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DEA ANN Approach in Supplier Evaluation System

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***Abstract*—**In Supply Chain Management (SCM), strengthening partnerships with suppliers is a significant factor for enhancing competitiveness. Hence, firms increasingly emphasize supplier evaluation processes. Supplier evaluation systems are basically developed in terms of criteria such as quality, cost, delivery, and flexibility. Because there are many variables to be analyzed, this process becomes hard to execute and needs expertise. On this account, this study aims to develop an expert system on supplier evaluation process by designing Artificial Neural Network (ANN) that is supported with Data Envelopment Analysis (DEA). The methods are applied on the data of 24 suppliers, which have long-term relationships with a medium sized company from German Iron and Steel Industry. The data of suppliers consists of variables such as material quality (MQ), discount of amount (DOA), discount of cash (DOC), payment term (PT), delivery time (DT) and annual revenue (AR). Meanwhile, the efficiency that is generated by using DEA is added to the supplier evaluation system in order to use them as system outputs.

***Keywords*—**Artificial Neural Network (ANN), Data Envelopment Analysis (DEA), Supplier Evaluation System.

I. Introduction

GLOBAL manufacturing and internalization force firms benefit from advanced management approaches such as Supply Chain Management (SCM). SCM, which integrates suppliers, manufacturers, distributors and customers [1] is diffused in the firms in order to improve flexibility, cost, quality and, delivery performances [2]. The effectiveness of relationships is considered to be essential for the success of SCM. Without providing a successful collaboration with suppliers, the corporation success cannot be achieved [3]. Proper supplier selection depends on the analysis of partnerships in terms of their certain attributes [4]. For both of local and global business area, evaluation of the suppliers that is based on their success on efficient firms has become crucial for long-term success [5]-[6]. Furthermore, supplier evaluation models provide advantage to managers about predicting what the success of the alternative suppliers will be in the future [4]. On this account, it is noticeable to say that supplier evaluation is a significant decision making problem not only for checking performance of suppliers but also alerting the success of suppliers.

There are many evaluation analyses that depend on quantitative or qualitative methods [1]. Artificial neural network (ANN) is one of the classification methods that can also be used for supplier evaluation. In this study, ANN is used, so besides classification for checking the success of current suppliers, prediction of suppliers for their long-term success in the future can also be analyzed. In this pursuit, a face to face interview was conducted with the managers of a firm from German iron and steel industry to find out what they expect from their suppliers and if suppliers are efficient their requirements. The data set of the 24 supplier firms in terms of a set of indicators, which are utilized by the main company is used for the evaluation process.

In the rest of the study, there are three main phases. In the second part, first of all supplier evaluation is overviewed with its basic concepts, and then evaluation methods used in the study are explained based on literature review. Part three includes the methodology explaining the way of ANN application with using DEA and its results. In the final section, the results are discussed and commented.

II. Literature Review

A. Supplier Evaluation System

SCM provides the integration of tasks such as purchasing, manufacturing and distribution for the different partners of supply chain. Increasing the overall competitiveness of a company is related to the efficiency of relationships between strategic partners [1]. Especially companies, which prefer to outsource materials, put increasing importance to some supportive approaches like supplier evaluation [6]-[7]-[8]. Supplier evaluation system that is generated according to the past experiences of firm is a significant factor to strengthen supplier partnerships [9]. Evaluation process of suppliers is established on different attributes and it compares the success of suppliers in terms of performing their needs [8]. Because there are many attributes of suppliers that affect the satisfaction of companies, supplier evaluation can be considered as a multi criteria decision problem [7]-[10]. Supplier evaluation decisions are made according to some variables of which have different priorities in different companies. Traditionally, cost and quality based variables are

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found as the basic ones, but today some variables such as delivery time, strategic behavior, and implementation of total quality management have also become very important [9]-[10].

B. Artificial Neural Network (ANN)

Human brain working structure serves as the basis of ANN systems. The most significant property of ANN systems is that they can learn from sample sets as brains, and have the ability to make decisions according to training with data from past. The structure of a typical ANN system includes layers. On layers, there are neurons connected to each other with weights. All neurons are in connection with another neuron from subsequent layer and their ability of processing comes from these connections named weights. The prediction or classification success of ANN system depends on how effectively these weights are generated. One of the most commonly used types of ANN is Multi Layered Perceptron (MLP), which has three different layers with different number of neurons. Input layer lets the inputs from environment in the neuron, output layer transmits the output to the environment and hidden layer takes place between two of them. Hidden layer provides generalization of the output when linkage between inputs and outputs is nonlinear [11] and it establishes linkages between input and output layers as a black box [12]. The general architecture of a MLP network system is shown in Fig. 1.

