Prediction of FOREX rates using Hybrid System

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CERTIFICATE

This is to certify that the Dissertation entitled **"Prediction of FOREX rates using a Hybrid System"** is a bonafide work of "**Nathan D'Lima" (St. Francis-45)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Masters"** in **"Computer Engineering"**.

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ABSTRACT

Currency exchange is the trading of one currency against another. Forecasting the foreign exchange rate is an uphill task. FOREX rates are influenced by many correlated economic, political and psychological factors. Like many economic time series, FOREX has its own trend, cycle and irregularity. Many methods have been used to predict the future FOREX rates. Some of the common methods include statistical analysis, time series analysis, etc. Some of the modern methods used are fuzzy systems, neural networks, hybrid systems, etc. These methods suffer from the problem of accurately predicting the exchange rates with low accuracy and precision.

The objective is to predict future exchange rates for the next 15 days with higher accuracy and precision. By using two different methods, i.e. a Neural network and a Hybrid system, a more accurate and robust method can be developed. An Artificial Neural Network (ANN) is used to predict the rise and fall of the FOREX market while an ANFIS system is used to predict the future rate. The results are evaluated in terms of Mean Square Error (MSE) and Mean Absolute Error (MAE).

Keywords – Artificial Neural Network, ANFIS, Hybrid System, Forex, Forecasting.

CONTENTS

List of Abbreviations

AFLS	Adaptive Fuzzy Logic System
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARNN	Autoregressive Recurrent Neural Network
AUD	Australian Dollar
BELFIS	Brain Emotional Learning Fuzzy Inference System
BP	Back Propagation
CAD	Canadian Dollar
CANFIS	Coactive Adaptive Neuro Fuzzy Inference System
CART	Classification and Regression Trees
CHF	Swiss Franc
CP	Closing Price
CSV	Comma Separated Value
EBPTA	Error Back Propagation Training Algorithm
EMA	Exponential Moving Average
EST	Eastern Standard Time
EUR	Euro
FIS	Fuzzy Inference System
FOREX / FX	Foreign Exchange
GBP	British Pound Sterling
GDP	Gross Domestic Product

GMT	Greenwich Meridian Time
GUI	Graphic User Interface
GUIDE	Graphical User Interface Design Environment
INR	Indian Rupee
JYP	Japanese Yen
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARS	Multivariate Adaptive Regression Splines
MLP	Multi Layer Perceptron
MSE	Mean Square Error
MYR	Malaysian Ringgit
NN	Neural Network
NZD	New Zealand Dollar
RBF	Radial Basis Function
RMSE	Root Mean Square Error
ROC	Rate of Change
RSSA	Recurrent Singular Spectrum Analysis
SMA	Simple Moving Average
SSA	Singular Spectrum Analysis
SVM	Support Vector Machine
TSK	Takagi-Sugeno-Kang
USD	US Dollar
VSSA	Vector Singular Spectrum Analysis

List of Figures

List of Tables

Chapter 1

Introduction

Foreign Exchange or Foreign Currency Exchange is commonly known as FOREX or FX. The foreign exchange market is a common place where currencies are traded. The FOREX market is used to determine the relative price between a particular currency pair. Foreign currency exchange works similar to the stock market. The relative price of a currency pair is dependent on the demand and supply of those currencies in the market. Unlike the stock market the FOREX market is always online. The most widely traded currency pairs are called majors (EUR/USD, USD/JPY, GBP/USD and USD/CHF) and commodity pairs (AUD/USD, USD/CAD, NZD/USD) due to the large volume of trading [2]. The international scope of currency trading means that there are always traders somewhere who are making and meeting demands for a particular currency. Currency is also needed around the world for international trade, as well as by central banks and global businesses. Central banks have relied on foreign-exchange markets since 1971 - when fixed-currency markets ceased to exist because the gold standard was dropped. Since that time, most international currencies have been "floated", rather than pegged to the value of gold.

Currencies trade on an open market, just like stocks, bonds, computers, cars, and many other goods and services. A currency's value fluctuates as its supply and demand fluctuates, just like anything else. An increase in supply or a decrease in demand for a currency can cause the value of that currency to fall. A decrease in the supply or an increase in demand for a currency can cause the value of that currency to rise. A big benefit to FOREX trading is that you can buy or sell any currency pair, at any time subject to available liquidity. This also means that there really is no such thing as a "bear market," in the traditional sense. You can make (or lose) money when the market is trending up or down [2]. The market is a very unpredictable entity. An increase in supply or a decrease in demand for a currency can cause the value of that currency to fall and vice versa. It is rare for two currency pairs to have the same relative value for a long period. They may have the same exchange rate momentarily but it changes almost instantaneously, depending on various factors.

1.1 Forex Markets

The exchange market is a decentralized marketplace, i.e. there is no centralized place where transactions are made. Currencies are traded in several market places all around the world. It is the largest financial market in the world which trades over $1.5 trillion daily [1]. One can trade any currency with any other at any time of the day. The market is open 24 hours a day from 5pm EST on Sunday until 4pm EST Friday. The reason that the markets are open 24 hours a day is that currencies are in high demand. The ability of the forex to trade over a 24-hour period is due in part to different time zones and the fact it is comprised of a network of computers, rather than any one physical exchange that closes at a particular time.

The forex market can be split into three main regions: Australasia, Europe and North America. Within each of these main areas there are several major financial centres. According to GMT, for instance, forex trading hours move around the world like this: available in New York between 01:00 pm – 10:00 pm GMT; at 10:00 pm GMT Sydney comes online; Tokyo opens at 00:00 am and closes at 9:00 am GMT; and to complete the loop, London opens at 8:00 am and closes at 05:00 pm GMT [21]. This enables traders and brokers worldwide, together with the participation of the central banks from all continents, to trade online 24 hours a day.

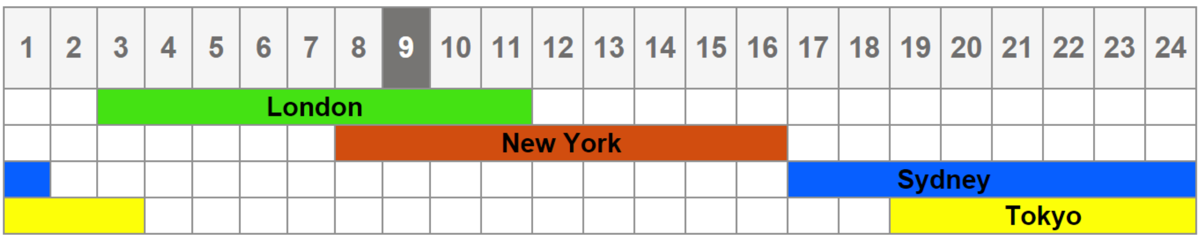

Figure 1.1: Timings of different forex markets [20]

As shown in Figure 1.1, there are some hours when the trading sessions overlap – New York and London (between 8:00 am to 12:00 noon EST), Sydney and Tokyo (between 7:00 pm to 2:00 am EST), London and Tokyo (between 3:00 am to 4:00am EST). The best time to trade is when the market is the most active and therefore has the biggest volume of trades. Actively traded markets will create a good chance to catch a good trading opportunity and make profits. The highest volume of trades occurs during the overlapping sessions.

1.2 Factors affecting FOREX

The FX market affected by a variety of factors which include inflation, rate of interest, capital account balance, role of speculators, cost of manufacture, debt, gross domestic product, political and economic stability, employment, macroeconomic and geopolitical events [15].

Inflation: If the rate of inflation in the India is lower than other countries comparatively, then Indian exports will increase. There will be an increase in demand for Rupee to buy Indian goods. Also foreign goods become cheaper and so Indian citizens will pay less ultimately import decreases. Therefore lower inflation rates tend to see an appreciation in the currency value of any country.

Rate of Interest: If rate of interest in India increase relatively to other countries, it will become attractive to invest money in India. Investor will get a higher return from saving in the Indian banks. Therefore demand for Indian Rupee will rise. Higher interest rate reduces purchase power of the consumer while the loan borrowers have to pay more interest.

Capital Account Balance: Countries having surplus in their financial account are benefited than countries with deficit. They can attract more capital from other countries and can see appreciation in the currency value relative to the countries with capital account deficit.

Speculators: Speculator is a person who takes more risk in investment, and can do a major change in the future price of the asset. If they believe the Indian Rupee will increase in near future, they start demanding Rupee now to earn profit in future. This kind of demand causes Indian Rupee value to rise. Such movement doesn't reflect any economic fundamentals; they are only due to positive sentiments of the financial markets.

Cost of Manufacture: If the country can produce goods at more economical rate, they can sell goods at attractive price. In anticipation to low rate export increases and in effect of this value of currency also increases. China is the best example of competitive market for economical goods in the world. It gives rise to the currency of any country in longer term.

Debt of country: Countries' spending more on public sector projects and fund for social upliftment of the society has more debt on the country. Such spending stimulates the domestic economy. Countries with higher public debt are not attractive to foreign investors. Because higher debt of the country leads to higher inflation ultimately increases debt to control inflation.

Gross Domestic Product: GDP gives best measure of health of country's economy. It is the number calculated by consolidation of total expenses of government, money spent by business, private consumption and exports of the country. Increment in GDP indicates economic growth. Foreign investors get attracted towards the countries with economically strong countries with good GDP. It leads to better valuation of the currency of the country because more and more money comes to the country.

Political Stability and Economic Performance: Countries with stable government can give better growth in economy through completion of the projects in hand. Investors invest their money in the countries with strong economic performance. As India has coalitions government and no party has got full majority so there are lot of problems for stability of the government and the government can't take decisions strongly. So, it causes loss of confidence in foreign investors. It affects economic growth and money moves out of the country.

Employment Data: Employment data indicates level of prosperity of economy. In most cases the value of currency increases as the number of unemployed people decreases. But sometimes high employment increases purchase power parity of the people and can lead to higher inflation in the country, so it can adversely affect valuation of the currency.

Relative strength of other currencies: Currency valuations are also equally affected by global parameters. A country's economic strength is compared with other countries strength and if other countries are strong money moves to those countries. It ultimately reduces valuation of the country with comparatively poor health of the economy.

Macroeconomic and geopolitical events: In the case of events like elections, wars, monetary policy changes, financial crisis, currency of the country is highly affected. Such macroeconomic and geopolitical events also affect other parameters. These events have the ability to change or reshape of the country including fundamentals of the country. For example, wars can put a huge economic strain on a country and greatly increase the volatility in a region, which could impact the value of its currency. It is important to keep up to date on these macroeconomic and geopolitical events.

1.3 Motivation

Until recently, FOREX trading in the currency market had been the domain of large financial institutions, corporations, central banks, hedge funds and extremely wealthy individuals. The emergence of the internet has changed all of this, and now it is possible for average investors to buy and sell currencies easily with the click of a mouse through online brokerage accounts. Banks, investment managers, hedge funds, corporations and individual investors are the traders in the FOREX market [3].

Banks: The greatest volume of currency is traded in the interbank market. This is where banks of all sizes trade currency with each other and through electronic networks. Big banks account for a large percentage of total currency volume trades. Banks facilitate forex transactions for clients and conduct speculative trades from their own trading desks. When banks act as dealers for clients, the bid-ask spread represents the bank's profit. Speculative currency trades are executed to profit on currency fluctuations.

Central Banks: Central banks are extremely important players in the forex market. Open market operations and interest rate policies of central banks influence currency rates to a very large extent. Central banks are responsible for forex fixing. This is the exchange rate regime by which a currency will trade in the open market. Floating, fixed and pegged are the types of exchange rate regimes. Any action taken by a central bank in the forex market is done to stabilize or increase the competitiveness of that nation's economy. Central banks (as well as governments and speculators) may engage in currency interventions to make their currencies appreciate or depreciate. During periods of long deflationary trends, for example, a central bank may weaken its own currency by creating additional supply, which is then used to purchase a foreign currency. This effectively weakens the domestic currency, making exports more competitive in the global market.

Investment Managers and Hedge Funds: After banks, portfolio managers, pooled funds and hedge funds make up the second-biggest collection of players in the forex market. Investment managers trade currencies for large accounts such as pension funds and endowments. An investment manager with an international portfolio will have to purchase and sell currencies to trade foreign securities. Investment managers may also make speculative forex trades. Hedge funds execute speculative currency trades as well.

Corporations: Firms engaged in importing and exporting conduct forex transactions to pay for goods and services. Consider the example of a German solar panel producer that imports American components and sells the final goods in China. After the final sale is made, the

Chinese yuan must be converted back to euros. The German firm must exchange euros for dollars to purchase the American components. Many companies trade forex to hedge the risk associated with foreign currency translations. The same German firm might purchase American dollars in the spot market, or enter into a currency swap agreement to obtain dollars in advance of purchasing components from the American company in order to reduce foreign currency exposure risk.

Individual Investors: The volume of trades made by retail investors is extremely low compared to that of banks and other financial institutions. But the forex trade is growing rapidly in popularity. Retail investor's base currency trades on a combination of fundamentals (interest rate parity, inflation rates, monetary policy expectations, etc.) and technical factors (support, resistance, technical indicators, price patterns).

1.4 Problem Definition

Current systems employ various methods to predict the future FX rates. Some of the common methods include statistical analysis, time series analysis, etc. Some of the modern methods used are fuzzy systems, neural networks, hybrid systems, etc. These methods suffer from the problem of accurately predicting the exchange rates with low accuracy and precision. Among the various methods, hybrid systems show better performance.

To increase the accuracy of predicting the future rates, a hybrid system comprising of an Artificial Neural Network (ANN) and an Adaptive Neuro Fuzzy Inference System (ANFIS) is proposed. The ANN will predict the trend of the FOREX market while the ANFIS model will be used to predict the future rate accurately.

1.5 Scope

This dissertation aims to predict the next 15 day's trend as well as exchange rate for the US Dollar to Indian Rupee (USD/INR) currency pair. In order to predict the trend and rate accurately, it is imperative to obtain historical exchange rates for the said currency pair. The collected data is then divided to form a training set which is roughly 75% of the records while the rest is used for testing the models for accuracy. The combined hybrid system will provide a flexible and robust system which can help forex traders to gain higher profits.

1.6 Objective

The objective of this dissertation is to predict future exchange rates with higher accuracy and precision. By using two different methods, i.e. a Neural network and a Hybrid system, a more accurate and robust method can be developed. An Artificial Neural Network (ANN) is used to predict the rise and fall of the FOREX market while an ANFIS system is used to predict the future rate. This is done mainly for individual investors who have neither the funds nor the tools to compete with the big players. The proposed system gives such traders a boost in the trading market.

1.7 Organization of the Report

The report is organized in 2 parts – part 1 and part 2. Part 1 consists of the review of literature which talks about the various methods used in the past. It also talks about the drawbacks of the existing systems. Part 2 consists of chapters 3, 4 and 5. Chapter 3 explains the proposed system in detail. Chapter 4 describes the implementation, analyses the results of the experiments and compares them with the existing systems. The last chapter draws conclusions from the previous works and the experiment results. It also discusses the future possibilities of the existing system and how it can be improved.

Chapter 2

Literature Survey

Kodogiannis and Lolis use Neural Networks and fuzzy systems to predict the foreign exchange rates in [6]. The methods used were a Multi-Layer Perceptron (MLP) neural network with standard Back Propagation (BP), Radial Basis Function (RBF), Autoregressive Recurrent Neural Network (ARNN), Modified ELMAN network and an Adaptive Fuzzy Logic System (AFLS) with Bisector of Area (BOA) defuzzification. The dataset for US Dollar (USD) to British Pound (GBP) comprises 1000 daily rates from end of 1997 to end of March 2000. The MLP uses two hidden layers and 5 inputs were used. RBF uses past 5 values as input and uses zero-order regularization Orthogonal Least Squares (OLS) to model the problem. ARNN uses two hidden layers with sigmoidal transfer functions and a single linear output node. Recurrency is used only in the first hidden layer. Modified Elman method uses 4 inputs, 2 hidden layers (16 and 24 nodes respectively) and a single output node with self-feedback in 16 context units and α equal to 0.25. The AFLS system uses multiple inputs and gives multiple outputs and a BOA defuzzification technique. Based on the Percent Relative Error, Root Mean Square Error (RMSE) and Standard Error Deviation, the AFLS system performs better than the other systems.

In [7], Abraham uses various hybrid soft and hard computing techniques. Soft computing techniques considered are – Neural Network (NN), and a Neuro-Fuzzy model. The hard computing methods used are – Multivariate Adaptive Regression Splines (MARS), Classification and Regression Trees (CART) and a hybrid CART-MARS technique. Exchange rates of Australian Dollar (AUD) with respect to US Dollar, Singapore Dollar, New Zealand Dollar, Japanese Yen and United Kingdom Pound are used for the period between January 1981 and April 2001. 70% of the data is used in testing while the rest is used in testing and validation. The Neural Network is trained using the Scaled Conjugate Gradient Algorithm (SCGA). The Adaptive Neuro Fuzzy Inference System (ANFIS) implementing a Takagi-Sugeno type FIS was modified to give multiple outputs. The MARS model is a spline regression model that uses a specific class of basis functions as predictors in place of the original data. CART is a tree based model useful for both classification and regression problems. CART is the most advanced decision-tree technology for data analysis, pre-processing and predictive modelling. A cooperative model is used where the forex values are fed to CART to provide some additional variable information to MARS. For modelling the forex data, we supplied MARS with the node information generated by CART. Based on the RMSE values of the test set, the hybrid CART-MARS system works better on a one pass training approach in terms of speed and accuracy. Soft computing models are more robust based on the easy interpretability of the neuro-fuzzy models.

