Annals of Operations Research
https://doi.org/10.1007/s10479-018-3027-4

ORIGINAL RESEARCH

Supply chain performance evaluation using fuzzy network data envelopment analysis: a case study in automotive industry

Yongbo Li[1] · Amir-Reza Abtahi[2] · Mahya Seyedan[3]

Abstract
Supply chain performance evaluation problems are evaluated using data envelopment analysis. This paper proposes a fuzzy network epsilon-based data envelopment analysis for supply chain performance evaluation. In the common data envelopment analysis models which are used for evaluation of decision-maker units efficiency, there are several inputs and outputs. One of the bugs of such models is that the intermediate products and linking activities are overlooked. Considering these intermediate activities and products, the current study evaluates the performance of decision-maker units in an automotive supply chain. There are ten decision-maker units in the supply chain in which there are three suppliers, two manufacturers, two distributors, and four customers. Moreover, the overall efficiency of input-oriented (input-based) model and input-oriented divisional efficiency are calculated. In order to improve the efficiencies, the projections onto the frontiers are obtained by using the outputs of the solved model and Lingo software. In order to show the applicability of the proposed model, it is applied on automotive industry, as a case study, to evaluate supply chain performance. Then, the overall efficiencies of DMUs and each sections (divisions) of DMUs were calculated separately. Therefore, every organization can apply this evaluation method for improving the performance of alternative factors.

Keywords Supply chain management · Performance measurement · Network DEA · Fuzzy DEA

1 Introduction

These days, lowest cost and best quality are factors that attract more customers so most of the enterprises try to win this competition (Wan et al. 2017). Supply chain consists of suppliers,

✉ Amir-Reza Abtahi
amir_abtahi@yahoo.com

1 School of Economics and Management, China University of Petroleum (East China), Qingdao 266580, People's Republic of China

2 Department of Information Technology Management, Kharazmi University, Tehran, Iran

3 Concordia Institute for Information Systems Engineering, Concordia University, Montreal, QC H3G 1M8, Canada

Published online: 23 August 2018

manufacturing plants, warehouses, customers, and distribution channels and is an inseparable part of modern business management offering services to customers (Christopher 1992; Five Winds International 2018; Pasandideh et al. 2015). Moreover, as an important competitive strategy, companies apply Supply chain management (SCM) to satisfy market demand (Chen 2011).

When there are a lot of sellers, manufacturers, distributors, and retailers in the supply chain, performance measurement becomes complex, because the attribution of results to a large number of involving elements is difficult (Jalali Naini et al. 2011).

Supply chain performance evaluation (Jakhar 2015), Supply chain risk management (Wu et al. 2013), manufacturing/distribution planning decisions (MDPDs) for overall effectiveness of supply chain management (Liang 2011), transportation problems in supply chains (Pramanik et al. 2015), supplier selection problem (Costa et al. 2018; Kannan 2018), supply chain vehicle location-routing problem (Govindan et al. 2014), closed loop supply chain network design problem (Devika et al. 2014; Govindan et al. 2015), and reverse logistic provider problem (Li et al. 2018) are some the problems of supply chain management. The most significant problems of supply chain is performance evaluation, which involves several layers of interconnected complex activities. We cannot evaluate supply chain performance by taking into account only input and final output, while ignoring internal activities and relations among suppliers, manufacturers, and customers. Performance improvement at the level of units in the supply chain (divisional efficiency improvement) leads to the overall performance improvement in the chain. In order to measure the supply chain performance, it is essential to take into account several layers of internal activities and relations (Tavana et al. 2013).

In addition, if we want to measure the performance of a supply chain, we can use different methods like Data Envelopment Analysis (DEA). DEA is a non-parametric technique for evaluating a set of homogeneous decision-making units (DMUs) with multiple inputs and outputs (Toloo and Tavana 2017).

Therefore, developing and applying a comprehensive and valid performance measurement system is one of the most important issues in the evaluation of supply chain performance. Relational network DEA is a method used for evaluation of supply chain. In many situations in the real world data are not definite, thus, fuzzy data can be used.

Hence, the following natural question arises: how can we evaluate the performance of a supply chain by considering fuzzy data? This is the most important question for managers and also the main motivation for this study.

We aim at defining a practically implementable method that can guide managers towards potential remedial actions and help them to find out performance of each section. In particular, we address the following question.

- Question: How can we model a supply chain (including suppliers, manufacturers, distributors, and customers) for evaluating performance, using fuzzy data envelopment analysis?

The target of this paper is to present a performance measurement model under uncertain conditions in supply chain network given the existence of shortages in the network. Using this model, we can measure the efficiency of the units by applying the amounts of input, output, and the movement of materials among the divisions of these units. In this study, designing, producing, and selling in several supply chains (that were taken as decision units) and also manufacturers, distributors, and customers were included. The model was suggested in the framework of fuzzy network DEA models and have been used in real case of a supply chain in the automotive industry. Compared to the common models, this model is more capable to reveal the deficiencies of supply chain. In addition, it has the ability to work with fuzzy data in real problems.

The paper is organized as follows. In Sect. 2, a number of previous studies in DEA and its applications in supply chain performance evaluation are reviewed and summarized. In Sect. 3, the mathematical details of the DEA model have been presented. In Sect. 4, the obtained results are analyzed and discussed in an automotive industry. Finally, all findings, discussions and future research directions are summarized in Sect. 5.

2 Literature review

Cost-minimization criteria and profit-maximization criteria are considered as two major criteria in the supply chain management (see, e.g., Camm et al. 1997; Cohen and Lee 1989). In addition, performance evaluation is a necessary step for realization of the aims of both cost-minimization and profit-maximization in supply chain management (Yang et al. 2011).

In this section, different aspects of the related literature are considered; (1) The indicators of supply chain performance evaluation; (2) Network data envelopment analysis; (3) Fuzzy data envelopment analysis; (4) Data envelopment analysis in the evaluation of supply chain performance. Previous studies and the latest research findings in the field of evaluation of performance of supply chains are examined.

When we want to analyze a supply chain network, for the first step we must survey completed structures for several enterprises, All these elements in real world are dynamic and uncertain (Long 2017). In various articles, the criteria and indicators of supply chain performance evaluation have been discussed. Garvin (1993) suggested five performance indices: quality, expenses, on-time delivery, services, and flexibility. Reviewing the previously introduced criteria of supply chain performance evaluation, Beamon (1999) categorizes these criteria into three groups (flexibility, output, and resources) and presents a framework for the evaluation of supply chain performance. According to Beamon (1999), the majority of past research on SCM has focused solely on expenses, time and flexibility, however, levels of attention to external operators such as lack of criteria integrity, lack of systematic view, and lack of non-expenditure operators have increased (Holmberg 2000; De Toni and Tonchia 2001; Chan and Qi 2003). Balfaqih et al. (2016) reviewed supply chain performance measurement systems and assembles an overview of those systems, approaches, techniques and criteria between 1998 and 2015. In a part of this study, DEA presented as a technique for development and evaluation of supply chain management.

Radial measurement DEA models can be used for the problems of supply chain performance evaluation with inter-connected relations (Chen 2011). However, these models are not suitable for problems in which radial and non-radial inputs should be included simultaneously. Radial forecast determines a proportional change in the level of inputs and outputs of deficient DMUs in order to obtain the borders. A number of studies have challenged radial forecasts in DEA, including (1) Criticizing the efficiency score as a performance index (Halme et al. 1999); (2) Rejecting this hypothesis that radial forecasts are sufficiently close to the intended plan or suitable enough; (3) Criticizing the decision-maker inflexibility in the selection of reference unit for a deficient DMU (Korhonen et al. 2001).

Tone (2001) presented an Epsilon-based Measure (EBM) which is a non-radial method for measuring time efficiency in cases that inputs and outputs do not change proportionally. In the radial methods of CCR and BCC, the changes in inputs and outputs are proportional. On the other hand, in non-radial surplus-based models (input surplus, output shortage), such proportions are not taken into account, and no independent changes take place in the surplus values in inputs and outputs.

Tone and Tsutsui (2009) showed that in radial network DEA method, the intermediate products or the relations among activities are not considered. In the same line, they introduced a DEA network model, which was based on the auxiliary variables. This model is used for the evaluation of decision-maker units' efficiency when intermediate products are involved.

Tone and Tsutsui (2010) stated that because there are radial and non-radial factors for the measurement of efficiency, a third factor can be used for measuring the efficiency of an integrated DEA. In this method, radial and non-radial measurements are combined with each other. They introduced a new diversity index which is used for determining the value of ε. This index shows the variations in the data. They also suggested an approach for employing the weights in the surplus value.

