USE OF ARTIFICIAL NEURAL NETWORKS IN FINANCIAL TIME SERIES PREDICTION AND FINANCIAL RISK PREDICTION

Slobodan Čabarkapa, Nenad Kojić, Ana Savić, ICT College, Belgrade
Boško Živković, Faculty of Economics, University of Belgrade, Belgrade

Sadržaj *– Veliki broj studija je dokazao da je veštačka inteligencija veoma moćan alat za predikciju finansijskih vremenskih serija, sposoban da ponudi znatno bolje rezultate od većine ostalih algoritama. Korisnost Value at Risk (VaR) metodologije, koja je postala standardna mera rizika korišćena od strane mnogih finansijskih institucija je veoma diskutabilna. Uprkos konceptualnoj jednostavnosti, njeno merenje postaje značajan statistički izazov, jer ni jedna od do sada razvijenih metodologija VaR-a ne daje sasvim zadovoljavajuće rezultate. Zbog sposobnosti da obrađuju nesigurne, nejasne ili nekompletne podatke, koji brzo fluktuiraju u veoma kratkim intervalima vremena, veštačke neuralne mreže su postale veoma važan metod za finansijske predikcije.*

Abstract *- A large number of studies have proved that artificial intelligent techniques are powerful tool for financial time series prediction and financial risk prediction, capable of outperforming most other known algorithms. Value at Risk (VaR) methodology which has become the standard measure of risk by financial institutions is questionable. Despite its conceptual simplicity, its measurement becomes a very challenging statistical problem, because none of the methodologies developed so far give satisfactory results. Because of their ability to deal with uncertain, fuzzy, or insufficient data which fluctuates rapidly in very short periods of time, artificial neural networks became a very important method for financial predictors.*

1. INTRODUCTION

Artificial Neural Networks (ANN), as artificial intelligence methods, have recently become very important in financial predictions. During the last two decades they have been widely applied to a variety of financial time series prediction and risk management tasks, and their importance in this field is growing.

ANNs were developed to replicate biological neural systems with physical models. ANN is a system composed of many simple processing elements operating in parallel, whose function is determined by network structure, connection strengths and the processing performed at computing elements or nodes.

Many researches on the applications of ANNs for solving financial problems have proven their advantages over statistical and other methods that do not include artificial intelligence. The reasons why ANNs often outperform classical statistical methods lie in their abilities to analyze incomplete, noisy data, to deal with problems that have no clear cut solution and to learn on historical data. Because of those advantages, they have shown success in predictions of financial data series that have high degree of volatility and fluctuations. It is mathematically proven (using the Ston-Weierstrass, Hahn-Banach and other theorems and corollaries) that three-layer neural networks having arbitrarily squashing transfer function are capable of approximating any nonlinear function [1].

2. NEURAL NETWORK METHODOLOGY

The neuron is the basic unit of a neural network (NN) model. Neurons are grouped into layers. There are three main types of layers: input, hidden and output. The input layer receives input data from external environment, and sends it to the hidden layer. In the hidden layer the information is processed and sent to the output layer neurons, where the network output is compared to the desired output and the network error is computed. The error information then flows backward through the network and the values of connection weights between the neurons are adjusted using the error term. The process is repeated in the network for a number of iterations that is necessary to achieve the output closest to the desired output. Finally, the network output is presented to the user. Neural network learning is basically the process by which the system arrives at the values of connection weights between neurons. Connection weight is the strength of connection between two neurons. If, neuron j is connected to neuron i, w_{ji} denotes the connection weight from neuron j to neuron i (w_{ij} is the weight of reverse connection from neuron i to neuron j). If neuron i is connected to neurons called $1, 2, \ldots, n$, their weights are stored in the variables $w_{1j}, w_{2j}, \ldots, w_{nj}$. A neuron receives as many inputs as there are input connections to that neuron, and produces a single output to other neurons according to transfer function.

The process of neural network design consists of four phases [2]:

- arranging neurons in various layers
- determining the type of connections between neurons (inter and intra layer connections)
- determining the way neurons receive input and produces output
- determining the learning rule for adjusting the connection weights.

The result of neural network design is the neural network architecture. The criteria to distinguish neural network architecture are: number of layers, type of connection between neurons, connection between input and output data, input and transfer function, type of learning, certainty of firing, temporal characteristics, learning time.

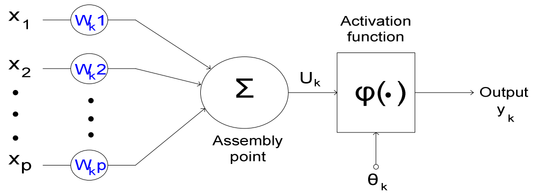
Connections in the network can be realized between two layers (inter layer connections) and between neurons in one layer (intra layer connections).

