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FINANCIAL TIME SERIES FORECASTING USING NEURAL NETWORKS: A CASE STUDY OF THE BUCHAREST STOCK EXCHANGE

TRIFAN, A[lina] L[ucia]

Abstract: *The purpose of this paper is to research an original field of engineering, but with important implications and applications in economics in general, particularly for the financial aspect. This study aims to investigate the performance of financial time series forecasting using artificial neural networks and to compare the results with the classical models (linear regression, GARCH-M). The case study is conducted on 45,216 daily data of Bucharest Stock Exchange for the period 11/21/2002 to 07/08/2010.*
Key words: *artificial neural networks, financial time series, forecasting, linear regression, GARCH-M*

1. INTRODUCTION

The analysis of past and present events has been developed into different techniques for solving the future behavior forecasting of certain data series. Forecasting different variables is the key activity in developing market strategies. Trading stock indices has gained tremendous popularity in most financial markets in the world, encouraged by the diversity of financial instruments and new indices, driving the growth in global investment opportunities, both for individual investors, but also institutional ones. Trading stock indices offers to the investors the opportunity to cover potential specific capital market risks and creates opportunity for profit for speculators and arbitrageurs.

Modern technologies use artificial intelligence to create systems that mimic human behavior. Artificial neural networks (ANN) possess remarkable capacity to learn, to adapt, to generalize, can solve nonlinear problems, interpolation and leveling data, can accommodate the nonlinear and complex scenarios for different statistical distributions. The possibility of financial time series forecasting and particularly, stock indices forecasting with ANN has profound implications in both research and practice. The interest showed in modeling financial time series using ANN is due to their ability to learn and memory, as well as their applicability in an impressive number of scientific fields.

Since 1991, banks began to use neural networks in decision-making process for granting credit and for financial forecasts, so many companies started to produce applications based on neural networks easy to use, containing various architectures and learning rules. Business impact was immediate and substantial, given widespread use of ANN in areas like finance, banks and stock exchanges, accounting, marketing, human resources. So today's business environment has become dependent on intelligent problem-solving techniques, continually being researched and developed methods, models in which rules are combined with neural networks genetic algorithms, fuzzy logic, neural-fuzzy and fuzzy expert systems.

2. LITERATURE REVIEW

McCulloch and Pitts (1943) achieve a first simulation of biological nervous system structure, performing logic functions in learning and build the binary probit model. Donald Hebb (1949) introduces the first law of learning. Frank Rosenblatt (1958) builds on previous studies and develops advanced models that have the ability to learn, most notably the Perceptron model - the simplest type of feedforward artificial neural network. Cowan (1967) introduces the sigmoid function as activation function. Paul Werbos (1974) publishes the learning method called backpropagation error, technique that enables to determine the parameters values for which the error is minimized.

Chenoweth and Obradovic (1996) apply artificial neural networks in finance, investigating the behavior of a forecasting system for S&P 500 stock index. Terna (1998) uses multiple neural networks to simulate the behavior of stock market investors, investigating the behavior of a small system composed of 10 buyers and 10 sellers. Leung et al. (1998) evaluate in terms of performance and investment return various techniques and models for time series forecasting, seeking to determine the direction of movement of stock indices using linear discrimination analysis, probit and logit analysis, probabilistic neural networks.

Tino (2001) describes a system that simulates trading options on the FTSE and DAX stock index, predicting the volatility of the two indices using delta-neutral trading strategy. Ho et al. (2002) develop a comparison between ANN and Box-Jenkins ARIMA method for predicting time series. Phua et al. (2003) obtain satisfactory results for the forecast of the Singapore Stock Exchange indices combining genetic algorithms and neural networks.

Kamruzzaman and Sarker (2004, 2006) conduct a comparative study of ANN and ARIMA models for forecasting the exchange rate and conclude in favor of the ANN. Santiago Maia and de Carvalho (2010) mix MLP neural networks with Holt's exponential smoothing method for the capital market forecasting.

Ebrahimpour et al. (2010) predict the development of equities listed on the stock exchange in Tehran, Iran and use a mix of MLP expert systems, combining three specific neural networks methods and compare its performance with neuro-fuzzy networks in which the Adaptive Network-Based Fuzzy Inference System (ANFIS) learning method is applied.

