International Research Journal of Applied Finance ISSN 2229 – 6891
Vol. VII Issue – 10 October, 2016 www.irjaf.com
DOI: 10.0710/article-2

Backpropagation Neural Network Model for Stock Trading Points Prediction

Chuan-Wen Chiang Jun-Biao Lin* Chin-ming Chen Yi-Ting Lin

Abstract

Due to the swift development of technology and the Internet, much stock data are digitized. It is now very convenient, and fast, to obtain the data from the file transfer; however, it is difficult for humans to analyze and systematize large amounts of complicated in formation in a short time. Artificial intelligence (AI) techniques are excellent in dealing with the complicated problems; they look to be the tools of predicting and analyzing the stock market information.

The Backpropagation Neural Network (BPN) approach in recent years has rapidly gained popularity, being used especially in finance areas such as the prediction of stock prices, the financial crisis prediction, the forecasting of exchange rate movements, and portfolio management. In these areas, the performance is outstanding. In this research, several technical indicators are applied to the analysis of a large number of historical data in order to enhance the predictability of the particular stocks.

The results of this research show that the combination of different indicators using the BPN approach is superior to the buy and hold strategy but still cannot predict positive returns of the target stocks after a period of training. The present study concludes that even though the BPN approach is good at forecasting stock price in the finance area, the input factors still play a significant role in determining the accuracy of trading decisions. In brief, settling on the appropriate input factors is still a crucial area of research in the future.

Keywords: Backpropagation neural network (BPN), technical indicators, stock forecasting.
JEL: C13, C32, G32

I. Introduction

Many factors affect the stock prices in the stock market: inflation rates, political issues, interest rates, economic environments, and many others. However, the stock market is a highly nonlinear dynamic system; the relationship between stock prices and these factors is hard to model through a mathematical formula.

There is much research on stock prediction that focuses on predicting the future price of a stock movement, but little on trading decisions such as buy/hold/sell points. For investors who would like to make a profit in the stock market, the trading decision plays an important role. Until now, there have been relatively few examples of research that focus on forecasting the turning points of a stock. This study applies the BPN approach to forecast the turning points of a target stock. However, due to the lack of information about a target stock, it is hard to define the trading signals; we need to rely on computational intelligence techniques instead.

In this research, some technical indicators and raw data are applied to enhance the predictability of particular stocks: Stochastic, RSI, MACD, DMI, BIAS, foreign capital, and the suspension of margin purchase. Possible turning points of the technical indices- using the technical indicators and raw data- could be detected and inputted to the BPN to train the model. The research studies the predictability and profitability of using BPN to forecast the turning point of a particular stock. The output from BPN is transformed into a simple trading strategy- for instance, buy/hold/sell decisions. The daily data of technical indicators from the Taiwan

DOI: 10.0710/article-2

stock market are applied to the research.

The rest of the research is divided into five sections: Section two reviews the literature on stock prediction; Section three illustrates the theories of technical indicators; Section four describes the development of the BPN model for stock trading point decision; Section five examines the experimental results of trading points. In Section six are the conclusions and the recommendations for future research.

II. Literature Survey

Predicting stock price variations is a difficult task as price movements seem to behave in a random manner. Over the decades, researchers and traders would have relied on various types of computational intelligence techniques to make their trading decisions.

As Khajanchi, A. and Li, E.-Y.,(1994) mentioned in their general introduction to neural networks (NNs), these imitated the working of the human neuron and depended on stimuli from the outside world. Neural networks that used artificial intelligence (AI) were called artificial neural networks or ANN. During the decades, neural networks have been applied to the finance area of stock price forecasting and were found to be useful. Kryzanowski, et al., (1993) applied the Boltzmann machine for ANNs to categorize stock returns as positive, neutral and negative. They found that the correct classification rate from results was more than 70% for all unseen data. As a result, they employed a neural network model to successfully pick stocks. Tsai, C.-F. and Wang, S.-P.,(2009) in their paper focused on combining ANN and decision trees to create a stock price forecasting model. The experimental results showed that the combined DT+ANN model has a 77% accuracy rate, which was higher than the single ANN and DT models over the electronic industry.