Some well known NN architectures with inter layer connections are:

- Perception NN, first NN, 1957, two-layered, fully connected
- ADALINE NN, 1962, two-layered, fully connected
- Back-propagation, 1974, first NN with one or more hidden layers, hierarchically connected
- ART, 1976, three-layered, resonance connection
- Hopfield neural network, recurrent network
- Feedforward Counterpropagation, 1987, three-layer, non-hierarchical.

Connections between neurons in one layer (intra layer) can be recurrent or on-center/off-surround. Some of the intra layer networks are: Hopfield's network (with recurrent connection), recurrent Back-propagation network, Kohonen's self-organizing network (on-center/off-surround connection), counterpropagation networks (on-center/off-surround connection)…

The overall stimulation of the mathematical neuron model is determined by the sensitivity threshold and the sum of all the input signals which would have been multiplied previously by the relevant weight coefficients. When the stimulation is higher than the sensitivity threshold the neuron is activated and its output signal has a maximal value. In contrast, when the stimulation is below the sensitivity threshold the neuron is inactive, and the output signal has a minimal value. The transition between active and inactive status is described by the activation function φ(.), and shown in picture 1.



Picture 1: Mathematical neuron model

The neural network parameters are defined during the course of the neural network training, during which the network adapts towards a sample of numerous known input and output values.

Every NN goes through three operative phases:

1. learning (training) phase, network learns on the training sample, the weights are fixed, adjusted in order to minimize the objective function
2. testing phase, network is tested on the testing sample while the weights are fixed
3. recall (operative) phase, network is applied to the new cases with unknown results.

3. APPLICATION OF ANN FOR FINANCIAL TIME SERIES PREDICTION AND EVALUATION OF RISK

Finance and investments are one of the most frequent areas of ANN applications. ANN provides a broad range of financial applications, more specifically in market risk quantification and portfolio optimization [3]. They have been applied to a variety of financial prediction and risk management tasks.

Numerous serious statistical and scientific studies have indicated that the stock market, as well as other financial markets, is to a certain degree predictable by means of newly developing methods and tools. But, one must be aware that Value at Risk (VaR) methodology which has become the standard measure of market risk by financial institutions is questionable. VaR is defined as the value that a portfolio might lose with a given probability, over a certain time horizon [1]. Despite its conceptual simplicity, its measurement becomes a very challenging statistical problem, because none of the methodologies developed so far give satisfactory results. Ex, the Delta Normal Method is based on a linearization of the portfolio, ant thus can perform poorly with portfolios that include large positions in options or instruments with option like payoffs. For some assets such as options or short-term securities, normality assumptions are highly questionable. The Monte Carlo or the Delta Gamma Approach are both based on normality assumptions that also contradict the skewness, and the heavy taildness that logarithmic returns of financial instruments are usually displaying. Financial returns are heteroskedastic (time changing volatility) and to a large extend unexpected. So, the heavy taildness of financial returns itself corrects the classical normality or linearity assumptions usually made for getting a quick and easy computable form of the VaR.

Due to the huge complex sets of random indicators that are driving the dynamics of stock prices (or daily returns), modeling or predicting financial markets behavior still remains a very challenging task. Non-linearity, skewness, fat tails, volatility clustering, leverages effects, co-movement in volatility of the existing financial returns, provides serious reasons for thinking about finding alternative predictive statistical methods, which can correct some of these facts. To overcome the non-linearity, skewness or the heteroscedasticity that financial time series are usually displaying, ANN can be used.

ANN represent one of the most powerful tools for non-parametric regression analysis due to their flexibility and high capacity of approximating unknown functions assisted by the increasing computational power of new computers and numerical optimization software. In most analyzed applications, the ANN results outperform statistical methods, such as multiple linear regression analysis [4], discriminative analysis [5] and others.

ANN is well-tested method for financial analysis on the stock market. It is used for: predicting stock performance, recommendation for trading, classification of stocks, predicting price changes of stock indexes, stock price prediction, modeling the stock performance, forecasting the performance of stock prices… [6].

Besides, it is used in [1]:

- Loan assessment – mortgage lending, forecasting the loan risk category as good/criticized/charge-off, underwriting loans and insuring mortgage loans.

- Stock and bond market – deciding when to buy and sell stocks, problem of buying and selling orders, discovering triangle patterns in stock prices on the stock exchange, recognizing buying and selling patterns of the live-cattle commodity futures markets.
- Risk rating and classification – bond rating, bond classification, classification of stock returns into high or low performance
- Forecasting the market – prediction of stock prices, forecasting futures market prices, prediction of monthly stock price movement, stock market prediction
- Forecasting returns – testing market efficiency, prediction of stock returns.

