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ORIGINAL RESEARCH

Evaluating sustainably resilient supply chains: a stochastic double frontier analytic model considering Netzero

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Abstract

In era of reglobalization, sustainably resilient supply chains (SCs) are imperative in corporations to improve performance and meet stockholders' expectations. However, sustainably resilient SCs could not be effective if are not assessed by using advanced frameworks, systems, and models. As such, developing a novel network data envelopment model (DEA) to appraise sustainably resilient SCs is our purpose in this article. To do so, we present a new double-frontier methodology to provide optimistic and pessimistic efficiency measures in network structures. Moreover, ideas of outputs weak disposability, chance-constrained programming, and discrete dominance are incorporated in a unified framework of modelling efficient and inefficient production technologies. The new network DEA model also can address dissimilar types of data, including undesirable and integer-valued and ratio outputs, stochastic intermediate products, and integer-valued inputs in a unified framework. Furthermore, an aggregated Farrell type efficiency measure is developed which allows to provide the complete ranking of units so that each decision-making unit (DMU) has its own rank in both overall and divisional point of view. We show the unique features of our developed model using a real case study in paint industry to evaluate the efficiency and reducing carbon dioxide (CO2) emissions. The results show that how well the proposed models can evaluate the sustainability and resilience of supply chains in the presence of uncertainty and with dissimilar types of data.

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1 Introduction

Considering sustainability concept in supply chain management (SCM) (Manupati et al., 2020) needs to be taken into account in organizations. “Globalization has forced companies to pay more attention to three main dimensions of sustainability such as financial, eco-friendly, and social under the name of the triple bottom line (TBL) across their SCM (Cloutier et al., 2020)”. Considering TBL in SCM provides organizations with numerous advantages such as enhanced production quality, decreased manufacture costs, decreased investment risk, and enhanced employee motivation (Kabadurmus & Erdogan, 2020; Shibin et al., 2020). Although sustainable SCM (SSCM) has addressed substantially over the last decade, the impact of sustainability interruptions on the whole resilience of the SSCM has not fully explored to date. (Fahimnia et al., 2017; Sazvar et al., 2021). Many businesses can prevent from irreparable loses such as bankruptcy and complete shutdown by investing in resilient SSCs (Sharifi et al., 2020). Nonetheless, the presence of resilient SSCs cannot provide organizations with competitive advantages if such SCs are not assessed by using powerful methodologies and techniques (Tavassoli et al., 2021). Thus, it is crucial to develop and apply sustainably resilient SCs assessment methods for improving the performance of business operations.

Sustainability in SCs has received considerable attention by practitioners and scholars over the last two decades (He et al., 2021). “While conventional SCs consider economic dimension and address factors such as costs decrease, production time reduction and on time delivery decrease of products, sustainable SCs (SSCs) deal with environmental and social dimensions in response to customers’ needs (Wang & Gunasekaran, 2017)”. In today’s highly competitive markets, environmental and social dimensions should be given as equal importance as economic dimension (Jabbour et al., 2020; Shadab et al., 2021). “Based on the concept of sustainability in SCs, organizations should not scarify the quality of living to destroy biological sources and pollute environment and that people should be respected in workplace with respect to their right (Rentizelas et al., 2020)”. To benefit from the advantages of SSCs, companies should focus on resources conservation, product innovations, processes optimization, cost saving and productivity increase by addressing the TBL across their SCs (Aslam et al., 2021; Kahi et al., 2017). As a result, considering sustainability dimensions in SCs leads to numerous benefits for businesses, employee and customers and society (Hong et al., 2019).

Resilience is another significant topic in SCs and is considered as SC risk management (Kaur & Singh, 2019; Yazdani et al., 2022). Recent swift changes in global markets have pushed organizations to address resilience concept in their SCs (Rajesh, 2019). This concept has brought into SC risk management in dealing with the SC problems caused by unexpected events such as flood, earthquake (Behzadi et al., 2017). Based on a definition SC resilience is the ability of SC for recoiling from disruptions aimed at delivering on promises to customers within a given time (Tukamuhabwa et al., 2015). The consequence caused by interruptions in SCs can result in decreasing market share followed by complete closure of a business. As such, SCs should be designed in a way that mitigate risks caused by unexpected disruptions promptly and effectively (Han et al., 2020).

In view of sustainability and resilience concepts in SC, it is crucial to address these concepts in measuring sustainability and resilience of SCs (Ramezankhani et al., 2018). "The measurement approaches of sustainably resilient SCs should be able to cover the complex network structures of SCs and evaluate them considering different indicators". In this regards, network data envelopment analysis (DEA) is recognized as a rigorous methodology of performance evaluation of the complex structures such as SCs (Zhou et al., 2019). Network DEA provides insights for the specific resources of organizational process inefficiency and assist management for devising targeted remedial measures (Avkiran, 2009). Because of unique advantages of network DEA, it has been used in many performance evaluation problems of SCs (Hensel et al., 2021; Kalantary & Farzipoor Saen, 2019).

In the current article some research questions are brought up with respect to the literature as follow: (1) how can we develop an integrated network DEA model for dealing with dissimilar types of data including undesirable and integer-valued and ratio outputs, stochastic intermediate products, and integer-valued inputs? (2) how different techniques including chance constrained programming (CCP[1]) and discrete dominance can be applied in an unified framework of modelling efficient and inefficient production technologies? (3) how a double-frontier approach can be proposed for providing optimistic and pessimistic efficiency measures? and (4) how aggregated Farrell type efficiency measure can be developed which allows for the complete ranking of units in both overall and divisional point of view?

In the current article, we evaluate sustainably resilient SCs using a novel stochastic double frontier analytic model. In the context of DEA, double frontiers mean that there are two efficiency measurements. One is the best or optimistic efficiency that we can measured them in the performance evaluation process. The other one is the worst or pessimistic efficiency that we measure DMUs' inefficiency (Ahmady et al., 2013; Farzipoor Saen, 2022; Fathi & Farzipoor Saen et al., 2021). The proposed model is developed based on a double-frontier approach extended in network structures. In addition, some specific assumptions and different types of data take into account for developing the proposed model. Providing optimistic and pessimistic efficiency measures is also another feature of our developed model. In our viewpoint, the current article provides some distinctive contributions as follow:

- A new general network DEA model is extended for dealing with dissimilar data, including undesirable and integer-valued, and ratio outputs, stochastic intermediate products, and integer-valued inputs.
- Different techniques such as CCP and discrete dominance are applied in a unified framework of modelling efficient and inefficient production technologies.
- A novel double-frontier approach is presented to provide optimistic and pessimistic efficiency measures.
- An aggregated Farrell type efficiency measure is developed which allows for the complete ranking of units in both overall and divisional points of views.

The rest of the current article is as follows: the related works come in Sect. 2. Our developed model is provided in Sect. 3. Thereafter, an empirical study is presented. Conclusion and research avenue are also presented in the last Section.

2 Background

In this section we provide a background on sustainable SCs, resilient SCs, DEA and network DEA. Furthermore, we identify knowledge gaps to fill.

[1] CCP is an optimization technique for addressing uncertainty in decision variables in modelling.

2.1 Sustainable SCs

SSCM is considered to manage actions, resources and information concerned SCs aimed at maximizing profit, simultaneously minimizing the ecological consequences, and increasing social well-being (Dabbous & Tarhini, 2021; Raj et al., 2021). There are some related works in the literature to evaluating sustainable SCs. Haghighi et al. (2016) developed a balanced scorecard-DEA approach for measuring SSCs. "The model presented by Haghighi et al. (2016) can deal simultaneously with qualitative and quantitative criteria while take environmental and sustainable indicators into account for assessing sustainability and resilience of SCs". Izadikhah and Farzipoor Saen (2018) assessed SCs from sustainability perspective by using a chance-constrained DEA methodology in the existence of desirable and bad outputs such as revenue and rate of inferior raw material. Chance constrained technique is significant technique for addressing optimization problems in uncertain environments (Azadi & Farzipoor Saen, 2012). Tseng et al. (2018) proposed a Fuzzy Delphi Method (FDM) and Analytical Network Process (ANP) model for considering both the linkage amongst measures and the fuzziness of prejudiced measures in sustainable SCs. Kalantary and Farzipoor Saen (2019) developed an inverse DEA model in dynamic network structures for evaluating sustainability of SCs. The proposed model by Kalantary and Farzipoor Saen (2019) determines some inputs and outputs sets in connection with the TBL for the performance evaluation. Wang et al. (2020) developed a modeling methodology by combining the multi-region input–output model and DEA approach, and multidimensional features for evaluating sustainability of global SCs. Samavati et al. (2020) presented a dynamic network double frontier DEA model to assess sustainable SCs. They used double frontier concept in dynamic network DEA context for estimating efficiency of sustainable SCs over multiple periods. Shadab et al. (2021) measured the performance of sustainable SCs by proposing a network DEA model. The model considered several scenarios with congestion assumption in network structures. They evaluated the performance of sustainable SCs of 20 resin firms in Iran using their developed model. Sadeghi et al. (2022) appraised the sustainability of SCs based on a network DEA model. They considered negative and positive values in their model and used super efficiency technique for ranking the SCs. Farzipoor Saen et al. (2022) assessed the sustainability of transport SCs through a network DEA model. They incorporated malmquist productivity index (MPI) in network DEA and considered bad outputs, non-discretionary and integer data in their model.

2.2 Resilient SCs

According to a definition resilience in SC is the capacity of an organization for surviving, adapting, and growing in response to swift changes (Munoz & Dunbar, 2015). The ability of organizations to forecast the impact plays a key role in achieving long-term and short-term goals if they recover their settings effectively in face of unexpected changes (Tukamuhabwa et al., 2015). Organizations with resilient SCs can mitigate transportation interruptions and a variety of supply interruptions that can happen when the upcoming big disaster would be (Gunasekaran et al., 2015). Because of considerable importance of assessment in resilient SCs some scholars have addressed it to date. Spiegler et al. (2012) established clarified performance indicators that capture the attributes of resilience in SCs. They applied the Integral of the Time Absolute Error (ITAE) as a rigorous tool for measuring resilient SCs. Chen et al. (2017) developed a system to assess SC reliability and resilience. The developed framework encapsulates risks that are in supply, demand, the company, and the external situation. Sahu et al. (2017) proposed an assessment multi-level system to assess resilient SCs. In order to address subjective assessment information in the developed system, they used fuzzy sets theory. Ramezankhani et al. (2018) developed a dynamic network DEA approach for evaluating the performance of resilient and sustainable SCs. Shi and Mena (2021) proposed an event-based Bayesian method to model the fundamental relations between variables at different time intervals for assessing resilience in SCs with respect to financial and operational indicators. The method concentrated on two main components of resilience recoverability and reliability. Izadikhah et al. (2021) evaluated sustainable and resilient SCs through a network DEA model with fuzzy and stochastic data. They also combined bad outputs in the model and assessed sustainability and reliance of transport SCs. Kazemi Matin et al. (2021) appraised the resilience and sustainability of blood SCs through a three stages network DEA. They considered a range of data in the model and showed that how well the model can assess the resilience and sustainability of blood SCs. Yazdani et al. (2022) assessed resilient SCs in food industry using an extended decision-making model. They used the best worst approach and fuzzy sets theory for measuring resilient SCs in the food industry. They also did some sensitivity analysis to show the reliability of their model.

