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Assessing sustainability of supply chains by double frontier network DEA: A big data approach

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ABSTRACT

Nowadays, performance evaluation of sustainable supply chain management (SSCM) is a very important topic for researchers and practitioners. Data envelopment analysis (DEA) is an appropriate method for assessing performance of SSCM in presence of Big Data. Network DEA (NDEA) can calculate efficiency of multi-stage processes. In this paper, an NDEA model for calculating optimistic and pessimistic efficiency is developed. Our proposed model can incorporate undesirable outputs. Also, our model can rank supply chains in terms of efficiency scores. A case study demonstrates efficacy of our proposed model.
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1. Introduction

Supply chain management (SCM) solely focuses on economic criteria and ignores social and environmental criteria. However, in sustainable SCM (SSCM) managers focus on triple bottom lines including social, environmental, and economic criteria (Dyllick and Hockerts, 2002). Assessing SSCM is one of the important issues in organizations (Seuring, 2013). Also, best-practice companies use Big Data resources and increase their performance (McAfee and Brynjolfsson, 2012). Science of Big Data has been applied to help researchers, planners, and policy makers. Big data is a term from dataset which are huge and complex (Ohlhorst, 2012). Also, Big Data has triggered demand of experts in information management so that more than 15 billion dollars were spent for processing information by AG, IBM, Oracle, Microsoft, HP, Dell, SAP, and EMC (Syed et al., 2013). Recently, emphasis has been on both Big Data and SSCM. Researches show linkage between sustainability and Big Data in SCM (Davenport, 2006). Hazen et al. (2014) discussed that whether Big Data can be used to increase operational and financial-based SCM results.

The Big Data deals with collection and storage of large data set (Dekker et al., 2013). However, it has encountered great challenges in using such information. Zhong et al. (2016) summarized challenges of SCM as following 5Vs:

Volume: An enormous volume of data is produced every second within SCM. For instance, it is computed that a producer can generate 5000 data samples per 33 minutes. As a result, in supply chains many datasets are collected and recorded.

Velocity: It is important to process dataset quickly. Velocity depends on several factors such as efficiency of data storage, confidence of data transferring, and speed of finding useful knowledge.

Verification: There is data with different quality. This data can be good or bad which should be verified. Good data should be selected.

Variety: Diverse sources and heterogeneous formats have caused data to be variable.

Value: Deriving value from Big Data is difficult because of obstacles created by the previous four factors. Furthermore, value of reports, statistics, and decisions obtained from Big Data are hard to measure.

One of the techniques for evaluating the SSCM is data envelopment analysis (DEA) (Mirhedayatian et al., 2014; Azadi et al., 2015). Furthermore, DEA models have been used along with Big Data (e.g., Li et al., 2017; Zhu et al., 2017; Chen and Jia, 2017; Chu et al., press). Recently, some researchers have attempted to integrate Big Data into DEA to evaluate efficiency of decision making units (DMUs) (Chen and Jia, 2017). Li et al. (2017) used Big Data theory for assessing efficiency of China's forest re-

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sources. Zhu et al. (2017) proposed DEA-based approach for assessing efficiency of natural resource utilization. As addressed by Zhu et al. (2017), Big Data causes many issues in DEA. For instance, abundant number of DMUs is a challenge in DEA. (Song et al., in press) discussed that viral use of Big Data and DEA have created new challenges and opportunities in efficiency assessment.

DEA is one of the most popular approaches in management science for evaluating relative efficiency of DMUs. In classical DEA models, internal interactions are not taken into account. Consequently, DMUs are treated as black boxes (Färe and Grosskopf, 2000). One the other hand, there are several network DEA (NDEA) models that consider DMUs along with internal interactions. Also, in classical DEA models, it is assumed that all outputs are "good". However, outputs might be "bad". For instance, waste and pollutions are undesirable outputs (Farzipoor Saen, 2010).

