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Modeling Chaotic Behavior of Dhaka Stock Market Index Values Using the Neuro-fuzzy Model

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Abstract: Stock market prediction is an important area of financial forecasting, which attracts great interest of stock investors, stock buyers/sellers, policy makers, applied researchers and many others who are involved in the capital market. This paper aims to develop an efficient model to predict the Dhaka Stock Market Index (DSPI) values using the appropriate forecasting model. It is widely believed that stock data are nonlinear, dynamic and chaotic. In this paper, we propose an adaptive network based fuzzy inference system (ANFIS) to predict DSPI values. We used the daily general DSPI values for the period of March 2003 to October 10, 2006 for the learning and October 11, 2006 to May 31, 2007 for validation. Results obtained by this model are also compared to the back-propagation ANN model and the traditional ARIMA model to show advantages of the proposed ANFIS model. The findings suggest that the ANFIS model can be used as a better predictor for daily general DSPI values as compared to the ANN and the ARIMA models. The review also discussed relevant patents related to our research.

Keywords: ANFIS, back-propagation, fuzzy sets and logics, neural network, stock market, time series forecasting.

1. INTRODUCTION

Knowledge about the daily stock market price values is important for (i) domestic/foreign stock investors who are interested to know the various features and characteristics of stock market to improve their investment performances, (ii) buyers and/or sellers whose success depends on the future values of stock, (iii) policy makers who are concerned with making wise financial policies, (iv) applied researchers who want to improve the model specifications of the stock market index series, and others. Thus, modeling the behavior of stock index values has drawn considerable attention in applied and theoretical literatures (e.g. Abraham, Philip and Saratchandran (2003) [1], Dutta, Jha, Laha and Mohan (2006) [2], Afolabi and Olude (2007) [3], Lin, Yu, Gregor and Irons (1995) [4], Wang and Leu (1996) [5]). The purpose of this paper is to develop an efficient model to predict the daily Dhaka stock price index (DSPI) values. Predicting stock price is generally believed to be a very difficult task even for the professional players, because stock market data observed in practice are chaotic and non-linear. Predictions of stock market movements are affected by many factors including political events, general economic conditions and investors' expectations. Stock market is the term given to the act of trading company shares, stocks and other securities and their derivatives. This market has a number of players ranging from an individual stockholder to a very large corporate trader. These players can be anybody coming from any part of the world. Trading in stock market can be done privately with an attorney or with a professional stock exchange dealer who has the power to execute the order. Thus, it is believed that stock market is very volatile in nature and that is the reason it is hard to predict. However, stock market experts are continuously researching and devising methods that could aid them and others in foreseeing an accurate stock market outcome. Due to continued studies, the changes in the stock market can now be modeled with relatively acceptable precision. The present paper is an endeavor to model the DSPI future movements by selecting appropriate models.

Traditional forecasting techniques (regression methods, Box and Jenkins approach [6] etc.) often fail to predict future values when the behavior of the time series is chaotic and non-linear. New methods have emerged that increase the accuracy of non-linear time series predictions, known as artificial intelligence (AI) based methods. If the system is non-linear, these methods have the potential to provide a viable solution through their versatile approach to self-organization. It has been found that these techniques yield better results compared to the statistical approaches when the time series is chaotic (e.g. see Wang and Leu (1996) [5], Kamruzzaman and Sarker (2003) [7], Kihoro, Otieno and Wafula (2000) [8], Serju (2002) [9], Jang (1993) [10]). In this paper, one such intelligent system, known as adaptive network based fuzzy inference system (ANFIS) is used to model and predict the daily DSPI values. A number of works have been carried out in literature to predict stock price index data using the statistical and artificial neural network (ANN) based methods. Although research (Muhammad and Rasheed [11], Hasan, Islam and Bashar [12], Rahman, Yahagata (2004) [13] and others) has been carried out to study DSPI using the conventional methods, in our knowledge, no empirical research is available to predict DSPI under the AI-

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based model. This paper takes this issue and thus, it is hoped that the findings of the study will be of interest to academics, investors, policy makers and others.

