FLANN BASED MODEL TO PREDICT STOCK PRICE MOVEMENTS OF STOCK INDICES

A THESIS SUBMITTED IN
PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS & INSTRUMENTATION ENGINEERING.

By

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CERTIFICATE

This is to certify that the thesis entitled **"FLANN based model to predict stock price movements of stock indices"** submitted by Sri Chinmoy Mohapatra in partial fulfillment of the requirements for the award of Bachelor of Technology Degree in Electronics and Instrumentation Engineering at National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/ Institute for the award of any Degree or Diploma.

Dr. G. Panda
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INTRODUCTION

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1.1 Introduction to Stock Market Prediction

Financial Forecasting or specifically Stock Market prediction is one of the hottest fields of research lately due to its commercial applications owing to the high stakes and the kinds of attractive benefits that it has to offer. Forecasting the price movements in stock markets has been a major challenge for common investors, businesses, brokers and speculators. As more and more money is being invested the investors get anxious of the future trends of the stock prices in the market. The primary area of concern is to determine the appropriate time to buy, hold or sell. In their quest to forecast, the investors assume that the future trends in the stock market are based at least in part on present and past events and data **[1].** However financial time-series is one of the most 'noisiest' and 'non-stationary' signals present and hence very difficult to forecast **[2][3]**.

The Dow Jones Industrial Average (DJIA) index was launched in 1896 with 12 stocks and is now the worlds most often quoted stock exchange index, based on a price-weighted average of 30 significant companies traded in the New York Stock Exchange (NYSE) and NASDAQ. The index gives a general indication of the behavior of the market towards different information. Another well known index, considered by researchers for prediction, is the Standard & Poor (S&P) 500. Many researchers in the past have applied various statistical and soft computing techniques such as neural networks to predict the movements in these stock indices. Generally technical indicators like moving averages and relative strength indices derived from the time series of these indices is employed in this regard.

Financial time-series has high volatility and the time-series changes with time. In addition, stock market's movements are affected by many macro-economical factors such as political events, firms' policies, general economic conditions, investors' expectations, institutional investors' choices, movement of other stock market, psychology of investors, etc **[4]**. Nevertheless there has been a lot of research in the field of stock market prediction across the globe on numerous stock exchanges; still it remains to be a big question whether stock markets can really be predicted and the numerous challenges that exist in its everyday application on the stock floor by the institutional investors to maximize returns. Generally there are three schools of thoughts regarding such prediction. The first school believes that no investor can achieve above average trading advantages based on historical and present information. The major theories include the Random Walk Hypothesis and the Efficient Market Hypothesis **[5] [6]**.

The second view is that of Fundamental Analysis. Analysts undertake in depth studies into the various macro-economic factors and look into the financial conditions and results of the industry concerned to discover the extent of correlation that may exist with the changes in the stock prices.

Technical Analysis presents the third view on market price prediction. Analysts attempt to extract trends in market using past stock prices and volume information. These trends give insight into the direction taken by the stock prices which help in prediction. Technical Analysts believe that there are recurring patterns in the market behavior, which can be identified and predicted. In the process they use number of statistical parameters called Technical Indicators and charting patterns from historical data.

1.2 Application of Statistical and Soft Computing Techniques to Financial Forecasting

As the underlying theory behind all these techniques is totally different they generally give quite contradictory results. More importantly, these analytical tools are heavily dependent on human expertise and justification in areas like, the location of reversal (or continuation) pattern, market pattern, and trend prediction. For such reasons researchers have stressed on developing models for accurate prediction based on various statistical and soft computing techniques.

One such statistical technique employed in this regard is the Auto Regressive Integrated Moving Average (ARIMA) based model. Different time-series in practice have different frequency components. However, there is no systematic approach or a suitable class of models available in the literature to accommodate, analyze and forecast time-series with changing frequency behavior via a direct method. The virtue of ARIMA (Auto Regressive Integrated Moving Average) is well characterized by Vandaele: "… can be viewed as an approach by which time-series data sifted trough a series of progressively finer sieves…" The aim of sifting some components is to identify so called “white-noise-processes” which has merely stochastic influences on the time series.

The recent advancement in soft computing has given new dimension to the field of financial forecasting. Tools based on ANN have increasingly gained popularity due to their inherent capabilities to approximate any nonlinear function to a high degree of accuracy. Neural networks are less sensitive to error term assumptions and they can tolerate noise, chaotic components **[7]**. Banks and Financial Institutions are investing heavily in development of neural network models and have started to deploy it in the financial trading arena. Its ability to 'learn' from the past and produce a generalized model to forecast future prices, freedom to incorporate fundamental and technical analysis into a forecasting model and ability to adapt according to the market conditions are some of the main reasons for its popularity. Radial Basis Function (RBF) **[8]**, Recurrent Neural Network (RNN) **[9]** and Backpropagation in Multilayer Perceptron (MLP) are the three most popular Artificial Neural Network (ANN) tool for the task. On top of these, evolutionary approaches such as Genetic Algorithm (GA) **[10]**, confluence of statistics and ANN, are receiving attention as well.

Chapter 2

A SURVEY OF EXISTING ANN MODELS FOR STOCK MARKET PREDICTION

A lot of research has gone into the development of models based on a range of intelligent soft computing techniques over the last two decades. Early models employed the Multi Layer Perceptron (MLP) architecture using Backpropagation algorithm, while a lot of recent work is based on evolutionary optimization techniques such as Genetic Algorithms (GA). This section describes briefly some of work that has gone into the field of application of ANN to stock price prediction.

In Japan, technology major Fujitsu and investment company, Nikko Securities joined hands to develop a stock market prediction system for TOPIX, the Tokyo based stock index, using modular neural network architecture **[14]**. Various economic and technical parameters were taken as input to the modular neural network consisting of multiple MLP used in parallel.

A study was done on the effect of change of network parameters of an ANN Backpropagation model on the stock price prediction problem **[15]**. The paper gives insights into the role of the learning rate, momentum, activation function and the number of hidden neurons to the prediction.

In addition to ANN using Backpropagation, the Probabilistic Neural Network (PNN) has also been employed to stock prediction **[16]**. In their work, the model is used to draw up a conservative thirty day stock price prediction of a specific stock: Apple Computers Inc. Due to their bulky nature owing to the large training data, the PNN are not popular among forecasters.

In the process lots of newer architectures came to the fore. (Ornes & Sklansky) **[17]** in their paper present a Visual Neural Network (VNN), which combines the ability of multi expert networks to give low prediction error rates with visual explanatory power of nonlinear dimensionality reduction. They conclude that the VNN is a powerful means of interactive neural network design, which provides both better prediction accuracy and good visual explanatory ability.

Another architecture introduced to the prediction problem is the Multi Branch Neural Network (MBNN) proposed by (Yamshita, Hirasawa & Hu, 2005) **[18]** and applied to the TOPIX (Tokyo

Stock Exchange). The simulations show that MBNN, based on the concept of Universal Learning Networks (ULN), have higher accuracy of prediction than conventional NNs.

In their paper, (Chen, Dong & Zhao, 2005) **[19]** investigate how the seemingly chaotic behavior of stock market could be well represented using Local Linear Wavelet Neural Network (LLWNN) technique. They considered the NASDAQ-100 index and S&P CNX NIFTY index (India). The LLWNN is optimized by using Estimation of Distribution Algorithm (EDA). Results show that the LLWNN model performs marginally better than conventional NN models. Hybrid architectures are also being deployed in recent times. (Raymond Lee, 2004) **[20]** propose a Hybrid Radial Basis Function Recurrent Network (HRBFN) stock prediction system called the iJADE stock advisor. The stock advisor was applied to major Hong Kong stocks and produced promising results in terms of efficiency, accuracy and mobility.

Another Hybrid AI approach to the implementation of trading strategies in the S&P 500 index futures market is proposed by (Tsiah, Hsu & Lai,) **[21]**. The Hybrid AI approach integrates the rule-based systems techniques with Reasoning Neural Networks (RN) to highlight the advantages and overcome the limitations of both the techniques. They demonstrate that the integrated futures trading system (IFTS) based on this hybrid model outperforms other conventional NN.

