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ESTIMATING MOST PRODUCTIVE SCALE SIZE DECOMPOSITION IN A FUZZY NETWORK DATA ENVELOPMENT ANALYSIS MODEL: ASSESSING THE SUSTAINABILITY AND RESILIENCE OF THE SUPPLY CHAIN

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Abstract. This paper estimates the Most Productive Scale Size (MPSS) in the NDEA model to appraise the sustainability and resilience of the supply chains. As the corresponding input and output criteria are not always accurately measurable, we also introduce the fuzzy version of our proposed NDEA model and apply the proposed model in a case study involving 10 Iranian supply chains of Companies Producing Soft Drinks (CPSDs). The considered-three-echelon supply chains include suppliers, manufacturers, and distributors. Mathematical analysis proves that the MPSS of the considered supply chain can be decomposed as the sum of the MPSS values of the individual stages. Thus, the supply chain is overall MPSS if and only if it is MPSS in every three stages. The results of this study reveal that the Behnoush supply chain is overall MPSS in all three stages, including supplier, manufacturer, and distributor, for any $\alpha \in \{0.1, 0.5, 1\}$. A sensitivity analysis has been performed to measure the impact of each criterion on the entire supply chain performance. The sensitivity analysis results indicate that the social and resilience criteria significantly impact the performance and ranking of supply chains. Finally, we discuss how to improve the sustainability and resilience of non-MPSS supply chains.

Mathematics Subject Classification. 68M10, 90B06, 90B99, 90C70, 90C90.

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1. Introduction

Pollution and environmental compatibility have raised global concerns, which in turn affect manufacturing industries throughout the world. The rise of such issues on a global scale reflects the urgent manufacturing companies' need to align their operations and strategies with environmental plans [39, 41, 55]. An economic assessment of greenhouse gas emissions in the European Union (EU) reveals that increasing economic activity by 2030 will lead to a further increase in greenhouse gas emissions by 89% [20].

A sustainable supply chain allows companies to achieve the highest efficiency in logistics performance and resource utilization while emphasizing three dimensions of sustainability, including social, economic, and environmental goals [63]. The concept of resilience also refers to the ability of the supply chain to overcome unexpected disruptions while still providing services and products with the desired quality and price at the right time and

Keywords. Fuzzy network data envelopment analysis, most productive scale size, sustainability, resilience, supply chain.

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place [43]. Sustainability has emerged as a critical industry aspect that extends beyond organizational boundaries and encompasses the supply chain. Resiliency in supply chains is another concern for organizations and industries. Nevertheless, there is still confusion about the perceptions, implementation methods, and assessment of the sustainability and resilience of the supply chains. There is a controversy on these concepts, as sustainability emphasizes efficiency while resilience seeks effectiveness. There is still no practice that can be taken to improve supply chain performance in both aspects. Sustainability and resilience considerations in supply chains have become an essential issue due to increasing customer expectations, stricter government regulations for environmental protection, natural resource scarcity, and rapid response to unexpected and unforeseen changes, so it should be investigated in the theoretical framework of the supply chain [29, 38].

The beverage industry has particular importance in the food and drink industry. Many types of fruits planted in Iran make it possible to produce various fruit juices. High-quality drinking and mineral water sources in Iran can make this country one of the exporters of bottled water. The Companies Producing Soft Drinks (CPSDs) are a highly competitive sector, including many smaller companies dominated by several multinational companies. Soft drink consumption has risen significantly over the past few decades. The soft drink market accounts for 14.03% of the consumer packaged goods market, which could be an interesting area for improving the performance of industrial sustainability [14]. Therefore, measuring the performance of the CPSDs supply chains based on sustainability and resilience criteria is an important part of the management effort. Although several studies have been conducted to appraise the supply chain performance of CPSDs, this type of research is quite rare in this country.

Data Envelopment Analysis (DEA) is one of the most prevalent mathematical methods to assess the efficiency of Decision-Making Units (DMUs) [11]. Traditional DEA models consider the system a whole unit in performance evaluation and ignore the system's internal communications [31]. However, in some cases, such as the supply chain, systems involve two or more segments with complex interrelationships and a variety of input and output criteria, including initial input, intermediate output, and desirable and undesirable output. The network DEA model has been developed to tackle such situations. Most productive Scale Size (MPSS), a fundamental issue in the DEA, can improve the system by maximizing the average efficiency of the DMU to reach the optimal scale. The concepts of efficiency and MPSS of a DMU are close; however, they are not equal *i.e.*, if a DMU is efficient, it is not necessarily MPSS because this DMU may be higher or lower than the efficiency frontier [2]. Although significant studies have been published on sustainability and resilience concepts, each concept has been developed independently in the literature. The integration of sustainability and resilience concepts has not yet been completely investigated. The primary purpose of this study is to estimate the MPSS in the NDEA model to appraise the sustainability and resilience of supply chains. Then, a fuzzy version of our model is developed to cover the uncertainty in some of the criteria. The most important features and novelties of this study in comparison with the existing relevant literature are as follows.

First, the proposed model can simultaneously determine the system's overall MPSS and components' MPSS in an integrated model. Second, for the first time, the proposed NDEA model can estimate the MPSS of the system in the presence of both deterministic and fuzzy data. Third, the proposed FNDEA model can concurrently measure the sustainability and resilience of the supply chain. Fourth, the developed FNDEA model can simultaneously consider initial inputs, external inputs, intermediate outputs, and desirable and undesirable outputs among supply chain segments. Fifth, the developed FNDEA model can be solved as crisp linear programming for each level of $\alpha \in [0,\ 1]$ *via* the α-cut approach. Sixth, the developed model has desirable features such as homogeneity, unit invariance, and projection. Finally, the effect of sustainability and resilience on the performance of each supply chain is examined separately. Understanding the interrelationships between the two concepts and how they affect supply chain performance can provide insights into joint management of these concerns for managers.

This study has structured as follows: Section 2 presents the background of DEA models and applications and reveals the research gap. Section 3 contains some preliminaries about MPSS. Section 4 presents the methodology to estimate MPSS in the NDEA model. In Section 5, the fuzzy version of our model is given. Section 6 explains the case study. Section 7 presents suggestions for improving supply chain sustainability and resilience. Finally, the conclusions are given in Section 8.

2. Literature review

2.1. DEA and MPSS measurement

Farrell [18] advised a new approach for appraising the efficiency of DMUs that have multiple inputs and a single output. Then Charnes *et al.* [9], based on the Farrell model, introduced the DEA model for appraising the efficiency of peer DMUs with multiple inputs and multiple outputs. Since then, DEA models have been applied in plentiful contexts and applications such as logistics and transportation [62, 65, 69], the energy sector [51, 57, 59], sustainable supplier selection [8, 53]; sustainable supply chain performance assessment [38, 39, 58], environmental and economic performance assessment [48, 64, 68].

Despite the advantages of the classic DEA model, it suffers from major shortcomings, such as ignoring the internal relationships of network components when evaluating its performance. Classical DEA models consider each system as a black box. However, this point of view is proper for an ordinary production system but not proper for intricate communication networks with series and parallel structures. Several models and approaches have been suggested to address this issue using NDEA (see, *e.g.*, [12, 17, 31, 36, 38, 40, 52, 54, 56]). One of the major drawbacks of the aforesaid NDEA models is that the input and output criteria must have exact values. Moreover, in some cases, NDEA models may encounter imprecise data. The imprecise data can shift the efficient frontier [49]. The fuzzy DEA models are employed when the input and output criteria are vague. There are several approaches to solving fuzzy DEA models, such as the tolerance method, defuzzification, α-cut, ranking, possibility, and credibility approach [22]. The classification and review of different approaches for solving fuzzy DEA models done by Hatami-Marbini *et al.* [21] show that the alpha-cut has been applied more than other approaches.

The concept of MPSS in DEA was first introduced by Banker [6]. Then, Cooper *et al.* [13] suggested a fractional objective function to estimate the MPSS. Also, Jahanshahloo and Khodabakhshi [27] developed a linear input-output orientation model for determining MPSS. Based on the concept of imprecise-chance-constrained programming, Khodabakhshi [35] proposed a new stochastic DEA model to determine MPSS. MPSS has been measured with stochastic data in recent years [16], the double frontiers approach [60], and the network DEA model [2]. Although the suggested model by Assani *et al.* [2] can estimate the MPSS of the system and its components, it cannot consider external inputs as well as imprecise data in MPSS measurements.

Despite the importance of the concept of MPSS and the frequency of studies on the efficiency of NDEA, it seems that MPSS has not been considered in the NDEA literature with fuzzy data. In this study, to fill this research gap, we propose a new radial NDEA model to assess the MPSS of the system with multi-stages in the presence of both deterministic and fuzzy criteria. The proposed model estimates the overall MPSS of the system. Moreover, it determines the MPSS of its components in a unified model. Moreover, the developed fuzzy NDEA model can simultaneously cover initial inputs, external inputs, intermediate outputs, and desirable and undesirable outputs among stages of each network. To solve our fuzzy NDEA model, we apply the alpha-cut approach suggested by Saati *et al.* [47].

2.2. Appraising supply chain sustainability and resilience

In recent years, measuring the efficiency of supply chains based on sustainability and resilience considerations has become an attractive matter for researchers and the industry [33, 34]. Considering the aspects of sustainability when appraising the efficiency of supply chains leads to improving the performance of companies in competitive markets [15]. It also helps companies reduce the pressure on shareholders and the media [25]. In addition to sustainability, attention to the concept of resilience should be considered to reduce supply chain disruptions [23]. Adopting sustainability and resilience concepts improves supply chain performance [32]. However, considering the aspects of sustainability and resilience simultaneously in evaluating the performance of supply chains, especially in the food industry, has not been sufficiently studied. Azadi *et al.* [4] suggested a new fuzzy DEA model for appraising the efficiency and effectiveness of suppliers in a sustainable supply chain management context. Their model can assess the supply chain's effectiveness, efficiency, and productivity under uncertain situations. Zhou *et al.* [70] proposed a dynamic double frontier NDEA model for assessing the sustainable supply chain. Their model can cover both desirable and undesirable indicators to assess detailed efficiencies. Kalantary and Saen [30] provided an inverse dynamic NDEA model for evaluating the sustainability of supply chains. Fathi and Saen [19] combined the double frontier and identical set of weights in the NDEA model to assess the sustainability of supply chains. Yu and Rehman Khan [66] presented a financing system for a green agricultural supply chain using game theory and content software. Agricultural suppliers were considered financiers and urban residents as investors. In addition, they linked the collective financing platforms of banks, networks, agricultural suppliers, and urban dwellers in this financing system. Izadikhah *et al.* [26] developed a fuzzy chance-constrained DEA model to appraise the sustainably resilient supply chains in public transport. Their model can only be used for DMUs that have a two-stage structure. In other words, their model does not work if a DMU has a multi-stage structure. Rehman Khan *et al.* [45] examined the role of China's Blockchain technology in a circular economy to increase organizational performance within the framework of the China–Pakistan Economic Corridor (CPEC). They showed that green practices with environmental and economic paths are positively correlated with corporate performance. Rehman Khan *et al.* [45] examined the impact of China Blockchain technology on sustainable supply chain management practices to improve corporate performance. The results showed that China's blockchain technology and green information systems positively affect sustainable supply chain performance. Using the theory of stochastic planning and fuzzy mathematical programming, Yu and Rehman Khan [67] examined a three-tier supply chain consisting of factories, distribution centers, and retailers to minimize supply chain costs and carbon emissions. The main question that should be answered in this sub-section is the importance of MPSS score estimation in a supply chain. First, achieving the optimal scale size in production systems (such as a supply chain) is an issue often found in the priority questions in the management agenda of various types of organizations. Estimating the MPSS score of the supply chain allows managers to not only know the best scale a supply chain can achieve but also how to move inefficient stages of a supply chain into the MPSS area. Second, not every efficient DMU (supply chain) can be an MPSS because, as discussed by Assani *et al.* [2], it may be located on the increasing or decreasing part of the efficient frontier. Third, the MPSS score is a measure that describes how an organization's resources should be organized and used to achieve optimal results. Fourth, the MPSS score can be used as a measure of the success of an industry or company in producing goods or services [46]. Table 1 compares previous research with the present study on the use of the MPSS score to evaluate supply chain performance with sustainability and resilience considerations.

