Green supply chains and performance evaluation: A multiplier network analytics model with common set of weights

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Abstract

Supply chains (SCs) are considered complicated systems consisting of many interactions, components, and flows. Green SCs have forced policymakers and managers to pay more attention to

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the environment rather than only focus on the economic aspect. Performance evaluation of complex systems, including green SCs is a critical issue in organizations. Most of the current models are unable to evaluate the performance of green SCs in an integrated framework. To address this issue in organizations, in this paper, our objective is to propose a powerful network data envelopment analysis (NDEA) to evaluate green SCs. The NDEA method is considered an effective approach to deal with complex settings including SCs. Our multiplier NDEA model for cost efficiency evaluation is presented based on the cost production possibility set (PPS). We formulate a common set of weight model based on the cost PPS. The proposed model maximizes the cost-efficiency of all decision making units (DMUs), simultaneously. In our model, the common set of weights and cost efficiency of each stage and the overall cost are obtained. Finally, we apply the developed model for assessing the sustainably of SCs in the wire and cable industry. The results show how well our developed model, based on common set of weights, can evaluate the performance of green SCs compared to the classic models.

Keywords: Green supply chain; Common set of weights; Network data envelopment analysis (NDEA).

1. Introduction

Complex systems consist of many interrelated parts that work in complicated ways. In these systems, due to the characteristics of the components and the rules of their interactions, it is difficult to infer the whole performance (Ethiraj and Levinthal, 2004). A supply chain (SC) is a type of complex system with many entities and interactions. There has been considerable attention on how the performance of SCs impacts society. To benefit from competitive advantages, many organizations have tried to address social concerns in their SC (Dubey et al., 2020). As such, these organizations encounter some complicated social responsibilities in terms of their activities that can affect the lives of people (Tseng et al., 2022). Thus, international organizations are under pressure to address environmental issues (Taleizadeh et al., 2022). Subsequently, managing green SC has received attention from governments, stakeholders, non-profit organizations, and people (Lee and Chung, 2022). The majority of organizations attempt to re-engineer their products and processes throughout their SCs to ensure that their activities have no negative effects on the society and environment (Zhang and Awasthi, 2014). Thus, green SC management (SCM) is an important perspective that affects the performance of SC.

Sustainable development needs to address people's needs by considering influential factors for the future (Lee and Chung, 2022). In the past, SCs concentrated on economic performance, while concerning today’s needs, they should take into account environmental performance as well. Sustainable businesses in a competitive market deal with green dimensions (Junaid et al., 2022). Green SCs are recognized as complex systems in which there are many interacting variables so that changing one variable leads to a significant effect on others (Pagell and Wu, 2009). Under such conditions, managers of companies should search for effective measures to improve their performance by considering green dimensions in SCs.

Assessing the efficiency of green SCs has been a crucial issue in organizations over the last two decades. It helps organizations to enhance their performance by taking environmental aspects into account and identifying bottlenecks (Izadikhah and Farzipoor Saen, 2018). Many significant organizational issues, such as resource allocation, production planning, and human resources planning, depend on the correct evaluation of SCs (Sufiyan et al., 2019). In this regard, the key question is how to gauge the performance of green SCs using an integrated model? How such model considers relationships between stages in SC? As such, developing and using powerful methods for performance measurement of green SCs are essential for organizations to improve performance. These models should cover the intricate structure of SCs. In this regard, network data envelopment analysis (NDEA) has been recognized as a rigorous method to measure the performance of green SCs (Ramezankhani et al., 2018). Thus, the objective of this study is to develop an NDEA model for assessing green SCs. Our study provides several innovations (contributions) as follows:

- A multiplier DEA model for cost efficiency evaluation is presented based on the cost production possibility set (PPS).
- For the first time, the common set of weights model is formulated based on cost PPS.
- The presented model maximizes the cost efficiency of all decision making units (DMUs), simultaneously.
- The presented method is formulated for a three-stage SC.
- The common set of weights and cost efficiency of each stage, as well as the overall cost, are obtained.

The organization of this paper is as follows: Section 2 discusses the literature review. In Section 3, the proposed model is given. A case study is discussed in Section 4. Conclusions are given in Section 5.

2. Literature review

2.1 Green supply chain management

Over the last few decades, the concept of green has been an integral part of SCM. The concept provides a coordinated SC using the integration of economic and ecological factors throughout the SC (Ahi and Searcy, 2013). Green SCs are designed to better manage the capital, material, and information flows related to the supply, manufacture, and distribution of goods and services (Adam et al., 2021). Green SCs provide several competitive advantages compared to conventional SCs (Erol et al., 2022; Buddress, 2013). In the ecological dimension, factors such as the use of land and water, renewable energy, carbon emissions, and recycled material are important. In economic dimensions, factors such as production costs, service quality, fuel costs, and transportation costs are considered. Integrating these factors in conventional SCs not only leads to innovation in products and services but also improves the performance of organizations (Friedman et al., 2022).

2.2 Performance measurement of green SCs

Some scholars have proposed approaches for assessing the green SCs. Erol et al. (2011) developed an approach for assessing green SCs of organizations through fuzzy entropy and fuzzy multi-attribute utility. They also proposed a managerial system for satisfying customers' needs in green SC. Shen et al. (2013) proposed a fuzzy approach for green suppliers' evaluation. They applied fuzzy set theory for translating subjective human perceptions into a solid deterministic value. They combined the linguistic preferences using fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to generate an overall performance score for each vendor. Mirhedayatian et al. (2014) developed an NDEA for assessing green SCs. They integrated dual-role factors, bad outputs, and fuzzy sets. Khodakarami et al. (2015) proposed a two-stage NDEA for evaluating green SCs. They also presented strategies for performance improvement of inefficient SCs based on inputs, intermediates, and outputs. Tajbakhsh and Hassini (2015) extended an NDEA model for addressing the intermediates in SCs. Uygun and Dede (2016) evaluated green SCs by combining fuzzy multi-criteria decision-making (MCDM) techniques. To do so, they integrated fuzzy decision-making trial and evaluation laboratory (DEMATEL), fuzzy analytic network process (ANP), and fuzzy TOPSIS. They also used the idea of strong efficiency in their extended NDEA and compared non-cooperative and centralized methods. A double frontier NDEA model was proposed by Badiezadeh et al. (2018) for the performance assessment of sustainable SCs. The model computes optimistic and pessimistic efficiencies in the existence of big data and bad outputs. Ramezankhani et al. (2018) used quality function deployment (QFD and MCDM in NDEA for measuring the environmental and resilience of

SCs. Sari and Suslu (2018) proposed a fuzzy TOPSIS method for evaluating green SCs in the hotel industry. Izadikhah and Farzipoor Saen (2018) evaluated green SCs using an NDEA model in the presence of bad outputs and uncertain data. They developed linear models for computing the overall efficiency of SCs. Samavati et al. (2020) presented a dynamic NDEA model to compute the efficiency of green SCs. Their model considered bad outputs in performance evaluation problems. Izadikhah et al. (2020) evaluated SCs using a stochastic network-enhanced Russell DEA model. The model addresses uncertainty in evaluating green SCs based on chance-constrained programming (CCP). Fathi and Farzipoor Saen (2021) evaluated sustainable SCs using the fuzzy Malmquist and network double frontier DEA model. They also used a common set of weights in their proposed model.

