# New Decision Making Algorithms for Stock Market

[株式市場における新しい意思決定アルゴリズム]

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***In the name of Allah (god), most gracious, most merciful***

***(Bismillah Ar-rahman Ar-raheem)***

***O my lord! Glory be to you, we have no knowledge save (except) what you have taught us. in truth(verily), it is you, the all-knower the all-wise(who are perfect in knowledge and wisdom).***

***God is truthful***

## *Abstract*

Stock market forecasting is one of the most challenging tasks in the world. Much research have tried to discover the secret mechanisms in the stock market, but the findings remain elusive. Some factors that influence the market have been revealed, but it is not comprehensive enough. The factors depend on variables like the stock markets, seasonal changes, government policy, the world economy, natural disasters, crude oil price, exchange rates, etc. For this reason, the stock market data is one of the most non-linear natural data.

Two types of forecasting are used in stock price forecasting drills by researchers. Most researchers predict the train of the previous trainer to see how closely they can extrapolate in the next few days. Very little research has been conducted with drills using decision-making (turning points) algorithms for the stock market. Moreover, the decision plays a leading role in profit-making in the stock market.

In this study, a new forecasting model has been proposed for stock market decision making. We integrated the neural network and data mining tools to estimate the stock market decision points to buy or sell. It is through the measurement of buy and sell points that people can estimate the transaction time which can caution shareholders of high risk. The key to effective shareholding is to identify the period of risk-free transaction.

Recently, research on stock forecasting has taken two interesting directions. One focuses on the prediction of the price variation in the short-term, and the other one focuses on the prediction of the turning points of the price. Commonly the turning points have a longer period than the price variation in the short-term, so the high frequency characteristic of data can be reduced. In addition, the turning point is more important than the non-turning point because it can yield a higher profit if it is predicted accurately. This paper focuses on the prediction for the turning points of the stock price movement.

Our research considers mainly ANN, Data mining, decision-making and hybrid algorithm. The Shannon entropy algorithm is also used at the data pre-processing stage. The Shannon entropy is a basic measure in information theory that calculates uncertainty. The entropy is used to find the nature of each share. It is possible to use other techniques for this purpose. The Shannon has some advantage over the others

in the stock price prediction. This technique may be used for all time series/ financial analysis.

We also introduced a new technique to find the turning points called local saturation methods (LSM) for piecewise linear representation (PLR). PLR reduces the high frequency and provides a certain decision for a certain period. The LSM is easy to implement and avoids high sensitivity threshold values. We used two types of data smoothing called normal data smoothing and weighted data smoothing, to find the LSM. LSM is also a new and challenging technique in predicting stock prices.

A new model has been proposed which hybridises historical information and current information, called the hybrid model or combined model. The data mining tool called the least square autoregression is used to retrieve the instantaneous property/attitude, and the neural network tool is used to reclaim the historical property/attitude. The combination of instantaneous and historical information yields better prediction ability. Sometimes, the output of these techniques show opposite properties/directions. An intelligent filter is used to avoid this problem. In this study, three decisions are taken, namely, buy, sell and no decision. We are trying to find the buy or sell points through the transaction. If no buy/sell is found, the decision is defaulted to no transaction or holding the shares.

Using the findings from this research, one may plan their investing and harvesting time. Shareholders want to reap a profit from their investments. Hence, there is a chance they may lose their wealth. At the same time, it is difficult to claim that our proposed model will earn shareholders a good profit. We want to state instead that if our methods are followed, the risk of investing will be significantly reduced. Finally, we integrated historical information (previous train) and current information (current influencing factor) to arrive at the decision to buy, sell or hold.

The proposed research model discusses only the stock markets data analysis, but it is applicable for all kinds of forecasting and decision-making problems. The historical data of the stocks data are based on research direction. Many online sources contain data on the stock price transaction. The data for this paper was collected mainly from the Google finance data store. Every working day witnesses many transactions in the stock market. The shareholders buy and sell their share and leave a trail of data that can be analysed.

# *Acknowledgements*

I kneel down to **ALLAH** be grateful to **HIM** for giving the righteous path. Without **HIS** help my efforts nothing. May **ALLAH** sends His pleasure upon his Beloved Prophet **Muhammad** (swt).

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# Chapter 1

# INTRODUCTION

## 1.1 Background

In the contemporary world, the stock market has become very accessible because shares can be easily bought or sold through the Internet or a telephone call. A large number of people invest their wealth in the share market. Our aim is to develop a guide for shareholders that, if utilised, will yield a profit. A several number of researches have been conducted in the area of time series forecasting from the early 1980s. Jan G. De Gooijer et. al [1] survey into time series forecasting until 2005. The research contents have been divided into 13 sections and have proved to be a promising field with ample ground for future investigations. The Financial time series forecasting remains an interesting field to the researcher. This series depends on many factors, including exchange rate, oil price, taxes, the political environment, government policies, natural disasters, local markets, international markets, seasonal change, other products, etc. For an accurate forecast, all the dependent factors must be accounted for, and so reaping a handsome profit is challenging and risky using the financial time series. Alternatively, the environment of the stock market is very complicated, dynamic, and heterogeneous, making it even more difficult to predict [2, 3, 4]. However, research in this area is draws attention as it is connected with monetary gains and losses.

The recorded history of the economy has mostly been in the form of time series. Economic behaviour is computed as the consumer price index, unemployment, gross national product, population, production etc [5]. The mathematical theory of time series has been an area of considerable activity in recent years. A successful application of statistical methods to the real world requires a melding of statistical theory and knowledge. Stock price prediction has interested most investors and financial analysts;however, finding the right time to buy or sell has remained a daunting task for investors because there are numerous other factors that may influence stock prices [6, 7]. A lot of historical data for stocks are available from other research sources. To understand the data sets or part of the data set, firstly, the data must be normalized by considering the weighted values. After this, the information/entropy is measured to arrive at each data set complexity. The data sets pass through the pre-processing step where the data mining tools are mainly used, followed by the intelligence tools to predict the data sets. The research uses data mining and ANN tools.

Data mining is a methodology that involves learning in the real world in a non-theoretical sense. Data mining finds structural patterns in data [8] and makes predictions through it. It provides a comprehensive illustration of the performance data. The objective is to beat financial markets and glean rewards. However, due to the complexity of the financial time series, there is some scepticism about its ability to predict [9]. The stock market is random and dynamic. The predicted future does not always meet with expectations. The Artificial Neural Network (ANN) attributes humanlike intelligence to machines. John Kelly [10] draws attention to the chasm between analysis and construction, and meaninglessness of nations such as concern an meaning for machines, the nation which are central to the human being. So, ANN is a powerful device that predicts the future. From the early 1990s to the present, the ANN is believed to predict the stock market with success. Other popular networks include the Fuzzy neural network, Genetic algorithm, etc. A hybrid system is frequently used. For the last decade, the ANN tools have been heavily researched and implemented in various fields like commerce, economics and finance. This tool has fixed many problems like the time series forecasting and performance measurement [11]. The flexibility and adaptability of the ANN tools have attracted the interest of

Business and Banking. Other attentive application areas include robotics, oil and medicine industries, computer engineering and electrical engineering.

This study combines the ANN, Data mining, decision-making and hybrid algorithm. At the data pre-processing stage, the Shannon entropy algorithm is also used. The entropy is used to find the nature of each share. During the data pre-processing stage, a common and popular method called smoothing is used. Smoothing numbers is a challenging task. Most researchers tend to use an arbitrarily chosen number or fixed number. But the data set is always varied. To fulfil these demands, we used the entropy values instead of the fixed or arbitrary number. The Shannon has some advantage in the prediction of stock prices. This technique may be used for all time series/ financial analysis. We also introduced a new technique for finding piecewise linear representation called local saturation methods (LSM). The LSM is easy to implement and avoids high sensitivity threshold values. LSM is also a new and challenging technique in stock price prediction.

## 1.2 Statement Of The Problem

This research explores stock price movements to investigate whether the market is right for buying/selling/holding the share. In this respect, the following problems were faced:

1. Finding the exact points to buy/sell. Even if the points correctly indicated the decision to buy/sell, it was difficult to claim that this was the best point to do so. This is the most challenging task for any financial research at present.

2. Deciding/predicting the stock market behavior accurately, because the stock market depends on many influences.

3. Accumulating the influencing factors The factors vary from share to share and market to market.

4. Proposing a technical strategy is difficult.

5. Offering risk-free algorithm.

6. The data are so vast that mining the internal significant data was a challenge.

We used ANN, data mining, decision tree and hybrid systems to fix the abovementioned problems. We know that the ANN and data mining are strong at predictiing. The purpose of using a decision tree was to combine the technical and intelligent decision-making. A hybrid technique was used to improve the performance.

## 1.3 Objectives

Financial researches are of interest to a range of stakeholders because it addresses wealth. A lot of people are directly affected by imbalances in the stock markets. Our aim was to aid the public to gain monetarily from imbalances in the financial market.. The purpose of this dissertation is as follows:

- To predict the proper buying and selling points through the stock market
- To compare our results with those of existing methods
- To test our methods in order to measure performance
- To overcome the above mentioned problems, we propose a new algorithm which may be easily understood and carried out.
- To reduce the risk of investment
- The trader and shareholder can easily plan using this model.

## 1.4 Synopsis Of Dissertation

The components of this dissertation are as follows: Chapter 1 is a brief description of the background, motivation and objectives of this research. Chapter 2 presents the real-time stock price prediction using data mining. Here, the least square auto-regression is used as a data mining tool, and the parameter of least square auto-regression is updated in real-time. Chapter 3 enhances performance by integrating new piecewise linear representation and ensemble neural network. We introduced a new model for the piecewise linear representation called local saturation method. Chapter 4 discusses the hybrid modelling for stock price prediction. Data mining and neural network were used to make the hybrid. The resultant performance also proved the hybrid algorithm to be promising. Chapter 5 contemplates possible future directions of this research.

# Chapter 2

# REAL TIME FORECASTING USING DATA MINING

The stock market is gaining in relevance with each day. Much research has been done in the area of finding a means to forecast the fluctuations. Yet, decision-making remains a challenging task. Taking risks or testing one's luck is a human trait prevalent among shareholders. They want to test their luck or take a risk by investing their last harvest. Misfortune can be avoided if some precaution is taken. This research hopes to alleviate one from that misery. It also hopes to glean a handsome profit from the stock market with the exception of natural disasters and other unforeseen incidents. Our proposed algorithm uses autoregressive methods to assist with the decision to buy as well as the selling point for any stock price. The proposed algorithm is useful for the shareholder and the trader. This decision-making tool can be essential to the formation of the business plan, and its viability is proven by the significant amount of profit that has already been yielded.

## 2.1 Introduction

Stock trading signals have become a very popular topic for research in financial engineering. Forecasting the stock price accurately is one of the most challenging tasks. The people who engage with the stock market do so in an environment of high risk and uncertainty. This is because of the frequent shifts in the stock market. A number of factors influence the stock price. They include: exchange rate, interest rate, political instability, natural disasters, government policies, the international stock market, etc. The ability to properly predict can result in effective decision-making, planning, organizing, controlling the opening price, scheduling, policy making, etc. The question of the predictability of the stock market is, therefore, important even outside the trading rooms.

Stock price prediction can be divided into two categories: share price prediction of the next day, and the predicted buying/selling points. Both are difficult to predict accurately because of many factors. Most of the research in this area has been done with how closely the shifts can be predicted. Much research has concerned itself with the share decision rules or financial decision-making. Also, it is more difficult to find the accurate point for trade. The proposed algorithm also concerns itself with the prediction of the buying and selling points. Linkai Luo, Xi Chen [12] has recently integrated the PLR and the weighted support vector machine to forecast the stock trading signals. The performance of the support vector machine (SVM) depends on many key parameters, and is difficult to decide correctly. In order to get satisfactory results, one needs to engage in several experiments by altering the setting. However, they used a fixed number of threshold values, which is not good for any time series. Chang et al. [13] proposed intelligent PLR with Back Propagation Neural Network (BPN) to predict the stock trading decision of whether to sell, buy or hold. They used the fixed threshold value to find the turning point for PLR. Genetic algorithm (GA) was then applied to tune the threshold value. Stepwise regression analysis was used to identify the influencing factors for any trade. There is a possibility the GA may divide the transactions of buying and selling in some parts because GA does not follow the entire sequence. To avoid this problem, Chang et al. used dynamic threshold values [14]. The basic difference between Chang [13] and [14] is the threshold optimizing technique. Alireza A. et al. [15] proposed a trading algorithm that will synchronize the trading phase by using the wavelet transformation. Firstly, one must filter the high frequencies and identify the low frequencies, which would almost equate to the normal moving average (NMA) value. By taking the high values for the moving number (MA), we can arrive at the trading phase.

The key reason for using PLR is the threshold value. Sometimes the training and testing phases do not suitable constitute the same threshold values. The threshold values are highly sensitive. We used the moving average instead of PLR. We get some advantages by using the MA. Firstly, no threshold values are required; Secondly, time-consuming methods (like GA, Fuzzy) which are used to adjust the threshold can be avoided; Thirdly, there is no need to handle highly sensitive parameters. Also, the high frequency values are reduced by using the high moving average number. The key advantage of using the MA is the moving average number (MAN). By measuring MAN, one can get an accurate decision for any time series. The Shannon entropy is used instead of arbitrarily fixing the MAN. The Shanon entropy is a powerful tool for measuring the complexity of any time series. Both the complexity of a time series and the MAN have a very close and interesting correlation. We are going to use this correlation to measure MAN accurately.

Stock market prediction is an interesting field for traders and shareholders, and it is difficult to know when one should be selling, buying and holding shares. Our previous research [16] real time forecasting aided the share market decision-making. It is better if the exact day of the selling or buying can be identified. Investors can reap more profits using this procedure. Recently, some researchers [17] proposed an instantaneous frequency type as suitable for a large class of signals called simple waves. The frequency is conditionally defined as a derivative of the phase of the signal. The frequency of a sinusoidal signal is a well-defined concept. The daily Istanbul Stock Exchange National 100 data set was predicted using the direction of movement [18]. Phichhang Ou et al. [19] proposed a new data mining technique called nonparametric volatility-based SVM. They also tested their model by using the Nikkei 225 index to forecast performance. Two classification tools, the Artificial Neural Network (ANN) and the SVM, were used, and ten technical indicators of both the networks were selected. Their contributions to research in stock market prediction exhibits and verifies the predictability of the stock price index direction. The simple 10 days MA and the weighted 10 days MA are used as the technical indexes.

The originality of this research resides in the proposed algorithm which can detect real time decision-making. In addition, this process can update its information in real time, and thereby, yield good forecasting results. Significant achievements of the research include, firstly, the methods of normal data smoothing and exponential data smoothing were used in the data preparation process to find the accurate decision point for trading instead of a long piecewise linear representation. Secondly, the decision-making tree and data mining technique were used to identify the predicted point. This assists in precise decision-making and bridging the relationship between the buying and selling points. Thirdly, the proposed algorithm can predict and update in real time. Decisions can be made on a daily basis. With this approach, the shareholder can buy or sell the selected stock, and the policy maker can make their own plan.

The rest of this paper is organized as follows. Section 2.2 reviews the related literature in the area of stock trading signals. Section 2.3 is concerned with data preparation. The entire model specification can be found in Section 2.4. Section 2.5 & 2.6 presents the empirical results and relevant discussion. In this section, the twenty four stock data that were collected from NASDAQ 100 and Tokyo Stock Market and Shanghai Stock Market is presented. Finally, conclusions are drawn and future directions of the research are explored.

## 2.2 Literature Review

The ability to predict the stock market is integral to the profit-maximisation of investors and traders. Many researchers have successfully used data mining techniques to profit from the stock market. Some researchers [20] proposed more than one method to gain multiple information about the future of the markets. They applied ten different techniques of data mining to predict the price movement of the HangSeng index of the Hong Kong stock market. This section briefly introduces stock trading signal/time series decision using data mining, and also discusses some research methods.

J.G. De Gooijer, R.J. Hyndman [1] reviewed research into time series forecasting from 1982 to 2005. This review covered over 940 papers. The paper examined exponential smoothing, ARIMA, seasonality, state space and structural models, nonlinear models, long memory models, ARCH-GARCH method. G. Preethi, B. Santhi [21] surveyed the recent literature in the area of NN, Data Mining, Hidden Markov Model and Neuro-Fuzzy system, which were used to predict the stock market fluctuation. They summarized 20 research activities published between 2009 and 2011. They extrapolated that the NN and the Markov model will be used exclusively in the time series and in the forecasting of the stock price.

Qiong Liu et al. [22] predicted the change of future interest rate and exchange rate. Some sought to recognize certain price patterns that are characteristic of future price changes. Their proposed theory presented the NN for a technical analysis of the stock market, and its application to a buying and selling timing prediction system for the stock market index of Japan. The Data Mining technique is very common for time series prediction [23, 24].

Qasem A. Al-Radaideh et al. [25] used the decision tree classifier (CRISP-DM) on the historical prices of the stocks to create decision rules that decide whether to buy or sell. Their method analysed only three companies' stock data. Also, they did not use any calculated indexes (only the website data). Our algorithm was tested using different stock market data and the shares were chosen based on their popularity. Recently, a multiagent approach to Q-Learning [26] has been used for daily stock market prediction. They divided the stock trading problem into the timing and the pricing problem to find the best buying and selling prices. Secondly, they separated the selling and buying information for Q-Learning. Ahmad Kazem et al. [24] used chaotic firefly algorithm and SVM for stock price prediction. They integrated the chaotic motion with a firefly algorithm as a simple optimization method, and the chaotic algorithm was incorporated to find the best hyperparameters of SVR.

## 2.3 Data Preparation

Any type of regression or prediction depends on the previous history or experiences. This trajectory intends to predict the decision-making that takes place in the stock market. Decision-making is a challenge for any business. It is only through proper decision-making that anyone can earn a profit from any sector. Data preparation or the preprocessing phase is the primary stage of decision-making. Statistical tools and decision-making algorithms are used in this stage. Firstly, the data is divided into training and testing sets. The primary data preprocessing step is done using the training sets. The data preprocessing steps are shown in the figure below.

