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Effect of External Factor on Share Price Forecasting

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Abstract - The stock market can be thought of as a highly complex and adaptive system. Variation in share price of the stock market can be considered as an indicator of the economical trend of a country. Thus, forecasting the behaviour of the stock market is at primary concern not only of the business community but also of the policy markers of a country. The fluctuation of share prices of the stock market depend on external and internal factors. The major difficulty in this regards is that most of these factors cannot be quantified in a model. The results in this research clearly illustrates that the historical data with external input factor (such as the average exchange rate) increases the more accurate share price forecasting ability of the neural network model.

Keywords - External Factor, Forecasting, Neural Network, S&P SL20 Index.

1. Introduction

Generally, stock markets represent the economic status of a country. Different stock markets have different characteristics based on the economics of the countries they represent [1]. Stock markets are complex, nonlinear, dynamic and chaotic [2]. Prediction of stock prices is one of the major challenges in the hands of business analysts for the interest of the financial and economic personnel and in general the policy makers and planners of a country. Techniques of prediction vary greatly according to the availability of information, quality of modeling and the underlying assumptions used. Neural networks are regarded as more suitable for stock prediction than other techniques mainly due to its ability to adaptation to the nature of observations (data); for instance in situation like financial markets in general it is impossible to incorporate the effects of some socio-economic factors directly in the models (e.g. Exchange rate of other non-western currencies, GDP, Consumer indices, etc.) [1]. We used the S&P SL20 index of Colombo Stock Exchange (CSE) in Sri Lanka and exchange rate between US $ and LKR data from 02nd January 2013 to 31st December 2013. The best feed forward ANN model and suitable parameters of each model are selected by using training data set with trial and error technique. The accuracy of each model was compared via Absolute fraction of variance (R2), Mean Absolute Deviation (MAD), Mean Square Error (MSE), Root Mean Square Error (RMSE) and visually. The results examined that the exchange rates which is an external factor affected the share price forecasting in ANNs.

2. Financial Market in Sri Lanka

Share trading in Sri Lanka dates back for a century, in 1896 when the Colombo Stock Brokers Association (CSBA) commenced the trading of shares in limited liability companies. Share trading however, was formalized in 1985 with establishment of the Colombo Stock Exchange (CSE). The CSE is the organization responsible for the operation of the stock market in Sri Lanka. The market value of the listed companies or Market capitalization of the CSE stood at LKR 2, 459.9 billion as at the end of 2013. The CSE has two main market indices (ASPI, S&P SL20), 20 sector price indices and total return indices which are based on the ASPI and S&P SL20 and sector indices. Index values are calculated on an on-going basis during the trading session, with the closing values published at the end of each session[1] .

2.1 S&P SL20 Index

The S&P SL20 covers the largest and most liquid stocks from the Sri Lankan equity market and is designed to be the basis for tradable products. The index is based on S&P Indices' global index methodology, which provides consistency, transparency and liquidity. The S&P SL20 seeks to be comprised of liquid and tradable stocks for easy and cost effective replication as trading instruments, with possible application as index funds and Exchange Traded Funds (ETFs). Index constituents are the 20 largest blue chip companies chosen from the universe of all stocks listed on Colombo Stock Exchange. The indices are calculated using a capped market capitalization-weightingscheme (capped at 15%)[1]. ***https://www.cse.lk***

2.2 Nature of Stock Market Indices

The time series of stock market indices are close to the behaviour of one dimensional brownian motion. It is shown in Fig. (1) that using the daily S&P SL20 index value. S&P SL20 is based on global index methodology and it is calculated in Sri Lankan Rupee (LKR). The base period of S&P SL 20 is December 17, 2004. The base value is 1000.

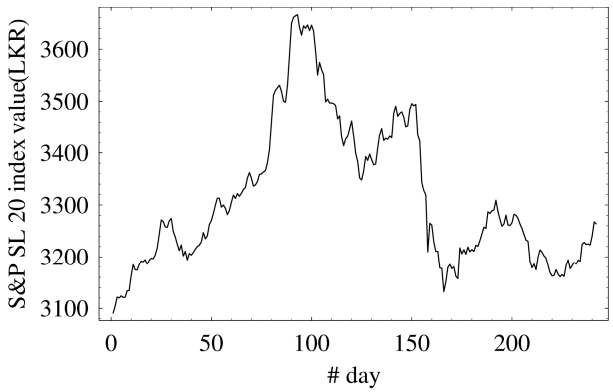

Fig. 1: Behaviour of the S&P SL20 index is very close to the one dimensional geometric brownian motion.

