AN INTEGRATED STOCK MARKET FORECASTING MODEL USING NEURAL NETWORKS

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This thesis focuses on the development of a stock market forecasting model based on an Artificial Neural Network architecture. This study constructs a hybrid model utilizing various technical indicators, Elliott's wave theory, sensitivity analysis and fuzzy logic. Initially, a baseline network is constructed based on available literature. The baseline model is then improved by applying several useful information domains to the different models. Optimizations of the Neural Network models are performed by augmenting the network with useful information at every stage.

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CHAPTER 1. INTRODUCTION

1.1 Description of Forecasting

Forecasting is the process of making projections about future performance based on existing historic data. An accurate forecast aids in decision-making and planning for the future. Forecasts empower people to modify current variables in the present to predict the future to result in a favorable scenario.

The selection and implementation of a proper forecasting methodology has always been an important planning and control issue for most firms and agencies. The organizational and financial stability of an organization depends on the accuracy of the forecast since such information will most likely be used to make key decisions in the areas of human resources, purchasing, marketing, advertising and capital financing.

When a variable is to be predicted, the difficulty of forecasting depends on various factors. Most importantly, the historic pattern of the variable and the underlying input factors that affect a variable may increase the complexity of the forecasting task. A volatile historic pattern may suggest that the factor to be forecast has a number of underlying factors, the effects of each dynamically changing over time. Some of these contributing factors may not be identifiable and hence require an amount of expert knowledge gained over time to be built into the forecasting model.

Forecasting a financial scenario such as the stock market would be a very important step when assessing the prudence of an investment. This step is very difficult due to complexity and presence of a multitude of factors that may affect the value of a certain financial instrument [4].

1.2 Forecasting Problems

The following are the major challenges that are identified in the field of forecasting

1. In certain cases, it may be difficult to ascertain a future scenario during forecasting. Regardless of the techniques that may be used, it is always assumed that there will be a variable measure of uncertainty.
2. Forecasting variables for which there are no existing paradigms or historical data is often prone to errors, primarily due to the lack of ability to understand underlying factors which could affect the forecast [1][40].
3. Selection and implementation of a proper forecasting methodology is very important due to the fact that different forecasting problems must to be addressed using different tailor made models to suit each [8].

1.3 Previous Research

Stock market forecasting involves the analysis of several hundred indicators to augment the decision making process. Stock market indicators are mostly proven statistical functions, some of which are very similar in nature [1]. Analysts are required to identify indicators that are useful to them by meticulous screening methods that may be time consuming and may have some undesired financial repercussions. Stock market trading has been considered a risky and volatile business and traders have generally resorted to two broad types of analysis [6]; use of traditional, proven indicators and the interpretation of patterns and charts. Using the former technique provides mediocre accuracy with a lower risk limit, while the latter provides high accuracy with a higher risk limit. The current research on stock market forecasting involves artificial intelligence techniques and real time computing to utilize the advantages of the above mentioned traditional techniques and provide an accurate forecast with a high confidence limit. One study required high computing power and a substantial amount of time for increasing the accuracy of the model [9].

Artificial Neural Networks have been used by several researchers for developing applications to help make more informed financial decisions. Simple Neural Network models do a reasonably good job of predicting stock market price motion, with buy/sell prediction accuracies considerably higher than traditional models. This performance is being improved by adding more complexity to the network architecture and using more historical data. Different types of network architectures such as Multi Layer Perceptrons, Generalized Feed Forward networks and Radial Basis Functions are becoming increasingly popular and are being tested for higher accuracy. Many researchers are also investigating the possibility of adding additional indicators that may help the Neural Network improve training and performance while testing on production data. Neural Networks show potential for minimizing forecasting errors due to the improvements made in training algorithms and increased availability of indicators.

1.4 Current Research

The research by Bogullu et al [6] involves training the Feed Forward Neural Networks to generate Buy – Sell trading signals. The predictability and the profitability results given by the trained Neural Networks are compared against rule-based models of the technical indicators [14]. Technical indicators are useful tools in predicting the direction of stock prices. However they suffer from the linguistic uncertainty that is inherent in any decisions resulting from heuristic based trading rules [15]. Several interesting questions arise in connection with the current research:

1. Can higher accuracy be generated by increasing network input factors without compromising the processing complexity and time?
2. Is additional data required if the number of input factors are increased for efficient learning?

3. Can the newly formulated network outperform the networks used for Baseline comparisons?

In light of these questions, this research has extended the work of Weckman et al [40].

This work initially replicates the models of Weckman et al [1] [40] by developing a network using the known baseline indicators. Next, additional indicators are used to improve the network's performance. The network indicators are then pruned by using a Self Organizing Map. The performance altering Elliott's wave indicator used fuzzy logic techniques to classify the probability of a trend change. To simulate real time trading, the final performance measure was buy/sell decisions. This ensemble of techniques was applied to stocks from five different sectors and three different growth/value sizes of the particular industry. This thesis presents an approach for incorporating enhanced techniques into the forecasting process.

1.5 Thesis Structure

The thesis has been organized into five chapters and is explained as follows. Chapter 1 introduces the forecasting problem and summarizes the previous and current work completed in the intended research. Chapter 2 provides background and literature survey of related work in stock market forecasting problems. It also covers the concepts of Neural Networks and its application to forecasting, as well as giving coverage of the areas of Elliott's wave theory and Indicator Analysis. Chapter 3 presents the methodology adopted for generating forecasting models using Neural Networks and model optimization techniques. Chapter 4 discusses the results of the forecasting models and analyzes the applicability of the technique to different types of stocks. Chapter 5 provides conclusions and suggestions for future implementation.

CHAPTER 2. BACKGROUND

This chapter discusses the background and related work in the area of forecasting using Artificial Neural Networks.

2.1 Artificial Neural Networks

2.1.1 Introduction

An Artificial Neural Network is defined as an information-processing paradigm inspired by the methods by which the mammalian brain processes information [7] [24] presented to it. They are an assortment of mathematical models that imitate some of the observed phenomena in a biological nervous system, most importantly adaptive biological learning. One unique and important property of the Artificial Neural Network model is the exceptional structure of the information processing system [34]. It is made of a number of highly interconnected processing elements that are very similar to neurons and are joined by weighted connections that are very similar to synapses (Figure 2-1).

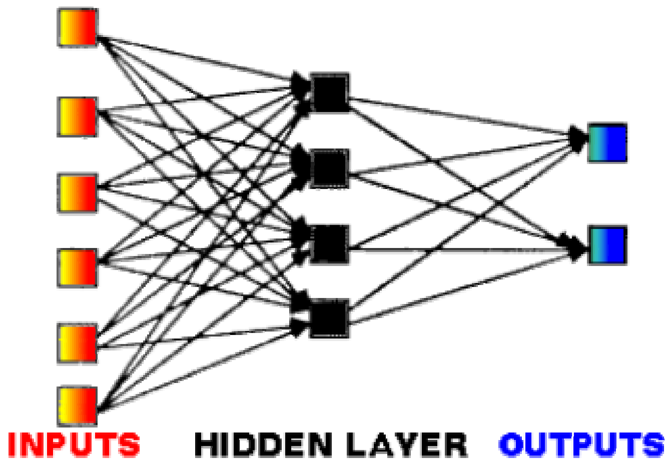

Figure 2-1 Schematic Diagram of a Neural Network

2.1.2 Applications of Neural Networks

Artificial Neural Networks have been used since about the late 1950's; but it wasn't until the mid-1980's that the algorithms became refined enough for a broad-spectrum of applications [35][41]. Today a number of complex real-world problems are being solved efficiently using Artificial Neural Networks. Artificial Neural Networks are efficient pattern recognition engines and strong classifiers, with the ability to generalize in making decisions about imprecise input data [16]. They offer excellent solutions to a variety of classification problems such as signal, speech and character recognition, as well as function approximation, prediction and system modeling where the underlying physical processes are not intelligible. Artificial Neural Networks may also be applied to solve control system problems, where the input variables are calculated and used to drive an output variable and the network learns the control function. A key advantage of Artificial Neural Networks lies in their flexibility against aberrations in the input variables and their latent potential of learning. They have been frequently identified as proficient at solving problems that are multifarious for conservative technologies (e.g., problems that do not have an algorithmic/heuristic solution process) and are often well suited to problems that are required to mimic biological intelligence[39].

2.1.3 Common Classification of Neural Networks

There are various architectures of Artificial Neural Networks that are commonly used. A very popular network architecture is the Multilayer Perceptron [28][26] which is generally trained with the back propagation of error, learning vector quantization, radial basis function, Hopfield, and Kohonen algorithms [18]. Some Artificial Neural Networks are classified as Feed Forward while others maybe recurrent (i.e., implement feedback) depending on the method of training employed and data processing through the network. Another popular method of classifying Artificial Neural Networks is by the training algorithms used, as some Artificial Neural Networks employ supervised training while others utilize unsupervised or self-organizing[20][21]. Supervised training methods are used when the network learns from a training set of data that has an output associated with each set of input. Unsupervised algorithms [12] effectively perform clustering of the data into similar groups based on the calculated attributes serving as inputs to the algorithms.

2.1.4 Neural Network Architectures and Training

Training is the procedure by which the Neural Network learns and understands the relationship between the input and the output variables. Learning in biological systems may be considered as modifications made to the weights (synaptic connections) that exist between the neurons [3]. Learning or training in an Artificial Neural Network is brought about by introduction of the network to a validated set of input/output data where the training algorithm iteratively adjusts the synaptic connection weights. These connection weights store the information learned by the network and are necessary to solve specific problems during the testing phase of the network validation process.

Neural Networks are characterized by the following properties:

- The pattern of connections between the various network layers (Network type)
- Number of neurons in each layer (complexity)
- Learning algorithm
- Neuron activation functions

Generally speaking, a Neural Network is a set of connected input and output units where each connection has a weight associated with it. The learning phase involves the network's ability to adjust the weights so as to be able to correctly forecast or classify the output target of a given set of input data. Given the numerous types of Neural Network architectures that have been developed in the literature, the important types of Neural Networks often used for forecasting and classification problems are discussed.

2.1.4.1 Multilayer Perceptrons:

Multilayer Perceptrons are layered Feed Forward networks classically trained with static back propagation algorithms. These networks are extensively used in countless applications requiring static pattern classification. Their key property is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are that they train relatively slowly, and require comparatively a large amount of training data sets [2].

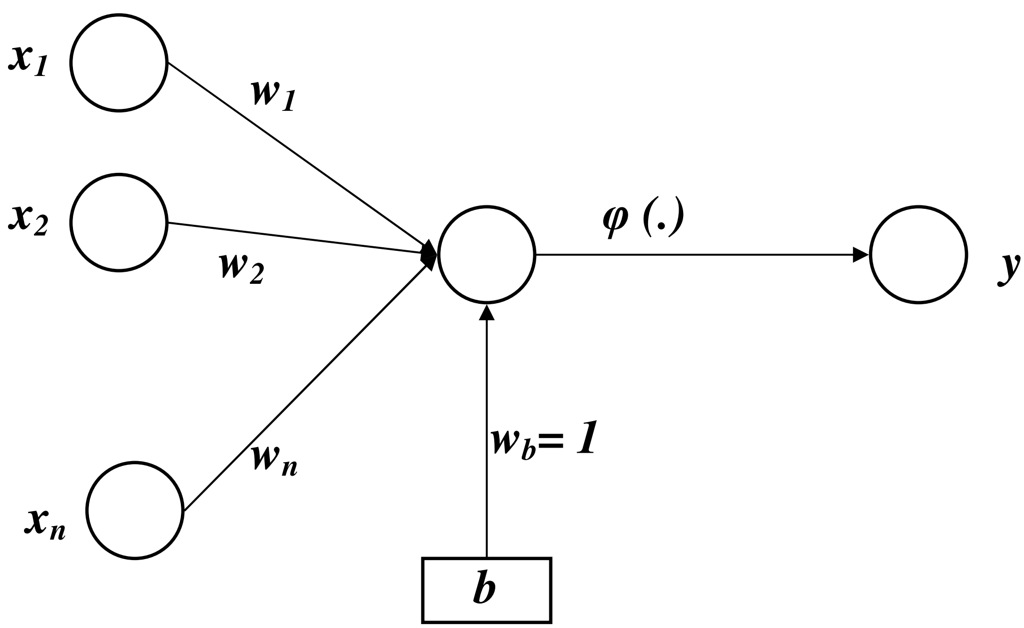

Figure 2-2 Functional Diagram of Perceptron

The basic concept of a single Perceptron was introduced by Rosenblatt in 1958 [28]. The Perceptron computes a single output from a set of input factors and then uses nonlinear activation function to the output (Figure 2-2).

$$y = \varphi (w_t x + b)$$

where

- ‘w’ is the weight vector of weights,
- ‘ x’ is the vector of inputs,
- ‘b’ is the bias and
- ‘φ’ is the activation function

Originally, the Perceptron used the Heaviside Step function but modern researchers prefer the hyperbolic tangent function or the logistic sigmoid function [29].

2.1.4.2 Generalized Feed Forward Networks:

Generalized Feed Forward networks are slack Multilayer Perceptrons so that connections can jump over one or more layers (Figure 2-3). In theory, Multilayer Perceptrons are adept at solving any problem that a Generalized Feed Forward network can solve. However, Generalized Feed Forward networks are often able to decipher the problem much more efficiently [31]. A classic example of this is the “exclusive or” function and the twin spiral problem. Without delving into the details of the problem, it is noted that a standard Multilayer Perceptron requires substantially more training epochs than the Generalized Feed Forward network containing a comparative amount of processing elements.

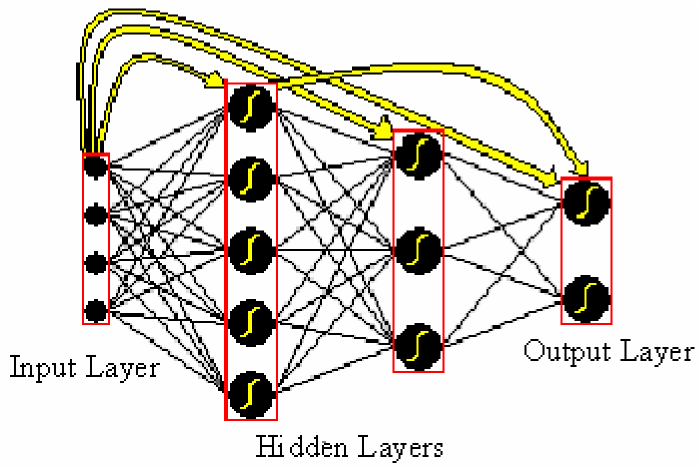

Figure 2-3 Generalized Feed Forward Nework (Adapted from NeuroSolutions)

2.1.4.3 Radial Basis Function:

Radial basis function networks are a type of nonlinear hybrid networks generally containing a single hidden layer of Perceptrons. The hidden layer generally uses Gaussian transfer functions (Figure 2-5), rather than the standard Sigmoidal functions (Figure 2-4) used by Multilayer Perceptrons.

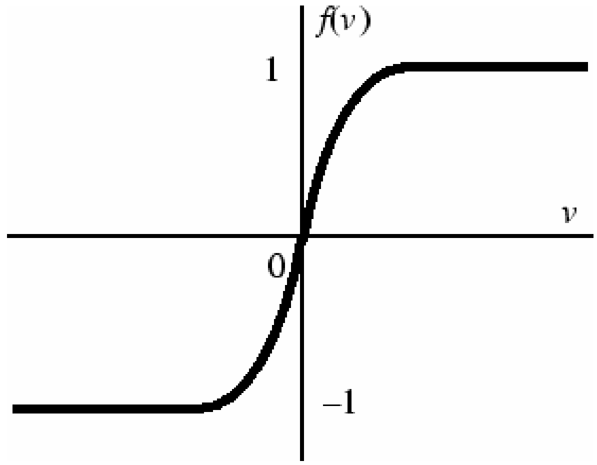

Figure 2-4 Sigmoid Function

The properties of the Gaussian transfer functions (Figure 2-5), namely the center and width are determined by unsupervised learning rules. The output layer typically involves supervised learning. These networks have a very high learning rate when compared to Multilayer Perceptrons.

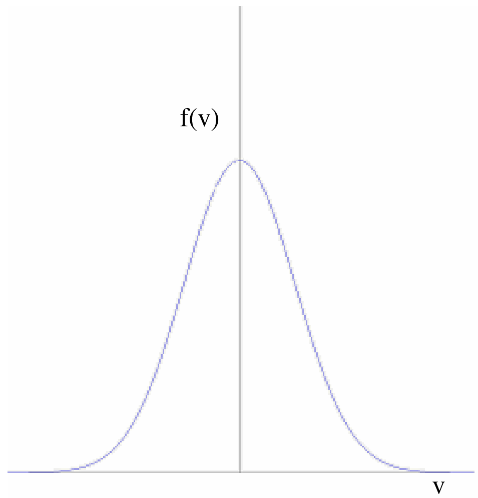

Figure 2-5 Gaussian Function

When a Generalized regression or probabilistic net is chosen, all the weights of the network can be computed analytically. This type of Radial basis function networks are employed only when the number of exemplars is small (<100) or dispersed thereby making clustering ill defined.

2.1.4.4 Self Organizing Maps

One of the most important issues in pattern recognition is feature extraction. Since this is such a crucial step, different techniques may provide a better fit to our problem. The ideas of Self Organizing Maps are rooted in competitive learning networks [17]. These nets are one layer nets with linear processing elements but use a competitive learning rule. In such nets there is one and only one winning element for every input pattern (i.e. the element whose weights are closest to the input pattern). Kohonen [19] proposed a slight modification of this principle with tremendous implications. Instead of updating only the winning element, in Self Organizing Maps the neighboring element weights are also updated with a smaller step size. This implies that in the learning process (topological) neighborhood relationships are created in which the spatial locations correspond to features of the input data. The data points that are similar in input space are mapped to small neighborhoods in Kohonen's Self Organizing Map layer. The Self Organizing Map layer can be a one or two-dimensional lattice, and the size of the net provides the resolution for the lattice (Figure 2-6).

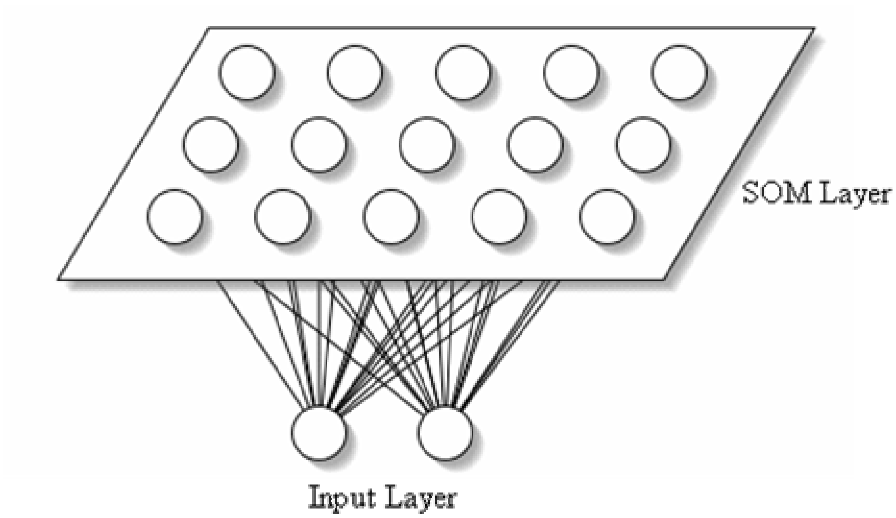

Figure 2-6 2-D Kohonen Self Organizing Map (Adapted from [18])

2.1.5 Neural-Network Training

The training phase in Neural Networks determines the following important parameters for a superior performance of the network

- Network parameters such as weights and biases that allow a network to map a given set of input patterns to desired outputs
- Method of determination of these parameters

The back propagation algorithm is a very commonly used training algorithm. The term back-propagation refers to the direction of propagation of error. The single most important goal of the training regimen is to adjust the weights and biases of the network in order to minimize the error in the output function also called the cost function. The fundamental idea is that the cost function has a particular surface over the weight space and therefore an iterative process such as the gradient descent method can be used for its minimization. The gradient descent method is based on the fact that the gradient of a function always points towards the direction of maximum increase of the function and therefore a negative gradient will provoke a "downhill" movement eventually reaching the minimum of the cost function. The single most important insight while using this method is that the function may mistake a local minimum for a global minimum. Therefore caution needs to be taken during the development of the model to avoid this incident.

The cost function, E needs to be minimized and its derivative with respect to the weight is calculated and denoted by $\partial E/\partial w$. Having obtained the derivative, the problem of adjusting weights is an optimization problem. Back-propagation uses a form of gradient descent [38] to update weights according to the formula:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}}$$

Where,

- w_{ij} denotes the weight of the synapse from node i to node j.
- $\eta > 0$ is the learning rate and
- $\partial E / \partial w_{ij}$, is the partial derivative of the error, E with respect to weight w_{ij}.

The network is generally initialized with random weights and the training algorithm modifies the weights as discussed above. Many alternative optimization techniques have been utilized. Variations of the basic method include methods such as the conjugate-gradient method, momentum learning, etc. Convergence to local minima can be avoided by using stochastic search algorithms like simulated annealing and genetic algorithms. Since these methods are global optimization procedures, they require longer times to run and are therefore costly to implement.

A collection of input and output factors used to train the learning system is called the training set. The testing set contains exemplars (data) that are not used for the training purpose. The testing set is generally used to evaluate the generalization capabilities of the network. A very important phenomenon while using the back-propagation algorithm is that the performance always improves with the number of training cycles or epochs.

However, the error on the testing set initially decreases with the number of cycles, and then increases (Figure 2-7).

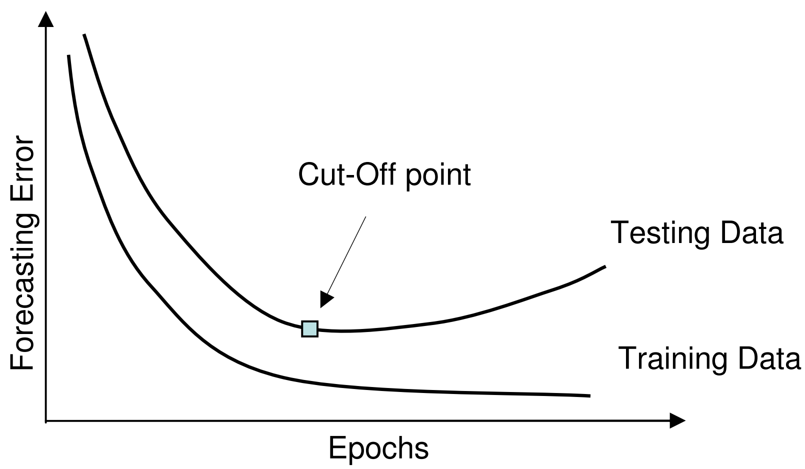

Figure 2-7 Cross Validation during Training

This phenomenon is called overtraining and is indicative of poor generalization capabilities. One solution to this problem is to split the training set into two sets – the initial training set and the validation set. After every fixed number of iterations, the error on the validation set is calculated. Training is terminated when this error starts to increase. This method is called early stopping or stopping with cross-validation.

2.2 Elliott's Wave Theory

2.2.1 History

Ralph Nelson Elliott was a businessman who discovered a sequence of waves, which reoccurred in stock market trading over a particular period of time. Elliott refined his studies and published the results initially in a monograph titled "The Wave Principle" in 1938. He published more on this principle in a sequence of articles in the Financial World magazine during 1939. He added to the Wave Principle by publishing another famous monograph in early 1946 titled Nature's Law. His work also contained a collection of various interpretive letters between 1938 and 1947 [13].

The wave theory according to R.N.Elliott was not only present in organized financial markets, but also in all human actions and advancements. Waves of different degrees arise regardless of the presence or absence of recording machinery. When the machinery is present, the patterns of waves are perfected and become visible to the experienced eye [27].

2.2.2 Principles of Elliott Wave Theory

The Elliott's wave theory is based on the fundamental premise that the stock market has a hidden order associated with it according to which the market moves [11]. The Elliott Wave Principle consists of empirically derived concepts developed after an extensive study of stock market movements. The form and structure of waves that was uncovered is simple to understand and elegant in its basic expression. It was discovered that all stock market movements typically occur in eight waves or sequences. Each wave in this sequence is a financial move that inhabits a programmed position consisting of direction and duration with a relation to the magnitude of the other 7 waves in the sequence. A 5-wave upward or bullish trend sequence rarely ends with an irregular set of waves at the top part of the movement. This results in an A-wave correction that is common, but the upward B-wave has a magnitude greater than the previous fifth wave. Due to this corrective trend in the bull market, the next C-wave correction is straight down, more severe in magnitude and lasts longer than a typical ABC correction.

