A Mathematical Programming Approach for Strategy Ranking

Reza Farzipoor Saen

Department of Industrial Management, Faculty of Management and Accounting, Islamic Azad University - Karaj Branch, Karaj, Iran, P. O. Box: 31485-313

Tel: 0098 (261) 4418144-6
Fax: 0098 (261) 4418156
E-mail: farzipour@yahoo.com

A Mathematical Programming Approach for Strategy Ranking

Abstract

Before working out their final strategic plan, managers must consider several feasible alternatives and contemplate various factors behind each of them. It is a very complicated task to rank the strategies. The objective of this paper is to propose a method that allows strategy to be evaluated on both ordinal and cardinal criteria on the one hand, and on the other hand is to use a method for ranking strategies without relying on weight assignment by decision makers. A numerical example demonstrates the application of the proposed method.

Keywords: Strategic Management, Strategy ranking, Cardinal and ordinal data, Minimax regret-based approach

1. Introduction

Strategic management can be considered as a collection of decisions and actions taken by the decision maker in consultation with all levels within the company to determine the long-term activities of the company. The experiences of many businesses, indicate that the highest profitability levels are found in businesses that possess both types of competitive advantage at the same time. In other words, businesses that have one or more value chain activities that truly differentiate them from key competitors and also have value chain activities that let them operate at a lower cost will consistently outperform their rivals that do not. So, the challenge for today's decision makers is to evaluate and choose business strategies based on core competencies and value chain activities that sustain both types of competitive advantage simultaneously. Among multiple strategies, managers choose one of those strategies. If the analysis identified a clearly superior strategy or if the current strategy will clearly meet future company objectives, then the decision is relatively simple. Such clarity is the exception, however, and strategic decision makers often are confronted with several viable alternatives rather than the luxury of a clear-cut choice. Under these circumstances, several criteria such as risk, ability of strategy to satisfy agreed-on objectives with the least resources and the fewest negative side effects influence the strategic choice.

Some approaches have been used for strategy selection and ranking in the past. Corner and Kirkwood (1991) surveyed multi-attribute decision analysis applications in operations

research literature and found many of the applications to address strategic decisions. Wind and Saaty (1980) applied the Analytic Hierarchy Process (AHP) to the portfolio decision of a firm whose management is concerned with the determination of the desired target portfolio and allocation of resources among its components. Wind (1987) presented an application for corporate strategy for evaluating strategic options on multiple and interdependent objectives to ensure effective utilization of resources. Hastings (1996) provided a method for ranking strategy on quantitative, qualitative and intangible criteria based on AHP. Chiou et al. (2005) proposed a fuzzy AHP to derive the weight of considered criteria and the final synthetic utility values, and then ranked the importance of the criteria as well as the sustainable development strategies. However, AHP has two main weaknesses. First subjectivity of AHP is a weakness. Second AHP could not include interrelationship within the criteria in the model. Chien et al. (1999) established a systematic approach that incorporates neural networks in conjunction with portfolio matrices to assist managers in evaluating and forming strategic plans. Based on the principle of dispersing risks, they also provided a linear integer programming model, which helps in allocating the annual budget optimally among proposed strategies. However, their proposed approach is computational burden. Meanwhile, their linear integer programming model considers just two factors including cost and profit of the strategy. Kajanus et al. (2001) presented the principles of even swaps method and its use was illustrated by applying it to a case of strategy selection in a rural enterprise in Finland. Nevertheless, in the case of strategies abundance, the pairwise comparison between strategies is computational burden. In addition, their proposed method suffers from subjective judgments.

However, all of the abovementioned references suffer from subjective judgments. A technique that can deal with both ordinal and cardinal data and not relying on weight assignment by decision makers is needed to better model such situation. A critical issue of traditional approaches are the correct choice of the weights. These must be assigned by the decision maker or a decision committee and are often very subjective measures. The basic idea of DEA is that the weights are chosen by an optimization procedure and not by the decision maker. Weights are assigned optimally for every input and output attribute. This makes the approach more robust against human inference.

To the best of author's knowledge, there is not any reference that deals with strategy ranking without relying on weight assignment by decision makers. The objective of this paper is to propose a method that allows strategy to be evaluated on both ordinal and cardinal criteria on the one hand, and on the other hand is to use a method for ranking strategies

without relying on weight assignment by decision makers. In summary, the approach presented in this paper has some distinctive contributions.

