

FORECASTING THE EFFECT OF STOCK REPURCHASE VIA AN ARTIFICIAL NEURAL NETWORK

KARN MEESOMSARN

MASTER OF SCIENCE IN STRATEGIC MANAGEMENT INFORMATION SYSTEM

MAE FAH LUANG UNIVERSITY

2009

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THE THESIS IS A PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN STRATEGIC MANAGEMENT INFORMATION SYSTEM

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2009

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ABSTRACT

A simple back-propagation artificial neural network (ANN) is utilized to forecast the effect of stock repurchase on the closing price of a company's common stocks. The input factors are composed of the present closing price, the index of the stock market and the amount of future-intended repurchase. A trend selection is created to group the repurchase days by selecting two records that are under the same conditions as the day before the next repurchase. The trend selection considers 5 parameters including the change of the closing price, the change of the volume, the change of the SET index, the relation of the change between the closing price and the SET index, and the relation of the change between the closing price and the volume. After training with several repurchase days having the same condition, the ANN-based prediction introduces higher accuracy than predicting with the classic accounting equation. This technique can provide more accuracy when there is the longer repurchase period for training because there will be more chance to select the most similar trends.

Keywords: ANN/ Backpropagation/ Stock repurchases/ Prediction.

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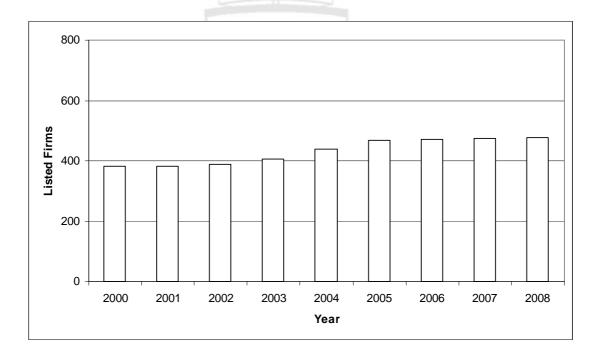
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CHAPTER 1

INTRODUCTION

1.1 Background

The Stock Exchange of Thailand was established over 30 years ago since 1975. The number of listed firms has increased every year from 381 firms in 2000 to 476 firms in 2008 as indicated in figure 1.1.



Source: The Stock Exchange of Thailand, 2008

Figure 1.1 The number of listed firms since 2000-2008.

The statistics obtained from the Stock Exchange of Thailand website show that the number of the listed firms that entered the market has increased continuously since 2000. It is expected that the numbers of the listed firms will continue to increase in the next couple of years. It is the policy objectives of the Stock Exchange of Thailand to expand the numbers of new listed firms in the future.

The percentage of firms repurchasing stocks increases in the long run as shown in Table 1.1. The total amount of repurchases is increasing but not smoothly. During the years 2000-2008, the amount is quite stable. But it started to drop in year 2007, and year 2008 is the lowest point. After year 2000, the amount of the repurchased stocks increased dramatically. The amount maintained at the relative high level until year 2007. But after year 2005, the firms repurchased more but distributed cash through dividends less. After year 2004, the total amounts of repurchases are all above 7,000 million baht.

Table 1.1 Summary Statistics of Repurchasing Firms.

	Number of	Percentage of Firms	Total	Total
Years	Repurchasing	Repurchasing	Amount	Amount
	Firms	Stock	Repurchases	Dividends
2000	34	8.92%	3,300.55	8,287.92
2001	36	9.31%	5,140.37	8,13.24
2002	37	9.43%	4,895.80	9,655.36
2003	45	10.96%	6,069.37	10,776.99
2004	51	11.60%	7,171.28	16,745.66
2005	64	13.81%	12,959.69	15,674.85
2006	79	16.88%	16,547.77	18,832.04
2007	73	15.41%	13,385.28	15,568.95
2008	66	14.02%	12,977.95	14,332.40

Source: The Stock Exchange of Thailand, 2008

Stock repurchasing is a very important financial strategy for firms in the stock market. Many firms use repurchase programs. Repurchasing stocks is another way for managers to distribute money to shareholders, thus there is somewhat similar to the role that dividends play. The managers can distribute excess capital to the shareholders by repurchase instead of investing the excess capital in a negative net present value project. In the world of information asymmetry, the managers repurchase stocks to signal their firms' misevaluation, especially undervaluation. Firms repurchase the stock to change leverage ratios. The stock repurchasing and the effect on stock price are both popular because of the benefits to the stockholders. Firms' values are based on the increasing price of common stocks which the holder can choose between selling or not. In addition, as the volume of repurchases must be large enough to make a significant change, only 1 % prediction error can cost a lot of fortune. The automatic prediction method is necessary because the speed of the process of the prediction to find the output is faster than the human does. The automatic prediction of stock repurchasing effects must be precise. Stock repurchases have become a part of the stock market, which has always been one of the most popular investments due to the high return. Therefore, this thesis proposed the automatic prediction of stock price after repurchase.

1.2 Objective

The objective of this thesis is to: Create a prediction method for the effect of stock repurchasing, which is the repurchase price. The prediction system is aiming to increase more accuracy and using less the input data.

1.3 Scope

The scope of the work described here covers:

- 1.3.1 The companies studied in this thesis use repurchase programs in the Stock Exchange of Thailand.
- 1.3.2 Sensitivity analysis in the case that changing values of the 5 factors consist of the change in closing prices, the change in volume, the change in the SET Index, the relation of the

changes between the closing prices and the SET index, and the relation of the changes between the closing prices and the volume.

1.4 Definition

ANN or Artificial Neural Network is mathematics to simulate the structure of biological neuron in a human brain. In most case, ANN is applied to solve non-linear problem data. The ANN model is used to find complex relationships between input and output data.

Stock repurchase is one of financial ways for companies to distribute money to shareholders. The stock repurchases also affect the stock price.

Backpropagation is a method of learning the artificial neural network. In the process of this algorithm, a training input pattern is presented to the input layer in the network. After that, the network computes the training input pattern from layer to layer until an output pattern is formed with the output layer.

Prediction is a particular trend that will occur in the future.

1.5 Expectation

The model used for forecasting the effect of stock repurchase via an artificial neural network is created to help investors. The investors can use this model to gain their profits when the company has announced the repurchase program. This thesis can be applied to other stock markets.

CHAPTER 2

THEORY AND LITERATURE REVIEW

2.1 Stock Exchange of Thailand

The Stock Exchange of Thailand (SET) is the national stock exchange of Thailand, which was set up under the security exchange of Thailand in 1974. It has started since 30 April 1975. The center is located in Bangkok. The Stock Exchange of Thailand is one of the major stock exchanges in Southeast Asia, which consists of 523 listed companies. At the end of 2007, the market capitalization is \$197 billion. The SET divides its operation trading hours into 2 sessions. The first session starts in the morning from 10:00 am. - 12:30 pm. The second session starts in the afternoon from 14:30 pm. - 16:30 pm. The operation hours open all days of the week except Saturdays, Sundays and holidays.

The Stock Exchange of Thailand provides trading features for stock brokers and traders to trade stocks and securities. Stock exchanges also provide another feature for the issue and restoration of the securities as financial instruments, including payments of income and dividends. The trade of the securities in the Stock Exchange of Thailand includes shares issued by listed companies, unit trusts, derivatives, pooled investment products and bonds.

2.1.1 SET Index

The Stock Exchange of Thailand Index or the SET Index is an index which represents the stock price in the market movement for common stocks traded in the SET. The SET Index was analyzed from the SET and the SET50. The SET Index is calculated from the prices of every common stock on the market. The SET50 Index is calculated from the 50 common stocks with high liquidity on the market and market capitalization. The SET also provides industry group indices and sector indices. Both types of indices are calculated from the prices of the common stocks at the same fundamentals which characterize each particular industry group and sector.

Although the SET Index has 25 sector indices, most investors are interested to invest in not more than 15 sectors because some sectors have so little liquidity that the investors are not interested to invest. Therefore, an introduction of only 8 sector indices is as follows.

- 1. Banking
- 2. Finance and Securities
- 3. Communication
- 4. Energy
- 5. Property
- 6. Electronic Components
- 7. Entertainment and Recreation
- 8. Building and Furnishing

2.1.2 Stock Repurchases

All companies creating profits regularly have two uses for their profits. First, a part of the profits is usually repaid to their stockholders in form of dividends type. For the remainder and termed retained earnings, the companies keep the profits inside and used them for investing in the future projects of the companies. If the companies can reinvest most of their retained earning profits, then they may do so. However, sometimes the companies may find some or all of their retained earnings cannot be reinvested to produce acceptable returns.

Stock repurchases are one of possible uses of retained earning profits. When a company repurchases its own stocks, it reduces the number of the company stocks held by the company as announced in public. If profits were to remain the same, this would have the effect of increasing earnings per share or EPS. So stocks repurchasing, particularly when a company's share price is undervalued or depressed, can provide a competitive return on investment.

A reason why all companies may keep a substantial portion of retained earnings rather than distributing it to the stockholders even if the companies are not able to reinvest or make them all profitably is considered very embarrassing for the companies to be under pressure to be on cut dividends. Normally, investors have more opposed reaction in dividend cut than delay or even restraint of the stock repurchase program. So, rather than paying out larger dividend periods of excess profitability that the companies have to reduce during leaner times, the companies prefer to pay out a conservative portion of the companies' earnings, perhaps a half, with the aim of maintaining an acceptable level of dividend.

Another reason why executives of the companies in particular may prefer the stock repurchases is that executive compensation is often tied to the executives' skill to meet earnings per share targets. In companies where there are few opportunities for growth, the stock repurchases may represent one of the ways of improving earnings per share of the companies in order to meet the targets. Therefore, protections should be in place to ensure the increasing earnings per share. This way will not affect executive or managerial rewards. Furthermore, the increasing earnings per share do not equal an increase in stockholder value. This investment is influenced by choices of the companies' accounting policy and falls to take into account the cost of capital and cash flows, which are the determinants of the stockholder value.

The stock repurchases avoid the accumulation of immoderate amounts of cash in companies. The companies with strong cash liquidity and limited needs for capital investment will accumulate cash on the balance sheet, which makes them more attractive targets for a takeover, since the cash can be used to pay for debts incurred to carry out the acquisition. The companies avoid takeover strategies and thus maintain a lean cash position. At the same time, the stock repurchases support the stock price, which makes the takeover more expensive. Types of the stock repurchases are as follows.

2.1.2.1 Open market stock repurchases are common stock repurchase programs most popular in the United States. The open-market stock repurchases represent almost 95% of all repurchases in the US. Many companies may or may not announce that it will repurchase some stocks in the open market from time to time as market conditions force and maintain the options of decision. The problems are when and how much number of intention of repurchase. The open market repurchases can extend for months or even years. However, daily stock repurchases are limited and restrict the amount of stocks that can be bought over a particular time.

2.1.2.2 Fixed price tender offer repurchases started from 1981, and tender offer repurchases were using a fixed price tender offer. A tender offer will ask the stockholders of the target firm to tender their shares in stock repurchase for the offered price. The offer may be made conditional upon receiving tenders of a minimum number of stocks. And it may permit withdrawal of the tendered stocks prior to the offer's last day of expiration. The stockholders decide whether or not to participate and the number of stocks to be tendered to the firm at the specified price. Frequently, officers and directors are precluded from participating in the tender offer. If the number of the tendered stocks exceeds the number of the sought one, the companies will purchase less than all stocks tendered at the purchase price basically from all who tender them at the purchase price. If the number of the tendered stocks is below the number of the sought one, the companies may choose to extend the offer's last day of expiration.

2.1.2.3 Dutch auction stock repurchases The introduction of the Dutch auction share repurchases was in 1981. The Dutch auction offers a price range within which the shares will be purchased. The stockholders are invited to tender their stocks at any price within the stated range. The firm then compiles these responses for creating a demand curve for the stocks. The purchase price is the lowest price that allows the firm to buy the number of the sought stocks in the offer, and the firm pays that price to all investors who have tendered them at or below that price. If the number of the tendered stocks exceeds the number of the sought one, then the company purchases less than all stocks tendered at or below the purchase price from all who tender them at or below the purchase price. If too few stocks are tendered, then the firm either cancels the offer or repurchases all tendered stocks at the maximum price.

2.1.3 Stock price fluctuation

The stock price fluctuation refers to the theory of supply and demand. Stocks are traded at places called exchanges. At these exchanges, there are many buyers and sellers of stocks of companies. Like commodities market, the price of a stock directly depends on the demand. However, many factors affecting the basis of the demand in particular may influence the stock price to increase or decrease. These factors are studied using methods of fundamental analysis and technical analysis to predict the changes in the stock price. For example, if investors have more demand to buy than to sell the stocks, the price will shift up because the stocks are rarer and the investors will pay the higher price for the rarer stocks. On the other hand, if the investors have a lot of stocks for sale and no other investor is interested in buying these stocks, the price will quickly fall down. The stock price also changes based on the forecast of the companies and whether their profits are expected for an increase or a decrease of the stock price.

As a result, the market can seem to fluctuate if there are the remains with the companies and a large number of stockholders try to sell millions of the stocks at a time when the price of the stocks falls down. There are not enough investors interested in buying these stocks that the stockholders are trying to sell because there is no real demand for the companies whose stocks are sold by the large number of the stockholders. Thus, they are forced to accept a lower price. Basically, the stocks perform their best, but it is up to the investors which stock they believe in. To go deeper will help understand better.

2.1.3.1 Demand and Supply In stock market investment, the stock price falls down when the sellers' demand is over the buyers'. However, if there are more investors who want to buy the stock than the number of the stockholders who are willing to sell the stocks they are holding, the price will shift up. As a result, the stock prices fluctuate daily. This is a classic example of the law of demand and supply in the world market.

2.1.3.2 Market Mind Effect Demand and supply for the stocks refers to market mind effect. Investors sell their equities and leave the company. On the other hand, if the investors forecast that the stocks will grow in future, they will buy more stocks to get better returns or profits on investment. Unfortunately, the most obvious factors of the market mind effect are interest rates, inflation rate, company earnings reports, company news or events, energy prices, war and terrorism as well as local and worldwide political stability. To make the news

popular and gain most viewers, great things can be bad actuality sometimes. Therefore, it is good to filter the information with extra care and not to let media control investor investment logic.

2.1.3.3 Individual Investor Needs is most difficult to find out but this is the main reason why the stock prices daily fluctuate. Investors who buy the stocks have decided the price to buy or sell even before they purchase any stocks. As a result, if everything remains the same, the stock prices may fluctuate due to investor activities. Moreover, seasonal investors have trading tools to find out when they should buy or sell for maximum profits and minimum risks. The investors can also take advantage of the daily price fluctuation if they understand how a technical analysis works.

2.1.4 Stock analytical models

There are several stock analytical models. However, the objective of the analysis is to determine which stock to buy and at what price, and there are two basic methodologies.

2.1.4.1 Fundamental analysis is a valuation of the stocks based on the analysis of fundamental factors, such as company income statements, company management and company competitors.

The fundamental analysis represents the historical data, but with the goal of making financial forecasts. There is a belief that the stocks are priced in a rational manner based on macroeconomic information, industry news, the company's income statement and several factors to conduct a company stock valuation and predict probable stock price evolution. An increase or a decrease of the stock price depends on a projection on company performance to evaluate company management and an internal company decision making process to calculate company credit risk.

The fundamental analysis refers that markets may influence the price of a security in the short run but that the correct or actual price will eventually reach. Profits can be made by trading the price of the security and then waiting for the market to recognize its mistake and compensate for the security.

2.1.4.2 Technical analysis is a stock analysis of price and volume data as well as other related market indicators of the future ways of price directions to determine the past market trends. Investors believe that the trends can predict the future. The technical analysis considers the charts and the graphs on the actual price and the volume of stock behavior of the

market. Technical analysts may use models and trading rules based on the price and the volume of stock transformations, such as the relative strength index, moving averages, regressions and price correlations, through recognition of chart patterns.

The technical analysis believed that the prices are largely determined by investor behavior and by supply and demand, even when demand may seem irrational. It can determine a direction or a trend of the actual price of the company, market, currency or commodity in the future. The technical analysis is based on the charts. The technical analysis chart gives direction ways of the price and volume information whereas the fundamental analysis does look at the facts of the company, market, currency exchange or commodity.

This thesis performs the fundamental analysis on the historical data. The closing price, the SET index and the volume of repurchase are input data used for learning algorithm in Neural Network. The output is the next day's closing price.

2.2 Artificial Neural Network¹

An artificial Neural Network is a mathematical abstraction to simulate the structure of biological neuron in a functional human brain. The brain is a highly complex, non-linear and parallel computer. In most case, neural networks solve non-linear problem data. The Neural Network model is used to find complex relationships between input and output data.

The artificial Neural Network is created to simulate biological neuron systems. The human brain consists primarily of nerve cells called neurons, linked together with other neurons called axons. Axons are used to transfer the nerve stimulated from one neuron to another neuron. A neuron is connected to the axons of other neurons called dendrites, which are extensions from the cell body of the neuron. The contact point between a dendrite and an axon is called a synapse. Neurologists have discovered the human brain learning by changing the strength of the synaptic connection between the neurons upon repeated stimulation.

Similar to the human brain structure, an ANN is composed of a connected assembly of nodes and directed links. In this section, the examiner ANN models, with the basic model called

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Satish Kumar. (2004). Neural Networks a classroom approach. Control Engineering, (pp. 42)

perceptron, show the models can train to solve classification problems. Consider the diagram of ANN shown in Figure 2.1. The table 2.1 shows a comparison between biological and artificial neural networks.

Table 2.1 Comparison between biological and ANN.

