the efficiency scores have elevated in 0.08 cases, reduced in 0.45 cases, and remained unaffected in 0.46 cases. As a result of the weights defined for the model, efficient supplier scores did not change. Other suppliers' efficiency scores vary from those in Table 8 as well, as a result of fluctuations in their efficiency scores for each stage and the weights assigned to each stage and period. The objective function of Model (2) changes based on the type of efficiency calculated about the weights assigned to stages and periods. Specifically, the objective function is

$\left(\min e = 1-\sum_{t=1}^{T} w_t \left[\sum_{a=1}^{A} \frac{w_a}{m+r} \sum_{i=1}^{m} \sum_{r=1}^{R} \frac{S_{ioa}^{t}}{R_{ioa}^{t}} + \frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right]\right)$ for overall efficiency, $\left(\min e = 1-\left[\sum_{a=1}^{A} \frac{w_a}{m+r} \sum_{i=1}^{m} \sum_{r=1}^{R} \frac{S_{ioa}^{t}}{R_{ioa}^{t}} + \frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right]\right)$ for periodic efficiency, $\left(\min e = 1-\sum_{t=1}^{T} w_t \left[\frac{1}{m+R} \sum_{i=1}^{m} \sum_{r=1}^{R} \frac{S_{ioa}^{t}}{R_{ioa}^{t}} + \frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right]\right)$ for partial efficiency, and $\left(\min e = 1-\frac{1}{m+r} \sum_{i=1}^{m} \sum_{r=1}^{R} \frac{S_{ioa}^{t}}{R_{ioa}^{t}} + \frac{S_{uoa}^{t-1,t}}{R_{uoa}^{t-1}}\right)$ periodic-partial efficiency. This method, i.e., inserting the weights inside the model, has several advantages over the decentralized strategy. The first advantage of this method is that the efficiency scores are calculated with the weight of stages and periods weights already included in the model, which makes it less computationally expensive than the first one. In addition, this method establishes a logically weighted relationship between the overall, partial, and periodic efficiency scores and the process components, allowing numerical values to be compared logically. Also, overall and partial efficiency scores produced by the first method fail to reflect the historical value of periods, ignoring the fact that recent efficiency scores tend to be a better indicator of future potential than unstable achievements in the past.

## 4. Findings and managerial implications

There are several managerial implications of our framework and discussion. Sustainable supply chain models have been developed in this study as a means of providing an overview of the multiple factors and relationships involved. This allows supply chain managers to anticipate the threats and risks that may impede their transition to sustainability and can make prudent decisions by adjusting the distance between analysis and simulation. Noteworthy is that the proposed models are independent of the criteria utilized in this study, so managers can modify them to suit their needs. In comparison to earlier research, this study's main contributions and benefits are the development of an expert-centered heuristic method based on the FISM, the introduction of a novel integrated approach to the FISM and the DNDEA, and the extension of the applicability of the ISM. This heuristic method helps provide a set of weights on which experts have agreed because they were derived by integrating their subjective preferences.

In addition, the fuzzy approach increases the realism of the method by reflecting the uncertainty of expert opinions. In general, developed models, as well as their complementing strategies, are reliable in obtaining accurate results. Considering the alternative solutions, the model proposed in this study always has valid solutions, which is a computational advantage, as compared to earlier research. However, analysts need to decide which characteristics they prefer to prioritize for evaluation purposes to achieve the best results for each situation. Chen et al.(2009) modeled the two-stage process efficiency as the weighted sum of divisional efficiencies. However, we clearly show that the overall efficiency of the multi-stage process can be modeled as the weighted harmonic mean of the individual efficiencies if the analysts used non-weighted models to determine the efficiency score.

In detail, the results of the models developed in this study differ from those obtained in Kalantary et al. (2018) because the company's current efficiency in the models here is affected by its past socio-environmental performance (Models 1 and 2). For the first time, incorporated weights of the stages were determined by a heuristic method based on the FISM, which denotes the relative importance of each division for process efficiency. Then, the periods are given weight to demonstrate their historical value for efficiency evaluations (Model 2).