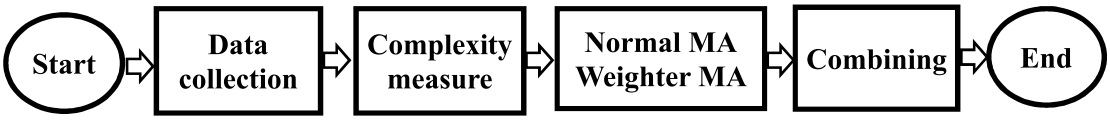


Figure 2.1: Data preprocessing steps

### 2.3.1 Data Collection

The proposed algorithm is tested by using three big share market's data, namely, the Shanghai Stock Market (SSM), the Tokyo Stock Market (TSM), and the NASDAQ100 Stock Market. Eight data sets were collected from each share market. The Shanghai Stock data covered a time period from 04/01/2010 to 18/08/2011, and contained approximately 381 days of transaction data. The Data Code is 600697, 600019, 600881, 600167, 600488, 600163, 600054, 600051 [12]. The popular and almost saturated stock were selected from TSM and NASDAQ100 Stock market. We were not selective about the data in the hope of showing good results. The Tokyo Stock Market data covered a time period from 10/05/2011 to 15/03/2013, with approximately 450 days of transaction data. The data hailed from four sectors, namely automotive, electrical machinery, communication, and machinery. The selecting stock indexes are TYO: 7203, TYO: 7267, TYO: 7751, TYO: 6503, TYO: 9984, TYO: 9437, TYO: 6305; TYO: 7011. The NASDAQ100 data covered a time period from 01/06/2011 to 15/03/2013, covering approximately 450 days of transaction data. The stock index selection from the NASDAQ Stock Market are CSCO, COST, ESRX, GILD, GOOG, AAPL, AMZN, and STX.

### 2.3.2 Data Normalizing

Stock markets change their prices frequently. It has been noticed that some minimum value was found in a certain period. We should consider either the time variant data or the frequency data only. If all the data is considered, the non-linear behavior effect will be very small in any network. So, it is necessary to reduce the non-varying data. Also, the time variant data retains the characteristics of the data. For this reason, only the upper portion or time variant data is taken for further analysis. We use the following equation to normalize all the data in the interval (0,1). $\mathrm{X_{old}}$, $\mathrm{X_{min}}$, & $\mathrm{X_{max}}$ are the original, minimum and maximum values of the raw data respectively, and $\mathrm{X_{new}}$ represents the normalized form of $\mathrm{X_{old}}$.

$$X_{new} = \frac{X_{old} - X_{min}}{X_{max} - X_{min}}$$

### 2.3.3 Complexity Measure

The complexity of the stock market formulates a relation that would assist in finding the proper time to sell and buy. Knowledge of this information would help one gauge the complexity or simplicity of the time series. A number of studies [27, 28] have been conducted to find the complexity for any time series and predict their behaviour such as regular, chaotic, uncertainty, size, etc. The main type of complexity parameters include entropies, fractal dimensions and Lyapunov exponents. We used the Shannon entropy to analyse the stock price complexity. Teixeira A. et al. [29] showed that the Shannon entropy measured the expected value effectively compared to other contesting methods. The Shannon entropy is a basic measure in information theory that calculates uncertainty. The Shannon entropy is calculated using the following formula.

$$\mathrm{H} = -\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{p}(\mathrm{x_i})\log_{\mathrm{b}}\mathrm{p}(\mathrm{x_i})$$

Where the Shannon entropy is denoted by H, $\mathrm{x_i}$ is a discrete value from the time series of X. The finite number of data is n, and $\mathrm{p}(\mathrm{x_i})$ shows the probability density function of the outcome of $\mathrm{x_i}$.It can be said that the complexity of a system is indicated by the amount of information available. Bigger entropies show a higher complexity for any time series and vice versa. According to the entropy value, the data set is judged to determine whether it is high or low complexity, and this information is used in the next section.

Table 2.1: The Average entropy of each 100 data in the data set

| Data set | Shannon's Entropy |
|---|---|
| Toyota | 5.24 |
| Honda | 5.45 |
| Asahi | 4.83 |
| Amazon | 5.60 |
| Cisco | 4.93 |

There is a strong relation between entropy and the quantity of the information for any data set. The Shannon entropy is good for any time series analysis. The average Shannon's entropy of 100 data is shown in Table 2.1, where five data sets are arbitrarily chosen.

### 2.3.4 Moving averages

A moving average (MA) is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles [30]. The threshold between the short term and the long term depends on the application, and the parameters of the moving average will be set accordingly. MA is a lagging indicator, because it is based on past prices. Data complexity uses a number of smoothing values. It is important to decide how much data will be taken for data smoothing: a higher complexity data takes a high value, and a lower complexity data takes a low value. The two basic and commonly used MAs are the normal moving average (NMA), and the weighted moving average (WMA). We have used these two types of data smoothing to find the accurate decision point.

### *Normal moving averages*

The NMA is commonly used by technical analysts/ financial applications. It is calculated by dividing the sum of a sample set of prices by the total number of samples in the series. NMA is the equally weighted average of a sample over a defined number of time periods. The NMA is calculated using the following equation:

$$\mathrm{NMA_m} = (\mathrm{V_m} + \mathrm{V_{m-1}} + \cdots + \mathrm{V_{m-n+2}} + \mathrm{V_{m-n+1}})/\mathrm{n}$$

Where, $\mathrm{V_m} + \mathrm{V_{m-1}} + \cdots + \mathrm{V_{m-n+2}} + \mathrm{V_{m-n+1}}$ is the original price and $\mathrm{n}$ is the number of sample days for smoothing. The normal moving average (NMA) data is used to find the number of decisions (buy and sell). The moving average value is taken from the large numbers (3*entropy number). The number of saturated points signify the number of decision points. The lower and higher saturated points mark the buying and selling points, respectively.

### *Weighted moving averages*

The weighted moving average (WMA) is a useful tool where one needs to measure recent changes/activities. This method also follows the lagging information or lagging trade, but the recent activity/change is affected more than the previous activity/change. We can say that WMA gives bigger weight to more recent price. The WMA is calculated by the following equation:

$$\begin{aligned}&\mathrm{WMA_m}\\&= \{\mathrm{nV_m} + (\mathrm{n}-1)\mathrm{V_{m-1}} + \cdots + 2 * \mathrm{V_{m-n+2}} + \mathrm{V_{m-n+1}}\}/\{\mathrm{n} + (\mathrm{n}-1) + \cdots + 2 + 1\}\end{aligned}$$

where, $\mathrm{V_m} + \mathrm{V_{m-1}} + \cdots + \mathrm{V_{m-n+2}} + \mathrm{V_{m-n+1}}$ is the original price and $\mathrm{n}$ is the number of sample days for smoothing. The weighted moving average data is used to find the exact decision point. The previous calculation measures the number of decision points. The moving average number and the entropy number have the same value. This calculation yields many decisions or saturated points.

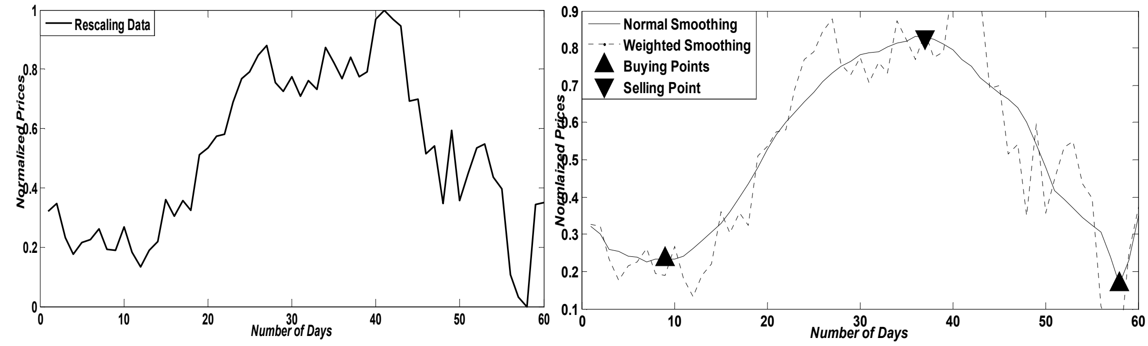


Figure 2.2: Graphical representation of data preprocessing steps

### 2.3.5 Combining

The result from NMA and WMA are combined to make a single output or combined output. The NMA saturated values may vary slightly from the exact values because the moving average number is high. The WMA identifies the exact timing for the decision, but this method involves many unnecessary decisions. After combining the two outputs, where the WMA decision points are closer to the NMA points, a decision is made. The NMA is used to find the number of decision points in the training data, and the WMA is used to find the decision points in the training data. So, one saturated point from the NMA and the nearest exact point from the WMA are used to make the decision. Ethical examples are shown in Fig. 2. where given 15 data points, smoothing is taken from normal smoothing, and given 5 data points, smoothing is taken from the weighted smoothing. It can be seen that three saturated points are found using normal smoothing technique. The nearest crossing between NMA and WMA is clearly seen.

## 2.4 Model Specification

The main purpose of any financial research is to develop a framework to benefit from the share market. For this a simple and effective method is proposed that ¥ is user-friendly and easy to implement. The proposed model is composed of data preparation, real time calculation and decision tree. Data preparation results in decision points and the parameter of the equation is calculated by using the decision point. The decision tree serves the purpose of a filter. The algorithm for the proposed model is shown in Figure 2.3.

Step 1: Start

Step 2: Data is divided into two data sets (training and testing)

Step 3: Data preparation (Rescaling, NDM, WDM)

Step 4: Finding the appropriate decision points (buying and selling points)

Step 5: Calculating the decision parameter for the regression equation (Using the least squares auto regression)

Step 6: Applying this auto regression equation to the test/future patterns

Step 7: Using a decision tree algorithm as a filter

Step 8: After any successful outcome, go to step 5

Step 9: Step 6 to Step 8 until the test/future data finished

Step10: End

Figure 2.3: The algorithm for proposed model

The flowchart of entire proposal is shown in Figure 2.4. The data preparation stage has already been discussed in an earlier section mainly using the moving average and the Shannon entropy. Every step has been discussed elaborately in the later section. In the flowchart, we can see the data separated into two training and test data set. We can also use future data after completing the test data or instead of the test data. The test data can also be used as a future data where it is modified by rescaling. So, there is no major change during the training stage or the parameter selection stage. After any decision, the parameter will update automatically by adding the new decision data. Because of our proposed model's ability to update the parameter in real time, our method is called real time prediction or forecasting.

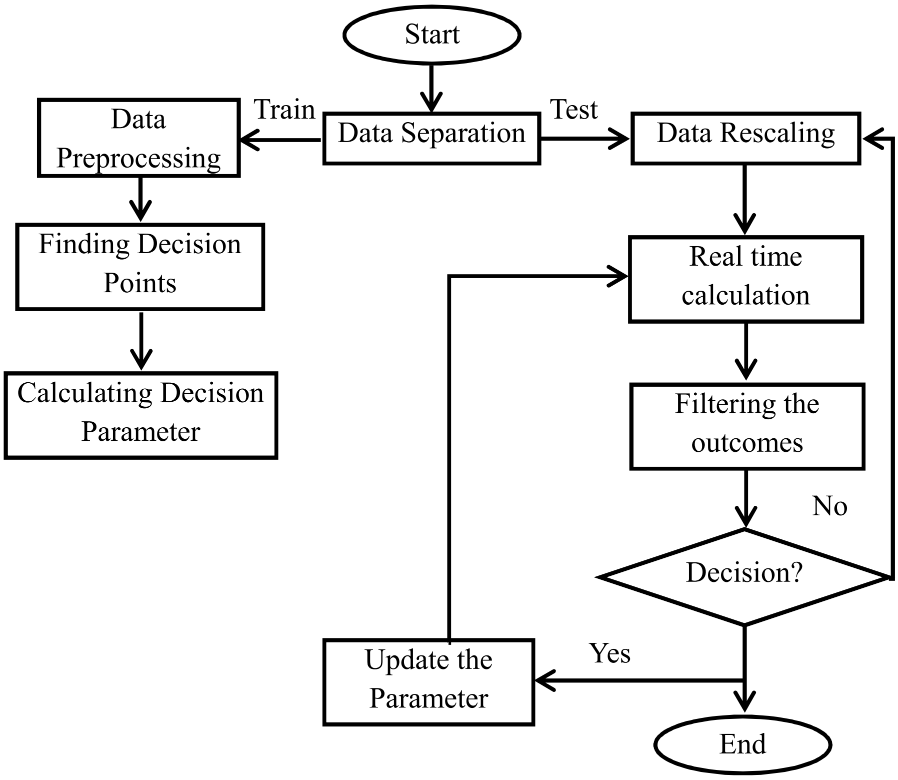


Fig. 2.4. Flowchart of entire proposal

### 2.4.1 Input Selection

The stock market depends or is influenced by a number of important issues. Input selection is challenging and one of the key factors contributing to accurate forecasting. Another important point that is influencing the factors varies with changes in the stock market. Finding the accurate technical index combination can be a challenge. Many researchers have investigated many technical indicators to predict the trading signal [31, 32]. There are some common factors, such as the moving average, transaction volume, bias and related strength. However, the combinations that will assist with the stock market predictions or help to obtain a profit remain unknown.

We have also investigated some of the indexes that are linked to decision-making. The proposed method tried to find how closely proper decision-making will commensurate with profit. Even as it is difficult to find appropriate technical indexes for all the stock markets, the following four technical indexes as shown in Table 2.2 have been used.

Table 2.2: The Technical indexes used in the input variables, $P_o(t)$, $P_c(t)$, $P_h(t)$, $P_l(t)$, $V(t)$, respectively, indicate the opening price, the closing price, the highest price, the lowest price, volume of transaction on the tth day.

| Technical index | Explanation |
|---|---|
| The opening price changes | $P_o(t) - P_o(t-1)$ |
| The closing price changes | $P_c(t) - P_c(t-1)$ |
| The volume of transaction changes | $V(t) - V(t-1)$ |
| The price change in a day | $P_h(t) - P_l(t)$ |

### 2.4.2 Parameter Estimation

This section diccusses the parameter estimation, methods and gives examples. The parameters of the equation are the vital feature for forecasting. The decision points are used to find the input variables. In order to simplify the equation, the selling and buying points are used as dependent variables and the value is +1 and -1, respectively. On the other hand, the input variables/technical indexes are used as independent variables. The least squares autoregression is used for forecasting.

#### *The least squares autoregression*

The method of least squares is a procedure that determines the best fitting line to the data [33].The least squares autoregression is the core of econometric analysis. Regression analysis is a widely used tool in financial time series investigation. It is used to describe and evaluate the relationship between financial variables or time series variables for forecasting tasks. While it is important to calculate the estimated regression coefficients without the aid of a regression program at least once to better understand how OLS works, easy access to regression programs makes it unnecessary. The ordinary least squares estimators of the nth order autoregression is [5].

$$Y_t + \sum_{i=1}^{n} \alpha_i Y_{t-1} = \theta_0 + \varepsilon_i$$

Where the roots is $m^n + \sum_{i=1}^{n} \alpha_i m^{n-i}$=0 , because the production of this section is closely related to multiple regression, we can rewrite the formula as

$$Y_t = \theta_0 + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \cdots + \theta_n Y_{t-n} + \varepsilon_i$$

Where $\theta_i = \alpha_i$, i=1,2,…,n. Also, the least squares estimator is asymptomatically equivalent to the estimatorg

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \cdot \\ Y_n \end{pmatrix} = \begin{pmatrix} Y_0 & \cdots & Y_{n-1} \\ \vdots & \ddots & \vdots \\ Y_{n-1} & \cdots & Y_0 \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \cdot \\ \alpha_n \end{pmatrix}$$

This is also called Yule-Walker estimators [5]. From the training data the following six data and their estimation parameters were randomly chosen and listed in Table 2.3.

The autoregressive models are more prominent models among the time series movement variability. Mainly, they are based on the least squares estimator. The deviance can make a important statistic for prediction. By adding the variables, if the deviance changes large/less, the prediction of $y$ effects as same [34].

Table 2.3: The example for parameter estimation

| | $\boldsymbol{\alpha_1}$ | $\boldsymbol{\alpha_2}$ | $\boldsymbol{\alpha_3}$ | $\boldsymbol{\alpha_4}$ |
|---|---|---|---|---|
| **TYO: 7267** | 0.371846 | -0.241440 | 2.562631 | -1.317373 |
| **TYO:7751** | 1.495754 | 1.549142 | 1.657155 | -5.007138 |
| **AMZN** | -0.496544 | 0.332445 | 2.151452 | -0.536098 |
| **STX** | 1.511480 | 0.313829 | 0.649607 | -2.569223 |
| **600488** | -1.757422 | 1.297488 | 2.106591 | 1.529086 |
| **600697** | -1.787020 | -0.074207 | 20237721 | 0.838129 |

### 2.4.3 Decision Tree

After arriving at the equation, we take each day's dependent variable for the outcome. A filter is used, which works as a means of selection for the next step. Some conditions apply in the filter stage which can help our profit calculation.