By illustrating a case study for the base realignment and closure (BRAC) decision process at the U.S. Department of Defense (DoD), Tavana et al. (2012) suggested three fuzzy DEA models with regarding to probability-possibility, probability-necessity and probability-credibility constraints. Puri and Yadav (2014) applied a fuzzy DEA model with undesirable fuzzy outputs on data from a banking sector in India. Results illustrated the influence of uncertainty in the data over the efficiency results. As another case study, in a resin production company, Azadi et al. (2015) expanded an integrated DEA model for choosing best sustainable suppliers that focused on Russell measure (ERM) model in a fuzzy context. Moreover, Olfat et al. (2016) evaluated the sustainability of airports by using fuzzy extension of SBM dynamic network approach. The evaluation was done through a multi-perspective, multi-system, and multi-process operation. Fuzzy numbers make it possible to omit vagueness of variables during analysis. Then Hatami-Marbini et al. (2017) stated an approach that all the variables, inputs and outputs are considered as fuzzy numbers. A lexicographic multi-objective linear programming (MOLP) is used to solve the model.

Chen and Yan (2011) presented a DEA network model for the evaluation of internal structure of supply chain. They discussed the view of organizing mechanisms to deal with the complexities of supply chain. They introduced network DEA models under the concepts of centralized, decentralized and mixed organization mechanisms and discussed all three different ones. In this study, the relationship between supply chain and divisions, and the relationship among the three different organization mechanisms were discussed in order for efficiency analysis. As a further development, they considered internal resource waste in supply chain.

Halkos et al. (2011) analyzed the two-stage DEA network model. They also studied various models with intermediate measures. In addition, they categorized models into four groups: (1) standard DEA approach (2) Relational DEA models (3) Network DEA (4) Game theoretic models.

Efficiency in top ten dairy companies in Iran. Khalili-Damghani et al. (2012) presented an article on two-stage fuzzy data envelopment analysis. Their mathematical model significantly reduced the amount of computations. Khalili-Damghani and Taghavifard (2012) suggested a three-stage DEA model for the evaluation of efficiency. In this model, fuzzy sets are used for non-definite data.

Extending the common DEA models proposed by Ton and Tsutsui and by taking into account the auxiliary value, Tavana et al. (2013) presented a network model for semiconductor industry. Variety in data and the importance of their relations in efficiency measurement were included in their study. Comparing the results obtained by this method with the results obtained by earlier methods, they concluded that their method was more efficient for networks with several internal relation layers and a large number of units. Mirhedayatian et al. (2014)

used DEA for evaluating GSCM. They considered linking activities in their model. In a case study, they evaluated the GSCM in the presence of dual-role factors, undesirable outputs, and fuzzy data. Moreover, GSCM is a valuable method for decreasing Traffic congestion and air pollution in order to evaluate transportation service providers. For this case of study, Azadi et al. (2014) proposes two approaches which are data envelopment analysis in order to find targets for two-stage network structures to plan in feasible region.

Khodakarami et al. (2015) proposed a structure for evaluation supply chain sustainability in resin producing companies. They did this evaluation in two-stage processes of DEA. Haghighi et al. (2016) evaluated sustainable supply chains with considering a novel hybrid BSC-DEA framework that this supply chain was plastic recycling companies in Mazandaran and Golestan provinces of Iran. By analyzing different BSC factors, strengths and weaknesses of each company are identified. Furthermore, Tavana et al. (2016) stated that in a supply chain with suppliers, manufacturers and distributors, a two-stage DEA method used for evaluating the performance of this three-level supply chain. Kao et al. (2017) measure the efficiencies of a supply network structure for different sections using DEA methods. In order to review articles in the field of data envelopment analysis models in evaluation of supply chain management, Soheilirad et al. (2017) reviewed 75 published articles between 1996 and 2016.

2.1 Research gap

Tables 1 and 2 represent a summary of papers that were discussed before in term of main findings of the research and show gaps and main points about the need of this research.

In order to evaluate supply chain performance, many studies have been managed by DEA approach. As was mentioned, the normal DEA approach has been employed for the measurement of two-stage network performance. In addition, fuzzy DEA approach was used for the evaluation of agility in dairy supply chain (by two-stage fuzzy DEA approach), fresh food products supply chain (by ranking data) and the evaluation of series processes which included on-time production, agility index, and objectives of supply chain (by three-stage fuzzy DEA). By extending the earlier models, a new model was suggested for the evaluation of supply chain performance in automotive industry. In this study, we used fuzzy set theory to reflect the subjective judgments of decision makers regarding the qualitative indicators; it could be useful in assessing the performance of competing supply chain networks.

3 Problem definition and model formulation

At first, we explain and define the problem. Secondly, the parameters and decision variables that we use in the model are presented. Finally, model formulation has been discussed as the results of this experiment.

3.1 Problem definition

Among supply chain entities, the effective and comprehensive performance evaluation methods may be denied because of tradeoff or cooperation. Most of the time maximizing the whole efficiency is more important of each sections of the supply chain. As it is evident in the most supply chains, the outputs of each level are usually the inputs of the next level. Supply chain performance evaluation can be done by DEA methods considering linking activities and multiple entities.

Table 1 Summary of using DEA in supply chain evaluation

References	Main findings
The index of supply chain performance evaluation	
Garvin (1993)	Performance indices: quality, expenses, on-time delivery, services, and flexibility
Beamon (1999)	Structure for the evaluating performance of supply chain
Jakhar (2015)	Traditional metrics of cost and quality used for developing a model on sustainability in supply
Balfaqih et al. (2016)	Review supply chain performance measurement systems 1998–2015
Long (2017)	How in supply chain networks with inter-organizational collaborations, a methodology for data-driven computational experiments can apply
Network data envelopment analysis	
Tone (2001)	A non-radial method, Epsilon-based Measure (EBM), for measuring time efficiency in cases that inputs and outputs do not change proportionally
Tone and Tsutsui (2009)	In radial network DEA method, the intermediate products or the relations among activities are not taken into consideration
Tone and Tsutsui (2010)	Radial and non-radial measurements are combined with each other—approach for employing the weights in the surplus value
Fuzzy data envelopment analysis	
Tavana et al. (2012)	Three fuzzy DEA models considering probability-possibility, probability-necessity and probability-credibility constraints
Puri and Yadav (2014)	Fuzzy DEA model with undesirable fuzzy outputs
Azadi et al. (2015)	Fuzzy integrated DEA model for evaluating the sustainability of suppliers
Olfat et al. (2016)	Efficiency performance of 28 airports based on their attention toward sustainable development principles by fuzzy dynamic network DEA
Hatami-Marbini et al. (2017)	Evaluation by fully fuzzified DEA (FFDEA) approach
Data envelopment analysis in the evaluation of supply chain performance	
Chen and Yan (2011)	Presented a DEA network model for the evaluation of internal structure of supply chain
Halkos et al. (2011)	Analyzed the two-stage DEA network model
Khalili-Damghani et al. (2011)	A combinatory approach for the evaluation of agile supply chain performance
Khalili-Damghani et al. (2012)	A two-stage fuzzy data envelopment analysis. Their mathematical model significantly reduced the amount of computations
Khalili-Damghani and Taghavifard (2012)	A three-stage DEA model for the evaluation of efficiency. In this model, fuzzy sets are used for non-definite data
Khalili-Damghani and Tavana (2013)	A fuzzy DEA network model for the evaluation agile supply chain
Tavana et al. (2013)	A new network model for semiconductor industry

Table 1 continued

References	Main findings
Mirhedayatian et al. (2014)	A novel network DEA model for evaluating the GSCM
Azadi et al. (2014)	Two DEA approaches to evaluate transportation service providers
Khodakarami et al. (2015)	Two-stage DEA models in resin producing companies for evaluating the sustainability of supply chains
Haghighi et al. (2016)	Performance evaluation in sustainable supply chains by using a novel hybrid BSC-DEA framework
Tavana et al. (2016)	Suppliers, manufacturers and distributors in three-level supply chain evaluated by a two-stage DEA method
Kao et al. (2017)	Evaluating the efficiencies of a three-stage DEA model