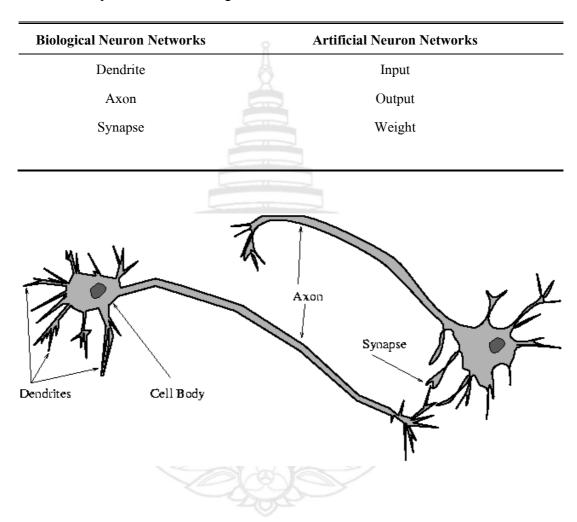


Figure 2.1 Biological neural networks.

The artificial neural networks emerged after the introduction of simplified neurons from Figure 2.1 (McCulloch & Pitts, 1943). These neurons were presented as models of biological neurons and as conceptual components that could perform a computational process. The basic model of the neuron finds the functions of a biological neuron.

The neuron has main regions of its structure. The cell body consists of the dendrites and the axons which end in the synapse. The cell body is the center of the cell, containing the nucleus and protein synthesis. Neurons have many dendrites and receive signals from other neurons. A neuron usually has only one axon which grows from a part of the cell body called the axon which conducts electric signals at the axon down its length. These electric signals are called action potentials. The other end of the axon may split into several spreads. The action potentials are the electric signals that the neurons use to communicate information to the brain. All these signals are identical. Therefore, the brain determines what types of information are being received based on the path that the signal takes.

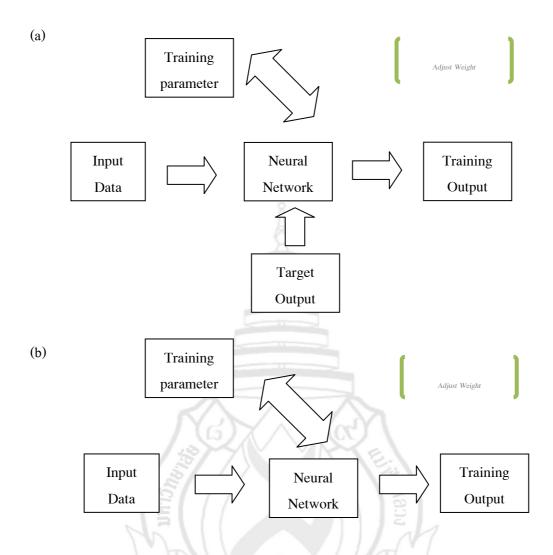
The artificial neural network model consists of two major learning paradigms, each of which corresponds to a particular learning process. These are supervised learning and unsupervised learning. Usually, any given type of network architecture can be employed in any tasks.

2.2.1 Supervised Learning

Supervised learning is the mainstream of neural network, a learning process for learning a function from training data. The basic block diagram of the supervised learning for neural network models can be described in figure 2.2(a). The training data consist of a number of input and output pairs. The output vector in the training data sets the functions for neural network learning. The output of training process can be a continuous value called regression, or can predict a class of the inputs called classification. The training procedures and the network adjust weight by the error signal that the output tries to follow to the desired output as close as possible. To achieve this, the learning procedure continues until the error is close to zero or below the predefined output. A common method of teaching artificial neural networks as the supervised learning method in terms of Back propagation Algorithm is popular.

-

¹ Tommy W S Chow, and Siu-Yeung Cho. (2007). Neural Networks and Computing. Imperial College Press, (pp. 6)



Source: Neural Networks and Computing, Imperial College Press, 2007

Figure 2.2 (a) Supervised Learning.

(b) Unsupervised Learning.

2.2.2 Unsupervised learning¹

Unlike the supervised learning, unsupervised learning does not have a teacher in the training data set. The learning process of the unsupervised learning is carried out from self-organizing behavior. In the course of training, no external factor is used to affect the weight

¹ Tommy W S Chow, and Siu-Yeung Cho. (2007). Neural Networks and Computing. Imperial College Press, (pp. 17)

adjustment of the network. The correct outputs are not available during the course of training. For instance, a typical unsupervised learning consists of an input layer and a competitive layer. Neurons on the competitive layer complete each other via a simple competitive learning rule to best represent a given input pattern. Through the competitive learning, the network output automatically reflects some statistical characteristics of input data such as data cluster, topological ordering etc. The unsupervised learning process is shown in figure 2.2(b).

2.2.3 Multilayer Feedforward Networks ¹

A Network is a more complex structure than that of a perceptron model. The additional complexities in a number of ways are described below:

A feedforward network consists of an input layer and a single layer of neurons. Such single-layer feedforward network is not capable of classifying nonlinear problems. Multilayer feedforward network has become the major and widely used supervised learning neural network architecture. In the feedforward networks, all connections are in one direction from input to output layers.

The multilayer network may contain several hidden layers between the input and the output layers. Such hidden layers are called intermediary layers and the nodes embedded in these layers are called hidden nodes. The resulting structure is known as a multilayer neural network. In a feed-forward neural network, the nodes in one layer are connected to the nodes in the next layer. The perceptron is a single-layer, feed-forward neural network because it has only one layer of the nodes. The output layer performs a complex mathematical operation. In a recurrent neural network, the links may connect the nodes within the same layer or the nodes from one layer to the previous layers as shown in Figure 2.3.

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¹ Tommy W S Chow, and Siu-Yeung Cho. (2007). Neural Networks and Computing. Imperial College Press, (pp. 14)

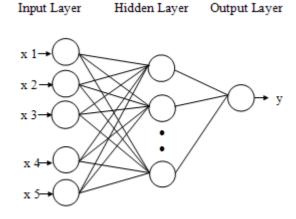


Figure 2.3 A multilayer artificial neural network.

2.2.4 Backpropagation Algorithm

Multilayer neural networks have been applied to solve difficult problems through employing various supervised learning procedures among which the error Backpropagation (BP) learning algorithm appears to be the most popular. This algorithm is an iterative gradient based algorithm proposed to minimize errors between the actual output vector of the network and the desired output vector. Because of the nonlinearity of neural models, algorithms for the supervised training are mainly based upon the nonlinear optimization methods. In the following, the batch-mode training using the backpropagation algorithm will be described.

For notation convenience, the layers are numbered from the bottom up beginning with 1. Analogous to the single-layer perceptron, layer 1 consists of fanout processing neurons that simply accept the individual elements of the input patterns and pass them directly to all units of layer 2. Each neuron on other layers receives the weight signal from each of neurons of the layer below. After the summation and the activation function operations, the output is distributed to all neurons of the upper layer next to this layer.

This thesis uses the supervised learning in a process of a function of training sets. Moreover, a multilayer neural network, the backpropagation algorithm (Raul Rojas, 1996), has been applied to solve the stock repurchase prediction output.

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¹ Satish Kumar. (2004). Neural Networks a classroom approach. Control Engineering, (pp. 167)

2.2.5 Absolute percentage error¹

Absolute percentage error is measure of accuracy in a fitted value in specifically trending statistics. It usually expresses the accuracy as a percentage.

$$APE = \left| \frac{A_t - F_t}{A_t} \right| *100 \tag{2.1}$$

The difference between the actual value A_i and the forecast value F_i , is divided by the actual value A_i again. The absolute value of this calculation is summed for every fitted or forecast point in time. This makes it a percentage error so one can compare the error of fitted time series that differ in levels.

This thesis applies the absolute percentage error to compare the output between classic prediction, proposed training and validation training.

2.3 Classic Prediction²

Classic Prediction is a financial tool to forecast the stock price after repurchase. In this thesis, the classic prediction is used to compare with the proposed training. The effect of the repurchase on the EPS and the market price per share of the remaining stocks can be analyzed as follows:

Earning Per Share (EPS) is generally considered to be the most important variable in determining a stock price

$$EPS_b = \frac{\text{Earnings}}{\text{TS}_b}, \tag{2.2}$$

¹ The free encyclopedia. (2008). **Absolute Percentage Error**. Retrieved Sep 3 2008, From http://en.wikipedia.org/wiki/absolute_percentage_error.

² Eugene F. Brigham, and Phillip R. Daves. (2002). Intermediate Financial Management 7th Edition. South-Western, (pp. 583-584)

where EPS_b, Earnings and TS_b are the earning per share before repurchase, total earnings and total stocks before repurchase respectively.

Price-Earning ratio (P/E) is a valuation ratio of a firm's current stock price compared to its per-share earnings

$$P/E_b = \frac{P_b}{EPS_b} \tag{2.3}$$

where P_b is the stock price of the firm before the repurchase is given by,

EPS after repurchase (EPS_a) is the earning per share after repurchase

$$EPS_{a} = \frac{Earnings}{TS_{a}}$$
 (2.4)

where TS_a is total stocks after repurchase.

The expected market price after repurchase (P_a) is the stock price that investors would receive.

$$P_{a} = (P/E_{b})(EPS_{a})$$
 (2.5)

2.4 Related Works

Generally, forecasting the effect of stock repurchase can be developed by applying three different information retrieval models including a statistical based approach, a time series based approach and a Neural Network approach. Finally, three different approaches are applied to the proposed research method in this thesis.

2.4.1 Statistical Approach

The statistical approach is commonly used for prediction in terms of finance. The main objective of the topic was to find the closing price after repurchasing. Grullon and Michaely (2002) used financial equations that the authors analyzed as methods based on earning per share, price-earning ratio, earning per share after repurchasing and the expected market price after

repurchase. Hellstrom (1999) created the stock trading model from a calculation formula. Forecasting accuracy, this technique depends on calculating functions and buying-selling rules.

The advantage of the statistical approach is that it is easy to understand for the common users of financial systems and does not have any complex form with simple mathematics. The disadvantages of this approach are to use too many historical data, which is hard to collect the data set. Moreover, the prediction is usually low accurate because the stock repurchase price prediction consists of many unpredictable factors in mathematics.

2.4.2 Time Series Approach

The time series approach is a sequence of the past data, and the model of time series is used to predict the future trend or future behavior based on the past known behavior data. A lot of data are measured for forecasting. A simple example is the closing price of the stock market based on the past repurchase.

The time series is used in many ways for Stock Market Forecasting Using Hidden Markov Models (Rafiul Hassan and Baikunth Nath 2000). The research objective was to predict the next day's closing price using Hidden Markov Models. The training data set was one and a half year daily data and the efficiency of the model was tested using the preceding three month's data. The input data for a stock at the daily market closing price values of the four variables featured opening, high, low and closing prices while using this information to predict next day's closing prices.

The advantage of the time series approach is the prediction accuracy. The disadvantages of this approach are that many historical data are used and it is hard for common users to understand because the method is complicated.

2.4.3 Neural Network Approach

The Neural Network approach is a mathematics model used to solve the non linear problems as such stock price prediction does. One of the methods is Neural Network feedforward model for predicting the next day closing price. Input data consist of closing price, high and low index, and volume with 10 hidden nodes (Merkl, 1996), using the feedforward neural network model to predict the daily stock. The input data use the stock price to predict an increase or a decrease of the next day closing price (Kaplan, 2001). The feedforward neural network was used

to forecast the closing price in Philippine. Weekly data were used by training with 4-32 input nodes and 3-16 hidden nodes (Bautista, 2001).

The advantage of the non linear approach is the speed of the process of prediction. The disadvantages of this approach are that many data sets are used for prediction and the prediction accuracy depends on the input factors that are relevant to the output. If the input factors do not cover the stock behavior, then the prediction accuracy also decreases.

2.4.4 Proposed Method

This thesis applies the Neural Network approach to develop the prediction of the stock price after repurchasing with less input factors. However, this stock repurchase prediction does not use all of raw data factors or historical data as input data but this thesis use only 3 input factors which are the closing price, the SET index and the volume of repurchase. The time series approach for developing the techniques is used for finding effect of the stock repurchase under the same condition. This stock repurchase case cannot use all time series data sets because some of the data are missing. Like when companies used repurchase programs, the data of repurchase appeared. However, if the companies did not use the repurchase programs, the data of repurchase were missing. If the forecast of all of training sets was done, the results would give lower accuracy than being selected by a trend selection. The detail of the trend selection is later discussed in Chapter 3. Figure 2.4 show the system of forecasting the effect of stock repurchase via an artificial neural network.

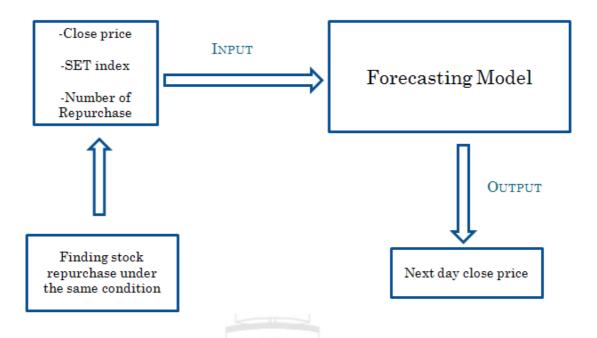


Figure 2.4 The system of forecasting the effect of stock repurchase via an artificial



CHAPTER 3

RESEARCH METHODOLOGY

In this chapter, the thesis uses an ANN based tool forecast for forecasting the stock market repurchase. The methodology for this research represents the price prediction for stock repurchase effect. The system overview is shown as figure 3.1.

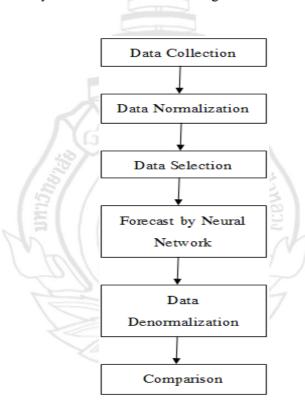


Figure 3.1 System overview

The system overview can be described by the following steps: data collection, data normalization, data selection, forecasting by neural network, data denormalization, and comparison.

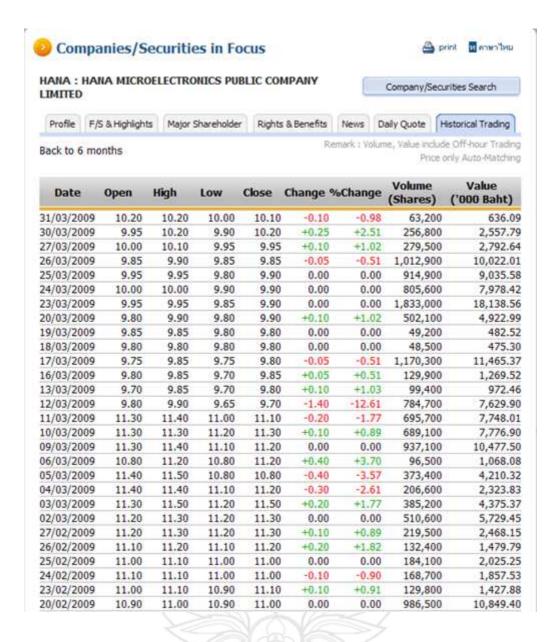
3.1 Data Collection

Referring to chapter 2, data collection is divided into 2 groups that consist of knowledge collection and historical statistics from the Stock Exchange of Thailand website. This thesis uses the historical statistics for the data collection. The input factors consist of the closing price, the SET index and the volume of repurchase.

- **3.1.1 Historical statistics.** Knowledge based historical statistics is a support technical analysis. The already closing price, the SET index and the volume of repurchase are enough input data for learning algorithm for the Artificial Neural Network to study the price moving pattern. Historical statistics data can be collected from 2 sources which are the Stock Exchange of Thailand and other Internet sources.
- 3.1.1.1 The Stock Exchange of Thailand can provide huge data in terms of company data. However, for technical analysis data older than 6 months, a permission to ask for the data is required. The advantage of this source is the data reliability but some data are lost.
- 3.1.1.2 The Internet provides the old data from the Stock Exchange of Thailand that the permission to ask for the data is required. More time is spent to collect the data and wasted on travel. So, some people upload the old data on the internet to help the investors. The advantage of this source is that the internet prepares only the technical analysis data and we do not spend more time to collect it. However, some data are lost.

To study the statistical information about the trading of the listed firms and collect historical trading from the Stock Exchange of Thailand is indicated in figure 3.2, 3.3 and 3.4 which show the data collection from the website www.set.or.th and select only the listed firms using repurchase programs. The data collection period starts from the 1st day that the listed firms use the repurchase programs. The amount of 105 days and 65 days of using the repurchase programs are considered as the sources.

In the experiment, the listed firm named HANA MICROELECTRONICS PUBLIC COMPANY LIMITED, HANA, is selected because this firm used the repurchase programs that the researcher collected from the first to the last day of using the repurchase programs.



Source: The Stock Exchange of Thailand, 2008

Figure 3.2 Example of historical trading of HANA.

The historical trading consists of the daily opening price (Open), the daily maximum price (High), the daily minimum price (Low), the daily closing price (Close), the yesterday closing price change (Change), the yesterday percentage closing price change (%Change), the trading share volume (Volume (share)) and the trading value (Value (thousand Baht)).





Symbol HANA Source HANA

Headline Form for Reporting Share Repurchases

Date/Time 27 Nov 2008 08:57:00

Form TS-3.2

Form for Reporting Share Repurchases
In the case where repurchasing the company's own shares is
for financial management purposes.
Hana Microelectronics Public Company Limited
Date November 26, 2008

- 1. Procedure for repurchasing shares
 - (/) On the Stock Exchange of Thailand
 The due date of the share repurchase project April 22, 2009
 (This process of share repurchase must be completed within 6 months)
 - () General offer
- 2. Share repurchasing for financial management purposes
 - 2.1 Date of the resolution of the board of directors to undertake share repurchases October 7, 2008
 - 2.2 The results of share repurchase Total Number of shares purchased 83,000,000 shares or equal to 9.99 % of paid-up capital.

Repurchased Number of shares Repurchase Lowest Total Date repurchased or Highest price price (Baht)

(Baht/share) (Baht/share)

November 26, 2008 496,700 8.45 8.40 4,175,115

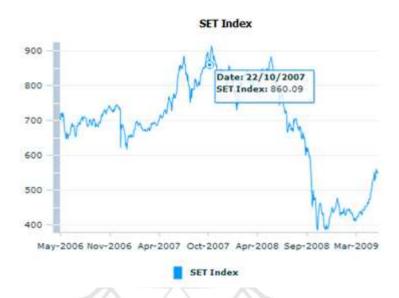
2.3 Cumulative number of shares repurchased Cumulative number of shares repurchased to date (including item 2.2) 736,700 shares or equal to 0.09% of paid-up capital which is 6,752,115 Baht in total.

