AN INTELLIGENT DECISION SUPPORT SYSTEM FOR SUPPLIER SELECTION

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Abstract: This study intends to develop an intelligent decision support system which integrates both fuzzy analytical hierarchy process (AHP) method and fuzzy data development analysis (DEA) for assisting organizations to make the supplier selection decision. A case study on an internationally well-known auto lighting OEM company shows that the proposed method is very well suitable for practical applications.

1 INTRODUCTION

Supply chain management consists of several connected logistics systems, which integrate the product and service moving into a system, and creates a continuous and seamless linking. Also, all the actions from raw materials to end customers for merchandises are fully coordinated. Due to such coordination, all the members inside the supply chain will be affected by other chain members either directly or indirectly. Therefore, it is very important to select suitable suppliers to overcome these problems. Regarding the supplier selection, some indicators, like production capacity, financial capability, quality, etc. should be put into account. Otherwise, supplier problem may become organization's crisis.

This study intends to present a novel performance evaluation method which integrates both fuzzy AHP method and fuzzy DEA for organizations to make the supplier selection decision. Though DEA has been applied in the area of performance evaluation for many decades, it posses its own limitations. They include a method to determine the weight constraints and integrity of the evaluation data. Definitely, the number of evaluation samples should also be two times of the sum of input and output numbers. In this study, we try to overcome these limitations. First, using fuzzy AHP method can find the indicators' weights. Then α -cut set and extension principle of fuzzy set theory simplifies the fuzzy DEA as a pair of traditional DEA model with α -cut level. Finally, fuzzy ranking using maximizing and minimizing set method is able to rank the evaluation samples.

A case study on an internationally well-known auto lighting manufacturer showed that the proposed method was more suitable for the practical applications after comparing with the traditional fuzzy DEA method. The case company is able to use the computational results to adjust her suppliers' inputs in order to obtain more promising performance.

2 BACKGROUND

This section will briefly present the general background of supplier evaluation, fuzzy AHP and fuzzy DEA.

2.1 Supplier Evaluation

Suppliers are the vendors who provide raw materials, components or service that an organization itself

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cannot offer. The selection of right suppliers is the first step of supply chain evaluation. In the current manufacturing environment for supply chain, suppliers are a vital part for an organization and a right supplier can furnish the company with quality products of required quantity at reasonable prices before the predetermined delivery schedule to sharpen company competitiveness and quicken company response to market and customer demands.

There have already been a number of methods proposed to evaluate the suppliers. They are Monte Carlo Simulation (Thompson, 1990), mathematical programming (Weber and Current, 1993), AHP (Mohanty and Deshmukh, 1993), DEA (Narasimhan et al., 2001), integrated AHP and DEA (Liu et al., 2005), and neural network (Kuo et al., 2008).

The attributes of indicators have great impact on the evaluation results. Among the 23 indicators proposed by Dickson (1966), quality, delivery deadline and previous performance are given primary importance in the 1960's manufacturing. After that, a number of researches proposed different indicators for assessing suppliers. They can be found in (Lehmann and O'Shaughnessy, 1982, Wilson, 1994, Weber et al., 1991, Smytka and Clemens, 1993, Swift, 1995, Choi and Hartley, 1996, Goffin et al., 1997, Narasimhan et al., 2001, Quayle, 2002, Schmitz and Platts, 2004, and Wang et al., 2004). After summarizing the evaluation indicators proposed in the earlier literatures, it is revealed that the supplier company itself should also be taken into consideration in addition to the product and delivery quality. These include the supplier's organizational structure, management and financial status.

2.2 Data Envelopment Analysis

DEA, which was developed by Charnes, Cooper and Rhodes (Banker et al., 1984), is a mathematical programming technique for measuring the relative performance of decision making units (DMUs) on the basis of the observed operation practice in a sample of comparable DMUs. It has typically been applied to analyze the relative production efficiency of DMUs in a setting of multiple incommensurate input and output variables.