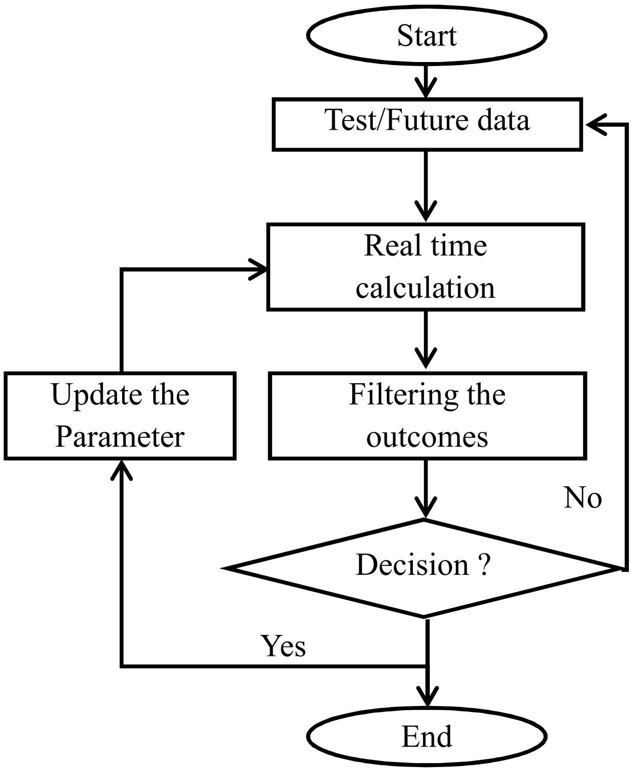


Figure 2.6: The algorithm for test sets

Some important concerns are considered in the filtering section. These concerns are as follows:

- Minimum transaction gaps between the two decisions: There are four transaction gaps. We find these values by training the data set. These values are the minimum transaction values for all cases. Some data also have greater values. But these values are used in thetesting phase.

- Minimum transaction gap between the same decision: There are six considered gaps. In most cases, we consider a minimum of six buying to selling gaps. Hence, in almost all cases there will be ten transaction gaps.

- Threshold values: The minimum threshold values are considered for any decision. The threshold values are considered as approximately -1 for buying points and +1 for selling points.

- Two consecutive selling/buying: The proposed method takes only one decision and then alters to the opposite decision (sell then buy or buy then sell). If shareholder buys one unit of share, s/he cannot sell more than once.

- The data set: We are using only three stock market data and 24 data set. Also, we considered only the popular data from TSM and Nasdaq100 stock market.

### 2.4.4 Desired output

In this stage, it is necessary to check whether it is all right to sell or buy or whether no transaction has taken place. If no transactions are found, this stage will be skipped and the procedure will start from the test/future variables. It can be clearly seen in Figure 4 that the equation is updated when any transaction is found. Similarly, there is an update of their independent parameter. So, the process updates real time. These processes will continue until the last data has come. After that the profit is calculated.

## 2.5 Results

The main goal for all financial research is to reap a profit. Hence, the profit or the benefit to the trader is an important issue for stock market prediction. But some calculations do not yield an accurate profit because some costs, like transaction costs, were not considered. To find the profit, the following formula is used

$$\text{Profit, P} = \left[\sum_{i=1}^{n} \frac{\{(1-m-o).S_i-(1+p).B_i\}}{(1+p).B_i}\right]$$

Where $m, p$ stands for the transaction cost of selling and buying of the ith transaction, o refers to the tax rate of the ith transaction. $S_i$ , $B_i$ represents the selling and buying price of the $i$th transaction, and $n$ signifies the number of transactions [5]. Profit is calculated for a single share. In my methodology, a transaction is complete when the shareholder engages in the process of the minimum buying and selling of shares. Many methods will not make a profit if they do not consider the tax rate and the transaction costs associated with selling and buying.

### 2.5.1 The Training Data Results

Our method inclines towards the investor/shareholder. Table 2.4, 2.5, 2.6 shows the training data set results. The results are separated based on different markets such as Tokyo stock market, Shahghai stock market and Nasdaq stock market. During the training period, 300 transaction data were taken from the Tokyo stock market and NASDAQ100 stock market, and 250 transaction data were taken from the Shanghai stock market.

The number of buying points ($N_B$), the number of selling points ($N_S$), minimum transaction gap between two selling decisions ( $MT_B$) and the minimum transaction gap between two buying decisions ($MT_S$) are indicated as $N_B, N_S$, $MT_B$ and $MT_S$, repectively. Of the training results, there are six (6) transaction gaps between the minimum transaction gap for selling and buying. The maximum value of $MT_B$, $MT_S$ is 35 for both cases and they belong to TYO: 7267 and TYO: 7203, respectively.

Table 2.4: The Training Data Results of TSM

| *Indexes* | *TYO: 7203* | *TYO: 7267* | *TYO: 6503* | *TYO: 7011* | *TYO: 9984* | *TYO: 9437* | *TYO: 6305* | *TYO: 7751* |
|---|---|---|---|---|---|---|---|---|
| $N_B$ | 7 | 6 | 9 | 12 | 9 | 10 | 7 | 10 |
| $N_S$ | 7 | 5 | 10 | 11 | 8 | 9 | 6 | 10 |
| $MT_B$ | 15 | 18 | 11 | 12 | 16 | 9 | 19 | 9 |
| $MT_S$ | 20 | 19 | 6 | 10 | 10 | 14 | 20 | 10 |

Table 2.5: The Training Data Results of NASDAQ100

| *Indexes* | *AAPL* | *CSCO* | *COST* | *GOOG* | *AMZN* | *STX* | *GILD* | *ESRX* |
|---|---|---|---|---|---|---|---|---|
| $N_B$ | 8 | 11 | 13 | 9 | 8 | 6 | 7 | 6 |
| $N_S$ | 9 | 10 | 14 | 8 | 8 | 6 | 7 | 6 |
| $MT_B$ | 9 | 6 | 9 | 11 | 11 | 30 | 35 | 17 |
| $MT_S$ | 11 | 10 | 10 | 14 | 11 | 35 | 28 | 16 |

Table 2.6: The Training Data Results of SSM

| *Indexes* | *600697* | *600019* | *600881* | *600167* | *600163* | *600051* | *600488* | *600054* |
|---|---|---|---|---|---|---|---|---|
| $N_B$ | 6 | 4 | 8 | 7 | 5 | 6 | 8 | 7 |
| $N_S$ | 6 | 4 | 7 | 8 | 6 | 5 | 7 | 6 |
| $MT_B$ | 24 | 20 | 14 | 14 | 19 | 18 | 11 | 14 |
| $MT_S$ | 28 | 34 | 13 | 25 | 23 | 17 | 9 | 24 |

### 2.5.2 The testing data results

The performance of the real time calculation is listed in Table 2.7,2.8,2.9. We evaluated our method by calculating the profit, the number of buying points ($N_B$), and the number of selling points ($N_S$). The TSM and NASDAQ100 were tested by the last 150 transaction data. In case of SSM, the first 250 transaction data were used for training and the remaining data were used for testing. In most cases, the testing data consisted of one third of the entire data.

The highest and lowest profit as shown in Table VII are 49.14% and 15.48% for index TYO: 9984 and index TYO: 6305, respectively. The minimum and maximum buying points are 5 and 13. The minimum and maximum selling points are 5 and 12, respectively.

Table 2.7: The Testing Data Results of TSE

| Indexes | TYO: 7203 | TYO: 7267 | TYO: 6503 | TYO: 7011 | TYO: 9984 | TYO: 9437 | TYO: 7751 | TYO: 6305 |
|---|---|---|---|---|---|---|---|---|
| Profit (%) | 36.54 | 29.03 | 45.98 | 46.62 | 49.14 | 38.14 | 29.59 | 15.48 |
| $N_B$ | 5 | 5 | 6 | 9 | 13 | 6 | 6 | 7 |
| $N_S$ | 6 | 5 | 7 | 9 | 12 | 7 | 7 | 6 |

Table 2.7 shows the results of the NASDAQ100 stock market. The lowest and highest profit (%) belong to the AAPL and GILD, and the values are 15.12%. and 39.90%, respectively. The number of buying and selling points range between 5 and 8. From the NASDAQ100 stock market, the proposed method yields a considerable outcome.

Table 2.8: The Testing Data Results of NASDAQ100

| Indexes | AAPL | CSCO | COST | GOOG | AMZN | ESRX | GILD | STX |
|---|---|---|---|---|---|---|---|---|
| Profit (%) | 15.12 | 26.12 | 34.89 | 17.98 | 35.95 | 22.12 | 39.90 | 23.04 |
| $N_B$ | 8 | 9 | 8 | 7 | 5 | 6 | 7 | 5 |
| $N_S$ | 8 | 9 | 7 | 8 | 5 | 6 | 8 | 6 |

The Shanghai Stock Market share data results are shown in Table 2.9. The minimum and maximum profit are -4.54% and 59.60%, respectively. These results are also comparatively good. The minimum and maximum buying points range between 4 and 9. The minimum and maximum selling points fall between 3 and10.

Table 2.9: The Testing Data Results of SSM

| Indexes | 600019 | 600697 | 600881 | 600167 | 600163 | 600051 | 600488 | 600054 |
|---|---|---|---|---|---|---|---|---|
| Profit (%) | -4.54 | 5.12 | 20.12 | 5.01 | 23.07 | 59.60 | 14.85 | 16.45 |
| $N_B$ | 5 | 4 | 5 | 7 | 4 | 9 | 5 | 6 |
| $N_S$ | 4 | 3 | 6 | 6 | 5 | 10 | 4 | 6 |

Two stock data were arbitrarily chosen from each market. A total of six data is graphically represented. The data representing closing price with buying and selling prices is shown in Figure 2.6. The proposed method has the generaligation ability.

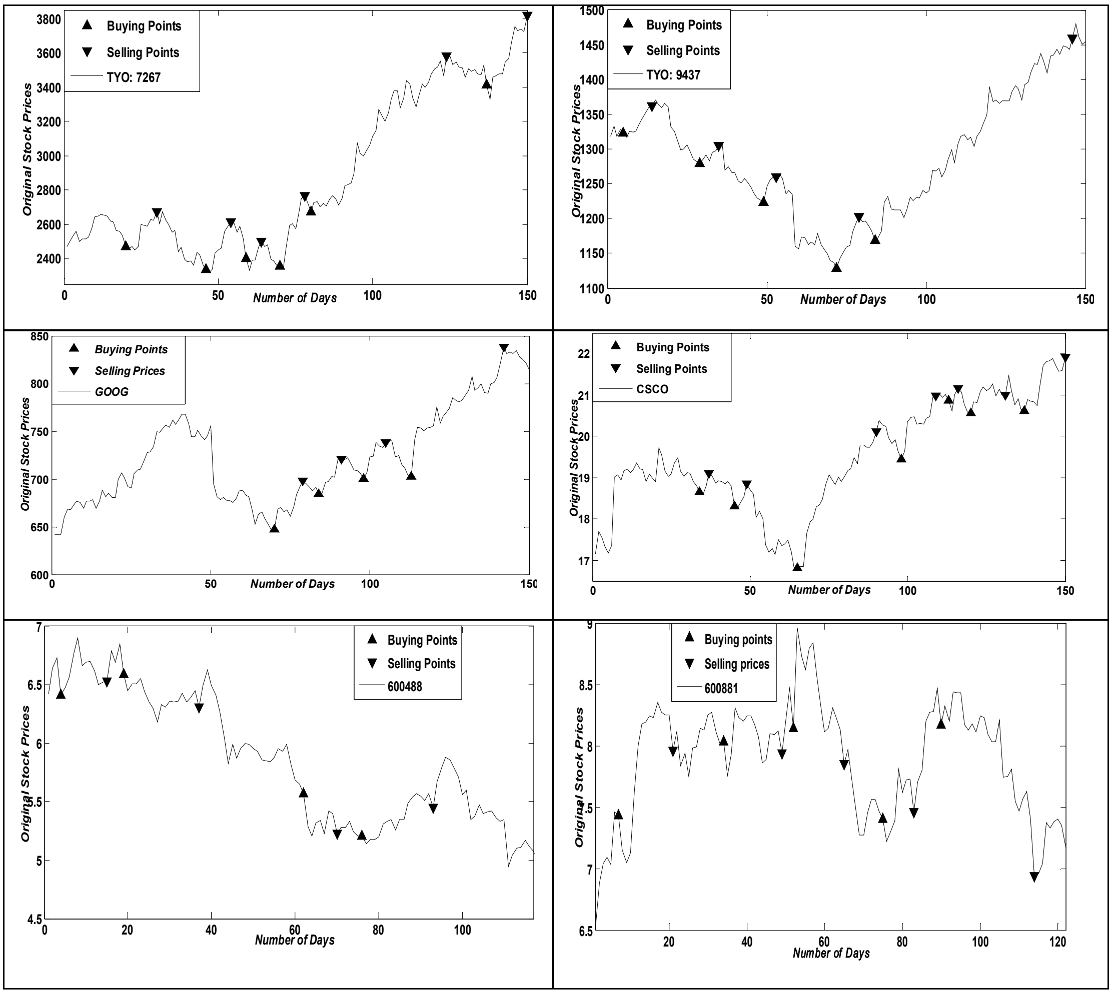


Figure 2.6: Graphical representation forecasting the turning points

## 2.6 Discussion

The results are compiled in Table 2.10. PLR-BNP, PLR-WSVM and Real-DM indicate peacewise linear representation (PLR) with neural network, PLR with weighted support vector machine [1] and Real time Decesion Making (Proposed algorithm), respectively. Of them, the proposed model has yielded the best results. The Real-DM has shown better results than the PLR-BNP in all instances. The Real-DM has also revealed itself as better than the PLR-WSVM in six of eight cases.

The data covered the up-trade, down-trade and steady state. PLR-BNP, PLR-WSVM and Real-DM shows that the minimum profits are -26.46 for share 600019, -15.32 for share 600488, and -4.54 for share 600019, respectively. According to PLR-BNP, PLR-WSVM and Real-DM, the maximum profit earned from the same share 600051 is 22.61%, 50.17%, and 59.60%, respectively.

We have taken some important considerations in the filtering section for the decision tree. For example, a minimum of four transaction gaps were taken. These values may be suitable for a particular group of data set, but it is not good for all stock data set. The same problem arises in the minimum transaction gap between the same transaction. The current methods do not consider the maximum transaction gap. Another important issue is that we did not consider the proper or habitual transaction gap, which is an area we can investigate in in the future. The proposed method cannot forecast more than one buying or selling point. Thus, the calculation may miss many important decisions.

The moving average number is one of the key factors that contribute to the recreation of the accurate decision points. The Shannon entropy number is used for this purpose. Even so, we could not derive any mathematical explanation or relation between the Shannon entropy and the Moving average number. In this research, only four technical indexes were used. In the future, we want to add other types of important technical indexes such as interest rates and exchange rates among others.

Table 2.10: The compiled results of the PLR-BNP, PLR-WSVM and Real-DM. the best results are highlighted using the bold font

| INDEXES | METHODS | PROFITS % | $N_B$ | $N_S$ |
|---|---|---|---|---|
| **600488** | PLR-BNP | -25.06 | 3 | 3 |
| | PLR- WSVM | -15.32 | 1 | 1 |
| | REAL-DM | **14.85** | 5 | 4 |
| **600054** | PLR-BNP | -23.87 | 3 | 3 |
| | PLR- WSVM | -2.40 | 3 | 3 |
| | REAL-DM | **16.45** | 6 | 6 |

| | | | | |
|---|---|---|---|---|
| **600019** | PLR-BNP | -26.46 | 6 | 6 |
| | PLR- WSVM | -13.36 | 3 | 3 |
| | REAL-DM | **-4.54** | 5 | 4 |
| **600881** | PLR-BNP | 1.46 | 7 | 7 |
| | PLR- WSVM | 4.43 | 2 | 2 |
| | REAL-DM | **20.12** | 5 | 6 |
| **600697** | PLR-BNP | 4.01 | 7 | 7 |
| | PLR- WSVM | **33.17** | 5 | 5 |
| | REAL-DM | 5.12 | 4 | 3 |
| **600051** | PLR-BNP | 22.61 | 2 | 2 |
| | PLR- WSVM | 50.17 | 3 | 3 |
| | REAL-DM | **59.60** | 9 | 10 |
| **600163** | PLR-BNP | 11.13 | 6 | 6 |
| | PLR- WSVM | 9.65 | 2 | 2 |
| | REAL-DM | **23.07** | 4 | 5 |
| **600167** | PLR-BNP | -2.03 | 4 | 4 |
| | PLR- WSVM | **18.64** | 4 | 4 |
| | REAL-DM | 5.01 | 7 | 6 |

There is no doubt that the least square is a powerful tool for forecasting the time series. The proposed method takes a while to yield profits. Thus, this research is more suitable for a simple shareholder and not a professional shareholder. the letter conduct their business using the share market. Our methodology can make decisions without referring to the previous history. A decision cam be made after arriving at the equation parameter.

## 2.7 Conclusion

A number of researchers have investigated the prediction of the stock market trading as they wanted to arm the consumer or shareholder with an advantage. Our methodology involves real time calculation for the decision-making algorithm. The shareholders are mostly concerned with the optimal time for selling or buying. We engaged in a significant amount of research to investigate these demands. Our method produces better results. The autoregression can accurately predict the decision point. Sometimes this method has earned profits from the share market; the opposite has also been observed to happen. The important issue is that the autoregression parameter updates after any decision. The novelty of our work is that firstly, we proposed a very simple method using the Moving average to measure the decision points for selling and buying. This method is also effective in predicting the right decision. Secondly, the Shannon entropy is used to find the data smoothing number,Most of the previous methods took a fixed or arbitrary moving average number. Thirdly, the minimum transaction gap was identified by investigating previous histories of all the stock market. Fourthly, the proposed method can update its parameter in real time. In this way, the network receives new information that adds to and enhances its prediction.

In the future, the proposed system can be explored by adding other factors or other soft computing techniques. Areas for further investigations are listed as follows:

The proposed algorithm cannot consider two consecutive selling points or two consecutive buying points. We will devote future research to finding the indicators that will consider two or more selling and buying points.

We want to use a band pass filter for the minimum and maximum transaction gap for each stock market.

The data smoothing number will be automatic or will imbibe a theoretical background. We will consider more theoretical background to find the appropriate smoothing number.Only three stock markets were considered for this research. In future researches, we will incorporate more well-known stock markets. Anyone can apply our method to any market and make a profit.In this research, the least squares autoregression were considered. In the future, more methods will be applied for more accurate forecasting.Many forecasting models are available. We want to apply a hybrid intelligent system such as the Neuro-Fuzzy, NN & Data mining, Fuzzy & Data Mining etc.