2.3 Data Envelopment Analysis (DEA)

DEA is considered an effective and powerful method for assessing DMUs such as industrial settings, healthcare centers, educational institutes, etc. Over the last few decades, some DEA models such as CCR (Charnes, Cooper, and Rhodes, 1978), BCC (Banker, Charnes, and Cooper, 1984), and SBM (Slack-based measure) proposed by Tone (2001) have been developed and applied in many decision-making areas. However, these models fail to evaluate the performance of DMUs with network structures, including SCs. NDEA, for the first time, was presented by Färe (1991), and Färe and Grosskopf (2000). Over the last two decades, the NDEA model has been developed and applied for solving performance evaluation problems in many real case studies.

3. The proposed model

In this section, we propose our new model for evaluating green SCs. Table 1 provides the used notations in this study.

Table 1. Notations

c	Vector of input costs	$\overline{x}_o$	Cost-value vector of DMU_o
x_o	Input vector of DMU_o	σ_o^*	The optimal objective value of model (5) for DMU_o
y_o	Output vector of DMU_o	θ	A free-signed variable
$\boldsymbol{\lambda}$	Vector of intensifier variable	Δ_j	Bias value of efficiency for DMU_j
T_c	PPS with constant returns to scale	μ_o^*	The optimal value of model (10) for DMU_o
x_i	The ith component of the input vector	$\overline{\Delta}_j$	The bias of efficiency for DMU_j in stage 1
ρ_o^*	The optimal value of model (2) for DMU_o	$\overline{\nabla}_j$	The bias of efficiency for DMU_j in stage 2
T_c^{cost}	Cost PPS with constant returns to scale	$\overline{z}_j$	Cost-value vector of DMU_j

Charnes et al. (1978) introduced the PPS based on constant returns to scale technology in the DEA context as follows:

$$T_c = \{\, (x,y) | x \geq \sum_{j=1}^{n} \boldsymbol{\lambda_j}\, x_{ij},\ y \leq \sum_{j=1}^{n} \boldsymbol{\lambda_j}\, y_{rj},\ \boldsymbol{\lambda_j} \geq 0, j = 1, \dots, n \,\} \tag{1}$$

where $x_o = (x_{1o}, \dots, x_{mo})$ and $y_o = (y_{1o}, \dots, y_{so})$ are the input and output vectors of DMU_o, respectively. To calculate cost efficiency, the minimum cost for each DMU*o* is calculated. Camanho and Dyson (2005) presented the minimum cost model as follows:

$$\begin{array}{lll}
\rho_o^* = Min & \sum_{i=1}^{m} c_i x_i & \\
s.t. & & \\
\sum_{j=1}^{n} \boldsymbol{\lambda_j}\, x_{ij} \leq x_i, & i = 1, \dots, m, & (2.1) \\
\sum_{j=1}^{n} \boldsymbol{\lambda_j}\, y_{ij} \geq y_{ro}, & r = 1, \dots, s, & (2.2) \\
x_i \geq 0, & i = 1, \dots, m & (2.3) \\
\boldsymbol{\lambda_j} \geq 0, & \mathrm{j} = 1, \dots, \mathrm{n}. & (2.4)
\end{array} \tag{2}$$

If we consider the optimal objective function of Model (2) as ρ_o^*, the value of the cost-efficiency (CE) of any DMU_o is calculated by the following equation:

$$CE_o = \frac{\rho_o^*}{cx_o} \tag{3}$$

where cx_o is the current cost of inputs of the DMU_o. It is clear that CE_o is a value belonging to the range (0,1]. If $CE_o = 1$, then we call DMU_o as cost-efficient. Otherwise, we call it cost-inefficient.

In Figure 1, a PPS is depicted, which includes two inputs. The contact point of the objective function line with the PPS determines the input coordinates of the DMU*o* to maximize its cost-efficiency value.

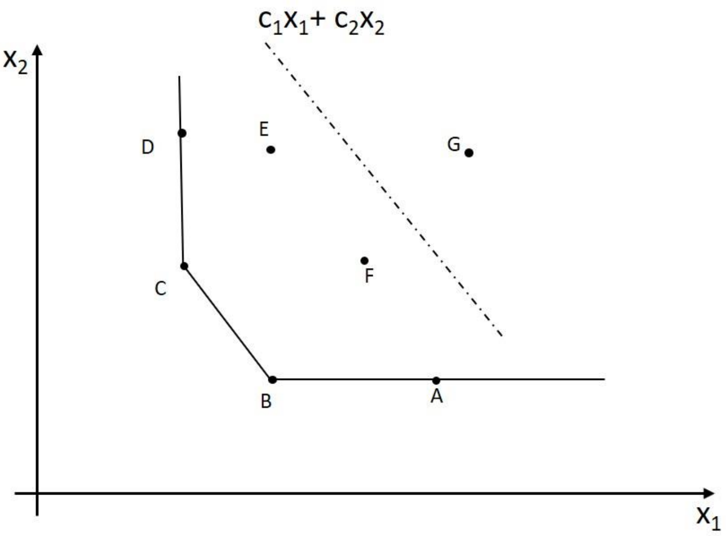

Figure 1. PPS with two inputs

Considering the input (x) and its price (c), for each $DMU_o \in \{DMU_1, \dots, DMU_n\}$, we have $cx_o = \bar{x}_o$ for each input elements. In this case, we have $\bar{x}_{1o} = c_1 \mathrm{x}_{1o}, \dots, \bar{x}_{mo} = c_m \mathrm{x}_{mo}$ and $DMU_o = (\bar{x}_o, y_o) \in R^{m+s}$. Moreover, for $DMU_j = (\bar{x}_j, y_j) \in R^{m+s}, j = 1, \dots, n$, the cost PPS is introduced as follows:

$$T_c^{cost} = \{ (x, y) | x \geq \sum_{j=1}^{n} \boldsymbol{\lambda_j} \, \bar{x}_{ij},\ \ y \leq \sum_{j=1}^{n} \boldsymbol{\lambda_j} \, y_{rj},\ \ \boldsymbol{\lambda_j} \geq 0, j = 1, \dots, n \} \tag{4}$$