There are instances of application of fuzzy logic based models to the stock market prediction as well. Hiemstra proposes a fuzzy logic forecast support system to predict the stock prices using parameters such as inflation, GNP growth, interest rate trends and market valuations **[22]**. According to the paper, the potential benefits of a fuzzy logic forecast support are better decision making due to the model-based approach, knowledge management and knowledge accumulation.

Another effort towards the development of fuzzy models for stock markets has been made by (Alaa Sheta, 2006) **[23]** using Takagi-Sugeno (TS) fuzzy models. Sheta uses the model for two non-linear processes, one pertaining to NASA and the other to prediction of next week S&P 500 index levels. The two steps involved in the process are 1) the determination of the membership functions in the rule antecedents using the model input data; 2) the estimation of the consequence parameters. Parameters are estimated using least square estimation.

The application of evolutionary optimization techniques such as Genetic Algorithm has given an entirely new dimension to the field of stock market prediction. (Badawy, Abdelazim & Darwish) **[24]** conducted simulations using GA to find the optimal combination of technical parameters to predict Egyptian stocks accurately. (Tan, Quek & Ng, 2005) **[25]** introduce a novel technique known as Genetic Complementary Learning (GCL) to stock market prediction and give comparisons to demonstrate the superior performance of the method. GCL algorithm is a confluence of GA and hippocampal complementary learning.

Another paper introducing Genetic algorithm approach to instance selection (GAIS) (Kyoung-jae-Kim, 2006) **[26]** for ANN in financial data mining has been reported. Kim introduces this technique to select effective training instances out a large training data set to ensure efficient and fast training for stock market prediction networks. The GA also evolves the weights that mitigate the well known limitations of the gradient descent algorithm. The study demonstrates enhances prediction performance at reduced training time.

A hybrid model proposed by (Kuo, Chen & Hwang, 2001) **[27]** integrates GA based fuzzy logic and ANN. The model involves both quantitative factors (technical parameters) and qualitative factors such as political and psychological factors. Evaluation results indicate that the neural network considering both the quantitative and qualitative factors excels the neural network considering only the quantitative factors both in the clarity of buying-selling points and buying-selling performance.

Another hybrid model involving GA proposed by (Hassan, Nath & Kirley, 2006) **[28]** utilizes the strengths of Hidden Markov Models (HMM), ANN and GA to forecast financial market behavior. Using ANN, the daily stock prices are transformed to independent sets of values that become input to HMM. The job of the GA is to optimize the initial parameters of HMM. The trained HMM is then used to identify and locate similar patterns in the historical data.

A similar study investigates the effectiveness of a hybrid approach based on Time Delay Neural Networks (TDNN) and GA (Kim & Shin, 2006) **[29]**. The GA is used to optimize the number of time delays in the neural network to obtain the optimum prediction performance.

Other studies and research in the field of stock market prediction using soft computing techniques include comparative investigation of both the ANN and the statistical ARIMA model (Schumann & Lohrbach, 1994) **[30]** for the German stock index (DAX).The ANN method uses the four layer counter propagation network. The paper compares the results provided by both the methods and concludes that the efficient market hypothesis does no hold good. A Data Compression Techniques for stock prediction (Azhar, Badros & Glodjo, 1994) **[31]** has been reported that uses the vector quantization method as an example of lossy data compression and Lempel-Ziv method as an example of lossless data compression technique to predict most of the well known indices across the globe.

Chapter 3

INTRODUCTION TO FUNCTIONAL LINKED ANN BASED MODEL

Introduction to FLANN based model
for stock market prediction

Structure of FLANN

Learning with FLANN

3.1 Introduction to FLANN based model for stock market prediction

This study proposes a Functional Link or FLANN architecture based model to predict the movements of prices in the DJIA and S&P500 stock indices. The functional link ANN is a novel single neuron based architecture first proposed by Pao **[11]**. It has been shown that this network may be conveniently used for functional approximation and pattern classification with faster convergence rate and lesser computational load than a Multi-layer Perceptron (MLP) structure. The structure of the FLANN is fairly simple. It is a flat net without any need for a hidden layer. Therefore, the computations as well as learning algorithm used in this network are simple. The functional expansion of the input to the network effectively increases the dimensionality of the input vector and hence the hyper-planes generated by the FLANN provide greater discrimination capability in the input pattern space. Various system identifications, control of nonlinear systems, noise cancellation and image classification systems **[12]** have been reported in recent times. These experiments have proven the ability of FLANN to give out satisfactory results to problems with highly non-linear and dynamic data **[13]**. Further the ability of the FLANN architecture based model to predict stock index movements, both for short term (next day) and medium term (one month and two months) prediction using statistical parameters consisting of well known technical indicators based on historical index data is shown and analyzed.

3.2 Structure of Functional Linked ANN

FLANN is a single layer, single neuron architecture, first proposed by Pao **[11]**, which has the exceptional capability to form complex decision regions by creating non-linear decision boundaries. The architecture of the FLANN is different from the linear weighting of the input pattern produced by the linear links of the better known Multi Layer Perceptron (MLP). In a FLANN, each input to the network undergoes functional expansion through a set of basis functions. The functional link acts on an element or the entire pattern itself by generating a set of linearly independent functions. The inputs expanded by a set of linearly independent functions in the function expansion block, causes an increase in the input vector dimensionality. This enables FLANN to solve complex classification problems by generating non-linear decision boundaries. In our experiment, the functional expansion block comprises of a set of trigonometric functions.

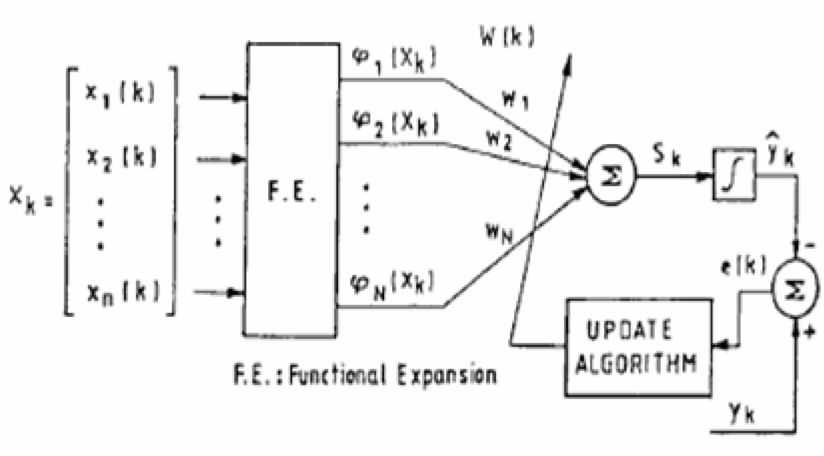

Figure 3.1 the figure shows the structure of FLANN with single output.

The basis functions for the FLANN, $B = \{\phi_i \in \mathrm{L}(\mathrm{A})\}_{i \in x}$ is to be selected keeping the following properties into consideration: **1)** $\phi_i = 1$**, 2)** the subset $B_j = \{\phi_i \in B\}^{j}_{i=1}$ is a linearly independent set, i.e., if $\sum_{i=1}^{N} w_i \phi_i = 0$, then w_i=0 for all $i = 1,2,3....j$, and **3)** $\sup_j \left[\sum_{i=1}^{j} \| \phi_i \|_A^2 \right]^{1/2} < \infty$. Let $B_N = \{\phi\}_{i=1}^{N}$ be a set of basis functions to be considered to the FLANN as shown in fig. 1. Thus, the FLANN consists of N basis functions $\{\phi_1, \phi_2, \phi_3, ..., \phi_N\} \in B_N$ with following input-output relationship for the ***j***th output

$\hat{y}_j = \rho(S_j)$;

Where, $$S_j = \sum_{i=1}^{N} w_{ji} \phi_i(X) \qquad (1)$$

Where $X \in A \subset R^n$, i.e., $X = \left[x_1 x_2 \, ... x_n \right]^T$ is the input pattern vector, $\hat{y} \in R^m$, i.e., $\hat{y} = [\hat{y}_1 \hat{y}_2 ... \hat{y}_m]^T$ is the output vector and $w_j = [w_{j1} w_{j2} ... w_{jN}]$ is the weight vector associated with the **j** th output of the network. The non-linear function considered in this case $\rho(\bullet) = \tanh(\bullet)$.

