Supplier Selection using Artificial Neural Network & Fuzzy Set Theory

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Abstract - **Suppliers are an important part of the supply chain. Selection of appropriate suppliers often becomes the key to success of the supply chain. Thus the evaluation and selection of suppliers becomes a very important activity in any company. Supplier selection is a well-known multi criteria decision making (MCDM) problem. In this paper we propose the use of Artificial Neural Network (ANN) to solve this MCDM problem. Fuzzy set theory has been used to generate the training data set for the ANN. First the criteria's that will be used to assess suppliers is decided upon. Next the importance associated with each criterion is decided and then the performance of each supplier on each criterion is decided. Due to the subjectivity involved in human assessment, it becomes difficult to represent the assessment in pure numbers. At the same time it is quite easy to represent the assessment in terms of linguistic variables. Hence we have chosen Fuzzy set theory to generate the training data set for the ANN, as it allows the decision makers to express their preferences in linguistic terms. These linguistic terms are then converted into fuzzy numbers by using fuzzy membership functions. Fuzzy mathematical operators are then used to determine a fuzzy score for each supplier. These fuzzy scores are then translated into crisp scores. We use the linguistic performance (Poor, Good, Very Good, and Excellent) of the supplier on the various criteria and the crisp score of the supplier for training the ANN. We see that the trained neural network is able to predict the crisp score for a new supplier with a high accuracy. ANN has been used for a regression problem.**

Keywords: neural network; supplier selection; fuzzy logic

I. INTRODUCTION

In contemporary supply chain management, the evaluation and selection of suppliers is performed by considering multiple criteria rather than considering a single factor of cost. Companies want to maintain long term partnership with suppliers. Their focus is on using fewer but reliable suppliers. It has been observed that in manufacturing companies, purchasing's share in the total turnover typically ranges between 50-90%. Thus purchasing activities within a supply chain play a strategic role in the profitability of a company. Hence choosing a supplier involves much more than scanning a price list. Supplier selection is a MCDM problem involving a wide range of qualitative and quantitative factors. The advantages of supply chain management have been presented by researchers and practitioners. A well designed and well implemented supply chain provides a competitive advantage to any company. Under such condition, building on the closeness and long term relationships between buyers and suppliers is a critical success factor to establish the supply chain system. Therefore, supplier selection becomes the most important issue to implement a successful supply chain system. Extensive multi-criteria decision making approaches have been proposed for supplier selection.

Weber et al., [15]; Degraeve et al., [6]; De Boer et al., [5] & Ho et al., [10] are some of the journal articles that have performed an extensive literature review regarding the supplier selection and evaluation models. Contemporary operations research provides many methods to solve the supplier selection problem. Some of the methods used are categorical methods, data envelopment analysis (DEA), cluster analysis (CA), case based reasoning (CBR), linear weighting models, total cost of ownership (TCO) model, mathematical programming model, statistical model, analytic hierarchy process (AHP), analytic network process (ANP), genetic algorithm (GA), fuzzy set theory and their hybrids. For further details on how these methods have been used to solve the supplier selection problem on can refer to the literature review journal articles mentioned above.

In this paper we propose an ANN to solve the supplier selection problem. This paper is organized as follows. In section II we introduce the basic concepts of fuzzy set theory. We then use one of the fuzzy set theory approaches to generate the training data for the ANN. In section III we propose the ANN to solve the supplier selection problem. We present the results, conclusion and future scope in section IV.

II. FUZZY SET THEORY

Fuzzy set theory introduced by Zadeh [17] is used to represent the vagueness of human thinking. Zadeh [18], while presenting the computational theory of perceptions, emphasizes the key role perceptions play in human recognition, decision, and execution processes. An appropriate approach to dealing with the qualitative and incomplete nature of information involved in supplier selection is to use expert's opinion for a subjective evaluation of suppliers followed by a fuzzy set theoretic analysis to take care of the fuzzy nature of these evaluations. The use of crisp numbers to quantify human perceptions does not reflect the imprecision and partial truth that surrounds human perception and decisions (Zadeh, [18]).

In this section we will review some basic definitions of fuzzy sets, fuzzy numbers and linguistic variables (Zimmerman, [19]).

A fuzzy set A in a universe of discourse X is characterized by a member ship function $\mu_A(x)$ which associates with each element x in X a real number in the interval [0,1]. The function value $\mu_A(x)$ is termed as the grade of membership of x in A.

