International Journal of Research in Advent Technology (IJRAT)
Vol. 1, No. 2, September 2013, ISSN: 2321–9637

NEURO FUZZY APRROACH FOR FINANCIAL FORECASTING

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ABSTARCT:
Financial forecasting or specially stock market prediction is one of the hottest field of research lately due to its commercial applications owing to high stakes and the kinds of attractive benefits that it has to offer. In this project we have analyzed various evolutionary computation algorithms for forecasting of financial data. The financial data has been taken from a large database and has been based on the stock prices in leading stock exchanges. We have designed three models and compared those using historical data from the stock exchanges. The models used were based on: Adaptive Neuro Fuzzy Inference System (ANFIS). And FLANN parameters updated by Least mean square.
The raw input for the experiment is the historical daily open, close, high, low and volume of the concerned index. However the actual input to the model was the parameters derived from these data. The results of the experiment have been depicted with the aid of suitable curves where a comparative analysis of the various models is done on the basis on various parameters including error convergence and the Mean Average Percentage Error (MAPE).

Keywords: *ANFIS;FLANN; MAPE.*

1. INTODUCTION

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 behaviour of the market towards different information. The other well known index, considered by researchers for prediction, are the Standard & Poor (S&P) 500 and the Bombay Stock Exchange. 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.

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, firm's policies, general economic conditions, investor's expectations, institutional investor's 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 behaviour, which can be identified and predicted. In the process they use number of statistical parameters called Technical Indicators and chart patterns from historical data.

1.1 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[14]. 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 behaviour via a direct method. The virtue of ARIMA[14] (Auto Regressive Integrated Moving Average) is well characterized by Vandaele: "… can be viewed as an approach by which time series data sifted through 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 Back-propagation 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.

The organisation of this report is as follows. Literature study is given in chapter 2. Chapter 3 gives the details of data collection and data processing necessary for the experiments. The detail explanation of problem statement and experimental set up is given in chapter 5 followed by conclusions in chapter 4.

2. WHY STOCK MARKET FORECASTING?

Due to the recent financial crisis, the world economy has gone down drastically. Financial time series is highly noisy, irregular, random, non-linear, non-seasonal and chaotic in nature. So it has always remained as a challenge for the common investors, stock buyers/sellers, policy makers, market researchers and capital market role players to gain knowledge about the daily stock market price values. Making money and gaining high profit is the dream of every investor, but it requires proper financial knowledge, analytical capability and ability for discovering the non-linear pattern hidden within the particular stock market data. As a lot of risk is involved in the stock market, the investors become highly insecure to invest their amount. It has been found that not only the economic factors but also the non-economic factors like political scenario, continuous terrorist attacks and the moods of typical individual investors have become the major role players in contributing the uncertainty in stock market. Researchers are highly motivated to develop more and more efficient and advanced models for making huge profits.

A share market is a place of high interest to the investors as it presents them with an opportunity to benefit financially by investing their resources on shares and derivatives of various companies. It is a chaos system; meaning the behavioural traits of share prices are unpredictable and uncertain. To make some sort of sense of this chaotic behaviour, researchers were forced to find a technique which can estimate the effect of this uncertainty to the flow of share prices. From the analyses of various statistical models, Artificial Neural Networks are analogous to nonparametric, nonlinear, regression models. So, Artificial Neural Networks (ANN) certainly has the potential to distinguish unknown and hidden patterns in data which can be very effective for share market prediction. If successful, this can be beneficial for investors and financers and that can positively contribute to the economy.

3. EXECUTION OF PROBLEM STATEMENT

As we have mentioned above, the main work of our project is, to predict the future stock prices for any financial data. Here we have taken the Case study as stock market because the availability of the data related to above domain is easily available. As this also plays main important factor to forecast the closing price of the index in each day of the forecasting period for any data.

The objective of our research work is to improve the accuracy of daily stock price prediction of stock market indices using artificial neural networks. We employ models using Adaptive neuro-fuzzy inference system (ANFIS) and Functional Link Neural Network architecture (FLANN) structure where parameters of each of the structure is updated using either LMS algorithm. Historical stock prices of different companies were obtained from published stock data on the Internet.

In this work we are going to predict the closing price of index in each day for particular company with the help of different factor like, simple moving average, accumulation/distribution line, on balance volume, price rate of change and main important factor is closing price, opening price, lowest value in the day, highest value in the day and the total volume of stocks traded in each day which are present on different stock exchange websites. So we can compare the results from both the approaches.

3.1 Representation of the problem statement

The following figure 3.1 depicts the problem statement.

- Here firstly we collect the raw data i.e. historical stock data of various companies from respective company's stock exchange web sites.
- Now, from the collected data we decide input and output factors which are use for future stock price prediction.
- The selected parameters are process using some technical indicators as describe in section 5.2. This process data is needed for giving the input to network.

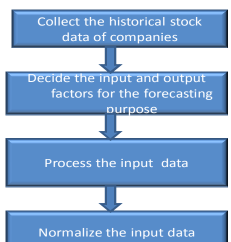


Figure 3.1 Representation of problem statement

- The input data is normalized for the proper behaviour of the network. The inputs are normalized to values between +1 and -1 or 0 and 1. This can be done by a number of normalization techniques. Here we used the data in terms of the maximum and minimum of the data set. The normalization is done using following equation:

  Y= (2*X – (Max+Min)) / (Max+Min) (1)

  Where Y= normalized value

  X= present value
- This normalized data is feed to both models i.e. ANFIS and FLANN which will provide us a prediction results. Further the results from both models are compared.
- The system will generates the suitable numerical output indicating the type of decision that will be suitable for the investor.