2.3. Research gap

The main findings of the literature review can be summarized as follows:

First: as seen in the literature review and Table 1, the assumption of all previous studies for MPSS estimation is that the data should be accurate. However, the DEA models may encounter fuzzy data.

Second: no studies have been performed to estimate the MPSS score of the supply chain and its components in a fuzzy environment.

Third: most of the listed papers in Table 1 do not simultaneously deal with the sustainability and resilience criteria. Also, the effect of sustainability and resilience criteria on supply chain performance and its components has been neglected in previous studies.

Position of this research: to the best of our knowledge, no study has been addressed to remedy the above issues. To fill the research gap, we suggest a new fuzzy NDEA model for estimating the MPSS of the whole system and its components. Then we use it to assess the sustainability and resilience of the supply chains.

TABLE 1. Comparison of this study with previous related researches (Table 1 compares the current study with previous research based on three factors including considering the aspects of sustainability and resilience, the nature of the data, and the MPSS score. However, the mentioned research may have attributes that the current research suffers from.).

Authors	Main purpose	Considering the aspect of		Nature of data	MPSS measurement
		Sustainability	Resilience		
Matin *et al.* [38]	Proposing a new NDEA model to appraise the efficiency of the blood supply chain.	Yes	Yes	Crisp	No
Fathi and Saen [19]	Evaluating the efficiency of supply chains *via* fuzzy Malmquist and NDEA model with sustainability considerations.	Yes	No	Fuzzy	No
Tavassoli *et al.* [58]	appraising the optimistic and pessimistic efficiency of the supply chain with sustainability considerations.	Yes	No	Fuzzy	No
Izadikhah *et al.* [26]	Sustainability and resilience assessment of supply chain *via* proposing a new fuzzy chance-constrained DEA model.	Yes	Yes	Fuzzy-stochastic	No
Wang *et al.* [61]	Appraising the efficiency of the supply chain in terms of static and dynamic periods with sustainability considerations using an input-output-oriented model.	Yes	No	Crisp	No
Kalantary and Sean [30]	Appraising the sustainability of the supply chains using the inverse dynamic NDEA model.	Yes	No	Crisp	No
Zhou *et al.* [70]	Sustainability measurement of the supply chains using dynamic double frontier fuzzy NDEA model.	Yes	No	Fuzzy	No
Assani *et al.* [2]	Estimating MPSS for the system with a multi-stage structure.	No	No	Crisp	Yes
Izadikhah and Sean [24]	Sustainability measurement of the supply chains using chance-constrained two-stage DEA model.	Yes	No	Stochastic	No
Badiezadeh *et al.* [5]	Proposing the NDEA model to appraise the sustainability of the supply chain in the presence of big data.	Yes	No	Crisp	No
Current study	Introducing a new NDEA to determine the MPSS of the supply chain in the presence of imprecise data.	Yes	Yes	Fuzzy	Yes

3. Preliminaries

DEA is a powerful mathematical programming model for appraising the performance of DMUs that uses multiple inputs to produce multiple outputs. Assume that $x_{ij}(i = 1,\dots,m)$ and $y_{rj}(r = 1,\dots,s)$ represent the ith and rth criteria of the jth $(j = 1,\dots,n)$ DMU, respectively. Also, we assume that we have a positive data set. Sets of inputs and outputs criteria are supposed to express the production possibility set (PPS) for variable return to scale as follows:

$$T_{\mathrm{VRS}} = \left\{ (X,Y) \middle| \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik}, \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk}, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, j = 1,\dots,n \right\}.$$

The proposed model by Jahanshahloo and Khodabakhshi [27] for estimating the MPSS in the traditional DEA is as follows:

Model-1

$$\begin{aligned} & \max \theta_k - \varphi_k \\ & \sum_{\lambda=1}^{n} \lambda_j x_{ij} \leq x_{ik}\varphi_k \\ & \sum_{\lambda=1}^{n} \lambda_j y_{rj} \geq y_{rk}\theta_k \\ & \sum_{\lambda=1}^{n} \lambda_j = 1 \\ & \lambda_j \geq 0, \qquad\qquad j = 1,\dots,n. \end{aligned}$$

"The objective function of the presented model 1 is linear, and both output and input orientations are considered simultaneously. Since $\theta_k = 1, \varphi_k = 1, \lambda_j = 1 (j \neq 0)$ is a solution corresponding to the objective function value of zero, it is clear that the optimal value of the objective function is non-negative, *i.e.*, $\theta_k \geq \varphi_k$ [27]." Having model 1, Jahanshahloo and Khodabakhshi [27] proved that the DMU_K is MPSS if and only if it satisfies two following conditions:

(i) The optimal objective function value of model 1 is zero.
(ii) All the slacks are zero for an optimal solution.

4. Estimating MPSS in network DEA approach

Model 1 is applied to appraise the efficiency of a system (DMU), considered a black box. However, in many situations, a system may consist of some components where a set of outputs are considered inputs for other components. In this section, we provide a new NDEA model to estimate the MPSS of the system and its individual stages. Then, a fuzzy version of our model is developed to cover the uncertainty in some of the criteria of the problem. The developed model in this section can estimate the overall MPSS of the system in uncertain situations and the MPSS of stages as well.

4.1. Production possibility set (PPS)

Consider n DMUs; each contains a three-stage process with a serial structure, as shown in Figure 1. The output criteria from stage p, $p = 1,\dots,q$, have three forms: z_{ej}^{pq}, presents intermediate output $e, e = 1,\dots,E$ of DMU_j that leaves stage p and enters as an input to stage q, y_{rj}^{Dp} and y_{rj}^{Up}, indicate desirable and undesirable

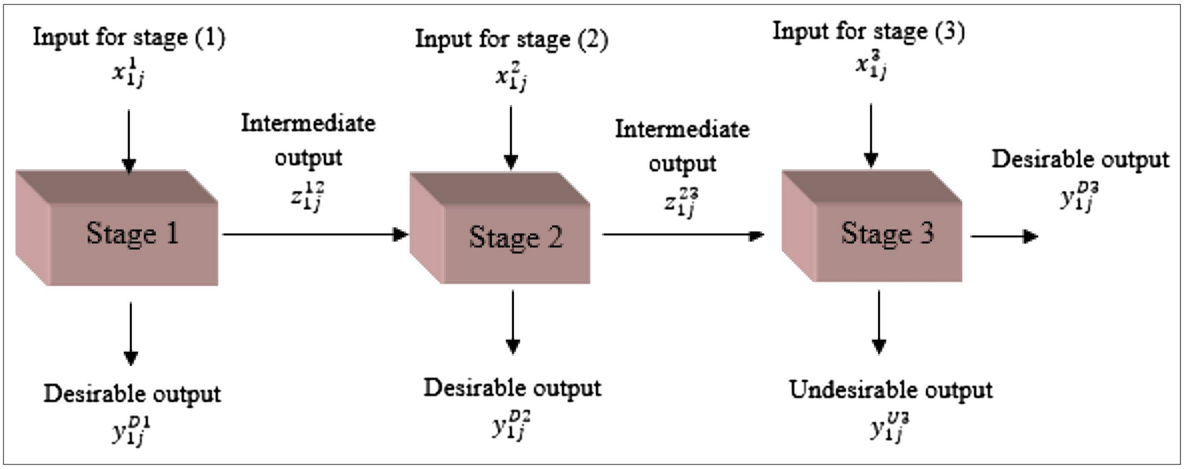

FIGURE 1. A typical three-stage process.

output $r, r = 1, \dots, s$ of DMU_j that leaves stage p and exits the system. Also, x_{ij}^p, $i = 1, \dots, m$ indicates input ith of DMU_j that enters stage p. Not that x_{ij}^p indicates the initial input in addition to external input that enters the system during the process. The total quantity of system inputs is the aggregate of the inputs used by all its stages $\{\sum_{p=1}^{q}\sum_{j=1}^{n} x_{ij}^p\}$; similarly, the total quantity of output generated by the system is the aggregate of the output generated by all its stages, $\{\sum_{p=1}^{q}\sum_{j=1}^{n} y_{rj}^p\}$.

The PPS ($x_{ij}^p, z_{ej}^{pq}, y_{rj}^{Dp}$, and y_{rj}^{Up}) can be expressed as the following constraints:

$$\sum_{j=1}^{n}\lambda_j^1 x_{1j}^1 \le x_{1k}^1 \quad (1)$$
$$\sum_{j=1}^{n}\lambda_j^2 x_{1j}^2 \le x_{1k}^2 \quad (2)$$
$$\sum_{j=1}^{n}\lambda_j^3 x_{1j}^3 \le x_{1k}^3 \quad (3)$$
$$\sum_{j=1}^{n}\lambda_j^1 y_{1j}^{U3} \le y_{1k}^{U3} \quad (4)$$
$$\sum_{j=1}^{n}\lambda_j^1 y_{1j}^{D1} \ge y_{1k}^{D1} \quad (5)$$
$$\sum_{j=1}^{n}\lambda_j^1 y_{1j}^{D2} \ge y_{1k}^{D2} \quad (6)$$
$$\lambda_j^1, \lambda_j^2, \lambda_j^3 \ge 0.$$
$$\sum_{j=1}^{n}\lambda_j^2 x_{1j}^2 \le x_{1k}^2 \quad (7)$$
$$\sum_{j=1}^{n}\lambda_j^1 z_{1j}^{12} - \sum_{j=1}^{n}\lambda_j^2 z_{1j}^{12} \ge 0 \quad (8)$$
$$\sum_{j=1}^{n}\lambda_j^2 z_{1j}^{23} - \sum_{j=1}^{n}\lambda_j^3 z_{1j}^{23} \ge 0 \quad (9)$$
$$\sum_{j=1}^{n}\lambda_j^1 = 1 \quad (10)$$
$$\sum_{j=1}^{n}\lambda_j^2 = 1 \quad (11)$$
$$\sum_{j=1}^{n}\lambda_j^3 = 1 \quad (12)$$

Constraints (1)–(3) are related to the inputs that enter the first, second, and third stages, respectively. Constraint (4) is related to the undesirable output that leaves the third stage. Constraints (5)–(7) are related to the desired output that leaves the first, second, and third stages, respectively. Constraints (8) and (9) ensure that the target value for (z_{ej}^p) as the output of stage p must be greater than or equal to that as the input of stage $p+1$. Constraints (10)–(12) correspond to the variable return to scale (VRS) condition.

