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Full Length Research Paper

A decision support system for supplier selection using fuzzy analytic network process (Fuzzy ANP) and artificial neural network integration

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Selection of appropriate supplier(s) for success of an organization is particularly a valuable necessity, hence apart from the common criteria such as logistics, service and quality, this paper discusses most of the key decision variables which can play a critical role in case of the supplier selection. In this study, analytic network process (ANP) method is used because it considers the relationship between the criteria themselves; criteria and alternatives. Pair wise comparison between the model elements is necessary in ANP method. However, the decision makers make their judgments in fuzzy environment and prefer to use linguistic variables with number interval instead of crisp number for stating judgments. For these reasons, a fuzzy set is required to give an answer for the uncertainty. In fuzzy ANP model, experts have been making fuzzy pair wise comparisons; however, the importance of compared criteria or their priority may be different. In such a case, the judgment of expert regarding pair wise comparisons of elements can change. The new evaluations of experts should be obtained. Getting the evaluation of experts in each case may delay decision making. To overcome this difficulty, data related to fuzzy pair wise comparisons that reflect expert opinion is used in different artificial neural network (ANN) models for training. There is no need to consult the experts in ANN comparison matrix values due to learning feature of ANN. Another superiority of ANN model is that the weights search by pair wise comparison matrix can be found by ANN without a need for fuzzy extent analysis method. This research results thus indicate that the supplier selection process appears to be the most significant variable in deciding the success of the supply chain. Therefore, supplier selection should be done according to many different qualitative and quantitative criteria.

Key words: Supplier selection, fuzzy analytic network process (FANP), artificial neural network (ANN).

INTRODUCTION

In today's highly competitive markets, supplier selection for success of organizations is crucial for competitiveness (Weber et al., 2000). Furthermore, the ever increasing complexity of the production process increases the importance of supplier selection. In many organizations, the cost of supplied raw material and semi product rises as far as 70% of total cost (Ghodsypour and O'Brien, 1998). Therefore, mistakes in the selection of supplier cause the following: production of sub-standard product, cancelation or delaying of orders, production problems and consequently the rise of cost and the customer dissatisfaction. The purpose of supplier selection is to select these suppliers, who will supply the needed services and products at the right time and quality. The aim of supplier selection is to identify supplier with the highest potential for meeting a company's needs consistently.

Supplier selection is difficult in decision making problem for organizations. The difficulties are stated below (Weber et al., 2000, Muralidharan et al., 2001; Benyoucef et al., 2003; Talluri and Sarkis, 2002):

1. Supplier selection should be in conformity with strategies of organizations.

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2. Supplier selection is done among a great number of alternatives.
3. Many different criteria should be considered in supplier selection. Qualitative criteria should be used together with quantitative ones.
4. Supplier performance can change according to different criteria. This makes supplier selection is too difficult. For example, a supplier may be valid according to quality criterion, but it may not be so strong according to price criterion.
5. Many decision makers from different departments should join the supplier selection process. However, the fact that decision makers make evaluations according to the needs of their departments makes the selection problem harder.

Literature contains many studies where different methods are used for supplier selection. However, it is obvious that weighted methods do not contain quantitative criteria and mathematical programming methods do not contain qualitative criteria (De Boer et al., 1998; Ghodsypour and O'Brien, 1998). Nevertheless the evaluation of suppliers should be done according to many different qualitative and quantitative criteria. Supplier selection involves various criteria including delivery performance, price, quality and so on. It often involves the selection of new while sacrificing the other. For example, one supplier is providing goods in best quality, but is not able to deliver on time. On the other hand, another supplier is providing poor quality, but delivery performance is satisfactory. Therefore, supplier selection is multi criteria decision making (MCDM) problem. In this study, analytic network process (ANP) method is used because it considers the relationship between the criteria themselves; criteria and alternatives. ANP is MCDM method that enables group study. In this study, an ANP model is formed that enables many different evaluation criteria.

Pair wise comparison between the model elements is necessary in ANP method. However, the decision makers make their judgments in fuzzy environment and preferred to use linguistic variables with number interval instead of crisp number for stating judgments. For these reasons, a fuzzy set is required to give an answer of the uncertainty. In fuzzy ANP model experts have been making fuzzy pair wise comparisons. However, the importance of compared criteria or their priority may be different. In such a case, the judgment of expert regarding pair wise comparisons of elements can change. When it is intended to use known ANP model for new case, it is necessary to establish new expert group. Unfortunately, establishing new expert group is difficult. If there is one expert instead of the group, it occurs subjectivity and biased problem. To overcome this difficulty the data related to fuzzy pair wise comparisons that reflect expert opinion is used in different artificial neural network (ANN) models for training. Thus, if an organization has not expert group, the ANN model can be applied to select best supplier with only one expert.

LITERATURE REVIEW

In literature, a great number of studies take place that employ different methods in supplier selection. Researchers classified these methods in different ways. De Boer et al. (1998) classified the present models for the problem of supplier selection in four categories: linear weighted models, models based on cost, mathematical models and statistical models. Degraeve et al. (2005) classified the supplier selection models in the two: supplier of a single product and supplier of more than one product. In another study, Aissaoui et al. (2006) made classification as a single source and multi source models by considering the number of sources.

In this study, we classified literature of supplier selection studies in three categories namely: the studies based on multi criteria decision making methods, studies based on fuzzy logic and studies based on artificial neural network. AHP is one of multi criteria decision making methods. Some of the AHP studies are as follows: Narasimhan (1983), Hill and Nydick (1992), Barbarasoğlu and Yazgaç (1997), Tam and Tummala (2001), Muralidharan et al. (2001), Bhutta and Huq (2002), and Handfield et al. (2002). Researchers applied ANP method with different approaches for supplier selection in literature. Üstün and Demirtaş (2008) integrated ANP with multi objective integer programming approach, and Tchebycheff procedure for supplier selection. Gupta (2006) applied ANP and goal programming. It is used ELECTRE, data envelopment (DEA) and VIKOR by De Boer et al. (1998), Liu et al. (2000), respectively. Sanayie et al. (2008) applied utility theory together with linear programming and used VIKOR methods.