  Along with that simultaneously we will validate the data using some statistical method and validate the data sets using k-fold cross validation method to get more appropriate results.

4. INPUT DATA SELECTION & PROCESSING

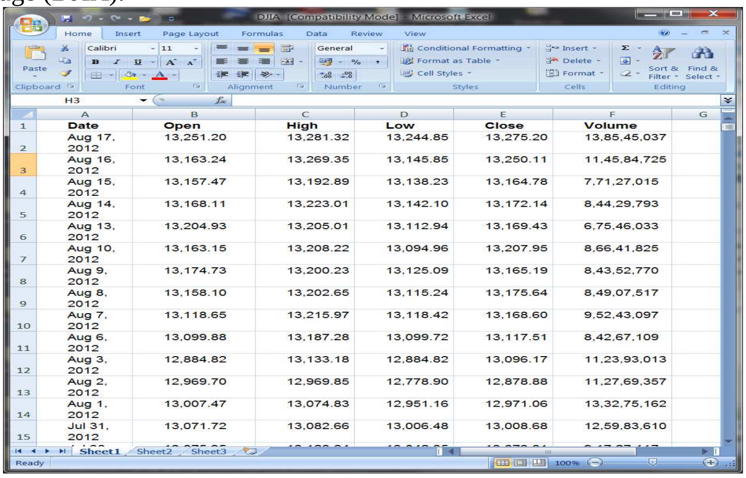
Prediction of financial market has long been an attraction for equity investors. Technical analysis [1] for stock exchange provides a framework for studying investor's behaviour, and generally focuses only on price and volume data. Typically, traders using this type of approach are unaware of a company's financial health. Traders using this approach have short term investment horizons, and access to only price and exchange data. With the advent of powerful computers stock prediction field has become important.

The Neural Network has been applied to a range trading market. Neural Network ability to deal with uncertain fuzzy or insufficient data, which fluctuate rapidly in very short periods of time, have become very important method for stock market prediction. Numerous research and application of neural network in solving problem has proven their advantage in relation to classical methods that do not include artificial intelligence. The most frequent areas of Neural Network applications are production/operations (53.5%) and finance (25.4%). The network inputs used in the work have been confined to readily available quantitative data.

Before the age of computers, people traded stock and commodities primarily on intuition. As the level of investing and trading grew, people searched for tools and methods that would increase their gains while minimizing their risks. The techniques like statistics, technical analysis, fundamental analysis and linear regression are all used to attempt, to predict and benefit from the market's direction. None of the techniques gives the consistently correct prediction and many analysts argue the usefulness of many of the approaches. However these methods are commonly used in practice and represent a base level standard for which neural network should outperform.

4.1 Collection of Data

To get the best possible performance in forecasting, it's desirable to take as much historical data as possible, so that the training data will also be huge, which will ensure effective training. The data for the stock market prediction experiment has been collected from different stock indices namely Dow Jones Industrial Average (DJIA), USA, Standards & Poor's 500 Index (S&P 500), USA and Bombay Stock Exchange (BSE) etc. 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 afterhours 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. Following figure shows the sample data of Dow Jones Industrial Average (DJIA).



	Date	Open	High	Low	Close	Volume
2	Aug 17, 2012	13,251.20	13,281.32	13,244.85	13,275.20	13,85,45,037
3	Aug 16, 2012	13,163.24	13,269.35	13,145.85	13,250.11	11,45,84,725
4	Aug 15, 2012	13,157.47	13,192.89	13,138.23	13,164.78	7,71,27,015
5	Aug 14, 2012	13,168.11	13,223.01	13,142.10	13,172.14	8,44,29,793
6	Aug 13, 2012	13,204.93	13,205.01	13,112.94	13,169.43	6,75,46,033
7	Aug 10, 2012	13,163.15	13,208.22	13,094.96	13,207.95	8,66,41,825
8	Aug 9, 2012	13,174.73	13,200.23	13,125.09	13,165.19	8,43,52,770
9	Aug 8, 2012	13,158.10	13,202.65	13,115.24	13,175.64	8,49,07,517
10	Aug 7, 2012	13,118.65	13,215.97	13,118.42	13,168.60	9,52,43,097
11	Aug 6, 2012	13,099.88	13,187.28	13,099.72	13,117.51	8,42,67,109
12	Aug 3, 2012	12,884.82	13,133.18	12,884.82	13,096.17	11,23,93,013
13	Aug 2, 2012	12,969.70	12,969.85	12,778.90	12,878.88	11,27,69,357
14	Aug 1, 2012	13,007.47	13,074.83	12,951.16	12,971.06	13,32,75,162
15	Jul 31, 2012	13,071.72	13,082.66	13,006.48	13,008.68	12,59,83,610

Figure 4.1 Sample Data of DJIA

4.2 Data Processing

Different technical and fundamental indicators [12][14][16][17][18][22] 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, some 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)

• 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.
ADO = ((Close – Low) – (High – Close))/ (High – Low) * Period's Volume
Every day's ADO has been taken in the experiment.