- The proposed model does not demand weights from the decision maker.
- The proposed model considers cardinal and ordinal data for strategy ranking.
- The proposed model deals with imprecise data in a direct manner.
- Strategy ranking is a straightforward process carried out by the proposed model.

This paper proceeds as follows. In Section 2, the method that ranks the strategies is introduced. Numerical example and managerial implications are discussed in Sections 3 and 4, respectively. Section 5 discusses concluding remarks.

2. Proposed method for ranking strategies

Data Envelopment Analysis (DEA) proposed by Charnes et al. (1978) (CCR model) and developed by Banker et al. (1984) (BCC model) is an approach for evaluating the efficiencies of Decision Making Units (DMUs). This evaluation is generally assumed to be based on a set of cardinal (quantitative) output and input factors. In many real world applications (especially strategy ranking problems), however, it is essential to take into account the presence of ordinal (qualitative) factors when rendering a decision on the performance of a DMU. Very often it is the case that for a factor such as strategy risk, one can, at most, provide a ranking of the DMUs from best to worst relative to this attribute. The capability of providing a more precise, quantitative measure reflecting such a factor is generally beyond the realm of reality. In some situations such factors can be legitimately quantified, but very often such quantification may be superficially forced as a modeling convenience. In situations such as that described, the data for certain influence factors (inputs and outputs) might better be represented as rank positions in an ordinal, rather than numerical sense. Refer again to the strategy risk example. In certain circumstances, the information available may permit one to provide a complete rank ordering of the DMUs on such a factor. Therefore, the data may be imprecise.

Outcome of DEA models is an efficiency score equal to one to efficient DMUs and less than one to inefficient DMUs. So, for inefficient DMUs a ranking is given but efficient DMUs can not be ranked. One problem that has been discussed frequently in the DMUs ranking literature, has been the lack of discrimination in DEA applications, in particular when there are insufficient DMUs or the number of inputs and outputs is too high relative to the

number of DMUs. In the strategy selection problem a difficulty arises when attempting to identify the "best", when multiple candidates have an efficiency score of 1. If a decision maker arbitrarily selects an efficient strategy, then there is a possibility that this system is a niche member performing well on few inputs and outputs, and doing poorly with a majority of input-output measures. This paper proposes to use a formulation called "Minimax Regret-based Approach" (MRA) to rank the strategies.

In this section, the model that can rank the efficiency of strategies in the presence of both ordinal and cardinal data (without relying on weight assignment by decision makers) is presented. Suppose that there are n strategies (DMUs) to be evaluated. Each DMU consumes m inputs to produce s outputs. In particular, DMU$_j$ consumes amounts $X_j = \{x_{ij}\}$ of inputs ($i=1$, …, m) and produces amounts $Y_j = \{y_{rj}\}$ of outputs ($r=1$, …, s). Without loss of generality, it is assumed that all the input and output data x_{ij} and y_{rj} ($i=1$, …, m; $r=1$, …, s; $j=1$, …, n) cannot be exactly obtained due to the existence of uncertainty. They are only known to lie within the upper and lower bounds represented by the intervals $\left[x_{ij}^L, x_{ij}^U\right]$ and $\left[y_{rj}^L, y_{rj}^U\right]$, where $x_{ij}^L > 0$ and $y_{rj}^L > 0$.

In order to deal with such an uncertain situation, the following pair of linear programming models has been developed to generate the upper and lower bounds of interval efficiency for each DMU (Wang et al. 2005):

$$Max\theta_{jo}^U = \sum_{r=1}^{s} u_r y_{rj_o}^U$$

s.t.

$$\sum_{i=1}^{m} v_i x_{ij_o}^L = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj}^U - \sum_{i=1}^{m} v_i x_{ij}^L \leq 0, \qquad j = 1,\cdots,n, \qquad (1)$$

$$u_r, v_i \geq \varepsilon \qquad \forall r,i.$$

$$Max\theta_{jo}^L = \sum_{r=1}^{s} u_r y_{rj_o}^L$$

s.t.

$$\sum_{i=1}^{m} v_i x_{ij_o}^U = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj}^U - \sum_{i=1}^{m} v_i x_{ij}^L \leq 0, \qquad j = 1,\cdots,n, \qquad (2)$$

$$u_r, v_i \geq \varepsilon \qquad \forall r,i.$$

where j_o is the DMU under evaluation (usually denoted by DMU$_o$); u_r and v_i are the weights assigned to the outputs and inputs; θ_{jo}^U stands for the best possible relative efficiency achieved by DMU$_o$ when all the DMUs are in the state of best production activity, while θ_{jo}^L stands for the lower bound of the best possible relative efficiency of DMU$_o$. They constitute a possible best relative efficiency interval $\left[\theta_{jo}^L, \theta_{jo}^U\right]$. ε is the non-Archimedean infinitesimal.