To obtain the cost efficiency according to PPS defined in Expression (4), we propose the following model:

$$\begin{aligned}
&\sigma_o^* = Min \qquad \theta \\
&s.t. \\
&\sum_{j=1}^{n} \boldsymbol{\lambda_j} \, x_{ij} \ \leq \theta \bar{x}_{io}, && i = 1, \dots, m, && (5.1) \\
&\sum_{j=1}^{n} \boldsymbol{\lambda_j} \, y_{ij} \ \geq y_{ro}, && r = 1, \dots, s, && (5.2) \\
&\theta \ \ free\ in\ sign, && && (5.3) \\
&\boldsymbol{\lambda_j} \geq 0, && \mathrm{j} = 1, \dots, \mathrm{n}. && (5.4)
\end{aligned} \tag{5}$$

Theorem 1: Model (5) is feasible and $\theta^* \in (0, 1]$.

Proof: Since $\boldsymbol{\lambda_j = 0 \ (j \neq o)}$, $\boldsymbol{\lambda_o = 1}$, and $\theta = 1$, a feasible solution can be considered for Model (5). In addition, since the objective function is minimum, it is clear that $\theta^* \in (0, 1]$. □

The optimal value of θ^* represents the cost efficiency of the $\mathrm{DMU_o}$. If $\theta^* = 1$, then the $\mathrm{DMU_o}$ is called cost-efficient. Otherwise, it is called cost-inefficient. The dual problem of Model (5) is as follows:

$$
\begin{aligned}
&\tau_o^* = Max \quad \textstyle\sum_{r=1}^{s} u_r y_{ro} \\
&s.t. \\
&\textstyle\sum_{r=1}^{s} v_i \bar{x}_{io} = 1, && && (6.1) \qquad (6)\\
&\textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{s} v_i \bar{x}_{ij} \leq 0, && j = 1, \dots, n, && (6.2)\\
&u_r \geq \varepsilon, v_i \geq \varepsilon, && r = 1, \dots, s, i = 1, \dots, m, && (6.3)
\end{aligned}
$$

Model (6) determines the optimal weight of $\mathrm{DMU_o}$, where T_c^{cost} is considered in (4). To increase the capability of Model (6), the idea of common set of weights can be used. Note that, for the first time, the common set of weights model is formulated based on cost PPS. In this way, the discrimination power of DEA models increases significantly. To this end, Model (7), based on the common set of weights, is introduced as follows: Model (7) maximizes the cost efficiency of all DMUs at the same time by introducing a common set of weights to be used for all DMUs. In Model (7), the input vector (x) and corresponding prices should be known. Thus, it is assumed that $cx_{io} = \bar{x}_{io}$, for each input element $(i = 1, \dots, m)$.

$$
\begin{aligned}
&Max \quad \{\textstyle\sum_{r=1}^{s} u_r y_{r1}, \dots, \sum_{r=1}^{s} u_r y_{rn}\} \\
&s.t. \\
&\textstyle\sum_{r=1}^{s} v_i \bar{x}_{ij} = 1, && && (7.1) \qquad (7)\\
&\textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{s} v_i \bar{x}_{ij} + \Delta_j = 0, && j = 1, \dots, n, && (7.2)\\
&u_r \geq \varepsilon, v_i \geq \varepsilon, && r = 1, \dots, s, i = 1, \dots, m, && (7.3)
\end{aligned}
$$

Model (7) has *‘n’* objective functions, thus it is a multiple-objective linear programming problem. The following linear counterpart Model (8), a single-objective function model, is obtained from Model (7). In Model (8), the summation of *‘n’* objective functions is used as a single objective function.

$$
\begin{aligned}
&Max \quad (\textstyle\sum_{r=1}^{s} u_r y_{r1} + \dots + \sum_{r=1}^{s} u_r y_{rn}) \\
&s.t. \\
&\textstyle\sum_{r=1}^{s} v_i \bar{x}_{ij} = 1, && j = 1, \dots, n, && (8.1) \qquad (8)\\
&\textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{s} v_i \bar{x}_{ij} \leq 0, && j = 1, \dots, n, && (8.2)\\
&u_r \geq \varepsilon, v_i \geq \varepsilon, && r = 1, \dots, s, i = 1, \dots, m, && (8.3)
\end{aligned}
$$

The counterpart of Model (8) can be considered as Model (9). In Model (9), Δ_j shows the deviation for each DMU_j $(j = 1, \dots, n)$.

$$
\begin{aligned}
& Min \quad \textstyle\sum_{j=1}^{m} \Delta_j \\
& s.t. \\
& \textstyle\sum_{r=1}^{s} \boldsymbol{v}_i \bar{x}_{ij} = 1, && j = 1, \dots, n, && (9.1) \quad (9) \\
& \textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{s} v_i \bar{x}_{ij} + \Delta_j = 0, && j = 1, \dots, n, && (9.2) \\
& u_r \geq \varepsilon, v_i \geq \varepsilon, && r = 1, \dots, s, i = 1, \dots, m, && (9.3)
\end{aligned}
$$

According to constraint (9.2), Δ_j can be interpreted as slack ϑ_j of the weighted outputs. Surplus π_j of the weighted inputs for each DMU_j is as follows:

$$\textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{s} v_i \bar{x}_{ij} + \Delta_j = 0 \ \rightarrow \ \sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{s} v_i \bar{x}_{ij} + \vartheta_j + \pi_j = 0$$

$$\textstyle\sum_{r=1}^{s} u_r y_{rj} + \vartheta_j - \left(\sum_{r=1}^{s} v_i \bar{x}_{ij} - \pi_j\right) = 0 \ \rightarrow \frac{\sum_{r=1}^{s} u_r y_{rj} + \vartheta_j}{\sum_{r=1}^{s} v_i \bar{x}_{ij} - \pi_j} = 1, \qquad j = 1, \dots, n \qquad (10)$$

The ϑ_j and π_j indicate the surplus and shortage of outflows and outputs, respectively. Consider Figure 2.