• 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 =

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

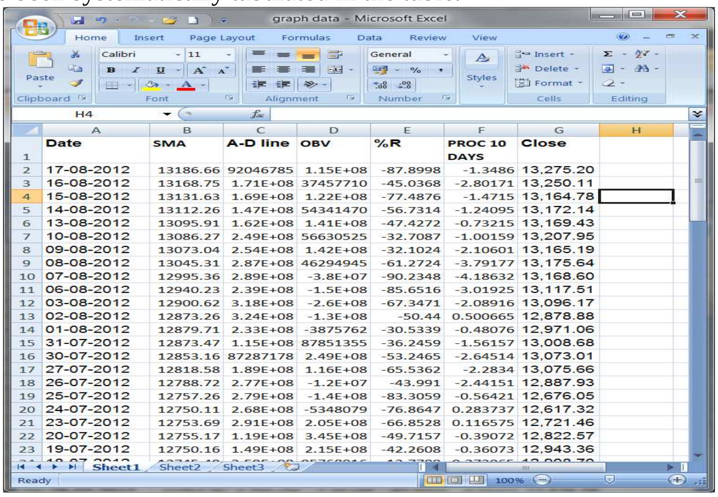
For example: n= 9 days

• Price Rate of Change (PROC):

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

$$\frac{(Today's close - close x - periods ago) * 100}{(close x - periods ago)}$$

We have chosen the above four parameters so that our analysis takes into account various factors into consideration including momentum factor, volume of trade and any random spurt in prices which are generally unstable. These five parameters along with the present day input form the six inputs into the system. However, many other parameters can be derived from the input data which portray various behaviours of the data set .These parameters have been systematically tabulated in the table.



	Date	SMA	A-D line	OBV	%R	PROC 10 DAYS	Close
2	17-08-2012	13186.66	92046785	1.15E+08	-87.8998	-1.3486	13,275.20
3	16-08-2012	13168.75	1.71E+08	37457710	-45.0368	-2.80171	13,250.11
4	15-08-2012	13131.63	1.69E+08	1.22E+08	-77.4876	-1.4715	13,164.78
5	14-08-2012	13112.26	1.47E+08	54341470	-56.7314	-1.24095	13,172.14
6	13-08-2012	13095.91	1.62E+08	1.41E+08	-47.4272	-0.73215	13,169.43
7	10-08-2012	13086.27	2.49E+08	56630525	-32.7087	-1.00159	13,207.95
8	09-08-2012	13073.04	2.54E+08	1.42E+08	-32.1024	-2.10601	13,165.19
9	08-08-2012	13045.31	2.87E+08	46294945	-61.2724	-3.79177	13,175.64
10	07-08-2012	12995.36	2.89E+08	-3.8E+07	-90.2348	-4.18632	13,168.60
11	06-08-2012	12940.23	2.39E+08	-1.5E+08	-85.6516	-3.01925	13,117.51
12	03-08-2012	12900.62	3.18E+08	-2.6E+08	-67.3471	-2.08916	13,096.17
13	02-08-2012	12873.26	3.24E+08	-1.3E+08	-50.44	0.500665	12,878.88
14	01-08-2012	12879.71	2.33E+08	-3875762	-30.5339	-0.48076	12,971.06
15	31-07-2012	12873.47	1.15E+08	87851355	-36.2459	-1.56157	13,008.68
16	30-07-2012	12853.16	87287178	2.49E+08	-53.2465	-2.64514	13,073.01
17	27-07-2012	12818.58	1.89E+08	1.16E+08	-65.5362	-2.2834	13,075.66
18	26-07-2012	12788.72	2.77E+08	-1.2E+07	-43.991	-2.44151	12,887.93
19	25-07-2012	12757.26	2.79E+08	-1.4E+08	-83.3059	-0.56421	12,676.05
20	24-07-2012	12750.11	2.68E+08	-5348079	-76.8647	0.283737	12,617.32
21	23-07-2012	12753.69	2.91E+08	2.05E+08	-66.8528	0.116575	12,721.46
22	20-07-2012	12755.17	1.19E+08	3.45E+08	-49.7157	-0.39072	12,822.57
23	19-07-2012	12750.16	1.49E+08	2.15E+08	-42.2608	-0.36073	12,943.36

Figure 4.2 Sample process data

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.

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× A) + (Previous EMA×(1- A)) ; A=2/(N+1) P – Current Price, A- Smoothing factor, N-Time Period
Accumulation/ Distribution Oscillator (ADO)	$\frac{\text{(C.P - L.P) - (H.P - C.P))}}{\text{(H.P - L.P)× (Period's Volume)}}$ C.P – Closing Price, H.P – Highest price, L.P – Lowest price
Stochastic Indicator	% K= (Today's Close - Lowest Low in K period) ×

(STOC)	100 / (Highest High in K period - Lowest Low in K period) %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	$\% R = \frac{\text{(Highest High in n period - Today's Close)} \times 100}{\text{(Highest High in n period - Lowest Low in n period)}}$
Relative Strength Index (RSI)	RSI = $100 - \frac{100}{1 + (U / D)}$
Price Rate Of Change (PROC)	$\frac{\text{(Today's Close - Close X-period ago)} \times 100}{\text{(Close X-period ago)}}$
Closing Price Acceleration (CPAcc.)	$\frac{\text{(Close Price - Close Price N-period ago)} \times 100}{\text{(Close Price N-period ago)}}$
High Price Acceleration (HPAcc.)	$\frac{\text{(High Price - High Price N-period ago)} \times 100}{\text{(High Price N-period ago)}}$

5. PROPOSED MODEL

Artificial intelligence prediction techniques have been re-ceiving much attention lately in order to solve problems that are hardly solved by the use of traditional methods. They have been cited to have the ability to learn like humans, by accumulating knowledge through repetitive learning activi-ties. Therefore the objective here is to propose new fore-casting techniques via the artificial approaches to manage demand in a fluctuating environment. In this study, a com-parative analysis based on regression technique and ANFIS is presented for prediction of the movie performance in future. The artificial techniques used in this study are explained as follows.

