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Developing a Nondiscretionary Slacks-based Measure Model for Supplier Selection in the Presence of Stochastic Data

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ABSTRACT

Supplier selection has a strategic importance for every company. Nondiscretionary Slacks-based Measure (SBM) model is one of the models in Data Envelopment Analysis (DEA). In many real world applications, data are often stochastic. A successful approach to the address uncertainty in data is to replace deterministic data via random variables, leading to Chance-constrained DEA (CCDEA). In this study, the concept of chance-constrained programming approach is used to develop nondiscretionary SBM model in the presence of stochastic data and also its deterministic equivalent which is a nonlinear program is derived. Furthermore, it is shown that the deterministic equivalent of the stochastic nondiscretionary SBM model can be converted into a quadratic program. Finally, a numerical example demonstrates the application of the proposed model.

Key words: Supply chain management, chance-constrained data envelopment analysis, nondiscretionary slacks-bared measure, supplier selection, quadratic program, sensitivity analysis

INTRODUCTION

According to Sonmez (2006), supplier selection is the process of finding the suppliers that are able to present products and/or services to the customer with appropriate quality, at the appropriate cost, quantities and time. As Amid *et al.* (2011) address, within new strategies for purchasing and manufacturing, suppliers play a key role in achieving corporate competitiveness. Consequently, correct selection of supphers is a critical element. Main cost of the most industries in manufacturing belongs to cost of raw materials and component parts which in most cases constitutes up to 70% of the total costs. Therefore, purchasing department plays an important role in efficiency and effectiveness of a firm, due to the contribution of supplier performance on expenditure, quality, delivery and service in accomplishing the objectives of a supply chain.

As Chamodrakas *et al.* (2010) describe, advanced industries should conform to market environment in which accessibility to global competition is an important factor. Consequently, in order to reduce production expenditures, it is important that expenses of companies be logical and reasonable. To this end, reducing the purchasing prices through selection of right supplier can be beneficial. In addition, some advanced production systems like just in time and mass customization manufacturing pay attention to quick provision of raw materials and outsourced components within expected quality and quantity. The fact that many businesses are turning to outside suppliers and manufacturers to obtain universal resources more effectively, emphasizes to importance of requirements of these issues.

Some mathematical programming approaches have been used for supplier selection in the past. Table 1 categorizes the reviewed papers based on applied techniques. Because of the intricacy of the decision making process involved in supplier, all the aforementioned references in Table 1, except for Data Envelopment Analysis (DEA), rely on some form of procedures that assign weights to various performance measures. The primary problem associated with arbitrary weights is that they are subjective and it is often a complex task for the decision maker to precisely assign numbers to preferences. As well, it is a daunting task for the decision maker to assess weighting information as the number of performance criteria is increased. In the meantime, they do not consider stochastic data.

Standard DEA models suppose that Decision Making Units (DMUs) carry out same obligations with same goals, employ similar inputs and create similar outputs. In real world, some factors are out of the control of decision makers and are called non-discretionary factors (Syrjanen, 2004).

Instances from the DEA literature include snowfall or weather in evaluating the efficiency of maintenance units, soil characteristics and topography in different farms, number of competitors in the branches of a restaurant chain and age of facilities in different universities (Saen, 2005).

It is suitable for solving optimization problems with random variables included in constraints and sometimes in the objective function as well (Charnes and Cooper, 1959). As Olson and Swenseth (1987) discuss, CCP was developed as a means of describing constraints in the form of probability levels of attainment. Consideration of chance constraints allows the decision-maker to consider objectives in terms of their attainment probability. If α is a predetermined confidence level desired by the decision-maker, the implication is that a constraint will have a probability of satisfaction of α. The probabilistic nature of this approach lends itself to multi-objective analysis.