2.3 DEA and network DEA

DEA is one of Operations Research (OR) recognized techniques and is applied to measuring efficiency of a number of peer decision making units (DMUs) (Razipour-GhalehJough et al., 2020; Sorkhi & Paradi, 2020; Xin et al., 2022). DEA uses inputs and outputs ratios for evaluating efficiency of DMUs. Charnes, Cooper, and Rhodes (CCR) (1978) pioneered DEA and (Banker-Charnes–Cooper) (BCC) (1984) extended the initial DEA model. Over the last few decades, DEA has been extended and applied by scholars as a powerful methodology for solving many appraisal problems in the real world. Although DEA provides decision makers and managers with several advantages, its traditional models such as CCR and BCC have some drawbacks. There is a notion in normal DEA models that more products using fewer resources is indication of superior performance. In spite of this, there are many DMUs like factories that produce bad outputs such as inferior products or toxic gases. It is obvious that in these cases producing more outputs does not mean better performance. The literature shows that initial attempts for taking bad or undesirable outputs into account in the DEA structure were made by Pittman (1983) and Färe et al. (1989). Liu et al. (2015), Piao et al. (2019), Kao and Hwang (2021) and Nemati et al. (2021) have also addressed bad outputs in DEA over the last few years.

Another drawback of traditional DEA is the existence of ratio data such as the percentage of discharged patients from a healthcare center in measuring efficiency of DMUs. Hollingsworth and Smith (2003) were among the first scholars to address efficiency measurement using DEA assuming ratio information. Emrouznejad and Amin (2009) developed a convexity assumption in DEA in response to ratio data. Olesen et al. (2017) presented the concept of potential ratio efficiency to address this issue, however, the proposed concept is unable to make difference between efficiency of DMUs. To increase discrimination power between efficiency of DMUs, Hatami-Marbini and Toloo (2019) proposed the modified multiplier in DEA structure. The presence of integer-valued data is another pitfall of traditional DEA models. There is an assumption that in efficiency measurement all inputs and output deal with real value while there might be some integer data such as the number of personnel or the number of fabricated products. Integer-valued data modeled in DEA context by Lozano and Villa (2006) for the first time. Kazemi Matin Kuosmanen (2009) developed Lozano and

Villa's (2006) using the notion of natural disposability and natural divisibility. Over the last decade, some scholars have addressed integer-valued DEA such as Wu and Zhou (2015), Khoveyni et al. (2019) and Chen et al. (2021). Furthermore, there are some observations in the real life that deal with stochastic data. For the first time stochastic data in DEA discussed by Sengupta (1982) by considering stochastic inputs and outputs in measuring efficiency. Over the last decade some scholars have addressed stochastic data in DEA such as Azadi and Farzipoor Saen (2011), Kaffash and Marra (2017), Tavassoli et al. (2020), Hosseini et al. (2021), and Izadikhah and Farzipoor Saen (2021).

DEA models in traditional structures address inputs and outputs into account; the operations of the internal components are ignored when evaluating performance. When a system deals with a number of components operating interdependently, overlooking the operations within a component may provide misleading efficiency evaluations (Moreno & Lozano, 2014). Thus, to assess efficiency of network structures, the operations of the components should be addressed. Efficiency assessment of network structures using network DEA originally presented by Färe and Grosskopf (1996). Tone and Tsutsui (2009) developed a network slacks-based measure (SBM) DEA model for performance evaluation of electric power companies that deal with network structures. Sueyoshi et al. (2010) proposed a range adjusted measure (RAM) two-stage network DEA that can deal with both bad outputs and good outputs. The model used for measuring productivity of US fossil fuels power plants. Yu et al. (2016) dynamic network DEA for performance appraisal of bus transit providers in the presence of shared inputs, undesirable and desirable outputs. Tavana et al. (2018) proposed a dynamic network DEA model for performance evaluation of network structures in the existence of bad and good carryovers and negative data. Esmaielzade and Kazemi Matin (2019) developed multi-period network DEA models for performance assessment of overall and specific time period efficiencies with series and parallel sub-processes for each time period. Samavati et al. (2020) proposed a double frontier network DEA model to evaluate sustainable SCs in the presence of desirable and undesirable outputs. Izadikhah and Farzipoor Saen (2021) developed a linear two-stage DEA model with stochastic data to evaluate sustainability of supply chains. To assess sustainably resilient supply chains in public transport, Izadikhah et al. (2021) proposed a fuzzy chance-constrained network DEA.

2.4 Knowledge gaps

The related works in the literature show that performance assessment of SCs with respect to sustainability and resilience criteria plays a quintessential role in organizations' achievements. However, a few studies have considered both sustainability and resilience aspects for measuring SCs. Furthermore, the existing studies are unable to consider dissimilar data such as integer-valued data, stochastic data, ratio data, desirable and undesirable outputs in network DEA models for performance evaluation. Moreover, approaches of outputs weak disposability, chance constrained programming (CCP), and discrete dominance have not been applied simultaneously in a unified framework of modeling efficient and inefficient production technologies. Additionally, aggregated Farrell type efficiency measure for the complete ranking of units in both overall and divisional points of views has not been developed in the double frontier approach. The gaps mentioned above is addressed in the current article by developing a stochastic analytical model in complexed structures to assess sustainably resilient SCs.

3 Proposed methodology

Now we develope our novel model to evaluate sustainably resilient SCs. Suppose there are n number of observed production units to be gauged based on m number of inputs and s nnumber of utputs. Denote by $\boldsymbol{x}_j = (x_{1j}, \ldots x_{mj}) \in \mathbb{R}^m_+$ and $\boldsymbol{y}_j = \left(y_{1j}, \ldots, y_{sj}\right) \in \mathbb{R}^s_+$ the inputs and the outputs vectrs of $DMU_j (j = 1, \ldots, n)$, with at least one positive element in each vector.

In traditional multiplier DEA models $\boldsymbol{v} = (v_1, \ldots, v_m) \in \mathbb{R}^m_+$ and $\boldsymbol{u} = (u_1 \ldots, u_s) \in \mathbb{R}^s_+$ as common weights are used for capturing preference information about inputs and outputs. respectively. Based on variable returns to scale (VRS) assumption (it is a type of frontier scale applied that shows increase or decrease in inputs values not neccessairly lead to a proportional change in the outputs values (Azadi et al., 2020), the ratio of (virtual) weighted outputs to (virtual) weighted inputs for any observed unit $j \in \{1, \ldots, n\}$ defines the (absolute) efficiency ratio of DMU_o as

$$E_j(\boldsymbol{u}, \boldsymbol{v}, u_0) = \frac{\sum_{r=1}^{s} u_r y_{rj} - u_0}{\sum_{i=1}^{m} v_i x_{ij}}, \tag{1}$$

which is well-defned for any feasible weights such that $\sum_{i=1}^{m} v_i x_{io} > 0$, (Podinovski, 2001). Here, u_0 is the intercept variable.

Now we present DEA models to estimate the optimistic and pessimistic efficiency scores. The following BCC model (Banker et al., 1984) evaluates the optimistic efficiency of DMU_o relative to the other observations:

$$\begin{aligned} &Eff_o(Optimistic) = \max_{\boldsymbol{u},\boldsymbol{v},u_0} E_o(\boldsymbol{u}, \boldsymbol{v}, u_0) \\ &\text{Subject to}: \quad E_j(\boldsymbol{u}, \boldsymbol{v}, u_0) \le 1, \qquad j = 1, \ldots, n, \\ &\qquad\qquad\quad \boldsymbol{u} \ge 0, \boldsymbol{v} \ge 0. \end{aligned} \tag{2}$$

Here, DMU$_o$ is the under evaluation unit. Equation (2) is changed to a linear programming (LP[2]) using approache proposed by (Charnes & Cooper, 1962) as follow:

$$\begin{aligned} &Eff_o(Optimistic) = \max_{\boldsymbol{u},\boldsymbol{v},u_0} \sum_{r=1}^{s} u_r y_{ro} - u_0 \\ &Subject\ to: \sum_{i=1}^{m} v_i x_{io} = 1, \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \le 0,\ j = 1, \ldots, n, \\ &u_r \ge 0, v_i \ge 0, r = 1, \ldots, s, i = 1, \ldots, m. \end{aligned} \tag{3}$$

At optimality, if there exist a set of positive weights $\left(\boldsymbol{u}^*, \boldsymbol{v}^*, u_0^*\right)$ for which $Eff_o(Optimistic) = 1$, then DMU$_o$ is BCC or technical efficient; otherwise it is inefficient.

Any feasible input/output weights can be utilized to rank observed DMUs with respect to the corresponding efficiency ratios (1). The BCC model (2) ranks the observations based on their most favurable (optimistic) input/output weights. However, it can not provide more

[2] In Mathematics, linear programming is a method of optimising operations with some constraints (Dantzig, 2002).

information about the efficiency ratio of the under evaluation unit compares with the other observations. To overcome this issue, an aggregate score of optimistic and pessimistic relative.

efficiencyies can be used for ranking observed DMUs without lots of computation and information.

The pessimistic relative efficiency of DMU_k is defined based on ideas presented by Wang et al. (2007) as follow:

$$Eff_o(Pessimistic) = \min_{\boldsymbol{u},\boldsymbol{v},u_0} E_o(\boldsymbol{u}, \boldsymbol{v}, u_0) \tag{4}$$
$$\text{Subject to} : E_j(\boldsymbol{u}, \boldsymbol{v}, u_0) \geq 1, \; j = 1, \ldots, n,$$
$$\boldsymbol{u} \geq 0, \boldsymbol{v} \geq 0.$$

By using Charnes and Cooper's transformations (1962), the fractional programming (4) is stated as the following LP:

$$E_o(Pessimistic) = \min_{\boldsymbol{u},\boldsymbol{v},u_0} \sum_{r=1}^{s} u_r y_{ro} - u_0 \tag{5}$$
$$\text{Subject to} : \sum_{i=1}^{m} v_i x_{io} = 1,$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \geq 0, \, j = 1, \ldots, n$$
$$u_r \geq 0, v_i \geq 0, r = 1, \ldots, s, i = 1, \ldots, m.$$

At this conjuction we present dual formulations.