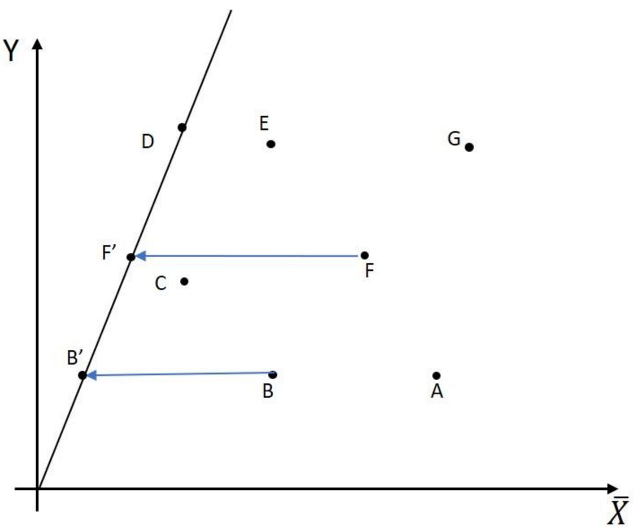

Figure 2. The one input and one output cost PPS

Now, according to the optimal value of Model (8), the cost-efficiency with the common set of weights for each DMU_j $(j = 1, \dots, n)$ can be determined using the expression $\sum_{r=1}^{s} \boldsymbol{u}_r^* y_{rj} - \sum_{r=1}^{s} \boldsymbol{v}_i^* \bar{x}_{ij}$. Now, consider a two-stage series network, which is shown in Figure 3.

Figure 3. A two-stage series network

If we formulate Model (6) based on Figure 3, we get Model (11):

$$\begin{aligned}
&\mu_o^* = Max \quad \textstyle\sum_{r=1}^{s} \boldsymbol{u_r} y_{r1} + \cdots + \sum_{r=1}^{s} \boldsymbol{u_r} y_{rn} \\
&s.t. \\
&\textstyle\sum_{r=1}^{s} v_i \bar{x}_{ij} = 1, && j = 1, \dots, n, && (11.1) \\
&\textstyle\sum_{f=1}^{l} w_f \bar{z}_{fj} - \sum_{r=1}^{s} v_i \bar{x}_{ij} \leq 0, && j = 1, \dots, n, && (11.2) \\
&\textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{f=1}^{l} w_f \bar{z}_{fj} \leq 0, && j = 1, \dots, n, && (11.3) \\
&u_r \geq \varepsilon, v_i \geq \varepsilon, && r = 1, \dots, s, i = 1, \dots, m, && (11.4) \\
&w_f \geq \varepsilon, && f = 1, \dots, l.
\end{aligned} \tag{11}$$

Note that the input of the first stage is *x* and the input of the second stage is *z*. If the cost of *x* equals c and the cost of z equals *b*, then we define $cx = \bar{x}$ and $bz = \bar{z}$. According to the idea of common set of weights, we have Model (12) as follows:

$$\begin{aligned}
&Min \quad \textstyle\sum_{j=1}^{n} (\bar{\Delta}_j + \bar{\nabla}_j) \\
&s.t. \\
&\textstyle\sum_{r=1}^{s} \boldsymbol{v_i} \bar{x}_{ij} = 1, && && (12.1) \\
&\textstyle\sum_{f=1}^{l} w_f \bar{z}_{fj} - \sum_{r=1}^{s} v_i \bar{x}_{ij} + \bar{\Delta}_j \leq 0, && j = 1, \dots, n, && (12.2) \\
&\textstyle\sum_{r=1}^{s} u_r y_{rj} - \sum_{f=1}^{l} w_f \bar{z}_{fj} + \bar{\nabla}_j \leq 0, && j = 1, \dots, n, && (12.3) \\
&u_r \geq \varepsilon, v_i \geq \varepsilon, && r = 1, \dots, s, i = 1, \dots, m, && (12.4) \\
&w_f \geq \varepsilon, && f = 1, \dots, l, && (12.5) \\
&\bar{\Delta}_j \geq 0, \bar{\nabla}_j \geq 0, && j = 1, \dots, n. && (12.6)
\end{aligned} \tag{12}$$

According to the optimal value obtained from Model (12), the cost-efficiency of the whole SC can be calculated as the cost-efficiency of the first and second stages. If the optimal value (v^*, w^*, u^*) is available in the evaluation of DMU*o*, then the cost-efficiency of the whole SC is

$\sum_{r=1}^{s} u^{*}{}_{r} y_{ro}$. The cost-efficiency of each stage equals $\sum_{f=1}^{l} \boldsymbol{w_f} \bar{z}_{fo} - \sum_{r=1}^{s} \boldsymbol{v_i} \bar{x}_{io}$ and $\sum_{r=1}^{s} \boldsymbol{u_r} y_{ro} - \sum_{f=1}^{l} \boldsymbol{w_f} \bar{z}_{fo}$.

Theorem 2: The cost efficiency of the whole SC equals the total cost-efficiency of the first and second stages.

Proof: According to Model (12), we can have $\sum_{f=1}^{l} \boldsymbol{w_f} \bar{z}_{fo} - \sum_{r=1}^{s} \boldsymbol{v_i} \bar{x}_{io} + \sum_{r=1}^{s} \boldsymbol{u_r} y_{ro} - \sum_{f=1}^{l} \boldsymbol{w_f} \bar{z}_{fo} = \sum_{r=1}^{s} \boldsymbol{u_r} y_{ro}$, which completes the proof. □

Theorem 3: The cost efficiency obtained from the common set of weights of Model (12) is smaller or equal to the cost efficiency of classic model.

Proof: In the common set of weights, an optimization problem is considered and a set of weights is calculated to maximize the efficiency of all DMUs. However, the classical model considers $DMU_o, o \in \{1, \ldots, n\}$ and calculates the best weights for DMU*o*. Therefore, the cost-efficiency obtained from the common set of weights is smaller or equal to the cost-efficiency of the classical model. □

Definition 1: According to the optimal common set of weights obtained from Model (12), we can define the CE of the whole SC and each stage. Also, the CE of the whole SC can be calculated using Expression (13). It is clear that the obtained efficiency scores are less than or equal to one.

$$CE = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{r=1}^{s} v_i \bar{x}_{ij}} \leq 1$$

$$CE\ of\ stage\ 1 = \frac{\sum_{f=1}^{l} w_f \bar{z}_{fj}}{\sum_{r=1}^{s} v_i \bar{x}_{ij}} \leq 1 \tag{13}$$

$$CE\ of\ stage\ 2 = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{f=1}^{l} w_f \bar{z}_{fj}} \leq 1$$

Fig. 4 presents a step-by-step description of how the current research is conducted and what are the research requirements. The first step is to present the problem statement and research questions as one of the most important parts of our research. Then, a new NDEA model is developed for addressing the problem and answering the research questions. Defining inputs and outputs by consulting with managers and decision-makers of the SC is the next step of our research. After that, we need to run the model using the collected data and GAMS software. In the final step, we need to analyze the obtained results and present managerial implications.