A fuzzy set A in the universe of discourse X is convex if and only if:

$$\mu_A(\lambda x_1 + (1 - \lambda)x_2) >= \min(\mu_A(x_1), \mu_A(x_2))$$
$$\text{for all } x_1, x_2 \text{ in x and all } \lambda \in [0,1]$$

The height of a fuzzy set is the largest membership grade attained by any element in that set. A fuzzy set A in the universe of discourse X is called normalized when the height of A is equal to 1.

A fuzzy number is a fuzzy subset in the universe of discourse X that is both convex and normal.

The α-cut of a fuzzy number n is defined as:

$$n^{\alpha} = \{ x_i : \mu_n(x_i) >= \alpha, x_i \in X\}, \text{ where } \alpha \in [0,1].$$

A positive trapezoidal fuzzy number (PTFN) n can be defined as (n_1, n_2, n_3, n_4). The membership function $\mu_n(x)$ = defined as:

$$\mu_n(x) = 0, \quad x < n_1,$$
$$\mu_n(x) = x-n_1/n_2-n_1, \quad n_1<=x<=n_2,$$
$$\mu_n(x) = 1, \quad n_2<=x<=n_3,$$

$$\mu_n(x) = x-n_4/n_3-n_4, \quad n_3<=x<=n_4,$$
$$\mu_n(x) = 0, \quad x>n_4.$$

For a trapezoidal fuzzy number n = (n_1, n_2, n_3, n_4) if $n_2 = n_3$, then n is called a triangular fuzzy number. A non fuzzy number r can be expressed as (r, r, r, r). By the extension principle (Dubois & Prade, [7]), the fuzzy sum + and fuzzy subtraction – of any two trapezoidal fuzzy numbers are also trapezoidal fuzzy numbers; but the multiplication × of any two trapezoidal fuzzy numbers is only an approximate trapezoidal fuzzy number. Given any two PTFZ m = (m_1, m_2, m_3, m_4) and n = (n_1, n_2, n_3, n_4) and a positive real number r, some fuzzy operations are defined below:

$$m + n = [m_1+n_1, m_2+n_2, m_3+n_3, m_4+n_4],$$
$$m - n = [m_1-n_4, m_2-n_3, m_3-n_2, m_4-n_1],$$
$$m \times r = [m_1r, m_2r, m_3r, m_4r],$$
$$m \times n \approx [m_1n_1, m_2n_2, m_3n_3, m_4n_4].$$

A linguistic variable is a variable whose values are expressed in linguistic terms (Zimmerman, [19]). The concept of a linguistic variable is very useful in dealing with situations, which are too complex or not well defined to be reasonably described in conventional quantitative expressions.

Let m = (m_1, m_2, m_3, m_4) and n = (n_1, n_2, n_3, n_4) be two trapezoidal fuzzy numbers. Then the distance between them can be calculated by using the vertex method as (Chen, [1])

$$d_v(m,n) = \sqrt{\left(\frac{1}{4}\right)[(m1-n1)^2 + (m2-n2)^2 + (m3-n3)^2 + (m4-n4)^2}$$

According to the vertex method two trapezoidal numbers m and n are identical if and only if $d_v(m,n) = 0$. Let m, n and p be three trapezoidal fuzzy numbers. Fuzzy number n is closer to fuzzy number m than the other fuzzy number p if and only if $d_v(m,n) < d_v(m,p)$ (Chen, [2]).

Ordoobadi [12] also uses fuzzy logic to develop a supplier selection model. Author proposes that this task can be done in a two step process. The first step is the identification of the supplier selection criteria and the second step is development of a methodology that uses these criteria for evaluation and ranking of suppliers. In order to identify a set of criteria that is well accepted, the author has surveyed the vendor selection literature. After a careful review of the criteria uncovered in the literature and eliminating the duplications five main criteria and several sub-criteria were identified by the author. The factors considered in supplier selection are situation specific and each company will develop its own selection criteria when faced with the problem of finding the appropriate suppliers. Once the criteria are set, we need a mechanism to record the decision maker's input in both the areas. In order to capture the subjectivity in the decision maker's preference fuzzy logic has been used by the author.

Many authors have used fuzzy set theory for supplier selection problem. Readers can find some of the approach in [4],[8],[11],[13] and [14]. We have used Ordoobadi's [12] approach to generate the training data for training the ANN.

The criteria could have a multi-level hierarchy. In the example above we have a three level hierarchy. Each of the criteria are required to be rated on the linguistic importance scale depending on how important it is for the company. We have used a trapezoidal membership function as the weights for the criteria. Please refer Table I and Figure 1.

