Predicting Direction of Stock Prices Index Movement Using Artificial Neural Networks: The Case of Libyan Financial Market

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Author's contribution

This work was carried out by the author. The author read and approved the final manuscript.

ABSTRACT

Aims: The aim of this paper is to present techniques indicators of artificial neural networks (ANNs) model using for predicting the exact movements of stock price in the daily Libyan Stock Market (LSM) index forecasting.
Study Design: Research paper.
Place and Duration of Study: Libyan stock market from January 2, 2007 to March 28, 2013.
Methodology: The data from an emerging market Libyan Stock Market are applied as a case study. Twelve technical indicators were selected as inputs of the proposed models. The forecasting ability of the ANN model is accessed using back-propagation neural network of errors such as *MAE, RMSE, MAPE* and R^2. Two comprehensive parameter setting experiments for both the technical indicators and the levels of the index in the market were performed to improve their prediction performances.
Results: The experimental statistical results show that the ANN model accurately predicted the direction of movement with the average prediction rate 91% of data analysis in its best case, which is a perfectly good outcome. The relationship strength between parameter combination and forecast accuracy measures such as *MAE, MAPE*, and *RMSE* is strong ($R^2 \geq 0.99$). The statistical and financial performance of this technique is evaluated and empirical results revealed that artificial neural networks can be used as a better alternative technique for forecasting the daily stock market prices.
Conclusion: This study proved the significance of using twelve particular technical

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market indicators which gave also useful results in predicting the direction of stock price movement. To improve ANN model capabilities, a mixture of technical and fundamental factors as inputs over different time period were used to be an effective tool in forecasting the market level and direction.

1. INTRODUCTION

Stock prices present a challenging task for traders and investors since the stock market is essentially dynamic, nonlinear, complicated, nonparametric, and chaotic in nature [1]. Thus, investors can hedge against potential market risks and speculators and arbitrageurs have opportunities to make profit by trading in stock price index [2]. The early Efficient Market Theory (EMT) claims that prices move in a random way and it is not possible to develop an algorithm of any kind that predicts stock prices [3]. Forecasting or predicting stock prices may be done following one or a combination of four approaches: fundamental analysis, technical analysis, time series forecasting and machine learning. Each approach has its own virtues as well as limitations. An artificial neural networks (ANNs) or neural networks (NNs) are computational theoretical modelling tools that have recently composed of several highly interconnected computational units called artificial neurons or nodes. Each node performs a simple operation on an input to generate an output that is forwarded to the next node in the sequence. This parallel processing allows for great advantages in data processing analysis and knowledge representation [4,5].

ANNs are widely applied in various branches such as computer science, engineering, medical and criminal diagnostics, biological investigation, analysing the business data, and econometric analysis research. They can be used for analysing relations among economic and financial phenomena, forecasting, data filtration, generating financial time-series, and optimisation [6,7,8,9]. ANN-based models are empirical in nature; however they have been shown to be able to decode non-linear financial time-series data, which sufficiently describe the characteristics of the stock markets [10]. Numerous researches such as: [11] and [12] have been made to compare ANNs with real-world data analysis statistical tools. Although, ANNs has have been successfully applied to loan evaluation, signature recognitions, financial time-series analysis forecasting and many other difficult pattern recognition problems that do not have an algorithmic solution or the available solution is too complex to be found and complex dimensionality [13,11,12,14]. If stock market return fluctuations are affected by their recent historic behaviour, ANN model which can prove to be better learning of predictors market price index [15]. ANN model often exhibit inconsistent and unpredictable performance on noisy data, while predicting the financial market's movements is more difficult is as considered by some researchers [16,17,18].

It is of interest to study the extent of stock price index movement predictability using data from emerging markets such as of the Libyan Stock Market (LSM). Since its establishment in 3rd June 2006 by decision no. (134) of the General People's Committee (GPC), to form a joint stock company with capital of 20 million Libyan dinars (LYD), divided into 2 million shares with a nominal value of 10 LYD per share, as the LSM has presented an outstanding growth as an emerging market. The LSM is characterised with high volatility in the market returns. Such volatility attracts many local and foreign investors as it provides high return possibility. The number of companies listed in the LSM increased to 12 in 2010 while it was

8 in 2007. The total trading volume increased rapidly from 37.4 million Libyan dinars in 2008 to reach 147.0 million LYD in 2010, and 1.5 million LYD shares were traded and increased to 12.9 million in 2010. The lowest total market capitalisation was 330 million LYD in 2007 with highest market capitalisation of 3.6 billion LYD in 2010 [19]. The LSM index starting from a base of 1000 in April 2008 and closing at 940.44 in June after a high of 1284.21 and a low of 874.14 points, down by 203.25 points, or 20%, it's clear that the second quarter of the year 2008 was relatively volatile and perhaps the most significant reasons behind the decline during 2008. In year 2010 the LSM index has jumped by 80% on April, reaching 1600 points, which represent the highest level since 2008, then it closed the year at 1354 points of the total market capitalisation, traded value, number of shares traded and number of trades realised in the market [19]. The Libyan stock market remains small size and largely underdeveloped, inefficient, illiquid when compared with other emerging Arab stock markets. The total period of (02/01/2007-30/12/2010) is in network training and validation values are obtained with different combinations of parameters for testing the ANN model (total of 3240.58 data points). The second sub-period of (02/01/2007-28/03/2013) is in sample period separately as a model input is used and prediction rate is calculated. These data points are the daily closing stock prices in the currency of the Libyan dinars (LYD). The LYD is tied with the USD with a conversion rate of approximately 1 USD = 1.27 LYD.

The core objective of this study is to predict the direction of movement in the daily LSM index and answer the why and when these computational tools are needed, the motivation behind their development, and their relation to biological systems and other modelling methodologies, the various learning rules and ANNs forecast is compared with the statistical forecasting result. To the best knowledge of the author, there is no study that deals with prediction using artificial neural networks (ANNs) in Libyan Stock Market. The major contributions of this study are to demonstrate and verify the predictability of stock price index direction using ANN model and the financial statistical technique, and then to compare the empirical results of these two techniques.

The rest of the paper is organised into seven sections as follows. Section 2 provides a brief overview of the theoretical literature. Section 3 proposes empirical chosen methodology. Section 4 describes the research data analysis and experiments. In Section 5, descriptive statistics are used simply to describe the sample. In Section 6, the empirical results are summarised and discussed. The last section provides a brief conclusion and future research.

2. LITERATURE REVIEW

In recent years, there have been a growing number of studies looking at the direction of movements of various kinds of neural network computing to traditional statistical methods of analysis [20]. Both academic researchers and practitioners have made tremendous efforts to predict the future movements of stock market prices index or its return and devise financial trading strategies to translate the forecasts into profits [21]. In the following sub-sections 2.1 and 2.2, we focus the review of previous studies on ANN model applied to financial market prices index prediction. It is worth mentioning here that, at the time of this research, literature review revealed that there is no reported research that applied the ANN for the prediction of stock price movements in Libyan stock market. In addition, there is no research found that deals with prediction using artificial neural networks (ANNs) to predict stock price movements in Libyan stock market.