In [8], Alizadeh, Rada, Balagh, and Esfahani use Multiple Regression, Neural Network, Sugeno-Yasukawa and ANFIS to forecast the exchange rates for US Dollar against Japanese Yen. Sugeno-Yasukawa approach produces a fuzzy model with 6 rules, 6 inputs, and 1 output. The inputs are the same as with the ANFIS model. A 10×5×1 feedforward multi-layer network with gradient descent learning algorithm is used with a tangent sigmoid activation function is used in each node. Based on the RMSE and mean error of the prediction (BIAS), ANFIS performs better than the other approaches. Performance of ANFIS and ANN are comparable, however, ANFIS provides a more meaningful presentation of rules that is not possible with ANN.

Pacelli, Bevilacqua and Azzollini use an optimal MLP neural network designed and tested by a multi-objective Pareto-based genetic algorithm to predict the trend of the exchange rate between US Dollar and Euro in [9]. Data for the Euro-Dollar exchange rates were collected from January 1999 to December 2009. The optimal MLP neural network topology has been designed and tested by means the specific genetic algorithm multi-objective Pareto-Based designed from Bevilacqua et al. [64], taking into account number of neurons for layer, number of layers and activation functions of all neurons per each layer. The first two ANN are designed with the construction technique trial and error and the third network with optimized construction technique mentioned above in para-graph 5. The third topology neural network designed with an optimized construction technique gives the best performance since it classifies correctly 120 examples of 120 in the training phase (performance of 100%) and 32 examples of 40 during validation (performance of 80%). The results show that the ANN can predict the trend of the exchange rate of EUR/USD to three days.

Kordos and Cwiok use an MLP neural network to determine the optimal buy and sell time on a stock exchange in [10]. The inputs in the training set consist of past stock prices and a number of technical indicators. The buy and sell moments on the training data that will become the output to the neural network. The training set has 15 features consisting of price change, simple moving average, rate of change, relative strength index, commodity channel index, stochastic oscillator and average true range along with the candle and shooting star formations. Experiments were conducted with four stocks of the USA market – Amazon, Apple, Microsoft and Yahoo. The training set comprised the data from 1/1/1995 to 12/31/2004 and the test set the data from 1/1/2005 to 1/1/2008. Two separate networks are used - one is trained to recognize the buy signals and the other one to recognize sell signals. A multilayer perceptron with two hidden layers and with hyperbolic tangent activation functions in all layers is used. Three learning algorithms – standard back propagation with momentum, modified back propagation and variable step search algorithm are used to train the system. The modified back propagation algorithm is more efficient in terms of convergence for a solution.

In [11], Gharlegi and Nor use a hybrid neuro-fuzzy system to forecast the exchange rate of Malaysian Ringgit against the US Dollar. Along with the neuro-fuzzy system, a neural network and random walk algorithm are also implemented. Monthly data from the Thomson Data Stream database from January 1998 to September 2010 were obtained. A total of 153 observations are used for each variable. The data set is divided into two parts. The first group of the data (129 observations) is utilized for training purpose and the second group of the data (24 observations) is utilized for prediction purpose. According to the relative price monetary model of exchange rate determination, money supply, national income, interest rate, inflation, and customer price index as well as producer price index are the variables that determine the behaviour of exchange rate. These variables were used as inputs for the neuro-fuzzy system and neural network. M2 is used as a representative for money supply, Industrial Production Index used as a proxy for national income due to the lack of availability of monthly data for national income. Federal fund rate is used for interest rate, other variables are used as they presented above. Output variable is the monthly return of the Malaysian Ringgit over USD exchange rate. To compare the performance of the models, four parameters are used – Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Variance Proportion (VP). The results show that the intelligent systems – neural network and neuro-fuzzy system outperform the random walk model in forecasting. The neuro-fuzzy system performs better than the neural network due to the fuzzy rule base system that incorporates the macroeconomic relationships among the variables. However, the intelligent systems are more accurate over a short-term forecasting.

Embrechts, Gatti, Linton, Gruber and Sick forecast the exchange rates by using an ensemble neural network and ensemble Kernel Partial Least Squares (K-PLS) method in [12]. Neural network forecasting methods are first compared on a benchmarked neural network time series prediction method for the Canadian Lynx time series. The K-PLS method is benchmarked in addition with support vector machines (SVM), a similar kernel-based method. Both one-step ahead and a rollout method for extended forecast horizons are applied for the currency exchange rates. Three different daily currency exchange rates are used. US Dollar per Indian Rupee for the period January 1, 2010 to December 14, 2011, US Dollar per Euro for the period January 1, 2010 to December 22, 2011 and the Australian Dollar per Euro for the period January 1, 2010 to December 22, 2011. For all-time series 669 data points (samples) were used for training and the remaining data from November 1, 2011 thereafter, 41 points, 51 and 51 points, respectively, were used for out-of-sample testing purposes. Performance metrics used are RMSE, q^2 and Q^2. The q^2 and Q^2 metrics are commonly not used for time series prediction validation, but are very appropriate because they are meaningful independent of the domain of the data and scaling. The RSME errors are the same for all the roll-out prediction methods, but that the K-PLS ensemble averaging has the best q^2 and Q^2 metrics, while the neural network ensemble averaging with weight initialization has the least number of misses in the number of buy/sell forecasts. It was found that the US per IR is quite predictable, while the USD per Euro is not predictable. The Australian Dollar (AUD) per Euro is somewhat predictable in a one-day-ahead mode, but not for long-term forecasts. The implementation on Le Cun's Efficient Back propagation, and refinements to this algorithm, are essential to be able to automate the neural network ensemble methods without modifying the learning parameter during training.

Kia, Fathian and Gholamian use MLP and RBF Neural Networks to improve prediction of the exchange rate using Autoregressive Integrated Moving Average (ARIMA) in [13]. ARIMA model is represented with the structure of ARIMA (p, d, q), where p is the auto regression factor, d is the integration factor, and q is the moving average factor. Initially the ARIMA model predicts the exchange rate and the error from that process is then given to the

MLP. The MLP model the error and the result of the MLP model is given as input to the RBF neural network. RBF neural network tries to catch the reminder error that could not be modeled by MLP because of its different nature and structure from RBF. This time the output of ARIMA model will be added to the output of the MLP and the remainder of this result is the real exchange rate. The method is evaluated using RMSE and directional success (D-stat). The time series of Euro to US Dollar exchange rate is used for the model design, validation and testing. The data is taken from the Federal Reserve Bank of St. Luis, economic research center's website. The dataset consists of 3440 daily exchange rate data in the dataset from 1 April 2001 to 31 July 2010. The days without data were padded with the average exchange rate value of the last three days. For the neural network learning purpose we used up to 7 days before as input of the network to predict the next day. A 7 days delay because of the weekly seasonal behavior of the exchange rate market. Data is partitioned using a 7:2:1 ratio for training set, validation set, and test set. The ARIMA model that best modeled the exchange rate time series was ARIMA (1, 1, 4). The multilayer perceptron that fitted the model was MLP (7-6-5-1). It means the network had 7 inputs, the exchange rate of 7 days before and two hidden layers with 3 and 2 nodes and 1 output node. The RBF that fitted the model was RBF (7-9-1). It means this RBF neural networks had 7 input nodes which was the data of 7 days before the day we wanted to forecast and 9 nodes in the hidden layer and 1 output node. The results show that the hybrid model performs better than the other single models in terms of error and directions status.

In [14] Fallahzadeh and Montazeri use a hybrid neuro-fuzzy system that is based on interval type-2 fuzzy c-means clustering to forecast the exchange rates. The proposed system uses interval type 2 (IT2) fuzzy sets for the antecedent part and an MLP network. IT2 fuzzy c-means is used for clustering data and finding range of center within each membership function. A Takagi-Sugeno-Kang (TSK) model is used for the consequent part of the rules. Along with the hybrid system, type-1 implementation of the system (T1FCMFNS) which is a combination of fuzzy c-means based type-1 fuzzy system with MLP neural network and another model (FLIT2FNS), an IT2 fuzzy system without clustering combined with FLANN neural network is compared. Exchange rates for two currency pairs – Euro to US Dollar and US Dollar to Swiss Franc are used from April 2005 to December 10 2012. The dataset includes 2000 records of which 80 percent are used in training and rest is used for testing. Each data point in the dataset consists of three indices. Closing price, %K and %D indices are used as inputs. %K and %D are stochastic indicators [5] [22] [23]. The MLP part of neuro-fuzzy system is made with one hidden layer contains 20 neurons. 50 epochs are used for training. For the forecasting of Euro to US Dollar, 7 rules are used while for the US Dollar to Swiss Franc 6 rules are used. MSE and convergence rates were used as performance measures of the system. The proposed neuro-fuzzy system, which combines an IT2FCM based type-2 fuzzy model with an MLP, outperforms the other methods and gives a more accurate one day ahead prediction.

Chandar, Sumathi and Sivanandam use a neural network based method to forecast the exchange rates in [16]. The neural network used is trained using three different learning algorithms – Batch Gradient Descent, Batch gradient descent with adaptive learning and a Resilient Back Propagation Algorithm. The neural network uses 1 input and gives 1 output. The hidden layer consists of 4 hidden neurons. The neurons in the hidden layer use a tansig transfer function and the output neuron uses a linear transfer function. Real data from January 2008 to December 2012 was collected from the Reserve Bank of India. Four currencies – Pound Sterling, US Dollar, Euro and Japanese Yen against the Indian Rupee are used for prediction. RMSE, MAE and MAPE are used as performance metrics. Resilient Back Propagation algorithms achieved a very close prediction in terms of RMSE, MAE and MAPE metrics. The empirical results suggest that forecasting exchange rates in India can be done adequately by using neural networks since it can better extract the hidden information.

In [17] Beneki and Yarmohammadi use Neural Networks and Singular Spectrum Analysis (SSA) to forecast the exchange rates. The nnetar forecasting function which a system of feed-forward neural networks with lagged inputs and one hidden layer is used. The function trains 25 neural networks by adopting random starting values and then obtains the mean of the resulting predictions to compute the forecasts. There exist two variations of the basic univariate SSA known as Vector SSA (VSSA) and Recurrent SSA (RSSA). The data used are the daily exchange rates in the United Kingdom, European Union, and China against the US Dollar between the dates 03/01/2012 and 01/03/2013. For training, roughly 2/3rd of the observations (192 observations) were used while the remaining 1/3rd (100 observations) were used in testing. Root Mean Square Error (RMSE) and Direction Change (DC) are used as measures for evaluating the accuracy of the system. For 1 and 3 steps ahead forecasting of the United Kingdom and European Union currencies, the neural network outperform both the basic VSSA and RSSA for all horizons. For the Chinese currency, VSSA and RSSA outperform the neural network. For 1 day ahead forecasts, VSSA is better than RSSA while for 3 day ahead forecasts RSSA performs better than VSSA. For forecasting exchange rates in UK and EU there is no real difference between the accuracy of any of the models. The basic VSSA model is 67% better than Neural Network with 95% confidence for 1 day ahead forecast and 68% better with 99% confidence for 3 day ahead forecast for the Chinese exchange rate. The NN model provides the worst DC prediction in comparison to Basic VSSA and Basic RSSA models. For UK, the Basic VSSA model provides the best DC prediction for 1 and 3 days ahead. For EU, Basic VSSA has the most favorable DC prediction at one step ahead, but NN appears to have the best DC prediction ability at three steps ahead. For China we see that Basic RSSA records the best DC prediction for 1 step ahead whilst Basic VSSA provides the best DC prediction at three steps ahead.

Chapter 3

Proposed System

The proposed system uses a combination of Artificial Neural Network (ANN) and a hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS). The ANN is used to predict the trend of the market while the ANFIS model will predict the actual change in price of the exchange rate. The forecast of currency exchange rate is done for the Indian Rupee (INR) against the US Dollar (USD). The proposed system is used to predict the trend and exchange price of the current day as well as for the next 2 weeks i.e. it does a prediction for 15 days ahead.

3.1. Artificial Neural Network

A neuron circuit (or processing element) is the fundamental building block of a neural network. A neuron circuit has multiple inputs and one output. The structure of a conventional neuron circuit often includes a multiplier circuit, a summing circuit, a circuit for performing a non-linear function (such as a binary threshold or sigmoid function), and circuitry functioning as synapses or weighted input connections [26].

An Artificial Neural Network is defined as a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs [24]. Neural networks are based on a simple model of neuron, called the formal neuron. It is directly inspired from the real neuron present in our nervous system. A real neuron usually consists of three parts: a dendrite, body and an axon. The dendrite receives inputs from other neurons or from an external stimulus. A soma (cell body) performs a non-linear processing of the signals from the dendrites. An axon transmits the output signal to other neurons or organs. The junctions that allow signal transmission between the axons and dendrites are called synapses. The process of transmission is by diffusion of chemicals called neurotransmitters across the synaptic cleft [25].

Similarly, the formal neuron works in three steps: an integration step, a non-linear step and a propagation step. During the integration step, all inputs x_i are weighted with parameters $w_{i,j}$. The non-linear step transforms the weighted sum of inputs into a non-linear function, depending on the type of output the network should provide. In the propagation step, the output is propagated to subsequent neurons or objects.

An Artificial Neural Network takes the inputs and based on the weights of the connections to the neuron, calculates the firing strength of than neuron. The network may contain one or more hidden layers that have two or more neurons in each layer. The output of each of the neurons acts as inputs to the subsequent layer. The final output layer calculates the output based on the inputs of the preceding layer.

3.1.1 Structure of the Neural Network

The proposed Artificial Neural Network system is used to predict the trend of the market. The structure consists of four inputs, one hidden layer with 5 neurons and a single output neuron as shown in Figure 2. The inputs given to the system are – Closing Price (CP) of the previous day, Simple Moving Average (SMA), Exponential Moving Average (EMA) and Rate of Change (ROC). The ANN makes use of a Standard Back Propagation Algorithm which implements the generalized delta learning rule [19].

The input vector (z_{4x1}) is taken as the combination of the four inputs. The hidden layer weights (V_{5x4}) and output layer weights (W_{1x5}) are initialized to small random values. The activation function of each neuron is given by equation 1. The output of the hidden layer is given by y_{5x1} in equation 2 and the value of the output layer is given by o in equation 3.

$$f(net) = \frac{2}{1+e^{-net}} - 1 \tag{1}$$

$$y_j = f(V_j^t z), \quad for\ j = 1,2,3,4,5 \tag{2}$$

$$o = f(W^t y) \tag{3}$$

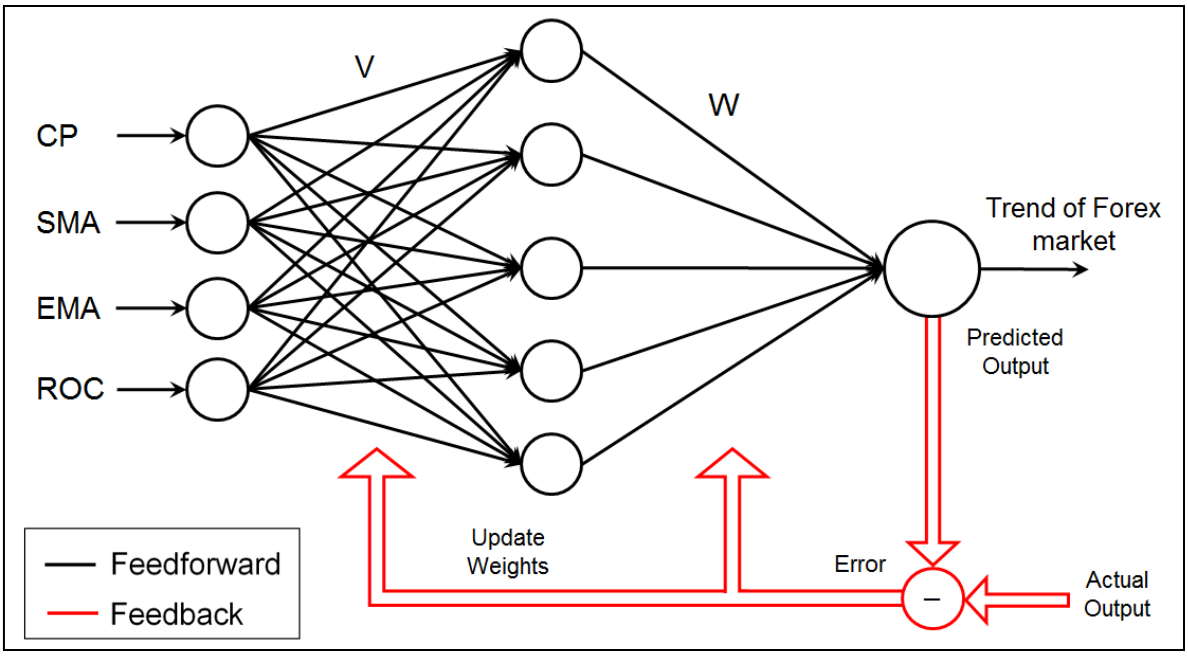

Figure 3.1: Structure of Artificial Neural Network

The desired output or target output is given by d that is used in learning and the feedback phase. The ANN makes use of a supervised learning method and requires a target output so as to calculate the error between the desired and actual values. This error is then used to update the system in the feedback phase. The cumulative cycle error (E) is given by equation 4. The error of the input to output mapping is computed as a sum over all continuous output errors in the entire training set. The learning procedure stops when the final error values is below the maximum error (E_{mac}).

$$E = E + \frac{1}{2}(d - o)^2 \tag{4}$$

During the feedback phase, the error generated by the feedforward phase is used to update the weights of the hidden layer and the output layer. The learning begins with the feedforward recall phase. An input pattern z is submitted and the response o is calculated. The error signal is then computed and propagated backwards towards the input nodes. The weights are first adjusted within the output weight matrix W and then the hidden layer weight matrix V is adjusted. The error signal vectors, δ_o and δ_y, for output and hidden layers respectively are computed as given in equation 5 and 6 respectively.

$$\delta_o = \frac{1}{2}(d-o)(1-o^2) \tag{5}$$

$$\delta_{yj} = \frac{1}{2}(1-y_j{}^2)\sum \delta_o W_j,\ \ for\ j = 1\ to\ 5 \tag{6}$$

After computing the error signal vectors, the weights at output and hidden layer are adjusted by equation 7 and 8 respectively.

$$W_j = W_j + \eta\delta_o y_{j,} \qquad j = 1 to 5 \tag{7}$$

$$V_{ji} = V_{ji} + \eta\delta_{yj} z_{i,} \qquad j = 1 to 5, i = 1 to 4 \tag{8}$$

The input patterns are given one at a time to the ANN. The system is trained for all the input patterns in the training set. The training of the system continues till all the patterns are used. Once all the input patterns are given to the system, the cycle error (E) is checked. If cycle error is more than the maximum error (E_{mac}) then the error is reinitialized to zero and the training cycle is initiated again by giving the input patterns to the system without reinitializing the weights. If the cycle error is less than the maximum error, then the system stops the training. The summary of the system is given in Figure 3.2 as a flowchart.