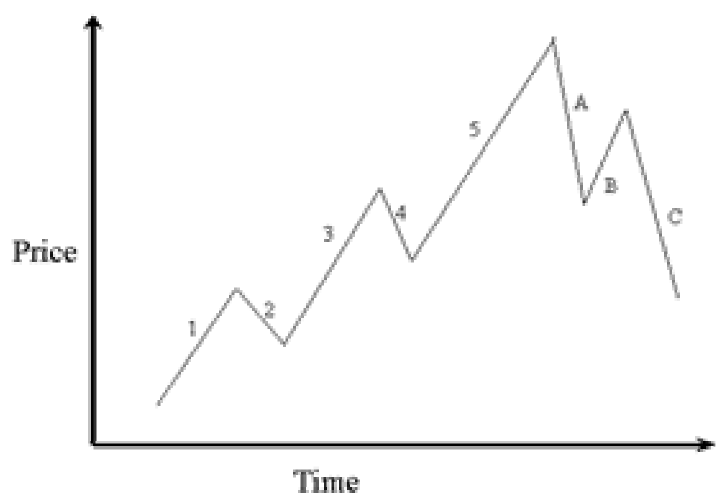

Figure 2-8 Elliott's Five Wave Pattern

The Figure 2-8 explains the bull market phase of five waves consisting of three waves up (Waves 1, 3, and 5), with two corrective waves down (waves 2 and 4). This is followed by three waves down (ABC Waves) in the bear phase of the cycle, completing the eight-wave sequence. It was further noted that these eight wave sequences appeared one after another and became part of a larger wave sequence. The naming convention started by analysts resulted in naming the smallest wave observed as a subminuette wave, and the waves were named in order of rising magnitude as follows:

- Subminuette
- Minuette
- Minute
- Minor
- Intermediate
- Primary
- Cycle
- Super cycle
- Grand super cycle

The most important principle in understanding the Elliott Wave Principle is that wave structures of the largest degree are composed of smaller sub waves, which are in turn composed of even smaller sub waves, and so on (Figure 2-9).

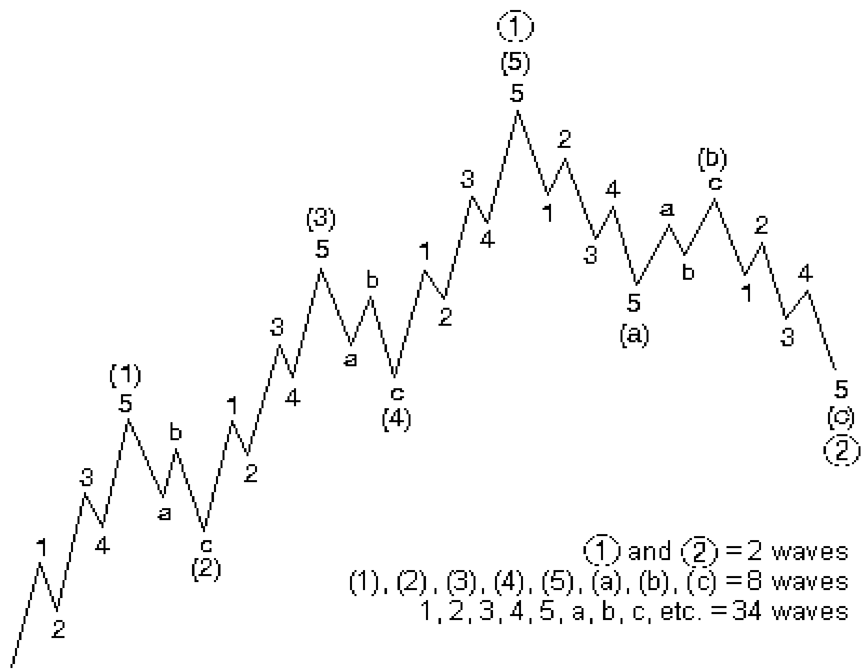

Figure 2-9 A Typical Elliott Wave Cycle. (Adapted from [13])

All the waves have approximately the same structure and behavior as the larger wave that they belong to. The stock market was analyzed using these tenets and nine wave degrees for time periods ranging from centuries to hours were identified. The study of patterns in Elliott Wave is very important because it tells the pattern in which the market is going to move rather than the direction of movement alone.

We can conclude that Elliott's Principle suggests the stock market expands and contracts in line with a set structure or form. The correction waves start after a 5 wave bull trend and progress downward in a three-wave structure. This is again followed by a five-wave bull (upward) momentum structure. An important conclusion of this fundamental tenet indicates that prices do not return to the low point of the previous 8 wave sequence, prices only approach the previous low.

2.2.3 Fibonacci Series and Elliott's Wave Theory

The Fibonacci series is the mathematical backbone of the Elliott's Wave Theory [10]. The properties of this sequence appear throughout nature and also in the arts and sciences. The ratio of 1.618, also called as the "Golden Mean", is very common in nature. It is obtained by dividing the Fibonacci number by its preceding number as the sequence extends into infinity. The ratio of 0.618, which is the inverse of 1.618, is also used in analyzing the wave patterns.

The wave counts of the impulsive and corrective patterns (5 + 3 = 8 total) are Fibonacci numbers. Breaking down wave patterns into their respective sub waves produces Fibonacci numbers indefinitely (Figure 2-10). Since Fibonacci ratios are found to occur in the proportions of one wave to another, waves are often related to each other by the ratios of 2.618, 1.618, 1, 0.618, 0.382 and 0.236 (Figure 2-11).

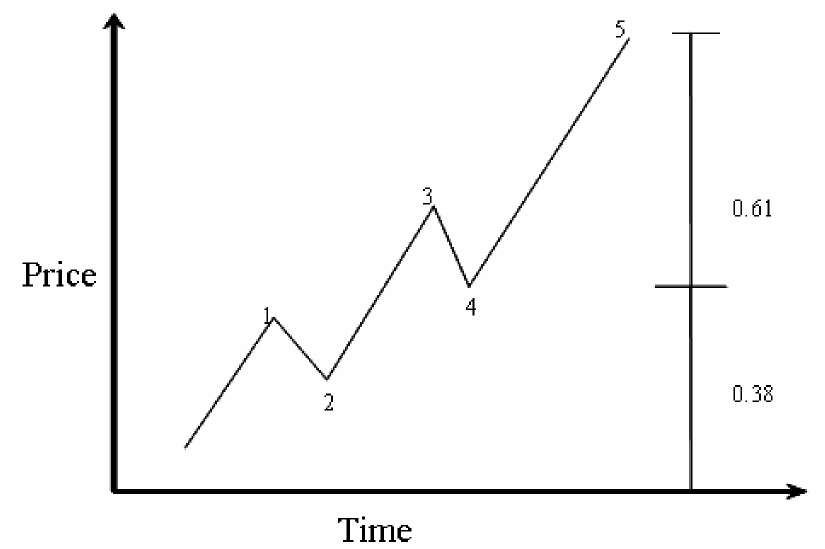

Figure 2-10 Fibonacci Ratios in Elliott Wave

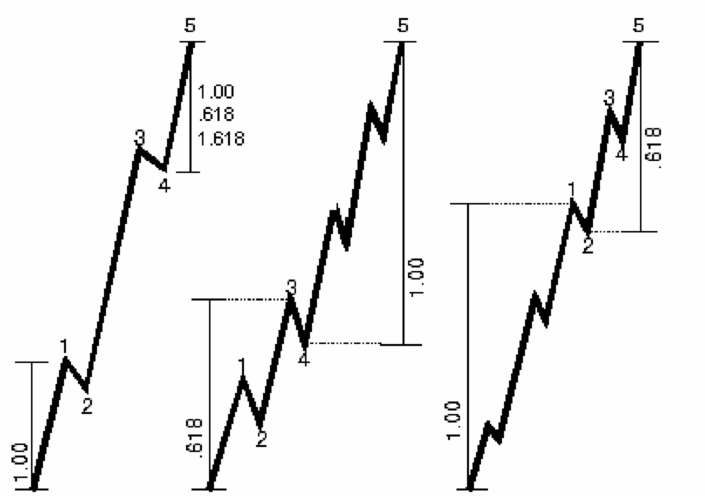

Figure 2-11 Fibonacci Ratio Possibilities in Elliot Wave

2.3 Stock Market Indicators

2.3.1 Introduction

An indicator may be defined as a series of data points that are derived from the price data of a security by applying a basic formula. Price data is a combination of open, close, high, or low over a period of time. For example, the average of 3 closing prices is one data point ((41+43+43)/3=42.33). However, one data point does not offer much information and does not make an indicator. A series of data points over a period of time is required to create valid reference points to enable analysis. By creating a time series of data points, a comparison can be made between present and past levels. An indicator offers a different perspective from which to analyze the price action [37].

The function of indicators may be classified into three broad categories: to alert, to confirm, and to predict. An indicator can act as an alert to study price action a little more closely. If momentum is waning, it may be a signal to watch for a break of support. Or, if there is a large positive divergence building, it may serve as an alert to watch for a resistance break-out [30].

Indicators can be used to confirm other technical analysis tools [40]. If there is a break-out on the price chart, a corresponding moving average crossover could serve to confirm the break-out. Or, if a stock breaks support, a corresponding low in the On-Balance-Volume (OBV) could serve to confirm the weakness [36].

2.3.2 Classification of Indicators

Indicators are mathematical/statistical functions that are applied over stock properties such as close, high, low and volume. These indicators are broadly classified into the following important categories:

- Market Momentum Indicators
- Market Volatility Indicators
- Market Trend Indicators
- Broad Market Indicators
- General Momentum Indicators

Analysts generally use at least one indicator from each of these categories for their forecasts [37]. The indicator is generally chosen by evaluating the accuracy of the model. Most often many indicators are overlooked and a good model may never be discovered for that particular stock. A common misconception with those new to Neural Networks is that the more inputs you give a Neural Network, the more information it has, so the resulting model will be better. If the input data is not relevant to the desired output, the network will have a more difficult time learning the associations between the relevant inputs and the desired output. The first step is to use a set of indicators commonly used in traditional technical analysis. Another approach is to use the Correlation Analysis. Correlation Analysis is useful for searching for linear relationships between the desired output and a set of proposed inputs. Specifically, correlation analysis determines if an input and the desired output move in the same direction by similar amounts. Using inputs with high (positive or negative) correlation values with the output often produce good models.

2.3.3 Basic Indicators

The following are some of the basic indicators that are used for creating the baseline model. These indicators are known to provide useful information for forecasting using Neural Networks.

2.3.3.1 Relative Strength Index

Relative Strength Index is a measure of the strength that is intrinsic in a field and is calculated using the amount of upward and downward price changes over a given period of time. It has a range of 0 to 100 with values typically remaining between 30 and 70. Overbought conditions are indicated by higher values of the Relative Strength Index while lower values indicate oversold conditions. The formula for computing the Relative Strength Index is as follows.

$$RSI = 100 - [100 / (1+RS)]$$

Where RSI = Relative Strength Index.

RS = Average of x days' up closes Average of x days' down closes.

In addition, the value is defined as 100 when no downward price changes occur during the period of calculation. The following are the indications from an RSI graph.

- The Relative Strength Index usually leads the price by forming peaks and valleys before the price data, especially around the values of 30 and 70.
- When the RSI diverges from the price, the price eventually follows a corrective trend towards the direction of the index.

2.3.3.2 Money Flow Index

The Money Flow Index is a measure of the strength of the monetary instrument flowing into or out of a stock traded in the open market. It is principally derived by comparing the volume of upward and downward price changes over a given period of time. The Money Flow Index is based on the quantity of Money Ratio, which is the ratio of positive money flow to negative money flow over the given period.

$$Money\ Flow = Typical\ \Pr ice \times Volume$$
$$Money\ Ratio = \frac{Positive\ Money\ Flow}{Negative\ Money\ Flow}$$
$$MFI = 100 - \frac{100}{1 + Money\ Ratio}$$

Positive money flow is defined as the sum of the prices multiplied by the volume on days when the price increases. Negative money flow is defined similarly, except that it includes only days when the price decreases. The Money Flow Index typically has a range of 0 to 100 with values rarely exceeding the bounds of 20 and 80. As in a Relative Strength Index, higher values indicate overbought conditions while lower values indicate oversold conditions. The difference between the two indicators is that the Money flow Index has a volume component that provides some amount of additional information to an analyst. Researchers also consider money Flow Index as typically using a more complex price model. When there are no downward movements in price the Money Flow Index is defined as 100. This is due to the fact that upon application of the formula, a "divide-by-zero" situation occurs.

2.3.3.3 Moving Average

This function returns the moving average of a field over a given period of time. The moving average is calculated by averaging together the previous values over the given period, including the current value.

$$MA = \frac{\sum_{1}^{n} \text{Closing Price}}{n}$$

Moving averages are useful for eliminating noise in raw data. Analysis of the moving average of the price yields a more general picture of the underlying trends.

2.3.3.4 Stochastic Oscillator (SO)

The stochastic oscillator may be defined as a measure of the difference between the current closing price of a security and its lowest low price, relative to its highest high price for a given period of time. The formula for this computation is as follows.

$$\%K = \frac{C - LX}{HX - LX} \times 100$$

Where,

- C is Recent closing price
- LX is Lowest low price during the period
- HX is Highest high price during the period
- $\%K$ is Stochastic Oscillator

The value is a percent rating for the closing price, relative to the trading range between its recent highest and lowest prices. A value of zero indicates that the security had a closing price at its lowest recent low. A value of 100 indicates it that the security had a closing price at its highest recent high. The value is often smoothed using a slowing period to eliminate noise in the trend graph.

2.3.3.5 Moving Average Convergence/divergence (MACD)

The MACD is the difference between the short and the long term moving averages for a field. The MACD is generally a specific instance of a Value Oscillator and is mostly used on the closing price of a security to detect price trends. When the MACD is on an increasing trend, prices are trending higher. If the MACD is on a decreasing trend, prices are trending lower.

The Moving Average Convergence/divergence indicator is traditionally traded against a 9-day exponential average of its value, called its signal line. The Moving

Average Convergence/divergence indicator Signal Line function is provided to generate this value.

$$EMA = [\alpha \times Today's\ Close] + [(1-\alpha) \times Yesterday's\ EMA]$$
$$MACD = [0.075\ EMA\ of\ Closing\ Prices] - [0.15\ EMA\ of\ Closing\ Prices]$$
$$Signal\ Line = 0.20\ EMA\ of\ MACD$$

Where,

- EMA is Exponential Moving Average
- α is the period multiplier

When the Moving Average Convergence/divergence indicator increases above its signal line, a buy signal is generated. When the Moving Average Convergence/divergence indicator decreases below its signal line, a sell signal is generated.

2.4 Fuzzy Logic

2.4.1 Introduction to Fuzzy Logic

Fuzzy set theory, originally introduced by Lotfi Zadeh in the 1960's, resembles human reasoning in its use of approximate information and uncertainty to generate decisions. Fuzzy theory was designed with a specific purpose of mathematically representing ambiguity. It was also developed to represent vagueness and provide formalized procedures for tackling the impreciseness inherent in many variables in a multitude of problems.

For the purposes of comparison, traditional computing demands precision inherent in all variables of the systems that are a part of the analysis. Thus Fuzzy set theory helps in imparting knowledge to the system in a more natural way by using fuzzy sets. This also helps in the simplification of numerous engineering and decision problems.

2.4.2 Fuzzy Set Theory

Fuzzy set theory implements classes or groupings of data with boundaries that are not sharply defined (i.e., fuzzy). Any methodology or theory implementing clear and lucid definitions such as classical set theory, arithmetic, and programming, may be fuzzified. This is achieved by generalizing the concept of a clear and crisp set of parameters to a fuzzy set with hazy boundaries. Most real world problems inevitably entail some degree of imprecision and noise in the variables and parameters measured and processed for the application. The inherent advantage of extending crisp theory and analysis methods to fuzzy techniques generates strong techniques to solve most real-world problems.

Fuzzy logic applications are a critical component of representing linguistic variables, where general terms such a "large," "medium," and "small" are each used to capture a range of numerical values. This may be explained in detail by temperature membership functions for translation of knowledge. The Figure 2-12 illustrates the method to define the fuzzy parameters of cold, cool, warm and hot using temperatures T_i.

While similar to conventional quantization, fuzzy logic allows these stratified sets to overlap.

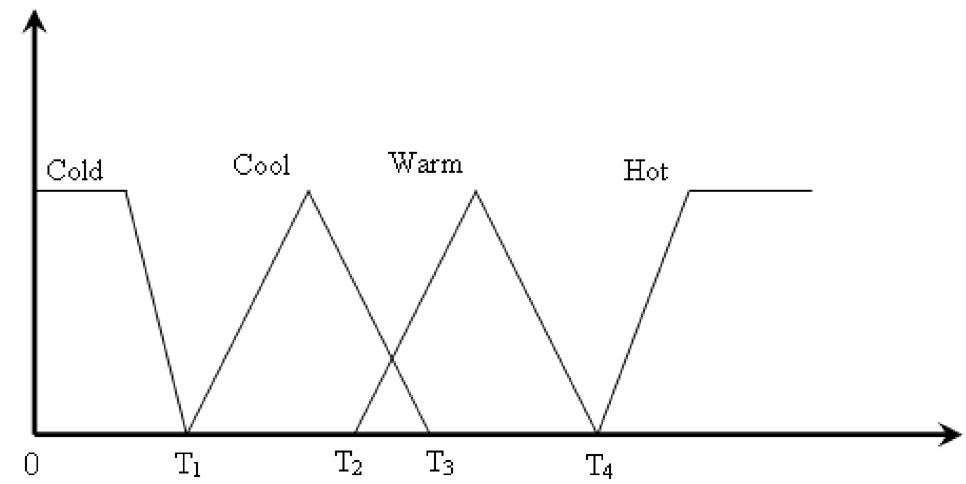

Figure 2-12 Fuzzy Sets Example

Fuzzy set theory is the common nomenclature used to identify fuzzy logic, fuzzy arithmetic, fuzzy mathematical programming, fuzzy topology, fuzzy graph theory, and fuzzy data analysis techniques.

Fuzzy logic emerged into the mainstream of information technology in the late 1980's and early 1990's. Fuzzy logic is a departure from classical Boolean logic in that it implements soft linguistic variables on a continuous range of truth values which allows intermediate values to be defined between conventional binary. It can often be considered a superset of Boolean or "crisp logic" in the way fuzzy set theory is a superset of conventional set theory.

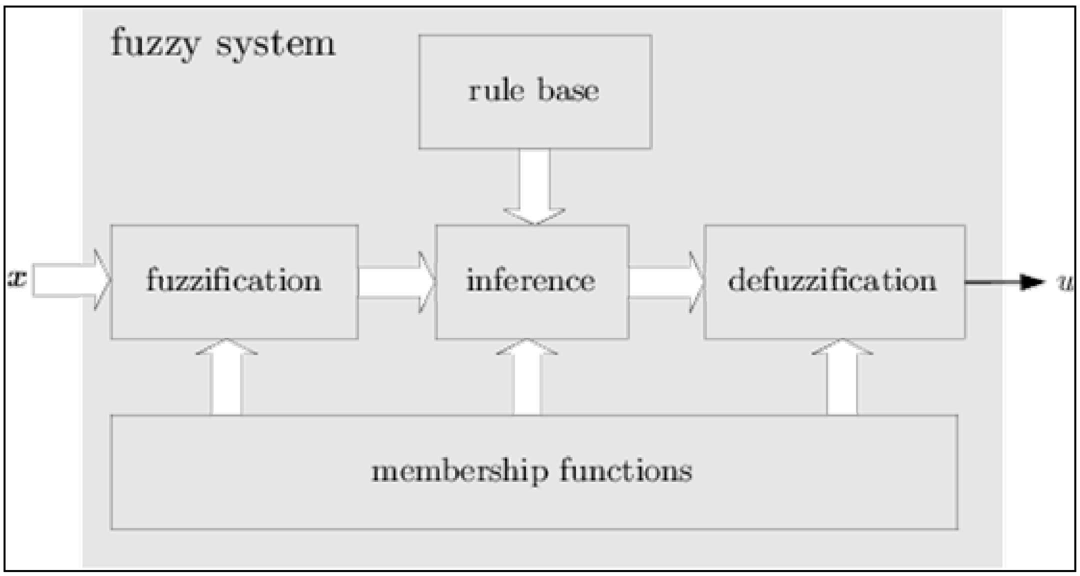

Figure 2-13 Fuzzy System Schematic Diagram (Adapted from [20])

Since fuzzy logic can handle approximate information in a systematic way, it is ideal for controlling nonlinear systems and for modeling complex systems where an inexact model exists or systems where ambiguity or vagueness is common. A typical fuzzy system consists of a rule base, membership functions, and an inference procedure. The Figure 2-13 shows a schematic layout of a fuzzy system.

CHAPTER 3. METHODOLOGY

The work of Weckman et al [40] was extended to test if the performance of Neural Network based forecasting model could be improved by increasing its knowledge domain. This chapter describes the implementation of a Neural Network model in a stock market scenario and the application of indicator pruning techniques and Elliot's wave theory. The primary objective of this research is to generate a one-day forecast of the closing price using the techniques mentioned.

3.1 Stock Market Data

The stock market data used in this research was derived from various sources on the World Wide Web, most notably, the financial websites maintained by Yahoo Inc. The Dow Jones Global Classification Standard (DJGCS) — which comprised of economic sectors, market sectors, industry groups and subgroups — provides correct and internationally accepted industry and sector classifications. The following are the broad economic sectors that are taken into consideration by typical stock market investors.

1. Basic Materials [BSC]
2. Consumer, Cyclical [CYC]
3. Energy [ENE]
4. Financial [FIN]

5. Healthcare [HCR]
6. Industrial [IDU]
7. Investment Products [IVP]
8. Consumer, Non-Cyclical [NCY]
9. Technology [TEC]
10. Telecommunications [TLS]
11. Utilities [UTI]

Stock selections for a typical investor are from different sectors of the stock market so as to minimize risk in investment. Also, stocks chosen in an investment portfolio have a mixture of growth and value stocks, thereby diversifying the portfolio and minimizing risk while increasing long term returns. The stocks listed in Table 3-1 Stocks Analyzedwere the stocks selected and analyzed in this research.

Sector	Ticker Symbol	Name
Financial [FIN]	BAC	Bank of America Corp
Financial [FIN]	JPM	JP Morgan Chase & Co.
Financial [FIN]	WB	Wachovia Corporation
Technology [TEC]	EMC	EMC corporation
Technology [TEC]	HPQ	HP Corporation
Technology [TEC]	STX	Seagate Technologies
Healthcare [HCR]	RHB	RehabCare
Healthcare [HCR]	AGP	AmeriGroup Corporation
Healthcare [HCR]	WLP	Well Point Inc.
Consumer Non-Cyclical [NCY]	AMR	AMR Corporation
Consumer Non-Cyclical [NCY]	CAL	Continental Airlines
Consumer Non-Cyclical [NCY]	DAL	Delta Airlines
Industrial [IDU]	F	Ford Motors Corporation
Industrial [IDU]	GM	General Motors Corporation
Industrial [IDU]	HMC	Honda Motor Corporation

Table 3-1 Stocks Analyzed

Preliminary data analysis is then performed and consists of identifying stock splits and adjusting the value of the stocks. Hence the data used for the different stocks consists of different time periods with the over lapping time periods are identified.

3.2 Analysis of Preliminary Indicators

The research starts with the development of a base line forecasting model based on research published by Weckman et al [1][40]. Accordingly the preliminary model developed was a Generalized Feed Forward network that has the following properties.

1. Input Processing Elements = 8
2. Hidden Layers: one layer containing 4 processing elements
3. Output Processing Elements = 1 (Closing Sales Price)
4. PE Transfer Function = TanhAxon
5. Maximum Number of Epochs = 5000

This model applied the stocks listed in Table 3-1 and the results form the baseline performance against which further models are compared. The GFF network as represented by NeuroSolutions is shown in Figure 3-1.

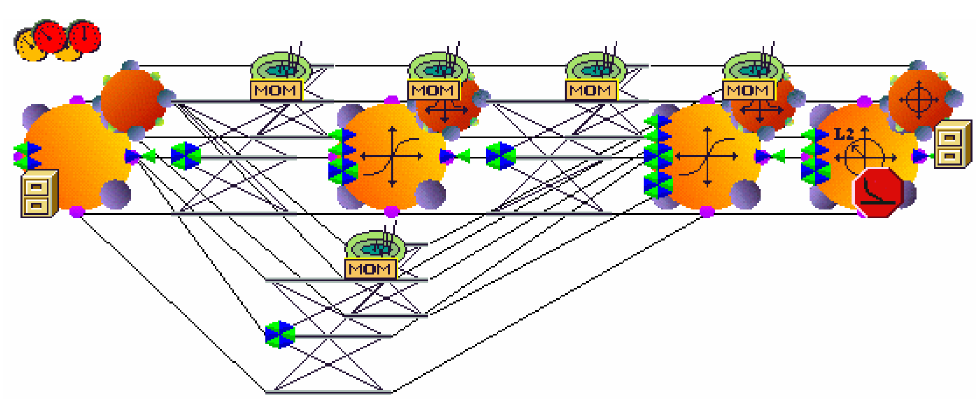

Figure 3-1 Generalized Feed Forward Network as represented by NeuroSolutions

The data required for analysis is compiled using spreadsheet management software, Microsoft Excel, which is then used by NeuroSolutions.

3.3 Indicator Selection Using Self Organizing Map

This process is performed to identify new indicators that provide more information to a Neural Network training algorithm, thereby aiding improvement in forecast generated. Indicators are classified into the following categories:

1. Market Momentum Indicators
2. Market volatility Indicators
3. Market Trend Indicators
4. Broad Market Indicators
5. General Momentum Indicators

A total of 56 commonly used indicators are selected and they are listed in Table 3-2 as follows

Accumulation/Distribution	Williams' Accumulation/Distribution
Average Directional Movement	Average True Range
Chaikin Oscillator	Average True Range Band (Bottom)
Commodity Channel Index	Average True Range Band (Top)
Commodity Channel Index (General)	Beta
Directional Movement Index	Beta On Decrease
Directional Movement Rating	Beta On Increase
Ease of Movement	Bollinger Band (Bottom)
Herrick Payoff Index	Bollinger Band (Top)
Minus Directional Indicator	Chaikin's Volatility
Money Flow Index	Keltner Channel (Bottom)
Money Flow Index (General)	Keltner Channel (Top)
On Balance Volume	Mass Index
Plus Directional Indicator	Trading Band (Bottom)
Price and Volume Trend	Trading Band (Top)
QStick Indicator	True Range
Stochastic Oscillator	Aroon Down
Williams' %R	Aroon Up
Velocity	Value Oscillator
Market Facilitation Index	Upside/Downside Ratio
Negative Volume Index	Acceleration
Positive Volume Index	MACD
Time Series Forecast	Momentum
Vertical Horizontal Filter	Rate-of-Change
Absolute Breadth Index	Relative Momentum Index
Absolute Breadth Index (Percent)	Relative Strength Index
New Highs/Lows Ratio	TRIX
New Highs-Lows Cumulative	Open-10 TRIN

Table 3-2 Input Indicators to a Self Organizing Map Network

The indicators mentioned are fed as input to a self-organizing map Neural Network. All Neural Networks that are implemented for this problem were developed using NeuroSolutions, proprietary software of NeuroDimension Inc. The indicators are decomposed based on their formulae and the presence or absence of a particular property is noted.