Fuzzy AHP and fuzzy ANP methods are widely used in fuzzy logic based studies. Some of supplier selection studies in FAHP method are as follows: Ghodsypour and O'Brien (1998), Zaim et al. (2003), Chan et al. (2008), and Chamodrakas et al. (2010). Önüt et al. (2009) used FANP together with fuzzy TOPSIS method. Güneri et al. (2009) used fuzzy linear programming, Lee et al. (2009) used fuzzy goal programming and Wang et al. (2009) used FAHP together with TOPSIS. Lin (2012) FANP is integrated with fuzzy multi-objective linear programming (FMOLP). Davood and Mellat-Parast (2012) developed grey-based decision-making model for supplier selection. Khaleiea et al. (2012) proposed novel intuitionist fuzzy clustering approach to aggregate decision maker's preferences in supplier selection problem.

Çelebi and Bayraktar (2008) applied one of the ANP based studies for supplier selection. They proposed model via ANN approach and DEA. Guosheng and Guohong (2008) worked on supplier selection by using Support Vector Machines (SVM) that eliminates some shortcomings in ANN. Kuo et al. (2010) used ANN and multi criteria decision making techniques select environment friendly supplier selection. Wu (2009) integrated decision tree and ANN approaches and used in supplier selection. Carrera (2007) developed a decision making method through ANN-ANP and used in supplier selection.

The reasons of using ANP method in this study are summarized as follows:

1. In ANP, the criteria priorities may be determined based on pair comparison rates by decision maker's judgment rather than arbitrary scales.
2. In ANP, decision-makers can be consider both tangible and intangible factors.
3. ANP can transform qualitative values into numerical values to make comparative analysis
4. ANP is so simple and intuitive approach that decision-makers can easily understand and apply it without having professional or special knowledge.
5. ANP can motivate all stakeholders and decision-makers to join the decision making process.

The fuzzy set theory could resemble human reasoning in use of approximate information and uncertainty to make decisions. Furthermore, fuzzy logic has been integrated with ANP to deal with vagueness and imprecision of decision making. Fuzzy ANP is based on pair wise comparisons. ANN model has been designed and trained from ANP results in order to obtain best supplier. Proposed model removes requirements of establishing new group. If there is only one expert as decision maker, his/her decision is accepted unbiased.

MATERIALS AND METHODS

Analytic network process (ANP) method

Saaty (1980) developed analytical hierarchical process (AHP) approach in order to solve multi criteria decision making (MCDM) problem. Interdependence and feedback were not considered for criteria and alternatives in the AHP. Saaty (1996) developed an analytical network process (ANP) to eliminate such weaknesses.

Decision makers (DMs) identify criteria and sub criteria for evaluation alternatives. Criteria and their sub criteria can be separately formed as a cluster. In addition, alternatives can also be considered as an alternative cluster. Relationships among clusters and elements inside clusters are defined as follows: *Unidirect* relationship means there is a relationship from one cluster to another. *Indirect* relationship means that there is no direct relation between two clusters but one cluster can be affected by third cluster. Another relationship is a *self-interaction* that there is a relationship among sub criteria in the same cluster. The last one is called interrelationship which represents a relationship among criteria. After completing network, pair wise comparisons are carried out among criteria, sub criteria and alternatives.

Priority values are obtained from pair wise comparison matrix. These values are located into a unweighted supermatrix. Weighted supermatrix is formed with multiplication of local weights of criteria and priorities of sub criteria from unweighted supermatrix. Limit supermatrix is obtained by taking adequate power of the weighted supermatrix. As a result, limit supermatrix shows the importance of alternatives.

One of the weakness of the ANP is that when the number of criteria and sub criteria are increased, number of pair wise comparison are dramatically become larger. Thus, it takes more time. Nevertheless, ANP provides more flexibility in constructing a decision model for real situations.

Fuzzy sets and fuzzy number

The fuzzy set was introduced by Zadeh (1965). In fuzzy set, instead of a certain number values, linguistic expressions can be defined easily. The linguistic expression allows precise modeling of imprecise statements such as "equally important", "very important" or "strongly important". An element may either belong to set or not in a classical set theory, but an element has a degree of membership in fuzzy set theory. A degree of membership function can be described as an interval [0, 1].

A fuzzy number is a special form of the fuzzy set. Fuzzy number includes a crisp real number, and interval of real numbers. It can be defined in different shapes such as triangular, trapezoidal or like. In this paper, a triangular fuzzy number (TFN) was used for intuitiveness and computational efficiency (Fasanghari and Roudsari, 2008). A TFN is shown simply as (*l, m, u*). l, m, u parameter represent smallest possible value (lower bound), mean value, the largest possible value (upper bound) respectively. $\mu_{\tilde{M}}$ is a membership function (Figure 1).

Membership function of TFN is presented as follows:

$$\mu_{\tilde{M}}(x)=\begin{cases} 0 & x<l \\ \dfrac{x-l}{m-l} & l\le x\le m \\ \dfrac{u-x}{u-m} & m\le x\le u \\ 0 & x>u \end{cases} \tag{1}$$

Fuzzy extent analysis method

For fuzzy ANP, Chang's (1996) extent analysis method was employed in the model. Variables for the extent analysis method are provided below;

Let $X=\{x_1,x_2,\ldots,x_n\}$ be an object set and $G=\{g_1,g_2,\ldots,g_m\}$ be a goal set. Each object is taken and extent analysis for each goal g_i is performed, according to this method. Thus, *m* extent analysis values for each object can be obtained with the following signs:

$M^1_{(g_i)}, M^2_{(g_i)}, \ldots, M^m_{(g_i)}, \quad i=1,2,\ldots,n$ where all the $M^j_{g_i}(j=1,2,\ldots,m)$ are triangular fuzzy numbers (TFNs). The extent analysis method steps are presented below:

Step 1

The value of fuzzy synthetic extent with respect to the i^{th} object is defined as:

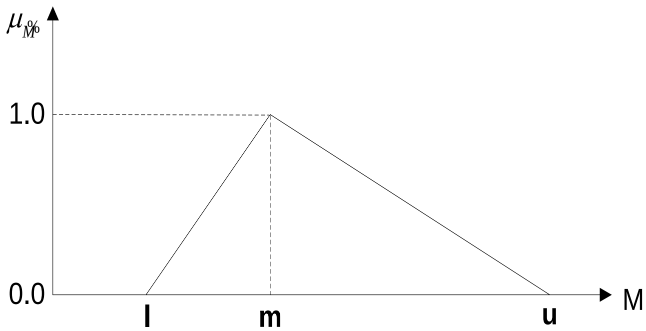

Figure 1. A triangular fuzzy number $\widetilde{M}$.