In order to judge whether a DMU is DEA efficient or not, the following definition is given.

Definition 1. A DMU, DMU$_o$, is said to be DEA efficient if its best possible upper bound efficiency $\theta_{jo}^{U*} = 1$; otherwise, it is said to be DEA inefficient if $\theta_{jo}^{U*} < 1$.

Now, the method of transforming ordinal preference information into interval data is discussed, so that the interval DEA models presented in this paper can still work properly even in these situations.

Suppose some input and/or output data for DMUs are given in the form of ordinal preference information. Usually, there may exist three types of ordinal preference information: (1) strong ordinal preference information such as $y_{rj} > y_{rk}$ or $x_{ij} > x_{ik}$, which can be

6

further expressed as $y_{rj} \geq \chi_r y_{rk}$ and $x_{ij} \geq \eta_i x_{ik}$, where $\chi_r > 1$ and $\eta_i > 1$ are the parameters on the degree of preference intensity provided by decision maker. Here, both χ_r and η_i are positive scalars used to distinguish rank positions strictly, with larger values, tending to provide greater discriminations in the resulting efficiency values. To determine these values, decision maker uses from his experiences. In addition, there is a mathematical model for determining the values of χ_r and η_i (see Cook et al. (1996)); (2) weak ordinal preference information such as $y_{rp} \geq y_{rq}$ or $x_{ip} \geq x_{iq}$; (3) indifference relationship such as $y_{rl} = y_{rt}$ or $x_{il} = x_{it}$. Since DEA has the property of unit-invariance, the use of scale transformation to ordinal preference information does not change the original ordinal relationships and has no effect on the efficiencies of DMUs. Therefore, it is possible to conduct a scale transformation to every ordinal input and output index so that its best ordinal datum is less than or equal to unity and then give an interval estimate for each ordinal datum.

Now, consider the transformation of ordinal preference information about the output y_{rj} ($j=1,..., n$) for example. The ordinal preference information about input and other output data can be converted in the same way.

For weak ordinal preference information $y_{r1} \geq y_{r2} \geq \cdots \geq y_{rn}$, we have the following ordinal relationships after scale transformation:

$$1 \geq \hat{y}_{r1} \geq \hat{y}_{r2} \geq \cdots \geq \hat{y}_{rn} \geq \sigma_r,$$

where σ_r is a small positive number reflecting the ratio of the possible minimum of $\{y_{rj}| j=1,..., n\}$ to its possible maximum. It can be approximately estimated by the decision maker. It is referred as the ratio parameter for convenience. The resultant permissible interval for each $\hat{y}_{rj}$ is given by

$$\hat{y}_{rj} \in [\sigma_r, 1], \qquad j = 1, \cdots, n.$$

For strong ordinal preference information $y_{r1} > y_{r2} > \cdots > y_{rn}$, there is the following ordinal relationships after scale transformation:

$$1 \geq \hat{y}_{r1}, \qquad \hat{y}_{rj} \geq \chi_r \hat{y}_{r,j+1} \ (j = 1, \cdots, n-1) \qquad \text{and} \qquad \hat{y}_{rn} \geq \sigma_r,$$

where χ_r is a preference intensity parameter satisfying $\chi_r > 1$ provided by the decision maker and σ_r is the ratio parameter also provided by the decision maker. The resultant permissible interval for each $\hat{y}_{rj}$ can be derived as follows:

$$\hat{y}_{rj} \in \left[\sigma_r \chi_r^{n-j}, \chi_r^{1-j}\right], \qquad j = 1, \cdots, n \quad \text{with} \quad \sigma_r \leq \chi_r^{1-n}.$$

To transform the ordinal preference information to interval data, geometrical spacing is utilized. For more details see Wang et al. (2005).

Finally, for indifference relationship, the permissible intervals are the same as those obtained for weak ordinal preference information.

