



INTEGRATING NEURAL NETWORK AND COLONIAL COMPETITIVE ALGORITHM: A NEW APPROACH FOR PREDICTING BANKRUPTCY IN TEHRAN SECURITY EXCHANGE

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ABSTRACT

Bankruptcy filings are as high today as ever, calling into question the efficacy of existing bankruptcy prediction models. This paper tries to provide an alternative for bankruptcy prediction by integrated Multi Layered Perceptron with Imperialist Competitive Algorithm (MLP-ICA) and Kohonen self organizing map. Research sample consist of 70 bankrupts and non-bankrupt company in 2001-2009 and in listed firms of Tehran Stock Exchange. Results indicate that MLP-ICA model outperform Kohonen self organizing map.

Keywords: Bankruptcy, Prediction, Neural network, Imperialist competitive algorithm.

INTRODUCTION

In today's dynamic economic environment, the number and the magnitude of bankruptcy filings are increasing significantly. Even auditors, who have good knowledge of firms' situations, often fail to make an accurate judgment on firms' going-concern conditions (e.g., (Hopwood *et al.*, 1994; McKee, 2003)). Therefore, bankruptcy prediction models have become important decision aids for organizations' stakeholders, including auditors, creditors, and stockholders. (Sun and Shenoy, 2007).

Bankruptcy prediction literature has experienced a rapid growth during recent decades and techniques employed to develop bankruptcy prediction Models have evolved from the simple univariate analysis (Beaver, 1966) and multiple discriminant analysis (MDA) (Altman, 1968), to logit and probit models (Ohlson, 1980; Zmijewski, 1984), to neural network models (NN) (Tam and Kiang, 1992), discrete hazard models (Shumway, 2001), Bayesian network (BN) models (Sarkar and Sriram, 2001), and genetic programming (McKee and Lensberg, 2002). Artificial neural networks (ANNs) as alternative classification technologies to statistical modeling have been frequently used in business largely due to improved prediction accuracy (Lee *et al.*, 2005). In particular, the back-propagation (BP) network, one of the supervised networks, has been the most popular neural network model used for bankruptcy prediction during the last decade (Tam and Kiang, 1992; O'Leary, 1998).

Although numerous theoretical and experimental studies reported the usefulness of the back-propagation neural network (BPN) in classification studies, there are several limitations in building the model. First, it is an art to find an appropriate NN model, which can reflect problem characteristics because there are large numbers of controlling parameters and processing elements in the layer. Second, the gradient descent search process to compute the synaptic weights may converge to a local minimum solution that is a good fit for the training examples. Finally, the empirical risk minimization principle that seeks to minimize the training error does not guarantee good generalization performance. To determine the size of the training set is also the main issue to be resolved in the generalization because the sufficiency and efficiency of the training set is one most commonly influenced factor (Shin *et al.*, 2005).

To overcome this disadvantage we try to utilize a new optimization approach as imperialist competitive algorithm (ICA) for training multi-layered perceptron (MLP). Artificial neural networks are often classified into two distinctive training types, supervised or unsupervised. The supervised networks (such as BPN) need input vectors and target vector together to make training possible. Often this target vector is available only in the retrospective way, which is the major limitation of supervised training. For the same reason, the supervised approach may also be unable to provide a real-time response to a problem. Because of the fast changing nature of information technologies today, it is difficult to assume that the improved accuracy of a study is easily transferable and applicable to future studies (Lee *et al.*, 2005). In today's fast changing business environment, we need to develop a method that can detect the changing pattern of a firm in a more timely fashion, rather than retrospectively. In such circumstances, unsupervised neural networks might be more appropriate technologies to be use. Unlike supervised networks, unsupervised neural networks need only input vectors for training (Lee *et al.*, 2005). One of the more important unsupervised neural networks is the Kohonen's self-organizing map (KN) proposed by Kohonen (1988).

