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# Robust approach to DEA technique for supplier selection problem: A case study at Supplying Automotive Parts Company (SAPCO)

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**Abstract**

In many industries such as automotive industry, there are a lot of suppliers dealing with the final products manufacturer. With growing numbers of suppliers, the suppliers' efficiency measurement often becomes the most significant concern for manufacturers. Therefore, various performance measurement models such as DEA, AHP, TOPSIS, are developed to support supplier selection decisions. After an exhaustive review of the supplier selection methods, we employ data envelopment analysis (DEA) for computing the relative efficiency of the suppliers and introducing the most efficient supplier as a benchmark. In reality, there are large amounts of uncertainty regarding the suppliers' measurements; therefore, we propose the robust optimization approach to the real application of DEA (RDEA). In this approach, uncertainties about incomes and outcomes of decision making units (DMUs) are involved in the relative suppliers' efficiencies. The proposed RDEA approach is utilized for the selection of suppliers which manufacture the automotive safety components in Supplying Automotive Parts Company (SAPCO), an Iranian leading automotive enterprise. Numerical example will illustrate how our proposed approach can be used in the real supplier selection problem when considerable uncertainty exists regarding the suppliers' input and output data

**Keywords:** Robust optimization; Supplier selection; Data envelopment analysis; Supply chain management

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## 1. Introduction

In the competitive business world, one of the main concerns is choosing the most efficient and committed suppliers for companies and their supply chains. These suppliers play a significant role in the future trades of the supply chain. Having an appropriate method for selecting and ranking the suppliers, companies are able to achieve a substantial cost diminution and also increase in their productivity. Regarding the significant role of suppliers in prosperity of each supply chain, a new stream in literature recently shaped which deals with suitable methods for supplier selection. The supplier selection is a decision making process by which suppliers are reviewed, assessed, and selected to become an efficient participant of a supply chain network. Since the efficient suppliers help a manufacturer or service-based company to improve overall supply chain's performance, the manufactures often tends to cooperate with top-rated suppliers.

Various multi-criteria decision making (MCDM) models and techniques were proposed to conduct the supplier selection process which is reviewed in literature review section. Among such techniques, Saen (2007) suggested data envelopment analysis (DEA) method for evaluating the suppliers in a supply chain. He took account of restriction on the weights in the whole constraints of the model along with dual role factors playing the role of inputs and outputs simultaneously. Comparing inputs and outputs of the suppliers in a linear programing model, the proposed DEA methods provided the ranking of efficient suppliers. By following the Saen's (2007) approach, we concentrate on DEA model to select the most efficient suppliers in an uncertain environment.

The suppliers' data uncertainty is brought about by several reasons. First, the suppliers are often independent organizations; thus, the estimation of their real input and output data may be technically difficult and imprecise for the manufacturer. Second, the suppliers may have incentives to conceal their real data and report a more beneficial data to improve their position from manufacturer's viewpoint. Third, there may be high fluctuations regarding input and output data derived from uncertain environment of the businesses or stock markets in a planning period. Such common fluctuation makes the precise estimations of suppliers' data impossible, not only for the manufacturer but also for suppliers.

In the real world assessment of the suppliers, there are frequently large amount of uncertainty regarding their activities, processes, products qualities, etc. Although, such uncertainties may dramatically alter suppliers' ratings and scores, the prior studies were mainly based on absolute data and did not involve uncertainty assessments in their decision making models. Therefore, the soft mathematical based models such as stochastic, fuzzy, or mixed uncertainty programming are able to produce more reliable solutions in the real situations where data perturbations or data obscurity in suppliers' assessments exist. To fill this gap, we focus on robust optimization approach where there is no predetermined information regarding the suppliers uncertainty.

Ben-Tal and Nemirovski (2000), first proposed a robust optimization approach (BN approach) for the linear programing problems to immune them against uncertainty. The robust optimization approach was also evolved by Bertsimas and Sim (2003, 2004 and 2006) which control the degree of conservatism of the solution (BA approach). Since the DEA results in a linear programing problem, Sadjadi and Omrani (2010) showed that the resultant linear programming of a DEA can be developed over uncertainty environment. They employed both BN and BA approaches of robust optimization and analyzed their performances in a real world DEA problem of electricity distribution companies.

Fuzzy and stochastic approaches of DEA are based on membership functions or probability distribution functions of input data. However, in real cases the uncertainty in data is inevitable and, at the same time, the Membership function or distribution of the uncertain data may be unknown. Robust DEA is a new approach to deal with this uncertainty in real problems when membership function or distributions of the uncertain data are unknown for decision maker. With regard to the fact that the high level of uncertainty is inherent in supplier assessment of the supplier selection problem, the objective of this study is utilizing the robust DEA to deal with such uncertainty. It is notable that, we used robust approach rather than other approaches to solve supplier selection problem when a company (SAPCO) should face with uncertain data. In this case, the company does not have any obvious information about distribution or membership functions of suppliers' data. We compare traditional DEA with BN and BA robust DEA in a real supplier selection problem to investigate how perturbations of output data affect the efficiencies of DMUs.

In Section 2, we present a review of different supplier selection methods. We classify the mathematical and heuristic methods used in the supplier selection problem. In Section 3, two different robust optimization approaches of BN and BA are proposed for the DEA problem of the supplier section problem.The importance and advantages of these approaches in the real supplier selection problem are also investigated in this section. Finally, Section 5 is devoted to the real world case study of suppliers' selection problem in an automotive company. We suggest the BN and BA approaches for selecting the most efficient suppliers from a given list of existent suppliers of the automotive safety components.

## 2. Literature review

Supplier selection techniques are the decision making mathematical models or qualitative approaches used to conduct the supplier selection process (Li and Fun, 1997). During the past few years, a large number of various techniques were developed in order to compute supplier's efficiencies and rank them according to their scores. In the proposed paper, the introduction of common supplier selection techniques is presented; thereafter, the literature of these techniques is reviewed.