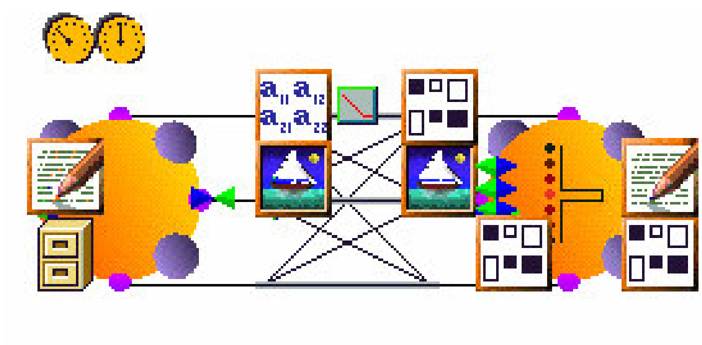

Figure 3-2 NeuroSolutions Representation of a Self Organizing Map

The properties checked for are close, high, low, period and volume and are coded in a binary fashion as shown in Table 3-3 SOM Indicators Coding Methodology. The self-organizing map based on the presence or absence of the properties, as shown in Figure 2-1, clusters the indicators. The clusters are then analyzed and indicators are chosen that are the closest to the cluster center.

Indicators	Close	High	Low	Period	Volume
Accumulation/Distribution	1	1	1	0	1
Average Directional Movement	1	1	1	1	0
Chaikin Oscillator	1	1	1	0	1
Commodity Channel Index	1	1	1	1	0
Commodity Channel Index (General)	1	0	0	1	0
Directional Movement Index	1	1	1	1	0
Directional Movement Rating	1	1	1	1	0
Ease of Movement	0	1	1	0	1
Herrick Payoff Index	0	1	1	0	1

Table 3-3 SOM Indicators Coding Methodology

The values for the chosen indicators are then calculated for of the all the stock market data. These are the inputs to the Generalized Feed Forward network as indicated in Figure 3-3. This network was trained multiple times with 10,000 epochs for each run. The best weights after cross validation was saved. The testing data was run over the network with the saved weights and the results were noted. This methodology may be depicted as a flow of operations as shown in Figure 3-4.

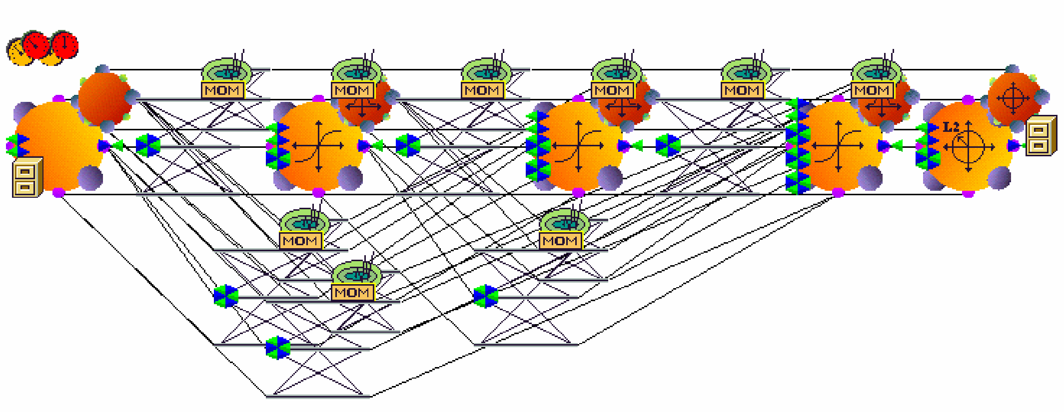

Figure 3-3 Final Generalized Feed Forward Network implementation

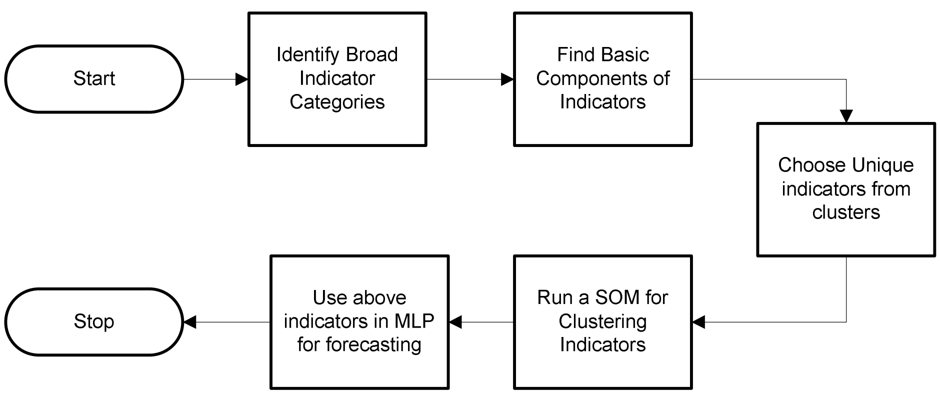

Figure 3-4 Self Organizing Map Methodology

3.4 Elliott Wave Implementation

In a real life continuous data set, a definitive threshold cannot be established, but each data point does have a certain degree of membership to a belief function [6] [39]. This concept is used to define the membership of Elliott Wave points in the current data set. A Fibonacci Ratio based percentage is calculated for a given data set and the membership functions for the Elliott Wave indicators are defined. The Elliott Wave and the turning point indicators are found to inculcate a wavy nature in the output that scaled the peaks and troughs of the actual wave. This helps immensely in the forecast of the short term direction of the price movement. A decision match is nothing but forecasting the right direction of movement of the price regardless of the magnitude. This concept is explained graphically in Figure 3-6 . Thus the decision mismatches reduced in the forecasting of a time series such as the stock market. Three fuzzy classes of high, medium and low are set indicating the probability of the point being an Elliott Turning Point (Figure 3-5). The fuzzy classes used are rectangular binding functions. The area depicts the probability of that point being an Elliott Turning Point.

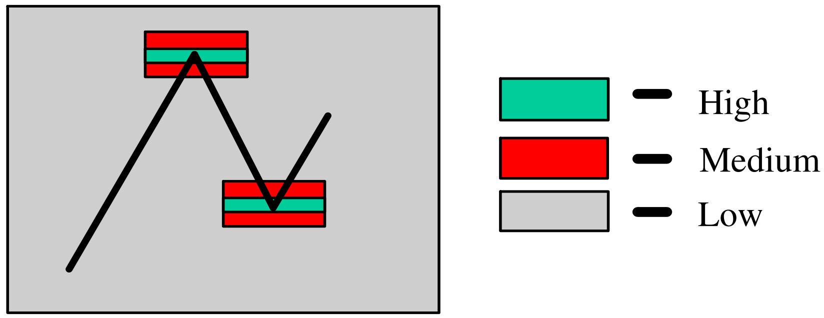

Figure 3-5 Probability of Data being Turning Point

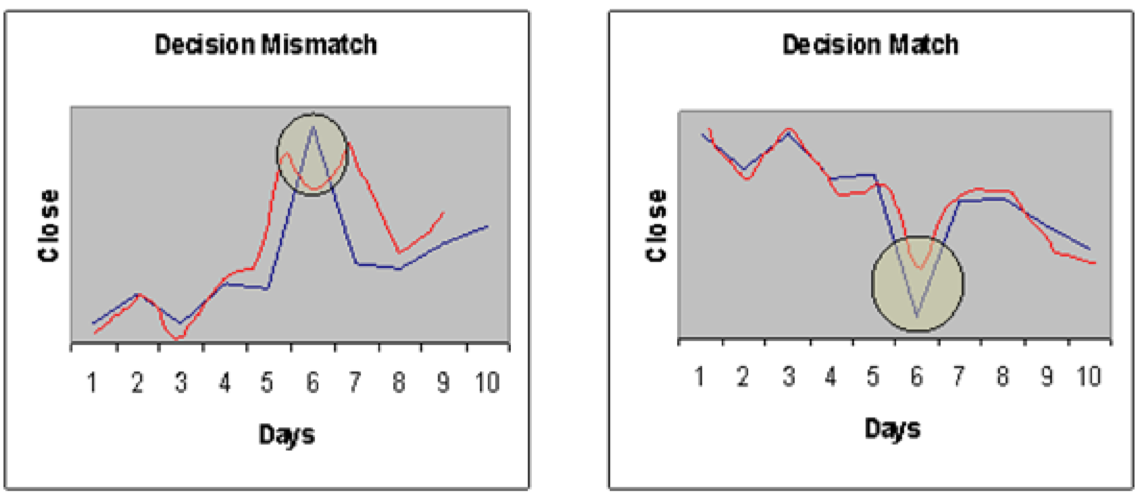

Figure 3-6 Forecasting Decisions

3.5 Summary

The methodology can be simply described as a process involving three major steps clearly shown in Figure 3-7.

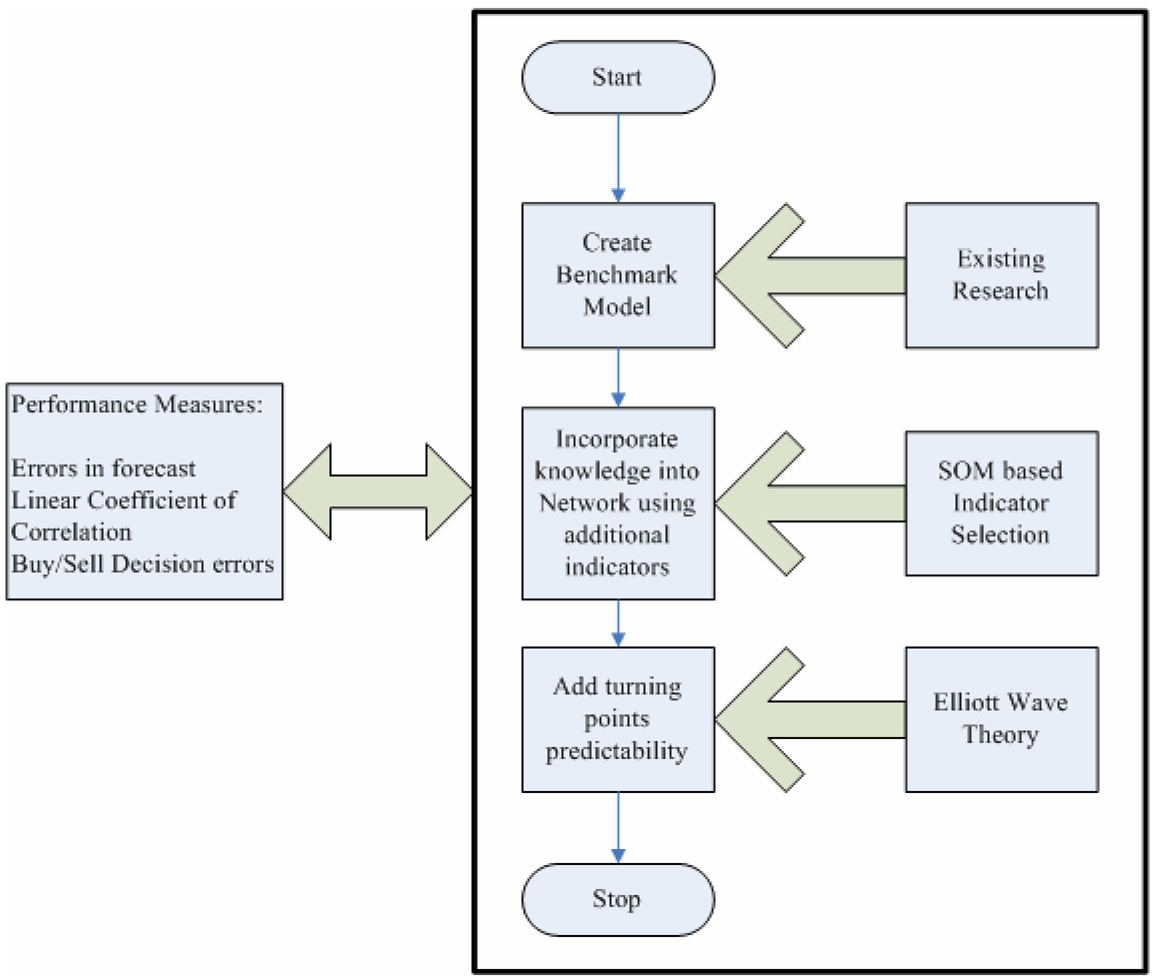

Figure 3-7 Methodology

CHAPTER 4. RESULTS AND DISCUSSION

4.1 Performance of the Benchmark Network

The benchmark network was selected based on the results and principles of network selection by Weckman et al [40]. Different network architectures using a multitude of factors were tested for the performance measures listed in Table 4-1

Performance Measures	Abbreviations
Mean Squared Error	MSE
Normalized Mean Squared Error	NMSE
Mean Absolute Error	MAE
Minimum Absolute Error	MinAE
Maximum Absolute Error	MaxAE
Linear Correlation Coefficient	r

Table 4-1 Performance Measures

The architectures that were tested are the Generalized Feed Forward and Multilayer Perceptrons. Different networks were constructed using different parameters. The parameters that were modified are the number of Perceptrons, number of layers, the step size and the method of weight update. The Table 4-2 indicates the results for the 3 different Multilayer Perceptrons and Generalized Feed Forward networks on the

Amerigroup Corporation (AGP) stock's closing price. The initial indicators used are as follows:

- Moving Average Convergence Divergence
- Money Flow Index
- Moving Average
- Relative Strength Index
- Stochastic Oscillator

	MLP#1	**MLP#2**	**MLP#3**	**GFF#1**	**GFF#2**	**GFF#3**
MSE	345.614	201.765	557.921	201.932	196.815	48.79
NMSE	3.089	1.803	4.986	1.805	1.759	1.340
MAE	15.848	10.589	21.352	10.848	10.368	7.03
Min AE	2.067	0.016	6.407	0.405	0.047	0.602
Max AE	37.177	31.610	43.268	31.398	31.376	31.186
R	0.627	0.812	0.807	0.885	0.821	0.893

Table 4-2 Initial Performance Statistics for AGP

From the Table 4-2, based on MSE, MAE and r, the third run of the Generalized Feed Forward network produced the best results. The performance statistics in the Table 4-2 indicate very clearly that on key performance measures, the Generalized Feed Forward network performed better than the Multi Layer Perceptron based network. The performance of the final Generalized Feed Forward benchmark network on all the stocks are listed in Table 4-3. These conclusions are more clearly depicted by graphs that show the closing price comparisons between the forecast value and the actual value.

	MSE	NMSE	MAE	Min AE	Max AE	r
AGP	48.79	1.34	7.03	0.60	31.19	0.89
AMR	41.11	1.37	6.86	0.03	2.64	0.87
BAC	35.46	3.24	5.57	1.50	18.23	0.86
CAL	107.39	1.15	7.50	0.00	1.65	0.86
DAL	82.32	1.04	11.29	0.01	4.31	0.78
EMC	80.44	11.11	4.35	1.60	6.76	0.82
F	80.82	10.89	3.88	1.38	7.29	0.82
GM	22.02	2.79	1.25	0.05	3.90	0.89
HMC	14.12	20.98	3.59	1.10	5.94	0.88
HPQ	38.07	13.06	5.12	0.08	14.82	0.91
JPM	61.97	1.76	6.12	0.00	3.87	0.92
RHB	34.67	1.08	6.68	0.05	3.94	0.86
STX	34.98	1.62	6.81	0.02	2.66	0.84
WB	24.54	2.42	4.36	0.01	9.34	0.83
WLP	180.39	1.53	18.56	0.08	18.61	0.93

Table 4-3 Performance of Benchmark Model

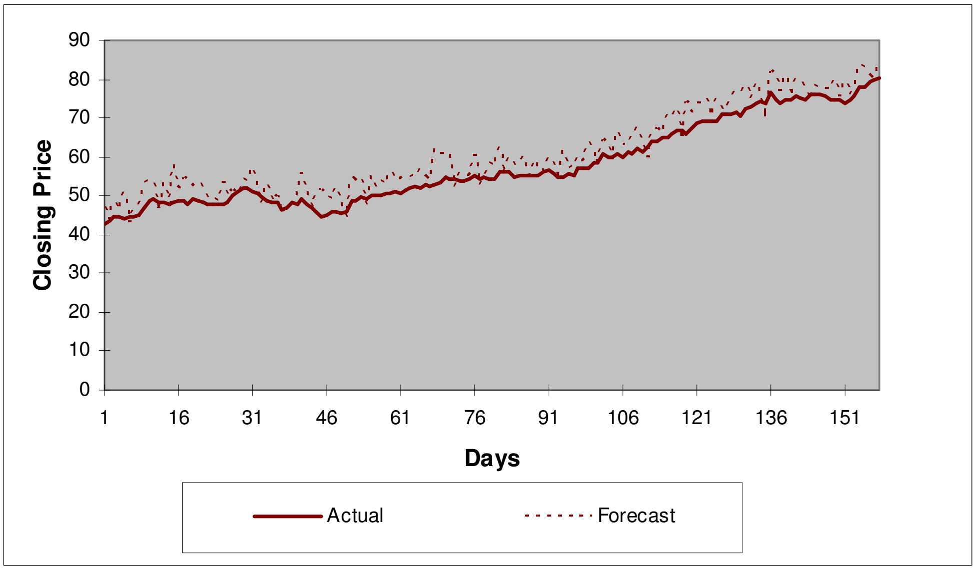

Figure 4-1 MLP Network Performance of AGP

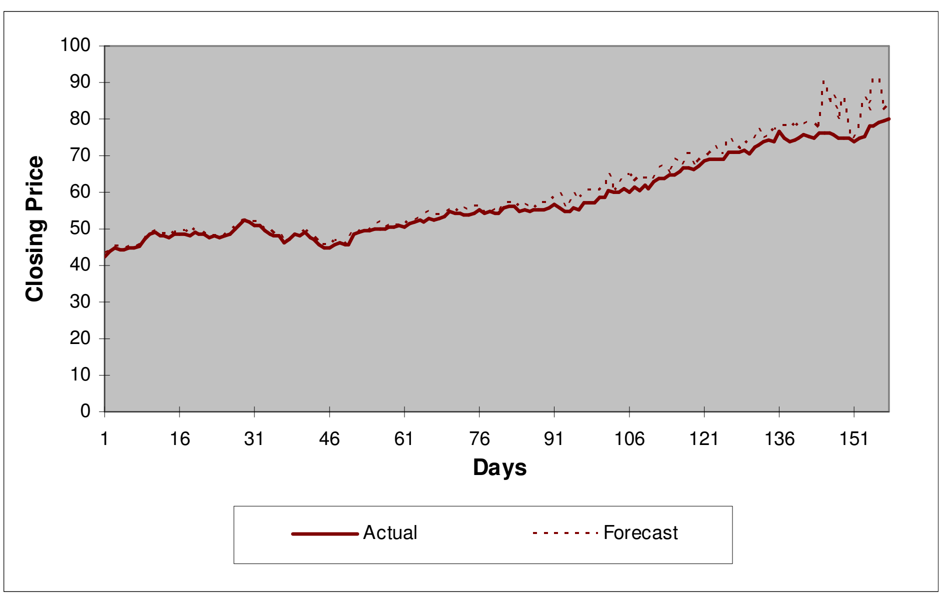

Figure 4-2 GFF Network Performance of AGP

The Figure 4-1 and Figure 4-2 show the graphs of the actual closing price and the forecasted closing price. The Figure 4-2 shows the performance of Generalized Feed Forward which is superior to Figure 4-1 showing the performance of a Multilayer Perceptron. Figure 4-2 also indicates that the predicted close values follow the actual close values more closely. Similar results were obtained for all the remaining stock prices.

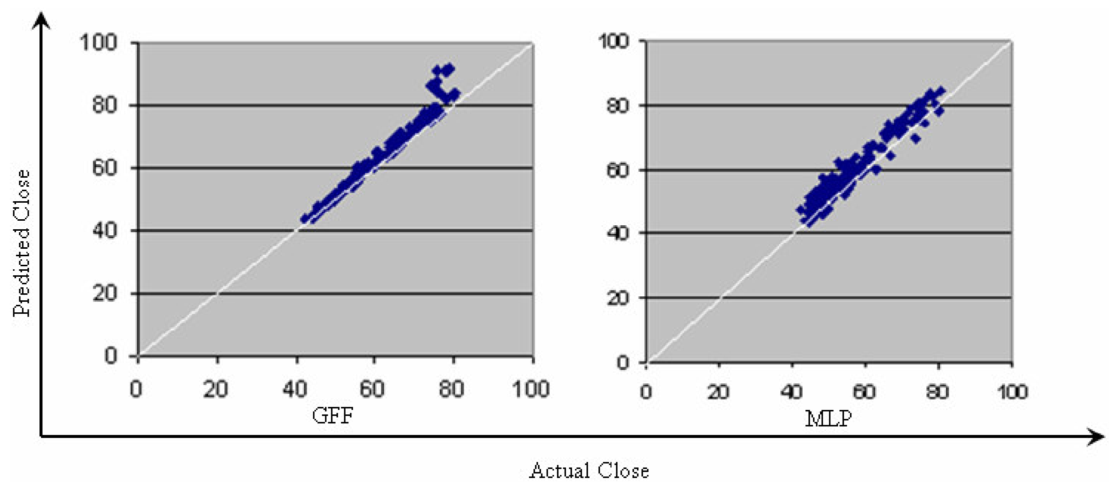

Figure 4-3 Distribution of Actual vs. Predicted Close of AGP

4.2 Indicator Analysis using Self Organizing Maps

The performance of the benchmark network developed in the previous section had the following short comings due to the limitations of the 5 indicators used for input:

- High Mean Squared Error (MSE)
- Low linear correlation coefficient (r)
- Poor forecasting results in unknown scenarios

These shortcomings can be overcome by providing the selected Generalized Feed Forward network with more information on trend, momentum and volatility of the closing price. This information can be supplied to the network using a variety of indicators. All the indicators cannot be provided to the network, due to the fact that the network becomes too complex and the evaluation time increases by a magnitude of 10. Therefore indicators representative of a particular information property have to be selected. This is carried out by coding the indicators based on their constituents in the formula. The following is the formula for the Ease of Movement indicator.

$$EoM = \frac{MA\{(\frac{High_t + Low_t}{2}) - (\frac{High_{t-1} + Low_{t-2}}{2})\}}{\frac{Volume}{High_t - Low_t}}$$

Where

- EoM = Ease of Movement
- MA = Moving Average

It is clear from the above formula that the Ease of Movement indicator utilizes the High, Low and Volume of the stock. Thus the columns High, Low and Volume receive a 1 during Self Organizing Map coding and all other fields receive a 0. A sample of this coded input is shown in Table 4-4.

Indicators	**Close**	**High**	**Low**	**Period**	**Volume**
Accumulation/Distribution	1	1	1	0	1
Average Directional Movement	1	1	1	1	0
Chaikin Oscillator	1	1	1	0	1
Commodity Channel Index	1	1	1	1	0
Commodity Channel Index (General)	1	0	0	1	0
Directional Movement Index	1	1	1	1	0
Directional Movement Rating	1	1	1	1	0
Ease of Movement	0	1	1	0	1
Herrick Payoff Index	0	1	1	0	1
Minus Directional Indicator	1	1	1	1	0

Table 4-4 SOM Indicators Coding Methodology

The self organizing map suggested the use of the indicators listed in Table 4-5 to generalize the knowledge provided by various indicators.

Type of Indicator	**Name**
Market Momentum Indicators	Money Flow Index
	Chaikin Oscillator
	Williams %R
Market Volatility Indicators	Mass Index
	Bollinger Band
	Trading Band (top)
Market Trend Indicators	Aroon Down
	Aroon Up
Broad Market Indicators	STIX
General Momentum Indicators	TRIX
	Relative Momentum Index

Table 4-5 SOM Indicators

These indicators are calculated for the closing price of all stocks. The period used in the calculation of all the indicators, where period is required as an input, is ten days which roughly translates into two business weeks.

These inputs derived from the self organizing map were then provided to the Generalized Feed Forward network selected in Table 4-2 for further enhancement of the models. The results of this model are listed in Table 4-6. The model was tested on data from the Amerigroup Corporation stock prices for comparison purposes.

Performance Measure	**GFF after SOM**
MSE	9.238
NMSE	1.284
MAE	2.176
Min Abs Error	4.623
Max Abs Error	3.132
r	0.980

Table 4-6 GFF Performance after SOM of AGP

The closing prices graph for the same stock is displayed in Figure 4-4. It is noted that the current model performed considerably better than the benchmark model. It is also apparent from Table 4-6 that the linear correlation coefficient has increased to 98% which suggests that the network has received considerable information from the indicators selected when using the self organizing map in Table 4-5. The results for the all the stocks are listed in Table 4-7.