# Chapter 3

# STOCK PRICE PREDICTION USING ENSEMBLE NN

Stock Prices are considered to be very dynamic and susceptible to quick changes because of the underlying nature of the financial domain, and in part because of the interchange between known parameters and unknown factors. Of late, several researchers have used Piecewise Linear Representation (PLR) to predict the stock market pricing. However, some improvements are needed to avoid the appropriate threshold of the trading decision, choosing the input index as well as improving the overall performance. In this paper, several techniques of data mining are discussed and applied for predicting price movement. For example, a new technique named Local Saturation Method (LSM) has been used to find the PLR; the weighted moving average has been applied to find recent price moves; the Shannon entropy has been used for measuring the data set complexity or nature; an intelligent system is used to select the new and important technical indexes; and finally, Ensemble Neural Networks (ENN) have been used in order to improve the overall performance. Our method has been tested by thirty problems, including up trade, down trade and steady state features. By applying all those techniques, the proposed algorithm shows good predictions with a hit rate of about 60 percent.

## 3.1 Introduction

Stock price movement is an essential issue for traders and shareholders. By being able to generate a proper prediction those concerned can engage in effective decision-making, planning, organizing, controlling the opening price, scheduling, policy making and so on. A number of factors influence the stock price such as exchange rate, interest rate, political issue, natural disaster, government policy, and the international stock market and so on. Therefore, the stock market's atmosphere is very difficult, dynamic and nonlinear, and depends on the customer's mentality. Predicting stock data with traditional time series analysis has proven to be difficult [35, 36].

The need for tools to monitor as well as control risk levels has become obvious for both industrial companies and financial institutions. The question of predictability in the stock markets is, therefore, important even outside the trading rooms. A lot of research had been done to predict the stock market movement. Stock market prediction is always an interesting field for traders and shareholders, and it is difficult to know when one should be selling the shares, buying the shares and holding shares. Very little survey or research had been done about share decision rules.

Link Luo, Xi Chen in [12] has integrated PLR and weighted support vector machine to forecast the stock trading signals recently. Support vector machine (SVM) performance depends on many key parameters; it is a difficult task to decide correctly. In order to get satisfactory results, one needs to engage in several experiments by altering the setting. However, they used a fixed number of threshold values, which is not good for any time series. A fixed threshold value may be fit for specific time series, but it is not suited for any time series. Also, their experimental results revealed poor accuracy. Ours is a method that can be applied for any time series analysis.

Chang et al. [13] proposed intelligent PLR with Back Propagation Neural Network (BPN) to predict stock trading decision of whether to sell, buy or hold. They used the fixed threshold value to find the turning point for PLR. Genetic algorithm (GA) was then applied to tune the threshold value. Stepwise regression analysis was used to identify the influencing factors for any trade. While their method is appropriate for finding the trading market, our proposal suggests some improvements to theirs. Furthermore, the use of GA is time-consuming. Firstly, we do not use the GA to tune the threshold value and we propose an ensemble neural network in order to improve performance. There is a possibility that the use of GA may divide the transactions of buy and sell in some parts because GA does not follow the entire sequence. To avoid this problem, Chang et al. used dynamic threshold values [14]. The basic difference in between Chang [13] and [14] is the threshold optimizing techniques.

The daily Istanbul Stock Exchange National 100 data set was predicted using the direction of movement [18]. Two classification tools, artificial neural network (ANN) and SVM was used, and ten technical indicators of both the networks were selected. Their contributions to research in stock market prediction exhibits and verifies the predictability of the stock price index direction. The simple 10 days MA and the weighted 10 days MA are used as technical indexes. They also showed better performance of ANN over SVM. The average performance of the neural network (NN) model was reported to be 75.74, and the average performance of SVM model was reported to be 71.52. Phichhang Ou et al. [19] used nonparametric volatility based SVM forecasting. They measured their model performance through NIKKEI 225 index. Chin-Fong T. et al. [37] used majority voting and bagging for stock price prediction. They concluded that ensemble classifiers had shown better performance than single classifiers. They claimed that there was no difference between the homogeneous and heterogeneous classifier ensembles in terms of majority voting and bagging. Abdulsalam S. O. et al. [38] used a data mining (DM) tool called a moving average (MA) method to uncover patterns and relationships, and to predict the future values of the time series data. The moving average method is a device that reduces fluctuations and obtains trend values with a fair degree of accuracy. They employed their method to describe the trends of stock market prices and predict the future stock market prices of three banks sampled.

With the development of neural networks, researchers and investors are hoping that the market mysteries can be unraveled. Although it is not an easy job due to its nonlinearity and uncertainty, many trials using various methods have been proposed. We used a new piecewise linear representation (PLR) technique called local saturation method (LSM) to find the accurate time to sell, buy and hold. The weighted moving average (WMA) carries more importance in current price movement. So, the WMA reacts more quickly to price changes than the native moving average. Data set complexity is measured by entropy value. The decision tree algorithm is used to select important influencing factors considering the customer profit. We integrate PLR and Ensemble Neural Network (ENN) to predict the stock market (PLR-ENN). Our model provides the solution for almost all kinds of forecasting problems.

The rest of this paper is organized such that Section 3.2 presents a review of the literature, including some related survey papers. The entire methodology is given in Section 3.3 This section's subsection is outlined in the following pattern: Data preprocessing, PLR, Input selection, and Ensemble neural networks. Section 3.4 presents the numerical results, graphical paradigm, and a comprehensive description of the findings. In this section, the thirty stock data are presented, which covers the three biggest stock markets, namely, NASDAQ Stock Market, Tokyo Stock Market, and Shanghai Stock Market. The details are provided in Section 3.5 Finally, conclusions and future directions of the research are provided.

## 3.2 Literature Review

Stock price forecasting has been in operation since the 1980s. The objective of long-term analysis is to gain profit from the financial market. Until now, stock pricing or financial time series forecasting is still considered one of the most complicated applications of modern time series forecasting. Even, earthquake forecasting was proposed using their previous time series data [39].

J.G. De Gooijer, R.J. Hyndman [1] reviewed research into time series forecasting from 1982 to 2005. It was published in the silver jubilee volume of the international journal of the forecasting, on the 25th founding date of the International Institute of Forecasters (IIF). This review covered over 940 papers. The paper examined exponential smoothing, ARIMA, seasonality, state space and structural models, nonlinear models, long memory models, ARCH-GARCH method. They compiled the reported advantages and disadvantages of each methodology and pointed out the potential future research fields.

G. Preethi, B. Santhi [21] surveyed the recent literature in the area of NN, Data Mining, Hidden Markov Model and Neuro-Fuzzy system used to predict the stock market fluctuation. They summarized 20 research activities, published between 2009 and 2011, and listed in Table 1. They claimed that the leading machine learning techniques in stock market index prediction area is NN and Neuro-Fuzzy systems. They expected that the NN and Markov model will be used exclusively in the time series and forecasting of stock price.

Yuehui C. et al. [40] investigated the seemingly chaotic behavior of stock markets using the flexible neural tree ensemble technique. They examined the 7-year Nasdaq-100 main index values and 4-year NIFTY index values. Evolutionary algorithm and particle swarm optimization algorithm were used to optimize the structure and parameter of a flexible neural tree. They claimed that the most prominent parameters that affect share prices were their immediate opening and closing values. Many researchers predicted time series by using NN, SVM, Fuzzy, and ENN [41]. Chang et al. [42] also applied their methods in the ensemble neural network. They used AdaBoost algorithm ensembles and two different kinds of neural net, traditional BPN neural networks and evolving neural networks. Between [42] and [13], the basic difference is the use of ensemble NN instead of NN. Iffat A. Gheyas et al. [43] proposed a homogeneous NN ensemble to forecast the time series. They optimized their method through the generalized regression NN ensemble. Their method was suitable both for short-term and long-term time series.

Table 3.1: G. Preethi, et all surveyed twenty papers which overlooks Neural Network, Data Mining, Markov Model and Neuro-Fuzzy system. NN, NF, DM, MA, ACO, MM, GA, T-2 indicate, respectively, Neural network, Neuro-Fuzzy, Data mining, Ant colony optimization, Markov Model, Genetic algorithm, Type-2.

| **Authors** | **Title** | **Publisher (year)** | **Area** |
|---|---|---|---|
| Dase R.K. and Pawar D.D. | Application of Artificial Neural Network for stock market predictions: A review of literature | IJMI (2011) | NN |
| Halbert White | Economic prediction using neural networks: the case of IBM daily stock returns | Neural Networks (1988) | NN |
| JingTao YAO and Chew Lim TAN | Guidelines for Financial Prediction with Artificial neural networks | ICONIP (2011) | NN |
| T. Hui-Kuang, K.H. Huarng | A Neural network-based fuzzy time series model to improve forecasting | Elsevier (2010) | NF |
| Akinwale Adio T, et al. | Translated Nigeria stock market price using artificial neural network for effective prediction | JATIT (2009) | NN |
| David Enke and Suraphan Thawornwong | The use of data mining and neural networks for forecasting stock market returns | Expert Systems with App., (2005) | DM, NN |
| K.S. Kannan, P.S. Sekar, et al. | Financial stock market forecast using data mining Techniques | IMECS (2010) | DM |
| Abdulsalam S. O. et al. | Stock Trend Prediction using Regression Analysis – A Data Mining Approach | AJSS journal (2011) | DM, MA |
| M. Suresh babu, et al. | Forecasting of Indian Stock Market Index Using Data Mining & Artificial Neural Network | IJAEA (2011) | DM, ACO |
| Y.L.Hsieh, Don-Lin Yang and Jungpin Wu | Using Data Mining to study Upstream and Downstream causal relationship in stock Market | *JCIS, Atlantis Press,* (*2006*) | *DM* |
| Md. Rafiul Hassan and Baikunth Nath | Stock Market forecasting using Hidden Markov Model: A New Approach | ISDA (2005) | MM |
| Ching-Hsue cheng, Tai ai-Liang Chen, L.Ying Wei | A hybrid model based on rough set theory and genetic algorithms for stock price forecasting | Information Science, (2010) | DM, GA |

| Authors | Title | Publisher (year) | Area |
|---|---|---|---|
| Kuang Yu Huang, Chuen-Jiuan Jane | A hybrid model stock market forecasting and portfolio selection based on ARX, grey system and RS theories | Expert Systems with App, (2009) | DM KM |
| Md. Rafiul H., B. Nath and Michael Kirley | A fusion model of HMM, ANN and GA for stock market forecasting | Expert Systems with App, (2007) | MM, NN, GA |
| Yi-Fan Wang, Shihmin Cheng and Mei-Hua Hsu | Incorporating the Markov chain concepts into fuzzy stochastic prediction of stock indexes | Applied Soft Computing, (2010) | MM, Fuzzy |
| H.L. Wong, Yi-Hsien Tu, Chi-Chen Wang, | Application of fuzzy time series models for forecasting the amount of Taiwan export | Expert Systems with App., (2010) | DM Fuzzy |
| S.Agrawal, M. Jindal,d G.N. Pillai | Preduction using Adaptive Neuro-Fuzzy Inference System (ANFIS) | IMECS,( 2010) | NM |
| George S. Atsalakis and Kimon P.Valavanis | Forecasting stock market short-term trends using a neuro-fuzzy based methodology | Expert Systems with App., (2009) | NM |
| G. S. Atsalakis, E.M. Dimitrakakis, C. D. Zopo. | Elliot Wave Theory and neurofuzzy systems, in stock market predictions: The WASP system | Expert Systems with App., (2011) | NM |
| M.H. Fazel Zarandi, et al. | A type-2 fuzzy rule-based experts system model for stock price analysis | Expert Systems with App., (2009) | T-2,Fuz. |

## 3.3 Methodology

The main purpose of this research is to develop a framework that will enable one to benefit from share market. In order to meet this requirement, a simple and effective method is proposed. Also, the method is user-friendly and easy to implement. Our method has some steps, which includes data preprocessing, PLR, input selection, and ensemble neural network. Stock price prediction has always been a subject of interest for most investors and financial analysts, but clearly, finding the best time to buy or sell has remained a very difficult task for investors because there are numerous other factors that may influence the stock price [6, 7].

The entire flowchart is shown in Figure 3.1 Stock price depends on many factors. For this reason, the stock price always fluctuates positively or negatively. The prices also vary during the length of a day. Firstly, the raw data is taken from any stock market, and applied to the pre-processing steps. Once this is done, the turning point is found.

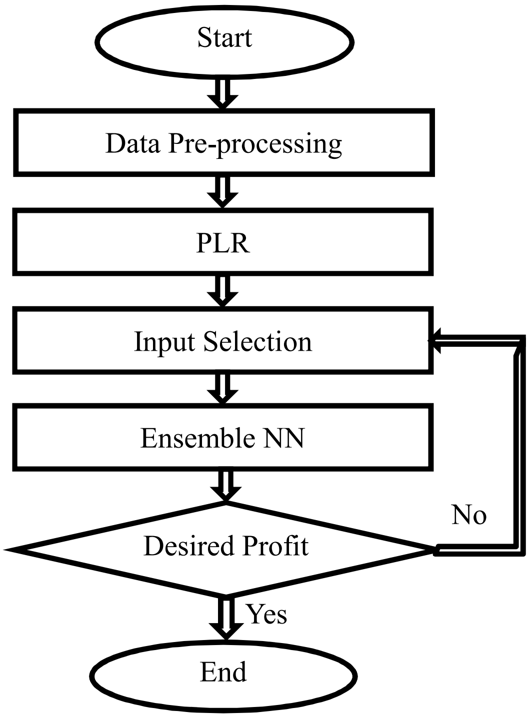


Figure 3.1: Flowchart of entire proposal

We select some important technical indexes or some combination of technical indexes using a decision tree algorithm. The ensemble neural network is used to predict the stock market. If the output of ensemble neural network does not earn the targeted profit, the decision tree algorithm selects other indexes. The decision tree algorithm is used as an intelligent formula. Finally, the processes are stopped.

### 3.3.1 Data Preprocessing

Data preprocessing has been divided into four sub-steps, including data collection, data rescaling, complexity measure, and data division, which is clearly shown in Figure 3.2. Each sub-step is discussed in brief in the following section.

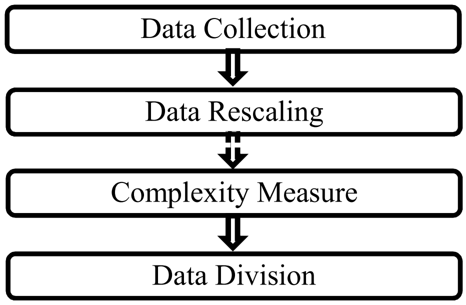

Figure 3.2: Data preprocessing steps

### *Data Collection*

The data was collected mainly from three big share markets, namely the Shanghai stock market (SSM), the Tokyo stock market (TSM), and the NASDAQ100 stock market. Seven data sets were collected from the Shanghai stock market. The Shanghai stock data covered a time period from 04/01/2010 to 18/08/2011, and contains approximately 391 days of transaction data. This data includes up trade, down trade and steady state. From the ten shares, four are divided into the downturn (Code: 600488, 600054, 600019, 600058), three into steady trend (Code: 600881, 600228, 600697), and the remaining three are classified as uptrend (Code: 600051, 600163, 600167) [12]. Ten data sets were collected from the Tokyo stock market. The Tokyo stock data covered a time period from 10/05/2011 to 15/03/2013, and approximately 450 days of transaction data. These data hark from five sectors, namely automotive, communication, electrical machinery, chemicals, and machinery. The selecting stock indexes are TYO: 7203, TYO: 7267, TYO: 9984, TYO: 9437, TYO: 7751, TYO: 6502, TYO: 3407, TYO: 4188, TYO: 6305; TYO: 7011, TYO: 6302. We gathered ten stock data sets arbitrary from NASDAQ100. The data covered a time period from 01/06/2011 to 15/03/2013, covering about 450 days of transaction data. The stock index selecting from the NASDAQ stock market are AAPL, AMZN, CSCO, COST, ESRX, FB, GILD, GOOG, NXPI, MSFT, and STX.

### *Data Rescaling*

Stock data have nonlinear characteristic. But, it has some minimum value in a certain period. We should consider either the time variant data or the frequency data. The time variant data retains the whole characteristics of data. For this reason, only the upper portion or time variant data is taken for further analysis. What should be noted is that, if we consider all the data, the nonlinear behavior effect will be very small in any network. We use the following equation to normalize all the data in the interval (0,1). $X_{old}, X_{min},$ & $X_{max}$ are the original, maximum and minimum values of the raw data respectively, and $X_{new}$ represents the normalized form of $X_{old}$.

$$X_{new} = \frac{X_{old} - X_{min}}{X_{max} - X_{min}}$$

## 3.3.2 A complexity measure for stock time series

The main purpose behind researching the complexity of the stock market is to contract the finding into a relation that expresses the proper turning point. Also, the complexity or simplicity of the time series is gauged by knowing this information. A number of studies have been conducted to find the complexity for any time series and predict their behavior such as regular, chaotic, uncertainty, size, etc. The main types of complexity parameters are entropies, fractal dimensions, Lyapunov exponents [27]. Ahmad kazem et al. [44] used the false nearest neighbor method to find the minimum sufficient embedding dimension, and the time series phase was reconstructed to reveal its hitherto unseen dynamics. We chose the Shannon entropy from these methods to find stock price complexity. Teixeira A. et al. [29] showed that Shannon entropy effectively measured the expected value. The Shannon entropy is a basic measure in information theory by calculating uncertainty. The Shannon entropy is calculated by the following formula

$$H = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i)$$

Where Shannon entropy is denoted by $H$, $x_i$ is a discrete value from the time series of X. The finite number of data is $n$, and $p(x_i)$ shows the probability density function of the outcome of $x_i$. We can say that the complexity of a system is due to the amount of information. Bigger entropy shows higher complexity for any time series while smaller entropy shows lower complexity to any time series. It also depends on the size. For this reason, the average entropy for hundred data is calculated from all data set. According to the entropy value, the data set is classified as high and low complexity, and this information is used in the next section. There is a strong relation between entropy and information for any data set. The Shannon entropy is good for any time series analysis. The average Shannon's entropy of 100 data is shown in table 3.2, where five data sets are chosen arbitrary.