Supplier selection as a decision-making process occurs when the user follows the supplier selection algorithm. According to the mentioned algorithm, identification of the necessities, requirements and criteria are the predecessors before execution of the supplier selection process. Supplier selection and evaluation which were a buyer's experience oriented approach have got utilized by Timmerman (1987) and Zenz (1994). In 80s of the last century, this approach has been introduced as a Multi Objective Programming by Weber et al. (2000). Supplier selection process based on classification of quantitative and qualitative variables illustrates the efficient suppliers. The simultaneous comparison between both kinds of variables would be very complicate. The conversion of qualitative variables to quantitative ones would minimize the probable appearance of NP-hard condition for a supplier selection problem. Hybrid system as an efficient sample of variable conversion methods has been employed by Wang et al. (2004).

The supplier's efficiency assessment is totally depended on the supplier selection criteria. By employing the questionnaire from purchasing agents, Dickson (1966) and Weber et al. (1991) ranked the main criteria for supplier selection problem. Although a large amount of supplier selection criteria and methods have been introduced, but each specific group of criteria is compatible with specific methods. In some cases in reality, financial criteria are preferred against others. Net Price and Financial Position are a pair of common financial criteria. Practical cost based optimization was presented by Degraeve and Roodhooft (1998,1999 and 2000). Total Cost of Ownership (TCO) approach is one of the basic and initial approaches in supplier selection problem which is based on financial criteria (Mendoza and Ventura, 2008). This approach intends to quantify the whole related costs to the vendors in monetary units. In addition to TCO, Cost Ratio method is also flexible financial method that covers a large number of variables of the real problems. It is insightful to note that an initial requirement for both of these methods is a developed and efficient accounting system. Naturally accuracy and capability for administration engage all of the users with large expenses. Flexibility, as an advantage for these methods, leads the users for considering a large group of elements and variables (Bhutta and Huq, 2002). This flexibility in accepted variables is also considerable as a disadvantage. In fact, a vast variation in number of variables will be result in complexity while reduction in variables has usually been preferred by decision makers. In Principal Component Analysis (PCA), the deviation between variables is obviously reduced. Covariance Matrix Analysis (CMA) is the most popular sub method in PCA which is based on statistical programming. Illustration of mean and variance for each group of variables is the first step of CMA algorithm. Then, the quantities of covariance are arranged around the initial coordinate system to represent a limited and efficient group of results. Actually, PCA inserts the decision-making variables in a new restricted mathematical dimension in order to develop the accuracy of decision-making in supplier selection procedure (Holand, 2008).

Fuzzy logic is another important method that widely is used in many supplier selection problems. Fuzzy Logic introduced by Zadeh (1965) was an ideal method for the problems which were based on fuzzy variables. Kumar and Vrat [17] applied fuzzy goal programming approach to solve vendor selection problems. Fuzzy mathematical modeling, as a new method in supplier selection, was proposed by Wang et al. [18] to solve vendor selection problems in fuzzy uncertain environment. Fuzzy Logic, as an expandable operational approach, has so many interfaces with other approaches.

Analytic Hierarchal Process (AHP) was presented by Saaty (1990) for dealing with decision making problems. AHP gives a comprehensive framework for structuring a decision-making problem, for representing and quantifying its components, for relating those components regarding overall goals, and for rating the alternatives. Therefore, AHP as a multiple criteria decision making method enables decision makers to evaluate complex problems hierarchically. Saaty (1990) organized 18 different compatible criteria as an AHP structure. Moreover, AHP has been combined with many other techniques to solve supplier selection problems. For example, Feng, Chen and Jiang (2005) integrated Fuzzy logic and AHP in supplier selection while Kumar and Roy (2010) presented a hybrid model that uses AHP and neural networks (NNs) for vendor performance assessment. Ghodsypour and O’Brien (1998) integrated AHP and linear programming to develop a decision support system for the suppler selection problem.

The multiple attribute utility theory (MAUT) is also another popular multi-criteria decision making method categorized under condition of risk or certainty techniques (Figueira, Greco and Ehrgott, 2005). MAUT under the risk condition first was utilized based on the theories of Von Neumann and Morgenstern (1946) while certainty in MAUT has been developed by Keeney and

Raiffa [24]. MAUT enjoys considerable advantages with regard to other similar methods. Firstly, the formulation of improvable and long term sourcing strategies by professionals achievement and secondly, the ability for conflicting attributes arrangement (Tahriri, Osman and Yusuff, 2008). The usage of MAUT models encounters considerable constraints in international supplier selection problem when it would be complex and risky.

Data Envelopment Analysis (DEA) as a non-parametric method was presented by Charnes, Cooper and Rhodes (1978) to solve the real problems base on linear programming. Comparative efficiency survey is one of the advantages of this method that encourages the users to consider this method as a practical method in the real world applications. With considering variables as inputs and outputs for DMUs, DEA calculates the relative efficiency of DMUs. Although the main advantage of this method is that the results extracted from the problem is usable in many real cases, the considerable disadvantage which always influences the accuracy of results is uncertainty in data. Therefore, incorrect results would be probably gained because of uncertainty in input and output data. In order to solve the problem of uncertainty in DEA, different methods are applied by different researchers. Recently, some researches employ DEA model as efficiency evaluation method in supply chains. Azadi et al. (2014) used DEA approach for evaluating supplier performance and selecting suppliers in sustainable supply chain management (SSCM). They developed DEA based on enhanced Russell measure model (ERM) with fuzzy parameters for this reason. Shafiee, Hosseinzadeh Lotfi and Mirhedayatian (2014) proposed an integrated model of DEA and balanced scorecard (BSC) for evaluating the performance of supply chains. Moreover, Mishra (2012) adopted DEA approach for analyzing the efficiency of different companies of a supply chain. Using DEA method, Mirhedayatian, Azadi and Farzinpoor (2014) focused on improving performance of green supply chain management (GSCM).