	MSE	NMSE	MAE	MinAE	Max AE	r
AGP	9.238	1.284	2.176	4.623	3.132	0.980
AMR	2.558	0.189	0.617	0.006	1.834	0.963
BAC	5.841	0.023	1.541	0.005	9.097	0.896
CAL	0.361	0.125	0.492	0.000	1.746	0.942
DAL	30.319	15.518	0.402	0.453	1.592	0.950
EMC	2.190	1.198	1.197	0.004	0.949	0.986
F	0.356	0.099	0.519	0.001	1.409	0.973
GM	4.717	0.160	1.535	0.001	9.555	0.966
HMC	4.147	3.918	1.814	0.020	4.252	0.948
HPQ	1.982	0.772	1.153	0.006	5.270	0.900
JPM	1.123	0.461	0.837	0.001	2.693	0.886
RHB	42.730	8.132	5.512	0.004	14.521	0.924
STX	0.273	0.173	0.409	0.006	1.707	0.926
WB	23.013	2.267	4.162	0.021	2.321	0.947
WLP	502.105	1.036	19.025	0.028	38.799	0.900

Table 4-7 Performance of SOM Model

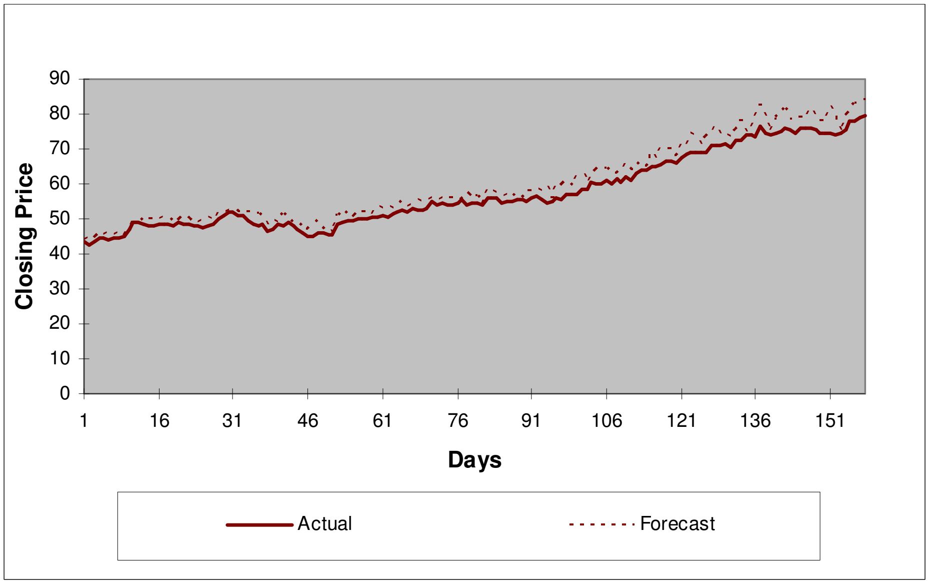

Figure 4-4 GFF with SOM Indicators Output

On visual inspection of Figure 4-4 it may be noted that the close output follows the actual close values in a consistent fashion. The only limitation of this model is that the output of the forecasting model, does not replicate the magnitude of the actual closing price and that the inconsistencies in forecasting the turning points are higher than expected. This analysis was carried out by taking the testing set of data and analyzing the number of correct price movements without considering the magnitude of movement (Table 4-8). Though the performance measures indicated a better model than the benchmark, the turning points have an accuracy of 57%, which is very low for a daily trading model.

Number of Testing Data Points	158
Number of correct change predictions	90
Number of incorrect change predictions	68
Percentage Accuracy	56.96%

Table 4-8 Price Movement Prediction Results

4.3 Elliott Wave Indicators Implementation

The performance of the network developed in the previous section had the following shortcomings:

- High Mean Squared Error (MSE)
- High Max and Min Absolute Error (Min Abs Error, Max Abs Error)
- Low percentage of accuracy in prediction of turning points.

These shortcomings were dealt with by developing two indicators based on the Elliott Wave principle. The first indicator uses the basic tenets of Elliott Wave discussed in Section 2.2 to develop a turning point indicator called the Elliott Wave Turning point Indicator (EWTP). The second indicator provides the magnitude information using Elliott Wave principles and is called the Elliott Wave Magnitude Indicator (EWM). The performance of this network is shown in Figure 4-5, Figure 4-66 and Table 4-9. The final networks performance on all the stocks is listed in Table 4-10.

Performance Measure	Final Network Properties
MSE	5.370
NMSE	0.867
MAE	6.806
Min AE	0.028
Max AE	2.613
r	0.996

Table 4-9 Final Network Performance

	MSE	NMSE	MAE	Min AE	Max AE	r
AGP	5.370	0.867	6.806	0.028	2.613	0.996
AMR	0.537	0.182	0.604	0.017	1.948	0.966
BAC	4.257	0.017	1.356	0.003	6.673	0.998
CAL	5.828	2.022	0.201	0.050	0.431	0.999
DAL	3.568	1.812	1.409	0.003	4.213	0.983
EMC	1.955	3.717	1.181	0.071	5.065	0.998
F	1.418	0.113	0.503	0.115	1.028	0.991
GM	3.752	0.128	1.459	0.016	6.842	0.961
HMC	1.020	0.632	0.293	0.038	0.799	0.997
HPQ	1.409	1.107	0.640	0.018	0.847	0.994
JPM	3.081	1.265	1.431	0.002	4.538	0.998
RHB	4.275	0.426	1.486	0.012	0.166	0.980
STX	0.257	0.163	0.419	0.002	1.561	0.953
WB	20.287	1.999	3.918	0.037	8.986	0.992
WLP	1.512	0.973	1.228	0.100	0.636	0.939

Table 4-10 Final Network Performance

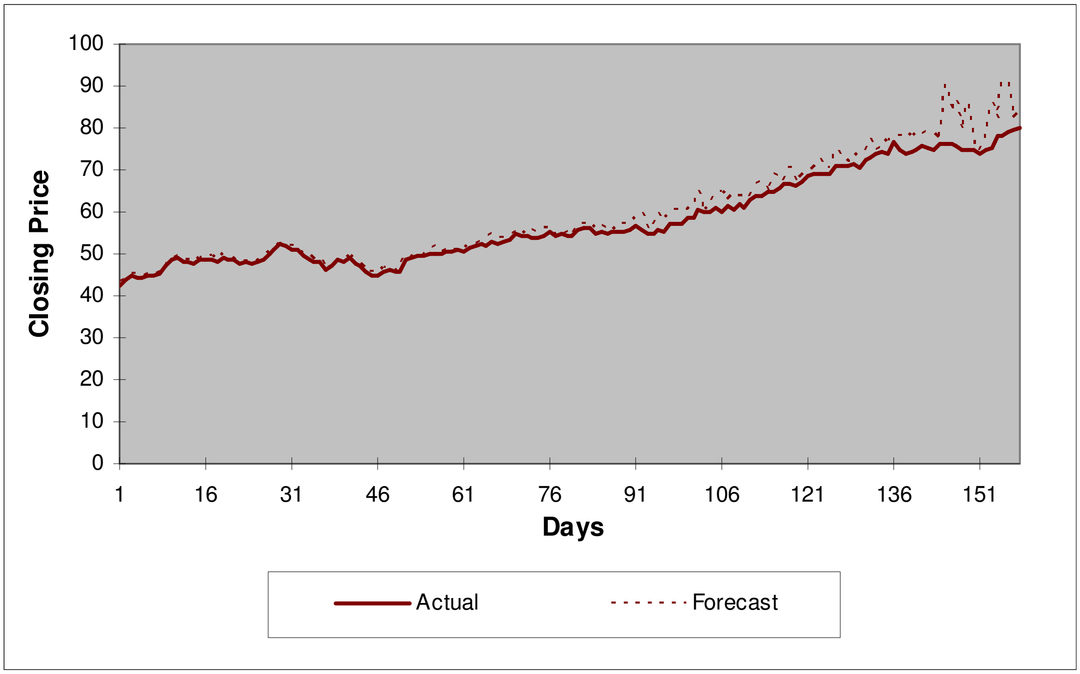

Figure 4-5 Final Network Output

It is clear from analyzing Figure 4-5 and Table 4-9 that the inclusion of the Elliott Wave indicators (EWTP and EWM) considerably improved the forecasting power of the network. Many investors judge the accuracy of the forecasting models by the amount of money generated based on the decisions implemented using the forecasted closing price. This aspect can be analyzed by creating a table of decisions based on the price movement forecast similar to Table 4-8. The result of this analysis is shown in Table 4-11. Comparable results were obtained for all the selected stocks.

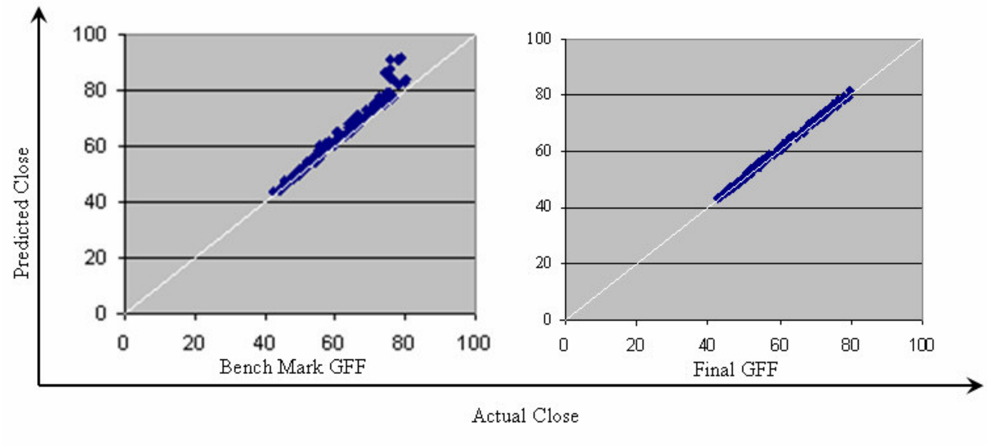

Figure 4-6 Predicted vs. Actual Closing Price Comparison

Number Of Testing Data Points	158
Number of correct change predictions	148
Number of incorrect change predictions	10
Percentage Accuracy	93.83%

Table 4-11 Final Change Prediction Results

Sensitivity analysis was performed on the final set of input indicators to ascertain the usefulness of all input indicators. The input indicators that were analyzed during sensitivity analysis are shown in Table 4-12.

Indicator Name	Symbol
Aroon Down	Aroon Down
Aroon Up	Aroon Up
Bollinger Band	BB(Bottom)
Chaikin Oscillator	CO
Moving Average Convergence Divergence	MACD
Mass Index	Mass Index
Money Flow Index	MFI
Moving Average	M Avg
Relative Momentum Index	RMI
Relative Strength Index	RSI
STIX Indicator	STIX
Stochastic Oscillator	SO
Trading Band (Top)	Tband(Top)
TRIX Indicator	TRIX
Williams' %R	Williams' %R
Elliott Wave turning point	EWTP
Elliott Wave magnitude	EWM

Table 4-12 Indicators used in Sensitivity Analysis

The following is the sensitivity analysis performed by varying inputs over two standard deviation lengths of the mean. The Figure 4-7 shows the resulting graph. The graph was truncated at a sensitivity value of 0.02, to exaggerate and clearly show the effect of some low sensitivity indicators.

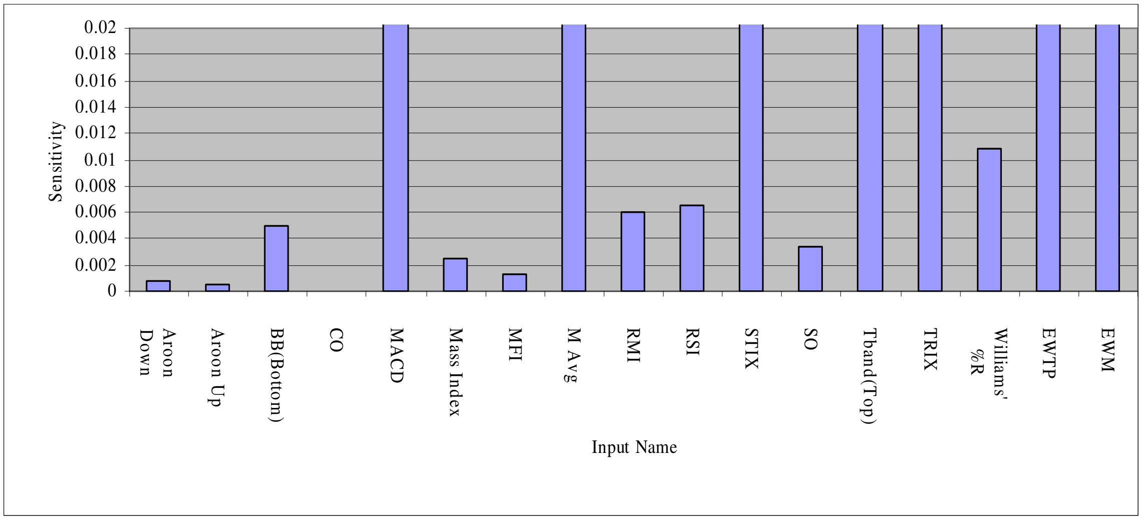

Figure 4-7 Relative Sensitivity of Indicators

It is obvious from the indicator analysis graph that all inputs except the Chaikin Oscillator have an impact on the output closing price. Even though the indicators Aroon Up and Aroon Down have low sensitivity on the output, they play a key role in providing consistent information to the network. This aspect was tested by removing the indicators with low sensitivity, but the resultant model had a marked decrease in the major performance factors. Thus all indicators selected with the exception of the Chaikin Oscillator played a pivotal role in the forecasting accuracy of the final model generated.

CHAPTER 5. CONCLUSIONS AND FUTURE RESEARCH

5.1 Conclusions

The thesis presents a novel and integrated approach to the problem of stock market forecasting. Stock markets are considered to be one of the most complex time series to model. This is due to the fact that stock markets have numerous underlying factors, most of which are currently not fully understood. Technical analysis of the stock market is a technique that does not require a thorough understanding of component factors. This concept can be utilized on a machine learning system such as an Artificial Neural Network, to understand the behavior of the stocks.

Initially a benchmark Neural Network was designed based on the published work of Weckman et al. [1][40]. In the process of developing the optimal benchmark, different network properties and architectures were tested. The optimal network was selected based on a set of performance measures. This network was tested on various stocks as listed in Table 3-1 to ensure the portability of the model across a spectrum of stocks.

The performance of this network was lacking in forecasting accuracy. More indicators were needed to impart the required knowledge for improving the performance of the network. Researchers and stock market analysts have historically used a large amount of indicators that have yielded very good results in different regimes of the financial market.

All indicators cannot be applied to a Neural Network, due to computing power and network complexity considerations. Therefore a unique method was devised to select a set of indicators that were representative of the genre of indicators. A Self Organizing Map was used to select networks based on their constituent properties.

These indicators were calculated for all the stocks and network analysis was performed to this improved network. The results were confirmed to improve the accuracy of forecasting by a significant amount. The network was still found to be lacking in forecasting turning points and magnitudes for new scenarios.

The Elliott Wave Theory possesses empirical rules that utilize the omni present principle of Fibonacci ratios and the Golden Ratio. These principles have been successfully used by traders to generate very accurate forecasts of the stock market. These principles were coded in the form of two indicators, namely the Elliott Wave turning point and the Elliott Wave magnitude indicators. This information aided the network's learning process thereby increasing the accuracy of the forecast both in terms of magnitude and direction.

In summary this research was able generate a final comprehensive stock market forecasting model by successively improving the Benchmark model by incorporating different techniques in a sequential fashion.

5.2 Future Research

This research focused primarily on developing a comprehensive Neural Network model for forecasting stock markets. There is an unambiguous scope for enhancement in the current research along the following directions.

Rule Extraction

The Neural Network stores knowledge gained during training in the form of connection weights or synapses. The knowledge gained by the network cannot be compared to the financial theories of the stock market. To draw this parallel of analysis, simple rules can be extracted from the model to corroborate the learning of the model with financial theories. This can lead to the development of a network that is based on sound financial principles.

Knowledge-Based Neurocomputing

An important consideration in the development of a Neural Networks is the time and cost of training. Knowledge-primed or hint-based training strategies can be used to considerably enhance the training routine. These procedures map the architecture of the Neural Network to the available domain knowledge. This significantly reduces the complexity of the training process. The process is also known to increase prediction accuracies.

Long-Term Forecasting

The proposed model is constructed by training the network on significantly large amounts of data to develop the forecast of the subsequent period. This may not be a financially attractive proposition because of the compounding nature of the errors. Therefore a long-term forecasting model would need to be generated to assess the performance of the model in a real-life investment situation.

Scalability

The research focuses on short term forecasting methodology of Stock Markets. Though the research cannot be directly extended to solve problems with other examples of noisy Time Series data, the model can be modified to suit a variety of applications. The processes involved in the course of this research can be scaled to other vertical applications such as demand forecasting and production planning.

Incorporating Low Probability Events

The research assumes that the underlying processes governing the stock market price movements are constant. The model may be improved by providing knowledge for incorporating low probability events such as a natural disaster.

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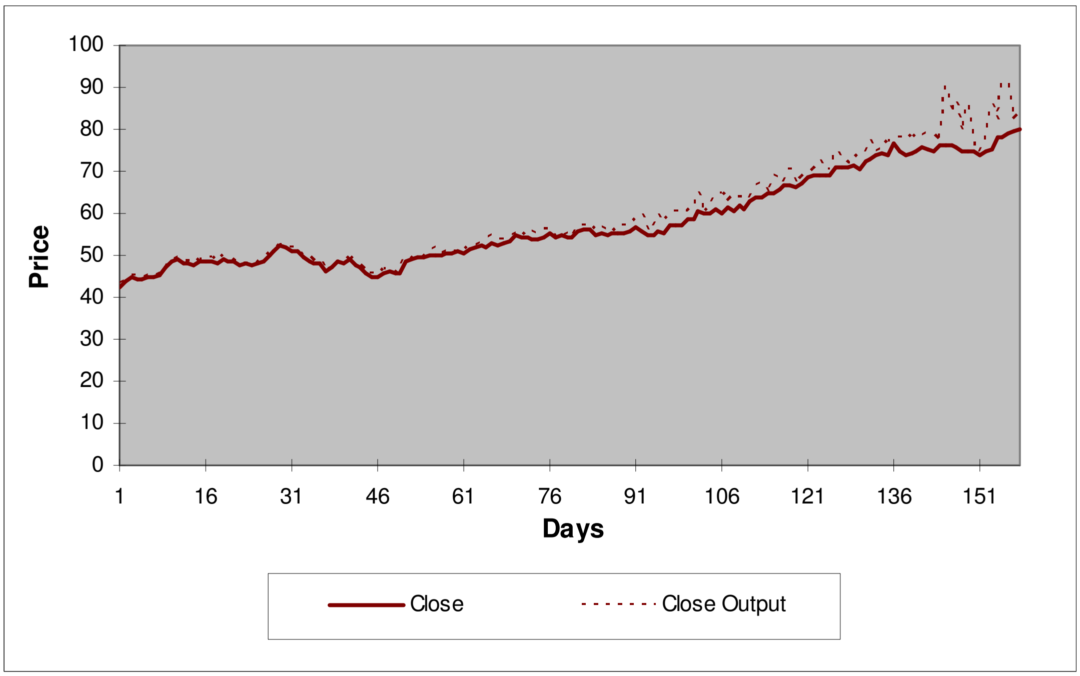
APPENDIX A

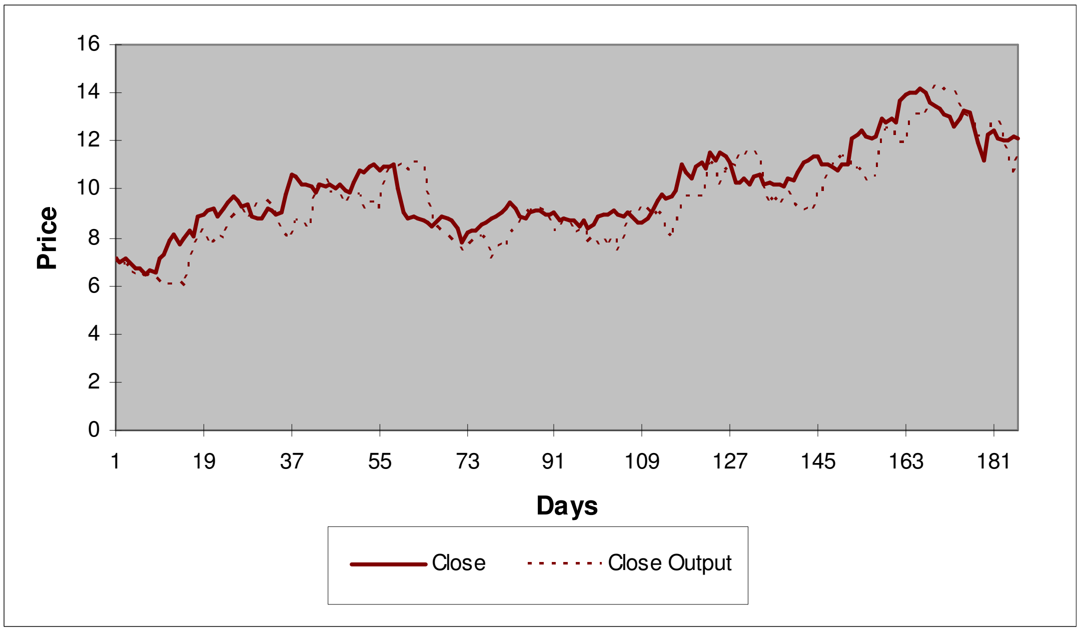
Results of the Benchmark model

AmeriGroup Corporation (AGP)



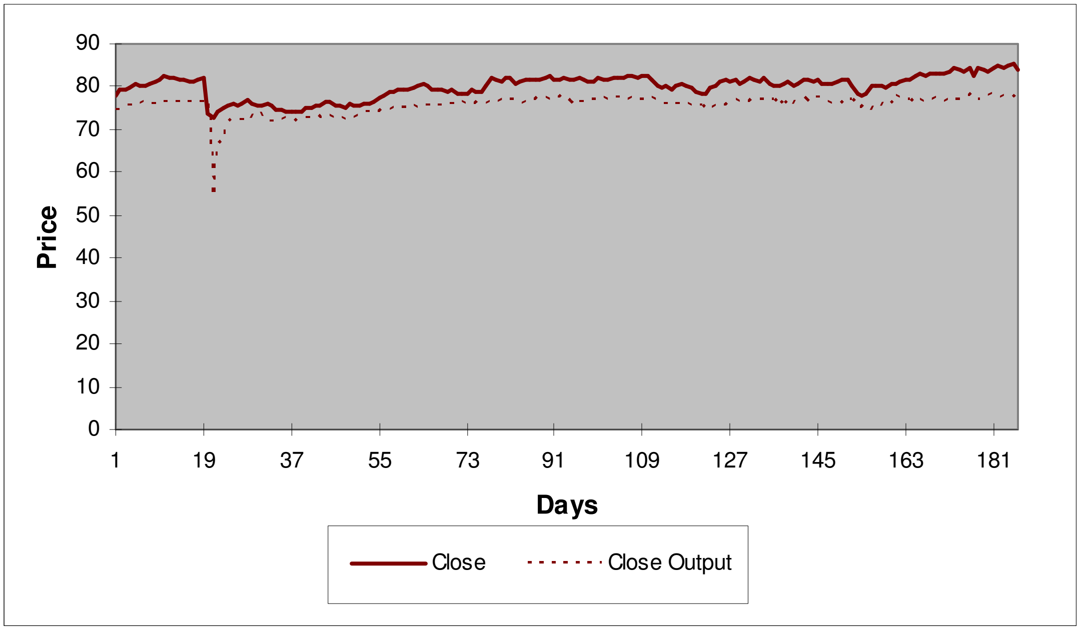
Performance	*Close*
MSE	48.78520096
NMSE	1.339588402
MAE	7.03098317
Min Abs Error	0.601563172
Max Abs Error	31.18588424
r	0.892726041

AMR Corporation (AMR)



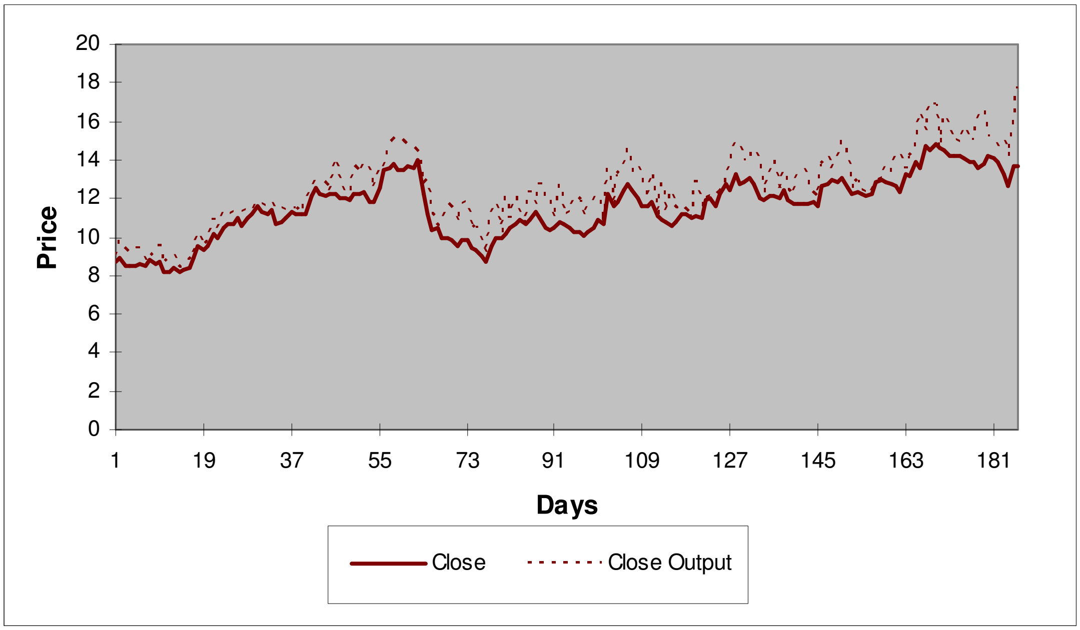
Performance	*Close*
MSE	41.10922549
NMSE	1.371017584
MAE	6.857004398
Min Abs Error	0.034558114
Max Abs Error	2.639845656
r	0.873316476

