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An Improved Model for Stock Price Prediction using Market Experts Opinion

Adebiyi, Ayodele. A.
Department of Computer and Information Sciences, Covenant University, Ota, Nigeria
ariyo_adebiyi@yahoo.com

Ayo, Charles K
Department of Computer and Information Sciences, Covenant University, Ota, Nigeria
ckayome@yahoo.com

Otokiti, Sunday O
Department of Business Studies, Covenant University, Ota, Nigeria
dr_atoki@yahoo.com

ABSTRACT

Several research efforts had been done to forecast stock price based on technical indicators which rely purely on historical stock price data. Nevertheless, their performance is not always satisfactory. However, there are other influential factors which can affect the direction of stock market which form the basis of market experts' opinion such as interest rate, inflation rate, foreign exchange rate, business sector, management caliber, government policy and political effects among others. In this paper, the effect of using market experts' opinion in addition to the use of technical and fundamental indicators for stock price prediction is examined. Input variables extracted from these hybrid indicators are fed into a fuzzy-neural network for improved accuracy of stock price prediction. The empirical results obtained with published stock data shows that the proposed model can be effective to improving accuracy of stock price prediction.

Keywords: Artificial Neural Networks, Fuzzy Logic, Technical and Fundamental Indicators, Market Experts Opinion.

1. Introduction

Stock price prediction has always been a subject of interest for most investors and professional analysts. Nevertheless, finding the best time to buy or sell has remained a very difficult task because there are numerous factors that may influence stock prices [1, 2, 3]. Several research efforts have been carried out to predict the market in order to make profit using different techniques with different results.

Artificial neural networks (ANNs) and fuzzy logic (FL) are two of the key technologies that have received growing attention in solving real world, nonlinear, time variant problems. The need to solve highly nonlinear, time variant problems has been on the increase as many of today's applications have nonlinear and uncertain behaviour which changes with time like stock market [4, 5].

The several distinguishing features of ANNs make them attractive and widely used for forecasting task in the domain of business, economic, and finance applications. First, artificial neural networks are data-driven self-adaptive methods in that there are few a priori assumptions made about the models for problems under study. Second, artificial neural networks can generalize after learning the data presented to them and correctly infer unseen part of the population. Third, ANNs are universal approximators in that it has been shown that a network can approximate any continuous function to any desired accuracy. Finally, ANNs are strong in solving nonlinear problems. Traditional techniques to time series predictions, such as the Box-Jenkins or Autoregressive Integrated Moving Average (ARIMA) assume that the time series under study are generated from linear processes which is inappropriate because real world systems are often nonlinear [6, 7, 8].

A review of previous studies on stock price forecasting shows that the use of technical indicators with ANN model is prevalent. In recent time, hybrid models have been effectively engaged in stock price prediction. Examples in literature where technical indicators have been used include the following: in [9, 10, 11, 12, 13, 14] technical indicators with ANNs model was used to forecast stock price. Other works that had applied ANN models with technical indices to stock price predictions with varying findings are in [15, 16, 17, 18, 19, 20, 21, 22, 23]. Similarly, in [8, 24, 25, 26] hybrid ANN with technical indicators was used and their findings showed that ANN combined with other techniques exhibit effectively improved forecasting accuracy of stock price prediction. However, O'Connor and Maddem in [18] used fundamental indicators with ANN and their findings revealed that ANN has forecast ability in stock market because it has better return than overall stock market.

From the above literature review, it is obvious that technical indicators with ANN model had been widely used, while there are only few cases of the use of fundamental indicators. This paper contrasts previous approaches by combining technical indicators, fundamental indicators and experts' opinion to improve stock price prediction using fuzzy-neural architecture. The technical analysis variables are the core stock market indices such as current stock price, opening price, closing price, volume, highest price and lowest price etc. Fundamental indicators are the company performance indices such as price per annual earning, return on asset, return on common equity, book value, financial status of the company, etc. while the experts opinion are other influential factors such as interest rate, inflation rate, foreign exchange rate, business sector, management caliber, government policy and political factors among others. Hence, the novelty of this work stems from the use of hybrid parameters for improving stock market prediction.