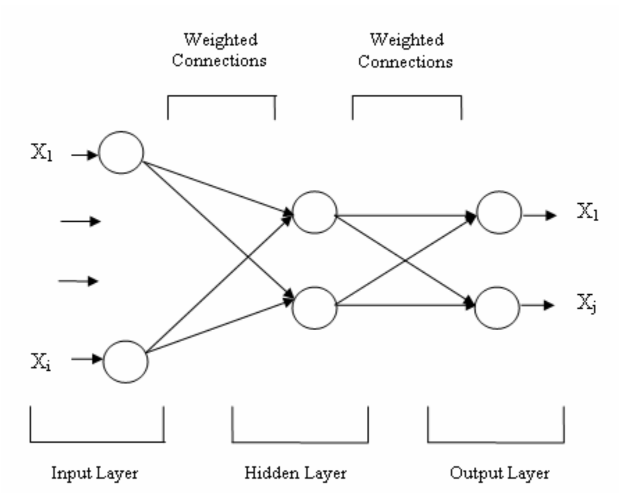

Fig. 1 Architecture of ANN (X_i refers to input values and X_j refers to output values)

First of all, the weights of inputs are summed up and then the total weight value is entered to the activation function in order to get an output from the neuron [13]-[14]. In each neuron, the summed weights are compared with threshold value. If the total value is bigger than threshold value, the neuron shares it with the subsequent neurons that are in the further layer. In the Equation (1), x_i and w_i respectively shows the value and weight of i th input. Besides them, θ shows threshold value and Y refers to output value. If the Y value is bigger than zero, than the neuron is activated and shared with neurons from the subsequent layers.

$$Y_k = f(\sum_{i=1}^{n} x_i w_i - \theta) \tag{1}$$

There are many useful activation functions for obtaining outputs. In our study, sigmoid function is used, because it is non linear and easily derived. In the Equation (2), x refers to activated weights of neurons.

$$sigmoid(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Using the learning rules, the weights are iteratively changed to reach the best weight values, which provide the most satisfactory outputs [15]. The network that provides the most satisfactory output is accepted as the best one. For obtaining the best network structure, many trials are necessary in order to find the best functions, best loads, best numbers of hidden layers, and best numbers of neurons in each layer. In literature, some rules are defined as to find the best numbers of hidden layers, such as n/2, 2n/3, n+1 and 2n+1 (n is the number of input neurons). According to some researchers, many times, an ANN system with one hidden layer is sufficient for complex systems. In addition, it is important to choose the number of neurons in each hidden layer smaller. Because larger number of neurons makes system memorize the data, memorization of the system causes high error in test results and prevents to generalize the results for the other sample data [16]. Furthermore, the most effective neuron numbers are chosen according to generation of minimum performance measure. In this study, mean square error (MSE) is taken into consideration as a performance measurement. The system, which gives the minimum MSE value, is chosen and considered as the most satisfactory one. The number of layers and neurons are determined in order to minimize the value of MSE. As it is shown in Equation (3), MSE is the average of differences between the expected values:

$$MSE = \frac{\sum_{i=1}^{n} (x_i - E(i))^2}{n} \tag{3}$$

n : the number of sample that is evaluated
x_i : network output related to real data of study
E(i) : the expected value

Practically, ANN provides many advantages to decision makers especially for complex problem solutions. Not only they have ability to learn from sample sets, but also their results can be generalized to other data sets. They do not require any modeling or programming for matching inputs to outputs. They can learn with noisy or missing data. Moreover, it is possible to train the system more quickly as compared to learning of experts. Hence, ANN is used in a wide range of applications in business management practices.

The methodology of this study describes the development of an ANN approach that classifies the suppliers according to their success performance as defined by DEA.

C. Data Envelopment Analysis (DEA)

Efficiency measurement studies mostly relied on statistical methodologies for a long time. Results of these methodologies can be reliable only if existences of their assumptions such as existence of Cobb-Dougles technology, constant scale elasticity, and unitary substitution elasticity are proved [17].