Table 2 Research gap

References	Method			
	FDEA	NDEA	SBM-DEA	EBM-DEA
Tone (2001)			*	*
Tone and Tsutsui (2009)		*	*	
Tone and Tsutsui (2010)		*		*
Chen and Yan (2011)		*		
Khalili-Damghani et al. (2011)		*		
Tavana et al. (2012)	*			
Khalili-Damghani et al. (2012)	*	*		
Khalili-Damghani and Taghavifard (2012)	*	*		
Khalili-Damghani and Tavana (2013)	*	*		
Tavana et al. (2013)		*	*	*
Mirhedayatian et al. (2014)		*	*	
Puri and Yadav (2014)	*			
Azadi et al. (2015)	*			
Khodakarami et al. (2015)		*	*	
Olfat et al. (2016)	*	*	*	
Haghighi et al. (2016)		*	*	*
Tavana et al. (2016)		*		
Hatami-Marbini et al. (2017)	*			
Kao et al. (2017)		*		
This paper	*	*	*	*

In applying conventional DEA, we will require crisp input and output data. We deal with fuzzy data in real world. Therefore, in real life problems, inputs and outputs are often imprecise. To deal with this situation, the notion of fuzziness was introduced in DEA and the DEA was extended to fuzzy DEA (FDEA) (Puri and Yadav 2014). Considering the research gaps and cases in the real world, decision-makers usually use fuzzy qualitative indices in order to measure inputs and outputs in every stage of DEA models. In order to measure supply chain performance and by using the NEBM model, the input and output variables and also the intermediate products were made fuzzy. In this way, a new method was created by which the efficiency of decision-maker units can be obtained by taking into account the fuzzy values. In this way, in addition to finding the efficient unit, the ranking of other units can be determined on the basis of their source sets.

3.2 Indices, parameters, and variables of the model

Tavana et al. (2013) suggested the NEBM model which could solve a multilayered internal linking activities and multiple entities for the simultaneous radial and non-radial measurement of DEA efficiency. Their model also can manage the diversity of the input and output data and their relative importance for measuring technical efficiency. The NEBM Model (1) is obtained on the basis of model input in order to change the radial measurement into non-radial measurement and vice versa.

$$
\begin{aligned}
&\gamma = \min \sum_{h=1}^{k} W_h \left(\theta_h - \varepsilon_i^h \sum_{i=1}^{m_h} \frac{w_i^{h-} s_i^{h-}}{x_{io}^h} \right) \\
&\text{s.t.} \\
&\sum_{j=1}^{n} x_{ij}^h \lambda_j^h + s_i^{h-} = \theta_h x_{io}^h, \quad i = 1, \ldots, m_h, h = 1, \ldots, k. \\
&\sum_{j=1}^{n} y_{rj}^h \lambda_j^h \geq y_{ro}^h, \quad r = 1, \ldots, s_h, h = 1, \ldots, k. \\
&\sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h')} \lambda_j^h = \sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h')} \lambda_j^{h'}, \; f_{(h,h')} = 1, \ldots, F_{(h,h')}, \forall (h, h') \\
&\theta_h \leq 1, \quad h = 1, \ldots, k \\
&\lambda_j^h \geq 0, \; j = 1, \ldots, n, \quad h = 1, \ldots, k \\
&s_i^{h-} \geq 0, \quad i = 1, \ldots, m_h, \quad h = 1, \ldots, k
\end{aligned}
\tag{1}
$$

The following notations and parameters are used in this model can be represented as follows:

j	Number of decision maker unit (DMU), $j = 1, \ldots, n$
i	Index of inputs, $i = 1, \ldots, m_h$
r	Index of outputs, $r = 1, \ldots, s_h$
h	Index of divisions, $h = 1, \ldots, k$
$f_{(h,h')}$	The number of intermediate measures sent from the hth division to the $h^{'}$th division, $f_{(h,h')} = 1, \ldots, F_{(h,h')}$
x_{ij}^h	The ith input of the hth division in jth supply chain
y_{rj}^h	The rth output of the hth division in jth supply chain
$z_{f_{(h,h')}j}^{(h,h^{'})}$	Linking intermediate products from division h to division $h^{'}$ of jth supply chain (or DMU)
w_i^{h-}	The ith input weight of the hth division $\sum_{i==1}^{n} w_i^{h-} = 1 (w_i^{h-} \geq 0, \forall i)$
ε_i^h	Parameter which depends on the degree of dispersion of the ith input in the hth division

W_h	The weight of the hth division and is determined by the decision makers
	And also the variables can be as follows too:
θ_h	The radial properties of the NEBM of the hth division
λ_j^h	The intensity vector corresponding to division h at DMU j
s_i^{h-}	The amount of slack in the ith input of the hth division
$\varepsilon_i^h \sum_{i=1}^{m_h} \frac{w_i^{h-} s_i^{h-}}{x_{io}^h}$	The non-radial properties of the NEBM model

In order to determine w_i^{h-} and ε_i^h, first the diversity matrix and the affinity matrix are made. By obtaining the affinity matrix vector, w_i^{h-} and ε_i^h parameters are calculated. ε_i^h is a parameter for changing the radial model into non-radial model and vice versa. This model is dependent on the degree of data dispersion. When $\varepsilon_i^h = 0$, data variance is low; when $\varepsilon_i^h = 1$, data dispersion is maximum.

Constraint 1 and 2 are applied to hth input and output units. The third constraint is applied to intermediate product. The left side of equation is related to the dispatched product from hth unit, and its right side is related to sending of the same product to h'th unit.

3.3 Model formulation and solving methodology

The following steps are used to create the fuzzy model:

Step 1: All fuzzy x, y, and z variables are written by fuzzy triangular values. By taking into account the fuzzy triangular values, which are usually used in the real world problems, the model can be extended, and an FNEBM model is obtained.

In every decision-maker unit $j = 1, \ldots, n$, there are m fuzzy values $(\overline{x_{ij}^h})$ $(i = 1, \ldots, m_h)$, and r fuzzy outputs $(\overline{y_{rj}^h})$ $(r = 1, \ldots, s_h)$. The intermediate measurement between hth unit and h'th unit is done by f fuzzy intermediates $(z_{f_{(h,h')}j}^{(h,h')})$ $(f_{(h,h')} = 1, \ldots, F_{(h,h')})$.

For the needed α-cut, according to the following equations, the upper limit and the lower limit of input membership function are calculated. Also, the intermediate measurement and the output are calculated by the followings:

$$(x_{ij}^{hL})_\alpha = \alpha x_{ij}^{h2} + (1-\alpha)x_{ij}^{h1}, \alpha \in [0,1], i = 1, \ldots, m_h, j = 1, \ldots, n, h = 1, \ldots, k \quad (2)$$

$$(x_{ij}^{hU})_\alpha = \alpha x_{ij}^{h2} + (1-\alpha)x_{ij}^{h3}, \alpha \in [0,1], i = 1, \ldots, m_h, j = 1, \ldots, n, h = 1, \ldots, k \quad (3)$$

Model (2) and (3) are the lower limit and the upper limit of inputs $(\overline{x_{ij}^h})$

$$(z_{f_{(h,h')}j}^{(h,h')L})_\alpha = \alpha z_{f_{(h,h')}j}^{(h,h')2} + (1-\alpha)z_{f_{(h,h')}j}^{(h,h')1}, \alpha \in [0,1], f_{(h,h')} = 1, \ldots, F_{(h,h')}, j = 1, \ldots, n, h = 1, \ldots, k \quad (4)$$

$$(z_{f_{(h,h')}j}^{(h,h')U})_\alpha = \alpha z_{f_{(h,h')}j}^{(h,h')2} + (1-\alpha)z_{f_{(h,h')}j}^{(h,h')3}, \alpha \in [0,1], f_{(h,h')} = 1, \ldots, F_{(h,h')}, j = 1, \ldots, n, h = 1, \ldots, k \quad (5)$$

Model (4) and (5) are the lower limit and the upper limit of intermediating measurement $(z_{f_{(h,h')}j}^{(h,h')})$

$$(y_{rj}^{hL})_\alpha = \alpha y_{rj}^{h2} + (1-\alpha)y_{rj}^{h1}, \alpha \in [0,1], r = 1, \ldots, s_h, j = 1, \ldots, n, h = 1, \ldots, k \quad (6)$$

$$(y_{rj}^{hU})_\alpha = \alpha y_{rj}^{h2} + (1-\alpha) y_{rj}^{h3}, \alpha \in [0,1], r = 1, \ldots, s_h, j = 1, \ldots, n, h = 1, \ldots, k \quad (7)$$

Model (6) and (7) are the lower limit and the upper limit of outputs $(\overline{y_{rj}^h})$

Step 2: For parametric model calculation, the definite model is used.

