Supplier Selection Using Data Envelopment Analysis in the Presence of Imprecise Data

E. Ertugrul KARSAK, Mehtap DURSUN
Industrial Engineering Department, Galatasaray University
Istanbul 34357, Turkey
E-mail addresses: ekarsak@gsu.edu.tr , mdursun@gsu.edu.tr

and

C. Okan ÖZOGUL
R&D Department, Havelsan, Ankara, Turkey

ABSTRACT

This paper aims to present a comprehensive methodology for supplier selection, incorporating both the financial and strategic aspects and the related imprecise as well as exact data into the decision making process. A data envelopment analysis (DEA) model that can take into consideration crisp, ordinal, and fuzzy data is developed for supplier selection. The DEA approach is performed by employing average cost per unit and lead time as the input variables, and number of bills received from the supplier without errors, supplier's experience and supplier reputation as the output variables. The assessment of suppliers versus experience and reputation are represented via ordinal data, while lead time and number of bills received without errors are stated using triangular fuzzy numbers. The proposed framework is illustrated through an example problem for supplier selection.

Keywords: Supplier selection, Data envelopment analysis, Imprecise data, Fuzzy data, Multi-criteria decision making.

1. INTRODUCTION

In today's increasingly competitive and changing environment, firms must focus on rapidly responding to customer demand and must be concerned with customer satisfaction. Firms also need to reorganize their supply chain management strategy, and establish a sound strategic alliance against competitors. Supply chain management attempts to reduce supply chain risk and uncertainty, thus improving customer service, and optimizing inventory levels, business processes, and cycle times, and resulting in increased competitiveness, customer satisfaction and profitability [1].

As firms become more dependent on their suppliers, poor decisions on the selection of suppliers and the determination of order quantities to be placed with the selected suppliers results in severe consequences. Firms need to pursue effective strategies to achieve higher quality, reduced costs and shorter lead times, which also enable to sharpen their competitive edges in the global market. Hence, supplier selection has become a critical issue for establishing an effective supply chain.

In the early 1980s, Evans [2] found price to be the most important attribute in the purchase of routine products. However, recent studies have discovered a shift away from price as a primary determinant of supplier selection [3]. Organizations, which practice the latest innovations in supply chain management, no longer accept commodity partnerships that are exclusively based on price. Other important factors such as quality, delivery time and flexibility are included in managing these inter-organizational relationships.

Due to high level of difficulty in controlling and predicting a wide variety of factors which affect the decision, supplier selection has become one of the most popular areas of research in purchasing with methodologies ranging from conceptual to empirical and modeling streams. Earlier studies on supplier selection focused on identifying the criteria used to select suppliers. Dickson [4] conducted one of the early works on supplier selection and identified 23 supplier criteria which managers consider when choosing a supplier. Ellram [5] noted that research on supplier selection tends to be either descriptive or prescriptive. Descriptive studies provide information on what buyers actually do in selecting suppliers. These studies have addressed a wide array of issues, and have been extended to identify supplier selection under specific buying conditions ([6], [7]). Prescriptive research in supplier selection has used a variety of methodologies including mathematical programming, weighted average methods, payoff matrices, analytic hierarchy process (AHP), analytic network process (ANP), fuzzy set theory, and metaheuristics. Linear programming, integer programming, goal programming, data envelopment analysis (DEA), and multi-objective programming can be listed among the mathematical programming techniques employed in supplier selection. An integrated use of some of these approaches is also presented in a number of supplier selection studies. The reader is referred to Ho et al. [8] for a comprehensive review of the use of these approaches in supplier selection.

DEA has been actively used in supplier evaluation and selection for more than a decade owing to its capability of handling multiple conflicting factors without the need of eliciting subjective importance weights from the decision-makers ([9], [10], [11]). One of the major limitations of the use of conventional DEA approach in supplier selection process is the sole consideration of cardinal data. Difficulty in predicting a number of factors considered in supplier selection demand ordinal and fuzzy data to be taken into account as well. Another major limitation is the poor discriminating power of DEA models resulting in a relatively high number of suppliers rated as efficient.

In this study, an imprecise DEA model is proposed to evaluate suppliers. The proposed approach enables both exact and imprecise data to be taken into consideration. Ordinal data and fuzzy data are used to express qualitative factors. The increased discriminating power of the proposed model attained while solving substantially reduced number of linear programs avoids the burden of selecting the best supplier among a relatively high number of suppliers that are rated as efficient by the conventional DEA model.