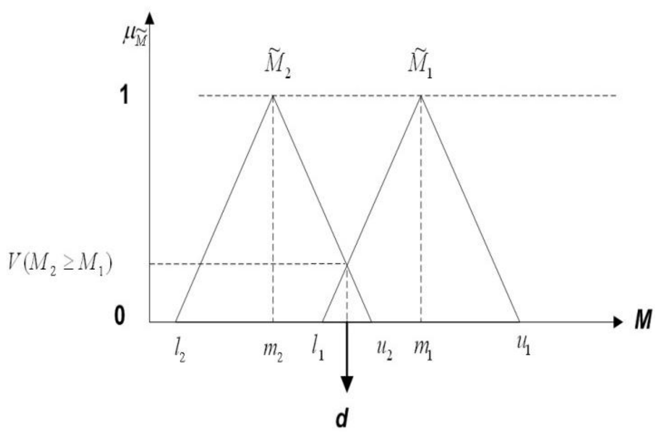

Figure 2. Intersection between M_1 and M_2.

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} \tag{2}$$

To obtain $\sum_{j=1}^{m} M_{g_i}^{j}$, perform the fuzzy addition operation of m extent analysis values for a particular matrix such that

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \tag{3}$$

and to obtain $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1}$ perform the fuzzy addition operation of $M_{g_i}^{j}$ $(j = 1, 2, ..., m)$ values such that

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right] = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \tag{4}$$

and then compute the inverse of the vector in Equation (11) such that

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right). \tag{5}$$

Step 2

The degree of the possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as

$$V(M_2 \geq M_1) = \sup[\min(\mu_{M_1}(x), \mu_{M_2}(y))] \tag{6}$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & \text{if } m_2 \geq m_1, \\ 0 & \text{if } l_1 \geq u_2, \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - u_1)} & \text{otherwise,} \end{cases} \tag{7}$$

where d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} (Figure 2). To compare M_1 and M_2, we need both the values of $V = (M_1 \geq M_2)$ and $V = (M_2 \geq M_1)$.

Step 3

The degree possibility for a convex fuzzy number to be greater than k convex fuzzy numbers, $M_i (i = 1, 2, ..., k)$ can be defined by

$$V(M \geq M_1, M_2, ..., M_k) = V\left[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and .....and } (M \geq M_k)\right]$$
$$= \min\ V(M \geq M_i), \quad i = 1, 2, ..., k \tag{8}$$

Assume that

$$d'(A_i) = \min V(S_i \geq S_k) \tag{9}$$

For $k = 1, 2, ..., n; k \neq i.$ Then the weight vector is given by

$$w' = (d'(A_1), (A_2), ...d'(A_n))^T, \tag{10}$$

where $A_i (i = 1, 2, ..., n)$ are n elements.

Step 4

Via normalization, the normalized weight vectors are

$$w = (d(A_1), d(A_2), ..., d(A_n))^T \tag{11}$$

where W is a non fuzzy number.

Artificial neural networks

Artificial neural networks (ANN) are systems that are constructed to make use of some organizational principles resembling those of the human brain (Haykin, 1994). An ANN is defined by Rumelhart and McClelland (1986) as "massively parallel interconnected network of simple (usually adaptive) elements and their hierarchical organizations which are intended to interact with objects of the real world in the same way as biological nervous systems do". The aim of the neural network is to transform the inputs into meaningful outputs. Neurons receive and provide information. A neuron is characterized by a state of activation that belongs to the range 0 (false) to 1 (true). ANNs gain their processing capability by connecting these simple neurons to other neurons with associated weights. The elements in ANN are organized into a sequence of layers which are adapted in supervise learning. A neural network's structure can be characterized by the connection pattern among elements, the transfer function for transforming input to output in elements, and the learning strategy. The several well-known supervised learning neural models are back propagation, learning vector quantization, and counter propagation network. The back propagation (BP) model is most extensively used and, therefore, selected herein. The BP neural network consists of three or more layers, including an input layer, one or more hidden layers, and an output layer. Firstly training data set is collected to develop a back propagation neural network model. Through a supervised learning rule, the data set comprises an input and an actual output (target). In the calculation phase, the propagation network receives the input data pattern and directly passes it onto the hidden layer. Each element of the hidden layer calculates an activation value by summing up the weighted inputs and then transforming the weighted input into an activity level by using a transfer function. Each element of the output layer is used to calculate an activation value by summing up the weighted inputs attributed to the hidden layer. Next, the actual network output is compared with the target or real value. If a difference arises, that is, an error term, the gradient-descent algorithm may be used to adjust the connected weights. If no difference arises, no learning is preceded with (Su and Hsieh, 1998).

PROPOSED MODEL

The steps of the proposed supplier selection model using fuzzy ANP based on ANN are as shown ın Figure 7.

Step 1

Set up an expert team: An expert team is formed in order to determine criteria, sub-criteria, alternatives and pair wise comparison matrices.

Step 2

Determine criteria, sub criteria: The number of criteria used in supplier selection model may vary according to characteristic of product and purchase conditions. Criteria and sub criteria were determined to evaluate alternatives extracted from literature and expert team's opinions.

Step 3

Generate ANP model: Each main criteria, criteria and sub criteria forms a cluster. The relationship among criteria of clusters or the relationship among sub criteria of other clusters forms a network structure.

The relationship among cluster's own sub criteria is defined by arc. The relationship among sub criteria shows whether cluster relationships are one or double ways.