NDEA model was suggested, for the first time, by Färe and Grosskopf (2000). Then, a multi-stage structure for NDEA model was proposed by Lewis and Sexton (2004). Tone and Tsutsui (2009) recommended a slack-based NDEA model which can deal with intermediate measures. Current NDEA models can calculate optimistic efficiency of DMUs and cannot measure both optimistic and pessimistic efficiency scores. To the best of our knowledge, there is no NDEA model to measure optimistic, pessimistic, and overall efficiency scores.

DEA with double frontiers determines two types of efficiency scores for DMUs. In the optimistic efficiency score, DMUs' efficiency scores are compared with efficiency frontier. In pessimistic efficiency score, DMUs' efficiency scores are compared with inefficiency frontier (Wang and Chin, 2009).

For the first time, in this paper, we incorporate NDEA and double frontier DEA models. Our proposed model can measure the optimistic and pessimistic efficiency scores of SSCM. Objective of this paper is to evaluate optimistic and pessimistic efficiencies using DEA in presence of undesirable outputs. Contributions of this paper are as follows:

- For the first time, we combine NDEA and double frontier DEA models.
- For the first time, we assess sustainability of supply chains by our new NDEA and double frontier DEA models.
- We deal with undesirable outputs.
- We rank DMUs by our developed model.
- A case study is given.

This paper is organized as follows: In Section 2, literature review is presented. In Section 3, our new model is proposed. A case study is given in Section 4. Section 5 presents managerial implications. Section 6 concludes the paper.

2. Literature review

2.1. DEA and NDEA model

DEA is a linear programming technique for assessing relative efficiency of DMUs. Charnes et al. (1978) developed DEA, for the first time, and called it CCR (Charnes-Cooper-Rhodes) model. Then, BCC (Banker-Charnes-Cooper) model was suggested by Banker et al. (1984). Since then, many DEA models have been developed. However, DEA is a black box technique. DEA assumes that DMUs consume multiple inputs to produce multiple outputs. In real world, there might be situations that we should consider internal interactions of DMUs. To deal with these situations, NDEA model was proposed by Färe and Grosskopf (1996; 2000). Yu and Lin (2008) utilized NDEA model to evaluate technical efficiency, service effectiveness, and technical effectiveness of networks. Badiezadeh and Farzipoor Saen (2014) developed an NDEA model to consider undesirable outputs, and calculated efficiency of production lines. Using NDEA model, Hua and Bian (2008) investigated relationship between efficiency of a DMU and its sub-DMUs in presence of undesirable outputs. Also, NDEA model was suggested by Tone and Tsutsui (2009) for calculating overall and partial efficiency of DMUs. Liang et al. (2008), Cook et al. (2010), and Chen et al. (2009) presented a model for dealing with DMUs with network structures.

2.2. Sustainable supply chain management

During past decades, companies have considered factors such as quality, flexibility, price, and reputation to select suppliers (Bai and Sarkis, 2010). Nowadays, sustainability factors play vital role in assessing performance of suppliers (Kleindorfer et al., 2005). Linton et al. (2007) assessed sustainability of supply chains by focusing on environmental and social factors. Golicic and Smith (2013) reviewed researches in field of green supply chain by meta- analysis. Then, they investigated positive and negative aspects of firms' performance. Carter and Robert (2008) introduced concept of sustainability in SCM and demonstrated relationship among social, economic, and environmental issues. Govindan et al. (2013) proposed a fuzzy multi-criteria approach for measuring sustainability of suppliers. Mirhedayatian et al. (2014) assessed green supply chains through NDEA. Azadi et al. (2015) suggested a new fuzzy DEA model for evaluating efficiency and effectiveness of suppliers in SSCM context. Khodakarami et al. (2015) developed two-stage DEA models for evaluating sustainability of supply chains.

Pagell and Wu (2009) assessed sustainability of 10 supply chains. Mani et al. (2016b) evaluated social sustainability in Indian manufacturing companies. Seuring et al. (2008) discussed that social aspects are relatively and significantly less researched than environmental issues. By focusing on total interpretive structure modeling, Dubey et al. (2016) assessed sustainability of SCM. Mani et al. (2016a) suggested concept of supply chain social sustainability (SCSS). SCSS addresses social concerns in upstream and downstream of supply chains. In addition, they suggested and validated scales for assessing SCSS by conducting interviews in Indian industry.