The inherited stochasticity of the stock market time-series can be explained via the complexity of the interaction between the participants of the market. The only successful approximation of the average behaviour of the stock price is given by the Geometric Brownian Motion [3] via the theory of stochastic differential equations. Despite no standard statistical theory is capable of explaining the so called critical crashes occur in the market [4]. Financial indices have a low overall correlation to the movements of future indices, but a high correlation to past indices movement action. The fluctuation of share price in the stock market depends on many factors some of which are external and some are internal [5]. One of the important internal factors can be a company's performance. The external factors may include changes in government policy, recessions, depressions, national calamities unpredicted natural disasters, Exchange rate etc. [5].

The major difficulty in this regards is that most of these factors cannot be quantified in a model. For example, there is no way one can directly quantify the political stability in a country; there is no way we can incorporate the effect of natural disasters in a statistical model for finance. Otherwise there is no clear relationship between share price and quantified factor. It is illustrated in Fig. (2) plotting S&P SL20 Vs exchange rate which is an external quantified factor.

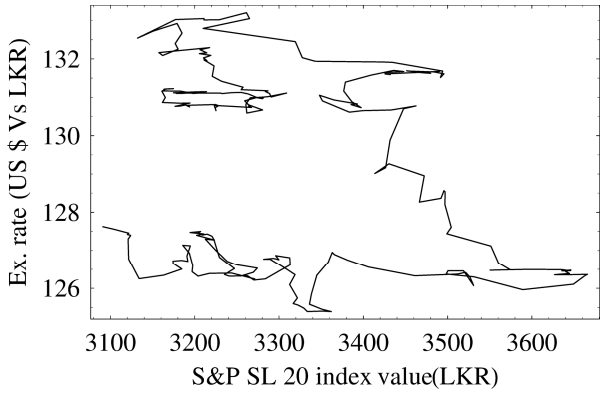

Fig. 2: Exchange rate between LKR and US $ Vs S&P SL20 index in 2013.

Increasing or stable stock price usually indicates signs of stable economic growth of a market (although there can be exceptional behaviours near a so called critical crash [4]). On the other hand, a stock market crash can be a result of an economic recession, depression or financial crisis. As he stock price movements indicate the general economical trend of a country, forecasting of stock market indices is an important issue in decision/ policy making pertaining to the economy of a country.

2.1 Forecasting Stock Market Indices

Forecasting is the prediction of values of a variable based on known past values of that variable or other related variables. Forecasts also may be based on expert judgments, which in turn are based on historical data and experience [6]. Techniques of prediction vary greatly according to the availability of information, quality of modeling and the underlying assumptions used.

Forecasting techniques can be broadly divided into two categories: Statistical and Artificial Intelligence (AI) based techniques. Box-Jenkins or ARIMA, Multiple Regressions and Exponential Smoothing are examples of statistical methods, whilst AI paradigms include fuzzy inference systems, genetic algorithm, ANNs, machine learning etc [7]. A glossary of commonly used ANN terminologies and their statistical equivalents is summarized in Table 1 [8], [9].

In recent years, ANNs have become extremely popular for prediction and forecasting in a number of areas, including finance, power generation, medicine, water resources and environmental science [8]. Many successful applications have proved that neural network is a very useful tool for time series and forecasting over the traditional time series

model [10]–[12]. and many studies have used ANN technique in financial area [1], [2], [11], [13]–[17]. Francesco and Bernd [18] demonstrated the effects of non-stationary on the neural network prediction. They indicated that detecting non stationarity and selecting an appropriate preprocessing technique is highly beneficial for improving the prediction accuracy.