By taking dual from the above stated LP for the optimistic and pessimistic models we get the following dual LPs (envelopment forms), respectively as follow:

$$Eff_o(Optimistic) = min\theta \tag{6}$$
$$Subject\ to : \left(\theta \boldsymbol{x}_o, \boldsymbol{y}_o\right) \in T_{VRS}$$

$$Eff_o(Pessimistic) = max\varphi \tag{7}$$
$$Subject\ to : \left(\varphi \boldsymbol{x}_o, \boldsymbol{y}_o\right) \in T'_{VRS}$$

In which $T_{VRS} = \{ (\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}_+^{m+s} | \boldsymbol{x} \geq \sum_{j=1}^{n} \lambda_j \boldsymbol{x}_j, \boldsymbol{y} \leq \sum_{j=1}^{n} \lambda_j \boldsymbol{y}_j, \sum_{j=1}^{n} \lambda_j = 1, \forall j : \lambda_j \geq 0\}$ denotes the production technology set under variable returns to scale (VRS) assumption and $T'_{VRS} = \{ (\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}_+^{m+s} | \boldsymbol{x} \leq \sum_{j=1}^{n} \lambda_j \boldsymbol{x}_j, \boldsymbol{y} \geq \sum_{j=1}^{n} \lambda_j \boldsymbol{y}_j, \sum_{j=1}^{n} \lambda_j = 1, \forall j : \lambda_j \geq 0\}$ denotes its transpod technology set.[3]

Overall performance assesment and completet ranking of production units is available by integrating these two different efficiencies (Wang et al., 2007). Now we extend the proposed models above in network structures. Suppose that there are n observed DMUs in general network case, which DMU_j $(j = 1, \ldots, n)$ comprises q stages. The kth stage $(k = 1, \ldots, q)$ use external inputs $\boldsymbol{x}_i^{(k)}\left(i = m^{(k-1)} + 1, \ldots, m^{(k)}\right)$ and the intermediate products $\boldsymbol{z}_g^{(k-1)}\left(g = h^{(k-2)} + 1, \ldots, h^{(k-1)}\right)$ for producing fabricated products $\boldsymbol{y}_r^{(k)}\left(r = s^{(k-1)} + 1, \ldots, s^{(k)}\right)$ and intermediate product $\boldsymbol{z}_g^{(k)}\left(g = h^{(k-1)} + 1, \ldots, h^{(k)}\right)$. A typical general series network is shown in Fig. 1.

[3] Please see Lins et al. (2005).

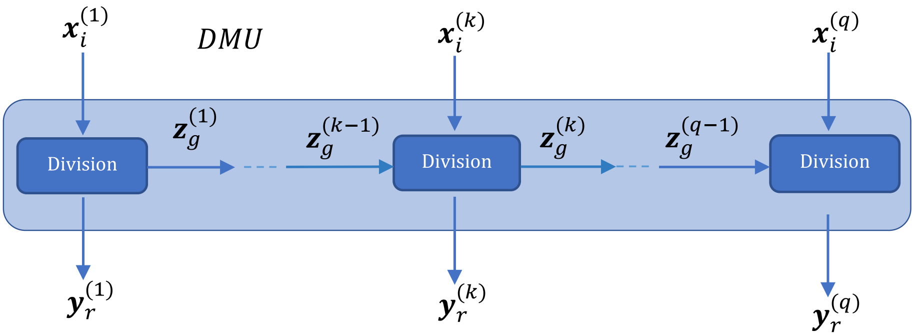

Fig. 1 General series network

For the general series network production systems with VRS assumption, the production technology set (Färe & Grosskopf, 2000) can be stated as follows:

$$\begin{aligned}T_{Network-VRS} = \{&(\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{y}) \in \mathbb{R}_{+}^{m^{(q)}+h^{(q)}+s^{(q)}} | \sum_{j=1}^{n} \lambda_j^{(k)} x_{ij}^{(k)} \leq x_i^{(k)}, \sum_{j=1}^{n} \lambda_j^{(k)} z_{gj}^{(k)} \geq z_g^{(k)},\\ &z_g^{(k)} \geq \sum_{j=1}^{n} \lambda_j^{(k+1)} z_{gj}^{(k)}, y_r^{(k)} \leq \sum_{j=1}^{n} \lambda_j^{(k)} y_{rj}^{(k)}, \sum_{j=1}^{n} \lambda_j^{(k)} = 1, \lambda_j^{(k)} \geq 0, j = 1, \ldots, n,\\ &k = 1, \ldots, q, i = m^{(k-1)} + 1, \ldots, m^{(k)}, r = s^{(k-1)} + 1, \ldots, s^{(k)}, g = h^{(k-1)} + 1, \ldots, h^{(k)}\}.\end{aligned} \tag{8}$$

Here, $\lambda_j^{(k)}$ variables are used to denote the intensity weights of DMU_j in division k.

Note that the transposed network technology set $T'_{Network-VRS}$ can also be defined as a similar extension of T'_{VRS} for the network series cases and can be extend to compute pessimistic efficiency scores.

DEA models in traditional structures assume that inputs and outputs data in production processes are non-negative real values. In spite of this, in many real situations this assumption can be true.

Without losing generality of the developed models and in order to address the real application, we assume the following different types of data in this study as follow:

- Non-integer (NI) and integer (I) inputs,
- Non-integer (NIO) and integer (IO) outputs,
- Deterministic (D) and stochastic (S) intermediates,
- Good (G) and bad (B) outputs,
- Absolute (A) and ration (R) positive outputs.

Thus, we consider the following decompositions of inputs, intermediate products and outputs index into mutually disjoint subsets:

$$Intermediaes = D \cup S$$

$$Outputs = NIO \cup IO$$

$$Outputs = G \cup B = G \cup (A \cup R)$$

Then we have intermediate and output vectors as follows:

$\boldsymbol{x} = \left(x^{I}, x^{NI}\right), \boldsymbol{z} = \left(z^{D}, z^{S}\right)$, $\boldsymbol{y} = \left(\boldsymbol{y}^{G}, \boldsymbol{y}^{B}\right)$, $\boldsymbol{y}^{B} = \left(\boldsymbol{y}^{IO}, \boldsymbol{y}^{NIO}\right)$ and $\boldsymbol{y}^{NIO} = \left(\boldsymbol{y}^{A}, \boldsymbol{y}^{R}\right)$.

For ease of presentation, it is assumed that all divisions follow a similar data structure. Developing this assumption for a variety of dissimilar data would be simple.

Mow, we provide our approaches for building alternative data structures:

i. The stochastic intermediate products $\tilde{z}_{g}^{S(k)}$ can be considered as random variables that follow a normal distribution. In the DEA framework, Charnes and Cooper's (1959) proposed chance-constrained programming (CCP) for dealing with stochastic and we use this approach in our modeling.
ii. To consider integer-valued outputs; i.e. $y^{I(k)} \in \mathbb{Z}_{+}^{|I|}$, we apply the approach proposed by Kuosmanen and Kazemi Matin (2009) and Kuosmanen et al. (2015).
iii. To address bad outputs, the weak disposability (WD) technique proposed by Shephard (1974) is applied in the current paper. Based on the WD axiom, $\left(\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{y}^{G}, \boldsymbol{y}^{B}\right) \in T$ implies that $\left(\boldsymbol{x}, \boldsymbol{z}, \alpha \boldsymbol{y}^{G}, \alpha \boldsymbol{y}^{B}\right) \in T$ for all $\alpha \in [0, 1]$. Kuosmanen (2005) and Kuosmanen and Kazemi Matin (2011) introduced and discussed the production technology set for satisfying the fundamental axioms, including weak disposability of good and bad outputs.
iv. To modeling undesirable ratio outputs $\boldsymbol{y}^{R}$, it should be noted that this type of data is unable to satisfy the conventional production assumptions. In the current article, we use the idea proposed by Oleson et al. (2015). Under VRS assumption and considering the axiom of selective (Podinovski, 2005) for the ratio outputs, the condition $\lambda_{j}^{(k)} y_{r}^{R(k)} \leq \lambda_{j}^{(k)} y_{rj}^{R(k)}$ is incorporated into the constraints of the VRS production technology set. That is for all ratio output items, the observed units applied in the convex combinations of volume inputs and outputs in constructing the production set are not allowed to operate worse than $y_{r}^{R(k)}$.

Employing these modellings, the production technology set in the presence of the above mentioned special data types, under VRS assumption can be presented as follows:

$$
\begin{aligned}
T_{Network-VRS}^{Sto-\ WD-Int-Ratio} = \Bigg\{ & \left(\left(\boldsymbol{x}^{I},\ \boldsymbol{x}^{NI}\right), \left(\boldsymbol{z}^{D},\ \tilde{\boldsymbol{z}}^{S}\right), \left(\boldsymbol{y}^{G}, \left(\boldsymbol{y}^{B,A},\ \boldsymbol{y}^{B,\ R},\ \boldsymbol{y}^{B,\ I}\right)\right)\right) | \sum_{j=1}^{n} \lambda_{j}^{(k)} x_{ij}^{(k)} \leq x_{i}^{(k)}, \\
& \sum_{j=1}^{n} \lambda_{j}^{(k)} z_{gj}^{D(k)} \geq z_{g}^{D(k)}, \quad \sum_{j=1}^{n} \lambda_{j}^{(k+1)} z_{gj}^{D(k)} \leq z_{g}^{D(k)}, \\
& \sum_{j=1}^{n} \lambda_{j}^{(k)} \tilde{z}_{gj}^{S(k)} \geq \tilde{z}_{g}^{S(k)}, \quad \sum_{j=1}^{n} \lambda_{j}^{(k+1)} \tilde{z}_{gj}^{S(k)} \leq \tilde{z}_{g}^{S(k)}, \quad y_{r}^{G(k)} \leq \sum_{j=1}^{n} \alpha_{j} \lambda_{j}^{(k)} y_{rj}^{G(k)}, \quad y_{r}^{B,\ A(k)} \\
& = \sum_{j=1}^{n} \alpha_{j} \lambda_{j}^{(k)} y_{rj}^{B,\ A(k)}, \quad \lambda_{j}^{(k)} y_{r}^{B,R(k)} \leq \lambda_{j}^{(k)} y_{rj}^{B,\ R(k)}, \quad y_{r}^{B,\ I(k)} \leq \sum_{j=1}^{n} \alpha_{j} \lambda_{j}^{(k)} y_{rj}^{B,\ I(k)} \quad \sum_{j=1}^{n} \lambda_{j}^{(k)} \\
& = 1, \quad y_{r}^{B,\ I(k)}, x_{i}^{I(k)} \in \mathbb{Z}_{+}, \quad \lambda_{j}^{(k)} \geq 0, \quad 0 \leq \alpha_{j} \leq 1, \quad \forall k,\ \forall i,\ \forall r,\ \forall g \Bigg\}.
\end{aligned}
$$