The rest of the paper is organized as follows. Section 2 provides a brief presentation of the conventional DEA model. Section 3 introduces a DEA model that can assess crisp, ordinal and fuzzy data. A hypothetical though typical supplier selection example is presented in the subsequent section to illustrate the results of the analysis. The concluding remarks and directions for future research are provided in the final section.

2. DATA ENVELOPMENT ANALYSIS

Data envelopment analysis (DEA) is a linear programming based decision technique designed specifically to measure relative efficiency using multiple inputs and outputs without *a priori* information regarding which inputs and outputs are the most important in determining an efficiency score. DEA considers n decision making units (DMUs) to be evaluated, where each DMU consumes varying amounts of m different inputs to produce s different outputs.

The relative efficiency of a DMU is defined as the ratio of its total weighted output to its total weighted input. In mathematical programming terms, this ratio, which is to be maximized, forms the objective function for the particular DMU being evaluated. A set of normalizing constraints is required to reflect the condition that the output to input ratio of every DMU be less than or equal to unity. The mathematical programming problem is then represented as

$$\max E_{j_0} = \frac{\sum_r u_r y_{rj_0}}{\sum_i v_i x_{ij_0}}$$

subject to (1)

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \le 1, \quad j = 1, ..., n$$

$$u_r, v_i \ge \varepsilon > 0, \quad r = 1,\ldots, s; \; i = 1, \ldots, m$$

where E_{j_0} is the efficiency score of the evaluated DMU (j_0), u_r is the weight assigned to output r, v_i is the weight assigned to input i, y_{rj} denotes amount of output r produced by the jth DMU, x_{ij} denotes amount of input i used by the jth DMU, and ε is an infinitesimal positive number. The weights in the objective function are chosen to maximize the value of the DMU's efficiency ratio subject to the "less-than-unity" constraints. These constraints ensure that the optimal weights for the DMU in the objective function do not denote an efficiency score greater than unity either for itself or for the other DMUs. A DMU attains a relative efficiency rating of 1 only when comparisons with other DMUs do not provide evidence of inefficiency in the use of any input or output.

The fractional program is not used for actual computation of the efficiency scores due to its intractable nonlinear and nonconvex properties [12]. Rather, the fractional program is transformed to an ordinary linear program given below that is computed separately for each DMU, generating n sets of optimal weights.

$$\max E_{j_0} = \sum_r u_r y_{rj_0}$$

subject to (2)

$$\sum_i v_i x_{ij_0} = 1$$

$$\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \le 0, \; j = 1, ..., n$$

$$u_r, v_i \ge \varepsilon > 0, \quad r = 1,\ldots, s; \; i = 1, \ldots, m.$$

The original DEA models assume that inputs and outputs are indicated as crisp numbers. Cook et al. [13] developed a model capable of handling ordinal inputs and outputs as well as factors represented using crisp data. Their approach assigns an auxiliary binary variable for every combination of ordinal variables and their distinct ranks on a predetermined scale.

3. DEA MODELS INCORPORATING EXACT, ORDINAL AND FUZZY DATA

Over the past decade, a number of researchers have published on DEA models incorporating imprecise data. Kao and Liu [14] developed an α–cut based approach to transform a fuzzy DEA model to a number of crisp DEA models. Since the efficiency values of DMUs are expressed by membership functions, a rank order of DMUs is obtained by employing fuzzy number ranking methods that may be shown to produce inconsistent outcomes. Despotis and Smirlis [15] proposed a DEA model dealing with exact and interval data. Although they claimed to decrease data manipulation efforts for the DEA model, their approach requires input and output weights to vary with respect to DMUs which would increase the number of variables by $(m + s)$ $(n – 1)$, for $i = 1, …, m$ and $r = 1, …, s$, for each linear program. Further, generalizing their approach to fuzzy data would be problematic since it is more reasonable to evaluate DMUs using the same level of α–cut for each linear program. Lertworasirikul et al. [16] have proposed a possibility approach for solving fuzzy DEA models where they determine the possibilistically efficient DMUs for predetermined possibility levels. Due to its extremely permissive nature, the possibility approach has a low discriminating power which often results in several efficient DMUs at all possibility levels.