Let $s_i^{p-}(i = 1, \ldots, m)$ and $s_r^{p+}(r = 1, \ldots, s)$ for pth stage be slack and surplus variable associated with the system constraint of DMU under evaluation. By adding the variables slack and surplus to relations (1)–(7), the inefficiency of the entire system and its components can be calculated with the following constraints.

$$\sum_{j=1}^{n} \lambda_j^1 x_{1j}^1 + s_1^{1-} = x_{1k}^1 \quad (13)$$

$$\sum_{j=1}^{n} \lambda_j^2 x_{1j}^2 + s_1^{2-} = x_{1k}^2 \quad (14)$$

$$\sum_{j=1}^{n} \lambda_j^3 x_{1j}^3 + s_1^{3-} = x_{1k}^3 \quad (15)$$

$$\sum_{j=1}^{n} \lambda_j^1 y_{1j}^{U3} + s_1^{U3-} = y_{1k}^{U3} \quad (16)$$

$$\sum_{j=1}^{n} \lambda_j^1 y_{1j}^{D1} - s_1^{D1+} = y_{1k}^{D1} \quad (17)$$

$$\sum_{j=1}^{n} \lambda_j^1 y_{1j}^{D2} - s_1^{D2+} = y_{1k}^{D2} \quad (18)$$

$$\lambda_j^1, \lambda_j^2, \lambda_j^3 \geq 0.$$

$$\sum_{j=1}^{n} \lambda_j^1 y_{1j}^{D3} - s_1^{D3+} = y_{1k}^{D3} \quad (19)$$

$$\sum_{j=1}^{n} \lambda_j^1 z_{1j}^{12} - \sum_{j=1}^{n} \lambda_j^2 z_{1j}^{12} \geq 0 \quad (20)$$

$$\sum_{j=1}^{n} \lambda_j^2 z_{1j}^{23} - \sum_{j=1}^{n} \lambda_j^3 z_{1j}^{23} \geq 0 \quad (21)$$

$$\sum_{j=1}^{n} \lambda_j^1 = 1 \quad (22)$$

$$\sum_{j=1}^{n} \lambda_j^2 = 1 \quad (23)$$

$$\sum_{j=1}^{n} \lambda_j^3 = 1 \quad (24)$$

4.2. Estimating MPSS for the system and the proposed model

In a general classification, the DEA uses three main approaches to evaluate DMUs: input-oriented, output-oriented, and non-oriented models. The input-oriented approach usually uses a model that minimizes input-related criteria while producing at least the given output levels. The output-oriented approach usually deals with a model that aims to maximize output-related criteria while using no more than the observed amount of any input. The non-oriented approach is designed to simultaneously minimize input-related criteria and maximize output-related criteria [50]. The non-oriented models can be used correctly depending on the study and management objectives. In this paper, intermediate outputs must be minimized and maximized simultaneously. Also, desirable and undesirable outputs should be maximized and minimized, respectively. Hence, a non-oriented model has been used to cover these situations. Given the PPS and Figure 1, the suggested NDEA model to estimate the MPSS of the system and its components is as follows:

Model-2

$$\max \, \Omega = \sum_{p=1}^{q} \theta_k^p - \sum_{p=1}^{q} \varphi_k^p + \varepsilon \sum_{p=1}^{q} \left(\sum_{i=1}^{m} s_i^{p-} + \sum_{r=1}^{s} s_r^{Up-} + \sum_{r=1}^{s} s_r^{Dp+} \right) \quad (2.1)$$

s.t.

$$\sum_{j=1}^{n} \lambda_j^p x_{ij}^p + s_i^{p-} = \varphi_k^p x_{ik}^p \qquad \forall i = 1, \ldots, m, \ \forall p = 1, \ldots, q \quad (2.2)$$

$$\sum_{j=1}^{n} \lambda_j^p y_{rj}^{Up} + s_r^{Up-} = \varphi_k^p y_{rk}^{Up} \qquad \forall r = 1, \ldots, s, \ \forall p = 1, \ldots, q \quad (2.3)$$

$$\sum_{j=1}^{n} \lambda_j^p y_{rj}^{Dp} - s_r^{Dp+} = \theta_k^p y_{rk}^{Dp} \qquad \forall r = 1, \ldots, s, \ \forall p = 1, \ldots, q \quad (2.4)$$

$$\sum_{j=1}^{n} \lambda_j^p z_{ej}^{pq} \geq \sum_{j=1}^{n} \lambda_j^q z_{ej}^{pq} \qquad \forall e = 1, \ldots, E,\ \forall p = 1, \ldots, q \tag{2.5}$$

$$\sum_{j=1}^{n} \lambda_j^p = 1 \qquad \forall p = 1, \ldots, q \tag{2.6}$$

$$\lambda_j^p, s_i^{p-}, s_r^{Up-}, s_r^{Dp+} \geq 0 \qquad i = 1, \ldots, m,\ r = 1, \ldots, s. \tag{2.7}$$

We use an asterisk in superscript to present optimal amounts. θ_k^p and φ_k^p, which are scalable, point out the increase or decrease factors applied to the input and output of DMU_k. The model illustrated by constraints (2.2)–(2.7) seeks λ_j^p to maximize the objective function. Constraints (2.2)–(2.4) are related to inputs, undesirable outputs, and desirable system outputs, respectively. Constraint (2.5) is related to intermediate outputs, and constraint (2.6) is related to the VRS condition.

Since $\theta_k^p = 1$, $\varphi_k^p = 1$, $\lambda_k^p = 1$ and, $\lambda_j^p = 0 (j \neq k)$ is a feasible solution, it is evident that the optimal value of the objective function is non-negative.

Definition 1. If $0 < \Omega \leq 1$, then the system under assessment is not overall MPSS.

Definition 2. If $\Omega = 0$ and is not zero slack ($s_i^{p-} \neq 0$ and/or $s_r^{Up-} \neq 0$ and/or $s_r^{Dp+} \neq 0$), then the system under assessment is weakly overall MPSS.

Definition 3. If $\Omega = 0$ and zero slack ($s_i^{p-} = 0$ and $s_r^{Up-} = 0$ and $s_r^{Dp+} = 0$), then the system under assessment is overall MPSS.

Definition 4. If $0 < \theta_k^p - \varphi_k^p \leq 1 (p = 1, \ldots q)$, then the pth stage of the system under assessment is not MPSS.

Definition 5. If $\theta_k^p - \varphi_k^p = 0 (p = 1, \ldots q)$ and is not zero slack ($s_i^{p-} \neq 0$ and/or $s_r^{Up-} \neq 0$ and/or $s_r^{Dp+} \neq 0$), then the pth stage of the system under assessment is weakly MPSS.

Definition 6. If $\theta_k^p - \varphi_k^p = 0 (p = 1, \ldots q)$ and zero slack ($s_i^{p-} = 0$ and $s_r^{Up-} = 0$ and $s_r^{Dp+} = 0$), then the pth stage of the system under assessment is MPSS.

The following discussions describe two desirable properties of the proposed model and reveal why this study uses the version of a radial DEA model to estimate MPSS in a network structure.

(i) *Homogeneity*: only two radial models (CCR and BCC) are applied for such a target if the homogeneity characteristic is considered. Not all non-radial models (*e.g.*, RAM, SBM, Russell) meet the desired characteristic [6].
(ii) *Unit invariance*: the proposed model satisfies the property of unit invariance. The unit of inputs and outputs should not influence the efficiency measure [13].
(iii) *Reference set*: the reference set for each stage of the supply chain under assessment can be presented as follow:

$$\text{RS}^p(k) = \left\{ j | \lambda_{jk}^{p*} > 0 \right\}, \qquad \{j = 1,\ \ldots,\ n\}. \tag{25}$$

5. Extension of the proposed model to estimate MPSS for the system in a fuzzy environment

In the previous section, the default of the proposed model is that the input and output criteria are accurately measurable. Nevertheless, the data collected for some criteria cannot be accurately estimated in some real-world problems. In this section, a new FNDEA model is developed to estimate the MPSS of the system and its stages to cover such situations. Any imprecise data is considered positive triangular fuzzy numbers (TFNs) to develop the model [10].

Definition 7. A TFN $\widetilde{A}$, represented by (a^L, a^M, a^R), is expressed by the membership function $\mu_{\widetilde{A}}$ given by:

$$\mu_{\widetilde{A}}(x) = \begin{cases} 0, & x < a^L, \\ \frac{x-a^L}{a^M-a^L} & a^L \le x \le a^M, \\ \frac{a^R-x}{a^R-a^M} & a^M \le x \le a^R, \\ 0, & x > a^R. \end{cases} \tag{26}$$

A TFN $\widetilde{A} = (a^L, a^M, a^U)$ is positive TFN if $a^L > 0$. Let $\widetilde{x}^p_{ij}, (i = 1, \ldots, m)$ be the ith fuzzy input of the jth DMU that enters the pth stage $(p = 1, \ldots, q)$. $\widetilde{y}^{Dp}_{rj}$ and $\widetilde{y}^{Up}_{rj}(r = 1, \ldots, s)$ represent the desirable and undesirable outputs of the jth DMU, respectively, which leave the pth $(p = 1, \ldots, q)$ stage and do not enter the other stages as input, and $\widetilde{z}^{pq}_{ej}(e = 1, \ldots, E)$ be the eth intermediate desirable output of jth DMU that leaves the pth $(p = 1, \ldots, q)$ stage and enters as input to other stages. The FNDEA model to determine the MPSS of the system and its stages can be expressed as follow:

Model-3

$$\max \widetilde{\Omega} = \sum_{p=1}^{q} \theta^p_k - \sum_{p=1}^{q} \varphi^p_k + \varepsilon \sum_{p=1}^{q} \left(\sum_{i=1}^{m} s^{p-}_i + \sum_{r=1}^{s} s^{Up-}_r + \sum_{r=1}^{s} s^{Dp+}_r \right) \tag{3.1}$$

s.t.

$$\sum_{j=1}^{n} \lambda^p_j \widetilde{x}^p_{ij} + s^{p-}_i = \varphi^p_k \widetilde{x}^p_{ik} \qquad \forall i = 1, \ldots, m,\ \forall p = 1, \ldots, q \tag{3.2}$$

$$\sum_{j=1}^{n} \lambda^p_j \widetilde{y}^{Up}_{rj} + s^{Up-}_r = \varphi^p_k \widetilde{y}^{Up}_{rk} \qquad \forall r = 1, \ldots, s,\ \forall p = 1, \ldots, q \tag{3.3}$$

$$\sum_{j=1}^{n} \lambda^p_j \widetilde{y}^{Dp}_{rj} - s^{Dp+}_r = \theta^p_k \widetilde{y}^{Dp}_{rk} \qquad \forall r = 1, \ldots, s,\ \forall p = 1, \ldots, q \tag{3.4}$$

$$\sum_{j=1}^{n} \lambda^p_j \widetilde{z}^{pq}_{ej} \ge \sum_{j=1}^{n} \lambda^q_j \widetilde{z}^{pq}_{ej} \qquad \forall e = 1, \ldots, E,\ \forall (p, q) \in E \tag{3.5}$$

$$\sum_{j=1}^{n} \lambda^p_j = 1 \qquad \forall p = 1, \ldots, q \tag{3.6}$$

$$\lambda^p_j, s^{p-}_i, s^{Up-}_r, s^{Dp+}_r \ge 0 \qquad i = 1, \ldots, m,\ r = 1, \ldots, s. \tag{3.7}$$

Here "$\sim$" presents fuzziness. As can be seen all fuzzy inputs, desirable and undesirable fuzzy outputs and intermediate fuzzy outputs are TFNs. Therefore, model 3 is as follows:

Model-4

$$\max \widetilde{\Omega} = \sum_{p=1}^{q} \theta^p_k - \sum_{p=1}^{q} \varphi^p_k + \varepsilon \sum_{p=1}^{q} \left(\sum_{i=1}^{m} s^{p-}_i + \sum_{r=1}^{s} s^{Up-}_r + \sum_{r=1}^{s} s^{Dp+}_r \right) \tag{4.1}$$

s.t.