Bank of America Corporation (BAC)



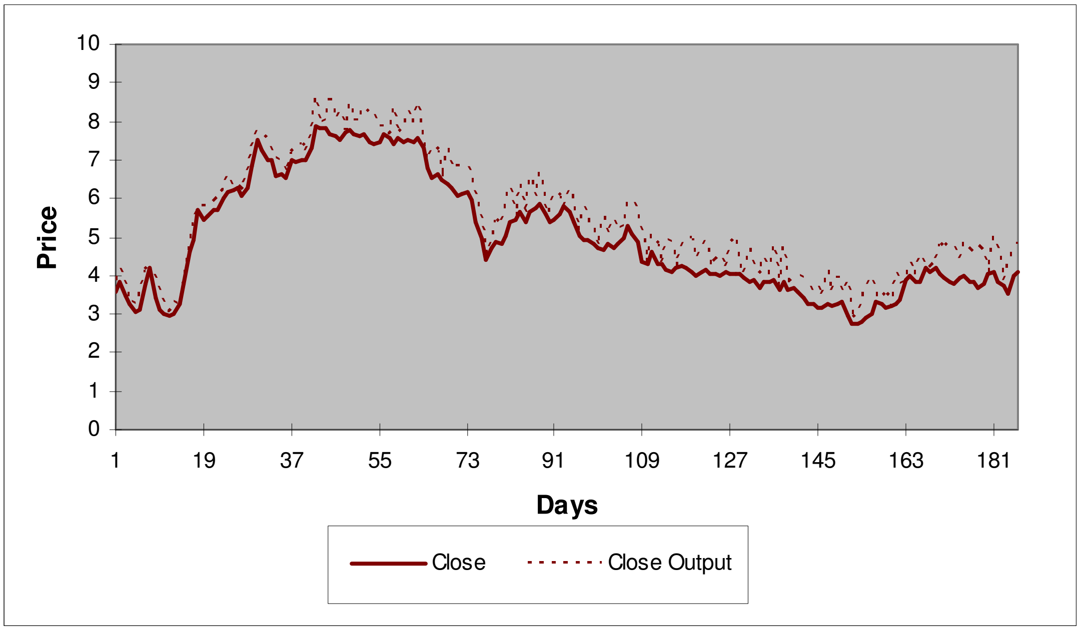
Performance	*Close*
MSE	35.46050117
NMSE	3.236322279
MAE	5.570943265
Min Abs Error	1.501220801
Max Abs Error	18.22727093
r	0.858790341

Continental Airlines (CAL)



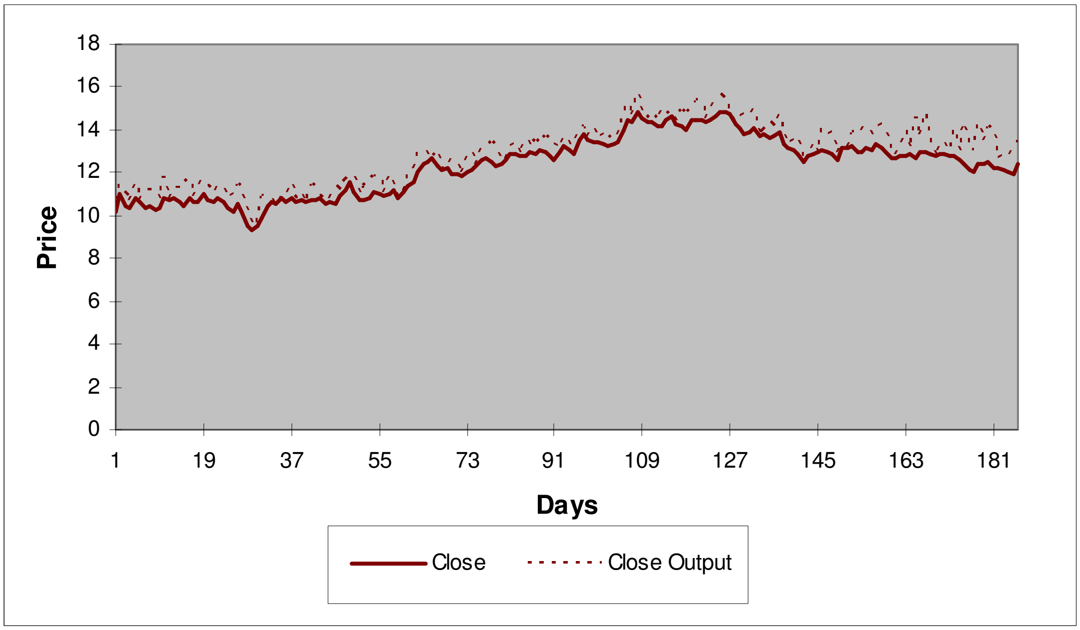
Performance	*Close*
MSE	107.3887466
NMSE	1.147717432
MAE	7.49828261
Min Abs Error	0.001298382
Max Abs Error	1.653088937
r	0.856458941

Delta Airlines (DAL)



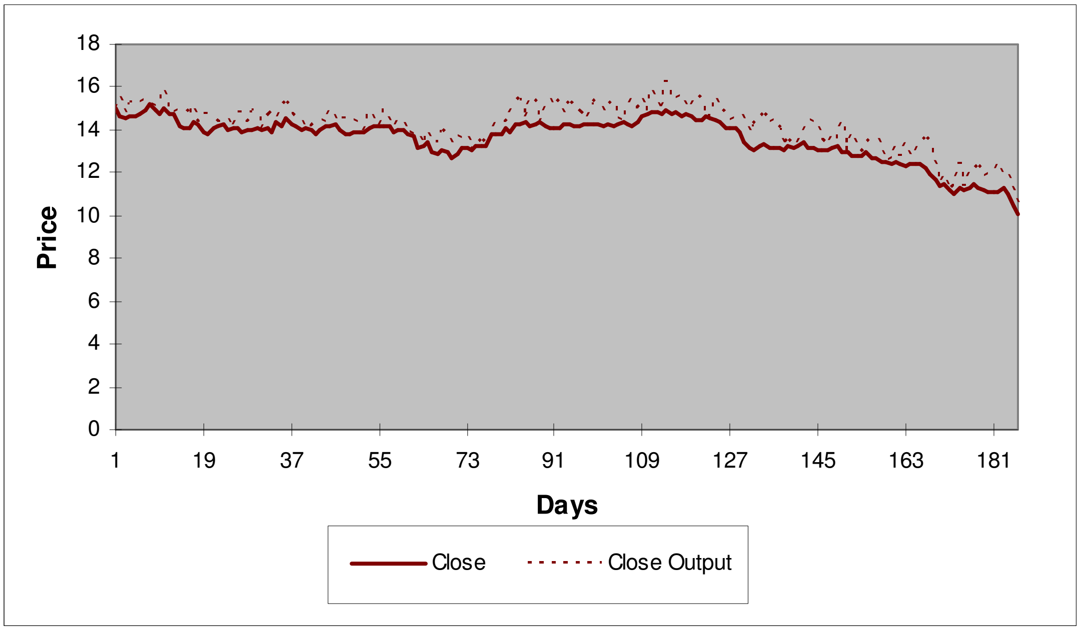
Performance	*Close*
MSE	82.3167141
NMSE	1.038127036
MAE	11.28951202
Min Abs Error	0.013179357
Max Abs Error	4.314315044
r	0.775779238

EMC Corporation (EMC)



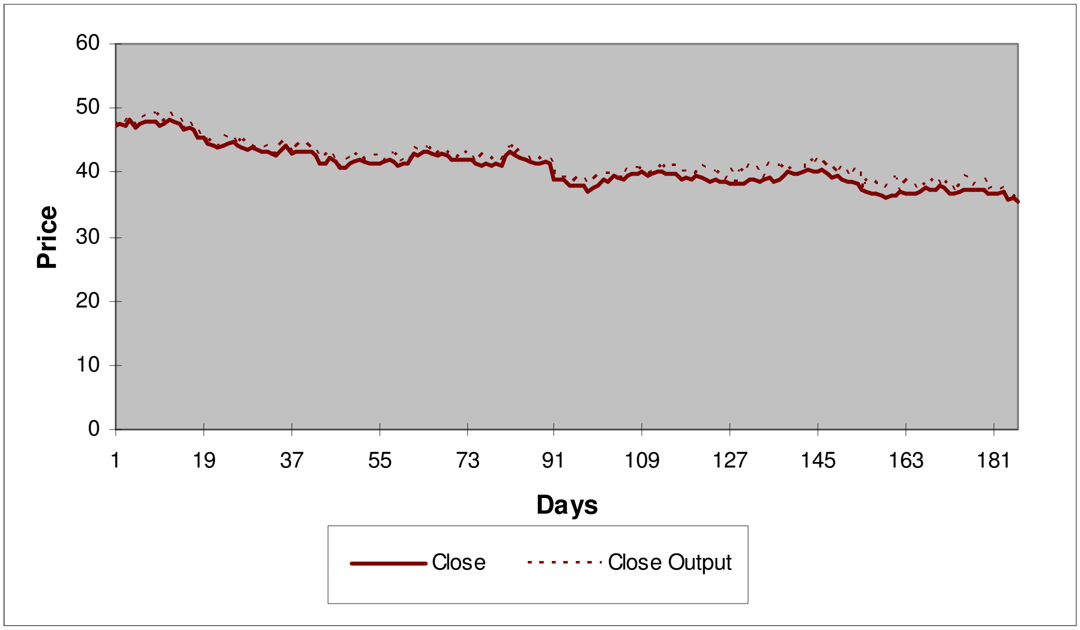
Performance	*Close*
MSE	80.44066616
NMSE	11.11416048
MAE	4.34915939
Min Abs Error	1.599176172
Max Abs Error	6.761079425
r	0.823126495

Ford Corporation (F)



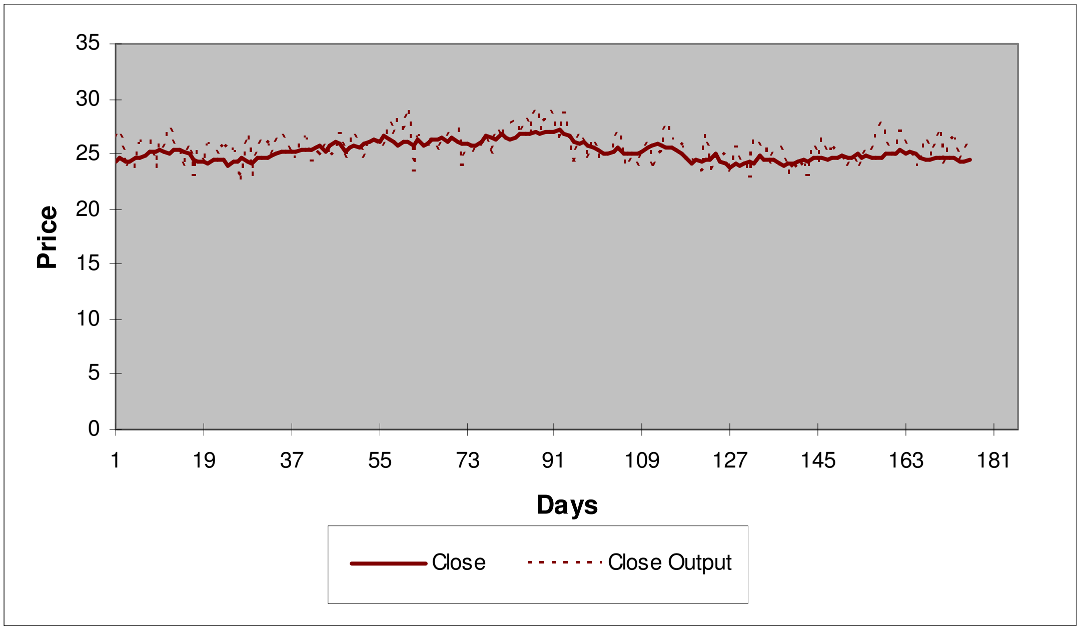
Performance	*Close*
MSE	80.82302559
NMSE	10.89355011
MAE	3.87865195
Min Abs Error	1.383214582
Max Abs Error	7.290372559
r	0.823156551

General Motors Corporation (GM)



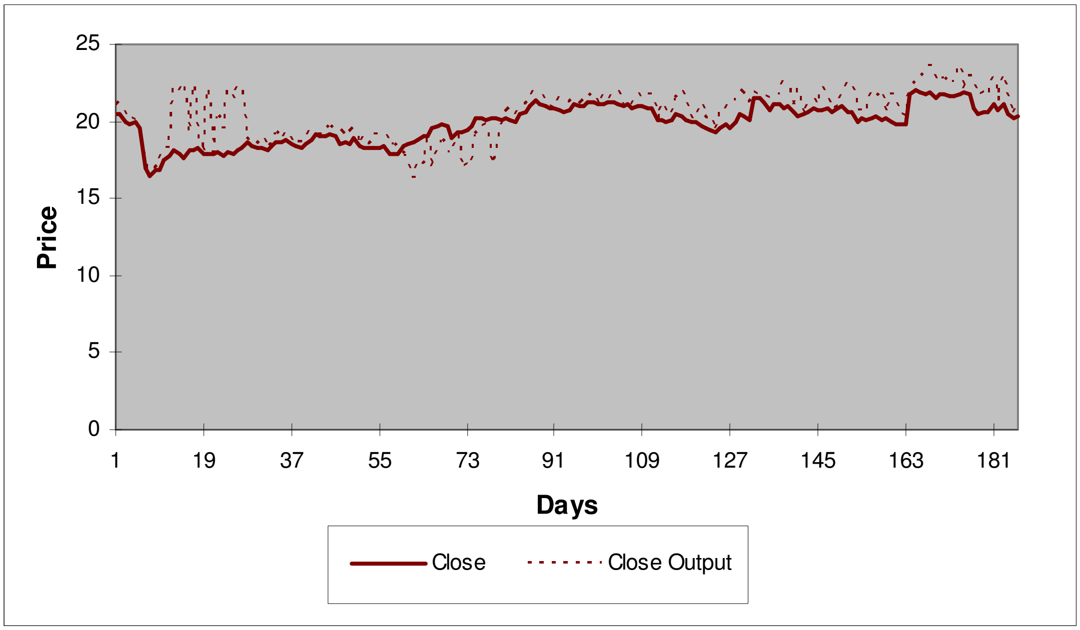
Performance	*Close*
MSE	22.02445996
NMSE	2.789370343
MAE	1.251067887
Min Abs Error	0.054807755
Max Abs Error	3.9026634
r	0.893618944

Honda Motor Corporation (HMC)



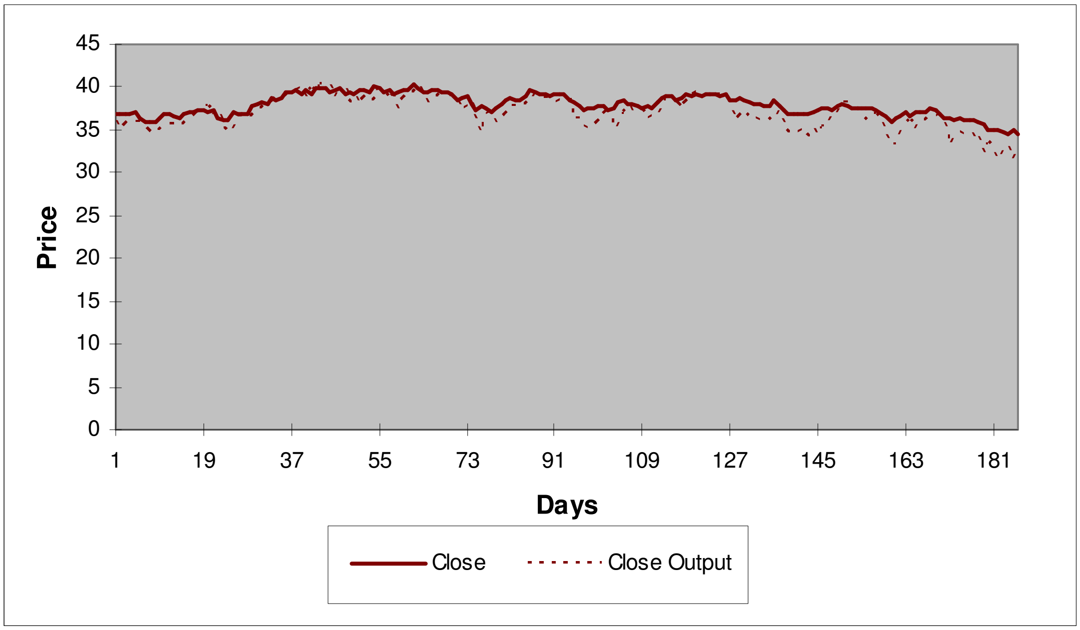
Performance	*Close*
MSE	14.11957752
NMSE	20.98133274
MAE	3.593698648
Min Abs Error	1.10367139
Max Abs Error	5.942607437
r	0.881200062

HP Corporation (HPQ)



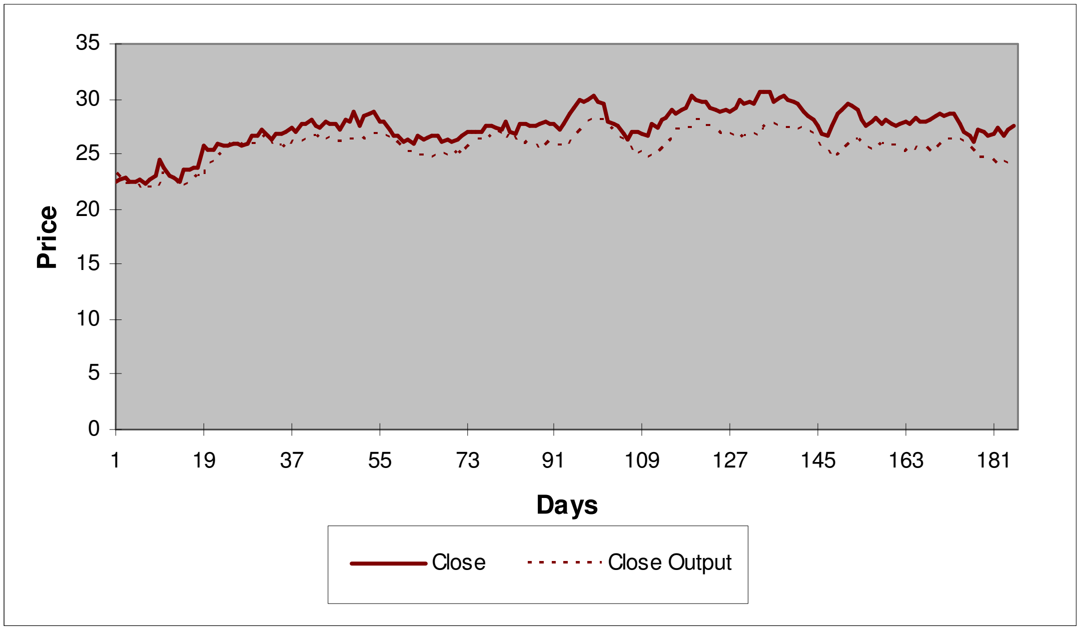
Performance	*Close*
MSE	38.07383201
NMSE	13.05742419
MAE	5.122629976
Min Abs Error	0.080420073
Max Abs Error	14.81580068
r	0.910922065

JP Morgan Chase & Company (JPM)



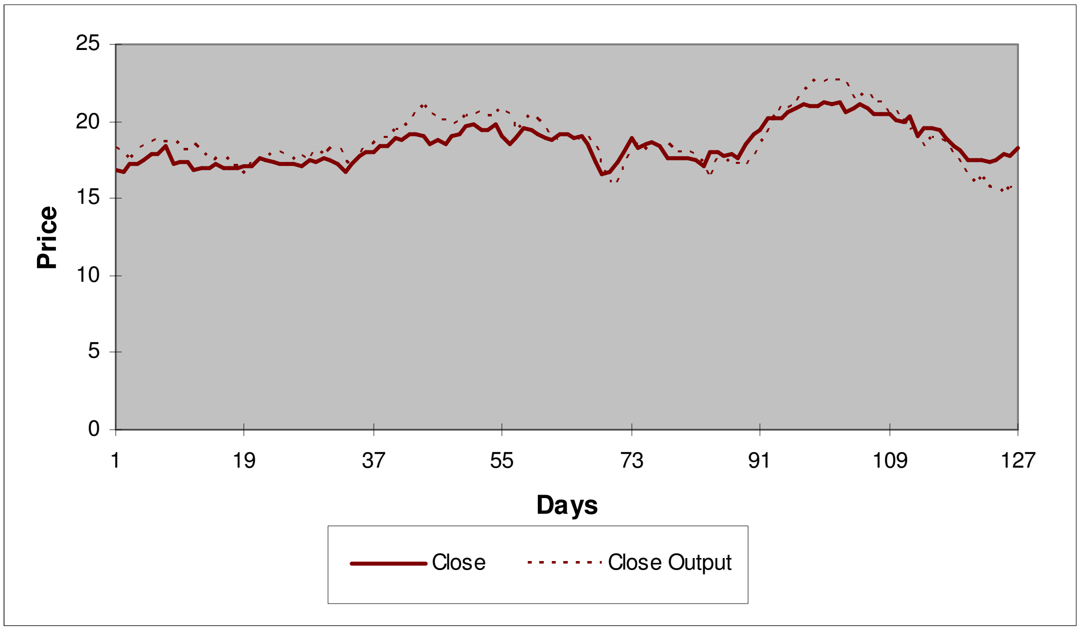
Performance	***Close***
MSE	61.9680788
NMSE	1.759761763
MAE	6.116980307
Min Abs Error	9.96226E-05
Max Abs Error	3.866072744
r	0.916361288

RehabCare (RHB)



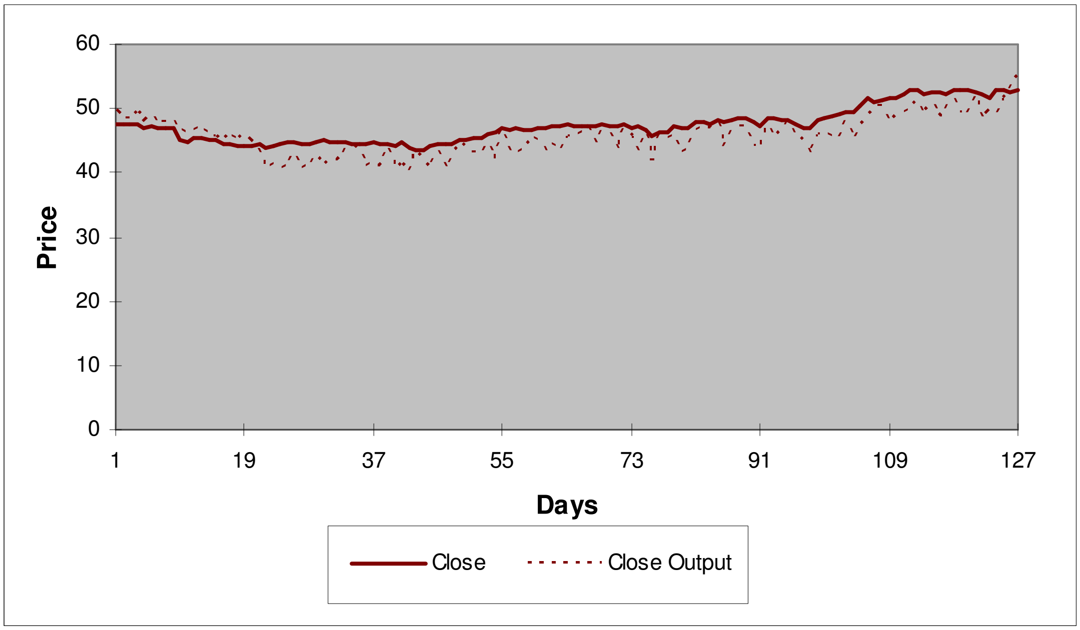
Performance	*Close*
MSE	34.66643388
NMSE	1.079563265
MAE	6.680116922
Min Abs Error	0.046421404
Max Abs Error	3.940264282
r	0.863385601

Seagate Technologies (STX)