2.1 Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) or neural networks (NNs) is an interconnected group of natural neurons that grew out of research in artificial intelligence specifically attempts to mimic the fault-tolerance and capacity to learn of biological neural systems by modelling the low-level structure of the brain [22], which the brain basically learns from experience. According to [23] an artificial neural network is a relatively crude electronic model based on the neural structure of the brain. The human nervous system consists of billions of neurons of various types and lengths relevant to their location in the body [24,25].

The Fig. 1 shows a schematic of an oversimplified biological neuron with three major functional units [26,27,28]: dendrites, cell body and axon. The cell body has a nucleus that contain information about heredity traits; the dendrites receive signals from other neurons and pass them over to the cell body; and the axon, which branches into collaterals, receives signals from the cell body and carries them away through the synapse to the dendrites/synapses of neigh boring neurons or nerve cell. It is the final part of a neuron to receive an electrical impulse and is also the area where the impulse is converted to a chemical signal. The axon terminal transfers information from its neuron into another neuron, though it does not come into physical contact with the other neuron [29,27]. Each axon terminal branches off from a neuron like fingers on a hand. Electrical information travels through a neuron extremely quickly [30]. While it is in the axon of the nerve, this signal is in the form of an electrical pulse. These pulses are very small, between 50 and 70 millivolts each. Once the electrical signal reaches the axon terminal, the information is converted into a chemical signal known as a neurotransmitter [31]. The axon terminal then sends the chemical signal into the dendrite of the next neuron, which then converts this information back into an electrical signal and sends it down to the next neuron [32]. This basic system of signal transfer was the fundamental step of early neuron-computing development and the operation of the building unit of artificial neural networks.
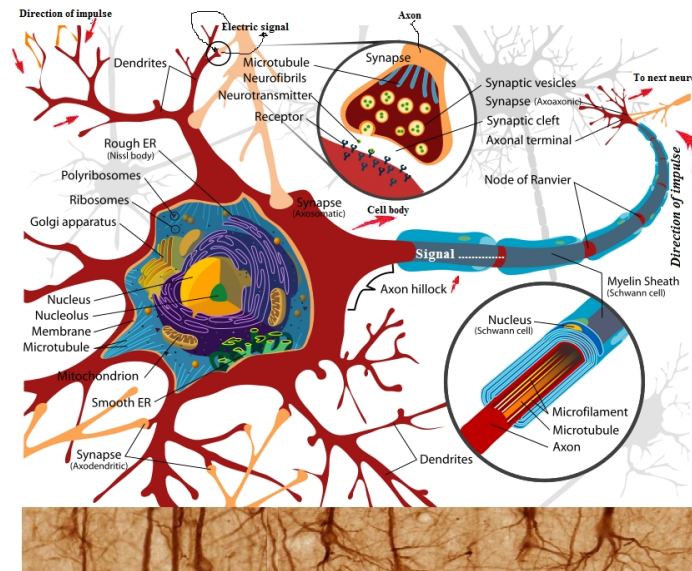

Fig . 1. Schematic of biological neuron
Source: adapted from (33,28]

Several economists advocate the application of neural networks to different fields in financial markets and economic growth methods of analysis [34,35,36,37]. ANN approach has been demonstrated to provide promising results in predict the stock market index or its price return [27]. [38] apply a neural network system to model the trading of S&P 500 index futures. The results of the study presented that the neural network system outperforms passive investment in the index. Based on the empirical results, they favour the implementation of neural network systems into the mainstream of financial decision making. [39] In his effort to predict stock market, he had created a three multi-layer, back propagation artificial neural networks using macro-economic indicators as inputs. His data set consisted of values for (6 variables) over a (150 months) period extending from June 1982 to December 1994. His networks were trained on the first (75 months) of the data set, and then tested on the remaining (75 months). [40] compare neural networks to discriminate analysis with respect to prediction of stock price performance. Empirical analyses find that a neural network models perform better than discriminate analysis in predicting future assignments of risk ratings to bonds.

Chen et al. [21] tried to predict the direction of Taiwan Stock Exchange Index return. The probabilistic neural network (PNN) is used to forecast the direction of index return. Statistical performance analysis of the PNN forecasts is compared with that of the generalised methods of moments (GMM) with Kalman filter and random walk. Empirical results showed that PNN demonstrate a stronger predictive power than the GMM–Kalman filter and the random walk prediction models. [41] qualified neural networks based on various technical market indicators to estimate the direction of the Istanbul Stock Exchange (ISE) 100 Index. The approach indicators used are MA, momentum, RSI, stochastic (K%), moving average convergence-divergence (MACD). The empirical results of the study presented that the direction of the ISE 100 Index could be predicted at a rate of 60.81%. [42] used ISE-30 and ISE-ALL indices to see the performances of several neural network models. While, the prediction performance of neural network models for daily and monthly data failed to outperform the liner regression model, these models are able to predict the direction of the indexes more accurately. [43] tested some smaller companies on UK indexes FTSE 100, FTSE 250 and FTSE Small Cap and concluded that in these markets the higher predictive ability of technical trading rules exists.

Several researches tend to crossbreed numerous artificial intelligence (AI) techniques approach used to predict stock market performance [44,45,46,47,48,49,50,16,21,51,52, 53,47,54]. [40] applied a hybrid AI approach to predict the direction of daily price changes in S&P 500 stock index futures. The hybrid AI approach integrated the rule-based systems and the neural networks technique. Empirical results demonstrated that reasoning neural networks (RN) outperform the other two ANN models (back-propagation networks and perceptron). Empirical results also confirmed that the integrated futures trading system (IFTS) outperforms the passive buy-and-hold investment strategy. [55] compared artificial neural network (ANN) performance and support vector machines (SVM) in predicting the movement of stock price index in Istanbul Stock Exchange (ISE) National 100 Index. Experimental results showed that average performance of ANN model at a rate of 75.74% was found significantly better in prediction than SVM model at a rate of 71.52%. [56] compared the ability of different mathematical models, such as ANN, (ARCH) and (GARCH) models, to forecast the daily exchange rates Euro/USD using time series data of Euro/USD from December 31, 2008 to December 31, 2009. Empirical analyses find that the ARCH and GARCH models, especially in their static formulations are better than the ANN for analysing and forecasting the dynamics of the exchange rates.

2.2 Learning Paradigms in (ANNs)

The ability to learn is a peculiar feature pertaining to intelligent systems, biological or otherwise. In artificial systems, learning (or training) is viewed as the process of updating the internal representation of the system in response to external stimuli so that it can perform a specific task. This includes modifying the network architecture, which involves adjusting the weights of the links, pruning or creating some connection links, and/ or changing the firing rules of the individual neurons [25].

