УДК 338.001.36
JEL Classification: C81;G33

Myachin V.G., Honchar L.A.

ARTIFICIAL NEURAL NETWORKS AS A MODERN TOOL FOR FORECASTING THE FINANCIAL CONDITION OF ENTERPRISES AND THE PROBABILITY OF THEIR BANKRUPTCY

Ukrainian State University of Chemical Technology, Dnipro

In this paper, bankruptcy prediction has been determined an important and widely studied topic. The goal of this study is to predict enterprise insolvency before the bankruptcy using artificial neural networks, to enable all parties to take remedial action. Artificial neural networks are widely used in finance and insurance problems. Generalized Regression Neural Network (GRNN) is used to evaluate the predictor variable used to predict the insolvency. The most important predictor variable influencing insolvency is consistently having the largest regression. Results showed that the most affecting factor in enterprise insolvency evaluation is the net income, total equity capital, cost of sales, sales, cash flows and loans. The Feed-forward back propagation neural network is used to predict the bankruptcy. The results of applying feed-forward back propagation neural network methodology to predict financial distress based upon selected financial ratios show abilities of the network to learn the patterns corresponding to financial distress of the enterprise. Artificial neural networks show significant signs for providing early warning signals and solvency monitoring. The proposed neural network is evaluated using confusion matrices.

Keywords: artificial neural networks; general regression network; feed-forward back propagation neural network; financial distress analysis.

The introduction

Bankruptcy prediction has been an important and widely studied topic. The prediction of the likelihood of failure of a company given a number of financial measures, how soon an “ill” business can be identified, possibility of identifying the factors that put a business at risk — these are of main interest in company lending. Recently researchers have used neural networks as a bankruptcy classification models. Artificial neural networks showed accurate results as discriminant analysis to early detect enterprise failures.

Analysis of last researches and publications

Beaver, Altman, Williams and Goodman, Sinkey and Altman, Haldeman and Narayanan have used discriminant analysis to solve bankruptcy prediction problem. Kaski, Sinkkonen and Peltonen introduced a method for deriving a metric, locally based on the Fisher information matrix, into the data space. A self-organizing map (SOM) is computed in the new metric to explore financial statements of enterprises. The metric measures local distances in terms of changes in the distribution of an auxiliary random variable that reflects what is important in the data.

Setting objectives and the purpose of the study

The goal of this paper is to evaluate the predictor variable used to predict the insolvency using Generalized Regression Neural Network (GRNN). Also the focus of this paper is to employ two data mining tools, namely backpropagation multi-layer perceptron (MLP) and the radial basis function network (RBFN), to quantitative bankruptcy prediction, since the backpropagation neural networks have played an important role for classification problems.

Presentation of the main material of research

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. An (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s). Fig. 1 represents the typical neural network. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

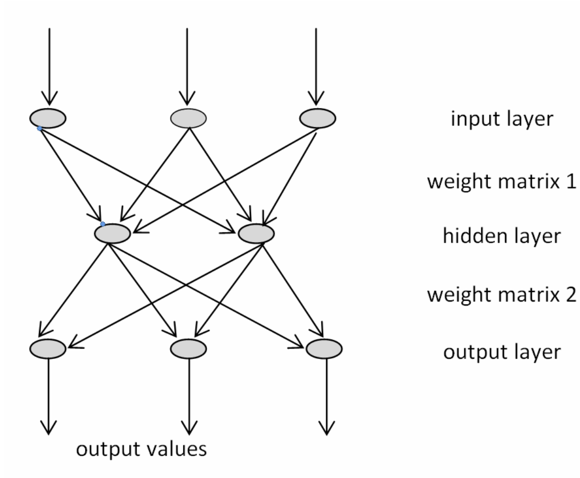

Fig. 1. A typical neural network

For the researcher and the financial analyst, the main advantage of ANNs is that there is no need to specify the functional relation between variables. Since they are connectionist-learning machines, the knowledge is directly imbedded in a set of weights through the linking arcs among the processing nodes. In order to train a neural network properly one needs a large set of representative "good quality' examples. In the case of bankruptcy problems, the researcher should be cautious when drawing conclusions from neural networks trained with only one or two hundred cases, as observed in most previous studies.

The GRNN was applied to solve a variety of problems like prediction, control, plant process modeling or general mapping problems. General regression neural network Specht and Nadaraya does not require an iterative training procedure as in back-propagation method.

The GRNN is used for estimation of continuous variables, as in standard regression techniques. It is related to the radial basis function network and is based on a standard statistical technique called kernel regression. By definition, the regression of a dependent variable y on an independent x estimates the most probable value for y, given x and a training set. The regression method will produce the estimated value of y, which minimizes the mean-squared error. GRNN is a method for estimating the joint probability density function (pdf) of x and y, given only a training set. Because the pdf is derived from the data with no preconceptions about its form, the system is perfectly general. Furthermore, it is consistent; that is, as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function. In GRNN, instead of training the weights, one simply assigns to w_{ij} the target value directly from the training set associated with input training vector i and component j of its corresponding output vector.