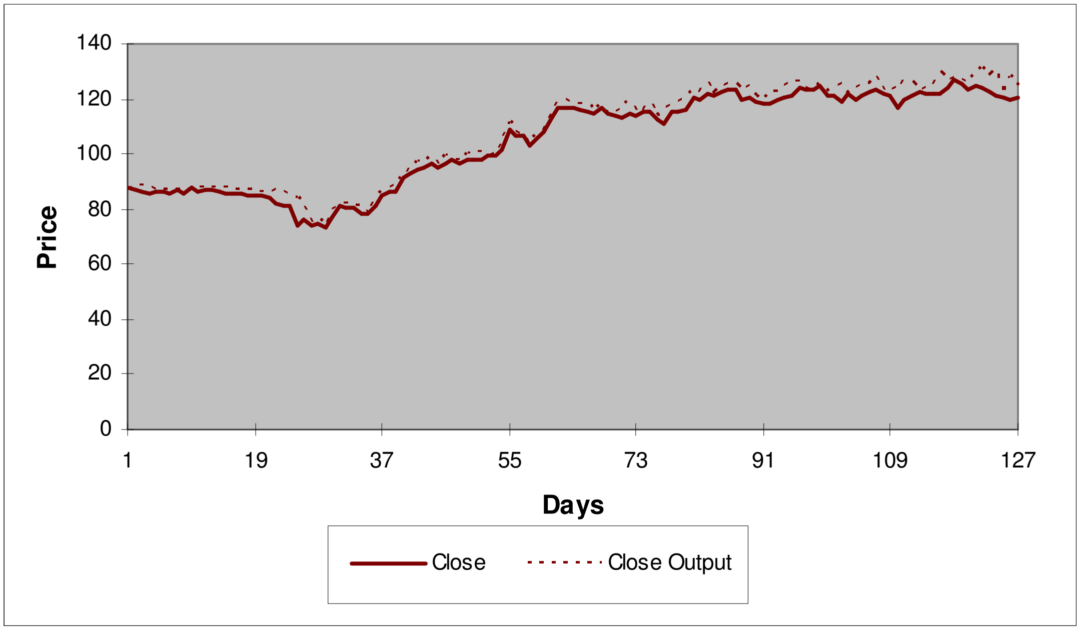
Performance	*Close*
MSE	34.97558348
NMSE	1.615945403
MAE	6.806768738
Min Abs Error	0.015566574
Max Abs Error	2.658979348
r	0.836828011

Wachovia Corporation (WB)



Performance	***Close***
MSE	24.54334376
NMSE	2.417838073
MAE	4.360653732
Min Abs Error	0.008481562
Max Abs Error	9.344475394
r	0.832991243

Well Point Inc (WLP)

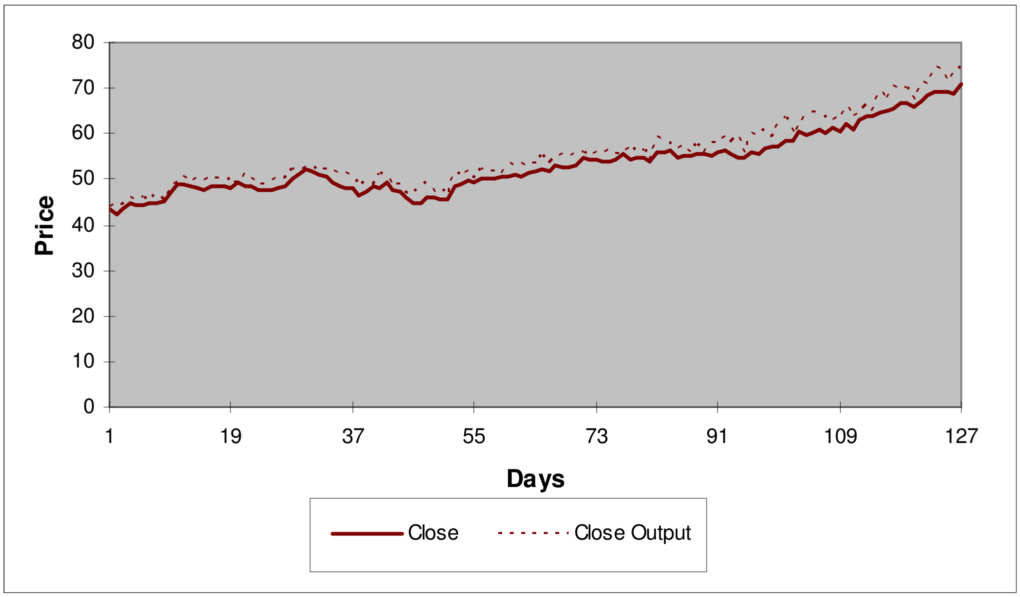


Performance	*Close*
MSE	180.3851052
NMSE	1.525936836
MAE	18.55906138
Min Abs Error	0.079445241
Max Abs Error	18.61145162
r	0.933737225

APPENDIX B

Results of the Intermediate SOM model

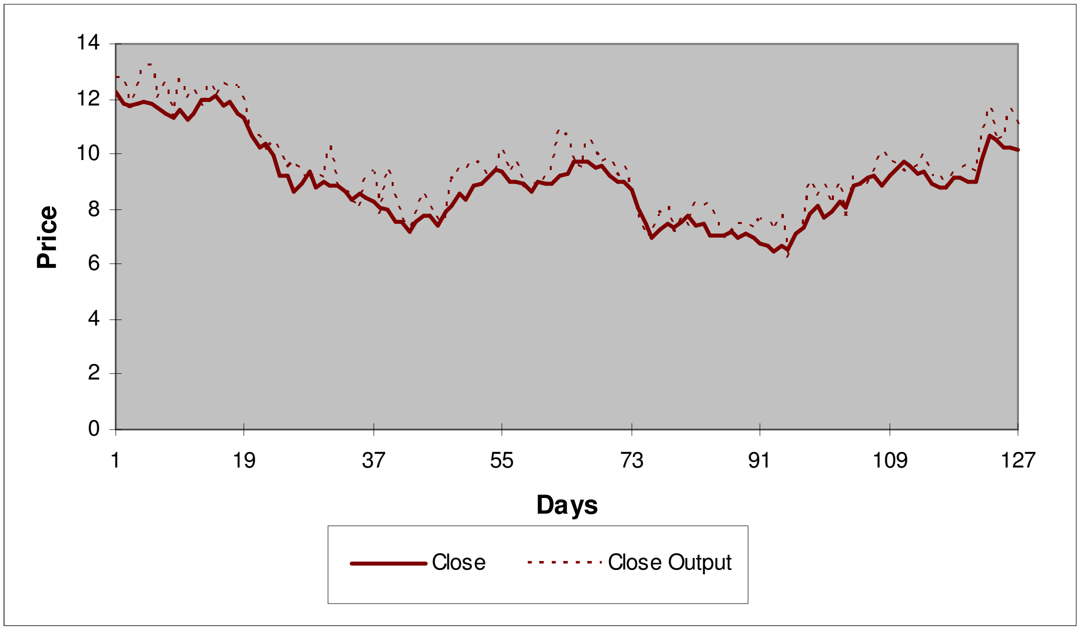
AGP



Performance	*Close*
MSE	9.237847017
NMSE	1.284291591
MAE	2.176071099
Min Abs Error	4.623023917
Max Abs Error	3.132171984
r	0.98045894

No. of Testing Data Points	158
No. of correct change predictions	90
No. of incorrect change predictions	68
Percentage accuracy	0.569620253

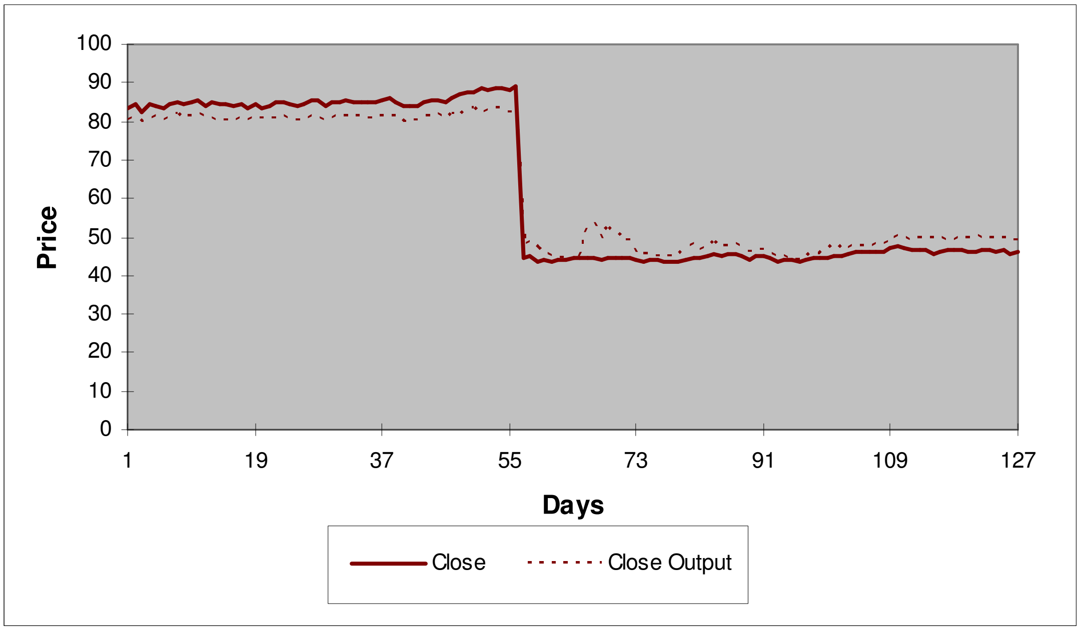
AMR



Performance	***Close***
MSE	2.557636454
NMSE	0.189051515
MAE	0.617245373
Min Abs Error	0.005766106
Max Abs Error	1.834193371
r	0.963475731

No. of Testing Data Points	273
No. of correct change predictions	149
No. of incorrect change predictions	124
Percentage accuracy	54.57875%

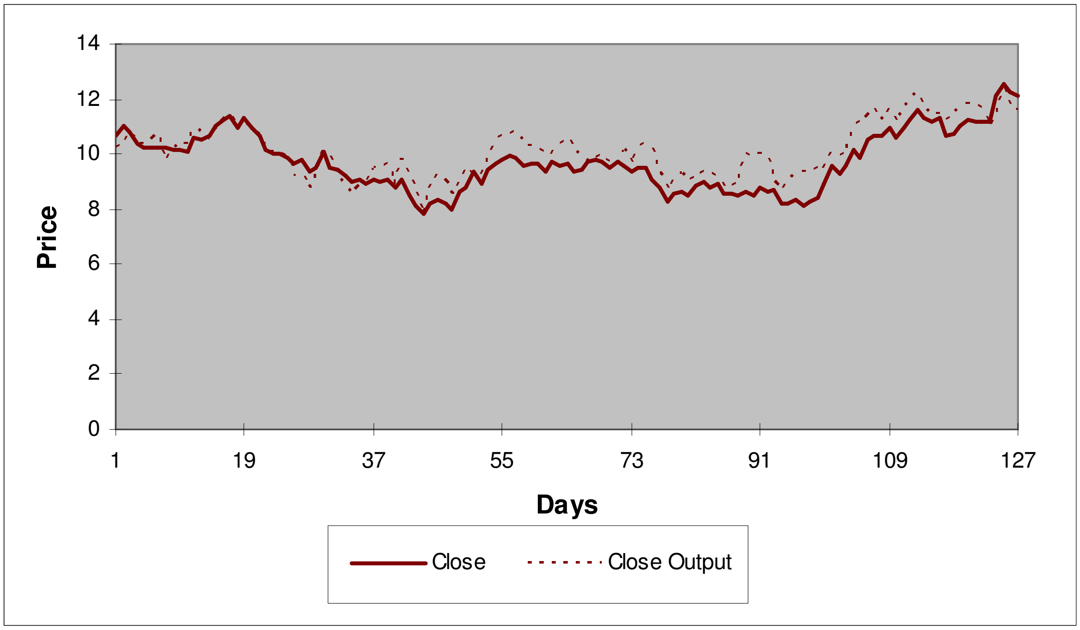
BAC



Performance	*Close*
MSE	5.841322828
NMSE	0.022688254
MAE	1.540529363
Min Abs Error	0.0053956
Max Abs Error	9.09680962
r	0.896253842

No. of Testing Data Points	274
No. of correct change predictions	159
No. of incorrect change predictions	115
Percentage accuracy	58.02920%

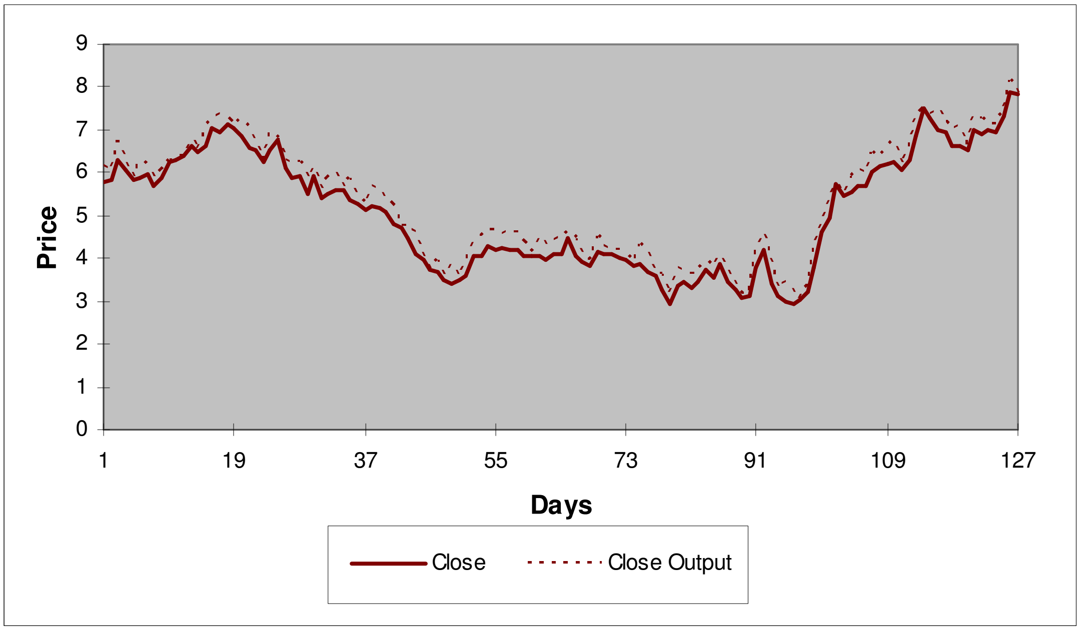
CAL



Performance	*Close*
MSE	0.361076018
NMSE	0.125242984
MAE	0.491885186
Min Abs Error	0.00030329
Max Abs Error	1.745505414
r	0.941700748

No. of Testing Data Points	275
No. of correct change predictions	210
No. of incorrect change predictions	65
Percentage accuracy	76.36364%

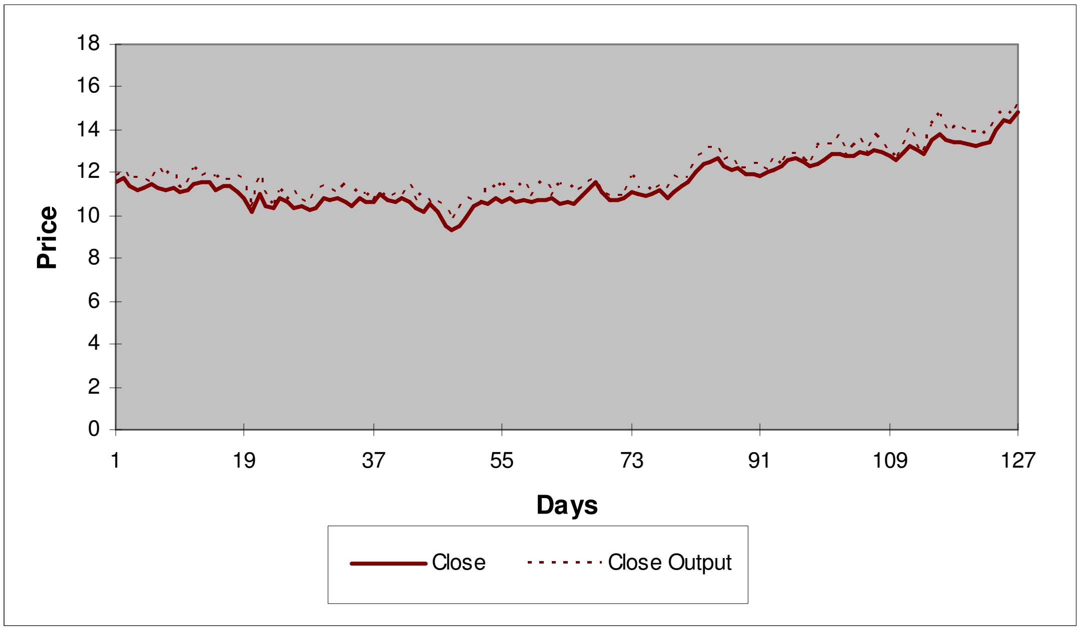
DAL



Performance	*Close*
MSE	30.31919759
NMSE	15.51751531
MAE	0.401726698
Min Abs Error	0.453333333
Max Abs Error	1.59161852
r	0.950411876

No. of Testing Data Points	274
No. of correct change predictions	208
No. of incorrect change predictions	66
Percentage accuracy	75.91241%

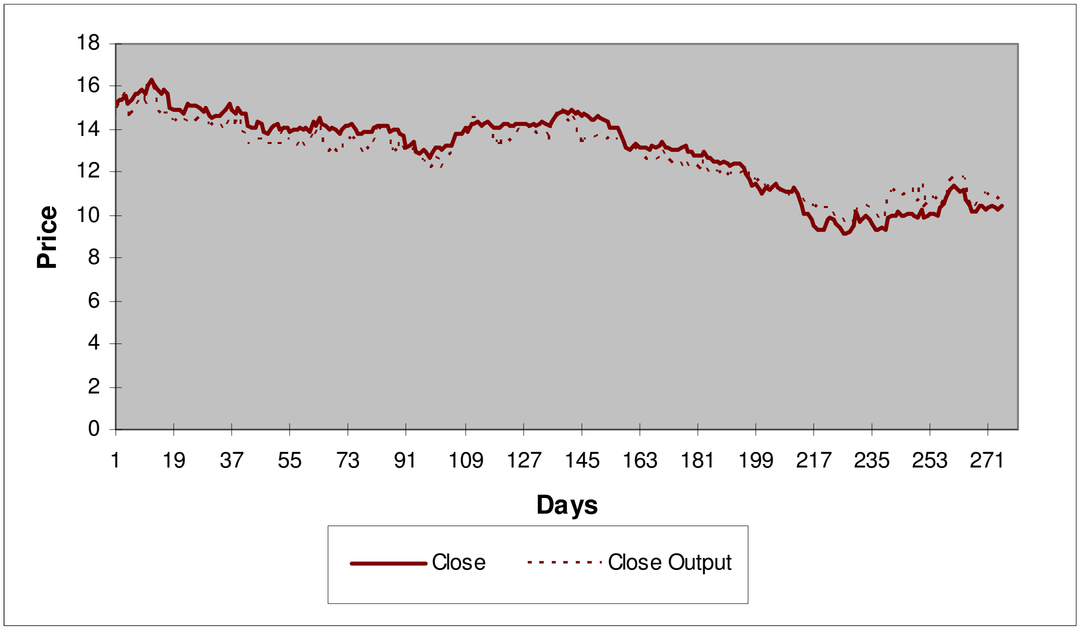
EMC



Performance	***Close***
MSE	2.190031772
NMSE	1.198044251
MAE	1.196790291
Min Abs Error	0.003971148
Max Abs Error	0.948737868
r	0.985691312

No. of Testing Data Points	275
No. of correct change predictions	173
No. of incorrect change predictions	102
Percentage accuracy	62.90909%

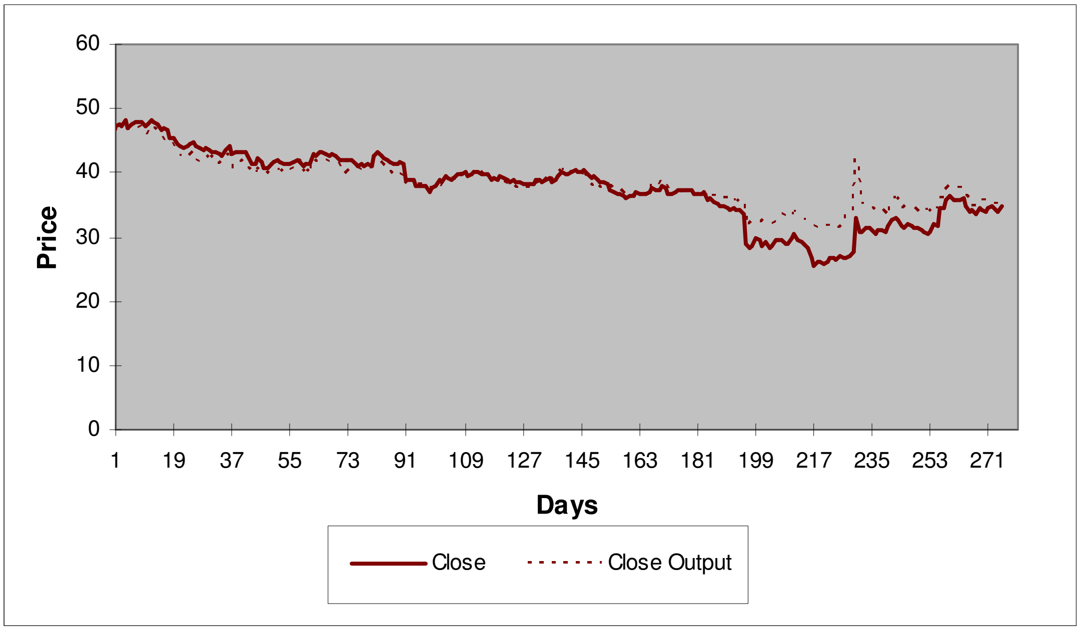
F



Performance	***Close***
MSE	0.355712644
NMSE	0.098908304
MAE	0.519338063
Min Abs Error	0.000719042
Max Abs Error	1.408803279
r	0.972725318

No. of Testing Data Points	275
No. of correct change predictions	196
No. of incorrect change predictions	79
Percentage accuracy	71.27273%

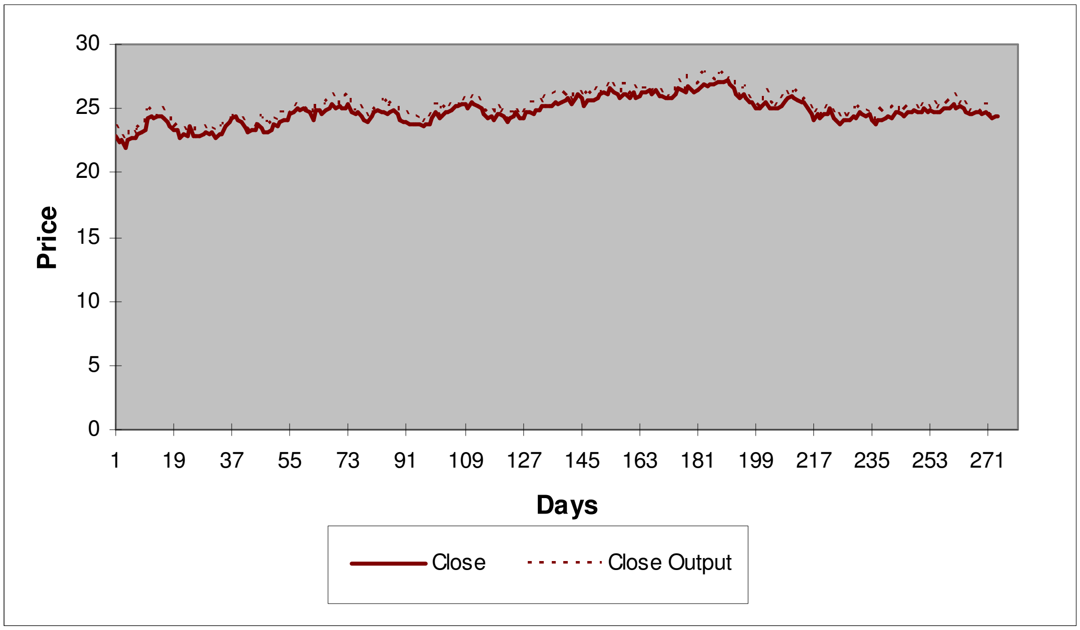
GM



Performance	*Close*
MSE	4.717391173
NMSE	0.160422282
MAE	1.535371793
Min Abs Error	0.000691529
Max Abs Error	9.554598016
r	0.966392511

No. of Testing Data Points	275
No. of correct change predictions	215
No. of incorrect change predictions	60
Percentage accuracy	78.18182%

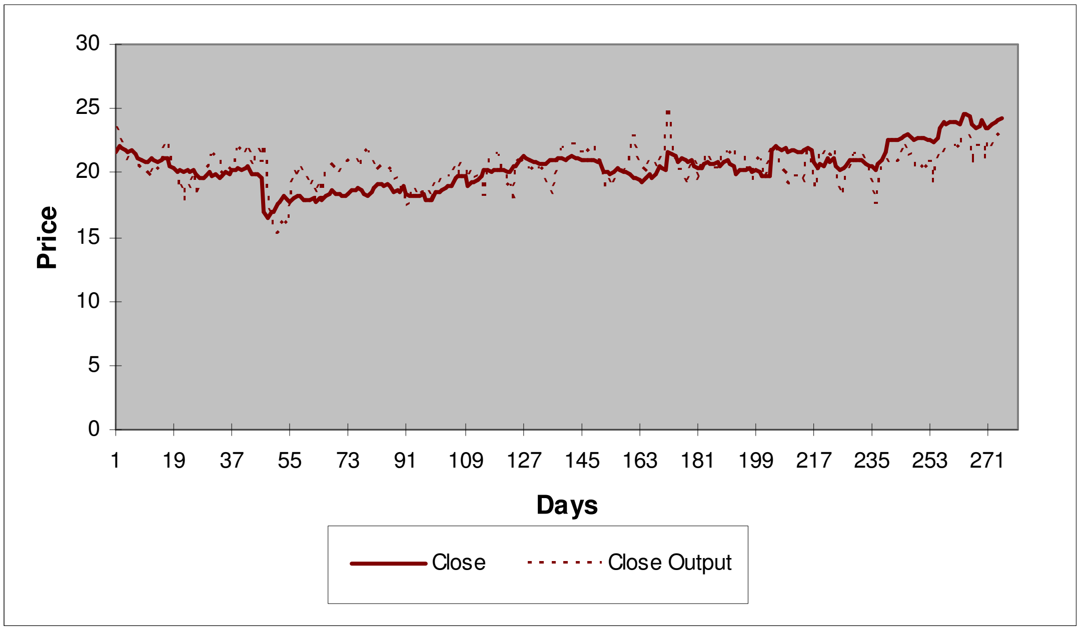
HMC



Performance	*Close*
MSE	4.147120042
NMSE	3.918178502
MAE	1.813930673
Min Abs Error	0.020281298
Max Abs Error	4.251973507
R	0.947694484