Using CCP technique for dealing with stochastic data, the production set can be stated as follows:

$$T_{Network-VRS}^{Sto-\ WD-Int-Ratio} = \left\{ \left(\left(\boldsymbol{x}^I,\ \boldsymbol{x}^{NI} \right), \left(\boldsymbol{z}^{\boldsymbol{D}},\ \tilde{\boldsymbol{z}}^{\boldsymbol{S}} \right), \left(\boldsymbol{y}^G, (\boldsymbol{y}^{B,A},\ \boldsymbol{y}^{B,\ R},\ \boldsymbol{y}^{B,\ IO} \right) \right) \mid \sum_{j=1}^{n} \lambda_j^{(k)} x_{ij}^{(k)} \leq x_i^{(k)}, \right.$$

$$\sum_{j=1}^{n} \lambda_j^{(k)} z_{gj}^{D(k)} \geq z_g^{D(k)}, \quad \sum_{j=1}^{n} \lambda_j^{(k+1)} z_{gj}^{D(k)} \leq z_g^{D(k)}, \Pr\left\{ \sum_{j=1}^{n} \lambda_j^{(k)} \tilde{z}_{gj}^{S(k)} \geq \tilde{z}_g^{S(k)} \right\}$$

$$\geq 1-\alpha, \quad \Pr\left\{ \sum_{j=1}^{n} \lambda_j^{(k+1)} \tilde{z}_{gj}^{S(k)} \leq \tilde{z}_g^{S(k)} \right\}$$

$$\geq 1-\alpha, \quad y_r^{G(k)} \leq \sum_{j=1}^{n} \alpha_j \lambda_j^{(k)} y_{rj}^{G(k)}, \ y_r^{B(k)}$$

$$= \sum_{j=1}^{n} \alpha_j \lambda_j^{(k)} y_{rj}^{B(k)}, \quad \lambda_j^{(k)} y_r^{B,R(k)} \leq \lambda_j^{(k)} y_{rj}^{B,\ \ R(k)}, \quad \sum_{j=1}^{n} \lambda_j^{(k)}$$

$$\left. = 1, \ y_r^{B,\ IO(k)}, x_i^{I(k)} \in \mathbb{Z}_+, \ \lambda_j^{(k)} \geq 0, \ 0 \leq \alpha_j \leq 1, \quad \forall k,\ \forall i,\ \forall r,\ \forall g \right\}.$$

Computational considerations in this paper are as follow:

(a) Given the normal distribution for the variables $\tilde{z}_{gj}^{S(k)}$, the probability constraint $Pr\left\{ \sum_{j=1}^{n} \lambda_j^{(k)} \tilde{z}_{gj}^{S(k)} \geq \tilde{z}_g^{S(k)} \right\} \geq 1-\alpha$ could be equivalently presented as $\sum_{j=1}^{n} \lambda_j^{(k)} \bar{z}_{gj}^{S(k)} + \Phi^{-1}(\alpha) u_g^{(k)} \geq z_g^{S(k)}$, with $\left(u_g^{(k)}\right)^2 = \sum_{j=1}^{n} \sum_{l=1}^{n} \lambda_j^{(k)} \lambda_l^{(k)} Cov\left(\tilde{z}_{gj}^{S(k)}, \tilde{z}_{gl}^{S(k)}\right) + Var\left(\tilde{z}_g^{S(k)}\right) - 2\sum_{j=1}^{n} \lambda_j^{(k)} Cov\left(\tilde{z}_{gj}^{S(k)}, \tilde{z}_g^{S(k)}\right)$, in which $E\left(\tilde{z}_{gj}^{S(k)}\right) = \bar{z}_{gj}^{S(k)}$ and $E\left(\tilde{z}_g^{S(k)}\right) = z_g^{S(k)}$ signify the expected values, Φ^{-1} is the inverse of cumulative distribution function (CDF) and $Var(.)$ and $Cov(.,.)$ are the variance and covariance operators.
Similarly, the stochastic inequality constraint $Pr\left\{ \sum_{j=1}^{n} \lambda_j^{(k+1)} \tilde{z}_{gj}^{S(k)} \leq \tilde{z}_g^{S(k)} \right\} \geq 1-\alpha$ can be ultimately transformed into $\sum_{j=1}^{n} \lambda_j^{(k+1)} \bar{z}_{gj}^{S(k)} - \Phi^{-1}(\alpha) u_g^{(k+1)} \leq z_g^{S(k)}$. See Cooper et al. (2002, 2004) for more details.

(b) In $T_{Network-VRS}^{Sto-WD-Int-Ratio}$, α_j is applied for showing the individual abatement factors concerning the WD axiom of bad outputs of DMU_j. Owing to the increase of abatement variables α_j and considering $\lambda_j^{(k)}$, the corresponding output constraints in $T_{Network-CRS}^{Sto-WD-Int-Ratio}$ are non-liner. To address that this, the following variable substitutions proposed by Kuosmanen (2005) is applied.

$\forall j, \forall k : \alpha_j \lambda_j^{(k)} = \delta_j^{(k)}, (1-\alpha_j)\lambda_j^{(k)} = \mu_j^{(k)}, \lambda_j^{(k)} = \delta_j^{(k)} + \mu_j^{(k)}.$

So, the production technology set with these different data structures, takes the following form:

$$T_{Network-VRS}^{Sto-WD-Int-Ratio} = \{ \left(\left(\boldsymbol{x}^I, \boldsymbol{x}^{NI} \right), \left(\boldsymbol{z}^{\boldsymbol{D}}, \boldsymbol{z}^{S} \right), \left(\boldsymbol{y}^G, (\boldsymbol{y}^{B,A}, \boldsymbol{y}^{B,R}, \boldsymbol{y}^{B,IO})) \right) \mid$$

$$\sum_{j=1}^{n} \left(\delta_j^{(k)} + \mu_j^{(k)} \right) x_{ij}^{(k)} \leq x_i^{(k)},$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)z_{gj}^{D(k)} \geq z_g^{D(k)}, \sum_{j=1}^{n}\left(\delta_j^{(k+1)}+\mu_j^{(k+1)}\right)z_{gj}^{D(k)} \leq z_g^{D(k)},$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)\overline{z}_{gj}^{S(k)} + \Phi^{-1}(\alpha)u_g^{(k)}$$

$$\geq z_g^{S(k)}, \sum_{j=1}^{n}\left(\delta_j^{(k+1)}+\mu_j^{(k+1)}\right)\overline{z}_{gj}^{S(k)} - \Phi^{-1}(\alpha)u_g^{(k+1)} \leq z_g^{S(k)},$$

$$\left(u_g^{(k)}\right)^2 = \sum_{j=1}^{n}\sum_{l=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)\left(\delta_l^{(k)}+\mu_l^{(k)}\right)Cov\left(\tilde{z}_{gj}^{S(k)}, \tilde{z}_{gl}^{S(k)}\right)$$

$$+ Var\left(\tilde{z}_g^{S(k)}\right) - 2\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)Cov\left(\tilde{z}_{gj}^{S(k)}, \tilde{z}_g^{S(k)}\right), y_r^{G(k)} \leq \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{G(k)},$$

$$y_r^{B,A(k)} = \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{B,A(k)}, \left(\delta_j^{(k)}+\mu_j^{(k)}\right)y_r^{B,R(k)} \leq \left(\delta_j^{(k)}+\mu_j^{(k)}\right)y_{rj}^{B,R(k)},$$

$$y_r^{B,I(k)} = \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{B,I(k)}, y_r^{B,IO(k)}, x_i^{I(k)} \in \mathbb{Z}_+,$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right) = 1, \delta_j^{(k)} \geq 0, \mu_j^{(k)} \geq 0, \forall k, \forall i, \forall r, \forall g\} \tag{9}$$

Note that the transposed technology set $T\prime_{Network-VRS}^{Sto-\ WD-Int-Ratio}$, follows a similar structure only with changing the role of inputs and outputs together.

Now we present double frontier efficiency evaluation in network DEA model with different type of data. In this paper, for overall performance evaluation of observed network production units, a weighted Farrell type efficiency score of the related subunits is suggested for both optimistic and pessimistic case. The two different scores for optimistic and pessimistic cases are then aggregated into a unified score for full rank of the observed DMUs.

To get the optimistic overall efficiency score of DMU_o concerning the other network production units in $T_{Network-VRS}^{Sto-WD-Int-Ratio}$ is suggested as follow:

$$Eff_o^N(Optimistic) = \min_{\theta,\delta,\mu,\overline{y}}\sum_{k=1}^{q}w^{(k)}\theta_o^{(k)} \qquad \text{(Model (1))}$$

$$Subject\ to$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)x_{ij}^{NI(k)} \leq \theta_o^{(k)}x_{io}^{NI(k)}, \forall i \in NI$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)x_{ij}^{I(k)} \leq \overline{x}_i^{(k)} \leq \theta_o^{(k)}x_{io}^{I(k)}, \quad \forall i \in I$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)z_{gj}^{D(k)} \geq z_{go}^{D(k)}, \forall g \in D$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)z_{gj}^{D(k)} \geq z_{go}^{D(k)}, \forall g \in D$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k+1)}+\mu_j^{(k+1)}\right)z_{gj}^{D(k)} \leq z_{go}^{D(k)}, \forall g \in D$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)\overline{z}_{gj}^{S(k)} + \Phi^{-1}(\alpha)u_g^{(k)} \geq z_{go}^{S(k)}, \quad \forall g \in S$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k+1)}+\mu_j^{(k+1)}\right)\overline{z}_{gj}^{S(k)} - \Phi^{-1}(\alpha)u_g^{(k+1)} \leq z_{go}^{S(k)}, \qquad \forall g \in S$$

$$\left(u_g^{(t)}\right)^2 = \sum_{j=1}^{n}\sum_{l=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)\left(\delta_l^{(k)}+\mu_l^{(k)}\right)Cov\left(\tilde{z}_{gj}^{S(k)}, \tilde{z}_{gl}^{S(k)}\right) + Var\left(\tilde{z}_g^{S(k)}\right)$$

$$-2\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)Cov\left(\tilde{z}_{gj}^{S(k)}, \tilde{z}_{gl}^{S(k)}\right), t \in \{k, k+1\}, \quad \forall g \in S$$

$$y_{ro}^{G(k)} \leq \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{G(k)}, \forall r \in G$$

$$y_{ro}^{B,A(k)} = \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{B,A(k)}, \forall r \in B \cap A$$

$$\left(\delta_j^{(k)}+\mu_j^{(k)}\right)y_{ro}^{B,R(k)} \leq \left(\delta_j^{(k)}+\mu_j^{(k)}\right)y_{rj}^{B,R(k)}, \forall r \in B \cap R$$

$$y_{ro}^{B,I(k)} = \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{B,I(k)}, \forall r \in B \cap I$$

$$\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right) = 1,$$

$$\overline{x}_i^{(k)} \in \mathbb{Z}_+, 0 \leq \theta_o^{(k)} \leq 1, \delta_j^{(k)} \geq 0, \mu_j^{(k)} \geq 0, \forall i \in I, \forall k, \forall j.$$

Here, DMU_o is the under evaluation unit and $\theta_o^{(k)}$ $(k = 1, \ldots, q)$ are efficiency variables associated with individual divisions. Also, $\sum_{k=1}^{q} w^{(k)} = 1$ that $w^{(k)}$ $(k = 1, \ldots, q)$ are pre-defined positive weights related to divisions used to combine division efficiencies into one composite optimistic score $E_o^N(Optimistic)$. Note that these weights are also used for the decision-makers to determine relative importance of each individual division.