Considering the m-dimensional input vector, (a) can be written as

$$S = W\Phi \qquad (2)$$

Where W is (m×N) weight matrix of FLANN given by, $W=[w_1 w_2 ... w_m]^T$, $\phi=[\phi_1(X)\phi_2(X)...\phi_N(X)]^T$ is the basis function vector, and $S=[S_1 S_2 ... S_N]^T$ is a matrix of linear outputs of FLANN. The m-dimensional output vector $\hat{y}$ may be given by

$$\hat{y} = \rho(S) = f_W(X) \qquad (3)$$

3.3 Learning with Functional Linked ANN

The learning of ANN can be described as approximating a continuous, multivariate function f(X) by an approximating function $f_W(X)$.Given a function the objective of the learning algorithm is to find the optimum weights such that $f_W(X)$ obtained approximates f(X) within an error e. This is achieved by recursively updating the weights. Let the training sequence be denoted by { X_k, y_k } and the weight of the network be W(k), where k is the discrete time index given by k= κ + λK where λ=0,1,2,….., and κ= 0,1,2,…,K. From (1) the j th output of FLANN t a given time k can be given as

$$\begin{aligned}\hat{y}_j &= \rho\left(\sum_{i=1}^{N} w_{ji}(k)\phi_i(X_k)\right)\\ &= \rho(w_j(k)\phi^T(X_k)) \qquad (4)\end{aligned}$$

For all $X \in A$ and j =1,2,3,…,m where $\phi=[\phi_1(X_k)\phi_2(X_k)...\phi_N(X_k)]$ .Let the corresponding error be denoted by $e_j(k)=y_j(k)-\hat{y}_j(k)$.The Least Mean Square (LMS) update rule for all the weights of the FLANN is given by

$$W(k+1)=W(k)+\mu\delta(k)\phi(X_k) \qquad (5)$$

Where, $W = [w_1(k)w_2(k)...w_m(k)]^T$ is the M×N dimensional weight matrix of the FLANN at the k-th time instant is

$$\delta(k) = [\delta_1(k)\delta_2(k)...\delta_m(k)]^T,$$

$$\text{And } \delta_j(k) = (1 - \hat{y}_j(k)^2)e_j(k) \qquad (6)$$

Similarly the Recursive Least Square (RLS) update rule for all weights of the FLANN is given by

$$W(k+1) = W(k) + e_j(k)zzk'(k) \qquad (7)$$

Where, $zzk(k) = z(k)/(1+q)$, $q = X(k).zk(k)$ and $zk(k) = R(k).X(k)$ (8)

The autocorrelation matrix R(k) is updated with the equation,

$$R(k+1) = R(k) - zzk(k).zk(k)' \qquad (9)$$

Which is initialized using the expression, $R(0) = \eta.I$ where I is the identity matrix and η is a constant.

The motivations for using trigonometric polynomials in the functional expansion stage are explained below. Of all the polynomials of N-th order with respect to an orthonormal system $\{\phi_i(x)\}_{i=1}^N$ the best approximation in the metric space L^2 is given by the N-th partial sum of its Fourier series with respect to this system. Thus, the trigonometric polynomial basis functions given by $\{1, \cos(\pi x), \sin(\pi x), \cos(2\pi x), \sin(2\pi x), ..., \cos(N\pi x), \sin(N\pi x)\}$ provide a compact representation of the function in the mean square sense. However, when the outer product terms are used along with the trigonometric polynomials for function expansion, better results were obtained in the case of learning of a two-variable function.

Chapter 4

NETWORK INPUT SELECTION AND DATA PREPROCESSING

The data for the stock market prediction experiment has been collected for two stock indices namely Dow Jones Industrial Average (DJIA), USA, Standards & Poor's 500 Index (S&P 500), USA. The time series data of all the stock indices were collected from 3rd January 1994 to 23rd October 2006. Thus there were 3228 data patterns for both DJIA and S&P 500 index. The data collected for the stock indices consisted of the closing price, opening price, and lowest value in the day, highest value in the day and the total volume of stocks traded in each day. (Note that one day's closing price of the index can be slightly different from next day's opening price, due to introduction of after hours trading between institutions private exchanges). The proposed forecasting model is developed to forecast the closing price of the index in each day of the forecasting period.

Different technical and fundamental indicators are used as inputs to the network. Technical indicators are any class of metrics whose value is derived from generic price activity in a stock or asset. Technical indicators look to predict the future price levels, or simply the general price direction, of a security by looking at past patterns. Out of the many technical indicators used by traders, 10 indicators have been chosen as input to the network which has been used before by many researchers for stock market forecasting problems. The details of the parameters and how they are calculated from the available data is given below:

- **Simple Moving Average (SMA):**

It's the simple average of the values by taking a window of the specified period. The various SMAs used in the experiment are:

1. 10 days (SMA10)
2. 20 days (SMA20)
3. 30 days (SMA30)

- **Exponential Moving Average (EMA):**

It is also an average of the values in the specified period but it gives more weight to recent values. Thus it approaches the actual values more closely.

Formula Used:

$$EMA = (P * A) + (previous\ EMA * (1 - A)) \quad (10)$$

P=> current price

A=> smoothing factor = 2/(1+N)

N=> no. of time periods

- **Accumulation/Distribution Line(ADO):**

It measures money flow in the security. It attempts to measure the ratio of buying to selling by comparing price movements of a period to the volume of that period.

$$A/DO = ((Close - Low) - (High - Close))/ (High - Low) * Period's\ Volume \quad (11)$$

Every day's ADO has been taken in the experiment.

- **Stochastic Oscillator(STOC):**

Stochastic Oscillator is a momentum indicator that shows the location of the current close relative to the high/low range over a set of number of periods. Closing levels that are consistently near the top of the range indicates accumulation (buying pressure) and those near the bottom of the range indicate distribution (selling pressure).

There are two lines: %K and %D

Formula Used:

$$\%K = [(Today's\ Close - Lowest\ low\ in\ K\ periods)/ (Highest\ high\ in\ K\ periods - Lowest\ low\ in\ K\ periods)] * 100 \quad (12)$$

%D is the SMA of %K for a particular period.

For this study: %K = 10 days and % D = 3 days

- **On Balance Volume (OBV):**

It is a momentum indicator that relates volume to price change.

Calculation of OBV:

If today's close > Yesterday's Close

OBV = Yesterday's OBV + Today's Volume

If today's close > Yesterday's Close

OBV= Yesterday's OBV – Today's volume

- **Williams %R(WILLIAMS):**

It is a momentum indicator that measures overbought/oversold levels.

Calculation of Williams %R =

$$\frac{(\text{Highest high in n periods} - \text{Today's close})}{(\text{Highest high in n-periods} - \text{Lowest low in n-periods})} * 100 \quad (13)$$

For this experiment: n= 9 days

- **Relative Strength Index (RSI) :**

It calculates the internal strength of the security. It has been used in most of the research papers.

Basic formula for RSI calculation:

$$RSI = 100 - (100/(1+ (U/D)) \quad (14)$$

For this study the periods have been taken as 9 days (RSI9) and 14 days (RSI14).

- **Price Rate of Change (PROC):**

The PROC indicator displays the difference between the current price and closing price x-time periods ago.

Calculation:

$$\frac{\textit{(Today's close – Close x-periods ago)}}{\textit{(Close x-periods ago)}} \; * \; 100 \qquad (15)$$

Through experimental results it’s found that x=12 is considered best for technical analysis.

- **Closing Price (CPACC) and High Price (HPACC) Acceleration:**

It’s the acceleration of the closing prices and the high prices in the given period.