Although the ANN based methods have been found to perform better compared to the conventional statistical methods, the drawback of ANN techniques is their prediction capabilities deteriorate over a short period of time especially when the time series data are very much chaotic. ANFIS has been proposed by many authors (Jang (1993) [10], Mandal, Shahid, Rahman and Islam (2006) [14], Douligeris and Develekos (1997) [15], Kholghl and Hesseini (2006) [16]) to overcome this drawback and develop a reliable prediction of the time series data. Thus, ANFIS is used in this paper to predict the DSPI future values. In addition, to compare the performance of ANFIS, DSPI is also predicted using the back-propagation ANN model and the ARIMA model. This paper is planned as follows: A brief description of the selected systems is given in section 2. The design of considered systems to predict DSPI is discussed in the third section. This is followed by a discussion on the relative performances of different considered methods. Section 5 reviews relevant patents of our study. The final section concludes the paper with some proposed future works.

2. ARCHITECTURES AND LEARNING

2.1. ANFIS

This architecture is proposed by Jang (2003) [10] and is developed based on the theory of fuzzy set and fuzzy logic. It is a combination of two intelligence systems, namely neural network (NN) system and fuzzy inference system (FIS) in such a way that the NN learning algorithm is used to determine the parameters of the FIS. NNs are non-linear statistical data modeling tools, which can capture and model any input-output relationship (or can learn to detect complex patterns in data). FIS is the process of formulating the mapping from a given input to an output using fuzzy logic. This mapping provides a basis from which decisions can be made or patterns can be discerned. The process of FIS involves: membership functions (mfs), fuzzy logic operators and if-then-rules. A typical ANFIS architecture is given in Fig. (**1**). and a detailed coverage can be found in Jang (2003) [10]. Fig. (**1**) shows that the structure of ANFIS has 5 layers (1 input layer, 3 hidden layers that represent mfs and fuzzy rules and 1 output layer) and it uses Sugeno-fuzzy inference model as the learning algorithm. As an example, the fuzzy if-then-rules for the first-order Sugeno-fuzzy model can be expressed as:

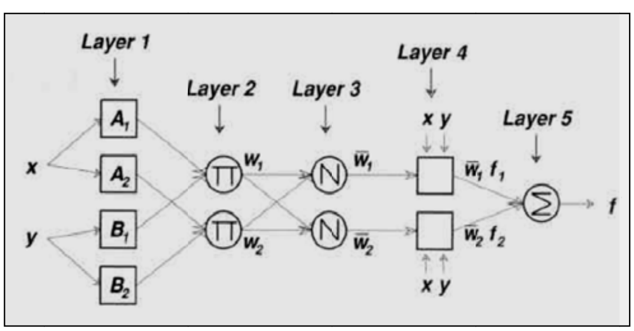


Fig. (1). An ANFIS architecture with a 2-input, 2-rule first-order Sugeno model.

Rule 1: If x (input 1) is A_1 and y (input 2) is B_1, then f_1 (output) = $p_1x + q_1y + r_1$

Rule 2: If x (input 1) is A_2 and y (input 2) is B_2, then f_2 (output) = $p_2x + q_2y + r_2$

In Fig. (**1**), the circular nodes represent fixed nodes, whereas the square nodes are nodes that have parameters to be learn. Each layer in this figure is associated with a particular step in the FIS. The following concepts are the processes, by which the input vector is fed through the ANFIS network layer by layer: Layer 1*: Fuzzy layer (generates mfs grades):* Input x to A_1 and A_2 and input y to B_1 and B_2 respectively, where A_1, A_2, B_1 and B_2 [fuzzy sets] are the linguistic expressions, which are used to distinguish the mfs represented by the premise parameters (PP). The relationship between the input-output mfs:

$$O^1_{A_i} = \mu_{A_i}(x)\,;\; O^1_{B_i} = \mu_{B_i}(y),\ i=1,2$$

where $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$ denote mfs. Any continuous and piecewise differentiable functions such as generalized bell-shape mfs, Gaussian-shaped mfs, triangular-shaped mfs and trapezoidal-shaped mfs can be used in this layer.

Layer 2*: Production layer (generate the firing strengths):* It is marked as Π and output is defined as

$$O^2_i = W_i = \mu_{A_i}(x) \times \mu_{B_i}(y)$$

where W_i, i =1,2 are weight functions of the next layer. Here the t-norm "product" is used as the fuzzy operator.