3.1.2 Input Variables

The Artificial Neural Network takes four inputs – Closing Price (CP), Simple Moving Average (SMA), Exponential Moving Average (EMA) and Rate of Change (ROC). The forex market is open 24 hours a day, however, no individual market is open throughout. There is always some market that is open at some place at all times. The opening price of the particular currency for the week is generally the initial trading price on Sunday and the closing price is the price for the last trade on Friday. The price for an individual market within the forex market usually refers to the opening and closing prices of that individual market. The Closing Price (CP) taken is usually the average of the entire day’s trade for the US Dollar to Indian Rupee (USD/INR) market. The input to the ANN is given as the CP of the previous day to predict the trend of the next day. The remaining three inputs use a period of 14 days as default. For predicting the trend over a short term, the period taken is usually 14 to 25 days [27]. In this approach, a 14 day default period is taken for SMA, EMA and

ROC. A 14 day period is chosen as literature shows that the trend usually tends to change after a 2 week period.

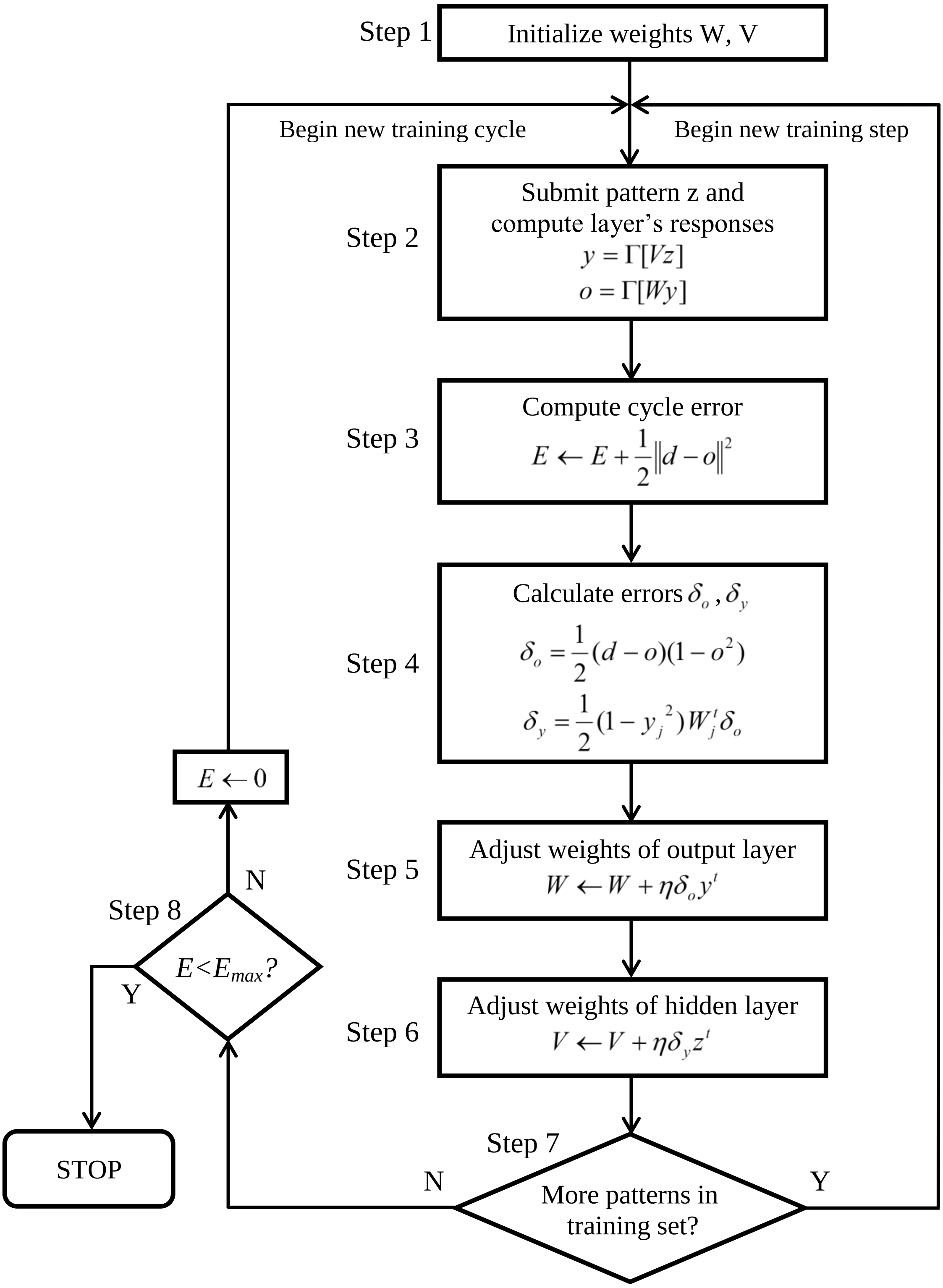

Figure 3.2: Training Algorithm Flowchart [19]

The Simple Moving Average (SMA) is taken by computing the average closing price of the currency over a specific number of periods, in this case, 14 days [5]. The moving average, as the name implies, moves along the time scale. As the SMA moves, the old data is dropped and the new data is included in the average as given in equation 9 [10]. The SMA shows the average value of the currency over time and as a result does not react fast to the changes in the price of the currency. The Exponential Moving Average (EMA) reduces the lag and reacts faster to the change in the price of the currency by applying more weight to the recent prices [5]. EMA makes use of CP as well as SMA to compute the value (equation 10) [10].

$$SMA(t) = \frac{1}{14}\sum_{i=1}^{t} CP_i \tag{9}$$

$$EMA(t) = \frac{2}{n+1}CP_t + (1-\frac{2}{n+1})SMA(t) \tag{10}$$

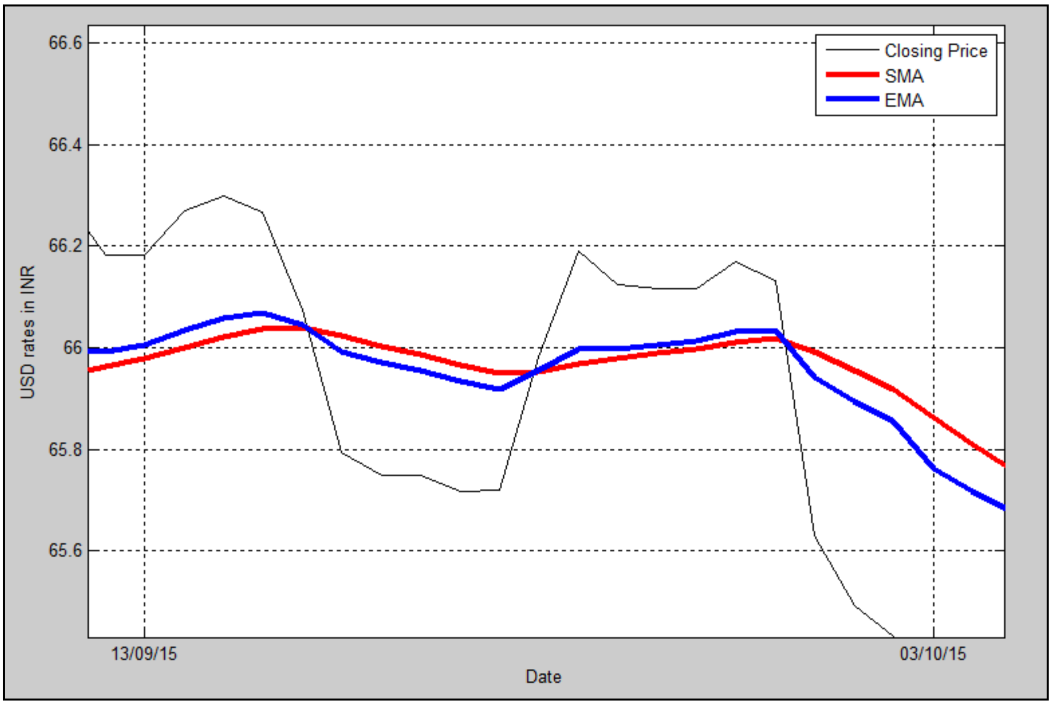

Figure 3.3: Plot of SMA and EMA with Closing Price

The moving averages are used together to generate crossover signals. The EMA moves faster as compared to the SMA. When the two averages cross each other, there is a change in the trend of the market as shown in Figure 3.3. When the price drops, the EMA falls faster than SMA and when the price increases the SMA is slow to react. SMA is a true average rate of the closing prices. When the fast moving EMA crosses the SMA from below, there is a rise in the price. When the EMA crosses the SMA from above, there is a fall in the price.

$$ROC = \left[\frac{(today's\, close - Close\ N\ days\ ago)}{Close\ N\ days\ ago} \right] .100 \tag{11}$$

The Rate of Change (ROC) indicator, also called as momentum, is an oscillator that measures the percent change in the price from one period to the next [5] as shown in Figure 3.4. The ROC calculation compares the current price with the price ‘n’ periods ago (equation 11). The price rises as long as the ROC remains positive and prices fall when ROC is negative. There is no upper limit for ROC, but there is a lower boundary. Prices can only fall by a maximum of 100% to zero whereas there is no limit for increase. Momentum is generally suited to trading ranges or zigzag trends, however, they can also be used to define the overall direction of the trend. The ROC measures the speed at which the prices change.

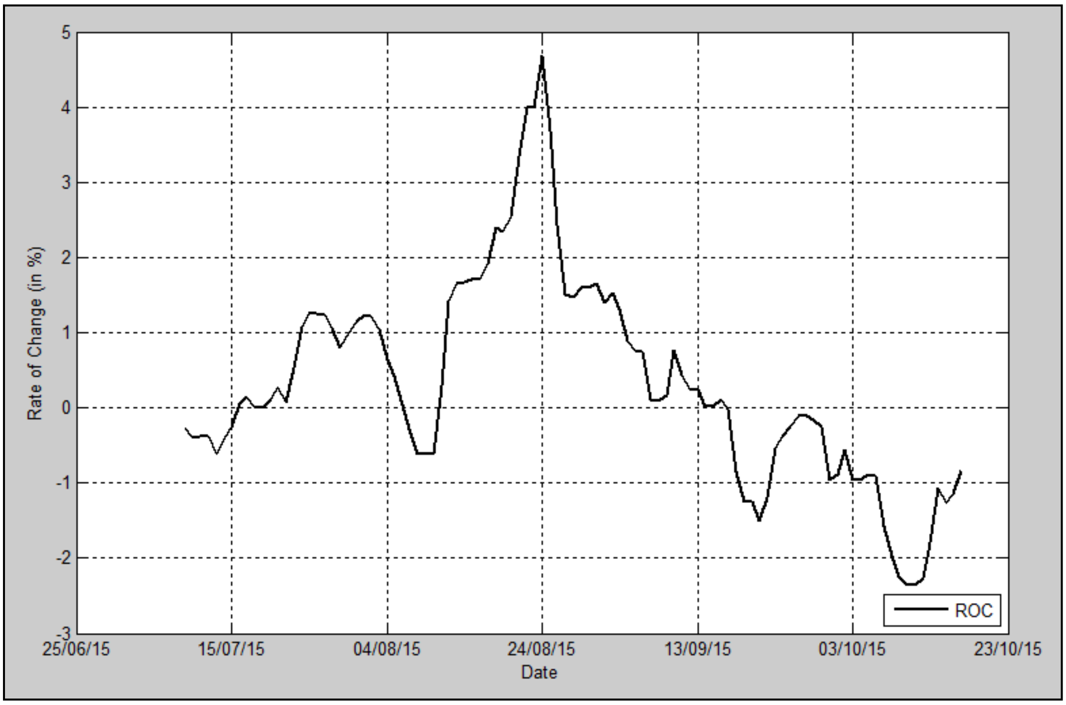

Figure 3.4: Rate of Change

3.1.3 Hidden Layer

The hidden layer of the ANN consists of neurons that act as an intermediate layer between the input layer and output layer. The error generated by the model is determined based on the number of neurons in the hidden layer. The optimal number of hidden neurons is found by experimental method. To find the optimal number of neurons, experiments were conducted by changing the number of hidden neurons from 4 to 10 while changing the learning constant (η) and the momentum (α) from 0.1 to 0.25 and a 0.05 increment per step. Figure 3.5 (a) to (g) shows the result obtained in training the system with different number of hidden neurons. The Mean Square Error values for each training set with different number of hidden neurons and varying Learning rate and Momentum is recorded. The minimum value of MSE for each set of hidden neurons is taken and a comparison of these values shows that 5 hidden neurons give the least MSE at $\eta = 0.1$ and $\alpha = 0.25$ as shown in Figure 3.5 (h).

The hidden layer takes 4 variables as input and along with the hidden weight (V) produces an output y which is then used as the input to the output layer. During the feedforward phase the hidden layer transfers the inputs to the output layer using the activation function defined in equation 1. In the feedback phase, the error generated at the output is propagated backwards towards the input layer. The hidden layer weight (V) is updated using the error signal vector δ_y as shown in equation 8.