The rest of the paper is organized as follows. Section 2 presents a review of basic concepts and modeling techniques used in this study. Section 3 describes the proposed hybrid model. Section 4 also describes the research methodology used. The implementation is presented in section 5, while section 6 discussed the results obtained. The paper is concluded in section 7.

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2. **Overview of Artificial Neural Networks and Fuzzy Logic**

In this section, the basic concepts and modeling approaches of artificial neural networks (ANNs) and fuzzy logic models for time series prediction are briefly reviewed.

2.1 ANNs approach to Time Series modeling

One of the significant advantages of the ANN models over other classes of nonlinear models is that ANNs are universal approximators that can approximate a large class of functions with high degree of accuracy. Their power comes from parallel processing of the information from data. No prior assumption of the model form is required in the model building process rather the network model is largely a function of the characteristics of the data [6]. One of the ANN models that is widely used in time series forecasting is backprogation neural network (BPNN) model. The main reason is that it provides an efficient way to manage the networks error function with respect to the weights adjustment and hence minimizes the discrepancy between real data and the output of the network model. For time series forecasting, the relationship between the output (y_t) and the inputs $(y_{t-1}, y_{t-2}, ..., y_{t-p})$ has the following mathematical representation:

$$y_t = w_0 + \sum_{j=1}^{q} w_j . g\left(w_{0j} + \sum_{i=1}^{p} w_{ij} . y_{t-1} \right) + \varepsilon_t \qquad (1)$$

where, $w_{ij} \, (i = 0,1,2,..., p, \; j = 1,2,..., q)$ and $w_j \, (j = 0,1,2,..., q)$ are model parameter often called connection weights; p is the number of input nodes; and q is the number hidden nodes. The activation function can take several forms. The most widely used activation function for output layer is the linear function. The logistic and hyperbolic functions are often used as the hidden layer transfer function that are shown in equations (2) and (3), respectively.

$$Sig(x) = \frac{1}{1 + \exp(-x)}, \qquad (2)$$

$$Tanh(x) = \frac{1 - \exp(-2x)}{1 + \exp(-2x)} \qquad (3)$$

Hence, the ANN model of (1), performs a nonlinear functional mapping from past observations to the future value y_t, i.e.

$$y_t = f(y_{t-1}, ..., y_{t-p}, w) + \varepsilon_t, \qquad (4)$$

where, w is a vector of all parameters and $f(.)$ is a function determined by the network structure and connection weights [6].

2.2 Fuzzy logic

One way to represent inexact data and knowledge, closer to human-like thinking, is to use fuzzy rules instead of exact rules when representing knowledge. Fuzzy systems are rule-based expert systems based on fuzzy rules and fuzzy inference. Fuzzy rules represent in a straightforward way commonsense knowledge and skills, or knowledge that is subjective, ambiguous, vague, or contradictory. This knowledge might have come from many different sources. Commonsense knowledge may have been acquired from long-term experience, from the experience of many people, over many years [28].

A fuzzy logic system consists of three main blocks: fuzzification, inference mechanism, and defuzzification. These components of fuzzy logic system are briefly described below [29].

2.2.1 Fuzzification

Fuzzification is a mapping from the observed numerical input space to the fuzzy sets defined in the corresponding universe of discourse. The *fuzzifier* maps a numerical value denoted by $x^{'} = (x_1, x_2, ..., x_m)$ into fuzzy sets represented by membership functions in U. The Gaussian functions, denoted by $\mu_{A_j^i}(x_j^{'})$ as expressed in equation (5).

$$\mu_{A_j^i}(x_j^{'}) = a_j^i \exp\left[-\frac{1}{2}\left(\frac{x_j - b_j^i}{c_j^i}\right)^2\right] \qquad (5)$$

where $1 \le j \le m$ refers to the variable (*j*) from m considered input variables; $1 \le i \le n_j$ considers the i membership function among all n_j membership functions considered for variable (*j*); a_j^i defines the maximum of each Gaussian function, here $a_j^i = 1.0; b_j^i$ is the center of the Gaussian function; and c_j^i defines its shape width.