Apart from these technical parameters which depend on the past value of the data for forecasting, it has been shown by Nial O’ Connor and Michael G. Madden (2006) that there are Fundamental Analysis Factors as well which affect the stock market and hence forecasting can be improved by incorporating them.

Fundamental analysis is the study of economic, industry, and company conditions in an effort to determine the value of a company's stock. Fundamental analysis typically focuses on key statistics in a company's financial statements to determine if the stock price is correctly valued.

Most fundamental information focuses on economic, industry, and company statistics. Some of the fundamental factors included in this project work are: Monthly average oil price, Quarterly Gross Domestic Product (GDP) growth rate, Quarterly corporate dividend rate, Monthly interest rates and inflation figures in terms of Commodity Price Index (CPI).

Table 4.1 Technical indicators and their calculation formulae

Technical Indicators	Formula
Simple Moving Average (SMA)	$\frac{1}{N}\sum_{i=1}^{N} x_i$ N = No. of Days. x_i = today's price
Exponential Moving Average (EMA)	$(P \times A) + (\text{Previous EMA} \times (1 - A))$; A=2/(N+1) P – Current Price, A- Smoothing factor, N-Time Period
Accumulation/ Distribution Oscillator (ADO)	$\frac{(\text{C.P - L.P}) - (\text{H.P - C.P})}{(\text{H.P - L.P}) \times (\text{Period's Volume})}$ C.P – Closing Price, H.P – Highest price, L.P – Lowest price
Stochastic Indicator (STOC)	$\%K = \frac{(\text{Today's Close - Lowest Low in K period})}{(\text{Highest High in K period - Lowest Low in K period})} \times 100$ $\%D$ = SMA of $\%K$ for the Period.
On Balance Volume (OBV)	If Today's Close > Yesterday's Close OBV = Yesterday's OBV + Today's Volume If Today's Close < Yesterday's Close OBV = Yesterday's OBV – Today's Volume
WILLIAM's %R	$\%R = \frac{(\text{Highest High in n period - Today's Close})}{(\text{Highest High in n period - Lowest Low in n period})} \times 100$
Relative Strength Index (RSI)	$\text{RSI} = 100 - \frac{100}{1 + (\text{U/D})}$
Price Rate Of Change (PROC)	$\frac{(\text{Today's Close - Close X-period ago})}{(\text{Close X-period ago})} \times 100$
Closing Price Acceleration (CPAcc.)	$\frac{(\text{Close Price - Close Price N-period ago})}{(\text{Close Price N-period ago})} \times 100$
High Price Acceleration (HPAcc.)	$\frac{(\text{High Price - High Price N-period ago})}{(\text{High Price N-period ago})} \times 100$

Table 4.1 gives a list of technical indicators along with the formula used to calculate them form the raw data in the form of daily open, close, high and low price.

Chapter 5

THE STOCK MARKET PREDICTION EXPERIMENT

Experiment Model Setup
Training Process
Testing Process

5.1 Experiment Model Setup

We use the Functional Link Neural Network architecture (FL-ANN) (Citation). It is single neuron architecture. Each input is split up into five branches each being a distinct function of the primary input. Thus effectively we now have five times the primary inputs we had considered that go as inputs to the single neuron. For our experiment we have taken 13 input parameters for each pattern. For a 13 different statistical parameters of the stock index lag values, the total input to the single neuron FL-ANN is 65 plus a bias. This gives us 66 weights that are to be trained using a suitable adaptive algorithm for a particular stock index. The neuron adds up the input-weight products and bias. The sum is then taken up by a suitable activation function to give the output of the network. For this particular case we used the tan hyperbolic activation function.The five distinct function applied to the each of branched input can be chosen as trigonometric functions, exponential functions, Chebychev polynomial functions.

In the FLANN model of stock market prediction, four trigonometric functions namely Cos πx, Cos $2\pi x$, Sin πx and Sin $2\pi x$ were used along with the variable x itself. An optimum value of the convergence coefficient was taken as 0.1 for all the prediction experiments.

The inputs have to be normalized for the proper behavior of the network. The inputs are normalized to values between +1 and -1. This can be done by a number of normalization techniques. One of the popular techniques we used was expressing the data in terms of the maximum and minimum of the data set.
All the values are normalized by using the following equation

$$Y = \frac{2*X - (Max + Min)}{(Max + Min)} \qquad (16)$$

Y: - normalized values.
X: - present value.

The total data set of a particular stock market index is split up into two, one for training of the network and the rest for testing the performance of the network after freezing the weights. In this experiment we take approx 2500 daily statistical data of the stock index as training set. The rest 600 values are set aside for testing.

5.2 Training Process

The training of the network takes place in the following fashion. The weight update is epoch based. The initial weights of the network are taken as 66 random values between -1 to +1. The input data set are also normalized prior to the network training. The weights remain unchanged till all of the training data set is fed into the network, compared with the desired output and their respective error stored. The mean error for the entire epoch is calculated, and then the adaptive weight update takes place. The Least Mean Square (LMS) update algorithm used in our experiment updates the weights by adding the product of the convergence constant, the respective input with the mean error for the epoch to the weights of the previous epoch. The cost function for the training process is the Mean Square Error (MSE). It is suitable to end the training of the network when the minimum level of the cost function is observed. Thus for each iteration (epoch), the mean square error is calculated and plotted. Each of the iterations involves training the network with the 2500-odd patterns, calculation of mean error, weight update and representing the MSE. The number of iteration is decided upon by gradient of the MSE curve. If it is observed that there is no significant decrease in the MSE then the training experiment can be stopped. There exists a trade-off between the time taken and quality of training. High number of iterations tends to give better training of the network at the cost of time taken to train.

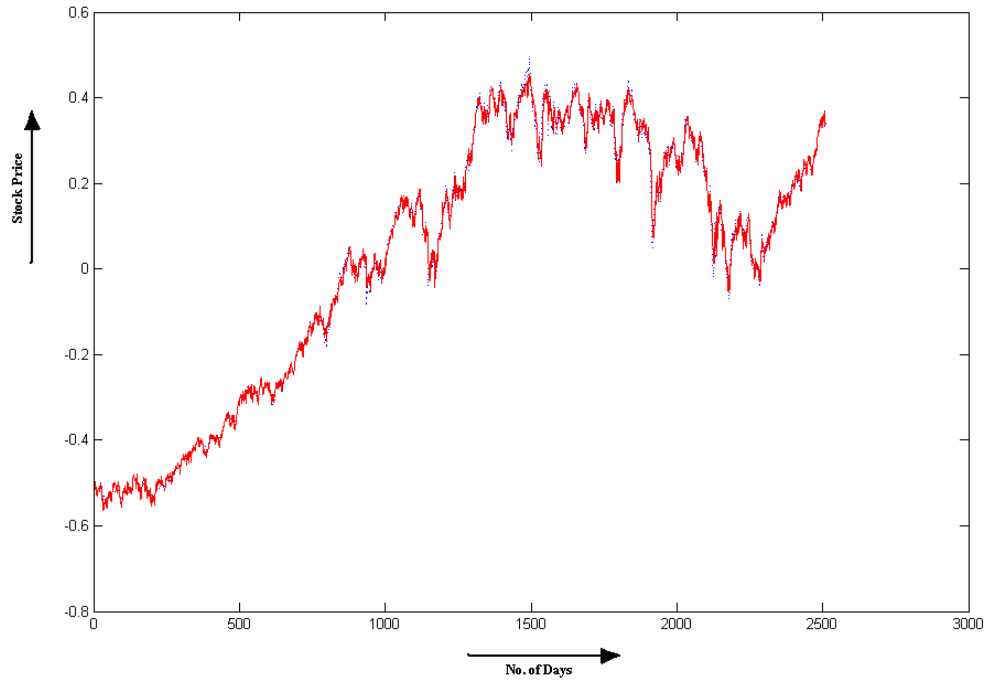

Figure 5.1 Plot of predicted vs. actual stock price at the last iteration of training for DJIA