It is, however, desirable that these two different approaches, supervised and unsupervised, be investigated so that the feasibility and effectiveness of diverse neural network algorithms may be better understood. As a result, this study would be an attempt to compare the efficiency of MLP-ICA and KN models as representative of supervised and unsupervised networks respectively. Other parts of this study are as follows: in part two, research literature relating with bankruptcy would be offered. In part three, introduction of utilized models and methodology of the research would be explained in details. In part four, the results of models would be offered and in last part, final conclusions of the study would be explained.

A LITERATURE REVIEW

Predicting bankruptcy researches which used neural networks can be studied from several views. Using input data for neural network, assigning research data to training and examine group, supervised or unsupervised networks, combining neural networks with other models and comparing different neural network are subjects that we can study about the neural networks. Using financial ratios as model input has a long history in bankruptcy literature that it dates back to 1960s. Altman (1968) financial ratios are most famous financial ratios in this field (Odom and Sharda, 1990; Coats and Fant, 1993; Rahimian *et al.*, 1993; Wilson and Sharda, 1994; Lacher *et al.*, 1995; Sharda and Wilson, 1996; Zhang *et al.*, 1999). In other hand there is norm multiple analyses in which industry norm of firm is calculated by using nonparametric regression and by this we can classify healthy and bankrupt firms (Andrés *et al.*, 2012). In this regard we can point to Zhou (2013) study in which he review the healthy and bankrupt firms in 5 different models by balanced and unbalanced samples.

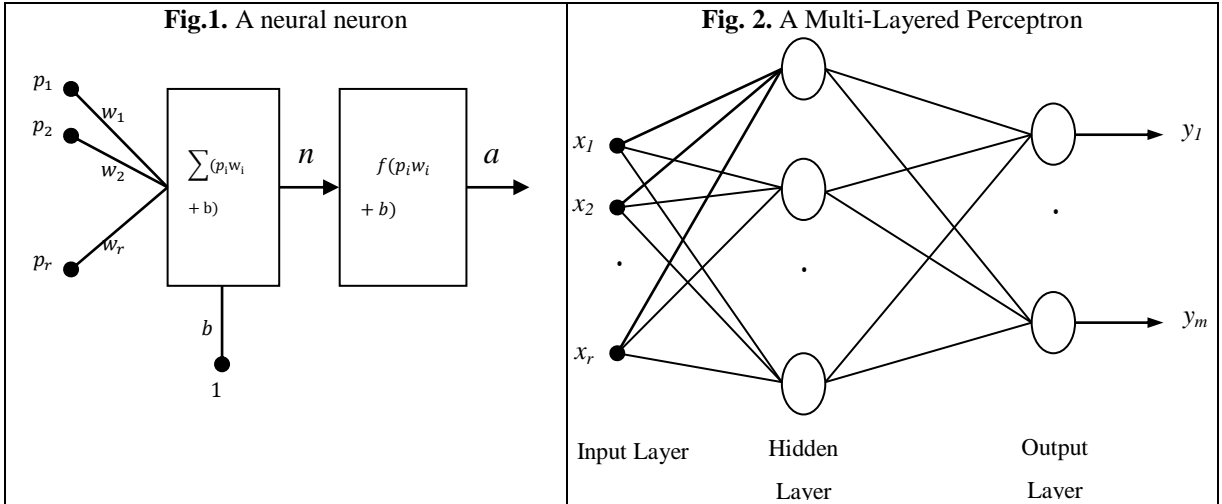
Most of the studies in this field used supervised network, however Martin-del-Brio and Serrano-Cinca (1995), (Kiviluoto, 1998), Alam *et al.* (2000), Lee *et al.* (2005) used unsupervised networks. Lee *et al.* (2005) compared supervised and unsupervised neural networks, in order to predicting Bankruptcy. They compared the back propagation algorithm as a representative for supervised algorithms with the algorithm of Kohonen as a representative for unsupervised algorithms in neural network. In this study, Altman (1968) variables have been applied. The number of utilized samples in present study is 113 pairs of bankrupt and healthy companies, which were chose among South Korea's stock exchanges. They concluded that back propagation algorithm has better performance compared with Kohonen algorithm.