Stochastic data envelopment analysis (SDEA), operates by variables with probable data. The first theoretical researches were performed by Land, Lovel and Thore (1993) and Olesen and Petersen (1995). On the other side, Kao and Liu (1995) suggested Fuzzy Data Envelopment Analysis (FDEA). According to their work, a multi ranking method for the purpose of classification of fuzzy numbers was presented. In this method, α-cuts quantities were compared with each other in order to eliminate the efficient α-cut. FDEA was also developed by other researchers (Guo and Tanaka, 2001, Leòn et al., 2003 and Wen and Li, 2009). Table 1 summarizes the categories of supplier selection methods.

**Table 1.** Categories of supplier selection techniques

| Supplier selection techniques | Researches |
|---|---|
| Integer Programming | Zeng , Li and Zhu (2006), Ghodsypour and O'Brien (2001), Dahel (2003), Talluri and Baker (2002), Ip, Yung and Wang (2004). |

**Table 1.** continue

| Supplier selection techniques | Researches |
|---|---|
| Goal Programming | Talluri and Narasimhan (2003), Hajidimitriou and Georgiou (2002), Cebi and Bayraktar (2003), Cakravastia and Takahashi (2004), Arunkumar et al.(2006), Karpak, Kumcu and Kasuganti (2001), Kameshwaran et al. (2007). |
| Analytic Hierarchy Process (AHP) | Ghodsypour and O'Brien (1998), Pi and Low (2006), Noorul Haq and Kannan (2006), Kahraman, Cebeci and Ulukan (2003), Wang, Huang and Dismukes ( 2005), Sha and Che (2005), Min (1994), Xia and Wu (2007), Dulmin and Mininno (2003), Liu and Hai (2005), Chan (2003), Yusuff and Yee (2003), Nydick and Hill (1992), Chamodrakas, Batis and Martakos. (2010). |
| Analytic Network Process (ANP) | Bayazit (2006), Shyur and Shih (2006). |
| Fuzzy Mathematical Programming | Lin and Chen (2004), Ohdar and Ray (2004), Bevilacqua and Petroni (2002), Chen, Lin and Huang, (2006), Chang, Wang and Wang (2006), Kwong et al. (2002), Morlacchi (1999). |
| Case-Based Reasoning (CBR) | Choy and Lee (2002, 2003, 2004), Choy and Lee (2003), Lau et al. (2005). |
| Principal Component Analysis (PCA) | Petroni and Braglia (2000) |
| Multiple Attribute Utility Theory (MAUT) | Teixeira de Almeida (2001), Min (1994). |
| Artificial Intelligence (AI) | Albino and Garavelli (1998). |
| Other Multi-Criteria Methods | Dulmin and Mininno (2003), Ho, Xu and Dey (2010), Teixeira (2007). |
| Data Envelopment Analysis (DEA) | Banker (1993), Giokas and Pentzaropoulos (2008), Premachandra (2001), Sadjadi and Omrani (2008), Zhang and Bartels (1998), Zhu and (1998, 2004). |
| Bootstrap Frontier Analysis | Bradley and Tibshirani (1993), Simar and Wilson (1998, 2000). |

Supplier selection in the real uncertain situation is the main reason of previous researches. In this regard, in recent years, robust optimization presented by Bertsimas and Sim (200, 2004 and 2006), which is becoming an alternative for stochastic or fuzzy programming, and sensitivity analysis (Sadjadi and Omrani, 2010). The advantage of using robust optimization approach in DEA (RDEA) is the immunity of the solution against data uncertainty. Therefore, the results extracted from the DEA are highly reliable to use in the real situations. Accordingly, in this research we propose the RDEA method for the real supplier selection problem under uncertain input and output data. We apply our method in the supplier selection problem in an Iranian leading automotive company, i.e. SAPCO.

## 3. Uncertain DEA for supplier selection problem

When a manufacturer is confronted a large number of component suppliers with distinguishing characteristics, analyzing these suppliers may become an immensely complicated problem. By computing the relative efficiency measurements of the suppliers, the DEA method enables the manufacturer to compare suppliers based on their efficiencies.

The fractional DEA model, proposed by Charnes, Cooper and Rhodes (1978), (Charnes–Cooper–Rhodes (CCR) model), computes the relative measurement using the weighted sum of variable inputs and outputs of DMUs, respectively. Let for the supplier $j$ (DMU), $x_{1j}$, $x_{2j}, \ldots, x_{mj}$ and $y_{1j}$, $y_{2j}, \ldots, y_{sj}$ denote $m$ inputs and $s$ outputs, respectively. Traditionally, in the fractional CCR DEA formulation, the ratio of weighted sum of outputs to the weighted sum of inputs is maximized as follows

$$
\begin{aligned}
& \max e_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}, \\
& subject\ to: \\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad \forall j, \\
& u_r, v_i \ge 0.
\end{aligned}
\tag{1}
$$

Let index $o$ in the model represents the supplier which is considered for maximizing the relative efficiency. Moreover, $v_i$and $u_r$denote inputs and outputs, respectively, which they should be determined by the model. Supplier $o$ is called perfectly efficient if other suppliers or combination of suppliers cannot create more than the supplier on at least one output without creating less in some other output or using more at least one input. For the sake of convenience, the fractional CCRDEA model can be transformed into the following linear programming model.

$$
\begin{aligned}
&\max e_o = \sum_{r=1}^{s} u_r y_{ro}, \\
&\textit{subject to}: \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \ , \ \forall j, \\
&\sum_{i=1}^{m} v_i x_{io} = 1 \ , \\
&u_r, v_i \ge 0.
\end{aligned} \tag{2}
$$

Since model 2 is linear programming, it is also more proper for robust optimization approach. In the subsequent section, two approaches for robust optimization are reviewed for immunizing linear DEA model (2) against uncertain input and output.