Table 3.2: Average entropy of each 100 data in the data set

| Data set | Shannon's Entropy |
|---|---|
| **Toyota** | 6.0824 |
| **Mazda** | 5.0714 |
| **Softbank** | 6.3117 |
| **Apple** | 6.6239 |
| **Yahoo** | 6.2182 |

### 3.3.3 PLR

In our proposed PLR measurement, the calculation has been slightly modified from previous researches. It is very close to the local minimum and local maximum finding method or local saturation method (LSM). PLR reduces the high frequency and provides a certain decision for a certain period. Akisato Kimura et al. [45] used PLR to reduce the feature dimension from long audio signal. PLR is used to find the turning point whether it is the buy, sell or hold point. Our method also represents buy and sell, respectively, the local minimum and the local maximum. Many researchers have tended to use many methods, namely Top-Down, Down-Top and Sliding Window are popular [12].

Let us consider a time series,$y = \{y_0, y_1, y_2, \dots \dots, y_n\}$, From this time series, we will find the approximate piecewise straight lines through the following

$$y_{plr} = \{L_1(y_0, y_1, \dots, y_{nL1}), L_2(y_{0L2}, y_{1L2}, \dots, y_{nL2}), \dots, L_m(y_{0Lm}, y_{1Lm}, \dots, y_{nLm})\}$$

Where $L_1, L_2, \dots, L_m$ represents the line and $m$ represents the number of lines, and

$$L_1 = t_1 * x_1 + c_1, \qquad L_2 = t_2 * x_2 + c_1, \ L_m = t_m * x_m + c_1$$

Here, the slope or gradient $t$ and the line $c$ intercept (where the line crosses the Y axis)

Finding Turning Point by Local Saturation Methods (LSD)

Local Saturation Method is used to find the proper buying, selling and holding time. LSM is explained using the following steps. A complete flow chart for LSD is shown in figure 3.3.

**Step1:** We have taken the closing stock price in order to find the PLR. The Weighted Moving Average method is used to smooth the data. The WMA places more importance on recent stock price moves and less weight on past data. The WMA is calculated by multiplying each of the previous day's data by a weight. This is why the WMA responds rapidly to the stock price movement [46]. The WMA works well to find the proper turning point. It helps to find big price variation points. The data sets are smoothed by reducing noise.

**Step2:** We perceive the tangent over the time series. These tangent points act as temporary turning points. The number of tangent points depends on how much data was taken during the data smoothing process. If we implement more data smoothing, it will lessen the number of tangent points or turning points, and vice-versa. We are taking less than ten data smoothing (such as 3 data points, 5 data points, and 7 data points smoothing).

**Step 3:** In this step, we identify the immature turning point. If two consecutive data points show two turning points, we consider these points as immature turning points.

Then, the total immature turning points over the series are reduced. Now, we get mature turning points and straight lines are drawn from these mature turning points.

The first point and the last point are considered the default turning points. The tangent points and turning point are calculated from smoothing data, but PLR is drawn from the raw data. We calculate the slope of each straight line because of the classification class (either buy or sell or hold). Ethical examples are shown in the fig. 4 where 5 data points' smoothing are taken.

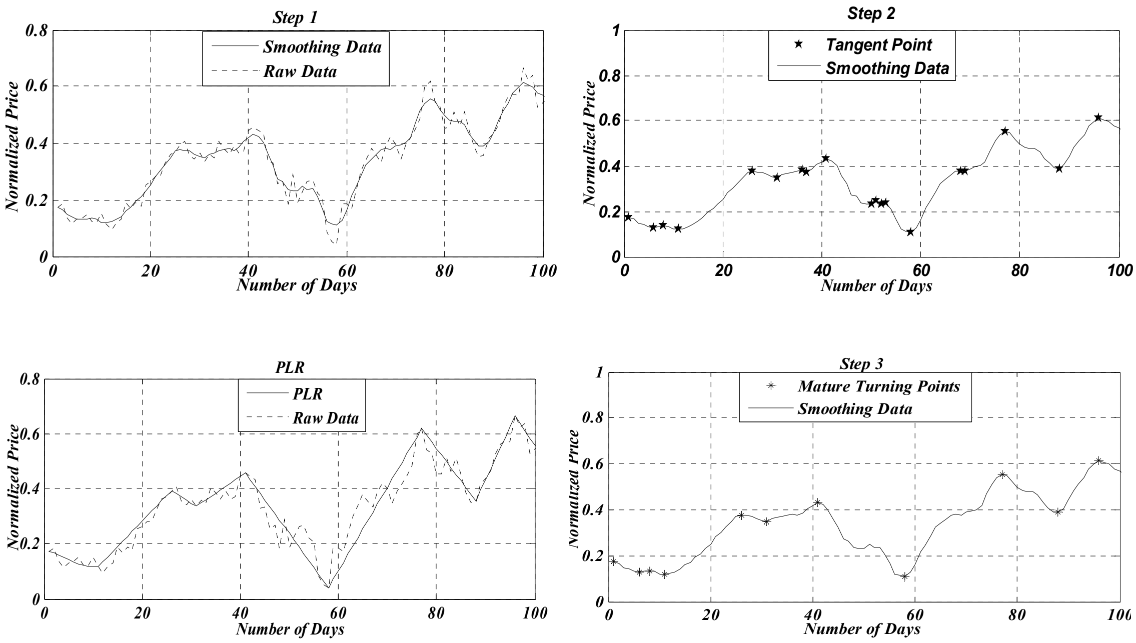


Figure 3.3: Graphical representation of LSM steps

The method faces a problem when it comes to finding the appropriate moving average number. The information or the complexities of time series are used to find the accurate turning point or proper trade. We know that the complexity depends on the information of any time series. So, we wanted to establish a relationship between the MA value and the complexity value. According to the data information, we can deduce two statements:

***If the data set has high entropy, we will take a high MA number***

***If the data set has low entropy, we will take a low MA number***

The main purpose behind measuring the entropy value is to predict the MA number. Firstly, PLR has been employed to take the MA value through a few fixed numbers. Now, there is some evidence that the MA value has been taken.

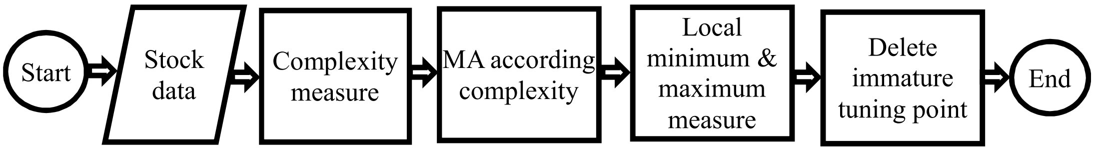


Figure 3.4: Complete flow chart for LSM

Our technique is one of the easiest ways to find an accurate PLR. The method we propose has a few advantages over previous ones. Firstly, there is no need to take threshold values. Threshold values maintain the full trade such as sell, buy or hold condition. This value is very sensitive to any kind of time series. We can avoid threshold selection in our method. Secondly, the optimization of the threshold values is time-consuming when effective learning is considered. If we avoid this, our learning procedure will be very easy and the learning time will be reduced. Thirdly, the Shannon entropy is used to find the complexity of the time series method, considering that the complexity of the moving average number can be automatic. Fourthly, the WMA is used to implement PLR, which helps to identify proper turning points. Fifthly, it is very easy to understand, implement and compare with the other methods. A complete flow chart for PLR is shown in Figure 3.4.

### 3.3.4 Input Selection

#### *Technical indexes*

Selecting input is another key factor of time series forecasting. A number of factors influence the stock market. Also, the stock markets have some data regarding their daily stock price. It is a challenging job to find the accurate technical index combination for forecasting. The stock market is affected by a number of factors. Many researchers have investigated the many technical indicators that help to predict the trading signal [31, 32]. There are some common factors, such as moving average, transaction volume, bias, related strength. Still, it is unknown which combination is fit for the stock market predictions.

We propose four new technical indexes which are closely related to the closing transaction price, and are an effective means to predict the stock price. Firstly, the slope of the time series can be proposed as a technical index. This technical index is very effective and essential. A positive slope reflects a positive value, and a negative slope reflects a negative value. Positive and negative values are very close to buying and selling transaction. The second proposal is a ten-day MA value of the volume of transaction. The third proposal is a ten-day MA of the amplitude of the price movement. The second and third proposed indexes are very close to the closing price transaction. Figur 3.5 charts their transaction. The last proposal is the difference between the normal moving average value and the weighted moving average value. The difference in value reveals a very significant effect to finding the turning point. If the difference is high, this effect should be a turning point, and if the difference is small, this effects no action. Also, if the difference is positive, the turning point should buy point and the difference is negative, the turning point should sell point.

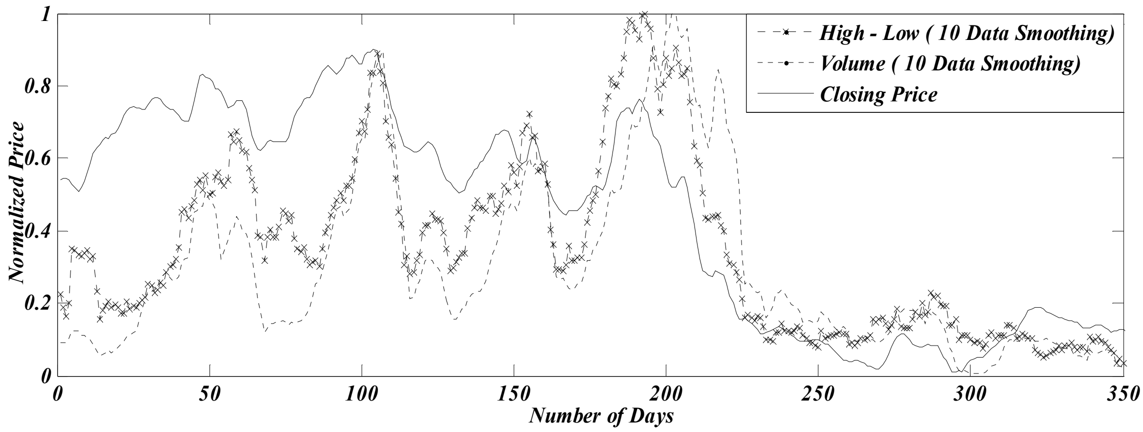


Figure 3.5: Comparison graph for three technical indexes for arbitrary selected stock

## *Decision Tree*

Decision Trees are common algorithms, which are used in various disciplines such as statistics, machine learning, pattern recognition, and data mining [47]. Decision trees are classifiers on a target attribute in the form of a tree structure. The observations to classify are composed of attributes and their target value. The nodes of the tree can be decision nodes and leaf nodes. Decision nodes test a single attribute-value to determine which branch of the sub-tree applies. Leaf nodes indicate the value of the target attribute [48]. There are many algorithms for decision tree induction: Hunt Algorithm, CART, ID3, C4.5, SLIQ, and SPRINT to maintain the most common. The recursive Hunt algorithm, which is one of the easiest to understand, relies on the test condition applied to a given attribute that discriminates the observations by their target values.

In most cases, decision tree implementations use pruning. This is a method where a node is not further split if its impurity measure or the number of observations in the node is below a certain threshold. The decision tree is a common situation, according to the knowledge–based recommenders. The existing knowledge domain can be incorporated in the models. The main advantages of building a classifier using a decision tree are that it is inexpensive to construct, and it is extremely fast at classifying unknown instances. Another appreciated aspect of the decision tree is that they can be used to produce a set of rules that are easy to interpret while maintaining accuracy when compared to other basic classification techniques. The decision trees are used as an intelligent technical indexes selector. The specific trees are selected for the specific data sets. The decision tree depends on the value of the profit values. Chang, et al. [13, 49] has shown a number of technical indices affecting the stock price movement. We use some input indexes, and in Table 3.3 presents some input indexes.

Table 3.3: Technical indices used in the input variables. $P_o(t)$, $P_c(t)$, $P_h(t)$, $P_l(t)$, $V(t), m, DS_N, DS_W$ respectively indicate the opening price, the closing price, the highest price, the lowest price, volume of transaction on the tth day, the slope for the closing price, normal data smoothing, and weighted data smoothing.

| **Technical index** | **Explanation** |
|---|---|
| The opening Price | $P_o(t)$ |
| The closing price | $P_c(t)$ |

| | |
|---|---|
| The volume of transaction | $V(t)$ |
| The Price change in a day | $P_h(t) - P_l(t)$ |
| The MA of transaction volume | $\overline{V}(t)$ (10MA of $V(t)$ ) |
| The MA of price changes | $\overline{P_h(t) - P_l(t)}$ (10 MA of $P_h(t) - P_l(t)$) |
| Slop of the closing price | m |
| Normal Data Smoothing | NSM |
| Weighted Data Smoothing | WSM |
| Difference of smoothing | NSM-WSM |

### 3.3.5 Ensemble Neural Network

In this section, bagging is used to produce data and NN ensemble is used to find the performance.

#### *Bagging*

Bagging, a shortened version of Bootstrap Aggregating, is a method that will improve the unstable prediction or classification task. Leo Breiman [50] introduced the concept of bagging to construct ensembles. The bootstrap is based on the statistical procedure of sampling with replacement. New data is created to train each classifier by bootstrapping from the original data. In the new data, many of the unique patterns may be repeated and many may be left out. Normally, the data size remains the same. Hence, diversity is obtained with the re-sampling procedure by the usage of different data subsets. Finally, when an unknown instance is presented to each individual classifier, a majority or weighted vote is used to infer the class, and when it is presented to predict, averaging is used to predict values. Table 3.4 shows the Bagging Algorithm steps.

Table 3.4: Bagging Algorithm

| |
|---|
| Given training set $S$, bagging works in the following |
| *Step 1.* Create n bootstrap samples $\{S_0, S_1, S_2, \dots\dots, S_n\}$ of $S$ as follows |
| For each $S_i$: Randomly drawing $\lvert S\rvert$ examples from $S$ with replacement |
| *Step 2.* For each $i = 0,1,2,\dots,n$ $h_i = learn\ (S_i)$ |
| *Step 3.* Output $H =< \{h_0, h_1, \dots, h_n\}$ majority vote or averaging |

There is a chance that a particular instance will be picked each time the probability is $1/\mathrm{n}$, and will not be picked each time probability is $1 - 1/\mathrm{n}$. Multiply these probabilities together for a sufficient number of picking opportunities, n, and the result is a formula of

$$(1 - 1/\mathrm{n})^{\mathrm{n}} \approx \mathrm{e}^{-1} = 0.368$$

On average, about 36.8% of the instances are not present in the bootstrap sample. So, each bootstrap sample contains only approximately $((1 - 0.368) = 0.632)$ 63.2% of the instances. If the learning algorithm is unstable, then bagging almost always improves the performance. Breiman [51] showed that bagging is effective in “unstable” learning algorithms where small changes in the training set result in large changes in predictions. Neural networks and decision trees are examples of unstable learning algorithms. Ten data sets are generated from every unit in stock market data by Bootstrap aggregation. Bagging reduces the variance, and hence improves the accuracy.

### *Neural Network*

The ensemble neural network is also known as Committee Methods, Model Combiner. The ensemble is a learning model where many neural networks are used together to solve a problem to facilitate better prediction or better classification over a single neural network. There are two major concerns in this instance: firstly, the individual data sets build techniques from the unitary patterns; secondly, the question of how output is going to be combined from every data set. Many methods are available to build individual data sets. Bagging and boosting are the most popular methods. Bagging generates a diverse ensemble of classifiers by introducing randomness into the learning algorithm's input [8].

By applying bagging, we created ten individual sets from every stock data. The complete ensemble process that was used in our stock market forecasting purpose is shown in Figure 3.6. PLR is created by using a number of straight lines, where each line is represented by an individual slope. Getting class, we consider a very small threshold value (nearly zero). Three classes are distinguished by the following ways

| | | |
|---|---|---|
| If slope value is greater than threshold class 1 | [ $m > T$ | Class 1] |
| If slope value is in between as threshold class 2 | [$-T \leq m \geq T$ | Class 2] |
| Otherwise class 3 | [ $m > -T$ | Class 3] |

[Here, $m$ and $T$ consider as the slope value and the threshold value respectively]

Therefore, majority voting is considered as output class. Also, our network is trained by supervised NN.