5.1 Adaptive network-based fuzzy inference system (ANFIS)

Adaptive network-based fuzzy inference system (ANFIS) [39]]can construct an input–output mapping based on both human knowledge in the form of fuzzy if-then rules with appropriate membership functions and stipulated in-put–output data pairs. It applies a neural network in determination of the shape of membership functions and rule extraction. ANFIS architecture uses a hybrid learning procedure in the framework of adaptive networks. This method plays a particularly important role in the induction of rules from observations within fuzzy logic.

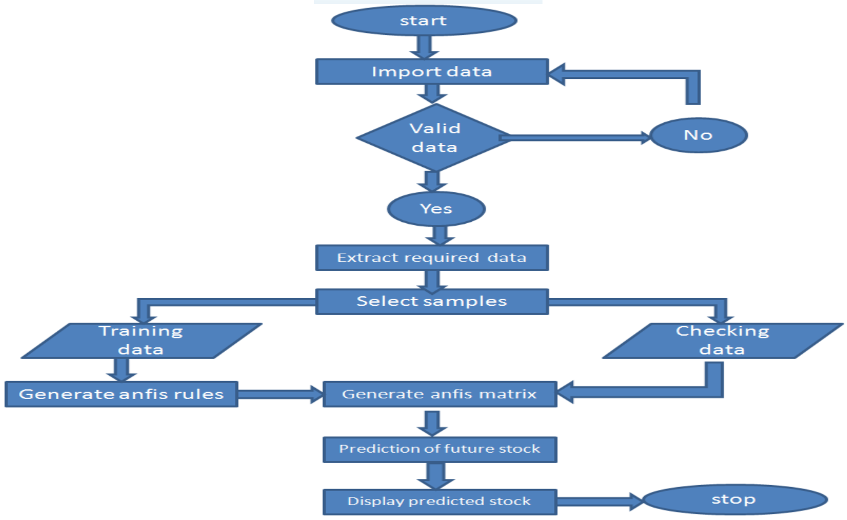


Figure 5.1 Work flow of proposed analysis-ANFIS

Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be feed-forward type. Due to these restrictions, the adaptive networks applications are immediate and immense in various areas.

The architecture of ANFIS can be given , as shown in the diagram bellow,

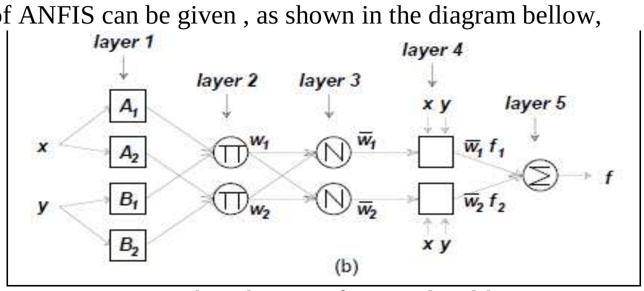


Figure 5.2 The architecture of proposed model-ANFIS

Layer 1 Every node I in this layer is a square node with a node function

$$O_i^1 = \mu A_i(x) \qquad (2)$$

Where x is the input to node I, and Ai is the linguistic label (high,low, etc) associated with this node function. In other words, Oi1 is the membership function of Ai and it specifies the degree to which the given x satisfies the quantifier Ai. Usually µA(x) is choose as bell-shaped with maximum equal to 1 and minimum equal to 0, such as,

$$\mu A_i(x) = \frac{1}{1+[(\frac{x-c_i}{a_i})^2]^{b_i}} \qquad (3)$$

Where {ai, bi, ci} is parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly. Parameters in this layer are referred to as premise parameters.

Layer 2 Every node in this layer is a circle node label as II which multiplies the incoming signals and sends the product out.

$$w_i = \mu A_i(x) \times \mu B_i(y), i = 1,2 \qquad (4)$$

Each node output represents the firing strength of a rule. Also T-norm operators that perform generalized AND can be used as a node function.

Layer 3 Every node in this layer is a circle node label N. the i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules firing strength.

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \qquad (5)$$

Outputs of this layer are called as normalized firing strength.

Layer 4 Every node I in this layer is a square node with a node function

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i \qquad (6)$$

Where wi is the output of layer 3 and {pi, qi, ri} is the parameter set. Parameters in this layer will be referred as consequent parameters.

Layer 5 The single node in this layer is a circle node labelled ∑ that computes the overall output as summation of all incoming signals

$$O_1^5 = overall output = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (7)$$

Thus we have constructed adaptive network which is functionally equivalent to type-3 fuzzy inference system.

5.2Purpose For Using Adaptive Neuro Fuzzy Inference System

The usage of artificial intelligence has been applied widely in most of the fields of computation studies. Main feature of this concept is the ability of self learning and self-predicting some desired outputs. The learning may be done with a supervised or an unsupervised way. Neural Network study and Fuzzy Logic are the basic areas of artificial intelligence concept. Adaptive Neuro-Fuzzy study combines these two methods and uses the advantages of both methods.

It not only includes the characteristics of both methods, but also eliminates some disadvantages of their lonely-used case. Operation of ANFIS looks like feed-forward back propaga-tion network. Consequent parameters are calculated forward while premise parameters are calculated backward. There are two learning methods in neural section of the system: Hybrid learning method and back-propagation learning method. In fuzzy section, only zero or first order. Since ANFIS combines both neural network and fuzzy logic, it is capable of handling complex and nonlinear problems. Even if the targets are not given, ANFIS may reach the optimum result rapidly. The architecture of ANFIS consists of five Sugeno inference systems or Tsukamoto inference system can be used. Layers and the number of neurons in each layer equals to the number of rules. In addition, there is no vagueness in ANFIS as opposed to neural networks.