2.3. Undesirable outputs and DEA

DMUs with more desirable outputs and less undesirable outputs relative to less input are identified as efficient (Cooper et al., 2007). For the first time, Färe et al. (1989; 1996) and Yaisawarng and Klein (1994) dealt with undesirable outputs. Seiford and Zhu (2002) suggested a DEA model for improving efficiency by augmenting desirable outputs and diminishing undesirable outputs. Korhonen and Luptacik (2004) evaluated eco-efficiency of 24 coal-fired power plants in a European country. Jahanshahloo et al. (2005) proposed a non-radial DEA model by taking into account both undesirable inputs and outputs. Using range adjusted measure (RAM) model, Sueyoshi and Goto (2011) integrated desirable and undesirable outputs. Jahanshahloo et al. (2013) assessed efficiency of DMUs using RAM model and super-efficiency in the presence of undesirable outputs.

2.4. Role of Big Data in supply chain

Waller and Fawcett (2013) discussed that Big Data are used in SCM for augmenting competencies and providing new capabilities. Dubey et al. (2017) addressed role of Big Data analytics in supporting world-class sustainable manufacturing (WCSM). Wang et al. (2016) assessed role of supply chain analytics (SCA) in logistics and SCM by applying Big Data methods. Impact of

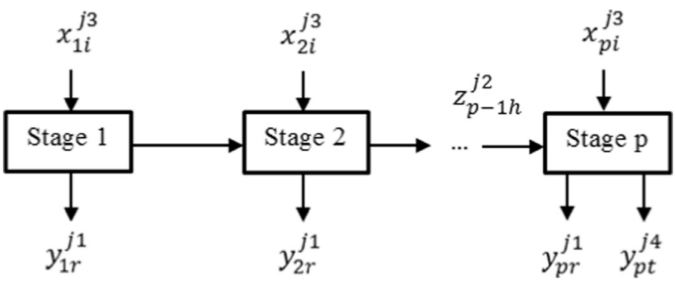

Fig. 1. Multi-stage network.

Big Data and predictive analytics on supply chain and organizational performance were evaluated by Gunasekaran et al. (2017). Using Big Data, Papadopoulos et al. (2017) examined a theoretical framework to explain flexibility in supply chain network. Li et al. (2017) investigated efficiency of forestry resources of China based on Big Data and DEA. Zhu et al. (2017) proposed a DEA model to evaluate efficiency of natural resource utilization of China from 2005 to 2012 based on Big Data. In another study, by applying a DEA model and Big Data and given undesirable outputs, Chen and Jia (2017) assessed environmental efficiencies of China's industry. (Chu et al., in press) proposed a DEA model and a Big Data approach for assessing environmental efficiency.

All the above authors focused only on optimistic efficiency assessment and did not calculate the optimistic, pessimistic, and overall efficiency of multi-stage networks. In this paper, for the first time, we combine double frontier DEA and NDEA models for calculating optimistic, pessimistic, and overall efficiency of SSCM in presence of undesirable outputs. Also, our proposed approach can rank efficient DMUs in case of ties among efficient DMUs.

3. Proposed model

Here, we calculate optimistic and pessimistic efficiency scores to determine overall efficiency of DMUs (SCM) in presence of undesirable outputs.

3.1. Optimistic efficiency score

To calculate relative efficiency of networks, Cook et al. (2010) proposed NDEA model. Fig. 1 depicts a typical network.

Now, suppose there is a set of DMUs ($j=1, \ldots, J$). Notations are defined as follows:

- x_{1i}^{j3} , $i=1,\ldots I$, the input vector into stage 1 that its weight is displayed by ν_{1i}.
- z_{ph}^{j2} , $h=1,\ldots S$, the output vector that leaves stage p-1 and enters as an input to stage p and we show its weight by η_{ph}.
- y_{pr}^{j1} , $r=1,\ldots R$, the output vector that exits stage p and its weight is displayed by u_{pr}.
- y_{pt}^{j4}, $t=1,\ldots T$, the undesirable output vector that its weight is displayed by μ_{pt}.