Now, let $\tilde{y}_{ij}$and $\tilde{y}_{ro}$ denote uncertain output parameters in model (2). To move uncertain parameters from the objective function to constraints, similar to Sadjadi and Omrani [82], the objective function can be substituted for objective $\max z$ and constraint $z \le \sum_{r=1}^{s} u_r \tilde{y}_{ro}$ . consequently, uncertain DEA model (2) for the supplier selection problem is transformed into the following LP model

$$
\begin{aligned}
&\max e_o = z, \\
&\textit{subject to}: \\
&z - \sum_{r=1}^{s} u_r \tilde{y}_{ro} \le 0, \\
&\sum_{i=1}^{m} v_i x_{io} = 1 \ , \\
&\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \ , \ \forall j, \\
&u_r, v_i \ge 0.
\end{aligned} \tag{3}
$$

## 4. Robust approach to DEA method for the supplier selection problem

The traditional DEA method was considered as one of the most powerful decision making methods for supplier selection problem; however, it requires certain and precise data to produce a group of genuine results. The availability of certain and precise data would be considered as an ideal assumption for model 2, while as discussed previously, certainty and precision of supplier’s data in the real world problems are often impossible.

During the past few years, some different methods have been proposed in order to deal with data uncertainty problem. These classical methods are commonly categorized in the group of stochastic or fuzzy programming methods. However, recently, the new method was introduced as robust optimization, which was a complementary method for the fuzzy or stochastic programming methods. In the robust optimization method, there is no necessity to know the distribution function of data; indeed, it just takes account of symmetric interval for uncertain data. To be more specific, uncertain parameters in the robust optimization models have to be independent, symmetric, and bounded but with an unknown exact distribution.

The two well-known robust optimization approaches were first introduced by Ben-Tal and Nemirovski (2000) (denoted by BN approach henceforth) and Bertsimas and Sim (2003,2004, 2006) (denoted by BA approach henceforth). Afterwards, Sadjadi and Omrani (2008) employed these two approaches for a DEA problem in evaluating electricity distribution companies.

Since DEA model (2) is a linear programming (LP) problem, let us consider the following LP model to review the BN and BA robust optimization models

$$\begin{aligned} &\min C'x, \\ &\textit{subject to}: \\ &\widetilde{A}x \geq b, \\ &x \in X. \end{aligned} \tag{4}$$

In the BN approach, it is assumed that $\tilde{a}_{ij}$ are uncertain actual parameters in $i$th inequality constraint of model (4). Uncertain parameter $\tilde{a}_{ij}$ can be obtained from the nominal value $a_{ij}$ by random perturbation as follows:

$$\widetilde{a}_{ij} = (1 + e\xi_{ij})a_{ij} \tag{5}$$

Where $e$ represents a given uncertainty level expressed as percentage of perturbations (for instance, $e = 0.01$) and $\varepsilon_{ij}$ are random variables distributed symmetrically in the interval [-1, 1]. In other words, random parameter $\tilde{a}_{ij}$ takes the value (but with unknown distribution) in interval $\left[a_{ij} - e\left|a_{ij}\right|, a_{ij} - e\left|a_{ij}\right|\right]$. As discussed by Bertsimas and Sim (2003), when uncertainty only emerges in parameters of constraints of LP (4) (i.e. matrix $A$ ), the resulting robust problem is as below:

$$\begin{aligned} &\min C'x, \\ &\textit{subject to}: \\ &Ax \geq b, \\ &\sum_j a_{ij}x_j - e\left[\sum_{j\in J}\left|a_{ij}\right| y_{ij} + \Omega\sqrt{\sum_{j\in J} a_{ij}^2 z_{ij}^2}\right] \geq b_i \ \forall i, \\ &-y \leq x_j - z_{ij} \leq y_{ij} \quad \forall i, j, \\ &x \in X, \end{aligned} \tag{6}$$

where $x_j$ is primary decision variable, and $z_{ij}$ and $y_{ij}$ are auxiliary decision variables used in robust formulation. The $x$ is an almost reliable solution to constraint $i$ of LP (4) with probability $k = \exp(\frac{-\Omega_i^2}{2})$. Hence, the reliability of the constraint can be controlled regarding the various values of $\Omega_i$.

Similar to Sadjadi and Omrani (2008), by employing BN robust model (6), the robust formulation of DEA model 3 can be formulated as follows.

$$
\begin{aligned}
&\max e_o = z, \\
&\textit{subject to}: \\
&\sum_{i=1}^{m} v_i x_{io} = 1, \\
&z - \sum_{r=1}^{s} u_r y_{ro} + e\left[\sum_{r=1}^{s} |y_{ro}| Y_{ro} + \Omega \sqrt{\sum_{r=1}^{s} y_{ro}^2 Z_{ro}^2}\right] \le 0, \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + e\left[\sum_{r=1}^{s} |y_{rj}| Y_{rj} + \Omega \sqrt{\sum_{r=1}^{s} y_{rj}^2 Z_{rj}^2}\right] \le 0, \ \forall j, \\
&-Y_{rj} \le u_r - Z_{rj} \le Y_{rj}, \ \forall j, r, \\
&u_r, v_i \ge 0.
\end{aligned}
\tag{7}
$$

Here, $v_i$ and $u_r$ are primary variables and $Y_{ro}$, $Y_{rj}$, $Z_{ro}$, and $Z_{rj}$ are auxiliary decision variables employed in robust formulation. Moreover, $z$ represents the efficiency of supplier under consideration. Since model (7) is a nonlinear problem (NLP), it can be solved by utilizing a nonlinear solver package.

One of the privileges of BA approach with respect to BN is that its resulting model still remains linear; hence, it is much easier to be solved (contrary to NLP (7)). For reviewing the BA approach, again, take LP model (4) into account where all elements of the matrix $A$ are subject to uncertain. Each uncertain parameter $\tilde{a}_{ij}$ is determined to belong to an interval centered at its nominal value $a_{ij}$ and half-length $\hat{a}_{ij}$. Bertsimas and Sim (2003, 2004, 2006) introduced $\eta_{ij} = \left(\tilde{a}_{ij} - a_{ij}\right)/\hat{a}_{ij}$ as the scale of deviation $\tilde{a}_{ij}$ from its nominal value; therefore, $\eta_{ij}$ takes the value (but with unknown distribution) in interval $[-1,1]$. Additionally, they assumed that the total scaled of deviation of all parameters in constraint $i$ should be restricted to $\Gamma_i$ (i.e., $\sum_{j=1}^{n} \eta_{ij} \le \Gamma_i \ \ \forall i$ ). Hence, all scaled deviation values can be expressed by set $Z = \left\{\eta \,\middle\|\, \eta_{ij} \right| \le 1, \ \sum_{j=1}^{n} \eta_{ij} \le \Gamma_i \ \ \forall i \Big\}$.