ANFIS structure herein described is based on the Taka-gi-Sugeno model which, as shown in [12], can be represented as 5-layer fuzzy neuronal networks. This example of a 5-layer fuzzy neuronal network is shown in Figure 5. The first layer is used for the input fuzzification. In the second layer the fuzzy rule performance weight is calculated. The third layer is the normalization layer. In the fourth layer, the consequent rule values are calculated and multiplied by the respective rule performance weight and the fifth layer does the defuzzification.

Another reason for using Anfis is The hybrid algorithm used in ANFIS structure consists of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data .The hybrid algorithm is composed of a forward pass and a backward pass. In the forward pass of the hybrid learning algorithm, the least squares method is used to op-timize the consequent parameters with the premise para-meters fixed. After the optimal consequent parameters are found, the backward pass starts immediately. In the back-ward pass of the algorithm, the gradient descent method is used to adjust optimally the premise parameters corres-ponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent pa-rameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm.

6. RESULTS

As mentioned earlier in this work we are going to predict the sale of particular movie with the help of different factor like, past box office performance, box office collection ,budget of movie, type of movie and important factor is online review‘s sentiment factor which are present on different movie web-sites. Then the results will be validated using statistical

6.1Results using ANFIS

The architecture and learning rules of adaptive networks have been described in previous chapter. Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feed forward type. Due to these minimal restrictions, the adaptive network's applications are immediate and immense in various areas. So here in ANFIS, we performed the prediction using neural network and fuzzy inference system which combining gives much more good results than existing one.

Again there is use of different type of membership functions as well as different numbers of membership function as it gives more precision in results.

So the ANFIS results will be compared through different errors, i.e. training, checking and testing errors and then we will come up with the results for best combination of Membership functions. Then the evaluation parameters will be MAPE and MSE errors which give the error measures for predicting the movie category.

6.2Computation of Input and Output Membership Functions

A membership function for a fuzzy set A on the universe of discourse X is defined as µA: X → [0, 1], where each element of X is mapped to a value between 0 and 1. This value, called membership value or degree of membership, quantifies the grade of membership of the element in X to the fuzzy set A. Membership functions allow us to graphically represent a fuzzy set. The x axis represents the universe of discourse, whereas the y axis represents the degrees of membership in the [0,1] interval.

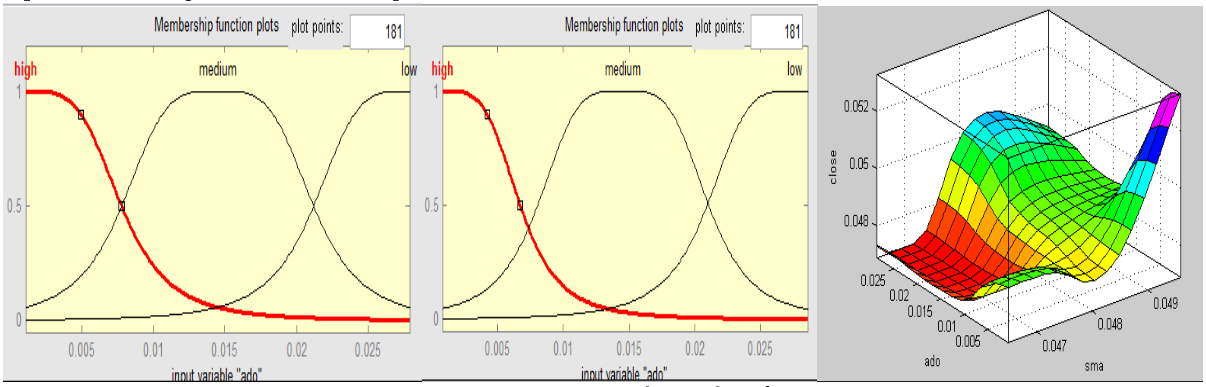


Figure 6.1 Input & Output MF's along with Surface view

Here all types of membership functions are evaluated on the basis of different types of errors like training, checking and testing error for estimating the accurate prediction values.

The training error is the difference between the training data output value, and the output of the fuzzy inference system corresponding to the same training data input value, (the one associated with that training data output value). The training error trnError records the root mean squared error (RMSE) of the training data set at each epoch.

The checking error is the difference between the checking data output value, and the output of the fuzzy inference system corresponding to the same checking data input value, which is the one as

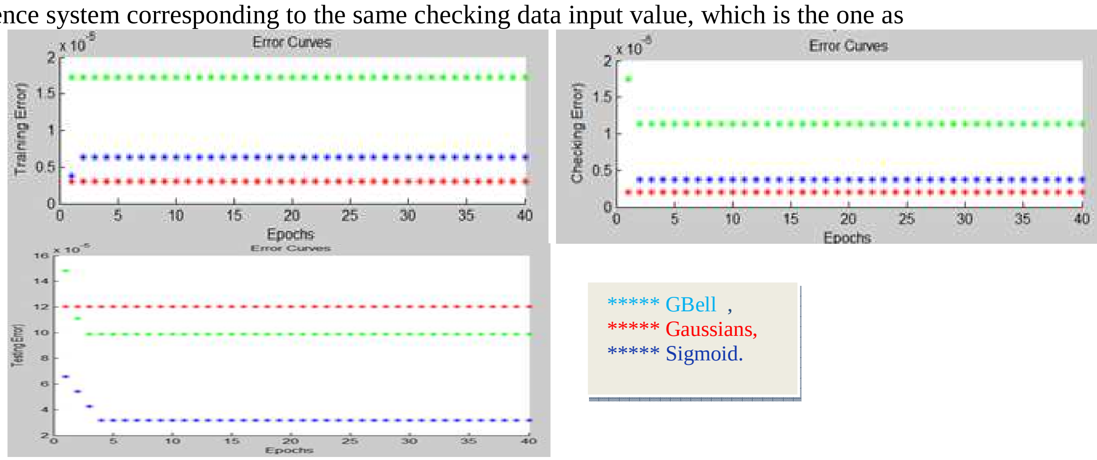


Figure 6.2 Training , Checking, Testing Errors for different types of MF

Located with that checking data output value. The checking error chkError records the RMSE for the checking data at each epoch. The training, checking and testing errors can be shown in fig7