Efficiency ratio of DMU_j can be measured as follows:

$$\theta_p=\left(\sum_{r=1}^{R_p}u_{pr}y_{pr}^{j1}+\sum_{h=1}^{S_p}\eta_{ph}z_{ph}^{j2}\right)\Bigg/\left(\sum_{h=1}^{S_{p-1}}\eta_{p-1h}z_{p-1h}^{j2}+\sum_{i=1}^{I_p}\nu_{p-1i}x_{p-1i}^{j3}+\sum_{t=1}^{T_p}\mu_{pt}y_{pt}^{j4}\right) \tag{1}$$

Weight of each stage is ratio of consumptions of stage divided by whole inputs which is as follows:

$$w_p=\left(\sum_{i=1}^{I_p}\nu_{p-1i}x_{p-1i}^{j3}+\sum_{h=1}^{S_{p-1}}\eta_{p-1h}z_{p-1h}^{j2}+\sum_{t=1}^{T_p}\mu_{pt}y_{pt}^{j4}\right)\Bigg/\left(\sum_{i=1}^{I_1}\nu_{1i}x_{1i}^{j3}+\sum_{t=1}^{T_p}\mu_{pt}y_{pt}^{j4}+\sum_{p=2}^{p}\left(\sum_{h=1}^{S_{p-1}}\eta_{p-1h}z_{p-1h}^{j2}+\sum_{i=1}^{I_p}\nu_{p-1i}x_{p-1i}^{j3}\right)\right), \tag{2}$$

By multiplying weights by efficiency scores, we get overall efficiency which is as follows:

$$\theta=\sum_{p=1}^{S_p}w_p\theta_p \tag{3}$$

Model (4) measures efficiency score of each DMU (supply chain).

$$Max\ \sum_{p=1}^{P}\left(\sum_{r=1}^{R_p}u_{pr}y_{pr}^{o1}+\sum_{h=1}^{S_p}\eta_{ph}z_{ph}^{o2}\right) \tag{4}$$

$$\begin{aligned}
&s.t.\\
&\sum_{i=1}^{I_1}\nu_{1i}x_{1i}^{o3}+\sum_{t=1}^{T_p}\mu_{pt}y_{pt}^{o4}\\
&\quad+\sum_{p=2}^{p}\left(\sum_{h=1}^{S_{p-1}}\eta_{(p-1)h}z_{(p-1)h}^{o2}+\sum_{i=1}^{I_p}\nu_{(p-1)i}x_{(p-1)i}^{o3}\right)=1,\\
&\left(\sum_{r=1}^{R_1}u_{1r}y_{1r}^{j1}+\sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{j2}\right)-\sum_{i=1}^{I_o}\nu_{1i}x_{1i}^{j3}\le 0,\\
&\left(\sum_{r=1}^{R_p}u_{pr}y_{pr}^{j1}+\sum_{h=1}^{S_p}\eta_{ph}z_{ph}^{j2}\right)\\
&\quad-\left(\sum_{i=1}^{\mathrm{I_p}}\mathrm{v}_{(p-1)i}\mathrm{x}_{p-1i}^{j3}+\sum_{\mathrm{h=1}}^{\mathrm{S_{p-1}}}\eta_{(p-1)h}\mathrm{z}_{(p-1)h}^{j2}+\sum_{t=1}^{T_p}\mu_{pt}y_{pt}^{j4}\right)\le 0,\\
&u_{pr},\ \eta_{ph},\ \nu_{pi},\ \nu_{1i},\mu_{pt}\ge\varepsilon.
\end{aligned}$$

If the efficiency score is equal to 1, the DMU under evaluation is efficient. On the other hand, if it is less than 1, the DMU under evaluation is inefficient. Results of model (4) produce optimistic efficiency score. Note that NDEA model proposed by Cook et al. (2010) can compute optimistic efficiency and cannot assess pessimistic efficiency. In addition, their model does not consider undesirable output. In this paper, we assess optimistic efficiency, pessimistic efficiency, and overall efficiency in presence of undesirable output.