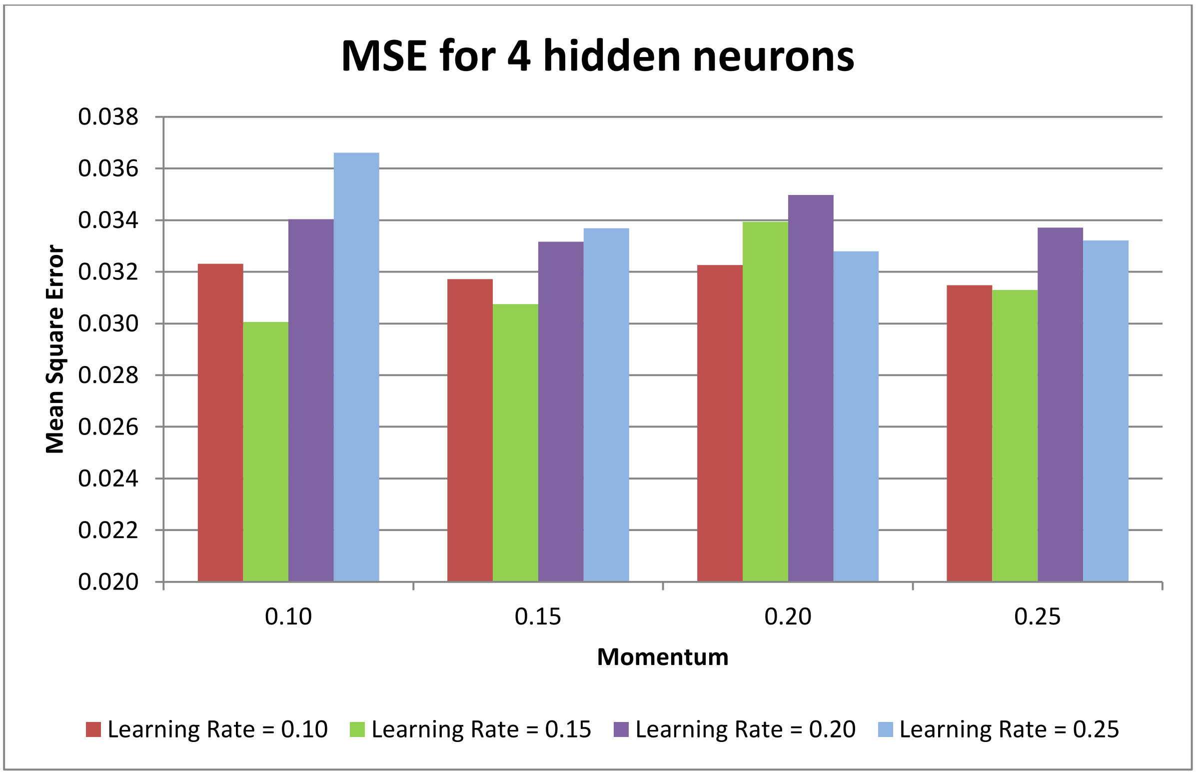

Figure 3.5 (a) Training error for 4 hidden neurons

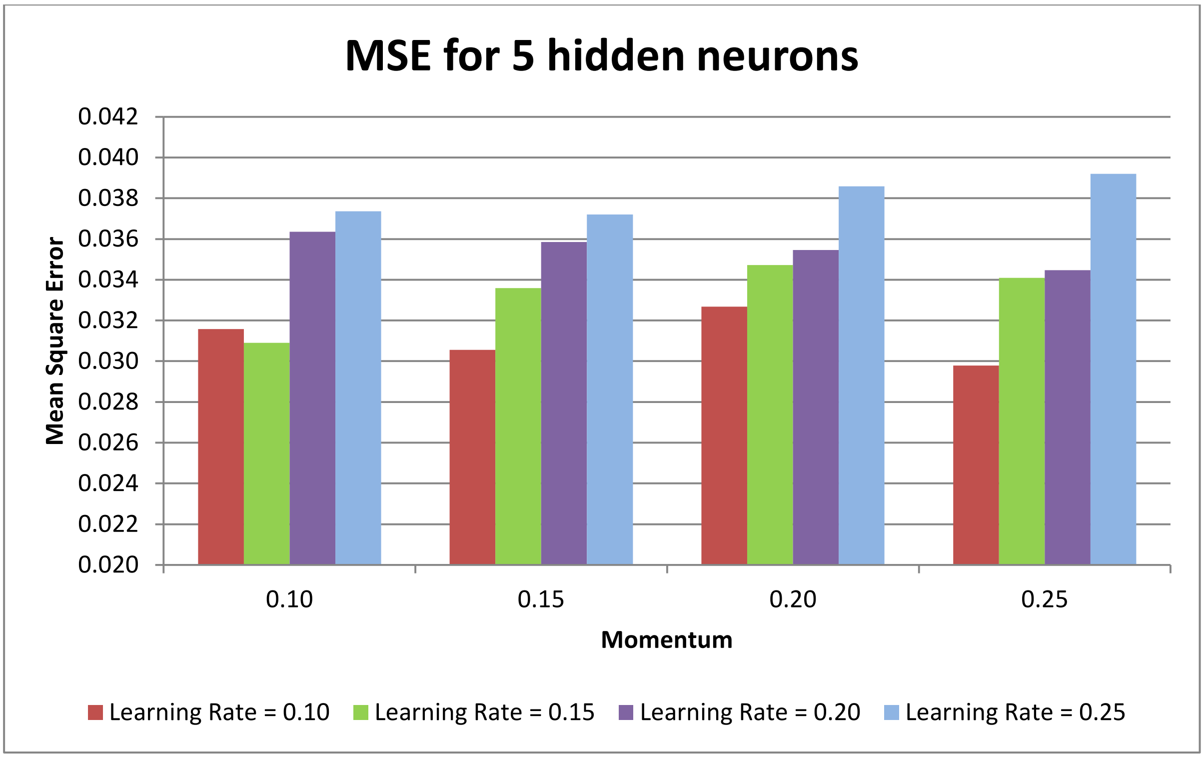

Figure 3.5 (b) Training errors for 5 hidden neurons

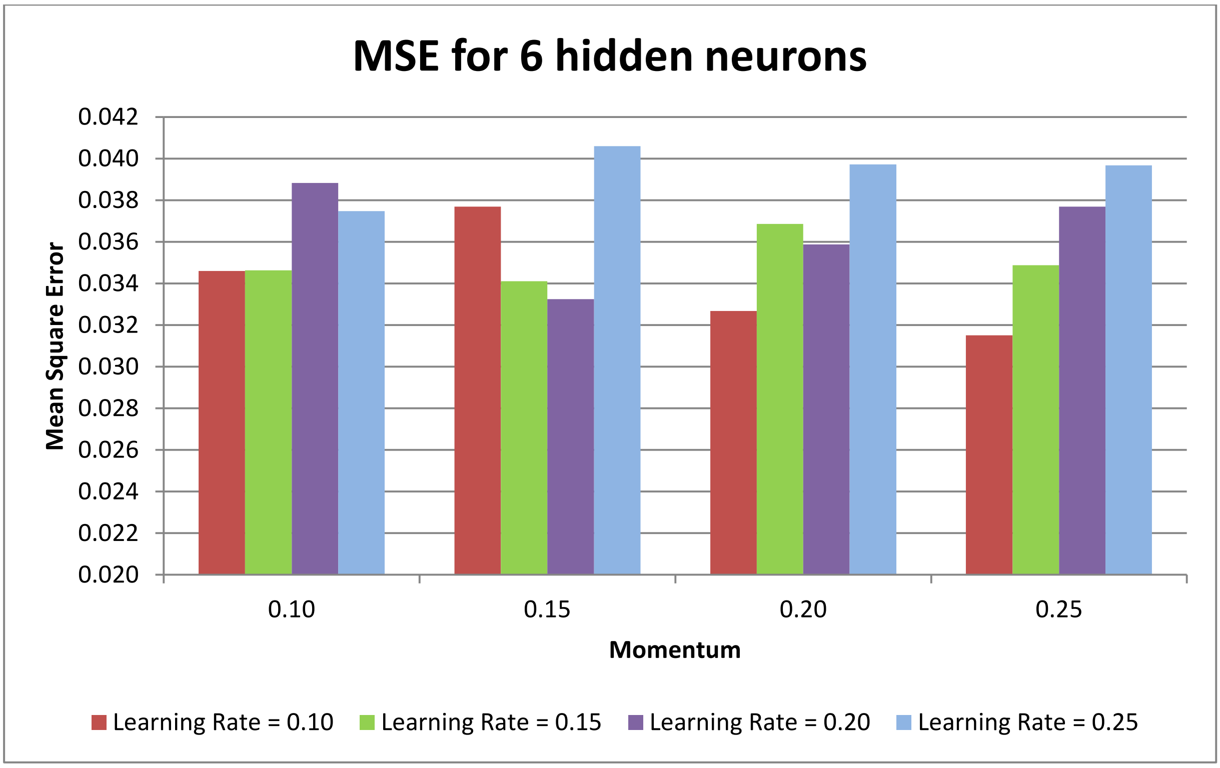

Figure 3.5 (c) Training errors for 6 hidden neurons

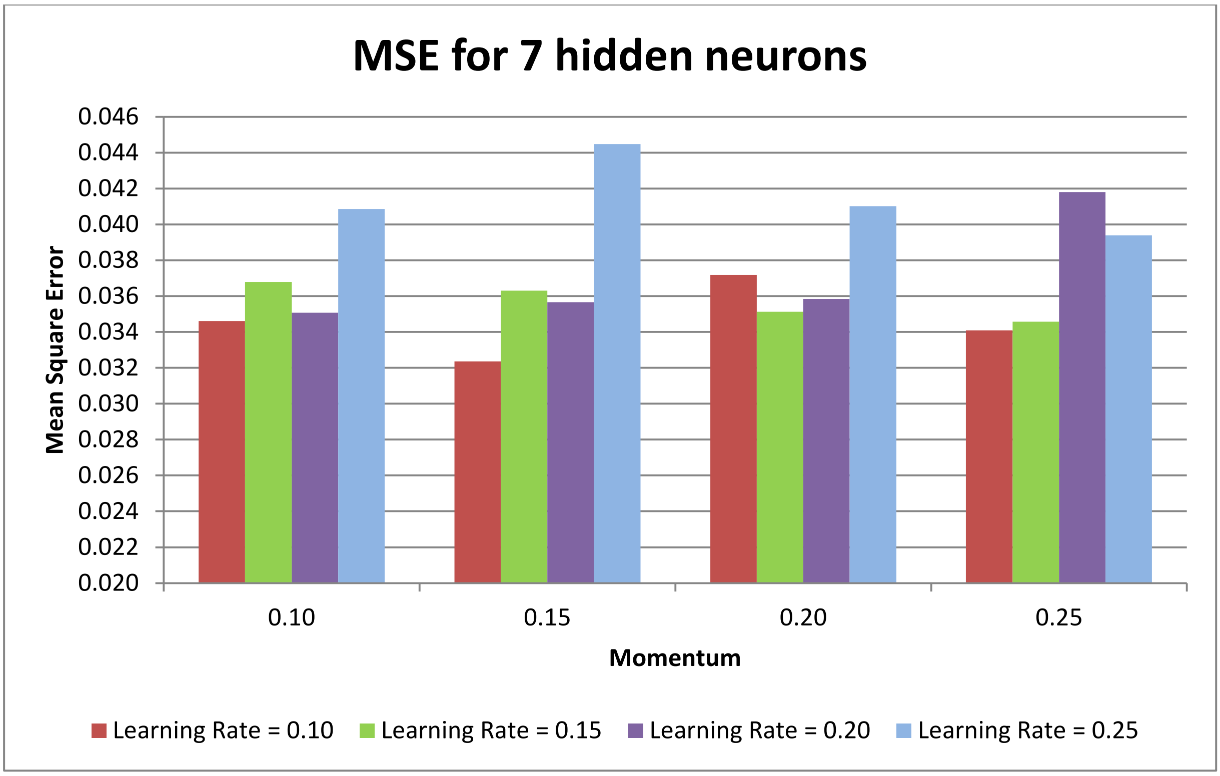

Figure 3.5 (d) Training errors for 7 hidden neurons

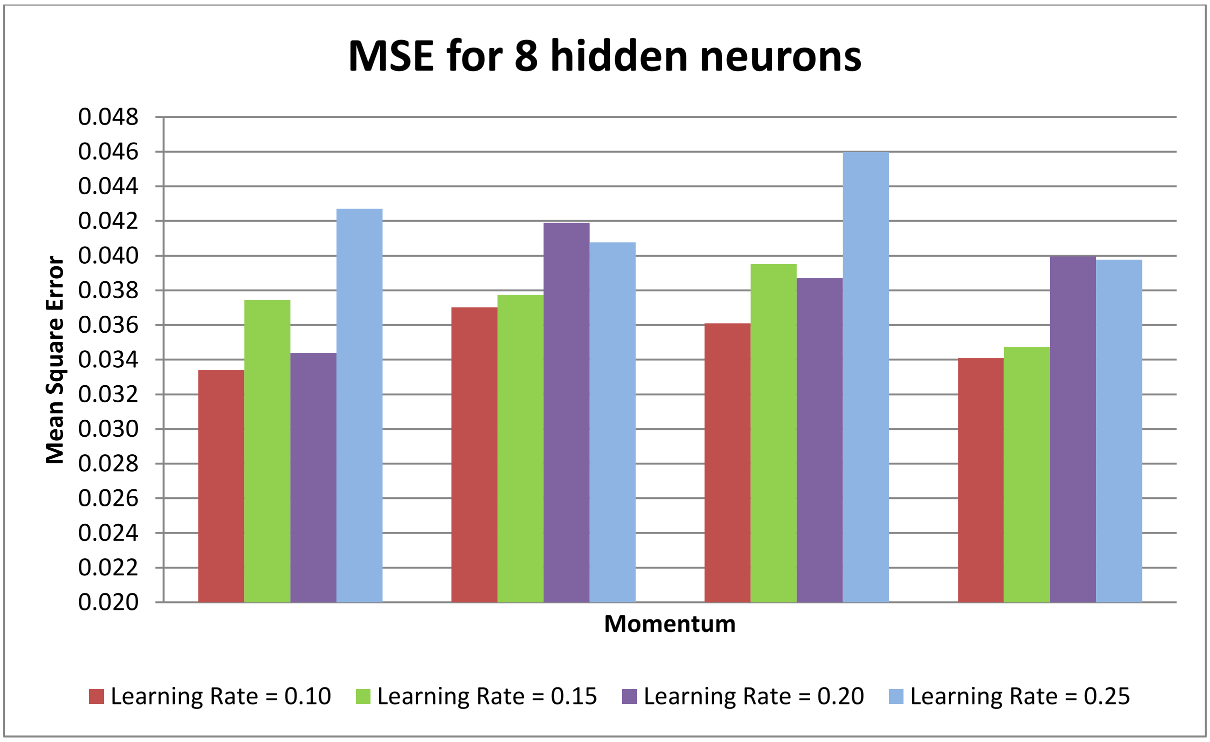

Figure 3.5 (e) Training errors for 8 hidden neurons

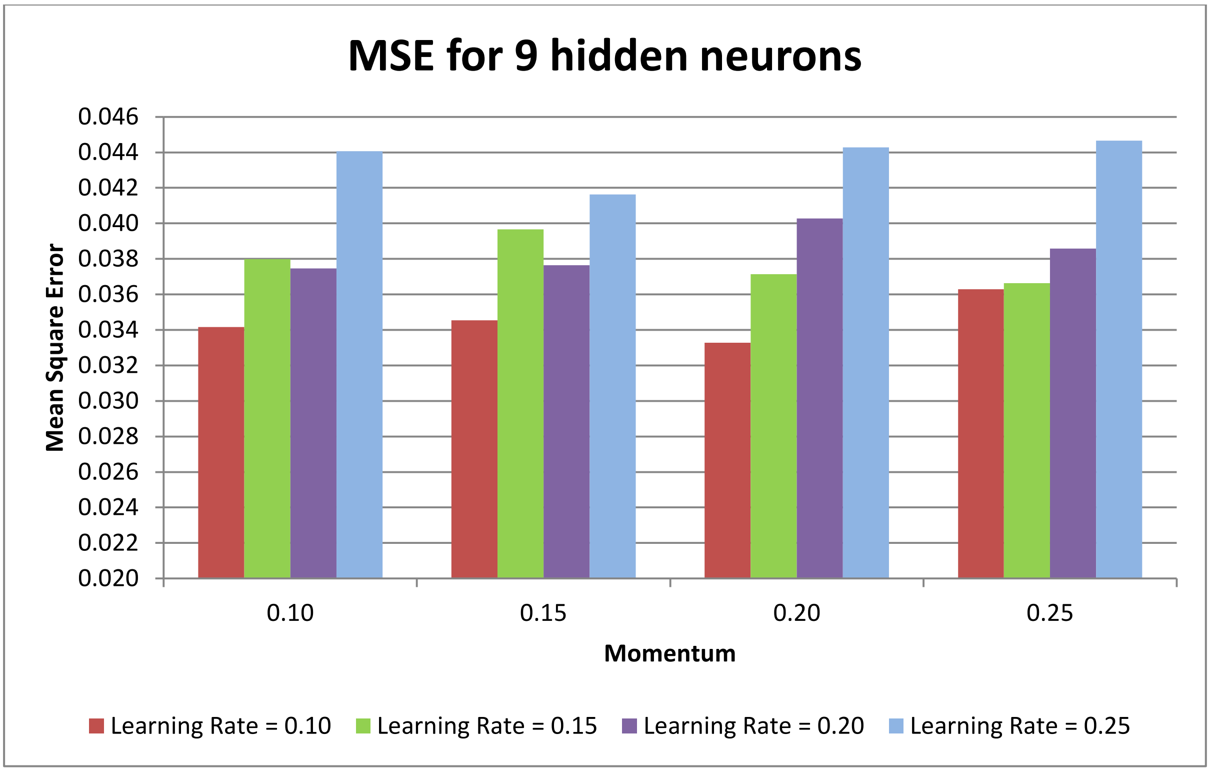

Figure 3.5 (f) Training errors for 9 hidden neurons

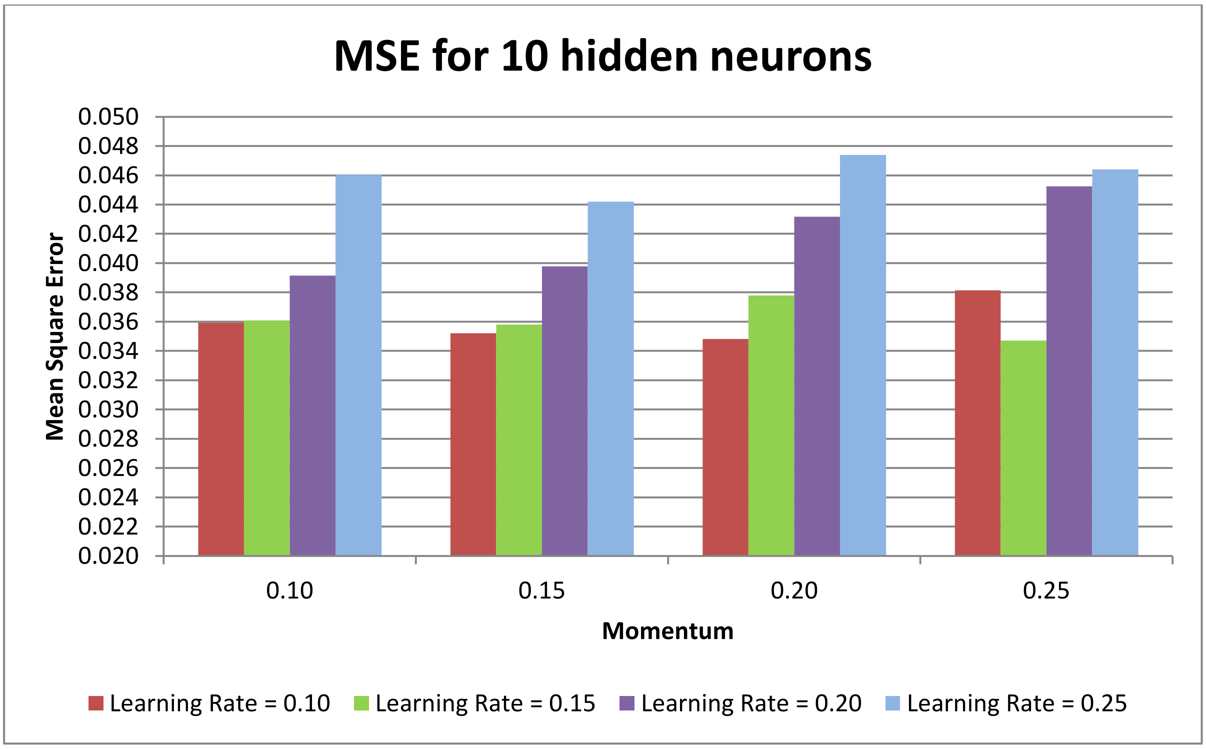

Figure 3.5 (g) Training errors for 10 hidden neurons

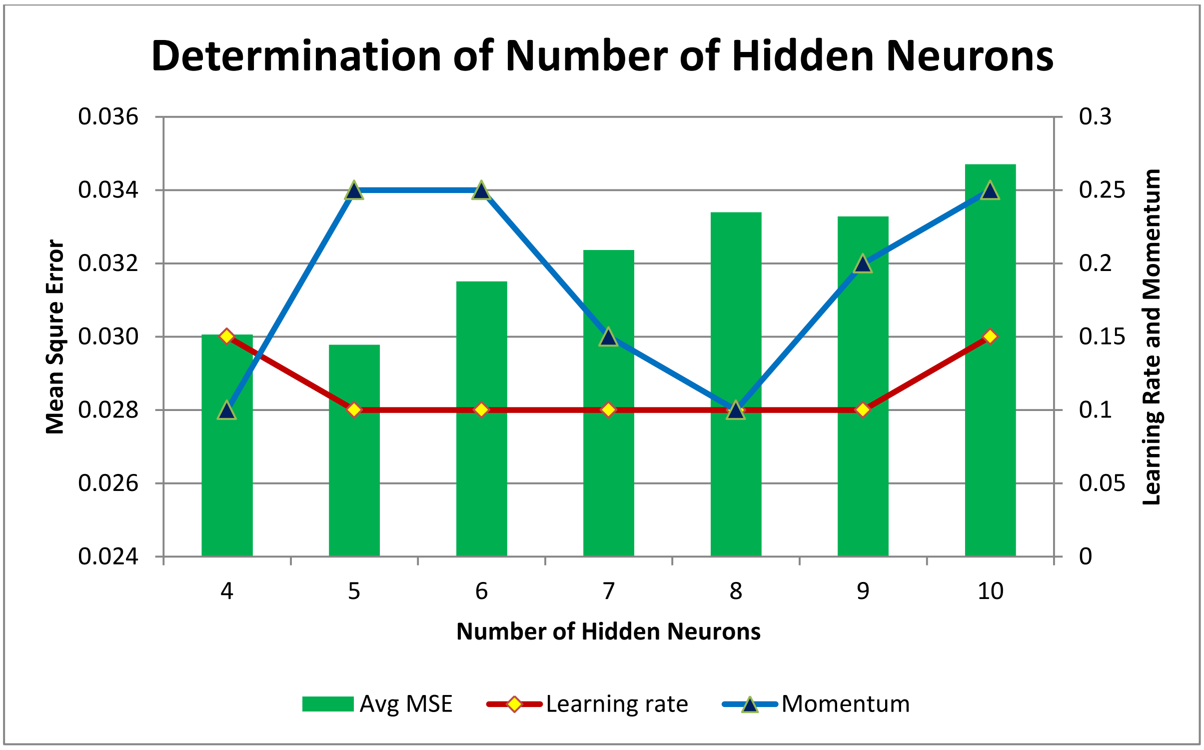

Figure 3.5 (h) Training errors for hidden neurons with varying Learning rate and Momentum

3.1.4 Output Layer

The output layer consists of a single neuron. The input to this neuron is taken from the output of the hidden layer (y). The weights (W) are initialized to small random values at the start of training. In the feedforward phase, the output neuron combines the output of the hidden layer and the weights to predict the trend of the forex market. This output (o) is then compared with the desired output (d) and the error that is generated is propagated backwards to the input layer. The error between the desired output and the actual output helps the system to learn the pattern that is provided as input. The weights of the output layer are then updated using the error signal vector (δ_o) as shown in equation 7.

3.1.5 Learning Factors

As described in section 3.1.1, the ANN utilizes a Standard Back Propagation algorithm called the Error Back Propagation Training Algorithm (EBPTA). This algorithm makes use of a generalized delta learning rule [19] along with gradient descent method. The algorithm uses a learning rate (η) with value of 0.1 and momentum (α) value of 0.25. The weights of the network are typically initialized to at small random values. The initialization strongly affects the ultimate solution. If all weights start out with equal weight values, and if the solution requires that unequal weights be developed, the network may not train properly. The learning based on the single pattern error reduction requires a small adjustment of weights which follows each presentation of the training pattern. This scheme is called incremental updating. The purpose of the momentum method is to accelerate the convergence of the error back-propagation learning algorithm. The method involves supplementing the current weight adjustments with a fraction of the most recent weight adjustment. Typically, α is chosen between 0.1 and 0.8. The size of a hidden layer is one of the most important considerations when solving actual problems using multilayer feedforward networks. The problem of the size choice is under intensive study with no conclusive answers available thus far for many tasks.

3.2. Adaptive Neuro Fuzzy Inference System

Fuzzy logic, neural network and genetic algorithm are complementary rather than competitive for system identification. Therefore it is advantageous to use these techniques in combination amongst themselves rather than exclusively. This gives rise to what is called the hybrid intelligent systems. One of the popular combinations that have been used extensively is the neuro fuzzy hybrid system. The essential part of neuro-fuzzy modelling comes from a common framework called adaptive network which unifies the neural network and the fuzzy model. In this resultant hybrid intelligent system, the neural network has the ability to recognize patterns and adapt to cope with changing environment. On the other hand the fuzzy inference system incorporates human knowledge and performs inference and decision making. The modeling by neuro-fuzzy method is concerned with model extraction from numerical data which represents the dynamic behavior of the system.

An adaptive network, as the name suggests, is a network structure consisting of a number of nodes connected through directional links. Each node represents a process unit, and the links between the nodes specify the causal relationship between the connected nodes. All or part of the nodes are adaptive, which means the outputs of these nodes depend on modifiable parameters pertaining to these nodes. The learning rule of the adaptive network is the steepest descent method in which the gradient vector is derived by successive invocations of the chain rule.

The important steps [29] of the neuro-fuzzy modelling approach are – Fuzzification of the input physical variables, Computation of the degree of satisfaction for the available linguistic terms, Conjunction of the premise and the fuzzy inferred parameters, and