As Charnes, Cooper, and Rhodes report their research in 1978, the breakthrough came in the field of non-parametric approach for evaluating efficiency. In the following years, Charnes and Cooper provided the definition of efficiency, and this definition forms the foundation of data envelopment analysis. They define efficiency as "100% relative efficiency is attained by any (unit) only when comparisons with other relevant (units) do not provide evidence of inefficiency in the use of any input or output." [18].

The data set in DEA is derived from a set of any administrative units, which have common input and output. These units are named as decision-making units (DMUs). In general terms, the technique is defined as "the efficiency measure of a DMU is defined by its position relative to the frontier of the best established mathematically by the ratio of weighted sum of outputs to weighted sum of inputs."[18].

DEA can be modeled in various ways. However, these can basically split into two groups such as input oriented and output oriented DEA. Input oriented DEA seeks for the minimum input values without changing output values whereas output oriented DEA searches the maximum output levels without changing input levels [19].

An input oriented DEA model can be described as the following. If n DMUs, which use the amount $X_j= \{x_{ij}\}$ of m kind of input to produce $Y_j= \{y_{rj}\}$ of r kind of output, are relatively evaluated, the following linear program is solved for n times for each DMU.

$$\min \alpha - \varepsilon\left[\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right]$$

$$ST:$$

$$\sum_{j=1}^{N} \lambda_i x_{ij} - \alpha x_{ij} - S_i^- = 0$$

$$\sum_{j=1}^{n} \lambda_i y_{rj} - S_r^+ = y_{rj}$$

$$\lambda_j \geq 0,\ j = 1...N \quad S_r^+, S_i^- \geq 0 \forall \text{ i and r},$$

α is free, ε is a non – Archimedean infinitesimal

A DMU is accepted as efficient as its α value is one and slack values (S_i^+, S_i^-) are zero. These efficient DMUs form an envelopment surface. By measuring the relative performance of each DMU to the envelopment surface, relative efficiencies are determined [20]. Efficient virtual unit of every inefficient unit can be determined by using the value of λ. If there are more than one efficient unit, a linear combination of efficient units proportional to their λ values, gives the virtual efficient unit for the inefficient unit [21].

The hypothetic values to carry each inefficient DMU to efficient frontier can be calculated with a reduction in input values proportional to α value. Therefore DEA can be defined as to derive relatively efficient DMU set in a set of DMU. It also indicates the possible improvements to carry a relatively nonefficient DMU to efficient frontier [21]-[22].

D. ANN and DEA Together in Literature

Both DEA and ANN applications do not have such strict assumptions. This advantage increases their implication areas. In literature, it is easy to find proposed models, which uses DEA and NN together.

As an early example of DEA-NN application, Costa and Markellos studied the efficiency of London Underground transport system for the time interval 1970 and 1994. Due to no improvement in the technology in this period, the differences between observed outputs were accepted as efficiency differences. The proposed multi layer perceptron (MLP) model could predict efficiencies similar to DEA [17]. Besides that MLP model has an advantage to provide information about production function whereas DEA cannot provide any clue [17]. According to Wang's study, ANN can be an option for efficiency measurement. He states that the structure of ANN is suitable to model concave functions with multidimensionality, and therefore, it can be used in creating efficiency frontier functions and estimating efficiencies of DMUs [23]. Santin and his colleagues compared parametric and nonparametric efficiency measurement techniques with multi-layer perceptron neural network for non-linear production function. The results showed how DEA could give slightly better results than MLP with variable returns to scale. Yet MLP is an applicable approach in efficiency measurement and a promising alternative to DEA and econometric techniques [24]. Wu, Yang and Liang predicted branch efficiency of a large Canadian bank with DEA-NN; their results were comparable with normal DEA [20]. Liao et al. tried to measure the efficiency and productivity growth for seven East Asian economies at the manufacturing level, for the period 1963 to 1998 by using DEA-neural network and stochastic frontier analysis neural network. Their aim was to predict efficiency with minimum assumptions and their results strengthen the findings about the applicability of NN in efficiency prediction [25]. In their study, Hu, Chung and Chan trained a Hopfield NN tried to get DEA results. Their study shows the applicability of HNN to predict DEA results. In addition to this result, they express that the abilities of ANN to learn and to work with data faults will extend the applicability of ANN to more complex DEA models in future [19]. Emrouznejad and Shale illustrated that a multilayer feed-forward DEA network can give satisfactory results with less computer resources requirement in terms of memory and CPU times than classical DEA [26].