Table 1: A summary of methods for suppliers selection

Technique name	References
Analytic hierarchy process (AHP)	Akarte *et al*. (2001), Muralidharan *et al*. (2002), Kahraman *et al*. (2003), Cebi and Bayraktar (2003), Chan (2003), Chan and Chan (2004), Liu and Hai (2005), Wang *et al*. (2004), Pi and Low (2006), Chan *et al*. (2007), Xia and Wu (2007), Kull and Talluri (2008), Hou and Su (2007), Wu *et al*. (2010) and Chamodrakas *et al*. (2010)
Analytic network process (ANP)	Sarkis and Talluri (2002), Bayazit (2006) and Gencer and Gurpinar (2007)
Data envelopment analysis (DEA)	Baker and Talluri (1997), Petroni and Braglia (2000), Liu *et al*. (2000), Forker and Mendez (2001), Ross*et al*. (2006), Garfamy (2006), Talluri *et al*. (2006), Saen (2007, 2008, 2009a-c), Saen (2010a-b), Sevkli *et al*. (2007), Azadi and Saen (2011, 2012) and Azadi *et al*. (2012)
Case-based reasoning (CBR)	Choy *et al*. (2002, 2003a-b, 2004, 2005).
Fuzzy set theory	Ohdar and Ray (2004), Jain *et al*. (2004), Chang *et al*. (2006), Chen *et al*. (2006), Sarkar and Mohapatra (2006), Florez-Lopez (2007), Keskin *et al*. (2010), Amid *et al*. (2006, 2011) and Sanayei *et al*. (2010)
Mathematical programming	Ghodsypour and O'Brien (2001), Karpak *et al*. (2001), Talluri and Narasimhan (2003, 2005), Hong *et al*. (2005), Narasimhan *et al*. (2006), Wadhwa and Ravindran (2007), Ng (2008), Kokangul and Susuz (2009), Sawik (2010) and Liao and Kao (2010)
Vague sets	Zhang *et al*. (2010)
Scatter search	Ebrahim *et al*. (2009)
Multi-attribute rating	Barla (2003) and Huang and Keskar (2007)

The selection of α can be a managerial decision. Chance constraints for stochastic functions based upon sampling information would often be normally distributed. Sampling information has long been used in business as a means of determining the expected value of functional coefficients in linearly constrained systems.

A main contribution on the stochastic DEA might be found in the work of Sengupta (1982, 1987, 1990, 1997, 1998, 2000) who has widely studied the research theme, using the CCP proposed by Charnes and Cooper (1963). An important feature of his studies is that stochastic variables are incorporated into DEA and afterward the stochastic DEA is reformulated into a deterministic equivalent. Land *et al.* (1993) utilized CCP (Charnes and Cooper, 1961; Cooper *et al.*, 1996) to develop efficient frontiers which envelop a given of observation most of time. Olesen and Petersen (1995) proposed a Chance-constrained DEA (CCDEA) model that uses piecewise linear envelopment of confidence regions for observed stochastic multiple inputs and multiple outputs. Cooper *et al.* (1996) incorporated Simon (1957) "satisficing concepts" into DEA model with chance constrained. Also, stochastic DEA approaches can be found in but not limited to Cooper *et al.* (1998), Huang and Li (1996) and Li (1998). Morita and Seiford (1999), proposed a measure for reliability of efficient DMUs as the amount of stochastic variations that remain the efficient DMU being efficient. A minimum efficiency score at a specified probability level is also used as a robustness measure. Moreover, they discussed some stochastic measures such as an expected efficiency score, a probability being efficient, an α percentile of efficiency score. Sueyoshi (2000) proposed a "DEA future analysis" that incorporates future information on outputs into its analytical framework. A stochastic DEA model is used as an initial starting formulation and then it is reformulated by both CCP and the estimation technique of PERT/CPM. Besides Huang and Li (2001) generalize two conventional DEA model by incorporating two conventional DEA model by incorporating random disturbances into input and output data. Cooper *et al.* (2002) proposed CCP models that are directed to determine where efficient and inefficient behavior will occur with associated probabilities. Their method replaces ordinary DEA formulations with stochastic counterparts in the form of a series of CCP models. Emphasis is on technical efficiency and inefficiencies which do not require costs or prices but which are nevertheless basic in that the achievement of technical efficiency is necessary for the attainment of "allocative", "cost" and other types of efficiencies.

Talluri *et al.* (2006) utilized the CCP model proposed by Land *et al.* (1993) for supplier selection, since it is a well-established methodology and provides an innovative and simple method to incorporate variability in input and output measures into the decision making process. The developed model in this paper uses CCP model proposed by Cooper *et al.* (2004). Since it has the advantages of model proposed by Land *et al.* (1993), it opens possible new routes for "sensitivity analysis". Additionally, it can be solved by a deterministic equivalent. Also, model utilized by Talluri *et al.* (2006) does not consider nondiscretionary factors while model utilized in this paper takes into account the nondiscretionary factors.

In summary, the approach presented in this study has some distinctive contributions that are as below:

- A stochastic nondiscretionary SBM model is developed and also its deterministic equivalent which is a nonlinear program is derived
- It is shown that the deterministic equivalent of the stochastic nondiscretionary SBM model can be converted into a quadratic program
- Sensitivity analysis of the stochastic nondiscretionary SBM model is discussed with respect to changes in parameters

- For the first time, the proposed model is used for the problem of supplier selection
- The proposed model deals with stochastic data in a direct manner

The objective of this paper was to propose a new stochastic SBM nondiscretionary model for supplier selection.