The company certifies that the information contained in this report and attached documents are true and complete in all respects.

Source: The Stock Exchange of Thailand, 2008

Figure 3.3 Example of Reporting Stock Repurchases.

The reporting of the stock repurchase consists of the repurchase date, the number of repurchased shares, the repurchase highest price and the repurchase lowest price. The important data to be trained in the neural network is the number of the repurchased shares.



Source: The Stock Exchange of Thailand, 2008

Figure 3.4 Example of historical chart of SET Index.

The SET Index is not included in the historical trading. Therefore, we collected the SET Index data from the historical chart of the Stock Exchange of Thailand website. The SET index is one of the input data for training.

3.1.2 Data Analysis

From topic 3.1.1, the explained data is the historical statistics which are collected from many sources and need to be initially analyzed. Data analysis can be explained as data correctness.

3.1.3 Data Correctness

This thesis uses the data correctness to verify correctness of the data from 2 types of resources consisting of the Stock Exchange of Thailand and the internet. The data correctness criteria can be divided into 2 groups which are repeated and unrepeated data.

3.1.3.1 Repeated data is historical data that the Stock Exchange of Thailand permits the investors to download. The data collected from the Stock Exchange of Thailand provide the investors with the date, the opening price, the high, low, closing price and the volume. The data collected from the internet are compared for the data correctness by randomly matching the opening price, the high, low, closing price and the volume. The results show that the data from the SET are the same as the ones collected from the internet.

3.1.3.2 Unrepeated data is verified for the data correctness before being used in the model.

3.2 Data Normalization

Data Normalization is a systematic way of ensuring that a database structure is suitable for general-purpose querying and free of certain undesirable characteristics. The data is normalized using the Excel program by the given input closing price, the SET index and the number of the volume repurchase which has the value between 0-1 ranges as shown in the following formula. More details are discussed in chapter 4.

$$X' = \frac{(X - Min)}{(Max - Min)} \tag{3.1}$$

By X' = Data after normalization

X = Data before normalization

Max = Max data value before normalization

Min = Min data value before normalization

3.2.1 Transforming Dataset into a matrix

Data sets are transformed into a matrix using MATLAB program. In this case, a transformed design procedure determines this matrix from the dataset via Microsoft excel before being trained in the Neural Network.

3.3 Data Selection

An analysis of (often large) observation data is set to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner. The relationships and summaries derived through a data mining exercise are often referred to as models or patterns.

The goal of the techniques described in this topic is to detect relationships or associations between the specific values of categorical variables in large data sets. To find days under the same condition, the techniques scan a database only once to make a count on the possible 2 day-datasets from which only the 2 day-datasets with a minimum support are used for finding days under the same condition which explores the possible frequent large data sets in the database.

3.3.1 Data Selection is used to select two days of repurchase training data to predict next day of forecast. At the n^{th} day, the amount of possible training sets (a_n) is formulated as a binomial coefficient:

$$a_n = \binom{n-1}{2} \tag{3.2}$$

where n > 2. Let S_N be the space of the possible training sets for predicting the n^{th} day. The most suitable training set (s_n) , which is an element in S_N ($s_n \in S_N$), is selected by examining direction vectors that present the situation of the stock market. A rule-based data cluster is then used to group the repurchase days that are under the same conditions as the day before the next repurchase.

The data sets from the Stock Exchange of Thailand are composed of many parameters which are divided into the input and output data. From topic 3.1, the data collection might not be enough and affect a decision making process of the system prediction. This thesis brings the dataset to find a Technical Indicator as shown in figure 3.5. Using the Technical Indicator will give these values usefulness to increase accuracy of prediction.

	Α	В	С	D	E	F	G	Н	1	J	K	L	M	N
1							Close	Volume	Volume	Value			Close vs SET	Close vs Vol
2	Date	High	Low	Avg	Close	Chg	Chg%	(thousand)	Chg%	(M.Baht)	SET Index	SET Chg%	Chg%	Chg%
3	4/5/2009	12.4	12.1	12.21	12.2	0.1	0.83	494	28.54	6.04	506.26	2.96	0.28	0.03
4	30/4/2009	12.4	12	12.16	12.1	0.1	0.83	353	62.32	4.3	491.69	1.69	0.49	0.01
5	29/4/2009	12	11.9	11.91	12	0.2	1.69	133	55.64	1.59	483.5	2.28	0.74	0.03
6	28/4/2009	11.9	11.7	11.76	11.8	0.1	0.85	59	3.39	0.7	472.72	-0.48	-1.77	0.25
7	27/4/2009	12	11.7	11.81	11.7	-0.2	-1.68	57	-171.93	0.67	474.99	0.19	-8.84	0.01
8	24/4/2009	12	11.7	11.9	11.9	0.2	1.71	155	-58.06	1.85	474.07	1.72	0.99	-0.03
9	23/4/2009	12	11.7	11.86	11.7	-0.3	-2.5	245	-323.27	2.91	466.06	1.18	-2.12	0.01
10	22/4/2009	12.4	11.9	12.01	12	-0.2	-1.64	1,037	74.06	12.47	460.62	-1.24	1.32	-0.02
11	21/4/2009	12.2	11.5	11.86	12.2	0.5	4.27	269	-66.91	3.2	466.38	0.02	213.5	-0.06
12	20/4/2009	11.7	11.4	11.66	11.7	0.2	1.74	449	27.62	5.24	466.28	2.08	0.84	0.06
13	17/4/2009	11.5	11.2	11.39	11.5	0.1	0.88	325	12.92	3.71	456.8	0.85	1.04	0.07
14	16/4/2009	11.4	10.7	11.09	11.4	0.6	5.56	283	-499.65	3.15	452.97	-0.2	-27.8	-0.01
15	10/4/2009	10.8	10.4	10.75	10.8	0.3	2.86	1,697	33.29	18.26	453.88	2.21	1.29	0.09
16	9/4/2009	10.5	10.3	10.47	10.5	0.3	2.94	1,132	66.7	11.86	444.07	0.11	26.73	0.04
17	8/4/2009	10.3	9.95	10.09	10.2	0.25	2.51	377	33.42	3.81	443.57	0.23	10.91	0.08
18	7/4/2009	10	9.85	9.93	9.95	-0.05	-0.5	251	65.34	2.5	442.56	-0.78	0.64	-0.01
19	3/4/2009	10.1	10	10.03	10	0	0	87	-2387.36	0.88	446.04	0.7	0	0
20	2/4/2009	10.1	10	10	10	-0.1	-0.99	2,164	80.82	21.66	442.96	2.99	-0.33	-0.01
21	1/4/2009	10.1	10	10.01	10.1	0	0	415	84.82	4.17	430.09	-0.33	0	0
22	31/3/2009	10.2	10	10.06	10.1	-0.1	-0.98	63	-306.35	0.64	431.5	0.44	-2.23	0
23	30/3/2009	10.2	9.9	9.96	10.2	0.25	2.51	256	-8.98	2.56	429.6	-2.54	-0.99	-0.28
24	27/3/2009	10.1	9.95	9.99	9.95	0.1	1.02	279	-262.72	2.79	440.81	0.32	3.19	0
25	26/3/2009	9.9	9.85	9.89	9.85	-0.05	-0.51	1,012	9.68	10.02	439.4	0.57	-0.89	-0.05
26	25/3/2009	9.95	9.8	9.87	9.9	0	0	914	11.93	9.04	436.92	-0.28	0	0
27	24/3/2009	10	9.9	9.9	9.9	0	0	805	-127.7	7.98	438.16	0	0	0
28	23/3/2009	9.95	9.85	9.89	9.9	0	0	1,833	72.61	18.14	438.17	1.99	0	0

Figure 3.5 Technical Indicator.

Considering parameters that have the effect of the closing price after repurchase by using the relation analysis between the closing price and other parameters, the ones having more effect with the closing price lead to the input parameters with the least number to help the Neural Network learn faster.

Besides, each input parameter has different values that might have different weight data.

A process to change each parameter to the same values and weight is called Data Normalization.

3.3.2 Trend Selection

The contribution of this thesis is trend selection. The trend selection is necessary because the historical data or the law data that are collected from chapter 2 cannot represent repurchase missing data. For example, when companies used repurchase programs, the data of repurchase appeared. However, if the companies did not use the repurchase programs, the data of repurchase was missing. If the forecast of all training sets was done, the results gave less accuracy. The trend selection uses only 2 days of repurchase training patterns at the same condition. The 5 factors of the trend selection consist of the change in closing price, the change in volume, the change in the SET index, the relation of change between the closing prices and the SET index and the relation of change between the closing prices. To consider these factors by choosing the 2 days of

repurchase training patterns at the same condition, the results give better accuracy of the stock repurchase prediction. How to use the trend selection is shown in chapter 4.

The trend selection is a classification technique to forecast the effect of stock repurchases, which is the problem of forecasting the stock price after repurchase. At each period, the decision is based on finding a trend of the day that has been repurchased under the same condition of a dataset of observations of the Stock Exchange of Thailand. Each observation in the dataset is represented by a vector containing the values of some financial numerical attributes, for instance, the change in the closing price, the change in the SET index, the change in the stock volume, the relation of the change between the closing prices and the SET index, and the relation of the change between the closing prices and the volume stock. More precisely, this thesis classifies those observations as "I" that refers to the period when the value increases from yesterday, "D" when the value decreases from yesterday, and "U" when the value is unchanged from yesterday. The detail of the factors is as follows:

- 3.3.2.1 Change in the closing price refers to the price change of a particular company's stock that is being traded in any stock market at that particular time.
- 3.3.2.2 Change in the volume is the daily number of stock of a security that changes hands between a buyer and a seller. It is also known as volume traded. Also see up volume and down volume.
- 3.3.2.3 Change in the SET index is a measure of a section of the <u>stock market</u>. Many indices are cited by news or financial services firms and are used to benchmark the performance of portfolios.
- 3.3.2.4 The relation of change between the closing prices and the SET index refers to the relationship of the closing price and the SET index that is the same or different ways when they were changed.
- 3.3.2.5 The relation of change between the closing prices and the volume refers to the relationship of the closing price and the volume that is the same or different ways when they were changed.

3.3.3 Data Training

This thesis applied this technique to find the effect of stock repurchase. Normally, to train all of possible training sets by changing the input in each value to find more accurate forecast value requires much time to train every possible set. The technique for finding the day under the same condition is used to examine and select direction vectors that present the situation of the stock market based on the day before next day of repurchase as shown in figure 3.6.

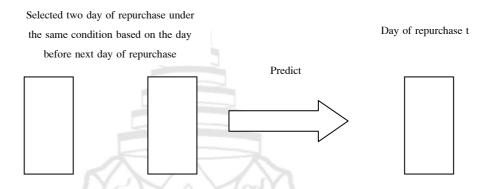


Figure 3.6 Proposed Method for training.

3.3.4 Validation Training

Validation training is used to forecast the effect of stock repurchase, which is another method to train that the repurchase days have passed. To forecast the next day effect of repurchase is shown in figure 3.7.

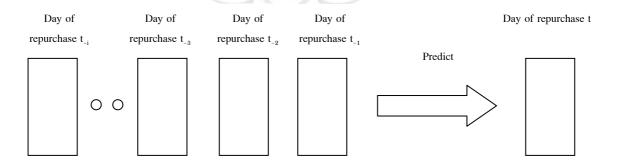


Figure 3.7 Validation training.

3.4 Forecast by Neural Network

A forecast by Neural Network, the first designed Artificial Neural Network model, is divided into 3 layers from neural network architecture consisting of input data, hidden layer and output data.

The general form of price prediction for stock repurchase is composed of three main parameters which are the closing price for the present day (CP_p), the market's index of the present day (Index_p) and the number of the intended stock repurchase for the next day (RP_n). To find the output of the next day's closing prices (CP_n), the operation of the trained ANN can be functionalized as:

$$[CP_n] = F_{ANN} \begin{pmatrix} CP_p \\ Index_p \\ RP_n \end{pmatrix}$$

Figure 3.8 The operation of trained ANN.

where F_{ANN} is a virtual function representing the transfer of the input factors to the output based on the trained ANN as shown in figure 3.8. The multi-layer back-propagation network ANN applied to model the effect of the stock repurchases is shown in figure 3.9.

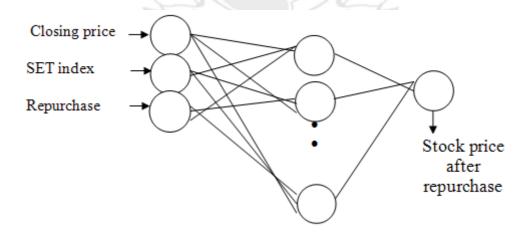


Figure. 3.9 The process for prediction in multi-layer artificial neural network.

In this thesis, the ANN architecture is composed of:

3.4.1 Supervised Learning: Backpropagation learning

3.4.2 Learning Rate: 0.05

3.4.3 Performance function: Mean Squared Error

3.4.4 Number of input node: 3

3.4.5 Number of output node: 1

3.4.6 Activation function: trainscg

3.4.7 Epochs for training: 1e6

3.4.8 Number of training pattern: 65

3.4.9 Number of testing pattern: 63

3.5 Data Denormalization

Data Denormalization is conversion of the data normalization way of ensuring a data value because, in terms of forecasting the effect of stock price after repurchases, the results have to be converted from the neural network output into the value before normalization. The denormalized data in Excel give the output next day closing price to change the value between 0-1 ranges into the data value before normalization as shown in the following formula. More details are discussed in chapter 4.

$$X = (X'(Max - Min)) + Min$$
(3.3)

By X = Data before normalization

X' = Data after normalization

Max = Max data value before normalization

Min = Min data value before normalization

3.6 Comparison

Referring to equation 2.1, to verify the ANN-based prediction errors is compared with the classic prediction, and their compared prediction accuracy is in terms of Absolute Percentage Error. It usually expresses the accuracy as a percentage.

$$APE = \left| \frac{A_{t} - F_{t}}{A_{t}} \right| *100$$

The difference between the actual value A_t and the forecast value F_t is divided by the actual value A_t again. The absolute value of this calculation is summed for every fitted or forecast point of time. This makes it a percentage error so one can compare the errors of the fitted time series that differ in level.

Below is the classic prediction equation, and this thesis can analyze equation (2.2)(2.4) and rewrite P_a referred from chapter 2 as follows:

$$P_{a} = \frac{P_{b}TS_{b}}{TS_{a}}$$
 (3.4)

3.7 System Requirements

Hardware

1. CPU: Pentium4 2.0GHz

2. Ram: 1GB

3. Hard disk: 80GB

4. VGA ATI X300 128bit 128MB

Software

1. MatlabR2008a

2. Microsoft office

3. Internet explorer

CHAPTER 4

RESULTS

This chapter explains research results step by step of forecasting the effect of stock repurchase via an artificial neural network and shows predicted error results of the proposed model, the validated model and the classic prediction.

4.1 Input Data Sets for Forecasting the Effect of Stock Repurchase via an Artificial Neural Network

This thesis uses the set of the repurchase prices of HANA and Major. The Major case is used for the test method in 4.4. The Hana case detail is shown as follows:

HANA MICROELECTRONICS PUBLIC COMPANY LIMITED, HANA, has traded the historical data in the Stock Exchange of Thailand market from the first day of repurchase on 25 November 2008 until the last day of repurchase on 24 April 2009. The trading historical data show especial Stock Exchange of Thailand office days. The total data sets are 100 days (data sets). An example of the data collected from the Stock Exchange of Thailand is shown in table 4.1.

Table 4.1 Example of data collected from SET on January 2009.

Data	Class	CET Indov	Repurchase
Date	Close	SET Index	(Thousand)
1/30/2009	11	437.69	10.1
1/29/2009	11	435.00	434.5
1/28/2009	11	448.35	705.6

Table 4.1 Example of data collected from SET on January 2009.(continued)

Date	Close	SET Index	Repurchase
			(Thousand)
1/27/2009	11.1	444.79	124.4
1/26/2009	11.1	436.73	
1/23/2009	10.7	433.52	40.1
1/22/2009	10.5	438.27	230.1
1/21/2009	10.6	431.23	20.0
1/20/2009	10.5	433.19	111.0
1/19/2009	10.4	435.71	125.9
1/16/2009	10.5	435.20	
1/15/2009	10.7	426.26	644.5
1/14/2009	10.5	439.51	60.0
1/13/2009	10.3	433.81	
1/12/2009	10.5	452.80	159.0
1/9/2009	10.5	459.06	279.4
1/8/2009	10.8	465.03	1300.0
1/7/2009	10.6	462.96	
1/6/2009	10.5	473.15	
1/5/2009	10.3	478.69	1186.5

4.1.1 Input Data of SET

- Close is the closing price at time t.

- SET index is the SET index at time t.

- Repurchase is the number of repurchase at time t+1.

4.1.2 Output Data of SET

- Next day Close is the closing price at time t+1.

4.1.3 Min-Max Normalization

Referring to chapter 3, this thesis found that values of the input data were 3 types which are different limited valuable data. An example is shown in figure 4.2 and table 4.3, indicating that weight average of each value was very different in the data ranges. Then the limited value of data in the same ranges was used before training in the artificial neural network called data normalization. Min-max normalization was used to the data normalization as shown as an example in table 4.4 and table 4.5.

Table 4.2 Example of closing price input data value before data normalization.

Close	Close	Close	Close	Close	Close
T-5	T-4	T-3	T-2	T-1	
8.5	8.65	8.7	8.8	9	9.1

Table 4.3 Example of three input data values before data normalization.

	T-5	T-4	T-3	T-2	T-1	
Close	8.5	8.65	8.7	8.8	9	9.1
SET index	401.84	392.92	423.79	424.79	437.06	445.31
Repurchase	26.3	908.3	324.2	910.5	219.0	147.8

Table 4.4 Example of closing price input data value after data normalization.