Among all these purposes, three main groups of applications can be recognized:

1. Prediction of stock performance by classifying stocks into classes: positive/negative return stocks, or well/neutrally/poor performance. They help in making investment decisions, but do not specify expected price or profit.
2. Stock price prediction. They try to predict prices for one or more days in advance, based on previous stock prices and related financial ratios.
3. Modeling stock performance and forecasting. They do predictions as well as factor significance estimation, sensitivity analysis among the variables that could impact the result, and other analysis of mutual dependencies.

4. EXAMPLES OF ARTIFICIAL INTELLIGENCE IN FINANCE

The first example of the application of neural networks in financial time series prediction is system developed by Tino, Schittenkopf, Dorffner, in 2000 [7]. The mentioned system is used for simulation of option trading with FTSE and DAX options. System predicts the volatility. The ANN is trained on the training set of 500 daily volatility values. Then, every algorithm is applied on a validation set of 125 days (the algorithms are used to trade with options in these 125 days). Finally, the best performing algorithm is chosen and applied to a test set of 5 days. Then, the “sliding window” technique is applied, shifted by 5 days, and then the process begins again. There were several prediction techniques incorporated in the system, among them two neural networks. One was used to predict the volatility difference for the next day and the other to predict the direction of the volatility difference (up or down). But, the conclusion was that the prediction accuracy does not always guarantee a profitable trading. It appeared that prediction accuracy and profitability of the trading strategy predictions are two different tasks.

The second example of ANNs application in finance is the experiment described in Diagne’s PhD thesis, in 2002 [3]. The simulation has been done with real financial data: the daily closing prices of Deutsche bank, BASF, Siemens and the DAX30, all traded in the Frankfurt stock exchange. The algorithms were used with 255 previous closing prices, with 5 previous closing prices used to predict the future market value of the next day. Then, the estimates were compared with the actual losses observed on the next day. The goodness of the estimation procedure has then been measured by computing the number of violation throughout the back testing. Only 3 violations have been observed for a period of 577 trading days, concluding that ANNs are powerful tool capable of outperforming most other known algorithms.

The last example will be an artificial intelligence technique presented by Kin, Lean, Ligang and Shouyang in 2006 [8]. In this experiment the least square support vector machine (LSSVM) technique is used to design a credit risk evaluation system to discriminate good creditors from bad ones. The real credit dataset was used to test the performance of LSSVM. The dataset included 1225 applicants, of which 323 were observed as bad creditors, and every applicant included the following 14 variables: year of birth, number of children, number of other dependents, is there a home phone, applicants income, applicants employment status, spouse’s income, residential status, value of home, mortgage balance outstanding, outgoings on mortgage or rent, outgoings on loans, outgoings on hire purchase, and outgoings on credit cards. In the experiment, a three-layer back-propagation neural network with 10 TANSIG neurons in the hidden layer and one PURELIN neuron in the output layer was used. The network training function was TRAINLM.

Using Kolmogorov-Smirnov statistic (KS), as the indicator in the credit risk evaluation, the comparison of different evaluation models has been done. Theoretically, KS statistic can range from 0 to 100. In reality, it goes from 20 to 70. If it’s lower than 20, the classifier is not worth using. If it’s higher than 70, it’s too good to be true and we should suspect problems with the way the problem is being calculated. For comparison, in this case, the classification results of: linear regression (LinR), logistic regression (LogR), artificial neural network (ANN) and least square support vector machine (LSSVM), are shown below.

Method	KS stat (%)
LinR	26.68
LogR	35.63
ANN	46.39
LSSVM	58.88

As it can be seen, AAN and LSSVM outperform other models, but the LSSVM performs the best. According to the authors, LSSVM model is a feasible solution to improve the accuracy of credit risk evaluation.

5. CONCLUSION

Taking into account the skewness, the heavy tailedness, often strong nonlinearity, and stochastic feature of the volatility of the market values of financial instruments, a consistent non-parametric measure is needed. Due to the huge complex sets of random indicators that are driving the dynamics of stock prices (or daily returns), modeling or predicting financial markets behavior still remains a very challenging task. Very similar problem is observed with risk prediction.

A large number of studies, during last two decades, proved that artificial intelligent techniques are powerful tool for financial time series prediction and for financial risk prediction, capable of outperforming most other known algorithms. For example, they are advantageous to statistical models of risk evaluation. They can reflect asymmetric behavior at the output and analyze nonlinearity of the input-output values. Artificial neural networks are among the most effective learning methods currently known. Motivated in their design by the human nervous system, they acquire the required information from the examples supplied to them, during their learning procedure, classifying patterns or making decisions based on past experiences.