Multi-Layer Perceptron Neural Network (MLP)

A neural network is composed of uniting some neural neurons. Neuron is a processing unit that plays essential role in functioning artificial neural network. Fig.1 represents a neural neuron, which is composed of some key elements such as weight, w , activation function, f , and bias, b . output of this neuron is calculated based on equation 1:

$$a = f(b + \vec{w} \cdot \vec{p}) \text{Equation 1}$$

Where p is input vector (r is the amount of input vector's dimension), w is the row vector of weight, b is the amount of bias, and f , the activation function and a , the neuron's output.



Middle layer or layers process received data from input layer and give it to output layer. Output of this network is obtained by applying equation 2:

$$y = f_{out}(\vec{b}_{out} + f_h(\vec{b}_h + \vec{p}W_h)W_{out}) \text{Equation 2}$$

In which p is input vector, b_h and b_{out} are biases of hidden and output layers respectively, W_h and W_{out} are weight matrices of hidden and output layers respectively, and f_h f_{out} are activation functions of neurons located in hidden and output layers and y output vector of network (Fig.2).

Activation function utilized in middle layers is tangent sigmoid function, which is calculated through equation 3.

$$Y_i = \frac{2}{(1 + \exp(-2X_j)) - 1} \text{Equation 3}$$

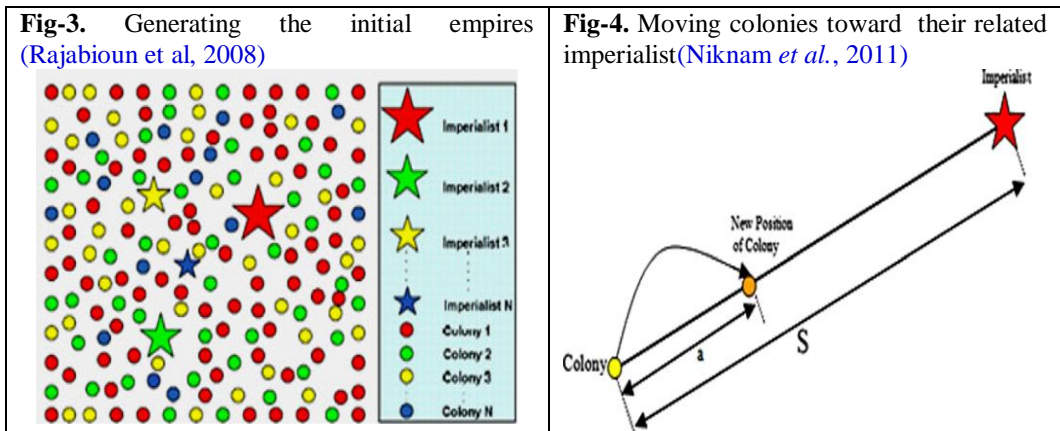
The performance indicator in network training is sum of squared error; in other words it is tried to update weight matrices and bias vectors so that mean square error is minimum. Equation 4 shows how to evaluate it.

$$MSE = \frac{1}{n} \sum_{i=1}^n (T - Out_{Net})^2 \text{Equation 4}$$

Imperialist Competitive Algorithm (ICA)

Imperialist competitive algorithm (ICA) is a new algorithm in the field of evolutionary computations and like other evolutionary algorithms. It is a population-based stochastic search algorithm. It has been introduced by Atashpaz and Lucas, recently (Atashpaz-Gargari and Lucas, 2007a, 2007b; Jasour *et al.*, 2008; Roshanaei *et al.*, 2008; Atashpaz-Gargari *et al.*, 2008a, 2008b; Rajabioun *et al.*, 2008a, 2008b). Since then, it is used to solve some kinds of optimization problem