Step 4

Determine fuzzy pair wise matrices: A special questionnaire survey, which consists of pair wise comparisons between elements, is applied to gather opinions of experts. They compare two elements between themselves by considering another element as a base. Experts identify levels of importance of elements from five different levels namely "equally important", "weekly important", "strongly important", "very strongly important" and "absolutely important" on five fuzzy scales (Table 1).

Step 5

Calculate weights based on fuzzy set: Linguistic expression of expert is converted into triangular fuzzy numbers. It is formed pair wise comparison matrices. Priority weights are calculated by considering matrix values in Chang's algorithm (Chang, 1996).

Step 6

Calculate weights based on artificial neural networks: In ANN training, the pair wise matrix values obtained from the expert group are used as input data, whereas output data is the weight values obtained from solution of these matrices. These values using in training of ANN are shown in Figure 3. The ANN models are formed by experts' opinions. Different ANN model has been developed for each of different pair wise comparison matrices. New different expert's pair wise comparison values are entered to trained ANN model.

Step 7

Form limit supermatrix: An unweighted supermatrix is formed by setting the importance weights elements on their suitable columns. The weight values found by using ANN model constitute elements of unweighted supermatrix. Elements in this matrix reflect the effect of the sub criteria on a row to other sub criteria on a column. Unweighted supermatrix may consist of zero values. In general, there exists interdependence between clusters, the sum of one column in the unweighted supermatrix is mostly bigger than 1. In case k displays a great random number, the supermatrix is increased to power 2k+1 and thus it approximates to limit namely importance weight. The new matrix which is called limit supermatrix, displays the importance of elements. All values are equal in the limit supermatrix.

Step 8

Determine best alternatives: The suppliers are lined up according to their decreasing weight values.

Step 9

Verify results: The values of local weights found by fuzzy ANP are compared by weights of ANN model that learns these values.

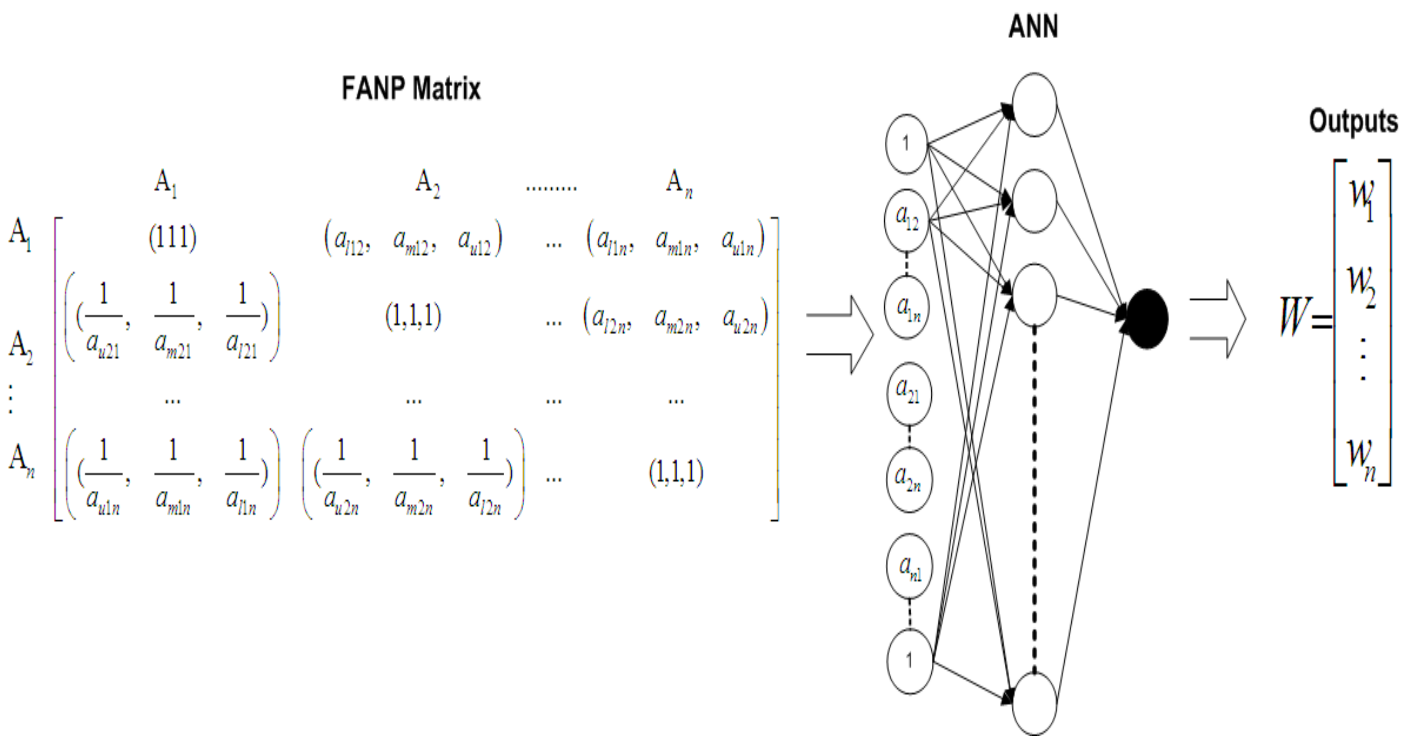

Figure 3. ANN model for developed approach.

RESULTS AND DISCUSSION

The application of the proposed supplier selection model is shown with an illustrative example.

Step 1: Set up an expert team

An expert team was founded by 12 persons. Team determined relations among criteria and sub criteria of fuzzy ANP and made pair wise comparisons between elements of the model of fuzzy ANP.

Step 2: Determine main criteria, criteria and sub criteria

In determining criteria and sub criteria, the opinions of team members were taken and data derived from literature (Carrera, 2007; Jharkhariaa and Shankar, 2005; Langey et al., 2003; Sarkis, 2003; Meade and Sarkis 1998; Ravi et al., 2005; Yang and Chen, 2006; Kannan and Tan, 2002; Langley et al., 2002). The criteria were gathered hierarchically in three phases. The three main criteria were on overall performance, supplier features and management ability. Total of thirteen criteria and forty-two sub criteria were determined (Table 2). Three suppliers were determined as alternatives and named as A, B and C.

