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THE DEVELOPMENT OF HYBRID INTELLIGENT SYSTEMS FOR

TECHNICAL ANALYSIS BASED EQUIVOLUME CHARTING

by

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A DISSERTATION

Presented to the Faculty of the Graduate School of the

UNIVERSITY OF MISSOURI-ROLLA

In Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

in

ENGINEERING MANAGEMENT

2007

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PUBLICATION DISSERTATION OPTION

This dissertation consists of the following three articles that were published/have been submitted for publication. Each article has been prepared in the style of the journal/proceeding to which it was published/has been submitted.

Paper 1 (pages 4-53) was accepted for publication in the JOURNAL EXPERT SYSTEMS WITH APPLICATIONS.

Paper 2 (pages 54-85) was published in the PROCEEDINGS OF THE 2006 AMERICAN SOCIETY OF ENGINEERING MANAGEMENT (ASEM) NATIONAL CONFERENCE.

Paper 3 (pages 86-144) has been submitted for publication in INTERNATIONAL JOURNAL OF INTELLIGENT SYSTEMS IN ACCOUNTING, FINANCE & MANAGEMENT.

ABSTRACT

In recent years, equivolume charting has become a popular technical analysis tool used by individual investors and brokerage firms for make better investment and trading decisions. While useful, any approach or modification that can help improve the performance of technical analysis based equivolume charting for trading stocks should be of great assistance to investors. To this end, this dissertation proposes the development of a hybrid intelligent system applied to the Volume Adjusted Moving Average (VAMA), a technical indicator developed from equivolume charting. A Neuro-Fuzzy based Genetic Algorithm (NF-GA) system of the VAMA membership functions that integrates neural networks, fuzzy logic, and genetic algorithms techniques for increasing the efficiency of the VAMA for trading stocks is presented. The NF-GA system takes advantage of the synergy among these intelligent techniques to provide effective trading decisions for investors. For the system, the neural networks help provide earlier VAMA trading signals, fuzzy logic helps the system handle the uncertainty of the trading signals, and the genetic algorithms help the system optimize the trading signals. The trading simulation was tested in different market trends, including trending-up, flat, and trending-down markets of past S&P 500 index data. The trading with and without a 0.50% transaction cost was also examined. The overall results show that the NF-GA system performed best and displays robustness when compared to other benchmarks, including the VAMA alone, the VAMA with neural networks assistance, the neuro-fuzzy system of the VAMA, and the-buy-and-hold trading strategy.

ACKNOWLEDGMENTS

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1. INTRODUCTION

This dissertation proposes the development of a hybrid intelligent system applied to technical analysis based equivolume charting for stock trading. A Neuro-Fuzzy based Genetic Algorithms (NF-GA) system of the Volume Adjusted Moving Average (VAMA) membership functions is introduced to evaluate the effectiveness of using a hybrid intelligent system that integrates neural networks, fuzzy logic, and genetic algorithms techniques for increasing the efficiency of technical analysis based equivolume charting for trading stocks.

For the dissertation, two preliminary research efforts were performed utilizing the Volume Adjusted Moving Average (VAMA) and Ease of Movement (EMV), two technical indicators developed from equivolume charting. The first preliminary research effort (Paper 1) used neural networks as a forecasting system to assist the stock trading signals of the VAMA and EMV. A Generalized Regression Neural Network (GRNN) was applied as the neural network architecture. For the VAMA, the GRNN was used to predict the future stock prices, as well as the future width size of the equivolume boxes typically utilized on an equivolume chart, for calculating the future value of the VAMA. For the EMV, the GRNN was used to predict the future value of the EMV. Three trading systems for both the VAMA and EMV were used to examine and compare the results. In this study, neural networks were shown to be useful for improving the performance of the VAMA and EMV alone by providing earlier and timelier trading signals.

The second preliminary research effort (Paper 2) developed a neuro-fuzzy system of the VAMA by applying fuzzy logic as an extension to the results of the combined neural networks and VAMA model from the first preliminary research effort in order to

extract an intelligent trading decision. This was done since the VAMA trading heuristic does not have as precise a threshold for making a decision of when to buy, sell, or hold a particular stock. Therefore, the interpretation of the VAMA trading heuristic depends on the experience and the sentiment of the individual investor. For the research, fuzzy logic was used for representing the linguistic uncertainty of the VAMA trading heuristics that were generated from the neural networks model, which was then used to extract a trading decision. The results showed that stock trading using this neuro-fuzzy modeling approach can help to improve the profitability of the combined neural network and VAMA model. This was facilitated by the synergy between the neural networks and fuzzy logic, which allows to model accommodate common sense, extract knowledge, and use human-like reasoning mechanisms to deal with the uncertainty and imprecision of the VAMA trading heuristics. The results also suggested that the neuro-fuzzy system of the VAMA, which was based on the gap between the closing price and VAMA line, the slope of the closing price line, and the slope of the VAMA line should be preferred to the neuro-fuzzy system of the VAMA which was based only on the gap between the closing price and VAMA line.

Nonetheless, the VAMA membership functions used in the neuro-fuzzy system were static and designed manually using an arbitrary trial-and-error approach. Therefore, those membership function's parameters may not provide an optimization of the results. To overcome this problem, a genetic algorithm (GA) is applied to tune the parameters of the VAMA membership functions in order to determine the suitable shape of the VAMA membership functions. An integration of neural networks, fuzzy logic, and genetic algorithms leads to the development of the neuro-fuzzy based genetic algorithm of the

VAMA membership function as a hybrid intelligent system (Paper 3). For the system, a modification of the neuro-fuzzy system of the VAMA from the second preliminary research is performed and used as a baseline system. A base-10 genetic algorithm is then used to tune the parameters of the membership functions of the VAMA used in the neuro-fuzzy system to get better optimal trading results. The results show that the hybrid intelligent system takes advantage of the synergy among the neural networks, fuzzy logic, and genetic algorithms techniques to intelligently generate more optimal trading decisions for the VAMA so that the investors can make the better decision for stock trading. The stock trading using the NF-GA performs best when compared to the results generated from using the VAMA alone, the VAMA with neural networks assistance, the neuro-fuzzy system of the VAMA, and the buy-and-hold trading strategy.

PAPER 1

**INTELLIGENT TECHNICAL ANALYSIS BASED EQUIVOLUME CHARTING
FOR STOCK TRADING USING NEURAL NETWORKS**

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Abstract

It has been long recognized that trading volume provides valuable information for understanding stock price movement. As such, equivolume charting was developed to consider how stocks appear to move in a volume frame of reference as opposed to a time frame of reference. Two technical indicators, namely the volume adjusted moving average (VAMA) and the ease of movement (EMV) indicator, are developed from equivolume charting. This paper explores the profitability of stock trading by using a neural network model developed to assist the trading decisions of the VAMA and EMV. The generalized regression neural network (GRNN) is chosen and utilized on past S&P 500 index data. For the VAMA, the GRNN is used to predict the future stock prices, as

well as the future width size of the equivolume boxes typically utilized on an equivolume chart, for calculating the future value of the VAMA. For the EMV, the GRNN is also used to predict the future value of the EMV. The idea is to further exploit the equivolume potential by using a forecasting system to predict the future equivolume measurements, allowing investors to enter or exit trades earlier. The results show that the stock trading using the neural network with the VAMA and EMV outperforms the results of stock trading generated from the VAMA and EMV without neural network assistance, the simple moving averages (MA) in isolation, and the buy-and-hold trading strategy.

Keywords: Neural Networks; Technical Analysis; Financial Forecasting; Stock Trading

1. Introduction

Technical analysis, also known as "charting", has been a part of financial practice for many decades (Lo et al., 2000). It is considered by many to be the original form of investment analysis, dating back to the 1800s (Brock et al., 1992). As opposed to fundamental analysis, which is the study of economic, industry, and company conditions in an effort to determine the intrinsic value of a company' stock (Cutler et al., 1989), technical analysis studies the historical data surrounding price and volume movements of the stock by using charts as the primary tool to forecast future price movements (Murphy, 1999). Technical analysis normally uses two techniques to evaluate the stock prices. The first technical analysis technique uses charts to study the movement of stock prices. The use of technical indicators is another technique that includes calculations or mathematic equations to investigate the trading decisions.

However, technical analysis has also been criticized and scorned by many academics and practitioners (Malkiel, 1995). This is due to its inconsistency with the theory of market efficiency. As such, many studies have been made to investigate the performance of technical analysis, but conclusions vary. Some researchers have found results consistent with market efficiency, such that technical analysis cannot predict the future stock prices (Allen & Karjalainen, 1999; Bessembinder & Chan, 1998; Jegadeesh, 2000; Ratner & Leal, 1999; Sullivan et al., 1999). Others have relied on technical analysis for successful stock price prediction (Blume et al., 1994; Brock et al., 1992; Lo et al., 2000; Neely et al., 1997; Neftci, 1991). In recent years, however, it is an undeniable fact that technical analysis has proven to be powerful for evaluating stock prices and is widely accepted among financial economists and brokerage firms. This is due to the fact that technical analysis appears to be a compromising tool since it offers a relative mixture of human, political, and economical events (Achelis, 1995).

Trading volume is a standard market measurement and is one of the principal sources of information that is important to interpreting price movement. Furthermore, academics and practitioners have long recognized that past trading volume may provide valuable information about future stock price (Lee & Swaminathan, 2000). Studies have been made to examine the role of trading volume in an area of stock market prediction and investment (Blume et al., 1994; Campbell et al., 1993; Kaastra & Boyd, 1995; Lee & Swaminathan, 2000).

Based on an awareness of the importance of trading volume for stock price movement, equivolume charting (Arms, 1996), which is an increasingly important and popular type of technical analysis chart, was developed to take the effect of volume into

consideration when studying stock market action. Equivolume charting is unique in the way that the trading volume is used to replace time on the horizontal axis of the chart. As a result, for this paper the equivolume charting will be of interest since this technique redefines the time-scale for use in technical analysis by considering how stocks appear to move in a volume frame of reference as opposed to a time frame of reference. Various studies have focused on the time-scale for technical analysis and financial markets forecasting, especially in high-frequency markets, such as the foreign exchange market (FX) (Ceballos Hornero & Sorrosal i Forradellas, 2002; Dacorogna et al., 1993; Dacorogna et al., 1996; Levitt, 1998). However, less research has focused on the stock market. Therefore, this paper will provide an exploration of technical analysis based on equivolume charting by using an intelligence method to assist the stock trading signals. Neural network (NN) will be used as the method of computational intelligence for this study since they typically perform well for classification, recognition, and forecasting of financial data. Neural networks have also become an important method for stock market prediction because of their ability to deal with uncertain, fuzzy, or insufficient data that fluctuate rapidly in very short periods of time (Schoeneburg, 1990). Furthermore, neural networks are able to decode nonlinear time series data that adequately describe the characteristics of the stock markets (Yao et al., 1999). Many researhers have utilized various types of neural networks for technical analysis and stock market prediction (Chenoweth et al., 1996; Enke & Thawornwong, 2005; Kim & Han, 2000; Kuo et al., 2004; Leigh et al., 2005; Saad et al., 1998).

The experiment will be developed using the volume adjusted moving average (VAMA) and the ease of movement (EMV) indicators from the equivolume chart. The

VAMA assigns a volume measure rather than a time parameter to the moving averages, while the EMV converts the information of the equivolume chart into a numerical equivalent and shows the relationship between volume and price change. The objective will be to examine whether the neural network can help to assist the VAMA and EMV trading signals to generate better profitability. The generalized regression neural network (GRNN) will be selected and developed on past S&P 500 index data. For the VAMA, the GRNN will be used to predict a future stock prices as well as the future width size of the volume boxes typically utilized on an equivolume chart so that the future value of VAMA can be considered for stock trading. For the EMV, the GRNN will also be used to predict the future value of EMV for stock trading. Trading strategies will then be developed and the results will be compared against the results generated from those without neural network assistance, the simple moving averages (MA) in isolation, and the buy-and-hold trading strategy.

The paper is organized as follows. A brief introduction of equivolume charting, VAMA, and EMV are given in Sections 2, 3, and 4, respectively. Section 5 discusses the neural network architecture being used. Section 6 provides the trading strategies. The empirical results and analysis are reported in Section 7. Finally, conclusions are discussed in Section 8.

2. Equivolume Charting

The concept of equivolume was invented by Richard W Arms Jr. (Arms, 1996) after his research with the Arms Index (Arms, 1996). The Arms Index takes the affect of volume into consideration when studying market action (i.e. a measure of the overall

market trading activity). Equivolume charting recognizes the fact that volume is a market measurement and important to the price movement. It was developed to consider how stocks appear to move in a volume frame of reference as opposed to a time frame of reference. Therefore, equivolume charting (see Fig. 1) uses volume to replace time on the horizontal axis of the chart. This results in a modification of the bar chart in the way that the volume information that appears across the bottom margin of bar chart is combined with the price information of the chart to create an equivolume box. As a result, each trading time period (days in our example) will be represented by a single equivolume box. In a figure and for the research, the top and bottom of the equivolume box represent the high and low prices of the day, respectively, and the width of the equivolume box represents the daily trading volume.

As shown in Fig. 1, the width of the equivolume box, as well as the horizontal axis of the chart, will vary depending upon the trading volume for the day. The height of the equivolume box will vary depending upon the trading price spread for the day. Therefore, heavy volume affects the box laterally and large changes in price movement affect it vertically. On the other hand, light volume produces a narrow box and small changes in price movement produces a short box. The shape of each equivolume box helps to show whether it was easy or difficult for that stock to move up or down at any particular period. For example, short and wide boxes tend to occur at turning points and show that the stock is having difficulty moving, while tall and narrow boxes are more likely to occur in established trends and show that the stock is moving easily. If both the height and width of the box increase substantially, the power box reflects superior confirmation of a breakout.

Driven by the concept of equivolume charting, the VAMA and EMV are two technical indicators that can be developed and applied using a mathematical calculation for stock trading instead of observing the pattern and/or shape of equivolume boxes on the equivolume chart. The following two sections provide a brief introduction to the VAMA and EMV, respectively. Readers who are interested in full information of equivolume charting, VAMA, and EMV should refer to (Arms, 1994; Arms, 1996).

3. Volume Adjusted Moving Average (VAMA)

Based on a concept of equivolume charting, the VAMA was developed by Richard Arms (Arms, 1996). It uses the same logic as the principles of equivolume charting by assigning a volume measure rather than a time parameter to the moving average. The VAMA is more helpful than a simple moving average (MA) since stocks tend to trade their heaviest volume at turning points (Arms, 1996). As with the MA, the VAMA is useful in trending markets but provides poor results in trading-range markets. The most popular method of interpreting the VAMA is similar to the MA, which is to compare the relationship of the VAMA with the stock price itself. Therefore, a buy signal is generated when the stock price rises above its VAMA and a sell signal is generated when the stock price falls below its VAMA. The VAMA is based on expanding the volume frame of reference for heavier trading volume and contracting it for smaller trading volume, with the changes in volume plotted as equivolume boxes on an equivolume chart. Therefore, the heavier the trading volume, the larger the effect on the moving averages. As a result, the VAMA assigns the majority of weight to the days with the most volume, while with the MA the weight is assigned equally across all data for simple averages. However, the

number of time (volume) intervals used in calculating the average for both the MA and VAMA should fit the market cycle to reach consistent profitability. For the MA calculation, the value is calculated by averaging the closing price of the stock over a period of time. For instance, let CP_i be the closing price of the stock for period i^{th} ($i = 1$, 2, 3... n) while n is the number of time periods. The formula for MA then becomes:

$$MA = \frac{\sum_{i=1}^{n} CP_i}{n} \tag{1}$$

For the VAMA calculation, the contribution of each closing price is based on their volume relative to other days. For example, a day whose volume is three times greater than other days will contribute three times more of its closing price. As a result, for the VAMA it must be decided how each day of volume is related to other days. This is exactly the same method required to decide how wide to plot the boxes on the equivolume charts. This calculation is arbitrary and somewhat complex depending on the user preferences. A simple method is to assign the contribution of closing price for calculating VAMA that is based on the user preference of a value of the volume increment from the trading volume range. The following paragraphs give a brief introduction for the VAMA calculation.

Suppose we would like to find a 5 period VAMA of the closing prices. Assuming the closing prices and trading volumes from day 1 to day 5 are as in Table 1 below.

Suppose further that we give the smaller-volume days, in which the trading volume does not exceed 15,000 shares, a volume increment value of one, and heavier volume days a larger value, depending upon an incremental of volume to each 5,000 shares or part thereof. Therefore, a day of over 15,000 but under 20,001 shares traded would be

assigned a volume increment of two. A day with at least 20,001 but not 25,000 shares would be assigned a volume increment of three, and so on. The VAMA calculation can be performed by assigning the contribution of each closing price based on a volume increment to a moving average. Thus, for a 5 VAMA, the contributing values of the closing prices for the specified 5 volume interval (5 VAMA) are summed up and then divided by 5. An example of the 5 volume interval VAMA calculation is shown in Table 2.

For this study, the calculation method to determine a value of volume increment will not be based on the trading volume range but will instead be based on a volume ratio approach for normalization purposes in order to make the neural network training more efficient. Additional information about this approach for calculating the VAMA will be explained briefly in Section 6.

4. Ease of Movement (EMV)

The ease of movement (EMV), which is a technical indicator that converts the information of the equivolume chart into a numerical equivalent, was also developed by Richard W. Arms Jr. (Arms, 1996). The EMV indicator demonstrates the relationship between the price change of the stock and its volume, and shows whether it is easier for the stock to move up or down at any given time. A high and positive (negative) value of EMV shows that prices move upward (down) on light volume, while a low value around zero identifies prices that are not moving, or that it takes heavy volume to move prices. The EMV has the advantage of complete objectivity in that a precise value can be established for each entry (Arms, 1996). That leads to the ability to manipulate the

numbers and develop exact, unequivocal signals (Arms, 1996). In order to develop the EMV calculation, three important pieces of information have to be performed. Each piece of information must be taken into consideration for placing a numerical value on each equivolume box. They include: the price range for the period, the volume for the period, and the price change from the prior entry. For the first two pieces of information, a box ratio (BR) will be used to express and reduce this information to a single number. For the last piece of information, a midpoints move (MPM) calculation is used to measure the effect. The BR, MPM, and EMV can be expressed by the following equations:

$$\text{BR}_t = \frac{\text{Volume}_t}{\left(\text{Highest Price}_t - \text{Lowest Price}_t\right)} \tag{2}$$

$$\text{MPM}_t = \left(\frac{\text{Highest Price}_t + \text{Lowest Price}_t}{2}\right) - \left(\frac{\text{Highest Price}_{t\text{-}1} + \text{Lowest Price}_{t\text{-}1}}{2}\right) \tag{3}$$

$$\text{EMV}_t = \frac{\text{MPM}_t}{\text{BR}_t} \tag{4}$$

According to equations (2)-(4), the subscript *t* and *t-1* represent the current day and previous day, respectively. Signals from EMV are generally taken from a smoothing value of EMV, which normally uses a simple moving average. The basic EMV trading rule is to buy when the smoothing value of EMV crosses above zero from below and to sell when the smoothing value of EMV crosses below zero from above. However, the EMV will not normally be used as a stand alone indicator, but in conjunction with the equivolume chart from which it is generated, or in conjunction with other technical indicators at hand. In this study, the stand-alone trading strategy and its use in conjunction with the MA and VAMA trading strategy of the EMV will be employed. In

addition, the Fibonacci numbers approach, which is one of the several approaches to set the interval lengths of a moving average (Kamich, 2003), will be used for the EMV in this study. The Fibonacci numbers are a sequence of numbers in which each successive number is the sum of the two previous numbers (Achelis, 1995). This technique has been discussed in (Dobson, 1984).

5. Neural Network Model

Artificial neural networks (NN) are an information-processing system that can emulate certain performance characteristics of the biological functions of the human brain. This technique has the ability to learn from its environment and to adapt in an interactive manner similar to the biological counterparts (Ham & Kostanic, 2001). A neural network is characterized by its pattern of connections between the neurons (architecture), its method of determining the weights on the connections (training or learning algorithm), and its activation function (Fausett, 1994). The basic concept of a neural network is that there is a set of connected units in both the input and output layers where each unit connection link has a weight associated with it. There is also the presence of the hidden units in the hidden layers located and connected between the input and output layers in order to give the neural network greater ability to learn complex non-linear functions and more efficiently learn the function being modeled. Each unit, know as a neuron or node, performs as a simple processing element. Given a set of input signals (input variables), each input unit receives the input signal associated with it and broadcasts this signal to all output units over the connection link. Next, an activation function (normally nonlinear) is applied to the sum of weighted input signals for each output unit

to determine its output signal (output variable). A learning process is then performed within a neural network architecture in an effort to adaptively respond to input signals according to a learning algorithm by adjusting the weights so as to be able to predict or classify the output signals. After the neural network has learned the input-output mapping function, the trained network can be used to perform certain prediction and classification tasks depending on the particular application (Ham & Kostanic, 2001). Applications of neural networks include prediction and forecasting, clustering, associative memory, and nonlinear system modeling, among others. To date, numerous types of neural networks have been developed. One network that is important and useful to the area of finance, especially stock market prediction, is the generalized regression neural network (GRNN). The following sub-section gives a brief introduction to the GRNN. The neural network modeling and performance measures used in this study are also presented in Sections 5.2 and 5.3, respectively.

5.1 Generalized Regression Neural Network (GRNN)

A generalized regression neural network (GRNN) was introduced by Donald Specht (Specht, 1991). This architecture is a one-pass learning algorithm with a highly parallel structure. Even with sparse data in a multidimensional measurement space, the algorithm provides smooth transitions from one observed value to another (Specht, 1991). It was introduced as a memory based neural network that would store all the independent and dependent training data available for a particular mapping. When presented with a new input vector, the GRNN uses a distance function to compute the weighted average of the dependent training data whose independent parameters are in close proximity to the input

vector (Heimes & Van Heuveln, 1998). Therefore, the GRNN can be used as a universal approximator for smooth functions, allowing it to solve any function-approximation and estimate any continuous variable problem when given enough data. The function approximation of the GRNN is based on nonlinear regression theory that can be implemented in a parallel processing neural network structure. Based on this regression theory, the GRNN uses a method that frees it from the necessity of assuming a specific functional form. Rather, the appropriate form is expressed as a probability density function (pdf). As a result, it is not limited and requires no prior knowledge of the appropriate form (Specht, 1991).

Let x be a vector of input variables (independent variables) and be used to predict a scalar value of output variable (dependent variable) y. If the pdf of these quantities is known, the conditional mean of y given x (the expected value of y given x) with minimum expected mean squared error is given by equation (5),

$$E[y/x] = \frac{\int_{-\infty}^{\infty} yf(x, y)\,dy}{\int_{-\infty}^{\infty} f(x, y)\,dy} \tag{5}$$

where the pdf of x and y is f(x, y). However, f(x, y) is not normally known. Therefore, it will be estimated from a sample of observations of x and y by using a nonparametric estimator. This estimator uses the class of consistent estimators propose by Parzen (1962). For instance, let x^i and y^i represent the sample values of x and y in the training set, respectively, while n is the number of observations and p is the dimension of x. As a result, the desired conditional mean of y given incoming input vector x with minimum expected mean squared error is given by

$$\hat{y}(x) = \frac{\sum\limits_{i=1}^{n} y^i W(x, x^i)}{\sum\limits_{i=1}^{n} W(x, x^i)} \tag{6}$$

where $W(x, x^i) = e^{(-D_i^2 / 2\sigma^2)}$ is the output of hidden units in the first hidden layer, $D_i^2 = (x - x^i)^T (x - x^i)$ is the squared distance between the incoming input vector x and the training vector sample x^i, y^i is the known output sample associated with the training vector sample x^i, and σ is a smoothing parameter of the radial basis function (this study uses σ equal to 1.00). The GRNN architecture is shown in Fig. 2.