$$\sum_{j=1}^{n} \lambda^p_j \left(x^{pL}_{ij}, x^{pM}_{ij}, x^{pR}_{ij} \right) + s^{p-}_i = \varphi^p_k \left(x^{pL}_{ik}, x^{pM}_{ik}, x^{pR}_{ik} \right) \qquad \forall i = 1, \ldots, m,\ \forall p = 1, \ldots, q \tag{4.2}$$

$$\sum_{j=1}^{n} \lambda_j^p \left(y_{rj}^{UpL}, y_{rj}^{UpM}, y_{rj}^{UpR}\right) + s_r^{Up-} = \varphi_k^p \left(y_{rk}^{UpL}, y_{rk}^{UpM}, y_{rk}^{UpR}\right) \qquad \forall r = 1,\ldots,s,\ \forall p = 1,\ldots,q \tag{4.3}$$

$$\sum_{j=1}^{n} \lambda_j^p \left(y_{rj}^{DpL}, y_{rj}^{DpM}, y_{rj}^{DpR}\right) - s_r^{Dp+} = \theta_k^p \left(y_{rk}^{DpL}, y_{rk}^{DpM}, y_{rk}^{DpR}\right) \qquad \forall r = 1,\ldots,s,\ \forall p = 1,\ldots,q \tag{4.4}$$

$$\sum_{j=1}^{n} \lambda_j^p \left(z_{ej}^{pqL}, z_{ej}^{pqM}, z_{ej}^{pqR}\right) \geq \sum_{j=1}^{n} \lambda_j^q \left(z_{ek}^{pqL}, z_{ek}^{pqM}, z_{ek}^{pqR}\right) \qquad \forall e = 1,\ldots,E,\ \forall (p,q) \in E \tag{4.5}$$

$$\sum_{j=1}^{n} \lambda_j^p = 1 \qquad \forall p = 1,\ldots,q \tag{4.6}$$

$$\lambda_j^p, s_i^{p-}, s_r^{Up-}, s_r^{Dp+} \geq 0 \qquad i = 1,\ldots,m,\ r = 1,\ldots,s. \tag{4.7}$$

We apply the suggested α-cut approach by Saati *et al.* [47] to solve the proposed fuzzy model (4). The alpha-cut method has been chosen because the proposed FNDEA model can easily be converted to a linear form. Also, based on $\alpha \in [0,1]$, the position of each DMU can be determined. $\alpha = 0$ indicates complete uncertainty, and $\alpha = 1$ indicates complete confidence. Note that α is an exogenous factor, which should be determined before running the model. The objective function and constraints in expressions (4.1)–(4.7) become as follows.

Model-5

$$\max \widetilde{\Omega} = \sum_{p=1}^{q} \theta_k^p - \sum_{p=1}^{q} \varphi_k^p + \varepsilon \sum_{p=1}^{q} \left(\sum_{i=1}^{m} s_i^{p-} + \sum_{r=1}^{s} s_r^{Up-} + \sum_{r=1}^{s} s_r^{Dp+} \right) \tag{5.1}$$

$$\sum_{j=1}^{n} \lambda_j^p \left[\left(\alpha x_{ij}^{pM} + (1-\alpha) x_{ij}^{pL}\right), \left(\alpha x_{ij}^{pM} + (1-\alpha) x_{ij}^{pR}\right) \right] + s_i^{p-}$$
$$= \left[\left(\alpha x_{ik}^{pM} + (1-\alpha) x_{ik}^{pL}\right), \left(\alpha x_{ik}^{pM} + (1-\alpha) x_{ik}^{pR}\right) \right] \qquad \forall i = 1,\ldots,m,\ \forall p = 1,\ldots,q \tag{5.2}$$

$$\sum_{j=1}^{n} \lambda_j^p \left[\left(\alpha y_{rj}^{UpM} + (1-\alpha) y_{rj}^{UpL}\right), \left(\alpha y_{rj}^{UpM} + (1-\alpha) y_{rj}^{UpR}\right) \right] + s_r^{Up-}$$
$$= \left[\left(\alpha y_{rk}^{UpM} + (1-\alpha) y_{rk}^{UpL}\right), \left(\alpha x_{rk}^{UpM} + (1-\alpha) x_{rk}^{UpR}\right) \right] \qquad \forall r = 1,\ldots,s,\ \forall p = 1,\ldots,q \tag{5.3}$$

$$\sum_{j=1}^{n} \lambda_j^p \left[\left(\alpha y_{rj}^{DpM} + (1-\alpha) y_{rj}^{DpL}\right), \left(\alpha y_{rj}^{DpM} + (1-\alpha) y_{rj}^{DpR}\right) \right] - s_r^{Dp+}$$
$$= \left[\left(\alpha y_{rk}^{DpM} + (1-\alpha) y_{rk}^{DpL}\right), \left(\alpha x_{rk}^{DpM} + (1-\alpha) x_{rk}^{DpR}\right) \right] \qquad \forall r = 1,\ldots,s,\ \forall p = 1,\ldots,q \tag{5.4}$$

$$\sum_{j=1}^{n} \lambda_j^p \left[\left(\alpha z_{ej}^{pqM} + (1-\alpha) z_{ej}^{pqL}\right), \left(\alpha z_{ej}^{pqM} + (1-\alpha) z_{ej}^{pqR}\right) \right]$$
$$\geq \sum_{j=1}^{n} \lambda_j^q \left[\left(\alpha z_{ej}^{pqM} + (1-\alpha) z_{ej}^{pqL}\right), \left(\alpha z_{ej}^{pqM} + (1-\alpha) z_{ej}^{pqR}\right) \right] \qquad \forall e = 1,\ldots,E,\ \forall (p,q) \in E \tag{5.5}$$

$$\sum_{j=1}^{n} \lambda_j^p = 1 \qquad \forall p = 1,\ldots,q \tag{5.6}$$

$$\lambda_j^p, s_i^{p-}, s_r^{Up-}, s_r^{Dp+} \geq 0 \qquad i = 1,\ldots,m,\ r = 1,\ldots,s. \tag{5.7}$$

As can be seen, all the coefficients in the fuzzy model (5) are intervals. The notation for arbitrary points in these intervals is displayed by the set of relations (27):

$$\begin{cases} \widehat{x}_{ij}^{p} \in \left[\left(\alpha x_{ij}^{pM} + (1-\alpha)x_{ij}^{pL}\right), \left(\alpha x_{ij}^{pM} + (1-\alpha)x_{ij}^{pR}\right)\right] \\ \widehat{y}_{rj}^{Dp} \in \left[\left(\alpha y_{rj}^{DpM} + (1-\alpha)y_{rj}^{DpL}\right), \left(\alpha y_{rj}^{DpM} + (1-\alpha)y_{rj}^{DpR}\right)\right] \\ \widehat{y}_{rj}^{Up} \in \left[\left(\alpha y_{rj}^{UpM} + (1-\alpha)y_{rj}^{UpL}\right), \left(\alpha y_{rj}^{UpM} + (1-\alpha)y_{rj}^{UpR}\right)\right] \\ \widehat{z}_{ej}^{pq} \in \left[\left(\alpha z_{ej}^{pqM} + (1-\alpha)z_{ej}^{pqL}\right), \left(\alpha z_{ej}^{pqM} + (1-\alpha)z_{ej}^{pqR}\right)\right]. \end{cases} \tag{27}$$

The developed model (5) is converted to the following model (6), after substituting coefficients mentioned in relations (27).

Model-6

$$\max\ \Omega = \sum_{p=1}^{q}\theta_k^p - \sum_{p=1}^{q}\varphi_k^p + \varepsilon\sum_{p=1}^{q}\left(\sum_{i=1}^{m}s_i^{p-} + \sum_{r=1}^{s}s_r^{Up-} + \sum_{r=1}^{s}s_r^{Dp+}\right) \tag{6.1}$$

s.t.

$$\sum_{j=1}^{n}\lambda_j^p\widehat{x}_{ij}^p + s_i^{p-} = \varphi_k^p\widehat{x}_{ik}^p \qquad \forall i=1,\ldots,m,\ \forall p=1,\ldots,q \tag{6.2}$$

$$\sum_{j=1}^{n}\lambda_j^p\widehat{y}_{rj}^{Up} + s_r^{Up-} = \varphi_k^p\widehat{y}_{rk}^{Up} \qquad \forall r=1,\ldots,s,\ \forall p=1,\ldots,q \tag{6.3}$$

$$\sum_{j=1}^{n}\lambda_j^p\widehat{y}_{rj}^{Dp} - s_r^{Dp+} = \theta_k^p\widehat{y}_{rk}^{Dp} \qquad \forall r=1,\ldots,s,\ \forall p=1,\ldots,q \tag{6.4}$$

$$\sum_{j=1}^{n}\lambda_j^p\widehat{z}_{ej}^{pq} \geq \sum_{j=1}^{n}\lambda_j^q\widehat{z}_{ej}^{pq} \qquad \forall e=1,\ldots,E,\ \forall (p,q)\in E \tag{6.5}$$

$$\sum_{j=1}^{n}\lambda_j^p = 1 \qquad \forall p=1,\ldots,q \tag{6.6}$$

$$\left(\alpha x_{ij}^{pM} + (1-\alpha)x_{ij}^{pL}\right) \leq \widehat{x}_{ij}^p \leq \left(\alpha x_{ij}^{pM} + (1-\alpha)x_{ij}^{pR}\right) \tag{6.7}$$

$$\left(\alpha x_{ik}^{pM} + (1-\alpha)x_{ik}^{pL}\right) \leq \widehat{x}_{ik}^p \leq \left(\alpha x_{ik}^{pM} + (1-\alpha)x_{ik}^{pR}\right) \tag{6.8}$$

$$\left(\alpha y_{rj}^{UpM} + (1-\alpha)y_{rj}^{UpL}\right) \leq \widehat{y}_{rj}^{Up} \leq \left(\alpha y_{rj}^{UpM} + (1-\alpha)y_{rj}^{UpR}\right) \tag{6.9}$$

$$\left(\alpha y_{rk}^{UpM} + (1-\alpha)y_{rk}^{UpL}\right) \leq \widehat{y}_{rk}^{Up} \leq \left(\alpha y_{rk}^{UpM} + (1-\alpha)y_{rk}^{UpR}\right) \tag{6.10}$$

$$\left(\alpha y_{rj}^{DpM} + (1-\alpha)y_{rj}^{DpL}\right) \leq \widehat{y}_{rj}^{Dp} \leq \left(\alpha y_{rj}^{DpM} + (1-\alpha)y_{rj}^{DpR}\right) \tag{6.11}$$

$$\left(\alpha y_{rk}^{DpM} + (1-\alpha)y_{rk}^{DpL}\right) \leq \widehat{y}_{rk}^{Dp} \leq \left(\alpha y_{rk}^{DpM} + (1-\alpha)y_{rk}^{DpR}\right) \tag{6.12}$$

$$\left(\alpha z_{ej}^{pqM} + (1-\alpha)z_{ej}^{pqL}\right) \leq \widehat{z}_{ej}^{pq} \leq \left(\alpha z_{ej}^{pqM} + (1-\alpha)z_{ej}^{pqR}\right) \tag{6.13}$$

$$\lambda_j^p, s_i^{p-}, s_r^{Up-}, s_r^{Dp+} \geq 0 \qquad i=1,\ldots,m,\ r=1,\ldots,s. \tag{6.14}$$