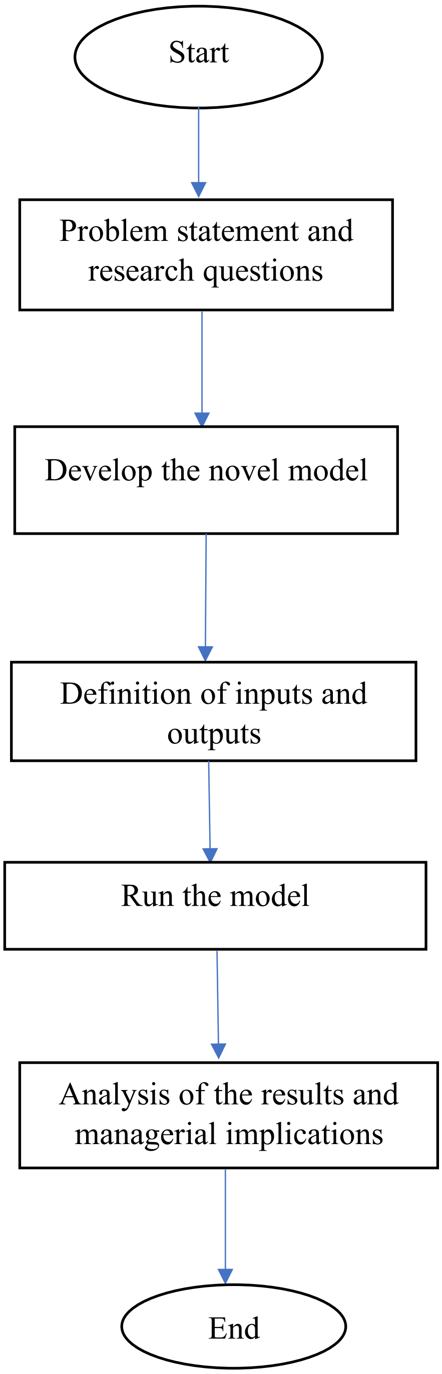

Fig. 4. The research stages

As is seen in Fig. 5, in the first stage (suppliers), there are two inputs called staff cost and raw material costs. CO2 emissions and the quantity of material are outputs of the first stage. Transportation cost and staff cost are considered inputs of stage 2 (producers). Moreover, the waste of products and the quantity of products are outputs of stage 2. Transportation cost and staff cost are inputs of the distributors' stage (stage 3). Profit is an output of stage 3. Table 2 depicts the inputs and outputs of each stage.

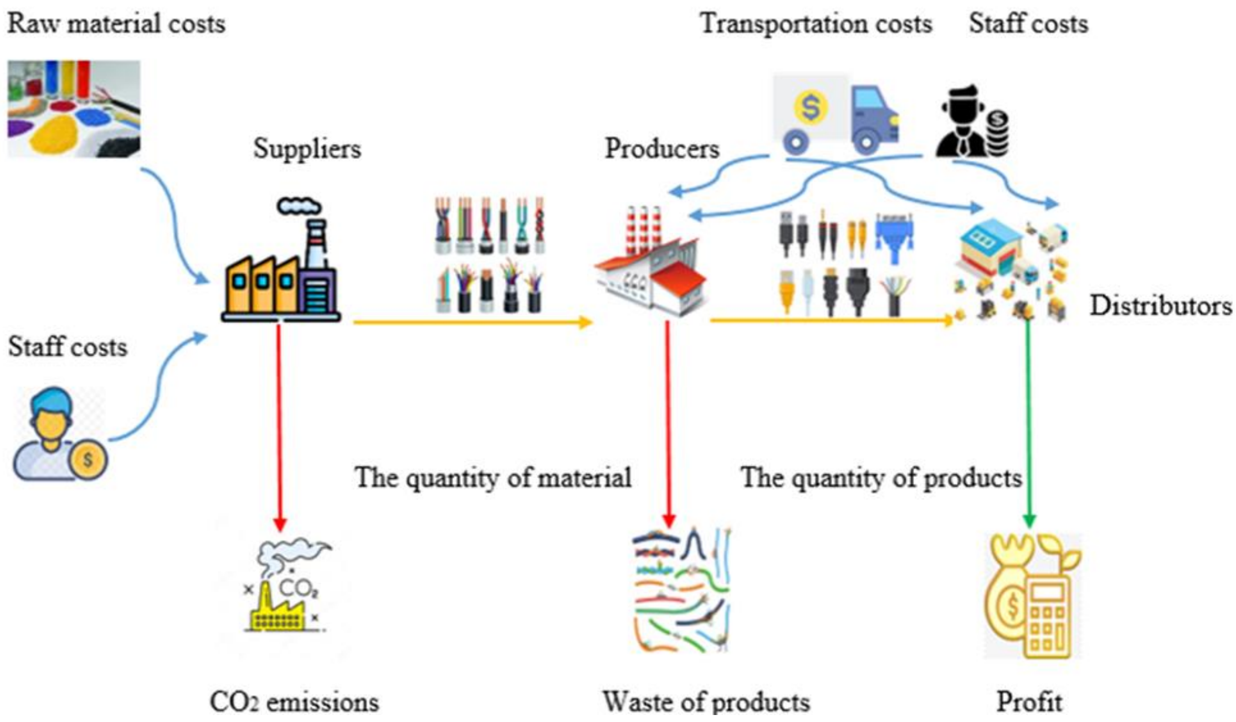

Figure 5. A supply chain structure

According to Fig. 5, Model (14) is formulated as follows: Model (14) minimizes the sum of all deviations of DMUs and calculates the cost efficiency of all DMUs using the common set of weights. In this way, the cost efficiency of all DMUs is minimized at the same time, which is fairer in contrast to the classic models of cost efficiency evaluation. In classic models, each DMU is considered one by one and the model considers the cost minimization of the DMU. Therefore, the upper bound of efficiency is obtained for each DMU$_o$. In Model (14), consider x^1, x^2, and x^3 as the independent inputs of the supplier, producer, and distributor, respectively. Note that $|x^1|= m_1$, $|x^2| = m_2$, and $|x^3| = m_3$. Also, z^1 and z^2 are the intermediate products between the supplier and producer and the producer and distributor, respectively, where $|z^1| = l_1$, and $|z^2| = l_2$. Moreover, w^2 and w^2 are considered undesirable outputs of the supplier and producer that leave the SC. Note that $|w^2| = p_1$, and $|w^2| = p_2$. Finally, y is considered as the final output of the SC and the distributor, where $|y| =$ r. If the cost of x^1 equals c^1, the cost of x^2 equals c^2, the cost of x^3 equals c^3, the cost of z^1

equals b^1, the cost of z^2 equals b^2, the cost of w^1 equals to e^1 , and the cost of w^2 equals e^2, then we define $c^1x^1 = \bar{x}^1$, $c^2x^2 = \bar{x}^2$, $c^3x^3 = \bar{x}^3$, $b^1z_1 = \bar{z}^1$, $b^2z_2 = \bar{z}^2$, $e^1w^1 = \bar{w}^1$, and $e^2w^2 = \bar{w}^2$.