According to Fig. 2, the GRNN architecture consists of 4 layers and processes the input variables from one layer to the next with no feedback path. Thus, it looks much like a feed-forward neural network, but its operation is fundamentally different. The input layer has input units that receive the input vector x and provide it to all of the units on the next layer, the pattern layer. The first hidden layer (the pattern layer) in the GRNN contains the radial units (hidden units) which compute the distance D_i^2 for a new input vector x and then sum up and apply a nonlinear activation function (usually the exponential activation function) to the result. The pattern units produce the quantities $W(x, x^i)$ and pass them on to the second hidden layer. The second hidden layer (the summation layer) contains units that help to estimate the weighted average for the output layer. This summation layer uses the first unit to compute the sum of the products of $W(x, x^i)$ and the associated known output sample y^i, and also uses the second unit to compute the sum of all $W(x, x^i)$. Finally, the output layer, which performs the estimated weighted average, has an output unit that merely divides the output of the first unit by the output of the second unit of the summation layer to yield the desired estimate of y. In addition, the

summation layer always has exactly one more unit than the output layer. In regression problems (as in this study), typically only a single output is estimated, and so the summation layer usually has two units. In case the problem has more than one output (i.e. output vector) to estimate, the operation can be performed as previous mentioned by using more units in the summation and output layers. The GRNN can also be viewed as a radial basis network (RBN) in which there is a hidden unit centered at every training case, but its estimated output is performed from a weighted average of the output of the training cases close to the given incoming input vector, while the RBN is performed from a weighted sum of the hidden layer outputs.

As mentioned by Specht (1991), the GRNN has some advantages compared with other nonlinear regression techniques, including fast learning that has no iterative procedure, an estimate that converges to the optimal regression surface as the number of samples becomes very large, an estimate that is bounded by the minimum and maximum of the observations, and an estimate that cannot converge to poor solutions corresponding to local minima of the error criterion, which occasionally happens with the back-propagation trained feed-forward neural network (BPN). Readers who are interested in more detail regarding the GRNN should refer to (Bishop, 1995; Heimes & Van Heuveln, 1998; Patterson, 1996; Specht, 1991).

5.2 Neural Network Modeling

For this study, past S&P 500 index daily data from January, 1998 to December, 2003 (1,508 days) is utilized. The training data set is from the period of January, 1998 to December, 2002 and is used for determining the specifications of the model and

parameters of the forecasting technique, while the testing data set is from the period of January, 2003 to December, 2003 and is used for out-of-sample evaluation of the forecasting model. The testing data set chosen in this study included a trending market, and as such is used to investigate the ability of various moving average tools, as well as the EMV, since moving averages and EMV are often useful in trending markets but give poor results in trading-range markets. The S&P 500 index data is selected in this study due to three main advantages: it represents approximately 75% of the value of the U.S. equity market, it represents leading companies in leading industries, and it has a diverse representation of companies.

Two NN systems are developed. For the first NN system, two GRNN models are developed. The first model (GRNN 1) is used for predicting the width size of the equivolume boxes typically utilized on an equivolume chart (i.e. predict how each day volume is related to other days). As mentioned in section 3, the calculation method used to decide how wide to plot the boxes on the equivolume chart is arbitrary and dependent on the users. This study uses a volume ratio to be a value of volume increment in order to decide the width size of the equivolume boxes. The volume ratio in this study is calculated by using each day's actual trading volume divided by the average of all trading volumes in the training set period. Thus, the target of this model is a volume ratio for the next day (VR_{t+1}). Since the target of this model deals with a volume, this study proposes to use two popular volume technical indicators, the Money Flow Index (MFI) and On Balance Volume (OBV), along with the daily data, including the opening price (OP_t), closing price (CP_t), highest price (HP_t), and lowest price (LP_t) to serve as input variables. Moreover, in order to capture the movement and the characteristics of volumes and

prices, closing price momentum (CP_t - CP_{t-1}), volume momentum (V_t - V_{t-1}), 10 and 20 day moving averages, 10 and 20 day volume moving averages, past 10 days volume, and past 5 days volume ratio are also provided as inputs variables. There are a total of 27 input variables selected for use in this model.

The second model (GRNN 2) is used for predicting the next day closing price (CP_{t+1}). This model has a total of 12 input variables. The first variable is the closing price (CP_t). The remaining input variables include the rate of return (R_t) and various technical indicators, including the Money Flow Index (MFI), On Balance Volume (OBV), the Relative Strength Index (RSI), closing price momentum (CP_t - CP_{t-1}), 10 and 20 day moving averages, %K and %D from the Stochastic Oscillator, the Moving Average Convergence/Divergence (MACD), and the signal line of MACD (SL). The target of this model is the rate of return for the next day (R_{t+1}). In this study, R_{t+1} is defined as follows:

$$R_{t+1} = \frac{\left(CP_{t+1} - CP_t\right)}{CP_t} \tag{7}$$

where CP_t and CP_{t+1} are the current closing price and next day closing price, respectively. Based on Equation (7), R_{t+1} will be converted to CP_{t+1} to develop the trading systems later in section 6. Finally, the 12 selected inputs are included in the base sets with five-day time lags to account for recent movements of the target. This gives 60 input variables employed to predict the next day rate of return. Furthermore, since the data in the financial environment tends to be noisy and there are different values in range among the input variables, which in turn prevents a NN model from focusing on the information underlying the data, a data normalization process is used that the input variables are scaled so as to fall within a specified range. Normalization is useful to make the network train more efficiently. For this study, normalization based on the mean and standard

deviations (z-score normalization) is used for the input variables of both the GRNN 1 and GRNN 2 models. The normalization using mean and standard deviation can be expressed as follows:

$$X' = \frac{\left(X - \bar{A}\right)}{\sigma_A} \tag{8}$$

where the values of an input or output (X) for attribute A are normalized to X'. The values $\bar{A}$ and σ_A are the mean and standard deviation of attribute A, respectivey, based on the data in the training set (Han & Kamber, 2001).

For the second NN system, there is a only one GRNN model, labeled as GRNN 3. GRNN 3 has a total of 17 input variables. The daily data, including closing price (CP_t), opening price (OP_t), highest price (HP_t), lowest price (LP_t), and volume (V_t) serve as the first five input variables. In order to capture the movement and the characteristics of prices and volumes, closing price momentum ($CP_t - CP_{t-1}$), highest price momentum ($HP_t - HP_{t-1}$), lowest price momentum ($LP_t - LP_{t-1}$), volume momentum ($V_t - V_{t-1}$), and 10 and 20 day of closing price, highest price, and lowest price moving averages are also provided as inputs variables. The remaining input variables include past values for the EMV value (EMV_t) and EMV momentum ($EMV_t - EMV_{t-1}$), and are used to capture the movement and characteristics of the EMV technical indicator. The target (output) of the GRNN 3 model is the EMV value for the next day (EMV_{t+1}). Finally, all input variables and target variables are also normalized based on the mean and standard deviation. Table 3 provides a summary of input and output variables of all NN models.

5.3 Performance Measures

The predictive forecasting performances of the NN models are evaluated using the testing data set (out of sample data). The traditional measure of Mean Square Error (MSE), will be used to examine the magnitude prediction power. The MSE can be expressed as in Equation (9),

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\text{Actual}_i - \text{Predict}_i\right)^2 \tag{9}$$

where n = total number of data

Since traditional measures of forecasting performance such as the MSE may not be strongly related to profits from trading (Pesaran & Timmermann, 1995), the percentage accuracy of correctly predicting the direction (SIGN) of the target will also be used to examine the direction power. In fact, the forecast performance based on SIGN is believed to match more closely to the profitability performance than do traditional criteria (Leitch & Tanner, 1991). Therefore, both of the MSE and SIGN will be selected as the performance measures to show the predictability results of the developed forecasting NN models in this study. This SIGN can be expressed as in Equation (10),

$$\text{SIGN} = \frac{\sum_{i=1}^{n} s_i}{n} \tag{10}$$

where $s = 1$ if $(p_{t+1} - a_t)*(a_{t+1} - a_t) > 0$ or $(p_{t+1} - a_t)$ and $(a_{t+1} - a_t) = 0$; otherwise $s = 0$, p_{t+1} is predict value on the next day, a_t and a_{t+1} are actual value on the current and next day, respectively, and n is total number of data. Since the EMV can be positive or negative value, the performance measure based on the term of positive/negative value of the target will be used for the GRNN 3 model. In this study, the percentage accuracy of

correctly predicting the positive/negative value of the target will be used to measure the positive/negative value power, as expressed in Equation (11),

$$\% \text{ accuracy of positive/negative} = \frac{\sum_{i=1}^{n} c_i}{n} \tag{11}$$

where

$c = 1$; if actual and predict are positive value or actual and predict are a negative value

$c = 0$; otherwise, n = total number of data

6. Trading Strategies

The trading strategies will be developed on the testing data set. The general trading steps include: a buy or sell position being taken at the market open, selling the entire position, and then exiting of the market at the end of the period. Transactions costs are excluded.

In order to perform the VAMA trading strategies, the post-processing process to calculate the VAMA both with and without help from the NN will be employed. Fig. 3 shows the system overview for finding the VAMA with the NN.

For the VAMA alone (without help from the NN), the post-processing process will start at the most recent time period (time t) and work backwards. The volume ratio (volume increment) of each day is multiplied by the closing price of each day and then cumulatively summing these values until the specified contributed volume number (i.e. the number of the summation of volume ratios) is reached (in this study using 5, 10, 13, 21, 55, and 63). Finally, the sum values are divided by that specified number of contributed volume to obtain the value of the VAMA. Note that only a fraction of the last

day volume ratio will likely be used. For the VAMA with the NN, the post-processing process will start at the predicted time period (time *t+1*) and work backwards. The volume ratio (volume increment) of each day is also multiplied by the closing price of each day, but at the starting time (time *t+1*), the predicted volume ratio is multiplied by the predicted closing price, and then these values are cumulatively summed until the specified number of contributed volume (i.e. the number of the summation of volume ratios) is reached (in this study using 5, 10, 13, 21, 55, and 63). Once again, the sum values are divided by that specified contributed volume number to obtain the value of the VAMA. Note that only a fraction of the last day volume ratio will likely be used.

To better understand the post-processing process, Tables 4 and 5 give a brief example calculation for the 5 VAMA alone and 5 VAMA with the NN based on the post-processing process, respectively.

Three trading strategies are used in this study for the VAMA: single moving average, single moving average with a filter, and two moving averages. For the single moving average with a filter, the filter is applied to handle the problem of receiving too many signals from the moving average, as well as help to increase the confidence of the moving average trading signals. The VAMA alone, simple moving average (MA) alone, and buy-and-hold trading strategy are considered for benchmarking to compare the results against the VAMA with the NN. The buy-and-hold strategy used in this study is based on buying stocks on the first day of the holding period, holding the position until the last day of the holding period, and then selling the entire position. Table 6 expresses three trading strategies used in this research for the VAMA with the NN, the VAMA alone, and the MA alone.

Several time or volume frames from different approaches, such as cycle length (5, 21, and 63), harmonic numbers (5 and 10), and Fibonacci numbers (5, 13 21, and 55) are utilized to see the sensitivity of the results. For the single moving average and single moving average with a filter, this study uses the length of the average to be equal to a quarter time (volume) frame (55 and 63) to fit the market cycle of the dataset used in this study for optimum profitability. Furthermore, this study uses the first day of the testing data set to be the first day to calculate a moving average for all three trading strategies. This is done since the first trading signal for the trading strategies can be taken at the turning point (sell signal changes to buy or buy signal changes to sell) in order to reach the better profitability. Therefore, the first trading signal will not be generated on the first day of the testing data set, but will be generated on the first turning point day.

For the EMV trading strategies, two main trading strategies are developed to examine the results. The EMV trading signals are taken from a smoothing value itself. The simple moving average (MA) will be used as a smoothing method. The first trading strategy is a stand alone trading strategy. In order to investigate the profitability of this trading strategy, several interval lengths of smoothing values, including a very short term period (weekly), a short term period (monthly), an intermediate period (quaterly), and the Fibonacci numbers approach will be utilized in this study. Based on the Fibonacci numbers approach, a 5-day EMV approximately represents a weekly period, a 21-day EMV approximately represents a monthly period, and a 55-day EMV approximately represents a quarterly period. The EMV with the NN used in this trading strategy will be benchmarked against both the EMV without the NN and the buy-and-hold trading strategy.

Since the EMV is not normally used as a stand alone indicator, the MA and VAMA indicators will be used along with the EMV to confirm the trading signals in this study. The MA and VAMA are chosen because the EMV trading signals are taken from a moving average method. Besides, the MA is the most popular use of moving average indicators, while the VAMA is a moving average indicator developed from equivolume chart similar to the EMV. Therefore, it may be a good idea to use the MA and VAMA for confirming the trading signals of the EMV. As such, the second trading strategy will be the EMV used in conjunction with the MA and VAMA. For this trading strategy, there are two sub-trading strategies that include a either one or two moving average trading strategies. All trading signals generated are voting signals in conjunction with the MA and VAMA. For the voting signals, a buy or sell signal will be generated when the trading signals from the EMV matching with the MA and VAMA trading signals. Moreover, in this trading strategy, the first trading signal of the MA and VAMA will be generated on the first day of the testing data set as opposed to the previous MA and VAMA trading strategies. This is done since the first voting trading signal can be performed on the first day of the testing data set in order to investigate the results through all of the testing data set periods purposed since the first EMV trading signal can be generated on the first day of the testing period. For the single moving average trading strategy, the interval lengths of the smoothing value of the EMV and closing prices (for calculating MA and VAMA) are also based on the Fibonacci numbers approach (5-day for weekly, 21-day for monthly, and 55-day for quarterly). The EMV with the NN used in this trading strategy will be benchmarked against the EMV without the NN, MA alone, VAMA alone, and the buy-and-hold trading strategy. For the two moving average trading

strategy, several short-term (fast) and long-term (slow) interval lengths for calculating two MA and two VAMA are investigated (5&55-day, 10&55-day, 13&55-day, and 21&55-day). The smoothing interval lengths of the EMV will follow as the slow MA and VAMA. Once again, the EMV with the NN used in this trading strategy will be benchmarked against the EMV without the NN, the MA alone, the VAMA alone, and the buy-and-hold trading strategy. Table 7 describes all of the trading strategies for the EMV with and without the NN as used in this study.

7. Empirical Results and Analysis

After performing forecasts for all NN models, the MSE and SIGN of all GRNN models, as well as the % accuracy of positive/negative of GRNN 3 model over the out-of-sample period (testing data set), were calculated and are provided in Table 8.

A trading simulation was performed to examine whether NN can help to assist the VAMA and EMV to generate higher profits than those of not using NN assistance. The results in Table 9, 10, and 11 presents the profitability details of a first NN system (GRNN 1 and GRNN 2) assisting the VAMA trading signals along with its benchmarks for the single moving average, single moving average with a filter, and two moving averages, respectively. The results include the gain or loss of the trading based on one share of the S&P 500 index and the number of trades for each time (volume) frame of interval lengths.

According to Tables 9 and 10, the single moving average and single moving average with a filter results are significant, and show the power of the NN when combined with the VAMA for outperforming the other benchmarking tools. The reason is that the signals

provided from the VAMA with the NN help the investors to receive an earlier and timelier signal than with the simple MA and VAMA alone, which are still a lagging technical indicator. This demonstrates the usefulness of combining these two methods (NN and VAMA), where the NN is used as a forecasting system to predict the future value of the computed VAMA. Interestingly, it was also found that with using other interval lengths of moving average, which are not fitted to the market cycle of the data set, such as weekly or monthly period (not shown in Tables), the results from the VAMA with the NN also outperform the results from the MA and VAMA alone but cannot overcome the buy-and-hold trading strategy. This provides confirmation that having the optimal lengths fit to the market cycle of the data set for calculating a moving average is an important criterion to be considered, even though the NN can assist the earlier trading signal decisions.

Regarding Table 11, the results of the two moving average trading strategies generated from the VAMA with the NN does not perform well when compared against other tools. This result is similar in average with the MA and VAMA alone, and a little higher than the buy-and-hold strategy. However, the most popular method of interpreting a moving average is to compare the relationship between a moving average of the stock's price with the stock price itself (i.e. single MA) (Achelist, 1995). On the other hand, two moving averages are used to handle the problem of defining when the price crosses the moving average line (besides using a filter) and shows how well the fast moving average line captures the slow moving average line for "crossover" buy and sell indications. Therefore, the single MA trading strategies would be preferred as this study has shown

the superior results of VAMA with the NN when examined using the single MA trading strategies.

The trading results of the second NN system (GRNN 3) assisting the EMV trading signals along with its benchmarks for use as a stand alone are reported in Table 12. The results are also shown as being based on trading one share of the S&P 500 index and provide the number of trades for each interval length of MA. Note that the interval lengths of MA provided in Table 12 are obtained from the Fibonacci numbers approach.

Even though the EMV performs well as a leading indicator, which typically works by measuring how overbought or oversold a stock is, the trading signals are generated from the MA method, which has a lagging problem. Therefore, this typically will result in later buy or sell signals. The results in Table 12 show that the EMV with the NN provides the greater profitability than the EMV without the NN assistance and the buy-and-hold trading strategy. This is due to the fact that the NN model improves performance of the EMV by providing earlier trading signals to reduce its lagging problem. The number of trades of the EMV with the NN (average 12.67 trades) is significant decreased when comparing against the EMV without the NN (average 24 trades). This may be due to the fact that the NN helps to eliminate whipsaw or unnecessary signals of the EMV. In fact, the lower number of trades helps investors from paying too many individual costs transactions. Furthermore, the results from both EMV with and without the NN assistance using the quarter interval (55-day EMV) are similar in the way that they outperform other intervals results since they are more fitting to the market cycle than the others. In fact, with a more optimal length of moving average for the smoothing value of the EMV, more

profitability can be reached. As a result, the suitable optimal length of a moving average of EMV for trading decisions is a problem that must be considered as well.

The results of the EMV with the NN used in conjunction with the MA and VAMA trading strategy for a single moving average and its benchmarks are shown in Tables 13 and 14, respectively. Tables 15 and 16 present the results of this trading strategy for two moving averages and their benchmarks. Once again, all results are based on one share of S&P 500 index being traded.

According to Tables 13-16, the stock trading combining the NN model and the EMV shows good performance of profitability for outperforming the other benchmarks. Again, this results since the NN model improves performance of the EMV by providing earlier trading signals, similar to the previous trading strategy. The average results in Tables 13 and 15 also shows that the EMV with the NN used in conjunction with the MA for a single moving average outperforms the results generated from two moving averages. This is similar to the average results of the EMV with the NN used in conjunction with the VAMA in Tables 14 and 16. Therefore, this would suggests that the single moving average would be preferred for the trading strategy of the EMV with the NN used in conjunction with the MA and VAMA based on the study results. In addition, the EMV, both with and without the NN used in conjunction with the MA and VAMA, show better profitability and a lower number of trades than the MA and VAMA used alone as reported in Tables 13-16. In fact, the EMV with the NN also shows a better profitability and lower number of trades than the EMV without the NN assistance. This demonstrates that the voting signals can help to eliminate the whipsaw signals and that the NN also helps to provide earlier signals.

8. Conclusions

This research shows the benefits of using a GRNN combined with the VAMA and EMV for stock trading. The testing dataset chosen in this study included a trending market, and as such was used to investigate the ability of various moving average tools, since moving averages and EMV are usually useful in trending markets and give poor results in trading-range markets. Two NN systems were developed in this study for predicting the next day closing price, as well as the next day equivolume boxes size (the width of boxes) in order to calculate the VAMA and for predicting the future value of EMV. Results from all trading strategies show that the VAMA and EMV with the NN can improve the performance of the VAMA and EMV alone by providing earlier trading signals. The results utilized from the VAMA and EMV with the NN outperform other benchmarking tools, including those without NN assistance, the MA, VAMA used alone, and the buy-and-hold strategy. Moreover, this study also found that the suitable optimal length (fit to the market cycle of data set) of a moving average is an important criterion to be considered, even though the NN can help to provide better VAMA and EMV trading signals. Further study should examine the combination of the NN and other intelligent techniques, such as a fuzzy logic system, for improving performance of the forecasting models. The trading simulation under a more realistic total profit scenario, i.e. one that includes transaction costs and taxes, should also be considered.

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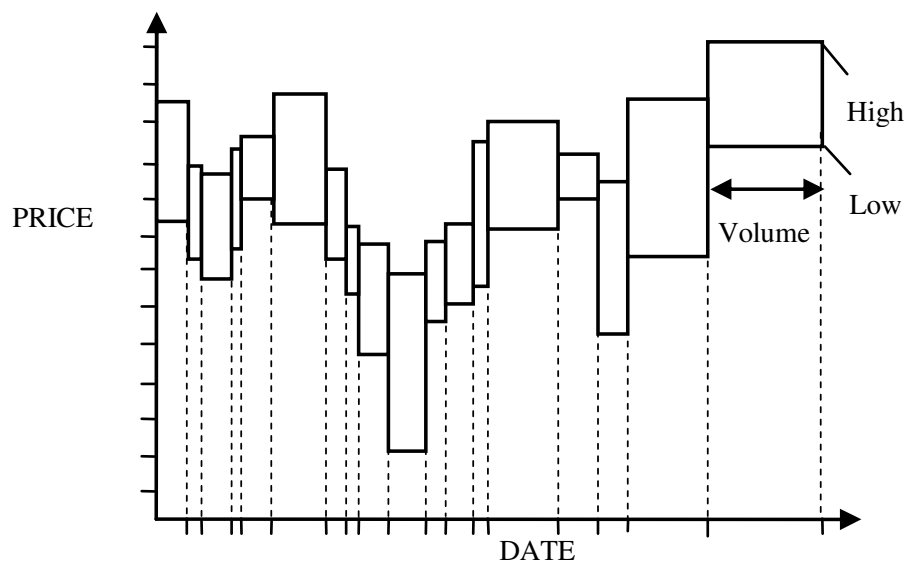
Fig. 1. Equivolume Charting.

Fig. 2. GRNN Architecture.

Inputs

GRNN 1

VR_{t+1}

Post-Processing

VAMA
with the NN
$(VAMA_{t+1})$

Inputs

GRNN 2

R_{t+1}

CP_{t+1}
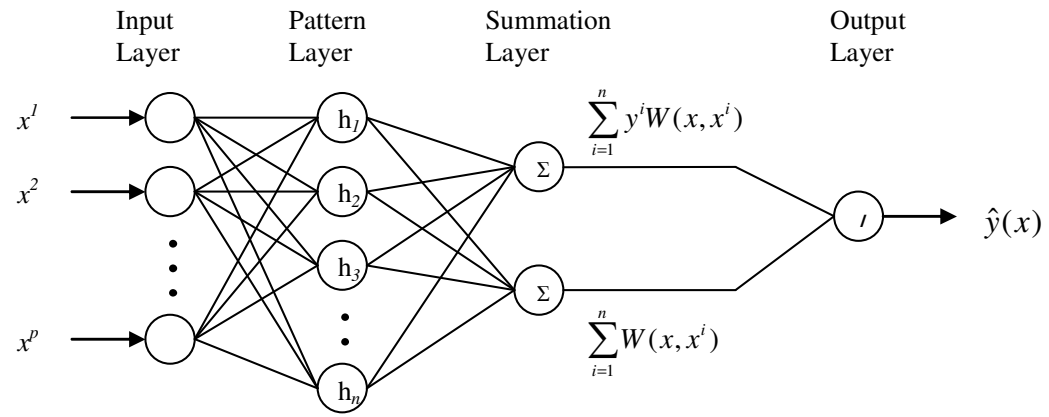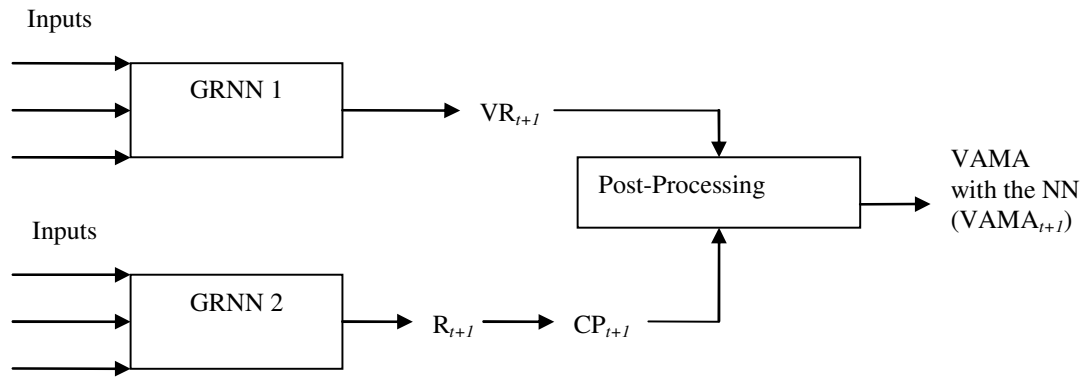
Fig. 3. System Overview to Find VAMA with the NN.