ANN approach learning has demonstrated their capability in financial modelling and prediction as the network is presented with training examples, similar to the way we learn from experience. In this paper, a three-layered feed-forward ANN model was structured to predict stock price index movement is given in Fig. 2. This ANN model consists of an input layer, a hidden layer and an output layer, each of which is connected to the other. At least one neuron would be employed in each layer of the ANN model. Inputs for the network were twelve technical indicators which were represented by twelve neurons in the input layer (see Table 2). The units in the network are connected in a feed forward manner, from the input layer to the output layer of the ANN model with connectivity coefficients (weights), [57]. The weights of connections have been given initial values. The error between the predicted output value and the actual value is back-propagated through the network for the updating of the weights. This method is proven highly successful in training of multi-layered neural networks. The network is not just given reinforcement for how it is doing on a task. Information about errors is also filtered back through the system and is used to adjust the connections between the layers, thus improving performance. This a supervised learning procedure that attempts to minimise the error between the desired and the predicted outputs [58]. If the error of the validation patterns increases, the network tends to be over adapted and the training should be stopped.
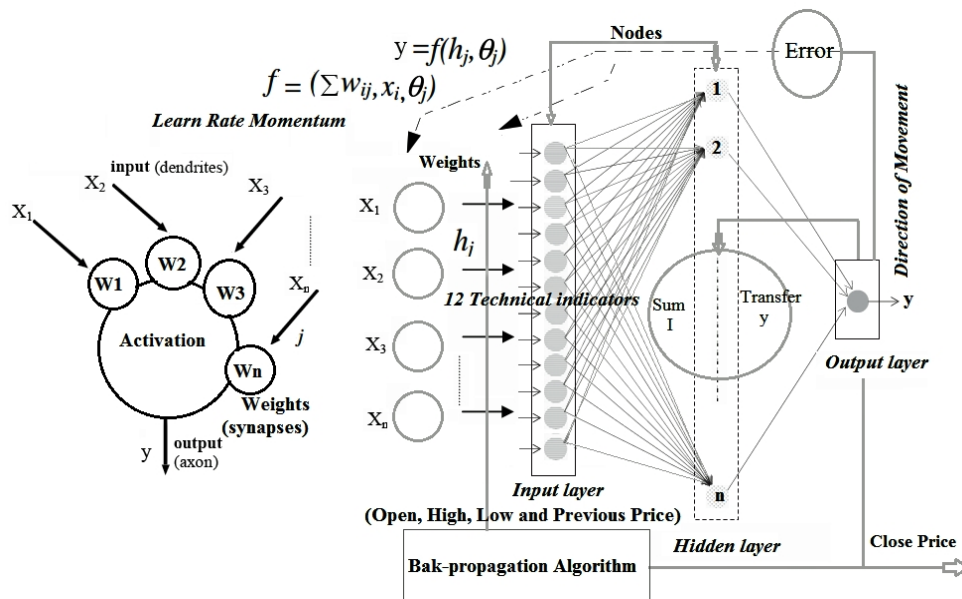

Fig. 2. A Neural network with three-layer feed forward
Source: author, 2013

The most typical activation function used in neural networks is the logistic sigmoid transfer function. This function converts an input value to an output ranging from 0 to 1. The effect of the threshold weights is to shift the curve right or left, thereby making the output value higher or lower, depending on the sign of the threshold weight. The output values of the units are modulated by the connection weights, either magnified if the connection weight is positive and greater than 1.0, or being diminished if the connection weight is between 0.0 and 1.0. If the connection weight is negative or (value < 0) then tomorrow close price value < than today's price (loss). While, If the output value is (smaller than 0.5 or value > = 0) then tomorrow close price value remains same as today's price (no loss); otherwise, it is classified as an increasing direction in movement. If (value > 0.5) then then tomorrow close price value > than today's price (profit). As shown in Fig. 2, the data flows from the input layer through zero, one, or more succeeding hidden layers and then to the output layer. The back-propagation (BP) algorithm is a generalisation of the delta rule that works for networks with hidden layers. It is by far the most popular and most widely used learning algorithm by ANN researchers [13]. Its popularity is due to its simplicity in design and implementation. The idea is to train a network by propagating the output errors backward through the layers. The errors serve to evaluate the derivatives of the error function with respect to the weights, which can then be adjusted. It involves a two stage learning process using two passes: a forward pass and a backward pass. The basic back propagation algorithm consists of three steps (Fig. 2). Although, the most commercial back propagation tools provide the most impact on the neural network training time an performance. The output value for a unit is given by the following Equation:

$$y = f(h_j)$$

$$= f\left(\sum_{i=1}^{n} w_{i,j} x_i, \theta_j\right)$$

$$= \begin{cases} 1 & w_{ij} x_i \geq \theta \\ 0 & w_{ij} x_i < \theta \end{cases} \qquad (i = 1, 2, \dots, n) \tag{1}$$

where y the output value is computed from set of input patterns, x_i of ith unit in a previous layer, w_{ij} is the weight on the connection from the neuron i^{th} to j, θ_j is the threshold value of the threshold function f, and n is the number of units in the previous layer. The function $f(x)$ is a sigmoid hyperbolic tangent function [59,60]:

$$f(x) = \tanh(x) = \frac{1 - e^{-z}}{1 + e^{-z}} \quad threshold : f(x) = \begin{cases} 0 & x < 0, 1 \\ 1 & \textit{if} \quad otherwise \end{cases} \tag{2}$$

where $f(x)$ is the threshold function remains the most commonly applied in ANN models due to the activation function for time series prediction in back-propagation:

$$y = f\left(\sum_{i=1}^{n} w_i x_i - u\right) = \left(\sum_{i=1}^{n} w_i x_i\right) \tag{3}$$

Once the output has been calculated, it can be passed to another neuron (or group of neurons) or sampled by the external environment. In terms of the weight change, Δw_{ij}, the formula equation is given as:

$$\Delta w_{ij} = \eta \delta_j x_i$$

(4)

where η is the learning rate (0<η<1), δ_j is the error at neuron j, x_i is an input vector and w_i the weights vector. This rule of LMS can also be rewritten as:

$$\Delta w_i = -\eta \left(t_i - x_i w_i\right) x_i$$

(5)

Although a high learning rate, η, will speed up training (because of the large step) by changing the weight vector, *w*, significantly from one phase to another. According to [61] suggests that $\eta \in \left[0.1, 1.0\right]$, Zupan and Gasteiger [62] recommend η ∈ [0.3, 0.6], and Fu [63] recommends η ∈ [0.0, 1.0].

3. EMPIRICAL METHODOLOGY

It is difficult to design artificial neural network (ANN) model for a particular forecasting problem. Modelling issues must be considered carefully because it affects the performance of an ANN. One critical factor is to determine the appropriate architecture, that is, the number of layers, number of nodes in each layer. Other network design decisions include the selection of activation functions of the hidden and output nodes, the training algorithm, and performance measures. The design stage involves in this study to determine the input (independent) and output (dependent) layers through the hidden layers in the case where the output layer is known to forecast future values. Output of the network was two patterns (0 or 1) of stock price direction. The output layer of the network consisted of only one neuron that represents the direction of movement. The number of neurons in the hidden layer was determined empirically. The determination of the formulation between input and output layers is called learning and through the learning process, model recognises the patters in the data and produces estimations. The architecture of the three-layered feed-forward ANN is explained in Fig. 2. The entire data set covers the period from January 2, 2007 to December 30, 2010 for network training and validation values, while data from January 2, 2007 to March 28, 2013 to test the predictive ability of the network. For this study the artificial neural networks are capable estimation models for financial and statistical performance to test the power of neural network in the prediction of stock price and its' movement. This process can be described below:

3.1 Statistical Performance Evaluation of the Model

In order to estimate the forecasting statistical performance of some methods or to compare several methods we should define error functions. [64] advised to use the following forecast accuracy measures: Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Standard Deviation of Errors (SDE), Mean Per cent Error (MPE) and Mean Absolute Per cent Error (MAPE), etc. In our study we use four performance criteria namely mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and goodness of fit R^2. The back-propagation

learning algorithm was used to train the three-layered feed-forward ANN structure in this study were the most used error functions is as following:

The mean absolute error is an average of the absolute errors $E = (P_i - p_j^|)$, where P_i

and $p_j^|$ are the actual (or observed) value and predicted value, respectively. Lesser values of these measures show more correctly predicted outputs. This follows a long-standing tradition of using the "ex-post facto" perspective in examining forecast error, where the error of a forecast is evaluated relative to what was subsequently observed, typically a census based benchmark [65,66]. The most commonly used scale-dependent summary measures of forecast accuracy are based on the distributions of absolute errors ($|E|$) or squared errors (E^2) observations (n) is the sample volume. The mean absolute error is given by:

$$Mean\ Absolute\ Error\ \ (MAE) = (\sum_{i=1}^{n}(|E|)/n)\ \ \ (i = 1,2,...,n)$$

(6)

The *MAE* is often abbreviated as the *MAD* ("D" for "deviation"). Both *MSE* and *RMSE* are integral components in statistical models (e.g., regression). As such, they are natural measures to use in many forecast error evaluations that use regression-based and statistical. The square root of the mean squared error as follows:

$$Mean\ Square\ Error\ (MSE) = (\sum_{i=1}^{n}(E^2)/n)\ \ \ (i = 1,2,...,n)$$

$$Root\ Mean\ Square\ Error\ (RMSE) = Sqrt(\sum_{i=1}^{n}(E^2)/n)\ \ \ (i = 1,2,...,n)$$

(7)

If the above *RMSE* is very less significant, the prediction accuracy of the ANN model is very close to 100%. Since percentage errors are not scale-independent, they are used to compare forecast performance across different data sets of the area using absolute percentage error given by $APE = (P_i - P_j^|)*100$. Like the scale dependent measures, a positive value of *APE* is derived by taking its absolute value $(|APE|)$ observations (n). This measure includes:

$$Mean\ Absolute\ Percentage\ Error\ (MAPE) = (\sum_{i=1}^{n}(|APE|)/n)\ \ \ (i = 1,2,...,n)$$

(8)

The use of absolute values or squared values prevents negative and positive errors from offsetting each other. However, there are other error measures (e.g. Theil-U or LINEX loss function) but they are less intuitive and infrequently used [67]. All these features and more make MATLAB an indispensable tool for use in this work.

$$Goodness\ of\ Fit\ (R^2) = 1 - \left((\sum_{i=1}^{n}E^2)/(\sum_{i=1}^{n}e_i^2)\right)\ \ \ (i = 1,2,...,n)$$

(9)

where $e_i = p_i - \bar{p}_i$, is the forecast error values. p_i, the actual values and p_i, denote the predicted values. The more R^2 correlation coefficient gets closer to one, the more the two data sets are correlated perfectly. As the aim of all of the prediction system models proposed in this study is to predict the direction of the stock price index forecasting, the correlation between the outputs do not directly reflect the overall performance of the network.

3.2 Financial Performance Evaluation of the Model

In order to evaluate the financial performance of the model, the correct predicted positions by the model have been compared. Prediction rate (PR) is evaluated used in the formula to calculate the prediction accuracy and is as follows:

$$Prediction \quad Rate \quad (PR) = \frac{1}{n}\sum_{i=1}^{n} R_i \qquad (i = 1,2,...,n)$$

(10)

where R_i the prediction result is for the ith trading day is defined by:

$$R_i = \begin{cases} 1 & if \quad PO_i = AO_i \\ 0 & otherwise \end{cases}$$

PO_i is the predicted output from the model for the ith trading day, and AO_i is the actual output for the ith trading day, n the total predicted outputs. The error level was determined 5% and it means that those outputs with the error level less than the defined value are considered as correctly predicted values.

4. DATA ANALYSIS AND EXPERIMENTS

The data used in this study include total stock price index which is composed of closing price, the high price and the low price of total price index. It should be reminded that the total period of (02/01/2007-28/03/2013) is divided into two sub-periods of training and validation period. First sub-periods of (02/01/2007-30/12/2010) is in network training and validation values are obtained with different combinations of parameters for testing the models. The second sub-period of (02/01/2007-28/03/2013) is in sample period for testing prediction rate model inputs. The whole data in the statistical population were employed in the analysis and this leads to non-selection of a specified sampling method. The total number of sample is 763 trading days. The number of sample with increasing direction is 443 while the number of sample with decreasing direction is 320. That is, 58% of the all sample have an increasing direction and 42% of the all sample have a decreasing direction. The research data used in this study is the direction of daily closing price movement in the LSM Index. The number of sample for each year is shown in Table 1.

Table 1. The number of sample in the entire data set

Description	Year				Total
	2007	**2008**	**2009**	**2010**	
Increase	112	127	95	109	**443**
%	57	66	49	61	**58**
Decrease	85	65	70	100	**320**
%	43	34	39	51	**42**
Total	197	192	179	195	**763**

Source: author, 2013

Since we attempt to forecast the direction of daily price change in the LSM index, technical indicators are used as input variables in the construction of prediction models. This study selects 12 technical indicators to make up the initial attributes, as determined by the review of domain experts along with the previous studies such as [67,17,41,16,25,2,42,55]. Table 2 demonstrates the titles of twelve technical indicators and their formulas, and summary statistics data for the selected indicators were calculated and given in Table 4.

5. DESCRIPTIVE STATISTICS

As mentioned previous in sub-section 2.2 and Fig. 2, the function of hidden layer is tan-sigmoid and the transferred function of output layer is linear in a three layer network, where input layer is simply distributing the inputs in various hidden layer and no processing takes place there, requires least number of training epochs. The parameters of neural network model include the number of neurons (n) in the hidden layer, value of learning rate (η), momentum coefficient (μ) and number of training epochs (ep) are professionally determine with ANN model parameters using neural networks toolbox of MATLAB software to implement the model. As suggested in the previous section 2, literature, a small value of η was selected as 0.1. The levels of the ANN parameters that are tested for choosing the best combination is presented in Table 3. Ten levels of neurons (n), five levels of momentum (μ) and 120 levels of epochs (ep) were tested in the parameter setting experiments. The parameter levels evaluated in parameter setting a total number of (10 * 5 * 120 = 6000) treatments for ANN model. Each parameter combination was applied to the training and validation data sets and prediction accuracy of the models were evaluated. Therefore, the training and validation performance were calculated for each parameter combination. The parameter combination that resulted in the best average of training and validation performances was selected as the best one for the prediction model.