This section presents DEA formulations initially developed by Karsak [17] to address decision problems involving the evaluation of relative efficiency of DMUs with respect to inputs and outputs that incorporate both exact and imprecise data. Imprecision in inputs and outputs are considered using ordinal data and fuzzy data. The concise development of the models is presented below.

Define $\tilde{x}_{ij} = \left(x_{ija}, x_{ijb}, x_{ijc}\right)$, for $0 \le x_{ija} \le x_{ijb} \le x_{ijc}$ as the fuzzy input i used by the jth DMU, and $\tilde{y}_{rj} = \left(y_{rja}, y_{rjb}, y_{rjc}\right)$ as the fuzzy output r produced by the jth DMU, where $0 \le y_{rja} \le y_{rjb} \le y_{rjc}$. Define

$$\left(x_{ij}\right)_\alpha^L = x_{ija} + \alpha_i\left(x_{ijb} - x_{ija}\right), \ \alpha_i \in [0,1],$$

$$\left(x_{ij}\right)_\alpha^U = x_{ijc} - \alpha_i\left(x_{ijc} - x_{ijb}\right), \ \alpha_i \in [0,1],$$

$$\left(y_{rj}\right)_\alpha^L = y_{rja} + \alpha_r\left(y_{rjb} - y_{rja}\right), \ \alpha_r \in [0,1],$$

$$\left(y_{rj}\right)_\alpha^U = y_{rjc} - \alpha_r\left(y_{rjc} - y_{rjb}\right), \ \alpha_r \in [0,1],$$

where $\left(x_{ij}\right)_\alpha^L$ and $\left(x_{ij}\right)_\alpha^U$ denote the lower and upper bounds of the α-cut of the membership function of $\tilde{x}_{ij}$, and similarly, $\left(y_{rj}\right)_\alpha^L$ and $\left(y_{rj}\right)_\alpha^U$ denote the lower and upper bounds of the α-cut of the membership function of $\tilde{y}_{rj}$, respectively. Let $\omega_i = v_i\alpha_i$, where $0 \le \omega_i \le v_i$. Then, $\sum_i v_i\left(x_{ij}\right)_\alpha^L$ and $\sum_i v_i\left(x_{ij}\right)_\alpha^U$ can be represented as

$$\sum_i v_i\left(x_{ij}\right)_\alpha^L = \sum_i v_i x_{ija} + \omega_i\left(x_{ijb} - x_{ija}\right),$$

$$\sum_i v_i\left(x_{ij}\right)_\alpha^U = \sum_i v_i x_{ijc} - \omega_i\left(x_{ijc} - x_{ijb}\right).$$

Similarly, define $\mu_r = u_r\ \alpha_r$, where $0 \le \mu_r \le u_r$. Then, $\sum_r u_r\left(y_{rj}\right)_\alpha^L$ and $\sum_r u_r\left(y_{rj}\right)_\alpha^U$ can be represented respectively as

$$\sum_r u_r\left(y_{rj}\right)_\alpha^L = \sum_r u_r y_{rja} + \mu_r\left(y_{rjb} - y_{rja}\right),$$

$$\sum_r u_r\left(y_{rj}\right)_\alpha^U = \sum_r u_r y_{rjc} - \mu_r\left(y_{rjc} - y_{rjb}\right).$$

Also, define $\boldsymbol{\gamma}_{\mathbf{rj}} = \left[\gamma_{r1j}, \ldots, \gamma_{rlj}, \ldots, \gamma_{rLj}\right]$ and $\boldsymbol{\delta}_{\mathbf{ij}} = \left[\delta_{i1j}, \ldots, \delta_{ilj}, \ldots, \delta_{iLj}\right]$ as the L-dimensional unit vectors, where

$$\gamma_{rlj} = \begin{cases} 1, \text{if } j \text{ is rated in the } l\text{th place w.r.t. the } r\text{th ordinal output} \\ 0, \text{otherwise} \end{cases}$$

$$\delta_{ilj} = \begin{cases} 1, \text{if } j \text{ is rated in the } l\text{th place w.r.t. the } i\text{th ordinal input} \\ 0, \text{otherwise} \end{cases}$$