Table 1

The closing prices and trading volumes

Period (Date)	Closing Price ($)	Trading Volume (Shares)
Day 1	927.57	15,765
Day 2	926.26	13,574
Day 3	931.66	20,525
Day 4	918.22	18,756
Day 5	914.60	15,716

Table 2
The 5 VAMA calculations

Period (Date)	Volume Increment	Closing Price ($)	5 VAMA
Day 1	2	927.57	(927.57+927.57+
		927.57	926.26+931.66+
Day 2	1	926.26	931.66)/5 =
Day 3	3	931.66	$928.944
		931.66	
		931.66	(931.66+918.22+
Day 4	2	918.22	918.22+914.60+
		918.22	914.60)/5 =
Day 5	2	914.60	$919.46
		914.60	

Table 3
Summary of network inputs and outputs

Network Model	Network Inputs	Network Outputs
GRNN 1	OP_t, CP_t, HP_t, LP_t, MFI_t, OBV_t, CP_t-CP_{t-1}, V_t-V_{t-1}, 10 MA_t, 20 MA_t, 10 volume MA_t, 20 volume MA_t, V_{t-9} to V_t, and VR_{t-4} to VR_t	VR_{t+1}
GRNN 2	CP_{t-4} to CP_t, R_{t-4} to R_t, MFI_{t-4} to MFI_t, OBV_{t-4} to OBV_t, RSI_{t-4} to RSI_t, CP_{t-4}-CP_{t-5}, CP_{t-3}-CP_{t-4}, CP_{t-2}-CP_{t-3}, CP_{t-1}-CP_{t-2}, CP_t-CP_{t-1}, 10 MA_{t-4} to 10 MA_t, 20 MA_{t-4} to 20 MA_t, $\%K_{t-4}$ to $\%K_t$, $\%D_{t-4}$ to $\%D_t$, $MACD_{t-4}$ to $MACD_t$, and SL_{t-4} to SL_t	R_{t+1} (will be converted to CP_{t+1})
GRNN 3	OP_t, CP_t, HP_t, LP_t, V_t, CP_t-CP_{t-1}, HP_t-HP_{t-1}, LP_t-LP_{t-1}, V_t-V_{t-1}, 10 MA_t, 20 MA_t, 10 highest price MA_t, 20 highest price MA_t, 10 lowest price MA_t, 20 lowest price MA_t, EMV_t, and EMV_t-EMV_{t-1}	EMV_{t+1}

Table 4.
Example of calculation for 5 VAMA alone based on the post-processing process
(current day (time *t*) is 01/05/2003)

Date	Closing Price (CP)	Volume Ratio (VR)	CPxVR
01/02/2003	$909.03	1.1957	$1,086.93
01/03/2003	$908.59	1.0855	$986.27
01/04/2003	$929.01	1.3597	$1,263.17
01/05/2003 (time *t*)	$922.93	1.4886	$1,373.87
		Sum = 5.1295	Sum = $4,710.24

5 VAMA = [$4,710.24 – (5.1295 – 5) x $909.03]/5 = $918.50

Table 5.

Example of calculation for 5 VAMA with the NN based on the post-processing process
(current day (time *t*) is 01/04/2003)

Date	Closing Price (CP)	Volume Ratio (VR)	CPxVR
01/02/2003	$909.03	1.1957	$1,086.93
01/03/2003	$908.59	1.0855	$986.27
01/04/2003 (time *t*)	$929.01	1.3597	$1,263.17
01/05/2003 (time *t+1*)	$925.67**	1.4019*	$1,297.70
		Sum = 5.0428	Sum = $4,634.07

5 VAMA with NN = [$4,634.07 – (5.0428 – 5) x $909.03]/5 = $919.03

Note: * = predicted value from GRNN 1, * * = predicted value from GRNN 2

Table 6.
Trading strategies for the VAMA with the NN, VAMA alone, and MA alone

Trading Strategy	VAMA with the NN	VAMA Alone	MA Alone
Single Moving Average	If predicted CP_{t+1} is more than predicted $VAMA_{t+1}$, then buy stocks at time $t+1$. If predicted CP_{t+1} is less than predicted $VAMA_{t+1}$, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If CP_t is more than $VAMA_t$, then buy stocks at time $t+1$. If CP_t is less than $VAMA_t$, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If CP_t is more than MA_t, then buy stocks at time $t+1$. If CP_t is less than MA_t, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.
Single Moving Average with Filter	If predicted CP_{t+1} is more than predicted $VAMA_{t+1}$ at least $2.00, then buy stocks at time $t+1$. If predicted CP_{t+1} is less than predicted $VAMA_{t+1}$ at least $2.00, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If CP_t is more than $VAMA_t$ at least $2.00, then buy stocks at time $t+1$. If CP_t is less than $VAMA_t$ at least $2.00, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If CP_t is more than MA_t at least $2.00, then buy stocks at time $t+1$. If CP_t is less than MA_t at least $2.00, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.
Two Moving Averages	If predicted fast $VAMA_{t+1}$ is more than predicted slow $VAMA_{t+1}$, then buy stocks at time $t+1$. If predicted fast $VAMA_{t+1}$ is less than predicted slow $VAMA_{t+1}$, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If fast $VAMA_t$ is more than slow $VAMA_t$, then buy stocks at time $t+1$. If fast $VAMA_t$ is less than slow $VAMA_t$, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If fast MA_t is more than slow MA_t, then buy stocks at time $t+1$. If fast MA_t is less than slow MA_t, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.

Table 7.
Trading strategies for the EMV with and without the NN

Trading Strategy	EMV with the NN	EMV without the NN
EMV Stand Alone	If MA of predicted EMV_{t+1} crosses above zero from below, then buy stocks at time $t+1$. If MA of predicted EMV_{t+1} crosses below zero from above, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If MA of EMV_t crosses above zero from below, then buy stocks at time $t+1$. If MA of EMV_t crosses below zero from above, then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.
EMV in conjunction with the MA and VAMA (Single Moving Average)	If MA of predicted EMV_{t+1} crosses above zero from below and CP_t is more than MA_t ($VAMA_t$), then buy stocks at time $t+1$. If MA of predicted EMV_{t+1} crosses below zero from above and CP_t is less than MA_t ($VAMA_t$), then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If MA of EMV_t crosses above zero from below and CP_t is more than MA_t ($VAMA_t$), then buy stocks at time $t+1$. If MA of EMV_t crosses below zero from above and CP_t is less than MA_t ($VAMA_t$), then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.
EMV in conjunction with the MA and VAMA (Two Moving Averages)	If MA of predicted EMV_{t+1} crosses above zero from below and fast MA_t ($VAMA_t$) is more than slow MA_t ($VAMA_t$), then buy stocks at time $t+1$. If MA of predicted EMV_{t+1} crosses below zero from above and fast MA_t ($VAMA_t$) is less than slow MA_t ($VAMA_t$), then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.	If MA of EMV_t crosses above zero from below and fast MA_t ($VAMA_t$) is more than slow MA_t ($VAMA_t$), then buy stocks at time $t+1$. If MA of EMV_t crosses below zero from above and fast MA_t ($VAMA_t$) is less than slow MA_t ($VAMA_t$), then sell stocks at time $t+1$. Else, no position is taken at time $t+1$.

Table 8.
Performance measure results

Network Model	MSE	SIGN	% Accuracy of Positive/Negative
GRNN 1 (VR_{t+1})	0.028550	70.52%	-
GRNN 2 (R_{t+1})	0.000266	74.50%	-
GRNN 2 (CP_{t+1})	0.006168	55.95%	-
GRNN 3 (EMV_{t+1})	0.037218	73.31%	64.68%

Table 9.
Single moving average results

CP and interval	MA		VAMA		VAMA with the NN		Buy-and-Hold	
	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades
CP&55	$173.20	16	$165.25	20	$234.31	22	$201.00	2
CP&63	$192.90	8	$159.33	20	$228.60	24	$201.00	2
Average	$183.05	12	$162.29	20	$231.46	23	$201.00	2

Table 10.

Single moving average with a filter results

CP and interval	MA		VAMA		VAMA with the NN		Buy-and-Hold	
	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades
CP&55	$181.37	12	$173.34	16	$220.71	16	$201.00	2
CP&63	$192.90	8	$186.96	10	$231.37	20	$201.00	2
Average	$187.14	10	$180.15	13	$226.04	18	$201.00	2

Table 11.
Two moving averages results

Fast & Slow interval	MA		VAMA		VAMA with the NN		Buy-and-Hold	
	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades
5&55	$210.94	4	$185.93	10	$213.90	8	$201.00	2
5&63	$223.02	4	$182.09	8	$206.83	10	$201.00	2
10&55	$213.48	4	$215.24	6	$224.50	6	$201.00	2
10&63	$215.89	4	$208.02	4	$201.35	6	$201.00	2
13&55	$231.82	4	$212.35	4	$210.45	4	$201.00	2
13&63	$231.00	4	$206.01	4	$203.05	4	$201.00	2
21&55	$196.85	4	$239.97	6	$199.97	4	$201.00	2
21&63	$199.98	4	$214.38	4	$213.13	4	$201.00	2
Average	$215.37	4	$208.00	5.75	$209.15	5.75	$201.00	2

Table 12.
EMV stand alone trading results

Interval (Fibonacci numbers)	EMV without the NN		EMV with the NN		Buy-and-Hold	
	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades
5 (week)	$103.75	40	$243.93	24	$201.00	2
21 (month)	$74.42	22	$243.81	6	$201.00	2
55 (quarter)	$216.02	10	$251.99	8	$201.00	2
Average	$131.40	24	$246.58	12.67	$201.00	2

Table 13.
EMV in conjunction with MA trading results (single moving average)

CP and interval	MA		EMV and MA		EMV with the NN and MA		Buy-and-Hold	
	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades
CP&5	$38.78	64	$105.18	30	$220.30	20	$201.00	2
CP&21	$122.72	32	$146.44	12	$258.54	4	$201.00	2
CP&55	$168.06	18	$236.69	2	$243.64	2	$201.00	2
Average	$109.85	38	$162.77	14.67	$240.83	8.67	$201.00	2

Table 14.
EMV in conjunction with VAMA trading results (single moving average)

CP and interval	VAMA		EMV and VAMA		EMV with the NN and VAMA		Buy-and-Hold	
	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades
CP&5	-$38.69	90	$89.69	32	$220.30	20	$201.00	2
CP&21	$72.63	38	$86.80	12	$258.54	4	$201.00	2
CP&55	$158.00	22	$202.98	4	$243.64	2	$201.00	2
Average	$63.98	50	$126.49	16	$240.83	8.67	$201.00	2

Table 15.
EMV in conjunction with MA trading results (two moving averages)

Fast & Slow interval	MA		EMV and MA		EMV with the NN and MA		Buy-and-Hold	
	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades
5&55	$154.59	6	$224.71	2	$240.98	2	$201.00	2
10&55	$142.90	6	$209.43	4	$220.58	4	$201.00	2
13&55	$154.01	6	$209.43	4	$220.58	4	$201.00	2
21&55	$196.85	4	$209.43	4	$220.58	4	$201.00	2
Average	$162.09	5.5	$213.25	3.5	$225.68	3.5	$201.00	2

Table 16.
EMV in conjunction with VAMA trading results (two moving averages)

Fast & Slow interval	VAMA		EMV and VAMA		EMV with the NN and VAMA		Buy-and-Hold	
	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades	Gain/loss	# trades
5&55	$142.44	12	$202.98	4	$243.64	2	$201.00	2
10&55	$163.75	6	$191.00	4	$220.58	4	$201.00	2
13&55	$169.14	6	$191.00	4	$220.58	4	$201.00	2
21&55	$175.10	8	$191.00	4	$220.58	4	$201.00	2
Average	$162.61	8	$194.00	4	$226.35	3.5	$201.00	2

PAPER 2

NEURO-FUZZY VOLUME ADJUSTED MOVING AVERAGES
FOR INTELLIGENT TRADING DECISIONS

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Abstract

Previous research has shown that the profitability of stock trading using neural networks to assist the trading heuristic of a Volume Adjusted Moving Averages (VAMA). However, the interpretation of the VAMA trading heuristic depends on the experience and the sentiment of the individual investor. This results since the VAMA trading heuristic does not have as precise a threshold for making a decision of when to buy, sell, or hold a particular stock. This research studies the effectiveness of applying fuzzy logic as an extension to the results of the combined neural networks and VAMA model to extract an intelligent trading decision. Fuzzy logic is used for representing the linguistic uncertainty of the VAMA trading heuristics that are generated from the neural networks model. The results show that stock trading using this neuro-fuzzy modeling approach can help to improve the profitability of the combined neural network and VAMA model.

Key Words: Financial Engineering, Stock Trading, Technical Analysis, Neuro-Fuzzy, Fuzzy Logic.

Introduction

Intelligent techniques, such as neural networks (NN) and fuzzy logic have been applied to a large variety of applications in finance and economics, especially in areas of stock

market prediction, investment, and technical analysis for many years. In the last few years, numerous research studies have been conducted in these areas by combining various computational techniques to develop intelligent or expert systems. Nonetheless, each computational technique has it own strengths and weaknesses. For example, fuzzy logic is good for knowledge representation and imprecision tolerance, but lacks learning capability, while neural networks are good for learning ability and forecasting, but lack explanatory capability. As a result, the hybrid intelligent system modeling often brings the advantages of these techniques together. Their synergy allows it to accommodate common sense, extract knowledge from raw data, use human-like reasoning mechanisms, deal with uncertainty and imprecision, and learn to adapt to a rapidly changing and unknown environment (Negnevitsky, 2002).

In this research, the integration of fuzzy logic and neural networks into an intelligent system is applied to the problem of using technical analysis for stock trading. A neuro-fuzzy system, which is a combination of the benefits of the forecasting ability of neural networks and a explanatory capability of fuzzy logic, is applied to the volume adjusted moving averages (VAMA) technical indicator to generate intelligent trading decisions. The objective of this research is to provide the initial neuro-fuzzy systems approach to help improve the trading heuristics of the combined neural networks and VAMA model. Fuzzy logic will be used for extracting the trading decision from the output of the previous combined neural network and VAMA model proposed by Chavarnakul and Enke (2005). The results of stock trading using this neuro-fuzzy modeling approach will be compared against the results generated from the VAMA alone and the combined neural networks and VAMA model.

The following will begin with a background of the VAMA technical indicator, followed by a brief introduction of neural networks. A review of neural networks with VAMA approach will then be discussed. A brief introduction of fuzzy logic concepts, including the neuro-fuzzy approach, will also be provided. The remainder of the paper will focus on the neuro-fuzzy with VAMA model approach. The empirical results and analysis will then be reported. Finally, the conclusions and further research will be discussed in the last section.

Volume Adjusted Moving Averages (VAMA)

The VAMA was developed by Richard Arms (Arms, 1996). It is a technical indicator based on a concept of equivolume charting (Arms, 1996). The VAMA assigns a volume measure rather than a time parameter to the moving average. The VAMA is based on expanding the volume frame of reference for heavier trading volume and contracting it for smaller trading volume, with the changes in volume plotted as equivolume boxes on an equivolume chart. Therefore, the heavier the trading volume, the larger the effect on the moving averages. As a result, the VAMA assigns the majority of weight to the days with the most volume, while with the simple moving average (MA) the weight is assigned equally across all data for simple averages. For example, a day whose volume is three times greater than other days will contribute three times more of its closing price. As with the MA, the VAMA is usually useful in trending markets, but provides poor results in trading-range market. The most popular method of interpreting the VAMA is similar to the MA, which is to compare the relationship of the VAMA with the stock

price itself. Therefore, a buy signal is generated when the stock price rises above its VAMA and a sell signal is generated when the stock price falls below its VAMA.

However, the number of time (volume) intervals used in calculating the average in both MA and VAMA should fit the market cycle to reach consistent profitability. In addition for the VAMA, it must be decided how each day volume is related to other days. This is exactly the same method required to decide how wide to plot the equivolume boxes on the equivolume chart. This calculation is arbitrary and somewhat complex depending on the user preferences. Readers who are interested in full information of equivolume charting and VAMA should refer to (Arms, 1994; Arms, 1996).

Neural Networks (NN)

Neural networks (NN) are an information-processing system that can emulate certain performance characteristics of the biological functions of the human brain. This technique has the ability to learn from its environment and to adapt in an interactive manner similar to its biological counterparts (Ham and Kostanic, 2001). A neural network is characterized by its pattern of connections between the neurons (architecture), its method of determining the weights on the connections (training or learning algorithm), and its activation function (Fausett, 1994).

The basic concept of a neural network is that there is a set of connected units in both the input and output layers where each unit connection link has a weight associated with it. During the learning phase, the network learns by adjusting the weights so as to be able to predict or classify the output target of a given set of input samples (Thawornwong and Enke, 2004). For full description of NNs, reader should refer to (Ham and Kostanic,

2001; Fausett, 1994). Examples of neural networks applications in stock market prediction and technical analysis have been discussed in (Kuo et al., 2004; Motiwalla and Wahab, 2000; Lam and Lam, 2000; Thawornwong et al., 2003; Yao et al., 1999; Saad et al., 1998; Chenoweth et al., 1996).

Neural Networks with VAMA Approach: A Review

In previous research, Chavarnakul and Enke (2005) have discussed the performance of neural networks combined with VAMA for stock trading. They used the Generalized Regression Neural Network (GRNN) (Specht, 1991) to predict future stock index prices as well as the width size of the volume boxes typically utilized on an equivolume chart in order to calculate the future value of the VAMA. The experiment was performed on past S&P 500 index data from January, 1998 to December, 2003. The training data set was from the period of January, 1998 to December, 2002, while the testing data set was from the period of January, 2003 to December, 2003.

In their research, two GRNN models were developed. The first model (GRNN 1) was used for predicting the future width size of the equivolume boxes typically utilized on an equivolume chart. For this model, the authors proposed using a volume ratio approach, which is calculated by using each day's actual trading volume divided by the average of all trading volumes in the training set period, to determine a value of volume increment in order to decide the width size of the equivolume boxes (i.e. decide how each day's volume related to other days). Therefore, the target of this model was a volume ratio for the next day (VR_{t+1}). There were 27 input variables selected for use in this model. They used the daily data, including the opening price (OP_t), closing price (CP_t), highest price

(HP$_t$), and lowest price (LP$_t$), along with two popular volume technical indicators, the Money Flow Index (MFI) and On Balance Volume (OBV), to serve as input variables. The closing price momentum (CP$_t$ - CP$_{t-1}$), volume momentum (V$_t$ - V$_{t-1}$), 10 and 20 day moving averages, 10 and 20 day volume moving averages, past 10 days volume, and past 5 days volume ratio were also provided as inputs variables to capture the movement and the characteristics of volume and prices.

The second model (GRNN 2) was used for predicting the next day closing price (CP$_{t+1}$). The target of this model was the rate of return for the next day (R$_{t+1}$), which was later converted to CP$_{t+1}$, to develop the trading systems. The closing price (CP$_t$), along with the rate of return (R$_t$), and various technical indicators, including the Money Flow Index (MFI), On Balance Volume (OBV), the Relative Strength Index (RSI), closing price momentum (CP$_t$ - CP$_{t-1}$), the Moving Average Convergence/Divergence (MACD), the signal line of MACD (SL), 10 and 20 day moving averages, and %K and %D from the Stochastic Oscillator were the 12 selected inputs variables. Finally, these selected inputs were included in the base sets with five-day time lags to account for recent movements of the target. This provided 60 input variables to the model to predict the next day rate of return.

The trading systems. The VAMA trading heuristics were used by comparing a crossover of the VAMA with NN (VAMA$_{t+1}$) developed from the post-processing of the outputs of both GRNN models and the next day closing price (CP$_{t+1}$) of the GRNN2. Based on the VAMA trading heuristics, a buy signal at time *t+1* was generated when the predicted CP$_{t+1}$ would rise above the VAMA$_{t+1}$, a sell signal at time *t+1* was generated when the

predicted CP_{t+1} fell below the $VAMA_{t+1}$. Otherwise, a hold position is taken. Figure 1 shows the diagram of the system overview for the neural networks with the VAMA approach.

Chavarnakul and Enke (2005) reported that the VAMA with NN approach can improve the performance of the VAMA alone by providing earlier trading signals. They showed that the results utilized from the VAMA with NN outperform other benchmarking tools, including the MA, VAMA used alone, and the buy-and-hold trading strategy.

However, the VAMA trading heuristic does not have as precise a threshold for making a decision of when to buy, sell, or hold a particular stock. The trading decision making depends on the experience and the sentiment of the individual investor. For example, many investors may not buy the stock immediately when the CP_{t+1} rises above the $VAMA_{t+1}$, but their trading decisions to buy may depend more upon the gap between the CP_{t+1} and $VAMA_{t+1}$ to confirm the continuation of an established up trend. In general, a more positive value of gap (CP_{t+1} - $VAMA_{t+1}$) serves to confirm that an established up trend is in tact. Besides, other factors, such as the slope of the closing price line and the slope of the VAMA line, may also impact the trading decisions of the investors.

Fortunately, intelligent technique likes fuzzy logic can be used to release this uncertainty by representing the linguistic uncertainty of the VAMA trading heuristics and extracting the decisions from the NN' outputs. The following section will provide a brief introduction of fuzzy logic concepts, along with fuzzy set and system construction.

Fuzzy Logic

Based on the concept of graded membership in fuzzy sets theory, fuzzy logic was

originally introduced by Zadeh (1965) as a mathematical way to represent vagueness in

everyday life (Shaout and Al-Shammari, 1998). It is determined as a set of mathematical

principles for knowledge representation based on degrees of membership rather than on

the crisp membership of classical binary logic (Negnevitsky, 2002). Instead of using

two-valued logic, for example, black or white, 0 or 1, and negative or positive as crisp

sets, fuzzy logic is multi-valued and uses the continuum of logical values as degrees of

membership for representing linguistic constructs, such as high, medium, low, very,

more, and less. As a result, the fuzzy logic provides an inference structure that enables

approximate human reasoning capabilities (Gupta and Rao, 1994).

Fuzzy sets. Let X be the universe of discourse and its elements be denoted as x. In

classical set theory, crisp set is a collection of distinct objects and is defined in such a

way as to dichotomize the elements of a given universe of discourse into two groups:

members and nonmembers (Lin and Lee, 1995). Crisp set A of X is defined as the

characteristic function $f_A(x)$

$$f_A(x) : X \rightarrow \{0, 1\} \tag{1}$$

where

$$f_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases}$$

Therefore, characteristic function $f_A(x)$ is equal to 1 if x belongs to set A and is equal to 0

if x does not belong to set A.

In the fuzzy theory, on the other hand, a fuzzy set is defined as a set with fuzzy boundaries (Negnevitsky, 2002). Fuzzy set A of X is defined as the membership function $\mu_A(x)$

$$\mu_A(x) : X \ \rightarrow Z \tag{2}$$

where Z is the membership space. For example, if Z is equal to [1, 0], the membership function $\mu_A(x)$ will be the degree to which x belongs to set A and can be a continuum of possible values. That is,

$$\mu_A(x) = \begin{cases} 1, \text{ if } x \text{ totally} \in A \\ 0, \text{ if } x \notin A \\ \text{a value between 0 and 1, if } x \text{ partly } \in A \end{cases}$$

Therefore, the value of $\mu_A(x)$ represents the degree of membership of element x in set A.

How to Build Fuzzy Logic System

For a fuzzy logic system, the development process is incorporated with the typical following steps:

- Begin with specifying the problem to determine the input and output variables (i.e. defining linguistic variables and their values). For example, linguistic variable volume has linguistic values high, medium, and low.

- Determining the fuzzy sets represented by the membership functions. The most popular membership functions include triangular, trapezoidal, and gaussian.

- Constructing the fuzzy rules (rule base). This is done by using a conditional statement form: IF - THEN.