The standard DEA model is selected as the reference unit. For each DMUs, the composite unit that consumes the lowest possible fraction of that DMU's current input levels to produce at least that DMU's current output levels. More formally, the reference units are identified simultaneously by solving the linear programming problem. By comparing n units with m inputs denoted by $x_i (i = 1,..., m)$ and outputs denoted by $y_r (r = 1,..., s)$, the efficiency measure for DMU k follows the linear programming problem as

$$\max \quad h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}$$

$$\text{s.t.} \tag{1}$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \qquad j = 1,..., n$$

$$v_r, u_i \ge \varepsilon; \; r = 1,..., s; \; i = 1,..., m$$

h_k = the relative efficiency of the kth DMU

y_r = The rth output value of the kth DMU

u_r = The virtual multiplier of the rth output value

x_i = The ith input value of the kth DMU

v_i = The virtual multiplier of the ith input value

2.3 Fuzzy DEA

Sengupta (1992) first incorporated the fuzzy theory into DEA in 1992 and studied the performance evaluation by using randomly found observation values. Such a random DEA theory was further examined by Cooper et al. (1996 and 1998) who focused more on theoretical exploration. In 2000, Kao and Liu proposed a supplier selection method with indefinite data. By using the α -cut and the extension principle of the fuzzy theory, they simplified the Fuzzy DEA method into a pair of traditional DEA analysis modes with α horizontal parameters. The efficiency value acquired in this study was fuzzy rather than definite as found traditionally. Thus, it was hard to rank the alternatives based on the efficiency values solely. Kao and Liu proposed to use two fuzzy values sequencing methods, i.e., "area estimation" and "the maximum and minimum sets," to rank the efficiency values obtained by using different α -cut methods. They revealed that "area estimation" is more effective and easier in ranking the fuzzy values when the exact form of the membership function remains unknown. When the α -cut approaches infinity, the method is theoretically faultless. While in the practical application, it is critical to select a right α -cut. Smaller α -cut values increase the effectiveness of the method and adequately large α -cut guarantees the correctness of the ranking. Therefore an appropriate α -cut value is vital for the right sequencing of the results.

3 METHODOLOGY

The proposed performance evaluation method consisted of three components: determination of indicators, fuzzy AHP and fuzzy DEA. Each part is discussed in the following subsections. Improvement analysis is made on some suppliers and comparison is made against the results of the fuzzy DEA.

3.1 Determination of Supplier Evaluation Indicators

For the purpose of obtaining more practical and objective results, besides including the indicators in the literatures, the case company's opinions have to be considered for determining the evaluation indicators.

3.2 Determination of Indicator Weights

After determining the evaluation factors, fuzzy AHP has been used for determining the indicator weights. The decision makers fill in an interval number in terms of the significance level and compare the indicators in pairs. A fuzzy number has been added and subtracted to ensure the goal of the results. The decision makers can rank the significance levels as 1~2, 2~4, 4~6, 6~8, and 8~9, the fuzzy positive reciprocal matrix. Based on the fuzzy positive reciprocal matrix, Lambda-Max method proposed by Csutora and Buckley (2001) is used to calculate the fuzzy weight in the fuzzy AHP. To ensure that the weights obtained are fuzzy, we use the adjustment coefficient to get the upper and the lower limit values of the weight for each dimension.

A consistency test shall be carried out to find the Consistence Index (C.I.) to ensure the conformity of the calculation results. In the positive reciprocal matrix, slight changes of a_{ij} result in minor fluctuation of λ_{max}. So the disparity between λ_{max} and n is an indicator of the conformity. The Consistency Ratio (C.R.) is defined as Equations (2) and (3).

$$C.R. = \frac{C.I.}{R.I.} \tag{2}$$

$$C.I. = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

The Random Indices (R.I) are random indicators. When C.R.= 0, the prior and the later judgments are consistent; the larger the C.R is, the larger the disparity that exists. According to Saaty (1977), the error when $C.R. \leq 0.1$ is acceptable.