(Atashpaz-Gargari and Lucas, 2007a, 2007b; Jasour *et al.*, 2008; Roshanaei *et al.*, 2008; Atashpaz-Gargari *et al.*, 2008a, 2008b; Rajabioun *et al.*, 2008a, 2008b). The algorithm is inspired by imperialistic competition. It attempts to present the social policy of imperialisms to control more countries and use their sources when colonies are dominated by some rules. If one empire loses its power, the rest of them will compete to take its possession. In ICA, this process is simulated by individuals that are known as countries. This algorithm starts with a randomly initial population and objective function which is computed for them. The most powerful countries are selected as imperialists and the others are colonies of these imperialists. Then the competition between imperialists take place to get more colonies. The best imperialist has more chance to possess more colonies. Then one imperialist with its colonies makes an empire. Fig. 3 shows the initial populations of each empire (Atashpaz-Gargari and Lucas, 2007a, 2007b; Jasour *et al.*, 2008; Roshanaei *et al.*, 2008; Atashpaz-Gargari *et al.*, 2008a, 2008b; Rajabioun *et al.*, 2008a, 2008b). If the empire is bigger, its colonies are greater and the weaker ones are less. In this figure Imperialist 1 is the most powerful and has the greatest number of colonies.

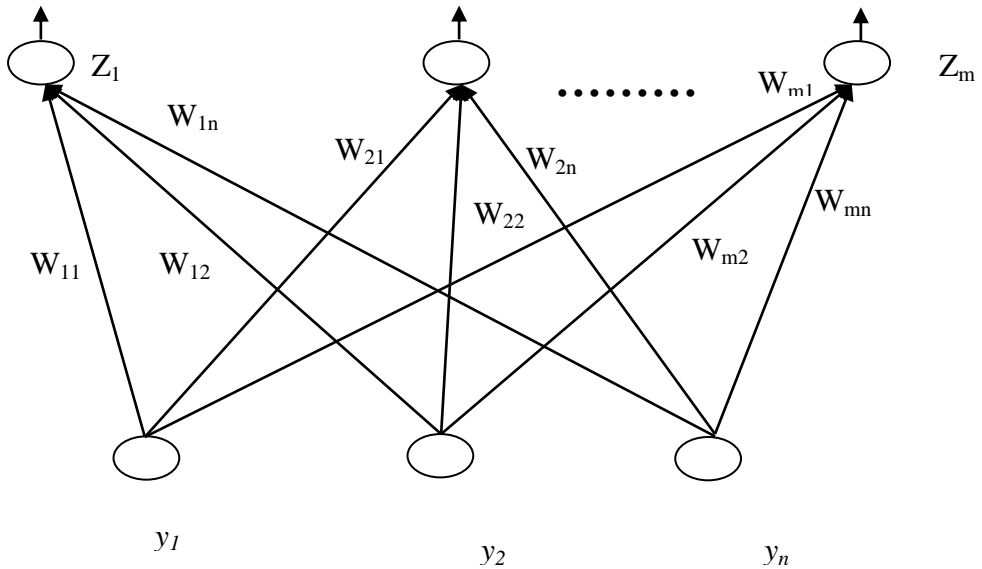


After dividing colonies between imperialists, these colonies approach their related imperialist countries. Fig. 4 represents this movement. Based on this concept each colony moves toward the imperialist by a units and reaches its new position. Where a is a random variable with uniform (or any proper) distribution, β , a number greater than 1, causes colonies move toward their imperialists from different direction and S is the distance between colony and imperialist (Niknam *et al.*, 2011).

$$a \sim U(0, \beta \times S)$$

It should be mentioned that every problem in optimization needs a cost function, which the process of optimization would be implemented for its minimization. Respecting efficiency index in this network, the cost function is determined based on the value of MSE. Along with each evolution circle (it is called decade in this algorithm) in imperialist competitive algorithm, the best countries would be utilized as weights of neural network and for those weights, the process of optimization would be continued until reaching the desired value of accuracy. However, other stop conditions such as certain number of iterations can be applied.