Although $\Gamma_i$ may take any real value in interval $[-n, n]$, for sake of simplicity, $\Gamma_i$ is chosen as an integer (see Bertsimas and Sim (2004) for detailed description). The decision maker is able to control the level of conservatism with respect to constraint $i$ by tuning parameter $\Gamma_i$. That is, $\Gamma_i = 0$ (res. $\Gamma_i = n$) implies the nominal parameter (res. the most conservative circumstance). By adjusting parameter $\Gamma_i \in (0, n)$, Bertsimas and Sim (2004) showed that one can achieve a robust model without excessively affecting the optimal cost. As discussed by Bertsimas and Sim (2004), uncertain LP (4) is equal to:

$$\begin{aligned}
&\min c'x,\\
&subject\,to:\\
&\sum_{j=1}^{n} a_{ij}x_j + \min_{\eta_{ij}\in Z_i}\sum_{j=1}^{n}\hat{a}_{ij}\left|x_j\right|\eta_{ij} \ge b_i, \quad \forall i,\\
&x \in X.
\end{aligned} \tag{8}$$

Using dual variables $p_i$ and $q_{ij}$, model (8) can be reformulated as follows; for detailed description, see Bertsimas and Sim (2003, 2004, 2006), and Sadjadi and Omrani (2008).

$$\begin{aligned}
&\min c'x,\\
&subject\,to:\\
&\sum_{j=1}^{n} a_{ij}x_j + \Gamma_i p_i - \sum_{j=1}^{n} q_{ij} \ge b_i, \quad \forall i,\\
&p_i + q_{ij} \ge ea_{ij}y_j, \quad \forall i, j,\\
&-y_j \le x_j \le y_j, \quad \forall j,\\
&p_i, q_{ij} \ge 0, \quad \forall i, j,\\
&x \in X.
\end{aligned} \tag{9}$$

There are two appealing features regarding formulation (9). First, since in the majority of the real word application, the matrix $A$ is sparse, the model maintains the sparsty of the matrix. Second, the model is an LP and global optimum can be easily found by a general LP solver. Adapting BA model (9) to uncertain DEA problem (3), the robust DEA model for supplier selection can be formulated as follows.

$$\begin{aligned}
&\max e_o = z,\\
&subject\ to:\\
&\sum_{i=1}^{m} v_i x_{io} = 1\ ,\\
&\sum_{r=1}^{s} u_r y_{ro} - z - \Gamma_o p_o - \sum_{r=1}^{s} q_{ro} \ge 0,\\
&\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - \Gamma_j p_j - \sum_{r=1}^{s} q_{rj} \ge 0, \ \forall j,\\
&p_j + q_{rj} \ge e\hat{y}_{rj} z_r, \quad \forall r, j,\\
&-z_r \le u_r \le z_r, \quad \forall r,\\
&u_r, v_i, p_j, q_{rj} \ge 0.
\end{aligned} \tag{10}$$

$x_{io}$ and $y_{ro}$ represent, in turn, nominal input and output of the supplier under consideration and $z$ symbolizes the supplier's efficiency. Moreover, $x_{ij}$ and $y_{ij}$ denote, in turn, $r$ th output and $j$ th input for supplier $j$, and $\tilde{y}_{ij}$ measures the precision of the output data estimation.

## 5. Case study of SAPCO

Supplying Automotive Parts Company (SAPCO) was founded in 1993 headquartered in Tehran, Iran and soon became the pioneer in auto-parts industry and now is the most exclusive and leading supplier of auto-parts of Iran-Khodro Company (IKCO), the largest Iranian automobile manufacturer. SAPCO is a multi-billion-Euros annual turnover enterprise and over 39 countries purchase Iranian auto parts. SAPCO has active contracts with 500 of international renowned supplier companies and enjoys their products and also their services. Consequently, SAPCO, as a principal subsidiary of IKCO, is vigorously involved in design, engineering, quality, and planning aspects of auto-parts.

In this research, we investigate the efficiency of safety parts suppliers in SAPCO. The RDEA results based on BA and BN robust approaches will be compared with the results of traditional DEA. For evaluating efficiency measures of the suppliers, five variables as inputs and outputs are took into consideration. The suppliers' inputs are the total cost of shipments (TC), the number of shipments per month (NS), and the cost of shipments (CS). Besides, the outputs include the number of shipments to arrive on time (NOT) and the number of bills received from the supplier without errors (NB). Our data series include the annual data regarding 21 companies supplying 3 different safety parts. Table 2 demonstrates the variables and outline statistics for the data set of the SAPCO case. Although, we assume the same uncertainty level for all suppliers, different uncertainty levels are also allowed in RDEA that may result in different efficiency measures.