Step 3: Generate ANP model

The relationships among the elements of the model were defined. Each main criterion was defined as a cluster. For example, there was an interaction between sub criteria belonging to main criteria of general performance, which was shown with an arc. Sum of sub criteria belonging to main criteria of general performance impressed the main criteria of management. At the same time, some sub criteria of the same main criteria was impressed from sub criteria belonging to main criteria of supplier features. The relationship between cluster and cluster's own sub criteria are shown in Figure 4.

Step 4: Determine fuzzy pair wise matrices

Pair wise forms were filled by members of the expert team in order to find importance of weight of criteria. One expert's fuzzy pair wise comparison matrix was formed in Table 3.

Step 5: Calculate weights based on fuzzy set

Chang's algorithm was applied in order to find criteria

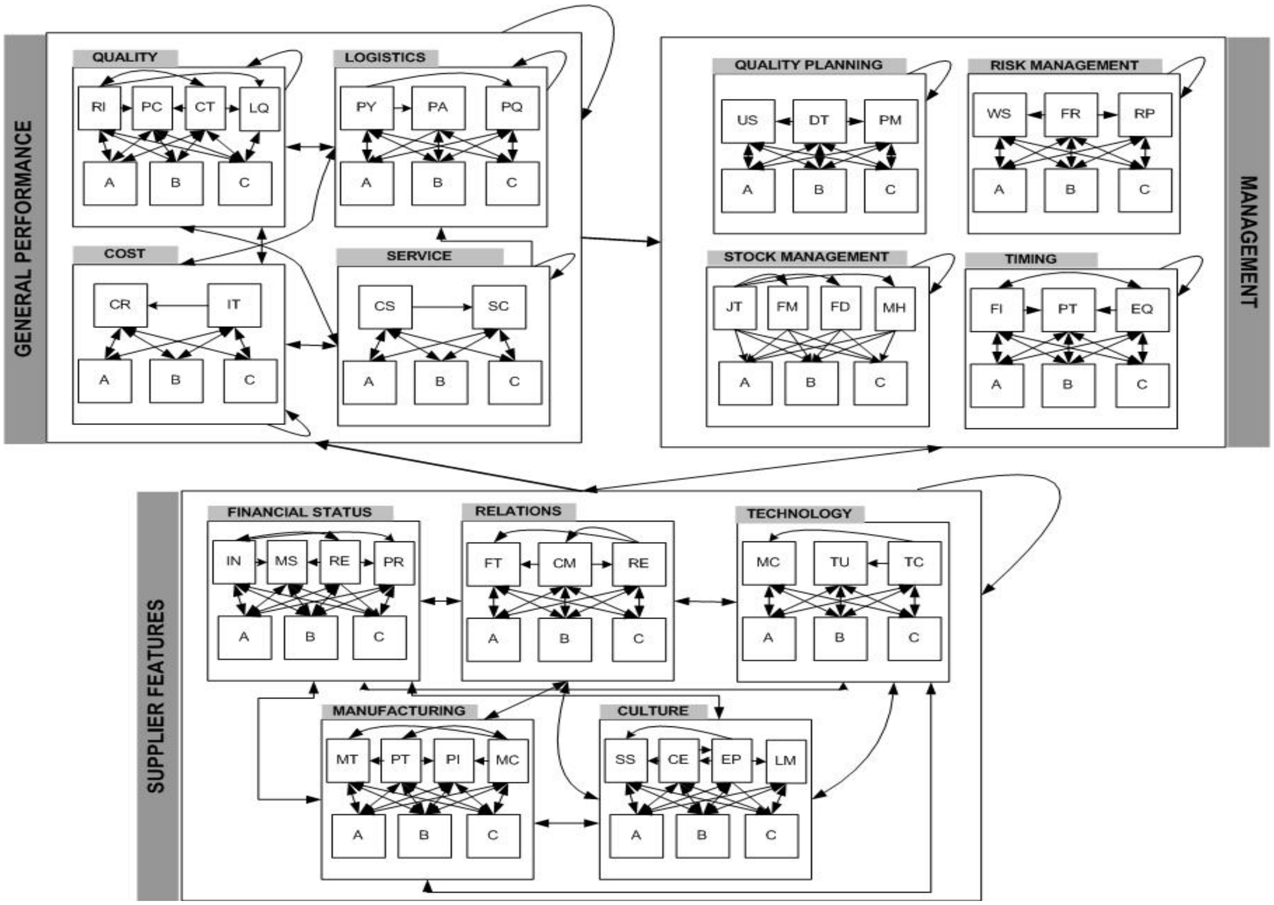

Figure 4. Relationships among criteria, sub criteria and clusters.

weights that take place in fuzzy pair wise comparison matrice. An excel software developed and later used in similar calculations for the solution due comparison matrix with dimensions 2 × 2, 3 × 3, 4 × 4 and 5 × 5 in the model. Every calculation procedure was repeated twelve times (for twelve experts). For logistic criteria example (Table 3), calculation of weights according to Chang algorithm, was stated as follows:

$$S_1=\left[(1,1,1)\oplus(1,1,1)\oplus(2/5,1/2,2/3)\right]\otimes\left[\frac{1}{11.16667},\frac{1}{9.5},\frac{1}{8.2333}\right]$$

$$=(2.4,2.5,2.6667)\otimes\left[\frac{1}{11.16667},\frac{1}{9.5},\frac{1}{8.2333}\right]$$

$$=(0.214925,0.263158,0.323887)$$

Similarly, consequent values of (0.238886, 0.315789, 0.425101) and (0.283582, 0.421053, 0.607287) were found for S_2 and S_3. Calculation results are given below:

$$V(S_1\geq S_2)=\frac{0.238806-0.323887}{(0.263158-0.323887)-(0.315789-0.238806)}=0.617815$$

$$V(S_1\geq S_3)=\frac{0.283582-0.323887}{(0.263158-0.323887)-(0.421053-0.238806)}=0.203354$$

$$V(S_2\geq S_1)=1.0$$

$$V(S_2\geq S_3)=\frac{0.283582-0.425101}{(0.315789-0.425101)-(0.421053-0.283582)}=0.573457$$

$$V(S_3\geq S_1)=1.0,$$

$$V(S_3\geq S_2)=1.0$$

$$d'(QU)=\min V(S_1\geq S_2,S_3)=min(0.617815,0.203354)=0.203354$$

$$d'(LO)=\min V(S_2\geq S_1,S_3)=min(1.0,0.573457)=0.573457$$

$$d'(CO)=\min V(S_3\geq S_1,S_2)=min(1.0,1.0)=1.0$$

Finally, $w=(0.203354,0.573457,1.0)^T$ was calculated.