Through the scale transformation above and the estimation of permissible intervals, all the ordinal preference information is converted into interval data and can thus be incorporated into interval DEA models.

In interval efficiency assessment, since the final efficiency score for each DMU is characterized by an interval, a simple yet practical ranking approach is thus needed for ranking the efficiencies of different DMUs. Here the MRA developed by Wang et al. (2005) is introduced. The approach is summarized as follows:

Let $A_i = \left[a_i^L, a_i^U\right] = \langle m(A_i), w(A_i) \rangle$ $(i = 1, \cdots, n)$ be the efficiency intervals of n DMUs,

where $m(A_i) = \dfrac{1}{2}(a_i^U + a_i^L)$ and $w(A_i) = \dfrac{1}{2}(a_i^U - a_i^L)$ are their midpoints (centers)

and widths. Without loss of generality, suppose $A_i = \left[a_i^L, a_i^U\right]$ is chosen as the best efficiency

interval. Let $b = \max_{j \neq i} \left\{a_j^U\right\}$. Obviously, if $a_i^L < b$, the decision maker might suffer the loss of efficiency (also called the loss of opportunity or regret) and feel regret. The maximum loss of efficiency he/she might suffer is given by

$$\max(r_i) = b - a_i^L = \max_{j \neq i}\left\{a_j^U\right\} - a_i^L.$$

If $a_i^L \geq b$, the decision maker will definitely suffer no loss of efficiency and feel no regret. In this situation, his/her regret is defined to be zero, i.e. $r_i = 0$. Combining the above two situations, there is

$$\max(r_i) = \max\left[\max_{j \neq i}(a_j^U) - a_i^L, 0\right].$$

Thus, the minimax regret criterion will choose the efficiency interval satisfying the following condition as the best (most desirable) efficiency interval:

$$\min_i\{\max(r_i)\} = \min_i\left\{\max\left[\max_{j \neq i}(a_j^U) - a_i^L, 0\right]\right\}.$$

Based on the above analysis, the following definition for ranking efficiency intervals is given.

8

Definition 2. Let $A_i = \left[a_i^L, a_i^U \right] = \left\langle m(A_i), w(A_i) \right\rangle$ $(i = 1, \cdots, n)$ be a set of efficiency intervals. The maximum loss of efficiency (also called maximum regret) of each efficiency interval A_i is defined as

$$R(A_i) = \max\left[\max_{j \neq i} (a_j^U) - a_i^L, 0 \right] = \max\left[\max_{j \neq i} \left\{ m(A_j) + w(A_j) \right\} - (m(A_i) - w(A_i)), 0 \right], \quad i = 1, \cdots, n.$$

It is evident that the efficiency interval with the smallest maximum loss of efficiency is the most desirable efficiency interval.

To be able to generate a ranking for a set of efficiency intervals using the maximum losses of efficiency, the following eliminating steps are suggested:

Step 1: Calculate the maximum loss of efficiency of each efficiency interval and choose a most desirable efficiency interval that has the smallest maximum loss of efficiency (regret). Suppose A_{i_1} is selected, where $1 \leq i_1 \leq n$.

Step 2: Eliminate A_{i_1} from the consideration, recalculate the maximum loss of efficiency of every efficiency interval and determine a most desirable efficiency interval from the remaining (n-1) efficiency intervals. Suppose A_{i_2} is chosen, where $1 \leq i_2 \leq n$ but $i_2 \neq i_1$.

Step 3: Eliminate A_{i_2} from the further consideration, re-compute the maximum loss of efficiency of every efficiency interval and determine a most desirable efficiency interval A_{i_3} from the remaining (n-2) efficiency intervals.

Step 4: Repeat the above eliminating process until only one efficiency interval A_{i_n} is left. The final ranking is $A_{i_1} \succ A_{i_2} \succ \cdots \succ A_{i_n}$, where the symbol "$\succ$" means "is superior to".

The above ranking approach is referred to as the MRA. In the next section, a numerical example is presented.

3. Numerical example

The data set for this example contains specifications on 27 strategies. The cardinal input considered is Total Cost of strategy (TC). The inputs and outputs selected in this paper are not exhaustive by any means, but are some general measures that can be utilized to evaluate strategies. In fact, criteria that are critical to strategic choices concerning the future will vary from company to company and over time, and will emerge from different parts of the strategy analysis. In an actual application of this methodology, decision makers must carefully identify appropriate inputs and outputs measures to be used in the decision making process. Risk is included as a qualitative input while Net Present Value (NPV) of the strategy will serve as the bounded data output. Risk is an intangible factor that is not usually explicitly included in evaluation model for strategy. This qualitative variable is measured on a strong ordinal scale. Payback time for the strategy is considered as cardinal output. Table 1 depicts the strategy's attributes.