In addition, the pessimistic efficiency score of DMU_o relative to other units in the transposed technology set $T\prime_{Network-VRS}^{Sto-\ WD-Int-Ratio}$ is suggested to be evaluated by the following maximization model.

$$Eff_o^N(Pessimistic) = \max_{\varphi,\delta,\ \mu,\ \bar{y}} \sum_{k=1}^{q} w'^{(k)}\varphi_o^{(k)} \qquad \text{(Model (2))}$$

$$
\begin{aligned}
& Subject\,to \\
& \sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)x_{ij}^{NI(k)} \geq \varphi_o^{(k)}x_{io}^{NI(k)}, \forall i \in NI \\
& \sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)x_{ij}^{I(k)} \geq \overline{x}_i^{(k)} \geq \varphi_o^{(k)}x_{io}^{I(k)}, \quad \forall i \in I \\
& \sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)z_{gj}^{D(k)} \leq z_{go}^{D(k)}, \forall g \in D \\
& \sum_{j=1}^{n}\left(\delta_j^{(k+1)}+\mu_j^{(k+1)}\right)z_{gj}^{D(k)} \geq z_{go}^{D(k)}, \forall g \in D \\
& \sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)\overline{z}_{gj}^{S(k)} - \Phi^{-1}(\alpha)u_g^{(k)} \leq z_{go}^{S(k)}, \quad \forall g \in S \\
& \sum_{j=1}^{n}\left(\delta_j^{(k+1)}+\mu_j^{(k+1)}\right)\overline{z}_{gj}^{S(k)} + \Phi^{-1}(\alpha)u_g^{(k+1)} \geq z_{go}^{S(k)}, \qquad \forall g \in S \\
& \left(u_g^{(t)}\right)^2 = \sum_{j=1}^{n}\sum_{l=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)\left(\delta_l^{(k)}+\mu_l^{(k)}\right)Cov\left(\tilde{z}_{gj}^{S(k)},\tilde{z}_{gl}^{S(k)}\right) + Var\left(\tilde{z}_g^{S(k)}\right) \\
& -2\sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right)Cov\left(\tilde{z}_{gj}^{S(k)},\tilde{z}_{gl}^{S(k)}\right), t \in \{k, k+1\}, \quad \forall g \in S \\
& y_{ro}^{G(k)} \geq \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{G(k)}, \forall r \in G \\
& y_{ro}^{B,A(k)} = \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{B,A(k)}, \forall r \in B \cap A \\
& \left(\delta_j^{(k)}+\mu_j^{(k)}\right)y_{ro}^{B,R(k)} \geq \left(\delta_j^{(k)}+\mu_j^{(k)}\right)y_{rj}^{B,R(k)}, \forall r \in B \cap R \\
& y_{ro}^{B,I(k)} = \sum_{j=1}^{n}\delta_j^{(k)}y_{rj}^{B,I(k)}, \forall r \in B \cap I \\
& \sum_{j=1}^{n}\left(\delta_j^{(k)}+\mu_j^{(k)}\right) = 1, \\
& \overline{x}_i^{(k)} \in \mathbb{Z}_{+}, 1 \leq \varphi_o^{(k)}, \delta_j^{(k)} \geq 0, \mu_j^{(k)} \geq 0, \forall i \in I, \forall k, \forall j.
\end{aligned}
$$

Here, $\varphi_o^{(k)}$ $(k = 1, \ldots, q)$ are decision variables associated with individual divisions and $\sum_{k=1}^{q} w'^{(k)} = 1$, where $w'^{(k)}$ $(k = 1, \ldots, q)$ are predefined positive weights related to divisions used to combine division scores into one composite pessimistic score $E_o^N(Pessimistic)$.

Remark 1 In these optimization models, new integer variables $\overline{x}_i^{(k)}$ are applied for precluding real objectives for integer-valued inputs, as such a subset of variables are limited to integer values.

Remark 2 If we assume that intermediate products among different production units are independent, then $Cov\left(\tilde{z}_{gj}^{S(k)}, \tilde{z}_{gl}^{S(k)}\right) = 0$ for $j \neq l$. This independence assumption leads to the following relation: $\left(u_g^{(t)}\right)^2 = \sum_{j=1}^{n}\left(\delta_j^{(t)} + \mu_j^{(t)}\right)^2 Var\left(\tilde{z}_{gj}^{S(t)}\right) + \left(1 - 2\left(\delta_o^{(t)} + \mu_o^{(t)}\right)\right) Var\left(\tilde{z}_{go}^{S(t)}\right)$.

Theorem 1 *Model* (1) *and Model* (2) *are always feasible and bounded*.

Proof Since for all k, $0 \leq w^{(k)} \leq 1$ and $0 \leq \theta_o^{(k)} \leq 1$, then the objective value of Model (1) is always bounded. To show the feasibility of this model, let $\theta_o^{(k)} = 1$ $\delta_o^{(k)} = \delta_o^{(k+1)} = 1$, $\delta_j^{(k)} = \delta_o^{(k+1)} = 0(\forall k, \forall j \neq o)$, and also $\mu_j^{(k)} = \mu_j^{(k+1)} = 0(\forall k \forall j)$. Furthermore, let $\overline{x_i}^{(k)} = x_{io}^{I(k)}(\forall i \in I)$. The values can address the constraints of model (1). including $\left(u_g^{(t)}\right)^2 = \left(\delta_o^{(t)} + \mu_o^{(t)}\right)^2 Var\left(\tilde{z}_{go}^{S(t)}\right) + Var\left(\tilde{z}_{go}^{S(t)}\right) - 2\left(\delta_o^{(t)} + \mu_o^{(t)}\right) Var\left(\tilde{z}_{go}^{S(t)}\right) = Var\left(\tilde{z}_{go}^{S(t)}\right) + Var\left(\tilde{z}_{go}^{S(t)}\right) - 2Var\left(\tilde{z}_{go}^{S(t)}\right) = 0$. This completes the proof for Model (1). The same proof can be for Model (2).

The new introduced composite optimistic and pessimistic efficiencies are measured relative to different technology sets, leads to different rankings for network production units. We note that the provided rank orders for two different views may be different because at optimistic case, units are evaluated relative to efficient frontier of the production set, while at pessimistic case, inefficient frontier is used in the evaluation. It is clear that any assessment results and ranking criteria addresses only one of these perspectives which is unrealistic.

An overall performance score is thus needed to provide an overall ranking for the observed network DMUs with different data structure. As Wang et al. (2007) suggested at optimality, the following geometric average efficiency (GAEff) of the two optimistic and pessimistic measures are used to aggregate and compute the overall and divisional performance measure of DMU_o:

$$GAEff_o^N(Overall) = \sqrt{\left(\sum_{k=1}^{q} w^{(k)}\theta_o^{*(k)}\right)\left(\sum_{k=1}^{q} w'^{(k)}\varphi_o^{*(k)}\right)} \tag{10}$$

$$GAEff_o^N(Divisionk) = \sqrt{\theta_o^{*(k)}\varphi_o^{*(k)}} \tag{11}$$

Remark 3 The new proposed double-frontier overall and divisional efficiency scores satisfy the following useful properties. Their proofs are straightforward.

P1 $GAEff_o^N(Overall)$ and $GAEff_o^N(Divisionk)(k = 1, \ldots, p)$ are monotonic in inputs.

P2 $GAEff_o^N(Overall)$ and $GAEff_o^N(Divisionk)(k = 1, \ldots, p)$ are unit invariant.

4 Empirical study

In this section we provide an empirical study for illustrating and validating our developed model. Owing to increasing population growth rate, economic growth rate and living standards over the last two decades, Iran has become one of the largest producers and consumers of industrial and building paints and coatings in Asia. The existence of huge oil reserves

Table 1 The factors applied to assess sustainably resilient SCs

Stages	Variables	Variables type	Variable type	Notation	Sustainable-resilient aspects	Measurement unit
Supplier	Material cost (Sueyoshi and Wang (2014)	Input	Real	$x_1^{(1)}$	Economic	Rial
	Staff cost (Sueyoshi and Wang (2014)	Input	Real	$x_2^{(1)}$	Economic	Rial
	Cost of safety and healthcare (Azadi et al., 2015)	Input	Real	$x_3^{(1)}$	Social	Rial
	CO_2 emission (Wang et al., 2013)	Output	Undesirable	$y_1^{B,A(1)}$	Environmental	Ton
	The quantity of material (Sueyoshi and Wang (2014)	Intermediate	Real	$z_1^{(1)}$	Economic	Ton
	Average inventory (Ramezankhani et al., 2018)	Intermediate	Stochastic	$\tilde{z}_2^{(1)}$	Resilience	Day
Manufacture	Transportation costs (Tajbakhsh and Hassini (2015)	Input	Real	$x_1^{(2)}$	Economic	Rial
	IT budget (Wu et al., 2016)	Input	Real	$x_2^{(2)}$	Economic	Rial
	The number of received warnings (Kuo et al., 2010)	Output	Integer/undesirable	$y_1^{B,I(2)}$	Social	Number

Table 1 (continued)

Stages	Variables	Variables type	Variable type	Notation	Sustainable-resilient aspects	Measurement unit
	The rate of inferior fabricated products (Kong et al., 2021)	Output	Ratio/undesirable	$y_2^{B,R(2)}$	Environmental	Ton
	The quantity of fabricated products (Kong et al., 2021)	Intermediate	Real	$z_2^{(2)}$	Economic	Ton
Distributor	The number of personnel (Tavassoli et al., 2021)	Input	Integer	$x_1^{I(3)}$	Economic	Person
	Annual sale (Samavati et al., 2020)	Output	Real	$y_1^{(3)}$	Economic	Ton
	Annual income (Samavati et al., 2020)	Output	Real	$y_2^{(3)}$	Economic	Rial

is the main reason of highly competitive paint and coating market in Iran and the region. Projected roughly $560 million in March 2020, this market has been dominated by internal manufacturers. In this case, we assess sustainably resilient SCs of 18 paint and coating producers in Iran using the proposed network DEA model. The SCs of our case comprise three stages: suppliers, manufacturers and distributors as stage 1, stage 2 and stage 3, respectively. In supplier stage we have three inputs including material cost, staff cost and cost of safety and healthcare. To consider NetZero (falling CO2 emissions to zero value) we propose CO_2 emissions as the undesirable output of stage 1. The quantity of material and the quantity of material are intermediate variables between stages 1 and 2. Transportation cost are IT budget are inputs of manufacturers stage and the number of received warnings and the rate of inferior fabricated products are the outputs of this stage. The quantity of fabricated products is intermediate variable between stages 2 and 3. The number of personnel is input of distributor stage and annual sale and annual income are outputs of this stage. Table 1 summarizes the factors used to assess sustainably resilient SCs in this paper. Tables 2, 3 and 4 provide the data set of the case study.