2.2.2 Inference Mechanism

Inference mechanism is the fuzzy logic reasoning process that determines the outputs corresponding to the fuzzified inputs. The fuzzy rule-based is composed by IF-THEN rules like

$R^{(l)}$: IF (x_1 is $A_1^{(l)}$ and x_2 is $A_2^{(l)}$ and … x_m is $A_m^{(l)}$) THEN (y is $w^{(l)}$),

where: $R^{(l)}$ is the *l*th rule with $1 \le l \le c$ determining the total number of rules; $x_1, x_2, ..., x_m$ and y are, respectively, the input and output system variable; $A_j^{(l)}$ are the antecedent linguistic terms in rule (*l*) with $1 \le j \le m$ being the number antecedent variables; and $w^{(l)}$ is the rule conclusion for that type of rules, a real number usually called fuzzy singleton. The conclusion, a numerical value can be considered as a pre-defuzzified output that helps to accelerate the inference process. The reasoning process combines all rule contributions $w^{(l)}$ using the centroid defuzzification formula in a weighted form, as indicated in equation (6). The equation maps input process states $(x_j^{'})$ to the value resulting from inference function $Y(x^{'})$.

$$Y(x^{'}) = \frac{\sum c_{l=1}\left(\prod_{j=1}^{m} \mu_{A_j^{(l)}}(x_j^{'})\right) w^{(l)}}{\sum_{l=1}^{c}\left(\prod_{j=1}^{m} \mu_{A_j^{(l)}}(x_j^{'})\right)} \qquad (6)$$

2.2.3 Defuzzification

Basically, defuzzification maps output fuzzy set defined over an output universe of discourse to crisp outputs. The common defuzzification strategies are the max criterion method, the mean of maximum method and the center of area method.

3. The proposed hybrid model

In this paper, a hybrid predictive model based on technical, fundamental indicators and experts' opinion using fuzzy neural architecture is proposed. The aim is to yield more accurate results in stock price prediction. Based on the idea behind technical analysis of investment trading, it is assumed that the behaviour of stock market in the future could be predicted with previous information given in the history [30]. Therefore, there exists a function in equation (7)

$$p(t+1) = f(p_{t-k}, ... p_t; x_{t-1}, ... x_t; y_{t-m}, ... y_t; ...) \qquad (7)$$

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where p is the stock price, x and y are the other influence factors such as daily highest price, daily lowest price, experts opinion etc. In the first phase, fuzzy logic is used to convert the input qualitative data of experts opinion linguistic variables into fuzzy values express in the range of [0, 1] using linear membership function. The three linguistic properties that was used are low, medium and high. The dependent variable criterions are based on [1, 10]. Fuzzy set *low* ranges from 1 to 4, fuzzy set *medium* ranges from 3 to 7 and fuzzy set *high* ranges from 6 to 10 and their membership expression are shown in equation (8), (9) and (10) respectively.

$$\mu_{low}(x) = \frac{1}{3}x - \frac{1}{3} \tag{8}$$

$$\mu_{medium}(x) = \frac{1}{4}x - \frac{3}{4} \tag{9}$$

$$\mu_{high}(x) = \frac{1}{4}x - \frac{3}{2} \tag{10}$$

In second phase, an artificial neural network is used in order to model the nonlinear data. Thus,

$$y_t = w_0 + \sum_{j=1}^{q} w_j . g\left(w_{0j} + \sum_{i=1}^{p} w_{ij} . y_{t-1} \right) + \varepsilon_t \tag{11}$$

where, $w_{ij}\,(i = 0,1,2,...,p,\ j = 1,2,...,q)$ and $w_j\,(j = 0,1,2,...,q)$ are model parameter often called connection weights; p is the number of input nodes; and q is the number hidden nodes. The study used three-layer (one hidden layer) multilayer perceptron models (a feedforward neural network model) trained with backpropagation algorithm. The activation function that was used is sigmoid function. The figure 1 depicts the fuzzy-neural architecture used in this study.