Layer 3: Normalized layer (normalize the firing strength): It is marked as N and is used to normalize W_i (i.e. it calculates the ratio of firing strength of the rules with the total firing strengths). It is defined as:

$$O^3_i = \overline{W}_i = W_i \Big/ \sum_{i=1}^{2} W_i\,,\ i = 1,2\,.$$

Layer 4: Defuzzy layer (calculates the output rules): Here an adaptive node $\overline{W}_i$ are outputs and $\{p_i, q_i, r_i\}$ are the parameter sets [known as consequent parameters (CP)] in this layer. The relationship between input and output is:

$$O^4_i = \overline{W}_i f_i = \overline{W}_i (p_i x + q_i y + r_i),\ i=1,2.$$

Layer 5: Total output layer (sum of all inputs from the layer 4): Its node is marked as Σ and computes the overall output. It can be expressed as:

$$O^5_i = \text{Output} = \sum_{i=1}^{2} \overline{W}_i f_i = \sum_{i=1}^{2} \overline{W}_i (p_i x + q_i y + r_i)\ .$$

The next step is to got familiar with how the ANFIS learns PP and CP for the mfs and the rules. From Fig. (**1**), it is clear that the final layer output can be expressed as a linear combination of the CP. In symbols,

$$f=(\overline{W_1}\,x)p_1+(\overline{W_1}\,y)q_1+(\overline{W_1})r_1+(\overline{W_2}\,x)p_2+(\overline{W_2}\,y)q_2+(\overline{W_2})r_2.$$

Thus, we have a set of total ANFIS parameters S, which is calculated as S = S1∪S2, where S1 = set of PP(non-linear) and S2 = set of CP(linear). The learning algorithm of ANFIS is a hybrid algorithm, which combines the gradient descent (GD) method and the least square

	FP	BP
S1	Fixed	GD
S2	LSE	Fixed
Signals	Node outputs	Errors signals

estimation (LSE) for an effective search of PP and CP. That means ANFIS uses a two pass process of learning algorithm to reduce the error: (i) Forward pass (FP) and (ii) backward pass (BP). The hidden layer is computed by the GD method of the feedback structure and the final output is estimated by the LSE. Activities in each pass can be summarized in the following way:

The two pass process is as follows:

FP: Present the input vector. Calculate the node outputs layer by layer (go forward until the layer 4). Identify S2 parameters using the LSE (here S1 is fixed) and compute error measure for each training pair.

BP: Error signals propagate backward and the PP are updated by the GD method (details, see Jang (2003) pp.4-5, [10]).

The output equation from the layer 5 can be rearranged in a more usable form:

$Y = XW$, where $X = [\,\overline{W}_1 x,\ \overline{W}_1 y,\ \overline{W}_1,\ \overline{W}_2 x,\ \overline{W}_2 y,\ \overline{W}_2\,]$ and $W = [p_1, q_1, r_1, p_2, q_2, r_2]^T$. When the input-output training pattern exists, the vector W can be solved using the ANFIS learning algorithm. ANFIS is available in the Fuzzy Logic Toolbox of MATLAB [17].

2.2. ANN

It consists of the following processing functions:

(i) Receiving inputs

(ii) Assigning an appropriate weight coefficient of inputs

(iii) Calculating weighted sum of inputs

(iv) Comparing this sum with some threshold, and finally

(v) Determining an appropriate output value. Fig. (**2**) presents a basic structure of ANN, which has 1 input layer, 2 hidden layers (with sufficient no. of neurons) and 1 output layer. Thus, each neuron receives an input P_{Rx1}, which is multiplied by weights W_{NxR} and bias b_{Nx1} to produce the net input as n = WP+b, where R are the number of elements in input vector and N are the number of neurons in the hidden layers. Passing net input through an activation function produces the output of the neurons. Usually, the sigmoid function $[y=f(x)=1/(1+e^{-x})]$ is used as the activation function. The properties of this function need to mimic the nerve cell which either fires or does not fire. Other used activation functions are hard limiter, pureline, transig, logsigmoid and others. Networks are trained so that a particular input leads to a specific target output. The training algorithm is the standard BP, which uses the GD technique to minimize error