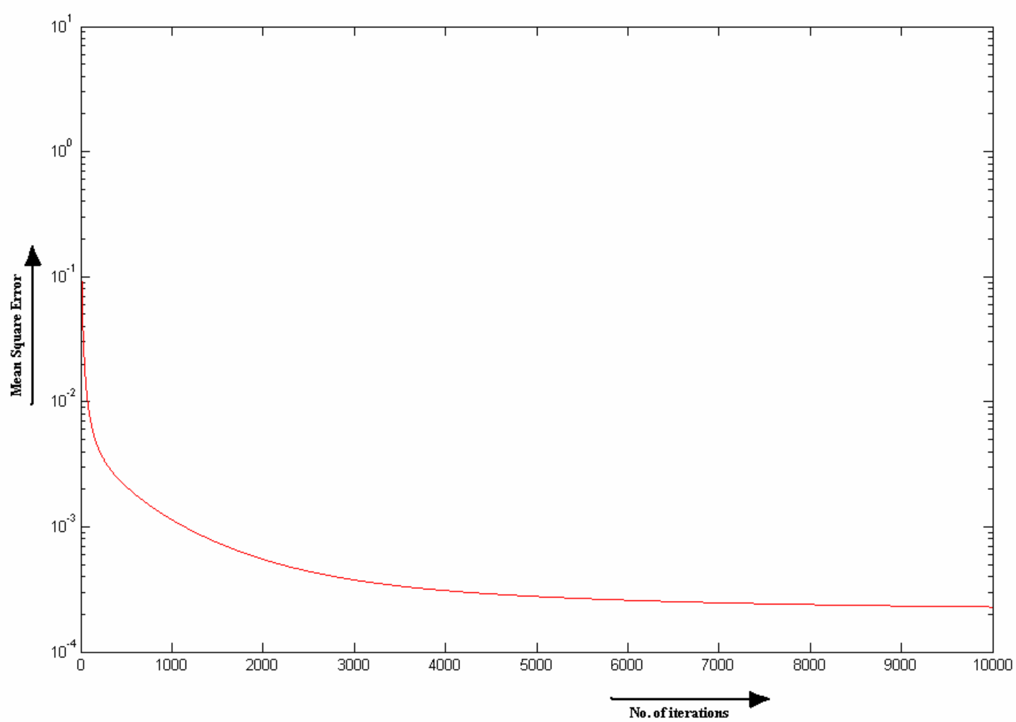

Figure 5.2 Plot of Mean Square Error of FLANN during training.

5.3 Testing Process

At the end of the training process of the network, the weights are frozen for testing the network on inputs that were set apart from the training set. The testing set patterns are the input to the network and the output, the predicted index close price is compared with desired output or actual close price. The percentage of error is recorded for each data set. The criteria for judging the quality of prediction shown by the model is the mean of all the percentage error of the testing data set. . The Mean Absolute Percentage Error (MAPE) is used to gauge the performance of the trained prediction model for the test data.The effort is to minimize the MAPE for testing patterns in the quest for finding a better model for forecasting stock index price movements The MAPE is given as

$$MAPE = \frac{1}{N}\sum_{j=1}^{N} \left| \frac{y_j - \hat{y}_j}{y_j} \right| \times 100 \qquad (17)$$

Chapter 6

SIMULATION RESULTS AND DISCUSSION

Prediction Performance
Discussion

6.1 Prediction Performance

6.1.1 EXPERIMENT 1: One day in advance prediction with Least Mean Square (LMS) update

Table 6.1 Results for one day advance prediction with LMS update

Stock Index	Input Variables To FLANN	Testing Period	MAPE
DJIA	EMA10, EMA30, ADO, CPAcc, HPAcc, STOC, RSI9, PROC 12, PROC 27.	390 days	0.64%
DJIA	EMA10, EMA20, EMA30 ADO, CPAcc, HPAcc, RSI9, RSI14, PROC12, PROC27, Williams.	658 days	0.74%
S&P 500	EMA10, EMA30, ADO, CPAcc, HPAcc, STOC, RSI9, PROC 12, PROC 27.	390 days	0.61%
S&P 500	EMA10, EMA30 ADO, CPAcc, HPAcc, STOC, RSI9, PROC12, PROC27.	658 days	0.65%

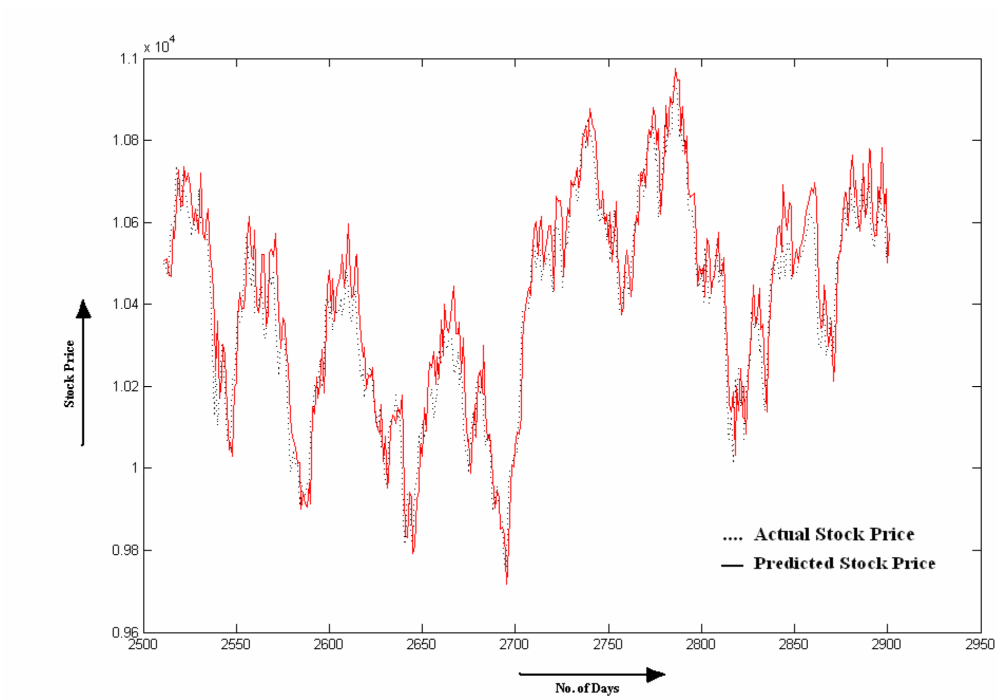

Figure 6.1 Plot of Predicted vs. Actual Stock prices for testing dataset of DJIA (one day in advance)

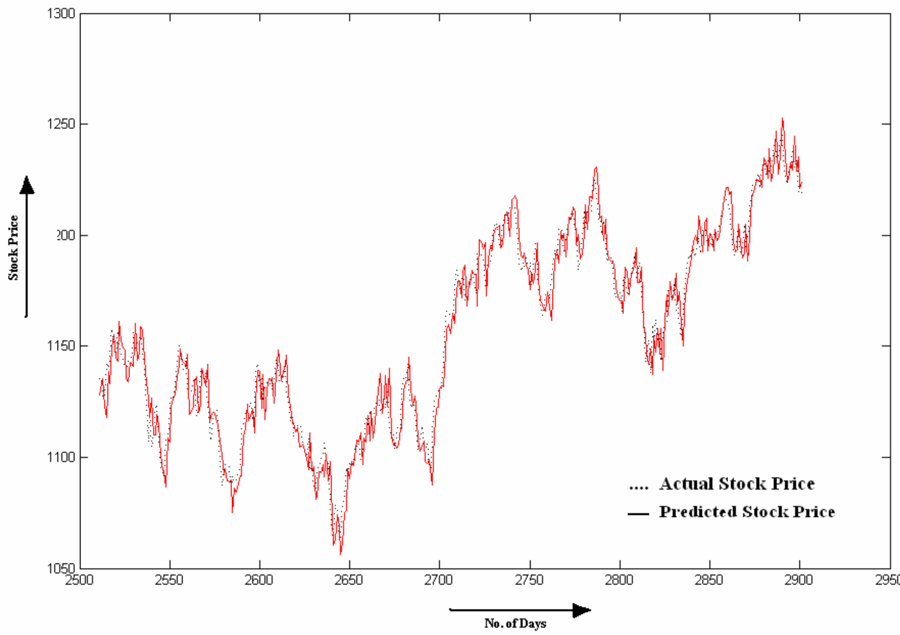

Figure 6.2 Plot of Predicted vs. Actual Stock prices for testing dataset of S&P500 (one day in advance)

6.1.2 EXPERIMENT 2: One month in advance prediction with LMS update

Table 6.2 Results for one month advance prediction with LMS update.