Table 2. Selected technical indicators and their formulas

Defined variables	Code	Formula equation	Description
Accumulation/distribution oscillator. It is a momentum indicator that associates changes in price	*A/D Oscillator*	$\dfrac{H_t - C_{t-1}}{H_t - L_t}$ where C_t is the closing price at time t, L_t the low price at time t, H_t the high price at time t	
It measures the variation of a security's price from its statistical mean	*CCI Commodity channel index*	$\dfrac{(M_t - SM_t)}{0.015 D_t}$	$where \quad M_t = (H_t + L_t + C_t)/3,$ $SM_t = \dfrac{\sum_{i=1}^{n} M_{t-i+1}}{n}, \ and$ $D_t = \dfrac{\sum_{i=1}^{n}\left|M_{t-i+1} - SM_t\right|}{n}$
It is a momentum indicator that measures overbought/oversold levels	*Larry William's (R%)*	$\dfrac{H_n - C_t}{H_n - L_n} * 100$	
Moving average convergence divergence	*MACD*	$MACD(n)_{t-1} + 2/n+1*$ $(DIFF_t - MACD(n)_{t-1})$	where $DIFF : EMA(12)_t - EMA(26)_t$, EMA is exponential moving average, $EMA(k)_t : EMA(k)_{t-1} + \alpha *$ $(C_t - EMA(k)_{t-1})$, α smoothing factor: $2/(1+k), k$ is time period of k day exponential moving average.
It measures the amount that a security's price has changed over a given time span	*Momentum*	$C_t - C_t - n$ price day	where C_t is the closing price at time t, n the

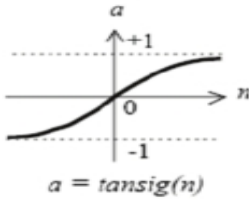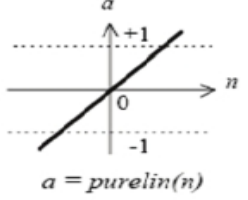| It displays the difference between the current price and the price *n* days ago	*ROC Price-rate-of-change*	$\dfrac{C_t}{C_t - n} * 100$	
Relative strength index. It is a price following an oscillator that ranges from 0 to 100. A method for analysing RSI is to look for divergence in which the security is making a new high.	*RSI*	$100 - \dfrac{100}{1 + (\sum_{i=0}^{n-1} Up_{t-1}/n)/(\sum_{i=0}^{n-1} Dw_{t-i}/n)}$	*where* Up_t means upward-price-change and Dw_t means downward-price-change at time *t*.
Simple 10-day moving average.	*Simple MA*	$\dfrac{C_t + C_{t-1} + ... + C_{t-n}}{n}$	It shows the average value of a security's price over a period of time. If the value of a security's price over a period of time. If the price moves above its MA, a buy signal is generated. If the price moves below its MA a sell signal is generated.
It compares where a security's price closed relative to its price range over a given time period	*Stochastic (K %)*	$\dfrac{C_t + L_{t-n}}{HH_{t-n} - LL_{t-n}} * 100$	*where* LL_t *and* HH_t, mean lowest low and highest high in the last *t* days, respectively.
Moving average of %K	*Stochastic (D%)*	$\dfrac{(\sum_{i=0}^{n-1} K_{t-i}\%)}{n}$	
Moving average of %D.	*Stochastic slow (D%)*	$\dfrac{(\sum_{i=0}^{n-1} D_{t-i}\%)}{n}$	
Weighted 10-day moving average	*WMA*	$\dfrac{((n)*c_t + (n-1)*c_{t-1} + ... + c_n)}{(n + (n-1) + ... + 1)}$	

Notes: In this study the original data were normalised in a range of [-1, 1].

Table 3. ANN parameter levels tested in parameter setting

Parameters	Level(s)	Tan-Sigmoid transfer function	Linear transfer function
Number of neurons (n)	10, 20,..., 50		
Learning rate (η)	0.1,0.2,...,0.5		
Momentum constant (µ)	0.01, 0.02,…,0.05		
Epochs (ep)	30, 60, 90,120		

Source: author calculation, 2013

Table 4 presents the summary statistics for each attribute. This study is to predict the directions of daily change of the LSM index is categorised as "0" or "1". "0" means that the next day's LSM index at time t is lower than today's LSM index at time t-1. If the LSM index at time t is higher than that at time t-1, direction t is "1". The original data were scaled into the range of [-1:0; 1:0] using max-min normalisation formula, which is used here to expresses the actual value using the following equation.

$$u = \frac{(x_i - x_{i,min})}{(x_{i,max} - x_{i,min})}(h_i - l_i) + l_i \qquad (i = 1,2,...,n)$$

(11)

where u and x_i represent normalised and actual value respectively. $x_{i,min}$ and $x_{i,max}$ represent minimum and maximum values of the attribute x_i. h_i upper bound of the normalising interval and l_i lower bound of the normalising interval. Max-min normalisation plans a value u of x_i in the range $(h_i - l_i)$ i.e. (-1.0; 1.0), in this case. As a value greater than 0 represents a buy signal while a value less than 0 represents a sell signal. $(i = 1,2,...,n)$ the number of observations. The aim of linear scaling is to independently normalise each feature component to the specified choice. It ensures the larger value input attributes do not overwhelm smaller value inputs, then helps to reduce prediction errors [16,18]. As we mentioned earlier in Table 2, twelve technical indicators are as input variables. The *Mean* and *Standard Deviation* of input variables is shown in Table 4.

Table 4. ANN parameter levels tested in parameter setting

Features name	Max	Min	Mean	Standard deviation
A/D Oscillator	23361.231	19502.12	44.450	11023.013
CCI	261.531	-252.224	-3.201	86.171
Larry William's (R%)	100.000	-0.051	38.423	26.427
MACD	1022.211	-661.294	24.112	165.720
Momentum	1101.090	-687.780	16.120	176.213
ROC	110.211	60.552	88.661	2.351
RSI	100.000	0.000	36.254	18.521
Simple MA	24410.260	1021.120	2365.171	1992.274
(K %)	88.004	2.012	29.810	12.371
(D%)	86.011	4.660	27.231	10.346
Slow (D%)	85.370	3.990	27.224	09.332
WMA	11210.231	2771.786	5131.170	1611.001

Source: author calculation, 2013

6. EXPERIMENTAL RESULTS

6.1 Comparison of Financial Performance

The total period of (02/01/2007-30/12/2010) is in network training and validation values are obtained with different combinations of parameters for testing the ANN model. The empirical results are presented in Table 5 and 6. The second sub-period of (02/01/2007-28/03/2013) is in sample period separately as a model input is used and prediction rate is calculated. The total of 6000 parameter combinations for the ANN model were tested and completed as presented in Table 3. Three parameters are considered as the best combinations and corresponding prediction accuracies are given in Table 5. Through these parameter combinations, we can now able to reach comparison experiments of the ANN model, based on the data sets presented in Table 5, including the average of training and validation performances for each case is calculated. The average of training and validation performance of the ANN model for these parameter combinations was varied between 87.58% and 87.99%. It can be assumed that both the training and validation performances of the ANN model are significant for parameter combination setting data set. The experiments were carried out for each year and the analysis results which are revealed separately in Table 6.