Defuzzification of the output. The steps are realized in sequentially arranged layers of the neural network which has an architecture to adjust the weights in the form of the parameters of the extracted rules. A neuro-fuzzy technique called Adaptive Network Based Fuzzy Inference System or semantically equivalent, Adaptive Neuro Fuzzy Inference System (ANFIS) [18] is proposed to predict the change in price of the USD/INR exchange rate. This ANFIS methodology comprises of a hybrid system of fuzzy logic and neural network technique. The fuzzy logic takes into account the imprecision and uncertainty of the system that is being modeled while the neural network gives it a sense of adaptability. Using this hybrid method, at first an initial fuzzy model along with its input variables are derived with the help of the rules extracted from the input output data of the system that is being modeled. Next the neural network is used to fine tune the rules of the initial fuzzy model to produce the final ANFIS model of the system. After building a model for the system based on ANFIS, the model can be used for forecasting the future values.

3.2.1. Structure of ANFIS model

The proposed ANFIS model is used to determine the exchange price of the US Dollar to Indian Rupee currency pair. The model will predict the average closing price for the current day and the next 14 days based on the closing price and simple moving average of the previous day. The input variables are similar to those mentioned in section 3.1.2.

Depending on the type of fuzzy reasoning and fuzzy if-then rules employed, fuzzy inference systems can be classified into three types [28] –

Type 1: The overall output is the weighted average of each rule's crisp output induced by the rule's firing strength (the product or minimum of the degrees of match with the premise part) and output membership functions. The output membership functions used must be monotonic functions.

Type 2: the overall fuzzy output is derived by applying "max" operation to the qualified fuzzy outputs (each of which is equal to the minimum of firing strength and the output membership function of each rule). Some of the methods used to choose the final crisp output based on the overall fuzzy output are centroid of area, bisector of area, mean of maxima, maximum criterion, etc.

Type 3: Takagi and Sugeno's fuzzy if-then rules are used. The output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output.

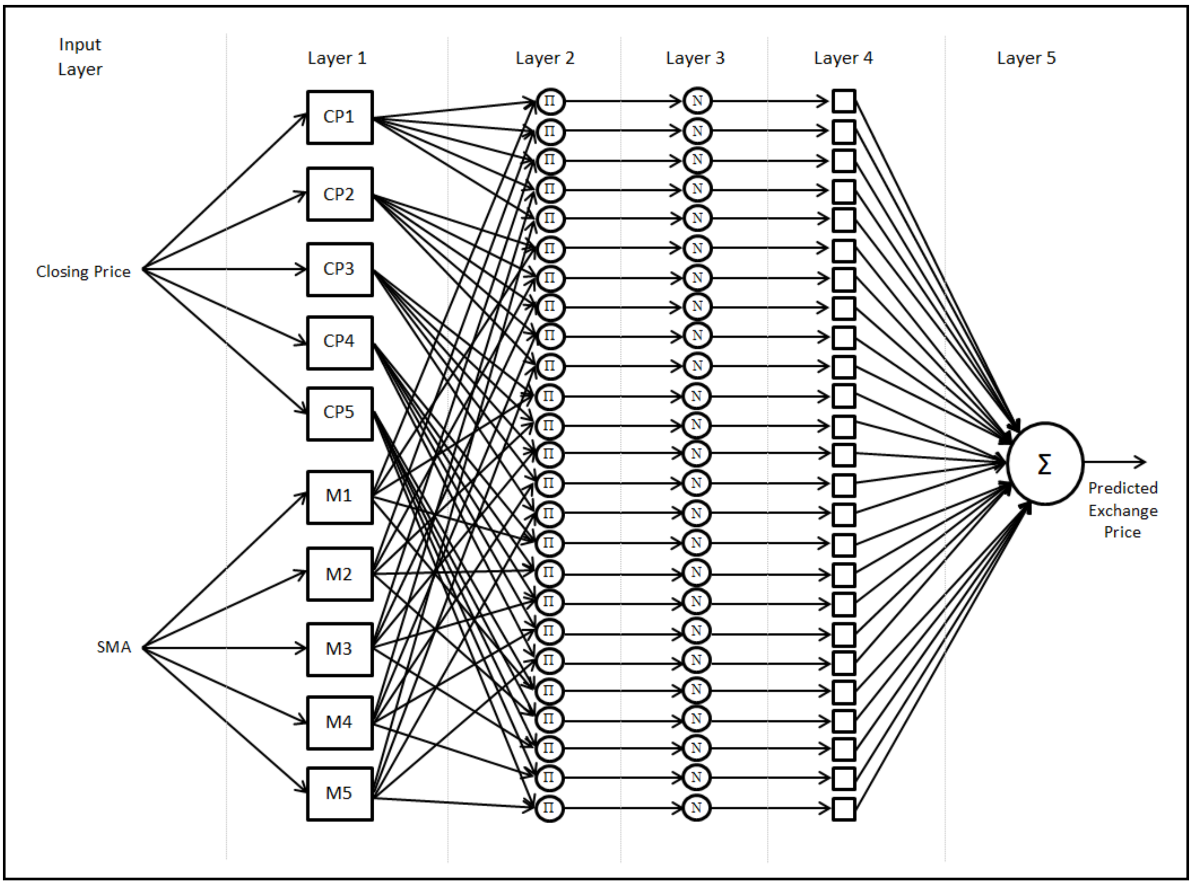

Figure 3.6 ANFIS Architecture

The proposed model (Figure 3.6) is a type 3 ANFIS which uses a first order Sugeno Fuzzy Inference System which is explained in detail in [30]. There are 5 layers. To reflect the adaptive capabilities, both circle and square nodes are used. The square node is an adaptive node that has parameters and the circle node is a fixed node without any parameters. Layer 1 and Layer 4 are adaptive layers and are denoted by square nodes. Layer 2, Layer 3 and Layer 5 are fixed layers denoted by circle nodes. To achieve the desired input-output mapping, these parameters are updated according to the given training data and a gradient based learning procedure.

Layer 1

Every node i in this layer is an adaptive node. This layer takes the inputs – Closing Price (CP) and Simple Moving Average (SMA) and generates a set of fuzzy membership functions to give as input to the first-order Sugeno FIS. The Membership Function (MF) associated with each input is CP_i and M_i respectively, where i is the number of MFs. The node function is given by equation 12.

$$O_{1,i} = \mu_{CP_i}(CP), \qquad for\ i = 1\ to\ 5, or$$
$$O_{1,i} = \mu_{M_{i-5}}(SMA), \qquad for\ i = 5\ to\ 10 \tag{12}$$

Both inputs employ a Gaussian membership function given by equation 13 where c_i is the center of the MF and σ_i is the width of the i^{th} MF [18]. Experiments were conducted to find the best MF for the inputs. The MFs used were Triangular MF (trimf), Trapezoidal MF (trapmf), Gaussian MF (gaussmf) and Generalized Bell MF (gbellmf). The Gaussian MF gave the best result in training and testing.

$$\mu_{CPi}(CP) = \exp\left(-\frac{1}{2}\frac{(CP_i - c_i)^2}{\sigma_i^2}\right) \tag{13}$$

Based on the experiments that were conducted to find the optimal number of MFs per input, 5 MFs give the best result in training. In the experiment, the number of membership functions per input was changed from 2 to 8, and the time for training and testing along with the MSE and MAE values were observed. As shown in Figure 3.7 (a) to (c), a trade-off is taken between the time taken for training and testing and the error obtained. 5 MFs provide an average training and testing time while giving an average MSE value and the best testing MAE value.

The output of this layer is a linguistic label associated with the node. It is the membership grade of a fuzzy set $CP = (CP_1, CP_2, CP_3, CP_4, CP_5)$ or $M = (M_1, M_2, M_3, M_4, M_5)$ and it specifies the degree to which the given input (CP or SMA) satisfies the quantifier CP or M. The parameters in this layer (c_i and σ_i) are called the premise parameters.

Layer 2

Every node in this layer is a fixed node, denoted by a circle node, labeled Π, whose output is the product of all the incoming signals. Each node represents the firing strength of a rule. The output of the i^{th} node is denoted by w_i as given in equation 14.Any T-norm operators that performs fuzzy AND can be used as the node function.

$$O_{2,i} = w_i = \mu_{CPj}(CP).\mu_{Mj}(SMA), \qquad where\ i = 1\ to\ 25\ and\ j = 1\ to\ 5 \tag{14}$$