3.3 Evaluation of Suppliers with DEA

The weights acquired in the first stage by using fuzzy AHP are used here. The standardized data are input for the calculation of fuzzy performance indicators and supplier selection.

3.3.1 Determination of Suppliers under Evaluation

The evaluation data on the previous suppliers of the company can be used to select suppliers of new components or in annual appraisal of all the suppliers.

3.3.2 Definition of Input and Output Indicators

The input items should cover the supplier's executive force, capability, quality system, flexibility and relationship with other suppliers, based on which the indicators are further expanded. The supplier productivity and operation efficiency are the major aspects of the output. In Fuzzy DEA, based on the objective function of DEA, max $h_k = \sum_{r=1}^{s} u_r y_r \Big/ \sum_{i=1}^{m} v_i x_i$, the larger the output using the less input, the better the performance is. It is necessary to transform the output indicators into fractional numbers as large as possible and the input indicators as small as possible.

3.3.3 Homogenized Data

Liu et al. (2005) addressed that the original DEA mode sets no limit to the weight range, so the original unit of the variables can be used, though the data shall be homogenized into values within the same value range so that the weight range of evaluation indicators is meaningful. Each indicator of different suppliers is differentiated as 1 at the highest and other indicators vary at equal proportion.

3.3.4 Fuzzy DEA

Although DEA is an effective method for efficiency evaluation, it fails to work out fuzzy values of incomplete data or data of large disparity. Kao and Liu (2000) developed a mode for such data by using the α -cut and the extension principle of the fuzzy theory to simplify the Fuzzy DEA mode into a traditional DEA mode with α horizontal parameters. At a given α, the upper and the lower limit value of efficiency can be found and the membership functions of the efficiency values can be constructed by using the efficiency values at different α levels. This method is similar to the traditional DEA analysis mode in the calculation of efficiency improvement, technological efficiency and scale efficiency.

By assuming that $\widetilde{X}_{ij}$ and $\widetilde{Y}_{rj}$ are fuzzy data, they can be expressed as the membership functions $\mu_{\widetilde{X}_{ij}}$ and $\mu_{\widetilde{Y}_{rj}}$ by using the fuzzy set theory. As for non-fuzzy, or crisp, data, the membership function is a degenerate one and the domain is limited to one value. Based on CCR model, it can be expressed as:

$$\widetilde{E}_k = \mathrm{Max}\,\frac{\sum_{r=1}^{s} u_r \widetilde{Y}_{rk}}{\sum_{i=1}^{m} v_i \widetilde{X}_{ik}} \tag{4}$$

s.t.

$$\sum_{r=1}^{s} u_r \widetilde{Y}_{rj} - \sum_{i=1}^{m} v_i \widetilde{X}_{ij} \le 0 \;,\; j = 1,\cdots,n$$

$$u_r, v_i \ge \varepsilon \quad r = 1,\cdots,s \quad i = 1,\cdots,m$$

3.3.5 Combining Fuzzy AHP with Fuzzy DEA

Thereafter, we can put the range of indicators obtained in Section 3.2 into fuzzy DEA model.

4 MODEL EVALUATION RESULTS

This section will apply the proposed method, integration of fuzzy AHP and fuzzy DEA methods, for studying the company according to the procedures presented in Section three. The company in this study is an internationally well-known auto lighting system OEM Company. Since the company under investigation has many outsourcing components, according to the purchasing manager's suggestion, this study selects speculum as the studying object since it plays a very important role in the auto lighting system design. Thus, the speculum vendors constitute the evaluation population.