The above plotted graphs show the training, checking and testing errors with respect to different numbers of input membership function. Here I have measured these errors for different types of membership function as well as different number of membership functions. From the Fig no 7, it can be seen that the error rate for the gbell type membership function is at lower side. This is because there is a difference between the tuning parameters for the different types of membership function. The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modelling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure (usually defined by the sum of the squared difference between actual and desired outputs). anfis uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation.
The various tuning parameters of different types of membership functions can be given as,

Table 6.1 Tuning Parameters for different membership functions

Type Of Membership Function	Tuning Parameters
GBell	$\mu A_i(x) = \dfrac{1}{1+[(\frac{x-c_i}{a_i})^2]^{b_i}}$
Gaussian	$f(x) = \exp(\dfrac{-0.5(x-c)^2}{\sigma^2})$
Sigmoidal	$sig(x;a,c) = \dfrac{1}{1+\exp[-a(x-c)]},$

The bell membership function has one more parameter than the Gaussian membership function, so it can approach a non-fuzzy set if the free parameter is tuned. Because of their smoothness and concise notation, Gaussian and bell membership functions are popular methods for specifying fuzzy sets. Both of these curves have the advantage of being smooth and nonzero at all points.

Because of their smoothness and concise notation, Gaussian and bell MFs are becoming increasingly popular for specifying fuzzy sets. Gaussian functions are well known in probability and statistics, and they possess useful properties such as invariance under multiplication (the product of two Gaussians is a Gaussian with a scaling factor) and Fourier transform (the Fourier transform of a Gaussian is still a Gaussian). The bell MF has one more parameter than the Gaussian MF, so it has one more degree of freedom to adjust the steepness at the crossover points. This can be again supported with the following results in which we are getting the lowest error parameters for the GBell membership.
However, since the triangular and trapezoidal MFs are composed of straight line segments, they are not smooth at the corner points specified by the parameters.
For sigmoidal membership function, this type of MF is although extremely flexible in specifying fuzzy sets, is not used often in practice because of its unnecessary complexity. Hence for further prediction, Gbell membership function will be preferred. Again the results are evaluated by considering the different number of membership functions.

The errors for the different types of membership function can be compared as given in the table 1

Table 6.2 Comparision of errors for different MF

Types Of MF	Training Error	Checking Error	Testing Error
G Bell	**$0.6*10^{-5}$**	**$0.4*10^{-5}$**	**$3*10^{-5}$**
Gaussian1	$0.3*10^{-5}$	$0.2*10^{-5}$	$12*10^{-5}$
Sigmoid	$1.8*10^{-5}$	$1.1*10^{-5}$	$10*10^{-5}$

Here from the results it indicates that the Gbell type membership functions gives the comparatively less errors than others because the generalized bell membership function is specified by three parameters and has the function name gbellmf.

So from the above analysis we can conclude that the results given by the membership function of type GBell are minimum amongst all. Here the purpose of taking the different number of membership function is to check the effectiveness on the precision on the error rate by having different number of input and output membership functions

Besides these errors, GBell is proved to be best for giving constant and less error at early epoch

6.3Accuracy Measurements

"To have an appropriate measure for assessing the accuracy of a forecast is perhaps one of the most contentious issues among researchers over the last fifty years".

The quality (accuracy) of a model can be estimated by examining the inputs (assumptions) to the model, or by comparing the outputs (forecasts) from the model. It claims that testing outputs is the only useful approach to evaluating forecasting methods. But the testing of input is the only worthwhile way to test models. But it is more reasonable to test both inputs, for improvement of a model, and outputs, for selection of the best model. Forecasting accuracy is regarded as an "optimist's term for forecast errors" .A forecast error, on the other hand, represents the difference between the forecast value and the actual value. It has been suggest that the following factors should be taken into consideration when selecting a measurement of accuracy:

- Prediction intervals: the errors should be obtained from a test that closely resembles the actual forecasting situation
- The error term should not be overly influenced by outliers
- The term should be independent of scale
- The error measures should be sensitive to changes in the model being tested
- Reliability
- Validity

In this case for checking the precision accuracy we will be considering the error factors like MAPE, MSE and RMSE which will be comparing the actual and predicted values.

6.3.1 Mean Squared Errors (MSE)

The mean squared error is an accuracy measure computed by squaring the individual error
for each item in a data set and then finding the average or mean value of the sum of those
Squares .MSE can be given as,

$$\text{MSE} = \frac{1}{N}\sum_{t=1}^{n} e^{2}t \qquad (1)$$

Where MSE = mean squared error
n = time periods
e2 = forecast error

The MSE is having the advantage of being easier to handle mathematically. By using Eqn(9).Since the ability of a forecasting method to detect large errors is often regarded as one the most important criteria, the MSE method has been popular for years.