Let $\left(E_{j_0}\right)^U$ and $\left(E_{j_0}\right)^L$ denote the upper and lower bounds of the α-cut of the membership function of the efficiency value for the evaluated DMU (j_0). Employing the substitutions given above, the general optimistic scenario DEA model incorporating crisp, fuzzy and ordinal data can be written as follows [17]:

$$\max\left(E_{j_0}\right)^U = \sum_{r\in C_R} u_r y_{rj_0} + \sum_{r\in F_R} u_r y_{rj_0c} - \mu_r\left(y_{rj_0c} - y_{rj_0b}\right) + \sum_{r\in O_R} \mathbf{w_r}\,\boldsymbol{\gamma}_{\mathbf{rj_0}}$$

subject to (3)

$$\sum_{i\in C_I} v_i x_{ij_0} + \sum_{i\in F_I} v_i x_{ij_0a} + \omega_i\left(x_{ij_0b} - x_{ij_0a}\right) + \sum_{i\in O_I} \mathbf{w_i}\,\boldsymbol{\delta}_{\mathbf{ij_0}} = 1$$

$$\sum_{r\in C_R} u_r y_{rj_0} + \sum_{r\in F_R} u_r y_{rj_0c} - \mu_r\left(y_{rj_0c} - y_{rj_0b}\right) + \sum_{r\in O_R} \mathbf{w_r}\,\boldsymbol{\gamma}_{\mathbf{rj_0}}$$
$$- \sum_{i\in C_I} v_i x_{ij_0} - \sum_{i\in F_I} v_i x_{ij_0a} + \omega_i\left(x_{ij_0b} - x_{ij_0a}\right) - \sum_{i\in O_I} \mathbf{w_i}\,\boldsymbol{\delta}_{\mathbf{ij_0}} \le 0$$

$$\sum_{r\in C_R} u_r y_{rj} + \sum_{r\in F_R} u_r y_{rja} + \mu_r\left(y_{rjb} - y_{rja}\right) + \sum_{r\in O_R} \mathbf{w_r}\,\boldsymbol{\gamma}_{\mathbf{rj}}$$
$$- \sum_{i\in C_I} v_i x_{ij} - \sum_{i\in F_I} v_i x_{ijc} - \omega_i\left(x_{ijc} - x_{ijb}\right) - \sum_{i\in O_I} \mathbf{w_i}\,\boldsymbol{\delta}_{\mathbf{ij}} \le 0,\ j = 1,2,\ldots,n;\ j \ne j_0$$

$$\mu_r - u_r \le 0, \quad r \in F_R$$

$$\omega_i - v_i \le 0, \quad i \in F_I$$

$$\mu_r \ge 0, \quad r \in F_R$$

$$\omega_i \ge 0, \quad i \in F_I$$

$$u_r \ge \varepsilon > 0, \quad r \in C_R, r \in F_R$$

$$v_i \ge \varepsilon > 0, \quad i \in C_I, i \in F_I$$

$$\Psi = \left\{ \left(\mathbf{w_r}, \mathbf{w_i}\right) \middle| \begin{array}{l} w_{rl+1} - w_{rl} \ge \varepsilon, w_{r1} \ge \varepsilon, \quad l = 1,2,\cdots,L-1; r \in O_R \\ w_{il+1} - w_{il} \ge \varepsilon, w_{i1} \ge \varepsilon, \quad l = 1,2,\cdots,L-1; i \in O_I \end{array} \right\}$$

In the above formulation, $\mathbf{w_r} = \left[w_{r1},\ldots,w_{rl},\ldots,w_{rL}\right]$ is an L-dimensional worth vector with w_{rl} denoting the worth of being rated in the lth place with respect to the rth output, and $\mathbf{w_i} = \left[w_{i1},\ldots,w_{il},\ldots,w_{iL}\right]$ is an L-dimensional worth vector with w_{il} denoting the worth of being rated in the lth place with respect to the ith input, for $\forall l$, and Ψ is the set of admissible worth vectors. In addition, C_R, O_R and F_R respectively represent the subsets of crisp, ordinal and fuzzy outputs, while C_I, O_I and F_I are the subsets of crisp, ordinal and fuzzy inputs, respectively.

The above formulation indicates an optimistic scenario since the inputs and the outputs of the evaluated DMU are adjusted at the lower bounds and the upper bounds of the membership functions, respectively, whereas the inputs and outputs are adjusted unfavorably for the other DMUs. Alternatively, when the inputs and the outputs of the evaluated DMU are adjusted respectively at the upper bounds and the lower bounds of the membership functions, and the inputs and outputs are adjusted favorably for the other DMUs in a way that the inputs are adjusted at the lower bounds and the outputs at the upper bounds, a pessimistic scenario DEA formulation is developed.