When the weight vector was normalized the consequent weight values of 0.114, 0.323 and 0.563 were found for QU, LO and CO criteria.

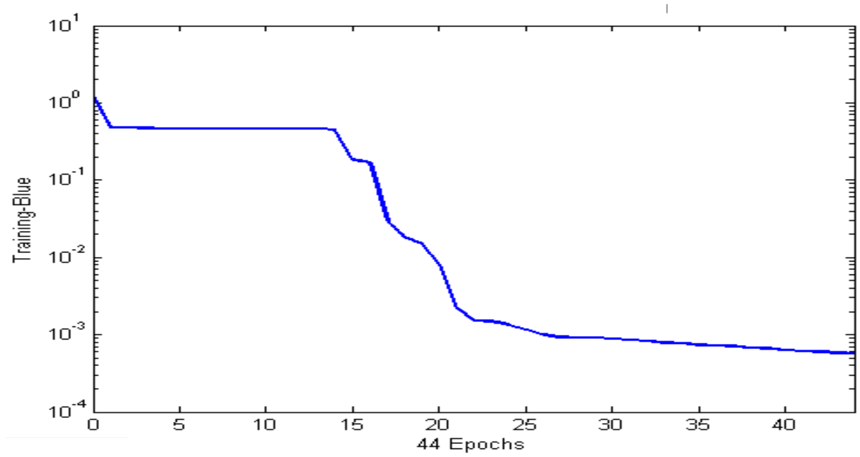

Figure 5. Performance graphic of tested ANN models.

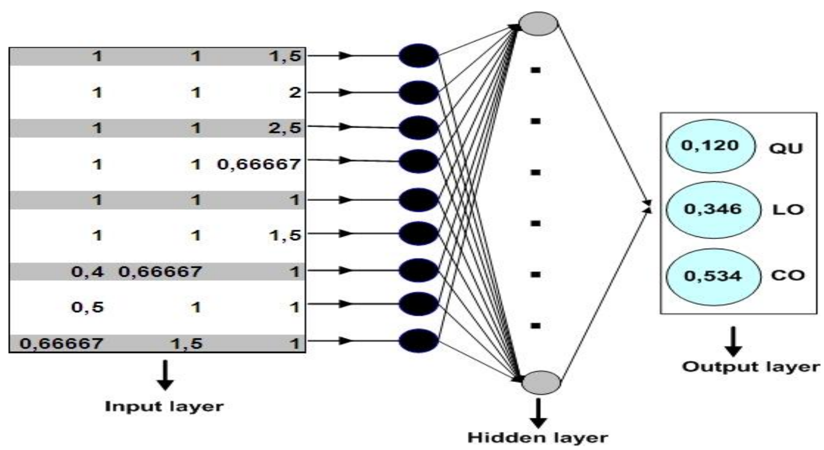

Figure 6. Network structure that calculates the weights of criteria according to logistic criteria.

Step 6: Calculate weights based on artificial neural networks

Learning of artificial neural network was completed by fuzzy pair wise comparison values obtained from pair wise comparison matrix. The comparison matrix based on logistic criteria was a pair wise comparison matrix with dimensions 3 × 3, and the purpose was to obtain three weight values. The developed ANN model was comprised of three layers. In an input layer, there were nine input cells, and an output layer there were three cells, and in a hidden layer, there were nine cells. Fuzzy ANP pair wise comparison matrix was used in order to obtain ANN input data. In this way, weight values of thirtysix (12 × 3) were obtained from twelve pair wise comparison matrix belonging to criteria in the model. These values used as output in the model. The model was trained by using Levenberg-Marquardt (TRAINLM) algorithm. Input matrix of $(36x9)^T$, output matrix of $(36x1)^T$, and three different test data (9 × 3) were used in the model. Training curve of the model is given Figure 5.

When fuzzy pair wise comparison values belonging to new expert were input into trained ANN model, QU, LO and CO values were obtained (Figure 6). Data relating to matrix dimension oncerning all ANN models that used in this study are given in Table 4.

Step 7: Form limit supermatrix

The obtained values from ANN model were placed in the appropriate column of unweighted supermatrix. The cluster weights were multiplied with the elements in that cluster and from this weighted matrix was obtained. The