- Perform the fuzzy inference by taking the crisp inputs, fuzzifying them in order to determine the degree of membership to which these inputs belong to each of the appropriate fuzzy sets, and then executing all the rules from the rule base which are active, aggregating the outputs of active rules into a single output fuzzy. After the defussification process, a new crisp output is generated. Mamdani-style fuzzy inference (Mamdani and Assilian, 1975) and Sugeno-style fuzzy inference (Sugeno, 1985) are examples of the popular fuzzy inferences.

As an applications of fuzzy logic in stock market prediction and technical analysis, Dourra and Siy (2002) used fuzzy logic and technical analysis to build an investment model system, Setnes and Drempt (1999) examined the applications of Takagi-Sugeno fuzzy models to the problem of stock market analysis on Dutch AEX-price index, and Lim and Wuncsh II (1999) used fuzzy logic to handle the uncertainty of specify precise thresholds of moving averages that are used to predict trends in time-series charts. Other applications have been discussed (Zhou and Dong, 2004; Dong and Zhou, 2002; Romahi and Shen, 2000).

Readers who are interested in full information of fuzzy logic should refer to (Negnevitsky, 2002; Lin and Lee, 1995; Klir and Yuan, 1995).

Neuro-Fuzzy Systems (NF)

Neural networks and fuzzy logic are natural complementary tools in building intelligent systems (Negnevitsky, 2002). Both are numerical model-free estimators and dynamic systems (Lin and Lee, 1995). As a result, they can perform well under an uncertainty and noisy environment, such as in the stock market. Neural networks are low-level

computational structures and have a good learning capability, while fuzzy logic has a good explanatory capability and deals with reasoning on a higher level. Integrated neuro-fuzzy systems can bring their advantages together and offer promising parallel low-level computation with a high-level reasoning and thinking approach. This synergy allows neural networks more transparency and fuzzy logic more capability for learning.

An integration of neural networks and fuzzy logic into neuro-fuzzy systems can be done in several ways. Based on the research of Gradojevic et al. (2002) and Pantazopoulos et al. (1997), a neuro-fuzzy combination system will be of interest in this research. This system is constructed by using fuzzy logic system as a post-processing to the neural networks' output to extract the decisions. The basic block diagram of a neuro-fuzzy combination system is illustrated in Figure 2.

Other integrated neuro-fuzzy systems, such as neuro-fuzzy inference systems where a fuzzy inference system is implemented in the framework of neural networks, and fuzzy neural networks where the inputs and learning algorithms of neural networks are fuzzified, have also been developed (Sprekelmeyer et al., 2000; Nauck and Kruse, 1997; Lin and Lee, 1995; Buckley and Hayashi, 1994; Gupta and Rao, 1994; Jang, 1993). Gupta and Rao (1994) also stated that neuro-fuzzy systems can be broadly classified as static (feed-forward) and dynamic (feedback) architecture.

Examples of neuro-fuzzy systems applied in stock market prediction, investment, and technical analysis have also been developed. Gradojevic et al. (2002) developed neuro-fuzzy combination to help the investment's decision-making for trading the FX market. Patazopoulos et al. (1997) developed neuro-fuzzy systems for predicting financial time series and show good results in the context of various trading strategies involving stocks

and options. Hobbs and Bourbakis (1995) developed a feedback fuzzy-based neural network with two hidden layers to predict stock prices.

Neuro-Fuzzy with VAMA Approach: A Proposed Methodology

The neuro-fuzzy with VAMA system proposed for this research is illustrated in Figure 3. The overall process is to apply a fuzzy logic system to the outputs generated from the testing data set of the neural networks with the VAMA model ($VAMA_{t+1}$ and CP_{t+1}), as proposed by Chavarnakul and Enke (2005). There are two neuro-fuzzy with VAMA systems developed for this research.

System 1. A modification of Bogullu (2002)'s concept is applied in this system. For this system, the gap or distance (d) between the CP and VAMA lines (linguistic values More and Less), the slope of the closing price line (S_{CP}) (linguistic value Steep and Flat), and the slope of the VAMA line (S_{VAMA}) (linguistic values Steep and Flat) serve as three linguistic inputs variables, while buy or sell trading signals (linguistic values Strong and Weak) serve as the linguistic output variable. This is done since the VAMA technical indicator uses a crossover operation for the trading heuristics. The significance of the signal in indicating the trend can be determined by studying the slope of the closing line, the slope of the VAMA line, and then examining the difference between these lines. The slope of the closing price signifies the trend and the slope of the VAMA helps to confirm the trend, while the difference between these lines helps in taking a buy or sell position, sometimes even prior to knowing the crisp value of the closing price as it cuts the VAMA line or after signal confirmation.

In order to determine the fuzzy sets of the linguistic variables in this system, the triangular membership function is used to represent the fuzzy sets. The triangular membership function used in this system can be expressed in Figure 4.

In Figure 4, variables x and y are represented the range of possible values of the linguistic variables (i.e. the universe of discourse). The var_x and var_y are the linguistic values of the linguistic variables whose degree of membership are calculated for any value x_i of the same domain.

Based on one day forecasting, the linguistic variable d is calculated from CP_{t+1} − $VAMA_{t+1}$, the linguistic variable S_{CP} from CP_{t+1} − CP_t, and the linguistic variable S_{VAMA} from $VAMA_{t+1}$ − $VAMA_t$, respectively. The CP_t and $VAMA_t$ are the current day closing price and VAMA, respectively. Therefore, the linguistic variable d can be –d or +d (negative, d < 0 or positive, d > 0), the linguistic variable S_{CP} can be −S_{CP} or +S_{CP}, as well as the linguistic variable S_{VAMA} can be −S_{VAMA} or +S_{VAMA}. The properties of all linguistic variables used in this system are summarized in Table 1.

The fuzzy rules are then developed to incorporate all linguistic variables and their linguistic values to perform the knowledge-base for use in the fuzzy inference. The fuzzy rules used in this system include:

1. IF –d is More, THEN the sell signal is Strong.

2. IF –d is Less and −S_{CP} is Steep, THEN the sell signal is Strong.

3. IF –d is Less and −S_{CP} is Flat and +S_{VAMA} is Steep, THEN sell signal is Strong.

4. IF –d is Less and −S_{CP} is Flat and +S_{VAMA} is Flat, THEN the sell signal is Weak.

5. IF +d is Less and −S_{CP} is Steep, THEN the sell signal is Strong.

6. IF +d is Less and −S_{CP} is Flat and +S_{VAMA} is Steep, THEN the sell signal is Strong.

7. IF +d is Less and −S_{CP} is Flat and +S_{VAMA} is Flat, THEN the sell signal is Weak.

8. IF +d is More, THEN the buy signal is Strong.

9. IF +d is Less and +S_{CP} is Steep, THEN the buy signal is Strong.

10. IF +d is Less and +S_{CP} is Flat and −S_{VAMA} is Steep, THEN the buy signal is Strong.

11. IF +d is Less and +S_{CP} is Flat and −S_{VAMA} is Flat, THEN the buy signal is Weak.

12. IF −d is Less and +S_{CP} is Steep, THEN the buy signal is Strong.

13. IF −d is Less and +S_{CP} is Flat and -S_{VAMA} is Steep, THEN the buy signal is Strong.

14. IF −d is Less and +S_{CP} is Flat and −S_{VAMA} is Flat, THEN the buy signal is Weak.

After defining the linguistic variables and linguistic values, as well as determining the fuzzy sets and fuzzy rules, the crisp inputs of d, S_{CP}, and S_{VAMA} are processed into the fuzzy inference. The Mamdani-style fuzzy inference (Mamdani and Assilian, 1975) is utilized in this system. Therefore, the crisp inputs of d, S_{CP}, and S_{VAMA} are fuzzified to determine the degree of membership to which these inputs belong to each of the appropriate fuzzy sets. For instance, in Figure 4, suppose x_i is the crisp input of +d and var_x and var_y are the linguistic values Less and More of +d, respectively. In this situation, x_i has the degree of membership value 0.75 for the linguistic value Less and 0.25 for the linguistic value More. Rule evaluation is then activated. The fuzzy inputs are applied to the fuzzy rules listed before and are executed by all the rules from the rule base which are active (e.g. x_i, which is represented crisp input -d, are executed by fuzzy rules 1, 2, 3, 4,

12, 13, and 14). All active rules' outputs are aggregated into a single output by using the Mamdani inference engine. This inference engine applies fuzzy operators AND (intersection) and OR (union) by using min and max operators, respectively.

As a result, the aggregated single output fuzzy set, which is represented by the aggregated shape of all active rules' outputs fuzzy sets, is generated. The last step in the fuzzy inference process is defuzzification in order to get a new crisp output which is the confidence of the trading signal for this system. One of the most popular defuzzification methods involves using the centroid technique, namely the centre of gravity (COG). The COG method is applied for this system. It finds the point where a vertical line would slice the single aggregate output fuzzy set into two equal masses (Negnevitsky, 2002). The COG method can be expressed as Equation (3).

$$COG = \frac{\int_a^b \mu_A(x)x\,dx}{\int_a^b \mu_A(x)\,dx} \tag{3}$$

where A is the fuzzy set of universe X, $\mu_A(x)$ is the membership function of fuzzy set A that is represented the degree to which x is an element of fuzzy set A for any element x of universe X, and values a and b are the interval of the fuzzy set A, respectively.

System 2. For this system, the concept of a filter moving average is applied. The filter is used to confirm the confidence of trading signals for the neural networks with VAMA output model. Although the neural networks can help to provide an earlier and timelier trading signals of the VAMA (Chavarnakul and Enke, 2005), investors may rely on their experiences and sentiments about how much the difference of the distance between CP_{t+1} and $VAMA_{t+1}$ that they are confident to perform their trades. This is based on a belief

that the distance between the moving average and closing price lines can be used as a basis to confirm the continuation of an establish trend (Lim and Wuncsh II, 1999). Since the moving average is the trend line for the stock market indices, this distance is thus an indicator of the stock market indices moving ahead or behind the trend (Gradojevic et al., 2002).

As a result, for this system the gap or distance (d) between the CP_{t+1} and $VAMA_{t+1}$ will be used as a filter and will be the only linguistic input variable of interest. The linguistic values of this variable will be Strong Negative (SN), Medium Negative (MN), Weak Negative (WN), STABLE, Weak-Positive (WP), Medium-Positive (MP), and Strong-Positive (SP). The trading signal will serve as the linguistic output variable and includes the linguistic values Strong-Sell (SS), Medium-Sell (MS), Weak-Sell (WS), HOLD, Weak-Buy (WB), Medium-Buy (MB), and Strong-Buy (SB). The triangular membership function is also used represented the fuzzy sets for this system, and is illustrated in Figure 5. The summary of the linguistic variables used in this system, including their linguistic values and membership function ranges, can be expressed in Table 2.

In Figure 5, variables var_e, var_f, var_g, var_h, var_i, var_j, and var_k are represented the linguistic values of the linguistic variables, while variables e and k represent the range of possible values of the linguistic variables (See Table 2 for the values of all of these variables for each linguistic variable).

The fuzzy rules used to perform the knowledge-base in the fuzzy inference of this system include:

1. IF d is SN, THEN the trading signal is SS.

2. IF d is MN, THEN the trading signal is MS.

3. IF d is WN, THEN the trading signal is WS.

4. IF d is STABLE, THEN the trading signal is HOLD.

5. IF d is WP, THEN the trading signal is WB.

6. IF d is MP, THEN the trading signal is MB.

7. IF d is SP, THEN the trading signal is SB.

The remaining methodology of system 2 is similar to system 1. The Mamdani-style fuzzy inference (Mamdani and Assilian, 1975) is applied to generate the aggregated single output fuzzy set. The COG of Equation (3) is also applied for the defuzzification process. Finally, the new crisp output, which is the confidence of the trading signal, is then generated.

The trading systems. As with Chavarnakul and Enke (2005), the assumptions of the trading systems include that transactions costs are excluded, and that a buy or sell position is taken at the market open, closing the entire position, and then exiting of the market at the end of the period. The following trading systems are developed and used for both of the neuro-fuzzy with VAMA systems proposed in this research:

- A buy position is taken when the value of the confidence of trading signal is greater than 0.50.

- A sell position is taken when the value of the confidence of trading signal is lower than -0.50.

- Otherwise, a hold position is taken.

Empirical Results and Analysis

The profitability of stock trading using the VAMA alone and the neural networks with VAMA were both used as benchmark tools for comparing the robustness of both neuro-fuzzy VAMA systems. Once again, the neuro-fuzzy systems were developed to the outputs results generated from the testing data set of the neural networks with VAMA approach. After performing testing of the trading systems, the results based on one share of S&P 500 index trading are shown in Table 3, where the values in the parenthesis represented the number of trades.

According to Table 3, several interval lengths of VAMA from different approached, such as Cycle length (5, 21, and 63) and Fibonacci numbers (5, 13 21, and 55) were chosen and utilized. The results show that the neuro-fuzzy with VAMA system 1 performs best among others with the average profit $179.45. When looking at each interval length, the neuro-fuzzy with VAMA system 1 provides superior results, better than the neural networks with VAMA approach in every interval length. The neuro-fuzzy system 2 provides poor results when compare against the neural networks approach in the CP&5 interval, but it performs well for other interval lengths. This results in the average profit of system 2 ($161.49) better than the average profit of the neural networks approach ($156.73).

Furthermore, since the interval lengths of VAMA should fit to the market cycle of the data set to reach the optimum profitability, the results based on the interval length of CP&55 and CP&63 should be of the most of interest, as Chavarnakul and Enke (2005) recommended that these interval lengths be approximately a quarter volume frame of calculating the average in VAMA and fit the market cycle of the data set being used. The

CP&55 and CP&63 results show that the neuro-fuzzy with VAMA systems are significant and outperform other approaches.

Therefore, based on the overall results, the neuro-fuzzy with VAMA systems can help to improve the trading decisions of the neural networks with VAMA approach. The synergy between the neural networks and fuzzy logic produces intelligent trading decisions that allow it to accommodate common sense, extract knowledge, and use human-like reasoning mechanisms to deal with the uncertainty and imprecision of the VAMA trading heuristics.

Comparison of Neuro-Fuzzy Systems

Based on the results of neuro-fuzzy systems in every interval length as reported in Table 3, the results of system 1 gives a better results than system 2. This results in the average profit of system 1 ($179.45) better than the average profit of systems 2 ($161.49), a 11.12% differential. The reason is that the knowledge-base in the system 1 (which is based on the gap between the closing price and VAMA lines, the slope of the closing price line, and the slope of the VAMA line) is that it may utilize more common sense and human-reasoning mechanisms to deal with the uncertainty of the VAMA trading heuristics than in system 2 which is based only on the gap between the closing price and VAMA lines. In fact, system 2 is similar to using a filter for the VAMA, in which a buy or sell will be taken when the gap is above or below the specific value.

The number of trades from system 2 is also significant lower than those from system 1. As a result, if transactions costs are included, system 1 trading would be more impacted. This results since the more investors trade, the more transactions costs are

executed. The reason for the lower number of trades may be because of the lower reasoning, knowledge-base, and the lower use of fuzzy sets for system 2. However, system 1 should be preferred overall since it provides significant better results in average and has a more common sense and human-reasoning mechanism as shown in the empirical results.

Conclusions and Further Research

The initial neuro-fuzzy with volume adjusted moving averages (VAMA) approach was proposed to help improve the trading heuristics of combining neural networks with the VAMA model. A neuro-fuzzy combination system, which uses fuzzy logic system as a post-processing to the neural networks' output, was used as an integration method of the neuro-fuzzy system. In this research, a fuzzy logic system was applied to the outputs of the neural networks with VAMA model proposed by Chavarnakul and Enke (2005) to extracting the VAMA trading heuristics. Two neuro-fuzzy with VAMA systems (system 1 and 2) were developed and shown to have superior performance to help improve the trading decisions of the neural networks with VAMA based on the overall results. This is facilitated by the synergy between the neural networks and fuzzy logic that results for making intelligent trading decisions. System 1, which was based on the gap between the closing price and VAMA lines, the slope of the closing price line, and the slope of the VAMA line, also generated better results (around 11.12%) than system 2, which was based on only the gap between the closing price and VAMA lines. This research suggested that system 1 should be preferred since it performed the best among other

approaches and has a more common sense and human-reasoning mechanism than system 2.

Further research beyond this initial neuro-fuzzy approach should lead to an intelligent system that can be used to generate and optimize membership functions of fuzzy logic for a more efficient model in order to improve performance and provide better profitability.

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Figure 1. The VAMA NN System Overview.
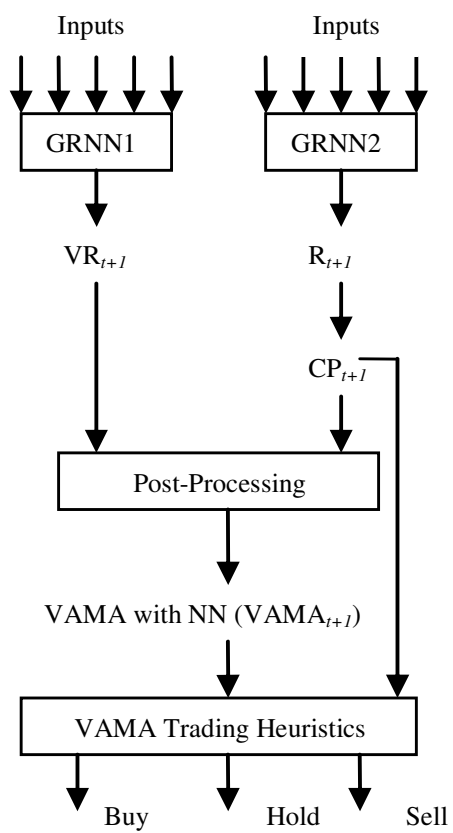
Figure 2. Neuro-Fuzzy Combination System.
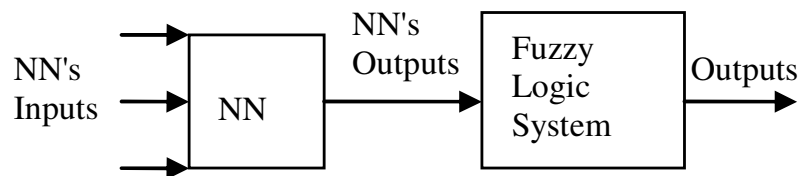
Figure 3. Neuro-Fuzzy with VAMA System.
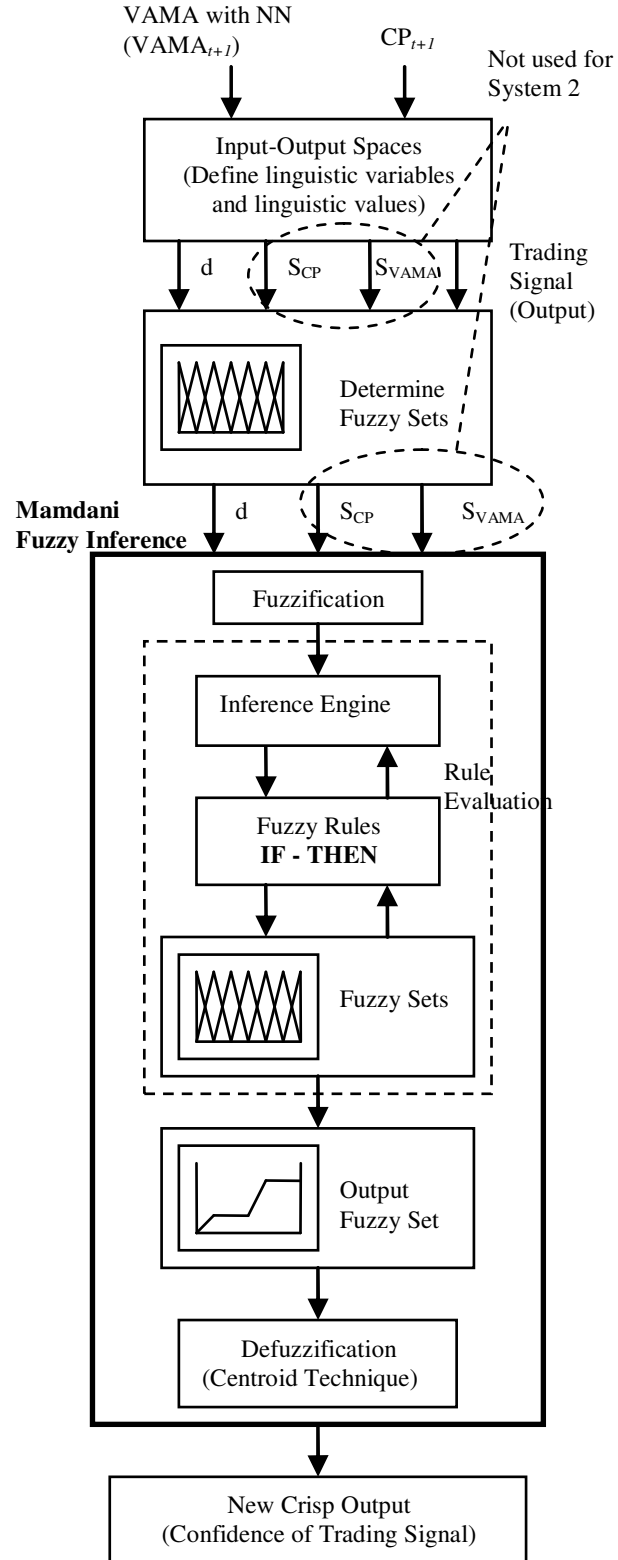
Figure 4. Triangular Membership Function System 1.
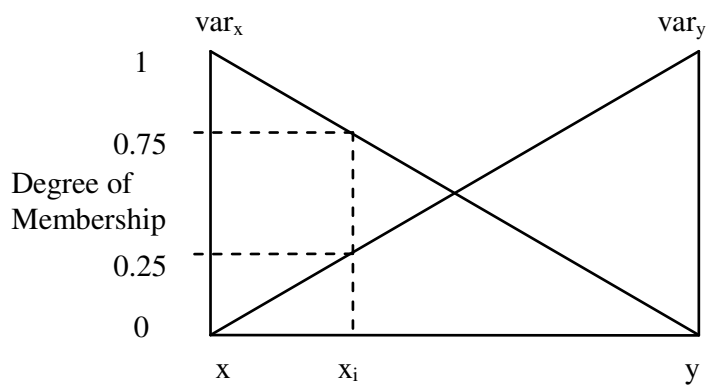
Figure 5. Triangular Membership Function System 2.
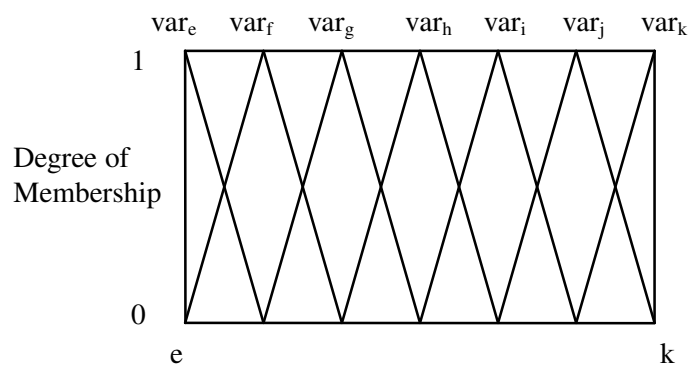
Table 1. Summary of Linguistic Variables System 1.
(See Figure 4 for the meaning of parameters x and y)

Linguistic Variables	Notation	Range [x,y]	Linguistic Values
d	$-d$	[-30,0]	More
$(CP_{t+1} - VAMA_{t+1})$			Less
	$+d$	[0,30]	Less
			More
S_{CP}	$-S_{CP}$	[-30,0]	Steep
$(CP_{t+1} - CP_t)$			Flat
	$+S_{CP}$	[0,30]	Flat
			Steep
S_{VAMA}	$-S_{VAMA}$	[-2.5,0]	Steep
$(VAMA_{t+1} - VAMA_t)$			Flat
	$+S_{VAMA}$	[0,2.5]	Flat
			Steep
	Sell	[-1,0]	Strong
Trading Signal			Weak
	Buy	[0,1]	Weak
			Strong

Table 2. Summary of Linguistic Variables System 2.