TABLE I: The linguistic importance scale

Low importance (L)	(0.0, 0.0, 0.2, 0.4)
Moderate importance (M)	(0.2, 0.4, 0.4, 0.6)
High importance (H)	(0.4, 0.6, 0.6, 0.8)
Very high importance (VH)	(0.6, 0.8, 1.0, 1.0)

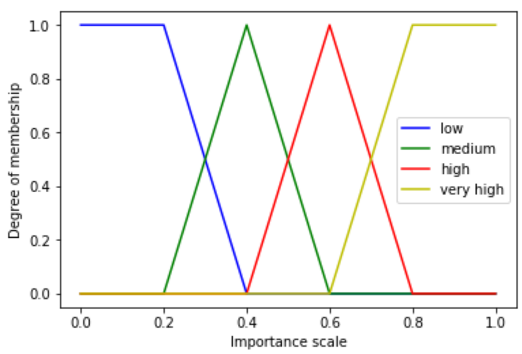

Figure 1: The membership functions for linguistic importance scale

The importance criteria for suppler selection is as shown in Figure 2. We thus have ten final criteria (coloured in green) in this example in figure 2 and we will rate supplier on these ten criteria. To find the fuzzy weight of criteria at the last level we will use fuzzy multiplication. For example the weight of criterion "change in quantity" will be a product of H*H*H.

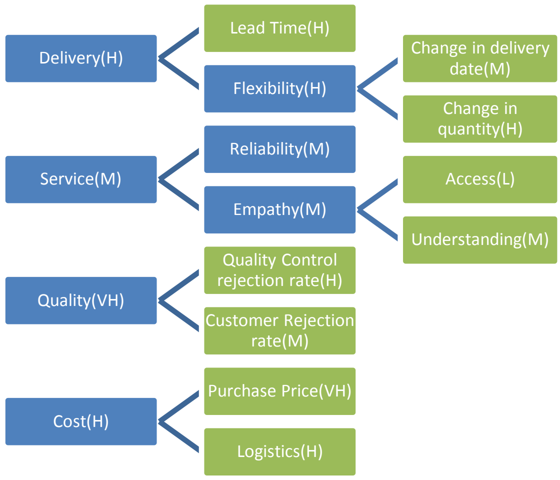

Figure 2: Example importance criteria for a company

Similarly we have the performance scale for assessing supplier performance.

TABLE II: The linguistic supplier performance scale

Poor (P)	(0, 0, 2, 4)
Good (G)	(2, 4, 4, 6)
Very Good (VG)	(4, 6, 6, 8)
Excellent (EX)	(6, 8, 1, 1)

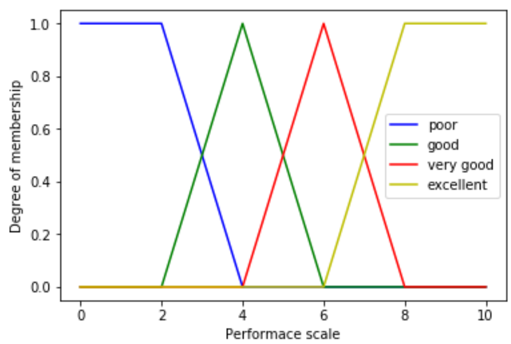

Figure 3: Membership function of linguistic performance

To generate data for ANN we generate 1000 suppliers and randomly rate then on the ten defined criteria and using fuzzy logic we generate the crisp scores. This is done as below:

Let w_i denote the fuzzy importance weight of criterion i. i = 1 to 10 in our example. Let r_{ji} denote the fuzzy performance rating of supplier j with respect to criterion i. j = 1to 1000 in our case. r_{ij} are generated randomly between P, G, VG and EX.

Fuzzy Score(j) = $\sum_{i=1}^{10} wi * rji$
Score(j) = Defuzzify(Fuzzy Score(j))
Defuzzification is done using center of area method.

III. ANN BASED MODEL

An artificial neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects. First, knowledge is acquired by the network from its environment through a learning process. Second, Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

In order to solve the supplier selection problem, a highly popular algorithm known as the back-propagation algorithm has been used. The back-propagation algorithm is a multilayer perceptron network based on the error-correction learning rule. It consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass an input vector is applied to the sensory nodes of the network and its effects propagates through the network layer by layer. During the forward pass the synaptic weights of the network are all fixed. A set of outputs is produced as the actual response of the network. During the backward pass the synaptic weights are all adjusted based on an error-correction rule (Haykin, [9]).