6.3.2 Root Mean Squared Errors (RMSE)

The term root mean square error (RMSE) is the square root of mean squared error (MSE). RMSE measures the differences between values predicted by a hypothetical model and the observed values. In other words, it measures the quality of the fit between the actual data and the predicted model. RMSE is one of the most frequently used measures of the goodness of fit of generalized regression models. In the application of regression models, unless the relationship or correlation is perfect, the predicted values are more or less different from the actual observations. These differences are prediction errors or residuals. These residuals are measured by the vertical distances between the actual values and the regression line.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e^{2}t}\,. \qquad (2)$$

The calculation of RMSE is done separately for training and checking error so that we can select the range of training and checking data appropriately.

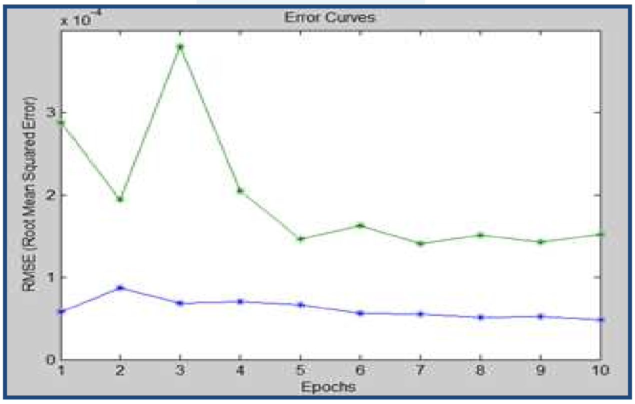


Figure 6.3 RMSE for training and Checking data

6.3.3Mean Absolute Percentage Error (MAPE)

The percentage error is given by pt = 100et /Yt. Percentage errors have the advantage of being scale independent, so they are frequently used to compare forecast performance between different data series. The most commonly used metric is Mean Absolute Percentage Error (MAPE) = mean (|pt |).
Measurements based on percentage errors have the disadvantage of being infinite or undefined if there are zero values in a series, as is frequent for intermittent data. Moreover, percentage errors can have an extremely skewed distribution when actual values are close to zero. With intermittent-demand data, it is impossible to use the MAPE because of the occurrences of zero periods of demand's he mean absolute percentage error is the mean or average of the sum of all of the percentage errors for a given data set taken without regard to sign so as to avoid the problem of positive and negative values cancelling one another.

The MAPE is given by

$$PE_t = (Y_t - F_t / Y_t) \times 100$$
$$MAPE = \frac{1}{n}\sum_{t=1}^{n} |PE_t| \qquad (3)$$

- Where PE = percentage error
- Y_t = actual observation for time period t
- F_t = forecast for the same period
- MAPE = mean absolute percentage error
- n = time periods

Here in this prediction case Of movie as it was mentioned that the results can be taken in different scenarios like in presence of either of the input or when all the inputs will be present, and then the prediction accuracy will be calculated by the different measures described above. The values of MAPE and MSE for ANFIS can be compared as,

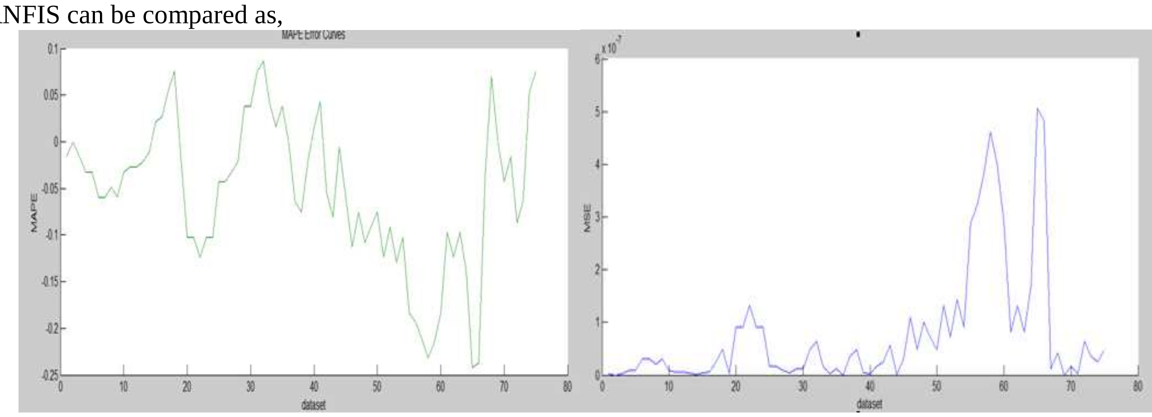


Figure 6.4 MAPE,MSE Errors

So here from the above observations in table 2 we can conclude that, the mean average percentage error of the second scenario i.e. with the sentiment rating, the prediction accuracy is more than the effect of no rating factor. But it is also giving very less percentage error for another option.

From the values we can conclude that the precision error is lowest in the presence of the sentiment rating than only having any of the factors. In the presence of either of the factors also the model is giving the good precision as the error factor very less.

6.4 MODELLING OF FLANN STRUCTURE

FLANN[12][17][22] is single neuron architecture. Each input is split up into five branches each being a distinct function of the primary input shown in figure 4.6. 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 6 input parameters for each pattern. For a 6 different statistical parameters of the stock index lag values, the total input to the single neuron FL-ANN is 30 plus a bias. This gives us 31 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 2πx, Sin πx and Sin 2πx 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 behaviour of the network. The normalization of input is done as discuss earlier in section 4.1

