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An Adaptive Network-Based Fuzzy Inference System (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange

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ABSTRACT

Stock market prediction is important and of great interest because successful prediction of stock prices may promise attractive benefits. These tasks are highly complicated and very difficult. In this paper, we investigate the predictability of stock market return with Adaptive Network-Based Fuzzy Inference System (ANFIS). The objective of this study is to determine whether an ANFIS algorithm is capable of accurately predicting stock market return. We attempt to model and predict the return on stock price index of the Istanbul Stock Exchange (ISE) with ANFIS. We use six macroeconomic variables and three indices as input variables. The experimental results reveal that the model successfully forecasts the monthly return of ISE National 100 Index with an accuracy rate of 98.3%. ANFIS provides a promising alternative for stock market prediction. ANFIS can be a useful tool for economists and practitioners dealing with the forecasting of the stock price index return.

1. Introduction

The findings of recent literature confirm that stock market returns are predictable from past returns and other macroeconomics and financial variables. The predictability of stock market returns led the researchers to investigate the sources of this predictability (Gencay, 1998). Prediction of stock price return is a highly complicated and very difficult task because there are too many factors such as political events, economic conditions, traders' expectations and other environmental factors that may influence stock prices. In addition, stock price series are generally quite noisy, dynamic, nonlinear, complicated, nonparametric, and chaotic by nature (Yudong & Lenan, 2009).

Soft computing techniques are widely applied to stock market problems. They offer useful tools in forecasting noisy environments like stock markets, capturing their non-linear behavior (Atsalakis & Valavanis, 2009a). Utilizing intelligent systems such as neural networks, fuzzy systems and genetic algorithms for the purpose of prediction in the field of finance has extensive applications. Lately, artificial neural networks (ANNs) and support vector machines (SVMs) have been successfully applied to solve the problems of predicting financial time series, including financial stock market prediction (Armano, Marchesi, & Murru, 2005; Avcı, 2007; Chu, Chen, Cheng, & Huang, 2009; Egeli, Ozturan, & Badur, 2003; Hiemstra, 1995; Hua & Sun, 2001; Huang & Tsai, 2009; Karaatli, Gungor, Demir, & Kalayci, 2005; Kim & Chun, 1998; Kim & Han, 2000; Kimoto, Asakawa, Yoda, & Takeoka, 1990; Leigh, Purvis, & Ragusa, 2002; Manish & Thenmozhi, 2006; Oh & Kim, 2002; Olson & Mossman, 2003; Pai & Lin, 2005; Saad, Prokhorov, & Wunsch, 1998; Takahashi, Tamada, & Nagasaka, 1998; Tan, Quek, & See Ng, 2007; Tay & Cao, 2001; Tay & Cao, 2002; Yao, Chew, & Poh, 1999; Yoon & Swales, 1991; Yudong & Lenan, 2009).

Although ANFIS has been applied in several studies, few of these have contributed to research in the financial area. This study contributes to the field of financial research. The main goal of this study is to explore the predictability of stock market return on the Istanbul Stock Exchange (ISE) National 100 Index with ANFIS. The ISE National 100 Index, which is the main market indicator of the ISE, is a market capitalization-weighted index and represents at least 75% of the total market capitalization, traded value, number of shares traded and number of trades realized in the market (Bildik, 2001).

The rest of the paper is organized as follows. Section 2 provides a review of prior literature. Section 3 introduces the basic theory of ANFIS. Section 4 describes the research design and experiments. Section 5 provides a detailed analysis of the experimental results. Section 6 discusses the major conclusions and findings of the study.

2. Literature review

There exist vast literatures which concentrate on the predictability of stock market. In the following section, we focus on the re-

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view of the previous studies regarding the prediction of stock market return with ANFIS.

Grosan, Abraham, Ramos, and Han (2005) apply a genetic programming technique (called Multi-Expression programming-MEP) for the prediction of Nasdaq-100 index of Nasdaq Stock MarketSM and the S&P CNX NIFTY stock index. The performance is compared with an artificial neural network trained using Levenberg–Marquardt algorithm, support vector machines, Takagi–Sugeno neuro-fuzzy inference system and a difference boosting neural network. The empirical results indicate that MEP is a novel promising technique for function approximation problems. MEP technique gives the lowest MAP values for both stock indices. Quek (2005) uses ANFIS and neuro-fuzzy network for forecasting investors' measures in the US Stock Exchange Trade. The model is successful for predicting stock price**s** in the US Stock Exchange.