Linguistic Variables	Linguistic Values	Membership Function Ranges
	SN (var_e)	[-30, -20]
	MN (var_f)	[-30, -10]
Gap (d)	WN (var_g)	[-20, 0]
Range	STABLE (var_h)	[-10, 10]
[-30, 30]	WP (var_i)	[0, 20]
	MP (var_j)	[10, 30]
	SP (var_k)	[20, 30]
	SS (var_e)	[-1, -0.67]
	MS (var_f)	[-1, -0.33]
Trading Signal	WS (var_g)	[-0.67, 0]
Range	HOLD (var_h)	[-0.33, 0.33]
[-1, 1]	SB (var_i)	[0, 0.67]
	MB (var_j)	[0.33, 1]
	WB (var_k)	[0.67, 1]

Table 3. The Profitability Results.

CP & Interval	VAMA Alone	NNs with VAMA	NF with VAMA # 1	NF with VAMA # 2
CP&5	-$40.74	$142.88	**$152.10**	$80.43
	(88)	(100)	(86)	(8)
CP&13	$72.52	$80.50	**$144.52**	$139.71
	(44)	(64)	(48)	(12)
CP&21	$79.88	$97.35	**$108.48**	$101.20
	(36)	(52)	(42)	(14)
CP&55	$165.25	$234.31	**$247.86**	$246.36
	(20)	(22)	(16)	(4)
CP&63	$159.33	$228.60	**$244.30**	$239.76
	(20)	(24)	(16)	(4)
Avg.	$87.24	$156.73	**$179.45**	$161.49
	(41.60)	(52.40)	(41.6)	(8.40)

PAPER 3

INTELLIGENT HYBRID STOCK TRADING SYSTEM FOR TECHNICAL ANALYSIS BASED EQUIVOLUME CHARTING

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SUMMARY

This paper presents the use of an intelligent hybrid stock trading system that integrates neural networks, fuzzy logic, and genetic algorithms techniques for increasing the efficiency of stock trading when using the Volume Adjusted Moving Average (VAMA), a technical indicator developed from equivolume charting. For the research, a Neuro-Fuzzy based Genetic Algorithm (NF-GA) system of the VAMA membership functions is introduced. The results show that the hybrid intelligent system takes advantage of the synergy among these techniques to intelligently generate more optimal trading decisions for the VAMA so that investors can make the better stock trading decisions.

1. INTRODUCTION

Technical analysis has played an important role in the stock market for many years. This is due to the fact that technical analysis offers a relative mixture of human, political, and economical events and becomes an important tool for stock market prediction (Achelis, 1995). As opposed to fundamental analysis, which is the study of economic, industry, and company conditions in an effort to determine the intrinsic value of a company' stock (Cutler *et al.*, 1989), technical analysis studies the historical data surrounding price and volume movements of the stock by using charts as the primary tool to forecast future price movements (Murphy, 1999). Technical analysis has also proven to be powerful for evaluating stock prices and is broadly accepted among financial analysts and brokerage firms. In fact, many Wall Street financial advisors practice and use technical analysis (Leigh *et al.*, 2002), and large investments are rarely made without applying this technical environment (Thawornwong, 2003). Moreover, all major brokerage firms publish technical commentary on the market and individual securities, and various analysts publish newsletters based on technical analysis (Brock *et al.*, 1992). Surveys among market participant also show that many investors use technical analysis techniques to make decisions on buying and selling (Fernández-Rodríguez *et al.*, 1999).

In recent years, intelligent techniques, such as neural networks (NN), fuzzy logic, and genetic algorithms (GAs) have been applied to a large variety of applications in areas of stock market prediction, investment, and technical analysis. Furthermore, in the last few years numerous research studies have been conducted in these areas by combining

various computational techniques to develop intelligent or expert systems. Nonetheless, each computational technique has it own strengths and weaknesses. For example, fuzzy logic is good for knowledge representation and imprecision tolerance, but lacks learning capability. Neural networks are good for learning ability and forecasting, but lack explanatory capability, while genetic algorithms are good for optimization, but rather poor for knowledge representation. As a result, the hybrid intelligent system modeling often brings the advantages of these techniques together. As stated by Negnevitsky (2002), this synergy allows it to accommodate common sense, extract knowledge from raw data, use human-like reasoning mechanisms, deal with uncertainty and imprecision, and learn to adapt to a rapidly changing and unknown environment.

In this study, one of the technical analysis tools which can be developed from the equivolume chart, namely the Volume Adjusted Moving Average (VAMA), will be of interest. The VAMA redefines the time-scale for use in technical analysis based on an awareness of the importance of trading volume, which is a very important basic element of technical analysis. The effectiveness of using a hybrid intelligent system that integrates neural networks, fuzzy logic, and genetic algorithms techniques applied to the VAMA for stock trading will be presented. The objective will be to examine whether the proposed hybrid intelligent system can help to assist the VAMA trading signals to generate better profitability than the previous neural networks model. The study will be performed on the previous work done by Chavarnakul and Enke (2006a) by now proposing a Neuro-Fuzzy based Genetic Algorithm (NF-GA) to generate better VAMA membership functions to improve performance and provide better profitability when compared to the original model. This hybrid intelligent system will apply fuzzy logic for representing the

linguistic uncertainty of the VAMA trading heuristics that are generated from the neural networks model and then use a base - 10 genetic algorithm to tune the parameters of the membership functions of the VAMA in order to determine the shape of the membership functions that can reach better trading results. The experiment will be utilized on past S&P 500 index data and compared against the results generated from the VAMA alone, the VAMA with neural network assistance, the neuro-fuzzy system of the VAMA, and the buy-and hold trading strategy. The simulation results based on different stock market trends (trending-up, trending-down, and flat market) will also be provided in order to test the robustness of the system.

The paper is organized as follows. A brief general background of equivolume charting, VAMA, and the use of intelligent systems for technical analysis is given in the next section. Section 3 discusses the overview of the VAMA with neural networks assistance. The proposed methodology of a hybrid intelligent system is introduced in Section 4. Section 5 provides a description of the trading systems. The empirical results and analysis are reported in Section 6. Finally, conclusions are discussed in Section 7.

2. BACKGROUND

This section describes the general background of equivolume charting, the volume adjusted moving average (VAMA), and the use of intelligent systems for technical analysis – each of which will be employed in the proposed system.

2.1. Equivolume Charting

The concept of equivolume was invented by Richard W Arms Jr. (Arms, 1996) after his research with the Arms Index (Arms, 1996). The Arms Index takes into consideration the affect of volume when studying market action (i.e. a measure of the overall market trading activity). Equivolume charting recognizes the fact that volume is a market measurement and important to the price movement. It was developed to consider how stocks appear to move in a volume frame of reference as opposed to a time frame of reference. Therefore, equivolume charting (see Figure 1) uses volume to replace time on the horizontal axis of the chart. This results in a modification of the bar chart in the way that the volume information that appears across the bottom margin of bar chart is combined with the price information of the chart to create an equivolume box. As a result, each trading time period (days in our example) will be represented by a single equivolume box. As seen in Figure 1, the top and bottom of the equivolume box represent the high and low prices of the day, respectively, and the width of the equivolume box represents the daily trading volume.

Also shown in Figure 1 are the width of the equivolume box, as well as the horizontal axis of the chart, each of which will vary depending upon the trading volume for the day. The height of the equivolume box will vary depending upon the trading price spread for the day. Therefore, heavy volume affects the box laterally and large changes in price movement affect it vertically. On the other hand, light volume produces a narrow box and small changes in price movement produces a short box. The shape of each equivolume box helps to show whether it was easy or difficult for that stock to move up or down at any particular period. For example, short and wide boxes tend to occur at turning points

and show that the stock is having difficulty moving, while tall and narrow boxes are more likely to occur in established trends and show that the stock is moving easily. If both the height and width of the box increase substantially, the power box reflects superior confirmation of a breakout.

Driven by the concept of equivolume charting, the VAMA is a technical indicator that can be developed and applied using a mathematical calculation for stock trading instead of observing the pattern and/or shape of equivolume boxes on the equivolume chart. The next sub-section provides a brief introduction to the VAMA . Readers who are interested in full information of equivolume charting and VAMA should refer to (Arms, 1994; Arms, 1996).

2.2. Volume Adjusted Moving Average (VAMA)

Based on a concept of equivolume charting, the VAMA was developed by Richard Arms (Arms, 1996). It uses the same logic as the principles of equivolume charting by assigning a volume measure rather than a time parameter to the moving average. The VAMA is more helpful than a simple moving average (MA) since stocks tend to trade their heaviest volume at turning points (Arms, 1996). As with the MA, the VAMA is useful in trending markets but provides poor results in trading-range markets. The most popular method of interpreting the VAMA is similar to the MA, which is to compare the relationship of the VAMA with the stock price itself. Therefore, a buy signal is generated when the stock price rises above its VAMA, and a sell signal is generated when the stock price falls below its VAMA. The VAMA is based on expanding the volume frame of reference for heavier trading volume and contracting it for smaller trading volume, with

the changes in volume plotted as equivolume boxes on an equivolume chart. Therefore, the heavier the trading volume, the larger the effect on the moving averages. As a result, the VAMA assigns the majority of weight to the days with the most volume, while for the MA the weight is assigned equally across all data for simple averages. However, the number of time (volume) intervals used in calculating the average for both the MA and VAMA should fit the market cycle to reach consistent profitability.

Instead of averaging the closing price of the stock over a period of time as the MA calculation, the contribution of each closing price for the VAMA calculation is based on their volume relative to other days. For example, a day whose volume is three times greater than other days will contribute three times more of its closing price. As a result, for the VAMA it must be decided how each day of volume is related to other days. This is exactly the same method required to decide how wide to plot the boxes on the equivolume charts. This calculation is arbitrary and somewhat complex depending on the user preferences. Based on the previous work done by Chavarnakul and Enke (2006a), this calculation was performed by using a volume ratio approach and will be used in this study. Additional information about this approach for calculating the VAMA will be explained briefly in Section 3.

2.3. Intelligent Systems for Technical Analysis

Stock markets are affected by many highly interrelated economic, political and even psychological factors, each interacting in a very complex manner (Yao *et al.*, 1999). Moreover, the fluctuations in the stock market are also high-level nonlinear models (Kuo *et. al.*, 2004). As a result, many studies have come to a convincing conclusion that the

stock market is a nonlinear dynamic system. With this characteristic, linear approaches are not capable of identifying dynamic or nonlinear relationships in financial stock price time series data (Chenoweth *et al.*, 1996). Therefore, predicting stock movement is a very difficult task. However, an appropriate nonlinear model approach, such as an intelligent system technique, may be able to discover more complex nonlinear relationships and handle the uncertainty and imprecision problems in the stock market (Weiss and Kulikowski, 1991). With regard to modeling technical analysis, various methods for technical analysis have been developed and are being used (Pring, 1985). In recent years, the application of intelligent techniques to both technical trading and finance has experienced significant growth (Dempster *et al.*, 2001). Neural Networks (NN), Fuzzy Logic (FL), and Genetic Algorithms (GAs) are significant examples of intelligent techniques that have been applied to a large variety of applications in technical analysis.

As stated by Schoeneburg, (1990), NN have ability to deal with uncertain, fuzzy, or insufficient data which fluctuate rapidly in very short periods of time. This technique has performed well for classification, recognition, and forecasting. The use of NN for technical analysis can be broadly classified into two major approaches. The first approach involves developing a NN model for forecasting the stock market movement to help improve the trading heuristics of technical analysis, given the current and historical of financial data. Examples of research methods for this approach have been discussed in (Chenoweth *et al.*, 1996; Kuo *et al.*, 2004; Yao *et al.*, 1999). Another approach is the use of NN to create the knowledge base of technical analysis to determine the optimal buy and sell trading signals, thereby eliminating the human involvement in the decision

making process. Several applications for this approach have been studied in (Chapman, 1994; Mizuno *et al.*, 1998; Wilson, 1994).

Fuzzy logic has the ability of explanation and knowledge representation. Fuzzy logic is an effective rule-based modeling system in intelligent techniques that not only tolerates imprecise information, but also provides a framework of approximate reasoning (Li and Xiong, 2005). As a result, fuzzy logic is very effective for dealing with the problems that have no precise answers (Dourra and Siy, 2002). This is often the case when using technical analysis since the subjective nature of technical indicators do not allow for precise thresholds, but provide the the decisions in some ranges of uncertainty (Dourra and Siy, 2002). Various examples of using fuzzy logic for technical analysis exist in the literature (Dourra and Siy, 2002; Lim and Wuncsh II, 1999; Setnes and Drempt, 1999). In addition, Dong and Zhou (2002) and Zhou and Dong (2004) have also applied a fuzzy logic based approach to detect technical patterns, such as the head-and-shoulder and triangle top patterns.

Genetic Algorithms (GAs) establish a class of search, adaptation, and optimization techniques based on the principles of natural evolution (Allen and Karjalainen, 1999). It is considered as an optimization method that manipulates a string of numbers in a manner similar to how chromosomes are changed in biological evolution (Passino, 2004). GAs are generally used to find technical trading rules and also used to find optimal parameters of trading rules for technical analysis. Numerous examples of GAs applications for technical analysis are available (Allen and Karjalainen, 1999; Neely, 1997; Schoreels *et al.*, 2004).

In the last few years, however, research with technical analysis has involved combining the various techniques in technical analysis with different intelligent system models, thereby bringing the advantages of each intelligent technique together. When used with technical analysis, a system that combines fuzzy logic and neural networks, also known as a "neuro-fuzzy" system, can provide a model that better captures and describes the uncertainty for the technical trading rules, while also creating a more reliable knowledge system through the learning ability of neural networks. Furthermore, by combining genetic algorithms and neural networks, the performance of the neural networks models for technical analysis can be improved by using genetic algorithms to optimize the neural network inputs and weight parameters. By combining fuzzy logic and genetic algorithms, the technical trading decisions generated from fuzzy logic can be made more effective by using genetic algorithms to select an appropriate set of fuzzy rules, thereby optimizing the membership functions of the fuzzy sets.

Various examples of combining intelligent systems with technical analysis exist. For instance, Kuo *et al.* (2001) developed a genetic algorithm based fuzzy neural network (GFNN) to formulate the knowledge base of fuzzy inference rules for measuring the qualitative (such as the political) and quantitative (technical index) factors on the stock market. Patazopoulos *et al.* (1997) developed neuro-fuzzy systems for predicting financial time series that show good results in the context of various trading strategies involving stocks and options. Lin *et al.* (2002) developed a model trading system by using a neuro-fuzzy framework on technical indicators in order to better predict the stock index.

3. VAMA WITH NEURAL NETWORKS ASSISTANCE: AN OVERVIEW

In previous research, Chavarnakul and Enke (2006a) discussed the performance of neural networks combined with VAMA for stock trading. The Generalized Regression Neural Network (GRNN) (Specht, 1991) was chosen and used to predict future stock index prices as well as the width size of the volume boxes typically utilized on an equivolume chart in order to calculate the future value of the VAMA. Figure 2 shows the diagram of the system overview for this approach.

As shown in Figure 2, two GRNN models were developed. The first model (GRNN 1) is used for predicting the future width size of the equivolume boxes typically utilized on an equivolume chart. For this model, a volume ratio approach is used to decide the width size of the equivolume boxes (i.e. decide how each day's volume related to other days) and is calculated by using each day's actual trading volume divided by the average of all trading volumes in the training set period. Therefore, the output of this model is a volume ratio for the next day (VR_{t+1}). This volume ratio is also used for the post-processing process to calculate the future value of the VAMA ($VAMA_{t+1}$). The second model (GRNN 2) is used for predicting the next day closing price (CP_{t+1}). The output of this model is the rate of return for the next day (R_{t+1}), which is later converted to CP_{t+1} and then process to the post-processing process to calculate the $VAMA_{t+1}$. Note that for the VAMA alone (without NN assistance), a current volume ratio (VR_t) and closing price (CP_t) are used in the post-processing process instead of using the outputs from the GRNN models. The following paragraphs provide the explaination of the post-processing process used to calculate the value of the VAMA both with and without NN assistance.

For the VAMA alone (without NN assistance), the post-processing process will start at the current time period (time t) and work backwards. The volume ratio of each day is multiplied by the closing price of each day and then cumulatively summing these values until the specified contributed volume number (i.e. the number of the summation of volume ratios) is reached. Finally, the sum values are divided by that specified number of contributed volume to obtain the value of the VAMA. Note that only a fraction of the last day volume ratio will likely be used. A brief example calculation for the 5 VAMA using alone based on the post-processing process is shown in Table I.

For the VAMA with NN assistance, the post-processing process will also start at the predicted time period (time $t+1$) and works backwards. The volume ratio of each day is also multiplied by the closing price of each day, but at the starting time (time $t+1$), the predicted volume ratio is multiplied by the predicted closing price, and then these values are cumulatively summed until the specified number of contributed volume (i.e. the number of the summation of volume ratios) is reached. Once again, the sum values are divided by that specified contributed volume number to obtain the value of the VAMA. Note that only a fraction of the last day volume ratio will likely be used. A brief example calculation for the 5 VAMA with NN assistance based on the post-processing process can be expressed as given in Table II.

Afterwords, the VAMA trading heuristics are then employed by comparing a crossover of the VAMA$_{t+1}$ developed from the post-processing of the outputs of both GRNN models and the next day closing price (CP$_{t+1}$) of the GRNN2. Based on the VAMA trading heuristics, a buy signal at time $t+1$ was generated when the predicted CP$_{t+1}$ would rise above the VAMA$_{t+1}$, a sell signal at time $t+1$ was generated when the

predicted CP_{t+1} fell below the $VAMA_{t+1}$. Otherwise, a hold position is taken. For the VAMA using alone, the VAMA trading heuristics can be performed in the same way by comparing a crossover of a current VAMA ($VAMA_t$) with the closing price (CP_t), and then taking a buy, sell, or hold position at time $t+1$.

4. PROPOSED METHODOLOGY

This section describes a proposed hybrid intelligent system that integrates neural networks, fuzzy logic, and genetic algorithms with the VAMA for stock trading. The motivation and need of the proposed methodology is given in Section 4.1. A brief introduction of fuzzy logic concepts is discussed in Section 4.2. Detail descriptions of basic genetic algorithms are provided in Section 4.3. Finally, the system development of a Neuro-Fuzzy based Genetic Algorithm (NF-GA) system of the VAMA membership functions is presented in Section 4.4.

4.1. Motivation and Need

Previous research conducted by Chavarnakul and Enke (2006a) has shown that the profitability of stock trading using neural networks to assist the trading heuristic of the VAMA. However, the VAMA trading heuristic does not have as precise a threshold for making a decision of when to buy, sell, or hold a particular stock. The trading decision making depends on the experience and the sentiment of the individual investor. For example, many investors may not buy a stock immediately when the CP_{t+1} rises above the $VAMA_{t+1}$, but their trading decisions to buy may depend more upon the gap between the CP_{t+1} and $VAMA_{t+1}$ to confirm the continuation of an established up trend. In

general, a more positive value of gap (CP_{t+1} - $VAMA_{t+1}$) serves to confirm that an established up trend is in tact. Besides, other factors, such as the slope of the closing price line and the slope of the VAMA line, may also impact the trading decisions of the investors. As a result, previous work (Chavarnakul and Enke, 2006b) performed preliminary research by integrating fuzzy logic and neural networks into a neuro-fuzzy system applied to the VAMA to better capture the linguistic uncertainty of the VAMA trading heuristics, and therefore generate intelligent trading decisions. However, the VAMA membership functions used in that neuro-fuzzy system were static and designed manually using an arbitrary trial-and-error approach. Therefore, those membership function's parameters may not provide an optimization of the results. With this limitation, intelligent technique likes genetic algorithms (GAs) can be used to tune the parameters of the VAMA membership functions to get more optimal trading results.

4.2. Fuzzy Logic: A Basic Introduction

Based on the concept of graded membership in fuzzy sets theory, fuzzy logic was originally introduced by Zadeh (1965) as a mathematical way to represent vagueness in everyday life (Shaout and Al-Shammari, 1998). It is determined as a set of mathematical principles for knowledge representation based on degrees of membership rather than on the crisp membership of classical binary logic (Negnevitsky, 2002). Instead of using two-valued logic (for example, black or white, 0 or 1, and negative or positive for crisp unambiguous sets), fuzzy logic is multi-valued and uses the continuum of logical values as degrees of membership for representing linguistic constructs, such as high, medium,

low, very, more, and less. As a result, the fuzzy logic provides an inference structure that

enables approximate human reasoning capabilities (Gupta and Rao, 1994).

4.2.1. Fuzzy Set Definition

Let X be the universe of discourse and its elements be denoted as x. In classical set

theory, crisp set is a collection of distinct objects and is defined in such a way as to

dichotomize the elements of a given universe of discourse into two groups: members and

nonmembers (Lin and Lee, 1995). Crisp set A of X is defined as the characteristic

function $f_A(x)$

$$f_A(x) : X \rightarrow \{0, 1\} \tag{1}$$

where

$$f_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases} \tag{2}$$

Therefore, the characteristic function $f_A(x)$ is set equal to 1 if x belongs to set A and is set

equal to 0 if x does not belong to set A. In the fuzzy theory, on the other hand, a fuzzy set

is defined as a set with fuzzy boundaries (Negnevitsky, 2002). Fuzzy set A of X is

defined as the membership function $\mu_A(x)$

$$\mu_A(x) : X \rightarrow Z \tag{3}$$

where Z is the membership space. For example, if Z is equal to [1, 0], the membership

function $\mu_A(x)$ will be the degree to which x belongs to set A and can be a continuum of

possible values. That is,

$$\mu_A(x) = \begin{cases} 1, \text{ if } x \text{ totally} \in A \\ 0, \text{ if } x \notin A \\ \text{a value between 0 and 1, if } x \text{ partly} \in A \end{cases} \tag{4}$$

Therefore, the value of $\mu_A(x)$ represents the degree of membership of element x in set A.

4.2.2. Fuzzy Logic System

For a fuzzy logic system, the basic idea is to incorporate the expert experience of a human operator in the design of a controller for the process (fuzzy logic control system), or in the design of decision making (fuzzy logic decision system) whose input-output relationship is described by a set of fuzzy IF-THEN rules involving linguistic variables rather than a complicated dynamic model (Lin and Lee, 1995). The typical architecture of a fuzzy logic system is shown in Figure 3.

Based on Figure 3, the development process of a fuzzy logic system is generally initiated with specifying the problem to determine the input and output variables (i.e. defining linguistic variables and their linguistic values), and then determining the fuzzy sets represented by the membership functions for the linguistic variables. As such, the degree of membership can be defined. Typically, the most popular membership functions include triangular, trapezoidal, and Gaussian. The next step is to construct the fuzzy rules (rule base) to define a link between the input and output variables. This is done by using a conditional statement, usually in the form of IF - THEN rules, in which the antecedents and consequents involve linguistic variables. The general form of the fuzzy rules is:

$$R \text{ (i): IF } x \text{ is } A_i,..., \text{ AND } y \text{ is } B_i \text{ THEN } z \text{ is } C_i \qquad i = 1, 2,..., n \tag{5}$$

where $x,\ldots,$ y, and z are linguistic variables and $A,\ldots,B,$ and C are linguistic values defined by fuzzy sets of $x,\ldots,$ y, and z, respectively. Finally, the fuzzy inference is then applied. The fuzzy inference is performed by taking the crisp inputs and using a fuzzification process to determine the degree of membership to which these inputs belong to each of the appropriate fuzzy sets. Next, all the rules from the rule base which are active are executed by using fuzzy operators, and then the outputs of active rules are aggregated into a single output fuzzy. Finally, a new crisp output is generated by using the defuzzification process. Generally, the Mamdani-style fuzzy inference (Mamdani and Assilian, 1975) and the Sugeno-style fuzzy inference (Sugeno, 1985) are examples of the popular fuzzy inferences.

4.3. Genetic Algorithms

Genetic algorithms (GAs) are search algorithms which are based on the mechanics of natural selection and natural genetics (Goldberg, 1989). This technique was invented by John Holland (1975) and his colleagues at the University of Michigan during the 1970s. GAs have theoretically and empirically been proven to be able to perform robust search capabilities in complex spaces, thus providing a valid approach to problems requiring efficient and effective searching (Gen and Cheng, 1997). For a given problem, GAs maintain a population of solution candidates and then evaluate the performance of each solution candidate according to a fitness function. Next, new solution candidates are created by selecting relatively fit members of the population and then reproducing them through the use of various operators. This process is repeated until the termination criterion is satisfied.