Gradually, the other soft computing (SC) approaches began to be developed in the finance area, especially the BPN approach. Most of the papers in the finance area advocated the use of the backpropagation algorithm in ANN for stock prediction. Lee, C.-H. and Park, K.-C., (1992) investigated using the backpropagation algorithm based ANN for stock prediction and good results had been obtained. Schoneburg, E., (1990) analyzed the possibility of predicting stock prices on a short-term, day-to-day basis with the help of NN by studying three important German stocks selected at random. Roman, J. and Jameel, A., (1996) mentioned a methodology that was based upon the observed backpropagation and recurrent neural networks (RNN) prediction accuracy, used for building portfolios across international stock market prediction, had proven to be effective for real stock market data for five countries over four years. Chen, W.-H. and Shih, J.-Y.,(2006) applied Support-Vector Machines (SVMs) and BPN for six Asian stock markets; the experimental results showed the superiority of both models when compared to earlier research.

In addition, Marijana, Z. MS, (1998) mentioned that neural networks were most implemented in forecasting stock prices, returns, and stock modeling, and that the most frequent methodology was the backpropagation algorithm. Her paper said that the backpropagation algorithm had the ability to predict with greater accuracy than other NN algorithms, no matter which data model was used. She also said that NN outperformed classical forecasting and statistical methods, such as multiple regression analysis and discriminate analysis. That meant the prediction approach would be very useful in assisting individuals in reaching a final decision. In the research, we try to use BPN approach to yield good predictions about future stock movements.

Other SC methods were also applied in the prediction of stock prices. These SC approaches employed quantitative inputs: technical indexes, and qualitative factors- like political effects- to automate stock market forecasting and trend analyses. Tang, Y., et al.,(2002) after completing several simulations for predicting several stocks based on the past historical data by using fuzzy neural network (FNN) with the backpropagation learning algorithm, concluded that the more data available for training the neural network, the better the prediction would be. If the training error is low, predicted stock values will be close to the real stock values. Liao, G.-C. and Tsao, T.-P., (2006) applied an FNN combined with a chaos-search genetic algorithm (CGA) and simulated annealing (SA) to short-term power system loading forecasting as a sample test. The results indicated that a more accurate load curve forecast could be achieved. Another piece of research using an FNN trained by genetic algorithms (GA), Graham, R., (2004) was applied to predict three-month U.S Treasury Bill rates. The authors concluded that an NN could be used to accurately forecast these rates.

As usual, there have been hybrid models of SC approaches; for instance, Kim, K.-J. and Han, I., (2000) proposed a GA approach to feature discretization and the determination of connection weights for ANN to predict the stock price index. This research proposed hybrid models of ANN and GA in order to train the network, and the GA was only used to improve the learning algorithm itself. In this research, the GA was employed not only to improve the learning algorithm, but also to reduce the complexity in the feature space. GA optimized the connection weights between layers and the thresholds for feature discretization. Experimental results showed that the GA approach to the feature discretization model outperformed the other two conventional models. Choudhry, R. and Garg, K., (2008) proposed a hybrid GA-SVM system for predicting the future direction of stock prices. The results showed that the correlation concept and the GA helped to improve the performance of the SVM system significantly.

In Chang, P.-C., et al., (2004) research, the technical analysis and the basic analysis were applied to investigate the trend of the weighted stock market index in Taiwan. The results indicated that the hybrid model of autoregressive integrated moving average was the best one in forecasting future fluctuations of the stock market index. Chang, P.-C., et al., (2009), indicated that the intelligent piecewise linear representation (IPLR) approach was very effective and encouraging in its predictions regarding the future trading points of a specific stock.