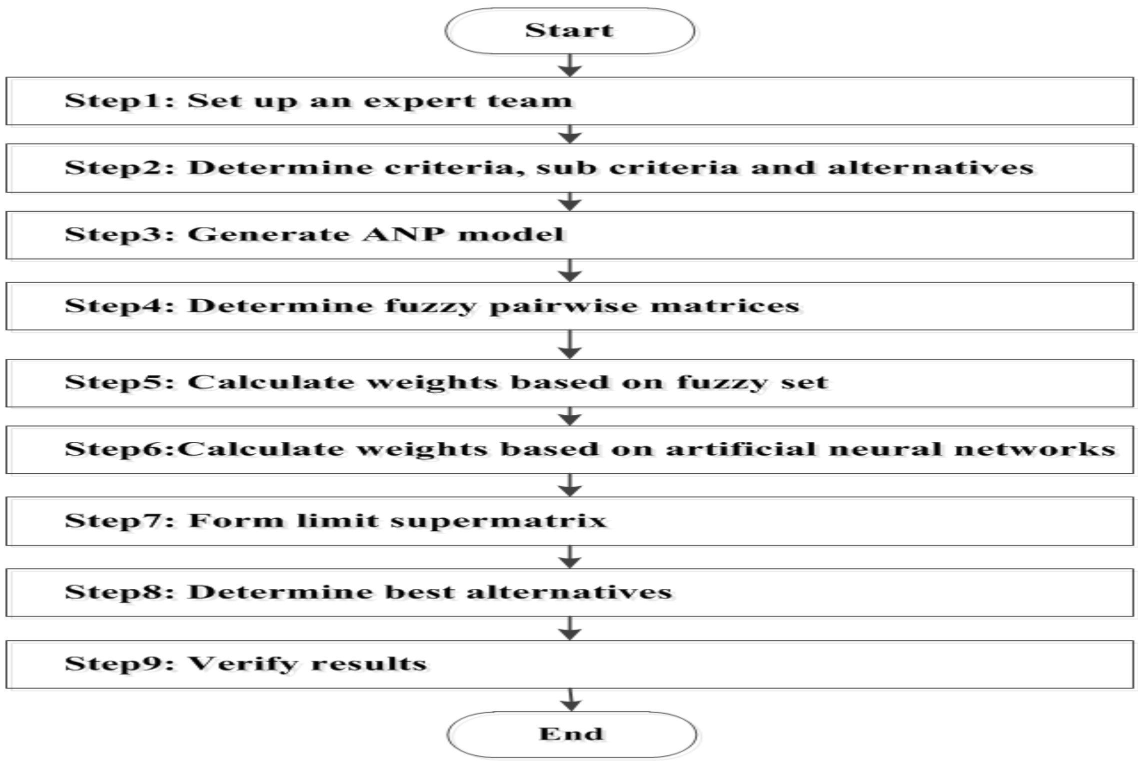

Figure 7. Steps of the proposed supplier selection model using fuzzy ANP based on ANN.

Table 1. Linguistic scales of importance.

Linguistic scale of importance	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Equally important	(1, 1, 1)	(1, 1, 1)
Weakly important	(2/3, 1, 3/2)	(2/3, 1, 3/2)
Strongly important	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly important	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)
Absolutely important	(7/2, 4, 9/2)	(2/9, 1/4, 2/7)

Table 2. Main criteria, criteria and sub criteria of model.

Main criteria	Criteria	Sub criteria
General performance	Cost (CO)	Item cost (IT)
		Cost reduction (CR)
	Service (SE)	Service capability (SC)
		Customer satisfaction (CS)
	Quality (QU)	Refurbished item (RI)
		Process (PC)
		Corrections (CT)
		Level of quality (LQ)
	Logistics (LO)	Payment (PY)
		Production quantity (PQ)
		Packaging (PA)
Supplier features	Technology (TE)	Technology using (TU)
		Manufacturing capability (MC)
		Technology capability (TC)

Table 2. Contd.

	Culture (CU)	Expertise (EP) Certifications (CE) Six sigma (SS) Lean manufacturing (LM)
	Financial status (FS)	Revenue (RE)) Profitability (PR) Market share (MS) Investment (IN)
	Relations (RL)	Feeling of Trust (FT) References (RE) Communication (CM)
	Manufacturing (MA)	Process improvement (PI) Machine capabilities (MC) Maintenance (MT) Production time (PT)
Management	Quality planning (QP)	Design and test capability (DT Performance measurement (PM) Usage (US)
	Risk management (RM)	Firm reputation (FR) Worker satisfaction (WS) Risk planning (RP)
	Stock management (SM)	Just in time management (JT) Flexible manufacturing (FM) Flexible distribution (FD) Material handling (MH)
	Timing (TI)	Project completing time (PT) First delivery time (FI) Equipment (EQ)

Table 3. Fuzzy comparison matrix based on logistic criteria of general performance cluster.

GP	QU	LO	CO
QU	(1,1,1)	(1,1,1)	(2/5,1/2,2/3)
LO	(1,1,1)	(1,1,1)	(2/3,1,3/2)
CO	(3/2,2,5/2)	(2/3,1,3/2)	(1,1,1)

weighted matrix was taken power to reach limit values. The new matrix which is called limit supermatrix displays the effects of elements on each other in the long run. The limit supermatrix represents the same structure as the weighted supermatrix. All columns of limit supermatrix are alike (Appendix).

Step 8: Determine the best alternative

The final priorities of the all elements in the matrix were determined by normalizing each column in the supermatrix. Therefore, the priorities of alternatives were seen in the column of alternatives in the limit super matrix. This matrix showed that A,B, and C suppliers have consequently 0.0341, 0.0187 and 0.0214 values. The results showed that alternative A has the highest value (Table 5).

Step 9: Verify results

The weight values of QU, LO and CO belonging to twelve experts calculated by fuzzy ANP and ANN, and difference

Table 4. Data on ANN model.

Matrix properties	Model 1	Model 2	Model 3	Model 4
Matrix dimension	2×2	3×3	4×4	5×5
Input data dimension	6×6	36×9	48×12	60×15
Output data dimension	6×1	36×1	48×1	60×1
Number of layers	3	3	3	3
Number of input layer nodes	6	9	12	15
Number of hidden layer nodes	4	9	10	12
Number of output layer nodes	2	3	4	5
Training function	TRAINLM	TRAINLM	TRAINLM	TRAINLM
Transfer function	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Iteration number	8	35	15	13
Performance	5.413e-022	0.00045	9.017e-005	4.447e-005

Table 5. Results.

Supplier	Ideal	Normal	Raw
A	1.0000	0.4587	0.0341
B	0.5504	0.2552	0.0187
C	0.6292	0.2886	0.0214

values of them (error) were given in Table 6.

Hypothesis test was applied in order to get the information as to whether there was a meaningful difference between weights obtained FANP and ANN. μ_1 was mean of the weight values found by fuzzy ANP. Similarly μ_2 was mean weight values found by ANN. The hypotheses in the model were:

$H_0: \mu_1 = \mu_2 = 0$ or $H_0: \Delta = 0$

$H_a: \mu_1 = \mu_2 \neq 0$ or $H_0: \Delta \neq 0$

The appropriate test statistic was test statistic for matched pairs:

$$t_c = \frac{\bar{D} - \Delta}{s_D / \sqrt{n}} \text{ with v=n-1.} \quad (12)$$

where Δ is average difference in scores between the two populations, $\bar{D}$ was average difference in scores. s_D was standard deviation of the difference scores, n was number of matched pairs. For QU criterion $\bar{D}$ and s_D were calculated as -0.000426 and 0.017019 respectively. Substituting these values into Equation 12 yielded.

$$t_c = \frac{-0.000426 - 0}{0.017019 / \sqrt{12}} = -0.09$$

The p-value was 0.932 for α is 0.05. Since this value was quite large, we cannot reject the null hypothesis and thus conclude that the two weight means do not differ significantly. Similar calculations were done for LO and CO criteria. The p-values for LO and CO criteria were 1.0 and 0.964 respectively. They are large and we conclude that difference scores between the weights found by ANP and ANN show do not differ significantly.