PROPOSED MODEL

DEA is a decision technique that has been widely used for performance analysis in public and private sectors. DEA developed by Charnes *et al.* (1978), is a nonparametric estimation method, in the sense that no choice of a parametric functional form is needed in the estimation of the frontier. DEA can be practical to any organization/industry where a rationally homogeneous set of DMUs use the identical set of inputs to produce an identifiable range of outputs. Traditional DEA models can merely measure radial efficiency (weak efficiency). To measure strong efficiency in DEA, Tone (2001) proposed SBM. This model deals directly with the input excesses and output shortfalls. SBM uses the Additive model and provides a scalar measure ranging from 0 to 1 that encompasses all of the inefficiencies that the model can identify (Cooper *et al.*, 2007). SBM does not deal with stochastic data and assume that all input and output data are exactly known.

The formulation for the SBM nondiscretionary model given by Saen (2005) is as below:

$$\begin{aligned}
\min \quad & \gamma = t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}} \\
\text{s.t.} \quad & 1 = t + \frac{1}{s}\sum_{r=1}^{s}\frac{s_i^+}{y_{ro}}, \\
& tx_o = X\Lambda + S^- \\
& ty_o = Y\Lambda - S^+ \\
& s_i^- \le \beta_i x_{io}, \quad i = 1, \ldots, m \\
& s_r^+ \le \gamma_r y_{ro}, \quad r = 1, \ldots, s \\
& \Lambda \ge 0, \; S^- \ge 0, \; S^+ \ge 0, \; t > 0
\end{aligned} \tag{1}$$

We can replace model (1) with:

$$\begin{aligned}
\min \quad & \gamma = t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}} \\
\text{s.t.} \quad & 1 = t + \frac{1}{s}\sum_{r=1}^{s}\frac{s_i^+}{y_{ro}}, \\
& tx_o = X\Lambda + S^- = 0 \\
& ty_o = Y\Lambda - S^+ = 0 \\
& s_i^- \le \beta_i x_{io}, \quad i = 1, \ldots, m \\
& s_r^+ \le \gamma_r y_{ro}, \quad r = 1, \ldots, s \\
& \Lambda \ge 0, \; S^- \ge 0, \; S^+ \ge 0, \; t > 0
\end{aligned} \tag{2}$$

Now, the new nondiscretionary SBM model is developed which permits the possible existence of stochastic variability in the data. As we know, the typical DEA models do not permit stochastic variations in input and output, hence, DEA efficiency measurement may be sensitive to such variations. For instance, a DMU which is measured as efficient relative to other DMUs, might turn inefficient if such random variations are considered. In what follows, the output oriented nondiscretionary SBM model is presented which allows for the possibility of stochastic alterations in input and output data.

We suppose that all inputs and outputs are random variables with a multivariate normal distribution and known parameters:

$$\begin{aligned}
&\min \gamma = t_o \\
&\text{s.t. } p\left\{\frac{1}{s}\sum_{r=1}^{s}\frac{s_i^+}{\tilde{y}_{ro}} - 1 \geq t\right\} \geq 1-\alpha \\
&\quad p\left\{\tilde{X}\Lambda \leq t\tilde{x}_o\right\} \geq 1-\alpha \\
&\quad p\left\{\tilde{Y}\Lambda \geq \tilde{t}y_o\right\} \geq 1-\alpha \\
&s_i^- \leq \beta_i x_{io}, \quad i = 1, \ldots, m \\
&s_i^+ \leq \gamma_r y_{ro}, \quad r = 1, \ldots, s \\
&\Lambda \geq 0,\ S^- \geq 0,\ S^+ \geq 0,\ t > 0
\end{aligned} \tag{3}$$

Definition 1: (Stochastic efficiency) DMU_o is DEA stochastic efficient if and only if the following two conditions are both satisfied:

- $\gamma^* = 1$
- $S^{-*} = S^{+*} = 0$

Now assume ς_r is the "external slack" for the rth output. Via 'external slack' we refer to slack outside the braces. We can select the value of this external slack which is not stochastic, so it satisfies:

$$p\left\{\frac{1}{s}\sum_{r=1}^{s}\frac{s_i^+}{\tilde{y}_{ro}} - t - 1 \geq 0\right\} = (1-\alpha) + \varsigma_r \tag{4}$$

There must then exist a positive number $s_r^+ > 0$ such that:

$$p\left\{\frac{1}{s}\sum_{r=1}^{s}\frac{s_i^+}{\tilde{y}_{ro}} - t - 1 \geq s_r^+\right\} = 1-\alpha \tag{5}$$

This positive value of s_r^+ permits a still further raise in $\tilde{y}_{ro}$ for any set of sample observations devoid of worsening any other input or output. It is easy to see that $\varsigma_r = 0$ if and only if $s_r^+ = 0$.