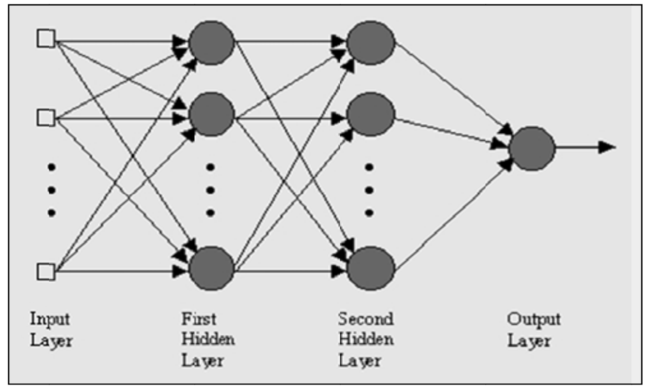


Fig. (2). An ANN architecture.

over all training data. During training, each desired output is compared with the actual output and the error at the output layer is calculated. The backward pass is the error BP and adjustments of weights. Thus, the network is adjusted based on a comparison of the output and the target until the network output matches the target. After the training process is completed, the network with specified weights can be used for testing a set of data different than those for training.

2.3. ARIMA

A general class of Box-Jenkins model for a time series is the ARIMA (or Autoregressive Integrated Moving Average Models), which includes the AR models with only autoregressive terms, the MA models with only moving average terms and the ARIMA models with both autoregressive and moving-average terms. An ARIMA model can be defined as

$$\Phi_p(B)x_t = \theta_q(B)e_t$$

where x_t is the DSPI values, $\Phi_p(B)$ is the AR polynomial of order p, $\theta_q(B)$ is the MA polynomial of order q and e_t is i.i.d $(0,\sigma^2)$ (for details see [6]).

3. PREDICTION OF DSPI

Our plan is to develop an efficient forecasting model that could predict the general DSPI for the following trading day based on inputs. An error and trial approach is used to design the topology of ANFIS. Initially, a number of networks are trained and the error gradient was observed. Training algorithm is used to update the mfs parameters of FIS, which is a hybrid rule. As a result, a decreased training error throughout the learning process is obtained. The performance of the networks is evaluated by decreasing or increasing the number of inputs and the premise rules. Best performance is obtained by a network consisting of 4 inputs with 2 mfs (type Gaussian-shaped) with each input. Thus, the previous 4 days index values are used as inputs to predict the DSPI future values for the fifth trading day. In our experiment, the number of mfs for each input was set to 2 and the type chosen was Gaussian shaped [see Figs. (**3a** to **3d**)] that had given better results in preliminary tests. Thus, the total number of ANFIS parameters |S| = 16 + 80 = 96. Calculation as follows: Each mf has 2 parameters, so, for 4 inputs we have $|S1|=2*2*4=16$. On the other hand, 4 inputs create 2^4 rules giving $|S2| =16*(4+1)=80$.

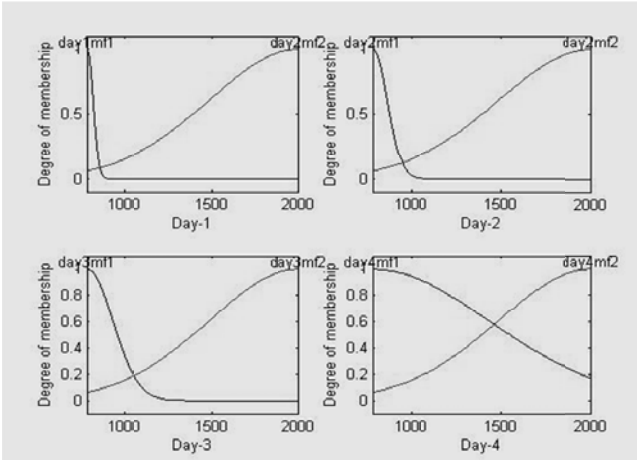


Fig. (3). Membership functions for (**a**) first (**b**) second (**c**) third and (**d**) fourth inputs

To compare the performance of ANFIS, DSPI is also predicted using the ANN and the ARIMA models. An ANN topology of 4:8:5:1, learning rate of 0.1 and a momentum parameter 0.95 is chosen using the error and trial method. The learning rate parameter controls the step size in each iteration (details, see [17], ch.3, pp.13-14). The momemtum parameter avoids getting stuck in local minima or slow convergence (details, see [17], ch.5, pp.12-13). We also performed the same prediction by using the ARIMA(4,0,0) model.