Using α-cut, all variables are determined in one α-cut level parametrically.

$$\gamma = \min \sum_{h=1}^{k} W_h \left(\theta_h - \varepsilon_i^h \sum_{i=1}^{m_h} \frac{w_i^{h-} s_i^{h-}}{(x_{io}^h)_\alpha} \right)$$

s.t.

$$\left(\sum_{j=1}^{n} (x_{ij}^h)_\alpha \lambda_j^h \right) + s_i^{h-} = \theta_h \left(x_{io}^h \right)_\alpha, i = 1, \ldots, m_h, h = 1, \ldots, k.$$

$$\left(\sum_{j=1}^{n} (y_{rj}^h)_\alpha \lambda_j^h \right) \geq \left(y_{ro}^h \right)_\alpha, r = 1, \ldots, s_h, h = 1, \ldots, k.$$

$$\sum_{j=1}^{n} \left(z_{f_{(h,h')}j}^{(h,h')} \right)_\alpha \lambda_j^h = \sum_{j=1}^{n} \left(z_{f_{(h,h')}j}^{(h,h')} \right)_\alpha \lambda_j^{h'}, f_{(h,h')} = 1, \ldots, F_{(h,h')}, \forall (h, h')$$

$$\theta_h \leq 1, h = 1, \ldots, k$$

$$\lambda_j^h \geq 0, j = 1, \ldots, n, h = 1, \ldots, k$$

$$s_i^{h-} \geq 0, i = 1, \ldots, m_h, h = 1, \ldots, k \quad (8)$$

where the parameters used to characterize this supply chain are defined as follows:

$\overline{x_{1j}^{h_s}}$	On-time delivery standard deviation of the h_sth supplier in the jth supply chain
$\overline{x_{2j}^{h_s}}$	The h_sth supplier's distance from the manufacturer in the jth supply chain
$\overline{x_{3j}^{h_s}}$	Price of the h_sth supplier in the jth supply chain
$\overline{y_{1j}^{h_s}}$	Quality (1 – Percentage of Returned Items) of the h_sth supplier in the jth supply chain
h_s	Numerator of the division in the suppliers level (h_s = 1, 2, 3)
$\overline{x_{1j}^{h_m}}$	Number of stoppages of the h_mth manufacturer in the jth supply chain
$\overline{x_{2j}^{h_m}}$	Number of machines of the h_mth manufacturer in the jth supply chain
$\overline{x_{3j}^{h_m}}$	Number of employees of the h_mth manufacturer in the jth supply chain
$\overline{y_{1j}^{h_m}}$	Work-in-Progress (WIP) reciprocal of the h_mth manufacturer in the jth supply chain
$\overline{y_{2j}^{h_m}}$	Flow time (FT) reciprocal of the h_mth manufacturer in the jth supply chain
$\overline{y_{3j}^{h_m}}$	Flexibility (percentage of the applied changes to the expected changes) of the h_mth manufacturer in the jth supply chain
h_m	Numerator of the division in the manufacturers level (h_m = 4, 5)
$\overline{x_{1j}^{h_d}}$	Cost per dollar revenue of the h_dth distributer in the jth supply chain
$\overline{x_{2j}^{h_d}}$	On-time delivery standard deviation of the h_dth distributer in the jth supply chain
$\overline{y_{1j}^{h_d}}$	Service level of the h_dth distributer in the jth supply chain

$\overline{y_{2j}^{h_d}}$	Successful customer order percentage of the h_dth distributer in the jth supply chain
h_d	Numerator of the division in the distributors level (h_d =6, 7)
$\overline{x_{1j}^{h_c}}$	Cancelled customer order percentage of the h_cth customer in the jth supply chain
$\overline{y_{1j}^{h_c}}$	Tenure of the h_cth customer in the jth supply chain
$\overline{y_{2j}^{h_c}}$	Order volume of the h_cth customer in the jth supply chain
$\overline{y_{3j}^{h_c}}$	Order commitment percentage of the h_cth customer in the jth supply chain
h_c	Numerator of the division in the customer level (h_c =8, 9, 10, 11)
$\overline{z_{f_{(h,h')}j}^{(h,h')}}$	Material flow from division h to division h', ($\forall(h, h')$)
$\overline{\bar{z}_{f_{(h,h')}j}^{(h,h')}}$	Average material flow from division h to division h', ($\forall(h, h')$)

Step 3: In this step, model is divided into optimistic and pessimistic conditions. In order to prevent this, we solve the model by calculation and an appropriate level of preciseness. To achieve this objective, in every α-cut, x, y, and z are transformed into an interval. In every interval, the mean of upper and lower limits is calculated.

$$(x_{ij}^{h})_\alpha = \frac{(x_{ij}^{hL})_\alpha + (x_{ij}^{hU})_\alpha}{2} = \frac{\alpha x_{ij}^{h2} + (1-\alpha)x_{ij}^{h1} + \alpha x_{ij}^{h2} + (1-\alpha)x_{ij}^{h3}}{2}$$
$$= \frac{2\alpha x_{ij}^{h2} + (1-\alpha)(x_{ij}^{h1} + x_{ij}^{h3})}{2}, \alpha \in [0, 1], i = 1, \ldots, m_h, j = 1, \ldots, n, h = 1, \ldots, k \tag{9}$$

$$(y_{rj}^{h})_\alpha = \frac{(y_{rj}^{hL})_\alpha + (y_{rj}^{hU})_\alpha}{2} = \frac{\alpha y_{rj}^{h2} + (1-\alpha)y_{rj}^{h1} + \alpha y_{rj}^{h2} + (1-\alpha)y_{rj}^{h3}}{2}$$
$$= \frac{2\alpha y_{rj}^{h2} + (1-\alpha)(y_{rj}^{h1} + y_{rj}^{h3})}{2}, \alpha \in [0, 1], r = 1, \ldots, s_h, j = 1, \ldots, n, h = 1, \ldots, k \tag{10}$$

$$\left(z_{f_{(h,h')}j}^{(h,h')}\right)_\alpha = \frac{\left(z_{f_{(h,h')}j}^{(h,h')L}\right)_\alpha + \left(z_{f_{(h,h')}j}^{(h,h')U}\right)_\alpha}{2}$$
$$= \frac{\alpha z_{f_{(h,h')}j}^{(h,h')2} + (1-\alpha)z_{f_{(h,h')}j}^{(h,h')1} + \alpha z_{f_{(h,h')}j}^{(h,h')2} + (1-\alpha)z_{f_{(h,h')}j}^{(h,h')3}}{2}$$
$$= \frac{2\alpha z_{f_{(h,h')}j}^{(h,h')2} + (1-\alpha)\left(z_{f_{(h,h')}j}^{(h,h')1} + z_{f_{(h,h')}j}^{(h,h')3}\right)}{2},$$
$$\alpha \in [0, 1], f_{(h,h')} = 1, \ldots, F_{(h,h')}, j = 1, \ldots, n, h = 1, \ldots, k \tag{11}$$

By putting (9–11) equations in Model (8), Model (12) is obtained. In this model, every variable has only one value.

$$\gamma = \min \sum_{h=1}^{k} W_h \left(\theta_h - \varepsilon_i^h \sum_{i=1}^{m_h} \frac{w_i^{h-} s_i^{h-}}{\frac{2\alpha x_{io}^{h2} + (1-\alpha)(x_{io}^{h1} + x_{io}^{h3})}{2}} \right)$$

s.t.

$$\left(\sum_{j=1}^{n}\frac{2\alpha x_{ij}^{h2}+(1-\alpha)(x_{ij}^{h1}+x_{ij}^{h3})}{2}\lambda_j^h\right)+s_i^{h-}$$
$$=\theta_h\frac{2\alpha x_{io}^{h2}+(1-\alpha)(x_{io}^{h1}+x_{io}^{h3})}{2},\ i=1,\ldots,m_h,\ h=1,\ldots,k.$$
$$\left(\sum_{j=1}^{n}\frac{2\alpha y_{rj}^{h2}+(1-\alpha)(y_{rj}^{h1}+y_{rj}^{h3})}{2}\lambda_j^h\right)\geq\frac{2\alpha y_{ro}^{h2}+(1-\alpha)(y_{ro}^{h1}+y_{ro}^{h3})}{2},$$
$$r=1,\ldots,s_h,\ h=1,\ldots,k.$$
$$\sum_{j=1}^{n}\frac{2\alpha z_{f_{(h,h')}j}^{(h,h')2}+(1-\alpha)(z_{f_{(h,h')}j}^{(h,h')1}+z_{f_{(h,h')}j}^{(h,h')3})}{2}\lambda_j^h$$
$$=\sum_{j=1}^{n}\frac{2\alpha z_{f_{(h,h')}j}^{(h,h')2}+(1-\alpha)\left(z_{f_{(h,h')}j}^{(h,h')1}+z_{f_{(h,h')}j}^{(h,h')3}\right)}{2}\lambda_j^{h'},\ f_{(h,h')}=1,\ldots,F_{(h,h')},\ \forall(h,h')$$
$$\theta_h\leq 1,\ h=1,\ldots,k$$
$$\lambda_j^h\geq 0,\ j=1,\ldots,n,\ h=1,\ldots,k$$
$$s_i^{h-}\geq 0,\ i=1,\ldots,m_h,\ h=1,\ldots,k \tag{12}$$

Step 4: In this step, α-cut is used. This is done for values between 0 and 0.9. The length of every step (interval) is 0.1. The model is solved 10 times with various αs (α-cut). The efficiency of every DMU is calculated 10 times.