Close	Close	Close	Close	Close	Close
T-5	T-4	T-3	T-2	T-1	
0.013333	0.053333	0.066667	0.093333	0.146667	0.173333

Table 4.5 Example of three input data values after data normalization.

	T-5	T-4	T-3	T-2	T-1	
Close	0.013333	0.053333	0.066667	0.093333	0.146667	0.173333
SET index	0.135351	0.034991	0.382313	0.393564	0.531616	0.624437
Repurchase	0.013032	0.533141	0.188701	0.534438	0.126666	0.08468

4.2 Techniques Used for Finding the Effect of Stock Repurchase

In chapter 3, the trend selection is used to find repurchase days under the same condition. After selecting the input data for training in the neural network, a preparation of the input data is set to the same range between 0-1 by the min-max normalization. In the next step, the data sets from HANA collected since the 1st day of 26 November 2008 on which the listed firm uses repurchase programs to the last day of using the repurchase programs on 22 April 2008, which is the especial SET office hours data, are analyzed. The amount of 105 days and 65 days of using the repurchase programs identify data elements.

Microsoft Excel filters functions used for finding days under the same condition to examine direction vectors that present the situation of the stock market based on the day before the next day of repurchase. The parameters presenting the situation of the stock market consists of the closing price, the SET index, the volume, the relationship between the closing price and the SET index, and the relationship between the closing price and the volume. To forecast the effect of the stock repurchase, two days of the repurchase day under the same condition were used as the day before the next day of repurchase is not the repurchase day as shown in figure 4.1. Assuming that the day before the next day of repurchase is also the repurchase day, only one day of the repurchase day that match the latest repurchase day is selected to forecast the next day of repurchase as shown in figure 4.2.

Date	Close	Volume	SET	Close vs Vol	Close vs Set	SET index	Repurchase Date	
t+1	unknow	unknow	unknow	unknow	unknow	unknow	6	Forecasting day
t	u	i	i	ui	ui	424.61		Day before next day of repurchase day
t-1	i	i	i	Ï	i	423.79	5	
t-2	u	i	i	ui	ui	410.58		
t-3	i	d	d	id	id	392.87		
t-4	u		į	ui	ui	392.92	4	Day under the same condition with day before next day of repurchase day
t-5	d	i	d	di	dd	387.32		
t-6	i	d	d	id	id	390.92		
t-7	u	d		ud	ui	401.84	3	Day under the same condition with day before next day of repurchase day
t-8	i	d	d	id	id	389.81	2	
t-9	d	i	i	di	di	395.22	1	
t-10	d	i	i	di	di	391.85		

Figure 4.1 Example of data sets selecting two days of repurchase day under the same condition as the day before next day which is not repurchase day.

Date	Close	Volume	SET	Close vs Vol	Close vs Set	SET index	Repurchase Date	
t+1	unknow	unknow	unknow	unknow	unknow	unknow	7	Forecasting day
t	i	i	i	i	i	424.79	6	Day before next day of repurchase day
t-1	u	i	i	ui	ui	424.61		
t-2	i	i	i	i	ij	423.79	5	Day under the same condition with day before next day of repurchase day
t-3	u	i	i	ui	ui	410.58		
t-4	i	d	d	id	id	392.87		
t-5	u	i	i	ui	ui	392.92	4	
t-6	d	i	d	di	dd	387.32		
t-7	i	d	d	id	id	390.92		
t-8	u	d	i	ud	ui	401.84	3	
t-9	i	d	d	id	id	389.81	2	
t-10	d	i	i	di	di	395.22	1	
t-11	d	i	i	di	di	391.85		

Figure 4.2 Example of data sets selecting one day of repurchase day that match the latest repurchase day.

Suppose days of the repurchase day under the same condition are more than two days, then the two days of the repurchase day are selected by the SET index nearest to the day before the next day of repurchase or the latest repurchase base day to forecast the next day of repurchase as shown in figure 4.3.

				Close vs	Close vs		Repurchase	
Date	Close	Volume	SET	Vol	Set	SET index	Date	
t+1	unknow	unknow	unknow	unknow	unknow	unknow	10	Forecasting day
t	Υ,	Υ,	i 🔻	i 💌	i i	445.94	9	Day before next day of repurchase day
t-1		i	i	i	i	445.31	8	Day under the same condition with day before next day of repurchase day
t-3		i	i	ï	ï	424.79	6	
t-5	i	i	i	i	i	423.79	5	

Figure 4.3 Example of data sets selecting day of repurchase day by SET index nearest to the day before next day of repurchase if days under the same condition are more than two days.

After selecting the days under the same condition from the direction vectors that present the situation of the stock market, then the input data sets that are selected by the technique are led to find the day under the same condition to train in the neural network to forecast the effect of the stock repurchase on the next day closing price.

4.3 Data Denormalization

Data Denormalization is to convert the data normalization way of ensuring a data value. As for forecasting the effect of the stock price after repurchases, the results have to be converted from the neural network output into value before normalization. The denormalized data in Excel which give the output of the next day closing price to change value between 0-1 ranges into the data value before normalization are shown in table 4.6 and 4.7.

Table 4.6 Example of data value of closing price output before data denormalization.

Close	Close	Close	Close	Close	Close
T-5	T-4	T-3	T-2		
0.0814	0.1182	0.1398	0.2126	0.1844	0.3857

Table 4.7 Example of data value of closing price output after data denormalization.

Close	Close	Close	Close	Close	Close
T-5	T-4	T-3	T-2	T-1	
8.76	8.89	8.97	9.25	9.14	9.90

4.4 Forecasting Measurement of the Effect of Stock Repurchase Method for Next Day of Repurchase Output

To verify the ANN-based prediction errors to be compared with the classic prediction ones, both of their prediction accuracy is compared in terms of Absolute Percentage Error. It usually expresses the accuracy as a percentage. The output value range of not more than 0.2 compared with the actual price is accepted.

The forecast of the effect of stock repurchase cases is divided by using 2 listed firms which are Hana and Major from the Stock Exchange of Thailand market. In each listed firm, the technique is used for finding days under the same condition by matching 2 days, 4 days and 7 days at the nearest or under the same condition and using the method from topic 4.2.

4.4.1 Classic Prediction Equation

To find the stock price after being repurchased on the classic prediction equation gives results as follows:

Table 4.8 Classic prediction equation of Hana case.

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
	(Days)	(Days)	
Classic prediction	26		53.8
equation	20		33.0

Prediction method: Classic prediction equation

Prediction output value range < 0.1: 26 days

Prediction output value range < 0.2: 9 days

Prediction accuracy: 35 days

Result percentage: 53.8 percent

Table 4.9 Classic prediction equation of Major case.

Prediction	Prediction output value range < 0.1	Prediction output value range < 0.2	Accuracy Result (%)
	(Days)	(Days)	
Classic prediction	22	17	60
equation	22	1 /	00

Prediction method: Classic prediction equation

Prediction output value range < 0.1: 22 days

Prediction output value range < 0.2: 17 days

Prediction accuracy: 39 days

Result percentage: 60 percent

From table 4.8 and 4.9, it can be shown that the classic prediction equation of both Hana and Major cases provides the average accuracy of 56.9 percent.

4.4.2 Proposed Training by selecting 2 Days under the same condition

To find the stock price after repurchase on the proposed training by selecting 2 days under the same condition and using the matching method gives results as follows:

Table 4.10 Proposed training by selecting 2 days of Hana case.

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
	(Days)	(Days)	
Proposed training by	30	15	71.4
selecting 2 days	30	13	/1.4

Prediction method: Proposed training by selecting 2 days under the same condition

Prediction output value range < 0.1: 30 days

Prediction output value range < 0.2: 15 days

Prediction accuracy: 45 days

Result percentage: 71.4 percent

Table 4.11 Proposed training by selecting 2 days of Major case.

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
	(Days)	(Days)	
Proposed training by	35	14	77.8
selecting 2 days	33	14	//.8

Prediction method: Proposed training by selecting 2 days under the same condition

Prediction output value range < 0.1: 35 days

Prediction output value range < 0.2: 14 days

Prediction accuracy: 49 days

Result percentage: 77.8 percent

From table 4.10 and 4.11, it can be shown that the proposed training by selecting 2 days of both Hana and Major cases provides the average accuracy of 74.6 percent.

4.4.3 Proposed Training by selecting 4 Days under the same condition

To find the stock price after repurchase on the proposed training by selecting 4 days under the same condition and using the matching method gives results as follows:

Table 4.12 Proposed training by selecting 4 days of Hana case.

Prediction	Prediction output value range < 0.1 (Days)	Prediction output value range < 0.2 (Days)	Accuracy Result (%)
Proposed training by	24	18	66.6
selecting 4 days	2 4	10	00.0

Prediction method: Proposed training by selecting 4 days under the same condition

Prediction output value range < 0.1: 24 days

Prediction output value range < 0.2: 18 days

Prediction accuracy: 42 days

Result percentage: 66.6 percent

Table 4.13 Proposed training by selecting 4 days of Major case.

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
	(Days)	(Days)	
Proposed training by	27	16	(9.2
selecting 4 days	27	16	68.2

Prediction method: Proposed training by selecting 4 days under the same condition

Prediction output value range < 0.1: 27 days

Prediction output value range < 0.2: 16 days

Prediction accuracy: 43 days

Result percentage: 68.2 percent

From table 4.12 and 4.13, it can be shown that the proposed training by selecting 4 days of both Hana and Major cases provides the average accuracy of 67.4 percent.

4.4.4 Proposed Training by selecting 7 Days under the same condition

To find the stock price after repurchase the on the proposed training by selecting 7 days under the same condition and using the matching method gives results as follows:

Table 4.14 Proposed training by selecting 7 days of Hana case.

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
	(Days)	(Days)	
Proposed training by	10	17	57.1
selecting 7 days	19	17	57.1

Prediction method: Proposed training by selecting 7 days under the same condition

Prediction output value range < 0.1: 19 days

Prediction output value range < 0.2: 17 days

Prediction accuracy: 36 days

Result percentage: 57.1 percent

Table 4.15 Proposed training by selecting 7 days of Major case.

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
W	(Days)	(Days)	
Proposed training by	10		(1.0
selecting 7 days	18	21	61.9

Prediction method: Proposed training by selecting 7 days under the same condition

Prediction output value range < 0.1: 18 days

Prediction output value range < 0.2: 21 days

Prediction accuracy: 39 days

Result percentage: 61.9 percent

From table 4.14 and 4.15, it can be shown that the proposed training by selecting 7 days of both Hana and Major cases provides the average accuracy of 59.5 percent.

4.4.5 Validation training

To find the stock price after repurchase on the basic method by training all repurchase days to pass and find the next days of repurchase gives results as follows:

Table 4.16 Validation training of Hana case.

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
	(Days)	(Days)	
Validation training	10	18	44.4

Prediction method: Validation training

Prediction output value range < 0.1: 10 days

Prediction output value range < 0.2: 18 days

Prediction accuracy: 28 days

Result percentage: 44.4 percent

Table 4.17 Validation training of Major case.

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
`	(Days)	(Days)	
Validation training	14	17	49.2

Prediction method: Validation training

Prediction output value range < 0.1: 14 days

Prediction output value range < 0.2: 17 days

Prediction accuracy: 31 days

Result percentage: 49.2 percent

From table 4.16 and 4.17, it can be shown that the validation training of both Hana and Major cases provides the average accuracy of 46.8 percent.

CHAPTER 5

DISCUSSION

This chapter discusses the result s of forecasting the effect of the stock repurchase from the previous chapter. The results can summarize the ways that the Artificial Neural Network back-propagation model is applied to the trend selection technique in this thesis contribution by selecting 2 days, 4 days and 7 days for training to be compared with other 2 methods which are the financial equation and the validation training.

5.1 Discussion

As the numbers of the listed firms in the Stock Exchange of Thailand tend to grow rapidly in the next future years and the numbers of the listed firms using the repurchase programs increase, it is interesting to do a research of characterizing the effect of the stock repurchase via an artificial neural network.

According to this thesis result, an ANN has been applied to forecast the effect of stock repurchasing. The back-propagation ANNs are trained by a set of the closing prices before and after repurchase, the amount of repurchase and the index of the stock market. The validity test is simulated from practical utilization so that the training data is a combination of two passing repurchase days, which face similar market's conditions as the day before the next repurchase. The prediction errors of the proposed and the classic methods are compared day-by-day. The ANN-based prediction is more accurate after several repurchase days have passed as there are more combinations of the training sets available.

The predictions compared among the classic predictions, the proposed training and the validation training are shown in table 5.1 for Hana's case and table 5.2 for Major's case.

Table 5.1 Measurement of three prediction accuracy of Hana's case

Prediction	Prediction output value range < 0.1	Prediction output value range < 0.2	Accuracy Result (%)
	(Days)	(Days)	
Classic prediction	26	0	53 9
equation	26	9	53.8
Proposed training by	20	15	71.4
selecting 2 days	30	15	71.4
Proposed training by	24	18	66.6
selecting 4 days	24	18	00.0
Proposed training by	19	(C) 17	57.1
selecting 7 days	39	17	37.1
Validation training	10	18	44.4

Table 5.2 Measurement of three prediction accuracy of Major's case

Prediction	Prediction output	Prediction output	Accuracy
	value range < 0.1	value range < 0.2	Result (%)
	(Days)	(Days)	
Classic prediction	22	17	60
equation	22	17	60
Proposed training by	a. A	1.4	77 0
selecting 2 days	35	14	77.8
Proposed training by			40.5
selecting 4 days	27	16	68.2
Proposed training by			
selecting 7 days	18	21	61.9
Validation training	14	17	49.2

The results give the satisfying ones as shown in table 5.1 and table 5.2 which indicate that the proposed training by selecting 2 days is better than selecting 4 days, 7 days, the classic prediction and the validation training.

The best result is the proposed training by selecting 2 days of repurchases because the limitation of the Neural Network architecture may compute a lot of training sets to increase more prediction errors. However, when the training sets increase by such as 4 days and 7 days, it does not make sure the prediction accuracy is better than 2 days. The results are shown in table 5.1 and 5.2.

The reasons why the results of the best case of the proposed training by selecting 2 days is still not accurate can be divided into 2 cases. First, the day before the next repurchase is not the repurchase day. Second, the day before the next repurchase is the repurchase day. However, there are many unpredictable factors on the basic of which demand and supply influences on the particular stock may increase and decrease the closing price.

CHAPTER 6

CONCLUSION

6.1 Conclusion

As the numbers of the listed companies using the stock repurchase tend to grow rapidly in the next future years, it is interesting to do a forecast the effect of the stock repurchase via an artificial neural network.

- 6.1.1 The artificial neural network with the technique used for matching days under the same condition can predict the effect of the stock repurchase price. The proposed training is flexible to the stock price fluctuation. However, this training cannot predict for more accuracy in terms of the more stock price fluctuation because the stock market has more direct effects changing rapidly within one day, such as news of the listed firms, investors' abnormally sold stock volume and etc. These factors affect the investors who have speculated the profit and the stock price fluctuation in the market.
- 6.1.2 The closing price is an indicator which arrives at the events or behavior in the stock market only one level, especially the events that have to continue more than one day because the factor that cannot cause that fluctuation is only the one that affects one exceeding day. Then, it can make a low accurate prediction when the factors change within one day because the continual buying-selling of most investors may influence the stock price fluctuation.
- 6.1.3 The ANN is flexible to support the fluctuation of the stock price after repurchase but cannot forecast it if the stock market fluctuates more because many internal and external factors have effects on the daily stock market, such as the oil price, Thai politics and epidemic, etc., which can influence the stock price after repurchase.

6.2 Future work and Suggestions

The proposed training by selecting 2 days of the repurchase prediction, which is the prediction error, demonstrates that there is the limitation of the repurchase nature because the companies do not use the repurchase programs in every period of the repurchase days. Another limitation of the stock repurchase prediction is many unpredictable factors on the basic of which demand and supply influences the particular stock that may increase and decrease the closing price. Therefore, in future work of this thesis, it is recommended that the forecast of the effect of the stock repurchase via the Artificial Neural Network is still not accurate because around 30 percent of the errors occur. Additionally, to improve the overall accurate performance in terms of the price prediction after repurchase, more studies are suggested as follows:

- 6.2.1 Add new input parameters to cover the stock behavior or events within the day of forecasting.
- 6.2.2 Change the Artificial Neural Network model to other models to forecast the price after repurchase as Hybrid technical analysis.



REFERENCES

- Grullon, G., & Michaely. R. (2002). Dividend, Share Repurchases, and the Substitution Hypothesis. **Journal of Finance** (57), 1649-1684.
- Eugene F. Brigham, & Phillip R. Daves. (2002). **Intermediate Financial Management**. (7ed.)

 Australia: South-Western.
- HUANG Hong, & ZHOU Zhong-guo. (2007). Stock Repurchase and the Role of Signaling: A Comparative Analysis between U.S. and China. **Journal of Modern Accounting and Auditing** (3), 56-62
- Brown, S.J. & Warner, J.B. (1985). Using Daily Stock Returns. The Case of Event Studies

 Journal of Financial Economics, (14), 3-31.
- Bartov E. (1991). Open-Market Stock Repurchases as Signals for Earnings and Risk Changes.

 Journal of Accounting & Economics (14), 275-295.
- Sebastian G. (2004). Stock Repurchase as an Alternative to Dividend Payout: Evidence from the Warsaw Stock Exchange, from http://www.cls.dk/caf/wp/sebastian-2.pdf
- Udo S. & Richard S. (2003). Stock Performance around Share Repurchase Announcements in Germany, Humboldt University Berlin, Germany
- Weisbach. M., & Stephens. C. (1998, February 1). Actual Share Reacquisitions in Open-Market Repurchase Programs. **Journal of Finance**, (53), 313-334.
- Vermaelen, T. (1981). Common Stock Repurchases and Market Signalling. **Journal of Finance Economic** 9, (2), 139-183.
- Hassan, M.R. Nath, B. & Kirley, M. (2006). "HMM based Fuzzy Model for Time Series Prediction" **IEEE International Conference**, .2120 2126.
- Bautista, C. (2001). Predicting the Phillippine stock price index using artificial neural network.

 Master of Science. University of the Philippines, Philippines.