3.2. Pessimistic efficiency score

For the first time, Wang and Chin (2009) developed double frontier DEA model. The double frontier DEA model computes two types of efficiency score. The first one assesses DMUs given efficiency frontier and is referred to optimistic efficiency score. The next one calculates DMUs given inefficiency frontier and is referred to pessimistic efficiency score. Traditional DEA models evaluate the best relative efficiency of DMUs and do not assess pessimistic efficiencies. Therefore, they cannot assess DMUs overall. By taking into account both optimistic and pessimistic efficiencies, all DMUs can

Table 1
Used factors in SSCM assessment.

Stages	Notations	Definitions
Supplier	x_{01}^3	Material purchasing cost
	x_{02}^3	Environmental cost
	x_{03}^3	Staff welfare cost
Manufacturer	y_{22}^4	CO2 emission
Distributor	y_{31}^1	Number of delivered products
	y_{32}^1	Revenue
Intermediate inputs/outputs	z_{11}^2	Number of products from supplier to manufacturer
	z_{21}^2	Number of green products

be fully ranked. Pessimistic efficiency score for DMUs with network structure is calculated as follows:

$$Min\ \varphi_o = \sum_{p=1}^{P}\left(\sum_{r=1}^{R_p} u_{pr}y_{pr}^{op} + \sum_{h=1}^{S_p}\eta_{ph}z_{ph}^{op}\right) \tag{5}$$

$$\begin{aligned}
&s.t.\\
&\sum_{i=1}^{I_1} \upsilon_{1i}x_{1i}^{o3} + \sum_{t=1}^{T_p}\mu_{pt}y_{pt}^{o4}\\
&\quad + \sum_{p=2}^{p}\left(\sum_{h=1}^{S_{p-1}}\eta_{(p-1)h}z_{(p-1)h}^{o2} + \sum_{i=1}^{I_p}\upsilon_{(p-1)i}x_{(p-1)i}^{o3}\right) = 1,\\
&\left(\sum_{r=1}^{R_1}u_{1r}y_{1r}^{j1} + \sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{j2}\right) - \sum_{i=1}^{I_o}\upsilon_{1i}x_{1i}^{j3} \geq 0,\\
&\left(\sum_{r=1}^{R_p}u_{pr}y_{pr}^{j1} + \sum_{h=1}^{S_p}\eta_{ph}z_{ph}^{j2}\right)\\
&\quad - \left(\sum_{i=1}^{I_p}\mathrm{v}_{(p-1)i}x_{p-1i}^{j3} + \sum_{h=1}^{S_{p-1}}\eta_{(p-1)h}z_{(p-1)h}^{j2} + \sum_{t=1}^{T_p}\mu_{pt}y_{pt}^{j4}\right) \geq 0,\\
&u_{pr},\ \eta_{ph},\ \upsilon_{pi},\ \upsilon_{1i}, \mu_{pt} \geq \varepsilon.
\end{aligned}$$

On the one hand, if efficiency score is equal to 1, the DMU under evaluation is pessimistically inefficient. On the other hand, if efficiency score is more than 1, the DMU under evaluation is non-pessimistically inefficient.

3.3. Overall efficiency

Use of optimistic and pessimistic efficiency scores lead to different ranking of DMUs. Therefore, a method is needed to rank DMUs. Overall efficiency score for DMU_j is obtained as follows:

$$\rho_j = \frac{\theta_o^*}{\sqrt{\sum_{j=1}^{J}\theta_j^{*2}}} + \frac{\varphi_o^*}{\sqrt{\sum_{j=1}^{J}\varphi_j^{*2}}},\quad j = 1,\ldots,J \tag{6}$$

4. Case study

In this section, 9 Iranian supply chains which produce tomato pastes are assessed. Table 1 reports used factors and notations. The factors are obtained by interviews with managers and experts in supply chains. Structure of supply chain is depicted in Fig. 2. Here, we have a multiple-stage supply chain: supplier (stage 1), manufacturer (stage 2), and distributor (stage 3). Inputs of supplier stage are material purchasing cost (economic factor), staff welfare cost (social factor), and environmental cost (environmental factor).