From another perspective, ANN can perform efficiently because of its learning capability and ability to represent non-linear functions. However, the quality of training data has unavoidable effects on ANN results. It can produce more effective results as it is trained with a more proper dataset. Pendharkar and Roger used DEA to preprocess their training data. They used DEA to separate examples, which approximately satisfy monotonicity property, from data set to derive a training set for learning monotonic forecasting function [27]. Wu, Chen and Yang developed a similar approach. They evaluate their experiment data with DEA to get scientifically more viable data. They calculated inputs for inefficient observations to carry them to efficiency frontier so they could use all the data in their data set in ANN development process. They trained a ANN to predict the output "yield" from input of fertilization such as nitrate nitrogen, phosphorus, potassium and the application rate of these inputs. The outcome shows that ANN gives more effective results with DEA efficient data set. They stated that their approach could be beneficial especially when collecting data is costly and requires a long time [28]. Liao proposed a model to optimize multi-response problem with censored data. In this study, all input-output combinations are acquired by training a back-propagation ANN and efficient combinations are drawn from data set. By using ANOVA significant factors, which are affecting efficiency are obtained [29].

In short, DEA and ANN can be used together for two main purposes. They can assist each other or be an option for each other. The observations from the literate show the applicability of DEA and ANN together successfully.

III. The Methodology

In the development of the ANN system that predicts efficiencies derived by an input oriented DEA, there are four main steps as the following; parameter definition, network design, network application process, and discussion of implementation results.

A. Parameter Definition

Supplier Performance Variables

Supplier evaluation is a multi-criteria decision process. Mostly, high expertise, much time and investment is required. ANN is one of the useful tools in multi-criteria decision-making problems. In this study, application of ANN in modeling the efficiencies of suppliers is aimed. In this sense, a face-to-face interview was conducted with the managers of a company from German iron and steel industry and it is decided to use the following six variables. The data set involves values of six variables for each supplier.

- Material quality (MQ): Quality level of materials determined by governmental standards.
- Discount on amount (DOA): Discount percentage on amount.
- Discount on cash (DOC): Discount percentage when the payment is made in cash.
- Payment term (PT): Length of time for post dated payments.
- Delivery time (DT): The time passed from order time to deliver time.
- Annual revenue (AR): Total amount of payments made to each supplier within a year (in 1000 Euro).

DEA Application

As it is always stressed in the literature, DEA measures relative efficiencies of similar DMU. Therefore, only 24 of total suppliers, which are similar to each other in terms of their products, inputs and output, are evaluated by DEA.

The variables; MQ, DOA, DOC, PT and DT are accepted as input variables. As output variable, only annual revenue (AR) is taken. It is assumed that sales can represent the output in generally.

The DEA performed in this study is input oriented DEA which is explained under Data Envelopment Analysis heading. Lindo 6.1 is used to calculate efficiencies. Firms are split into two groups as "efficient firms" and "inefficient firms". Efficient firms are the firms, which have α value 1, and the other firms, which have α value smaller than one, are inefficient. As a result of DEA, a new variable is obtained that is named as "efficiency".

B. Network Design

Network design process starts with the configuration of training, testing and if necessary cross validation data set. As it is explained before, the supplier evaluation variables such as MQ, DOA, DOC, PT, DT and AR are defined as the inputs of ANN system. Moreover, the efficiency categories, which are generated according to DEA results, are defined as the outputs of ANN system. In the network design, the data of 24 suppliers of the main company is used. Eleven suppliers are randomly chosen for a training set, and six for cross validation set and the rest of the data is kept for testing process. It is known that although the error may be seen decreasing in the training set, it may increase again in the test set. It is caused because of the memorization of network. In order to prevent memorizing, the cross validation data set should be formed and cross validation error should be taken into consideration for evaluation. The DEA-ANN system design utilized in this study is shown in Fig. 2.