$$
\begin{aligned}
& Min \quad \sum_{j=1}^{n}(\Delta_j^1 + \Delta_j^2 + \Delta_j^3) \\
& s.t. \\
& \sum_{i_1=1}^{m_1} v_{i_1}^1 \bar{x}_{i_1j}^1 = 1, && j = 1, \dots, n, \quad (14.1) \\
& \sum_{f_1=1}^{l_1} k_{f_1}^1 \bar{z}_{f_1j}^1 - \sum_{i_1=1}^{m_1} v_{i_1}^1 \bar{x}_{i_1j}^1 - \sum_{h_1=1}^{p_1} g_{h_1}^1 \bar{w}_{h_1j}^1 + \Delta_j^1 \le 0, && j = 1, \dots, n, \quad (14.2) \\
& \sum_{f_2=1}^{l_2} k_{f_2}^2 \bar{z}_{f_2j}^2 - \sum_{i_2=1}^{m_2} v_{i_2}^2 \bar{x}_{i_2j}^2 - \sum_{f_1=1}^{l_1} k_{f_1}^1 \bar{z}_{f_1j}^1 - \sum_{h_2=1}^{p_2} g_{h_2}^2 \bar{w}_{h_2j}^2 + \Delta_j^2 \le 0, && \\
& && j = 1, \dots, n, \quad (14.3) \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{f_2=1}^{l_2} k_{f_2}^2 \bar{z}_{f_2j}^2 - \sum_{i_3=1}^{m_3} v_{i_3}^3 \bar{x}_{i_3j}^3 + \Delta_j^3 \le 0, && j = 1, \dots, n, \quad (14.4) \\
& u \ge \varepsilon, k^1 \ge \varepsilon, k^2 \ge \varepsilon, v^1 \ge \varepsilon, v^2 \ge \varepsilon, v^3 \ge \varepsilon, && (14.5) \\
& g^1 \ge \varepsilon, g^2 \ge \varepsilon, && (14.6) \\
& \Delta_j^1 \ge 0, \Delta_j^2 \ge 0, \Delta_j^3 \ge 0, && j = 1, \dots, n. \quad (14.7)
\end{aligned}
\tag{14}
$$

In Model (14), constraints (14.1), (14.3), and (14.4) are written for each stage. Note that Δ_j^1, Δ_j^2, and Δ_j^3 for each $j = 1, \dots, n$, show the deviance from cost efficiency of three stages. In Model (14), the undesirable outputs that leave the SC are considered as inputs.

Definition 2: According to the obtained optimal CSW from model (13), we can define the cost efficiency of the whole SC as well as each stage. According to constraints (13.2), (13.3), and (13.4). Also, the cost-efficiency of the whole SC can be calculated using relation (15). It is clear that the efficiency scores are less than or equal to one.

$$
\begin{aligned}
& CE = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i_1=1}^{m_1} v_{i_1}^{*1} \bar{x}_{i_1j}^1 + \sum_{i_2=1}^{m_2} v_{i_2}^{*2} \bar{x}_{i_2j}^2 + \sum_{i_3=1}^{m_3} v_{i_3}^{*3} \bar{x}_{i_3j}^3 + \sum_{h_1=1}^{p_1} g_{h_1}^{*1} \bar{w}_{h_1j}^1 + \sum_{h_2=1}^{p_2} g_{h_2}^{*2} \bar{w}_{h_2j}^2} \le 1, \quad j = 1, \dots, n \\
& CE\ of\ stage\ 1 = \frac{\sum_{f_1=1}^{l_1} k_{f_1}^{*1} \bar{z}_{f_1j}^1}{\sum_{i_1=1}^{m_1} v_{i_1}^{*1} \bar{x}_{i_1j}^1 + \sum_{h_1=1}^{p_1} g_{h_1}^{*1} \bar{w}_{h_1j}^1} \le 1, \quad j = 1, \dots, n \\
& CE\ of\ stage\ 2 = \frac{\sum_{f_2=1}^{l_2} k_{f_2}^{*2} \bar{z}_{f_2j}^2}{\sum_{i_2=1}^{m_2} v_{i_2}^{*2} \bar{x}_{i_2j}^2 + \sum_{f_1=1}^{l_1} k_{f_1}^{*1} \bar{z}_{f_1j}^1 + \sum_{h_2=1}^{p_2} g_{h_2}^{*2} \bar{w}_{h_2j}^2} \le 1, \quad j = 1, \dots, n \\
& CE\ of\ stage\ 3 = \frac{\sum_{r=1}^{s} u_r^* y_{rj}}{\sum_{f_2=1}^{l_2} k_{f_2}^{*2} \bar{z}_{f_2j}^2 + \sum_{i_3=1}^{m_3} v_{i_3}^{*3} \bar{x}_{i_3j}^3} \le 1, \quad j = 1, \dots, n
\end{aligned}
\tag{15}
$$

4. Case study

Wire and cable production in Iran dates back to the 1960s. In this paper, we evaluate eighteen Iranian wire and cable SCs (DMUs). The data was collected by referring to archives and documents of companies. To evaluate green SCs, we consider three stages, including suppliers, producers, and distributors. Fig. 5 shows the structure of SC.

Table 2. The inputs, outputs, and intermediate measures

Stages	Notations	Definitions	References	Status	Category
Supplier inputs	x_1^1	Raw materials cost (Rials)	Amindoust et al. (2012); Aydın Keskin et al. (2010)	Desirable	Economic
	x_2^1	Staff cost (Rials)	Amindoust et al. (2012); Kuo et al. (2010)	Desirable	Economic
Supplier intermediate	z_1^1	The quantity of material (Tons)	Badiezadeh et al. (2018)	Desirable	Economic
Supplier output	w_1^1	CO_2 emission (Rials)	Badiezadeh et al. (2018)	Undesirable	Environmental
Producer inputs	x_1^2	Staff cost (Rials)	Amindoust et al. (2012); Kuo et al. (2010)	Desirable	Economic
	x_2^2	Transportation cost (Rials)	Bhatia et al. (2019)	Desirable	Economic
Producer intermediate	z_1^2	The quantity of product (Tons)	Khodakarami et al. (2015)	Desirable	Economic
Producer output	w_1^2	Waste of product (Tons)	Giannakis et al. (2016)	Undesirable	Environmental
Distributor inputs	x_1^3	Staff cost (Rials)	Amindoust et al. (2012); Kuo et al. (2010)	Desirable	Economic
	x_2^3	Transportation cost (Rials)	Bhatia et al. (2019)	Desirable	Economic
Distributor output	y	Profit (Rials)	Izadikhah et al. (2018); Badiezadeh et al. (2018)	Desirable	Economic

Table 3 depicts the dataset of the supplier (Stage 1).