3.1. Data Sets

The data set used in this paper is the daily general DSPI closing values, which are collected from the Dhaka Stock Market Exchange for the period of March 3, 2003 to May 31, 2007. The index calculation algorithm according to the International Organization of Securities and Exchange Commission (IOSCO) is given by:

$$\frac{Previous\ Day\ Closing\ Values\ x\ Closing\ Market\ \text{Capitalization}}{Opening\ Market\ \text{Capitalization}}$$

where Market Capitalization = Σ(Last traded price x Total no. of indexed shares). DSPI is a weighted index accounting for companies across major industry groups such as bank, cement, engineering, fuel and power, insurance, pharmaceuticals and chemicals, textiles, tannery, industries and others. The training and testing data sets are depicted in the Fig. (**4**).

3.2. System Model

Considering the input variables, the following system model was selected to predict DSPI values:

$$P_{5\text{th day\_DSPI}} = f(\text{Ist day\_DSPI},\ \text{2nd day\_DSPI},\ \text{3rd day\_DSPI},\ \text{4th day\_DSPI})$$

4. RESULTS AND DISCUSSION

Selected systems performances have been measured by the following error measures: mean absolute percentage error

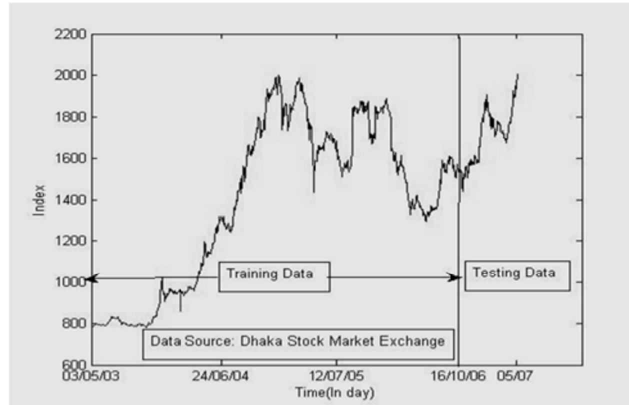


Fig. (4). Training and Testing Data Sets

(MAPE), root mean square percentage error (RMSPE) and also by the coefficient of determination R^2. MAPE and RMSPE are used to measure the accuracy of prediction through representing the degree of scatter. R^2 is a measure of the accuracy of prediction of the trained network models. Higher R^2 values indicate better prediction. The formulae for MAPE, RMSPE and R^2 are as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\text{Actual DSPI}_i - \text{Predicted DSPI}_i}{\text{Actual DSPI}_i}\right| \tag{1}$$

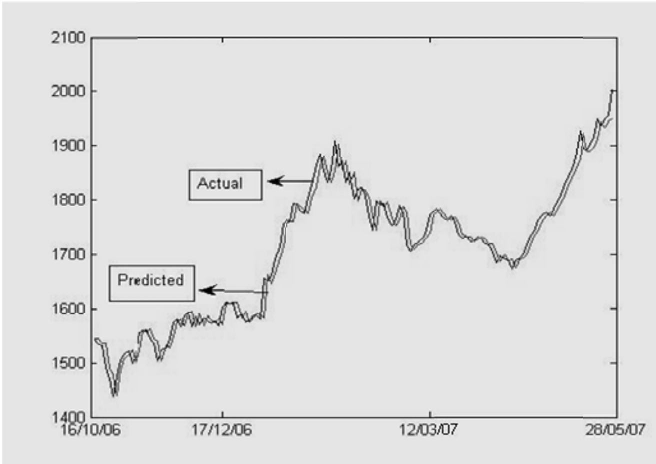
$$\text{RMSPE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\text{Actual DSPI}_i - \text{Predicted DSPI}_i}{\text{Actual DSPI}_i}\right)^2} \tag{2}$$