Table 2 The data set associated with stage 1

Number of Supply chain	DMUs	Stage 1					
		Inputs		Output		Intermediates	
		Material cost (1,000,000 Rial)	Staff cost (100,000 Rial)	Cost of safety and healthcare (100, 000 Rial)	CO_2 emissions (100,000 Ton)	The quantity of material (Ton)	Average inventory (Day) Mean, Variance
1	Sayan	515,470	15,120	7300	124	4703	8.5, 3.25
2	Hermes	383,410	11,780	9500	91	3419	8, 2
3	Rangvareh	452,530	14,380	6800	121	4245	7.75, 2.74
4	Bajak	685,790	24,190	6125	169	6301	7.75, 2.74
5	Azin	429,710	13,270	4700	113.5	4193	6.375, 1.60
6	Hana Rang	254,150	85,240	3550	74	2297	8, 2
7	Hermes Fam	538,620	17,190	7184	139.2	4875	6.625, 1.42
8	Azin Rang	551,780	18,390	9260	151	5019	8.75, 2.18
9	Serv Rang	397,100	11,190	5730	103	3597	8, 1.5
10	Rangin	217,580	71,530	7520	71	1973	6.5, 2.07
11	Marron	485,700	17,950	4300	139	4384	8.5. 3.25
12	Asan Rang	441,600	15,720	6180	125	3997	8.75, 2.18
13	Shabrang	567,800	19,720	9300	147	5124	7.5, 0.75
14	Soor	234,600	88,370	8480	83	2109	7, 1.5
15	Takrang	519,200	17,210	3520	130.4	4971	9, 0.5
16	Gita Asa	352,400	10,180	4100	89	3295	6.5, 2.25
17	Pars	547,100	20,750	5700	141.5	5064	8, 2.5
18	Arovin	4,103,00	10,930	3490	117	3801	6.375, 1.60

Table 3 The data set associated with stage 2

Number of Supply chain	DMUs	Stage 2				
		Inputs		Outputs		Intermediate
		Transportation cost (10,000 Rial)	IT budget (10,000 Rial)	The number of received warnings	The rate of inferior fabricated products	The quantity of fabricated products (Ton)
1	Sayan	306,718	198,423	5	0.004	4679
2	Hermes	210,653	112,390	3	0.007	3387
3	Rangvareh	287,124	207,170	5	0.005	4201
4	Bajak	334,908	265,410	7	0.005	6243
5	Azin	219,781	157,610	4	0.003	4167
6	Hana Rang	160,770	91,250	8	0.008	2278
7	Hermes Fam	315,420	194,514	7	0.005	4837
8	Azin Rang	337,194	249,140	5	0.004	4972
9	Serv Rang	231,720	157,250	5	0.006	3564
10	Rangin	145,360	87,370	8	0.009	1904
11	Marron	301,780	246,100	6	0.006	4341
12	Asan Rang	263,170	193,500	7	0.005	3957
13	Shabrang	374,950	272,160	5	0.007	5018
14	Soor	151,300	101,183	4	0.007	2013
15	Takrang	349,100	291,590	5	0.003	4948
16	Gita Asa	157,790	117,830	7	0.005	3269
17	Pars	371,800	278,100	7	0.007	4991
18	Arovin	245,400	181,500	6	0.004	3768

Table 4 The data set associated with stage 3

Number of supply chain	DMUs	Stage 3		
		Input	Outputs	
		The number of personnel	Annual sale (Ton)	Annual income (100,000 Rial)
1	Sayan	15	4517	6,014,200
2	Hermes	9	3301	4,485,145
3	Rangvareh	12	4195	5,593,129
4	Bajak	19	6205	8,315,590
5	Azin	10	4158	5,728,000

Table 4 (continued)

Number of supply chain	DMUs	Stage 3		
		Input	Outputs	
		The number of personnel	Annual sale (Ton)	Annual income (100,000 Rial)
6	Hana Rang	7	2217	2,814,720
7	Hermes Fam	13	4837	6,375,100
8	Azin Rang	15	4961	6,605,240
9	Serv Rang	10	3564	5,057,470
10	Rangin	7	1817	2,275,000
11	Marron	11	4301	5,751,260
12	Asan Rang	9	3915	5,382,000
13	Shabrang	14	4978	6,745,000
14	Soor	8	2013	2,617,000
15	Takrang	13	4895	6,738,000
16	Gita Asa	10	3175	4,309,000
17	Pars	14	4997	6,527,000
18	Arovin	12	3753	4,817,100

The following optimistic and pessimistic models have been customized based on Model (1) and Model (2) for the presented case study. Here, DMU_o is considered as the under evaluation unit. It is also assumed that intermediate stochastic variables are independent.

Optimistic evaluation	Pessimistic evaluation
$\min_{\theta,\delta,\mu,\overline{y}} w^{(1)}\theta_o^{(1)} + w^{(2)}\theta_o^{(2)} + w^{(3)}\theta_o^{(3)}$	$\max_{\varphi,\delta,\ \mu,\ \bar{y}} \ w'^{(1)}\varphi^{(1)} + w'^{(2)}\varphi^{(2)} + w'^{(3)}\varphi^{(3)}$
Subject to	Subject to
$\sum_{j=1}^{18}\left(\delta_j^{(1)} + \mu_j^{(1)}\right)x_{ij}^{NI(1)} \le \theta_o^{(1)}x_{io}^{NI(1)}, i = 1, 2, 3,$	$\sum_{j=1}^{18}\left(\delta_j^{(1)} + \mu_j^{(1)}\right)x_{ij}^{NI(1)} \ge \varphi_o^{(1)}x_{io}^{NI(1)}, i = 1, 2, 3,$
$\sum_{j=1}^{18}\left(\delta_j^{(1)} + \mu_j^{(1)}\right)z_{1j}^{D(1)} \ge z_{1o}^{D(1)},$	$\sum_{j=1}^{18}\left(\delta_j^{(1)} + \mu_j^{(1)}\right)z_{1j}^{D(1)} \le z_{1o}^{D(1)},$
$\sum_{j=1}^{18}\left(\delta_j^{(2)} + \mu_j^{(2)}\right)z_{1j}^{D(1)} \le z_{1o}^{D(1)},$	$\sum_{j=1}^{18}\left(\delta_j^{(2)} + \mu_j^{(2)}\right)z_{1j}^{D(1)} \ge z_{1o}^{D(1)},$
$\sum_{j=1}^{18}\left(\delta_j^{(1)} + \mu_j^{(1)}\right)\overline{z}_{2j}^{S(1)} + \Phi^{-1}(\alpha)u_2^{(1)} \ge z_{2o}^{S(1)},$	$\sum_{j=1}^{18}\left(\delta_j^{(1)} + \mu_j^{(1)}\right)\overline{z}_{2j}^{S(1)} - \Phi^{-1}(\alpha)u_2^{(1)} \le z_{2o}^{S(1)},$
$\sum_{j=1}^{18}\left(\delta_j^{(2)} + \mu_j^{(2)}\right)\overline{z}_{2j}^{S(1)} - \Phi^{-1}(\alpha)u_2^{(2)} \le z_{2o}^{S(1)},$	$\sum_{j=1}^{18}\left(\delta_j^{(2)} + \mu_j^{(2)}\right)\overline{z}_{2j}^{S(1)} + \Phi^{-1}(\alpha)u_2^{(2)} \ge z_{2o}^{S(1)},$
$\left(u_2^{(t)}\right)^2 = \sum_{j=1}^{18}\left(\delta_j^{(t)} + \mu_j^{(t)}\right)^2 Var\left(\tilde{z}_{2j}^{S(t)}\right) + \left(1 - 2\left(\delta_o^{(t)} + \mu_o^{(t)}\right)\right)Var\left(\tilde{z}_{2o}^{S(1)}\right),$ $t \in \{1, 2\}$	$\left(u_2^{(t)}\right)^2 = \sum_{j=1}^{18}\left(\delta_j^{(t)} + \mu_j^{(t)}\right)^2 Var\left(\tilde{z}_{2j}^{S(t)}\right) +$ $\left(1 - 2\left(\delta_o^{(t)} + \mu_o^{(t)}\right)\right)Var\left(\tilde{z}_{2o}^{S(t)}\right), t \in \{1, 2\}$
$y_{1o}^{B,A(1)} = \sum_{j=1}^{n}\delta_j^{(1)}y_{1j}^{B,A(1)},$	$y_{1o}^{B,A(1)} = \sum_{j=1}^{n}\delta_j^{(1)}y_{1j}^{B,A(1)},$
$\sum_{j=1}^{18}\left(\delta_j^{(2)} + \mu_j^{(2)}\right)x_{ij}^{NI(2)} \le \theta_o^{(2)}x_{io}^{NI(2)}, i = 1, 2,$	$\sum_{j=1}^{18}\left(\delta_j^{(2)} + \mu_j^{(2)}\right)x_{ij}^{NI(2)} \ge \varphi_o^{(2)}x_{io}^{NI(2)}, i = 1, 2,$