Table 1: Glossary of ANN and statistical terminology

ANNs	Statistics
Input	Independent variable
Output	Predicted value
Training values	Dependent variables
Errors	Residuals
Training or learning	Estimation
Error (cost) function	Estimation criteria
Patterns or training pairs	Observations
Weights	Parameter estimates
Generalization	Interpolation and extrapolation

3. Artificial Neural Networks

ANN model is a nonparametric method and it can be used to forecast future results by learning the historical data patterns without any strict theoretical assumptions [10]. Since 1943, when Warren McCulloch and Walter Pitts presented the first model of an artificial neuron research in the field of neural networks has been attractive in many different avenues. The fundamental unit or building block of an artificial neural network is the *neuron* (or processing element) itself. The processing element is also called an *artificial neuron* (or perceptron).

3.1 The Perceptron Verses Biological Neuron

The perceptron is a mathematical model of a biological neuron, whereas in actual neurons the dendrite receives electrical signals from the axons of other neurons, in the perceptron these electrical signals are represented as numerical values. At the synapses between the dendrite and axons electrical signals are modulated in various amounts. This is also modeled in the perceptron by multiplying each input value by a value called the weight. An actual neuron fires an output signal only when the total strength of the input signals exceed a certain threshold. This phenomenon in a perceptron is modeled by calculating the weighted sum of the inputs to and applying a step unction on the sum to determine its output. As in biological neural networks, this output is fed to other perceptrons.

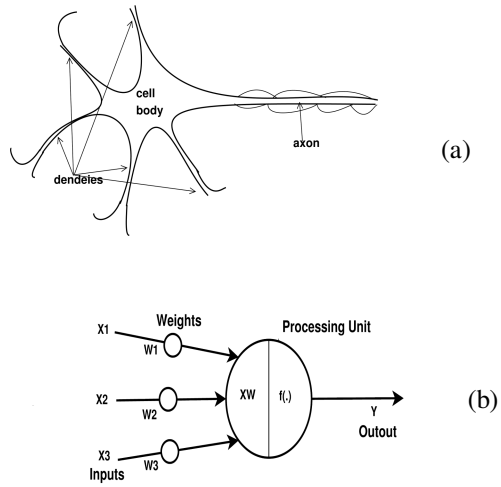

Fig. 3: (a) represents the biological neuron and (b) represent the perceptron in artificial neural network.

3.2 The ANN Architecture

The ANN architecture defines the network structure, that is the number of neurons in the network and their interconnectivity. The commonest type of ANN consists of three groups or layers of units. They are the input layer, the hidden layer and the output layer. These are represented in Fig. (4).

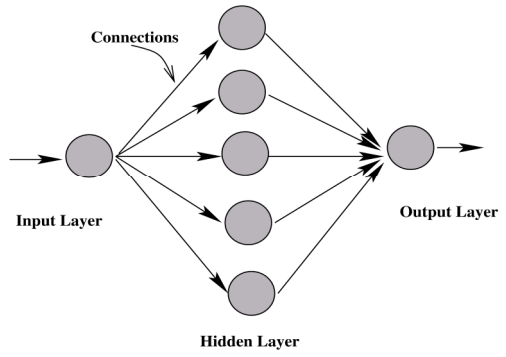

Fig. 4: Layers in neural network

According to the number of layers, a network can be either single layer network which has only input layer and output layer, or multi layer network. According to the interconnection scheme, a network can be either feed-forward network or recurrent network and its connections either symmetrical or asymmetrical.

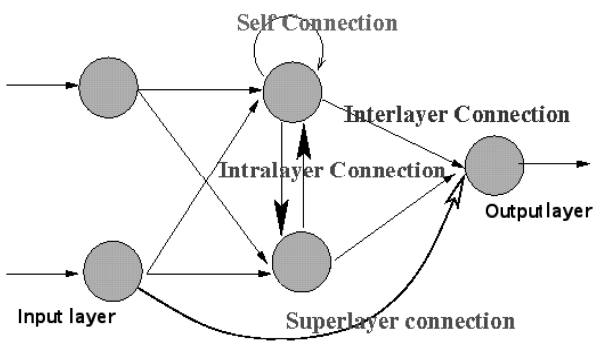

Fig. 5: Interconnections between nodes and layers

The Neural network has mainly two mode operations, called training mode and testing mode. After training, the network can be correctly identified each of input patterns. Then, It can be used to perform similar pattern. One of learning algorithms has to be used for training the network.

