SUPPLIER SELECTION UNDER UNCERTAINTY: A FUZZY-SET APPROACH

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Abstract

Traditionally, the evaluation and selection of suppliers have been a major purchasing function. A growing concern for just in-time purchasing, global sourcing, and long-term partnership between buyers and suppliers makes selecting a right supplier become more critical decision making process. Consequently, a rigorous and systematic method for evaluating suppliers is a must. However, assessing the values of factors (e.g., quality, delivery, and service) selected for evaluating suppliers contains elements of uncertainty. Although several methods have been developed for uncertainty analysis, they may not be proper tools for evaluating suppliers under uncertainty.

In this paper, a methodology using a fuzzy-set approach in combination with a multicriterion decision-making (MCDM) technique is developed to use as a tool for evaluating suppliers under uncertainty. An numerical example is presented to demonstrate the method in practice.

I. INTRODUCTION

Traditionally, the evaluation and selection of suppliers have been a major purchasing function. Some statistics reflect the importance on the subject. For example, supplier selection ranked the second frequent topic of doctoral dissertations in the areas of purchasing and material management during two decades.(Williams, 1986) A growing concern for just in-time purchasing and long-term partnership between buyers and suppliers makes selecting a right supplier become more critical decision making process. Consequently, a rigorous and systematic method for evaluating suppliers is a must.

Decision makers (i.e., buyers) can select several factors (e.g., quality, delivery, and service) to use as input variables for evaluating each supplier. However, assessing the values of input variables contains elements of uncertainty, particularly in case of new-buy and global sourcing.(Alguire, 1994) For example, sometimes it is difficult that

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decision makers precisely estimate the quality of purchased goods. Uncertainty can exist in the estimated value representing the degree of the quality. In this case, the models proposed in the literature (i.e., categorical models, weighted point models, and cost ratio models) may not be proper tools for evaluating suppliers because they do not adequately account for uncertainty in the values of input variables.

Several methods have been developed for uncertainty analysis. These include probabilistic analysis, interval analysis, and fuzzy set analysis.(Zimmermann, 1987, Lee et al., 1991) In probabilistic analysis, statistical measures of input variables are used to estimate the mean and standard deviation of the results. This method is precluded if the input variables have a nonprobabilistic nature. Interval analysis uses ranges for input variables to estimate plausible ranges of the results. However, it is difficult to define the intervals of input variables when the boundaries of the intervals are uncertain. A fuzzy-set approach, pioneered by Zadeh (1965), is useful for uncertainty analysis where (interval) values of input variables are uncertain and/or a probabilistic data base is not available. The fuzzy-set approach has been widely applied to characterize the uncertainties of realistic situations. (Bogardi & Bardossy, 1983, Anandalingam & Westfall, 1988, Ayynb, 1991)

In this paper, a methodology using a fuzzy-set approach in combination with a multicriterion decision-making (MCDM) technique is developed to use as a tool for evaluating suppliers under uncertainty. In the methodology, the uncertainty in input values and its impact on results are represented by an application of fuzzy-set theory and incorporated directly into the supplier selection process.

II. REVIEW OF SUPPLIER SELECTION METHODS

Supplier selection models can be categorized into two groups: descriptive and prescriptive models.(Ellram, 1990) The purpose of descriptive models is to identify the criterion or attributes to be important for supplier selection. Descriptive models become a basis of prescriptive models to which they are applied. Specific review of this literature is beyond the scope of this paper and only prescriptive models will be briefly discussed.

Several prescriptive models have been

suggested in the literature. Among them three methods are commonly used in practice. These include categorical methods, weighted point methods, and cost ratio method.(Thompson, 1988) Categorical methods evaluate suppliers based on preidentified criteria to which equal importance or weight is assigned. These methods are highly subjective, but relatively simple and easy to implement. The weighted point methods, so-called linear averaging methods, rate suppliers based on scores measured by each varying weighted criterion. A composite index is obtained by linearly averaging and summing each score for each criterion. Cost ratio method seeks true cost by incorporating internal costs related to supplier performance. For example, return and expedition costs due to poor quality and late delivery are converted into a percentage of total material cost. The net adjusted cost is then obtained by applying this cost ration to price quotations. This method requires comprehensive cost data for each supplier and sometimes it is difficult to identify the exact value of internal cost.

There are several variations of typical weighted point method. These include matrix model (Gregory, 1986), analytic process analysis (Narasimhan, 1983, Nydick & Hill, 1992), and vendor profile analysis (Thompson, 1988). A matrix model used by Texas Instruments rates suppliers based on several predetermined factors (i.e., proposal responsiveness, technology, quality, cost and general) which is then divided into several subfactors. The total weights of subfactors should be same as those of major factors. As a final step, subcategory scores are added and divided by the weighted total of the major category. The supplier with the highest score is selected.

Analytic hierarchy process (AHP) decomposes major evaluation factors into subelements hierarchically. The method utilizes pairwise comparison matrix among same level of elements to derive relative weights. Eigenvector procedure or normalized geometric averages is used for ranking suppliers.