Trinkle (2006) uses ANFIS and neural network to forecast the annual excess returns of the three publicly traded companies. The predictive ability of these two techniques is compared with an autoregressive moving average (ARMA) model. The results reveal that the ANFIS and neural network techniques are able to generate forecasts with significant predictive ability. Afolabi and Olatoyosi (2007) use fuzzy logics, neuro-fuzzy networks and Kohonen's self-organizing plan for forecasting stock price. The results demonstrat**e** that the deviation in Kohonen's self-organizing plan is less than that in other techniques.

Abbasi and Abouec (2008) investigate the current trend of stock price of the Iran Khodro Corporation at Tehran Stock Exchange by utilizing an Adaptive Neuro-Fuzzy Inference System. The findings of the research demonstrate that the trend of stock price can be forecast with a low level of error. Chang and Liu (2008) develop a Takagi–Sugeno–Kang-type fuzzy rule-based system for forecasting Taiwan Stock Exchange price deviation. This model successfully forecasts stock price variation with accuracy close to 97.6% in TSE index and 98.08% in MediaTek. Yunos, Shamsuddin, and Sallehuddin (2008) develop a hybrid neuro-fuzzy with ANFIS to predict daily movements of the Kuala Lumpur Composite Index (KLCI). Four technical indicators are chosen to analyze the data. The experimental results show that ANFIS method is competent in forecasting the KLCI compared to ANN.

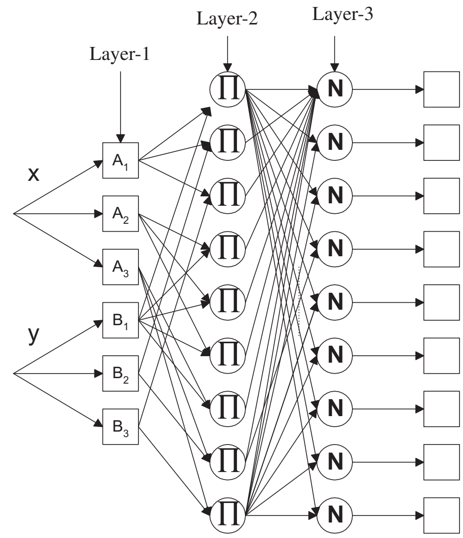
Atsalakis and Valavanis (2009b) develop a neuro-fuzzy adaptive control system to forecast the next day's stock price trends of the ASE and the NYSE index. The experimental results reveal that the proposed system performs very well in trading simulations, returning results superior to the buy and hold strategy. It also demonstrates solid and superior performance in terms of percentage of prediction accuracy of stock market trend. The review paper of Atsalakis and Valavanis (2009a) that summarizes the related literature can be useful for interested readers.

3. Theory of ANFIS

In this section, we present the basic theory of ANFIS model. Both artificial neural network and fuzzy logic are used in ANFIS' architecture (Avcı, 2008; Avcı & Akpolat, 2006; Avcı, Turkoglu, & Poyraz, 2005). ANFIS consists of *if–then* rules and couples of input–output. Also for ANFIS training, learning algorithms of neural network are used (Avcı, 2008; Avcı, Hanbay, & Varol, 2007; Avcı et al., 2005; Avcı, Turkoglu, & Poyraz, 2006; Jang, 1993; Turkoglu & Avcı, 2008).

To simplify the explanations, the fuzzy inference system under consideration is assumed to have two inputs (x and y) and one output (z). For a first order of Sugeno fuzzy model, a typical rule set with base fuzzy *if–then* rules can be expressed as

$$\text{If } x \text{ is } A_1 \text{ and} y \text{ is } B_1 \text{ then } f_1 = p_1 x + q_1 y + r_1 \quad (1)$$



where p, r, and q are linear output parameters. The ANFIS' architecture with two inputs and one output is as shown in Fig. 1.

This architecture is formed by using five layers and nine *if–then* rules:

Layer-1: Every node i in this layer is a square node with a node function.

$$O_{1,i} = \mu_{Ai}(x), \text{ for } i = 1,2,3 \quad O_{1,i} = \mu_{Bi-3}(y), \text{ for } i = 4,5,6 \quad (2)$$

where x and y are inputs to node i, and A_i and B_i are linguistic labels for inputs. In other words, $O_{1,i}$ is the membership function of A_i and B_i. Usually $\mu_{Ai}(x)$ and $\mu_{Bi}(y)$ are chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{Ai}(x), \mu_{Bi-3}(y) = \exp\left(\left(-(x_i - c_i)/(a_i)\right)^2\right) \quad (3)$$

where a_i, c_i is the parameter set. These parameters in this layer are referred to as premise parameters.

Layer-2: Every node in this layer is a circle node labeled Π which multiplies the incoming signals and sends the product out. For instance,

$$O_{2,i} = w_i = \mu_{Ai}(x) \cdot \mu_{Bi-3}(y), \quad i = 1,2,3,\ldots,9 \quad (4)$$

Each node output represents the firing strength of a rule.