At the moment, ANNs represent one of the most powerful tools for non-parametric regression analysis due to their flexibility and high capacity of approximating unknown functions, assisted by the increasing computational power and numerical optimization software. Because of their ability to deal with uncertain, fuzzy, or insufficient data which fluctuates rapidly in very short periods of time, ANNs have become a very important method for financial predictors, and in the years coming, their usage will definitely increase.

LITERATURA

[1] Zekic M, PhD thesis, „Neural Networks in Investment Profitability Predictions“, University of Zagreb, Faculty of Oranizational and Informatics, Varazdin, 2000.

[2] Zahedi F, „Intelligent Systems for Business, Expert Systems with Neural Network“, Wodsworth Publishing Inc, 1993.

[3] Diagne M, PhD Thesis, „Financial Risk Management and Portfolio Optimization Using Artificial Neural Networks and Extreme Value Theory“, University of Kaiserslautern, Mathematics Department/Financial Mathematics, Germany, 10.October 2002.

[4] Refenes, A.N., Zapranis, A., Francis, G., „Stock Performance Modeling Using Neural Networks: A Comparative Study with Regression Models“, Neural Networks, vol. 7, No. 2, 1994, p 375-388.

[5] Swales, G.S.Jr., Yoon, Y., „Applying Artificial Neural Networks to Investment Analysis“, Financial Analyst s Journal, September-October, 1992, pp. 78-80.

[6] Pissarenko D, BSc Thesis at Computer Studies, „Neural Networks For Financial Time Series Prediction: Overview Over Recent Research“, University of Derby, Austria, 2002.

[7] Tino P, Schittenkopf C, and Dorffner G. „Temporal pattern recognition in noisy non-stationary time series based on quantization into symbolic streams: Lessons learned from financial volatility trading“, Adaptive Information Systems and Modelling in Economics and Management Science, Nr. 46, July 2000, Viena University of Economics and Business Administration.

[8] Kin K.L., Yu L, Liang Z, Shouyang W, „Credit risk evaluation with least square support vector machine“, First international conference, RSKT 2006, Chongqing, China, July 24-26, 2006.

[9] Haefke C, White H, Gottschling A, „Closed Form Integration of Artificial Neural Networks with Some Application to Finance“, Computing in Economics and Finance, Society for Computational Economics, 366, 2000.

[10] Schoeneburg E, „Stock Price Prediction Using Neural Networks: A Project Report“, Neurocomputing, vol. 2, 1990, p. 17-27.

[11] Kaastra I., Boyd M., „Designing a neural network for forecasting financial and economic time series“ Neurocomputing Vol.10, pp.215-236, Elsevier Science B.V., 1996.

[12] Herbrich R, Keilbach M, Graepel T, Bollmann-Sdorra P, Obermayer K, „Neural Networks in Economics: Background, Applications and New Developments“, Advances in Computational Economics: Computational Techniques for Modelling Learning in Economics, 1998.

[13] Haykin S., „Neural networks- a comprehensive foundation“, MacMillan collage Publishing Company, Inc., 1994.

[14] Simpson P., *Artificial neural system*, Pergamon, Elmsford, NY, 1990.

[15] Hopfield J. J., Tank D. W, „Neural computations of decision in optimization problems“, Biol. Cybern., Vol. 52, p. 141-152, 1985

[16] Tankut Yalcinoy, Halis Altun, „Comparison of Simulation Algorithms for the Hopfield Neural Network: An Application of Economic Dispatch“, Turk J Elec Engin, vol 8, no. 1, 2000, Tubitak, Turkey.

[17] Daniel Graupe, „Principles of artificial neural networks“, University of Illinois, Chicago, 1997.

[18] Kartalopoulos, S.V., „Understanding Neural Networks and Fuzzy Logic, Basic Concepts and Application“, IEEE Press, 1996.

[19] Jorion P, „Value at Risk“, 2nd edition, McGraw-Hill, USA, 2002.

[20] Savić A, Kojić N, „Quantification of IT Operational Risk in Accordance with Basel II“, Balcor 2007, 8 th Balcan Conference on Operational Research, Belgrade-Zlatibor, 14.-17. septembar 2007.

[21] Čabarkapa S, Kojić N, „Predikcija Internet saobracaja primenom neuralnih mreza“, INFOTEH, Jahorina, 26-28. mart, 2008.

[22] Čabarkapa S, Kojić N, Savić A, Živković B, “One Artificial Neural Network Implementation For Credit Risk Prediction”, Balcor 2009, Constanta, Romania, 02-06 September 2009.