Step 5: Using mean of rankings which has been calculated by 10 executions (RUNs) of DMU, DMUs are ranked.

Step 6: The obtained values show the efficiencies of DMUs. For calculating the efficiencies of various internal sections (divisions) of DMUs, the efficiencies of these sections (divisions) are calculated by the previously-mentioned method. Therefore, the efficiencies of peripheral DMUs are calculated 10 times. They can also be evaluated and ranked on the basis of ranking means.

In this section, by using fuzzy mean method and by considering the inputs, outputs, and the intermediate values defined by fuzzy sets, we managed to make Tavana et al.'s model (2013) fuzzy. In this way, the model can be used in real problems, in which the non-definiteness of data is unavoidable.

4 Experimental results

In the previous section, our model was presented. By using triangular fuzzy sets for inputs, outputs, and transfer of materials among the units, we managed to reformulate the main model. In this section, an example is presented and the model is analyzed and evaluated. In order to apply this model in the real world problems and to show the efficiency of processes and the capability of the model, automotive industry is taken as an example. The automotive industry covers a wide range of companies and organizations involved in design, development, manufacturing, marketing, and selling of motor vehicles. The automotive industry is not only one of the world's most important economic sectors by revenue, but also takes up a

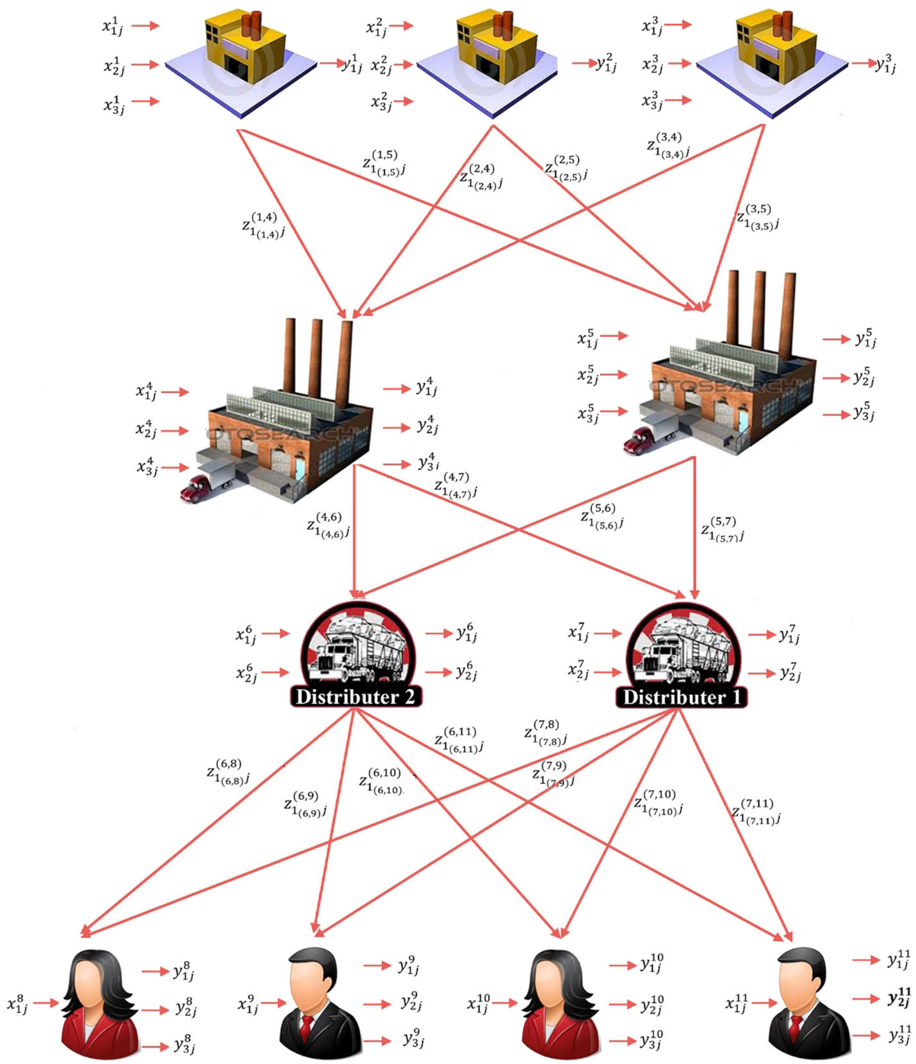


Fig. 1 The supply chain structure

leading role in quality expectations, product variety and process complexity. As a result of globalization and customer requirements, car manufacturers offer a large range of vehicle models and options. The enormous product variety-induced complexity and the pressure of tough competitions make it hard for an efficient logistics. This is why industrial computing plays a major role throughout the entire automotive supply chain, from allocation and storage of raw materials and components to production and delivery in a timely manner.

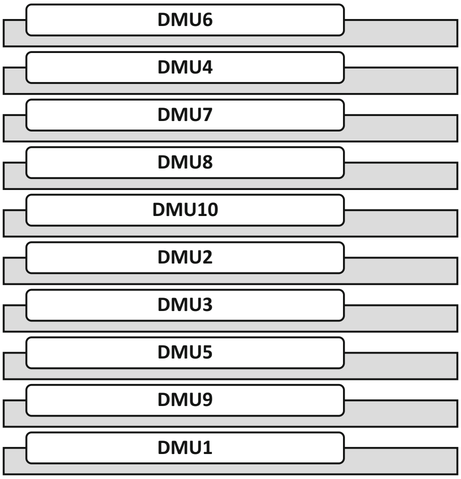
The case of the study includes designing, producing, and the selling of integrated circuit products in 10 supply chains (DMUs). As can be seen in Fig. 1, it includes 3 suppliers, 2 manufacturers, 2 distributors, and 3 customers.

By Lingo 14.0 software, the model has been codified for various αs (Sect. 4). In Table 3, the efficiency of the model is observed for 10 RUNs.

Table 3 The efficiency of the model observed from 10 RUNs

	$\alpha = 0$	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	Average
DMU 1	0.67374	0.673358	0.672975	0.672592	0.672209	0.671826	0.671442	0.671058	0.670675	0.670296	0.672017
DMU 2	0.914059	0.913676	0.913292	0.912907	0.912522	0.912135	0.911747	0.911358	0.910968	0.910576	0.912324
DMU 3	0.909223	0.909102	0.908979	0.908852	0.908723	0.908592	0.908457	0.90832	0.908179	0.908035	0.908646
DMU 4	0.98075	0.980312	0.979876	0.97944	0.979006	0.978572	0.978139	0.977707	0.977276	0.976846	0.978793
DMU 5	0.882242	0.882142	0.882041	0.88194	0.881841	0.881742	0.881642	0.881542	0.881441	0.88134	0.881791
DMU 6	1	1	1	1	1	1	1	1	1	1	1
DMU 7	0.973299	0.973299	0.973299	0.973299	0.973299	0.973299	0.973299	0.973299	0.973299	0.973299	0.973299
DMU 8	0.952234	0.952644	0.953063	0.953493	0.953934	0.954387	0.954851	0.955328	0.955819	0.956074	0.954183
DMU 9	0.745092	0.744991	0.744892	0.744793	0.744695	0.744598	0.744502	0.744407	0.744313	0.744219	0.74465
DMU 10	0.946231	0.946231	0.946231	0.946231	0.946231	0.946231	0.946231	0.946231	0.946231	0.946231	0.946231

Fig. 2 The ranking of DMUs



The final ranking of DMUs is done by using the mean of rankings obtained from DMUs in 10 executions (RUNs).

The ranking of DMUs, on the basis of their efficiencies in 10 executions (RUN), is as Fig. 2.

Now, the efficiencies of 11 various units of each DMU is obtained separately (divisional efficiency) and also by classifying these sections (divisions) into suppliers, manufacturers, distributors, and customers in two ways with different αs. In Table 4, the efficiencies of the sections (divisions) of DMU1 are shown. The ranking of the units has been in Table 5.

