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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, Mamaysky, & Wang, 2000). It is considered by many to be the original form of investment analysis, dating back to the 1800s (Brock, Lakonishok, & Lebaron, 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, Poterba, & Summers, 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, Timmermann, & White, 1999). Others have relied on technical analysis for successful stock price prediction (Blume, Easley, & O'Hara, 1994; Brock et al., 1992; Lo et al., 2000; Neely, Weller, & Dittmar, 1997; Neftci, 1991). In recent years, however,

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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 (Achelist, 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, Grossman, & Wang, 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, Muller, Nagler, Olsen, & Pictet, 1993; Dacorogna, Gauvreau, Muller, Olsen, & Pictet, 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, Tan, & Poh, 1999). Many researhers have utilized various types of neural networks for technical analysis and stock market prediction (Chenoweth, Obradovic, & Stephenlee, 1996; Enke & Thawornwong, 2005; Kim & Han, 2000; Kuo, Li, Cheng, & Ho, 2004; Leigh, Hightower, & Modani, 2005; Saad, Prokhorov, & Wunsch, 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 2–4, 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 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

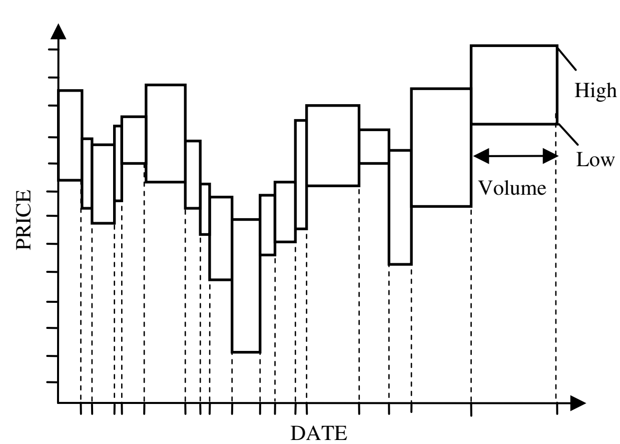

Fig. 1. Equivolume charting.

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 the 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 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 ith ($i = 1, 2, 3, \ldots, n$) while n is the number of time periods. The formula for MA then becomes:

$$\mathrm{MA} = \frac{\sum_{i=1}^{n} \mathrm{CP}_i}{n} \tag{1}$$

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 5000 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,

Table 1
Closing prices and trading volumes for the VAMA example

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	
Day 2	1	926.26	(927.57 + 927.57 + 926.26 + 931.66 + 931.66)/5 = $928.944
Day 3	3	931.66	
		931.66	
		931.66	
Day 4	2	918.22	
		918.22	(931.66 + 918.22 + 918.22 + 914.60 + 914.60)/5 = $919.46
Day 5	2	914.60	
		914.60	

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 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:

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

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

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

According to Eqs. (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 (Achelist, 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 nonlinear 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 associted with it and broadcasts this signal to all output units over the connection link. Next, an activation function (normally

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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 (1508 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 US 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:

$$R_{t+1} = \frac{(\mathrm{CP}_{t+1} - \mathrm{CP}_t)}{\mathrm{CP}_t} \tag{7}$$

where CP_t and CP_{t+1} are the current closing price and next day closing price, respectively. Based on Eq. (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:

$$X' = \frac{(X - \overline{A})}{\sigma_A} \tag{8}$$

where the values of an input or output (X) for attribute A are normalized to X'. The values $\overline{A}$ and σ_A are the mean and standard deviation of attribute A, respectively, 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 Eq. (9),

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

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 Eq. (10),

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

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 a positive or negative value, the performance measure based on the 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 Eq. (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.

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}

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

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)	CP × VR
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 = [$4710.24–(5.1295–5) × $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)	CP × VR
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 = $4634.07
5 VAMA with NN = [$4,634.07–(5.0428–5) × $909.03]/5 = $919.03			

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

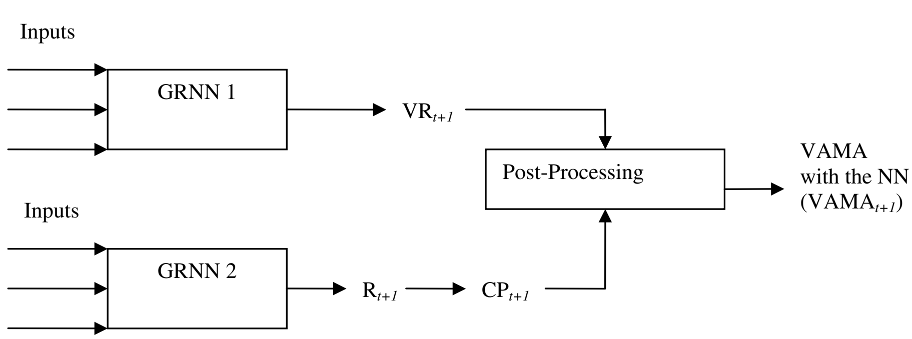

Fig. 3. System overview to find VAMA with the NN.

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 (quarterly), 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 and 55-day, 10 and 55-day, 13 and 55-day, and 21 and 55-day). The smoothing interval lengths of the EMV will follow as the slow MA and

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 thanMA_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 a 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 $t+1$

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.

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%

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 Tables 9–11 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 lagging technical indicators. 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

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 and 55	$173.20	16	$165.25	20	$234.31	22	$201.00	2
CP and 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 and 55	$181.37	12	$173.34	16	$220.71	16	$201.00	2
CP and 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 and slow interval	MA		VAMA		VAMA with the NN		Buy-and-hold	
	Gain/loss	# Trades	Gain/loss	# Trades	Gain/loss	# Trades	Gain/loss	# Trades
5 and 55	$210.94	4	$185.93	10	$213.90	8	$201.00	2
5 and 63	$223.02	4	$182.09	8	$206.83	10	$201.00	2
10 and 55	$213.48	4	$215.24	6	$224.50	6	$201.00	2
10 and 63	$215.89	4	$208.02	4	$201.35	6	$201.00	2
13 and 55	$231.82	4	$212.35	4	$210.45	4	$201.00	2
13 and 63	$231.00	4	$206.01	4	$203.05	4	$201.00	2
21 and 55	$196.85	4	$239.97	6	$199.97	4	$201.00	2
21 and 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

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.

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

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

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 and 5	$38.78	64	$105.18	30	$220.30	20	$201.00	2
CP and 21	$122.72	32	$146.44	12	$258.54	4	$201.00	2
CP and 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 and 5	−$38.69	90	$89.69	32	$220.30	20	$201.00	2
CP and 21	$72.63	38	$86.80	12	$258.54	4	$201.00	2
CP and 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

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

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

Fast and 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 and 55	$154.59	6	$224.71	2	$240.98	2	$201.00	2
10 and 55	$142.90	6	$209.43	4	$220.58	4	$201.00	2
13 and 55	$154.01	6	$209.43	4	$220.58	4	$201.00	2
21 and 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 and 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 and 55	$142.44	12	$202.98	4	$243.64	2	$201.00	2
10 and 55	$163.75	6	$191.00	4	$220.58	4	$201.00	2
13 and 55	$169.14	6	$191.00	4	$220.58	4	$201.00	2
21 and 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

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

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