In Fig. 2, input vector that enters stage 1 is displayed by x_{1i}^3 . z_{11}^2 is output vector that leaves stage 1 and enters stage 2 as an input. z_{21}^2 is output vector that exits stage 2 and enters as an input to stage 3. Desirable and undesirable outputs are depicted by y_{2t}^4. Dataset dates back to 2014 which are shown in Table 2. The figures in Table 2 are obtained via surveys from companies which produce tomato pastes.

Environmental costs are defined as costs related to actual or potential damage of natural valuable items through economic activities. Environmental costs are considered as input. Intermediate inputs/outputs include two stages. The intermediate inputs/outputs in manufacturer stage are number of products from supplier to manufacturer (economic factor) and intermediate inputs/outputs in distributor are number of green products (economic factor). Note that Khodakarami et al. (2015) considered number of green products as an economic factor. CO_2 emission (environmental factor) is output of manufacturer stage which is regarded as undesirable output. Outputs of distributor stage are revenue (economic factor) and number of delivered products (economic factor).

To assess efficiency of SSCM, each supply chain is treated as a DMU. The optimistic and pessimistic efficiency scores for each supply chain are obtained by Models (7) and (8). To calculate optimistic efficiency, the undesirable outputs are considered as inputs.

$$Max\theta_o = \left(\sum_{r=1}^{R_3}u_{3r}y_{3r}^{o1} + \sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{o2} + \sum_{h=1}^{S_2}\eta_{2h}z_{2h}^{o2}\right) \tag{7}$$

$$\begin{aligned}
&s.t.\\
&\sum_{i=1}^{I_0}\upsilon_{0i}x_{0i}^{o3} + \sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{o2} + \sum_{h=1}^{S_2}\eta_{2h}z_{2h}^{o2} + \sum_{t=1}^{T_2}\mu_{2t}y_{2t}^{o4} = 1,\\
&\sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{j2} - \sum_{i=1}^{I_o}\upsilon_{0i}z_{0i}^{j3} \leq 0,\\
&\sum_{h=1}^{S_2}\eta_{2h}z_{2h}^{j2} - \left(\sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{j2} + \sum_{t=1}^{T_2}\mu_{2t}y_{2t}^{j4}\right) \leq 0,\\
&\sum_{r=1}^{R_3}u_{3r}y_{3r}^{j1} - \sum_{h=1}^{S_2}\eta_{2h}z_{2h}^{j2} \leq 0,\\
&u_{pr},\ \eta_{ph},\ \upsilon_{pi},\ \upsilon_{1i} \geq \varepsilon.
\end{aligned}$$

Model (7) cannot calculate pessimistic efficiency scores. Therefore, model (8) is proposed to calculate pessimistic efficiency scores given undesirable outputs.

$$Min\ \varphi_o = \left(\sum_{r=1}^{R_3}u_{3r}y_{3r}^{o1} + \sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{o2} + \sum_{h=1}^{S_2}\eta_{2h}z_{2h}^{o2}\right) \tag{8}$$

$$\begin{aligned}
&s.t.\\
&\sum_{i=1}^{I_0}\upsilon_{0i}x_{0i}^{o3} + \sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{o2} + \sum_{h=1}^{S_2}\eta_{2h}z_{2h}^{o2} + \sum_{t=1}^{T_2}\mu_{2t}y_{2t}^{o4} = 1,\\
&\sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{j2} - \sum_{i=1}^{I_o}\upsilon_{0i}z_{0i}^{j3} \geq 0,\\
&\sum_{h=1}^{S_2}\eta_{2h}z_{2h}^{j2} - \left(\sum_{h=1}^{S_1}\eta_{1h}z_{1h}^{j2} + \sum_{t=1}^{T_2}\mu_{2t}y_{2t}^{j4}\right) \geq 0,\\
&\sum_{r=1}^{R_3}u_{3r}y_{3r}^{j1} - \sum_{h=1}^{S_2}\eta_{2h}z_{2h}^{j2} \geq 0,\\
&u_{pr},\ \eta_{ph},\ \upsilon_{pi},\ \upsilon_{1i} \geq \varepsilon.
\end{aligned}$$