C. Network Application Process

Neuro-Solutions for Excel software are used for training and testing the designed neural network system. In order to find the optimum number of hidden layers and choose the number of neurons in each layer, the neural network software is run for different numbers of layers and neurons. First, the training process was started with a network that has one hidden layer with one neuron. Then, it was repeated for increasing the number of neurons in the layer up to 10. This training process was also run for different numbers of hidden layers up to 5 and for different numbers of neurons in each hidden layers up to 10. The selection of an ANN system depends on the value of MSE.

The training results of the system given in Table I show that minimum MSE value is obtained when the system is designed with one hidden layer with two neurons. Therefore, the best network structure has one hidden layer and two neurons on it. The further prediction or classification decisions should be made by using this neural network structure.

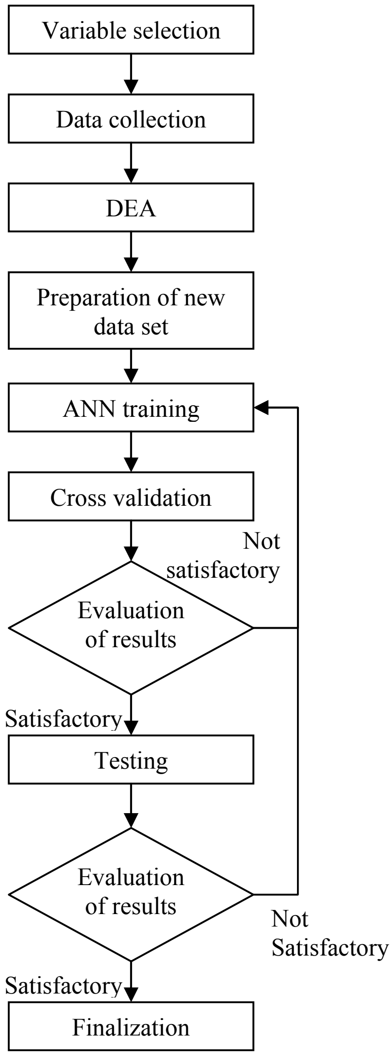

Fig. 2 DEA-ANN development process

TABLE I
TRAINING RESULTS

	TRAINING RESULTS of CROSS VALIDATION SET	
Best Network	Hidden Layers (HLs)	1
	Neurons for HL 1	2
	Minimum MSE	0,206
	Trial Number	13

Furthermore, the testing results of the system are given in Table II. As it is seen from MSE and other performance measure values, 'efficient' groups are learned by the system more successfully than 'inefficient' test groups'. Therefore, it is expected from the system to classify 'efficient' groups more similar with output value of real data.

TABLE II
TESTING RESULTS

	TEST RESULTS		
Best Network	Performance Measure	Efficient Group	Inefficient Group
	MSE Mean Square Error	0,097	0,106
	NMSE Normalized Mean Square Error	0,399	0,435
	MAE Mean Absolute Error	0,187	0,222

In parallel with testing results, the classification results show that in total, all of 'efficient' data and 2 of 3 'inefficient' data from testing set are classified correctly by the selected ANN system. The test results can be seen in Table III.

TABLE III
CLASSIFICATION RESULTS

Output \ Desired	**Efficient**	**Inefficient**
Efficient	3	1
Inefficient	0	3

The result corresponds that in summary; approximately 86 percent of the test sample can be successfully classified according to their success performance. A well designed ANN system can provide information about in which efficiency category suppliers most probably take place if their success criterion is known. If a decision maker has the data about a new candidate supplier, it should be evaluated by using this structure and then the system results are used for strategic decisions on suppliers. However, it is expected that by using this chosen network structure, 'efficient' suppliers will be classified and predicted more successfully than 'inefficient' suppliers.

IV. CONCLUSION

DEA does not have very strict assumptions. Thus, it can be performed in a wide range. Yet, it still requires time, knowledge, and more computer resource than ANN. Since ANN is a perfect tool to simulate human brain, it has a huge learning capacity. As a result, its application area is enormous. In this study, we attempted to get DEA results by training an ANN in a supplier evaluation system. Although the data set of suppliers is very small, the results show that a very small sized data set can give meaningful results in training ANN. As a result of this study, by developing an appropriate ANN, long calculations of DEA can be avoided and the efficiency of suppliers can be easily predicted or checked.

For future research, ANN can be used in prediction of hypothetical units and slacks which can give insight for improvement.

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