Layer-3: Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rules firing strength to the sum of all rule's firing strengths:

$$O_{3,i} = \bar{w}_i = w_i/(w_1 + w_2 + \ldots + w_9), \quad i = 1,2,3,\cdots,9 \quad (5)$$

Layer-4: Every node i in this layer is a square node with a node function

$$O_{4,i} = \bar{w}_i \cdot f_i = w_i \cdot (p_i x + q_i y + r_i), \quad i = 1,2,3,\ldots,9 \quad (6)$$

where w_i is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer-5: The single node in this layer is a circle node labeled $\sum$ that computes the overall output as the summation of all incoming signals:

$$O_{5,i} = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (7)$$

4. Research design and experiments

4.1. Data set

The research data used in this study are monthly macroeconomic indicators, the DJI, DAX, BOVESPA Indices and the return of the ISE National 100 Index. We obtain the monthly data set from the Central Bank of the Republic of Turkey (CBRT) Electronic Data Delivery System and Matriks Information Delivery Services Inc. The whole data set covers the period from January 1990 to December 2008, a total of 228 pairs of observations. The data set is divided into two parts. The first group of the data (122 pairs of observations) is utilized for training the model. The second group of the data (106 pairs of observations) is utilized for testing the model.

In light of the previous literature, it is hypothesized that stock market index return can be predicted by range financial and macroeconomic variables. Variables such as earnings yield, cash flow yield, book-to-market ratio, size, short-term interest rates, long-term interest rate, expected inflation, dividend yields, yield spreads between long- and short-term government bonds, yield spreads between low- and high-grade bonds, lagged price–earnings ratios, lagged returns, consumer price index, industrial production, government and private consumption, gross national product and gross domestic product are shown to have predictive power for stock returns (Campbell, 1987; Fama & French, 1988a, 1988b, 1990, 1993; Fama & Schwert, 1977; Keim & Stambaugh, 1986). In this study, we select six macroeconomic variables as feature subsets by the review of domain experts and prior researches (Chen, Leung, & Daouk, 2003; Huang, Nakamori, & Wang, 2005; Karaatli et al., 2005; Leung, Daouk, & Chen, 2000; McMillan, 2003). The DJI (Dow Jones Industrial Average), DAX (Deutsche Aktien Index) and BOVESPA (Bolsa de Valores de São Paulo) Indices are also used as input variables, because they have positive correlation with the ISE. Table 1 gives the list of input variables.

Output variable is the monthly return of the ISE National 100 Index. Following the literature, we calculate the index return as follows:

$$r_t = \ln\left(\frac{y_t}{y_{t-1}}\right) \quad (8)$$

where r_t denotes the return at time t, and y_t and y_{t-1} are the index values for time t and $t-1$, respectively.

4.2. Experimental studies

In this study, in input layer, there are republic gold selling price, US Dollar exchange rates, interest rates on deposits, consumer price index, industrial production index, interest rates on Treasury bill, closing price of DJI, DAX and BOVESPA. The return of the ISE National 100 Index is in the output layer. The related illustration is given in Fig. 2.

Table 1
List of input variables.

Republic gold selling price
US Dollar exchange rates
Interest rates on deposits
Consumer price index
Industrial production index
Interest rates on Treasury bill
Closing price of DJI
Closing price of DAX
Closing price of BOVESPA

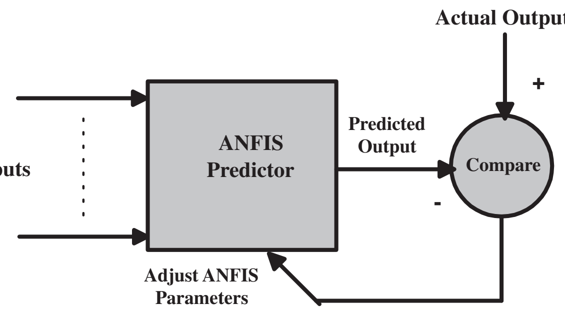


Fig. 2. Proposed model block diagram.

The hybrid learning algorithm for ANFIS has been used in this study. The variants of the algorithm used in the study are two input membership functions and three input membership functions for each of all the inputs, respectively. These input membership functions are gbell and gauss.

In the training, a variable number of input membership functions (2) and (3) were used. The data set of the system available included 228 data patterns. Moreover, the efficiency of the proposed method was demonstrated by using the fourfold cross validation test. In fourfold cross validation, data set was randomly split into five exclusive subsets (X_1,..., X_4) of approximately equal size and the holdout method was repeated four times. These folds contain 75, 25, 70, and 58 samples, respectively. At each time, one of the two subsets was used as the test set and the other two subsets were put together to form a training set. The advantage of this method is that it is not important how the data are divided. Every data point appears in a test set only once and appears in a training set twice. Consequently the verification of the efficiency of the proposed method against the over-learning problem could be demonstrated.