Vendor profile analysis (VPA) incorporates uncertainty associated with the estimates of vendor performance using Monte Carlo simulation technique. The technique randomly generates performance rating between high and low ranges and then multiplying this value by each criterion weight. The summated values for all criteria generate probability distribution by repeating a number of iterations.

Other methods include dimensional analysis (Willis & Huston, 1990), sequential elimination procedure (Parasuraman, 1978), cluster analysis (Hinkle et al., 1969), total cost based approach (Monczka & Trecha, 1988, Smytka & Clemens, 1993), payoff matrix (Soukup, 1987), and operations research oriented methods such as mixed integer-linear programming (Bender et al., 1985). In summary, except for VPA model, all of the methods discussed above use point estimates or fixed interval estimates and thus cannot adequately account for uncertainty.

III. FUZZY SETS AND FUZZY NUMBERS

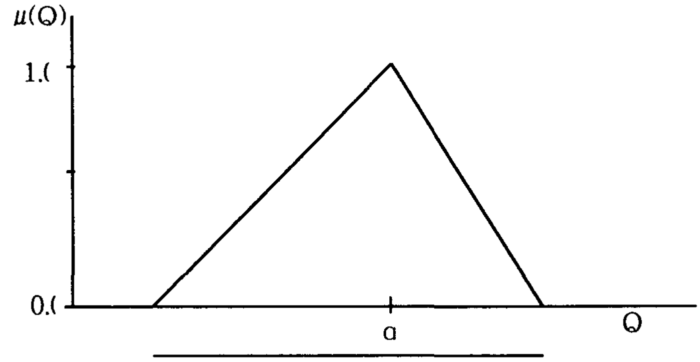
Fuzziness or uncertainty represents situations where membership in sets cannot be defined on a yes/no basis because the boundaries of the sets are vague. The central concept of fuzzy-set theory is the membership function, which represents numerically the degree to which an element belongs to a set. In a classical set, a sharp or unambiguous distinction exists between the members and nonmembers of the set. In other words, the value of the membership function of each element in the classical set is either 1 for members (those that certainly belong to the set) or 0 for nonmembers (those that certainly do not). However, it is sometimes difficult to make a sharp or precise distinction between the members and nonmembers of a set. For example, the boundaries of the sets of very poor· quality, beautiful women, or numbers much greater than 1.0 are fuzzy.

Since the transition from member to nonmember appears gradual rather than abrupt, the fuzzy set introduces vagueness (with the aim of reducing complexity) by eliminating the sharp boundary dividing members of the set from nonmembers.(Klir & Folger, 1988) Thus, if an element is a member of a fuzzy set to some degree, the value of its membership function can be between 0 and 1. When the membership function of an element can only have values 0 or 1, the fuzzy-set theory reverts to the classical-set theory.

A special class of fuzzy sets is described by fuzzy numbers, which are values that belong to a given set with a degree of membership. As an example of fuzzy numbers, let Q be a fuzzy number and its membership function $\mu(Q)$ be denoted by (Figure 1):

$$\mu(Q) = \begin{cases} 1 - (q - Q)/\gamma & , Q \leq q \\ 1 - (Q - q)/\delta & , Q > q \end{cases} \tag{1}$$

where q = the center value of the fuzzy number Q; and γ ($\gamma > 0$) and δ ($\delta > 0$) = the left and right fuzziness from the center value q, respectively. When the values of γ and δ are equal to zero, Q is a nonfuzzy number by convention. As the values of γ and δ increase, Q becomes fuzzier and fuzzier.



<Figure 1> Membership Function of Fuzzy Number Q

IV. METHODOLOGY FOR SUPPLIER SELECTION

In this section, a multicriterion decision-making methodology is provided to assist buyers in evaluating and ranking suppliers in situations where there are conflicting objectives (e.g., maximizing quality of purchased goods while minimizing price); the objectives have different preferences (weights); and the values of input attributes are uncertain. A fuzzy-composite programming algorithm (Lee et al., 1990) is employed to formulate the methodology, which is organized into the following sequential format: (1) identify basic attributes; (2) group the basic attributes into progressively fewer, more generalized, groups; and (3) evaluate and rank the suppliers.

1. Identification of Basic Attributes

To represent both potential benefits and problems of each supplier, basic attributes should be identified. These attributes are then used as the input variables for evaluating each supplier. Figure 2 shows an example of basic (first-level) attributes. Because the selection of the basic attributes tends to be case specific (e.g., traditional purchasing versus JIT purchasing), it is difficult to generalize. In other words, the kind of basic attributes varies with purchasing environment, and the number of basic attributes depends largely on the level of analysis desired (preliminary or detailed).