In an analogous manner, presume $\xi_i > 0$ represents 'external slack' for the ith input chance-constraint. We select its value to satisfy:

$$p\left\{\tilde{X}\Lambda - t\tilde{x}_o \leq 0\right\} = (1-\alpha) + \xi_i \tag{6}$$

There must then exist a positive number $s_i^- > 0$ such that:

$$p\left\{\tilde{X}\Lambda + s_i^- \leq t\tilde{x}_o\right\} = 1-\alpha \tag{7}$$

Such a positive value of s^{-}_{i} permits a decrease in $\tilde{x}_o$ for any sample without worsening any other input or output to the indicated probabilities. It is easy to show that $\xi_i = 0$ if and only if $s^{-}_{i} = 0$.

Consequently for the constraint 3 of Model (3) we have:

$$p\left\{\tilde{Y}\Lambda + t\tilde{y}_o \geq 0\right\} = (1-\alpha) + \zeta_r \tag{8}$$

and

$$p\left\{\tilde{Y}\Lambda + t\tilde{y}_o \geq s_r^+\right\} = 1-\alpha \tag{9}$$

Using relations (4-9), can replace Model (3) with following model:

$$\begin{aligned}
&\min \quad \gamma = t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}} \\
&\text{s.t. } p\left\{\frac{1}{s}\sum_{r=1}^{s}\frac{s_i^+}{\tilde{y}_{ro}} - t - 1 \geq s_r^+\right\} = 1-\alpha \\
&p\left\{\tilde{X}\Lambda + s_i^- \leq t\tilde{x}_o\right\} = 1-\alpha \\
&p\left\{\tilde{Y}\Lambda - t\tilde{y}_o \geq s_r^+\right\} = 1-\alpha \\
&s_i^- \leq \beta_i x_{io} \quad i = 1,\ldots,m \\
&s_r^+ \leq \gamma_r y_{ro} \quad r = 1,\ldots,s \\
&\Lambda \geq 0,\ S^- \geq 0,\ S^+ \geq 0,\ t > 0
\end{aligned} \tag{10}$$

We can replace the first constraint of Model (10) with:

$$p\left\{\frac{1}{s}\sum_{r=1}^{s}\frac{s_i^+}{\tilde{y}_{ro}} - t - 1 \geq s_r^+\right\} = \alpha \tag{11}$$

This reorients the inequality in the braces and replaces (1-α) with α. It next follows that:

$$p\left\{\tilde{z} \leq \frac{s_r^+ - \left(\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}} - t - 1\right)}{\sigma_r^o(\lambda)}\right\} = \alpha \tag{12}$$

Where:

$$\tilde{z} = \frac{\left(\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{\tilde{y}_{ro}} - t - 1\right) - \left(\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{\tilde{y}_{ro}} - t - 1\right)}{\sigma_r^o(\lambda)} \tag{13}$$

We can also write Eq. 13 as:

$$\Phi(a) = \alpha$$

Where:

$$a = \frac{s_+^r - \left(\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{\tilde{y}_{ro}} - t - 1\right)}{\sigma_r^o\ (\lambda)}$$

This comes from:

$$\int_{-\infty}^{\alpha} f(y)\ dy + \int_{\alpha}^{\infty} f(y)\ dy = 1 \tag{14}$$

$$\Phi\ (\alpha) = \int_{-\infty}^{\alpha} f(y)dy = \alpha \tag{15}$$

with f the density function for the standard normal variable. From Eq. 15, we have:

$$\frac{s_+^r - \left(\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}} - t - 1\right)}{\sigma_r^o\ (\lambda)} = \Phi^{-1}\ (\alpha) \tag{16}$$

Therefore:

$$t + \frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}} - 1 + s_r^+ - \Phi^{-1}\ (\alpha)\ \delta_r^o\ (\lambda) = 0 \tag{17}$$

We can replace the constraint 2 of Model (10) with following relation:

$$p\left\{\tilde{X}\Lambda - t\tilde{x}_o \leq -s_i^-\right\} = 1 - \alpha \tag{18}$$

It follows that:

$$p\left\{\tilde{z} \leq \frac{-s_i^- - (X\Lambda - tx_o)}{\sigma_i^I\ (t,\ \lambda)}\right\} = 1 - \alpha \tag{19}$$

i.e.:

$$\Phi\ (\alpha') = 1\text{-}\alpha \tag{20}$$

Where:

$$\alpha' = \frac{-s_i^- - (X\Lambda - tx_o)}{\sigma_i^I\ (t,\ \lambda)}$$

This comes from:

$$\int_{-\infty}^{\alpha'} f(x)\,dx + \int_{\alpha'}^{\infty} f(x)\,dx = 1 \tag{21}$$

$$\Phi(\alpha') = \leftarrow \int_{-\infty}^{a} f(x)\,dx = 1-\alpha \tag{22}$$

Now $-\Phi^{-1}(\alpha) = \Phi^{-1}(1-\alpha)$, by virtue of the symmetry related with the normal distribution, so from relation (20) we have:

$$\frac{-s_i^- - (X\Lambda - tx_o)}{\sigma_i^I(t,\lambda)} - \Phi^{-1}(\alpha) \tag{23}$$