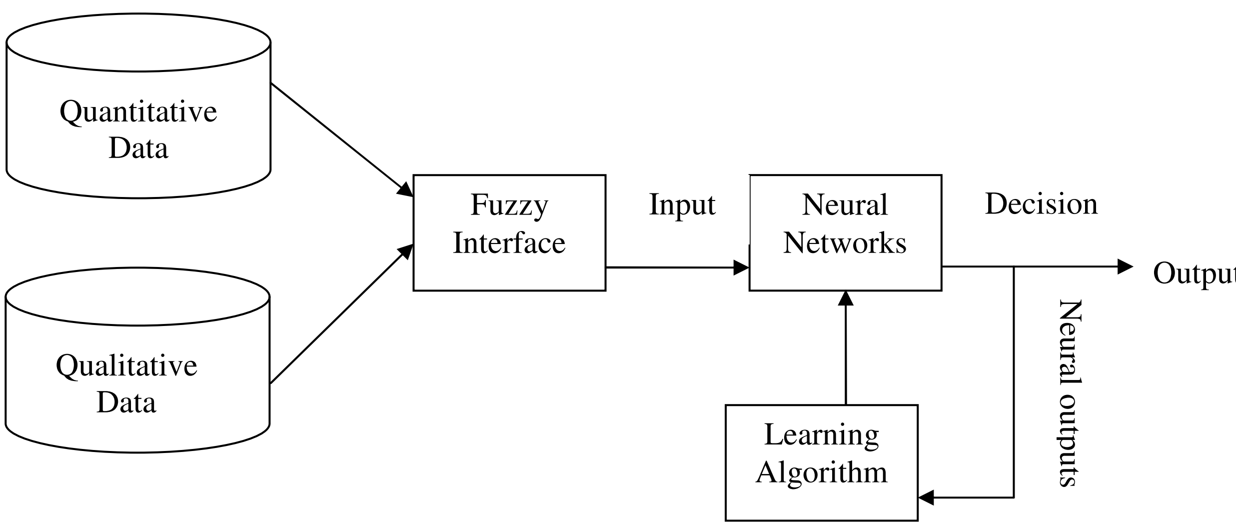

Fig.1: Proposed Fuzzy-Neural Architecture for Stock Prediction

In this paper three different models for the empirical investigation and validation of the proposed model was used as indicated in table 4. The first model used ANN only. The inputs to the ANN model are purely technical analysis variables of historical stock data. The second and third models are hybrid models that combined artificial neural networks and fuzzy logic. The inputs of second model are technical and fundamental analysis variables only while the inputs to the third model combined both the technical and fundamental variables with the market experts' opinion

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variables. The fundamental variables consist of financial ratios such as P/E, ROA, and ROE. P/E is equal to the market price per share of stock divided by the earning per share. The ROA measures a firm's performance in using the asset to generate income. ROE measures the rate of return earned on the common stockholders' investment. The experts opinion consist of inflation rate (I), management quality (M), government policy (G) and political factors (T) etc. For the hybridized approach 20 input variables was identified and used to train the network comprising both technical, fundamental variables, and experts' opinion variables as indicated in model 3 of table 4.

Table 4: The Input and Output Parameters of the Models used in this Study

Model	Technique	Input	Output
1	ANN	$O_{i-1}, O_{i-2}, H_{i-1}, H_{i-2}, L_{i-1}, L_{i-2}, C_{i-1}, C_{i-2}, V_{i-1}, V_{i-2}$	y(t+1)
2	FL+ ANN	$O_{i-1}, O_{i-2}, H_{i-1}, H_{i-2}, L_{i-1}, L_{i-2}, C_{i-1}, C_{i-2}, V_{i-1}, V_{i-2}, P_{i-1}, P_{i-2}, R_{i-1}, R_{i-2}, E_{i-1}, E_{i-2}$	y(t+1)
3	FL+ ANN	$O_{i-1}, O_{i-2}, H_{i-1}, H_{i-2}, L_{i-1}, L_{i-2}, C_{i-1}, C_{i-2}, V_{i-1}, V_{i-2}, P_{i-1}, P_{i-2}, R_{i-1}, R_{i-2}, E_{i-1}, E_{i-2}, M_{i-1}, I_{i-2}, G_{i-1}, T_{i-2},$	y(t+1)