3.3 Learning Algorithm

Learning in artificial systems can be formulated as optimization of an objective function (cost function or error function) which quantifies the system's performance. A typical approach to this optimization is to follow the gradient of the objective function with respect to the tunable parameters of the system. Frequently this is accomplished directly, by calculating the gradient explicitly and updating the parameters by a small step in the direction of locally greatest improvement [19], [20].

We can define objective function in several area:

- Mutual entropy
- Maximum likelihood function
- Mean square error

For example, the back propagation algorithm techniques uses a gradient descent technique for minimizing the "Mean Square Error" criterion [20].

4. The Back-Propagation Learning Algorithm

The back-propagation algorithm was developed by "Paul Werbos" in 1974 and rediscovered independently by "Rumelhart" and "Paker" [21].

Back-propagation is a kind of gradient descent technique with backward error propagation. It is a supervised learning algorithm for training multi-layer neural networks for function approximation and pattern classification by minimizing a suitably defined error metric (e.g. the mean square error between the target and network outputs of the network for a training set) using gradient descent technique. Back-propagation algorithm has been modified by using several techniques. Further, it has a stochastic behaviour and it was satisfied the stability conditions.

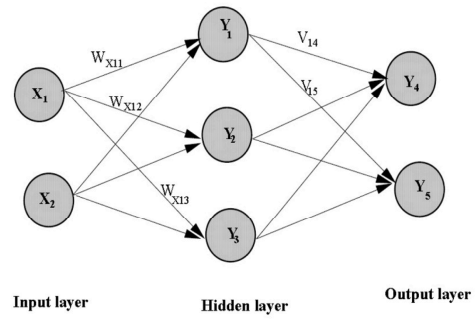

Fig. 6: 2 – 3 – 2 ANN model.

Fig.(6) shows a architecture of 2 – 3 – 2 ANN model. The output value of the neuron Y_{Oj} of the $I_n - H_n - O_n$ feed-forward network architecture can be described by the form

$$Y_{O_j} = f\left(\sum_{i=1}^{H_n} v_{ij}.f\left(\sum_{k=1}^{I_n} w_{x_k i} x_k\right)\right), \qquad (1)$$

where I_n and H_n are the number of neurons in the input layer and hidden layer respectively. $W_{xk\ i}$ - Weight of connect between network input *xk* and neuron i in hidden layer. Y_{oj} - Output signal of neuron j in output layer. *Vij* - Weight of connections between neuron i in hidden layer and neuron *j* in output layer and is a activation function used in both layers. In matrix form it can be represented as,

$$Y_O = f\left(V^T f\left(W^T X\right)\right) \qquad (2)$$

The training data set consists of input signals $X = (x_1, x_2, \ldots, x_n)$ assigned with corresponding target output T. During the training session of the network, a pair of patterns is presented (X_k, T_k). The difference between the network and target outputs yeils an error signal. Then error for the jth neuron in the output layer is

$$E_j = T_j - Y_{0j}. \qquad (3)$$

The mean square error for the k th patterns is

$$E_k = \frac{1}{m}\sum_{r=1}^{m} (T_r - Y_r)^2 \qquad (4)$$

where m is the number of nodes in the output layer. Since the inputs and the target outputs are fixed the target of approximating the function at known points is to minimize the MSE for all inputs by choosing the optimal set of weights. This minimization is performed with respect to the set of all weights (including the hidden weights and the output weights) via the fastest possible path the MSE could converge to zero (which known as the *steepest descent algorithm*).

5. Share Price Forecasting

As in any forecasting model, the selection of appropriate model input is extremely important for generalization ability [8], [22]. According to the input data we choose, S&P SL20 of the CSE could be forecasted in three different ways: namely,

- Case I: Use consecutive last 30 days and next day value as input and output vectors respectively. (This case has been discussed in [11].)
- Case II: Use the average exchange rate between US $ and LKR on last 30 days as an additional input of the case I.
- Case III: Replace each 30th day value of case I, by the additional input of case II.