4. ILLUSTRATIVE EXAMPLE

In this section, the proposed DEA-based methodology is illustrated through a hypothetical but typical supplier selection problem. The attributes to be minimized are viewed as inputs, whereas the ones to be maximized are considered as outputs for the supplier selection study. The decision framework involves the evaluation of the relative efficiency of 14 suppliers with respect to two inputs, namely “average cost per unit” and “lead time”, and three outputs, namely “number of bills received from the supplier without errors”, “supplier’s experience” and “supplier reputation”. “Lead time” and “number of bills received from the supplier without errors” that cannot be assessed by exact data are represented as triangular fuzzy numbers, whereas “supplier’s experience” and “supplier reputation” are given as ordinal data using a 5-point Likert scale. In the 5-point scale, 5 represents the best score and 1 represents the worst score, respectively. Input and output data concerning the suppliers are given in Table 1.

In order to rectify the problems due to the significant differences in the magnitude of inputs and outputs, max-value normalization is applied to the “average cost per unit”, “lead time” and “number of bills received from the supplier without errors” data. The maximization of the discrimination among consecutive rank positions and the minimum importance attached to performance attributes can be assured by using the maximum feasible value for ε, which can be determined by maximizing ε subject to the constraint set of the respective DEA formulation for $j = 1, \ldots, n$, and then by defining $\varepsilon_{\max} = \min_j \left(\varepsilon_j\right)$.

The optimistic scenario efficiency scores for the suppliers are calculated using formulation (3), while the pessimistic scenario efficiency scores are computed employing a pessimistic scenario DEA formulation. The optimistic and pessimistic scenario efficiency scores for the suppliers, which are obtained using $\varepsilon = 0.076$ computed as described above, are given in Table 2. Six suppliers, namely Sup_1, Sup_6, Sup_7, Sup_9, Sup_{11} and Sup_{13}, are determined as efficient regarding the optimistic approach due to its permissive nature, while Sup_{13} is the only efficient supplier according to the pessimistic approach. The pessimistic approach which results in a single efficient supplier has a high discriminating power. It is also worth noting that the proposed methodology determines the best supplier with a significant saving in computations compared to earlier fuzzy DEA models presented in [14], i.e. by solving only 28 linear programs and without using a fuzzy number ranking method.

Table 1. Data used to assess the relative efficiency of suppliers

Supplier (Sup_i)	Cost per unit ($)	Lead time (days)	Nr. of bills without errors	Experience	Reputation
Sup_1	7.5	(12,14,15)	(90,100,115)	2	3
Sup_2	11.4	(11,12,13)	(110,125,135)	1	4
Sup_3	10.2	(19,20,21)	(175,200,225)	4	2
Sup_4	12	(13,14,15)	(55,65,75)	2	2
Sup_5	13.4	(19,20,22)	(65,75,100)	2	2
Sup_6	8.4	(12,13,15)	(175,205,225)	3	3
Sup_7	7.6	(11,13,17)	(85,120,135)	1	4
Sup_8	12.6	(20,22,23)	(175,190,200)	3	3
Sup_9	8.2	(11,12,14)	(50,90,100)	4	2
Sup_{10}	11	(17,19,20)	(260,275,300)	5	3
Sup_{11}	7.8	(11,14,15)	(175,200,250)	2	3
Sup_{12}	11.6	(21,22,23)	(75,90,100)	4	1
Sup_{13}	10.2	(13,14,15)	(300,325,340)	5	4
Sup_{14}	12.6	(17,19,21)	(150,175,190)	4	3

5. CONCLUSIONS

The proposed approach is a sound and effective tool that enables qualitative as well as quantitative aspects to be taken into account, and thus improves the quality of complex supplier selection decisions. However, one shall note the limitations of the analysis which may also indicate directions for future research.

First, although the proposed approach enables to systematically incorporate the qualitative factors into the decision process, subjective judgment may still be required in selecting the inputs and outputs as well as interpreting the results of the analysis. Furthermore, in this study, triangular fuzzy numbers are used to represent fuzzy values due to their intuitive appeal and mathematical ease in computations. The use of nonlinear membership functions for fuzzy data would necessitate approaches for solving nonlinear programming models to be developed.

Future research will also focus on the implementation of the proposed approach in supplier selection problems using real-world data.