4.1 Indicator Determination

After referring to company's current indicators, literatures and company's managers, this study decided to formulate five main dimensions (the first level of AHP) including supplier's operation capability, supplier's capability, quality system, flexibility, and supplier relationship. From these five dimensions, we can extend a total of eleven evaluation indicators (second level of AHP) as illustrated in Table 1. The AHP structure is for input items, while the output items are also shown in the lower part of Table 1. It indicates that the company emphasizes more on the production and operational efficiencies, respectively. Production efficiency can be divided into production line efficiency and production employee's efficiency, while supplier asset operational efficiency and business volume are the two major extensions for operational efficiency. Basically, it is supposed that inputs and outputs are closely related. The scoring of indicators is provided by the company and the statistical data is collected from 2003 to 2005.

4.2 Fuzzy Weight Determination of Evaluation Indicators

There are a total of twelve respondents. Since each person has different perception on the level of importance, the questionnaire let the respondents directly determine their own range values for each importance level. Then the comparison matrix can be formulated for calculation and to make a consistent test. After summarization, the final results of fuzzy weights are depicted in Table 1.

4.3 Data Normalization

Since there is no constraint for the weights' ranges of input and output variables, the original DEA model can keep the original units for the variables. However, due to the range of weight, it is necessary to normalize the data and make them in the same value range. This can be helpful to provide the evaluation indicator weight range. Data normalization is conducted so as to let indicators have the largest value as one. For the selected product item, the case company only has ten suppliers totally.

4.4 Performance Evaluation Analysis

This study integrates both fuzzy AHP and fuzzy DEA methods to evaluate speculum suppliers' performance. In the above, we can apply fuzzy AHP to get the range of weights for output indicators. After putting them into fuzzy DEA model, we can analyze the performance evaluation. From the calculation of LINGO based on the concept of α-cut, Table 2 lists the fuzzy performance value of each supplier under the α-cut levels as 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1.0.

Table 2 reveals that only supplier D has the highest performance value. The other nine suppliers' performance values are all smaller than 1. Therefore, DEA's dual model can help us solve the problem of how to adjust the input and output indicators in order to improve the performance. First, rank every supplier's fuzzy performances using maximizing and minimizing set method. Then, get the total utility value $U_T(i)$ for every fuzzy efficiency value $\widetilde{\mathrm{E}}_{\mathrm{k}}$, as illustrated in Figure 1. It indicates that $\widetilde{\mathrm{E}}_{\mathrm{D}} > \widetilde{\mathrm{E}}_{\mathrm{C}} > \widetilde{\mathrm{E}}_{\mathrm{B}} > \widetilde{\mathrm{E}}_{\mathrm{H}} > \widetilde{\mathrm{E}}_{\mathrm{F}} > \widetilde{\mathrm{E}}_{\mathrm{G}} > \widetilde{\mathrm{E}}_{\mathrm{I}} > \widetilde{\mathrm{E}}_{\mathrm{E}} > \widetilde{\mathrm{E}}_{\mathrm{A}} > \widetilde{\mathrm{E}}_{\mathrm{J}}$ and supplier D is the best supplier.

4.5 Improving Efficiency Analysis

Above section has shown that supplier D is the best supplier after sorting all the suppliers' fuzzy performance. Here, we take α =0 level, for instance, in order to provide the possible range for improving the target value. This is for those suppliers with low performance. Basically, the difference of performance scores is the largest as α is equal to 0 from examining each supplier's fuzzy performance under eleven α levels. In other words, when analyzing and improving unknown or missing data, it is feasible to consider improving and analyzing both the relatively high-test and lowest efficiency values. Through this procedure, we can know the required improvement range for the supplier with missing or unknown data. The adjusting equations for inputs are illustrated in Equations (5) and (6).

$$(\mathrm{x}^*_{\mathrm{ik}})^L = \theta * (\mathrm{x}_{\mathrm{ik}})^{\mathrm{L}} - (\mathrm{s}^{-*}_{\mathrm{i}})^L \quad (5)$$

$$(\mathrm{x}^*_{\mathrm{ik}})^U = \theta * (\mathrm{x}_{\mathrm{ik}})^{\mathrm{U}} - (\mathrm{s}^{-*}_{\mathrm{i}})^L \quad (6)$$

Since the computation of fuzzy DEA with indicators' weights uses the normalized data for analysis and the analysis improvement applies the original scores for computation, it is necessary to multiply $\mathrm{s}^{-*}_{\mathrm{i}}$ and $\mathrm{S}^{+*}_{\mathrm{r}}$ with the largest value of all the indicators during normalization while adjusting input and output items. Table 3 presents the improved goals under the levels of α =0.