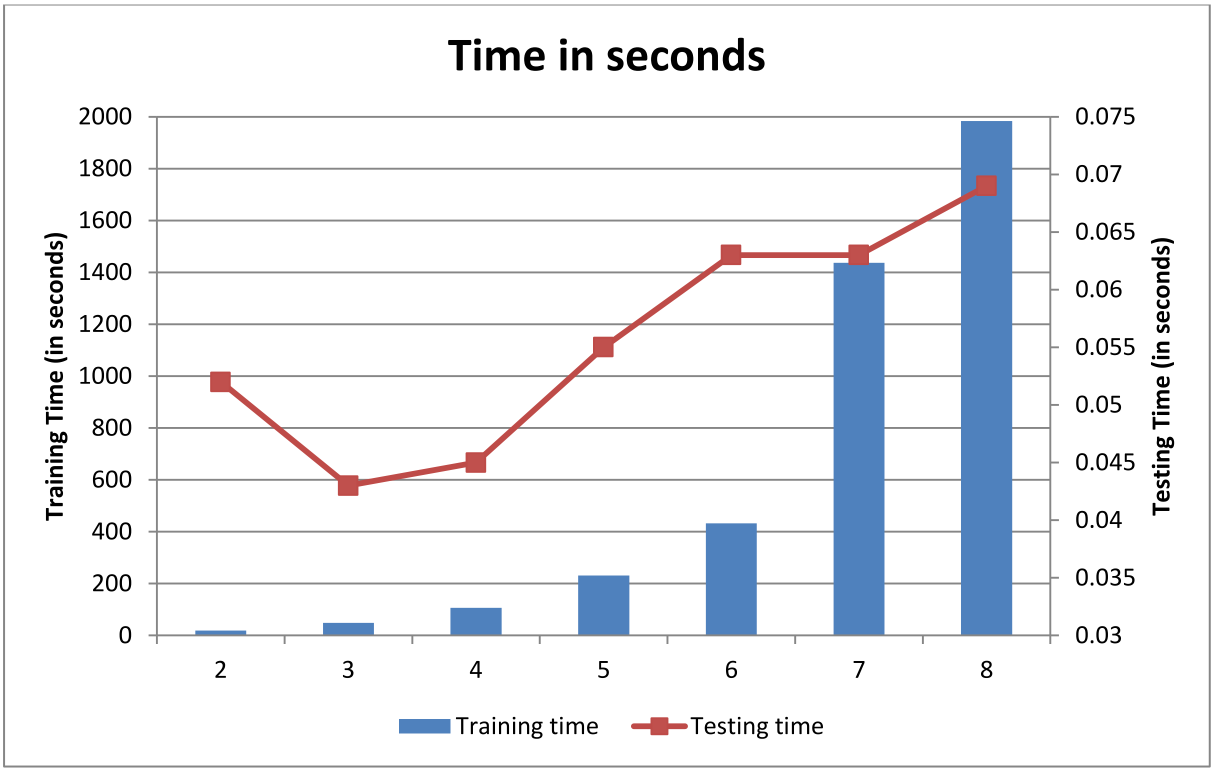

Figure 3.7 (a) Training and Testing time for different MFs

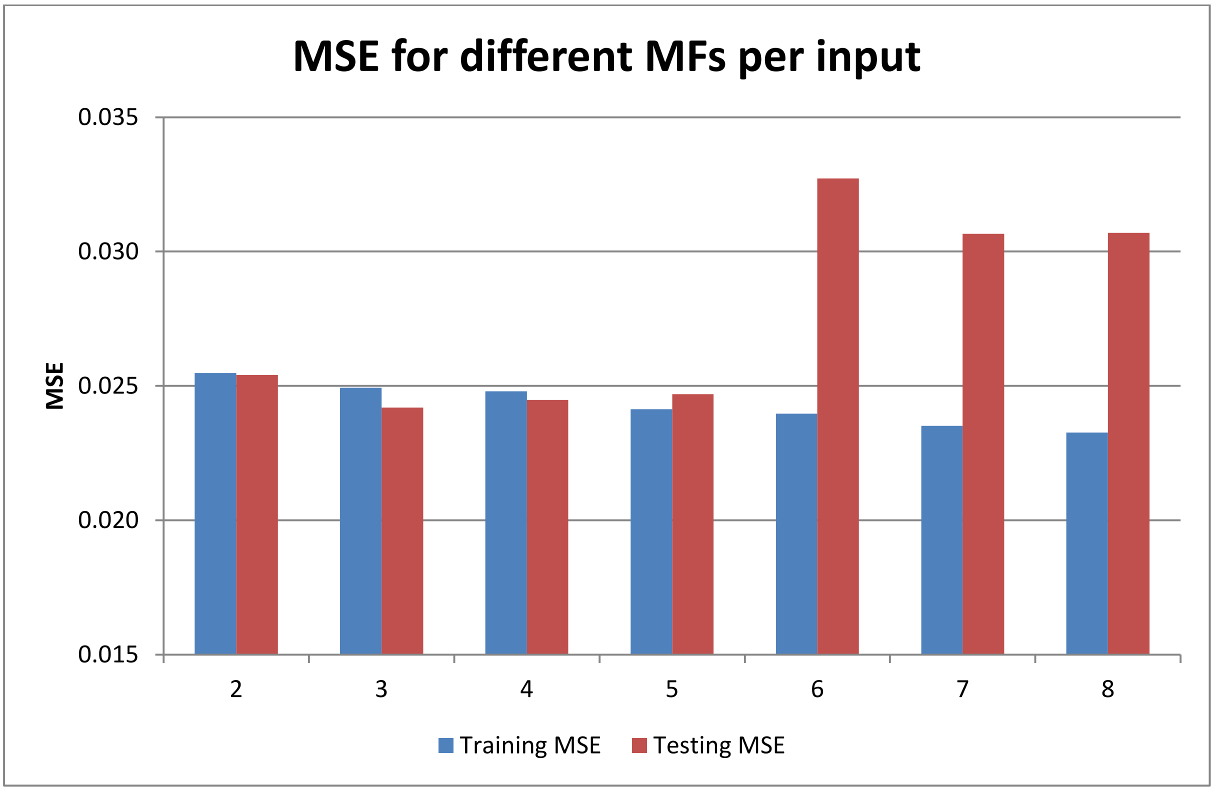

Figure 3.7 (b) Training and Testing MSE for different MFs

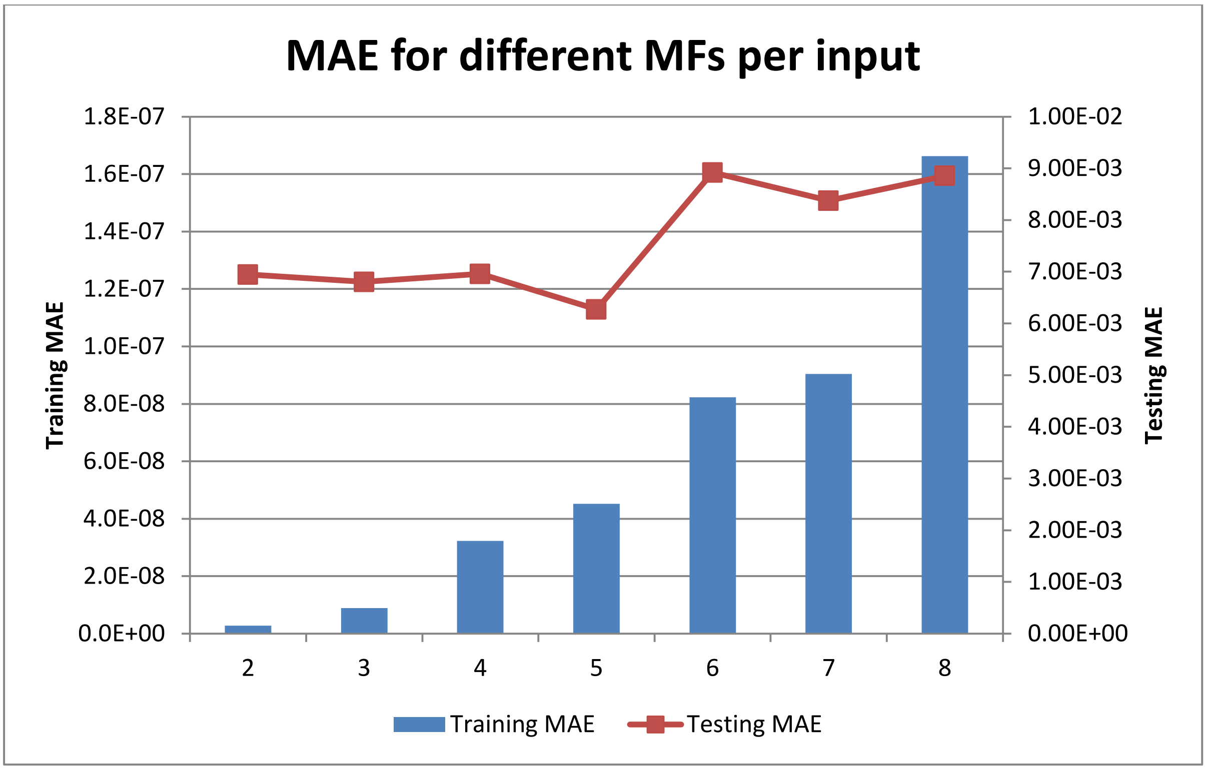

Figure 3.7 (c) Training and Testing MAE for different MFs

Layer 3

Every node in this layer is a fixed node, denoted by a circle node, labelled N. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all the rule's firing strengths using equation 15. As the output of Layer 2 is the firing strength (w_i) of the rules, the output of this layer is called the normalized firing strengths and is denoted by $\overline{w_i}$ as defined in equation (15).

$$O_{3,i} = \overline{w_i} = \frac{w_i}{\sum w_i}, \qquad where\ i = 1\ to\ 25 \tag{15}$$

Layer 4

This is an adaptive layer and is denoted by a square node. Every node i in this layer gives the output of the Sugeno FIS. The FIS used in the type 3 ANFIS model is a First-order Sugeno FIS which describes the output within the fuzzy region specified by the antecedent (inputs) of the rule in terms of a first order polynomial as given in equation 16. The parameter set of this node is given by the coefficients of the first order polynomial (p_i, q_i, r_i). These parameters are referred to as the consequent parameters.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i.CP + q_i.SMA + r_i), \qquad where\ i = 1\ to\ 25 \qquad (16)$$

Layer 5

Layer 5 consists of a single fixed node denoted by a circle node with the label Σ. This node computes the overall output as the summation of the incoming signals from Layer 4 as given in equation 17. The final output generated at this layer is the change is exchange price between the Indian Rupee and US Dollar. The change in price is then added to the input closing price of the previous day to get the average closing price of the next day.

$$change\ in\ price = O_{5,1} = \sum \overline{w_i} f_i = \frac{\sum w_i f_i}{\sum w_i}, \quad where\ i = 1\ to\ 25 \qquad (17)$$

3.2.2. Rule generation

The number of rules generated in ANFIS is based on the type of input space partitioning [31]. There are 3 main partitioning types – grid, tree and scattering partitioning. These types of partitioning are implemented using genfis1, genfis2 and genfis3 in [32]. In genfis1, grid clustering of the inputs is done and the rules are generated by taking every possible combination of the input membership functions. Subtractive clustering is used in genfis2 to extract a set of rules to model the data behaviour by using a cluster centre and radius to cluster the data. Fuzzy c-means clustering is used in genfis3, which allows each data point to belong to multiple clusters with varying degrees of membership. The proposed system uses genfis1 to generate rules for the system. 2 inputs with 5 membership functions each generates a total of 25 rules. Grid clustering can lead to curse of dimensionality where the number of rules increases exponentially even if the number of inputs and membership functions are moderate. Due to the large input dataset and a small number of inputs, grid clustering is used. The rules of the system with 2 inputs and a single output are given below. The output is f_i where i is the number of rules. The parameters $p_i,\ q_i,\ and\ r_i$ are based on the values of the antecedents of the rule and are updated with each input pattern. For example, after training the system (6067 records over 500 epochs), the parameter values for

f_1 are 5.44, -3.273, and -73.93 for $p_1,\ q_1,\ and\ r_1$ respectively. The values of the parameters change on each iteration and every retrain of the system.

$$Rule\ 1: If\ CP\ is\ CP_1\ and\ SMA\ is\ M_1, then\ f_1 = p_1.CP + q_1.SMA + r_1$$
$$Rule\ 2: If\ CP\ is\ CP_1\ and\ SMA\ is\ M_2, then\ f_2 = p_2.CP + q_2.SMA + r_2$$
$$Rule\ 3: If\ CP\ is\ CP_1\ and\ SMA\ is\ M_3, then\ f_3 = p_3.CP + q_3.SMA + r_3$$
$$Rule\ 4: If\ CP\ is\ CP_1\ and\ SMA\ is\ M_4, then\ f_4 = p_4.CP + q_4.SMA + r_4$$
$$Rule\ 5: If\ CP\ is\ CP_1\ and\ SMA\ is\ M_5, then\ f_5 = p_5.CP + q_5.SMA + r_5$$
$$Rule\ 6: If\ CP\ is\ CP_2\ and\ SMA\ is\ M_1, then\ f_6 = p_6.CP + q_6.SMA + r_6$$
$$Rule\ 7: If\ CP\ is\ CP_2\ and\ SMA\ is\ M_2, then\ f_7 = p_7.CP + q_7.SMA + r_7$$
$$Rule\ 8: If\ CP\ is\ CP_2\ and\ SMA\ is\ M_3, then\ f_8 = p_8.CP + q_8.SMA + r_8$$
$$Rule\ 9: If\ CP\ is\ CP_2\ and\ SMA\ is\ M_4, then\ f_9 = p_9.CP + q_9.SMA + r_9$$
$$Rule\ 10: If\ CP\ is\ CP_2\ and\ SMA\ is\ M_5, then\ f_{10} = p_{10}.CP + q_{10}.SMA + r_{10}$$
$$Rule\ 11: If\ CP\ is\ CP_3\ and\ SMA\ is\ M_1, then\ f_{11} = p_{11}.CP + q_{11}.SMA + r_{11}$$
$$Rule\ 12: If\ CP\ is\ CP_3\ and\ SMA\ is\ M_2, then\ f_{12} = p_{12}.CP + q_{12}.SMA + r_{12}$$
$$Rule\ 13: If\ CP\ is\ CP_3\ and\ SMA\ is\ M_3, then\ f_{13} = p_{13}.CP + q_{13}.SMA + r_{13}$$
$$Rule\ 14: If\ CP\ is\ CP_3\ and\ SMA\ is\ M_4, then\ f_{14} = p_{14}.CP + q_{14}.SMA + r_{14}$$
$$Rule\ 15: If\ CP\ is\ CP_3\ and\ SMA\ is\ M_5, then\ f_{15} = p_{15}.CP + q_{15}.SMA + r_{15}$$
$$Rule\ 16: If\ CP\ is\ CP_4\ and\ SMA\ is\ M_1, then\ f_{16} = p_{16}.CP + q_{16}.SMA + r_{16}$$
$$Rule\ 17: If\ CP\ is\ CP_4\ and\ SMA\ is\ M_2, then\ f_{17} = p_{17}.CP + q_{17}.SMA + r_{17}$$
$$Rule\ 18: If\ CP\ is\ CP_4\ and\ SMA\ is\ M_3, then\ f_{18} = p_{18}.CP + q_{18}.SMA + r_{18}$$
$$Rule\ 19: If\ CP\ is\ CP_4\ and\ SMA\ is\ M_4, then\ f_{19} = p_{19}.CP + q_{19}.SMA + r_{19}$$
$$Rule\ 20: If\ CP\ is\ CP_4\ and\ SMA\ is\ M_5, then\ f_{20} = p_{20}.CP + q_{20}.SMA + r_{20}$$
$$Rule\ 21: If\ CP\ is\ CP_5\ and\ SMA\ is\ M_1, then\ f_{21} = p_{21}.CP + q_{21}.SMA + r_{21}$$
$$Rule\ 22: If\ CP\ is\ CP_5\ and\ SMA\ is\ M_2, then\ f_{22} = p_{22}.CP + q_{22}.SMA + r_{22}$$
$$Rule\ 23: If\ CP\ is\ CP_5\ and\ SMA\ is\ M_3, then\ f_{23} = p_{23}.CP + q_{23}.SMA + r_{23}$$
$$Rule\ 24: If\ CP\ is\ CP_5\ and\ SMA\ is\ M_4, then\ f_{24} = p_{24}.CP + q_{24}.SMA + r_{24}$$
$$Rule\ 25: If\ CP\ is\ CP_5\ and\ SMA\ is\ M_5, then\ f_{25} = p_{25}.CP + q_{25}.SMA + r_{25}$$

Chapter 4

Experiments and Results

This chapter describes the various experiments conducted on the dataset. The experimental setup is described in detail in section 4.1. Section 4.2 describes the data set used for the experiments and implementation. Section 4.3 gives a detailed explanation of the implementation details and the User Interface (UI). The remainder of the chapter explains the performance parameters used and the results of the experiments conducted based on those parameters.

4.1. Experimental Setup

The proposed Artificial Neural Network system and the neuro-fuzzy hybrid ANFIS model are implemented in MATLAB R2013a. Separate experiments to determine the number of hidden neurons and the number of membership functions are explained in sections 3.1.3 and 3.2.1 respectively. The specifications of the system used are given below. The text in parenthesis indicates the minimum requirement for MATLAB R2013a [33].

System Specifications:

System: DELL Inspiron 15R N5010 laptop

Processor: Intel® Core™ i5 CPU M840 (Any Intel or AMD x86 processor supporting SSE2 instruction set)

Frequency: 2.67 GHz and 2.66 GHz

Graphics Processor: Dedicated 1 GB ATI Mobility Radeon HD 550v (NVIDIA GPU with compute capability 2.0 or higher)

RAM: 4GB (2 X 2 GB) 2 DIMM DDR3 1333Mhz (At least 2048 MB recommended)

Battery: 6-cell Lithium Ion

Operating System: 64-bit Windows 7 Home Basic with Service Pack 1 (64-bit Windows 7, 8 or 10 with current service packs)

Disk Space: 2 GB (1 GB for MATLAB only, 3–4 GB for a typical installation)

4.2. Data

The data used in the implementation and experiments are taken from [4]. Real data for the US Dollar to Indian Rupee exchange is used. The dataset contains 8089 exchange rates for the period between November 1st 1993 and December 10th 2015. The average closing rates (bid price) is considered, based on which the inputs – Simple Moving Average (SMA), Exponential Moving Average (EMA) and Rate of Change (ROC) are calculated as explained in detail in section 3.1.2. The data is divided into two parts – training and testing. Both ANN and ANFIS models use the same training and testing data. The training dataset consists of 75% of the data which is approximately 6067 records and the remaining 25% (approximately 2022 records) are used for testing the system. The data is stored in a comma separated values (csv) file. The file stores the date and the exchange rate for that particular date. The file is pre-processed to change the date format from a slash notation (dd/mm/yyyy) to a comma notation (dd,mm,yyyy) to enable easy reading of the file in MATLAB via the csvread command. Figure 4.1 gives a snippet of the original csv file after pre-processing.

4.3. Implementation

The proposed Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) are implemented using MATLAB R2013a. The Graphic User Interface (GUI) is created using the MATLAB Graphical User Interface Design Environment (GUIDE) which provides tools for designing user interfaces and automatically generates the MATLAB code for constructing the UI which can later be modified to program behaviour of the application [33][34].

The system's GUI is in 3 parts – Initial, Training and Prediction. The main GUI screen is shown in Figure 4.3. It is a simple screen which allows the user to browse through the computer's directories to select a comma separated values (csv) file that contains the data. If the selected file is not a csv file, then an error is generated. Once a suitable csv file is selected, the Load button is activated. The load button loads the data and calculates the remaining inputs to the system as explained in section 3.1.2 and displays a graph of the closing price, SMA and EMA of the 100 most recent records on the main screen. The date is converted to a number for easy access. Once the data is loaded, the Train button is activated. Figure 4.2 shows a snippet of the csv file after the remaining inputs are calculated that is given as input for the training of the system.

	A	B	C	D	E
8063	14	11	2015	65.949	
8064	15	11	2015	65.949	
8065	16	11	2015	65.9395	
8066	17	11	2015	65.854	
8067	18	11	2015	66.0156	
8068	19	11	2015	65.9693	
8069	20	11	2015	65.9597	
8070	21	11	2015	65.891	
8071	22	11	2015	65.891	
8072	23	11	2015	66.1542	
8073	24	11	2015	66.2338	
8074	25	11	2015	66.2173	
8075	26	11	2015	66.4056	
8076	27	11	2015	66.634	
8077	28	11	2015	66.726	
8078	29	11	2015	66.726	
8079	30	11	2015	66.5807	
8080	1	12	2015	66.3712	
8081	2	12	2015	66.4363	
8082	3	12	2015	66.5509	
8083	4	12	2015	66.678	

Figure 4.1 Original data csv file after pre-processing

4.3.1. Training

The Training interface (Figure 4.4) is activated on Train button key press. The interface allows the user to train the ANN and the ANFIS models separately. There is a Predict button which remains inactive till both the systems are trained. When the system is being trained, the training and clear buttons remain inactive. After training the train button is deactivated. The training of the two systems can be done in any order. The interface shows the training Mean Square Error (MSE) and Mean Absolute Error (MAE) for both systems along with the actual and predicted values in a table.