For example {Input,output} data patterns were :
Case I:

$$\left\{ \begin{pmatrix} x_1 & x_2 & \dots & x_{29} & x_{30} \\ x_2 & x_3 & \dots & x_{30} & x_{31} \\ \dots & \dots & \dots & \dots & \dots \end{pmatrix}_{N\times 30}, \begin{pmatrix} x_{31} \\ x_{32} \\ \dots \end{pmatrix}_{N\times 1} \right\}$$

Case I:

$$\left\{ \begin{pmatrix} x_1 & x_2 & \dots & x_{29} & x_{30} & E_{30}^1 \\ x_2 & x_3 & \dots & x_{30} & x_{31} & E_{31}^2 \\ \dots & \dots & \dots & \dots & \dots & \dots \end{pmatrix}_{N\times 30}, \begin{pmatrix} x_{31} \\ x_{32} \\ \dots \end{pmatrix}_{N\times 1} \right\}$$

Case III:

$$\left\{ \begin{pmatrix} x_1 & x_2 & \dots & x_{29} & E_{30}^1 \\ x_2 & x_3 & \dots & x_{30} & E_{31}^2 \\ \dots & \dots & \dots & \dots & \dots \end{pmatrix}_{N\times 30}, \begin{pmatrix} x_{31} \\ x_{32} \\ \dots \end{pmatrix}_{N\times 1} \right\}$$

where x_n represents the S&P SL20 value on nth day, E_j represents the average exchange rate over the range from i^{th} day to j^{th} day and N is the number of the data patterns.

The S&P SL20 daily recorded data exchange rate have been collected for the period 02nd Jan. 2013 to 31st Dec. 2013 from the *www.cse.lk* and *www.quandl.com/data/CURRFX/LKRUSD-Currency-Exchange-Rates-LKR-vs-USD* respectively. There are 242 data points. The first (200) have been taken as the training data set. It has been used to select suitable parameters and best network architecture by modifying the weights. The rest of the data (42) has been considered as the testing data set which is not use to train the network.

The input range required for the network must be determined. Therefore Linear Scaling formula was used to normalize the share price and Exchange rate. Let us assume that the input range is from I_{min} to I_{max} . The formula for transforming each datum x to an input value I is [23]–[25]

$$x' = I_{min} + (I_{max} - I_{min})\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right). \qquad (5)$$

The one hidden layer network is sufficient to simulate complicated systems with different accuracy. Increasing the number of hidden layers also increases computation time and the danger of over fitting which leads to poor out-of-sample forecasting performance [8], [24]. Therefore, the one hidden layer structure has been considered in this research. Transfer functions such as sigmoid are commonly used for time series data because they are nonlinear and continuously differentiable which are desirable properties for network learning [24]. Therefore sigmoidal function has been selected as a transfer function of the network.

There is no systematic way to determine the parametric structure of a training model and moreover, in most commonly used methods for selecting the number of the hidden layer nodes and parameters are by “trial and error” [26]. Forecasting future n days of S&P SL20 has been discussed in [11] and it clearly has been shown that the ANN model forecasting is more accurate than the ARIMA (1, 1, 1) model and forecasting ability decreases with increasing number of future days. Reference [11] has been decided that the best feed-forward ANN architecture for next n^{th} day forecasting of S&P SL20 is 30 – 10 – 1 and the suitable parameters are

Learning rate..... 0.9
Momentum term ….....0.1
Number of iterations ….. 1500.

which have been selected by using training data set together with trial and error technique. The weights have been initialized randomly (uniformly distributed in the interval [−1, 1]). The MSE has been evaluated to determined the best network architecture. Therefore the best feed-forward ANN architectures for forecasting next day of S&P SL20 were selected as 30 − 10 − 1 for case I, III and 31 − 10 − 1 for case II with above parameters.

6. Results

MSE has been used as the sole indicator for performance measurement during training. Fig. (7) shows the MSE of all cases with respect to each iteration in the training period. Although the error rate has considerably small fluctuations, there is no growing variance in every case. At the end of training MSE were 0.0040, 0.0053 and 0.0040 for case I, II and III respectively. In Fig. (8) shows behaviour of network predicted values and target values for each case in the training. It is clearly show that the training data agrees very well to the network output except several points. After training network models corresponding final weights used to forecast the testing data set. There were 42 data points. After preparing normalized input-output data pattern, case III could be forecast 13 points and case I and II could be able to forecast 12 data points. The Table 2 and Fig.(9) show the results forecasted here.