$$R^2 = 1-[ESS/TSS] \tag{3}$$

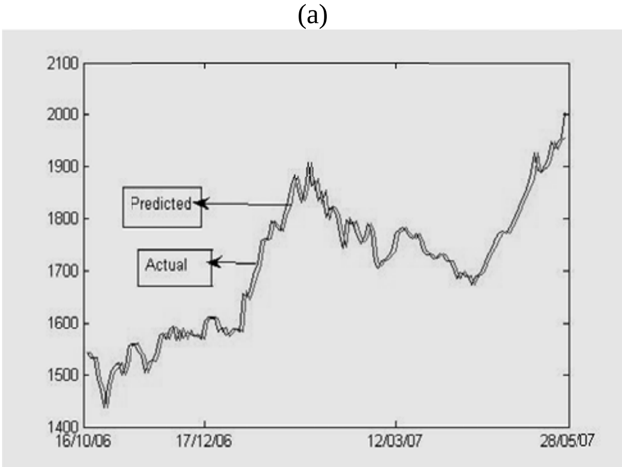
where ESS is the sum of squares of differences between actual and predicted DSPI values and TSS is the sum of squares of actual DSPI. Fig. (**5**) to Fig. (**6**) show test results for the one-day ahead prediction of the DSPI values. The result obtained by ANFIS network as compared to other networks shows better performance, which allows to predict the movement of the target with a minimal error. To realize this, the testing periods between 901 days (October 16, 2006) and 1041 days (May 30, 2007) are plotted in the Fig. (**5**). The difference between actual and predicted DSPI during learning period and testing period is shown in the Fig. (**6**).

Table **1** summarizes the performances of different considered systems, achieved for the DSPI values using the different error measures (1) to (3). Test results of ANFIS show that most of the times, the difference between actual and predicted DSPI values is 16.75. The results (see Table **1**) when compared to the ANN and ARIMA show that daily DSPI prediction capability of ANFIS is higher than these two models. See also Fig. (**6a–c**), where it can be proved again that ANFIS has longer time forecasting capability of daily DSPI values as compared to the other two models. The lowest RMSEP value and the

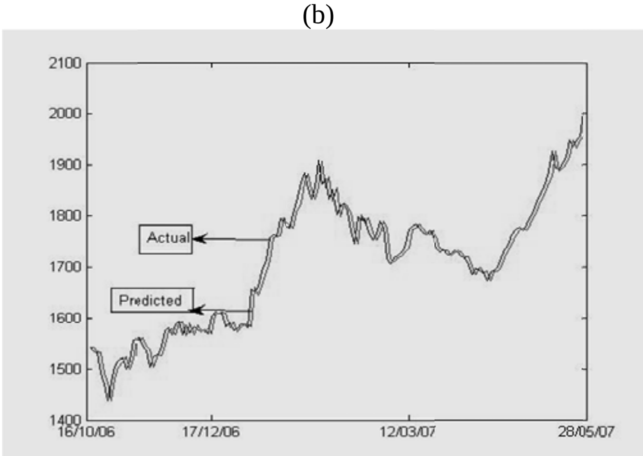
R^2 value (indicates the accuracy of prediction is 99%) for ANFIS again outperform ANN and ARIMA. Thus, the study shows that ANFIS can be used to predict daily DSPI with an average percentage error w.r.t. to actual DSPI 0.97%.



(a)



(b)

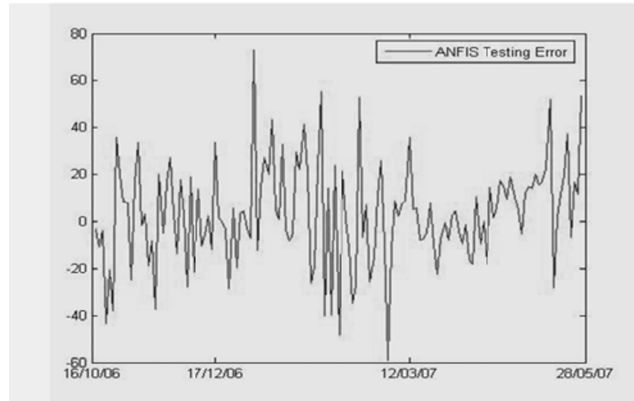


(c)