4.6 Comparison with the Original Fuzzy DEA

In order to prove the proposed method's feasibility, original DEA is adopted for the purpose of comparison. Its model is identical to the current study. The two major differences are that there is no weight constraint for each indicator and it is not necessary to normalize the data. The total utility values of fuzzy performance using the original fuzzy DEA are all 1s. It reveals that in the original fuzzy DEA is not able to discriminate these suppliers, since the number of DMUs is not more than two times of the indicator number. After integrating fuzzy AHP into the fuzzy DEA model, the proposed model is able to discriminate the efficiency values. In the original fuzzy DEA model, since the number of suppliers is too few, there is no meaning for the evaluation results. Thus, there should be at least thirty suppliers if the original fuzzy DEA is applied. Since the case company only has ten suppliers, this is the reason for all the efficiency values being 1s. From the practical view point, no matter in the traditional or high-tech industries, it is very common that there won't be too many suppliers for a certain component. Some company may only have two to three suppliers for one component. The reason is that the company prefers spending more time to maintain each other's relationship on a few suppliers instead of having a lot of suppliers. Thus, the current proposed method is more suitable for industrial practical situations. Our results are also very consistent to company's own evaluation results after discussing with the senior managers.

5 CONCLUSIONS

In this study, fuzzy DEA is employed for supplier selection and evaluation and AHP with fuzzy values are introduced to define the weight range of indicators weight. In this way, significant indicators are used in the supplier performance evaluation. The two stages of fuzzy AHP and fuzzy DEA single out the supplier to the best benefit of the company effectively. This method is applicable to all industries and is quite easy and simple if the evaluation indicators and weights are available. The calculation process is not so complicated. After one supplier is chosen, the other suppliers with poor performance can find improvement schemes. Comparison is made against the fuzzy DEA without including the evaluation indicators to expose the impact of the evaluation indicators identified on the supplier selection.

A case study on an internationally well-known auto lighting system OEM Company showed that the proposed method really has the above advantages. Through the results provided by the proposed method, the present company can make some adjustments for her suppliers in order to obtain more attractive outcomes.

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Table 1: The average weighted range for each evaluation indicator.

Input Indicators		Range of Weights
Implementation capability	Delivery schedule (V_1)	$0.264 \le V_1 \le 0.381$
	Cost analysis (V_2)	$0.136 \le V_2 \le 0.192$
Manufacturing capability	R&D capability (V_3)	$0.073 \le V_3 \le 0.124$
	Manufacturing process capability (V_4)	$0.186 \le V_4 \le 0.245$
Quality system	Quality management system (V_5)	$0.104 \le V_5 \le 0.173$
	Manufacturing process inspection system (V_6)	$0.045 \le V_6 \le 0.098$
	Outbound quality (V_7)	$0.253 \le V_7 \le 0.380$
Flexibility	Emergency order processing capability (V_8)	$0.143 \le V_8 \le 0.220$
	Response speed of exceptional process (V_9)	$0.2129 \le V_9 \le 0.364$
Supplier relationship	Supplier's financial capability (V_{10})	$0.076 \le V_{10} \le 0.129$
	Supplier's coordination (V_{11})	$0.150 \le V_{11} \le 0.254$
Output indicators		
Production efficiency	Production line efficiency (U_1)	$0.436 \le U_1 \le 0.602$
	Employee's production efficiency (U_2)	$0.168 \le U_2 \le 0.227$
Operation efficiency	Business volumn ratio (U_3)	$0.134 \le U_3 \le 0.202$
	Supplier's asset operational efficiency (U_4)	$0.030 \le U_4 \le 0.046$

Table 2: The fuzzy performance indicator value of each supplier under 11 different α -cut levels.