In Table 6, the efficiencies of DMU1 sections (divisions) have been presented separately for suppliers, manufacturers, distributors, and customers. Table 7 show the ranking of these units have for all DMUs.

Now we have obtained the efficiencies of the units. In order to measure the performance of deficient units, the method presented by Tone and Tsutsui (2009) is employed and the efficiency projections of these deficient units onto efficiency frontier (border) is obtained. In order to do such calculations, we need shortage value, surplus value, and λ. These values are calculated by the software. By these values, the projection of inputs, outputs, and intermediates are obtained.

The efficient units are considered as reference models for deficient unit. By making a direct comparison between a deficient unit and its reference efficient unit, every deficient unit can be evaluated. The reference units of deficient units have been presented in Table 8. In this Table, for example, the reference sets of unit 2 are 1 and 9. It means that unit 2 of DMU1 and unit 2 of DMU9 are the references of unit 2 in DMU 1.

5 Discussion and managerial implications

The proposed DEA based approach provides useful managerial implications in measuring efficiency of supply chain. This study proves that DEA is a useful decision-making tool in supply chain. The following highlights the managerial implications inferred from solutions obtained by DEA models.

Table 4 The efficiencies of the sections (divisions) of DMU1

	α = 0	α = 0.1	α = 0.2	α = 0.3	α = 0.4
Suppliers					
Division1	1	1	1	1	1
Division2	0.998835	0.998711	0.998586	0.998459	0.998331
Division3	0.726163	0.725487	0.724807	0.724122	0.723433
Manufacturers					
Division4	0.410782	0.409704	0.408628	0.407554	0.406481
Division5	0.695524	0.693796	0.692068	0.690342	0.688617
Distributers					
Division6	0.954144	0.954093	0.954042	0.95399	0.953938
Division7	0.791348	0.791643	0.791936	0.792227	0.792516
Customers					
Division8	0.2	0.199791	0.199583	0.199378	0.199175
Division9	0.281617	0.281495	0.281375	0.281256	0.281138
Division10	1	1	1	1	1
Division11	0.140989	0.141002	0.141015	0.141028	0.141041

	α = 0.5	α = 0.6	α = 0.7	α = 0.8	α = 0.9	Average
DMU1						
Suppliers						
Division1	1	1	1	1	1	1
Division2	0.998201	0.998071	0.997939	0.997806	0.997675	0.998584
Division3	0.72274	0.722043	0.721342	0.720637	0.719964	0.724802
Manufacturers						
Division4	0.405409	0.404339	0.40327	0.402203	0.401191	0.40863
Division5	0.686892	0.685169	0.683446	0.681725	0.680002	0.692069
Distributers						
Division6	0.953884	0.95383	0.953775	0.953719	0.953687	0.954041
Division7	0.792802	0.793086	0.793368	0.793647	0.793978	0.791934
Customers						
Division8	0.198974	0.198776	0.198579	0.198384	0.198191	0.199585
Division9	0.281022	0.280906	0.280792	0.28068	0.280467	0.281376
Division10	1	1	1	1	1	1
Division11	0.141054	0.141067	0.14108	0.141093	0.141031	0.141015

One of the most important aspects of efficiency evaluation by data envelopment analysis is the identification of deficiency sources and determining the optimum levels of inputs and outputs for deficient units. The identification of these sources of deficiency reveals the weaknesses of deficient units. Also, finding the optimum levels of input, output, and intermediates can help us remove causes of deficiency and to improve efficiency.

Based on the value of inputs, outputs, and intermediates and their differences with their projections that were mentioned in the tables, the necessary changes can be made to improve the efficiency.

Table 5 The ranking of the units

DMU1	DMU2	DMU3	DMU4	DMU5	DMU6	DMU7	DMU8	DMU9	DMU10
Division1	Division1	Division3	Division1	Division1	Division1	Division1	Division1	Division1	Division1
Division10	Division3	Division4	Division2	Division5	Division2	Division2	Division3	Division2	Division2
Division2	Division4	Division5	Division4	Division8	Division3	Division3	Division4	Division3	Division3
Division6	Division5	Division6	Division5	Division9	Division4	Division4	Division5	Division4	Division4
Division7	Division6	Division7	Division6	Division3	Division5	Division5	Division6	Division5	Division5
Division3	Division7	Division8	Division7	Division4	Division6	Division6	Division7	Division7	Division6
Division5	Division8	Division9	Division9	Division2	Division7	Division7	Division8	Division11	Division7
Division4	Division10	Division11	Division10	Division6	Division8	Division9	Division9	Division6	Division8
Division9	Division11	Division2	Division11	Division10	Division9	Division10	Division11	Division8	Division9
Division8	Division2	Division1	Division8	Division7	Division10	Division11	Division10	Division10	Division11
Division11	Division9	Division10	Division3	Division11	Division11	Division8	Division2	Division9	Division10

Table 6 The efficiencies of DMU1 sections (divisions)

	α = 0	α = 0.1	α = 0.2	α = 0.3	α = 0.4
Suppliers	0.9282783	0.928047	0.927813	0.927578	0.927342
Manufacturers	0.5161362	0.514818	0.513501	0.512185	0.510871
Distributers	0.8646059	0.864745	0.864884	0.865021	0.865156
Customers	0.4657179	0.465641	0.465565	0.46549	0.465415

	α = 0.5	α = 0.6	α = 0.7	α = 0.8	α = 0.9	Average
DMU1						
Suppliers	0.9271031	0.926863	0.926621	0.926378	0.926144	0.998046
Manufacturers	0.5095578	0.508246	0.506935	0.505626	0.504351	0.721921
Distributers	0.8652892	0.865421	0.865551	0.86568	0.865847	0.404173
Customers	0.4653419	0.465269	0.465197	0.465126	0.465008	0.684884

Table 7 The ranking of units for all DMUs

DMU1	DMU2	DMU3	DMU4	DMU5
Suppliers	Manufacturers	Manufacturers	Manufacturers	Manufacturers
Manufacturers	Distributers	Distributers	Distributers	Suppliers
Customers	Customers	Suppliers	Customers	Customers
Distributers	Suppliers	Customers	Suppliers	Distributers
DMU6	**DMU7**	**DMU8**	**DMU9**	**DMU10**
Suppliers	Suppliers	Manufacturers	Suppliers	Suppliers
Manufacturers	Manufacturers	Distributers	Manufacturers	Manufacturers
Distributers	Distributers	Customers	Distributers	Distributers
Customers	Customers	Suppliers	Customers	Customers

In order to explain the results of the model that was presented, the outputs of the supply chain are used. For instance, for α = 0, we evaluate DMU 1:

DMU 1 with an efficiency of 0.67 is identified as the last unit in terms of efficiency. By identifying the causes of deficiency, it is put within the borders of efficiency.

Among the 11 units in this DMU, the first supplier and the third customer were assigned an efficiency score of 1. The other units, whose efficiencies are lower than 1, are recognized as deficient units. For instance, the fourth customer with an efficiency score of 0.14 has the lowest score. Using reference sets and the projection of inputs, outputs, and intermediates onto the efficiency frontier (border), we can enhance the efficiency of the unit. In this way, the overall efficiency of DMU is increased. DMU was divided into the 4 layers of suppliers, manufacturers, distributors, and customers; then, the efficiency of these layers was calculated separately. Manufacturers had the highest efficiency score (0.92) and the customers had the lowest score (0.46).

When there is a product in the supply chain which passes through only group of sections, the efficiency can still be calculated. In the rest of DMUs and various αs, the same thing can be done.