Table 5: Description of Input Variables used in this study

Technical Analysis Variables		Fundamental and Expert Opinion Variables	
O_{i-1}	the opening price of day *i-1*	P_{i-1}	the price per annual earning of year *i-1*
O_{i-2}	the opening price of day *i-2*	P_{i-2}	the price per annual earning of year *i-2*
H_{i-1}	the daily high price of day *i-1*	R_{i-1}	return on asset of trading year *i-1*
H_{i-2}	the daily high price of day *i-2*	R_{i-2}	return on asset of trading year *i-2*
L_{i-1}	the daily low price of day *i-1*	E_{i-1}	return on equity of trading year *i-1*
L_{i-2}	the daily low price of day *i-2*	E_{i-2}	return on equity of trading year *i-2*
C_{i-1}	the closing price of day *i-1*	M_{i-1}	management quality as at trading day *i-1*
C_{i-1}	the closing price of day *i-2*	I_{i-1}	inflation rate as at trading day *i-1*
V_{i-1}	the trading volume of day *i-1*	G_{i-1}	government policy as at trading day *i-1*
V_{i-2}	the trading volume of day *i-2*	T_{i-1}	political effect as at trading day *i-1*

4. Methodology

The central objective of this paper is to improve the accuracy of stock price prediction by the combination of technical indicators (quantitative data), fundamental indicators and market experts' opinion (qualitative data) using fuzzy neural architecture. In order to achieve this aim the following steps were carried out as described in the subsection below.

4.1 Data Collection and Pre-processing

Data selection and pre-processing are crucial step in any modeling effort. In

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order to generalize the new predictive model, different dataset of historical stock prices from different companies were collected from Nigeria Stock Exchange (NSE) except the financial indices which are obtained from published annual report and expert's opinion. The stock data are divided into two sets: the training and testing data which are scaled to the range of (0, 1) using min-max normalization equation (9).

$$x_{ni} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \qquad (12)$$

where x_i is the real-world stock value, x_{ni} is the scaled input value of the real-world stock value x_i and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the unscaled dataset. The network predicted values, which are in the range (0, 1), are transformed to real-world values with the following equation:

$$x_i = x_{ni}(x_{\max} - x_{\min}) + x_{\min} \qquad (13)$$

4.2 Input Variables

The basic input data includes: raw data such as the daily open, high, low and close prices, and trading volumes of NSE which formed the technical variables in table 1. Table 2 consists of fundamental variables while the market expert opinion variables are listed in table 3.

Table 1: Stock Variables (Technical Indicators)

Variable	Description
O	Opening price of a stock for a specific trading day
C	Closing price of a stock for a specific trading day
V	Stock transactions volume (Buy/Sell)
H	Highest stock price within a specified time interval (day, month etc.)
L	Lowest stock price within a specified time interval (day, month etc.)

Table 2: Stock Variables (Fundamental Indicators)

Variable	Description
P/E	Price per annual earning
ROA	Return on Asset
ROE	Return on Common Equity

Table 3: Possible Stock Price Influence Factors (Experts Opinion)

Variable	Description
M	Management Quality
I	Inflation Rate
G	Government Policy
T	Political Effects

5. Implementation

For the implementation of the different models, we experimented with the different neural network model

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configurations to determine the best performance in each of the model using Matlab Neural Network Tools Box version 7. The algorithm of the ANN experiment is shown in figure 2 below. Training data and testing data was carefully selected and the various outcomes of the different network structure models implemented with Matlab Neural Network Tools Box version 7. In training the network model, the test data were not used. It was trained for 3,000 epochs for each training set. The output of neural network model was analysed by comparing the predicted values with the actual values over a sample period. For the output of the proposed model to be considered useful for trading decision support, overall hit rate of level of accuracy should be considerably high enough to be acceptable. The empirical results are presented in the next section.

(1) Define the output
(2) Choose the appropriate network architecture and algorithm. Multi-layer perceptron model trained with backpropagation algorithm was primarily chosen.
(3) Determine the input data and preprocess if necessary.
(4) Choose appropriate learning function.
(5) Choose the appropriate network structure.
(6) Perform the training and testing for each cycle.
(7) If the network produce acceptable results for all cycles, perform step 8 else perform step 5 to try other appropriate network structures else perform step 4 to try with other learning algorithm else perform step 3 to add or remove from input set. Otherwise, go back to step 2 to try different neural network architecture.
(8) Finish - record the results.

Figure 2: Algorithm for ANN predictive model.