Whereas case III has been produced a average trend behaviour of the target values, case I have been observed that the average behaviour with up and down fluctuation effect. Although case I and III have been given the satisfactory forecasting, the network values in case II (Green line or ▲ symbol) have been excellently agreed with up and down fluctuations and average behaviour of target values in Fig. (9). The data in Table 3 are the several error measurements for each cases. These approaches clearly indicate that the historical data with external input factor (such as the average exchange rate) increases the more accurate share price forecasting ability of the neural network model.

7. Discussion

There are several different approaches to share price forecasting. Francesco and Bernd [18] demonstrated the effects of non-stationary on the neural network prediction. They indicated that detecting nonstationarity and selecting an appropriate preprocessing technique is highly beneficial for improving the prediction accuracy. Reference [11] has shown that ANN forecast more accurate than ARIMA(1, 1, 1) model and it is best with increasing number of forecasting days for S&P SL20 index of CSE. As with any forecasting model, the selection of appropriate inputs for the model is extremely important [8]. Further the fluctuations of share price index depends on a number of external and internal factors [4], [27]. Most of the current economic potential of CSE is the tourism sector and April, May and June are the best months for traveling in Sri Lanka. Tourist arrivals have steadily increased each year since the end of the war due to improve security and have doubled since 2009. It may be a one of reason for the special behaviour of Day point between 50 − 75 in Fig. (8). It is also a external factor to affect the share price behaviour. The results in this research clearly illustrates that the historical data with external input factor (such as the average exchange rate) increases the more accurate forecasting ability of the neural network model.

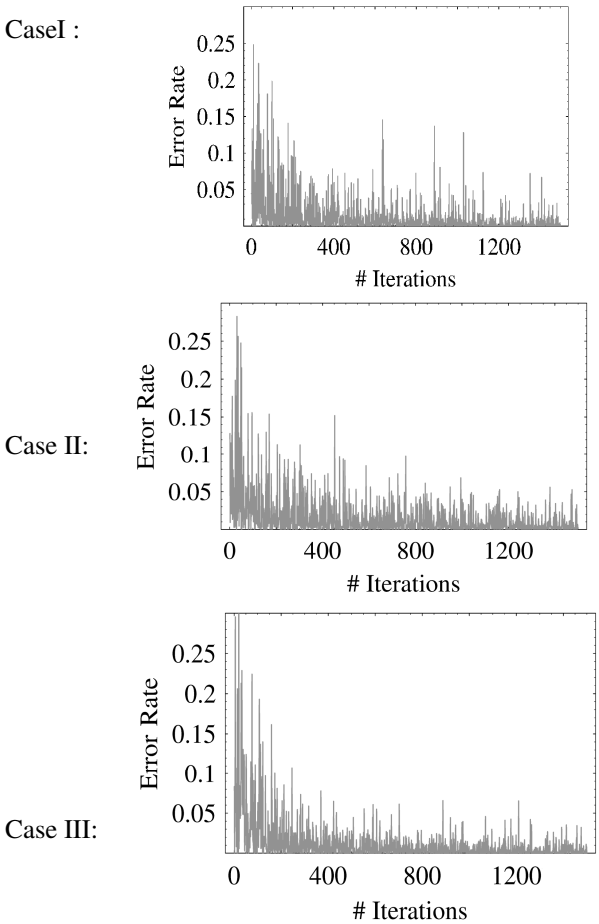

Fig. 7: Convergence of the MSE verses number of iterations in the training. The error rate tends to stabilize but with almost constant variance.