2. Composite Procedure

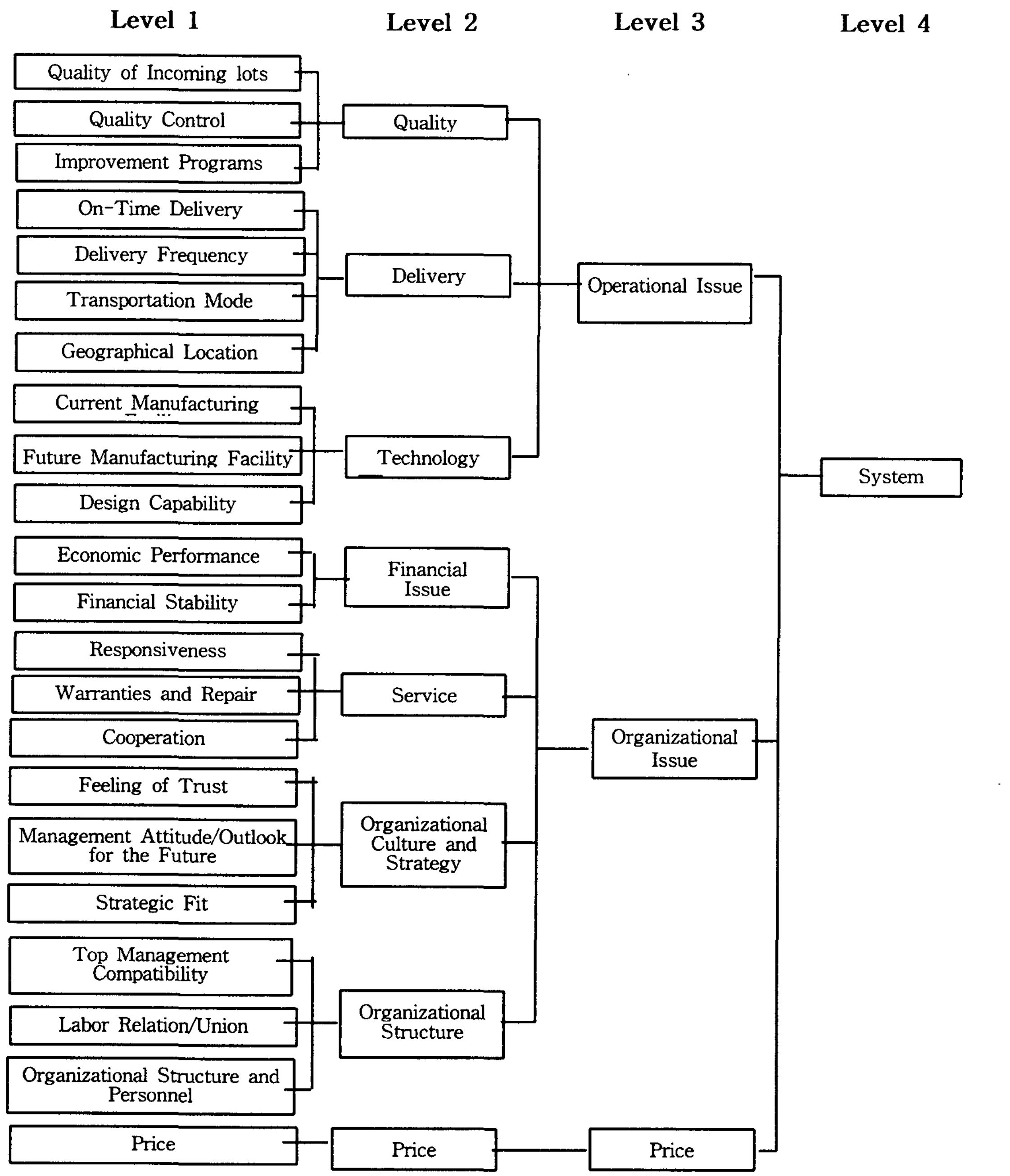
The composite procedure involves a step-by-step regrouping of a set of various basic attributes to form a single attribute, as shown in Figure 2. The set of basic (first-level) attributes is grouped into a smaller subset of second-level attribute. For example, the basic attributes "quality of incoming lots," "quality control," and "improvement programs" can be grouped into "quality," which is an element of the subset of second-level attributes. The same way of grouping is used to form other second-level attributes, in this case, "delivery," "technology," "financial issue," "service," "organizational culture and strategy," and "organizational structure."

Next, the second-level attributes "quality," "delivery," and "technology" are grouped under the third-level attribute "operational issue," and the second-level attributes "financial issue," "service," "organizational culture and strategy," and "organizational structure" under the third level indicator "organizational issue."

Finally, the fourth-level (system) attribute can be formed by grouping the third-level attributes, in this case, "operational issue," "organizational issue," and "price."