6. Results and Discussion

After several experiments with different network architectures, the network predictive model that gave the most accurate daily stock price prediction in model 1 was 10-17-1. This model was created with artificial neural networks. The data used was purely technical analysis variables which are quantitative in nature. The input variables to the model consist of ten technical variables. For model 2 that combined technical and fundamental analysis variables using fuzzy neural approach. The network predictive model that gave the best accurate daily stock price prediction was 16-22-1. The proposed hybrid model (model 3), which combined the quantitative and qualitative data of technical, fundamental and experts' opinion respectively using fuzzy neural approach. The best-fitted network that gave the best forecasting accuracy with test data is composed of twenty inputs, twenty-six hidden and one output neurons 20-26-1. The results presented in table 6 were the findings from testing period (out of sample test data) over different models. Similarly, figure 3-5 illustrates the correlation of the level accuracy among different models.

From the empirical results, the forecasting accuracy level of model 1`compared with model 2 are quite impressive. However, the performance of model 2 was better than model 1 in the level of accuracy on many occasions from the different test data. From the figure 5, it is obvious that model 3 is the best of all the three predictive models. There is a great improvement in terms of forecasting accuracy in comparison to results of model 1 and 2. The stock price prediction accuracy of the proposed model that combined technical, fundamental indicators and experts' opinion to create a predictive model was the best. Hence, the proposed predictive model can be used successfully as decision-support in real-life trading in a way that will enhance the profiting of investors or traders for daily trading.

Table 6: Sample of Empirical Results of Daily Stock Price Prediction using different model

Sample Period	Actual Value	Predicted Values		
		Model 1	Model 2	Model 3
12/10/2008	18.03	18.25	18.21	18.04
12/11/2008	17.4	17.73	17.56	17.66
12/12/2008	16.6	16.25	16.36	16.63
12/15/2008	16.95	17.41	16.45	17.20
12/16/2008	17.13	17.49	17.27	17.27
12/17/2008	17.62	18.13	17.47	17.29
12/18/2008	17.54	17.54	17.47	17.73
12/19/2008	16.16	16.94	16.47	15.82
12/22/2008	16.56	15.68	16.69	16.85
12/23/2008	16.27	16.58	16.66	16.20
12/24/2008	16.1	16.23	16.25	16.37
12/26/2008	16.05	16.60	15.69	16.27
12/29/2008	15.95	16.45	15.86	16.01
12/30/2008	15.8	16.19	15.86	15.85

7. Conclusion

Technical indices had been widely used in forecasting stock prices with artificial neural networks. Nevertheless, their performance is not always satisfactory. Also, in recent times, hybrid models that combine ANNs and other intelligent techniques with technical indices had been engaged in order to improve accuracy level of stock price prediction with varying results.

In this paper, an improved predictive model for stock price prediction based on experts' opinion with technical and fundamental indices using fuzzy-neural architecture is presented. The empirical results confirmed superior performance of the proposed model to improve forecasting accuracy of stock price over the conventional approach of using ANN model with technical indicators. Therefore, the proposed predictive model has the potential to enhance the quality of decision making of investors in the stock market by offering more accurate stock prediction. In future work, the critical impact of specific experts' opinion variables on quality of stock price prediction will be examined.