The proposed fuzzy model (6) is a non-linear programming model. The following exchange variables are used to transform the nonlinear model into a linear one:

$$\begin{cases} \overline{x}_{ij}^{p} = \lambda_j^p \widehat{x}_{ij}^{p} & \forall (i,j), \\ \overline{y}_{rj}^{Dp} = \lambda_j^p \widehat{y}_{rj}^{Dp} & \forall (i,j), \\ \overline{y}_{rj}^{Up} = \lambda_j^p \widehat{y}_{rj}^{Up} & \forall (i,j), \\ \overline{z}_{ej}^{pq} = \lambda_j^p \widehat{z}_{ej}^{pq} & \forall (i,j). \end{cases} \tag{28}$$

By applying the substitutions listed in (28), the developed model (6) can be presented as the following linear programming model:

Model-7

$$\max \Omega = \sum_{p=1}^{q} \theta_k^p - \sum_{p=1}^{q} \varphi_k^p + \varepsilon \sum_{p=1}^{q} \left(\sum_{i=1}^{m} s_i^{p-} + \sum_{r=1}^{s} s_r^{Up-} + \sum_{r=1}^{s} s_r^{Dp+} \right) \tag{7.1}$$

s.t.

$$\sum_{j=1}^{n} \overline{x}_{ij}^{p} + s_i^{p-} = \varphi_k^p \overline{x}_{ik}^{p} \qquad \forall i = 1, \ldots, m,\ \forall p = 1, \ldots, q \tag{7.2}$$

$$\sum_{j=1}^{n} \overline{y}_{rj}^{Up} + s_r^{Up-} = \varphi_k^p \overline{y}_{rk}^{Up} \qquad \forall r = 1, \ldots, s,\ \forall p = 1, \ldots, q \tag{7.3}$$

$$\sum_{j=1}^{n} \overline{y}_{rj}^{Dp} - s_r^{Dp+} = \theta_k^p \overline{y}_{rk}^{Dp} \qquad \forall r = 1, \ldots, s,\ \forall p = 1, \ldots, q \tag{7.4}$$

$$\sum_{j=1}^{n} \overline{z}_{ej}^{pq} \geq \sum_{j=1}^{n} \overline{z}_{ej}^{pq} \qquad \forall e = 1, \ldots, E,\ \forall (p,q) \in E \tag{7.5}$$

$$\sum_{j=1}^{n} \lambda_j^p = 1 \qquad \forall p = 1, \ldots, q \tag{7.6}$$

$$\lambda_j^p \left(\alpha x_{ij}^{pM} + (1-\alpha) x_{ij}^{pL} \right) \leq \overline{x}_{ij}^{p} \leq \lambda_j^p \left(\alpha x_{ij}^{pM} + (1-\alpha) x_{ij}^{pR} \right) \tag{7.7}$$

$$\lambda_j^p \left(\alpha x_{ik}^{pM} + (1-\alpha) x_{ik}^{pL} \right) \leq \overline{x}_{ik}^{p} \leq \lambda_j^p \left(\alpha x_{ik}^{pM} + (1-\alpha) x_{ik}^{pR} \right) \tag{7.8}$$

$$\lambda_j^p \left(\alpha y_{rj}^{UpM} + (1-\alpha) y_{rj}^{UpL} \right) \leq \overline{y}_{rj}^{Up} \leq \lambda_j^p \left(\alpha y_{rj}^{UpM} + (1-\alpha) y_{rj}^{UpR} \right) \tag{7.9}$$

$$\lambda_j^p \left(\alpha y_{rk}^{UpM} + (1-\alpha) y_{rk}^{UpL} \right) \leq \overline{y}_{rk}^{Up} \leq \left(\alpha y_{rk}^{UpM} + (1-\alpha) y_{rk}^{UpR} \right) \tag{7.10}$$

$$\lambda_j^p \left(\alpha y_{rj}^{DpM} + (1-\alpha) y_{rj}^{DpL} \right) \leq \overline{y}_{rj}^{Dp} \leq \lambda_j^p \left(\alpha y_{rj}^{DpM} + (1-\alpha) y_{rj}^{DpR} \right) \tag{7.11}$$

$$\lambda_j^p \left(\alpha y_{rk}^{DpM} + (1-\alpha) y_{rk}^{DpL} \right) \leq \overline{y}_{rk}^{Dp} \leq \lambda_j^p \left(\alpha y_{rk}^{DpM} + (1-\alpha) y_{rk}^{DpR} \right) \tag{7.12}$$

$$\lambda_j^p \left(\alpha z_{ej}^{pqM} + (1-\alpha) z_{ej}^{pqL} \right) \leq \overline{z}_{ej}^{pq} \leq \lambda_j^p \left(\alpha z_{ej}^{pqM} + (1-\alpha) z_{ej}^{pqR} \right) \tag{7.13}$$

$$\lambda_j^p, s_i^{p-}, s_r^{Up-}, s_r^{Dp+} \geq 0 \qquad i = 1, \ldots, m,\ r = 1, \ldots, s. \tag{7.14}$$

The developed model (7) is of type fuzzy linear mathematical programming for $\alpha \in [0,1]$. Clearly, for each α, there is an optimal solution for the model.

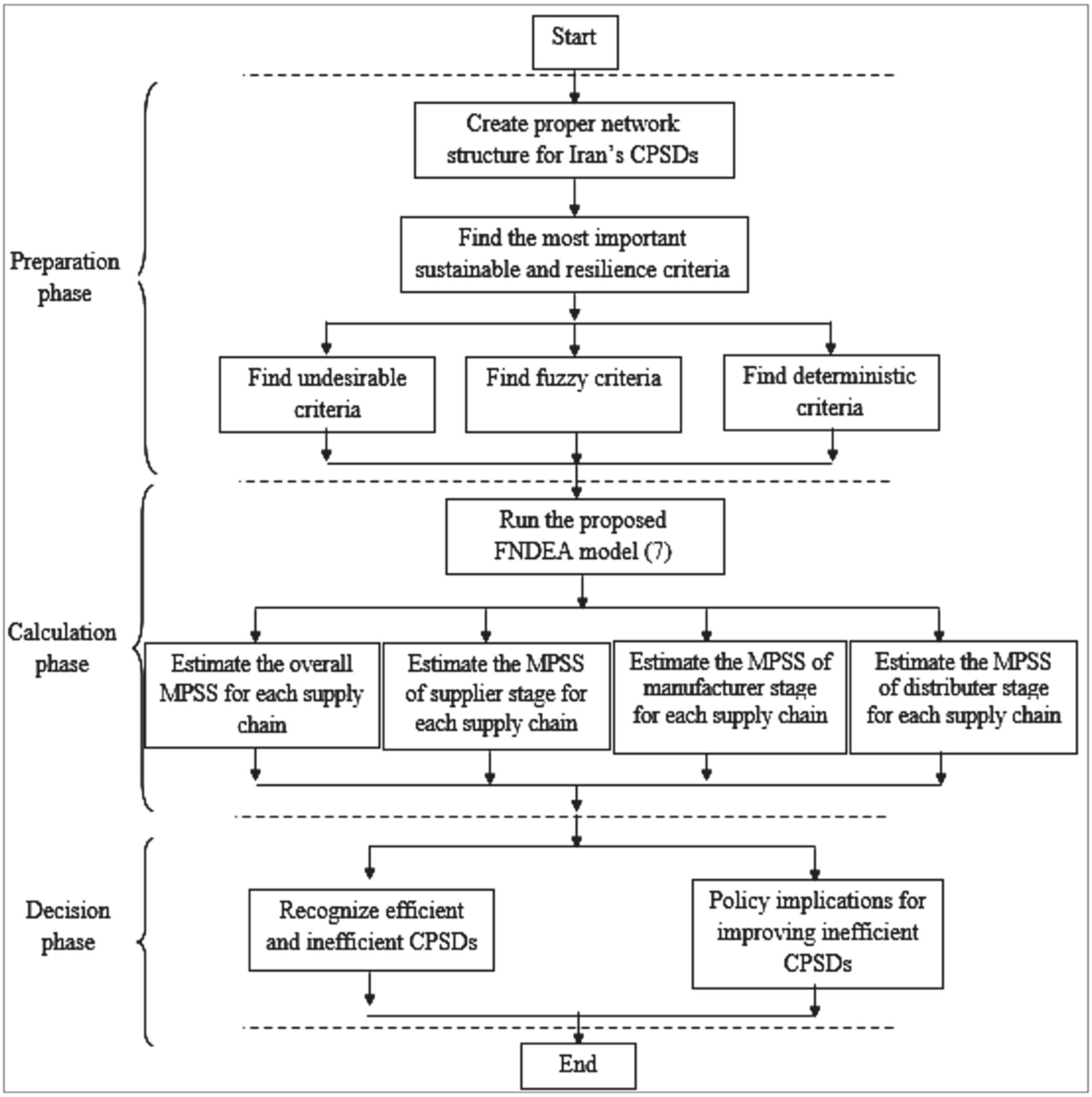

FIGURE 2. Major phases of the study.

6. CASE STUDY

6.1. The main phases of the proposed method

Figure 2 shows the main phases of the proposed method for appraising the sustainability and resilience of 10 supply chains of Iranian Companies Producing Soft Drinks (CPSDs). In the preparation phase, it is realized that there are many criteria for assessing the sustainability and resilience of CPSD's supply chain. After careful consideration, we detect 51 appropriate criteria for evaluating the supply chain. Then, to determine the most effective criteria for the performance of the whole supply chain from the supplier to the distributor stages, we performed a factor analysis. Experts have completed one hundred and twenty-five questionnaires and analyzed them by SPSS software. Finally, 31 major criteria were identified (Tab. 2). Next, deterministic and fuzzy criteria

TABLE 2. Summary of case study input data.

Stages	Type of criteria	Criteria	Nature of criterion	Max	Min	Average	Standard deviation
Supplier stage	Inputs	Cost of material (1000 $)	Deterministic	349	288	312.7	21.63
		Environmental cost (1000 $)	Deterministic	45	14	25.8	9.30
		Transportation cost (1000 $)	Deterministic	370	210	300.5	54.38
		Staff cost (1000 $)	Deterministic	110	75	91.9	10.12
	Desirable outputs	Flexibility of supplier	Fuzzy	(0.7 0.9 1)	(0.1 0.3 0.5)	–	–
		Quality of product	Fuzzy	(0.7 0.9 1)	(0.3 0.5 0.7)	–	–
	Undesirable outputs	Transportation delay (Minute)	Deterministic	1963	623	986.5	483.27
Manufacturer stage	Inputs	Staff cost (1000 $)	Deterministic	120	85	101.9	10.123
		Transportation cost (1000 $)	Deterministic	192	125	149.4	20.53
	Undesirable outputs	Transportation delay (Minute)	Deterministic	1988	348	1023.7	413.37
		CO_2 emission (100 000 ton)	Deterministic	527	309	412.8	71.28
Distributor stage	Inputs	Staff cost	Deterministic	37	26	30.40	3.45
		Cost of work safety and labor health	Deterministic	23	8	12.5	4.41
	Desirable outputs	Services	Fuzzy	(0.7 0.9 1)	(0.1 0.3 0.5)	–	–
		Number of delivered products to customer	Deterministic	11 553	9590	10 408.3	590.97
		On-time delivery to the customer	Fuzzy	(0.5 0.7 0.9)	(0 0.1 0.3)	–	–
Links	Intermediate outputs	The number of parts from supplier to manufacturer	Deterministic	320	217	276.7	34.52
		The number of green products from the manufacturer to distributor	Deterministic	639	479	551.9	53.40

are identified. In the computational phase, the amount of MPSS for each supply chain is estimated in addition to its components, including supplier, manufacturer, and distributor, by running the proposed FNDEA model (7). Finally, efficient and inefficient supply chains and the causes of inefficiencies are presented in the decision-making phase. Subsequently, suggestions are provided for improving the efficiency of inefficient supply chains.