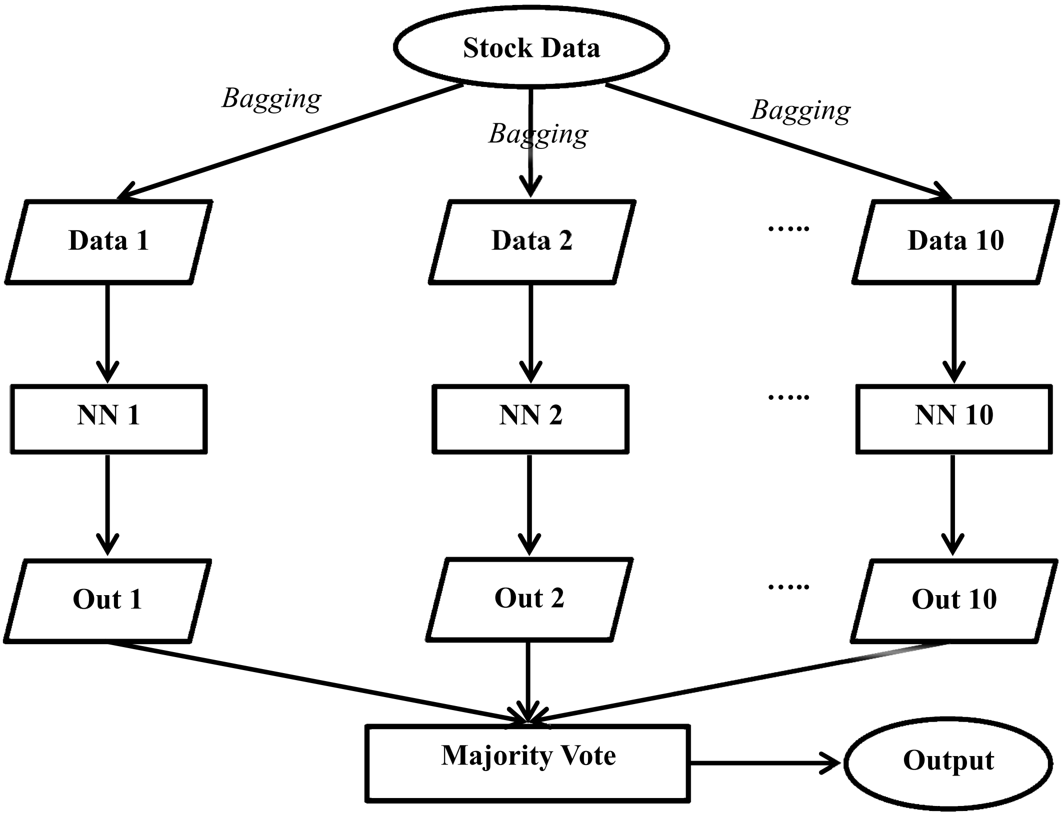


Figure 3.6: Ensemble Neural Network

## 3.4 Results

The most important issue for stock market prediction is the profit or benefit for the customer or trader. To find the profit, the following formula is used

$$\text{Profit, P} = \left[\sum_{i=1}^{n} \frac{\{(1-a-c).S_i-(1+b).B_i\}}{(1+b).B_i}\right]$$

Where $a, b$ stands for the transition cost of selling and buying of the $i$th transaction, $c$ refers to the tax rate of the $i$th transaction. $S_i, B_i$ represents the selling and buying price of the $i$th transaction, and $n$ signifies the number of the transition. Profit is calculated for a single share. In my methodology, a transaction is complete when the shareholder engages in the process of minimum buying and selling. Many methods do not make a profit if they do not consider the tax rate and the transition costs associated with selling and buying.

Two main factors are considered when evaluating our methods, which includes accuracy and profit. Both are considered in conjunction with customers or shareholders. To evaluate our method, seven shares are taken from the Shanghai Stock Exchange. Firstly, three shares are subjected to downtrend, two shares to the steady trend and the last two to uptrend. Table 3.5, 3.6, 3.7 shows the performance results of PLR-ENN. $N_B \& N_S$ represents a number of buyers and sellers, respectively.

During testing, some important considerations are made which are discussed below:

Two consecutive buying: It is possible, because investors can buy two times or more. But at times of sale, investors can sell all their shares at the same time.

Two consecutive selling: It is impossible, because investors cannot sell more without stock. The first sale is considered as a sell point, and the next one is considered as an unnecessary turning point.

First turning point: The first turning point should represent the buy point. If the first turning point is the sell point, it will be considered an immature turning point. Also, we are unable to sell shares without buying shares.

Last turning point: Last turning point should be the sell point. If instead the last turning point is the buy point, then the last point of the trade will be considered as a sell point.

Two turning points: If the two consecutive turning points represent two transactions days, it will be considered as an immature turning point. These two turning points should be reduced by our method. After one sell/buy decision, a minimum of two days are considered where there is no action.

The most important issue when it comes to predicting the share market is to profit from the stock market. Our method inclines towards the investor/shareholder. By considering the above condition, our method works very well. Whenever any investment is made in terms of money/any decision/any sectors, some time will be consumed in taking further decisions. Our method has found the more accurate turning points and made a significant amount of profit.

The parameter setting of the ENN, including the number of networks, transfer function, learning rate, etc. is listed in Table 3.5. These parameters influence the network performances.

Table 3.5: Parameters setting for Ensemble Neural network

| **Number of network** | **Transfer function** | **Learning Rate** | **Iteration** | **Momentum** | **Hidden Layer** | **Bias** | **Hidden neuron** |
|---|---|---|---|---|---|---|---|
| 10 | Sigmoid | 0.1 | 1000 | 1.0 | 01 | 1 | 3-5 |

The performances of the PLR-ENN are listed in Table 3.6,3.7,3.8 in Shanghai stock market, the Tokyo stock market, and Nasdaq stock market respectively. We evaluate our method by calculating the profit, accuracy, the number of buy points ($N_B$), and number of sell point ($N_S$).

From table 3.6, the Shanghai stock data covered a time period from 04/01/2010 to 18/08/2011 and the last 120 transaction data are used for the test. Among the listed stock from SSM, the index 600051 shows the highest profit, and that is 108.95% profit. The highest accuracy as shown in Table 3.6 is 85.12. There is no negative profit margin.

Table 3.6: Prediction results of SSM data by PLR-ENN

| **Indexes** | **600488** | **600054** | **600019** | **600058** | **600881** | **600228** | **600697** | **600051** | **600163** | **600167** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Profit** | 21.36 | 14.94 | 23.34 | 62.43 | 33.79 | 76.31 | 37.70 | 108.95 | 80.89 | 97.54 |
| **Accu.** | 82.24 | 74.14 | 70.85 | 84.12 | 78.43 | 85.12 | 76.91 | 84.24 | 83.12 | 81.87 |
| $\mathbf{N_B}$ | 6 | 5 | 2 | 8 | 5 | 6 | 6 | 7 | 6 | 6 |
| $\mathbf{N_S}$ | 6 | 5 | 2 | 8 | 5 | 6 | 6 | 7 | 6 | 6 |

In Table 3.7, ten data results are presented, which is collected from TSM. TSM is the second largest stock exchange in the world by aggregate market capitalization of its listed companies. The collected data from TSM covering from 10/05/2011 to 15/03/2013 time period and the last 150 transaction data are tested. The highest and lowest profit margins, as shown in the table, are 113.08% and 38.31% for index 6502 and index 9437, respectively. The height and lowest accuracy are 88.23% and 68.25%. Our method shows very good outcome.

Table 3.7: Prediction results of TSM data by PLR-ENN

| **Indexes** | **7203** | **7267** | **3407** | **4188** | **9984** | **9437** | **7751** | **6502** | **6305** | **7011** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Profit** | 79.52 | 85.27 | 64.49 | 101.50 | 56.89 | 38.31 | 82.70 | 113.08 | 83.32 | 85.16 |
| **Accu.** | 88.23 | 75.62 | 79.16 | 83.45 | 68.25 | 73.14 | 81.21 | 87.91 | 80.98 | 80.12 |
| $\mathbf{N_B}$ | 6 | 6 | 3 | 6 | 12 | 5 | 11 | 4 | 4 | 3 |
| $\mathbf{N_S}$ | 6 | 6 | 3 | 6 | 12 | 6 | 11 | 4 | 4 | 3 |

The prediction results of the NASDAQ100 stock market are shown in Table 3.8. The historic data cover the financial time-series data from 01/06/2011 to 15/03/2013 and almost 450 transaction data. The last 150 transaction data are taken to evaluate the performances. NASDAQ100 stocks data also show very good outcome. The percentage of profit cover 22.85 to 77.18 and the percentage of accuracy are 73.15 to 85.21.

Table 3.8: Prediction results of NASDAQ100 data by PLR-ENN

| **Indexes** | **AAPL** | **AMZN** | **CSCO** | **COST** | **ESRX** | **GILD** | **GOOG** | **MSFT** | **NXPI** | **STX** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Profit** | 28.11 | 22.85 | 40.24 | 32.04 | 34.82 | 59.01 | 36.73 | 32.52 | 73.25 | 77.18 |
| **Accu.** | 77.12 | 75.13 | 82.12 | 80.12 | 82.12 | 85.21 | 75.74 | 73.64 | 82.45 | 73.15 |
| $\mathbf{N_B}$ | 7 | 7 | 7 | 8 | 7 | 4 | 4 | 12 | 4 | 6 |
| $\mathbf{N_S}$ | 7 | 7 | 7 | 8 | 7 | 4 | 4 | 12 | 4 | 6 |

The graphical representation for nine data set, including closing price and their predicted trading signal are shown in Figure 3.7. The data are chosen arbitrarily from three stock markets (each three). The experiment results show PLR–ENN can mine the hidden knowledge. We can say that PLR-ENN has a powerful tool for stock price prediction and has excellent generalization capability.

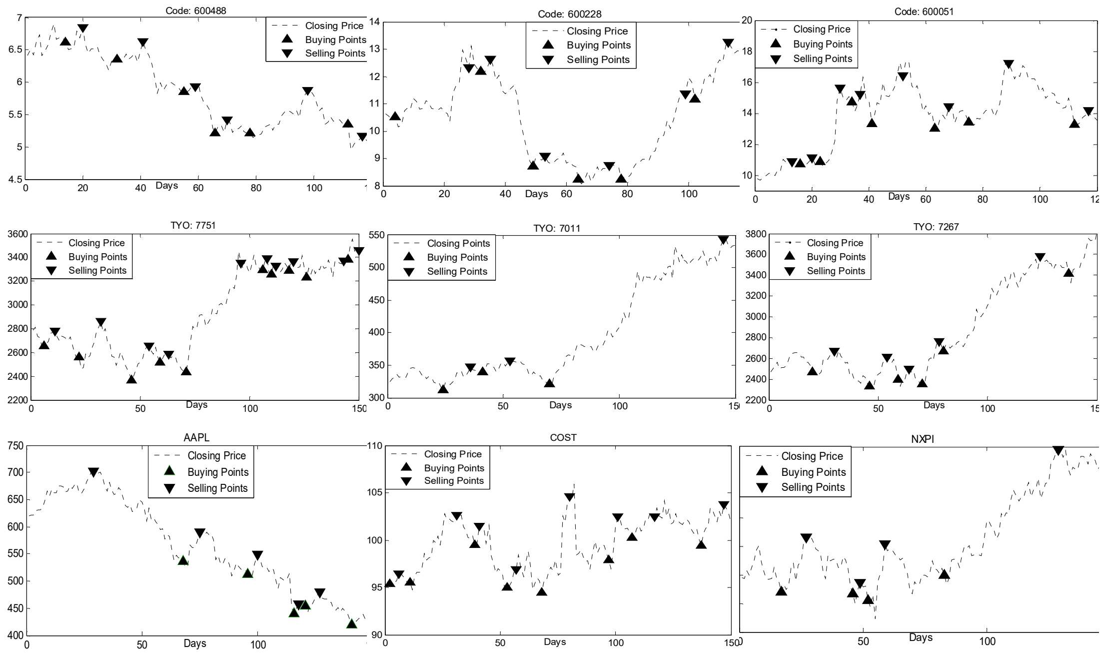


Figure 3.7: Graphical example of predicting turning points.

## 3.5 Discussion

The comparison results for the Shanghai Stock Market are represented in Table 3.9. We can see that PLR-ENN shows the best performance. When it comes to predicting with accuracy, the PLR-ENN representation is almost double for every case. Our method does not yield any negative profit compared to the others. PLR-BPN, PLR-WSVM, and PLR-ENN shows that the minimum profit are -37.05%, -15.32%, and 14.94%, respectively, and the maximum profit are 22.61%, 50.17%, and 118.95%, respectively.

Shannon's entropy numbers are used as a moving average number. But we cannot say that this technique is the most effective for every dataset. The stock data set information or entropy depends on time. It does not show the same entropy value throughout a certain period. The complexity value depends on the entropy value. It is a difficult task to find the accurate or exact number of moving averages, but the entropy measurement technique helps us to find the most accurate moving average number of predictions. Our method ensures the highest profit and the highest accuracy. So, PLR-ENN shows a higher generalized ability than PLR–WSVM and PLR–BPN.

Table 3.9: The comparison of values vis-à-vis PLR–WSVM, PLR–BPN and PLR-ENN. The best results are indicated in the bold font.

| Indexes | Method | ACC | Profit | $N_B$ | $N_S$ |
|---|---|---|---|---|---|
| **600488** | PLR − BNP | 33.88 | -25.06 | 3 | 3 |
| | PLR − WSVM | 35.52 | -15.32 | 1 | 1 |
| | PLR − ENN | 82.24 | 21.36 | 6 | 6 |
| **600054** | PLR − BNP | 30.21 | -23.87 | 3 | 3 |
| | PLR − WSVM | 40.63 | -2.40 | 3 | 3 |
| | PLR − ENN | 74.14 | 14.94 | 5 | 5 |
| **6000019** | PLR − BNP | 27.98 | -26.46 | 6 | 6 |
| | PLR − WSVM | 34.72 | -13.36 | 3 | 3 |
| | PLR − ENN | 70.85 | 23.34 | 2 | 2 |
| **600058** | PLR − BNP | 33.51 | -37.05 | 3 | 3 |
| | PLR − WSVM | 44.50 | 22.16 | 1 | 1 |
| | PLR − ENN | 84.12 | 66.43 | 8 | 8 |
| **600881** | PLR − BNP | 33.15 | 1.45 | 7 | 7 |
| | PLR − WSVM | 33.16 | 4.43 | 2 | 2 |
| | PLR − ENN | 39.79 | 78.43 | 5 | 5 |
| **600228** | PLR − BNP | 31.02 | 4.61 | 8 | 8 |
| | PLR − WSVM | 39.04 | 33.17 | 2 | 2 |
| | PLR − ENN | 85.12 | 86.31 | 6 | 6 |
| **600697** | PLR − BNP | 31.02 | 4.01 | 7 | 7 |
| | PLR − WSVM | 39.04 | 33.17 | 5 | 5 |
| | PLR − ENN | 76.91 | 37.70 | 6 | 6 |
| **600051** | PLR − BNP | 33.16 | 22.61 | 2 | 2 |
| | PLR − WSVM | 36.32 | 50.17 | 3 | 3 |
| | PLR − ENN | 84.24 | 118.95 | 7 | 7 |
| **600163** | PLR − BNP | 27.84 | 11.13 | 6 | 6 |
| | PLR − WSVM | 35.23 | 9.65 | 2 | 2 |
| | PLR − ENN | 83.12 | 80.89 | 6 | 6 |
| **600167** | PLR − BNP | 37.82 | -2.03 | 4 | 4 |
| | PLR − WSVM | 44.56 | 18.64 | 4 | 4 |
| | PLR − ENN | 81.87 | 105.54 | 6 | 6 |

The decision tree algorithm is used as a technical index selector or more effective indexes for the specific dataset. We know that the decision tree algorithm is a knowledge-based algorithm. So, there are times when it is difficult to find effective indexes or group of indexes. It is also possible that the training period suits some indexes, but the testing period witnesses a decrease in the performance. The decision trees or decision rule algorithms are an effective method to find a group of dataset for the stock price prediction. The general advantages of decision trees are that they are well-understood, have been successfully applied in many domains, and represent a model that can be interpreted relatively easily [52].

The immature data are reduced when PLR is measured. There is little scope to delete an important turning point. In most cases, manual inspection reveals that our method can find turning points successfully. Furthermore, the weighted data smoothing, normal data smoothing, and decision rule will be applied combinely to find this solution.

Undoubtedly, the ensemble neural network has a strong predictive capability. Bagging creates data diversity, so all necessary information can train the neural network. The network will be suited to forecasting after the training. If anyone can reprocess their data properly, he or she can get a significant profit from the stock market. Also, longer time is needed to find the money that can be invested in order to get the profit. Our method does not work adequately when it comes to short term prediction.

## 3.6 Conclusion

Many researchers have investigated on how to predict the stock market trades properly as they wanted to present the benefit to the consumer or shareholder. We have charted a methodology that will foster a simple way for the consumer or shareholder considering which strategy of buy/sell/hold they can reap the advantage from. Our method shows better results than PLR-BNP and PLR-WSVM. Firstly, we employed a very simple method to measure PLR, and this method is also more useful than others. Secondly, our method improves on previous claims of accuracy. Thirdly, in most cases, our results yielded a higher margin of profit compared to other methods.

Fourthly, we proposed four new technical indexes, which are very effective for finding turning point or buy/ sell/ hold point.

In the future, the proposed system can be explored by adding other factors or other soft computing techniques. Areas for further investigations are listed as follows:

The data smoothing number will be automatic or will approach a theoretical background. We will consider more theoretical background to find the appropriate smoothing number.

This paper considered the weighted moving average method of data smoothing. Furthermore, the general smoothing average, the weighted moving average, and exponential smoothing average will combine to find more proper turning point or trade point. Only three stock markets are considered for this research. In the future, we will consider more well-known stock markets. Anyone can apply our method to any market and can reap a profit.

There are many forecasting models available. We will apply a hybrid intelligent system for prediction such as Neuro-Fuzzy, NN & Data mining, Fuzzy & Data Mining etc.

# Chapter 4

# A HYBRID SYSTEM INTEGRATING FOR STOCK PRICE FORECASTING

The stock price is one of the most nonlinear real time series methods. People invest their money to profit from the share market. Investments usually take place when the stock prices are booming, and shares are sold when prices are going down. It is difficult and interesting to predict the stock market. A new hybrid model has been proposed to forecast the stock market. The least squares autoregression and the neural network tools are used for hybrid purposes. The least square autoregression is used to retrieve the instantaneous property. The neural network is used to reclaim the historical property. A combination of instantaneous and historical information can provide good prediction. The proposed algorithm shows a handsome profit.

## 4.1 Introduction

The stock market is an important body for traders and investors. It is also a source of immense uncertainty. Even people who do not understand the nature of stock time series want to profit from the market despite this uncertainty. A number of factors influence the stock price, such as exchange rates, interest rates, political issues, natural disasters, government policies, the international stock market, etc. When shareholders sell/buy their shares, they leave a trail of transaction. This transaction data is the only source that researchers can examine when investigating the stock market. Personal transactions by individual shareholders are also important for research; however, this data is not readily available on the internet.