Table 1 presents the financial ratios which are considered as predictor variables used in the study [1]. The first three predictor variables are liquidity ratios, whilst the fourth measures the self-financing capacity of the bank. Ratios five, six and seven relate profit to various items on the balance sheet. Ratio nine relates the cost of sales to sales and ratio nine relates the cash flow of the bank to the debts.

Table 1

Predictor variable of datasets

S. No	Predictor Variable Name
1	Current assets/total assets
2	Current assets-cash/total assets
3	Current assets/loans
4	Reserves/loans
5	Net income/total assets
6	Net income/total equity capital
7	Net income/loans
8	Cost of sales/sales
9	Cash flow/loans

Both MLP (backpropagation multi-layer perceptron) and RBFN (radial basis function network) are multi-layer neural networks and can be trained by the backpropagation algorithm [2]. Additionally, MLP and RBFN have been also widely used in other fields, such as function approximations and management sciences [2, 3].

The generalization ability of the backpropagation MLP and RBFN are examined by the holdout method [2], which is a common technique for assessing the classifier accuracy. In the holdout method, 80% and 20% of the given data are randomly partitioned into a training set and a testing set, respectively. Subsequently, the training set and the testing set are employed to construct a backpropagation neural network and are used to estimate classifier accuracy, respectively.

Using the holdout method, 80% of the 77 selected firms (i.e., 61 firms) and 20% of those (i.e., 16 firms) are randomly partitioned into a training set and a testing set, respectively. Actually, the holdout method is repeated five times by the random subsampling. Thus, the overall estimated accuracy is equal to the average of the accuracies obtained by individual iterations.

Additionally, for a backpropagation MLP and an RBFN, there is no upper or lower limits to the size of a training data set. Moreover, they cannot explicitly interpret which variables are influential factors for the output [4]. For the probit method, this approach can present a crisp relationship between explanatory and response variables of the given data from a statistical viewpoint and does not assume a

Table 2.

Comparisons of three classification models

Aspect	Method		
	Profit	Back Propagation MLP	RBFN
Theory Based	Possibility theory	Neural network	Neural network
I/O Relationship	Crisp function	Block box	Zero-order Sugeno fuzzy inference system
Statistical Assumption	Yes	No	No
Data Requirement	More	Less	Less
Training Time	None	More	More

multivariate normality. In particular, the probit method assumes that the cumulative probability distribution is the standardized normal distribution [5]. The differences between the probit method, the backpropagation MLP and the RBFN are briefly summarized in Table 2 [2,4,5,6]. It can be seen that the drawback of the backpropagation MLP and the RBFN is the fact that they take a lot more time generating a nonlinear mapping. Nevertheless, they have the attractive advantage of not requiring any statistical assumptions.

The experimental results are further analyzed as follows:

1. In comparison with the discriminant analysis, it seems that the probit method is a promising multivariate technique that should be given considerable consideration when solving real problems like bankruptcy prediction.

2. It is seen that a RBFN is superior to the other methods. This may demonstrate that the RBFN can perform excellent approximations for curve fitting problems. The analytical results may lead to the potential applicability or related methodological development of the nonlinear regression tools considering non-additivity of the interaction among attributes, such as fuzzy rule-based systems, in the bankruptcy prediction.

Actually, the backpropagation MLP and a RBFN are powerful tools because of their nonlinear and nonparametric adaptive-learning properties and there being less constraint on the number of observations. Although an advantage of the multivariate techniques is to indicate which variables are influential, due to each method having its unique advantages, decision makers should select an appropriate tool to solve the problems they face.

Conclusions and recommendations for further research

Results showed that the most affecting factor in enterprise insolvency evaluation is the net income, total equity capital, cost of sales, sales, cash flows and loans. It is also aimed to predict enterprise insolvency before the bankruptcy using feed-forward back propagation neural network. The results of applying the supervised neural network in classification of financial distress based upon the selected financial variables showed that artificial neural networks are able to learn the patterns corresponding to financial distress of the enterprise. Even with the limited data used in this study, artificial neural networks showed significant signs for providing early warning signals and solvency monitoring.

The improvement in generalization ability of the backpropagation MLP will be taken into account. It is known that too few training patterns or too many weights in a network may result in poor generalization ability [9]. Other than these principles, several useful methods proposed to construct a network for improving generalization can be found in, and will be considered in the future works.

REFERENCES

1. Al-Shayea Q.K. Evaluation of Banks Insolvency Using Artificial Neural Networks / Qeethara Kadhim Al-Shayea, Ghaleb Awad El-Refae // Recent Researches in Artificial Intelligence and Database Management. – 2010. – No. 5. – P.113-118.

2. Yi-Chung Hu. Applying backpropagation neural networks to bankruptcy prediction / Yi-Chung Hu, Fang-Mei Tseng // International Journal of Electronic Business Management. – 2005. – Vol.3. – No. 2. – P.97-103.