	α	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
A	L	0.7510	0.7530	0.7549	0.7569	0.7588	0.7608	0.7628	0.7648	0.7668	0.7689	0.7709
	U	0.7981	0.7939	0.7898	0.7872	0.7848	0.7825	0.7801	0.7778	0.7755	0.7732	0.7709
B	L	0.9679	0.9686	0.9693	0.9701	0.9768	0.9716	0.9722	0.9730	0.9737	0.9745	0.9752
	U	0.9802	0.9797	0.9792	0.9787	0.9782	0.9777	0.9772	0.9767	0.9762	0.9758	0.9752
C	L	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975
	U	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975	0.9975
D	L	1	1	1	1	1	1	1	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
E	L	0.0001	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110
	U	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110	0.8110
F	L	0.8110	0.9155	0.9212	0.9245	0.9274	0.9306	0.9338	0.9368	0.9400	0.9432	0.9464
	U	0.9155	0.9797	0.9759	0.9721	0.9683	0.9646	0.9609	0.9572	0.9536	0.9500	0.9464
G	L	0.9836	0.8529	0.8584	0.8641	0.8698	0.8757	0.8816	0.8876	0.8936	0.8998	0.9059
	U	0.8743	0.9729	0.9673	0.9549	0.9458	0.9383	0.9315	0.9250	0.9156	0.9122	0.9059

Table 2: The fuzzy performance indicator value of each supplier under 11 different α -cut levels. (cont.)

H	L	0.9823	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694
	U	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694	0.9694
I	L	0.9694	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245
	U	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245	0.7245
J	L	0.7245	0.6416	0.6463	0.6510	0.6559	0.6608	0.6658	0.6708	0.6760	0.6811	0.6865
	U	0.6369	0.7490	0.7410	0.7332	0.7255	0.7180	0.7106	0.7038	0.6949	0.6922	0.6865

Table 3: The goal range after improvement of input indicators for supplier A under α =0 level.

Supplier Number	V_1	V_2	V_3	V_4	V_5	V_6
Original total score	10	1	1	50	20	20
Original score	4	0.95	0.89	36	14	14
$\theta*$ (L)	0.751	0.751	0.751	0.751	0.751	0.751
$\theta*$ (U)	0.798	0.798	0.798	0.798	0.798	0.798
s_i^{-*} (L)	0*7	0*1	0*0.3	0*15.5	0*6	0*7
s_i^{-*} (U)	0*7	0*1	0*0.3	0*15.5	0*6	0*7
Goal after improvement (L)	4.51	0.71	0.08	10.51	4.51	4.51
Goal after improvement(U)	4.79	0.76	0.09	11.17	4.79	4.79
Goal after actual improvement (L^*)	5.21	0.76	0.91	38.83	15.21	15.21
Goal after actual improvement (U^*)	5.49	0.71	0.92	39.49	15.49	15.49

Supplier Number	V_7	V_8	V_9	V_{10}	V_{11}
Original total score	1	1	10	5	20
Original score	0.72	0.75	5	3	[10.5,15.5]
$\theta*$ (L)	0.751	0.751	0.751	0.751	0.751
$\theta*$ (U)	0.798	0.798	0.798	0.798	0.798
s_i^{-*} (L)	0*0.4	0*0.4	0*7	0*4	0*9.5
s_i^{-*} (U)	0*0.4	0*0.4	0*7	0*4	0*9.5
Goal of improvement (L)	0.21	0.19	3.76	1.50	3.38
Goal of improvement (U)	0.22	0.20	3.99	1.60	7.58
Goal of actual improvement (L^*)	0.78	0.80	6.01	3.40	12.42
Goal of actual improvement (U^*)	0.79	0.81	6.25	3.50	16.62