Model (7) shows efficiency frontier and maximizes efficiency score. However, model (8) shows inefficiency frontier and minimizes inefficiency score. The efficiency frontier implies supply

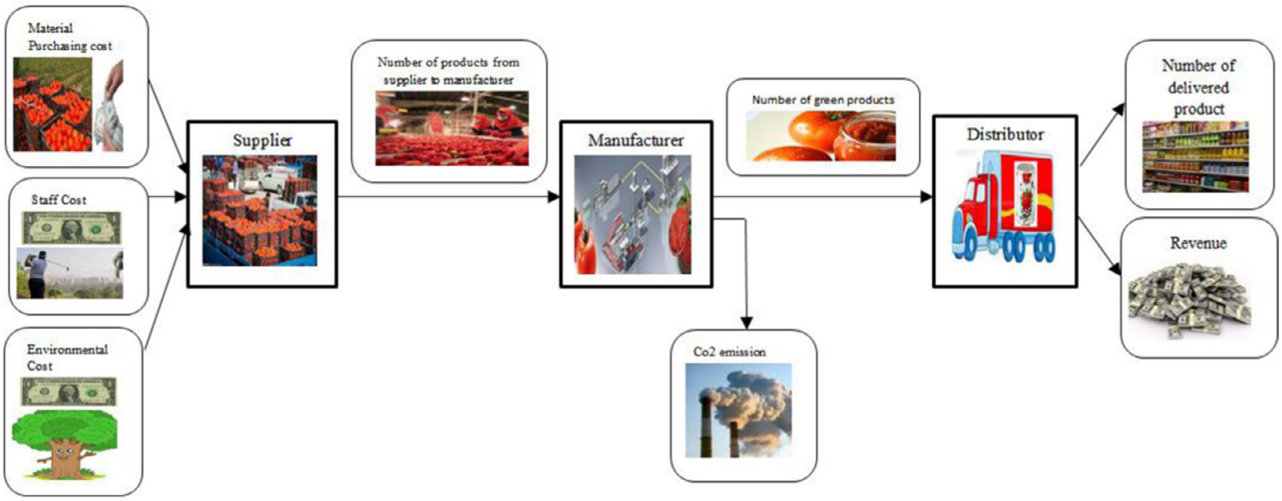

Fig. 2. Structure of supply chain.

Table 2
Dataset.

DMUs	Supply chains	Inputs			Intermediate inputs/ outputs		Outputs		
		x_{01}^3 (1000$)	x_{02}^3 (1000$)	x_{03}^3 (1000$)	z_{11}^2	z_{21}^2	y_{22}^4 (100,000) tons	y_{31}^1	y_{32}^1 (1000$)
1	Oila	400	30	10	320	315	170	1500	1100
2	Daland	360	60	12	295	290	165	2000	1280
3	Sahar	330	55	16	290	282	163	2200	980
4	Kambiz	455	25	20	310	312	175	2700	1200
5	Mohsen	370	37	19	280	270	192	1900	840
6	Urum Ada	332	80	17	210	200	150	1890	965
7	Rojin	355	87	9	235	220	155	1995	1115
8	Mahram	300	95	8	255	235	137	1650	700
9	Chin Chin	295	50	15	315	318	122	3000	1400

Table 3
Results.

DMUs	Optimistic efficiency (model 7)	Pessimistic efficiency (model 8)
1	0.89	1.1
2	0.92	1.21
3	0.87	1.17
4	0.96	1.16
5	0.85	1.04
6	0.76	1.18
7	0.9	1.19
8	0.88	1
9	1	1.36

Table 4
Results obtained from Expression (6).