In brief, a considerable amount of research has studied the hybrid models of soft computing approaches, especially the BPN approach. Nevertheless, the investors were more interested in being provided with simple trading decisions, for instance, about buy/hold/sell decisions instead of learning about the predictions of the stock price itself. The study done by us has focused on providing trading signals to investors according to the stock price variations.

III. Technical Indicators

Technical analysis is the study of market action using past prices and trading volumes for the purpose of forecasting future price trends. Technical analysis assumes that stock prices move in trends, and that the information which affects prices enters the market over a finite period of time, not instantaneously. Technical analysis contradicts the long held Efficient Market Hypothesis (EMH). The EMH states that market prices follow a random path and cannot be predicted based on their past behavior. According to the EMH, all information that enters the market affects the prices instantaneously. If the EMH were true, it would not be possible to use AI techniques to predict the market. However, due to the success of technical analysts in the financial world and a number of studies appearing in academic literature successfully using AI

DOI: 10.0710/article-2

techniques to predict the market, EMH is widely believed to be a null hypothesis now.

Technical analysts make use of technical indicators, which are mathematical formulations which give us clues about the trend of the market. The following are the technical indicators used in the research.

III.1 Relative Strength Index (RSI)

The RSI, developed by J. Welles Wilder, is an extremely useful and popular momentum oscillator. The RSI compares the magnitude of a stock's recent gains to the magnitude of its recent losses, and turns that information into a number that ranges from 0 to 100. It takes a single parameter: the number of time periods used in the calculation.

Wong, W.-K., et al. state that the calculation of the RSIt,p at the time of period p uses only the closing prices and is the ratio of up-closes, Ui, to down-closes, Di, over the time period selected. The definition of an index set It,p={i:t-p≤i≤t}, followed by defining

$$\overline{U}_{t,p} = \text{Average of } U_i \text{ over } I_{t,p}$$

$$\overline{D}_{t,p} = \text{Average of } D_i \text{ over } I_{t,p}$$

And thereafter the Relative Strength is given as follows:

$$RS_{t,p} = \frac{\overline{U}_{t,p}}{\overline{D}_{t,p}}$$

The RSI at time t for period p is then defined as:

$$RSI_{t,p} = 100 - \frac{100}{1 + RS_{t,p}}$$

Readings of 100 imply that there are pure upward price movements, while readings of 0 imply that there are pure downward price movements. Therefore, a reading close to 100 indicates an overbought market, while a reading around 0 indicates an oversold market. Generally, a buy signal when the RSI touches the lower bound (typically set at 30) indicates that the market is oversold and hence a time to buy. It generates a sell signal when the RSI touches the upper bound (typically set at 70) which indicates that the market is overbought and hence a time to sell.

III.2 Moving Average Convergence Divergence (MACD)

It is one of the most often used indicators employed by the different stock trending simulator software applications. Yan, W. and Clack, C.-D state the MACD is usually calculated in the 26-week and 12-week cycles of the stock market. Commodity traders often use daily data with MACD but still use 26-period and 12-period exponential moving averages (EMA) in the analysis. Implications are that there are 26-day and 12-day cycles in commodity markets. The use of the MACD indicator can be applied to almost any market at any time interval. Using this method is easy and straightforward. It can work well for any time lapse, both for long and middle terms and intraday trading systems.

According to Fernandez-Blanco, P., et al. state, a 26-day EMA is the first moving average and a 12-day EMA is the second one in a traditional MACD. The MACD line is formed by subtracting the long (first) moving average from the short (second) moving average. That is, MACD= EMA (12)-EMA (26).

The main buying and selling signals take place when the short curve of the MACD intersects with its moving average. The buying signals occur when the short line of the MACD intersects in ascending form with the line of its moving average. A selling signal, on the other hand, takes place when the short line of the MACD intersects in descending trend to its moving average.