**Table 2.** Outline statistics over data

| Component | DMU No. | Input data | | | Output data | |
|---|---|---|---|---|---|---|
| | | $x_1$ | $x_2$ | $x_2$ | $y_1$ | $y_2$ |
| Lightening system | 1 | 118500 | 225 | 1280 | 1068 | 962 |
| | 2 | 114350 | 228 | 1450 | 1424 | 1403 |
| | 3 | 116215 | 224 | 2575 | 2499 | 2447 |
| | 4 | 121760 | 233 | 1685 | 1671 | 1619 |
| | 5 | 118005 | 226 | 2110 | 2064 | 2020 |
| | 6 | 115010 | 231 | 2235 | 2009 | 1897 |
| | 7 | 116190 | 229 | 2015 | 1926 | 1892 |

**Table 2.** continue

| Component | DMU No. | Input data $x_1$ | Input data $x_2$ | Input data $x_2$ | Output data $y_1$ | Output data $y_2$ |
|---|---|---|---|---|---|---|
| Breaking system | 1 | 71300 | 175 | 2520 | 2375 | 2290 |
| | 2 | 62980 | 170 | 3155 | 2744 | 2700 |
| | 3 | 65650 | 181 | 2040 | 1938 | 1890 |
| | 4 | 67235 | 166 | 2430 | 2239 | 2204 |
| | 5 | 67030 | 171 | 2300 | 2085 | 1979 |
| | 6 | 70085 | 169 | 2010 | 1926 | 1902 |
| | 7 | 65230 | 172 | 3220 | 3201 | 3099 |
| Safety belt | 1 | 12405 | 61 | 3070 | 2894 | 2836 |
| | 2 | 10990 | 80 | 4200 | 4178 | 4096 |
| | 3 | 13710 | 69 | 4550 | 4406 | 4339 |
| | 4 | 12770 | 66 | 4400 | 4100 | 4067 |
| | 5 | 14275 | 82 | 1160 | 804 | 711 |
| | 6 | 12505 | 69 | 3550 | 3332 | 3290 |
| | 7 | 12835 | 74 | 3600 | 2980 | 2906 |

## 6. Results and discussion

In this section, an efficiency measure is evaluated for each supplier based on data of Table 2. Tables 3 puts on display the detailed information concerning the optimal efficiency measures of three groups of safety component suppliers. Our calculation procedure founded upon on three different methods. The values in the first column are the results that have been obtained based on DEA method. In the next three columns, BN approach of RDEA (model (7)) has been used to evaluate the supplier's efficiency measures. Finally, in the last three columns, BA approach of RDEA (model (10)) has been considered to solve the SAPCO's supplier selection problem. The results of both BA and BN approaches are calculated according to three values for uncertainty levels $e = 0.01, 0.05$, and 0.1. From the table, we find that the higher the uncertainty level, the lower the efficiency of all suppliers will be.

**Table 3.** The results from different approaches

| Component | DMU No. | DEA | BN approach | | | BA approach | | |
|---|---|---|---|---|---|---|---|---|
| | | | e=0.01 | e=0.05 | e=0.10 | e=0.01 | e=0.05 | e=0.10 |
| Lightening system | 1 | 0.841 | 0.836 | 0.815 | 0.789 | 0.825 | 0.761 | 0.688 |
| | 2 | 1 | 0.995 | 0.977 | 0.955 | 0.98 | 0.905 | 0.818 |
| | 3 | 1 | 0.995 | 0.978 | 0.956 | 0.98 | 0.905 | 0.818 |
| | 4 | 1 | 0.995 | 0.978 | 0.956 | 0.98 | 0.905 | 0.818 |
| | 5 | 1 | 0.995 | 0.978 | 0.956 | 0.98 | 0.905 | 0.818 |
| | 6 | 0.922 | 0.916 | 0.892 | 0.869 | 0.903 | 0.834 | 0.754 |
| | 7 | 0.98 | 0.974 | 0.956 | 0.935 | 0.961 | 0.887 | 0.802 |
| Braking system | 1 | 0.948 | 0.942 | 0.925 | 0.904 | 0.929 | 0.858 | 0.776 |
| | 2 | 0.902 | 0.897 | 0.876 | 0.856 | 0.885 | 0.816 | 0.738 |
| | 3 | 0.963 | 0.957 | 0.938 | 0.917 | 0.944 | 0.871 | 0.788 |
| | 4 | 0.942 | 0.936 | 0.915 | 0.894 | 0.924 | 0.853 | 0.771 |
| | 5 | 0.912 | 0.906 | 0.885 | 0.864 | 0.894 | 0.825 | 0.746 |
| | 6 | 0.983 | 0.977 | 0.954 | 0.931 | 0.964 | 0.890 | 0.804 |
| | 7 | 1 | 0.995 | 0.978 | 0.956 | 0.98 | 0.905 | 0.818 |
| Safety belt | 1 | 0.948 | 0.943 | 0.926 | 0.906 | 0.929 | 0.857 | 0.775 |
| | 2 | 1 | 0.995 | 0.978 | 0.956 | 0.98 | 0.905 | 0.818 |
| | 3 | 1 | 0.995 | 0.978 | 0.956 | 0.98 | 0.905 | 0.818 |
| | 4 | 0.996 | 0.989 | 0.97 | 0.948 | 0.976 | 0.901 | 0.815 |
| | 5 | 0.697 | 0.692 | 0.675 | 0.654 | 0.683 | 0.630 | 0.570 |
| | 6 | 0.937 | 0.944 | 0.926 | 0.905 | 0.934 | 0.899 | 0.858 |
| | 7 | 0.832 | 0.827 | 0.811 | 0.793 | 0.816 | 0.753 | 0.681 |

For investigating the trends of results in three DEA approaches, Figures 1, 2 and 3 are presented. These figures illustrate efficiency measures of suppliers of lightening system, braking system and safety belts, respectively. From Figures 1, 2 and 3, we know that efficiency measures of SAPCO's suppliers calculated by DEA are higher than robust ones. Moreover, BA approach of DEA often provides the more efficiency measures than BN approach. These differences between the results are due to the variations which have been employed by these approaches. In the case of sensitivity analysis on uncertainty level $e$ in BA and BN approaches, it is a salient fact that a reversal relationship exists between $e$ and the values of the efficiency measures. However, when $e$ increases, the immunity to incorrect data and robustness of the result enhances. Since, the same uncertain intervals are considered for all suppliers, the ranking of suppliers in different approaches remains unchanged.