Much research have been done to predict stock price movement by using hybrid systems. The shareholders's activities are of interest to researchers when they are investing or withdrawing from the stock market. The proposed research also predicts the investing and harvesting time for shareholders. Investments usually take place when the stock prices are booming, and shares are sold when prices are going down. Unforseen factors can influence the stock markets, such as when the Great East-North Japan Earthquake disaster (GEJE) struck Japan and indirectly affected the share market. Through this incident, many share indexes experienced a continuous fall, and it took approximately one year for recovery. Incidents like this are very difficult to forsee, and hampers the kind of transparency that we are trying to arrive at with the share market. We proposed a new hybrid model which is very effective and easy to implement. Many researchers [7, 49, 31, 13] use a high sensitive threshold. The proposed method presents a new technique which can be used to avoid the threshold factors. We use the less sensitive moving average number instead of the threshold. The Shannon entrophy is used to get the proper moving average number. The entropy is a key factor of the quantum information model. It measures how much uncertainty there is in the state of a physical system [53]. The normal moving average and weighted moving average are used in the training data to get the proper decision points. The NMA provides the number of decision points, and the WMA shows the exact points where decisions were made. It may differ slightly from the NMA points. It should be maintained that the selling/buying points for both NMA and WMA.

The hybrid system has become increasingly popular.The proposed method accumulates the data mining tools and the artificial neural network tools to forecast the turning points in the stock market. The hybrid system has two main focuses. Firstly, the instantaneous changes/effects or information may provide DM during the period being predicted. The least square autoregressive is a tool that can show the effect of the changes. Secondly, the historical information or facts may provide the NN during the period being predicted. We know that multilayer back propagation has been propagated, popularized, interpreted, enhanced and implemented in different ways across a variety of application domains [54]. If the information/fact accumulates properly for forecasting, the shareholders may get a proper prediction model. Finally, we use a new XNOR gate for hybridization. We also calculate profit while considering all costs.

Informations/facts are integral to research. R. de A. Araújo [55]et al. proposed a hybrid model to predict stock markets. They wanted to adjust the time phase to overcome the problem of the daily fluctuations of of the financial time series. An experimental analysis was conduced using relevant high-frequency financial time series. A hybrid Kohonen Self Organizing Map for predicting stock price was proposed [56].

Tasai, C.-F. [57] combined ANN and decision trees to create a stock price forecasting model. They were able to predict with an accuracy of 77%. Artificial Neural Network (ANN) is the most commonly used technique in many prediction problems. We also used ANN, and it helped us secure a good rate of success when forecasting the stock price. Decision trees are another data mining technique which may forecast the stock market [58]. Jigar Patel et al. svvurately predicted stock markets using four models to compare, namely, ANN, SVM, random forest and naive-Bayes and two different ways of inputting data into these models.

Akhter Mohiuddin Rather et al. proposed a hybrid model using the autoregressive moving average model, exponential smoothing and recurrent neural network. We also used autoregressive moving average and NN for this research. Our findings confirmed their results. Some researchers are interested in the hybrid system [59, 60, 61, 62]. The efficient market hypothesis states that it is not possible to predict the stock prices because stock markets meander in a random and arbitrary manner. Despite this, shareholders remain eager to profit from the stock markets.

This paper is organized as follows. Section 4.2 presents the data sources. Section 4.3 describes the data preprocessing steps. In Section 4.4 presents examines the influencing factors and their explanations. The proposed model and its learning process is presented in Section 4.5. In Section 4.6, the experiment's results are presented. The final remarks of this work are presented in Section 4.7.

## 4.2 Data

The stock market historical data is available on the Internet. A lot of sources provide the stock market data. Many websites can be accessed through mobile applications that receives information in real time.Even if shareholders are at work, they can easily check their specific stock indexes within seconds.

### 4.2.1 Data collection

The stock market data were collected from three big share market, namely, the New York Stock Exchange (NYSE), the Tokyo Stock Market (TSM), and the Financial Times Stock Exchange 100 Index (FTSE 100). The FTSE 100 companies represent about 81% of the entire market capitalisation of the London Stock Exchange. The data was collected from Google/finance/index/historical prices [63]. The Stock Market data covered a time period from 1/1/2013 to 1/12/2015, and contained approximately 504 days of transaction. The popular and almost saturated stocks were selected.

Five sectors and ten data sets were selected from each stock market. The selected sectors were energy, healthcare, industrial, financial, and consumer non-cyclical and the selected symbol are XOM, CVX, JNJ, PFE, GE, MMM, C, BAC, PG, MO collected from the NYSE market. From the TSM, automotive, chemicals, machinery, electric machinery, and banking sectors were chosen, and the indexes are TYO:7203, TYO:7267, TYO:3407, TYO:4188, TYO:6302, TYO:5631, TYO:6758, TYO:6702, TYO:8309, and TYO:8306. In the market FTSE 100, selected sector/industry are oil and gas, banking, mining, supermarket, and engineering, and the indexes are BG, BP, STAN, HSBC, RIO, GLEN, SBRY, MRW, IMI, MRO.

### 4.2.2 Data normalized

The value of stock price varies. For a certain period, some fixed value can be seen. The value of stock can be divided into two prices, namely fixed price and variable price. We will consider only the variable price for our research, and include the fixed price when we calculate the profit. The data was normalized as follows

$$Data_{normalized} = Data_{variable}/max(Data_{variable})$$

$$\text{Where, } Data_{variable} = Data_{total} - Data_{fixed}$$

### 4.2.3 Dividing

The normalized data was divided into two parts (train and test). The first 300 data was used for training, and the rest was used for testing. The training data was used to gauge their internal characteristics and deploy them for the purpose of forecasting. The testing data is used to find the decision point, it does not affect the testing values.

## 4.3 Data analyzing

The training data was used in this section. We will measure data complexity, proper decision points, transaction gap and unit impulse analogy, which will then be used in the testing.

### 4.3.1 Data Complexity

Entropy is a concept of quantum information theory. It measures how much uncertainty there is in the state of a physical system [53]. Knowledge of this information would help one gauge the complexity or simplicity of the time series. A number of studies [27, 28] have been conducted to find the complexity for any time series and predict their behaviour as being regular, chaotic, etc. The main types of complexity parameters include entropies, fractal dimensions and Lyapunov exponents. We used the Shannon entropy to analyse the stock price complexity. Teixeira A. et al. [29] showed that the Shannon entropy measured the expected value effectively compared to other contesting methods. The key concept of classical information theory is the Shannon entropy. The Shannon entropy is a basic measure in information theory that calculates the uncertainty by the following formula.

$$H = -\sum_{i=1}^{n} p(x_i)\log_b p(x_i)$$

Where the Shannon entropy is denoted by $H$, $x_i$ is a discrete value from the time series of X. The finite number of data is $n$, and $p(x_i)$ shows the probability density function of the outcome of $x_i$. It can be said that the complexity of a system is indicated by the amount of information available. Bigger entropies show a higher complexity for any time series and vice versa. According to the entropy value, the data set is judged to determine whether it is high or low complexity, and this information is used in the next section.

Table 4.1: The Average entropy of each 100 data in the data set

| **Data set** | **Shannon's Entropy** |
|---|---|
| Asahi | 4.8356 |
| Mitsubishi | 4.7867 |
| Microsoft | 5.0464 |
| NXP | 4.9873 |
| Hitachi | 5.0414 |

There is a strong relation between entropy and the size of the information available for any data set. The Shannon entropy is good for any time series analysis. The average Shannon entropy of 100 data is shown in Table 2.1, where five data sets were arbitrarily chosen.

### 4.3.2 Finding decision Points

The two basic and commonly used MAs are the normal moving average (NMA), and the weighted moving average (WMA). We have used these two types of data smoothing to find the accurate decision point. Data complexity uses a number of smoothing values. It is important to decide how much data will be taken for data smoothing: a higher complexity data yeilds a high value, and a lower complexity data yields a low value.

The NMA is commonly used by technical analysts/ financial applications. It is calculated by dividing the sum of a sample set of prices by the total number of samples in the series. NMA is the equally weighted average of a sample over a defined number of time periods. The NMA is calculated using the following equation:

$$\mathrm{NMA_m} = (\mathrm{V_m} + \mathrm{V_{m-1}} + \cdots + \mathrm{V_{m-n+2}} + \mathrm{V_{m-n+1}})/\mathrm{n}$$

Where, $\mathrm{V_m} + \mathrm{V_{m-1}} + \cdots + \mathrm{V_{m-n+2}} + \mathrm{V_{m-n+1}}$ is the original price and n is the number of sample days for smoothing. The normal moving average (NMA) data is used to find the number of decisions points to buy and sell. The moving average value is taken from the large numbers (3*entropy number). The number of saturated points signify the number of decision points. The lower and higher saturated points mark the buying and selling points, respectively.

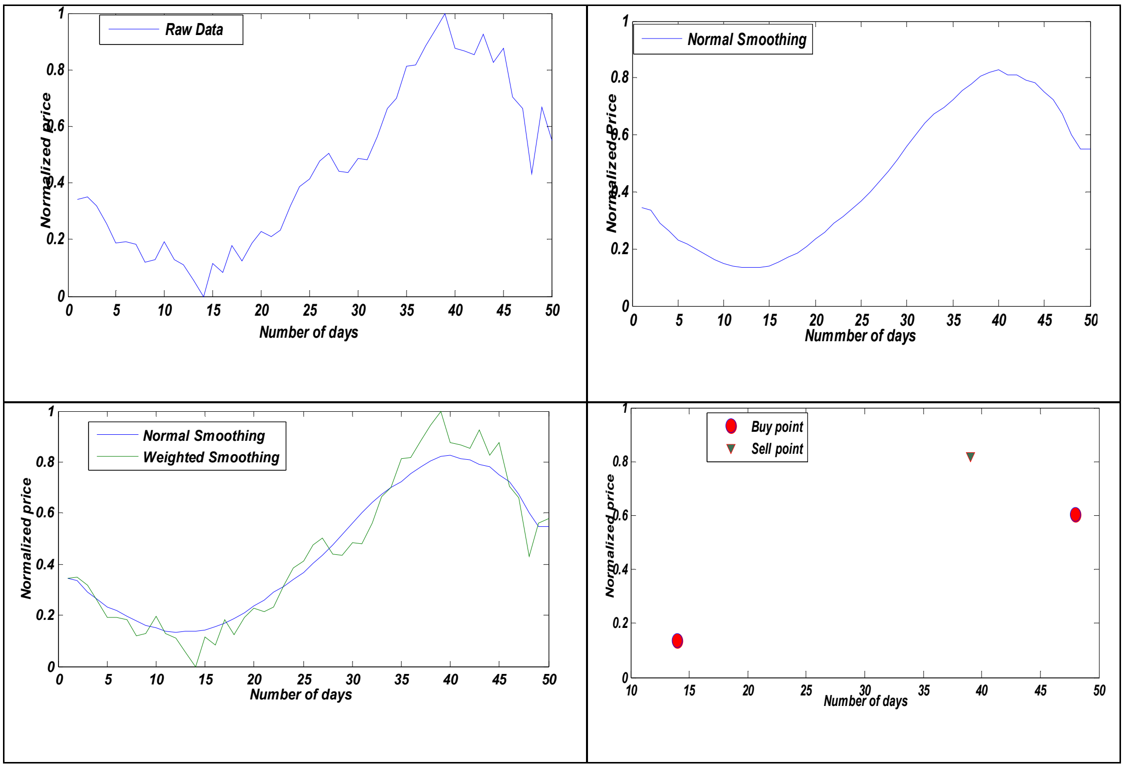


Figure 4.1: Graphical representation of finding decision points

The weighted moving average (WMA) is a useful tool where one needs to measure recent changes/activities. The recent activity/change is affected more than the previous activity/change. We can say that WMA gives a higher weight to recent prices. The WMA is calculated by the following equation:

$$\mathrm{WMA_m} = \{\mathrm{nV_m} + (\mathrm{n}-1)\mathrm{V_{m-1}} + \cdots + 2 * \mathrm{V_{m-n+2}} + \mathrm{V_{m-n+1}}\}/\{\mathrm{n} + (\mathrm{n}-1) + \cdots + 2 + 1\}$$

where, $\mathrm{V_m} + \mathrm{V_{m-1}} + \cdots + \mathrm{V_{m-n+2}} + \mathrm{V_{m-n+1}}$ is the original price and $\mathrm{n}$ is the number of days sampled for smoothing. The weighted moving average data is used to find the exact decision point.

The result from NMA and WMA are combined into a single output. Where the WMA decision points are closer to the NMA points, a decision is made. The NMA is used to find the number of decision points in the training data, and the WMA is used to find the decision points in the training data. Examples are shown in Fig. 4.1, where presented with 15 data points, smoothing is taken from normal smoothing, and presented with 5 data points, smoothing is taken from the weighted smoothing.

### 4.3.3 Data Transaction Gap

The transaction between the decisions (buy/sell), the transaction between the same transaction (buy or sell) be measured in this section. We are also interested in the maximum and minimum transaction. The number of buy points ($\mathrm{N_B}$), the number of sell point ($\mathrm{N_S}$), minimum transaction gap between two sell decision( $\mathrm{MT_B}$) and the minimum transaction gap between two buy decisions ($\mathrm{MT_S}$) are indicated as $\mathrm{N_B}, \mathrm{N_S}$, $\mathrm{MT_B}$ and $\mathrm{MT_S}$, repectively. Table 4.2, show the training data set results of the three markets.

Table 4.2: The results of training data

| Indexes | XOM | JNJ | GE | TYO: 7011 | TYO: 9984 | TYO: 7267 | BG | HSBC |
|---|---|---|---|---|---|---|---|---|
| $N_B$ | 8 | 10 | 9 | 12 | 9 | 6 | 12 | 8 |
| $N_S$ | 9 | 9 | 10 | 11 | 8 | 5 | 12 | 8 |
| $MT_B$ | 14 | 11 | 11 | 12 | 16 | 18 | 10 | 11 |
| $MT_S$ | 12 | 13 | 14 | 10 | 10 | 19 | 13 | 16 |

### 4.3.4 Compare with Unit impulse

Each decision can be compared to an impulse response, the decision to hold can be equated to an output of zero. Each decision to sell can be represented as a +1 pulse and each decision to buy represented as a -1 pulse. Figure 4.2 presents a hypothetical example, where the time series is 50, as it is affected by two decisions to sell and one decision to buy.

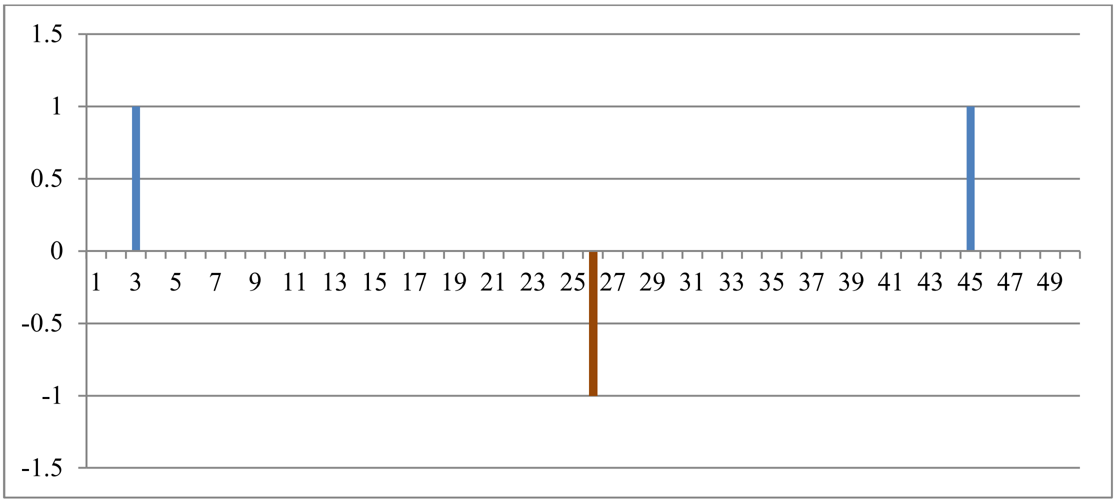


Figure 4.2: A hypothetical example for decision making points

Considering only one decision would make it akin to a unit impulse function. We can also represent the same unit impulse equation for a single decision.

One of the simplest discrete time signals is the unit impulse (or unit sample), which is defined as

$$\delta[n] = \begin{cases} 0, & n \neq 0 \\ 1, & n = 0 \end{cases}$$

$\delta[n]$ is referred to interchangeably as the unit impulse or unit sample [64, 65]. There is the relationship between the unit impulse function ($\delta(t)$) and the unit step function ($u(t)$).

$$\delta(t) = \frac{du(t)}{dt}$$

Since $u(t)$ is discontinuous at $t = 0$ and consequently is not differentiable. We consider an approximation to the unit step $u_\Delta(t)$, where $\Delta \rightarrow 0$, now the equation is

$$\delta_\Delta(t) = \frac{du_\Delta(t)}{dt}$$

Then $\delta(t) = \lim_{\Delta \rightarrow 0} \delta_\Delta(t)$

We also write that $\lim_{\Delta \rightarrow 0} \delta_\Delta(t) = 0$ with $t \neq 0$

This represents a unit impulse at time zero. We can translate the impulse from a time of zero to $t = T$

So, $\delta(t - T) = 0$ for $t \neq T$ and $\int_{-\infty}^{\infty} \delta(t - T)dt = 1$

Applying Laplace transforms, $\mathcal{L}[\delta(t - T)] = \frac{\sinh(s\varepsilon)}{s\varepsilon} e^{-sT}$

So the Laplace transformation of a unit impulse at time T is $e^{-sT}$ and we realize the unit impulse at time zero is 1.