Hellstrom, T. (2001). **Optimization of Trading Rules**. Sweden: Department of Computing Science, Umea University.

Kaplan, C. (2001). "Collective Intelligence": A New Approach to Stock Price Forecasting. IN IEEE System, Man, and Cybernetics Conference, n.p:IQ Company.

Merkl, D. (1996). **Partially Recurrent Neural Networks in Stock Forecasting**. Artificial Intelligence in Economics and Management. Vienna: Vienna University of Technology.







A.1 Data of Hana

Table A.1 Data Collection of Hana

Dete	C lass	Volume	SET	Repurchase	Days of Repurchase	
Date	Close	(thousand)	Index	(thousand)		
4/5/2009	12.2	494	506.26	506.26		
30/4/2009	12.1	353	491.69			
29/4/2009	12	133	483.5			
28/4/2009	11.8	59	472.72			
27/4/2009	11.7	57	474.99			
24/4/2009	11.9	155	474.07			
23/4/2009	11.7	245	466.06			
22/4/2009	12	1,037	460.62 902.9		65	
21/4/2009	12.2	269	466.38	200.8	64	
20/4/2009	11.7	449	466.28	410.1	63	
17/4/2009	11.5	325	456.8	245	62	
16/4/2009	11.4	283	452.97	41.6	61	
10/4/2009	10.8	1,697	453.88	1616.6	60	
9/4/2009	10.5	1,132	444.07	979.9	59	
8/4/2009	10.2	377	443.57	142	58	
7/4/2009	9.95	251	442.56	163.1	57	
3/4/2009	10	87	446.04	20.7	56	
2/4/2009	10	2,164	442.96	1700	55	
1/4/2009	10.1	415	430.09	208.6	54	
31/3/2009	10.1	63	431.5			

Table A.1 Data collection of Hana(continued)

D.4.	Classic	Volume	SET	Repurchase	Days of	
Date	Close	(thousand)	Index	(thousand)	Repurchase	
30/3/2009	10.2	256	256 429.6 110		53	
27/3/2009	9.95	279	440.81			
26/3/2009	9.85	1,012	439.4	972.9	52	
25/3/2009	9.9	914	436.92	850	51	
24/3/2009	9.9	805	438.16	700	50	
23/3/2009	9.9	1,833	438.17	1412.5	49	
20/3/2009	9.9	502	429.64	468.4	48	
19/3/2009	9.8	49	427.72	30	47	
18/3/2009	9.8	48	426.2	39.1	46	
17/3/2009	9.8	1,170	422.32	918.4	45	
16/3/2009	9.85	129	424.61 86		44	
13/3/2009	9.8	99	424.79	200		
12/3/2009	9.7	784	415.04	410.7	43	
11/3/2009	11.1	695	414.41	20	42	
10/3/2009	11.3	689	417.41			
9/3/2009	11.2	937	411.27			
6/3/2009	11.2	96	419.51	12.3	41	
5/3/2009	10.8	373	417.11			
4/3/2009	11.2	206	206 417.86			
3/3/2009	11.5	385	413.09			
2/3/2009	11.3	510	416.52	416.52		
27/2/2009	11.3	219	431.52	431.52		
26/2/2009	11.2	132	431.94			

Table A.1 Data collection of Hana(continued)

		Volume	SET	Repurchase	Days of
Date	Close	(thousand)	Index	(thousand)	Repurchase
25/2/2009	11	184	184 434.24		
24/2/2009	11	168	431.32	126.8	40
23/2/2009	11.1	129	434.99	104.5	39
20/2/2009	11	986	434.67	915.8	38
19/2/2009	11	262	441.62	170.6	37
18/2/2009	11.2	2,680	439.6	338.2	36
17/2/2009	11.3	406	438.22	54	35
16/2/2009	11.3	300	446.64	167.3	34
13/2/2009	11	513	445.77	320.5	33
12/2/2009	11	85			32
11/2/2009	<u> </u>	66 444.1 48.4		31	
10/2/2009	11.1	131	31 443.17 23		30
6/2/2009	11.1	390	444.39	444.39 298.9	
5/2/2009	10.8	39	433.44	27.5	28
4/2/2009	10.5	20	433.04 4.2		27
3/2/2009	10.6	323	430.69	174.8	26
2/2/2009	10.8	48	427.85		
30/1/2009	11	18	437.69	10.1	25
29/1/2009	11	524	524 435 434.5		24
28/1/2009	11	843	3 448.35 705.6		23
27/1/2009	11.1	520	444.79	444.79 124.4	
26/1/2009	11.1	371	436.73		
23/1/2009	10.7	274	274 433.52 40.1		21

Table A.1 Data collection of Hana(continued)

Data	Class	Volume	SET	Repurchase	Days of	
Date	Close	(thousand)	Index	(thousand)	Repurchase	
22/1/2009	10.5	255	438.27	230.1	20	_
21/1/2009	10.6	67	431.23	20	19	
20/1/2009	10.5	187	433.19	111	18	
19/1/2009	10.4	319	435.71	125.9	17	
16/1/2009	10.5	91	435.2			
15/1/2009	10.7	1,081	426.26	644.5	16	
14/1/2009	10.5	456	439.51	60	15	
13/1/2009	10.3	262	433.81			
12/1/2009	10.5	326	452.8	159	14	
9/1/2009	10.5	438	459.06	279.4	13	
8/1/2009	10.8	2,589	465.03	1300	12	
7/1/2009	10.6	1,250	462.96	Na N		
6/1/2009	10.5	577	473.15	M		
5/1/2009	10.3	2,088	478.69	1186.5	11	
30/12/2008	10	722	449.96			
29/12/2008	10.4	964	446.7			
26/12/2008	10.7	277	446.62			
25/12/2008	10.6	242	444.64			
24/12/2008	10.6	737	439.17			
23/12/2008	10.8	1,113	440.4			
22/12/2008	10.9	354	434.08			
19/12/2008	11	1,432	447.01			
18/12/2008	11.1	2,026	451.72	460.5	10	

Table A.1 Data collection of Hana(continued)

Date	Close	Volume	SET	Repurchase	Days of	
		(thousand)	Index	(thousand)	Repurchase	
17/12/2008	10.2	1,565 445.94		562.1	9	
16/12/2008	9.7	795	445.31	147.8	8	
15/12/2008	9.1	514	437.06	219	7	
12/12/2008	9	1,658	424.79	910.5	6	
11/12/2008	8.8	1,208	424.61			
9/12/2008	8.8	1,072	423.79	324.2	5	
8/12/2008	8.7	297	410.58			
4/12/2008	8.7	189	189 392.87			
3/12/2008	8.65	1,605	392.92	908.3	4	
2/12/2008	8.65	187	187 387.32			
1/12/2008	8.75	150	390.92			
28/11/2008	8.5	416	416 401.84 26.3		3	
27/11/2008	8.5	542	389.81	181.7	2	
26/11/2008	8.45	1,482	395.22	496.7	1	
25/11/2008	8.95	949	391.85	391.85		
24/11/2008	9.3	431	386.12			

A.2 Trend of Hana

Table A.2 Trend of Hana

Date	Close	Volume	SET	Close vs. Vol.	Close vs. Set	Repurchase (thousand)	Days of Repurchase
4/5/2009	i	i	i	ii	ii		
30/4/2009	i	i	i	ii	ii		
29/4/2009	i	i	i	ii	ii		
28/4/2009	i	i	d	ii	id		
27/4/2009	d	d	i	dd	di		
24/4/2009	i	d	i	id	ii		
23/4/2009	d	d	i	dd	di		
22/4/2009	d		d	di	dd	902.9	65
21/4/2009	i	S d	/i	id	ii	200.8	64
20/4/2009	į.	۶ (i	i	ii	ii	410.1	63
17/4/2009	i	\h <u>i</u>	ì	ii	ii	245	62
16/4/2009	i	d	d	id	id	41.6	61
10/4/2009	i	T	i	ii	ii	1616.6	60
9/4/2009	i	i	i	ii	ii	979.9	59
8/4/2009	i	i	i	ii	ii	142	58
7/4/2009	d	i	d	di	dd	163.1	57
3/4/2009	u	d	i	ud	ui	20.7	56
2/4/2009	d	i	i	di	di	1700	55
1/4/2009	u	i	d	ui	ud	208.6	54
31/3/2009	d	d	i	dd	di		

Table A.2 Trend of Hana (continued)

Date	Close	Volume	SET	Close	Close	Repurchase	Days of
Date	Close	voiume	SEI	vs. Vol.	vs. Set	(thousand)	Repurchase
30/3/2009	i	d	d	id	id	110	53
27/3/2009	i	d	i	id	ii		
26/3/2009	d	i	i	di	di	972.9	52
25/3/2009	u	i	d	ui	ud	850	51
24/3/2009	u	d	d	ud	ud	700	50
23/3/2009	u	i	i	ui	di	1412.5	49
20/3/2009	i	i	i	ii	ii	468.4	48
19/3/2009	u	i	i	ui	ui	30	47
18/3/2009	u	d	i	ud	ui	39.1	46
17/3/2009	d	i	d	di	dd	918.4	45
16/3/2009	i	Ši	d	ii	id	86	44
13/3/2009	i	d	í	id	ii	200	
12/3/2009	d	~ \i	i	di	di	410.7	43
11/3/2009	d		d	di	dd	20	42
10/3/2009	i	d	i	id	ii		
9/3/2009	u	i	d	ui	ud		
6/3/2009	i	d	i	id	ii	12.3	41
5/3/2009	d	i	d	di	dd		
4/3/2009	d	d	i	dd	di		
3/3/2009	i	d	d	id	id		
2/3/2009	u	i	d	ui	ud		
27/2/2009	i	i	d	ii	id		
26/2/2009	i	d	d	id	id		

Table A.2 Trend of Hana (continued)

_				Close	Close	Repurchase	Days of
Date	Close	Volume	SET	vs. Vol.	vs. Set	(thousand)	Repurchase
25/2/2009	u	i	i	ui	ui		
24/2/2009	d	i	d	di	dd	126.8	40
23/2/2009	i	d	i	id	ii	104.5	39
20/2/2009	u	i	d	ui	ud	915.8	38
19/2/2009	d	d	i S	dd	di	170.6	37
18/2/2009	d	i	i	di	di	338.2	36
17/2/2009	u	i	d	ui	ud	54	35
16/2/2009	i	d	i	id	ii	167.3	34
13/2/2009	u	i	i	ui	ui	320.5	33
12/2/2009	u	i	d	ui	ud	77.7	32
11/2/2009	d	d	/ j/ "	dd	di	48.4	31
10/2/2009	u	d d	d	ud	ud	23	30
6/2/2009	ì	71	i	ii	ii	298.9	29
5/2/2009	i		i	ii	/ ji//	27.5	28
4/2/2009	d	d	i	dd	di	4.2	27
3/2/2009	d	\i	i	di	di	174.8	26
2/2/2009	d	i	d	di	dd		
30/1/2009	u	d	i	ud	ui	10.1	25
29/1/2009	u	d	d	ud	ud	434.5	24
28/1/2009	d	i	i	di	di	705.6	23
27/1/2009	u	i	i	ui	ui	124.4	22
26/1/2009	i	i	i	ii	ii		
23/1/2009	i	i	d	ii	id	40.1	21

Table A.2 Trend of Hana (continued)

Date	Close	Volume	SET	Close	Close	Repurchase	Days of
Date	Close	voiume	SEI	vs. Vol.	vs. Set	(thousand)	Repurchase
22/1/2009	d	i	i	di	di	230.1	20
21/1/2009	i	d	d	id	id	20	19
20/1/2009	i	d	d	id	id	111	18
19/1/2009	d	i	i	di	di	125.9	17
16/1/2009	d	d	i	dd	di		
15/1/2009	i	i	d	ii	id	644.5	16
14/1/2009	i	i	i	ii	ii	60	15
13/1/2009	d	d	d	dd	dd		
12/1/2009	u	d	d	ud	ud	159	14
9/1/2009	d	d	d	dd	dd	279.4	13
8/1/2009	i	Ši	/ <u>i</u> / "	ii	ii	1300	12
7/1/2009	i	ĝ (i /	d	ii	id	200	
6/1/2009	ï	d	d	id	id	M	
5/1/2009	i		i	ii	ii	1186.5	11
30/12/2008	d	d	i	dd	di		
29/12/2008	d	i	i	di	di		
26/12/2008	i	i	i	ii	ii		
25/12/2008	u	d	i	ud	ui		
24/12/2008	d	d	d	dd	dd		
23/12/2008	d	i	i	di	di		
22/12/2008	d	d	d	dd	dd		
19/12/2008	d	d	d	dd	dd		
18/12/2008	i	i	i	ii	ii	460.5	10

Table A.2 Trend of Hana (continued)

Date	Close	Volume	Close		Close	Repurchase	Days of
Date	Close	v olume	SET	vs. Vol.	vs. Set	(thousand)	Repurchase
17/12/2008	i	i	i	ii	ii	562.1	9
16/12/2008	i	i	i	Åii	ii	147.8	8
15/12/2008	i	d	i	id	ii	219	7
12/12/2008	i	i	i	ii	ii	910.5	6
11/12/2008	u	i	i	ui	ui		
9/12/2008	i	i	i	ii	ii	324.2	5
8/12/2008	u	i	i	ui	ui		
4/12/2008	i	d	d	id	id		
3/12/2008	u	i	i	ui	ui	908.3	4
2/12/2008	d	io	d	di	dd		
1/12/2008	i	d	d	id	id		
28/11/2008	u	E d	/i	ud	ui	26.3	3
27/11/2008	W	d	d	id	id	181.7	2
26/11/2008	d		i	di	di	496.7	1
25/11/2008	d	(Line	i	di	di		

A.3 Hana Validation Method

Table A.3 Hana Validation Method

Data	Day of Forecast	Prediction
2 Data	Day 3	16.24
3 Data	Day 4	16.22
4 Data	Day 5	16.29
5 Data	Day 6	16.51
6 Data	Day 7	16.65
7 Data	Day 8	17.47
8 Data	Day 9	18.24
9 Data	Day 10	19.66
10 Data	Day 11 Day 12 Day 13	17.93
11 Data	Day 12	18.77
12 Data	Day 13	17.98
13 Data	Day 14	17.90
14 Data	Day 15	17.68
15 Data	Day 16	17.89
16 Data	Day 17	10.51
17 Data	Day 18	10.69
18 Data	Day 19	10.77
19 Data	Day 20	10.63
20 Data	Day 21	10.84
21 Data	Day 22	11,28
22 Data	Day 23	11.15

Table A.3 Hana Validation Method(continued)

Data	Day of Forecast	Prediction
23 Data	Day 24	11.12
24 Data	Day 25	11.19
25 Data	Day 26	10.69
26 Data	Day 27	10.60
27 Data	Day 28	10.94
28 Data	Day 29	11.21
29 Data	Day 30	11.26
30 Data	Day 31	11.10
31 Data	Day 32	11.05
32 Data	Day 33	11.15
33 Data	Day 34	11.48
34 Data	Day 34 Day 35 Day 36	11.41
35 Data	Day 36	11.37
36 Data	Day 37	11.14
37 Data	Day 38	11.16
38 Data	Day 39	11.14
39 Data	Day 40	11.17
40 Data	Day 41	11.31
41 Data	Day 42	11.25
42 Data	Day 43	9.76
43 Data	Day 44	9.98
44 Data	Day 45	9.95
45 Data	Day 46	9.92

Table A.3 Hana Validation Method(continued)

Data	Day of Forecast	Prediction
46 Data	Day 47	9.98
47 Data	Day 48	10.07
48 Data	Day 49	10.00
49 Data	Day 50	10.03
50 Data	Day 51	9.93
51 Data	Day 52	10.04
52 Data	Day 53	10.27
53 Data	Day 54	10.23
54 Data	Day 55	10.10
55 Data	Day 56	10.12
56 Data	Day 57	10.03
57 Data	Day 57 Day 58 Day 59	10.36
58 Data	Day 59	10.56
59 Data	Day 60	10.94
60 Data	Day 61	11.58
61 Data	Day 62	11.60
62 Data	Day 63	11.82
63 Data	Day 64	12.28
64 Data	Day 65	12.02

A.4 Hana Classic

Table A.4 Hana Classic

Data	Close	Stock Volume	Stock Volume	Repurchase	Classic	Repurchase
Date	t-1	t-1	å t	Volume	Prediction	Day
22/4/2009	12.2	805,955,860	805,052,960	902,900	12.21	65
21/4/2009	11.7	806,156,660	805,955,860	200,800	11.70	64
20/4/2009	11.5	806,566,760	806,156,660	410,100	11.51	63
17/4/2009	11.4	806,811,760	806,566,760	245,000	11.40	62
16/4/2009	10.8	806,853,360	806,811,760	41,600	10.80	61
10/4/2009	10.5	808,469,960	806,853,360	1,616,600	10.52	60
9/4/2009	10.2	809,449,860	808,469,960	979,900	10.21	59
8/4/2009	9.95	809,591,860	809,449,860	142,000	9.95	58
7/4/2009	10	809,754,960	809,591,860	163,100	10.00	57
3/4/2009	10	809,775,660	809,754,960	20,700	10.00	56
2/4/2009	10.1	811,475,660	809,775,660	1,700,000	10.12	55
1/4/2009	10.2	811,684,260	811,475,660	208,600	10.20	54
30/3/2009	9.85	811,794,260	811,684,260	110,000	9.85	53
26/3/2009	9.9	812,767,160	811,794,260	972,900	9.91	52
25/3/2009	9.9	813,617,160	812,767,160	850,000	9.91	51
24/3/2009	9.9	814,317,160	813,617,160	700,000	9.91	50
23/3/2009	9.9	815,729,660	814,317,160	1,412,500	9.92	49
20/3/2009	9.8	816,198,060	815,729,660	468,400	9.81	48
19/3/2009	9.8	816,228,060	816,198,060	30,000	9.80	47
18/3/2009	9.8	816,267,160	816,228,060	39,100	9.80	46

Table A.4 Hana Classic(continued)