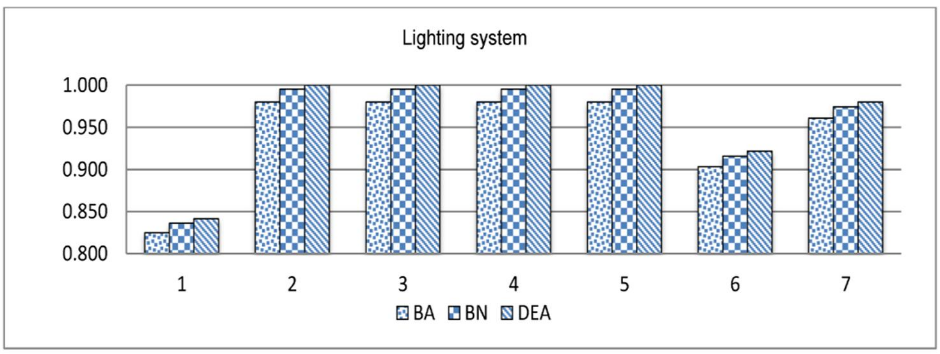


**Figure 1.** Comparison of the results from BA, BN, and DEA models on lighting system suppliers (e=0.01)

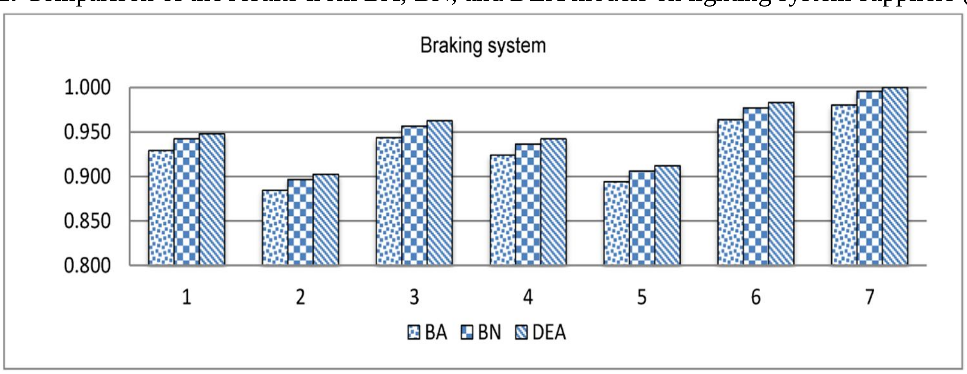


**Figure 2**. Comparison of the results from BA, BN, and DEA models on braking system suppliers (e=0.01)

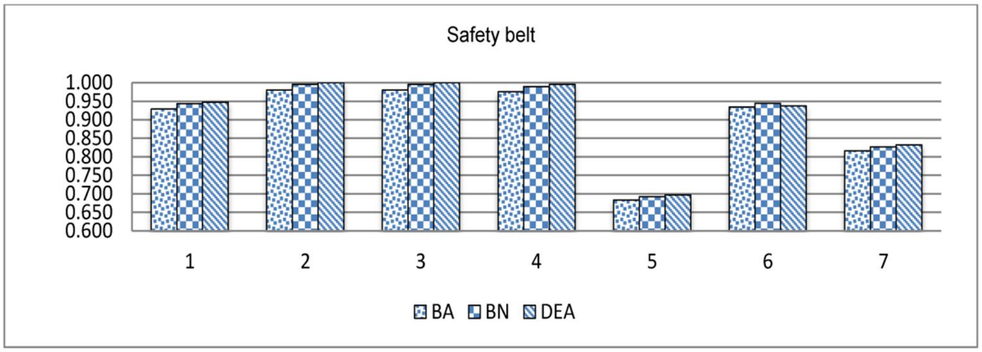


**Fig. 3.** Comparison of the results from BA, BN, and DEA models on safety belt suppliers (e=0.01)

## 7. The model extension

One of the main downsides of CCR model of DEA in the real world application of supplier selection problem is the lack of decision maker judgments. Hence, all weights of input and output data regarding the suppliers under consideration are freely allocated (Saen, 2007). This enables the suppliers to obtain high efficiency measure by concealing their real data and reporting a more beneficial data. The most common technique for involving the decision maker's judgments into the CCR model of DEA is the weight restriction inclusion.

There are several types of weight restrictions which can be employed in DEA, such as absolute, relative, and input-output weight restrictions (Cooper, Seford and Zhu, 2011). In all of these types of restrictions, the decision maker or his expert consultants define acceptable intervals for the weights of DMUs based on their assessments and preferences.

When the weight restrictions are imposed on the product of these weights with the respective input and output values, they referred to as virtual input or virtual output. Wong and Beasley (1990) for the first time considered restrictions on virtual weights. They proposed restriction on virtual inputs or virtual outputs ratio, for example, the proportion of the total virtual input to output of DMU accounted for by output $r$ is constrained to place in the interval $[a_r, b_r]$ as follows:

$$a_r \leq \frac{u_r y_{ro}}{\sum_{r=1}^{s} u_r y_{ro}} \leq b_r. \tag{11}$$

The parameters $a_r$ and $b_r$ are decision-maker-specified constants which incorporate his preferences in the weights of the supplier's output data. Taking inequity (11) into account, an output-orientation DEA model will be achieved. Note that input-orientation model is also possible by considering the inequality for input data. However, since in this research, the uncertainty is cased by parameter, we pursue the input-orientation models. As discussed by Wong and Beasley (1990), for enforcing the restriction on virtual values, the restriction may only be added in respect of DMU$_o$, leaving free the relative virtual values of the other DMUs. Consequently, under the uncertainty of supplier's data, we are able to import constraint (11) to model (3). The resulting weight-restricted DEA model is as follows:

$$\begin{aligned}
&\max e_o = z,\\
&\textit{subject to}:\\
&z-\sum_{r=1}^{s}u_r\,\widetilde{y}_{ro}\le 0,\\
&\sum_{i=1}^{m}v_i x_{io}=1\ ,\\
&\sum_{r=1}^{s}u_r\,\widetilde{y}_{rj}-\sum_{i=1}^{m}v_i x_{ij}\le 0\ ,\ \forall j,\\
&a_r\sum_{r=1}^{s}u_r\,\widetilde{y}_{ro}-u_r\,\widetilde{y}_{ro}\le 0,\\
&u_r\,\widetilde{y}_{ro}-b_r\sum_{r=1}^{s}u_r\,\widetilde{y}_{ro}\le 0,\\
&u_r,v_i\ge 0.
\end{aligned}\tag{12}$$