"Take in Table 1"

Suppose the parameters of degree of preference intensity about the strong ordinal preference information are given (or estimated) as $\eta_2 = 1.12$ and $\sigma_2 = 0.01$. Using the transformation technique described in previous section, an interval estimate for risk of each strategy can be derived, which is shown in the Table 2. For example, the transformation result for strategy$_{23}$ is as follows:

$$\hat{x}_{2,23} \in \left[0.01(1.12)^{26}, \ 1.12^0\right] = \left[0.1904007, \ 1\right]$$

"Take in Table 2"

Therefore, all the input and output data are now transformed into interval numbers and can be evaluated using interval DEA models. Table 3 reports the results of efficiency assessments for the 27 strategies obtained by using interval DEA models (1) and (2). The non-Archimedean infinitesimal was set to be $\varepsilon = 0.0001$.

"Take in Table 3"

Based on the definition 1, strategies 10, 17, 20, and 27 all have the possibility to be DEA efficient. If they are able to use the minimum inputs to produce the maximum outputs, they

are DEA efficient (efficient in scale); otherwise, they are not DEA efficient. Although strategies 10, 17, 20, and 27 all have the possibility to be DEA efficient, due to the differences in the lower bound efficiencies, their performances are in fact different.

In order to rank the efficiencies of the 27 strategies (DMUs), the MRA is employed to compute the maximum loss of efficiency for each strategy (see appendix). As computations show, $strategy_{20}$ is selected as the best strategy.

4. Managerial implications

No organization has unlimited resources. No firm can take on an unlimited amount of debt or issue an unlimited amount of stock to raise capital. Therefore, no organization can pursue all the strategies that potentially could benefit the firm. Strategic decisions thus always have to be made to eliminate some courses of action and to allocate organizational resources among others. Most organizations can afford to pursue only a few corporate-level strategies at any given time. It is a critical mistake for managers to pursue too many strategies at the same time, thereby spreading the firm's resources so thin that all strategies are jeopardized.

The strategic management process results in decisions that can have significant, long-lasting consequences. One major component of strategic management is strategy selection. Erroneous strategic decisions can inflict severe penalties and can be exceedingly difficult, if not impossible, to reverse. Most strategists agree, therefore, that strategy evaluation is vital to an organization's well-being. Strategy evaluation is important because organizations face dynamic environments in which key external and internal factors often change quickly and dramatically.

Strategy analysis and choice seeks to determine alternative courses of action that could best enable the firm to achieve its mission and objectives. The firm's present strategies, objectives, and mission, coupled with the external and internal audit information, provide a basis for generating and evaluating feasible alternative strategies. Unless a desperate situation faces the firm, alternative strategies will likely represent incremental steps to move the firm from its present position to a desired future position. Strategists never consider all feasible alternatives that could benefit the firm, because there are an infinite number of possible actions and an infinite number of ways to implement those actions. Therefore, a manageable set of the most attractive alternative strategies must be developed. The advantages, disadvantages, trade-offs, costs, and benefits of these strategies should be determined.

Strategy selection has long been recognized as a multi-criteria problem. The joint consideration of multiple criteria complicates the selection decision, even in the case of experienced managers, because competing strategies have different levels of success under multiple criteria. This paper introduces a technique that can help strategists evaluate the feasible strategies and choose a specific strategy. Without the technique, personal biases, politics, emotions, personalities, and halo error (the tendency to put too much weight on a single factor) unfortunately may play a dominant role in the strategy ranking process. This paper has following advantages for strategists:

- With respect to dynamic environments in which key external and internal factors often change rapidly and considerably, this paper helps strategists to react quickly and accurately.

- Since classical techniques always require intuitive judgments that have biases, this paper helps strategists to select and rank the strategies without relying on intuitive judgments.

- The increasing number of decision making criteria, complicates the strategy ranking process. This paper presents a robust model to solve the multiple-criteria problem.