Kohonen's Self-Organizing Map (KN)



A one-dimensional KN with input $y = (y_1, y_2, \dots, y_n)^T \in R^n$ and output $z = (z_1, z_2, \dots, z_m)^T \in R^m$ is shown in fig. 5. For the i th output neuron, z_i is given by :

$$z_i = \sum_{j=1}^n w_{ij}y_j = w_i^T y \tag{Equation 5}$$

Where w_{ij} is the ij th weight, and $w_i = (w_{i1}, w_{i2}, \dots, w_{in})^T$, the i th weight vector. To train the KN, the winning output neuron is determined first by comparing the similarity between the input y and the weight vectors $\{w_i, i = 1, \dots, m\}$. The weight vector of the winning output neuron is then updated. A common measure of similarity between two vectors is the Euclidean distance (Kohonen, 1988),

$$\Pi_i = \|y - w_i\|^2, \tag{Equation 6}$$

Where Π_i is the intensity. The weight vectors of the KN are updated as follows (Kohonen, 1988):

$$w_i^{new} = w_i^{old} + \eta (y - w_i^{old})\delta_i, \quad i = 1, \dots, m, \tag{Equation 7}$$

Where $\eta, \eta > 0$, is the learning rate, and δ_i is unity for the winning neuron that has the smallest Π_i , but is zero otherwise. The learning algorithm given by Eq.7 reduces to

$$\begin{aligned} w_i^{new} &= (1 - \eta)w_i^{old} + \eta y && \text{Equation 8} \\ w_j^{new} &= w_j^{old}, \quad j = 1, \dots, m, \quad j \neq i \end{aligned}$$

The convergence of the learning algorithm given by Eq. (8) is given in Ritter and Schulten (1988).

RESEARCH METHODOLOGY

The definition provided in this study for bankruptcy is the same definition in 141 article of Iranian commercial law for bankruptcy so that we regard firms with accumulated losses more than half of capital as a bankrupt company. The procedure is as follows: after selecting population and sample, research data is extracted and divided into two data sets of training and testing. By using first type of data, we would elaborate on neural network training and then by applying remaining data we

would test considered networks. Applied population in this study consists of firms present in Tehran stock exchange during period of 2001-2009 inclusive in 141 article of Iranian commercial law for bankruptcy. Therefore, those firms that had following conditions were used for neural network training:

1-Those firms inclusive in 141 article of Iranian commercial law, should have been accepted in Tehran stock exchange at least since 1999 (because data of two years before bankruptcy would be used)

2-Those firms selected in this study as bankrupt were not financial brokerage companies.

3-They are included in trade act of 141 during period of 2001 till 2009 (they have accumulated losses greater than half of capital)

Through examinations accomplished by researchers in present study, 80 firms during this period are included in the act. Because the number of firms for neural network training is important, it has been tried to apply most of available data for neural networks training as much as possible. However, the ratios of some firms had considerable difference with other samples in the study and it would lead to decrease in performance of neural network, hence some of bankrupt firms would be eliminated from the study. Consequently, the number of bankrupt firms in this study reached to 70. Also, in an industry that every bankrupt company is active, a healthy company, which has nearest amount of assets to that company, was selected. It is done so because a neural network with training data from healthy firms is able to distinguish between these firms and bankrupt companies. Healthy firms are selected from those firms that bankrupt pairs were present at Tehran's stock exchange. There was a problem with this matter that due to having small size of industry in some of industries, selecting healthy pair for bankrupt firms was not feasible, hence it was tried to select among healthy firms in upstream and downstream industry, and in the case of lack of these companies, a healthy company with the same assets from a non-similar industry would be selected. It can be considered as one of limitations in this study.

In next step, research data is divided into two sets of training and testing data sets. To do so, among research data, some shall be selected randomly and assigned to these sets. Therefore, 20-80 percent of data was assigned to training and testing respectively.