No. of Testing Data Points	274
No. of correct change predictions	189
No. of incorrect change predictions	85
Percentage accuracy	68.97810%

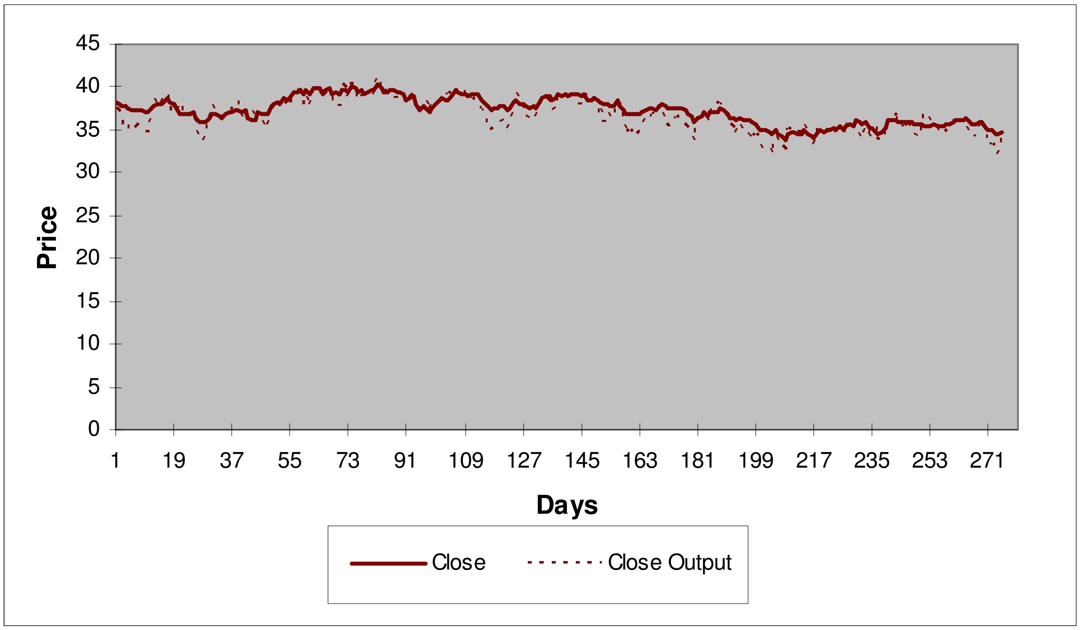
HPQ



Performance	*Close*
MSE	1.981658156
NMSE	0.772060196
MAE	1.152977293
Min Abs Error	0.005818168
Max Abs Error	5.269892379
r	0.899925337

No. of Testing Data Points	275
No. of correct change predictions	175
No. of incorrect change predictions	100
Percentage accuracy	63.63636%

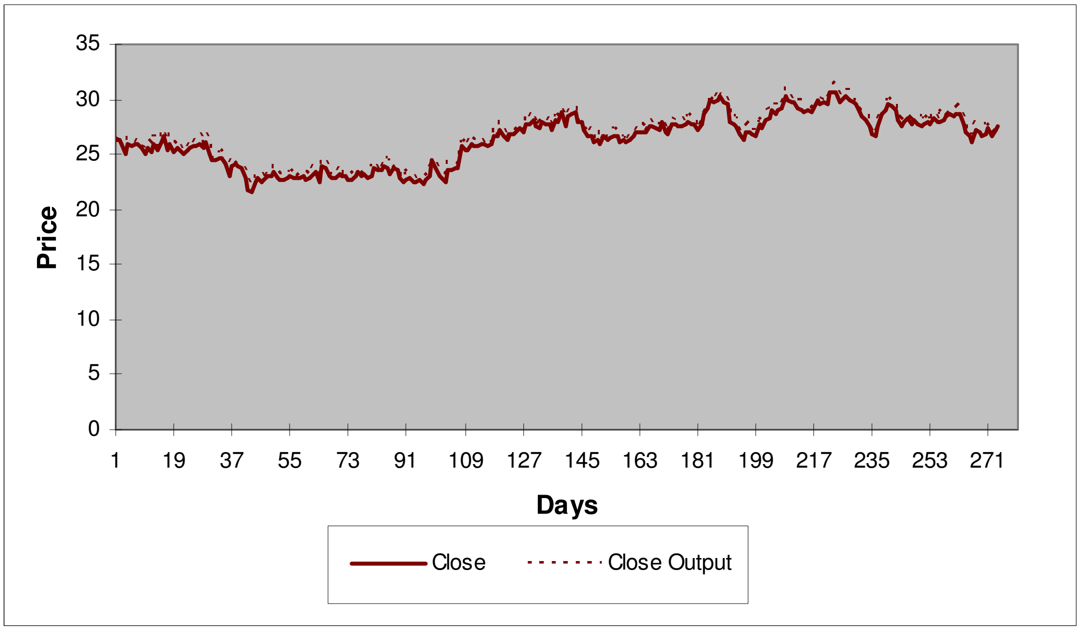
JPM



Performance	***Close***
MSE	1.122929073
NMSE	0.460987202
MAE	0.836601493
Min Abs Error	0.000830999
Max Abs Error	2.692641625
r	0.886060818

No. of Testing Data Points	275
No. of correct change predictions	215
No. of incorrect change predictions	60
Percentage accuracy	78.18182%

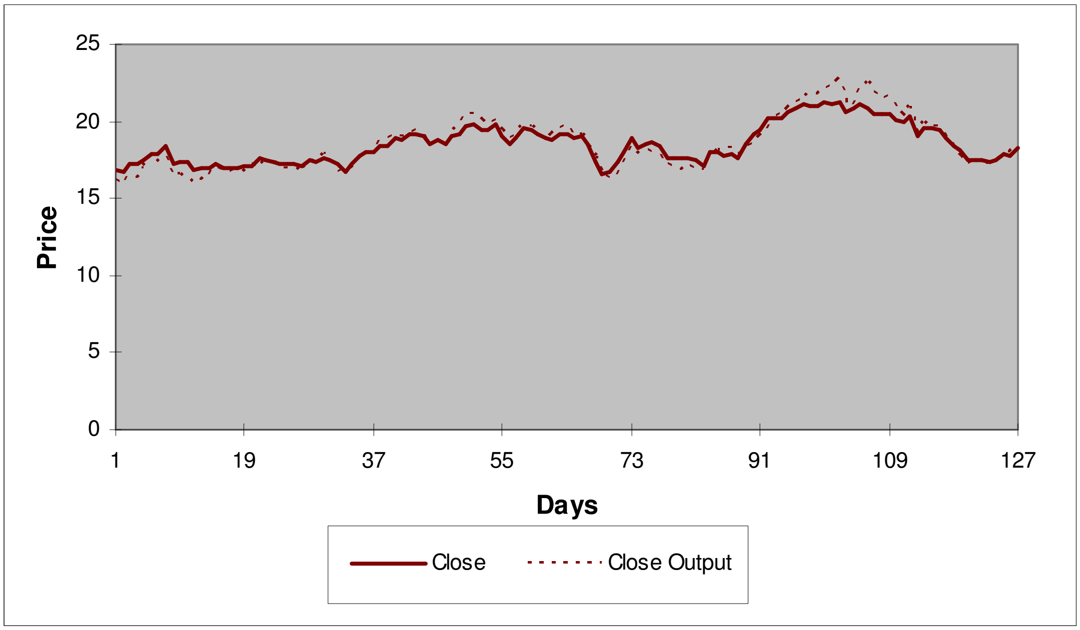
RHB



Performance	***Close***
MSE	42.72967143
NMSE	8.131775849
MAE	5.51226345
Min Abs Error	0.004114549
Max Abs Error	14.52139233
r	0.923858393

No. of Testing Data Points	274
No. of correct change predictions	213
No. of incorrect change predictions	61
Percentage accuracy	77.73723%

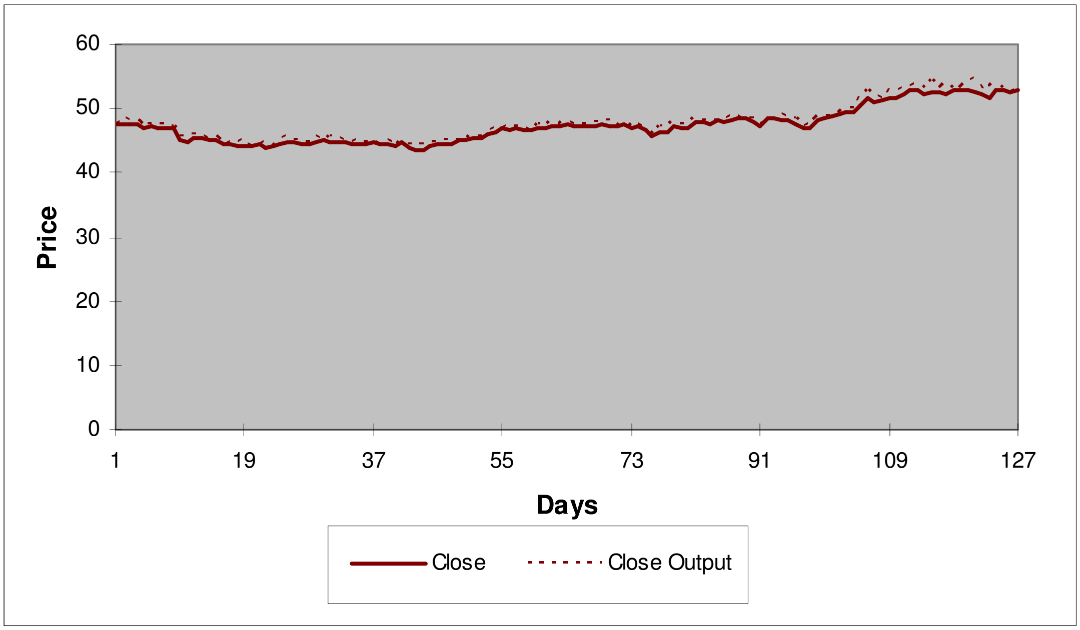
STX



Performance	*Close*
MSE	0.273316308
NMSE	0.172561269
MAE	0.40890251
Min Abs Error	0.006374168
Max Abs Error	1.706876089
r	0.925677312

No. of Testing Data Points	127
No. of correct change predictions	102
No. of incorrect change predictions	25
Percentage accuracy	80.31496%

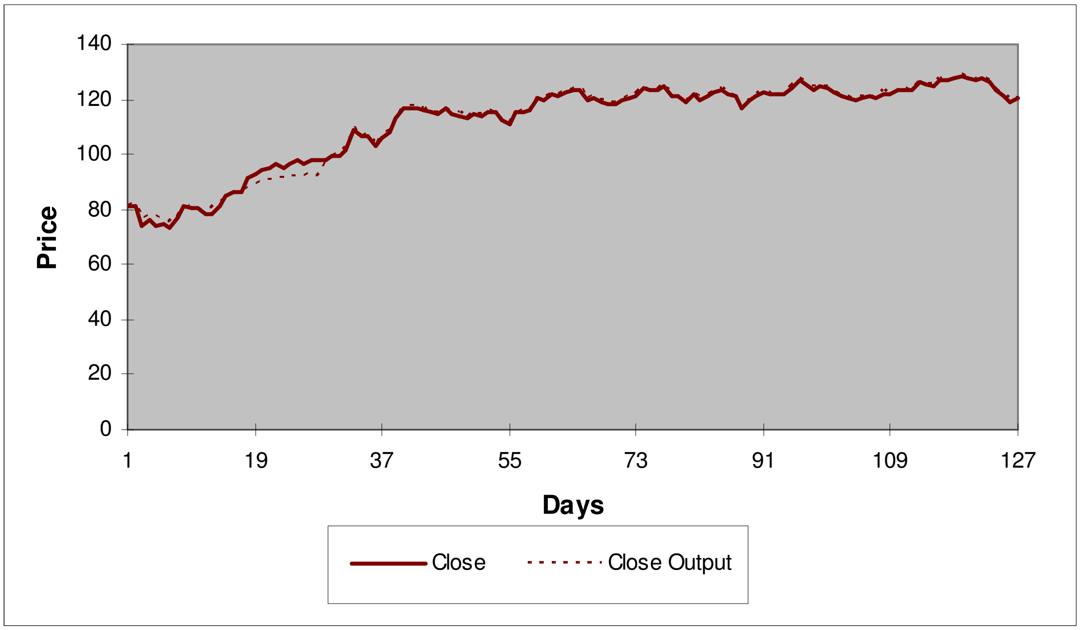
WB



Performance	*Close*
MSE	23.01260562
NMSE	2.267040489
MAE	4.162225606
Min Abs Error	0.020733685
Max Abs Error	2.320791443
r	0.947567809

No. of Testing Data Points	275
No. of correct change predictions	184
No. of incorrect change predictions	91
Percentage accuracy	66.90909%

WLP

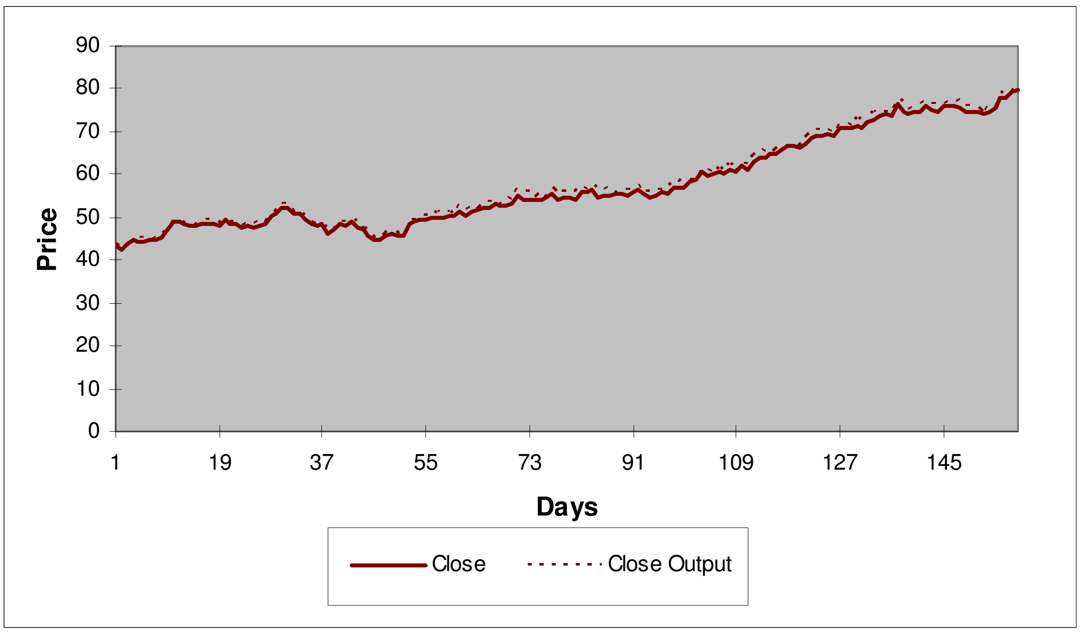


Performance	***Close***
MSE	5.021045804
NMSE	1.035705498
MAE	19.02542735
Min Abs Error	0.028474895
Max Abs Error	38.79913251
r	0.899617949

No. of Testing Data Points	183
No. of correct change predictions	157
No. of incorrect change predictions	26
Percentage accuracy	85.79235%

APPENDIX C

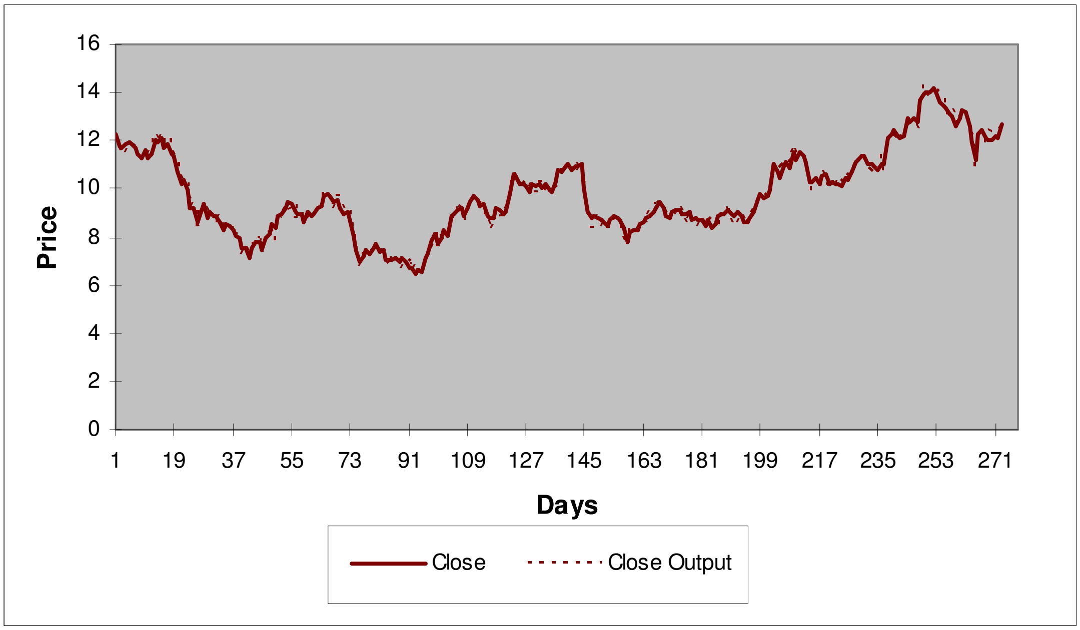
Final Model Results
AGP



Performance	***Close***
MSE	5.369763711
NMSE	0.867207963
MAE	6.806080835
Min Abs Error	0.027765904
Max Abs Error	2.612698686
r	0.995744687

No. of Testing Data Points	158
No. of correct change predictions	148
No. of incorrect change predictions	10
Percentage accuracy	93.82911%

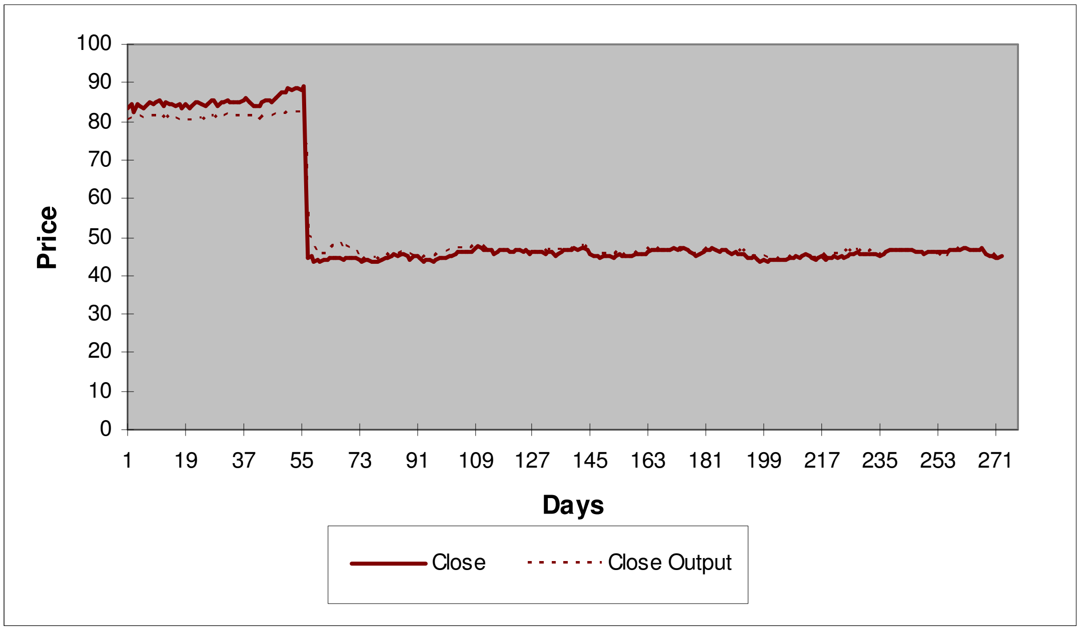
AMR



Performance	***Close***
MSE	0.537027011
NMSE	0.182064442
MAE	0.603707153
Min Abs Error	0.016692251
Max Abs Error	1.947810514
r	0.966350952

No. of Testing Data Points	273
No. of correct change predictions	255
No. of incorrect change predictions	18
Percentage accuracy	93.49817%

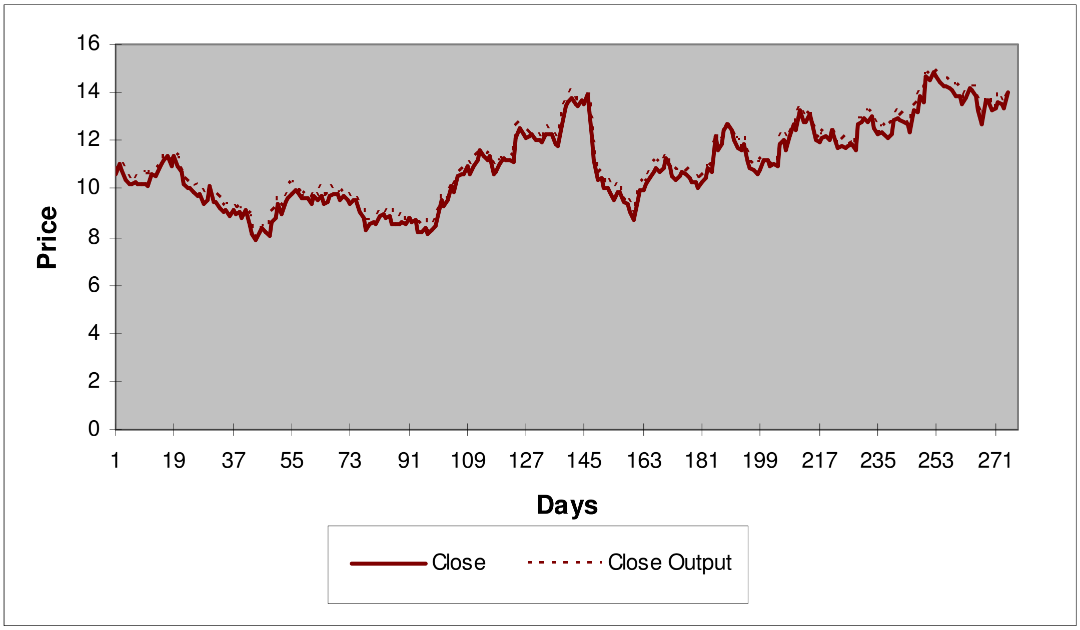
BAC



Performance	***Close***
MSE	4.257235492
NMSE	0.016535508
MAE	1.356063318
Min Abs Error	0.002946916
Max Abs Error	6.672908482
r	0.998101207

No. of Testing Data Points	273
No. of correct change predictions	258
No. of incorrect change predictions	15
Percentage accuracy	94.59707%

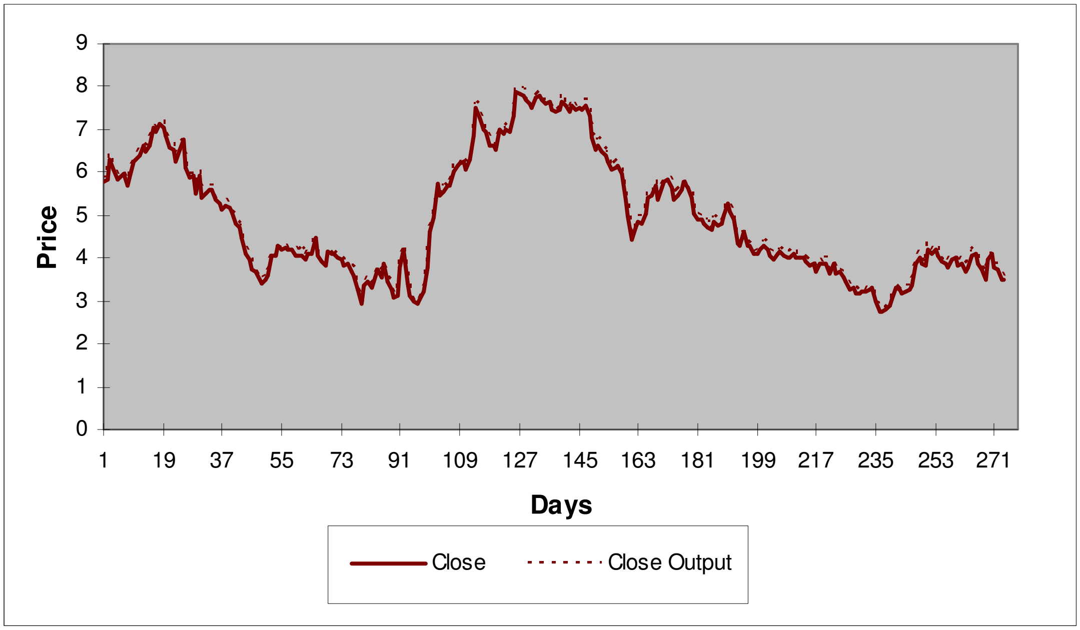
CAL



Performance	***Close***
MSE	5.828103228
NMSE	2.021538401
MAE	0.200968788
Min Abs Error	0.050053178
Max Abs Error	0.430922632
r	0.998818662