Table 3. The dataset of supplier

Supply chains (DMUs)	Suppliers			
	Inputs		Output	Intermediate
	Raw materials (Rials)	Staff costs (Rials)	CO2 emission (Tons)	The quantity of material (Tons)
1	186,764,274,000	15,947,107,000	77,193	4,573
2	141,874,392,000	12,328,943,000	71,648	3,459
3	234,483,712,000	19,657,849,000	89,857	5,832
4	155,938,536,000	13,583,932,000	74,839	3,843
5	126,839,189,000	10,927,102,000	60,582	3,099
6	199,849,103,000	16,193,032,000	88,028	4,821
7	174,193,745,000	14,936,519,000	75,373	4,301
8	267,037,653,000	22,086,432,000	94,517	6,551
9	135,855,194,000	11,744,728,000	68,294	3,347
10	119,387,563,000	9,183,645,000	55,735	2,918
11	189,643,532,000	16,573,927,000	80,172	4,658
12	231,726,133,000	18,936,753,000	85,725	5,682
13	171,549,253,000	14,093,642,000	74,537	4,254
14	215,927,472,000	16,458,283,000	79,338	5,315
15	150,716,753,000	12,194,653,000	72,842	3,732
16	181,947,542,000	14,649,549,000	76,532	4,421
17	244,832,204,000	21,329,842,000	85,527	6,013
18	139,764,918,000	12,019,847,000	69,382	3,401

Table 4 shows the dataset of the producer (Stage 2).

Table 4. The dataset of producer

Supply chains (DMUs)	Producers			
	Inputs		Output	Intermediate
	Staff costs (Rials)	Transportation costs (Rials)	Waste of product (Tons)	The quantity of product (Tons)
1	18,836,534,000	7,854,648,000	12.5	4,047
2	13,028.764,000	5,581,753,000	17.2	3,079
3	22,748,739,000	9,503,813,000	24.6	5,374
4	14,438,028,000	6,483,931,000	17.9	3,353
5	11,946,272,000	4,183,547,000	10.4	2,581
6	20,183,837,000	8,083,759,000	14.7	4,395
7	16,648,025,000	6,723,937,000	14.2	3,827
8	24,146,927,000	11,735,952,000	32.5	6,108
9	12,583,284,000	4,973,573,000	15.8	2,915
10	10,536,653,000	3,725,532,000	10.1	2,501
11	19,462,632,000	8,138,692,000	13.4	4,218
12	21,534,832,000	9,964,263,000	21.5	5,274
13	15,583,027,000	6,473,352,000	15.7	3,872
14	18,083,764,000	8,132,947,000	19.3	4,937
15	14,194,539,000	5,973,643,000	15.5	3,389
16	18,287,464,000	7,295,028,000	13.7	3,972
17	23,037,634,000	11,592,193,000	22.5	5,483
18	12,574,927,000	5,385,739,000	14.3	2,983

Table 5 shows the dataset of the distributor (Stage 3).

Table 5. The dataset of distributor

Supply chains (DMUs)	Distributors		
	Inputs		Output
	Staff costs (Rials)	Transportation costs (Rials)	Profit (Rials)
1	8,847,934,000	4,193,754,000	301,483,645,000
2	5,837,354,000	3,382,941,000	239,849,474,000
3	11,847,743,000	5,683,102,000	397,643,283,000
4	6,519,750,000	3,840,646,000	291,745,929,000
5	4,693,293,000	2,693,293,000	199,847,029,000
6	9,813,536,000	4,792,194,000	328,947,184,000
7	7,593,736,000	3,927,736,000	284,734,283,000
8	13,193,847,000	6,984,283,000	443,037,653,000
9	5,064,236,000	3,295,185,000	235,965,653,000
10	3,927,183,000	2,017,473,000	181,845,532,000
11	9,249,282,000	4,319,523,000	327,826,142,000
12	11,034,273,000	4,782,538,000	381,736,428,000
13	7,362,843,000	3,843,543,000	232,748,273,000

14	9,573,193,000	4,043,173,000	312,473,849,000
15	6,194,544,000	3,295,036,000	265,938,692,000
16	8,325,932,000	3,947,421,000	284,930,213,000
17	12,794,642,000	5,938,183,000	432,038,674,000
18	5,684,937,000	3,149,294,000	237,893,173,000

4.1. Results and managerial implications

Using Model (13), Table 6 reports the results. As is seen, in stage 1, DMUs #3, #13, #14, and #15 are cost-efficient (green) and the rest are inefficient. DMU#4 is the only green SC in the third stage and there is no green DMU in stage #2. Although DMUs #13 and #14 are green in stage #1, they are in the last place in terms of overall greenness with 0.62 and 0.68, respectively. Though DMUs #13 and #14 perform relatively well in stage #2, they have the lowest greenness in stage #3. This means that DMUs #13 and #14 should take steps to improve their greenness in the distributor stage. DMU #3 is green in stage #1 but not green in stages #2 and #3. Unlike DMU #3, DMU #15 has lower greenness in the producer stage at 0.89 and higher greenness in the distributor stage at 0.91.

Table 6. The results

Supply chains (DMUs)	CE S1	CE S2	CE S3	CE Supply Chain
1	0.98	0.86	0.86	0.73
2	0.98	0.96	0.9	0.84
3	1	0.9	0.85	0.77
4	0.99	0.85	1	0.85
5	0.98	0.82	0.89	0.72
6	0.97	0.88	0.86	0.74
7	0.99	0.87	0.86	0.74
8	0.99	0.91	0.83	0.75
9	0.99	0.86	0.93	0.8
10	0.99	0.85	0.85	0.72
11	0.98	0.88	0.89	0.78
12	0.99	0.91	0.83	0.75
13	1	0.9	0.69	0.62
14	1	0.92	0.73	0.68
15	1	0.89	0.91	0.81
16	0.98	0.87	0.83	0.71
17	0.98	0.89	0.9	0.79
18	0.98	0.86	0.92	0.78

The results of such comparisons are depicted in Fig. 6. As is seen, stage #1 has higher greenness with changes between 0.98 and 1. However, stages #2 and #3 fluctuate a lot in the wide range of 0.82 to 0.96. Fig. 6 introduces DMU #13 as the worst DMU, while DMUs #2 and #4 are the best ones.