Thus:

$$tx_o - X\Lambda + s_j^- - \Phi^{-1}(\alpha)\sigma_j^I(\lambda) = 0 \tag{24}$$

Therefore, the deterministic equivalent for model (10) is as below:

$$\begin{aligned}
&\min \qquad \gamma = t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}\\
&t + \frac{1}{s}\sum_{r=1}^{s}\frac{s_i^+}{y_{ro}} - 1 + s_r^+ - \Phi^{-1}(\alpha)\delta_r^o(\lambda) = 0\\
&tx_o - X\Lambda + s_i^- - \Phi^{-1}(\alpha)\,\sigma_i^I(\lambda) = 0\\
&ty_o - Y\Lambda + s_i^- - \Phi^{-1}(\alpha)\,\sigma_i^I(\lambda) = 0\\
&s_i^- \le \beta_i x_{io} \quad i = 1,\ldots,m\\
&s_r^+ \le \gamma_r y_{ro} \quad r = 1,\ldots,s\\
&\Lambda \ge 0,\ S^- \ge 0,\ S^+ \ge 0,\ t > 0
\end{aligned} \tag{25}$$

To derive equations for $\sigma^I_i(\lambda)$ note that:

$$\begin{aligned}
\sigma_r^o(\lambda)^2 &= \mathrm{Var}\left\{\sum_{j=1}^{n}\lambda_j\tilde{y}_{rj} - \tilde{y}_{ro}\right\} = \mathrm{Var}\left\{\sum_{j=1}^{n}\lambda_j y_{rj} + (\lambda_o - 1)y_{ro}\right\}\\
&\mathrm{Var}\left(\sum_{j=1}^{n}\lambda_j y_{rj}\right) + \mathrm{Var}\,((\lambda_o - 1)y_{ro}) + 2\mathrm{Cov}\left(\sum_{j=1}^{n}\lambda_j y_{rj},\ (\lambda_o - 1)y_{ro}\right)
\end{aligned}$$

Therefore:

$$\sigma_r^o(\lambda)^2 = \sum_{j\ne o}\sum_{k\ne o}\lambda_i\lambda_k\ \mathrm{Cov}(\tilde{y}_{rk},\ \tilde{y}_{rj}) + 2(\lambda_o - t)\sum_{j\ne o}\lambda_k\ \mathrm{Cov}(\tilde{y}_{rk},\ \tilde{y}_{rj}) + (\lambda_o - t)^2\,\mathrm{Var}\,(y_{ro})$$

Similarly, for the constraints 2 and 3 of model (25) we have:

$$\begin{aligned}
\sigma_i^I(t,\lambda)^2 &= \sum_{j\ne o}\sum_{k\ne o}\lambda_j\lambda_k\ \mathrm{Cov}(\tilde{x}_{ij},\ \tilde{x}_{ik}) + 2(\lambda_o - t)\sum_{j\ne o}\lambda_k\ \mathrm{Cov}(\tilde{x}_{ij},\ \tilde{x}_{io}) + (\lambda_o - t)^2\,\mathrm{Var}\,(\tilde{x}_{io})\\
\sigma_r^o(\lambda)^2 &= \sum_{j\ne o}\sum_{k\ne o}\lambda_i\lambda_k\ \mathrm{Cov}(\tilde{y}_{rk},\ \tilde{y}_{rj}) + 2(\lambda_o - t)\sum_{j\ne o}\lambda_k\ \mathrm{Cov}(\tilde{y}_{rk},\ \tilde{y}_{rj}) + (\lambda_o - t)^2\,\mathrm{Var}\,(\tilde{y}_{ro})
\end{aligned}$$

It is obvious, from the forms of σ°_{r} (λ), σ^{I}_{i} (t, λ) and σ°_{r} (t, λ) that model (25) is a non-linear program. We demonstrate that this non-linear program can be transformed to a quadratic program. Assume that, w°_{r}, w^{I}_{i} are nonnegative variables. Replacing w°_{r}, w^{I}_{i}, respectively, by σ°_{r} (λ), σ^{I}_{i} (λ) and adding the following quadratic equality constraints:

$$(w_r^{\circ})^2 = (\sigma_r^{\circ}(\lambda))^2,\ (w_i^I)^2 = \left(\sigma_i^I(\lambda)^2\right),\ (w_r^{\circ})^2 = \left(\sigma_r^{\circ}(t,\lambda)\right)^2$$