Optimistic evaluation	Pessimistic evaluation
$\sum_{j=1}^{n}\left(\delta_j^{(2)}+\mu_j^{(2)}\right)z_{2j}^{D(2)} \geq z_{2o}^{D(2)}$,	$\sum_{j=1}^{n}\left(\delta_j^{(2)}+\mu_j^{(2)}\right)z_{2j}^{D(2)} \leq z_{2o}^{D(2)}$,
$\sum_{j=1}^{n}\left(\delta_j^{(3)}+\mu_j^{(3)}\right)z_{2j}^{D(2)} \leq z_{2o}^{D(2)}$,	$\sum_{j=1}^{n}\left(\delta_j^{(3)}+\mu_j^{(3)}\right)z_{2j}^{D(2)} \geq z_{2o}^{D(2)}$,
$y_{1o}^{B,I(2)} = \sum_{j=1}^{18}\delta_j^{(k)}y_{1j}^{B,I(2)}$,	$y_{1o}^{B,I(2)} = \sum_{j=1}^{18}\delta_j^{(k)}y_{1j}^{B,I(2)}$,
$\left(\delta_j^{(2)}+\mu_j^{(2)}\right)y_{2o}^{B,R(2)} \leq \left(\delta_j^{(2)}+\mu_j^{(2)}\right)y_{2j}^{B,R(2)}$, $j=1,\ldots,18$,	$\left(\delta_j^{(2)}+\mu_j^{(2)}\right)y_{2o}^{B,R(2)} \geq \left(\delta_j^{(2)}+\mu_j^{(2)}\right)y_{2j}^{B,R(2)}$, $j=1,\ldots,18$,
$\sum_{j=1}^{18}\lambda_j^{(3)}x_{1j}^{I(k)} \leq \overline{x}_3^{(3)} \leq \theta_o^{(3)}x_{1o}^{I(3)}$,	$\sum_{j=1}^{18}\lambda_j^{(3)}x_{1j}^{I(k)} \geq \overline{x}_3^{(3)} \geq \varphi_o^{(3)}x_{1o}^{I(3)}$,
$y_{ro}^{G(3)} \leq \sum_{j=1}^{n}\lambda_j^{(3)}y_{rj}^{G(3)}, r=1,2$	$y_{ro}^{G(3)} \geq \sum_{j=1}^{n}\lambda_j^{(3)}y_{rj}^{G(3)}, r=1,2$
$\sum_{j=1}^{18}\left(\delta_j^{(1)}+\mu_j^{(1)}\right)=1, \sum_{j=1}^{18}\left(\delta_j^{(2)}+\mu_j^{(2)}\right)=1$,	$\sum_{j=1}^{18}\left(\delta_j^{(1)}+\mu_j^{(1)}\right)=1, \sum_{j=1}^{18}\left(\delta_j^{(2)}+\mu_j^{(2)}\right)=1$,
$\sum_{j=1}^{18}\lambda_j^{(3)}=1$,	$\sum_{j=1}^{18}\lambda_j^{(3)}=1$,
$\overline{x}_3^{(3)} \in \mathbb{Z}_+, 0 \leq \theta_o^{(1)}, \theta_o^{(2)}, \theta_o^{(3)} \leq 1, \delta_j^{(1)}, \delta_j^{(2)} \geq 0, \mu_j^{(1)}, \mu_j^{(2)}, \lambda_j^{(3)} \geq 0, j = 1,\ldots,18.$	$\overline{x}_3^{(3)} \in \mathbb{Z}_+, 1 \leq \varphi_o^{(1)}, \varphi_o^{(2)}, \varphi_o^{(3)}, \delta_j^{(1)}, \delta_j^{(2)} \geq 0, \mu_j^{(1)}, \mu_j^{(2)}, \lambda_j^{(3)} \geq 0, j = 1,\ldots,18.$

4.1 Results and discussions

"In the case study*, *we applied two customized optimistic and pessimistic models considering dissimilar data such as integer and real valued inputs and outputs, good and bad outputs, stochastic intermediate products and the hybrid data". To compute the efficiency scores, we used Lingo 18.0 software on an Intel CORE i5 processor. Tables 5, 6, 7, 8 and 9 present the efficiency scores of sustainably resilient SCs of 18 paint and coating producers with $\alpha = 0.001, 0.01, 0.05, 0.1$ and 0.3, respectively. The tables show divisional and overall efficiency scores for three stages using the proposed optimistic and pessimistic models. As it is seen, Rangin company is the most efficient DMU with overall efficiency 1.414 when we apply $\alpha = 0.001$. Moreover, while the most efficient DMU with $\alpha = 0.01, 0.05$ and 0.1 is Asan Rang company, when we apply $\alpha = 0.3$ Hermes company becomes the most efficient unit with efficiency scores 1.06863. Arovin has the worse performance with efficiency score 0.962 among 18 paint and coating producers with $\alpha = 0.001, 0.01, 0.05, 0.1$ and 0.3. A closer look at results shows that when we apply optimistic models with α different levels, the majority of DMUs are efficient. However, when we apply pessimistic models less DMUs become efficient. Based on the geometric average efficiency results for $\alpha \in \{0.001, 0.01, 0.05\}$, the unique raking of 18 paint and coating producers are as follows:

$$
\begin{aligned}
DMU_{12} &\succ DMU_2 \succ DMU_5 \succ DMU_{11} \succ DMU_{15} \succ DMU_7 \succ DMU_6 \\
&\succ DMU_{13} \succ DMU_3 \succ DMU_9 \succ DMU_{17} \succ DMU_{16} \succ DMU_{10} \\
&\sim DMU_4 \succ DMU_8 \succ DMU_{14} \succ DMU_1 \succ DMU_{18}
\end{aligned}
$$

Here, the symbol $\succ$ means "superior to" and the symbol $\sim$ represents "indifference". Comparing efficiency scores with $\alpha = 0.1$ and $\alpha - 0.3$ demonstrates the ranking of DMUs has changed significantly when we compute geometric average efficiency. This means that when α level changes considerably, it may influence the performance of DMUs. Another important finding of the current study shows all DMUs are efficient at stage 2 with $\alpha = 0.001, 0.01, 0.05, 0.1$ when we apply the optimistic models. Nevertheless, companies of Rangvareh, Serv Rang and Asan Rang are not efficient at stage 2 with $\alpha = 0.3$ using the optimistic models. Furthermore, results show that our proposed optimistic and pessimistic models provide decision-makers with a complete rank of DMUs.

4.2 Managerial implications

The stochastic double frontier analytic model developed in the current article can assist practitioners in several ways. Given unexpected situations such as disasters the performance of SCs can be very vulnerable. Mangers and decision makers of SCs should be able to manage these situations and reduce stochastic risks in order to benefit from a resilient performance. As such, our proposed model is an appropriate tool for evaluating performance of SCs under uncertain environment and mitigating stochastic risks. We used CCP in our proposed model to address uncertainty for assessing sustainably resilient supply chains. In this case, uncertainty was analyzed by using different values of Alpha. As can be seen in the results tables, the performance of sustainably resilient supply chains can be changed by changing Alpha values. Furthermore, managers and decision makers are interested in considering three sustainability dimensions including economic, ecological and social in assessing their SCs. The model presented in this paper take these dimensions into account and satisfy different stockholders' needs aimed at sustainable development. The developed model not only provides managers and decision makers with divisional assessment but also overall assessment. This in turn

Table 5 The efficiency scores with Alpha 0.001

Alpha = 0.001														Ranking
No of SC	DMUs	Optimistic Efficiency				Pessimistic Efficiency				Geometric Average Efficiency				
		Eff1	Eff2	Eff3	Eff (Overall)	Eff1	Eff2	Eff3	Eff (Overall)	Eff1	Eff2	Eff3	Eff (Overall)	
1	Sayan	0.99	1	0.93	0.93	1.01	1.06	1	1.02	0.99	1.02	0.96	0.97	16
2	Hermes	1	1	1	1	1	1.2	1.22	1.14	1	1.09	1.1	1.06	2
3	Rangvareh	0.99	0.99	0.911	0.97	1.04	1	1.16	1.07	1.01	0.99	1.02	1.01	8
4	Bajak	1	1	1	1	1	1	1	1	1	1	1	1	13
5	Azin	1	1	1	1	1.08	1	1.3	1.12	1.03	1	1.14	1.05	4
6	Hana Rang	1	1	1	1	1.007	1	1.14	1.04	1.003	1	1.06	1.01	8
7	Hermes fam	1	1	1	1	1	1	1.15	1.05	1	1	1.07	1.02	7
8	Azin Rang	1	1	0.93	0.97	1	1	1.06	1.02	1	1	0.99	0.99	14
9	Serv Rang	1	1	0.9	0.96	1.01	1	1.2	1.07	1.004	1	1.03	1.01	8
10	Rangin	1	1	1	1	1	1	1	2	1	1	1	1.41	1
11	Marron	1	1	1	1	1	1	1.27	1.09	1	1	1.12	1.04	5
12	Asan Rang	1	0.99	1	1	1.004	1	1.44	1.14	1	0.99	1.2	1.06	2
13	Shabrang	1	1	1	1	1	1	1.14	1.04	1	1	1.06	1.01	8
14	Soor	1	0.99	0.87	0.95	1	1	1	1	1	0.99	0.93	0.97	16
15	Takrang	1	1	1	1	1.06	1	1.15	1.07	1.02	1	1.07	1.03	6
16	Giti Asa	1	1	0.9	0.96	1.04	1	1	1.04	1.01	1	0.94	0.99	14
17	Pars	1	1	1	1	1.02	1	1.07	1.03	1.009	1	1.03	1.01	8
18	Arovin	1	1	0.75	0.91	1.03	1	1	1.01	1.01	1	0.86	0.95	18

Table 6 The efficiency scores with Alpha 0.01

Alpha = 0.01														
No of SC	DMUs	Optimistic efficiency				Pessimistic efficiency				Geometric average efficiency				Ranking
		Eff1	Eff2	Eff3	Eff(Overall)	Eff1	Eff2	Eff3	Eff(Overall)	Eff1	Eff2	Eff3	Eff(Overall)	
1	Sayan	0.99	1	0.8	0.93	1.01	1.06	1	1.02	1.006	1.03	0.89	0.977	17
2	Hermes	1	1	1	1	1	1.2	1.22	1.14	1	1.09	1.1	1.0686	2
3	Rangvareh	1	1	0.91	0.97	1.04	1	1.16	1.07	1.02	1	1.03	1.02	9
4	Bajak	1	1	1	1	1	1	1	1	1	1	1	1	13
5	Azin	1	1	1	1	1.08	1	1.3	1.12	1.04	1	1.14	1.0625	3
6	Hana Rang	1	1	1	1	1.007	1	1.14	1.05	1	1	1.06	1.0246	7
7	Hermes fam	0.99	1	1	0.99	1.004	1	1.15	1.05	1	1	1.07	1.0259	6
8	Azin Rang	1	1	0.93	0.97	1	1	1.06	1.02	1	1	0.99	0.999	10
9	Serv Rang	1	1	0.9	0.96	1.01	1	1.2	1.07	1	1	1.03	1.0172	10
10	Rangin	1	1	1	1	1	1	1	1	1	1	1	1	13
11	Marron	1	1	1	1	1	1	1.27	1.09	1	1	1.12	1.0444	4
12	Asan Rang	1	1	1	1	1.004	1	1.44	1.14	1	1	1.2	1.072	1
13	Shabrang	1	1	1	1	1	1	1.14	1.04	1	1	1.06	1.0235	8
14	Soor	1	1	0.87	0.95	1	1	1	1	1	1	0.93	0.978	16
15	Takrang	1	1	1	0.99	1.06	1	1.15	1.019	1	1	1.07	1.0353	5
16	Giti Asa	1	1	0.9	0.96	1.04	1	1	1.04	1.02	1	0.94	1.0071	12
17	Pars	1	1	1	1	1.02	1	1.07	1.03	1.01	1	1.03	1.0161	11
18	Arovin	1	1	0.75	0.91	1.03	1	1	1.01	1.01	1	0.86	0.962	18