No. of Testing Data Points	275
No. of correct change predictions	263
No. of incorrect change predictions	12
Percentage accuracy	95.63636%

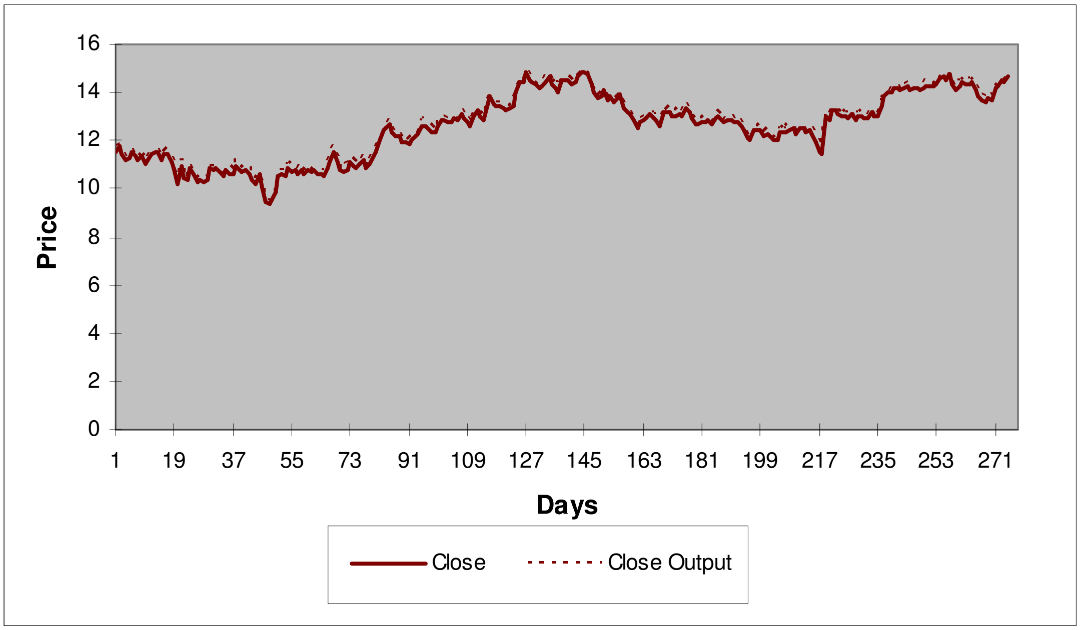
DAL



Performance	*Close*
MSE	3.568274493
NMSE	1.811855497
MAE	1.408527979
Min Abs Error	0.003333333
Max Abs Error	4.213333333
r	0.983171582

No. of Testing Data Points	274
No. of correct change predictions	266
No. of incorrect change predictions	8
Percentage accuracy	97.17153%

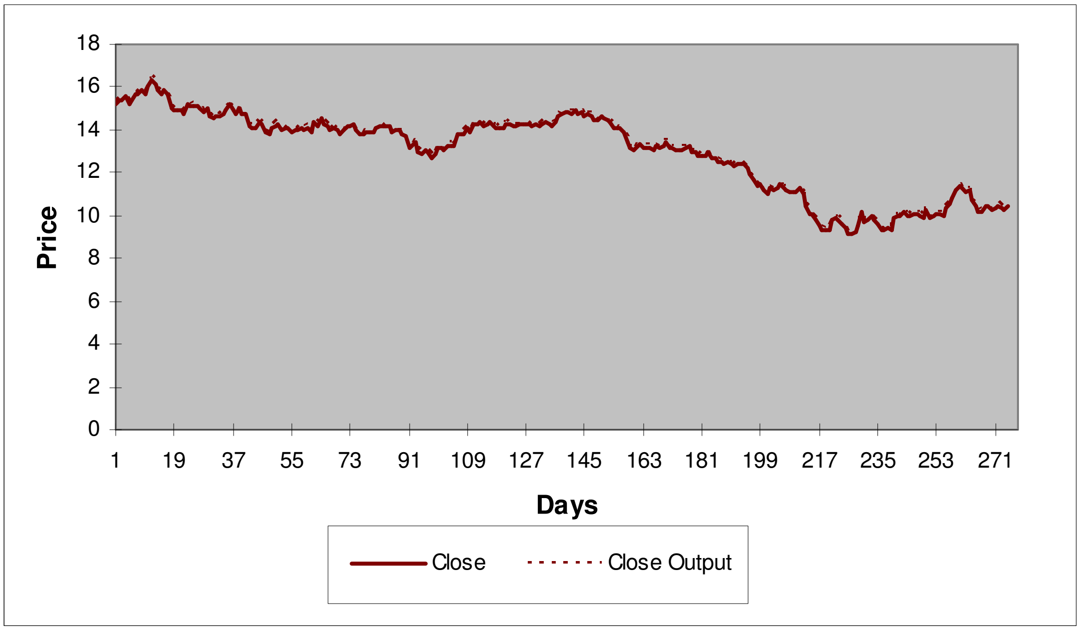
EMC



Performance	*Close*
MSE	1.955406889
NMSE	3.716696844
MAE	1.180652233
Min Abs Error	0.070982714
Max Abs Error	5.064519258
r	0.997921743

No. of Testing Data Points	275
No. of correct change predictions	263
No. of incorrect change predictions	12
Percentage accuracy	95.72727%

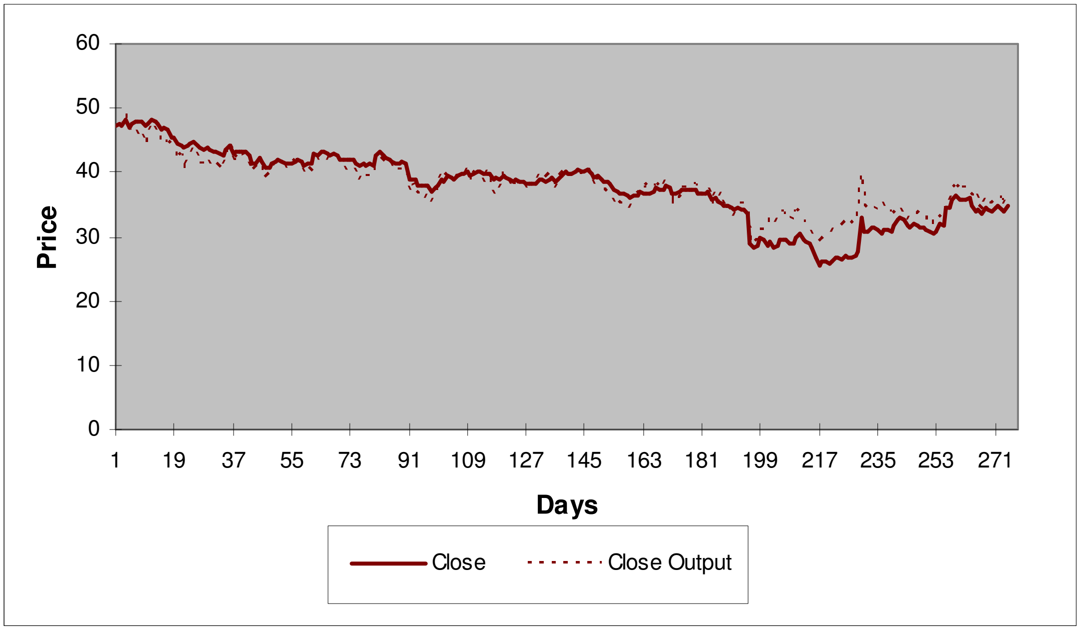
F



Performance	*Close*
MSE	1.417559688
NMSE	0.11271889
MAE	0.502675338
Min Abs Error	0.114877561
Max Abs Error	1.028113058
r	0.990866476

No. of Testing Data Points	275
No. of correct change predictions	266
No. of incorrect change predictions	9
Percentage accuracy	96.90909%

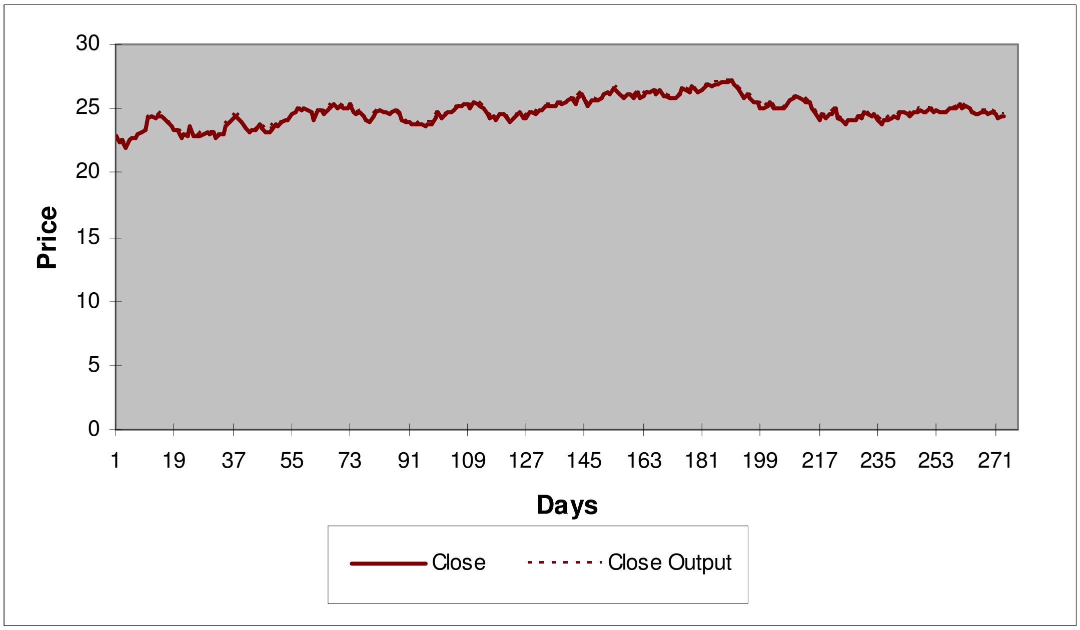
GM



Performance	*Close*
MSE	3.751624809
NMSE	0.127579883
MAE	1.459430414
Min Abs Error	0.016484721
Max Abs Error	6.841533999
r	0.961030293

No. of Testing Data Points	275
No. of correct change predictions	258
No. of incorrect change predictions	17
Percentage accuracy	93.90909%

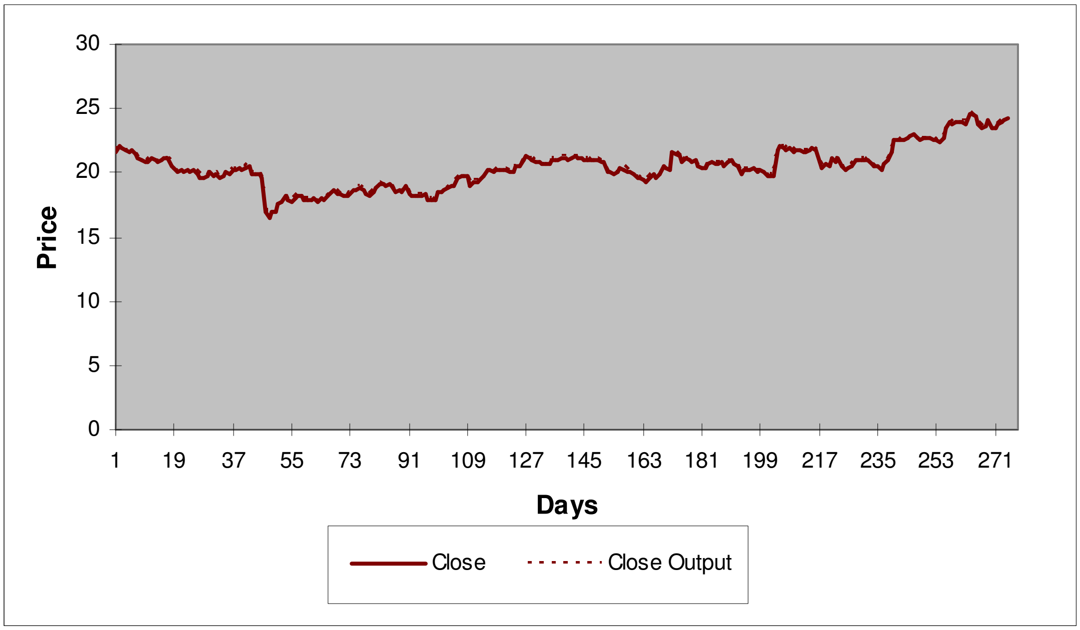
HMC



Performance	***Close***
MSE	1.019504482
NMSE	0.631993112
MAE	0.292926656
Min Abs Error	0.037644844
Max Abs Error	0.799095816
r	0.997334054

No. of Testing Data Points	274
No. of correct change predictions	269
No. of incorrect change predictions	5
Percentage accuracy	98.26642%

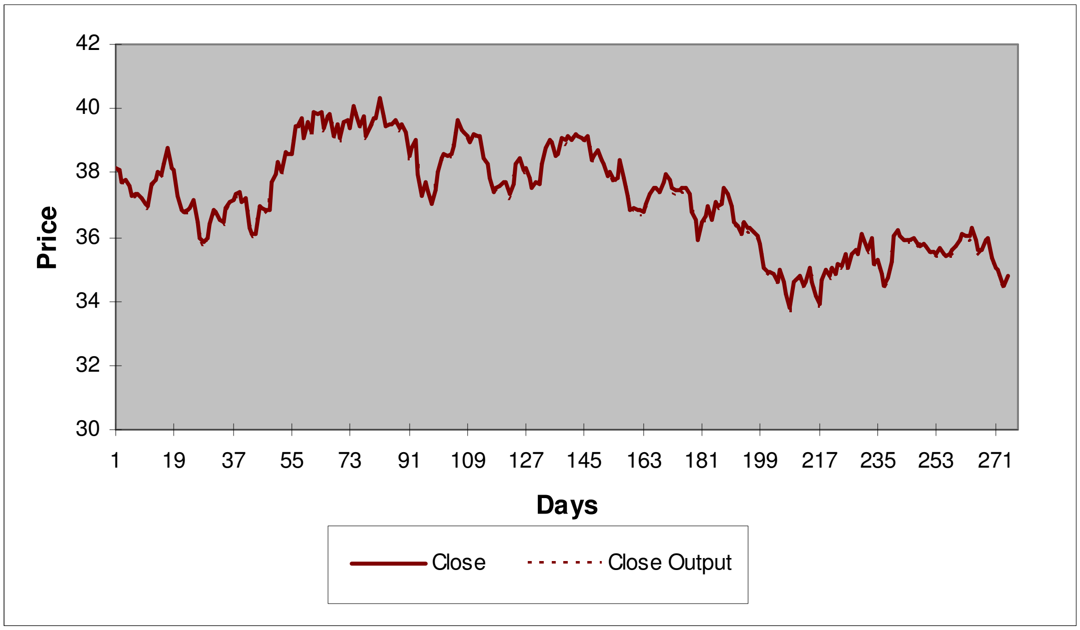
HPQ



Performance	***Close***
MSE	1.408989219
NMSE	1.107359063
MAE	0.640282869
Min Abs Error	0.01758849
Max Abs Error	0.847420205
r	0.994390039

No. of Testing Data Points	275
No. of correct change predictions	269
No. of incorrect change predictions	6
Percentage accuracy	97.72727%

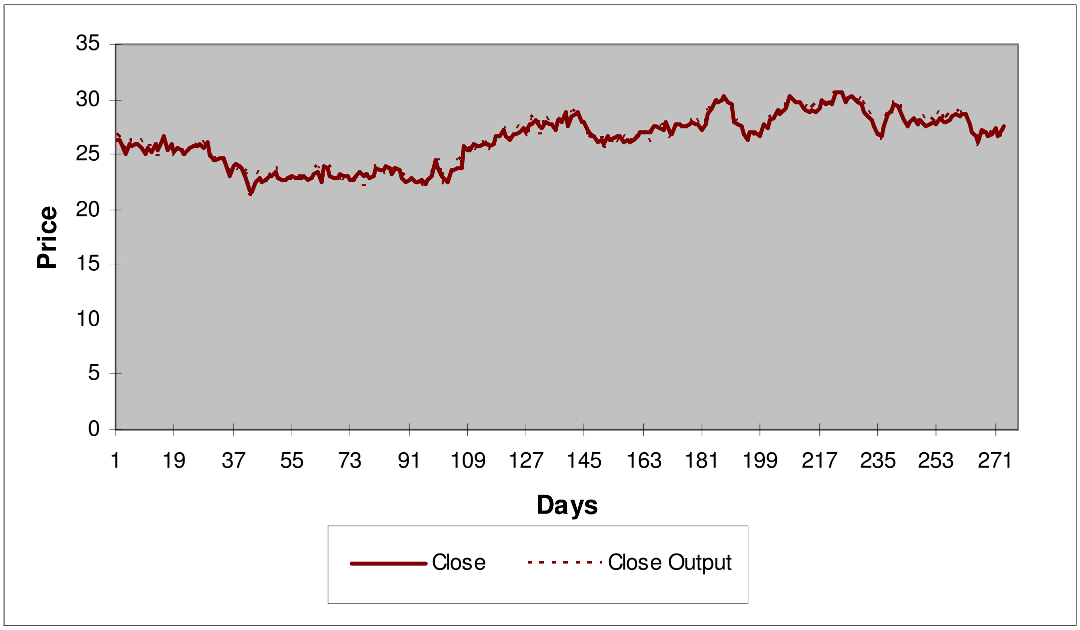
JPM



Performance	***Close***
MSE	3.081341386
NMSE	1.264958739
MAE	1.431104819
Min Abs Error	0.001819564
Max Abs Error	4.537908029
R	0.998345431

No. of Testing Data Points	275
No. of correct change predictions	270
No. of incorrect change predictions	5
Percentage accuracy	98.36364%

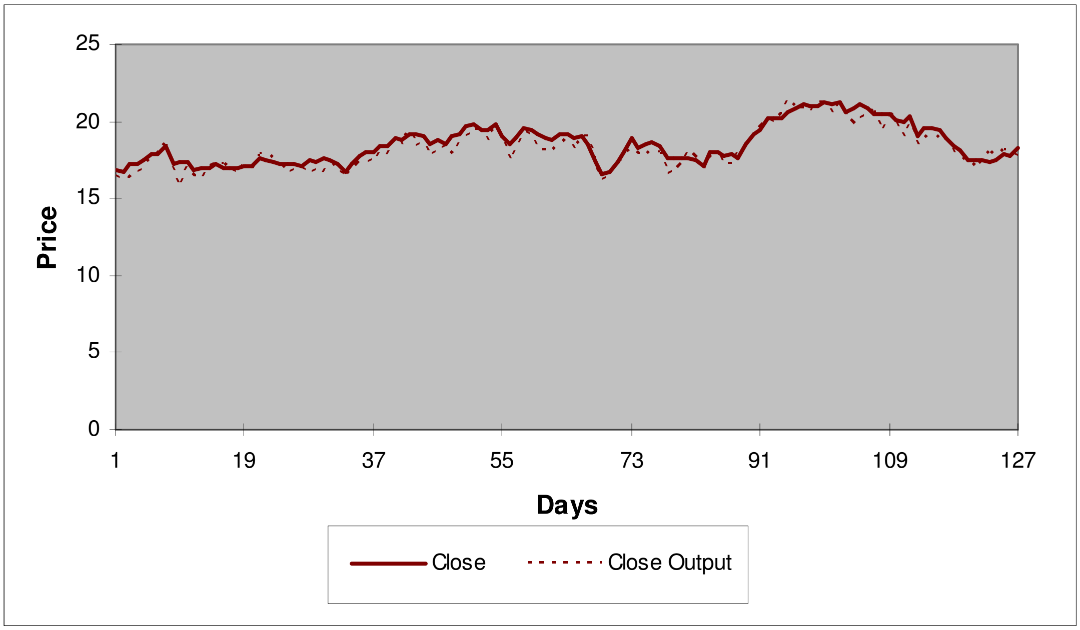
RHB



Performance	*Close*
MSE	4.274747562
NMSE	0.425815386
MAE	1.485770902
Min Abs Error	0.011712066
Max Abs Error	0.166409859
R	0.979754775

No. of Testing Data Points	274
No. of correct change predictions	254
No. of incorrect change predictions	20
Percentage accuracy	92.70073%

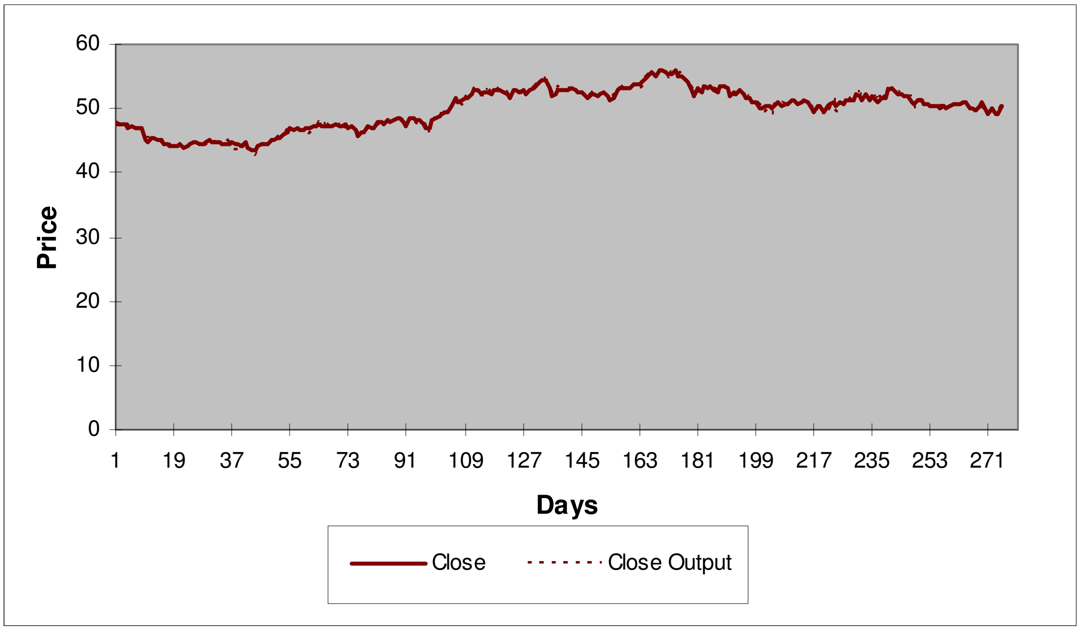
STX



Performance	*Close*
MSE	0.257478204
NMSE	0.162561708
MAE	0.418947599
Min Abs Error	0.00182261
Max Abs Error	1.561193414
R	0.95336365

No. of Testing Data Points	127
No. of correct change predictions	117
No. of incorrect change predictions	10
Percentage accuracy	91.92913%

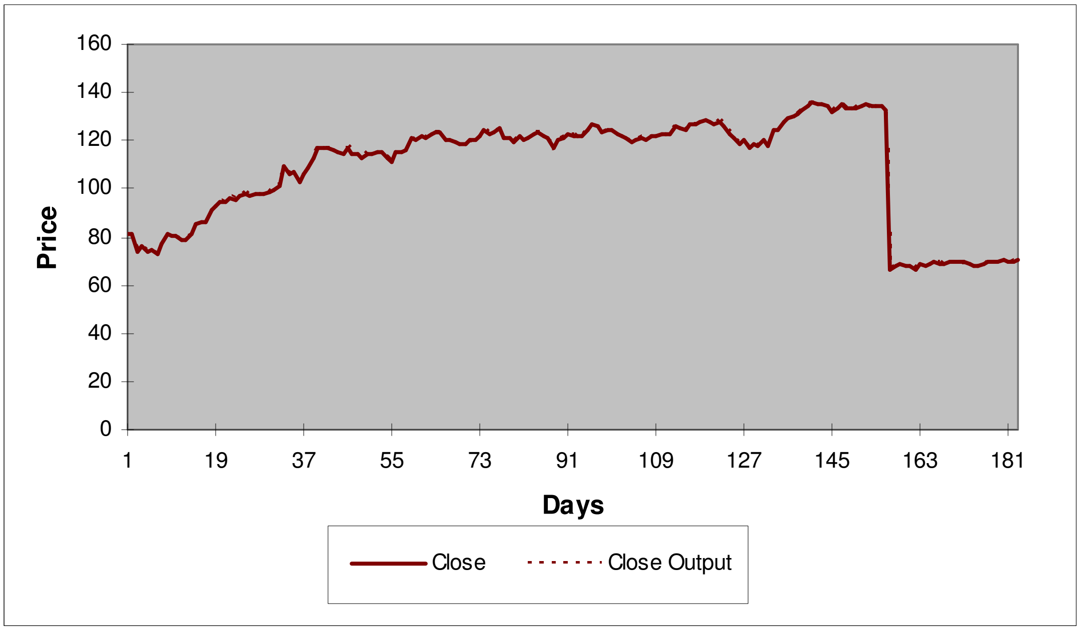
WB



Performance	***Close***
MSE	20.28728098
NMSE	1.998560621
MAE	3.918353226
Min Abs Error	0.03708962
Max Abs Error	8.98556136
R	0.9924306

No. of Testing Data Points	275
No. of correct change predictions	252
No. of incorrect change predictions	23
Percentage accuracy	91.63636%

WLP



Performance	*Close*
MSE	1.512244855
NMSE	0.972601811
MAE	1.227613975
Min Abs Error	0.100305974
Max Abs Error	0.635639617
R	0.938942476

No. of Testing Data Points	183
No. of correct change predictions	174
No. of incorrect change predictions	9
Percentage accuracy	95.0819%