Hence, model (25) is transformed to a quadratic programming problem:

$$(w_r^{o})^2 = \sum_{i\neq 0}\sum_{j\neq 0}\lambda_i\lambda_j \operatorname{Cov}(\tilde{y}_{ri},\ \tilde{y}_{rj}) - 2\sum_{j\neq 0}\lambda_i \operatorname{Cov}(\tilde{y}_{ri},\ \tilde{y}_{ro}) + \operatorname{Var}(\tilde{y}_{ro})$$
$$(w_i^{I})^2 = \sum_{j\neq 0}\sum_{k\neq 0}\lambda_i\lambda_k \operatorname{Cov}(\tilde{x}_{ij},\ \tilde{x}_{ik}) - 2\sum_{j\neq 0}\lambda_i \operatorname{Cov}(\tilde{x}_{ij},\ \tilde{x}_{io}) + \operatorname{Var}(\tilde{x}_{io})$$
$$(w_r^{o})^2 = \sum_{i\neq 0}\sum_{j\neq 0}\lambda_i\lambda_j \operatorname{Cov}(\tilde{y}_{ri},\ \tilde{y}_{rj}) - 2t\sum_{i\neq 0}\lambda_i \operatorname{Cov}(\tilde{y}_{ri},\ \tilde{y}_{ro}) + (t)^2\operatorname{Var}(\tilde{y}_{ro})$$

$$\begin{aligned}
&\min\ \ \gamma = t - \frac{1}{m}\sum_{i=1}^{1}\frac{S_i^-}{x_{io}}\\
&t + \frac{1}{s}\sum_{r=1}^{s}\frac{S_r^+}{y_{ro}} - 1 + S_r^+ - \Phi^{-1}(\alpha)\delta_r^{\circ}(\lambda) = 0\\
&tx_o\text{-}X\Lambda + S_i^- + \Phi^{-1}\ (\alpha)\sigma_i^I(\lambda) = 0,\\
&ty_o\text{-}Y\Lambda\text{-}S_i^-\text{-}\Phi^{-1}\ (\alpha)\sigma_i^I(\lambda) = 0,\\
&s_i^- \le \beta_i x_{io}\quad i = 1, ..., m,\\
&\Lambda \ge 0,\ \ S^- \ge 0,\ \ S^+ \ge 0,\ t>0
\end{aligned}$$

Where:

$$(w_r^{\circ})^2 = \sum_{i\neq o}\sum_{j\neq o}\lambda_i\lambda_j \operatorname{Cov}(\tilde{y}_{ri},\ \tilde{y}_{rj}) - 2\sum_{i\neq o}\lambda_i \operatorname{Cov}(\tilde{y}_{ri},\ \tilde{y}_{ro}) + V_{ar}\ (\tilde{y}_{ro})$$
$$(w_r^{I})^2 = \sum_{i\neq o}\sum_{k\neq o}\lambda_i\lambda_k \operatorname{Cov}(\tilde{x}_i,\ \tilde{x}_k) - 2\sum_{j\neq o}\lambda_i \operatorname{Cov}(\tilde{x}_{ij},\ \tilde{x}_{io}) + V_{ar}\ (\tilde{x}_{io})$$
$$(w_r^{\circ})^2 = \sum_{i\neq o}\sum_{j\neq o}\lambda_i\lambda_j \operatorname{Cov}(\tilde{y}_{ri},\ \tilde{y}_{rj}) - 2t\sum_{i\neq o}\lambda_i \operatorname{Cov}(\tilde{y}_{ri},\ \tilde{y}_{ro}) + (t)^2\ V_{ar}\ (\tilde{y}_{ro})$$

NUMERICAL EXAMPLE

The idea for this example is taken from Saen (2009c) and Maital and Vaninsky (2001). The example contains specifications on twenty suppliers (DMUs). These DMUs consume two inputs to produce two outputs. The data set are in Table 2. Distance and cost were used as inputs for the DEA model. The outputs utilized in the study are supplier variety and R and D expenditures. Moreover, assume that cost, supplier variety and distance are nondiscretionary variables, i.e., these factors are exogenously fixed and cannot be changed by suppliers (at least in the short term).