Table 7 The efficiency scores with Alpha 0.05

Alpha = 0.05														
No of SC	DMUs	Optimistic efficiency				Pessimistic efficiency				Geometric average efficiency				Ranking
		Eff1	Eff2	Eff3	Eff(Overall)	Eff1	Eff2	Eff3	Eff(Overall)	Eff1	Eff2	Eff3	Eff(Overall)	
1	Sayan	1	1	0.8	0.93	1.01	1.06	1	1.024	1.006	1.03	0.894	0.977	17
2	Hermes	1	1	1	1	1	1.2	1.22	1.142	1	1.09	1.105	1.0686	2
3	Rangvareh	0.99	1	0.91667	0.97	1.04	1	1.16	1.07	1.02	1	1.034	1.02	9
4	Bajak	1	1	1	1	1	1	1	1	1	1	1	1	13
5	Azin	1	1	1	1	1.08	1	1.3	1.129	1.04	1	1.14	1.062	3
6	Hana Rang	1	1	1	1	1.007	1	1.14	1.05	1.003	1	1.069	1.024	7
7	Hermes fam	1	1	1	1	1.004	1	1.15	1.052	1.002	1	1.074	1.025	6
8	Azin Rang	1	1	0.93333	0.97	1	1	1.066	1.022	1	1	0.99	0.99	15
9	Serv Rang	1	1	10.9	0.96	1.01	1	1.2	1.07	1.005	1	3.616	1.017	10
10	Rangin	1	1	1	1	1	1	1	1	1	1	1	1	13
11	Marron	1	1	1	1	1	1	1.27	1.09	1	1	1.128	1.0444	4
12	Asan Rang	1	1	1	1	1.004	1	1.44	1.14	1.002	1	1.201	1.072	1
13	Shabrang	1	1	1	1	1	1	1.142	1.04	1	1	1.069	1.0235	8
14	Soor	1	1	0.875	0.95	1	1	1	1	1	1	0.935	0.978	16
15	Takrang	1	1	1	1	1.061	1	1.153	1.07	1.03	1	1.074	1.035	5
16	Giti Asa	1	1	0.9	0.96	1.048	1	1	1.04	1.02	1	0.948	1.0071	12
17	Pars	1	1	1	1	1.02	1	1.071	1.03	1.012	1	1.035	1.0161	11
18	Arovin	1	1	0.75	0.916	1.03	1	1	1.01	1.015	1	0.866	0.962	18

Table 8 The efficiency scores with Alpha 0.1

Alpha = 0.1														Ranking
No of SC	DMUs	Optimistic efficiency				Pessimistic efficiency				Geometric average efficiency				
		Eff1	Eff2	Eff3	Eff(Overall)	Eff1	Eff2	Eff3	Eff(Overall)	Eff1	Eff2	Eff3	Eff(Overall)	
1	Sayan	0.999	1	0.8	0.933	1.013	1.06	1	1.024	1.006	1.03	0.894	0.9779	17
2	Hermes	1	1	1	1	1	1.2	1.22	1.142	1	1.097	1.105	1.0686	2
3	Rangvareh	0.99	1	0.91	0.972	1.28	1.04	1	1.166	1.13	1.021	0.9574	1.065	3
4	Bajak	1	1	1	1	1	1	1	1	1	1	1	1	13
5	Azin	1	1	1	1	1.087	1	1.3	1.129	1.04	1	1.1401	1.06255	4
6	Hana Rang	1	1	1	1	1.007	1	1.142	1.05	1	1	1.069	1.02468	7
7	Hermes fam	0.97	1	1	0.99	1	1	1.153	1.052	0.987	1	1.074	1.0211	9
8	Azin Rang	1	1	0.93	0.97	1	1	1.066	1.022	1	1	0.997	0.99975	15
9	Serv Rang	1	1	0.9	0.966	1.011	1	1.2	1.07	1.005	1	1.039	1.01728	10
10	Rangin	1	1	1	1	1	1	1	1	1	1	1	1	13
11	Marron	1	1	1	1	1	1	1.272	1.09	1	1	1.128	1.04446	5
12	Asan Rang	1	1	1	1	1.004	1	1.444	1.149	1.002	1	1.201	1.0722	1
13	Shabrang	1	1	1	1	1	1	1.142	1.047	1	1	1.069	1.02353	8
14	Soor	1	1	0.875	0.958	1	1	1	1	1	1	0.935	0.97894	16
15	Takrang	1	1	1	1	1.061	1	1.153	1.071	1.03	1	1.074	1.0352	6
16	Giti Asa	1	1	0.9	0.966	1.048	1	1.1	1.049	1.023	1	3.462	1.00715	12
17	Pars	1	1	1	1	1.025	1	1.071	1.032	1.012	1	1.035	1.0161	11
18	Arovin	1	1	0.75	0.916	1.03	1	1	1.01	1.015	1	0.866	0.96223	18

Table 9 The efficiency scores with Alpha 0.3

Alpha = 0.3														
No of SC	DMUs	Optimistic efficiency				Pessimistic efficiency				Geometric average efficiency				Ranking
		Eff1	Eff2	Eff3	Eff(Overall)	Eff1	Eff2	Eff3	Eff(Overall)	Eff1	Eff2	Eff3	Eff(Overall)	
1	Sayan	1	1	0.8	0.9333	1.013	1.061	1	1.0248	1.0066	1.0301	0.8944	0.97798	16
2	Hermes	1	1	1	1	1	1.203	1.2222	1.142	1	1.0971	1.1055	1.06863	1
3	Rangvareh	1	0.799	0.9166	0.9052	1.043	1	1.1666	1.0702	1.0217	0.894	1.0341	0.98428	14
4	Bajak	1	1	1	1	1	1	1	1	1	1	1	1	12
5	Azin	1	1	1	1	1.087	1	1.3	1.129	1.0426	1	1.1401	1.06255	2
6	Hana Rang	1	1	1	1	1.007	1	1.1428	1.05	1.0035	1	1.069	1.02468	6
7	Hermes fam	0.9714	1	1	0.9904	1.004	1	1.1538	1.0526	0.9876	1	1.0741	1.021084	7
8	Azin Rang	1	0.8013	0.9333	0.9115	1	1	1.0666	1.0222	1	0.8951	0.997	0.96529	17
9	Serv Rang	1	1	0.9	0.9666	1.0116	1	1.2	1.0706	1.0058	1	1.0392	1.01728	9
10	Rangin	1	1	1	1	1	1	1	1	1	1	1	1	12
11	Marron	1	1	1	1	1	1	1.2727	1.0909	1	1	1.1281	1.04446	3
12	Asan Rang	1	0.7847	1	0.92822	1.0045	1	1.4444	1.1497	1.0023	0.885	1.2018	1.03302	5
13	Shabrang	0.9777	1	1	0.9925	1	1	1.1428	1.047	0.9888	1	1.069	1.01973	8
14	Soor	1	1	0.875	0.9583	1	1	1	1	1	1	0.935	0.97894	15
15	Takrang	1	1	1	1	1.055	1	1.1538	1.0699	1.0275	1	1.074	1.03434	4
16	Giti Asa	1	1	0.9	0.9666	1.048	1	1.1	1.0493	1.0237	1	0.994	1.00715	11
17	Pars	1	1	1	1	1.025	1	1.0714	1.0325	1.0129	1	1.0351	1.0161	10
18	Arovin	1	1	0.75	0.9166	1.03	1	1	1.0101	1.015	1	0.866	0.96223	18

helps them to identify inefficiency resources and take some measures to improve their SCs' efficiency. By doing so, managers and decisions makers in organizations can be aware of which stage of their SC need to be improved. Moreover, they can better plan with respect to their priorities at each stage and allocate the required resources for performance improvement under different levels of uncertainty. In addition, evaluating performance in complex settings such as SCs is a major challenge for management. This paper demonstrates how well network DEA models including our developed model can consider all interactions in SCs' structures in an integrated and provide an accurate assessment of SCs' performance. It should be noted that the proposed models can be applied in many other complex settings in the presence of uncertainty such as stock markets and humanitarian supply chain where managers deal with considerable capital and people's life. Also, in any organization management is interested in taking significant decisions based on precise and true results. As the model proposed considers all type of data in measuring performance in a network structure, it provides management with such results to take any decisions. In this regard, it is clear that taking wrong decisions using wrong results can impose irreparable costs to organizations. Last and but not least, the results show that which supply chains are efficient with respect to the presented definitions under different situations and can be considered as benchmarks for other supply chain to improve performance divisional and overall.

5 Conclusions and future research

Sustainable SCs and resilient SCs have addressed separately over the last two decades. However, the relation of sustainability and resilience in SCs has not been addressed adequately to date despite its substantial role in improving organizations' performance. Integrating sustainability and resilience concepts into SCs provides several advantages such as costs reduction, disruptions decrease, employees' spirit increase, production quality improvement, customer satisfaction increase and environmental performance improvement (Kaur et al., 2020). Hence, managers and decision makers of organizations need to take sustainability and resilience concepts into account their strategic decisions (Miller & Engemann, 2019).

In this paper we presented a new stochastic double frontier network DEA to evaluate the performance of sustainably resilient SCs. The developed model takes both optimistic and pessimistic efficiency measures into account for computing performance results. The model has been developed based on different concepts such as weak disposability, chance-constrained programming, and discrete dominance in the network DEA context. Dealing with different type of data such as stochastic, ratio, integer, desirable and undesirable is another significant advantage of the proposed model. We also applied aggregated Farrell type efficiency measure for providing a complete rank of DMUs which shows the discrimination power of the proposed model. The results of also show how well our developed model can evaluate the performance of sustainably resilient SCs of 18 paint and coating producers. Based on the model proposed in this study we provide some research avenues. A research study can be developing a new double frontier network DEA considering fuzzy data suitable for uncertain environments. Another future research is to develop other network DEA models such as SBM and range adjusted measure (RAM) and contrast the results obtained with the results of this study.

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