III.3 Stochastic (KD Line)

Stochastic is a technical indicator, developed by George Lane in the early 1960's, that compares a security's closing price with its price range for a given time period. Lane observed that when a stock is rising, it tends to close near the high of the time period and a falling stock closes near its low. In an attempt to rationally quantify this empirical dynamic, he constructed a formulaic process by which a stochastic or "educated guess" as to the direction of an instrument's price could be applied. The Stochastic is displayed as two lines. The main line is called %K and is calculated using the high, low, and closing price. The second line, called %D, is a moving average of %K. The formula for %K is as follows:

$$\%K = 100\left[\frac{(C - L5_{close})}{(H5 - L5)}\right]$$

where C is the most recent closing price, L5 is the lowest price for the last five trading periods, and H5 is highest price for the same five trading periods. %D is a smoothed version of the %K line. Usually, three periods are used. The %D formula is as follows:

$$\%D = 100 * \left(\frac{H3}{L3}\right)$$

where H3= the three period sum of (C- L5) and L3 is the three period sum of (H5- L5).

The Stochastic turns the information into a number that ranges from 0 to 100. The numbers above 80 are strong and indicate that the trend is nearing highs. The numbers below 20 are also strong and indicate that the trend is nearing lows. The slow stochastic provides more accurate signals and is easier to interpret.

III.4 Directional Movement Index (DMI)

Directional Movement Index is a technical indicator developed by Welles Wilder JR. in 1978. DMI is plotted as three lines on a scale of 0 to 100; the main use of this indicator is to show the strength of a trend. The direction of these lines and the use of crossovers can show the changes in the current market. The concept of DMI is based on the assumption that in an upward trend today's highest price is higher than yesterday's highest price, and in a downward trend today's lowest price is lower than yesterday's lowest price. Thus, the difference between today's high and yesterday's high corresponds to the Plus Directional Movement (+DI). The difference between today's low and yesterday's low is the Minus Directional Movement (-DI). Both of the movements indicate only upward or downward movement, not values.

The application for DMI is in looking at the +DI and -DI lines themselves. When the +DI line crosses above the -D line a buy signal is initiated. This indicates that the positive price direction is greater than the negative. Conversely, once the +D line crosses below the -D line, a sell trigger is present. The negative price movement is overtaking the positive.

To calculate the Directional Indicators (+DI and -DI), further calculation of the True Range

DOI: 10.0710/article-2

(TR) is necessary. The true range is always positive and is defined as the current highest value of the difference among today's highest price minus today's lowest price (H_t-L_t); today's highest price minus yesterday's closing price (H_t-C_{t-1}); and today's lowest price minus yesterday's closing price(L_t-C_{t-1}). Then the Plus and Minus Direction Movement is calculated. The sum of the +DI is divided by the sum of the True Range over the same period, usually using a constant value of 14 on daily data. On the contrary, the calculation of the -DI is the same.

However, the key to the DMI indicator is the Average Directional Index (ADX). The ADX is the average of the difference of these two lines, which is used in order to smooth the two DI lines. Therefore, when looking at reversals the ADX should be above both lines- once it turns lower, we should see a change in market direction. For a good sell signal, the +D should be greater than -D and both should be greater than ADX, that is +D＞-D＞ADX. By contrast, for a good buy signal, +D should be lower than –D and both should be lower than ADX- that is to say, +D＜-D＜ADX.

III.5 Deviation Rate (BIAS)
Deviation rate is a moving average principle derived from technical indicators, and its function is to measure fluctuations in share price when moving average process deviation occurs. The deviation was divided into positive and negative values; when the share price is above the moving average, it is positive. By contrast, when the stock price is below the moving average, it is the negative. When the stock price and the moving average are the same, it is the zero.

$$BIAS = \frac{\left(C - \overline{A}_n\right)}{\overline{A}_n}$$

where C is today's closing price, $\overline{A}$ is the average over n periods.