In summary, the suppositions are as below:

- Distance is not controllable
- Cost is 50% under control
- Supplier variety is not controllable
- R and D expenditure is controllable

Table 2: Related attributes for 20 suppliers

	Inputs				Outputs			
	Distance		Cost		Supplier variety		R and D expenditures	
Supplier (DMU)	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
1	6	0.5	70	7	25	3	10	2
2	5	1.0	130	8	17	2	12	3
3	11	2.0	125	5	15	1	50	4
4	8	1.0	100	4	25	2	55	5
5	9	1.0	90	1	30	3	70	7
6	6	2.0	75	5	50	5	15	5
7	18	1.0	150	10	14	1	35	5
8	25	1.0	280	20	65	0.5	42	2
9	12	1.0	160	10	50	3	60	4
10	10	1.0	135	9	40	2	70	9
11	12	1.0	120	4	10	4	75	10
12	10	2.0	95	2	5	1	45	2
13	7	1.0	70	2	12	2	43	10
14	11	2.0	140	5	30	1	5	4
15	20	3.0	140	20	80	2	5	2
16	23	2.0	150	25	65	4	8	2
17	25	3.0	120	15	78	3	7	2
18	10	1.0	70	1	40	2	25	1
19	12	1.0	115	5	5	1	65	4
20	5	2.0	80	5	17	1	10	3

DMU: Decision-making units, R and D: Research and development

Table 3 reports the results of efficiency assessments for the 20 suppliers obtained by model 25 which are calculated with $\alpha = 0.05$. The efficient suppliers are 4, 5, 6, 9, 10, 11 and 19. These suppliers are efficient because the following two conditions are both satisfied:

- $\gamma^* = 1$
- $S^{-*} = S^{+*} = 0$

This example shows the applicability of the proposed model using chance-constrained DEA with non-discretionary factors and stochastic data in SBM model context. As is seen, in Table 3 suppliers were selected in uncertain environment with $\alpha = 0.05$. Supplier selection in such uncertain environment reduces the material purchasing cost and enhances company competitiveness which is why many experts suppose that the supplier selection is the most significant activity of a purchasing department.

Sensitivity analysis is the study of how the variation (uncertainty) in the output of a mathematical model can be apportioned to different sources of variation in the input of a model. Table 4 shows the sensitivity of results in terms of different α values. In fact, sensitivity analysis performed in Table 4 shows that how the uncertainty in the output of a model can be apportioned to different source of uncertainty in the model input.

With respect to definition 1, Table 5 implies that the DMUs 3, 6, 9, 11, 12, 13, 17 and 18 are efficient. The ranking results of Tables 3 and 5 depict there are some differences among the ranks.

Table 3: The efficiency scores for the 20 suppliers with $\alpha = 0.05$

Supplier (DMU)	S^-_1	S^-_2	S^+_1	S^+_2	Efficiency scores ($\alpha = 0.05$)
1	0.0	1.5	0.0	0.852	0.946
2	0.0	0.0	0.0	0.977	1.000
3	0.0	0.0	0.0	0.220	0.999
4	0.0	0.0	0.0	0.000	1.000
5	0.0	0.0	0.0	0.000	1.000
6	0.0	0.0	0.0	0.000	1.000
7	0.0	1.5	0.0	44.400	0.931
8	1.7	0.0	46.1	0.000	0.447
9	0.0	0.0	0.0	0.000	1.000
10	0.0	0.0	0.0	0.000	1.000
11	0.0	0.0	0.0	0.000	1.000
12	0.0	0.0	0.0	0.159	1.000
13	0.0	0.0	0.0	0.000	1.000
14	0.0	0.0	0.0	14.200	0.715
15	2.6	0.0	0.0	7.200	0.272
16	0.0	6.1	0.0	12.300	0.224
17	0.0	1.5	2.1	0.000	0.843
18	1.3	0.0	0.0	4.070	0.907
19	0.0	0.0	0.0	0.000	1.000
20	0.0	0.0	0.0	0.817	0.999

DMU: Decision-making units, R and D: Research and development

Table 4: Efficiency scores (γ*) for different α

DMU	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$
1	0.850	0.828	0.808	0.788	0.763
2	1.000	1.000	1.000	1.000	0.999
3	0.902	0.875	0.850	0.825	0.798
4	1.000	1.000	1.000	0.982	0.960
5	1.000	1.000	1.000	0.999	0.989
6	1.000	1.000	0.986	0.965	0.947
7	0.917	0.897	0.861	0.768	0.552
8	0.407	0.398	0.388	0.379	0.369
9	0.899	0.869	0.841	0.822	0.804
10	1.000	1.000	1.000	0.984	0.981
11	1.000	1.000	0.999	0.982	0.974
12	1.000	0.923	0.884	0.845	0.812
13	0.982	0.962	0.953	0.940	0.912
14	0.579	0.546	0.515	0.474	0.452
15	0.182	0.160	0.139	0.133	0.126
16	0.217	0.209	0.203	0.184	0.175
17	0.839	0.832	0.829	0.823	0.811
18	0.887	0.873	0.861	0.842	0.836
19	1.000	1.000	0.984	0.981	0.974
20	0.724	0.589	0.511	0.434	0.353