Jagric et al. (2010) stresses the importance of psychological factors explaining the behavior of stock market investors through them.

3. CASE STUDY

3.1 Data

The data sets used for this study were daily closing prices for a total of 22 companies listed on Bucharest Stock Exchange and two representative Romanian stock indices BET and BET-C. The period of analysis is in the range 11/21/2002 to 07/08/2010. For optimal use of available data, their sizing was performed in two samples: the training data set (11/21/2002 to 12/21/2007) and the data set used for validation and testing (03/01/2008 to 08/07/2010).

3.2 Methodology

In order to implement the neural network was considered as representative the following relationship:

$$KD_{t+1} = f_2(w_2 \cdot f_1(w_1 \cdot x)) \quad (1)$$

where:

$$KD_t = K_t - D_t \quad (2)$$

K and D are specific technical analysis stochastic indicators, calculated for the KD trading system;

f_1 and f_2 represent the transfer (activation) functions, the unipolar sigmoid (logistic) function was used, which has the following expression:

$$\boldsymbol{f}(\boldsymbol{x}) = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{k}\cdot\boldsymbol{x}}}, \boldsymbol{k} > 0 \quad (3)$$

w_1 and w_2 are the weights matrices for the connections between inputs and hidden layer and between hidden nodes layer and output layer, respectively.

In this study a MLP neural network with three layers was implemented and backpropagation with a momentum term techniques were applied. Repeated tests have found the optimal values of training parameters: learning rate and momentum (which can take values between 0 and 1) as the learning rate 0.1 and 0.7 for momentum.

4. RESULTS

Classical models results, obtained using EViews program, were compared in terms of indicators R^2, adjusted R^2, *DW* statistics, but also usig other performance indicators calculated for models based on AI (the number of correct forecasts, *h*, the ratio between the number of correct projections (*h*) and total number of forecasts (*N*), called Hit Rate, *HR* and the root mean square error, *RMSE*).

$$HR = h/N \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \varepsilon_i^2} \quad (5)$$

Model	R^2	$\bar{R}^2$	h (N=15144)	HR	RMSE
Linear Regression	0.7244	0.7232	12,160	0.8030	1.1010
GARCH-M	0.7382	0.7368	12,172	0.8038	1.0891
ANN	-	-	13,262	0.8757	0.8598

Tab.1. Comparative average results for statistics and performance indicators

5. CONCLUSION

The comparative table of results of the analyzed models shows that the model based on the use of artificial neural networks obtained the best valuee for the performance indicators (making 13,262 accurate predictions of the total number of 15,144, having a hit rate of 87.57% and the RMSE indicator value is the smallest, 0.8598).

The classical models proposed for analysis, primarily aimed at the comparison with models based on AI, obtained lower values for the performance indicators, as follows: GARCH-M model correctly predicted a total of 12,172 possible price developments of the total 15,144 forecasts, HR: 80.38% and the RMSE value is over unit: 1.0891, while linear regression model had the lowest performance, 12,160 accurate forecasts at the same total number, HR: 80.30% and RMSE: 1.1010.

Although having experienced superior values of performance compared to conventional models, models based on AI can be difficult to understand, apply and interpret, leaving open other possible options for better choices and combinations of parameters (learning rates, momentum, the choice of certain algorithms, linguistic variables, membership functions).

The same restrictions may be noticed, however, also using classical models, that do not cover certain and correct choice of model variables. So the human factor characterized by experience, multiple attempts, intuition remains part of the decision both in building classical models and using models based on artificial intelligence.

What stands out for models based on the use of neural networks is their ability to capture and copy human characteristics (learning, generalization and making patterns, classifications).

6. FURTHER RESEARCH

ANN cannot be used, however, to explain the causal relationships between input and output variables, the algorithms used having a „black box” structure. Neural networks cannot be initialized with a set of a priori knowledge and must follow a learning algorithm, a process that has a temporal component that can not always guarantee success.

Thus, the disadvantage of neural networks in terms of lack of transparency in the process of collecting, handling and processing of input data in output data led to the development of fuzzy expert systems, a special case of expert systems. While neural networks have the information represented in the form of specific links, called weights, fuzzy systems are based on fuzzy logic, representing the information into fuzzy sets.

The goal of a future research will be the implementation of a hybrid neuro-fuzzy system and the test of its performance achieved as used for financial time series forecasting.

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