Stock Index	**Input Variables To FLANN**	**Testing Period**	**MAPE**
DJIA	EMA10,EMA20,EMA30,ADO, CPAcc,HPAcc,RSI9,RSI14	650 days	2.91%
DJIA	EMA10, EMA20, EMA30 ADO, CPAcc, HPAcc, RSI9, RSI14, PROC12, PROC27, WILLIAMS, OBV,STOC	650 days	2.75%
DJIA	EMA10,EMA20,EMA30,Proc12, Proc 27, RSI9,RSI14,STOC	650 days	3.029%
DJIA	EMA10,EMA20,EMA30, ADO,RSI9	650 days	2.92%
DJIA	EMA10,EMA20,EMA30	650 days	2.88%
DJIA	ADO, CPAcc, HPAcc, RSI9, RSI14, PROC12, PROC27, WILLIAMS, OBV,STOC	650 days	16.6%
DJIA	EMA10, EMA30 ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27,OBV,STOC	650 days	3.61%
DJIA	EMA10, EMA30 ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27,OBV,STOC , WILLIAMS	650 days	5.9%

DJIA	11 VARIABLES EXCEPT EMA20 AND WILLIAMS	650 days	6.3%
DJIA	EMA 10, EMA 20, EMA 30, ADO, CP Acc, HP Acc, RSI 9, WILLIAMS	60 days	1.39%
S&P 500	EMA10, EMA20, EMA30 ADO, CPAcc, HPAcc, RSI9, RSI14, PROC12, PROC27, WILLIAMS, STOC	658 days	2.95%
S&P 500	EMA10, EMA20, EMA30 ADO, CPAcc, HPAcc, RSI9, RSI14, PROC27, WILLIAMS	658 days	2.66%
S&P 500	EMA10, EMA20, EMA30 ADO, CPAcc, HPAcc, RSI9, RSI14, PROC27, WILLIAMS	60 days	2.22%
S&P 500	EMA10, EMA20, EMA30 ADO, CPAcc, HPAcc, PROC12, PROC27, RSI9, RSI14.	60 days	2.09%

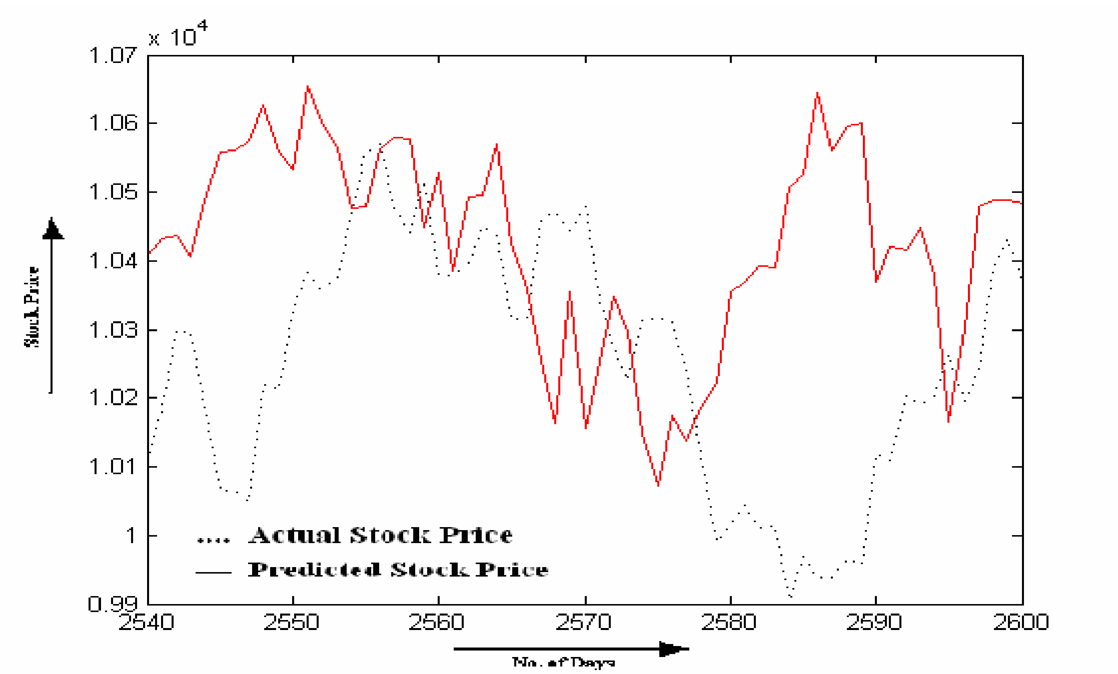

Figure 6.3 Plot of Predicted vs. Actual Stock prices for testing dataset (60 days) of DJIA (one month in advance)

6.1.3 EXPERIMENT 3: Two months in advance prediction with LMS update

Table 6.3 Results for two month advance prediction with LMS update.

Stock Index	**Input Variables To FLANN Model**	**Testing Period**	**MAPE**
DJIA	EMA20, EMA30, ADO, CPAcc, RSI9, RSI14, OBV, PROC 27, Williams.	60 days	2.25%

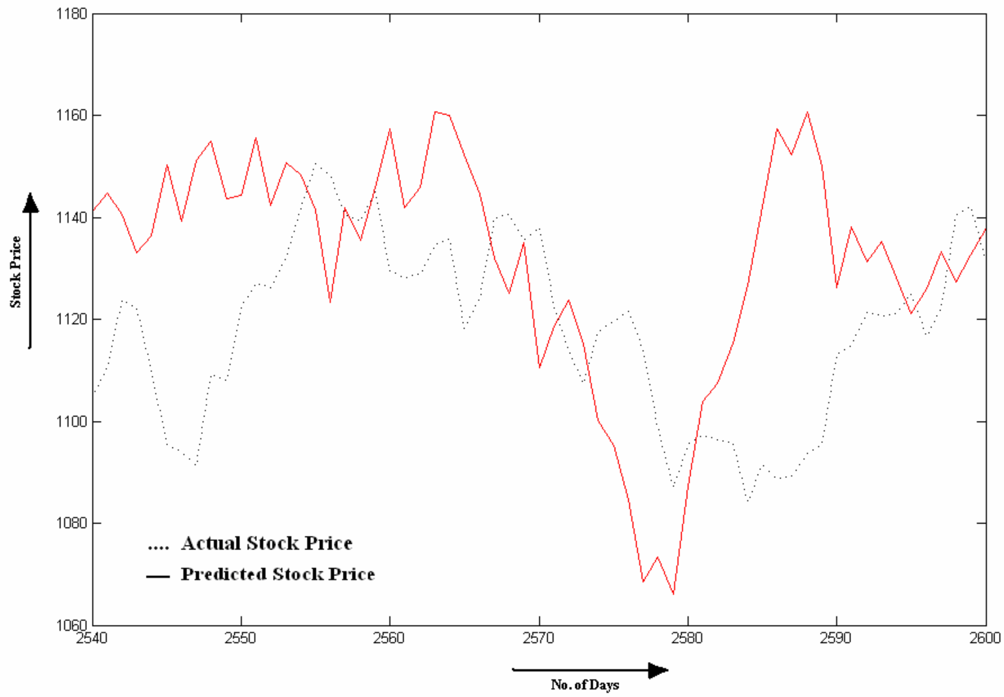

Figure 6.4 Plot of Predicted vs. Actual Stock prices for testing dataset (60 days) of S&P500 (one month in advance)