6.2. Data set

Here, the proposed model is implemented to estimate the MPSS of 10 supply chains of Iranian CPSDs with sustainability and resilience considerations. Figure 3 provides the supply chain structure for each CPSD consisting of suppliers, manufacturers, and distributors.

As shown in Figure 3 and Table 2, the costs of material, environment, transportation, and staff are inputs for the supplier stage to display the economic and environmental dimensions of sustainability. The supplier's flexibility and the product's quality have been selected as desirable outputs of the supplier stage, which correspond to the resilience and economic dimension of sustainability, respectively. The transportation delay is

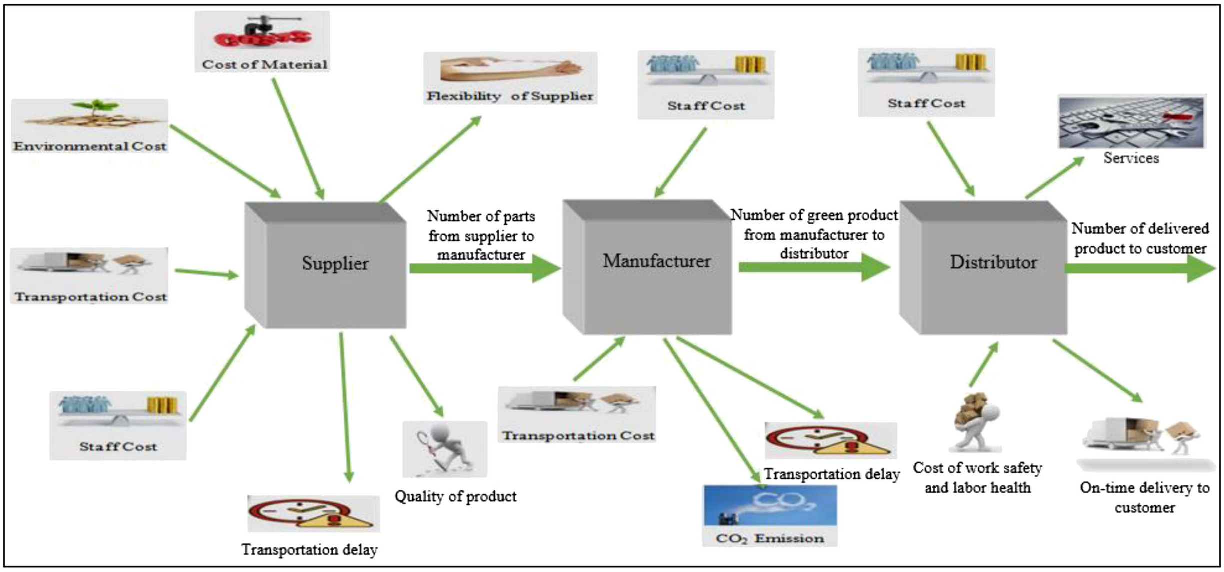

FIGURE 3. The structure of each supply chain.

considered as the undesirable output of the supplier stage, which corresponds to supply chain resilience. The number of products from the supplier stage to the manufacturer stage is considered an intermediate output, which is corresponded to the economic dimension of sustainability.

The inputs of the manufacturer stage include the staff and transportation costs, which correspond to the economic dimension of sustainability. Also, transportation delay and CO_2 emission are considered undesirable outputs of the manufacturer stage, which indicates supply chain resilience and environmental dimension of sustainability, respectively. The number of products from the manufacturer to the distributor is considered an intermediate output which is corresponded to the economic dimension of sustainability.

The inputs of the distributor stage are staff cost and the cost of laborers' safety and health, which corresponds to the economic and social dimensions of sustainability. The customer service level and on-time delivery to customers have been selected as desirable outputs for the distributor stage, which correspond to supply chain resilience. Finally, the number of delivered products to customers is considered a desirable output which is corresponded to the economic dimension of sustainability. Table A.1 (see appendix) presents resilience and sustainability criteria to appraise the supply chain performance with its resources.

Due to the qualitative nature of some criteria such as quality of product, the flexibility of supplier, customer service level, and on-time delivery to customers, we utilize the linguistic terms and formulate them into fuzzy sets approach. This study applies the triangular membership function for the fuzzy criteria. Table 3 shows the linguistic variables for the quality criterion. Also, Figure 4 shows the triangular membership function of fuzzy data.

6.3. Results

Table 4 presents the results of the developed model for different levels of $\alpha \in \{0.1, 0.5, 1\}$ for ten supply chains of Iranian CPSDs and their components, including supplier, manufacturer, and distributor stages. The proposed model has been coded using Lingo 17.0 software.

The first column of Table 4 describes the name of each supply chain. Columns 2, 3, and 4 of Table 4 describe the results of running model (7) for different levels of $\alpha \in \{0.1, 0.5, 1\}$ to estimate MPSS at the supplier stage. Note that a score of 0 ($\Omega^{1*} = \theta^{1*} - \varphi^{1*} = 0$) implies that the supply chain under evaluation is MPSS at

TABLE 3. Linguistic variables for fuzzy criteria.

TFNs	Linguistic terms
$(0.7, 0.9, 1)$	Very High (VH)
$(0.5, 0.7, 0.9)$	High (H)
$(0.3, 0.5, 0.7)$	Medium (M)
$(0.1, 0.3, 0.5)$	Weak (W)
$(0, 0.1, 0.3)$	Very Weak (VW)

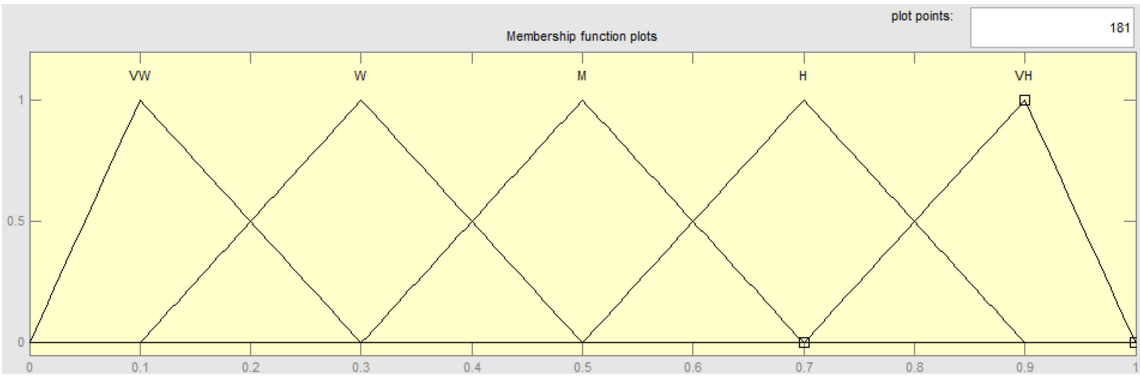

FIGURE 4. The triangular membership function for fuzzy data.

the supplier stage. The supply chains of Behnoush, Damdaran, and Pegah in the supplier stage are MPSS for all levels of $\alpha \in \{0.1, 0.5, 1\}$. It implies that these supply chains at the supplier stage have an optimal status from utilizing resources and producing outputs viewpoint. These MPSS supply chains are benchmarks for all non-MPSS supply chains. The remaining supply chains at the supplier stage for which $\Omega^{1*} = \theta^{1*} - \varphi^{1*} \neq 0$ are not MPSS. For instance, the optimal solution for Abali is $\Omega^{1*} = 0.06$, $\theta^{1*} = 0.06$ and $\varphi^{1*} = 0$. Hence, given Definition 4, this supply chain is not MPSS at the supplier stage. Nevertheless, this supply chain has a good performance in comparison to the non-MPSS supply chain. Column 5 of Table 4 reports the ranking of each supply chain at the supplier stage. According to this ranking, the lowest score of MPSS in the supplier stage for different levels of $\alpha \in \{0.1, 0.5, 1\}$ belongs to Varna supply chain.

Columns 6, 7, and 8 of Table 4 describe the results of running the model for different levels of $\alpha \in \{0.1, 0.5, 1\}$ to estimate MPSS at the manufacturer stage. As can be seen, there has been no change in the ranking and MPSS score of supply chains in the manufacturer stage for different levels of α. This is due to the lack of fuzzy criteria in the inputs and outputs of this stage. The supply chains of Behnoush, Damdaran, and Pegah in the manufacturer stage for different levels of $\alpha \in \{0.1, 0.5, 1\}$ are MPSS. Column 9 of Table 4 reports the ranking of each supply chain at the manufacturer stage. The lowest score of MPSS in the manufacturer stage for different levels of $\alpha \in \{0.1, 0.5, 1\}$ belongs to Kafir supply chain.

Columns 10, 11, and 12 of Table 4 describe the results of the running model for different levels of $\alpha \in \{0.1, 0.5, 1\}$ to estimate MPSS at the distributor stage. Given the results presented in Table 4, only the Behnoush supply chain has been able to be MPSS for levels $\alpha \in \{0.1, 0.5, 1\}$ at the distributor stage. The score of the Pegah supply chain in the distributor stage for levels $\alpha \in \{0.1, 0.5, 1\}$ are 0, 0, and 0.06, respectively. This means that this supply chain is MPSS for levels $\alpha \in \{0.1, 0.5\}$ and is also close to MPSS for level $\alpha = 1$. Column 13 of Table 4 reports the ranking of each supply chain in the distributor stage.

The last two columns of Table 4 report the overall score of MPSS and the ranking of 10 Iranian CPSDs Supply chains. As can be seen, the number of MPSS supply chains is 3 (Behnoush, Damdaran, and Pegah) for

$\alpha = 0.1$ and reduces to 2 (Behnoush and Pegah) and 1 (Behnoush) for $\alpha = 0.5$ and $\alpha = 1$, respectively. These results indicate that the change in the alpha level leads to a change in the efficiency score and ranking of the supply chains. Hence, the results are more realistic. The results can provide managers with in-depth insights into the performance of each supply chain in situations ranging from uncertainty to complete confidence. The details of results for the supplier, manufacturer, and distributor stages for different levels $\alpha \in \{0.1, 0.5, 1\}$ are presented in Tables A.2, A.3, and A.4, respectively (see appendix).

Table A.2 shows that Behnoosh, Damdaran, and Pegah supply chains are MPSS in the supplier stage because $\Omega^{1*} = 0$ and all the slack and surplus variables corresponding to these supply chains are zero. The rest of the supply chains are non-MPSS. For example, the MPSS score of the Abali supply chain in the supplier stage is equal to 0.06. Suppose this supply chain wants to reach the efficient frontier. In that case, it must reduce its transportation costs by 23% ($s_3^{1-} = 0.23$) and also increase the quality of products by 16% ($s_2^{D1+} = 0.16$). Similar interpretations can be derived for other inefficient supply chains in both manufacturer, and distributor stages.

7. Suggestions for improving supply chain sustainability and resilience

This sub-section identifies the causes of inefficiency in each stage (supplier, manufacturer, and distributor). Then suggestions are presented for improving inefficiency. For this purpose, the impact of each sustainability and resilience criterion on the efficiency of each supply chain in the supplier, manufacturer, and distributor stages is investigated by eliminating the criteria individually. The sensitivity analysis results can provide valuable information for decision-makers regarding the causes of inefficiency in each stage of the supply chain.