Table 5. Three parameters are considered as the best combinations of ANN model

No	η	ep	μ	n	Training	Validation	Average
1	0.023	60	0.037	20	80.49	94.67	87.58
2	0.1	120	0.019	30	82.56	93.42	87.99
3	0.025	90	0.041	30	81.99	93.51	87.75

Source: author calculation, 2013

Table 6 shows that the average predication rate values (91%) as the measure of financial performance of the ANN model for three different parameter combination (0.1; 120; 0.019; 30) is relatively better than others. Therefore, the prediction rate values performance of this parameter combination can be adopted as the best of the ANN model, since its average training and validation performance (82.56%; 93.42%) is relatively greater than the others.

As shown in Table 6, the best adaptation of the neural network model outputs with prediction rate (PR) values is 91%, which means 91% of data analysis is correctly predicted by the ANN model. Table 6 also shows that the prediction rate values performances are different for each year. For the selected parameter combination, the best prediction rate values rate performance (92%) was obtained in 2009 and 2010, while the worst one (88%) was obtained in 2013. For the other parameter combinations, the prediction rate values performances in 2013 were generally lesser than the other years. However, therefore, based on the experimental results given, the best parameter combination of ANN model is (η = 0.1; ep = 120; μ = 0.019; n = 30) with an average prediction rate values performance (91%).

Table 6. Financial prediction performance (%) of ANN model

Parameter combination (η ep μ n)			
	(0.023; 60; 0.037; 20)	(0.1; 120; 0.019; 30)	(0.025; 90; 0.041; 30)
Year	*(Training; validation)* (80.49; 94.67)	*(Training; validation)* (82.56; 93.42)	*(Training; validation)* (81.99; 93.51)
	Prediction rate	*Prediction rate*	*Prediction rate*
2007	0.89	0.91	0.90
2008	0.89	0.89	0.91
2009	0.90	0.92	0.88
2010	0.91	0.92	0.92
2012	0.88	0.91	0.90
2013	0.87	0.88	0.87
Average	**0.89**	**0.91**	**0.90**

Note: The Libyan Stock Market closed following the eruption of the Libyan civil war in 15 February 2011. It remained closed until reopening the following year on 15 March 2012.
Source: author calculation, 2013

6.2 Comparison of Statistical Performance

Statistical performance of the three parameter combination is compared in Table 6. As already is mentioned in sub-section 3.1, *MAE, RMSE, MAPE* and R^2, measures are used in order to compare the statistical performance of parameters combinations. *MAE, MAPE* and *RMSE* are used as error measurement. Table 7 shows that the error measurements are used for ANN model in order to compare the statistical performance of parameters combinations. Goodness of fit R^2 is also referred to as the coefficient of multiple correlations.

As is shown in Table 8, the parameter combination (0.1; 120; 0.019; 30) is relatively better than others. Therefore, this combination in terms of financial and statistical performances is the best one. In all cases the relationship strength between parameter combination and forecast accuracy measures such as *MAE, MAPE,* and *RMSE* is strong ($R^2 \geq 0.99$). *MAPE* and *RMSE* measure the residual errors, which gives a global idea of the difference between the predicted and actual values. Although, the *MAE* is very similar to the *RMSE* but it is less sensitive to large forecast errors (Fig. 3). The longer *MAE* means higher bias level and less accurate forecast to predict prices, but it does not mean that *MAE* is not suitable to predict stock market fluctuations. It seems that *MAE* method is more suitable to predict stock market fluctuations rather than short moving average. According to Table 8, as good as ANN model can be, is a powerful tool in predicting direction of LSM index movement and the current study results is in consistent with the previous studies such as [17,41,42,68,55].

Table 7. Statistical performance of ANN model

Parameter combination (η ep μ n)											
(0.023; 60; 0.037; 20)				**(0.1; 120; 0.019; 30)**				**(0.025; 90; 0.041; 30)**			
Year	**R^2**	**MAE**	**MAPE**	**RMSE**	**R^2**	**MAE**	**MAPE**	**RMSE**	**R^2**	**MAE**	**MAPE**	**RMSE**
2007	0.9965	2.22E-06	0.001201	0.000022	0.9992	4E-06	0.000240	2E-05	0.9956	5.13E-06	0.001102	6.31E-06
2008	0.9993	3.01E-06	0.001300	1.02E-05	0.9977	7E-06	0.003331	4E-07	0.9989	7.16E-06	0.003001	0.000020
2009	0.9979	0.000910	0.001002	0.000120	0.9996	1E-08	0.005664	1E-05	0.9989	0.000004	0.002230	0.000210
2010	0.9906	0.000066	0.001160	3E-06	0.9925	2E-06	0.000600	3E-05	0.9995	2.27E-06	0.001511	4.22E-05
2012	0.9980	3.01E-06	0.000201	7E-05	0.9998	9E-05	0.001017	0.000312	0.9982	0.000002	0.001060	0.000009
2013	0.9981	4.41E-05	0.001510	0.000044	0.9999	7E-06	0.004230	2E-05	0.9988	0.000015	0.002001	0.000112

Source: author calculation, 2013

Table 8. Statistical performance forecasting results of ANN model

Model	No of Obs.	R^2	PR	MAE	RMSE	MAPE
ANN	6	0.993	0.91	0.000002	0.00003	0.0006

Source: author calculation, 2013

Fig. 3 shows that the *MAE, RMSE* and *MAPE* calculated for the forecast period using the empirical antiracial natural network model in predicting direction of LSM index movement results are given in Table 8. The ANN models correctly predict the signs of stock price indexes up to 91% for entry data.
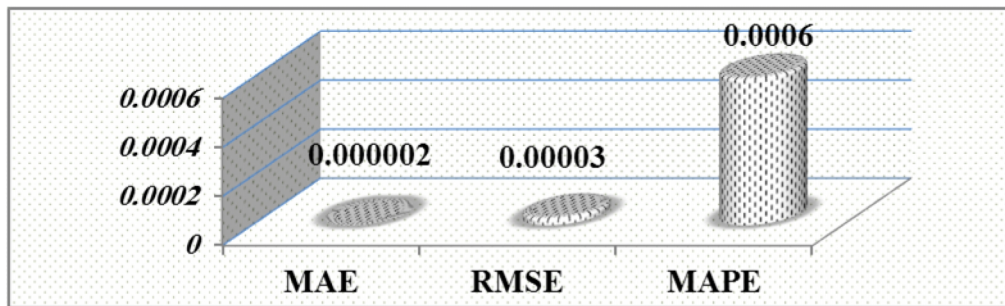

Fig. 3. *MAE, RMSE* and *MAPE* of neural network model
Source: author calculation from Table 8, 2013

The best results of the ANN model in predicting direction of LSM index is based in the paired samples *T*-test. The experimental results of *T*-test are given in Table 9. Table 9 shows that the mean performances of ANN model is significant level at α = 0.05, which give us some very important clues. That is, the performance of the ANN shows superior predicting power in forecasting the LSM index movement.