3. Trade-Off Analysis Using Fuzzy Numbers

As mentioned earlier, assessing the values of the basic attributes selected for evaluating suppliers contains elements of uncertainty. In this paper, the values of basic attributes are estimated as fuzzy numbers to characterize their uncertainty. As explained in Equation (1), the fuzzy numbers are values that belong to a

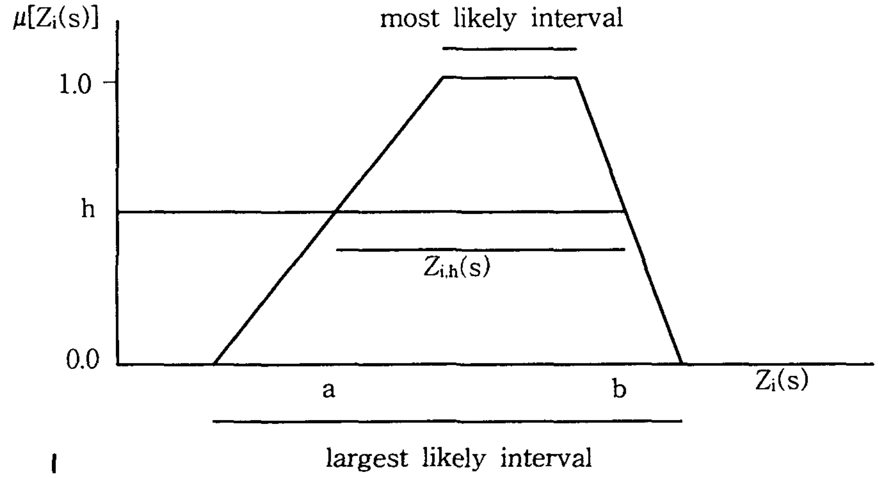


<Figure 2> Example of Composite Structure

given set (internal) with a certain degree of membership only. The uncertainty in a basic attribute value may be represented by two intervals (i.e., the most likely interval and the largest likely interval), which can then be used to construct the membership function of the basic attribute, as shown in Figure 3.

For a mathematical formulation of the procedure for evaluating suppliers under uncertainty, let $Z_i(s)$ be a fuzzy number for the i-th basic attribute, and let its membership function $\mu[Z_i(s)]$ be a trapezoidal shape (Figure 3), where s is one element (supplier's name) of the discrete set of suppliers. It should be noted that if the trapezoidal shape is reduced to a vertical line, it represents a so-called crisp (nonfuzzy) number. A level-cut concept can be used to define the interval of each basic attribute at various degrees of membership.(Dong & Shah, 1987) As shown in Figure 3, $Z_{i,h}(s)$ is the interval value of the i-th basic attribute at the membership degree h (i.e., $a \le Z_{i,h}(s) \le b$).

Since the units of basic attributes such as quality and price are different, thus making it difficult to compare them directly, the actual value of each basic attribute $[Z_{i,h}(s)]$ should be transformed into an index. Using the best value of $Z_i(BESZ_i)$ and the worst value of $Z_i(WORZ_i)$ for the i-th basic attribute, the actual value $Z_{i,h}(s)$ can be transformed into an index value $V_{i,h}(s)$ denoted by (Figure 4):



<Figure 3> Estimate of the i-th Basic Attribute as a Fuzzy Number

(1) If $BESZ_i < WORZ_i$, then

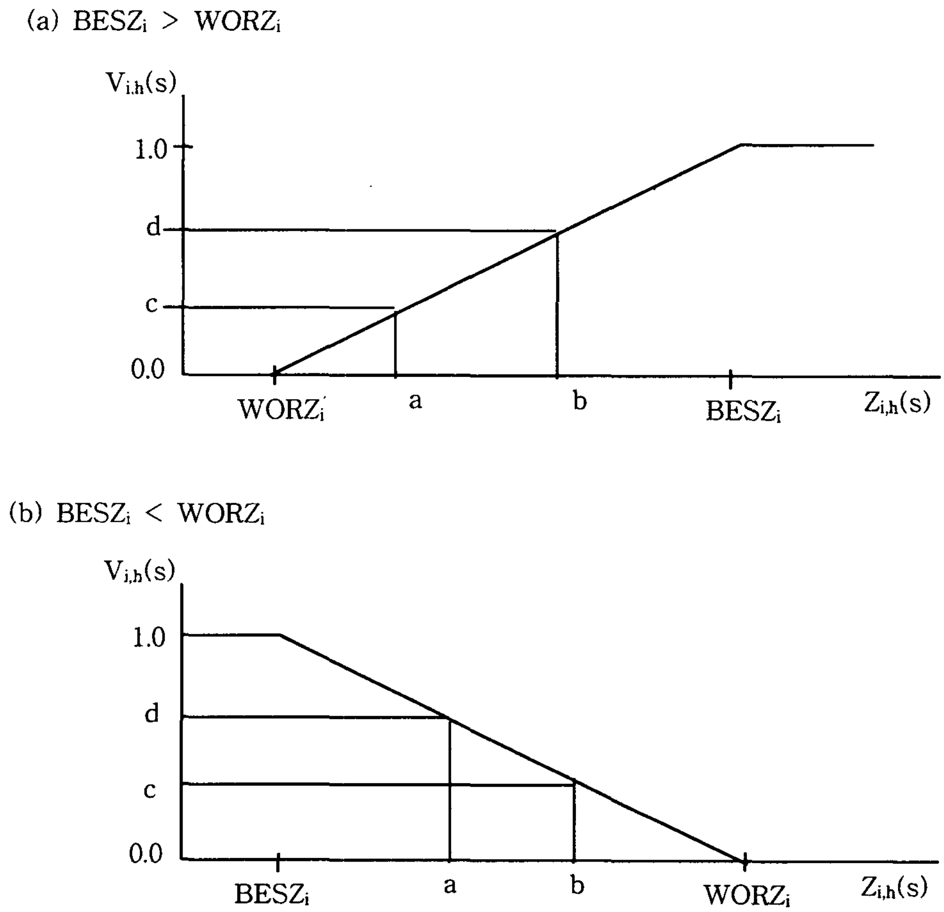
$$V_{i,h}(s) = \begin{cases} 1 & , Z_{i,h}(s) \leq BESZ_i \\ \dfrac{[Z_{i,h}(s) - WORZ_i]}{(BESZ_i - WORZ_i)} & , BESZ_i < Z_{i,h}(s) < WORZ_i \\ 0 & , Z_{i,h}(s) \geq WORZ_i \end{cases} \quad (2)$$