Therefore, it can be concluded that there is no meaningful difference between fuzzy ANP and ANN models' scores.

Conclusion

Supplier selection is increasingly becoming a greater decision making problem. Organizations have to make supplier evaluations according to many different criteria. In this study, a detailed ANP model is developed in which many qualitative and quantitative criteria take place. Also, relations between ANP and criteria can be evaluated. However, fuzzy set is used because experts aimed to express their judgment in uncertainty situations. ANN model is developed to determine the weights from pair wise comparisons matrixes. In case expert judgments on ANN models change, matrix weighted values will be easily obtained without taking their judgments. Thus, there will be no need for transaction procedure to evaluate pair wise comparisons obtained from many experts. In addition to this, when there is only one expert, the subjectivity and unbiased will be eliminated because information has been obtained from a lot of experts'

Table 6. Data of model (3x3 matrix).

Expert	Criteria	FANP weights	ANN weights	Error
	QU	0.11445	0.11445	2.39E-08
1	LO	0.32275	0.32804	0.0052941
	CO	0.56281	0.50675	0.056055
	QU	0.22559	0.18584	0.039747
2	LO	0.32372	0.31758	0.0061377
	CO	0.4507	0.50675	-0.056055
	QU	0.4507	0.4507	5.25E-08
3	LO	0.32372	0.31758	0.0061377
	CO	0.22559	0.18584	0.039746
	QU	0.70781	0.70781	-9.64E-09
4	LO	0.14609	0.14609	2.88E-09
	CO	0.14609	0.18584	-0.039747
	QU	0.43374	0.43374	-5.79E-08
5	LO	0.36276	0.36276	-4.04E-08
	CO	0.20351	0.1748	0.028707
	QU	0.047879	0.047879	9.55E-08
6	LO	0.66257	0.66257	1.61E-08
	CO	0.28955	0.31144	-0.02189
	QU	0.33333	0.33333	-4.64E-08
7	LO	0.33333	0.32804	0.005294
	CO	0.33333	0.32804	0.0052939
	QU	0.66257	0.66257	-2.04E-07
8	LO	0.28955	0.31758	-0.028028
	CO	0.047879	0.047879	-7.28E-08
	QU	0.32275	0.32804	0.0052941
9	LO	0.56281	0.56281	7.96E-08
	CO	0.11445	0.11445	1.04E-07
	QU	0.14609	0.14609	9.96E-08
10	LO	0.70781	0.70781	1.13E-07
	CO	0.14609	0.1748	-0.028706
	QU	0.14609	0.18584	-0.039746
11	LO	0.14609	0.14609	2.82E-08
	CO	0.70781	0.70782	-3.58E-07
	QU	0.33333	0.33333	-5.65E-08
12	LO	0.33333	0.31758	0.015752
	CO	0.33333	0.31144	0.02189

judgments. The advantages of adapting artificial neural network to fuzzy ANP model can be summarized as follows:

1. In case expert judgments change according to supplier qualifications, it won't be necessary to reform the pair wise comparisons matrix in fuzzy ANP model.
2. The cost of forming expert (or decision) group will decrease.
3. The difficulty of reducing the group decision to one single decision will be eliminated.
4. It is possible to reduce calculations for the solution of fuzzy pair wise comparisons.
5. The weights can be directly calculated without using any method.

It will be attractive for researchers to apply other neural network learning methods as Hebbian learning, Boltzmann learning and memory based learning. Multi-layer perceptions have been used in this study. Researchers should use radial-basis function networks and support vector machines instead of multilayer perceptions. Researchers should also use different fuzzy logic methods as intuitionistic fuzzy sets with neural networks. Thus, it will be possible to see which fuzzy set-neural network integration has an advantage in dealing with the supplier selection problem.

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APPENDIX

	IT	CR	SC	CS	RI	PC	CI	LQ	PY	PQ	PA	TU	MC	TC	EP
IT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CR	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
SC	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
CS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RI	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
PC	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CT	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
LQ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PY	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
PQ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PA	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
TU	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MC	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
TC	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
EP	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CE	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
SS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
LM	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
RE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
PR	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
MS	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
IN	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
FT	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
RE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
CM	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PI	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
MC	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PT	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
DT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PM	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
US	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
FR	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
WS	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
RP	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
JT	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FM	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FD	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MH	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PT	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FI	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
EQ	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
A	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
C	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

APPENDIX Contd.

	CE	SS	LM	RE	PR	MS	IN	FT	RE	CM	PI	MC	MT	PT	DT
IT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CR	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
SC	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
CS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RI	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
PC	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CT	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
LQ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PY	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
PQ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PA	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
TU	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MC	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
TC	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
EP	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CE	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
SS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
LM	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
RE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
PR	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
MS	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
IN	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
FT	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
RE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
CM	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PI	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
MC	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PT	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
DT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PM	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
US	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
FR	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
WS	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
RP	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
JT	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FM	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FD	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MH	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PT	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FI	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
EQ	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
A	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
C	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

APPENDIX Contd.

	PM	US	FR	WS	RP	JT	FM	FD	MH	PT	FI	EQ	A	B	C
IT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CR	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
SC	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
CS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RI	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
PC	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CT	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
LQ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PY	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
PQ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PA	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
TU	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MC	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
TC	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
EP	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CE	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
SS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
LM	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
RE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
PR	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
MS	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
IN	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
FT	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
RE	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
CM	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PI	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
MC	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PT	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
DT	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PM	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
US	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
FR	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
WS	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
RP	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
JT	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FM	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FD	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
MH	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
PT	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
FI	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
EQ	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
A	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
C	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01