Table 2. DEA efficiency values of suppliers

Supplier (Sup_i)	Optimistic scenario efficiency score	Pessimistic scenario efficiency score
Sup_1	1.000	0.988
Sup_2	0.993	0.800
Sup_3	0.742	0.724
Sup_4	0.703	0.552
Sup_5	0.363	0.321
Sup_6	1.000	0.953
Sup_7	1.000	0.981
Sup_8	0.555	0.539
Sup_9	1.000	0.960
Sup_{10}	0.848	0.828
Sup_{11}	1.000	0.961
Sup_{12}	0.519	0.505
Sup_{13}	1.000	1.000
Sup_{14}	0.701	0.620

6. REFERENCES

[1] D. Simchi-Levi, P. Kaminsky, E. Simchi-Levi, **Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies**, New York: McGraw-Hill, 2003.

[2] R.H. Evans, "Product Involvement and Industrial Buying", **International Journal of Purchasing and Materials Management,** Vol. 17, No. 2, 1981, pp. 23-28.

[3] M. Bevilacqua, A. Petroni, "From Traditional Purchasing to Supplier Management: A Fuzzy Logic-based Approach to Supplier Selection", **International Journal of Logistics: Research and Applications**, Vol. 5, No. 3, 2002, pp. 235-255.

[4] G. Dickson, "An Analysis of Vendor Selection Systems and Decisions", **Journal of Purchasing**, Vol. 2, 1966, pp. 28-41.

[5] L.M. Ellram, "The Supplier Selection Decision in Strategic Partnerships", **International Journal of Purchasing and Materials Management,** Vol. 26, No. 4, 1990, pp. 8-14.

[6] E.J. Wilson, "The Relative Importance of Supplier Selection Criteria: A Review and Update", **International Journal of Purchasing and Materials Management,** Vol. 30, No. 3, 1994, pp. 34-41.

[7] V.R. Kannan, K.C. Tan, "Supplier Selection and Assessment: Their Impact on Business Performance", **Journal of Supply Chain Management**, Vol. 38, No. 4, 2002, pp. 11-21.

[8] W. Ho, X. Xu, P.K. Dey, "Multi-criteria Decision Making Approaches for Supplier Evaluation and Selection: A Literature Review", **European Journal of Operational Research**, Vol. 202, 2010, pp. 16-24.

[9] C.A. Weber, "A Data Envelopment Analysis Approach to Measuring Vendor Performance", **Supply Chain Management**, Vol. 1, No. 1, 1996, pp. 28-39.

[10] J. Liu, F-Y. Ding, V. Lall, "Using Data Envelopment Analysis to Compare Suppliers for Supplier Selection and Performance Improvement", **Supply Chain Management**, Vol. 5, No. 3, 2000, pp. 143-150.

[11] S. Talluri, J. Sarkis, "A Model for Performance Monitoring of Suppliers", **International Journal of Production Research**, Vol. 40, No. 16, 2002, pp. 4257-4269.

[12] A. Charnes, W.W. Cooper, E. Rhodes, "Measuring the Efficiency of Decision Making Units", **European Journal of Operational Research**, Vol. 2, 1978, pp. 429-444.

[13] W.D. Cook, M. Kress, L.M. Seiford, "Data Envelopment Analysis in the Presence of Both Quantitative and Qualitative Factors", **Journal of Operational Research Society**, Vol. 47, 1996, pp. 945-953.

[14] C. Kao, S.T. Liu, "Fuzzy Efficiency Measures in Data Envelopment Analysis", **Fuzzy Sets and Systems**, Vol. 113, 2000, pp. 427-437.

[15] D.K. Despotis, Y.G. Smirlis, "Data Envelopment Analysis with Imprecise Data", **European Journal of Operational Research**, Vol. 140, 2002, pp. 24-36.

[16] S. Lertworasirikul, S-C. Fang, J.A. Joines, H.L.W. Nuttle, "Fuzzy Data Envelopment Analysis (DEA): A Possibility Approach", **Fuzzy Sets and Systems**, Vol. 139, 2003, pp. 379-394.

[17] E.E. Karsak, "Using Data Envelopment Analysis for Evaluating Flexible Manufacturing Systems in the Presence of Imprecise Data", **International Journal of Advanced Manufacturing Technology**, Vol. 35, No. 9-10, 2008, pp. 867-874.

ACKNOWLEDGEMENT

This research has been financially supported by Galatasaray University Research Fund.