(2) If $BESZ_i > WORZ_i$, then

$$V_{i,h}(s) = \begin{cases} 1 & , Z_{i,h}(s) \geq BESZ_i \\ \dfrac{[Z_{i,h}(s) - WORZ_i]}{(BESZ_i - WORZ_i)} & , WORZ_i < Z_{i,h}(s) < BESZ_i \\ 0 & , Z_{i,h}(s) \leq WORZ_i \end{cases} \quad (3)$$

For example, the less the price, the better the choice. Because the best value (lowest price) is less than the worst value (highest price), Equation (2) ($BESZ_i < WORZ_i$) should be used to calculate the index value for the price. As another example, the higher the degree of the quality of a goods, the better the choice. In this case, Equation (3) should be used to obtained the index value for the quality. To calculate the index of the i-th basic attribute, one should therefore select either Equation (2) or (3) according to the characteristics of the i-th basic attribute.

To assign the values $BESZ_i$ and $WORZ_i$, one of two options can be used. The first option is to find, from among all the given suppliers, the best value for the i-th basic attribute and let that value be $BESZ_i$, and likewise, find the worst value for the i-th basic attribute, and let it be $WORZ_i$. The second option is to assign $BESZ_i$ and $WORZ_i$ according to the option of buyers. Since the actual value $Z_{i,h}(s)$ is an interval with lower bound a and upper bound b (Figure 3), the index value $V_{i,h}(s)$ resulting from $Z_{i,h}(s)$ is also an interval (Figure 4).



<Figure 4> Transferring Actual Value $Z_{i,h}(s)$ into Index $V_{i,h}(s)$

Next, index values, $L_{j,h}(s)$, of the second-level composite attributes can be calculated by using the index values of the basic attributes, or

$$L_{j,h}(s) = \{ \sum_{i=1}^{n_j} w_{i,j}[V_{i,h,j}(s)]^{Pj} \}^{(1/Pj)} \qquad (4)$$

where n_j = the number of elements in the second-level group j; $V_{i,h,j}(s)$ = the index value of the i-th basic attribute in the second-level group j of basic attributes; $w_{i,j}$ = the weight reflecting the importance of each of the basic attributes in group j ($\sum w_{i,j} = 1$); and P_j = the balancing factor among attributes for group j.

Using the index values of the second-level attributes, index values, $L_{k,h}(s)$, of the third-level composite attributes can be defined as:

$$L_{k,h}(s) = \{ \sum_{j=1}^{n_k} w_{j,k}[L_{j,h,k}(s)]^{Pk} \}^{(1/Pk)} \qquad (5)$$

where n_k = the number of elements in the third-level group k; $L_{j,h,k}(s)$ = the index value of the second-level group j in the third group k; $w_{j,k}$ = the weight expressing the importance among elements in the third-level group k; and p_k = the balancing factor for the third-level group k.

As shown in Figure 2, there are three third-level attributes: operational issue, organizational issue, and price. Therefore, the index value, $L_h(s)$, of the final composite (system) attribute can be calculated by compositing the index values of the three third-level attributes as follows:

$$L_h(s) = \{ \sum_{k=1}^{3} w_k[L_{k,h}(s)]^p \}^{(1/p)} \qquad (6)$$

where $L_{k,h}(s)$ = the index value of the third-level group k in the final group (system); w_k = the weight representing the importance among elements in the final group; and p = the balancing factor for the final group.

It should be noted that the process of computing the index value is applicable to fewer or more than the four levels (Figure 4) used in this paper.

4. Determination of weights and Balancing Factors

In Equations (4), (5), and (6), weights (w) and balancing factors (p) have been given to each attribute and group. These represent a double-weighting scheme. Thus, the calculation result is sensitive to this weighting scheme.

Weight represents the relative importance between attributes in a group. Thus, the greater the importance of an attribute, the greater should be the weight assigned to it. In this paper, an AHP approach, developed by Satty (1988), are employed to obtain the relative weight of each of the attributes in a group based on a paired comparison of each of the attributes, as was the case in Narasimhan (1983).