5. Concluding remarks

Strategic decisions deal with the long-term future of the entire organization. The decisions are rare and typically have no precedent to follow. In addition, strategic decisions usually commit substantial resources and demand a great deal of commitment. Moreover, they are directive, they set precedents for more detailed (tactical level) decisions and future actions throughout the organization. To rank the strategies a method was introduced.

The problem considered in this study is at initial stage of investigation and much further researches can be done based on the results of this paper. Some of them are as follows: Similar research can be repeated for the case that some of the strategies are slightly non-homogeneous. One of the assumptions of all the classical models of strategy evaluation is based on complete homogeneity of strategies, whereas this assumption in many real applications cannot be generalized. In other words, some criteria (inputs and/or outputs) are not common for all the strategies occasionally. Therefore, there is a need to a model that deals with these conditions. Comparing the results of performance of proposed method with fuzzy DEA will be another research topic. To transform the ordinal preference information to

interval data, geometrical spacing was utilized. Comparing statistical properties of linear spacing and geometrical spacing and their effects on the result of efficiency could be an interesting topic for future study.

Appendix

R(strategy$_1$)= .855557, R(strategy$_2$)= .752023, R(strategy$_3$)= .829391, …, R(strategy$_{27}$)= .133532

Obviously, strategy$_{20}$ has the smallest maximum loss of efficiency. So, strategy$_{20}$ is rated as the best strategy and eliminated from the further consideration. Therefore for the remaining strategies, maximum losses of efficiency are recalculated as follows:

R(strategy$_1$)= .855557, R(strategy$_2$)= .752023, R(strategy$_3$)= .829391, …, R(strategy$_{27}$)= .133532

Among the above regrets, the maximum loss of efficiency of strategy$_{27}$ is the smallest, so strategy$_{27}$ is rated as the second best strategy and eliminated from the further consideration. So, for the remaining strategies, maximum losses of efficiency are recalculated and shown below:

R(strategy$_1$)= .855557, R(strategy$_2$)= .752023, R(strategy$_3$)= .829391, …, R(strategy$_{26}$)= .755492

Since strategy$_{17}$ has the smallest maximum loss of efficiency. So, it is rated as the third best strategy and eliminated from the further consideration. Repeating the above process, the ranking order of 27 strategies is obtained as follows:

strategy$_{20}$ ≻ strategy$_{27}$ ≻ strategy$_{17}$ ≻ strategy$_{10}$ ≻ strategy$_{25}$ ≻ strategy$_2$ ≻ strategy$_7$ ≻ strategy$_{15}$ ≻ strategy$_{26}$ ≻ strategy$_{21}$ ≻ strategy$_{19}$ ≻ strategy$_{16}$ ≻ strategy$_{11}$ ≻ strategy$_9$ ≻ strategy$_1$ ≻ strategy$_3$ ≻ strategy$_{14}$ ≻ strategy$_{22}$ ≻ strategy$_6$ ≻ strategy$_8$ ≻ strategy$_{24}$ ≻ strategy$_{13}$ ≻ strategy$_5$ ≻ strategy$_{23}$ ≻ strategy$_{18}$ ≻ strategy$_4$ ≻ strategy$_{12}$.

Therefore, strategy$_{20}$ is selected as the best strategy.

References

Banker, R. D., Charnes, A., Cooper, W. W. (1984) Some Methods for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science, 30(9), 1078-1092.

Charnes, A., Cooper, W. W., Rhodes, E. (1978) Measuring the Efficiency of Decision Making Units. European Journal of Operational Research, 2(6), 429-444.

Chien, T. W., Lin, C., Tan, B., Lee, W. C. (1999) A Neural Networks-Based Approach for Strategic Planning. Information & Management, 35(6), 357-364.

Chiou, H. K., Tzeng, G. H., Cheng, D. C. (2005) Evaluating Sustainable Fishing Development Strategies using Fuzzy MCDM Approach. Omega, 33(3), 223-234.

Cook, W. D., Kress, M., Seiford, L. M. (1996) Data Envelopment Analysis in the Presence of Both Quantitative and Qualitative Factors. Journal of the Operational Research Society, 47(7), 945-953.

Corner, J., Kirkwood, C. (1991) Decision Analysis Applications in the Operations Research Literature 1970-1989. Operations Research, 39(2), 206-219.

Hastings, S. (1996) A Strategy Evaluation Model for Management. Management Decision, 34(1), 25-34.