7.1. Sensitivity analysis for the supplier stage

Table 5 provides the sensitivity analysis results for sustainability and resilience criteria in the supplier stage. Column 1 presents the name of each supply chain. Columns 2–6 report the results of supplier stage ranking after removing the sustainability and resilience criteria. The last column of Table 5 shows the original ranking of supply chains. The sign of (–) indicates that the original ranking does not change. The main results extracted from the sensitivity analysis for the supplier stage are as follows:

- *Finding 1*: Table 5 reveals that a small number of supply chains are sensitive to the cost of material, environmental cost, and transportation cost criteria. This implies that these criteria should not be targeted to increase the efficiency of supply chains.
- *Finding 2*: the results shown in Table 5 reveal that most supply chains (such as Behnoush, Zam Zam, Sara, and Ramak) are so sensitive to supplier flexibility and product quality criteria that their rankings are reduced after removing the criteria. This means that the aforesaid supply chains have efficiently utilized supplier flexibility and product quality criteria.
- *Finding 3*: after removing the mentioned criteria in Table 5, the rankings of some supply chains (for example, the quality of product criterion for Abali and the environmental cost criterion for Khazar and Sara) improve. This finding shows that the aforementioned supply chains can boost their efficiency by increasing the quality of products and decreasing environmental costs.
- *Finding 4*: the costs of material, environment, and transportation seem to be almost the same for all supply chains, and the main competition is on the criteria of staff cost, supplier flexibility, and product quality.

7.2. Sensitivity analysis for manufacturer stage

Table 6 shows the results of the sensitivity analysis for sustainability and resilience criteria in the manufacturer stage. Column 1 presents the name of each supply chain. Columns 2–4 report the results of manufacturer stage ranking after removing the sustainability and resilience criteria. Also, the last column of Table 6 shows the original ranking of supply chains.

TABLE 4. The results of proposed model (7).

Supply chain	Estimating MPSS for supplier stage			Rank	Estimating MPSS for manufacturer stage			Rank	Estimating MPSS for distributor stage			Rank	Estimating MPSS for supply chain	Rank
$\alpha = 0.1$	θ^{1*}	φ^{1*}	Ω^{1*}		θ^{2*}	φ^{2*}	Ω^{2*}		θ^{3*}	φ^{3*}	Ω^{3*}		Ω^{*}(overall)	
Behnoush	1	1	0	1	1	1	0	1	1	1	0	1	0	1
Abali	0.06	0	0.06	2	0.59	0.46	0.24	4	2.36	1.21	1.15	8	1.45	6
Kafir	1.86	1.42	0.44	6	0.76	0.29	0.47	7	1.24	0.23	1.01	7	1.92	8
Zam Zam	0.56	0.43	0.16	4	0.09	0.01	0.08	2	0.34	0.06	0.28	2	0.52	2
Khazar	3.78	2.36	1.42	7	0.36	0.08	0.28	6	2.06	1.16	0.90	4	1.32	4
Damdaran	1	1	0	1	1	1	0	1	1	1	0	1	0	1
Sara	1.23	0.98	0.25	5	0.26	0.11	0.15	3	1.48	0.55	0.94	6	1.34	5
Ramak	0.26	0.12	0.14	3	1	1	0	1	0.89	0.41	0.93	5	1.07	3
Pegah	1	1	0	1	1	1	0	1	1	1	0	1	0	1
Varna	2.36	1.81	0.55	8	0.89	0.62	0.27	5	1.59	0.76	0.80	3	1.62	7
$\alpha = 0.50$	θ^{1*}	φ^{1*}	Ω^{1*}		θ^{2*}	φ^{2*}	Ω^{2*}		θ^{3*}	φ^{3*}	Ω^{3*}		Ω^{*}(overall)	
Behnoush	1	1	0	1	1	1	0	1	1	1	0	1	0	1
Abali	0.16	0.02	0.14	3	0.59	0.46	0.24	4	2.96	1.63	1.33	9	2.56	7
Kafir	1.93	1.22	0.71	6	0.76	0.29	0.47	7	1.10	0.06	1.04	8	2.22	6
Zam Zam	1.68	1.51	0.17	2	0.09	0.01	0.08	2	0.46	0.11	0.35	4	0.60	3
Khazar	3.52	1.98	1.54	7	0.36	0.08	0.28	6	2.21	1.26	0.95	7	2.77	8
Damdaran	1	1	0	1	1	1	0	1	0.12	0.03	0.09	2	0.09	2
Sara	1.45	1.16	0.29	5	0.26	0.11	0.15	3	1.79	0.85	0.94	6	1.38	5
Ramak	0.36	0.13	0.23	4	1	1	0	1	0.56	0.26	0.30	3	0.53	4
Pegah	1	1	0	1	1	1	0	1	1	1	0	1	0	1
Varna	2.78	0.69	2.09	8	0.89	0.62	0.27	5	2.03	1.36	0.67	5	3.03	9
$\alpha = 1$	θ^{1*}	φ^{1*}	Ω^{1*}		θ^{2*}	φ^{2*}	Ω^{2*}		θ^{3*}	φ^{3*}	Ω^{3*}		Ω^{*}(overall)	
Behnoush	1	1	0	1	1	1	0	1	1	1	0	1	0	1
Abali	0.52	0.16	0.36	4	0.59	0.46	0.24	4	3.06	1.79	1.27	10	2.68	8
Kafir	2.23	1.45	0.78	6	0.76	0.29	0.47	7	1.53	0.32	1.21	8	2.46	7
Zam Zam	1.52	1.11	0.41	5	0.09	0.01	0.08	2	0.44	0.06	0.38	4	0.87	5
Khazar	4.22	2.78	1.44	7	0.36	0.08	0.28	6	2.69	1.28	1.44	9	3.16	9
Damdaran	1	1	0	1	1	1	0	1	0.19	0.6	0.13	3	0.13	3
Sara	1.55	1.22	0.33	3	0.26	0.11	0.15	3	1.79	0.85	0.94	6	1.42	6
Ramak	0.39	0.18	0.21	2	1	1	0	1	0.89	0.41	0.48	5	0.69	4
Pegah	1	1	0	1	1	1	0	1	0.09	0.03	0.06	2	0.08	2
Varna	2.78	0.53	2.25	8	0.89	0.62	0.27	5	2.32	1.26	1.06	7	3.58	10

- *Finding 5*: given Table 6, the highest sensitivity is related to the criteria of staff cost and transportation delays. For example, after eliminating the staff cost criterion, the performance of some supply chains in the manufacturer stage (such as Khazar, Ramak, and Varna) has been improved. This finding shows that these inefficient supply chains need strategies to boost their performance in terms of staff costs and transportation delays. Based on the findings, the staff costs should be reduced *e.g.*, by training them properly, optimizing schedules, and reducing turnover of staff. Also, Transportation delays should be reduced by *e.g.*, eliminating unreliable suppliers, improving internal communications, and choosing vendors that are closer to the warehouse.
- *Finding 6*: the results presented in Table 6 report that some supply chains are very sensitive to the staff cost (Abali, Zam Zam, and Sara) and transportation delay (Abali and Zam Zam) criteria. Because after removing the criteria, their rank and performance dropped drastically. These results reveal that the aforementioned supply chains have utilized these criteria, efficiently.

TABLE 5. Results of sensitivity analysis for supplier stage at $\alpha = 0.5$.

Supply chain	Supplier stage ranking after removing						Original rank
	Cost of material	Environmental cost	Transportation cost	Staff cost	Flexibility of supplier	Quality of product	
Behnoush	–	–	–	2	3	4	1
Abali	2	–	2	3	4	1	3
Kafir	–	7	8	7	–	7	6
Zam Zam	3	–	6	5	5	5	2
Khazar	–	6	–	6	–	6	7
Damdaran	–	–	–	–	2	3	1
Sara	–	4	3	8	8	9	5
Ramak	–	5	–	9	9	8	4
Pegah	–	–	–	3	–	2	1
Varna	–	–	5	4	10	10	8

TABLE 6. Results of sensitivity analysis for manufacturer stage at $\alpha = 0.5$.

Supply chain	Manufacturer stage ranking after removing				Original rank
	Staff cost	Transportation cost	Transportation delay	CO_2 emission	
Behnoush	–	–	–	–	1
Abali	6	-	6	–	3
Kafir	5	7	4	–	6
Zam Zam	8	–	5	5	2
Khazar	3	6	8	–	7
Damdaran	–	–	–	–	1
Sara	7	–	2	2	5
Ramak	2	–	3	8	4
Pegah	–	–	–	–	1
Varna	4	–	7	4	8

– *Finding 7*: the results of sensitivity analysis in the manufacturing stage show that most supply chains have little sensitivity to the criteria of transportation costs and CO_2 emission. These results reveal that supply chains have relatively analogous performance concerning these criteria, and thus the criteria cannot be considered a competitive advantage for the supply chains in the manufacturing stage.

7.3. Sensitivity analysis for distributor stage

Table 7 shows the results of the sensitivity analysis for sustainability and resilience criteria in the distributor stage. Column 1 presents the name of each supply chain. Columns 2–6 report the results of distributor stage ranking after removing the sustainability and resilience criteria. The most important findings from the sensitivity analysis for the distributor stage are as follows:

– *Finding 8*: based on the results reported in Table 7, it seems that most supply chains are very sensitive regarding the cost of work safety and labor health, and on-time delivery to the customer criteria. Because after removing these two criteria, significant changes have occurred in the ranking of supply chains. For example, after the removal of these criteria, the performance of Abali and kafir supply chains has improved. This result reveals that the aforesaid supply chains could improve their performance by increasing the on-time delivery to the customer of the product and decreasing the cost of work safety and labor health. This

TABLE 7. Results of sensitivity analysis for distributor stage at $\alpha = 0.5$.

Supply chain	Distributor stage ranking after removing					Original rank
	Staff cost	Cost of work safety and labor health	Services	Number of the delivered product to the customer	On-time delivery to the customer	
Behnoush	–	–	–	–	–	1
Abali	–	4	–	8	6	9
Kafir	–	5	–	9	5	8
Zam Zam	7	9	7	6	–	4
Khazar	6	7	6	–	8	7
Damdaran	4	1	–	–	–	2
Sara	5	6	5	5	9	6
Ramak	2	3	–	–	1	3
Pegah	–	–	–	–	3	1
Varna	3	2	4	4	7	5

study shows that the cost of work safety and labor health should be reduced *e.g.*, by inspecting the workplace, establishing a regular health and safety program, and training employees in the context of work safety and labor health. In contrast, after removing these criteria, the performance of the supply chains of Zamzam and Sara has been weakened. These results reveal that the aforementioned supply chains have utilized these criteria efficiently.

– *Finding 9*: according to the results in Tables 5–7, Behnoush is the only supply chain that has been able to maintain its ranking in all three stages of supplier, manufacturer, and distributor after removing the criteria. Therefore, the Behnoush supply chain can be considered a benchmark for other inefficient supply chains.

8. Conclusions

Appraising supply chain sustainability and resilience due to social pressures, scarcity of natural resources, increasing customer expectations, and stricter government regulations are considered important issues to be investigated theoretically. Data envelopment analysis is a powerful mathematical tool to measure the efficiency of the supply chain. Classical DEA models cannot assess the efficiency of DMUs with imprecise data. One of the classical DEA models is the input-output orientation model developed by Jahanshahloo and Khodabakhshi [27]. The proposed model estimates the most productive scale size. However, it needs precise input-output data and ignores the internal structures of DMUs.