DMU: Decision-making units, R and D: Research and development

Therefore, stochastic data leads to different results. This shows that if there are stochastic data, then we must apply stochastic models. Note that the results rely on the specified probability level

Table 5: The efficiency scores for 20 suppliers using Model (6)

Supplier (DMU)	S^{-}_{1}	S^{-}_{2}	S^{+}_{1}	S^{+}_{2}	Efficiency scores ($\alpha = 0.05$)
1	3.7	0.00	0.00	0.54	0.892
2	0.0	1.00	0.753	0.126	0.958
3	0.0	0.00	0.00	0.00	1.000
4	0.0	0.00	0.64	0.00	1.000
5	0.0	0.70	0.237	0.00	0.974
6	0.0	0.00	0.00	0.00	1.000
7	0.0	9.68	0.00	37.20	0.835
8	2.9	42.70	0.00	0.00	0.516
9	0.0	0.00	0.00	0.00	1.000
10	0.0	0.06	0.95	0.00	0.922
11	0.0	0.00	0.00	0.00	1.000
12	0.0	0.00	0.00	0.00	1.000
13	0.0	0.00	0.00	0.00	1.000
14	0.0	0.189	0.00	17.60	0.845
15	0.0	0.00	0.00	14.60	0.213
16	0.0	21.90	0.00	12.30	0.224
17	0.0	0.00	0.00	0.00	1.000
18	0.0	0.00	0.00	0.00	1.000
19	0.0	0.00	0.82	0.00	1.000
20	0.0	0.00	0.00	0.617	0.953

α. The stochastic model applied in this numerical example permits the data errors and provides probabilistic results. In general, if the data are under uncertainty and probabilistic situations and a rough estimate is required, the stochastic models might be favored.

CONCLUSION

Supplier plays an important role in company successes. Though, as the marketplace becomes more global, supplier is now seen as a significant area where industries can cut expenditures and improve their patron service quality. In order to raise their competitive advantages, many firms consider Supply Chain Management (SCM) outsourcing as very significant. A successful supplier choice plays a significant role in building the long-term relationships between the outsourcing firm and a supplier.

In this study, nondiscretionary SBM model was discussed. In addition to developing stochastic version of the nondiscretionary SBM model, we attained the deterministic equivalent of the stochastic version which can be changed to a quadratic problem. As a numerical example, the proposed approach was also applied to data of twenty suppliers. Sensitivity analysis of the proposed model was illustrated.

The problem considered in this study is at initial stage of investigation and further researches can be done based on the results of this study. Some of them are as follow:

- Similar research can be repeated for supplier selection in the presence of both deterministic data and fuzzy data
- Similar research can be repeated for supplier selection in the presence of both stochastic data and slightly non-homogeneous DMUs
- This study used the proposed model for supplier selection. It seems that more fields (e.g., market selection, technology selection, personnel selection, etc.) can be applied

NOMENCLATURE

j = I, ... , n collection of suppliers (DMUs)
r = I, ... , s the set of outputs
i = I, ... , m the set of inputs
$A \in R^{m \times n}$ = A matrix with m rows and n columns:

$$X = [x_1, \ldots, x_n] \in R^{m \times n}$$

$$Y = [y_1, \ldots, y_n] \in R^{m \times n}$$

DMU_o = The DMU under investigation
y_{rj} = The rth output of jth DMU
x_{ij} = The ith input of jth DMU
y_{ro} = The rth output of the DMU_o
x_{io} = The ith input of the DMU_o
$\sim$ = Used to identify the inputs and outputs as random variables with a known joint probability distribution
γ = The best possible relative efficiency achieved by DMU_o
Φ^{-1} = Inverse of standard normal distribution function
$S^- \in R^m$ = Excesses in inputs
S^+ = Shortage in outputs
s_r^+ = rth output shortfalls
s_i^- = ith input excesses
σ_r^O = Standard deviation of rth output
σ_i^I = Standard deviation of ith input
α = Risk that is between zero and 1
$Vary_{ro}$ = rth output variance of the DMU_o
$Varx_{IO}$ = ith input variance of the DMU_o
ξ, ς and ζ = The external slacks
$\tilde{z}$ = Standard normal random variable
β_i, γ_γ = Represent parameters (to be prescribed)
t = A variable which helps a nonlinear model to be converted to a linear model
Λ = $[\lambda_j]$ vector of DMU loadings, determining best practice for the DMU_o

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