In addition, analyzing the model's efficiency scores reveals that it has much greater discriminative power than the null model. As an example, three suppliers (TECH A.T, KARAN, and HAMRAH) had an overall efficiency score of 1 in the null model, while using Models (1) and (2), there is only one efficient DMU (KARAN) in which their efficiency score is unity. One of the reasons why KARAN is the only supplier that has earned the highest efficiency score is that it has experienced bigger changes in the carry-overs (Kalantary et al., 2018). It means the supplier concerned has invested the most in the socio-environmental dimensions of sustainability. In the sensitivity analysis of the sustainability dimensions, Moradi et al. (2022) also proved that the highest changes in the efficiency of NMI suppliers could accrue in the socio-environmental dimensions [38]. Therefore, investing in those dimensions could have a sizeable effect on the performance of suppliers.

Unlike the null model, the present study focuses on the process structure, stages, and time to pinpoint the cause of inefficiencies for each supplier annually. For all the developed models, the highest efficiency score goes to KARAN, and the lowest score goes to SIRIN.S.N. Moreover, considering Model 1, the efficiency score of the 11 inefficient suppliers ranges from 0.6409 to 0.9994 (Table 8). When the efficiency is calculated as the weighted harmonic mean of the components (Equation 18), it varies between 0.6298 to 0.9998 (Table 8), and when considering Model 2, it varies between 0.6195 and 0.9998 (Table 9). Compared with the Model (1), the weights assigned to the models lead to some changes in efficiency scores and supplier ratings, such as:

When the overall and periodic efficiency of the multi-stage process is modeled as a weighted harmonic mean of the multiple stages, the other supplier's efficiency scores decrease relative to Model (1), except for two suppliers (PARSHAM-2013, STEEL-2013), whose period efficiencies have increased. For instance, DMU 3 has an overall efficiency score of 0.7208, as opposed to 0.8046 in the Model (1).

In general, STEEL.P tended to increase the most in 2013 (0.0169), and D.L. KARAN had the largest downward trend in 2014 (0.1047) in periodic efficiency, compared with the results of Model (1). Therefore, changes in suppliers' efficiency can be attributed to fluctuations in stages' efficiency and the weights assigned to them. Also, four suppliers received a different ranking based on harmonic weight.

The implementation of the weighted model (Model 2) compared with the unweighted model (Model 1) produced some changes in the efficiency scores. Specifically, after implementing the proposed weighted model, the efficiency of other suppliers decreased in the period 2011-2015, except for four suppliers whose efficiency increased periodically. For instance, the DMU periodic efficiency score in 2013 was 0.9871, compared with 0.9690 in Model 1. Due to the choice of weights here, the DNDEA model introduces some sort of value judgment, with STEEL.P experiencing the most dramatic rise in 2013 (0.0181) and BARAN experiencing the greatest decline in 2011 (0.0612). Due to this, the efficiency scores of Model 1, in most cases, are larger than those of Model 2 and Equation 18, in which the weights of the stages are equal. In addition, in some cases, the ranking of the suppliers has changed. The most change in rating goes to TECH.AT, as this supplier has declining periodic efficiency in the final years, and Model 2 gives a higher weight to the efficiency of the last period.

## 5. Conclusion

This study provides an integrated DNDEA framework to address shortcomings in previous sustainable supply chain models. Nevertheless, particular suggestions can be addressed in future research. This study assumed that all experts have the same importance and that there is no preference between experts, whereas they may possess varying levels of expertise and experience due to unequal access to resources. For this reason, researchers should consider a different approach to expressing the opinions raised by experts and decision-makers. For example, they can classify experts into several categories with varying levels of importance in which the opinion of the higher category may have greater importance than those of the lower one. Then, two CSWs will introduce from the point of view of the best and the worst experts, which can be analyzed and compared. Moreover, the first decentralized strategy described in this study defined the overall efficiency as the sum of the weighted harmonic mean of the individual components. Future studies should thus exploit the weighted sum of stages and investigate the effectiveness of the changes in the calculation approach in the multi-stage processes. It is necessary to do additional research into new models and computational techniques to construct DEA-based models in situations like multi-stage production processes and methods for aggregating individual preferences. So, using the fuzzy ISM-based weighting algorithm to synthesize expert opinions as a stand-alone method could be a breakthrough in this field. This study will provide more alternative ways to measure multi-stage process performance by enriching DEA theory and providing new ways to improve management and reduce risk in the supply chain, thereby helping NMI managers make better decisions to improve management and reduce risks in the supply chain to achieve sustainability.

## Conflicts of Interest Statement

We certify that all named authors have read, reviewed, and approved the manuscript and that there is no conflict of interest related to this manuscript and the authors. Furthermore, all authors have approved the order of authors listed in the manuscript.

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