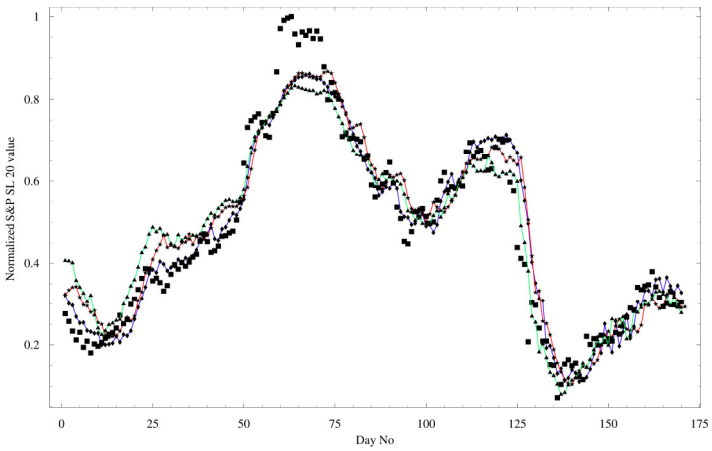

Fig. 8: ■ symbol represents the target S&P SL20 training data values. Blue, Green and Red lines represent the network output for case I, II and Case III respectively.

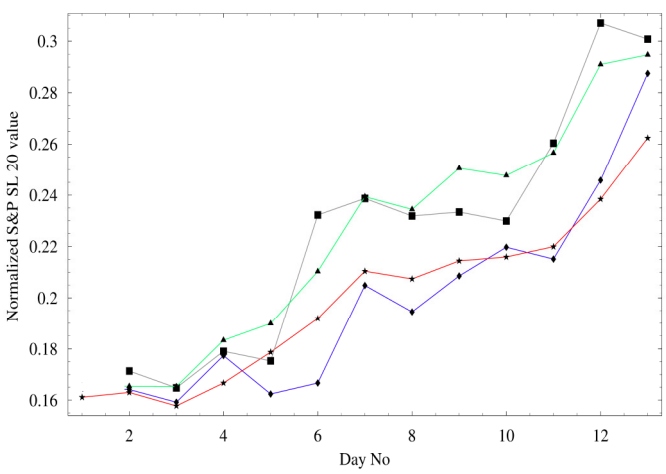

Fig. 9: Gray line (■ symbol) represents the target S&P SL20 testing data values. Blue (or ♦ symbol), Green (or ▲ symbol) and Red (or ★ symbol) lines represent the network output for case I, II and Case III respectively.

Table 3 shows the several error measurements for each case. Here *Yi* , *Ti* and *N* are network value, target value and number of data points respectively. The best score for R^2 measure is 1 and for other measures are zero.

Table 2: S &P SL20 target values and network output for each case.

Day No	Target Value	Network Value		
		Case I	Case II	Case III
1	0.158895	-	-	0.166116
2	0.171361	0.164165	0.165408	0.163022
3	0.164806	0.159224	0.165324	0.157778
4	0.179063	0.177368	0.183374	0.166698
5	0.175308	0.162410	0.189947	0.178724
6	0.232248	0.166695	0.210349	0.191927
7	0.238699	0.204892	0.239371	0.210450
8	0.231866	0.194583	0.234432	0.207439
9	0.233413	0.208591	0.250491	0.214441
10	0.229919	0.219750	0.247657	0.215958
11	0.260362	0.215139	0.256561	0.219949
12	0.306993	0.245783	0.290952	0.238436
13	0.300768	0.287467	0.294700	0.262394

Table 3: Error Measurements.

Error Measurements	Formula	Case I	CaseII	CaseIII
R^2	$1-\frac{\sum_{i=1}^{N}(Y_i-T_i)^2}{\sum_{i=1}^{N}Y_i^2}$	0.9724	0.9974	0.9779
MAD	$\frac{\sum_{i=1}^{N}\lvert Y_i-T_i\rvert}{N}$	0.0266	0.0093	0.0236
MSE	$\frac{\sum_{i=1}^{N}(Y_i-T_i)^2}{N}$	0.0011	0.0001	0.0009
RMSE	$\sqrt{\frac{\sum_{i=1}^{N}(Y_i-T_i)^2}{N}}$	0.0339	0.0118	0.0230

R^2 - Absolute Fraction of Variance,
MAD - Mean Absolute Deviation,
MSE - Mean Square Error,
RMSE - Root Mean Square Error.

8. Conclusion

The forecasting ability of the network model can be improved had various socio-economic indicators (e.g. exchange rate, export prices of commodity, cost of living index, GDP etc.) been used as input factors in addition to

historical data.

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