Table 9. *T*-test results of financial prediction ANN model

Model	No of Obs.	Mean	Std.dev	t	p
ANN	6	91%	3.28	4.066	0.059

Source: author calculation, 2013

The ANN model accurately predicted the direction of movement with prediction rate 91% of data analysis in its best case, which is a perfectly good outcome. In addition, the detailed empirical analysis of models parameters and selection of efficient parameter values may result in higher prediction accuracy. The set of technical indicators analysis adopted in our ANN models considered as the most appropriate for stock price prediction in emerging economy such as Libyan Stock Market. Although the prediction performance of ANN outperforms studies in the review of literature, it is still likely that the statistical forecast performance of the model is still possible to be improved performance over traditional techniques by doing the following: the model parameters should be adjusted by systematic experimentation comprehensive or the input variable sets requisite to to be modified by choosing those input that are more realistic in reflecting of the financial market performance.

7. CONCLUSION AND FUTURE RESEARCH

This paper aims to find the answer of the following question: whether the Libyan forecasted LSM index through the learning procedure techniques of ANN model or not. The issue of accurately predicting the direction of movements of the stock market price levels is highly significant for formulating the best market trading solutions. It is fundamentally affecting financial trader's decisions to buy or sell of an instrument that can be lucrative for investors. It can be concluded that successful prediction of stock prices may promise attractive benefits for investors. LSM index behaviour, however, is extremely complicated and very difficult. In addition, stock market is can be affected by many macro-economic factors such as political events, investors' expectations, institutional investors' choices, firms' policies, general economic conditions, interest rates, foreign exchange rates, movement of other stock market, psychology of investors and consumer price index etc. Consequently, it is very important to design and develop a model with the capability in predicting the LSM index behaviour which "learns" from observed data. This study attempted to predict the direction of stock price movement in emerging market such as the Libyan Stock Market closing price levels using ANN model based on the daily data from period 2007 to 2013. The forecasting ability of the model is accessed using *MAE, RMSE, MAPE* and R^2, which can be a future work for interested readers.

The key experimental results obtained, can give some very significance conclusions of this study is as follows. Firstly, it shows that how forecasting the stock market price could be achieved by using the proposed model. This model of ANN showed significant performance in predicting the direction of stock price movement. Thus, ANN model can be used as a better alternative technique for forecasting the daily stock market prices for this area. The ANN model accurately predicted the direction of movement with the average prediction rate 91% of data analysis in its best case, which is a perfectly good outcome. In all cases the relationship strength between parameter combination and forecast accuracy measures such as *MAE, MAPE*, and *RMSE* is strong ($R^2 \geq 0.99$). Furthermore, this study proved the significance of using twelve particular technical market indicators which gave also useful results in predicting the direction of stock price movement. To improve ANN model capabilities, a mixture of technical and fundamental factors as inputs over different time period were used to be an effective tool in forecasting the market level and direction.

The limitations of current study that provide some suggestions for future research are mentioned in the following: (1) each method has its own strengths and weaknesses. Future researches are suggested to use technical indicators of this study and other combining techniques models by integrating ANN with other classification models such as random walk [see, e.g., 69], Support Vector Machines SVM, Genetics Algorithm GA and Generalised Autoregressive Conditional Heteroskedasticity GARCH models to predict the LSM index movements. The weakness of one method can be balanced by the strengths of another by achieving a systematic effect. (2) Hybrid ANN model can also be used in the prediction of stock price indexes. Thus, these models grew to include: (SVM), (GA), (GARCH) and financial time series prediction. (3) Another important issue that should be mentioned here is the differences among the prediction performances for each year. It can be shown from the experimental results that the year of 2011 is not included because Libya had a devastating political crisis in 2011. The crisis in the revaluation had affected the stock market initially. The stock market has been closed for 12-months. Under such circumstances of political crisis, a decrease in the prediction performance of technical indicators can be considered acceptable.

COMPETING INTERESTS

Author has declared that no competing interests exist.

REFERENCES

1. Abu-Mostafa YS, Atiya AF. Introduction to financial forecasting. Applied Intelligence. 1996;6(3):205-213.
2. Manish K, Thenmozhi M. Support vector machines approach to predict the S&P CNX NIFTY index returns. In Proceedings of 10th Indian institute of capital markets conference, Mumbai, India; 2006. Accessed 12 March 2013.
    Available: http://ssrn.com/abstract=962833.
3. Fama E. Efficient capital markets: a review of theory and empirical work. Journal of Finance. 1970;25:383-417.
4. Hecht-Nielsen R. Applications of counter propagation networks. Neural Networks. 1988;1:131-139.
5. Schalkoff RJ. Artificial neural networks. McGraw-Hill: New York; 1997.
6. Hawley DD, Johnson JD, Raina D. Artificial neural systems: a new tool for financial decision-making. Financial Analysis Journal. 1990;63-72.
7. Shtub A, Versano R. Estimating the cost of steel pipe bending, a comparison between neural networks and regression analysis. International Journal of Production Economics. 1999;62(3):201-207.
8. Garcia R, Gencay R. Pricing and hedging derivative securities with neural networks and a homogeneity hint. Journal of Econometrics. 2000;94(1-2):93-115.
9. Hamm L, Brorsen BW. Trading futures markets based on signals from a neural network. Applied Economics Letters. 2000;7(2):137-40.
10. Lapedes A, Farber R. Nonlinear signal processing using neural networks. IEEE conference on Neural Information processing systems- Natural and synthetic; 1987.
11. Sharda R, Patil R. Neural networks as forecasting experts: an empirical test. Proceedings of the 1990 International Joint Conference on Neural Networks, Washington DC: USA. 1990;1:491-494.
12. Tang Z, Fishwick PA. Feed forward neural nets as models for time series forecasting. ORSA Journal on Computing. 1993;5(4):374-385.
13. Bishop C. Neural networks for pattern recognition. Oxford University Press: Oxford; 1995.
14. Dacha K. Causal modeling of stock market prices using neural networks and multiple regression: a comparison report. Finance India. 2007;(3):923-930.
15. Tang A, Fishwick S. Time series forecasting using neural networks vs. Box-Jenkins methodology. Simulation. 1991;57(5):303-310.
16. Kim K. Financial time series forecasting using support vector machines. Neurocomputing. 2003;55:307-319.
17. Kim K, Han I. Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. Expert Systems with Applications. 2000;19:125-132.
18. Manish K, Thenmozhi M. Forecasting stock index movement: a comparison of support vector machines and random forest. In Proceedings of ninth Indian institute of capital markets conference, Mumbai, India; 2005. Accessed 12 March 2013.
    Available: http:// ssrn.com/abstract=876544.
19. Libyan Stock Market Reports; 2007-2010. Accessed 2 January 2013.
    Available: www.lsm.gov.ly.

20. Hertz J, Krogh A, Palmer RG. Introduction to the theory of neural computation. Redwood City: Addison Wesley; 1991.

21. Chen AS, Leung MT, Daouk H. Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index. Computers and Operations Research. 2003;30(6):901-923.

22. Pesaran MH, Timermann MA. Recursive modelling approach to predicting stock returns. University of Cambridge Press: Cambridge; 1999.

23. Anderson JA, Rosenfeld E. Neurocomputing: foundations of research. MIT Press: Cambridge, MA; 1988.

24. Rumelhard DE, Mcclelland JL. Parallel Distributed Processing - Explorations in the Micro-structure of Cognition. Foundations. 1986;1:294.