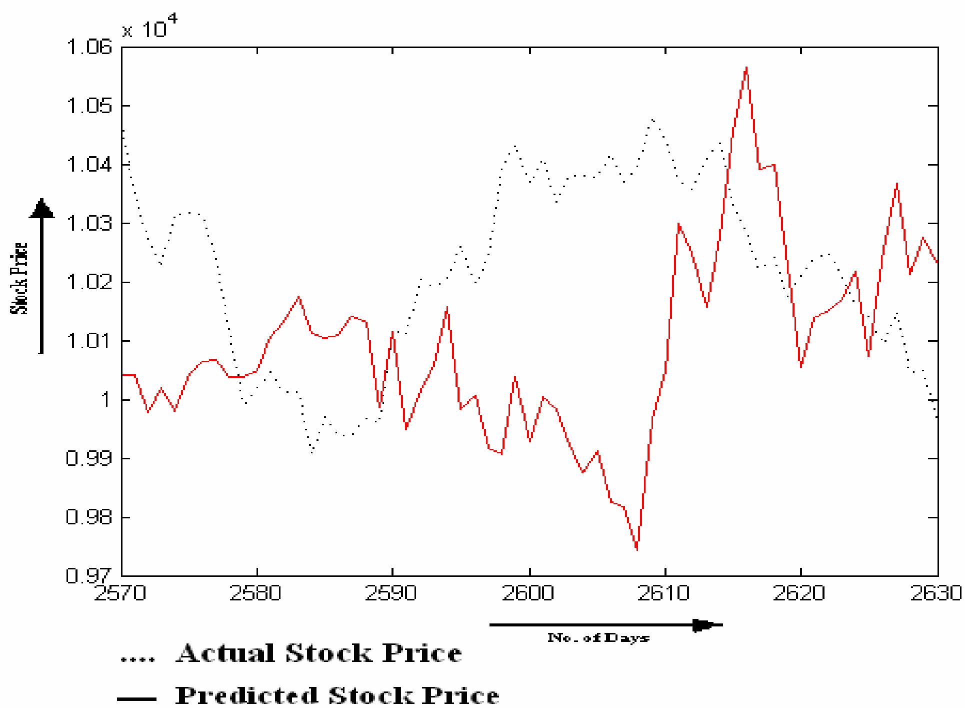

Figure 6.5 Plot of Predicted vs. Actual Stock prices for testing dataset (60 days) of DJIA (two months in advance)

6.1.4 EXPERIMENT 4: Variable Days in Advance prediction with Recursive Least Square (RLS) update

Table 6.4 Comparison of performance varying the number of days in advance prediction with RLS update

Stock Index	Input Variables To FLANN Model (Technical Indicators)	Input Variables To FLANN Model (Fundamental Factors)	Testing Period	MAPE using RLS	Prediction No. of Days in Advance
DJIA	EMA10, EMA30, ADO, CPAcc, HPAcc, STOC, RSI9, PROC 12, PROC 27.	Oil price	390 days	0.58%	1 day
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27	Interest rate	60 days	2.66%	15 days
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27	Interest rate, Oil price, GDP rate.	60 days	2.19%	30 days
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27	Interest rate	60 days	1.46%	35 days
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27	Interest rate	60 days	1.05%	40 days
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27	Interest rate	590 days	2.66%	40 days
DJIA	EMA20, EMA30, ADO, CPAcc, RSI9, RSI14, OBV, PROC 27, Williams.	Oil Price	60 days	2.49%	60 days

6.1.5 EXPERIMENT 5: One month in Advance prediction using both technical parameters and fundamental factors with RLS update

Table 6.5 Stock market predictions for one month in advance (using technical and fundamental factors) with RLS update.

Stock Index	Input Variables To FLANN Model (Technical Indicators)	Input Variables To FLANN Model (Fundamental Factors)	Testing Period	MAPE using RLS	RLS Initialization constant
DJIA	EMA10,EMA20,EMA30, ADO, CPAcc, HPAcc, RSI9, Williams.	Oil price	60 days	2.54%	1000
DJIA	EMA10,EMA20,EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27, Stoc.	Interest rate	60 days	2.26%	1000
DJIA	EMA10,EMA20,EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27, Stoc.	GDP growth (Quarterly)	60 days	2.26%	1000
DJIA	EMA10,EMA20,EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Corporate Dividend rate	60 days	2.19%	1000
DJIA	EMA10,EMA20,EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27	Dividend, Interest rate, GDP growth rate.	60 days	2.19%	1000
DJIA	EMA10,EMA20,EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27	Dividend, Interest rate, Oil price	60 days	2.20%	1000

Table 6.6 Stock market predictions for one month in advance using combinations of technical and fundamental factors with RLS update.

Stock Index	Input Variables To FLANN Model (Technical Indicators)	Input Variables To FLANN Model (Fundamental Factors)	Testing Period	MAPE using RLS	RLS Initialization constant
DJIA	EMA10, EMA20, EMA30.	Dividend, Interest rate, Oil price, GDP rate.	60 days	2.23%	1000
DJIA	EMA10, EMA20, EMA30, ADO	Dividend, Interest rate, Oil price, GDP rate.	60 days	2.42%	1000
DJIA	EMA10, EMA20, EMA30, PROC12	Dividend, Interest rate, Oil price, GDP rate.	60 days	2.38%	1000
DJIA	EMA10, EMA20, EMA30, CPAcc.	Dividend, Interest rate, Oil price, GDP rate.	60 days	2.24%	1000
DJIA	EMA10, EMA20, EMA30, RSI9.	Dividend, Interest rate, Oil price, GDP rate.	60 days	2.33%	1000
DJIA	EMA10, EMA20, EMA30, OBV.	Dividend, Interest rate, Oil price, GDP rate	60 days	2.07%	1000
DJIA	EMA10, EMA20, EMA30, STOC.	Dividend, Interest rate, Oil price, GDP rate	60 days	2.52%	1000
DJIA	EMA10, EMA20, EMA30.	Dividend, Interest rate, Oil price, GDP rate, CPI rate.	60 days	2.23%	1000

6.1.6 EXPERIMENT 6: Effect of RLS initialization constant on one month in advance prediction.

Table 6.7 comparison of prediction performance varying the RLS initialization constant (one day advance prediction)

Stock Index	Input Variables To FLANN Model (Technical Indicators)	Input Variables To FLANN Model (Fundamental Factors)	Testing Period	MAPE using RLS	RLS Initialization constant
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.58%	0.001
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.01%	0.005
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.06%	0.01
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.09%	0.1
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.18%	1
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.19%	10
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.19%	100
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.19%	1000
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	2.19%	10000
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, PROC12, PROC27.	Oil price, Interest rate, GDP growth rate.	60 days	53.3%	100000

6.1.7 EXPERIMENT 7: Comparison of computations required for training between RLS and LMS update.

Table 6.8 Computation Comparison between LMS and RLS algorithm for prediction problem

Experiment Details	LMS computations (training set * iterations required for training)	RLS Computations (training set * iterations required for training)
One day ahead with technical parameters	2510*4000 =10040000	2510*5 = 12550
One month ahead with technical parameters	2510*3500 =8785000	2510*15 =37650
Two months ahead with technical parameters	2510*2000 = 5020000	2510*80 = 200800

Table 6.9 Comparison of prediction performance between RLS and LMS update

Stock Index	Input Variables To FLANN	Days in advance prediction	Testing Period	MAPE (LMS)	MAPE (RLS)
DJIA	EMA20, EMA30, ADO, CPAcc, RSI9, RSI14, OBV, PROC 27, Williams.	60 days	60 days	2.25%	2.45%
DJIA	EMA10, EMA20, EMA30, ADO, CPAcc, HPAcc, RSI9, Williams.	30 days	60 days	2.33%	2.54%
DJIA	EMA10, EMA30, ADO, CPAcc, HPAcc, STOC, RSI9, PROC 12, PROC 27.	1 day	390 days	0.64%	0.58%
DJIA	EMA10, EMA20, EMA30 ADO, CPAcc, HPAcc, RSI9, RSI14, PROC12, PROC27, Williams.	1 day	658 days	0.74%	0.61%

6.2 Discussion

The purpose of Experiment 1 is to investigate the performance of the model for one day in advance prediction using LMS update algorithm by providing certain technical indicators as inputs. Different combinations of technical indicators were tried as inputs based on a trial and error method to distinguish which combination gives out the best result. The model gives out a prediction performance with a best MAPE of 0.64% for DJIA and 0.61% for S&P 500 index. With many input parameter combinations, spikes were observed in the predicted output which showed certain parameters had negative sensitivity towards the output. An exercise was made to identify those input parameters which were then removed as inputs to improve the performance of the network. Combinations of testing set length were used to gauge the robustness and generalization capabilities of the model. Table 6.1 shows that the model performed quite consistently both for a small testing set as well as a large testing set.