Kajanus, M., Ahola, J., Kurttila, M., Pesonen, M. (2001) Application of Even Swaps for Strategy Selection in a Rural Enterprise. Management Decision, 39(5), 394-402.

Wang, Y. M., Greatbanks, R., Yang, J. B. (2005) Interval Efficiency Assessment Using Data Envelopment Analysis. Fuzzy Sets and Systems, 153(3), 347-370.

Wind, Y. (1987) An Analytic Hierarchy Process based Approach to the Design and Evaluation of a Marketing Driven Business and Corporate Strategy. Mathematical Modeling, 9(3-5), 285-291.

Wind, Y., Saaty, T. (1980) Marketing Applications of the Analytic Hierarchy Process. Management Science, 26(7) 641-658.

Table 1 Related attributes for 27 strategies

Strategy No. (DMU)	Inputs		Outputs	
	TC (10000\$) x_{1j}	Risk* x_{2j}	NPV (10000\$) y_{1j}	Payback time (year) y_{2j}
1	7.2	15	[50, 65]	1.35
2	4.8	7	[60, 70]	1.1
3	5	23	[40, 50]	1.27
4	7.2	16	[1, 3]	.66
5	9.6	24	[45, 55]	.05
6	1.07	3	[1, 2]	.3
7	1.76	8	[4, 5]	1
8	3.2	17	[10, 20]	1
9	6.72	9	[9, 12]	1.1
10	2.4	2	[5, 8]	1
11	2.88	18	[25, 35]	.9
12	6.9	10	[10, 15]	.15
13	3.2	25	[8, 12]	1.2
14	4	19	[20, 35]	1.2
15	3.68	11	[40, 55]	1
16	6.88	20	[75, 85]	1
17	8	1	[10, 18]	2
18	6.3	21	[9, 15]	1
19	.94	12	[10, 13]	.3
20	.16	5	[1, 4]	.8
21	2.81	26	[25, 30]	1.7
22	3.8	13	[0.8, 1.2]	1
23	1.25	27	[2, 4]	.5
24	1.37	14	[1, 5]	.5
25	3.63	4	[8, 12]	1
26	5.3	22	[65, 80]	1.25
27	4	6	[190, 220]	.75

* Ranking such that $27 \equiv$ highest rank,…, $1 \equiv$ lowest rank ($x_{2, 23} > x_{2, 21} > … > x_{2, 17}$)

Table 2 Interval estimate for the 27 strategies after the transformation of ordinal preference information

Strategy No. (DMU)	Risk
1	[.0488711, .2566751]
2	[.0197382, .1036668]
3	[.1210031, .635518]
4	[.0547357, .2874761]
5	[.1355235, .7117802]
6	[.012544, .0658821]
7	[.0221068, .1161068]
8	[.0613039, .3219732]
9	[.0247596, .1300396]
10	[.0112, .0588233]
11	[.0686604, .36061]
12	[.0277308, .1456443]
13	[.1517863, .7971939]
14	[.0768997, .4038832]
15	[.0310585, .1631217]
16	[.0861276, .4523492]
17	[.01, .0525208]
18	[.0964629, .5066311]
19	[.0347855, .1826963]
20	[.0157352, .0826425]
21	[.1700006, .8928571]
22	[.0389598, .2046198]
23	[.1904007, 1]
24	[.0436349, .2291742]
25	[.0140493, .073788]
26	[.1080385, .5674269]
27	[.0176234, .0925596]

Table 3 The efficiency interval for the 27 strategies

Strategy No. (DMU)	Efficiency Interval
1	[.144443, .419936]
2	[.247977, .720323]
3	[.170609, .210524]
4	[.0425437, .16333]
5	[.0852112, .104152]
6	[.0875352, .368205]
7	[.166212, .707172]
8	[.090317, .293553]
9	[.145532, .448773]
10	[.300161, 1]
11	[.189221, .261913]
12	[.0282147, .0774364]
13	[.0861227, .152351]
14	[.12231, .290935]
15	[.223673, .540124]
16	[.210202, .239594]
17	[.489805, 1]
18	[.0430496, .175404]
19	[.224815, .281638]
20	[.999693, 1]
21	[.22552, .257214]
22	[.092779, .380647]
23	[.079943, .101363]
24	[.072842, .212788]
25	[.234906, .740475]
26	[.244508, .294906]
27	[.866468, 1]