D (Close	Stock Volume	Stock Volume	Repurchase	Classic	Repurchase
Date	t-1	t-1	t	Volume	Prediction	Day
17/3/2009	9.85	817,185,560	816,267,160	918,400	9.86	45
16/3/2009	9.7	817,271,560	817,185,560	86,000	9.70	44
12/3/2009	11.1	817,682,260	817,271,560	410,700	11.11	43
11/3/2009	11.2	817,702,260	817,682,260	20,000	11.20	42
6/3/2009	11	817,714,560	817,702,260	12,300	11.00	41
24/2/2009	11.1	817,841,360	817,714,560	126,800	11.10	40
23/2/2009	11	817,945,860	817,841,360	104,500	11.00	39
20/2/2009	11	818,861,660	817,945,860	915,800	11.01	38
19/2/2009	11.2	819,032,260	818,861,660	170,600	11.20	37
18/2/2009	11.3	819,370,460	819,032,260	338,200	11.30	36
17/2/2009	11.3	819,424,460	819,370,460	54,000	11.30	35
16/2/2009	11	819,591,760	819,424,460	167,300	11.00	34
13/2/2009	M	819,912,260	819,591,760	320,500	11.00	33
12/2/2009	11_	819,989,960	819,912,260	77,700	11.00	32
11/2/2009	11.1	820,038,360	819,989,960	48,400	11.10	31
10/2/2009	11.1	820,061,360	820,038,360	23,000	11.10	30
6/2/2009	10.8	820,360,260	820,061,360	298,900	10.80	29
5/2/2009	10.5	820,387,760	820,360,260	27,500	10.50	28
4/2/2009	10.6	820,391,960	820,387,760	4,200	10.60	27
3/2/2009	11	820,566,760	820,391,960	174,800	11.00	26
30/1/2009	11	820,576,860	820,566,760	10,100	11.00	25
29/1/2009	11	821,011,360	820,576,860	434,500	11.01	24
28/1/2009	11.1	821,716,960	821,011,360	705,600	11.11	23

Table A.4 Hana Classic (continued)

	Close	Stock Volume	Stock Volume	Repurchase	Classic	Repurchase
Date	t-1	t-1	t	Volume	Prediction	Day
27/1/2009	10.7	821,841,360	821,716,960	124,400	10.70	22
23/1/2009	10.5	821,881,460	821,841,360	40,100	10.50	21
22/1/2009	10.6	822,111,560	821,881,460	230,100	10.60	20
21/1/2009	10.5	822,131,560	822,111,560	20,000	10.50	19
20/1/2009	10.4	822,242,560	822,131,560	111,000	10.40	18
19/1/2009	10.7	822,368,460	822,242,560	125,900	10.70	17
15/1/2009	10.5	823,012,960	822,368,460	644,500	10.51	16
14/1/2009	10.5	823,072,960	823,012,960	60,000	10.50	15
12/1/2009	10.5	823,231,960	823,072,960	159,000	10.50	14
9/1/2009	10.8	823,511,360	823,231,960	279,400	10.80	13
8/1/2009	10.3	824,811,360	823,511,360	1,300,000	10.32	12
5/1/2009	11.1	825,997,860	824,811,360	1,186,500	11.12	11
18/12/2008	10.2	826,458,360	825,997,860	460,500	10.21	10
17/12/2008	9.7	827,020,460	826,458,360	562,100	9.71	9
16/12/2008	9.1	827,168,260	827,020,460	147,800	9.10	8
15/12/2008	9	827,387,260	827,168,260	219,000	9.00	7
12/12/2008	8.8	828,297,760	827,387,260	910,500	8.81	6
9/12/2008	8.65	828,621,260	828,297,760	323,500	8.65	5
3/12/2008	8.5	829,530,260	828,621,260	909,000	8.51	4
28/11/2008	8.5	829,556,560	829,530,260	26,300	8.50	3
27/11/2008	8.45	829,738,260	829,556,560	181,700	8.45	2
26/11/2008	8.95	830,234,960	829,738,260	496,700	8.96	1

A.5 Hana Proposed Method Day 2

Table A.5 Hana Proposed Method Day 2

Day Passing	Selected Days	Forecast	Prediction
2 Day	1(2),2	Day 3	8.76
3 Day	1(3),2(2)	Day 4	8.89
4 Day	3(3),4(5)	Day 5	8.97
5 Day	3(3),4(5)	Day 6	9.25
6 Day	5(5),6	Day 7	9.14
7 Day	2(3),7	Day 8	9.90
8 Day	6(5)(SET),8	Day 9	10.55
9 Day	8(5)(SET),9	Day 10	11.73
10 Day	1(3),7(2)	Day 11	11.14
11 Day	10(3)(SET),11(5)(SET)	Day 12	11.33
12 Day	11(5),12	Day 13	10.70
13 Day	2(2),13	Day 14	10.50
14 Day	13(5),14(2)(SET)	Day 15	10.57
15 Day	13(50,15	Day 16	10.87
16 Day	1(3),13(3)	Day 17	10.75
17 Day	1(5),17	Day 18	10.59
18 Day	2(5),18	Day 19	10.68
19 Day	18(5),19	Day 20	10.57
20 Day	1(5),20	Day 21	10.88
21 Day	13(5),15(5)	Day 22	11.53
22 Day	4(5),22	Day 23	11.08

Table A.5 Hana Proposed Method Day 2 (continued)

Day Passing	Selected Days	Forecast	Prediction
23 Day	20(5)(SET),23	Day 24	11.00
24 Day	14(5),24	Day 25	11.00
25 Day	17(4)(SET),20(4)(SET)	Day 26	11.06
26 Day	17(5)(SET),26	Day 27	10.53
27 Day	26(3)(SET),27	Day 28	10.93
28 Day	15(5)(SET),28	Day 29	11.35
29 Day	28(5)(SET),29	Day 30	11.10
30 Day	24(5)(SET),30	Day 31	11.08
31 Day	27(5),31	Day 32	11.00
32 Day	30(3)(SET),32	Day 33	11.00
33 Day	4(5),33	Day 34	11.49
34 Day	7(5),34	Day 35	11.30
35 Day	32(5),35	Day 36	11.27
36 Day	23(5)(SET),36	Day 37	11.14
37 Day	31(5)(SET),37	Day 38	11.00
38 Day	32(5)(SET),38	Day 39	11.16
39 Day	34(5),39	Day 40	11.01
40 Day	26(3)(SET),40(5)	Day 41	11.43
41 Day	39(5)(SET),41(5)	Day 42	11.27
42 Day	40(5),42(5)	Day 43	10.72
43 Day	7(5)(SET),41(5)	Day 44	10.04
44 Day	16(5)(SET),44	Day 45	9.81
45 Day	42(5)(SET),45	Day 46	9.80
46 Day	25(5)(SET),46	Day 47	9.80

Table A.5 Hana Proposed Method Day 2 (continued)

Day Passing	Selected Days	Forecast	Prediction
47 Day	33(5)(SET),47	Day 48	9.95
48 Day	6(5)(SET),48	Day 49	9.90
49 Day	47(5)(SET),49	Day 50	9.90
50 Day	24(5)(SET),50	Day 51	9.91
51 Day	38(5)(SET),51	Day 52	9.87
52 Day	39(5)(SET),41(5)(SET)	Day 53	10.71
53 Day	31(5)(SET),37(5)(SET)	Day 54	10.27
54 Day	51(5)9SET),54	Day 55	10.11
55 Day	52(5)(SET),55	Day 56	10.00
56 Day	46(5)(SET),56	Day 57	9.96
57 Day	55(5)(SET),57	Day 58	10.40
58 Day	29(5)(SET),58	Day 59	10.75
59 Day	58(5)(SET),59	Day 60	11.04
60 Day	59(5)(SET),60	Day 61	11.94
61 Day	53(5)(SET),61	Day 62	11.51
62 Day	60(5)(SET),62	Day 63	11.82
63 Day	62(5)(SET),63	Day 64	12.59
64 Day	34(5)(SET),64	Day 65	12.16

A.6 Hana Proposed Method Day 4

 Table A.6 Hana Proposed Method Day 4

Day Passing	Selected Days	Forecast	Prediction
4 Day	1(2),2(0),3(3),4(5)	Day 5	9.80
5 Day	1(2),3(3),4(5),5(2)	Day 6	9.10
6 Day	1(2),4(2),5(5),6	Day 7	9.30
7 Day	2(3),5(3),6(3),7	Day 8	9.70
8 Day	5(5),6(5),7(3),8	Day 9	10.40
9 Day	5(5),6(5),8(5),9	Day 10	11.20
10 Day	1(3),7(2),9(1)(SET),10(1)(SET)	Day 11	10.50
11 Day	8(3)(SET),9(3)(SET),10(3)(SET),11(3)(SET)	Day 12	11.50
12 Day	9(5)(SET),10(5)(SET),11(5)(SET),12	Day 13	10.70
13 Day	1(1),2(2),7(1),13	Day 14	10.60
14 Day	2(2),(SET)3(1)(SET),13(5),14(2)(SET)	Day 15	11.40
15 Day	10(5)(SET),11(5)(SET),12(5)(SET),15	Day 16	10.80
16 Day	1(3),3(2),7(2),13(3)	Day 17	10.95
17 Day	1(5),12(2)(SET),15(2)(SET),17	Day 18	10.70
18 Day	2(5),7(3),13(2),18	Day 19	10.80
19 Day	2(5),7(3),18(5),19	Day 20	10.60
20 Day	1(5),15(2)(SET),17(5),20	Day 21	10.70
21 Day	10(5)(SET),11(5)(SET),12(5)(SET),15(5)(SET)	Day 22	11.30
22 Day	4(5),17(2)(SET),20(2)(SET),22	Day 23	11.10
23 Day	1(5)(SET),17(5)(SET),20(5)(SET),23	Day 24	11.20
24 Day	14(5),18(2)(SET),19(2)(SET),24	Day 25	11.10
25 Day	1(4)(SET),17(4)(SET),20(4)(SET),23(4)(SET)	Day 26	11.00

Table A.6 Hana Proposed Method Day 4(continued)

Day Passing	Selected Days	Forecast	Prediction
26 Day	17(5)(SET),20(5)(SET),23(5)(SET),26	Day 27	10.70
27 Day	13(3)(SET),23(2)(SET),26(3)(SET),27	Day 28	11.20
28 Day	11(5)(SET),12(5)(SET),15(5)(SET),28	Day 29	11.50
29 Day	12(5)(SET),15(5)(SET),28(5)(SET),29	Day 30	11.10
30 Day	14(5)(SET),24(5)(SET),25(3),30	Day 31	11.20
31 Day	23(3)(SET),26(3)(SET),27(5),31	Day 32	11.10
32 Day	14(3)(SET),24(3)(SET),30(3)(SET),32	Day 33	11.10
33 Day	4(5),22(5)(SET),32(3)(SET),33	Day 34	11.40
34 Day	7(5),28(3)(SET),29(3)(SET),34	Day 35	11.40
35 Day	24(3)(SET),30(3)(SET)32(5),35	Day 36	11.40
36 Day	20(5)(SET),23(5)(SET),26(5)(SET),36	Day 37	11.00
37 Day	26(3)(SET),27(5)(SET),31(5)(SET),37	Day 38	11.20
38 Day	30(3)(SET),32(5),35(5),38	Day 38 Day 39	11.20
39 Day	7(5),29(3)(SET),34(5),39	Day 40	11.50
40 Day	23(3)(SET),26(3)(SET),36(3)(SET),40(5)	Day 41	11.80
41 Day	7(5),34(5),39(5),41(5)	Day 42	11.10
42 Day	26(3)(SET),36(3)(SET),40(5),42(5)	Day 43	9.80
43 Day	7(5),34(5),39(5),41(5)	Day 44	10.35
44 Day	16(5),19(3)(SET),21(5),44	Day 45	10.00
45 Day	36(3)(SET),40(5),42(5),45	Day 46	10.00
46 Day	3(5),25(5),30(3)(SET),46	Day 47	10.30
47 Day	4(5),22(5),33(5),47	Day 48	10.00
48 Day	6(5)(SET),28(SET),29(5)(SET),48	Day 49	10.10
49 Day	22(5),33(5),47(5),49	Day 50	10.00

Table A.6 Hana Proposed Method Day 4(continued)

Day Passing	Selected Days	Forecast	Prediction
50 Day	14(5),24(5),30(5),50	Day 51	9.90
51 Day	32(5),35(5),38(5),51	Day 52	10.05
52 Day	7(5),34(5),39(5),41(5)	Day 53	10.5
53 Day	13(3),27(5),31(5),37(5)	Day 54	10.1
54 Day	32(5)(SET),38(5)(SET),51(5)(SET),54	Day 55	10.10
55 Day	36(5)(SET),43(5)(SET),52(5)(SET),55	Day 56	10.30
56 Day	3(5),25(5),46(5),56	Day 57	10.15
57 Day	40(5),42(5),45(5),57	Day 58	10.20
58 Day	28(5)(SET),29(5)(SET),48(5)(SET),58	Day 59	10.60
59 Day	29(5)(SET),48(5)(SET),58(5)(SET),59	Day 60	11.20
60 Day	48(5)(SET),58(5)(SET),59(5)(SET),60	Day 61	11.50
61 Day	18(5)(SET),19(5)(SET),53(5)(SET),61	Day 62	11.50
62 Day	58(5)(SET),59(5)(SET),60(5)(SET),62	Day 61 Day 62 Day 63	11.90
63 Day	59(5)(SET),60(5)(SET),62(5)(SET),63	Day 64	12.30
64 Day	34(5)(SET),39(5)(SET),41(5)(SET),64	Day 65	12.10

A.7 Hana Proposed Method Day 7

Table A.7 Hana Proposed Method Day 7

Day Passing	Selected Days	Forecast	Prediction
7 Day	1,2,3,4,5,6,7	Day 8	10.00
8 Day	1,2,4,5,6,7,8	Day 9	10.30
9 Day	3,4,5,6,7,8,9	Day 10	11.30
10 Day	1,5,6,7,8,9,10	Day 11	10.30
11 Day	2,5,6,7,8,9,10,11	Day 12	11.50
12 Day	5,6,7,8,9,10,11,12	Day 13	10.70
13 Day	2,3,7,8,11,12,13	Day 14	10.90
14 Day	1,2,3,7,9,13,14	Day 15	11.40
15 Day	7,8,9,10,11,12,15	Day 16	10.80
16 Day	1,2,3,7,13,14,15	Day 17	10.95
17 Day	1,4,8,10,12,15,17	Day 18	10.80
18 Day	2,3,7,13,14,16,18	Day 19	10.80
19 Day	2,7,13,14,16,18,19	Day 20	10.60
20 Day	1,4,12,13,15,17,20	Day 21	11.00
21 Day	6,8,9,10,11,12,15	Day 22	11.10
22 Day	4,11,12,15,17,20,22	Day 23	11.30
23 Day	1,12,15,17,20,22,23	Day 24	11.10
24 Day	1,7,13,14,18,19,24	Day 25	11.20
25 Day	1,13,16,17,20,21,23	Day 26	11.00
26 Day	1,16,17,20,21,23,26	Day 27	10.80
27 Day	3,7,18,19,24,25,27	Day 28	11.20
28 Day	8,9,10,11,12,15,28	Day 29	11.30

Table A.7 Hana Proposed Method Day 7(continued)

Day Passing	Selected Days	Forecast	Prediction
29 Day	9,10,11,12,15,28,29	Day 30	11.20
30 Day	2,13,14,18,19,24,30	Day 31	11.00
31 Day	3,7,18,24,25,27,31	Day 32	11.20
32 Day	14,16,18,21,24,30,32	Day 33	11.10
33 Day	4,17,20,22,25,32,33	Day 34	11.30
34 Day	3,7,13,28,29,31,34	Day 35	11.50
35 Day	14,16,21,24,30,32,35	Day 36	11.30
36 Day	1,17,20,23,26,33,36	Day 37	11.20
37 Day	3,7,25,27,31,34,37	Day 38	11.00
38 Day	14,16,24,30,32,35,38	Day 39	11.50
39 Day	7,25,27,31,34,37,39	Day 40	11.10
40 Day	16,23,26,32,36,38,40	Day 41	11.80
41 Day	7,19,31,34,37,39,41	Day 42	11.10
42 Day	16,26,32,36,38,40,42	Day 43	9.90
43 Day	7,19,31,34,97,39,41	Day 44	10.35
44 Day	16,19,21,38,40,42,44	Day 45	10.20
45 Day	16,21,36,38,40,42,45	Day 46	10.00
46 Day	3,25,30,37,39,41,46	Day 47	10.10
47 Day	4,22,23,33,36,43,47	Day 48	10.00
48 Day	6,11,12,15,28,29,48	Day 49	9.90
49 Day	4,22,23,33,43,47,49	Day 50	10.10
50 Day	13,14,18,19,24,30,50	Day 51	10.00
51 Day	32,35,38,42,44,45,51	Day 52	10.05
52 Day	3,7,25,34,39,41,46	Day 53	10.20

Table A.7 Hana Proposed Method Day 7(continued)

Day Passing	Selected Days	Forecast	Prediction
53 Day	13,27,31,34,37,39,41	Day 54	10.10
54 Day	32,35,38,40,45,51,54	Day 55	10.30
55 Day	20,23,26,36,43,52,55	Day 56	10.10
56 Day	3,24,25,30,46,50,56	Day 57	10.15
57 Day	38,40,42,45,51,54,57	Day 58	10.40
58 Day	11,12,15,28,29,48,58	Day 59	10.70
59 Day	11,12,28,29,48,58,59	Day 60	10.80
60 Day	11,28,29,48,58,59,60	Day 61	11.60
61 Day	14,18,19,30,50,53,61	Day 62	11.60
62 Day	28,29,48,58,59,60,62	Day 63	11.80
63 Day	29,48,58,59,60,62,63	Day 64	12.20
64 Day	7,34,39,41,46,56,64	Day 65	12.20