The balancing factor p ($p \geq 1$) reflects the relative importance assigned to the largest of the index values of attributes in a group and limits the ability of one indicator to substitute for another.(Zeleny, 1982, Lee, 1992) In other words, with an appropriately high balancing factor, an indicator that must not be compromised, such as quality, will not be substituted for by one such as delivery. As a general rule, p = 3 or greater should be assigned for very critical attributes (i.e., attributes where undesirable outcome might fatally flaw a supplier); otherwise p = 1 or p =

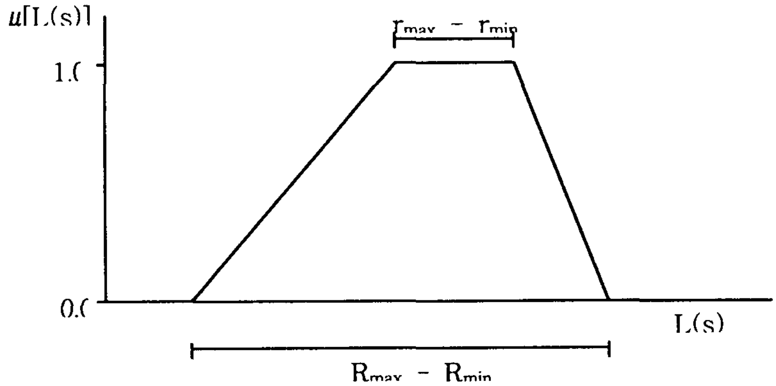
2 seems to be a good choice.(Lee et al., 1991)

5. Ranking Suppliers

To formulate a procedure for ranking different suppliers, let L(s) be the fuzzy number representing the final composite (system) attribute for supplier s. That is, the index value, L(s), of the final composite attribute is interpreted as a fuzzy number. With the help of two index values $L_{h=1}(s)$ and $L_{h=0}(s)$ in Equation (6), the membership function, $\mu[L(s)]$, of the fuzzy number L(s) can be appropriately calculated from the piecewise linear function (Figure 5):

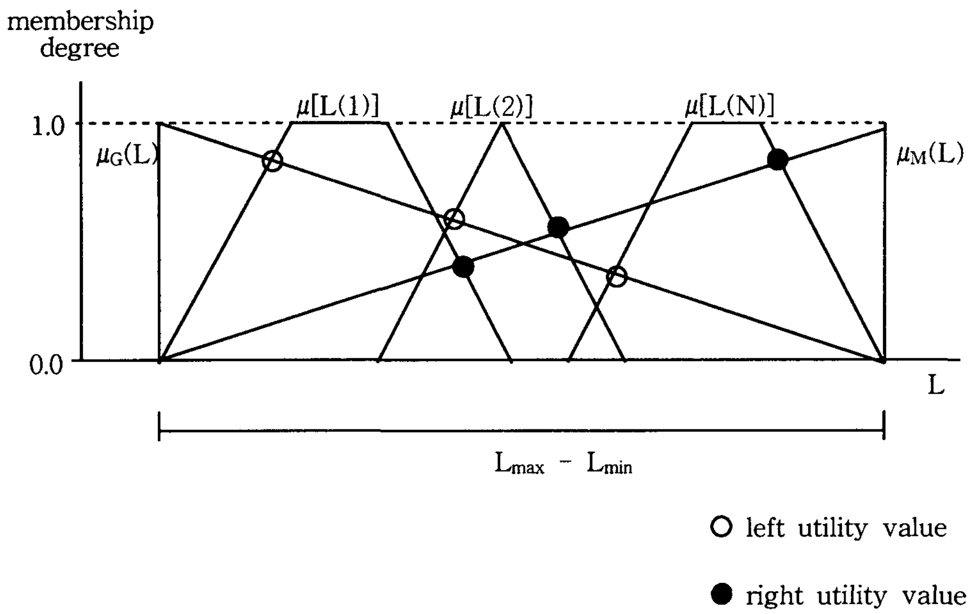
where r_{min} and r_{max} = lower and upper bound values, respectively, of the index value $L_{h=1}(s)$ of the final composite attribute obtained by using $Z_{i,h=1}(s)$; and R_{min} and R_{max} = lower and upper bound values, respectively, of the index value $L_{h=0}(s)$ of the final composite attribute calculated by using $Z_{i,h=0}(s)$.

If there are N suppliers, there are N fuzzy numbers [L(s), s = 1, ..., N] that are restricted by the membership function of Equation (7). To rank these N fuzzy numbers, several ranking methods can be used.(Li, 1992) However, the fuzzy numbers' ranking (i.e., the suppliers'



<Figure 5> Membership Function for Fuzzy Number L(s)

$$\mu[L(s)] = \begin{cases} 1 & , r_{min} \le L(s) \le r_{max} \\ [L(s) - R_{min}]/(r_{min} - R_{min}) & , R_{min} \le L(s) < r_{min} \\ [L(s) - R_{max}]/(r_{max} - R_{max}) & , r_{max} < L(s) \le R_{max} \\ 0 & , \text{otherwise} \end{cases} \quad (7)$$



<Figure 6> Ranking Method of Fuzzy Numbers

ranking) could vary according to the ranking method used. For this paper, the ranking method developed by Chen (1985) will be used because it is suitable for ranking fuzzy numbers whose membership functions have triangular or trapezoidal forms (Figure 5).(Tseng & Klein, 1988) Chen's ranking method determines the ranking of N fuzzy numbers by using a maximizing set and a minimizing set (Figure 6).