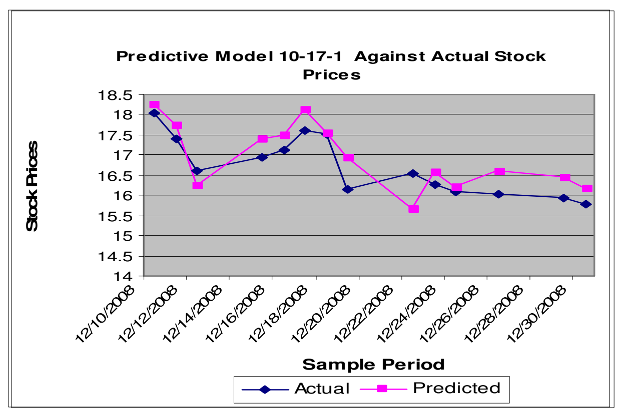

Figure 3: Model 1

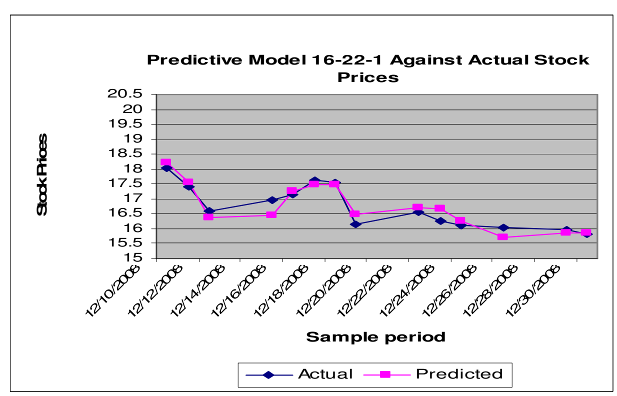

Figure 4: Model 2

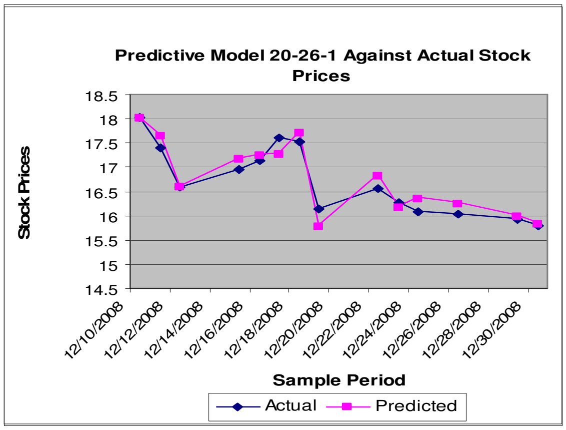

Figure 5: Model 3

References:

[1] C. Pei-Chann and L. Chen-Hao, "A TSK type fuzzy rule based system for stock prediction", International Journal of Expert Systems with Applications, Vol. 34, 2008, pp.135-144.

[2] G.R. Weckman, J.H. Marvel, S. Lakshminarayanan, and A. Snow, "An integrated stock market forecasting model using neural networks", Int. J. Business Forecasting and Marketing Intelligence, Vol. 1, No. 1, 2008, pp.30–49.

[3] A.A. Adebiyi, C.K. Ayo, and S.O. Otokiti, "Stock Price Prediction using Hybridized Market Indicators", Proceedings of International Conference on Artificial Intelligence and Pattern Recognition, MutiConf'09, Orlando USA, 2009, pp. 362-367.

[4] Robert Fuller, *Neural Fuzzy System*, Abo Akademic University, ISBN 951-650-624-0, ISSN 0358-5654, 1995, pp. 153.

[5] Emdad Khan, "Neural Fuzzy Based Intelligent Systems and Applications" In: Lakhmi C.J. and Martin N.M (Eds), *Fusion of Neural Networks, Fuzzy Systems, and Genetic Algorithms Industrial Application*, The CRC Press International Series on Computational Intelligence, New York, 2000, pp.107-139.

[6] K. Mehdi and B. Mehdi, "An artificial neural network (p,d,q) model for timeseries forecasting", International Journal of Expert Systems with Applications vol. 37, 2010, pp.479-489.

[7] G. Zhang, B. Patuwo, and M.Y.Hu, "Forecasting with artificial neural networks: The state of the art, International Journal of Forecasting, vol. 14, 1998, pp. 35-62.

[8] M. Khasel, M. Bijari and G.A.R Ardali, "Improvement of Auto-Regressive Integrated Moving Average models using Fuzzy logic and Artificial Neural Networks (ANNs)", International Journal of Neurocomputing Vol. 72, 2009, pp. 956-967.

[9] P.K.H Phua, X.T. Zhu, and H.K. Chung., "Forecasting Stock Index Increments Using Neural Networks with Trust Region Methods", Proceedings of the International Joint Conference on Neural Networks, Vol. 1, 2003, pp. 260-265.

[10] A.S. Chen, M.T. Leung, and H. Daouk, "Application of neural networks to an emerging financial market: forecasting and trading the

Taiwan Stock Index“, Journal of Computers & Operations Research, Vol.30, 2003, pp. 901-923.

[11] H. Kunhuang, and T.H.K. Yu, “The application of neural networks to forecast fuzzy time series”, Physical A: Statistical Mechanics and its applications, Vol. 363, No. 2, 2006, pp. 481-491.

[12] X. Zhu, H. Wang, L. Xu and H. Li, “Predicting stock index increments by neural networks: The role of trading volume under different horizons“, Expert Systems with Applications, Vol. 34, No. 4, 2007, pp. 3043-3054.