B.1 Data of Major

 Table B.1 Data Collection of Major

Date	Close	Volume (thousand)	SET Index	Repurchase (thousand)	Days of Repurchase
3/7/2009	6.7	1,051	583.48		
2/7/2009	6.7	2,373	586.42		
30/6/2009	6.85	1,296	597.48		
29/6/2009	6.85	583	601.6		
26/6/2009	6.95	5,056	595.8	1450	65
25/6/2009	6.75	2,190	590.6	1060	64
24/6/2009	6.6	1,536	581.43	340.7	63
23/6/2009	6.65	2,471	569.85	244.9	62
22/6/2009	6.75	5,045	582.29	2000	61
19/6/2009	6.6	2,499	588.98	72.5	60
18/6/2009	6.5	4,898	570.43	200	59
17/6/2009	6.7	4,321	586.14		
16/6/2009	6.7	4,059	596.54	650	58
15/6/2009	6.7	10,203	611.92	1000	57
12/6/2009	7.1	6,879	628.55		
11/6/2009	7.25	18,292	627.07	923.7	56
10/6/2009	6.95	8,819	624.55	1550	55
9/6/2009	6.8	9,046	607.73		
8/6/2009	6.85	16,813	600.03		
5/6/2009	6.8	22,185	604.57	1000	54
4/6/2009	6.25	11,222	593.6	500	53

Table B.1 Data Collection of Major (continued)

Date	Close	Volume	SET Index	Repurchase	Days of
Date	Close	(thousand)	SET THUEX	(thousand)	Repurchase
3/6/2009	6.2	3,331	582.25	1000	52
2/6/2009	6.2	3,474	574.3	600	51
1/6/2009	6.3	8,483	579.98	1500	50
29/5/2009	6.15	12,048	560.41	2000	49
28/5/2009	6.2	2,968	555.43	500	48
27/5/2009	6.2	10,738	555.41	311.2	47
26/5/2009	6.15	3,528	542.69	900	46
25/5/2009	6.2	15,932	550.51	2500	45
22/5/2009	6.15	4,247	554.02	100	44
21/5/2009	6.05	12,261	548.77	1000	43
20/5/2009	6	7,474	561.41		
19/5/2009	6.1	18,574	556.47	300	42
18/5/2009	6	5,243	540.22		
15/5/2009	5.9	32,155	533.92		
14/5/2009	6.6	9,333	526.55		
13/5/2009	6.65	12,857	552.71		
12/5/2009	6.8	11,735	544.54		
11/5/2009	7	6,832	535.18		
7/5/2009	7.05	9,292	527.72		
6/5/2009	7.05	13,574	523.15		
4/5/2009	6.85	13,857	506.26		
30/4/2009	6.4	7,362	491.69		
29/4/2009	6.35	7,847	483.5		

Table B.1 Data Collection of Major (continued)

Date	Close	Volume	SET Index	Repurchase	Days of
		(thousand)		(thousand)	Repurchase
28/4/2009	6.2	4,791	472.72		
27/4/2009	6.3	10,037	474.99		
24/4/2009	6.35	5,157	474.07		
23/4/2009	6.3	2,932	466.06		
22/4/2009	6.25	5,561	460.62		
21/4/2009	6.25	3,089	466.38	200	41
20/4/2009	6.4	3,520	466.28		
17/4/2009	6.2	2,504	456.8		
16/4/2009	6.2	7,713	452.97	300	40
10/4/2009	6.35	1,818	453.88		
9/4/2009	6.1	6,234	444.07	300	39
8/4/2009	6.4	4,976	443.57	200	38
7/4/2009	6.55	6,098	442.56	300	37
3/4/2009	6.65	1,801	446.04	300	36
2/4/2009	6.7	3,812	442.96	250	35
1/4/2009	6.55	2,142	430.09	100	34
31/3/2009	6.55	2,399	431.5	200	33
30/3/2009	6.55	2,160	429.6	350	32
27/3/2009	6.9	2,270	440.81	250	31
26/3/2009	6.95	2,555	439.4	200	30
25/3/2009	6.8	1,355	436.92	150	29
24/3/2009	6.9	4,149	438.16	350	28
23/3/2009	6.75	2,208	438.17		

Table B.1 Data Collection of Major (continued)

Date	Close	Volume (thousand)	SET Index	Repurchase (thousand)	Days of Repurchase
20/3/2009	6.45	1,484	429.64	265.9	27
19/3/2009	6.6	2,366	427.72	250	26
18/3/2009	6.5	1,775	426.2	250	25
17/3/2009	6.45	1,422	422.32	300	24
16/3/2009	6.5	1,458	424.61	231.9	23
13/3/2009	6.45	2,179	424.79	400	22
12/3/2009	6.2	650	415.04	85.9	21
11/3/2009	6.2	1,920	414.41	500	20
10/3/2009	6.05	1,965	417.41	200	19
9/3/2009	5.9	3,162	411.27	400	18
6/3/2009	6.2	1,326	419.51	200	17
5/3/2009	6.25	1,628	417.11		
4/3/2009	6.25	3,952	417.86		
3/3/2009	5.75	3,716	413.09	450	16
2/3/2009	6.05	3,263	416.52	500	15
27/2/2009	6.4	3,131	431.52	600	14
26/2/2009	6.4	3,756	431.94		
25/2/2009	6.7	4,794	434.24		
24/2/2009	7	2,938	431.32		
23/2/2009	7.4	2,271	434.99		
20/2/2009	7.75	772	434.67		
19/2/2009	7.75	2,502	441.62		
18/2/2009	7.8	3,644	439.6		

Table B.1 Data Collection of Major (continued)

Date	Close	Volume (thousand)	SET Index	Repurchase (thousand)	Days of Repurchase
17/2/2009	7.75	2,794	438.22		
16/2/2009	7.95	1,949	446.64		
13/2/2009	7.8	5,261	445.77		
12/2/2009	7.7	2,944	440.63		
11/2/2009	7.8	4,080	444.1		
10/2/2009	8	4,220	443.17		
6/2/2009	8	6,293	444.39		
5/2/2009	7.6	2,241	433.44		
4/2/2009	7.5	2,800	433.04		
3/2/2009	7.45	3,893	430.69		
2/2/2009	7.3	1,299	427.85		
30/1/2009	7.45	1,474	437.69		
29/1/2009	7.35	5,683	435		
28/1/2009	7.65	4,428	448.35		
27/1/2009	7.45	4,419	444.79		
26/1/2009	7.3	2,606	436.73		
23/1/2009	7.2	8,975	433.52		
22/1/2009	6.95	5,948	438.27		
21/1/2009	6.85	1,532	431.23		
20/1/2009	6.85	3,803	433.19		
19/1/2009	6.9	2,826	435.71	600	13
16/1/2009	6.9	7,182	435.2	1000	12
15/1/2009	6.7	4,826	426.26	800	11

Table B.1 Data Collection of Major (continued)

Date	Close	Volume (thousand)	SET Index	Repurchase (thousand)	Days of Repurchase
14/1/2009	6.7	4,329	439.51	1000	10
13/1/2009	6.5	5,152	433.81	500	9
12/1/2009	6.5	1,913	452.8	750	8
9/1/2009	6.6	3,855	459.06	700	7
8/1/2009	6.7	2,436	465.03	600	6
7/1/2009	6.9	2,642	462.96	700	5
6/1/2009	6.95	2,280	473.15	500	4
5/1/2009	7.1	6,629	478.69	905	3
30/12/2008	6.95	5,001	449.96	1300	2
29/12/2008	6.8	4,090	446.7	950	1
26/12/2008	7.05	4,084	446.62		
25/12/2008	7.05	3,494	444.64		

B.2 Trend of Major

Table B.2 Trend of Major

Date	Close	Volume	SET	Close vs.	Close vs.	Repurchase	Days of
			Q	Vol.	Set	(thousand)	Repurchase
3/7/2009	u	d	d	ud	ud		
2/7/2009	d	i	d	di	dd		
30/6/2009	u	i	d	ui	ud		
29/6/2009	d	d	i	dd	di		
26/6/2009	i	i	i	ii	ii	1450	65
25/6/2009	i	i	i	ii	ii	1060	64
24/6/2009	d	d	i	dd	di	340.7	63
23/6/2009	d	d /	d	dd	dd	244.9	62
22/6/2009	i		d	ii	id	2000	61
19/6/2009	1 5	d	i	id	Į Į į	72.5	60
18/6/2009	d		d	di	dd	200	59
17/6/2009	u	2/11/6	d	uí	ud		
16/6/2009	u	d	d	ud	ud	650	58
15/6/2009	d		đ	di	dd	1000	57
12/6/2009	d	d	i	dd	di		
11/6/2009	i	i	i	ii	ii	923.7	56
10/6/2009	i	d	i	id	ii	1550	55
9/6/2009	d	d	i	dd	di		
8/6/2009	i	d	d	id	id		
5/6/2009	i	i	i	ii	ii	1000	54
4/6/2009	i	i	i	ii	ii	500	53

Table B.2 Trend of Major (continued)

Date	CI	3 7.1	CET	Close vs.	Close vs.	Repurchase	Days of
Date	Close	Volume	SET	Vol.	Set	(thousand)	Repurchase
3/6/2009	u	d	i	ud	ui	1000	52
2/6/2009	d	d	d	dd	dd	600	51
1/6/2009	i	d	iΩ	id	ii	1500	50
29/5/2009	d	i	i	di	di	2000	49
28/5/2009	u	d	i	ud	ui	500	48
27/5/2009	i	i	i	ii	ii	311.2	47
26/5/2009	d	d	d	dd	dd	900	46
25/5/2009	i	i	d	ii	id	2500	45
22/5/2009	i	d	_i_	id	ii	100	44
21/5/2009	i	i i	d	it	id	1000	43
20/5/2009	d	d/	i	dd	di		
19/5/2009	i ĝ	(i /	i	ii	Zii	300	42
18/5/2009	in	d	i	id	ii		
15/5/2009	d	D\i\	i	di	di		
14/5/2009	d	d	d	dd	dd		
13/5/2009	d	i	i	di	di		
12/5/2009	d	i		di	di		
11/5/2009	d	d	70	dd	di		
7/5/2009	u	d	i	ud	ui		
6/5/2009	i	d	i	id	ii		
4/5/2009	i	i	i	ii	ii		
30/4/2009	i	d	i	id	ii		
29/4/2009	i	i	i	ii	ii		

Table B.2 Trend of Major (continued)

Date	Close	Volume	SET	Close vs. Vol.	Close vs.	Repurchase (thousand)	Days of Repurchase
28/4/2009	d	d	d	dd	dd		
27/4/2009	d	i	i Å	di	di		
24/4/2009	i	i	iX	ii	ii		
23/4/2009	i	d	i	id	ii		
22/4/2009	u	i	d	ui	ud		
21/4/2009	d	d	i	dd	di	200	41
20/4/2009	i	i	i	ii	ii		
17/4/2009	u	d	i)	ud	ui		
16/4/2009	d	í	d	di	dd	300	40
10/4/2009	i	d d	í	id	ii		
9/4/2009	d	<i>\$</i> //i//	i	di	di	300	39
8/4/2009	d	d	i	dd	3 di	200	38
7/4/2009	d	`\ i (,	d	di	dd	300	37
3/4/2009	d	d	i	dd	di	300	36
2/4/2009	i T	i	i	ii	ii	250	35
1/4/2009	u	d	d	ud	ud	100	34
31/3/2009	u			ui	ui	200	33
30/3/2009	d	d	d	dd	dd	350	32
27/3/2009	d	d	i	dd	di	250	31
26/3/2009	i	i	i	ii	ii	200	30
25/3/2009	d	d	d	dd	dd	150	29
24/3/2009	i	i	d	ii	id	350	28
23/3/2009	i	i	i	ii	ii		

Table B.2 Trend of Major (continued)

Date	Close	Volume	SET	Close vs. Vol.	Close vs.	Repurchase (thousand)	Days of Repurchase
20/3/2009	d	d	i	dd	di	265.9	27
19/3/2009	i	i	i Å	ii	ii	250	26
18/3/2009	i	i	iX	ii	ii	250	25
17/3/2009	d	d	d	dd	dd	300	24
16/3/2009	i	d	d	id	id	231.9	23
13/3/2009	i	i	i	ii	ii	400	22
12/3/2009	u	d	i	ud	ui	85.9	21
11/3/2009	i	d	d	id	id	500	20
10/3/2009	i	d	,i,	id	ii	200	19
9/3/2009	d	i i	d	di	dd	400	18
6/3/2009	d	8 /d/	i	dd	di	200	17
5/3/2009	u	d	d	ud	dud		
4/3/2009	i	`\{(i	ii	ü		
3/3/2009	d	$ i \mathbb{Z}$	d	di	dd	450	16
2/3/2009	d		d	di	dd	500	15
27/2/2009	u	d	d	ud	ud	600	14
26/2/2009	d	d	d	dd	dd		
25/2/2009	d	i	i	di	di		
24/2/2009	d	i	d	di	dd		
23/2/2009	d	i	i	di	di		
20/2/2009	u	d	d	ud	ud		
19/2/2009	d	d	i	dd	di		
18/2/2009	i	i	i	ii	ii		

Table B.2 Trend of Major (continued)

Date	Close	Volume	SET	Close vs. Vol.	Close vs.	Repurchase (thousand)	Days of Repurchase
17/2/2009	d	i	d	di	dd		
16/2/2009	i	d	i Å	id	ii		
13/2/2009	i	i	iX	ii	ii		
12/2/2009	d	d	d	dd	dd		
11/2/2009	d	d	i	dd	di		
10/2/2009	u	d	d	ud	ud		
6/2/2009	i	i	i	ii	ii		
5/2/2009	i	d	i)(id	ii		
4/2/2009	i	d	i	id	ii		
3/2/2009	i	i i	í	ii	ii		
2/2/2009	d	d/	d	dd	dd		
30/1/2009	i	đ	i	id	Zii		
29/1/2009	d	`\ i (d	di	dd		
28/1/2009	ì		i	ii	li ii		
27/1/2009	i Ţ		i	ii	ii		
26/1/2009	i	d	i	id	ii		
23/1/2009	i	i	d	ii	id		
22/1/2009	i	i	i	ii	ii		
21/1/2009	u	d	d	ud	ud		
20/1/2009	d	i	d	di	dd		
19/1/2009	u	d	i	ud	ui	600	13
16/1/2009	i	i	i	ii	ii	1000	12
15/1/2009	u	i	d	ui	ud	800	11

Table B.2 Trend of Major (continued)

Data Cla	Cl	X 7.1	O.E.T.	Close vs.	Close vs.	Repurchase	Days of
Date	Close	Volume	SET	Vol.	Set	(thousand)	Repurchase
14/1/2009	i	d	i	id	ii	1000	10
13/1/2009	u	i	d	ui	ud	500	9
12/1/2009	d	d	d	dd	dd	750	8
9/1/2009	d	i	d	di	dd	700	7
8/1/2009	d	d	i	dd	di	600	6
7/1/2009	d	i	d	di	dd	700	5
6/1/2009	d	d	d	dd	dd	500	4
5/1/2009	i	i	i	ii	ii	905	3
30/12/2008	i	Tí.	\i_\	ii	ii	1300	2
29/12/2008	d	d	í	dd	di	950	1
26/12/2008	u	\$\vec{\pi}{i} \/	i	ui	ui		

B.3 Major Validation Method

Table B.3 Major Validation Method

Data	Day of Forecast	Prediction
2 Data	Day 3	7.80
3 Data	Day 4	7.15
4 Data	Day 5	7.6
5 Data	Day 6	6.70
6 Data	Day 7	7.10
7 Data	Day 8	6.50
8 Data	Day 9	6.90
9 Data	Day 10	6.90
10 Data	Day 10 Day 11 Day 12 Day 13	6.95
11 Data	Day 12	6.90
12 Data	Day 13	7.25
13 Data	Day 14	8.60
14 Data	Day 15	6.55
15 Data	Day 16	5.75
16 Data	Day 17	7.90
17 Data	Day 18	6.35
18 Data	Day 19	6.05
19 Data	Day 20	6.80
20 Data	Day 21	6.30
21 Data	Day 22	6.65
22 Data	Day 23	6.85

Table B.3 Major Validation Method(continued)

Data	Day of Forecast	Prediction
23 Data	Day 24	6.95
24 Data	Day 25	6.70
25 Data	Day 26	6.95
26 Data	Day 27	6.55
27 Data	Day 28	7.10
28 Data	Day 29	7.25
29 Data	Day 30	7.45
30 Data	Day 31	7.50
31 Data	Day 32	6.75
32 Data	Day 33	6.75
33 Data	Day 34	6.95
34 Data	Day 34 Day 35 Day 36	6.80
35 Data	Day 36	6.65
36 Data	Day 37	6.55
37 Data	Day 38	6.85
38 Data	Day 39	6.30
39 Data	Day 40	6.40
40 Data	Day 41	6.75
41 Data	Day 42	7.60
42 Data	Day 43	8.10
43 Data	Day 44	6.25
44 Data	Day 45	6.40
45 Data	Day 46	6.75
46 Data	Day 47	6.20

Table B.3 Major Validation Method(continued)

Data	Day of Forecast	Prediction
47 Data	Day 48	6.55
48 Data	Day 49	6.35
49 Data	Day 50	6.80
50 Data	Day 51	6.40
51 Data	Day 52	6.30
52 Data	Day 53	6.70
53 Data	Day 54	6.80
54 Data	Day 55	7.15
55 Data	Day 56	7.65
56 Data	Day 57	8.30
57 Data	Day 58	6.90
58 Data	Day 58 Day 59 Day 60	7.40
59 Data	Day 60	6.90
60 Data	Day 61	6.95
61 Data	Day 62	6.95
62 Data	Day 63	6.60
63 Data	Day 64	6.95
64 Data	Day 65	7.50