The maximizing set M is a fuzzy subset with membership function $\mu_M(L)$ given as:

$$\mu_M(L) = \begin{cases} (L - L_{min})/(L_{max} - L_{min}) & , L_{min} \le L \le L_{max} \\ 0 & , \text{otherwise} \end{cases} \quad (8)$$

where for s = 1, ..., N, L_{min} = min[min $L_{h=0}(s)$] and L_{max} = max[max $L_{h=0}(s)$]. The right utility value, $U_R(s)$, for a given supplier s is then defined as:

$$U_R(s) = \max\left(\min \{\mu_M(L), \mu[L(s)]\} \right) \quad (9)$$

The minimizing set G is a fuzzy subset with membership function $\mu_G(L)$ given as:

The left utility value, $U_L(s)$, for a given

$$\mu_G(L) = \begin{cases} (L - L_{max})/(L_{min} - L_{max}) & , L_{min} \le L \le L_{max} \\ 0 & , \text{otherwise} \end{cases} \quad (10)$$

supplier s is then defined as:

$$U_L(s) = \max (\min \{\mu_G(L), \mu[L(s)]\}) \quad (11)$$

The total utility or ordering value for a given supplier s is:

$$U(s) = [U_R(s) + 1 - U_L(s)]/2 \quad (12)$$

The supplier that has the highest ordering value in the discrete set of suppliers is then selected as the best.

V. NUMERICAL EXAMPLE

A numerical example is provided to show how the proposed methodology (Equations 2 through 12) can be put in practice. Currently, a buyer has three potential suppliers. To evaluate both benefits and problems of each supplier, the buyer selected 22 basic attributes, which correspond to the first-level attributes on Figure 2.

Table 1 contains hypothetical data of the basic attributes for each supplier. The lower the values of geographical location and price, the choice the better. On the other hand, the higher the values of the remaining basic attributes, the better the choice. Except for values of the geographical location and the price, all values of basic attributes were assigned by transferring qualitative definitions (such as poor, good, and excellent) into numerical values. For example, the basic attribute on quality of incoming lots can be characterized with qualitative definitions, and numerical values corresponding the qualitative definitions can then be obtained using Figure 7. The membership function of trapezoidal or triangular shape (Figure 7) may be used to represent the uncertainty in each qualitative measure, as was the case in Lee (1992). The value on geographical location is the distance (miles) between the buyer and the supplier, and the value on price is dollars per unit.

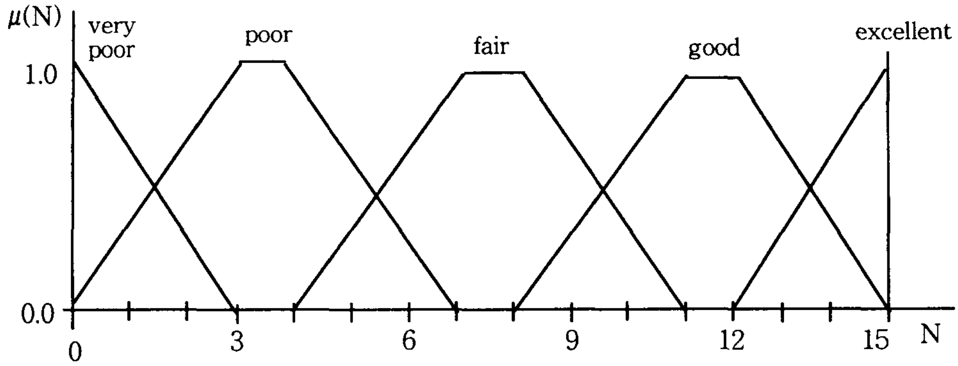
Table 2 displays the best and the worst values for the 22 basic attributes and the weights and balancing factors assigned to each attribute and group are shown in Table 3. With the help of Table 1, 2, and 3, a fuzzy composite program

(Lee et al., 1990) was used to select which of the three suppliers best satisfies the buyer's desire. The program is microcomputer-based, and it uses the methodology described in the previous section. Table 4 shows the results of calculation by the program. In Table 4, the higher the ordering value, the better the choice. Therefore, supplier A may be selected as the best supplier.