Table 8 The reference sets of deficient units

DMU	Ref DIV1	Ref DIV2	Ref DIV3	Ref DIV4	Ref DIV5	Ref DIV6	Ref DIV7	Ref DIV8	Ref DIV9	Ref DIV10	Ref DIV11
1	1	1,9	2, 3, 6, 7*, 10	6, 7, 8, 9, 10	4, 5, 6, 7	1, 2, 5, 7	6, 7, 8–10	3, 5, 8	3, 8, 10	1	4, 7, 10
2	2	5, 6, 9, 10	2	2	2	2	2	2	3,5****,6,8	2	2
3	2, 5, 6, 9	6,7,9	3	3	3	3	3	3	3	4, 6, 7	3
4	4	4	2, 3, 5, 8, 10	4	4	4	4	3, 5, 6	4	4	4
5	5	5, 6, 9, 10	2**, 3, 5, 8, 10	5, 7, 8, 9, 10	5	2, 5, 10	1, 6, 7, 8, 10	5, 8	3, 8	1, 2	7, 10
6	6	6	6	6	6	6	6	6	6	6	6
7	7	7	7	7	7	7	7	3,5,8	7	7	7
8	8	6,7,9	8	8	8	8	8	8	8	4, 5, 6***	8
9	9	9	9	9	9	1, 2, 6, 7, 10	9	3, 8, 10	3, 4, 7, 8	1, 4, 5	4, 6
10	10	10	10	10	10	10	10	10	10	1, 7	10

*In $\alpha = 0.9$ DMU7 is not a reference set
**In $\alpha = 0, 0.1,$ and 0.2 DMU2 are not reference sets
***In $\alpha = 0.9$ DMU9 is only a reference set
****In $\alpha = 0$ DMU5 is not a reference set

Table 9 The projection of the efficiency of the second section of DMU1

	x_{ij}^{h}	x_{ij}^{h*}	s^{h-*}
x_{1j}^{21}	2.88	2.759998	0.1200017
x_{2j}^{21}	675	658.6212	16.378755
x_{3j}^{21}	1	1	0
	y_{rj}^{h}	y_{rj}^{h*}	s^{h+*}
y_{1j}^{21}	86	86	0
	$z_{f_{(h,h')}j}^{(h,h')}$	$z_{f_{(h,h')}j}^{(h,h')*}$	λ^{h*}
$z_{f_{(2,4)}j}^{(2,4)1}$	328	291.7624	0.8895196
$z_{f_{(2,5)}j}^{(2,5)1}$	108	96.06811	0.8895196

Table 10 The overall efficiency scores of the supply chains for the four models

DMU	Overall efficiency scores			
	NSBM	FNEBM	NEBM	NCCR
1	0.66	0.67	0.711	0.756
2	0.945	0.912	0.97	1
3	0.889	0.908	0.917	0.95
4	0.975	0.978	0.981	0.981
5	0.858	0.881	0.874	0.887
6	1	1	1	1
7	0.973	0.973	0.973	0.973
8	0.927	0.954	0.957	0.957
9	0.684	0.744	0.718	0.746
10	0.909	0.946	0.924	0.946

For example, in order to calculate the projection of the efficiency of the second section of DMU 1 ($\alpha = 0.1$) for the first fuzzy value, the values of input, intermediate, and output are changed according to Table 9:

In this section, an example was presented in order to evaluate the efficiency of the units by the model introduced in the third section.

For various fuzzy αs, this approach was examined and the efficiencies were calculated. For deficient units, the projections of efficiency were calculated. In this way, the necessary changes can be made to improve the efficiencies.

Table 10 and Fig. 3 present the efficiency scores measured by the NSBM model, the NEBM model, the NCCR model (all of these three models are obtained from the article Tavana et al. (2013)) and FNEBM model (12). The results from these four models show that the sixth supply chain is the only efficient DMU. In addition, the result from the NCCR model also indicates that the second supply chain is also efficient. Tavana et al. (2013) explained the reason of this exception. Figure 3 also shows that the efficiency scores of the supply chains obtained from the FNEBM model are between the efficiency scores obtained from the NSBM and the NCCR models. Up to DMU 8, it is below than NEBM model, then for DUM 9 and 10 it is upper than NEBM model.

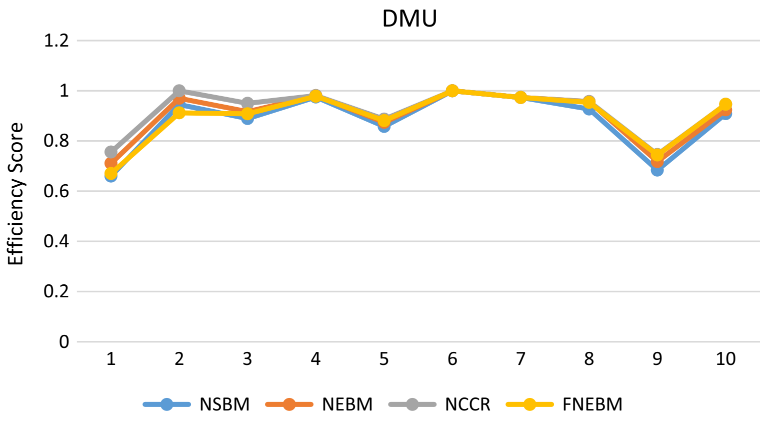


Fig. 3 The overall efficiency scores of the DMUs for the four models

6 Conclusions and future research

Performance evaluation of the automotive industry is a challenging issue mainly because of multi-dimensionality of the evaluation process together with existence of subjectivity and imprecision which makes the decision making process subject to uncertainty.

Today, evaluation and improvement of the performance is considered as one of the effective factors in the success of every organization. Among the various indices, performance evaluation is particularly important. The results obtained by this analysis help organizations get an intuition of their units' performance. In this way, they can improve their performance by removing the causes of deficiencies. Currently, various methods have been introduced to evaluate efficiency. The non-parametric DEA is one of the methods which have the highest applications. This method is based on non-linear programming. Using this method, we can calculate the relative efficiency of a set of homogenous decision-maker units that receive a number of similar inputs and produce a number of similar outputs. In this way, their performance can be compared with each other. By taking into account the shortage values in the model and the fuzzy-making of inputs, outputs, and intermediate values, a model is presented for the evaluation of the performance. This model divides units into two groups on efficient and deficient units. Also, the causes of deficiency can be identified.

The contributions of this research can be stated as follows: (1) the model was made fuzzy and was reformulated by fuzzy input, output, and intermediate values, (2) the overall efficiencies of DMUs were calculated, (3) the efficiencies of the sections (divisions) of DMUs were calculated separately (divisional efficiencies). Also, the mean of these efficiencies (with different αs) was calculated, (4) the efficiencies of the layers of DMUs (supplier, manufacturer, distributor, and customer) are calculated separately, (5) for deficient units, their correspondent reference units are determined and (6) the images (contrasts-opposites) of deficient units on efficiency border (limit) are obtained.

The suggestion of the researcher on the basis of the findings of study could be using this method in various evaluations, for example using this method in reverse supply chain (Govindan et al. 2015). Moreover, the usage of the suggested model and the proposed solution could be used in different supply chain. Furthermore, the fuzzy input and output were applied to face the uncertainties. However, fuzzy constraints can apply to deal with uncertainties and other fuzzy approaches for fuzzy modeling and non-definite data.

Acknowledgements The authors would like to thank the anonymous reviewers and the editor for their insightful comments and suggestions. The work funded by National Social Science Foundation of China. Grant Number: 14 BJL045; The Fundamental Research Funds for the Central Universities of China. Grant Number: 15CX05006B.

References

Azadi, M., Jafarian, M., Saen, R. F., & Mirhedayatian, S. M. (2015). A new fuzzy DEA model for evaluation of efficiency and effectiveness of suppliers in sustainable supply chain management context. *Computers & Operations Research, 54,* 274–285.

Azadi, M., Shabani, A., Khodakarami, M., & Saen, R. F. (2014). Planning in feasible region by two-stage target-setting DEA methods: An application in green supply chain management of public transportation service providers. *Transportation Research Part E: Logistics and Transportation Review, 70,* 324–338.

Balfaqih, H., Nopiah, Z. M., Saibani, N., & Al-Nory, M. T. (2016). Review of supply chain performance measurement systems: 1998–2015. *Computers in Industry, 82,* 135–150.

Beamon, B. M. (1999). Measuring supply chain performance. *International Journal of Operations & Production Management, 19*(3), 275–292.

Camm, J. D., Chorman, T. E., Dull, F. A., Evans, J. R., Sweeney, D. J., & Wegryn, G. W. (1997). Blending OR/MS, judgment, and GIS: Restructuring P&G's supply chain. *Interfaces, 27*(1), 128–142.

Chan, F. T. S., & Qi, H. J. (2003). An innovative performance measurement method for supply chain management. *Supply Chain Management, 8*(3), 209–223.

Chen, C., & Yan, H. (2011). Network DEA model for supply chain performance evaluation. *European Journal of Operational Research, 213*(1), 147–155.

Chen, Y. J. (2011). Structured methodology for supplier selection and evaluation in a supply chain. *Information Sciences, 181*(9), 1651–1670.

Christopher, M. (1992). *Logistics and supply chain management: Strategies for reducing costs and improving services* (Vol. 1). London: Financial Times.

Cohen, M. A., & Lee, H. L. (1989). Resource deployment analysis of global manufacturing and distribution networks. *Journal of Manufacturing and Operations Management, 2,* 81–104.