DMUs	Supply chains	Overall efficiency	Rank
1	Oila	0.64	6
2	Daland	0.69	2
3	Sahar	0.65	5
4	Kambiz	0.68	3
5	Mohsen	0.6	9
6	Urum Ada	0.63	7
7	Rojin	0.67	4
8	Mahram	0.61	8
9	Chin Chin	0.76	1

chains that are sustainable (efficient). However, the inefficiency frontier depicts supply chains that are not sustainable (inefficient). To measure overall efficiency and rank supply chains, Expression (6) is used. Table 3 displays optimistic and pessimistic efficiency scores. Optimistic efficiency scores for DMUs #9 and #6 are 1 and 0.76, respectively, that are the best and the worst supply chains. In Table 3, the pessimistic efficiency score of DMU #9 is 1.36 which is non-pessimistically inefficient. The pessimistic efficiency score for DMU #8 is 1 which is pessimistically inefficient.

Table 4 shows the overall efficiency of supply chains obtained from Eq. (6). As is seen, DMU #9 has the best overall efficiency score. In other words, it is the most sustainable supply chain. The last column of Table 4 shows rank of each DMU. As is seen, there is no tie among DMUs and our model can fully rank DMUs. This implies high discrimination power of our proposed approach.

5. Managerial implications

The SSCM is a vital topic for organizations. Managers need to design a suitable performance measurement model for assessing sustainability of supply chains. Generally speaking, size and complexity of the SSCM are significant factors in evaluating efficiency scores. Moreover, to assess SSCM, there might be undesirable outputs such as CO_2 emission and air pollutants. Due to existence of undesirable outputs, conventional DEA models cannot evaluate SSCM as it is necessary that inputs to be minimized and outputs to be maximized.

In assessing sustainability of supply chains there might be Big Data. Big Data can be used to address environmental crises such as CO_2 emission and air pollutants. We can have better understanding of environmental impacts on SSCM. Big Data can be used to evaluate social crises (Robert et al., 2008).

Furthermore, to assess SSCM, we need to calculate optimistic and pessimistic efficiency scores. NDEA model is suitable to solve this type of problems. To the best of our knowledge, there is no reference to evaluate both optimistic and pessimistic efficiency scores of SSCM in presence of undesirable outputs.

6. Conclusions

In past decade, managers have paid attention to SSCM. SSCM gives opportunity to companies to be distinguished from others by considering environmental, social, and economic factors. Big Data in SSCM is a challenge which needs to be studied. Big Data is a global problem if we cannot interpret or utilize it. Many companies boast that they are collecting large amount of data from varieties of sources. As a result, Big Data has appeared as a discipline. Big Data can prepare possible solutions for data analysis, knowledge extraction, and advanced decision-makings. We believe that Big Data will have substantial impact on sustainable supply chain. Given Big Data in supply chains, we need tools to utilize them.

One of the important industrial sectors in Iran is tomato paste industry. However, there are Big Data in supply chains of tomato paste. We developed new NDEA model to deal with Big Data. In this paper, sustainability of supply chains of tomato paste industry was assessed by taking into account economic, social, and environmental criteria. In addition, role of Big Data in SCM was discussed. As well, optimistic, pessimistic, and overall efficiency of supply chains were determined. To assess SSCM performance, it is essential to evaluate internal structure of SSCM. In this paper, a new NDEA model was suggested to assess optimistic and pessimistic efficiency of SSCM given undesirable outputs. Our models can deal with big data. They can compute optimistic and pessimistic efficiencies given numerous DMUs and criteria. The only caution is that number of DMUs should be at least thrice criteria (Bowlin, 1998).

Further researches can be done based upon this paper. Some of topics are as follows:

- Similar research can be done for assessing SSCM in presence of fuzzy and stochastic data.
- Similar research can be done for assessing SSCM in presence of dual-role factors.

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