GAs offer a number of advantages over conventional parameter optimization techniques that are less likely to converge to local optimum, which occasionally happens with the back-propagation (NN based learning) and hill-climbing or gradient techniques due to the stochastic nature of the selection and recombination operators (Allen and Karjalanen, 1999). GAs are often not difficult to implement and interface onto existing applications and models due to their inherent simplicity and versatility (Goldberg, 1994). GAs are able to sustain reliable results with a predictable margin of error since they are population-based algorithms that rely on sampling the given population (Goldberg, 1994). Finally, GAs can also be implemented to problems with a non-differentiable or discontinuous objective function, to which gradient-based methods such as Gauss-Newton would not be applicable (Allen and Karjalanen, 1999).

4.3.1. Elements of Genetic Algorithms

String representation: For GAs, each solution candidate is represented as string of numbers called a "chromosome" or an "individual" where a "gene" represents each number slot in a chromosome. A "population" is formed by a set of chromosomes where each chromosome contains a given number of traits. A "trait" is a decimal or binary number that is decoded from a chromosome and represents the parameter or variable that is varied and is to be used to optimize the fitness function. Typically, a chromosome is a concatenation of several traits and each trait contains several digit or bit positions of the gene. The base-10 decimal algorithm (a gene can hold any number between 0-9) and base-2 binary algorithm (a gene can hold only 0 and 1) are commonly used for string representation.

Test of fitness: A "test of fitness" is a process that evaluates the population of solution candidates by using a fitness function. The chosen fitness function is a performance index that is to be optimized, such as cost or time, such that the fitness function is the objective function in the optimization problem.

Selection: A "selection" is an operator that selects which parent chromosomes should incorporate to create an offspring (new chromosome) for the next generation. Basically, the good performing chromosomes should be allowed to survive to the next generation, while the poorly performing chromosomes are eliminated, based on their fitness value. An "offspring" is a new chromosome that is created by performing "crossover" and "mutation" operators based on selected parent chromosomes.

Crossover: A "crossover" is an operator that generates new chromosomes that are likely to contain good characteristics from the previous generation. The crossover can be done by mating selected pairs of parent chromosomes with a given crossover probability (usually, set close to 1), at an arbitrary point in the string representation.

Mutation: A "mutation" is an operator that is represented as a change in the gene after crossover. The most common way is to flip a digit or bit in a chromosome. The mutation is usually performed with a low probability level (typically range from 0.01 to 0.001). Otherwise, it would defeat the order building being generated through selection and crossover (Bauer, 1994). The mutation prevents the solution from trapping in a local minimum.

Termination criterion: The GAs stop running when it reaches a specified number of generations or when the GAs cannot find a better solution. A "generation" represents a

single iteration of the GAs process. The typical number of generations for simple GAs can range from 50 to over 500 (Mitchell, 1996).

4.3.2. Basic Steps in Genetic Algorithms

In order to program GAs, the basic steps used in GAs are described as follows:

Step1: Define the problem variable domain as a chromosome of a fixed length, and then generate an initial population of chromosomes of size N, choose the crossover probability (p_c), and the mutation probability (p_m).

Step 2: Define a fitness function, and then evaluate the fitness function value for each chromosome.

Step 3: Perform the GAs operators, including selection, crossover, and mutation.

Step 4: Evaluate the fitness function value for each new chromosome.

Step 5: The better chromosomes are made part of the next generation and poorly chromosomes are eliminated.

Step 6: The process repeats until the termination criterion is satisfied; otherwise, return to Step 3.

4.4. System Development

The hybrid intelligent system is comprised of three phases. For the first phase, a modification of the neuro-fuzzy system of the VAMA proposed by Chavarnakul and Enke (2006b) will be performed and used as a baseline system. The second phase will be constructed by applying the GAs to tune the VAMA membership functions of the neuro-fuzzy system by using the training data set. A based - 10 GAs programmed using

MATLAB developed by Passino (2004) is modified and utilized in this phase. Finally, the third phase will then be developed by applying the shape of the VAMA membership functions derived from the second phase to the neuro-fuzzy system developed in the first phase using the testing data set to generate the confidence of trading signal, eventually allowing execution of the trading systems. Figure 4 shows the diagram of the hybrid intelligent system. The details of the neuro-fuzzy modeling and the tuning VAMA membership functions are presented in Section 4.4.1 and 4.4.2, respectively. The trading systems are also presented in the Section 5.

4.4.1. Neuro-Fuzzy System Modeling

The integration of neural networks and fuzzy logic into neuro-fuzzy systems can also be done in several ways. An Adaptive Neural Fuzzy Inference System (ANFIS) proposed by Jang (1993), the fuzzy neural networks (Gupta and Rao, 1994), and the Fuzzy Adaptive Learning COntrol Network (FALCON) (Lin and Lee, 1991) are examples of the integrated architectures.

In this study, a neuro-fuzzy combination architecture is utilized based on the research of Gradojevic *et al.* (2002) and Pantazopoulos *et al.* (1997). For the proposed NF-GA system as illustrated in Figure 4, a fuzzy logic system is used as an extension to the forecasting outputs of the previous combined neural networks and VAMA model to extract the trading decisions. This neuro-fuzzy system is also used as a benchmarking model to show the effectiveness of GAs for tuning the VAMA membership functions that will be described in Section 4.4.2.

As suggested by Chavarnakul and Enke (2006b), three variables, including the gap or distance (d) between the CP and VAMA lines, the slope of the closing price line (S_{CP}), and the slope of the VAMA line (S_{VAMA}) serve as the linguistic inputs variables, while the trading signal (buy or sell) serves as the linguistic output variable in the system. This is done since the VAMA technical indicator uses a crossover operation for the trading heuristics. The significance of the signal in indicating the trend can be determined by studying the slope of the closing line, the slope of the VAMA line, and then examining the difference between these lines. The slope of the closing price signifies the trend and the slope of the VAMA helps to confirm the trend, while the difference between these lines helps in taking a buy or sell position, sometimes after signal confirmation, or even prior to knowing the crisp value of the closing price as it cuts the VAMA line. All linguistic input variables are also normalized into a specific range between -1 and 1 by using a min-max normalization as expressed in Equation (6).

$$v^* = \frac{\left[2v - \left(\max.(v) + \min.(v) \right) \right]}{\max.(v) - \min.(v)} \tag{6}$$

where v is the input before normalizing. v^* is the input after normalizing, and the max and min of v are derived from data in the training set.

For the membership function, the triangular membership function is used to represent the fuzzy sets of the linguistic variables for this neuro-fuzzy system. This triangular membership function is illustrated in Figure 5, where the Var_a, Var_b, Var_c, and Var_d represent the linguistic values of the linguistic variables. Note that the membership function of the linguistic input variables will be converted later to a general form (provided in the next section) for tuning with GAs.

In addition, the linguistic variable d is calculated from CP_{t+1} – $VAMA_{t+1}$, the linguistic variable S_{CP} from CP_{t+1} – CP_t, and the linguistic variable S_{VAMA} from $VAMA_{t+1}$ – $VAMA_t$, respectively, based on one day forecasting of the previous neural networks models. The CP_t and $VAMA_t$ are the current day closing price and VAMA, respectively. Therefore, the linguistic variable d can be –d or +d (negative, d < 0 or positive, d > 0), the linguistic variable S_{CP} can be –S_{CP} or +S_{CP}, and the linguistic variable S_{VAMA} can be –S_{VAMA} or +S_{VAMA}. The properties of all linguistic variables used in this system, including their linguistic values are summarized in Table III.

The modified fuzzy rules of Chavarnakul and Enke (2006b), which incorporate all linguistic variables and their linguistic values to perform the knowledge-base for the fuzzy inference used in this system, are used and described as follows:

R (1): IF +d is "More" and –S_{CP} is "Flat", THEN sell is "Weak".

R (2): IF –d is "Less" and –S_{CP} is "Steep", THEN sell is "Strong".

R (3): IF –d is "Less" and –S_{CP} is "Flat" and +S_{VAMA} is "Steep", THEN sell is "Strong".

R (4): IF –d is "Less" and –S_{CP} is "Flat" and +S_{VAMA} is "Flat", THEN sell is "Weak".

R (5): IF +d is "Less" and –S_{CP} is "Steep", THEN sell is "Strong".

R (6): IF +d is "Less" and –S_{CP} is "Flat" and +S_{VAMA} is "Steep", THEN sell is "Strong".

R (7): IF +d is "Less" and –S_{CP} is "Flat" and +S_{VAMA} is "Flat", THEN sell is "Weak".

R (8): IF –d is "More" and +S_{CP} is "Flat", THEN buy is "Weak".

R (9): IF +d is "Less" and +S_{CP} is "Steep", THEN buy is "Strong".

R (10): IF +d is "Less" and +S_{CP} is "Flat" and –S_{VAMA} is "Steep", THEN buy is "Strong".

R (11): IF +d is "Less" and +S_{CP} is "Flat" and –S_{VAMA} is "Flat", THEN buy is "Weak".

R (12): IF –d is "Less" and +S_{CP} is "Steep", THEN buy is "Strong".

R (13): IF –d is "Less" and +S_{CP} is "Flat" and –S_{VAMA} is "Steep", THEN buy is "Strong".

R (14): IF –d is "Less" and +S_{CP} is "Flat" and –S_{VAMA} is "Flat", THEN buy is "Weak".

Finally, this system applies the Mamdani-style fuzzy inference (Mamdani and Assilian, 1975) for the fuzzy inference. The Centre of Gravity (COG) method is also used for the defuzzification method to generate the new crisp output which is the confidence of trading signal. The COG method can be expressed as Equation (7).

$$COG = \frac{\int_{p}^{q} \mu_A(x)x\,dx}{\int_{p}^{q} \mu_A(x)\,dx} \tag{7}$$

where A is the fuzzy set of universe X, $\mu_A(x)$ is the membership function of fuzzy set A that represents the degree to which x is an element of fuzzy set A for any element x of universe X, and the values p and q define the intervals of the fuzzy set A.

4.4.2. Tuning VAMA Membership Functions Using Genetic Algorithms

Once a neuro-fuzzy system has been designed, its performance depends on many parameters. The correct choice of the shape of membership functions for the linguistic variables is one of the factors that plays an important role in the performance of the system. To solve this problem, several research trials have been performed with the GAs to tune the parameters of the membership functions in order to determine the suitable shape of the membership functions for better performance. These include Herrera *et al.* (1995), Karr (1991), Karr and Gentry (1993), and Lin and Yao (2002).

For the proposed NF-GA system, the GAs are used to tune the VAMA membership functions in order to provide better trading results. The goal of GAs is to maximize the finess function to determine the suitable parameters of the membership functions for the

linguistic input variables d, S_{CP}, and S_{VAMA} of the neuro-fuzzy system. Since the GAs are performed based on the training data set, the values of the linguistic input variables d, S_{CP}, and S_{VAMA} used in GAs are calculated based on the actual values of the VAMA and CP from the training data set instead of those generated from the GRNN models. The general form of the membership function (as shown in Figure 6) is also used as the default shape of the membership function that will be tuned for these linguistic input variables.

In Figure 6, the Var_a, Var_b, Var_c, and Var_d represent the linguistic values of the linguistic input variables. Variables a_1, a_2, a_3, a_4, b_1, b_2, b_3, and b_4 are the parameters used to specified the shape of the membership functions for linguistic input variables and will be tuned by GAs. Also, it can be seen that if a_1 and a_2 are equal to -1, values of a_3, a_4, b_1, and b_2 are equal to 0, and b_3 and b_4 are equal to 1, then this membership function is exactly the same as the triangular membership function of the neuro-fuzzy system as described in the previous section and shown in Figure 5.

Let membership function $\mu_A(x)$ denotes the degree to which any element x of the universe of discourse belongs to fuzzy set A. A calculation of the degree of membership function based on Figure 6 can be expressed as follows in Equations (8)-(11):

$$\mu_{Var_a}(x) = \begin{cases} 1 & \text{if } x \leq a_2 \\ 0 & \text{if } x \geq a_4 \\ 1 + (x - a_2)\left(\dfrac{-1}{a_4 - a_2}\right) & \text{if } a_2 < x < a_4 \end{cases} \tag{8}$$

$$\mu_{\text{Var}_b}(x) = \begin{cases} 0 & \text{if } x \le a_1 \\ 1 & \text{if } x \ge a_3 \\ \left(\dfrac{x - a_1}{a_3 - a_1}\right) & \text{if } a_1 < x < a_3 \end{cases} \tag{9}$$

$$\mu_{\text{Var}_c}(x) = \begin{cases} 1 & \text{if } x \le b_2 \\ 0 & \text{if } x \ge b_4 \\ 1 + (x - b_2)\left(\dfrac{-1}{b_4 - b_2}\right) & \text{if } b_2 < x < b_4 \end{cases} \tag{10}$$

$$\mu_{\text{Var}_d}(x) = \begin{cases} 0 & \text{if } x \le b_1 \\ 1 & \text{if } x \ge b_3 \\ \left(\dfrac{x - b_1}{b_3 - b_1}\right) & \text{if } b_1 < x < b_3 \end{cases} \tag{11}$$

For the string representation, a base - 10 GAs is utilized where each digit can lie between 0-9. The parameter set of a_1, a_2, a_3, a_4, b_1, b_2, b_3, and b_4 (as shown in Figure 6) of the membership functions for each linguistic input variables are encoded into a digit string as a chromosome. Since there are three linguistic input variables (d, S_{CP}, and S_{VAMA}), each chromosome is consist of a string of 24 traits (8 parameters x 3 variables), where each trait is programmed as a decimal number with 4 significant digits for the gene. Therefore, each chromosome length will have a string of 96 fixed digited. The chromosome data structure used in the system is expressed in Figure 7.

For each trait, the first digit of the gene determines the sign of the trait. The value of 0-4 indicates that the trait is negative, while the value of 5-9 indicates that the trait is positive. The second digit is used to represent the value that is placed to the left of the decimal point, whereas the last two digits are used to represent the values that are placed

to the right of the decimal point. The upper and lower limits on each trait are also set in order to specify the value of each trait that lies into this specific interval range. Table IV shows the summary of the upper and lower limit of the trait for each parameter used in this study. Therefore, when the program generates a random initial population or a new population, the value of each trait will be limited to fall between the upper and lower limits as illustrated in Table IV. For example, a value of "-0.64" for parameter a_1 can be represented with the trait "1064", while the value of "1.00" for parameter b_3 can be represented with the trait "5100".

For the fitness function, the maximization of the objective function shown in Equation (12) is used for evaluating each chromosome in this system.

$$F = \frac{1}{1+e^2} \tag{12}$$

where e is the root mean square error (RMSE) expressed in Equation (13) as follow:

$$e = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{Y}_i - Y_i\right)^2} \tag{13}$$

where N is the total number of data, $\hat{Y}_i$ is the output generated from the neuro-fuzzy system and represents the confidence of the trading signal based on trading on day t ranged between -1 to 1 (the negative value indicates a sell signal and the positive value indicates a buy signal as mentioned in Table III), and Y_i is the desired output (confidence of trading signal) which can be explained as follows.

Let p_t be the opening price on the tth ($t = 1, 2, 3,..., n$) day. Let $g_{t+1} = p_{t+1} - p_t$ be the dollar gain or loss based on trading on day t. Therefore, if $g_{t+1} < 0$, then the sell signal is indicated, while if $g_{t+1} > 0$, then the buy signal is indicated. The desired output is then the min-max normalization of the g_{t+1} ranged into -1 to 1 by using Equation (6). As

previously mentioned, the GAs use the training data set. Therefore, the market trend of the training data set may affect the shape of the membership functions that are derived by the GAs to provide a bias trading signal for the system. This can occur when applying this shape of membership functions to the testing data set in the third phase, which may not be the same market trend as in the training data set. For example, if the training data set is in a trending-up market, a buy trading signal may be generated more often. As a result, when applying this set of membership functions to the testing data set, which is then defined as a trending-down market, too many buy signals may occur, causing additional loss of profitability since sell positions are generally taken more often in a trending-down market. Therefore, in order to reduce this bias, the values of the min and max used for the normalization of the g_{t+1} may have to be adjusted instead of using the exact min and max values based on the training data set. For this study, this can be done by using an arbitrary heuristic approach. First, after ranking the g_{t+1} values of all training data and eliminating the outlier values, the max (min) value will then be set equal to the max (min) value of the rest training data if the training data set is in a trending-up (down) market. Next, for the min (max) value, the value will be set equal to the previous min (max) value of the remaining training data after eliminating the outlier values. Finally, both values of the min and max are then used to develop the normalization.

For the selection method, the elitism strategy, where the fittest chromosome in each generation will be carried over to the next generation without being modified by the crossover and mutation, is applied in this study. The roulette wheel selection technique, where the probability of selection is proportional to chromosome's fitness value, is also used for the other chromosomes. The one-point crossover is employed where a crossover

point on the strings is randomly selected and the two parent chromosomes interchange their digit strings to the right of this point. The crossover probability is set to 0.70 as suggested by Negnevitsky (2002), since this value generally produces good results. For the mutation, a digit will mutate and be replaced by another digit between 0-9. The mutation probability is then set to 0.001. The population size of 25 is used and the generation number of 50 is applied for the termination criterion. The summary of the setup values used for GAs in this proposed system is shown in Table V.

5. TRADING SYSTEMS

After running the GAs and using the training data set to get a suitable shape for the VAMA membership functions, the testing data set is then applied to the system to generate the confidence of the trading signal for the trading systems. The results will be compared against the results generated from the VAMA alone, the VAMA with the NN assistance, the neuro-fuzzy system of the VAMA, and the buy-and-hold trading strategy. For the proposed NF-GA system and the neuro-fuzzy system, a "buy" position is taken when the value of the confidence of the trading signal is greater than 0.50, while a "sell" position is taken when the value of the confidence of trading signal is less than -0.50. Otherwise, a "hold" position is taken. These threshold values (0.50 and -0.50) are chosen based on the idea that when the trading position is taken, a significant signal is necessary to provide confidence (i.e. have more degree of membership) of a strong buy or sell signal, as illustrated in Figure 8.

For the trading systems, both trading with and without transaction costs will be performed in order to study the effects of the transaction costs to the system. A 0.50%

transaction cost will be applied such that a 0.50% transaction cost is paid for each unit of stock being traded. For the investment strategy, all money is invested in a long (buy) position after the first buy signal and remains invested in the position (i.e. subsequent buy signals are ignored). The position will then be closed at the first sell signal after a buy (i.e. subsequent sell signals are ignored). This process is repeated again when a new buy signal is generated. For this study, the trading simulation will be performed based on one unit of the S&P 500 index. The trading also assumes that an exact amount of money will be used to perform the stock trading for each trade (i.e. using amount of money for the investment equal to exactly one unit price of the S&P 500 index for each trade). That is, neither reinvestment of profits, nor reduction of losses will be allowed in the investment strategy. The other general assumptions include that a buy or sell position is taken at the market open, no short sales are allowed, and an investor closes the entire position and then exits the market at the end of the trading period. The buy-and-hold strategy used in this study is also based on buying stocks on the first day of the holding period, holding the position until the last day of the holding period, and then selling the entire position. To measure the profitability, the results will be presented as the investment dollars gained or lost, as well as the total stock return accumulated over the entire trading period, calculated as follows:

$$\text{Accumulated Return, AR (\%)} = \sum_{N} R_t \tag{14}$$

where N is the number of trading days before an investor closes the position and R_t is the stock return from closing the position at the market open of the stock at day t, calculated as:

$$R_t = \frac{(OP_t - OP_i)}{OP_i} \times 100 \tag{15}$$

where OP_t and OP_i are the current opening price (day t) and previous opening price at day i, respectively.

6. EMPIRICAL RESULTS AND ANALYSIS

For this study, past S&P 500 index daily data was utilized. All proposed systems and benchmarks were tested over difference stock market trends by using a testing data set that included a trending-up market, flat market, and trending-down market in order to investigate the robustness of the system. This was done since the VAMA is often useful in trending markets, but gives poor results in flat markets. For the trending-up market, the testing data set was from the period of January 2003 to December 2003 (the first day closing price of the stock is $908.59 and the last day is $1,111.92). This model uses the period of January 1998 to December 2002 as the training data set. For the flat market, the testing data set was from the period of January 2000 to December 2000 (the first day closing price of the stock is $1,399.42 and the last day is $1,320.28) and uses the period of January 1995 to December 1999 as the training data set. Finally, for the trending-down market the testing data set is from the period of January 2002 to December 2002 (the first day closing price of the stock is $1,165.27 and the last day is $879.82), while the training data set was from the period of January 1997 to December 2001.

The results in Tables VI, VII, and VIII present the profitability details for the testing data set trading in the trending-up, flat, and trending-down markets, respectively, both with and without the 0.50% transaction costs, for the proposed NF-GA system and associated benchmarks. The results are shown based on the trading of one unit of the

S&P 500 index and include the total amount of dollars gained or lost, the accumulated returns of the trading, and the number of trades for each of the VAMA interval lengths (described in the next paragraph). In addition, for the proposed NF-GA system, the results were also generated based on the best chromosomes in the GAs process.

As seen in Tables VI, VII, and VIII, several interval lengths of VAMA are used. The numbers were inspired from periodic cycle length (5, 21, and 63), representing approximately weekly, monthly, and quarterly interval lengths, and Fibonacci numbers (5, 13 21, and 55). From the Tables, it can be seen that the overall results for trading with and without 0.50% transaction costs show that the NF-GA system performs best compared to others in every market trend. This illustrates the robustness of the proposed NF-GA system. Although in the flat market the VAMA technical indicator will usually not perform well, the NF-GA system also shows the best trading performance. The reason is that the trading signals provided from the NF-GA system help investors to make better trading decisions due to the synergy of the integration of the NN, fuzzy logic and GAs techniques. This occurs since the NN forecast helps to provide the earlier VAMA trading signals, fuzzy logic helps to handle the uncertainty of these trading signals by using the VAMA membership functions, and the GAs helps to optimize these trading signals by tuning the VAMA membership functions. For example, as shown in Table VI for the trending-up market, the NF-GA system provided the average accumulated returns over the whole trading period that were greater than using the VAMA alone, the VAMA with the NN assistance, the NF of the VAMA, and the buy-and-hold trading strategy by a differential return of 17.58%, 10.91%, 3.46%, and 4.76%, respectively, for the trading without the transaction costs, and with a differential of 33.12%, 33.89%, 10.00%, and

2.72%, respectively, for the trading without the 0.50% transaction costs. The results are similar for the other market trends. Figures 9 and 10 present the plots comparison of the average profitability results (shown in accumulated returns) for each approach in different market trends based on the results of Tables VI-VIII for the trading with and without the 0.50% transaction costs.

Based on Figures 9 and 10, once again it can be seen that the NF-GA system has the highest of the average accumulated returns and outperforms the other approaches in every market trend. The results in Figure 10 also clearly show that the transaction costs have less impact to the NF-GA system when compare to the other approaches (except the buy-and-hold). This result since the NF-GA system generated a significant lower number of trades compared to the others (except the buy-and-hold). In fact, the lower number of trades helps keep investors from paying too many individual transaction costs. Therefore, as shown in Figure 10, the NF-GA system has reduced the negative change in profitability when transaction costs are considered, as compared to the others (except the buy-and-hold). Moreover, as illustrated in Tables VI and VIII for the trending-up and trending-down markets, respectively, the average accumulated returns for the NF-GA system were dropped by 3.25% and 2.14%, respectively, when the trading with the 0.50% transaction costs were applied, while for other approaches (except the buy-and-hold) the profitability was dropped at least 10% or more. However, for the flat market results shown in Table VII, the number of trades for the NF-GA system was high when compared with other market trends (average 31.20 trades). This is due to the fact that the VAMA is the trend following indicator that usually provides higher numbers of trades in flat markets without defined trends. This results in reducing of the average accumulated

returns for the NF-GA system by 15.61% when the 0.50% transaction costs were applied. However, this NF-GA system still has less impact from the effects of the transaction costs as compared to the others (except the buy-and-hold) since for the other approaches the average returns dropped more than 23% or more for the flat market.