	A	B	C	D	E	F	G
1	Date	CP	SMA	EMA	ROC	Target	
8067	736285	65.854	65.649	65.677	0.55381	0.1616	
8068	736286	66.016	65.675	65.721	0.86463	-0.0463	
8069	736287	65.969	65.696	65.733	0.50979	-0.0096	
8070	736288	65.96	65.715	65.748	0.23098	-0.0687	
8071	736289	65.891	65.728	65.75	-0.17513	0	
8072	736290	65.891	65.739	65.76	-0.02124	0.2632	
8073	736291	66.154	65.769	65.82	-0.18453	0.0796	
8074	736292	66.234	65.802	65.86	0.013288	-0.0165	
8075	736293	66.217	65.832	65.883	0.32848	0.1883	
8076	736294	66.406	65.873	65.944	0.6516	0.2284	
8077	736295	66.634	65.927	66.022	0.95219	0.092	
8078	736296	66.726	65.984	66.083	1.1782	0	
8079	736297	66.726	66.037	66.129	1.1782	-0.1453	
8080	736298	66.581	66.076	66.143	0.97241	-0.2095	
8081	736299	66.371	66.097	66.134	0.78537	0.0651	
8082	736300	66.436	66.121	66.163	0.63727	0.1146	
8083	736301	66.551	66.152	66.205	0.88162	0.1271	
8084	736302	66.678	66.19	66.255	1.089	-0.158	
8085	736303	66.52	66.213	66.254	0.95461	0	
8086	736304	66.52	66.235	66.273	0.95461	0.0761	
8087	736305	66.596	66.261	66.306	0.66798	0.1215	
8088	736306	66.718	66.294	66.35	0.73044	0.0219	
8089	736307	66.74	66.325	66.381	0.78862	-0.074	
8090	736308	66.665	66.35	66.392	0.39138	0	

Figure 4.2 Input csv file for training

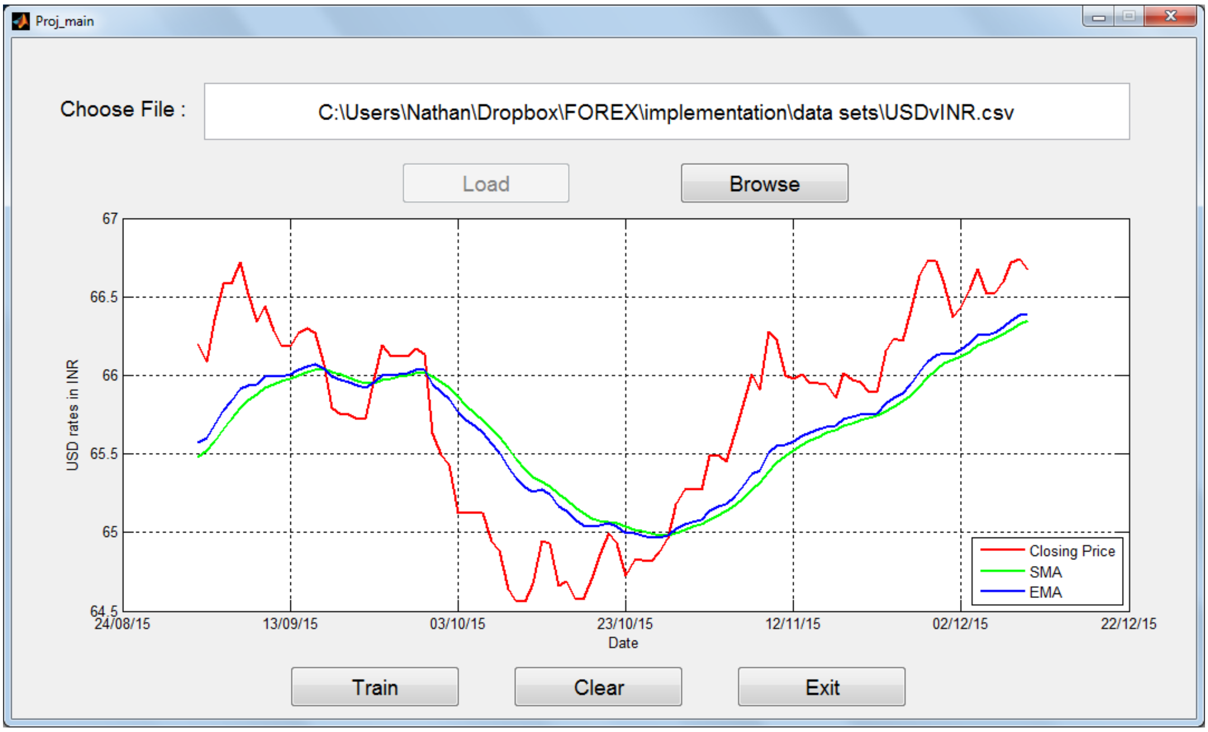

Figure 4.3 Initial Graphical User Interface

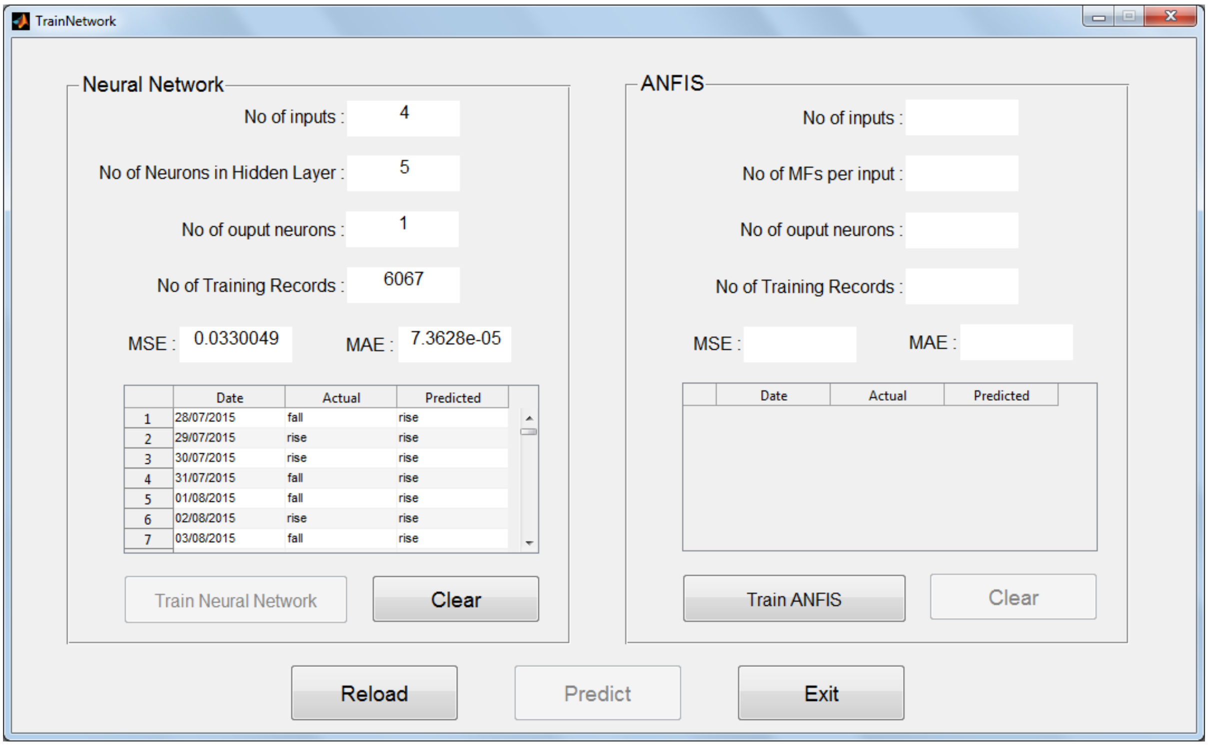

Figure 4.4 (a) Training of Artificial Neural Network

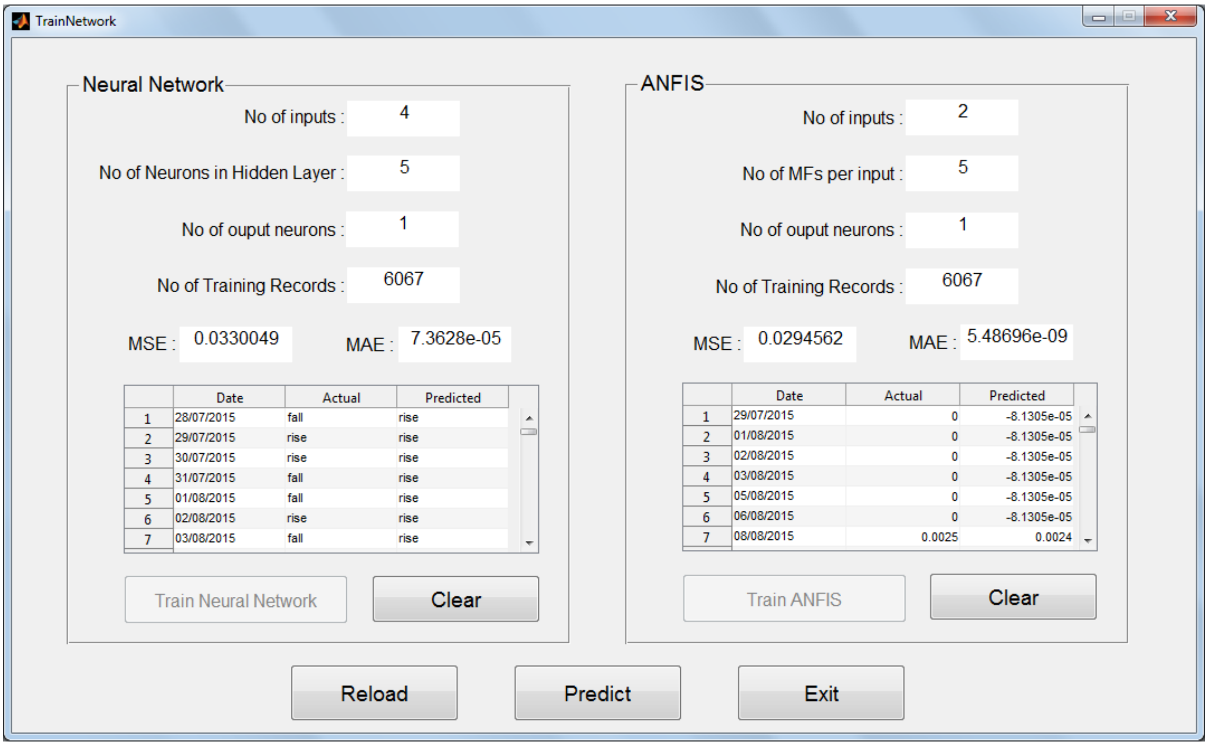

Figure 4.4 (b) Training of Adaptive Neuro Fuzzy Inference System

Table 4.1 Training time for ANN and ANFIS in seconds

	ANN	ANFIS
Training Time	443.882	239.644

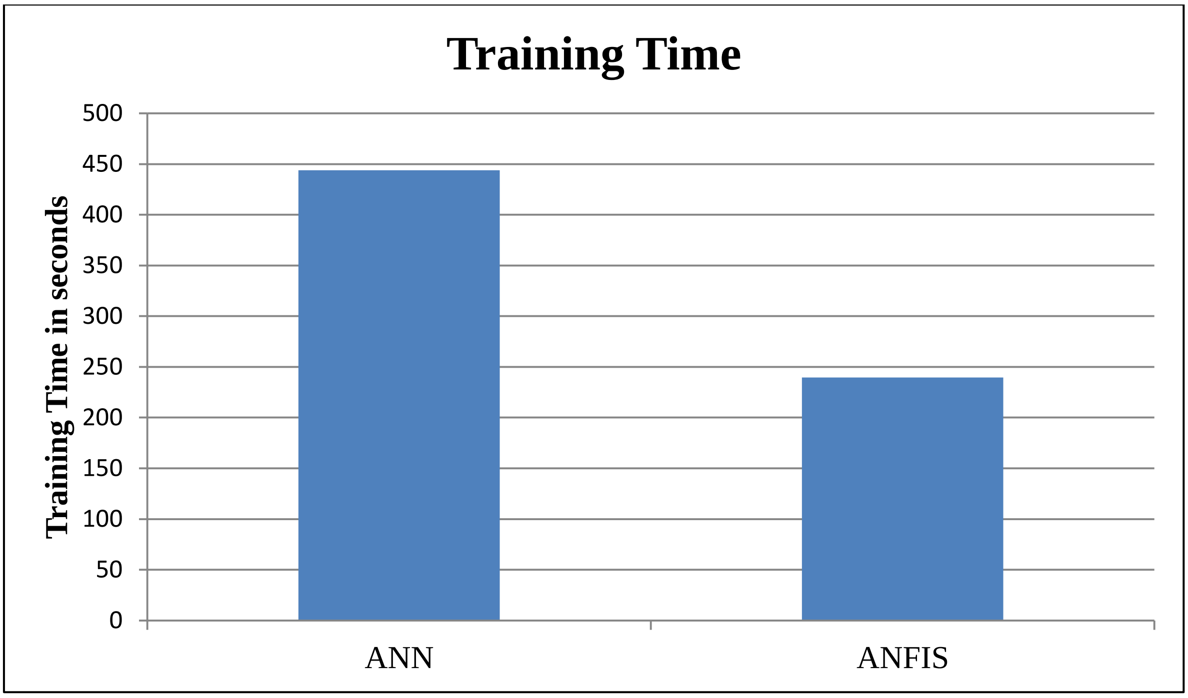

Figure 4.5 Training Time in seconds

Table 4.1 shows the training time in seconds for the proposed system. Figure 4.5 shows the plot of the training time. As seen the training time for the ANN is larger than that of the ANFIS model. The time taken for training the ANN is approximately 85% higher than the time taken to train the ANFIS model. The training set consists of approximately 6067 random records from the dataset and it was run over 500 epochs.

Figure 4.6 shows the Mean Square Error values for the proposed system. Table 4.2 gives a description of the MSE values. The values show that ANFIS is better in training the system to predict the future rates as compare to the ANN. A lower value of MSE indicates that the ANFIS model predicts the exchange rate with better accuracy and a smaller error exists between the actual and predicted values. The higher MSE value for ANN indicates that ANN can predict the exchange rate but not as accurately.

Table 4.2 MSE for ANN and ANFIS during Training

	ANN	ANFIS
Mean Square Error	0.03307	0.02946

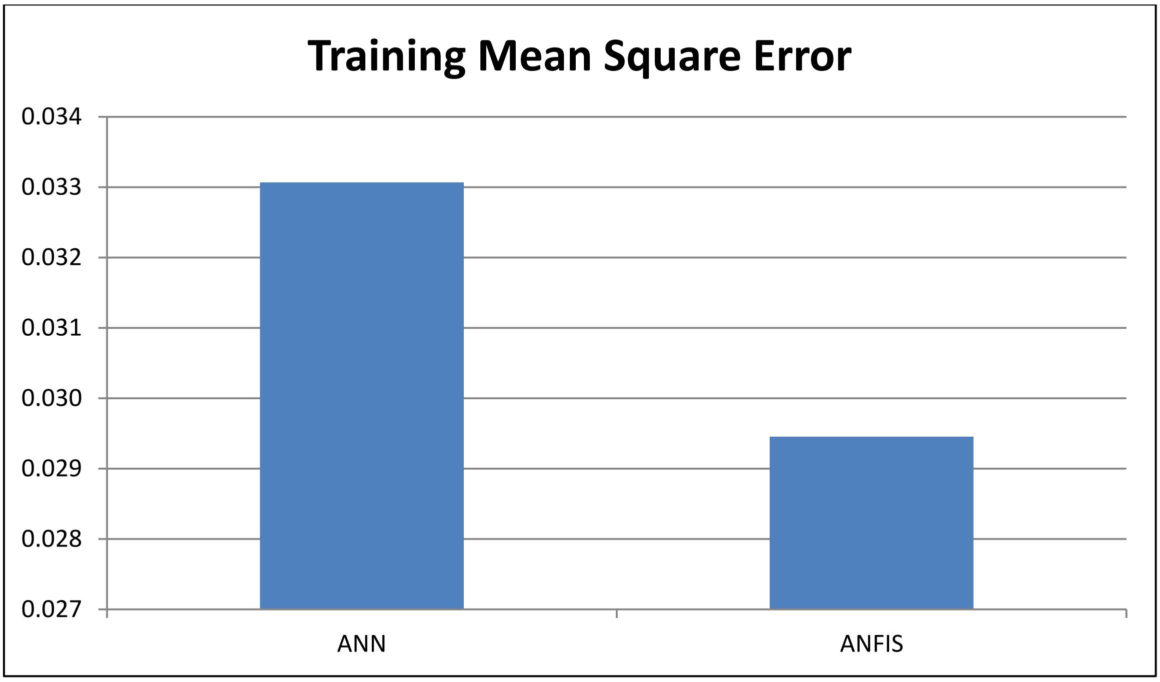

Figure 4.6 Training Mean Square Error

Table 4.3 shows the Mean Absolute Error for the proposed system during training. The plot for MAE cannot be plotted due to the large difference in the values between ANN and ANFIS. The MAE value for ANN is greater than ANFIS by an order of 10^4 i.e. the MAE value of ANFIS is 10000 times better than that of ANN. The values show that ANFIS is very accurate as compared to the ANN. The extremely small MAE values indicate that the errors between the actual and predicted values are extremely miniscule and the prediction is very accurate. The ANN also has a very small MAE value (order of 10^{-5}) but in comparison to ANFIS is quite large

Table 4.3 MAE for ANN and ANFIS during Training

	ANN	ANFIS
Mean Absolute Error	7.36×10^{-5}	5.49×10^{-9}

4.3.2. Testing

The Prediction interface is activated on the key press of the Predict button in the Training Interface. Here the past values as well as current values can be predicted. The system takes a date input in the format 'dd/mm/yyyy' and predicts the trend and that day's exchange price. The range of dates for which the system can recall the values or predict the values is from 1st November 1993 to the current date. If the input is the current date, then the system doesn't show any value for the actual trend and price. The system shows the actual trend and price. Every prediction retrains the both the ANN and ANFIS models. A table to the right shows the prediction for the next 15 days based on the current days predicted closing price. A Refresh button allows the system to retrain itself and predict the future rates without the user having to give any input date. This increases usability as a user can see the predicted future rates without the need to give any input to the system. The future rates however may be slightly inaccurate due to the absence of a target value to train the system. Figure 4.7 (a) shows the current days exchange rate from [36] and Figure 4.7 (b) shows the proposed system's predicted value and the future rates.