Basic attribute	Supplier A		Supplier B		Supplier C	
	MLI[a]	LLI[b]	MLI	LLI	MLI	LLI
Quality of incoming lots	15-15	12-15	11-12	8-15	11-12	8-15
Quality control	15-15	12-15	11-12	8-15	7-8	4-11
Improvement programs	11-12	8-15	7-8	4-11	11-12	8-15
On-time delivery	7-8	4-11	11-12	8-15	15-15	12-15
Delivery frequency	7-8	4-11	11-12	8-15	15-15	12-15
Transportation mode	11-12	8-15	15-15	12-15	15-15	12-15
Geographical location (miles)	500-500	500-500	200-200	200-200	100-100	100-100
Current manufacturing facility	15-15	12-15	11-12	8-15	7-8	4-11
Future manufacturing facility	11-12	8-15	7-8	4-11	7-8	4-11
Design capability	11-12	8-15	7-8	4-11	11-12	8-15
Economic performance	11-12	8-15	7-8	4-11	7-8	4-11
Financial stability	11-12	8-15	11-12	8-15	7-8	4-11
Responsiveness	7-8	4-11	11-12	8-15	11-12	8-15
Warranties and repair	15-15	12-15	11-12	8-15	11-12	8-15
Cooperation	7-8	4-11	11-12	8-15	11-12	8-15
Feeling of trust	11-12	8-15	11-12	8-15	15-15	12-15
Management attitude/outlook	11-12	8-15	7-8	4-11	15-15	12-15
Strategic fit	11-12	8-15	7-8	4-11	11-12	8-15
Top management compatibility	11-12	8-15	15-15	12-15	11-12	8-15
Labor relations/union	7-8	4-11	11-12	8-15	15-15	12-15
Organizational structure	11-12	8-15	15-15	12-15	11-12	8-15
Price (dollars/unit)	14-14	14-14	13-13	13-13	11-11	11-11

[a] MLI refers to most litkely interval. [b] LLI refers to largest likely interval.

<Table 1> Basic attribute values



<Figure 7> Membership functions [μ(N)] for numerical values (N) corresponding to qualitative definitions

Basic attribute	Best values	Worst values
Quality of incoming lots	15	0
Quality control	15	0
Improvement programs	15	0
On-time delivery	15	0
Delivery frequency	15	0
Transportation mode	15	0
Geographical location (miles)	0	500
Current manufacturing facility	15	0
Future manufacturing facility	15	0
Design capability	15	0
Economic performance	15	0
Financial stability	15	0
Responsiveness	15	0
Warranties and repair	15	0
Cooperation	15	0
Feeling of trust	15	0
Management attitude/outlook	15	0
Strategic fit	15	0
Top management compatibility	15	0
Labor relations/union	15	0
Organizational structure	15	0
Price (dollars/unit)	0	14

<Table 2> Best and worst values of basic attributes

Basic attribute[a]	Weight	Balancing factor
Quality of incoming lots	0.57	2
Quality control	0.30	2
Improvement programs	0.13	2
On-time delivery	0.45	1
Delivery frequency	0.29	1
Transportation mode	0.13	1
Geographical location (miles)	0.13	1
Current manufacturing facility	0.59	1
Future manufacturing facility	0.20	1
Design capability	0.21	1
Economic performance	0.50	1
Financial stability	0.50	1
Responsiveness	0.34	1
Warranties and repair	0.33	1
Cooperation	0.33	1
Feeling of trust	0.30	1
Management attitude/outlook	0.40	1
Strategic fit	0.30	1
Top management compatibility	0.42	1
Labor relations/union	0.33	1
Organizational structure	0.25	1
Quality	0.51	2
Delivery	0.30	2
Technology	0.19	2
Financial Issue	0.21	1
Services	0.38	1
Organizational culture/strategy	0.21	1
Organizational structure	0.20	1
Operational issue	0.48	3
Organizational issue	0.22	3
Price (dollars/unit)	0.30	3

[a] Refer to Figure 2 to identify the level of each attribute and the group to which each attribute belongs.

<Table 3> Weights and balancing factors

Ranking	Supplier	Ordering value
1	A	0.604
2	C	0.562
3	B	0.507

<Table 4> Ranking of suppliers

VI. CONCLUSIONS

Assessing the values of the basic attributes selected for evaluating suppliers contains elements of uncertainty. This paper shows that the uncertainty inherent in these elements and its impact on results can be characterized by using fuzzy-set theory.

The multicriterion decision-making methodology presented in this paper can be a useful tool for determining a preferred supplier where there are conflicting objectives, the objectives are of varying degrees of importance, and the values of input attributes (such as quality, delivery, and technology) are uncertain. The methodology allows decision makers to incorporate associated uncertainties directly into the supplier selection process so decisions can be made that are more realistic and appropriate than those made without taking uncertainty in account.

For the numerical example, supplier A was the most preferred of the three potential suppliers (Table 4). However, it should be noted that the final result (the suppliers' ranking) may vary with the values of weights (w) and balancing factors (p) assigned to each attribute and group (Equations 4, 5, and 6). Therefore, a sensitivity analysis is needed to investigate the effect for the weights and balancing factors. Because the selection of different basic attributes may also lead to different results, care must be taken to select all of critical attributes so that other attribute selection will not radically alter the result of the analysis.

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