Model validation is the process by which the input vectors from input/output data sets. These are not used for training the ANFIS. They are presented to the trained model to see how well the trained model works. Some statistical methods, such as the root-mean squared (RMS), the coefficient of multiple determinations (R^2) and the coefficient of variation (Cov) might be used to compare predicted and actual values for model validation.

The error can be estimated by the RMS and is defined as:

$$\mathrm{RMS} = \sqrt{\frac{\sum_{m=1}^{n}(y_{\mathrm{pre,m}} - t_{\mathrm{mea,m}})^2}{n}}, \quad (9)$$

In addition, the coefficient of multiple determinations (R^2) and the coefficient of variation (Cov) in percent are defined as follows:

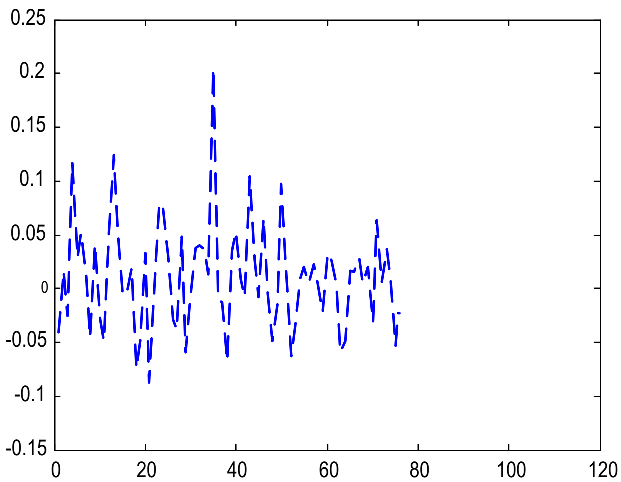
$$R^2 = 1 - \frac{\sum_{m=1}^{n}(y_{\mathrm{pre,m}} - t_{\mathrm{mea,m}})^2}{\sum_{m=1}^{n}(t_{\mathrm{mea,m}})^2} \quad (10)$$

$$\mathrm{Cov} = \frac{\mathrm{RMS}}{|\bar{t}_{\mathrm{mea,m}}|}100 \quad (11)$$

where n is the number of data patterns in the independent data set, $y_{\mathrm{pre,m}}$ indicates the predicted, $t_{\mathrm{mea,m}}$ is the measured value of one data point m, and $\bar{t}_{\mathrm{mea,m}}$ is the mean value of all measured data points.

5. Results and discussions

The computer program was performed on MATLAB (version 5.3, The MathWorks Inc., USA) environment by using the fuzzy toolbox. ANFIS topologies with various input membership functions were



trained. Fig. 3 also shows actual and ANFIS-predicted values of modeling system for two gbell input membership functions. The related test results (RMS, Cov and R^2) are shown in Table 2.

In general, the training accuracy improves by decreasing the number of input membership functions, as indicated by the smaller RMS and Cov values and R^2-values (Table 2). On the other hand, beyond a certain point the errors obtained begin to increase together with the complexity of the ANFIS. If the number of input membership functions is increased, the ANFIS has more complex network structure. So, the convergence to the target error rate takes more iteration. This situation is very time consuming. As shown in Table 2, G^* values of algorithm by using two gauss input membership functions appeared to be most optimal topology. This topology gained 0.0068 RMS value, 45.8163 Cov value and 0.9827 R^2 value, respectively. These values are really promising. As a result, it can be said that ANFIS is an appropriate technique for the prediction of stock market return.

6. Conclusions

Predicting the stock market index return is important and of great interest because successful prediction of stock prices may promise attractive benefits. It usually affects a financial trader's decision to buy or sell an instrument. These tasks are highly complicated and very difficult because there are too many factors that may influence stock prices. Soft computing techniques have been successfully applied to solve the problems of stock markets. In this study, the adaptive neural fuzzy inference system (ANFIS) is adopted to predict stock market return on the ISE National 100 Index. The study shows that the performance of stock price prediction can be significantly enhanced by using ANFIS. Based on the experimental results, 0.0068 RMS value, 45.8163 Cov value and 0.9827 R^2 value were obtained by using ANFIS predictor, respectively. These values are very satisfying. The prediction performance of this method shows the advantages of ANFIS. It is rapid, easy to operate, and not expensive. The findings demonstrate the learning and predicting potential of the ANFIS model in financial applications. Furthermore, these results indicate that ANFIS can be a useful tool for stock price prediction in emerging markets, like Turkey.

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