3. The use of artificial neural network in predicting bankruptcy and its comparison with genetic algorithm in firms accepted in Tehran Stock Exchange / Masoud Taherinia, Darush Javid Masoumeh Zebardast // Journal of Novel Applied Sciences. – 2014. – Vol.3. – No. 2. – P.151-160.

4. Brйdart X. Bankruptcy Prediction Model Using Neural Networks / Xavier Brйdart // Accounting and Finance Research. – 2014. – Vol.3. – No. 2. – P.124-128.

5. Kasgari A.A. The Bankruptcy Prediction by Neural Networks and Logistic Regression / Ahmad Ahmadpour Kasgari, Seyyed Hasan Salehnezhad, Fatemeh Ebadi // International Journal of Academic Research in Accounting, Finance and Management Sciences. – 2013. – Vol.3. – No. 4. – P.146-152.

6. Fernandez F.G. Use of Artificial Neural Networks to Predict The Business Success or Failure of Start-Up Firms / Francisco Garcia Fernandez, Ignacio Soret Los Santos, Javier Lopez Martinez, Santiago Izquierdo Izquierdo, Francisco Llamazares Redondo // Artificial Neural Networks – Architectures and Applications. – 2013. – P.245-256.

Received 03.05.2018

Reviewer: Dr.e.s., ass. prof. L.D. Harmider

ШТУЧНІ НЕЙРОННІ МЕРЕЖІ ЯК СУЧАСНИЙ ІНСТРУМЕНТ ДЛЯ ПРОГНОЗУВАННЯ ФІНАНСОВОГО СТАНУ ПІДПРИЄМСТВ І ЙМОВІРНОСТІ ЇХ БАНКРУТСТВА

М'ячин В.Г., Гончар Л.А.

У статті показано, що прогнозування банкрутства є важливою і актуальною темою для будь-якого господарюючого суб'єкта. Метою дослідження є аналіз методів прогнозування банкрутства підприємств до їх банкрутства з використанням штучних нейронних мереж. Штучні нейронні мережі широко використовуються в питаннях фінансів, страхування та для оцінювання фінансового стану підприємств. Узагальнена регресивна нейронна мережа (GRNN) найбільш часто використовується для оцінювання ймовірності банкрутства підприємств. Результати дослідження показали, що найбільш значущим чинником в оцінці банкрутства підприємства є чистий дохід, загальний власний капітал, собівартість продажів, обсяг виручки, грошові потоки і кредити. Для прогнозування банкрутства найбільш часто використовується нейронна мережа зі зворотним поширенням помилки. Результати застосування методології нейронної мережі зі зворотним поширенням помилки для прогнозування фінансового банкрутства на основі обраних фінансових коефіцієнтів показують потенційні можливості нейронних мереж вивчати закономірності, відповідні фінансовій неспроможності підприємства. Штучні нейронні мережі мають значні можливості як для забезпечення моніторингу платоспроможності підприємств, так і для раннього попередження їх банкрутства.

Ключові слова: штучні нейронні мережі; нейронна мережа із зворотним розповсюдженням помилки; аналіз фінансового банкрутства підприємства.

ИСКУССТВЕННЫЕ НЕЙРОННЫЕ СЕТИ КАК СОВРЕМЕННЫЙ ИНСТРУМЕНТ ДЛЯ ПРОГНОЗИРОВАНИЯ ФИНАНСОВОГО СОСТОЯНИЯ ПРЕДПРИЯТИЙ И ВЕРОЯТНОСТИ ИХ БАНКРОТСТВА

Мячин В.Г., Гончар Л.А.

В статье показано, что прогнозирование банкротства является важной и актуальной темой для любого хозяйствующего субъекта. Целью исследования является анализ методов прогнозирования банкротства предприятий до их банкротства с использованием искусственных нейронных сетей. Искусственные нейронные сети широко используются в вопросах финансов, страхования и для оценки финансового состояния предприятий. Обобщенная регрессионная нейронная сеть (GRNN) наиболее часто используется для оценки вероятности банкротства предприятий. Результаты исследования показали, что наиболее значимым фактором в оценке банкротства предприятия является чистый доход, общий собственный капитал, себестоимость продаж, объём выручки, денежные потоки и кредиты. Для прогнозирования банкротства наиболее часто используется нейронная сеть с обратным распространением ошибки. Результаты применения методологии нейронной сети с обратным распространением ошибки для прогнозирования финансового банкротства на основе выбранных финансовых коэффициентов показывают потенциальные возможности нейронных сетей изучать закономерности, соответствующие финансовой несостоятельности предприятия. Искусственные нейронные сети обладают значительными возможностями как для обеспечения мониторинга платежеспособности предприятий, так и для раннего предупреждения их банкротства.

Ключевые слова: искусственные нейронные сети; нейронная сеть с обратным распространением ошибки; анализ финансового банкротства предприятия.