Experiment 2 investigates the performance for one month in advance prediction with LMS update and using technical indicators as inputs. Plotting the graphs of predicted and actual close prices, large deviations in the form of spikes were observed at numerous inflection points. Therefore, several more experiments were conducted, varying the selection of technical indicators as input to the network. This was done in an attempt to identify and eliminate less important statistical parameters and rogue parameters which adversely affected the network prediction performance. The results of such experiments, listed in the table clearly show that the network performance due to elimination of certain parameters does not vary considerably, rendering them unimportant to the prediction model. Parameters were also identified in the process which when eliminated caused considerable deterioration in the prediction performance. In an effort to reduce the number of input to the network and at the same time enhance the performance of the prediction model, the input parameters were varied on a trial-error basis to gain insight into the extent of usefulness of the technical indicators to the prediction model. The Stochastic Oscillators, SMA, On Balance Volume (OBV) and William's technical indicators were not found to affect the prediction performance significantly. On the other hand, technical indicators such as Exponential Moving Averages (EMA), Relative Strength Index (RSI) and Accumulation Distribution Oscillator (ADO) and Price Rate of Change (PROC) were found to be essential to the model. The best performance obtained in this case is 1.39% MAPE for DJIA and 2.09% for S&P500 index. It is also observed that the model performs much better on shorter testing sets than on larger testing sets.

Experiment 3 is carried out to check the model's performance for even longer term prediction i.e. two months in advance prediction using LMS for weight update. The MAPE obtained in this case for DJIA is 2.25%.

Experiment 4 examines the stock price prediction performance of the model for variable days in advance ranging from next day to 15, 30, 35, 40 to 60 days using the more powerful

Recursive Least Square (RLS) weight update algorithm. The RLS is faster computationally but less stable than LMS algorithm. It is observed that the RLS update algorithm provides comparable to if not better results than the LMS. The lowest MAPE of 0.58% is observed for next day prediction followed by MAPE of 1.05% for 40 days in advance prediction.

Experiment 5 is carried out to investigate the effect of including key fundamental factors in improving the prediction performance of the model. Five fundamental factors namely – oil price, interest rates, GDP growth rate (US), Commodity price index and corporate dividend rates are taken as input one at a time. The results are described in Table 6.5. The experiment highlights that including a single fundamental factor as input to the model along with other technical parameters does not cause significant drop in prediction error.

An extension to the experiment is carried out by taking different combinations of technical parameters and fundamental factors. The exponential moving averages (EMA 10, 20 and 30) along are mainly considered for technical parameters. The best prediction (MAPE : 2.07%) is found to be with 8 variables including EMAs, OBV, oil price, interest rates, GDP rate and corporate dividend rate.

Experiment 6 involves comparing the prediction performance by varying the initialization constant of the RLS update equation for one month in advance prediction for DJIA. The initialization is varied from 0.001 to 100000. The results are shown in Table 6.7. It shows that while the lowest error is achieved with a initialization of 0.05, the MAPE remains constant for higher initializations from 1 to 10000. The model fails at an initialization of 100000.

Experiment 7 reaffirms the superiority of the RLS update algorithm over LMS in terms of computational efficiency in training. Table 6.8 compares the computation required for training for three cases: one day, one month and two months in advance. It is observed that the LMS takes roughly 800 times more computations in case of one day in advance prediction and 25 times more computations for two months in advance prediction.

Method	Accuracy	Sample Size
RBF (Komo et al, 1994)	> 90%	1/88 – 12/92
Support Vector Machine (Yang et al, 2002)	≈0.92*	1/01-6/01
(i) ANN+GA; (ii) RNN; + Technical Indices; (iii) Buy & Hold (Armano et al, 2005)	(i) 55.5% (ii) 53.6% (iii) 55.5%	5/92-4/00, 6/93-5/01 (Two datasets)
(i) BP (ii) Two-stage BP (Oh & Kim, 2002)	(i) 0.18# (ii) 0.08#	1/90-8/00
Box-Jenkins and Transfer Function model (Wu & Lu, 1993)	0.2427*	02/81-12/90
(i) TDNN (ii) RNN (iii) PNN (Saad et al, 1998)	(i) ≈ 86.2% (ii) ≈94.6% (iii)≈86.5%	01/87-02/96
Dynamic adaptive ensemble Case Base Reasoning (Chun & Park, 2005)	1.5914$	01/00-06/04
Lyapunov Gradient Descent (Cristea & Okamoto, 1998)	48%-51%	Not available
Ijade (Hybrid radial basis recurrent network) (Lee, 2004)	4.31-14.29*	1990-1999
Fuzzy rough system (Wang, 2003)	>= 93%	01/01-05/02
Neural Sequential Associator (Matshuba, 1991)	≈95%	75 days
Multilayer perceptron Ensembles (Abdullah & Ganapathy, 2000)	≈59.74%	03/91-07/98
Adaptive RTRL (Catfolis, 1996)	0.026#	1980-1994
Neural Oscillatory-based RNN (Lee & Liu, 2001)	1.073-5.347#	1990-1999
ARIMA-based RNN (Wang & Leu, 1996)	Acceptable accuracy	01/91-05/95
Fuzzy Grey System (Wang, 2002)	≈91%	09/00-04/01
Evolving ANN+GA (Hayward, 2004)	32.4-54.98%	01/97-01/04
(i) Multiple Regression Analysis (ii) Feedforward NN (iii) Simple RNN (Kohara et al, 1997)	(i) ≈53% (ii) ≈57% (iii) ≈57%	08/89-03/91
Reinforcement Learning (Lee, 2001)	2.62-4.99*	03/94-08/94
GA+BP (Fu & Xu, 1997)	0.02-0.038#	03/94-08/94

(*: Root mean square error $: Mean average prediction error; #: Average error; RNN: Recurrent neural network; ANN: Artificial neural network; TDNN: Time delay NN, PNN: Probabilistic NN; BP: Backpropagation; GA: Genetic Algorithm; ARIMA: Autoregressive integrated moving average)

Figure 6.6 A Comparison of results obtained by other models.

Figure 6.6 shows the comparison of performance of various stock market prediction models for short term prediction developed by researchers in recent years. It is seen that the FLANN based model for the prediction problem gives a performance that is better than many of the models described in the figure.

Chapter 7

CONCLUSION

The Functional Link Artificial Neural Network based stock market prediction model is introduced. With the use of FLANN, the model for prediction of stock market indices becomes simpler and involves lesser computations compared to other such model reported earlier. Experiments show that the FLANN based model gives enhanced performance with both LMS as well as RLS update algorithm for all three – one day, one month and two month advance stock market prediction problems. But using all the technical indicators as inputs to the model unnecessarily loads the network and diminishes prediction performance. Inclusion of certain fundamental factors to the inputs does not necessarily improve performance. However, some combinations of technical and fundamental parameters give better results. The RLS algorithm is computational much more efficient than the LMS but is susceptible to instability problems. The FLANN model is observed to give better performance with low initialization constants. In all, the FLANN based stock market prediction model is an effective approach to foresee the market levels in short and medium term future.

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