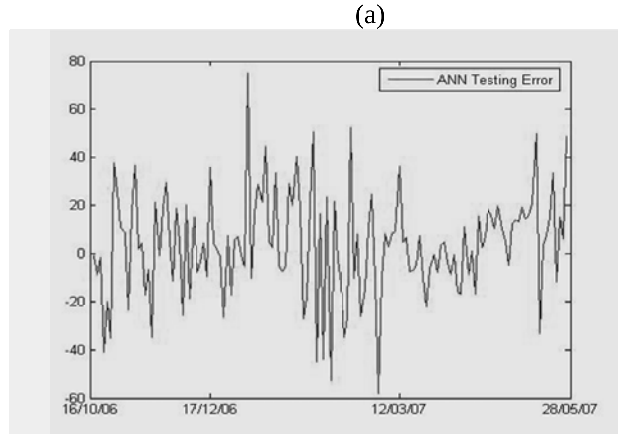
Fig. (5). Result obtained during (**a**) ANFIS testing (**b**) ANN testing (**c**) ARIMA testing

5. REVIEW OF RECENT PATENTS

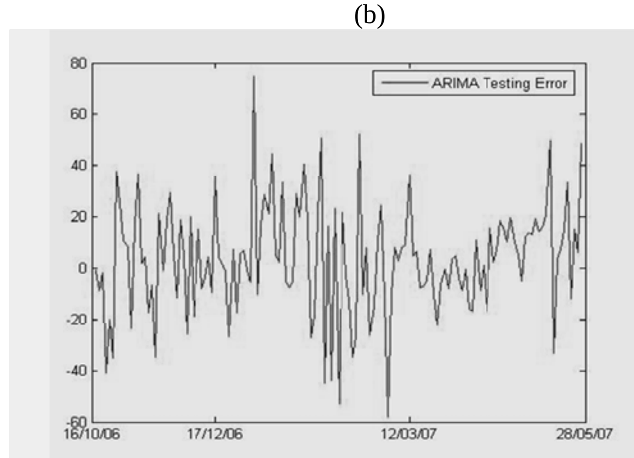
A method is proposed in the patent US7966241 [18] for understanding the feelings or market sentiments of a company's stock or the market as a whole. The authors use a sentiment index for understanding the stock prices of a company.



(a)



(b)



(c)

Fig. (6). Testing error (**a**) ANFIS (**b**) ANN (**c**) ARIMA.

The recent patent application US0144425 [19] provides an internet based method of operating a prediction market wherein the articles are properly wagered in peer-to-peer contests over a computer network. Here, the title of the goods passes to the participant who best predicts the outcome of a future event.

Table 1. Performance measures of different considered systems.

Measures	ANFIS		ANN		ARIMA	
	Train	Test	Train	Test	Train	Test
MAE	12.14	16.75	12.79	16.79	12.89	16.90
MAPE(%)	0.80	0.97	0.87	0.99	0.89	0.99
RMSE	21.68	20.92	22.25	21.9	22.90	21.95
RMSEP(%)	1.35	1.24	1.44	1.27	1.46	1.29
R^2	0.99	0.99	0.97	0.96	0.98	0.94

A method of automatic time series prediction using an information system to predict for a market is evaluated by the patent US0137848 [20]. This method accepts a proposition about one or more time series and monitors those time series. For example, when new data is available, this method evaluates the proposition to determine if the proposition is true, false or neither.

Patent application US0089222 [21] used a system and method for predicting the value of a stock. The inventors applied a least square (LMS) prediction algorithm and computed prediction parameter to predict the stock of a country.

In the US8001074 [22], a computer implemented method of extracting time series behavior based on time series information is described. Here, computer implemented method includes generation fuzzy rules from time series data to predict a time series.

6. CURRENT & FUTURE DEVELOPMENTS

The stock index values play an important role in controlling the dynamics of the capital market. As a result, the appropriate prediction of the stock index values is a crucial factor for the success of many businesses, fund managers, policy makers and many others. The index is multi-dimensional, dynamic and chaotic. Traditional time series forecasting techniques to predict time series data are based on the assumptions of linearity and stationary.

New methods have emerged that increase the accuracy of the time series prediction when the series are non-linear and chaotic. This paper proposes an ANFIS model to predict the DSPI future values. The result obtained by this model is also compared to the back-propagation ANN model and the traditional ARIMA model to show advantages of the proposed ANFIS model. Results show that the ANFIS can predict daily DSPI values with more accuracy as compared to the ANN and the ARIMA models. The proposed models in this paper could also be used to predict DSE 20 index, all stock indices and other related complex capital market dynamics.

7. ACKNOWLEDGEMENT

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8. CONFLICT OF INTEREST

The authors declare no conflict of interest.

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