25. Armano G, Marchesi M, Murru AA. Hybrid genetic-neural architecture for stock indexes forecasting. Information Sciences. 2005;170:3-33.

26. Chiang WC, Urban NL, Baldridge GW. A neural network approach to mutual fund net asset value forecasting. Omega, The International Journal of Management Science. 1996;215(2):205-215.

27. Basheer IA, Hajmeer M. Artificial neural networks: fundamentals, computing, design and application. Journal of Microbiological Methods. 2000;34:3-31.

28. Breedlove SM, Watson NV, Rosenzweig MR. Biological Psychology: An Introduction to Behavioral, Cognitive, and Clinical Neuroscience. 6th ed. Sinauer Associates, Inc. USA; 2010.

29. Jain AK, Mao J, Mohiuddin KM. Artificial neural networks: a tutorial. Comput. IEEE. 1996;31-44.

30. Zhou WJ, Jie WJ, George ZZ, Po Guo S. Forecasting stock indices with back propagation neural network. Expert Systems with Applications. 2011;37:7056-7064.

31. Rasband MN. The axon initial segment and the maintenance of neuronal polarity. Nature Reviews Neuroscience. 2010;11:552-562.

32. Silverthorn DU. Human Physiology: an Integrated Approach. Pearson. ISBN 978-0-321-55980-7. 2010:253.

33. Brown and Benchmark. Introductory Psychology Electronic Image Bank. Times Mirror Higher Education Group Inc; 1995.

34. Bierens HJ. Comment on artificial neural networks: an econometric perspective. Econometric Reviews. 1994;13(1):93-97.

35. Kuan, C.M. and White, H. Artificial neural networks: an econometric perspective. Econometric Views. 1994;13(1):1-91.

36. Kaastra I, Boyd MS. Forecasting futures trading volume using neural networks. Journal of Futures Markets. 1995;15(8):953-70.

37. Trippi RR, DeSieno D. Trading equity index futures with a neural network. Journal of Portfolio Management. 1992;19(1):27-33.

38. Witkowska D. Neural networks as a forecasting instrument for the Polish Stock Exchange. International Advances in Economic Research. 1995;1(3):232-241.

39. Harvey CR. Predictable risk and returns in emerging markets. The Review of Financial Studies. 1995;8:773–816.

40. Yoon Y, Swales G. Predicting stock price performance. Proceeding of the 24th Hawaii International Conference on System Sciences. 1997;4:156-162.

41. Diler AI. Predicting direction of ISE national-100 index with back propagation trained neural network. Journal of Istanbul Stock Exchange. 2003;7(25-26):65-81.

42. Altay E, Satman MH. Stock market forecasting: artificial neural networks and linear regression comparison in an emerging market. Journal of Financial Management and Analysis. 2005;18(2):18-33.

43. Bokhari J, Cai C, Hudson R, Keasey. The predictive ability and profitability of technical trading rules: does company size matter?. Economics Letters. 2005;86: 21-27.

44. Baba N, Kozaki M. An intelligent forecasting system of stock price using neural networks. In Proceedings of the international joint conference on neural networks. Baltimore, MD: USA; 1992:371-377.

45. Hiemstra Y. Modeling structured nonlinear knowledge to predict stock market returns. In R.R. Trippi (ed.), Chaos and nonlinear dynamics in the financial markets: theory, evidence and applications: Chicago, IL; Irwin; 1995;163-175.

46. Kim SH, Chun SH. Graded forecasting using an array of bipolar predictions: application of probabilistic neural networks to a stock market index. International Journal of Forecasting. 1998;14:323-337.

47. Russell S, Norvig P. Artificial intelligence: a modern approach. 3rd ed. Prentice Hall: Upper Saddle River, NJ; 2010.

48. Takahashi T, Tamada R, Nagasaka K. Multiple line-segments regression for stock prices and long-range forecasting system by neural networks. In Proceedings of the 37th SICE annual conference, Chiba, Japan. 1998:1127-1132.

49. Leigh W, Purvis R, Ragusa JM. Forecasting the NYSE composite index with technical analysis, pattern recogniser, neural network, and genetic algorithm: a case study in romantic decision support. Decision Support Systems. 2002;32(4):361-377.

50. Oh KJ, Kim KJ. Analysing stock market tick data using piecewise nonlinear model. Expert Systems with Applications. 2002;2:249-255.

51. Pai PF, Lin CS. A hybrid ARIMA and support vector machines model in stock price forecasting. Omega. 2005;33:497-505.

52. Tan TZ, Quek C, See NgG. Biological brain-inspired genetic complementary learning for stock market and bank failure prediction. Computational Intelligence. 2007;23(2):236-261.

53. Chu HH, Chen TL, Cheng CH, Huang CC. Fuzzy dual-factor time-series for stock index forecasting. Expert Systems with Applications. 2009;36(1):165-171.

54. Bennett CC, Hauser K. Artificial intelligence framework for simulating clinical decision-marketing: a markova decision process approach. Artificial Intelligence in Medicine. 2013;57:9-19.

55. Kara Y, Boyacioglu MA, Baykan OK. Predicting direction of stock price index movement using artificial neural networks and support vector machines: the sample of the Istanbul Stock Exchange. Expert systems with Applications. 2011;38: 5311-5319.

56. Pacelli V. Forecasting exchange rates: A comparative analysis. International Journal of Business and Social Science. 2012;3(10):145-156.

57. Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. Nature. 1986;323:533-536.

58. Haykin S. Neural networks: an introduction. Macmillan College publishing Co; 1994.

59. Masters T. Practical neural network recipes in C++. Academic press inc., San Diego, CA., USA, ISBN: 0-12-479040-2; 1993:6.

60. Barndorff-Nielsen OE, Jensen JL. Networks and chaos: statistical and probabilistic aspects. London: Chapman and Hall; 1993.

61. Wythoff BJ. Back-propagation neural networks: a tutorial. Chemometrics and Intelligent Laboratory Systems. 1993;18(2):115-155.

62. Zupan J, Gasteiger J. Neural networks for chemists: an introduction. VCH: New York; 1993.

63. Fu L. Neural networks in computer intelligence. McGraw-Hill: New York; 1995.

64. Makridakis SG, Wheelwright SC, Hyndman RJ. Forecasting: methods and application. 3rd ed. New York: John Wiley and Sons; 1998.

65. Fildes R. The evaluation of extrapolative forecasting methods. International Journal of Forecasting. 1992;8:81-98.
66. Poon SH. A practical guide to forecasting financial market volatility. Chichester: Jhon Wiley and Sons, ltd; 2005.
67. Achelis SB. Technical analysis from A to Z. Probus Publishing: Chicago; 1995.
68. Sinaei H, Mortazavi S, Teymoriasl Y. Index forecasting of Tehran Stock Exchange by means of artificial neural networks. Journal Account Auditing Investing. 2006;41(12):59-83.
69. Sun B, Xie C, Wang G, Zhang J. The combining prediction of the RMB exchange rate series based on diverse architectural artificial neural network ensemble methodology. BIC-TA. 2010:743-749.

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