Figure 4.7 (a) Current price

As shown in Figure 4.7 (b), the predicted exchange price is 66.74 while the actual live price is 66.79 rupees to a dollar. The prediction is very close to the actual live exchange price. Figure 4.8 shows the predicted values for the next 1 month (excluding weekends) from an online prediction tool [37]. The predicted value from the online tool for the current day (11/12/2015) is 67.56 while the live rate is 66.79. This prediction is not as accurate as the proposed system.

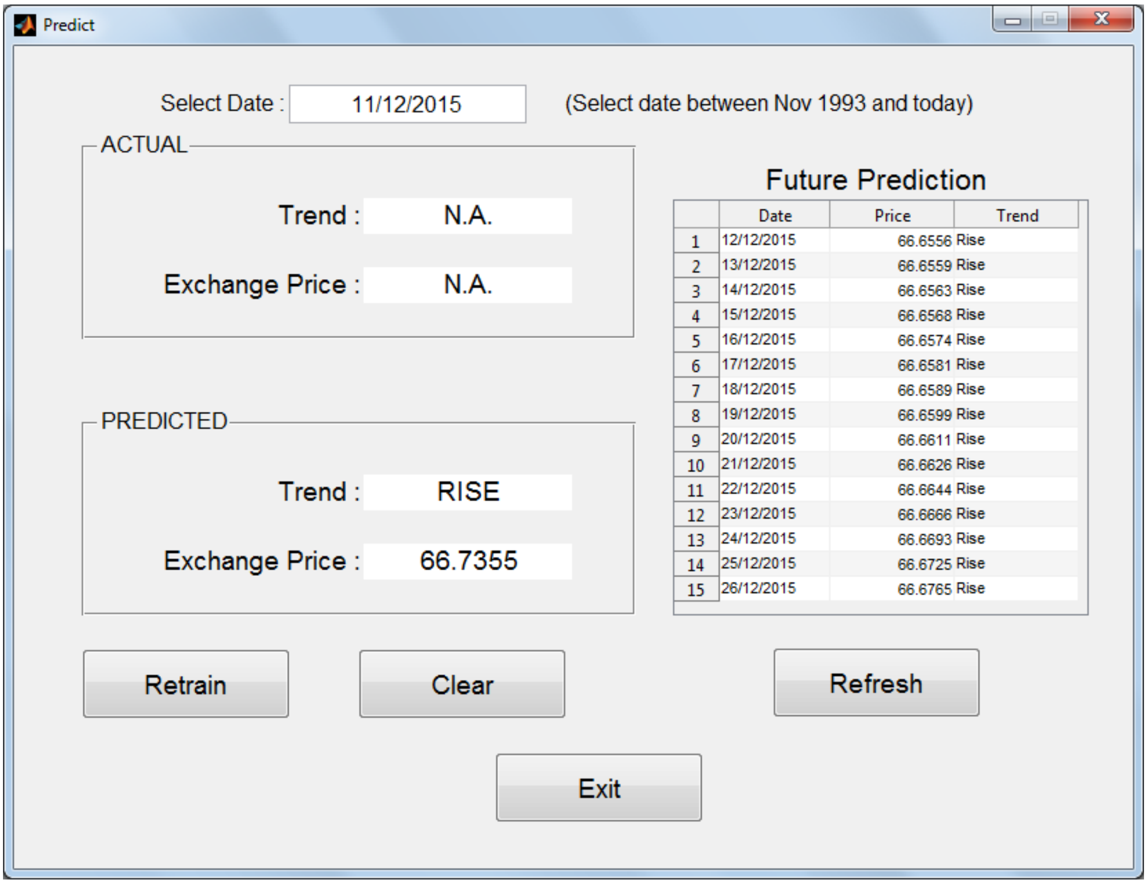

Figure 4.7 (b) Prediction of future rates

US Dollar To Rupee Forecast For The Week And Month				
Date	Week Day	Rate	Max	Min
2015/11/30	Monday	67.21	68.55	65.86
2015/12/1	Tuesday	67.37	68.72	66.02
2015/12/2	Wednesday	67.35	68.70	66.00
2015/12/3	Thursday	67.44	68.79	66.09
2015/12/4	Friday	67.61	68.96	66.26
2015/12/7	Monday	67.61	68.96	66.26
2015/12/8	Tuesday	67.66	69.02	66.31
2015/12/9	Wednesday	67.74	69.09	66.38
2015/12/10	Thursday	67.70	69.05	66.35
2015/12/11	Friday	67.56	68.91	66.21
2015/12/14	Monday	67.59	68.94	66.24
2015/12/15	Tuesday	67.62	68.97	66.27
2015/12/16	Wednesday	67.36	68.71	66.02
2015/12/17	Thursday	67.24	68.58	65.89
2015/12/18	Friday	67.70	69.06	66.35
2015/12/21	Monday	67.95	69.31	66.59
2015/12/22	Tuesday	68.08	69.44	66.72
2015/12/23	Wednesday	68.12	69.48	66.75
2015/12/24	Thursday	68.20	69.56	66.83
2015/12/25	Friday	68.25	69.62	66.89
2015/12/28	Monday	68.38	69.75	67.01
2015/12/29	Tuesday	68.65	70.02	67.28

Figure 4.8 Online Prediction Tool

As Figure 4.7 (b) and 4.8 shows, the future prediction is rising constantly based on the current trend of the system, however, the prediction of the proposed system is more plausible as it predicts a rise in the exchange rate by a small margin as compared to the online prediction tool. The tool does not retrain but simply provides a monthly prediction every month. There is no update in the values based on the current values. The proposed system makes use of the current values to retrain the system and obtain more accurate predictions. In both cases, there is no target value to compare the prediction values, and hence there may be an error in the future prediction of the exchange rate.

Table 4.4 Testing time for ANN and ANFIS in seconds

	ANN	ANFIS
Testing Time	18.658	0.052

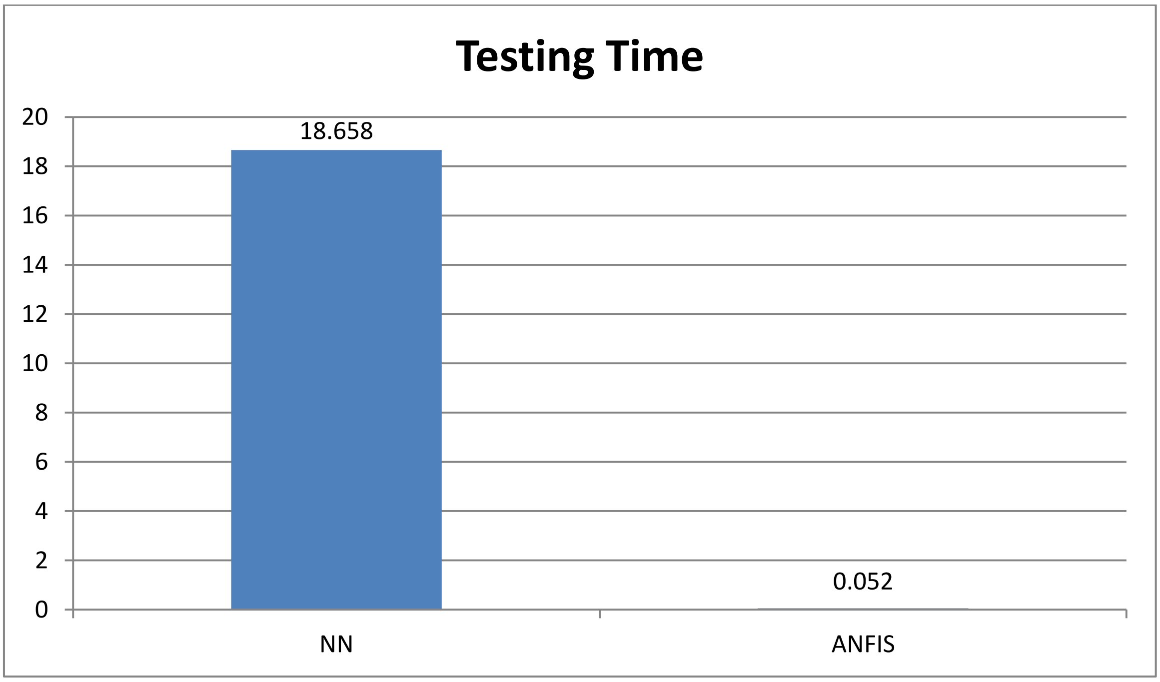

Figure 4.9 Testing Time in seconds

Table 4.4 gives the testing time of the system and Figure 4.9 shows a plot of the testing times. Testing uses 2022 randomly selected records from the dataset. The ANN takes more time in testing the system due to recalculation of the firing strength of each of the neurons in the hidden layer and output layer. The ANFIS model does not need to recalculate the premise and consequent parameters of the rules. It uses the values optimized during the training process for the testing phase. As a result, the testing time for ANFIS is much lesser than the testing time of ANN. The ANFIS model makes use of a first-order Sugeno FIS which provides the output of the 25 rules as a weighted average which is much faster than calculating the value of the activation function of the neurons.

Table 4.5 shows the testing Mean Square Error for the proposed system. Figure 4.10 is a plot of the MSE values. The values of MSE during the testing phase show that ANN is more accurate in prediction than ANFIS. This is because random records are chosen at random for testing. Some of the records used in training and testing may be the same. The ANN has a better recall accuracy than ANFIS as it uses the trained model to predict the values. The ANFIS model does not recall any values but recalculates the values based on the model generated during testing. This causes the MSE values for ANFIS to be slightly higher.

Table 4.5 MSE for ANN and ANFIS during Testing

	ANN	ANFIS
Mean Square Error	0.00312	0.02802

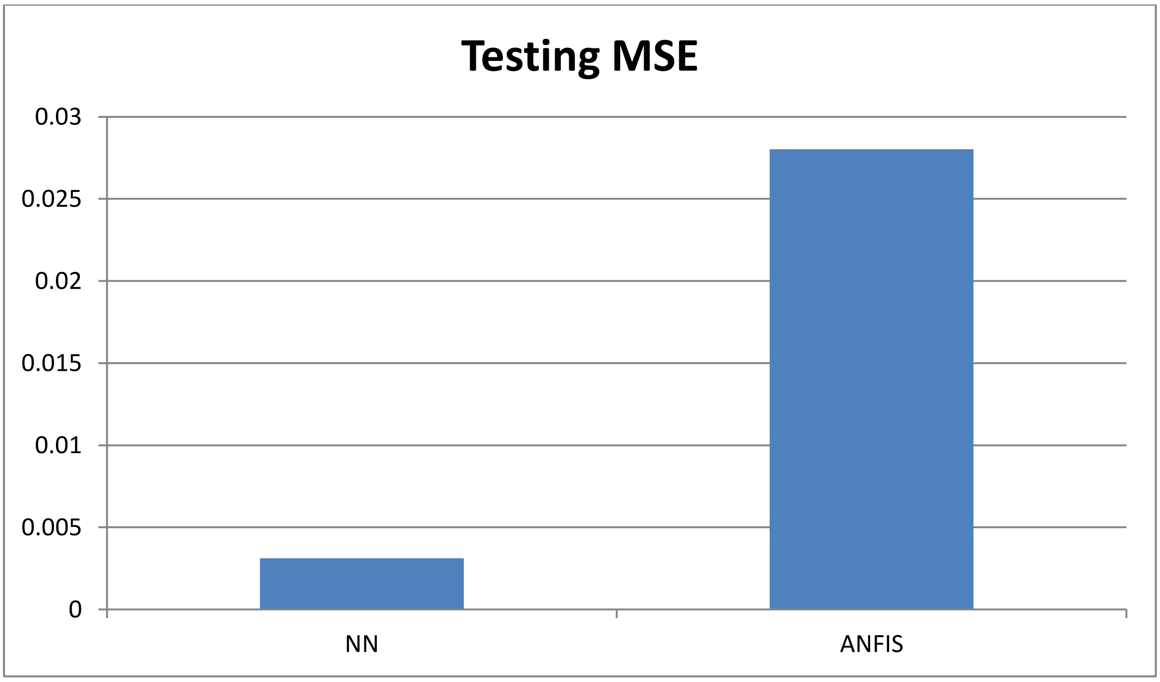

Figure 4.10 Testing Mean Square Error

Table 4.6 gives the Mean Absolute Error for the testing phase. The MAE values however show that the ANFIS is far more accurate in testing than the ANN model. The plot for MAE cannot be plotted due to the large difference in the values between ANN and ANFIS. The values show that ANFIS is 10^7 times (10 million) better than ANN in accurately forecasting the future exchange rates.

Table 4.6 MAE for ANN and ANFIS during Testing

	ANN	ANFIS
Mean Square Error	0.25	8.86×10^{-8}

4.4. Performance Parameters

The performance of the proposed system is based on 3 parameters – Time, Mean Square Error and Mean Square Error. All three parameters are negative-oriented scores, i.e. lower the value, better the result [38]. Two more performance parameters – Relative Error and Mean Absolute Percentage Error can be used. However, a divide by zero error prevents the use of these performance measures.

4.4.1. Time

The first performance parameter is the running time. For the proposed system, the training and testing time are taken. The time taken in training the model is larger than the time taken for testing. Training uses 75% of the records taken randomly from the dataset while testing uses 25% of the records chosen randomly. The testing phase makes use of the model generated during the training phase to test the data and does not retrain the system.

4.4.2. Mean Square Error

The Mean Square Error (MSE) is a quadratic scoring rule which measures the average magnitude of the error [38]. It is defined as the mean of the sum of squared error between the predicted and the actual values as given in equation (18). The distinct advantage of MSE is that is avoids the use of absolute values and is more sensitive to large outliers. The existence and probability of occurrence of outliers is described better by the normal distribution of MSE [40]. It can closely reconstruct the error distribution in case of large outliers. In case of a small number of samples, MSE may not be able to model the outliers.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(predicted_i - actual_i)^2 \tag{18}$$

4.4.3. Mean Absolute Error

The Mean Absolute Error (MAE) as the name suggests is the average of the absolute errors between the predicted and the actual values as given in equation 19. It is the simplest measure of forecast accuracy. MAE tells us how big of an error we can expect from the forecast on average [39]. When comparing different models, MSE gives an unbiased error and follows a normal distribution. Variations of the same model will have similar error distributions [40]. MAE is used when the number of samples is small and there are few outliers. However, when calculating model error sensitivities, MSE is preferred. MAE is used along with MSE to assess model performance since MAE gives a better measure of accuracy of a system.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left\| predicted_i - actual_i \right\| \tag{19}$$

Table 4.7 gives a summary of the performance parameters used for the proposed system. It shows the values for training and testing. The values show that the hybrid ANFIS system outperforms the ANN system in almost every aspect. This goes to show that the ANFIS model is more accurate in predicting the future exchange rates.

Table 4.7 Summary of Performance Parameters.

Method	**Training**			**Testing**		
	Time	**MSE**	**MAE**	**Time**	**MSE**	**MAE**
ANN	443.882	0.033	$7.36\text{x}10^{-5}$	18.658	0.003	0.25
ANFIS	239.644	0.024	$5.49\text{x}10^{-9}$	0.052	0.023	$8.68\text{x}10^{-8}$

Chapter 5

Conclusion

The foreign exchange market is global market where currencies are bought and sold. It determines the relative values of different currency pairs. The market is active for 9 hours in each country, but overlapping FOREX markets ensure that the market remains open 24 hours a day. The exchange rate is never constant; it changes every second with every trade that is made. The volume of trading is highest during these overlapping times. The primary purpose of the FOREX is to assist international trade and investment.

The FOREX market is a chaotic time-series. Forecasting of such a chaotic and ever-changing market is a difficult task. There have been many statistical, non-statistical, linear, and non-linear methods used in attempts to forecast the exchange rates. Off late, new hybrid methods have emerged to forecast the future rates of the foreign exchange market. As shown by literature as well as the experiments conducted, hybrid methods outperform the other methods in accurately forecasting the future exchange rates.

Experiments were performed on live data for the US Dollar to Indian Rupee currency pair. The dataset contained 8089 records from 1st November 1993 to 10th December 2015, 75% of which was used to train the system and the rest was used in testing. The proposed system makes use of an Artificial Neural Network (ANN) to predict the trend of the market while a hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) is used to predict the future exchange rates. Results of the experiments show that the ANFIS model can predict the rates more accurately than the ANN. It is faster in training and testing in terms of time taken. The performance parameters – Time, MSE, and MAE – show a better and more accurate system for lower values. The testing MSE and MAE for the ANFIS model is slightly larger than the testing values since the system is not retrained and uses random values to test the system. Some values tend to go outside the training data range and hence give larger errors. The ANN retrains the system and hence gives a lower testing MSE but a larger MAE values than the training phase. The performance measures (MSE and MAE) also prove that the hybrid ANFIS model is better in predicting the future rates.

This method of predicting the future exchange rates can be made more accurate and robust by using the various factors that affect the forex rates as input to the system. Other models of ANFIS, like CANFIS and BELFIS can also be utilized to provide a better and more accurate forecast and also provide multiple output parameters.

Chapter 6

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