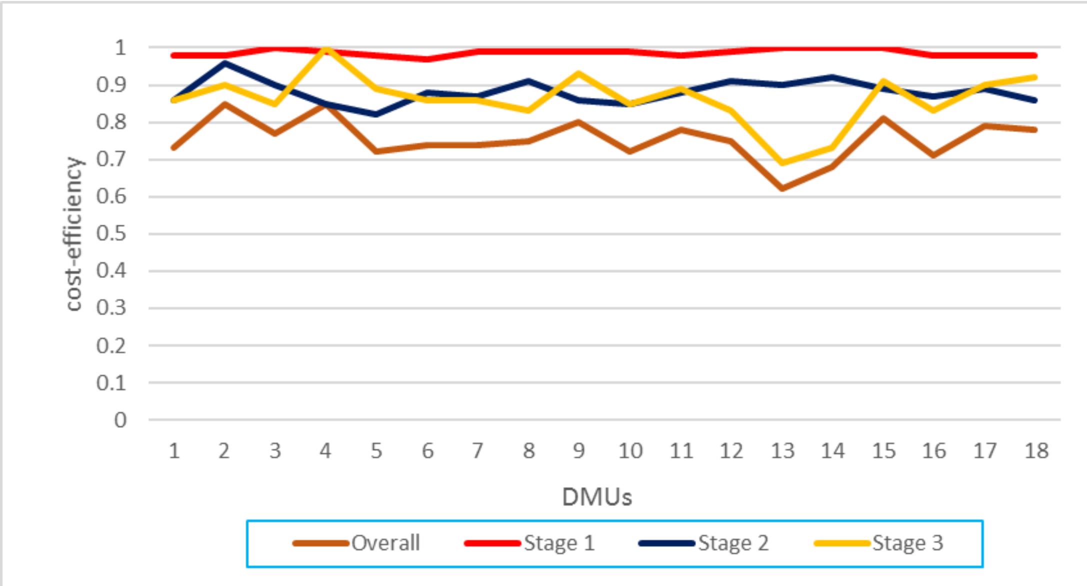

Figure 6. The results

As is seen in the case study, managing intricate systems with lots of entities and interactions is one of the major challenges for managers. Our model supports managers in several ways. By using the proposed model, managers can consider many components and interactions for a better understanding of their SC. It helps them to understand how each input, intermediate, or output can affect the performance of SCs. Moreover, by providing the overall efficiency and divisional efficiency of SCs, managers can scrutinize their efficiency. Addressing the environmental concerns in the performance evaluation of green SCs is another feature of the proposed model that can help managers to lessen pressure from public opinions and governments. Developing a new model as developed in this study can help society to take step toward sustainability targets by addressing economic and environmental criteria. Our model can address some efforts for decreasing the negative effects of organizations' products in terms of environmental issues. These attempts optimistically impact the improvement of environmental performance through decreasing wasting materials and products, decreasing environmental accidents and enhancing society health. Our novel model make contribution to the literature DEA based on cost PPS. In addition, we formulated common set of weights model based on cost PPS in the DEA structure. Our model can calculate the efficiency scores for all stages at the same time.

Considering the cost PPs defined in (4) and the classic efficiency evaluation provided in Model (5), the cost efficiency of supply chains is calculated and listed in Table 7. As is seen in Table 7, most supply chains are cost efficient and the classical model cannot discriminate the cost efficiency scores of DMUs. However, our proposed model can fully rank DMUs.

Table 7. The classic cost efficiency scores

Supply chains (DMUs)	Cost efficiency
1	0.9880
2	1.0000
3	1.0000
4	1.0000
5	1.0000
6	1.0000
7	0.9846
8	0.9798
9	1.0000
10	1.0000
11	1.0000
12	1.0000
13	0.8147
14	0.9542
15	1.0000
16	0.9556
17	1.0000
18	0.9717

5. Conclusions and future research

Green practices in SCs have been significant for many businesses over the last few decades. These practices can help organizations reduce costs and increase profit and reputation. Concerns related to ecological issues are important owing to their considerable effects on all business dimensions. Because of the presence of institutes and organizations with environmental objectives, many businesses try to address environmental concerns. In this regard, green SCs are a powerful approach for organizations to differentiate their businesses from rivals. To improve the performance of green SCs, it is essential to apply rigorous techniques, including network DEA.

In this paper, we developed an effective network DEA model for assessing green SCs. The model is developed based on the cost PPS. In the network DEA model, we formulated a common set of weight model based on cost PPS. Despite classical cost-efficiency models, our model maximizes the cost-efficiency of all DMUs, simultaneously. In the evaluation of each DMU, the classical model considers the best conditions for the DMU. In this way, the objective of the classical models is to consider the best weights for the DMU. It also provides the overall efficiency as well as divisional efficiency for each SC. Our model was applied in the wire and cable industry for the performance evaluation of green SCs.

Our developed model is a multiplier NDEA model that is suitable for evaluating complex systems such as SCs. In this model, the cost PPS is considered in the performance evaluation process. Moreover, the concept of common set of weights is considered based on cost PPS for a better evaluation of SCs. Another advantage of the proposed model is to maximize the cost efficiency of all SCs, simultaneously. In addition, the common set of weights and cost efficiency of each stage, as well as the overall costs are obtained.

One main limitation of the proposed model is that the provided model cannot guarantee the relative efficiency scores. Note that this is the main shortcoming of NDEA models that exist in this study as well. Also, this research assumes data certainty. However, in the real world, there might be uncertainty in the data.

Some research avenues can be developed based on the proposed model in this paper. We developed our model based on certainty in decision variables. However, there are many situations that green SCs deal with uncertainty in decision variables. For example, price is a variable that depends on supply and demand conditions. In this case, the performance measurement of green SCs can be developed using techniques such as chance-constrained programming (CCP) or fuzzy theory to address uncertainty in decision variables. In addition, there are some strong and weak disposability assumptions in efficiency analysis using the DEA technique. Therefore, our proposed model can be developed based on strong and weak disposability assumptions, and the results can be compared. This paper assumes certainty. However, dealing with uncertainty can be another future research topic.

Compliance with Ethical Standards:

Conflict of Interest: Authors declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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