Now, let us consider BN robust optimization approach for LP (12). Conforming BN robust model (6) to an uncertain LP, the BN robust model of weight-restricted DEA (12) can be written as follows:

$$\begin{aligned}
&\max e_o = z,\\
&\textit{subject to}:\\
&\sum_{i=1}^{m}v_i x_{io}=1\ ,\\
&z-\sum_{r=1}^{s}u_r y_{ro}+e\left[\sum_{r=1}^{s}\left|y_{ro}\right|Y_{ro}+\Omega\sqrt{\sum_{r=1}^{s}y_{ro}^2Z_{ro}^2}\right]\le 0,\\
&\sum_{r=1}^{s}u_r y_{rj}-\sum_{i=1}^{m}v_i x_{ij}+e\left[\sum_{r=1}^{s}\left|y_{rj}\right|Y_{rj}+\Omega\sqrt{\sum_{r=1}^{s}y_{rj}^2Z_{rj}^2}\right]\le 0,\ \forall j,\\
&a_r\sum_{r=1}^{s}u_r y_{ro}-u_r y_{ro}+e\left[\sum_{r=1}^{s}a_r\left|y_{ro}\right|Y'_{ro}+u_r\left|y_{ro}\right|+\Omega\sqrt{\sum_{r=1}^{s}a_r^2y_{ro}^2Z'^2_{ro}+y_{ro}^2Z'^2_{ro}}\right]\le 0,\\
&u_r y_{ro}-b_r\sum_{r=1}^{s}u_r y_{ro}+e\left[b_r\left|y_{ro}\right|+\sum_{r=1}^{s}b_r\left|y_{ro}\right|Y''_{ro}+\Omega\sqrt{y_{ro}^2Z''^2_{ro}+\sum_{r=1}^{s}b_r^2y_{ro}^2Z''^2_{ro}}\right]\le 0,\\
&-Y_{rj}\le u_r-Z_{rj}\le Y_{rj}\,,\ \forall j,r,\\
&-Y'_{ro}\le u_r-Z'_{ro}\le Y'_{ro},\ \forall r,\\
&-Y''_{ro}\le u_r-Z''_{ro}\ \le Y''_{ro}\,,\ \forall r,\\
&u_r,v_i\ge 0,
\end{aligned}\tag{13}$$

Where $Y_{ro}$, $Y'_{ro}$, $Y''_{ro}$, $Y_{rj}$, $Z_{ro}$, $Z'_{ro}$, $Z''_{ro}$, and $Z_{rj}$ are auxiliary decision variables employed in the BN approach. Since weight-restricted DEA model (12) is an LP, with uncertainty in output, the robust DEA model based on BA approach (9) is formulated as follows:

$$
\begin{aligned}
& \max e_o = z, \\
& subject\ to: \\
& \sum_{i=1}^{m} v_i x_{io} = 1, \\
& \sum_{r=1}^{s} u_r y_{ro} - z - \Gamma_o p_o - \sum_{r=1}^{s} q_{ro} \geq 0, \\
& \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - \Gamma_j p_j - \sum_{r=1}^{s} q_{rj} \geq 0, \ \ \forall j, \\
& a_r \sum_{r=1}^{s} u_r y_{ro} - u_r y_{ro} - \Gamma'_o p'_o - \sum_{r=1}^{s} q'_{ro} \leq 0, \\
& u_r y_{ro} - b_r \sum_{r=1}^{s} u_r y_{ro} - \Gamma''_o p''_o - \sum_{r=1}^{s} q''_{ro} \leq 0, \\
& p_j + q_{rj} \geq e\hat{y}_{rj} z_{rj}, \quad \forall r, j, \\
& p'_o + q'_{ro} \geq e\left( a_r \sum_{r=1}^{s} \hat{y}_{ro} + \hat{y}_{ro} \right) z'_{ro}, \quad \forall r, \\
& p''_o + q''_{ro} \geq e\left( \hat{y}_{ro} + b_r \sum_{r=1}^{s} \hat{y}_{ro} \right) z''_{ro}, \quad \forall r, \\
& -z_{rj} \leq u_r \leq z_{rj}, \quad \forall r, j, \\
& -z'_{ro} \leq u_r \leq z'_{ro}, \quad \forall r, \\
& -z''_{ro} \leq u_r \leq z''_{ro}, \quad \forall r, \\
& u_r, v_i, p_j, q_{rj}\, p'_o, q'_{ro}, p''_o, q''_{ro} \geq 0,
\end{aligned} \tag{14}
$$

where $p_j, q_{rj}, p'_o, q'_{ro}, p''_o$, and $q''_{ro}$ are dual variables utilized in the BA approach. Moreover, in both BA and BN approaches, $z$ represents the efficiency of supplier under consideration when each relative virtual output of the supplier is restricted to a pre-specific interval, i.e., $\left( a_r \leq u_r y_{ro} \middle/ \sum_{r=1}^{s} u_r y_{ro} \leq b_r \right)$.

## 8. Conclusion

We consider data envelopment analysis model in a supplier selection problem of Supplying Automotive Parts Company. In such real problems, the reliable data about suppliers often does not exist due to several reasons. We propose two main robust optimization approaches to immune DEA results against suppliers' data uncertainty. In the case study of SAPCO, we concentrate on main safety parts which include brake system, safety belt, and lighting system. It is shown that the efficiency quantity suppliers in traditional DEA are higher than robust ones due to the effect of uncertain data. Moreover, BA approach of DEA often gives the more efficiency quantity for suppliers than BN approach.

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