In addition, when considering each interval length of the VAMA results for all market trends, the overall results of the NF-GA system still outperforms the other approaches. Although the results generated from the NF-GA system for the 21 length VAMA without transaction costs for the trending-up market (shown in Table VI) and the trending-down market (shown in Table VIII) were not the best, when the transaction costs were applied the results from the NF-GA system became the best due to the lower number of trades. This demonstrates the effectiveness of the NF-GA system in that it provides a lower number of trades and more optimal trading decisions when made.

For the GAs performance, it can be seen from the trading profitability results for every market trend, with and without the 0.50% transaction costs of the NF-GA system, that the results were improved from the NF system that utilized fixed VAMA membership functions. In addition, the NF system results performed well for the trending-up market but provided poor results in other market trends. This implies that the fixed shape of the VAMA membership functions in the NF system may be more suitable in the trending-up market data set used in this study, compared to other market trends. However, when the GAs was applied to tune the VAMA membership functions of the NF system, the system generated better trading results and performed best among the others when considering other market trends. As such, the GAs appear useful for determining the appropriate shape of the VAMA membership functions. Figure 11 also shows the

example of the GAs performance for the 63 VAMA for the flat market. As seen in the figure, the best and average fitness value of the population is improved as the number of generations is increased, highlighting the search and evolutionary performance of the GAs, as mentioned before.

7. CONCLUSIONS

Research and testing have shown the benefits of using a hybrid intelligent system applied to the VAMA technical indicator for stock trading. The Neuro-Fuzzy based Genetic Algorithm (NF-GA) system of the VAMA membership functions that integrated the Neural Networks (NN), Fuzzy Logic (FL), and Genetic Algorithms (GAs) was introduced. The system applied fuzzy logic as an extension to the results of the previous combined neural networks and VAMA model proposed by Chavarnakul and Enke (2006a) and used a base - 10 genetic algorithms to tune the parameters of the membership functions of the VAMA to get better trading results. The results show that this proposed NF-GA system can help to provide a lower number of trades and more optimal trading decisions to generate better profitability trading results when comparing with using the VAMA alone, the VAMA with the NN assistance, the neuro-fuzzy system of the VAMA, and the buy-and-hold trading strategy.

This added performance of the NF-GA system occurs due to a synergy among the intelligent techniques that helps the system provide the right trading decisions for the investors. For the system, the NN helps provide earlier VAMA trading signals, fuzzy logic helps the system handle the uncertainty of the trading signals, and the GAs helps the system to optimize the trading signals. The overall results also show that the NF-GA

system performed best and showed the robustness of the system among the other benchmarks in different market trends, including trending-up, flat, and trending-down markets of the past S&P 500 index data. Future study should examine other integrated architectures of intelligent techniques to the hybrid intelligent system for improving the performance of the system. A trading simulation using different stocks under the portfolio construction should also be considered.

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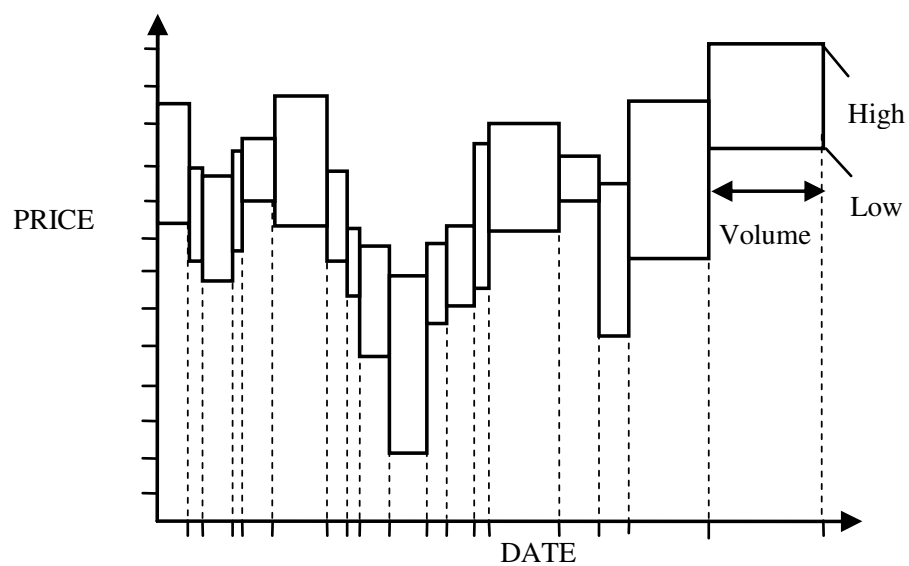
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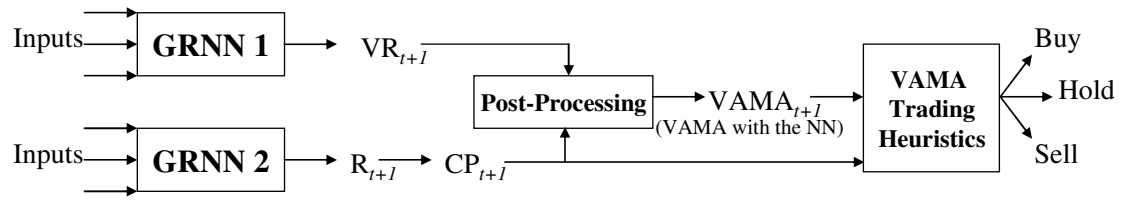
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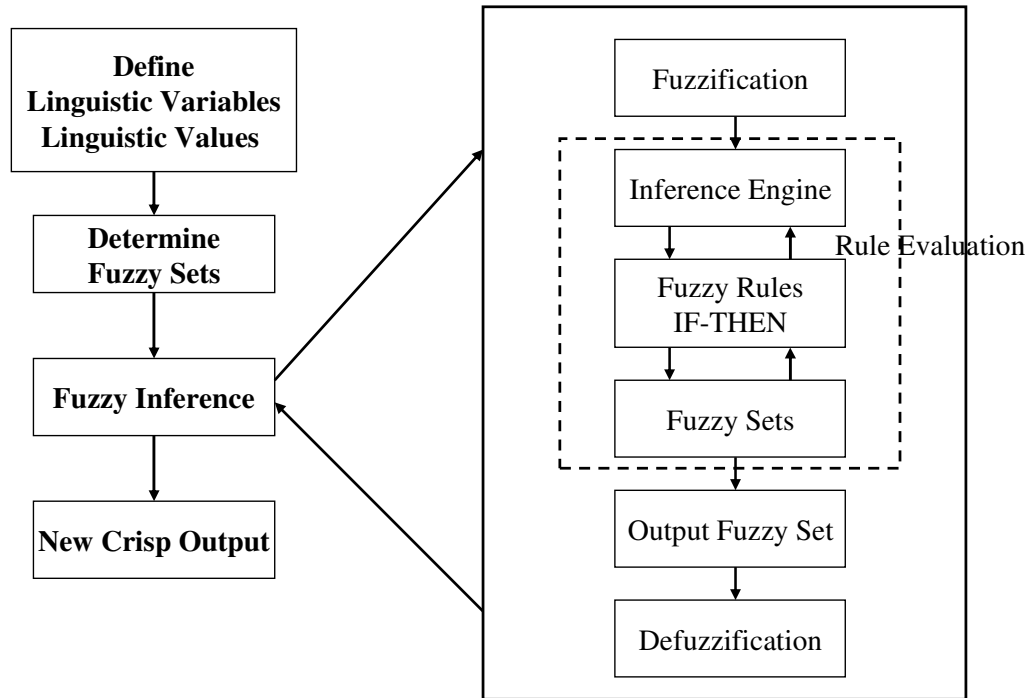
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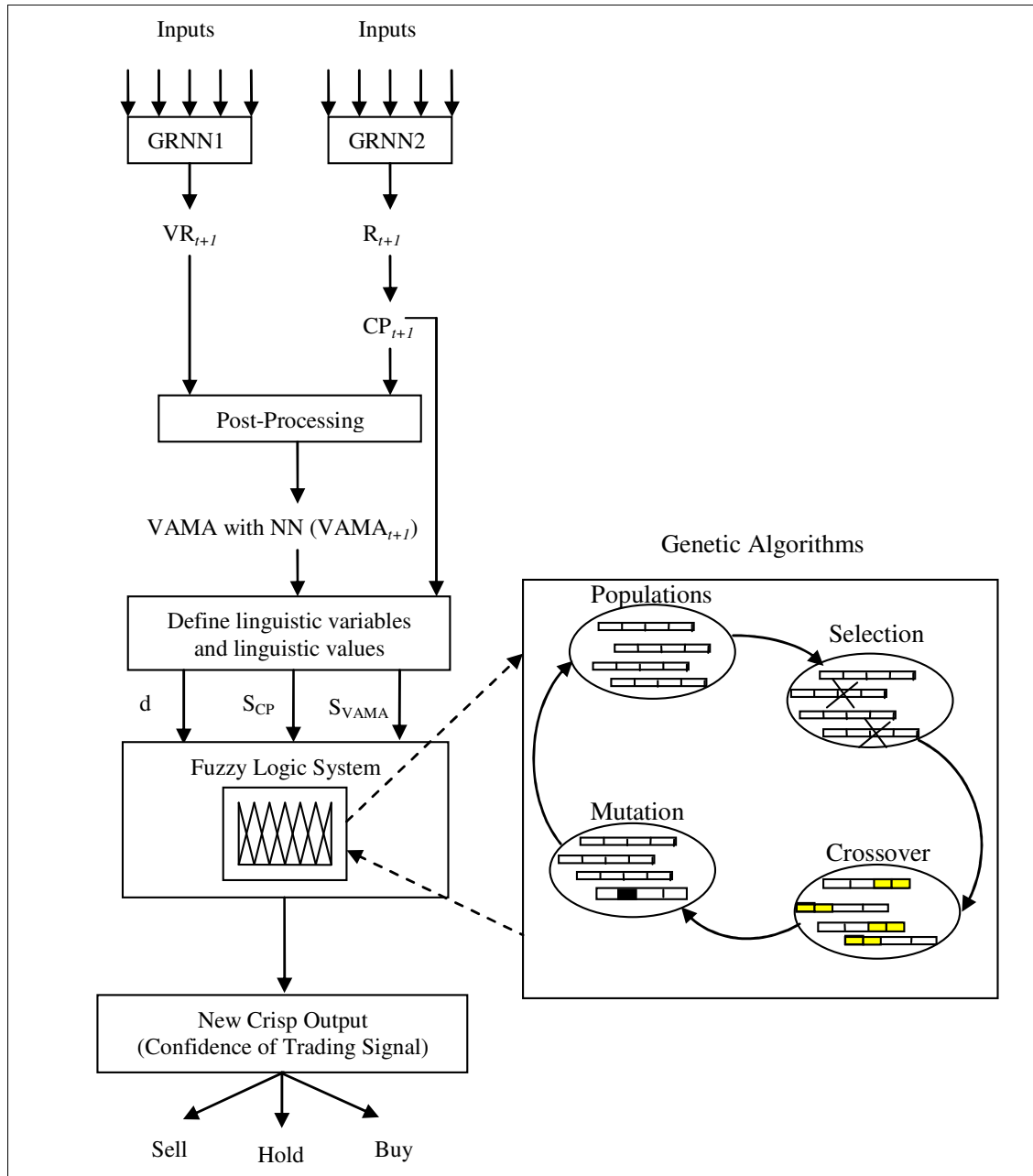
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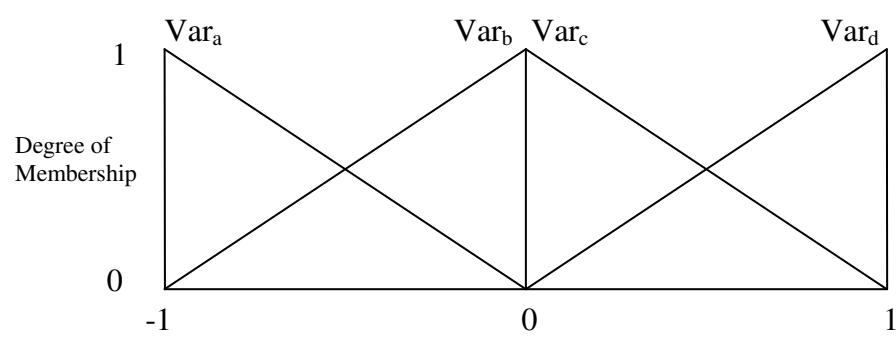
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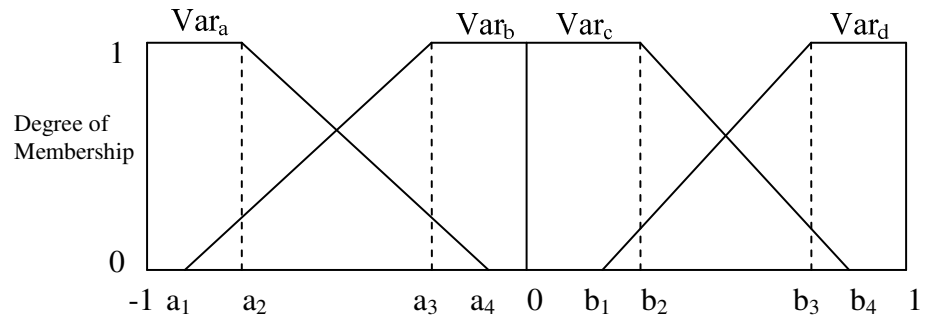
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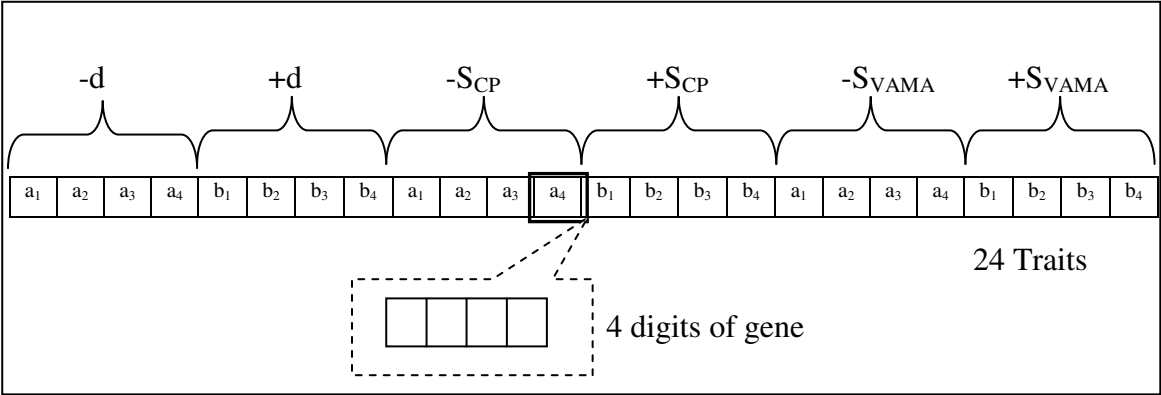
Figure 7. Chromosome data structure
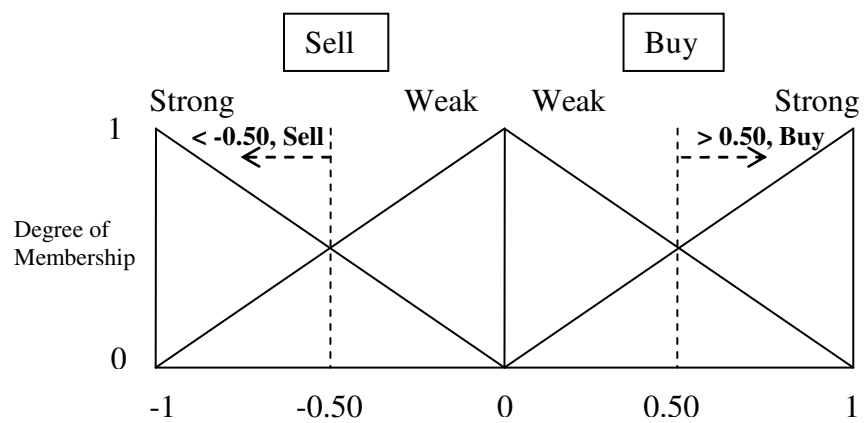
Figure 8. Trading decisions
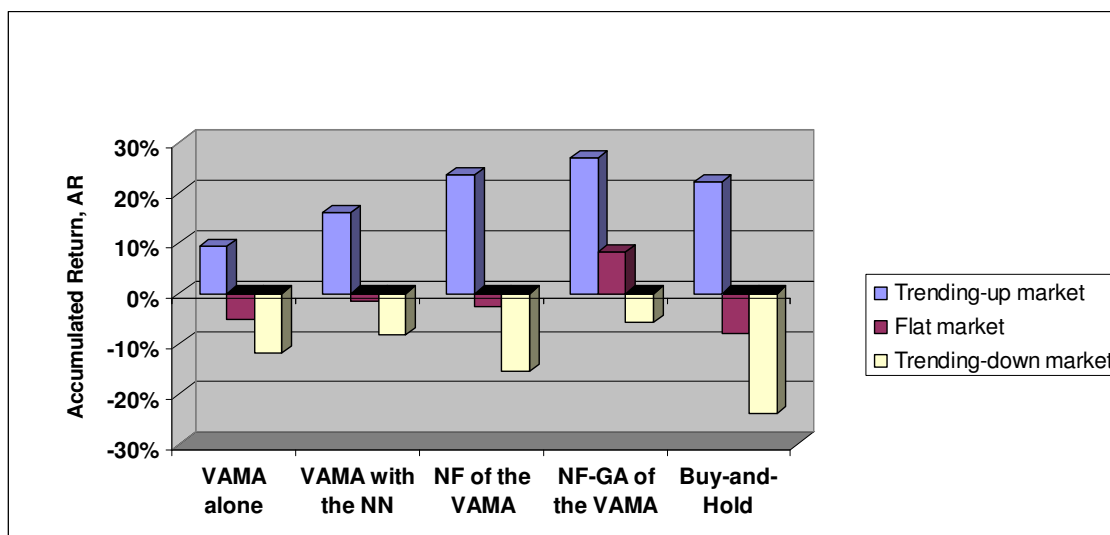
Figure 9. Comparison of trading performance (without transaction costs)
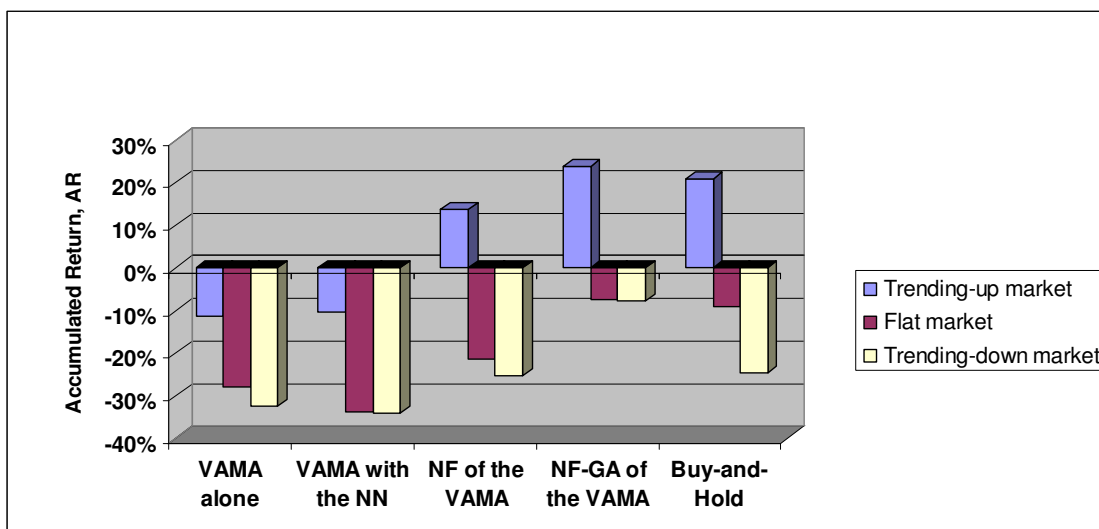
Figure 10. Comparison of trading performance (with 0.50% transaction costs)
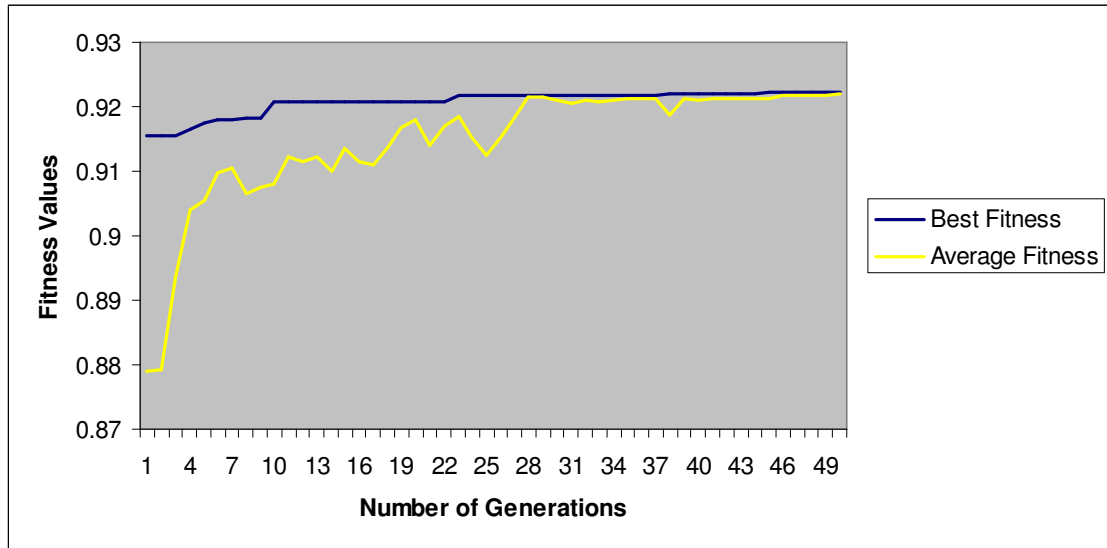
Figure 11. GAs performance (63 VAMA, Flat Market)

Table I. Example of calculation for 5 VAMA using alone
(current day (time t) is 01/05/2003)

Date	Closing Price (CP)	Volume Ratio (VR)	CPxVR
01/02/2003	$909.03	1.1957	$1,086.93
01/03/2003	$908.59	1.0855	$986.27
01/04/2003	$929.01	1.3597	$1,263.17
01/05/2003 (time t)	$922.93	1.4886	$1,373.87
		Sum = 5.1295	Sum = $4,710.24

5 VAMA = [$4,710.24 – (5.1295 – 5) x $909.03]/5 = $918.50

Table II. Example of calculation for 5 VAMA with NN assistance
(current day (time *t*) is 01/04/2003)

Date	Closing Price (CP)	Volume Ratio (VR)	CPxVR
01/02/2003	$909.03	1.1957	$1,086.93
01/03/2003	$908.59	1.0855	$986.27
01/04/2003 (time *t*)	$929.01	1.3597	$1,263.17
01/05/2003 (time *t+1*)	$925.67**	<u>1.4019*</u>	<u>$1,297.70</u>
		Sum = 5.0428	Sum = $4,634.07

5 VAMA with NN = [$4,634.07 – (5.0428 – 5) x $909.03]/5 = $919.03

Note: * = predicted value from GRNN 1, * * = predicted value from GRNN 2

Table III. Summary of linguistic variables

Linguistic Variables	Notation	Range	Linguistic Values
d (CP_{t+1} – $VAMA_{t+1}$)	-d	[-1,0]	More (Var_a) Less (Var_b)
	+d	[0,1]	Less (Var_c) More (Var_d)
S_{CP} (CP_{t+1} – CP_t)	$-S_{CP}$	[-1,0]	Steep (Var_a) Flat (Var_b)
	$+S_{CP}$	[0,1]	Flat (Var_c) Steep (Var_d)
S_{VAMA} ($VAMA_{t+1}$ - $VAMA_t$)	$-S_{VAMA}$	[-1,0]	Steep (Var_a) Flat (Var_b)
	$+S_{VAMA}$	[0,1]	Flat (Var_c) Steep (Var_d)
Trading Signal	Sell	[-1,0]	Strong (Var_a) Weak (Var_b)
	Buy	[0,1]	Weak (Var_c) Strong (Var_d)