The ANN model is constructed as a three layer perceptron architecture. The number of input neurons is ten which is equal to the number of supplier selection criteria that is being considered in this model. The number of hidden layer neurons is also ten. This is obtained by means of trial and error experiments. There is one output neuron in the output layer. Thus we have constructed a 10-10-1 multilayer perceptron architecture as shown in Figure 4.

We use Keras with Tensorflow backend to implement our neural network. We use 900 suppliers for training and 100 for testing the trained network. The various parameters used for training are as follows:

Loss function: Mean squared error (MSE)
Activation function: tanh for hidden layer and linear for output layer
Number of epochs: 200
Batch size (for batch gradient descent): 32
Optimizer: Adam
We used the default parameters for adam optimizer in keras with learning rate of 0.001, beta_1 of 0.9 and beta_2 of 0.999

We have used ANN for a regression problem rather than a classification problem. We are predicting the crisp scores of the suppliers based on the linguistic performance rating of a supplier.

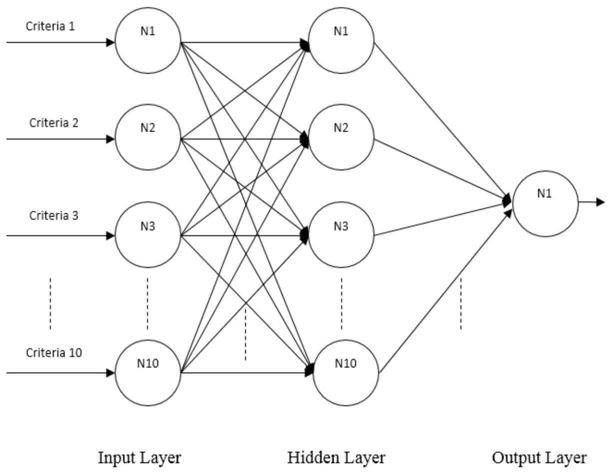

Figure 4: ANN Architecture

IV. RESULTS

It is found that the after successful training the ANN is correctly able to predict the supplier scores with a high accuracy. The mean squared error is only 0.3. This shows that when a meaningful data is supplied for the training purpose the machine learning of ANN is capable of correctly predicting the supplier's score. The comparison of the test data of actual vs predicted is shown in figure 5. The suppliers in test group were sorted in increasing order of actual supplier score for better visual comparison. The MSE is 0.3

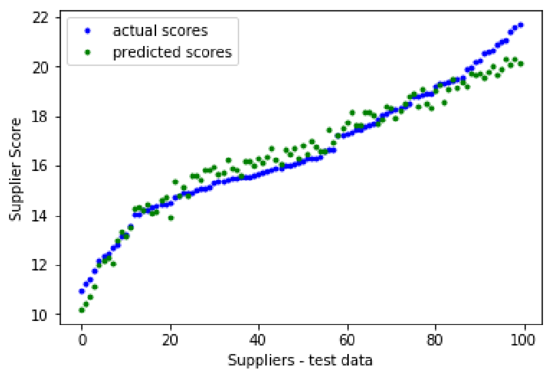

Figure 5: Actual vs Predicted supplier scores

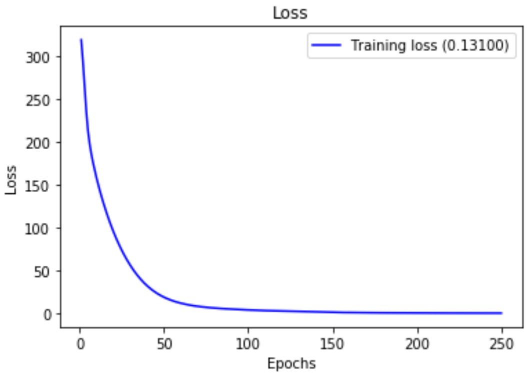

Figure 6: Training loss(MSE) curve

We can see from the training loss curve that the learning plateaus at around 100 epochs, in our model we train till 200 epochs for a training MSE close to 0.16. When we test on this model we see a test MSE of 0.3. This shows that there is not much over-fitting and so the model will generalize well to new data

The supplier selection MCDM problem in general is characterized by uncertain and imprecise data. Fuzzy set theory seems to be an adequate technique to deal with such problems as it has the ability to remove the imprecision associated with subjectivity. This is why the training set data was generated using fuzzy set theory.

To the best of our knowledge only one author has previously used ANN to solve the supplier selection problem (Wei et al., [16]). Our approach of using the Fuzzy set theory to generate the training set data and then training the ANN using back-propagation algorithm is an innovative application to the supplier selection problem.

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