The main purpose of this study was to estimate the most productive scale size in the NDEA model to evaluate the sustainability and resilience of supply chains. A fuzzy version of our model was developed to cover the uncertainty in some of the criteria. The proposed method in this paper was applied to estimate the MPSS of ten Iranian companies producing soft drinks with sustainability and resilience considerations. This is the first study to estimate the MPSS of the supply chains involving supplier, manufacturer, and distributor components formulated by network structures in a fuzzy environment. The developed model in this study estimates the overall MPSS of supply chains in terms of sustainability and resilience criteria and also the MPSS of stages. This study showed that Behnoush's supply chain is overall MPSS in all three stages, including supplier, manufacturer, and distributor for any $\alpha \in \{0.1, 0.5, 1\}$. Then, a sensitivity analysis was performed to discover the causes of inefficiency in each stage of the supply chain. This paper provides the following policy implications relating to inefficient supply chains:

– *First*: the results of sensitivity analysis show that in the supplier stage, staff cost, the flexibility of the supplier, and the quality of the product have a significant impact on the performance of the supply chain.

Supply chains in the manufacturing sector were also more sensitive to staff costs and transportation delays. Finally, in the distribution sector, the highest sensitivity is related to the cost of work safety and labor health, and on-time delivery to the customer. The criteria mentioned in all three stages can be considered a competitive advantage for inefficient supply chains because after removing these criteria, the ranking of supply chains has changed significantly.

– *Second*: the results of sensitivity analysis reveal that social and resilience criteria have a great impact on the performance and ranking of supply chains. In other words, supply chains performed relatively similar in terms of both economic and environmental criteria. Hence this study recommends that inefficient supply chains can dramatically improve their performance by focusing on social and resilience criteria.
– *Third*: reducing the uncertainty in the criterion of on-time delivery to customers can improve the performance of supply chains and, as a result, increase their efficiency.
  Using an internal supplier can significantly reduce the delivery time of the product to the customer. Also, ordering smaller quantities more frequently can play a significant role in reducing product delivery time to the customer. Integration of suppliers and the creation of an incentive are other approaches to reduce the uncertainty in the criterion of on-time delivery to customers.

The following topics are suggested for prospective scholars:

– Formulating a stochastic-fuzzy NDEA may generate more reliable results if a probability distribution can represent the uncertain criteria.
– The proposed model in this paper considers the supply chain activities as being static. This implies that the supply chain MPSS is based on the current elements of inputs and outputs. However, this contradicts the practical situation. To remedy this problem, dynamic fuzzy NDEA models can play an essential role in measuring the efficiency of the supply chain in a multi-period. Thus, it will be a topic for future discussion.

Appendix A.

Table A.1. Supply chain performance evaluation criteria.

Sustainability and resilience aspects	Criteria	Authors
Economic	Cost of material	Ahmady *et al.* [1], Boudaghi and Saen [7], Tavassoli and Saen [53]
	Transportation cost	Matin *et al.* [38], Boudaghi and Saen [7].
	Staff cost	Tavassoli and Saen [53], Pandey *et al.* [42], Jain and Khan [28]
	Quality of product	Tavassoli and Saen [53], Pandey *et al.* [42], Jain and Khan [28]
	Number of shipment	Mahdiloo and Sean [37], Azadi and Saen [3]
Environmental	CO_2 emission	Tavassoli *et al.* [58], Sarkhosh-Sara *et al.* [48]
	Environmental cost	Mirhedayatian *et al.* [39], Boudaghi and Saen [7]
Social	Cost of work safety and labor health	Matin *et al.* [38], Boudaghi and Saen [7], Tavassoli and Saen [53]
Resilience	Flexibility of supplier	Matin *et al.* [38], Pourhejazy *et al.* [44], Zsidisin and Wagner [71]
	Transportation delay	Matin *et al.* [38], Pourhejazy *et al.* [44]

Table A.2. Estimating MPSS for supplier stage at different levels $\alpha \in [0.1, 0.5 \text{ and } 1]$.

Supply chain $\alpha = 0.1$	$\Omega^{1*} = \theta^{1*} - \varphi^{1*}$	θ^{1*}	φ^{1*}	s_1^{1-}	s_2^{1-}	s_3^{1-}	s_4^{1-}	s_1^{U1-}	s_1^{D1+}	s_2^{D1+}
Behnoush	0	1	1	0	0	0	0	0	0	0
Abali	0.06	0.06	0	0	0	0.23	0	0	0	0.16
Kafir	0.44	1.86	1.42	1.03	0.26	0	0	0.15	1.26	10.60
Zam Zam	0.16	0.56	0.43	0	0	0.63	0	0.25	2.60	0
Khazar	1.42	3.78	2.36	1.63	2.03	0.56	0	0	0.56	0.96
Damdaran	0	1	1	0	0	0	0	0	0	0
Sara	0.25	1.23	0.98	1.63	1.36	0	0.06	0.36	1.32	0
Ramak	0.14	0.26	0.12	0	0	0.36	0.12	0	0.69	0
Pegah	0	1	1	0	0	0	0	0	0	0
Varna	0.55	2.36	1.81	2.69	3.06	0	0.89	0.63	1.36	12.30
Supply chain $\alpha = 0.5$	$\Omega^{1*} = \theta^{1*} - \varphi^{1*}$	θ^{1*}	φ^{1*}	s_1^{1-}	s_2^{1-}	s_3^{1-}	s_4^{1-}	s_1^{U1-}	s_1^{D1+}	s_2^{D1+}
Behnoush	0	1	1	0	0	0	0	0	0	0
Abali	0.14	0.16	0.02	0.56	0	0.13	0	0.06	0.12	0
Kafir	0.71	1.93	1.22	1.26	0.09	0	0	0.16	1.65	9.22
Zam Zam	0.17	1.68	1.51	0	0	0.71	0	0.22	2.36	0
Khazar	1.54	3.52	1.98	1.23	3.09	0.12	0	0.09	0.16	1.26
Damdaran	0	1	1	0	0	0	0	0	0	0
Sara	0.29	1.45	1.16	2.03	1.22	0	0	0	2.69	0
Ramak	0.23	0.36	0.13	0	0	1.36	0.16	0	0.19	0
Pegah	0	1	1	0	0	0	0	0	0	0
Varna	2.09	2.78	0.69	2.21	2.96	0	1.03	0.20	2.26	11.56
Supply chain $\alpha = 1$	$\Omega^{1*} = \theta^{1*} - \varphi^{1*}$	θ^{1*}	φ^{1*}	s_1^{1-}	s_2^{1-}	s_3^{1-}	s_4^{1-}	s_1^{U1-}	s_1^{D1+}	s_2^{D1+}
Behnoush	0	1	1	0	0	0	0	0	0	0
Abali	0.36	0.52	1.90	0	0	2.36	0.06	0	0.35	0.36
Kafir	0.78	2.23	1.45	1.30	0	0	0	0.42	2.03	8.13
Zam Zam	0.41	1.52	1.11	0	0	0.71	0	0.20	2.10	0.86
Khazar	1.44	4.22	2.78	1.23	3.09	0.12	0	0.09	0.16	1.26
Damdaran	0	1	1	0	0	0	0	0	0	0
Sara	0.33	1.55	1.22	1.96	1.26	0	0	0	1.81	0
Ramak	0.21	0.39	0.18	0	0	1.13	0	0	0	0.98
Pegah	0	1	1	0.09	0	0.06	0	0	0	0
Varna	2.25	2.78	0.53	2.86	1.83	0	2.40	0	1.05	13.13

Table A.3. Estimating MPSS for manufacturer stage at different levels $\alpha \in [0.1, 0.5 \text{ and } 1]$.

Supply chain	$\Omega^{2*} = \theta^{2*} - \varphi^{2*}$	θ^{2*}	φ^{2*}	s_1^{2-}	s_2^{2-}	s_1^{U2-}	s_2^{U2-}
Behnoush	0	1	1	0	0	0	0
Abali	0.24	0.59	0.46	2.6	8.59	0.24	0.16
Kafir	0.47	0.76	0.29	6.29	0	3.80	0
Zam Zam	0.08	0.09	0.01	2.69	16.9	1.05	0
Khazar	0.28	0.36	0.08	21.63	0	12.6	6.56
Damdaran	0	1	1	0	0	0	0
Sara	0.15	0.26	0.11	11.09	3.35	2.59	2.12
Ramak	0	1	1	0	0	0	0
Pegah	0	1	1	0	0	0	0
Varna	0.27	0.89	0	5.96	6.45	0	0

TABLE A.4. Estimating MPSS for distributor stage at different levels $\alpha \in [0.1, 0.5$ and $1]$.

Supply chain $\alpha = 0.1$	$\Omega^{3*} = \theta^{3*} - \varphi^{3*}$	θ^{3*}	φ^{3*}	s_1^{3-}	s_2^{3-}	s_1^{D3+}	s_2^{D3+}
Behnoush	0	1	1	0	0	0	0
Abali	1.15	2.36	1.21	12.69	2.64	0.16	0
Kafir	1.01	1.24	0.23	10.13	0	1.36	0.60
Zam Zam	0.28	0.34	0.06	5.96	1.69	0	0.96
Khazar	0.90	2.06	1.16	10.63	1.38	0.40	0.24
Damdaran	0	1	1	0	0	0	0
Sara	0.94	1.48	0.55	10.63	0	1.59	0.19
Ramak	0.93	0.89	0.41	9.69	0	2.21	0.47
Pegah	0	1	1	0	0	0	0
Varna	0.80	1.59	1.76	20.29	0.06	2.11	0
Supply chain $\alpha = 0.5$	$\Omega^{3*} = \theta^{3*} - \varphi^{3*}$	θ^{3*}	φ^{3*}	s_1^{3-}	s_2^{3-}	s_1^{D3+}	s_2^{D3+}
Behnoush	0	1	1	0	0	0	0
Abali	1.33	2.96	1.63	12.92	2.86	0.24	0
Kafir	1.04	1.10	0.06	11.10	0.06	2.03	0
Zam Zam	0.35	0.46	0.11	4.26	2.09	0	0.82
Khazar	0.95	2.21	1.26	11.03	2.08	0.46	0.21
Damdaran	0.09	0.12	0.03	0	0	0	0
Sara	0.94	1.79	0.85	11.03	0	0	1.26
Ramak	0.30	0.56	0.26	8.49	0	1.26	1.57
Pegah	0	1	1	0	0	0	0
Varna	0.77	2.03	1.36	18.16	1.26	1.58	1.69
Supply chain $\alpha = 1$	$\Omega^{3*} = \theta^{3*} - \varphi^{3*}$	θ^{3*}	φ^{3*}	s_1^{3-}	s_2^{3-}	s_1^{D3+}	s_2^{D3+}
Behnoush	0	1	1	0	0	0	0
Abali	1.27	3.06	1.79	11.03	3.06	0.12	0.02
Kafir	1.21	1.53	0.32	1.19	6.56	5.90	0
Zam Zam	0.38	0.44	0.06	5.66	2.12	0.09	0.51
Khazar	1.44	2.69	1.28	16.89	0	0	1.69
Damdaran	0.13	0.19	0.6	0	0	0	0
Sara	0.94	1.79	0.85	5.51	2.16	0	1.52
Ramak	0.48	0.89	0.41	10.49	0	2.36	0
Pegah	0.06	0.09	0.03	0	0	0	0
Varna	1.06	2.32	1.26	12.16	4.26	0.47	0.92

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