[13] M.T. Philip, K. Paul, S.O. Choy, K. Reggie, S.C. Ng, J. Mak, T. Jonathan, K. Kai, and W. Tak-Lam W, “Design and Implementation of NN5 for Hong Stock Price Forecasting”, Journal of Engineering Applications of Artificial Intelligence, Vol. 20, 2007, pp. 453-461.

[14] E. Avci, “Forecasting Daily and Sessional Returns of the Ise-100 Index with Neural Network Models”, Dogus Universitesi Dergisi, Vol. 2, No. 8, 2007, pp.128-142**.**

[15] Y. Chen, B. Yang and A. Abraham, “Time-series forecasting using flexible neural tree model”, Journal of Information Sciences, Vol. 174, No 4., 2005, pp. 219-235.

[16] F. Giordano, M. La Rocca, and C. Perna, “Forecasting nonlinear time series with neural networks sieve bootstrap”, Journal of Computational Statistics and Data Analysis, Vol. 51, 2007, pp. 3871-3884.

[17] A. Jain and A.M. Kumar, “Hybrid neural networks models for hydrologic time series forecasting”, Journal of Applied Soft Computing, Vol. 7, 2007, pp. 585-592.

[18] W. Huang, Y. Nakamori and S. Wang, “Forecasting stock market movement with support vector machine”, Journal of Computers and Operations Research, Vol. 32 No. 10, 2005, pp.2513.

[19] T.H. Roh, “Forecasting the Volatility of Stock Price Index”, Journal of Expert Systems with Applications, Vol. 33, 2007, pp. 916-922.

[20] S. Stansel. and S. Eakins, “Forecasting the direction of change in sector stock indexes: An application of neural networks”, Journal of Asset Management, Vol. 5, No1, 2004, pp.37-48.

[21] T. Kimoto, K. Asakawa, M.Yoda and M. Tajeoka, “Stock Market Prediction System with Modular Neural Networks”, Proceedings of the IEEE International Joint Conference, on Neural Networks, 1990, pp. 1-16.

[22] K. Kamijo and T. Tanigawa, “Stock Price Pattern Recognition: A Recurrent Neural Network Approach”,. Proceedings of the IEEE International Joint Conference on Neural Networks, 1990, pp. 215-221
.

[23] L. Kyungjoo, Y. Sehwan, and J.J. John, “Neural Network Model vs. SARIMA model in Forecasting Korean Stock Price Index”, Issues in Information Systems, Vol. 8, No. 2, 2007, pp. 372-378.

[24] Y.H. Wang, "Nonlinear neural network forecasting model for stock index option price: Hybrid GJR–GARCH approach", Expert Systems with Applications, Vol. 36, No. 1, 2007, pp. 564-570.

[25] H.J. Kim and K.S. Shin, "A hybrid approach based on neural networks and genetic algorithms for detecting temporal patterns in stock markets", Applied Soft Computing, Vol. 7, 2007, pp. 569–576.

[26] S. Yan, "A Novel Prediction Method for Stock Index Applying Grey Theory and Neural Networks", The 7th International Symposium on Operations Research and Its Applications (ISORA'08), 2008, pp.104-111.

[27] N. O'Connor and M.G. Madden, "A neural network approach to predicting stock exchange movements using external factors", Applications and innovations in intelligent network to investment analysis", Financial Analysts Journal, 2006, pp. 78-80.

[28] K. K. Nikola, *Foundation of Neural Networks, Fuzzy System Systems and Knowledge Engineering*, The MIT Press, Cambridge, Massachusetts, London, England 1998.

[29] P.J.C. Branco .and J.A. Dente, "Design of an ElectroHydraulic System Using Neuro-Fuzzy Techniques" In: C.J. Lakhmi and N.M. Martin (Eds), *Fusion of Neural Networks, Fuzzy Systems, and Genetic Algorithms Industrial Application,* The CRC Press International Series on Computational Intelligence, New York, 2000, pp.69-103.

[30] R.J. Li, "Forecasting stock market with fuzzy neural networks", Proceedings of the Fourth International Conference on Machine Learning and Cybernetics, Guangzhou, 2005, pp. 18-21.

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