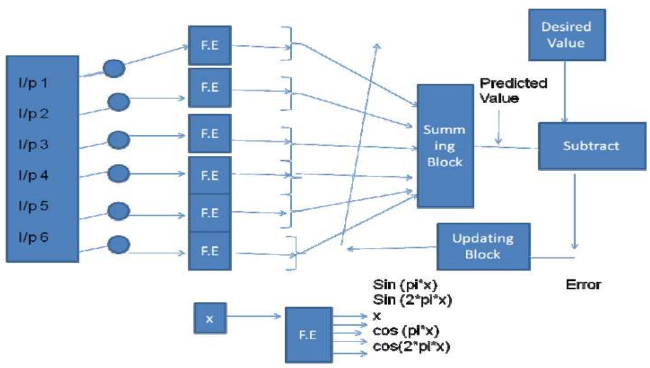


Figure 6.6 Learning with Functional Linked ANN

6.5 FLANN and ANFIS Comparison

Here the final comparison is based on the different error evaluation factors like MAPE errors. The FLANN based stock market prediction model using LMS and RLS based weight update mechanism is structurally simple and involves lesser computations. The use of the technical indicators as input to the model unnecessarily loads the network and does not improves the prediction performance. Some technical indicators have greater effect on the prediction performance than others. MAPE is used to gauge the performance of FLANN model.

ANFIS uses the approach of neuro fuzzy technique which incorporates the rule based part from fuzzy logic and learning algorithms from neural network. It uses hybrid algorithm for calculating the error factor and giving final output. As it used the combine concept of neuro-fuzzy it is proved to be efficient than FLANN for predicting results, which can be justified with the results mentioned throughout this chapter.

The MAPE error for both the methods can be represented as table 6.5.

Table 6.5 MAPE comparison of models

	MAPE
ANFIS	0.0538
FLANN-LMS	0.64
FLANN-RLS	0.58

The figures 6.1, 6.2, 6.4 and 6.5 and table 6.2, 6.3 indicates the efficiency of ANFIS against FLANN. The mean average percentage error is very less in ANFIS than FLANN.

The final prediction accuracy can be seen in the figure 6.9 where it indicates that the predicted values from ANFIS are much closer to actual output than in FLANN.

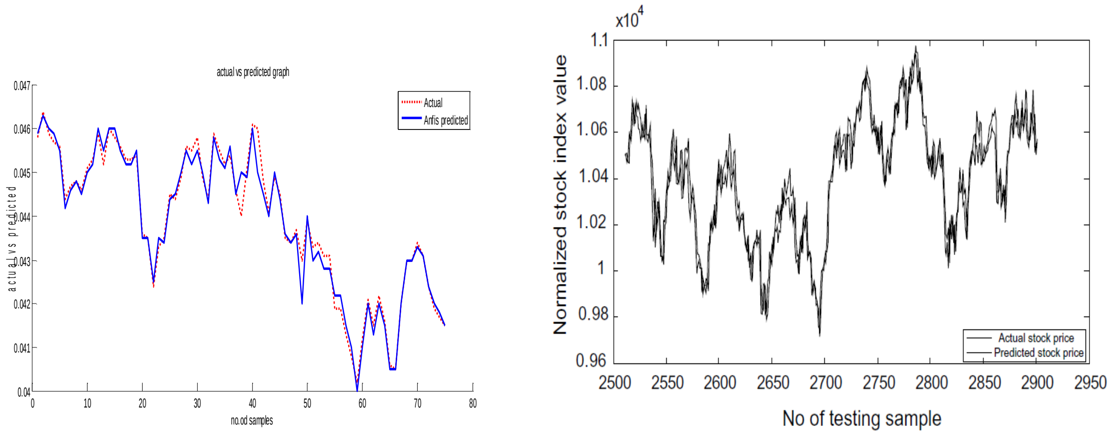


Figure 6.7 (a) Actual v/s predicted values of ANFIS (b)Actual v/s Predicted using FLANN

So from the figure 11 it clearly indicates that the prediction accuracy given by ANFIS is much closer to actual output than the existing approach of using auto regression. Again the prediction done using one important factor like sentiment gives closer values than the prediction done without the same values and it can be verified with the help of MAPE and MSE errors.

8. Conclusion

Accurate stock prediction is always a very challenging task. The problem of stock index prediction is one of the most popular targets for various prediction methods in the area of finance and economics. As researchers and investors strive to out-perform the market, the use of neural networks to forecast stock market prices will be a continuing area of research. The ultimate goal is to increase the yield from the investment. It has been proven already through research that the evaluation of the return on investment in share markets through any of the traditional techniques is tedious, expensive and a time consuming process. In conclusion we can say that if we train our system with more input data set it generate more error free prediction price.

Starting from the calculation of various parameters associated with the Stock exchange data, in this work we have formulated a comparison of FLANN model in which parameters are updated by least mean square (LMS) and Adaptive neuro0fuzzy inference system (ANFIS) and results are compiled. In this work we are trying to demonstrate the capability of Adaptive neuro-fuzzy inference system (ANFIS) for prediction problem. Here, we selected the stock market as domain for prediction purpose. The accuracy and effectiveness of the proposed models can been confirmed by the experiments on historic stock data collected from stock exchange.. With the use of FLANN and ANFIS, the model for prediction of stock market indices becomes simpler and involves lesser computations compared to other such model reported earlier.

Starting with popularity and prevalent use of the neuro-fuzzy systems, specially ANFIS, we explained the inherent difficulties of its designing and parameter setting process. To tackle this problem, suitable approach is to perform design of experiment technique to identify the most statistically significant factors on the performance of the ANFIS. For future works, one can completely accomplish this approach in other proposed neuro fuzzy systems and also can use different popular application problem.

Equipped with the proposed models, companies will be able to better harness the predictive power of reviews and conduct businesses in a more effective way. So the proposed S-ANFIS(input processed with sentiment analysis) model is general frameworks for sales performance prediction as it is a self learning model and would certainly benefit from the development of more sophisticated models for sentiment analysis and future quality prediction.

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