B.4 Major Classic

Table B.4 Major Classic

Data	Close	Stock Volume	Stock Volume	Repurchase	Classic	Repurchase
Date	t-1	t-1	t t	Volume	Prediction	Day
26/6/2009	6.75	5,341,955,000	5,341,810,000	145,000	7.05	65
25/6/2009	6.6	5,343,015,000	5,341,955,000	1,060,000	7.10	64
24/6/2009	6.65	5,343,355,700	5,343,015,000	340,700	7.05	63
23/6/2009	6.75	5,343,600,600	5,343,355,700	244,900	7.15	62
22/6/2009	6.6	5,345,600,600	5,343,600,600	2,000,000	7.00	61
19/6/2009	6.5	5,345,673,100	5,345,600,600	72,500	6.90	60
18/6/2009	6.7	5,345,873,100	5,345,673,100	200,000	7.00	59
16/6/2009	6.7	5,346,523,100	5,345,873,100	650,000	7.00	58
15/6/2009	7.25	5,347,523,100	5,346,523,100	1,000,000	7.75	57
11/6/2009	6.95	5,348,446,800	5,347,523,100	923,700	7.45	56
10/6/2009	6.8	5,349,996,800	5,348,446,800	1,550,000	7.30	55
5/6/2009	6.25	5,350,996,800	5,349,996,800	1,000,000	6.75	54
4/6/2009	6.2	5,351,496,800	5,350,996,800	500,000	6.70	53
3/6/2009	6.2	5,352,496,800	5,351,496,800	1,000,000	6.70	52
2/6/2009	6.3	5,353,096,800	5,352,496,800	600,000	6.80	51
1/6/2009	6.15	5,354,596,800	5,353,096,800	1,500,000	6.45	50
29/5/2009	6.2	5,356,596,800	5,354,596,800	2,000,000	6.50	49
28/5/2009	6.2	5,357,096,800	5,356,596,800	500,000	6.40	48
27/5/2009	6.15	5,357,408,000	5,357,096,800	311,200	6.35	47
26/5/2009	6.2	5,358,308,000	5,357,408,000	900,000	6.40	46

Table B.4 Major Classic (continued)

	Class	Ctools Wal	Ctools Val	Danwakaa	Classis	Damusshass
Date	Close	Stock Volume	Stock Volume	Repurchase	Classic	Repurchase
	t-1	t-1	t	Volume	Prediction	Day
25/5/2009	6.15	5,360,808,000	5,358,308,000	2,500,000	6.45	45
22/5/2009	6.05	5,360,908,000	5,360,808,000	100,000	6.45	44
21/5/2009	6.1	5,361,908,000	5,360,908,000	1,000,000	6.50	43
19/5/2009	6.25	5,362,208,000	5,361,908,000	300,000	6.65	42
21/4/2009	6.2	5,362,408,000	5,362,208,000	200,000	6.60	41
16/4/2009	6.1	5,362,708,000	5,362,408,000	300,000	6.50	40
9/4/2009	6.4	5,363,008,000	5,362,708,000	300,000	6.40	39
8/4/2009	6.55	5,363,208,000	5,363,008,000	200,000	6.55	38
7/4/2009	6.65	5,363,508,000	5,363,208,000	300,000	6.65	37
3/4/2009	6.7	5,363,808,000	5,363,508,000	300,000	6.70	36
2/4/2009	6.55	5,364,058,000	5,363,808,000	250,000	6.85	35
1/4/2009	6.55	5,364,158,000	5,364,058,000	100,000	6.75	34
31/3/2009	6.55	5,364,358,000	5,364,158,000	200,000	6.75	33
30/3/2009	6.9	5,364,708,000	5,364,358,000	350,000	7.10	32
27/3/2009	6.95	5,364,958,000	5,364,708,000	250,000	7.25	31
26/3/2009	6.8	5,365,158,000	5,364,958,000	200,000	6.80	30
25/3/2009	6.9	5,365,308,000	5,365,158,000	150,000	6.90	29
24/3/2009	6.45	5,365,658,000	5,365,308,000	350,000	6.45	28
20/3/2009	6.6	5,365,923,900	5,365,658,000	265,900	6.60	27
19/3/2009	6.5	5,366,173,900	5,365,923,900	250,000	6.50	26
18/3/2009	6.45	5,366,423,900	5,366,173,900	250,000	6.75	25
17/3/2009	6.5	5,366,723,900	5,366,423,900	300,000	6.80	24
16/3/2009	6.45	5,366,955,800	5,366,723,900	231,900	6.95	23

Table B.4 Major Classic (continued)

D :	Close	Stock Volume	Stock Volume	Repurchase	Classic	Repurchase
Date	t-1	t-1	t	Volume	Prediction	Day
13/3/2009	6.2	5,367,355,800	5,366,955,800	400,000	6.70	22
12/3/2009	6.2	5,367,441,700	5,367,355,800	85,900	6.70	21
11/3/2009	6.05	5,367,941,700	5,367,441,700	500,000	6.55	20
10/3/2009	5.9	5,368,141,700	5,367,941,700	200,000	6.40	19
9/3/2009	6.2	5,368,541,700	5,368,141,700	400,000	6.30	18
6/3/2009	5.75	5,368,741,700	5,368,541,700	200,000	5.85	17
3/3/2009	6.05	5,369,191,700	5,368,741,700	450,000	6.15	16
2/3/2009	6.4	5,369,691,700	5,369,191,700	500,000	6.70	15
27/2/2009	6.9	5,370,291,700	5,369,691,700	600,000	7.30	14
19/1/2009	6.9	5,370,891,700	5,370,291,700	600,000	7.30	13
16/1/2009	6.7	5,371,891,700	5,370,891,700	1,000,000	7.10	12
15/1/2009	6.7	5,372,691,700	5,371,891,700	800,000	7.00	11
14/1/2009	6.5	5,373,691,700	5,372,691,700	1,000,000	6.80	10
13/1/2009	6.5	5,374,191,700	5,373,691,700	500,000	6.70	9
12/1/2009	6.6	5,374,941,700	5,374,191,700	750,000	6.80	8
9/1/2009	6.7	5,375,641,700	5,374,941,700	700,000	6.90	7
8/1/2009	6.9	5,376,241,700	5,375,641,700	600,000	7.10	6
7/1/2009	6.95	5,376,941,700	5,376,241,700	700,000	7.10	5
6/1/2009	7.1	5,377,441,700	5,376,941,700	500,000	7.25	4
5/1/2009	6.95	5,378,346,700	5,377,441,700	905,000	7.10	3
30/12/2008	6.8	5,379,646,700	5,378,346,700	1,300,000	6.80	2
29/12/2008	7.05	5,380,596,700	5,379,646,700	950,000	7.05	1

B.5 Major Proposed Method Day 2

Table B.5 Major Proposed Method Day 2

Day Passing	Selected Days	Forecast	Prediction
2 Day	1(1),2	Day 3	7.20
3 Day	2(5),3	Day 4	6.95
4 Day	1(3),4	Day 5	7.50
5 Day	4(3),5	Day 6	6.80
6 Day	1(5),6	Day 7	6.60
7 Day	5(5),7	Day 8	6.70
8 Day	4(5),8	Day 9	6.50
9 Day	7(2)(SET),9	Day 10	6.90
10 Day	2(3)(SET),10	Day 11	6.80
11 Day	9(5),11	Day 12	6.90
12 Day	2(5)(SET),12	Day 13	6.90
13 Day	4(5),8(5)	Day 14	8.60
14 Day	9(3)(SET),14	Day 15	6.15
15 Day	7(5)(SET),15	Day 16	5.95
16 Day	9(3)(SET)14(5)	Day 17	7.90
17 Day	1(5)(SET),17	Day 18	5.90
18 Day	16(5)(SET),18	Day 19	6.15
19 Day	10(5),9	Day 20	6.20
20 Day	1(3)(SET),20	Day 21	6.30
21 Day	13(5),21	Day 22	6.45
22 Day	12(5)(SET),22	Day 23	6.80
23 Day	20(5),23	Day 24	6.45

 Table B.5 Major Proposed Method Day 2(continued)

Day Passing	Selected Days	Forecast	Prediction
24 Day	8(5)(SET),24	Day 25	6.70
25 Day	22(5)(SET),24	Day 26	6.70
26 Day	25(5)(SET),26	Day 27	6.55
27 Day	25(5)(SET),26(5)(SET)	Day 28	6.90
28 Day	26(3)(SET),28	Day 29	7.10
29 Day	14(5)(SET),29	Day 30	7.15
30 Day	2(5)(SET),30	Day 31	7.20
31 Day	1(5)(SET),31	Day 32	6.55
32 Day	24(5)(SET),32	Day 33	6.75
33 Day	21(3),33	Day 34	6.55
34 Day	14(5),34	Day 35	6.90
35 Day	30(5)(SET),35	Day 36	6.75
36 Day	31(5)(SET),36	Day 37	6.55
37 Day	7(5)(SET),37	Day 38	6.90
38 Day	36(5)(SET),38	Day 39	6.10
39 Day	10(5),19(5)	Day 40	6.40
40 Day	30(5)(SET)35(5)(SET)	Day 41	6.25
41 Day	10(5),19(5)	Day 42	7.60
42 Day	38(5)(SET),41(5)(SET)	Day 43	8.10
43 Day	28(5),43	Day 44	6.25
44 Day	19(5)(SET),44	Day 45	6.20
45 Day	43(5)(SET),45	Day 46	6.25
46 Day	32(5)(SET),46	Day 47	6.40
47 Day	43(5)(SET),47	Day 48	6.30

Table B.5 Major Proposed Method Day 2(continued)

Day Passing	Selected Days	Forecast	Prediction
48 Day	21(5)(SET),48	Day 49	6.15
49 Day	39(5),49	Day 50	6.70
50 Day	44(5)(SET),50	Day 51	6.40
51 Day	46(5)(SET),51	Day 52	6.20
52 Day	48(5)(SET),52	Day 53	6.45
53 Day	47(5)(SET),53	Day 54	6.90
	1(5)(SET),31(5)(SET)10(5)(SET)	,5	
54 Day	5	Day 55	7.05
55 Day	1(5)(SET)55	Day 56	7.25
56 Day	1(5)(SET),6(5)(SET)	Day 57	8.30
57 Day	7(5)(SET),57	Day 58	6.90
58 Day	9(5),11(5)	Day 59	7.40
59 Day	57(5)(SET),59	Day 60	6.70
60 Day	55(5)(SET),60	Day 61	6.75
61 Day	28(5)(SET),61	Day 62	6.95
62 Day	32(5)(SET),62	Day 63	6.80
63 Day	36(5)(SET),63	Day 64	6.85
64 Day	54(5)(SET),64	Day 65	6.95

B.6 Major Proposed Method Day 4

 Table B.6 Major Proposed Method Day 4

Day Passing	Selected Days	Forecast	Prediction
4 Day	1,2,3,4	Day 5	7.50
5 Day	1,3,4,5	Day 6	6.90
6 Day	1,4,5,6	Day 7	6.70
7 Day	1,4,5,7	Day 8	6.50
8 Day	4,5,7,8	Day 9	6.90
9 Day	2,5,7,9	Day 10	6.70
10 Day	1,6,8,10	Day 11	6.90
11 Day	5,7,9,11	Day 12	7.10
12 Day	2,3,10,12	Day 13	7.40
13 Day	4,5,7,8	Day 14	8.60
14 Day	4,8,9,14	Day 15	6.15
15 Day	5,7,9,15	Day 16	5.95
16 Day	9,11,13,14	Day 17	7.90
17 Day	1,6,8,17	Day 18	6.50
18 Day	7,15,16,18	Day 19	6.15
19 Day	3,10,12,19	Day 20	6.20
20 Day	10,12,19,20	Day 21	6.40
21 Day	11,13,14,21	Day 22	6.90
22 Day	2,3,12,22	Day 23	6.60
23 Day	10,19,20,23	Day 24	6.65
24 Day	4,8,17,24	Day 25	6.85
25 Day	3,12,22,25	Day 26	6.70

Table B.6 Major Proposed Method Day 4(continued)

Day Passing	Selected Days	Forecast	Prediction
26 Day	12,22,25,26	Day 27	6.65
27 Day	12,22,25,26	Day 28	7.30
28 Day	22,25,26,28	Day 29	6.80
29 Day	4,8,24,29	Day 30	7.40
30 Day	2,25,26,30	Day 31	7.10
31 Day	1,17,27,31	Day 32	6.65
32 Day	8,24,29,32	Day 33	6.85
33 Day	11,13,21,33	Day 34	6.55
34 Day	9,14,21,34	Day 35	6.70
35 Day	25,26,30,35	Day 36	6.85
36 Day	17,27,31,36	Day 37	6.95
37 Day	7,16,18,37	Day 38	6.60
38 Day	27,31,36,38	Day 39	6.10
39 Day	10,19,20,23	Day 40	6.55
40 Day	25,26,30,35	Day 41	6.35
41 Day	10,19,30,23	Day 42	7.60
42 Day	31,36,38,41	Day 43	8.10
43 Day	9,11,28,43	Day 44	6.80
44 Day	10,19,20,44	Day 45	6.30
45 Day	28,42,43,45	Day 46	6.15
46 Day	24,29,32,46	Day 47	6.20
47 Day	30,35,42,47	Day 48	6.40
48 Day	12,21,34,48	Day 49	6.25
49 Day	37,39,40,49	Day 50	6.80

Table B.6 Major Proposed Method Day 4(continued)

Day Passing	Selected Days	Forecast	Prediction
50 Day	10,19,44,50	Day 51	6.30
51 Day	29,32,46,51	Day 52	6.70
52 Day	13,21,48,52	Day 53	6.25
53 Day	35,42,47,53	Day 54	6.90
54 Day	1,31,38,41	Day 55	7.05
55 Day	10,44,50,55	Day 56	7.00
56 Day	1,6,38,41	Day 57	8.30
57 Day	7,37,40,57	Day 58	6.70
58 Day	9,11,33,52	Day 59	7.40
59 Day	37,40,57,59	Day 60	6.80
60 Day	44,50,55,60	Day 61	6.95
61 Day	28,43,45,61	Day 62	6.75
62 Day	28,43,45,61 32,46,51,62	Day 63	6.60
63 Day	36,38,41,63	Day 64	6.85
64 Day	53,54,56,64	Day 65	7.15

B.7 Major Proposed Method Day 7

Table B.7 Major Proposed Method Day 7

Day Passing	Selected Days	Forecast	Prediction
7 Day	1,2,3,4,5,6,7	Day 8	6.90
8 Day	1,3,4,5,6,7,8	Day 9	6.60
9 Day	2,4,5,6,7,8,9	Day 10	6.90
10 Day	1,2,3,5,6,8,10	Day 11	6.70
11 Day	3,5,6,7,9,10,11	Day 12	7.10
12 Day	2,3,7,9,10,11,12	Day 13	7.10
13 Day	1,4,5,6,7,8,11	Day 14	8.60
14 Day	1,4,6,8,10,13,14	Day 15	6.25
15 Day	1,4,5,6,7,8,15	Day 16	5.85
16 Day	4,8,9,11,13,14,16	Day 17	7.90
17 Day	5,6,7,8,15,16,17	Day 18	6.10
18 Day	5,7,8,15,16,17,18	Day 19	6.55
19 Day	2,3,10,12,16,17,19	Day 20	6.05
20 Day	2,3,10,12,17,19,20	Day 21	6.40
21 Day	9,10,13,14,17,19,21	Day 22	6.85
22 Day	2,3,10,12,19,20,23	Day 23	6.60
23 Day	10,14,16,18,19,20,23	Day 24	6.95
24 Day	4,7,8,15,16,18,24	Day 25	6.70
25 Day	2,3,10,12,19,22,25	Day 26	6.80
26 Day	2,3,12,19,22,25,26	Day 27	6.85
27 Day	2,3,12,19,22,25,26	Day 28	6.90
28 Day	19,20,22,23,25,26,28	Day 29	7.00

 Table B.7 Major Proposed Method Day 7 (continued)

Day Passing	Selected Days	Forecast	Prediction
29 Day	4,6,8,17,24,27,29	Day 30	6.95
30 Day	2,3,12,22,25,26,30	Day 31	7.10
31 Day	1,6,17,24,27,29,31	Day 32	6.65
32 Day	4,8,17,24,29,31,32	Day 33	6.90
33 Day	9,11,13,14,21,30,33	Day 34	6.75
34 Day	9,11,13,14,21,33,34	Day 35	6.90
35 Day	3,12,22,25,26,31,35	Day 36	6.95
36 Day	1,6,17,27,31,32,36	Day 37	6.55
37 Day	5,7,15,16,18,36,37	Day 38	6.50
38 Day	1,6,17,27,31,36,38	Day 39	6.70
39 Day	10,14,19,20,21,23,34	Day 40	6.20
40 Day	12,22,25,26,28,30,35	Day 41	6.40
41 Day	10,14,19,20,21,23,34	Day 42	7.60
42 Day	1,17,27,31,36,38,41	Day 43	8.10
43 Day	9,11,28,33,35,42,43	Day 44	6.35
44 Day	10,13,19,20,21,34,44	Day 45	6.20
45 Day	9,11,28,33,42,43,45	Day 46	6.50
46 Day	4,8,24,29,32,41,46	Day 47	6.40
47 Day	22,25,26,30,35,42,47	Day 48	6.30
48 Day	9,13,14,21,33,34,48	Day 49	6.35
49 Day	15,16,18,37,39,40,49	Day 50	6.30
50 Day	10,19,20,23,44,47,50	Day 51	7.00
51 Day	4,8,24,29,32,46,51	Day 52	6.40
52 Day	13,14,21,33,34,48,52	Day 53	6.45

Table B.7 Major Proposed Method Day 7 (continued)

Day Passing	Selected Days	Forecast	Prediction
53 Day	25,26,30,35,42,47,53	Day 54	7.40
54 Day	1,17,27,31,36,38,41	Day 55	7.05
55 Day	10,19,20,23,44,50,55	Day 56	7.25
56 Day	1,6,27,31,36,38,41	Day 57	8.30
57 Day	5,7,15,16,37,40,57	Day 58	6.90
58 Day	9,11,13,21,33,48,52	Day 59	7.40
59 Day	5,7,18,37,40,57,59	Day 60	6.80
60 Day	10,19,20,44,50,55,60	Day 61	6.85
61 Day	2,28,43,45,54,56,61	Day 62	6.95
62 Day	8,24,29,32,46,51,62	Day 63	6.80
63 Day	1,6,31,36,38,41,63	Day 64	6.75
64 Day	2,3,12,53,54,56,64	Day 65	7.05



CURRICULUM VITAE

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