Costa, A. S., Govindan, K., & Figueira, J. R. (2018). Supplier classification in emerging economies using the ELECTRE TRI-nC method: A case study considering sustainability aspects. *Journal of Cleaner Production, 201*, 925–947.

De Toni, A., & Tonchia, S. (2001). Performance measurement systems-models, characteristics and measures. *International Journal of Operations & Production Management, 21*(1/2), 46–71.

Devika, K., Jafarian, A., & Nourbakhsh, V. (2014). Designing a sustainable closed-loop supply chain network based on triple bottom line approach: A comparison of metaheuristics hybridization techniques. *European Journal of Operational Research, 235*(3), 594–615.

Five Winds Asset Management International (2018). https://fivewindsam.com/. Accessed Aug 2018.

Garvin, D. A. (1993). Manufacturing strategic planning. *California Management Review, 35*(4), 85–106.

Govindan, K., Jafarian, A., Khodaverdi, R., & Devika, K. (2014). Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International Journal of Production Economics, 152*, 9–28.

Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research, 240*(3), 603–626.

Haghighi, S. M., Torabi, S. A., & Ghasemi, R. (2016). An integrated approach for performance evaluation in sustainable supply chain networks (with a case study). *Journal of Cleaner Production, 137,* 579–597.

Halkos, G., Tzeremes, N., & Kourtzidis, S. (2011). The use of supply chain DEA models in operations management: A survey. Online at http://mpra.ub.uni-muenchen.de/31846/.

Halme, M., Joro, T., Korhonen, P., Salo, S., & Wallenius, J. (1999). A value efficiency approach to incorporating preference information in data envelopment analysis. *Management Science, 45*(1), 103–115.

Hatami-Marbini, A., Ebrahimnejad, A., & Lozano, S. (2017). Fuzzy efficiency measures in data envelopment analysis using lexicographic multiobjective approach. *Computers & Industrial Engineering, 105*, 362–376.

Holmberg, S. (2000). A systems perspective on supply chain measurements. *International Journal of Physical Distribution & Logistics Management, 30*(10), 847–868.

Jakhar, S. K. (2015). Performance evaluation and a flow allocation decision model for a sustainable supply chain of an apparel industry. *Journal of Cleaner Production, 87,* 391–413.

Jalali Naini, S. G., Aliahmadi, A. R., & Jafari-Eskandari, M. (2011). Designing a mixed performance measurement system for environmental supply chain management using evolutionary game theory and balanced scorecard: A case study of an auto industry supply chain. *Resources, Conservation and Recycling, 55*(6), 593–603.

Kannan, D. (2018). Role of multiple stakeholders and the critical success factor theory for the sustainable supplier selection process. *International Journal of Production Economics, 195*, 391–418.

Kannan, D., de Sousa Jabbour, A. B. L., & Jabbour, C. J. C. (2014). Selecting green suppliers based on GSCM practices: Using fuzzy TOPSIS applied to a Brazilian electronics company. *European Journal of Operational Research, 233*(2), 432–447.

Kao, T. W. D., Simpson, N. C., Shao, B. B., & Lin, W. T. (2017). Relating supply network structure to productive efficiency: A multi-stage empirical investigation. *European Journal of Operational Research, 259*(2), 469–485.

Khalili-Damghani, K., & Taghavifard, M. (2012). A three-stage fuzzy DEA approach to measure performance of a serial process including JIT practices, agility indices, and goals in supply chains. *International Journal of Services and Operations Management, 13*(2), 147–188.

Khalili-Damghani, K., Taghavi-Fard, M., & Abtahi, A. R. (2012). A fuzzy two-stage DEA approach for performance measurement: Real case of agility performance in dairy supply chains. *International Journal of Applied Decision Sciences, 5*(4), 293–317.

Khalili-Damghani, K., Taghavifard, M., Olfat, L., & Feizi, K. (2011). A hybrid approach based on fuzzy DEA and simulation to measure the efficiency of agility in supply chain: Real case of dairy industry. *International Journal of Management Science and Engineering Management, 6*(3), 163–172.

Khalili-Damghani, K., & Tavana, M. (2013). A new fuzzy network data envelopment analysis model for measuring the performance of agility in supply chains. *The International Journal of Advanced Manufacturing Technology, 69*(1–4), 291–318.

Khodakarami, M., Shabani, A., Saen, R. F., & Azadi, M. (2015). Developing distinctive two-stage data envelopment analysis models: An application in evaluating the sustainability of supply chain management. *Measurement, 70,* 62–74.

Korhonen, P., Tainio, R., & Wallenius, J. (2001). Value efficiency analysis of academic research. *European Journal of Operational Research, 130*(1), 121–132.

Li, Y., Kannan, D., Garg, K., Gupta, S., Gandhi, K. & Jha, P. C. (2018). Business orientation policy and process analysis evaluation for establishing third party providers of reverse logistics services. *Journal of Cleaner Production, 182*, 1033–1047.

Liang, T. F. (2011). Application of fuzzy sets to manufacturing/distribution planning decisions in supply chains. *Information Sciences, 181*(4), 842–854.

Long, Q. (2017). A framework for data-driven computational experiments of inter-organizational collaborations in supply chain networks. *Information Sciences*. https://doi.org/10.1016/j.ins.2017.03.008.

Mirhedayatian, S. M., Azadi, M., & Saen, R. F. (2014). A novel network data envelopment analysis model for evaluating green supply chain management. *International Journal of Production Economics, 147,* 544–554.

Olfat, L., Amiri, M., Soufi, B. J., & Pishdar, M. (2016). A dynamic network efficiency measurement of airports performance considering sustainable development concept: A fuzzy dynamic network-DEA approach. *Journal of Air Transport Management, 57,* 272–290.

Pasandideh, S. H. R., Niaki, S. T. A., & Asadi, K. (2015). Bi-objective optimization of a multi-product multi-period three-echelon supply chain problem under uncertain environments: NSGA-II and NRGA. *Information Sciences, 292,* 57–74.

Pramanik, S., Jana, D. K., Mondal, S. K., & Maiti, M. (2015). A fixed-charge transportation problem in two-stage supply chain network in Gaussian type-2 fuzzy environments. *Information Sciences, 325,* 190–214.

Puri, J., & Yadav, S. P. (2014). A fuzzy DEA model with undesirable fuzzy outputs and its application to the banking sector in India. *Expert Systems with Applications, 41*(14), 6419–6432.

Soheilirad, S., Govindan, K., Mardani, A., Zavadskas, E. K., Nilashi, M., & Zakuan, N. (2017). Application of data envelopment analysis models in supply chain management: A systematic review and meta-analysis. *Annals of Operations Research*, 1–55. https://doi.org/10.1007/s10479-017-2605-1.

Tavana, M., Kaviani, M. A., Di Caprio, D., & Rahpeyma, B. (2016). A two-stage data envelopment analysis model for measuring performance in three-level supply chains. *Measurement, 78,* 322–333.

Tavana, M., Mirzagoltabar, H., Mirhedayatian, S. M., Farzipoor Saen, R., & Azadi, M. (2013). A new network epsilon-based DEA model for supply chain performance evaluation. *Computers & Industrial Engineering, 66*(2), 501–513.

Tavana, M., Shiraz, R. K., Hatami-Marbini, A., Agrell, P. J., & Paryab, K. (2012). Fuzzy stochastic data envelopment analysis with application to base realignment and closure (BRAC). *Expert Systems with Applications, 39*(15), 12247–12259.

Toloo, M., & Tavana, M. (2017). A novel method for selecting a single efficient unit in data envelopment analysis without explicit inputs/outputs. *Annals of Operations Research, 253*(1), 657–681.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 130*(3), 498–509.
Tone, K., & Tsutsui, M. (2009). Network DEA: A slacks-based measure approach. *European Journal of Operational Research, 197*(1), 243–252.
Tone, K., & Tsutsui, M. (2010). An epsilon-based measure of efficiency in DEA-A third pole of technical efficiency. *European Journal of Operational Research, 207*(3), 1554–1563.
Wan, S. P., Xu, G. L., & Dong, J. Y. (2017). Supplier selection using ANP and ELECTRE II in interval 2-tuple linguistic environment. *Information Sciences, 385*, 19–38.
Wu, D., Wu, D. D., Zhang, Y., & Olson, D. L. (2013). Supply chain outsourcing risk using an integrated stochastic-fuzzy optimization approach. *Information Sciences, 235,* 242–258.
Yang, F., Wu, D., Liang, L., Bi, G., & Wu, D. D. (2011). Supply chain DEA: Production possibility set and performance evaluation model. *Annals of Operations Research, 185*(1), 195–211.