Table IV. Summary of upper and lower limits of parameters

Parameter	Upper Limit	Lower Limit
a_1	-0.5	-1
a_2	-0.5	-1
a_3	0	-0.5
a_4	0	-0.5
b_1	0.5	0
b_2	0.5	0
b_3	1	0.5
b_4	1	0.5

Table V. Setup values for GAs

GAs' Parameters	Values
Population Size	25
Gene Length	4
Number of Traits	24
Chromosome Length	96
Number of Generations	50
Crossover Probability (p_c)	0.70
Mutation Probability (p_m)	0.001

Table VI. Trending-up market trading results

TRADING WITHOUT TRANSACTION COST

VAMA interval lengths	VAMA alone			VAMA with the NN			NF of the VAMA			NF-GA of the VAMA			Buy-and-Hold		
	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.
5 VAMA	-$40.74	-4.78	88	$142.88	13.88	100	$162.24	16.51	22	$185.15	20.00	10	$201.00	22.12	2
13 VAMA	$72.52	7.65	44	$80.50	7.57	64	$201.32	23.91	8	$205.12	25.63	4	$201.00	22.12	2
21 VAMA	$79.88	7.98	36	$97.35	9.64	52	$281.20	30.15	16	$262.11	28.67	4	$201.00	22.12	2
55 VAMA	$165.25	18.16	20	$234.31	24.65	22	$211.42	21.91	24	$263.23	28.74	6	$201.00	22.12	2
63 VAMA	$159.33	17.50	20	$228.60	24.10	24	$224.64	24.63	26	$277.76	31.35	6	$201.00	22.12	2
Average	$87.25	9.30	41.60	$156.73	15.97	52.40	$216.16	23.42	19.20	$238.67	26.88	6	$201.00	22.12	2

TRADING WITH THE 0.50% TRANSACTION COST

VAMA interval lengths	VAMA alone			VAMA with the NN			NF of the VAMA			NF-GA of the VAMA			Buy-and-Hold		
	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.
5 VAMA	-$466.35	-48.52	88	-$333.93	-36.01	100	$61.57	5.40	22	$139.54	14.82	10	$190.91	20.91	2
13 VAMA	-$139.77	-14.31	44	-$226.59	-24.35	64	$165.71	19.69	8	$186.62	23.39	4	$190.91	20.91	2
21 VAMA	-$90.78	-10.01	36	-$154.60	-16.33	52	$208.14	21.89	16	$242.46	26.40	4	$190.91	20.91	2
55 VAMA	$65.06	8.03	20	$125.42	13.46	22	$96.78	9.74	24	$235.29	25.47	6	$190.91	20.91	2
63 VAMA	$59.20	7.37	20	$110.10	11.92	24	$98.81	11.45	26	$248.78	28.05	6	$190.91	20.91	2
Average	-$114.53	-11.49	41.60	-$95.92	-10.26	52.40	$126.20	13.63	19.20	$210.54	23.63	6	$190.91	20.91	2

Table VII. Flat market trading results

TRADING WITHOUT TRANSACTION COST

VAMA interval lengths	VAMA alone			VAMA with the NN			NF of the VAMA			NF-GA of the VAMA			Buy-and-Hold		
	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.
5 VAMA	$132.34	10.29	94	$155.48	12.45	112	-$132.23	-8.57	42	$172.63	13.05	30	-$115.85	-8.00	2
13 VAMA	$9.65	1.00	46	$34.08	2.95	72	-$92.42	-5.57	42	$59.18	4.76	30	-$115.85	-8.00	2
21 VAMA	-$151.06	-10.03	36	-$75.20	-4.89	64	-$98.30	-6.07	34	$67.99	5.39	36	-$115.85	-8.00	2
55 VAMA	-$217.35	-15.22	30	-$157.46	-10.80	40	$35.39	3.43	36	$166.72	12.29	32	-$115.85	-8.00	2
63 VAMA	-$163.52	-11.32	24	-$111.63	-7.58	36	$40.61	3.67	36	$73.00	6.21	28	-$115.85	-8.00	2
Average	-$77.99	-5.06	46	-$30.95	-1.57	64.80	-$49.39	-2.62	38	$107.90	8.34	31.20	-$115.85	-8.00	2

TRADING WITH THE 0.50% TRANSACTION COST

VAMA interval lengths	VAMA alone			VAMA with the NN			NF of the VAMA			NF-GA of the VAMA			Buy-and-Hold		
	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.	Gain/Loss	AR (%)	# of Td.
5 VAMA	-$538.67	-36.58	94	-$647.09	-42.40	112	-$432.05	-29.38	42	-$39.93	-2.01	30	-$129.76	-8.91	2
13 VAMA	-$318.51	-21.90	46	-$479.34	-32.90	72	-$391.58	-26.41	42	-$151.86	-10.22	30	-$129.76	-8.91	2
21 VAMA	-$407.60	-27.84	36	-$531.07	-36.68	64	-$339.37	-22.92	34	-$186.69	-12.57	36	-$129.76	-8.91	2
55 VAMA	-$431.02	-29.99	30	-$443.00	-30.59	40	-$220.69	-14.51	36	-$59.64	-3.75	32	-$129.76	-8.91	2
63 VAMA	-$334.81	-23.15	24	-$368.98	-25.42	36	-$214.70	-14.28	36	-$125.46	-7.78	28	-$129.76	-8.91	2
Average	-$406.12	-27.89	46	-$493.90	-33.60	64.80	-$319.68	-21.50	38	-$112.72	-7.27	31.20	-$129.76	-8.91	2

Table VIII. Trending-down market trading results

TRADING WITHOUT TRANSACTION COST

VAMA interval lengths	VAMA alone			VAMA with the NN			NF of the VAMA			NF-GA of the VAMA			Buy-and-Hold		
	Gain/ Loss	AR (%)	# of Td.	Gain/ Loss	AR (%)	# of Td.	Gain/ Loss	AR (%)	# of Td.	Gain/ Loss	AR (%)	# of Td.	Gain/ Loss	AR (%)	# of Td.
5 VAMA	-$232.92	-21.50	90	-$301.67	-30.89	114	-$224.38	-21.87	26	-$136.90	-14.81	8	-$276.64	-23.94	2
13 VAMA	-$158.46	-13.73	52	-$67.97	-4.21	64	-$182.75	-16.99	26	-$56.77	-5.63	4	-$276.64	-23.94	2
21 VAMA	-$69.95	-6.36	36	$22.73	3.17	42	-$84.23	-8.11	20	-$56.77	-5.63	4	-$276.64	-23.94	2
55 VAMA	-$91.69	-9.51	18	-$17.07	-1.80	20	-$125.30	-13.83	12	$17.40	2.22	4	-$276.64	-23.94	2
63 VAMA	-$69.77	-7.46	14	-$67.68	-7.17	20	-$173.51	-17.13	14	-$43.35	-4.10	2	-$276.64	-23.94	2
Average	-$124.56	-11.71	42	-$86.33	-8.18	52	-$160.88	-15.59	19.60	-$55.28	-5.59	4.40	-$276.64	-23.94	2

TRADING WITH THE 0.50% TRANSACTION COST

VAMA interval lengths	VAMA alone			VAMA with the NN			NF of the VAMA			NF-GA of the VAMA			Buy-and-Hold		
	Gain/ Loss	AR (%)	# of Td.	Gain/ Loss	AR (%)	# of Td.	Gain/ Loss	AR (%)	# of Td.	Gain/ Loss	AR (%)	# of Td.	Gain/ Loss	AR (%)	# of Td.
5 VAMA	-$676.15	-66.06	90	-$857.83	-87.30	114	-$352.96	-34.59	26	-$173.53	-18.64	8	-$286.81	-24.69	2
13 VAMA	-$414.11	-39.46	52	-$381.16	-36.01	64	-$306.72	-29.76	26	-$76.60	-7.57	4	-$286.81	-24.69	2
21 VAMA	-$246.81	-24.20	36	-$181.82	-17.76	42	-$182.72	-17.98	20	-$76.60	-7.57	4	-$286.81	-24.69	2
55 VAMA	-$178.45	-18.37	18	-$115.24	-11.74	20	-$180.92	-19.66	12	$0.12	0.21	4	-$286.81	-24.69	2
63 VAMA	-$134.65	-14.35	14	-$166.04	-17.05	20	-$239.66	-23.93	14	-$53.70	-5.06	2	-$286.81	-24.69	2
Average	-$330.03	-32.49	42	-$340.42	-33.97	52	-$252.60	-25.18	19.60	-$76.06	-7.73	4.40	-$286.81	-24.69	2

APPENDIX

SOFTWARE CODING IN MATLAB

```
%NF-GA CODE
%This code is modified and developed based on a base-10 GA programming by
% Kevin Passino (2004) available at
% http://www.ece.osu.edu/~passino/ICbook/Code/ga.m
clear all;
close all;
clc;
rand('state',0);
NUM_TRAITS = 24; % Number of traits in each individual
HIGHTRAIT =...
[-0.5 0 -0.5 0 0.5 1 0.5 1 -0.5 0 -0.5 0 0.5 1 0.5 1 -0.5 0 -0.5 0 0.5 1 0.5 1];% Upper limit
                                                                    %of a trait

LOWTRAIT =...
[-1 -0.5 -1 -0.5 0 0.5 0 0.5 -1 -0.5 -1 -0.5 0 0.5 0 0.5 -1 -0.5 -1 -0.5 0 0.5 0 0.5];% Lower
                                                                    %limit of a trait
SIG_FIGS = [3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3]; % Number of genes in each
                                                                    %trait
DECIMAL = [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]; % Order of magnitude the
                                                                    %trait
MUTAT_PROB = 0.001; % Probability of mutation
CROSS_PROB = 0.7; % Probability of crossover
SELF_ENTERED = 0; % "0" a random initial population, "1" a specified initial
                  %population
POP_SIZE = 25; % Number of individuals in the population
ELITISM = 1; % Elitisim ON/OFF, 1/0
MAX_GENERATION = 50; % Number of times the loop will run
popcount = 1; % Initialize the generation count, set it to one for the first population
```

```
if SELF_ENTERED == 0 % Make a random initial population for based-10 operation
                     % by specifying the matrix of initial traits
   for pop_member = 1:POP_SIZE
      for current_trait = 1:NUM_TRAITS,
         trait(current_trait,pop_member,popcount) =...
            (rand-(1/2))*(HIGHTRAIT(current_trait)-LOWTRAIT(current_trait))+...
            (1/2)*(HIGHTRAIT(current_trait)+LOWTRAIT(current_trait));
      end
   end
else
   for pop_member = 1:POP_SIZE
      for current_trait = 1:1:NUM_TRAITS,
         trait(current_trait,pop_member,popcount) = 0;
      end
   end
end


% Determine the length of the chromosome and starting point of each trait


CHROM_LENGTH = sum(SIG_FIGS)+ NUM_TRAITS; % Length of the chromosome
TRAIT_START(1)=1;
for current_trait = 1:NUM_TRAITS,
   TRAIT_START(current_trait+1)=
TRAIT_START(current_trait)+SIG_FIGS(current_trait)+1;
end


%Main loop of GA
while popcount <= MAX_GENERATION
   for pop_member = 1:POP_SIZE
      for current_trait = 1:NUM_TRAITS,
         if trait(current_trait,pop_member,popcount) > HIGHTRAIT(current_trait)
```

```
            trait(current_trait,pop_member,popcount) =...
            (rand-(1/2))*(HIGHTRAIT(current_trait)-LOWTRAIT(current_trait))+...
            (1/2)*(HIGHTRAIT(current_trait)+LOWTRAIT(current_trait));
        elseif trait(current_trait,pop_member,popcount) < LOWTRAIT(current_trait);
            trait(current_trait,pop_member,popcount) =...
            (rand-(1/2))*(HIGHTRAIT(current_trait)-LOWTRAIT(current_trait))+...
            (1/2)*(HIGHTRAIT(current_trait)+LOWTRAIT(current_trait));
        end
          if trait(current_trait,pop_member,popcount) < 0
            pop(TRAIT_START(current_trait),pop_member)=0;
          else
            pop(TRAIT_START(current_trait),pop_member)=9;
          end
temp_trait(current_trait,pop_member)= abs(trait(current_trait,pop_member,popcount));
temp_trait(current_trait,pop_member)=...
temp_trait(current_trait,pop_member)/10^(DECIMAL(current_trait)-1);
for make_gene = TRAIT_START(current_trait)+1:TRAIT_START(current_trait+1)-1,
  pop(make_gene,pop_member)=temp_trait(current_trait,pop_member)-...
  rem(temp_trait(current_trait,pop_member),1);
      temp_trait(current_trait,pop_member)=...
  (temp_trait(current_trait,pop_member)-pop(make_gene,pop_member))*10;
end
      end % Ends "for current_trait=..." loop
        end   % Ends "for pop_member=..." loop
% Maximize fitness function (1/(1+RMSE^2) of output from NF and desired output)
sumfitness = 0;                  % Re-initialize for each generation
   for chrom_number = 1:POP_SIZE, % Test fitness
     a=newfis('NF1');
     a.input(1).name='d';
     a.input(1).range=[-1 1];
     a.input(1).mf(1).name='NegMore';
```

```
a.input(1).mf(1).type='trapmf';

a.input(1).mf(1).params=...

[-2 -1.5 trait(1,chrom_number,popcount) trait(2,chrom_number,popcount)];

a.input(1).mf(2).name='NegLess';

a.input(1).mf(2).type='trapmf';

a.input(1).mf(2).params=...

[trait(3,chrom_number,popcount) trait(4,chrom_number,popcount) 0 0];

a.input(1).mf(3).name='PosLess';

a.input(1).mf(3).type='trapmf';

a.input(1).mf(3).params=...

[0 0 trait(5,chrom_number,popcount) trait(6,chrom_number,popcount)];

a.input(1).mf(4).name='PosMore';

a.input(1).mf(4).type='trapmf';

a.input(1).mf(4).params=...

[trait(7,chrom_number,popcount) trait(8,chrom_number,popcount) 1.5 2];

a.input(2).name='Scp';

a.input(2).range=[-1 1];

a.input(2).mf(1).name='ScpNegsteep';

a.input(2).mf(1).type='trapmf';

a.input(2).mf(1).params=...

[-2 -1.5 trait(9,chrom_number,popcount) trait(10,chrom_number,popcount)];

a.input(2).mf(2).name='ScpNegFlat';

a.input(2).mf(2).type='trapmf';

a.input(2).mf(2).params=...

[trait(11,chrom_number,popcount) trait(12,chrom_number,popcount) 0 0];

a.input(2).mf(3).name='ScpPosFlat';

a.input(2).mf(3).type='trapmf';

a.input(2).mf(3).params=...

[0 0 trait(13,chrom_number,popcount) trait(14,chrom_number,popcount)];

a.input(2).mf(4).name='ScpPosSteep';

a.input(2).mf(4).type='trapmf';
```

```
a.input(2).mf(4).params=...
[trait(15,chrom_number,popcount) trait(16,chrom_number,popcount) 1.5 2];
a.input(3).name='Svama';
a.input(3).range=[-1 1];
a.input(3).mf(1).name='SvamaNegSteep';
a.input(3).mf(1).type='trapmf';
a.input(3).mf(1).params=...
[-2 -1.5 trait(17,chrom_number,popcount) trait(18,chrom_number,popcount)];
a.input(3).mf(2).name='SvamaNegFlat';
a.input(3).mf(2).type='trapmf';
a.input(3).mf(2).params=...
[trait(19,chrom_number,popcount) trait(20,chrom_number,popcount) 0 0];
a.input(3).mf(3).name='SvamaPosFlat';
a.input(3).mf(3).type='trapmf';
a.input(3).mf(3).params=...
[0 0 trait(21,chrom_number,popcount) trait(22,chrom_number,popcount)];
a.input(3).mf(4).name='SvamaPosSteep';
a.input(3).mf(4).type='trapmf';
a.input(3).mf(4).params=...
[trait(23,chrom_number,popcount) trait(24,chrom_number,popcount) 1.5 2];
a.output(1).name='Signal';
a.output(1).range=[-1 1];
a.output(1).mf(1).name='SS';
a.output(1).mf(1).type='trimf';
a.output(1).mf(1).params=[-2 -1 0];
a.output(1).mf(2).name='WS';
a.output(1).mf(2).type='trimf';
a.output(1).mf(2).params=[-1 0 0];
a.output(1).mf(3).name='SB';
a.output(1).mf(3).type='trimf';
a.output(1).mf(3).params=[0 1 2];
```

```
a.output(1).mf(4).name='WB';
a.output(1).mf(4).type='trimf';
a.output(1).mf(4).params=[0 0 1];
a.rule(1).antecedent=[1 3 0];
a.rule(1).consequent=[4];
a.rule(1).weight=1;
a.rule(1).connection=1;
a.rule(2).antecedent=[2 1 0];
a.rule(2).consequent=[1];
a.rule(2).weight=1;
a.rule(2).connection=1;
a.rule(3).antecedent=[2 2 4];
a.rule(3).consequent=[1];
a.rule(3).weight=1;
a.rule(3).connection=1;
a.rule(4).antecedent=[2 2 3];
a.rule(4).consequent=[2];
a.rule(4).weight=1;
a.rule(4).connection=1;
a.rule(5).antecedent=[3 1 0];
a.rule(5).consequent=[1];
a.rule(5).weight=1;
a.rule(5).connection=1;
a.rule(6).antecedent=[3 2 4];
a.rule(6).consequent=[1];
a.rule(6).weight=1;
a.rule(6).connection=1;
a.rule(7).antecedent=[3 2 3];
a.rule(7).consequent=[2];
a.rule(7).weight=1;
a.rule(7).connection=1;
```

```
a.rule(8).antecedent=[4 2 0];

a.rule(8).consequent=[2];

a.rule(8).weight=1;

a.rule(8).connection=1;

a.rule(9).antecedent=[3 4 0];

a.rule(9).consequent=[3];

a.rule(9).weight=1;

a.rule(9).connection=1;

a.rule(10).antecedent=[3 3 1];

a.rule(10).consequent=[3];

a.rule(10).weight=1;

a.rule(10).connection=1;

a.rule(11).antecedent=[3 3 2];

a.rule(11).consequent=[4];

a.rule(11).weight=1;

a.rule(11).connection=1;

a.rule(12).antecedent=[2 4 0];

a.rule(12).consequent=[3];

a.rule(12).weight=1;

a.rule(12).connection=1;

a.rule(13).antecedent=[2 3 1];

a.rule(13).consequent=[3];

a.rule(13).weight=1;

a.rule(13).connection=1;

a.rule(14).antecedent=[2 3 2];

a.rule(14).consequent=[4];

a.rule(14).weight=1;

a.rule(14).connection=1;

channel = ddeinit('excel','5VAMA_2000.xls'); %training data set file

data = ddereq(channel, 'r12c15:r1265c17'); %load training data set

A = evalfis(data,a);
```

```
      n = length(A);
      target = ddereq(channel,'r12c19:r1265c19'); %desired output
      RMSE = norm(A-target)/sqrt(n);
      fitness_bar(chrom_number)= 1/(1+RMSE^2);
   end
    % Next, compute the fitness function
  for chrom_number = 1:POP_SIZE,       % Test fitness
 fitness(chrom_number)= fitness_bar(chrom_number);
sumfitness = sumfitness + fitness(chrom_number);
  end


% Next, determine the most fit and least fit chromosome and
% the chrom_numbers (bestmember and worstmember)


[bestfitness(popcount),bestmember]=max(fitness);
[worstfitness(popcount),worstmember]=min(fitness);


% Next, save these


bestindividual(:,popcount)=trait(:,bestmember,popcount);
worstindividual(:,popcount)=trait(:,worstmember,popcount);


% Compute the average fitness


avefitness(popcount) = sumfitness / POP_SIZE;


%Create the next generation
  for pop_member = 1:POP_SIZE,
      if ELITISM ==1 & pop_member==bestmember  % If elitism on
             parent_chrom(:,pop_member)=pop(:,pop_member);
      else
```

```
        pointer=rand*sumfitness; % Make the pointer for the roulette wheel


        member_count=1;        % Initialization
        total=fitness(1);


        while total < pointer,
          member_count=member_count+1;
          total=total+fitness(member_count);
        end


% Next, make the parent chromosome


  parent_chrom(:,pop_member)=pop(:,member_count);
        end
    end


% Reproduce section


for parent_number1 = 1:POP_SIZE,    % Crossover
        if ELITISM ==1 & parent_number1==bestmember % If elitism on
                child(:,parent_number1)=parent_chrom(:,parent_number1);
        else
          parent_number2=parent_number1;  % Initialize who the mate is
          while parent_number2 == parent_number1
      parent_number2 = rand*POP_SIZE; % Choose parent number 2 randomly
      parent_number2 = parent_number2-rem(parent_number2,1)+1;
          end
    if CROSS_PROB > rand        % If true then crossover occurs


      site = rand*CHROM_LENGTH;   % Choose site for crossover
      site = site-rem(site,1)+1;  % and make it a valid integer number for a site
```

```
child(1:site,parent_number1)=parent_chrom(1:site,parent_number1);
child(site+1:CHROM_LENGTH,parent_number1)=...
   parent_chrom(site+1:CHROM_LENGTH,parent_number2);
    else                % No crossover occurs


% Copy non-crossovered chromosomes into next generation


child(:,parent_number1)=parent_chrom(:,parent_number1);
        end
   end  % End the "if ELITISM..." statement
end  % End "for parent_number1=..." loop


% Mutate children


  for pop_member= 1:POP_SIZE,
      if ELITISM ==1 & pop_member==bestmember  % If elitism on
            child(:,pop_member)=child(:,pop_member); % Do not mutate
      else
       for site = 1:CHROM_LENGTH,
    if MUTAT_PROB > rand        % If true then mutate
      rand_gene=rand*10;            % Creat a random gene


      while child(site,pop_member) == rand_gene-rem(rand_gene,1),
        rand_gene=rand*10;
      end;
      child(site,pop_member)=rand_gene-rem(rand_gene,1);
      if rand_gene == 10
          site=site-1;
      end
     end  % End "if MUTAT_PROB > rand ...
        end  % End for site... loop
```

```
        end  % End "if ELITISM..."
    end  % End for pop_member loop


% Create the next generation


  pop=child;
  popcount=popcount+1;


% Next, convert the population (pop) to the base-10


for pop_member = 1:POP_SIZE
        for current_trait = 1:NUM_TRAITS,
trait(current_trait,pop_member,popcount)=0; % Initialize variables
place_pointer=1;
for gene=TRAIT_START(current_trait)+1:TRAIT_START(current_trait+1)-1,
 place=DECIMAL(current_trait)-place_pointer;
 trait(current_trait,pop_member,popcount)=...
 trait(current_trait,pop_member,popcount)+...
   (pop(gene,pop_member))*10^place;
 place_pointer=place_pointer+1;
end


% Determine sign of the traits and fix


if pop(TRAIT_START(current_trait),pop_member) < 5
  trait(current_trait,pop_member,popcount)=...
    -trait(current_trait,pop_member,popcount);
end
        end % Ends "for current_trait=..." loop
end    % Ends "for pop_member=..." loop
end  % End the main loop.
```

VITA

Thira Chavarnakul was born in Bangkok, Thailand, on August 20, 1974. He received his B.Eng. in Civil Engineering from Chulalongkorn University, Thailand, in 1996. Afterward, he worked as a structural engineer for 5 years. He performed structural design, analysis, and supervision of more than 20 construction projects in Thailand. He has also registered as a professional engineer in Civil Engineering with a higher level in Thailand. He earned his M.B.A. degree from Chulalongkorn University, Thailand, and his M.S. in Engineering Management from the University of Missouri – Rolla in 2002 and 2003, respectively. In January 2004, he enrolled at the University of Missouri – Rolla to pursue a Ph.D. in Engineering Management with a concentration in financial engineering under the guidance of Dr. David Enke. He has published conference and journal papers, some of which are included in this dissertation. He also received the Outstanding Graduate Student Research Award 2006-2007 from the Engineering Management and Systems Engineering Department, University of Missouri – Rolla. He received his Ph.D. in Engineering Management and Graduate Certificate in Financial Engineering in August 2007. Upon his graduation, Thira plans to pursue a career in academia in Thailand.