$\mathcal{L}[\delta(t)] = \lim_{T \rightarrow 0} \frac{e^{-sT}}{s}$=1

In the future, we will try to determine the frequency of each impulse function, because we know the limit for each impulse function.

## 4.4 Input selection

Selecting the input is another important issue of time series forecasting. The stock markets contain some data regarding their daily stock price. It is challenging to find the accurate technical index combination for forecasting. The stock market is affected by a number of factors. Many researchers have investigated the many technical indicators that help to predict the trading signal [31, 32]. There are some common factors, such as moving average, transaction volume, bias and related strength. Still, it is unknown as to which combination best in line with the stock market predictions.

We propose four new technical indexes which are closely related to the closing transaction price, and are an effective means to predict the stock price. The slope of the time series can be proposed as a technical index. This technical index is very effective and essential. A positive slope reflects a positive value, and a negative slope reflects a negative value. Positive and negative values are very close to buying and selling transactions. The proposal is a ten-day MA of the amplitude of the price movement. The second and third proposed indexes are very close to the closing price transaction. The last proposal is the difference between the normal moving average value and the weighted moving average value. The difference in value reveals a very significant effect to finding the turning point.

## 4.5 Methodology

The main purpose of this research is to develop a framework that will enable shareholders to benefit from the share market. In order to meet this requirement, a simple and effective hybrid model is proposed that is user-friendly and easy to implement. Our method has some steps, which includes data preprocessing, data mining, and neural network, XNOR gate, filtering and calculation profit. Stock price prediction has always been a subject of interest for most investors and financial analysts, but clearly, finding the best time to buy or sell has remained a very difficult task for investors because there are numerous other factors that may influence the stock price.

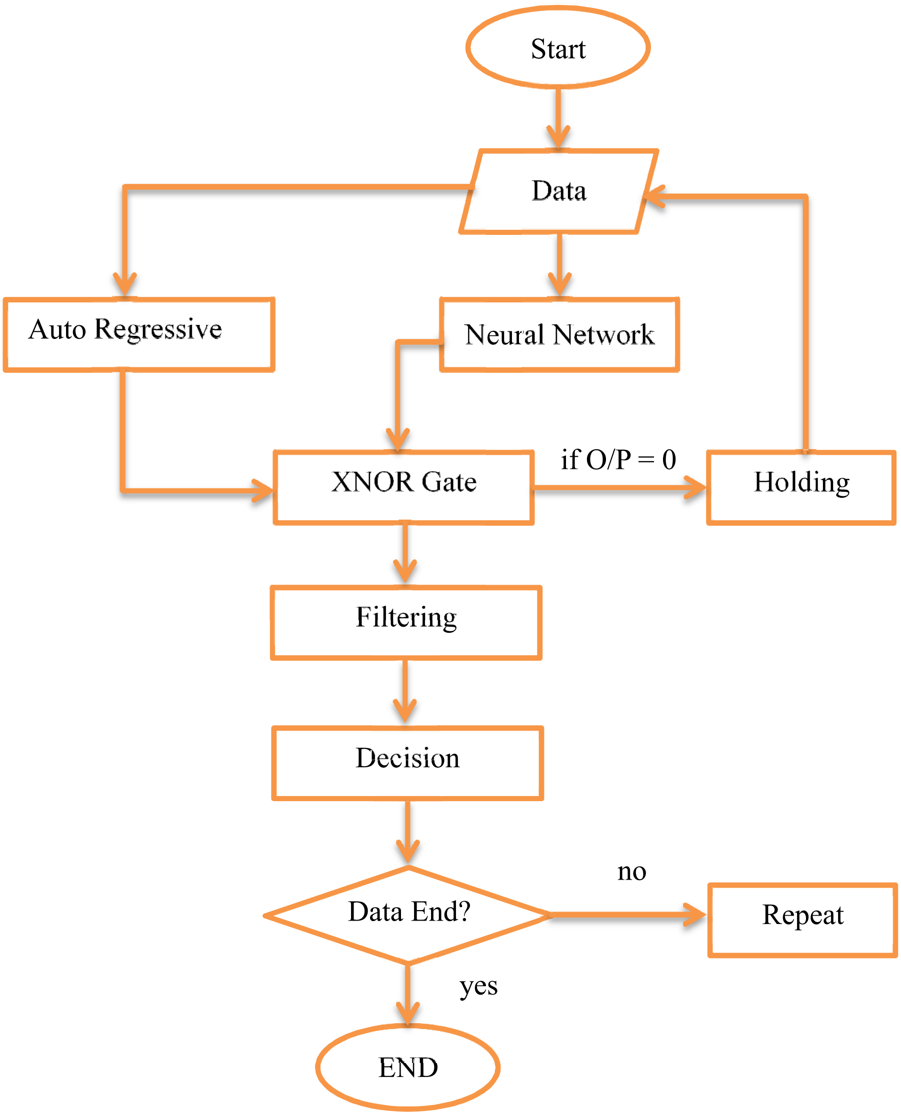


Figure 4.3: Flowchart of proposal

The entire flowchart is shown in Figure 4.3. Stock price depends on many factors. For this reason, the stock price always fluctuates positively or negatively. The prices also vary during the length of a day. Firstly, the raw data is taken from any stock market, and applied to the pre-processing steps. Once this is done, the turning point is found. The forecast variable is the closing price. The evaluation of the predictive model for accurate prediction is done.

### 4.5.1 Auto Regressive

The least squares determines the best fitting line to the data [33]. Regression analysis is used widely in financial time series investigation. It also measures and describes the relationship between financial variables or time series variables for forecasting tasks. While it is important to calculate the estimated regression coefficients without the aid of a regression program at least once to better understand how OLS works, easy access to regression programs makes it unnecessary. The ordinary least squares estimators of the nth order autoregression is [5].

$$Y_t + \sum_{i=1}^{n} \alpha_i Y_{t-1} = \theta_0 + \varepsilon_i$$

Where the root is $m^n + \sum_{i=1}^{n} \alpha_i m^{n-i} = 0$ , because the production of this section is closely related to multiple regression, we can rewrite the formula as

$$Y_t = \theta_0 + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \cdots + \theta_n Y_{t-n} + \varepsilon_i$$

Where $\theta_i = \alpha_i$, i=1,2,…,n. Also, the least squares estimator is asymptomatically equivalent to the estimator

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \cdot \\ Y_n \end{pmatrix} = \begin{pmatrix} Y_0 & \cdots & Y_{n-1} \\ \vdots & \ddots & \vdots \\ Y_{n-1} & \cdots & Y_0 \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \cdot \\ \alpha_n \end{pmatrix}$$

This is also called Yule-Walker estimators [5]. From the training data the following six data and their estimated parameters were randomly chosen and listed in Table 4.3.

Table 4.3: The example for parameter estimation

| | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\alpha_4$ |
|---|---|---|---|---|
| **Honda** | 0.371846 | -0.241440 | 2.562631 | -1.31737 |
| **Canon** | 1.49575 | 1.54914 | 1.65715 | -5.0071 |
| **STX** | 1.51148 | 0.313829 | 0.649607 | -2.569223 |
| **Baoshan** | -1.75742 | 1.29748 | 2.10659 | 1.529086 |
| **Tourism** | -1.42532 | -0.428787 | 1.107020 | 0.47134 |
| **Amazon** | -0.496544 | 0.33244 | 2.15145 | -0.53609 |

The deviance can be an important statistic for prediction. If the deviance changes too much or too little after adding the variables, the prediction of y effects as same [34]

### 4.5.2 Network

Multilayer neural networks can map the inputs in a nonlinear manner. The key power provided by such networks is that they admit fairly simple algorithms where the form of the nonlinearity can be learned from training the data. The models are extremely powerful, useful, and relatively easy to understand, and can be applied to a vast array of real-world scenarios [66]. For this reason, we use three layers of backpropagation. The backpropagation training method is simple even for complex models having hundreds or thousand of parameters.

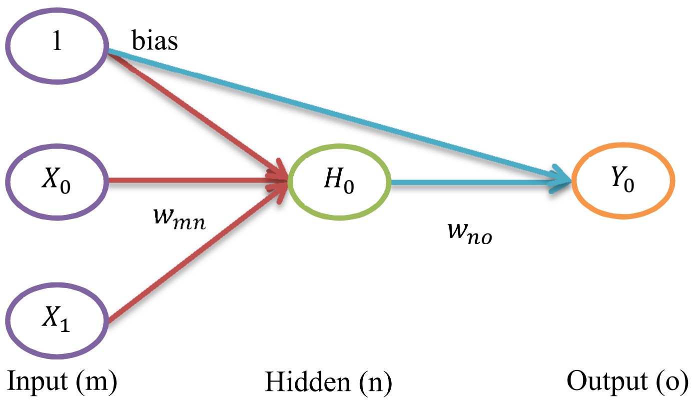


Figure 4.4: Simple three layer neural network

Figure 4.4 shows a simple three-layer neural network, namely, input layer, a hidden layer and output layers. There is a single bias unit that is connected to each unit other than the input layer. We are interested in the use of such networks to forecast the future transaction of stock markets. There are a number of activation functions, but everyone does not satisfy the network demand. We use sigmoid function, which is one class of functions that has all the properties. Back propagation is a procedure that calculates the derivatives, through calculations proceeding backwards from outputs to inputs. This is a technique that adapts the weights or the parameters of a nonlinear system by using derivatives or the equivalent [54].

### 4.5.3 Assembling

We combine the two outputs from neural network and least square auto-regression. For this purpose, the XNOR gate are used. The output of XNOR is as followes

Table 4.4: XNOR gate truth table

| Input 1 (DM) | Input 2 (NN) | Output |
|---|---|---|
| 0 | 0 | 1 |
| 0 | 1 | 0 |
| 1 | 0 | 0 |
| 1 | 1 | 1 |

An XNOR is a digital logic gate, two or more input units and the one output unit. This gate is logical complement of the exclusive OR (XOR) gate. If the output from the DM and NN are same the output will be high or 1, otherwise the output is high. The logic to use this function is that, if the output from two is same direction than we think that it will decide for buying or selling. Otherwise, the network output will go no descesion or hold the share.

### 4.5.4 Filtering

We will filter the output from the XNOR gate. Firstly, we assemble the output from DM and NN then divided into two.

$$\frac{(\text{DM output}) \ + \ (\text{NN output})}{2} \approx \text{threshold}$$

The combine output compare with the predefined threshold value. We also check the individual output. We consider the same priority for decision making. If the one output is so high that cross the value the threshold value, but the other one is small. In that condition, we consider no decision or hold the share. We consider the higher decision priority for decision, when the output of both network high and same direction. Otherwise, the network will provide no action.

### 4.5.5 Calculating Profit

If we find a pair of decision, then we will calculate the profit. The process will continue until the data finished. After the all data execution finished, we will calculate the grand total profit. We also consider the taxes, buying cost, selling cost for accurate profit calculation.

## 4.6 Results

We select three countries stock market and covered thirty stock shares, ten from each. They are secondary share markets. The most important issue to get the profit or benefit from the stock market. The consumers or shareholder can get a handsome profit from their investment. To find the profit, the following formula is used

$$\text{Profit, } P = \left[\sum_{i=1}^{n} \frac{\{(1-a-c).S_i-(1+b).B_i\}}{(1+b).B_i}\right]$$

Where $a, b$ stands for the transition cost of selling and buying of the $i$th transaction, $c$ refers to the tax rate of the $i$th transaction. $S_i, B_i$ represents the selling and buying price of the $i$th transaction, and $n$ signifies the number of the transition. Profit is calculated for a single share. In my methodology, a transaction is complete when the shareholder engages in the process of minimum buying and selling. Without considering the tax rate and the transition costs associated with selling and buying may does not provide profit in practically.

Three main factors are considered when evaluating our methods, which includes profits, number of buy points and number of sell points. They are considered in conjunction with customers or shareholders. To evaluate our method, show in the table 4.5, and 4.6,and 4.7.

Table 4.5: The Testing Data Results of NYSE

| Indexes | XOM | CVX | JNJ | PFE | GE | MMM | C | BAC |
|---|---|---|---|---|---|---|---|---|
| **Profit** | 26.1 | 22.9 | 54.2 | 45.3 | 44.0 | 59.60 | 34.85 | 16.45 |
| $\mathbf{N_B}$ | 6 | 8 | 7 | 7 | 9 | 8 | 7 | 6 |
| $\mathbf{N_S}$ | 6 | 7 | 6 | 8 | 8 | 9 | 6 | 6 |

Table 4.5 shows the results of the NYSE stock market. The lowest and highest profit (%) belong to the BAC and MMM, and the values are 16.4%. and 59.60%, respectively. The number of buying and selling points range between 5 and 8. From the NYSE stock market, the proposed method yields a considerable outcome. Table 4.6 shows the results of the TSE stock market, it also shows good profit. Table 4.7 shows the FTSE100 stock market results.

Table 4.6: The Testing Data Results of TSE

| Indexes | TYO: 7203 | TYO: 7267 | TYO: 3407 | TYO: 7011 | TYO: 4188 | TYO: 6302 | TYO: 5631 | TYO: 6758 |
|---|---|---|---|---|---|---|---|---|
| **Profit** | 36.54 | 29.03 | 45.98 | 46.62 | 49.14 | 38.14 | 29.59 | 15.48 |
| $\mathbf{N_B}$ | 6 | 7 | 6 | 9 | 13 | 6 | 6 | 7 |
| $\mathbf{N_S}$ | 6 | 6 | 7 | 9 | 12 | 7 | 7 | 6 |

Table 4.7: The Testing Data Results of FTSE100

| Indexes | BG | BP | STAN | HSBC | RIO | GLEN | MRW | IMI |
|---|---|---|---|---|---|---|---|---|
| **Profit** | 55.12 | 46.12 | 44.89 | 67.98 | 55.95 | 22.12 | 49.90 | 33.04 |
| $\mathbf{N_B}$ | 7 | 8 | 8 | 8 | 6 | 5 | 7 | 5 |
| $\mathbf{N_S}$ | 8 | 9 | 7 | 8 | 5 | 6 | 8 | 6 |

## 4.7 Conclusion

This study involves with improving the prediction capability for share market. There are two methods are used for prediction. For data mining tools, the least square autoregressive tools are used. And the soft computing tools, the multilayer backpropagation are used. For measuring the performance of this model, three big markets, namely NYSK, TSE and FTSE100 stock market data is used. The performance shows a handsome profit earns from each stock market. The network has some shortcoming.

The network cannot provide two same decisions.

The proposed model provides the same priority for DM and NN. But, DM and NN does not provide the same information for all sectors.

Selected turning points may not the appropriate the exact turning points in that time series.

The network is only few influence factors and exact two years data for research. May, many important influence factors and many research data are missing.

The main contribution of this research is as follows: Firstly, the study provides a new hybrid model where data mining and artificial neural network used together. The DM focus on the instantaneous information or changes and the NN focus on their historical information or historical track.

Secondly, the new technique for combination XNOR gate are used. Which is very effective and simple.

Thirdly, the normal data smoothing and weighted data smoothing are used in the data preprocessing step, which is new and effective for finding the decision points.

Fourthly, the Shinnons entropy is used to find the entropy/information of the data. The best for using the entropy is that it can be used to quantify the resources needed to store information.

Fifthly, the moving average number is used instead of threshold values. The threshold value is highly sensitive for networks than the moving average number.

If future, we will try to find some combination among the influential factors. That may differ indexes to the indexes and market to market. We also will find the internal significant among the influence factor.

We will provide a mathematical explanation about the methodology. Especially, we will find the frequency by using the inverse Laplace transform.

We will try to predict more than one same transaction. Such as, two buying/selling predict.

# Chapter 5

# FUTURE DIRECTION

The movements of the stock market is of huge interest to shareholders and the financial planner. The shareholders want to know when shares are booming or heading towards a slump. They spend a lot of their time trying to understand the stock market price. Sometimes, investors gain a small profit from their small investments. Once they are hooked, rapid positive changes in the share market induces them to invest more. They are also on the lookout for avenues where they can take loans because they want to increase the size of their investments. It often happens that they lose their money and end in debt.

The research has shown a handsome profit, but it is still challenging to predict the time to buy/sell. The computerized analysis is very easy, with no need to invest money in the real market. Also, the prediction of a negative profit during research does not adversely affect the project since no real money was invested. In the practical field, one has to be involved inthe cost of spending. The future of research in the stock market are as follows:

Firstly: The individual shareholder's attitude. Even if the data is large, it will still be easy to plan. Also, the individual shareholder's data will be secret, and we will have to contact them to acquire the secret data. Through this data, we will be able to know the worst affected shareholder after incidents like earthquakes. Our primary target will be to analyse the individual shareholder's data. After that, we can easily organize a group through programs like Individual Component Analysis, Principle Component Analysis or Self-Organizing Map.

Secondly: The money invested by newcomers should be limited with a steady increase bolstered by gains. A large number of people lost sunstantially in the beginning because thethey invested without understanding the nature of the stock market. Our future target is to save the newcomer from such an upset. We want to set an investment ceiling for newcomers where further involvement in the share market is a signal of their gains per month. We want to give a proper term and condition for newcomers. The trader should not be able to get more benefit from the inexperienced newcomers.

Thirdly: In the future, we want to find the factors influencing specific stock markets and stocks. Shareholders can draw predictions through knowledge of these factors.

Fourthly: We will find the best combination for each stock market. It will vary from stock to stock, so a lot of work remains to be done in this sector. Our main target is that no one should lose their wealth from the stock market.

Fifthly: We can say that the shareholder is also an owner of the company, and all owners benefit from their ownership. We want to fashion a policy that may yield the basic level of profit for shareholders. Sixthly: We want to provide a recovery system for the stock market, which would be part of the stock market insurance. May be the insurance money should be drawn from the company or planner.

The stock price is one of the most nonlinear real time series. The main goal of any financial research is to harvest some profit from one's investment. Similarly, people invest to profit from the share market, and would prefer to take the precautions against ending up empty-handed.

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