Research Variables

Since financial ratios have long history in predicting bankruptcy, we tried to apply financial ratios for this aim and also due to special limitations in Altman's proposed variable (1968)(Odom and Sharda, 1990; Coats and Fant, 1993; Rahimian *et al.*, 1993; Wilson and Shard, 1994; Lacher *et al.*, 1995; Sharda and Wilson, 1996), we considered these variable as input variable. These ratios including;

- (1) Working capital/total assets; (2) retained earnings/total assets; (3) earnings before interest and taxes/total assets; (4) exchange value equity/book value of total debt; (5) sales/total assets.

Utilized data is financial ratios of two years before bankruptcy in bankrupt firms and selecting healthy pairs.

In order to training neural network using supervised algorithms, output data or target data is needed; thereby a neural network can be familiar with the relationship between ratios of each healthy company and bankrupt one and also their outputs.

In this research as well as other researches which are used for classification, we segregate the outputs of research with two different class definitions. 0 shows healthy firms and 1 shows bankrupt firm.

Predicting accuracy is calculate on the base of network output and real output. This error is occurring when we classify healthy firm as bankrupt firm and vice versa. Final comparative review in this study will be applied with regard to MLP-ICA neural network and KN neural network-colonial rivalry in accurate classification rate of healthy and bankrupt firms. (Accurate prediction percentage)

NETWORK TESTING AND RESULTS ANALYSIS

After training research networks, it is the turn of offering test data to the research and recording relevant results. Details related to the way of prediction in these models have been provided in table.1. According to table.1, MLP-ICA neural network could have classified 85.71 % of healthy firms and 78.57 % of bankrupt ones properly. Also, error type 1 for this model is 14.29% and error type 2 is 21.43%. Total results indicate that the performance of MLP-ICA network was in such a way that 82.14% of firms present in test data have been classified properly.

Table-1. The results obtained from testing KN and MLP-ICA networks

Model	Sum of prediction	Status	The number of correct predictions	The number of correct predictions	The errors type 1 and 2	The percentage of correct predictions	The error type 1 or 2
MLP-ICA	28	healthy	14	12	2	85.71%	14.29%
		bankrupt	14	11	3	78.57%	21.43%
		total	28	23	5	82.14%	17.86%
KN	28	healthy	14	10	4	71.42%	28.58%
		bankrupt	14	11	3	78.57%	21.43%
		total	28	21	7	75%	25%

Looking at performance of KN in table.2, it could be found that it has suitable power in predicting bankruptcy. The details about prediction of this network indicate that its performance is similar to the model of MLP-ICA relatively. KN could show a 71.42% performance for predicting healthy firms with 10 correct predictions out of 14 predictions, also KN model could have classified 78.57 % of healthy firms properly and error type 1 for this model is 28.58% and error type 2 is 21.43%. In relation to predicting bankrupt firms we can see no difference between the performance of MLP-ICA and KN and the results confirm that the prediction accuracy of the KN model is lower than the other MLP-ICA model.

CONCLUSION

The main purpose of this study is to investigate two different training (or learning) types of neural networks using their representative networks—the MLP-ICA network (supervised) versus the Kohonen self-organizing feature map (unsupervised)—in terms of their performance accuracy in the area of bankruptcy prediction. Applied data in this study includes 70 bankrupt firms inclusive in 141 article of Iranian commercial law relating bankruptcy and 70 healthy firms in period of 2001-2009 that are working in Tehran stock exchange.

We divided study data to training and examining and allocated 80 and 20 percent of all study data to each group. With regard to accuracy of prediction as a measure for research model performance, it indicated that MLP-ICA network has better performance in compare with KN model with 85.71 of healthy firms and 78.57 % of bankrupt firms. Generally we find that although in order to classification of bankrupt firms is no difference between the performance of MLP-ICA and KN models but in general (healthy and bankrupt firms) the MLP-ICA model outperform the KN model.

RESEARCH LIMITATION

Being small of population of accepted firms in Tehran's stock exchange caused we could not pair non-bankrupt firms with bankrupt ones in all of industrial aspects.

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