Generally speaking, a buy signal when the deviation rate＜-20% indicates that the market is oversold and hence a time to buy. It generates a sell signal when the deviation rate＞20%, indicating that the market is overbought and hence a time to sell.

IV. Methodology
This research attempts to develop a trading point prediction system so that investors can implement a good trading strategy by applying it.

As applied in this research, neural network analysis assumes that human learning can be emulated by a network of massively interconnected but very simple processing units. These unique features make them valuable for solving many practical forecasting problems. These networks are highly suited to address the stock market return prediction problem. The theoretical foundation for the algorithm of the ANN models is based on Khajanchi's theory. A brief description of the neural network model and the backpropagation algorithm is presented as follows.

IV.1 Backpropagation Neural Network
Neural networks imitate the working of the human neuron and depend on stimuli from the outside world. Neural networks using artificial intelligence (AI) are called artificial neural networks or ANN. The BPN approach is one of the neural networks. The ability of a BPN to discover nonlinear relationships in input data makes them ideal for modeling nonlinear dynamic systems such as the stock market. Often the network use raw data and derived data

from technical and fundamental analyses. Through a preset learning algorithm and series of training iterations, the BPN learns to recognize patterns in the data sets and assigns weights to each single processor- called a node or processing element. A node is where the data is converted into values between 0 and 1 by applying a sigmoid transfer function in the network. Figure1 is the model of a neural network.

In addition, the nodes are organized into layers. The first layer is called the input layer and the last layer is the output layer. The inner layers, one or more, are known as hidden layers. The input nodes receive input values from outside the ANN's environment, whereas the output nodes send their output values there. A hidden or an output node receives input signals from the incoming connections and values from its local memory. Two layers of architecture will contain an input layer and an output layer; three-layer architecture will include a hidden layer in the middle (unobservable variables); and a more complex network will have a fourth threshold layer. Figure 2 is an example of BPN that has three-layer architecture including a hidden layer.

The advantages of neural networks over statistical models are (1) NNs requires no predefined knowledge of the underlying relationships between input and output variables; (2) NNs' associative ability make them robust enough to tolerate missing and inaccurate data; and (3) NNs' performance doesn't diminish even with multi-collinearity problems, violations of set assumptions, high influence points, and transformation problems encountered in regression analysis.

IV.1.1 The Learning Environment

One of the most important factors in constructing a neural network is deciding on what the network will learn. The goal of most of these networks is in helping investors decide when to buy or sell securities based on previous market indicators. The challenge is determining which indicator and input data will be used, and gathering enough training data to train the system appropriately. The input data may be raw data on volume, price, or daily change, but it may also include derived data such as technical indicators or fundamental indicators. Determining the proper input data is the first step in training the network. The second step is presenting the input data in such a way that allows the network to learn properly without overtraining it. Various training procedures have been developed to train these networks.

IV.1.2 Neural Network Training

Training a network involves presenting input patterns in such a way so that a system minimizes its errors and improves its performance. The most common training algorithm used when designing financial neural networks is the backpropagation algorithm. However, the major problem in training a neural network is deciding when to stop training. Overtraining occurs by having too many hidden nodes or training for too many time periods.

IV.2 Data

IV.2.1 Candidate Stocks Screening

According to Chang, P.-C., et al. (2009), a set of candidate stocks is selected based on the following criteria: 1) capital size; 2) monthly sales; 3) earnings per share (EPS); 4) transaction volume per day; and 5) marginal cost of capital (MCC). When a stock has a small or medium size of capital, increasing monthly sales, high EPS, large volumes of stock transactions, and if the marginal cost of capital is low, the situation is ideal. This is because in the Taiwan stock market, the prices of large capital stocks always fluctuate very slowly. According to recent market statistics, a small- or medium-size market has a better profit margin. The reason is that the probability of the annual growth and stock price variation will be more significant during the year.

IV.2.2 Input Variables Selection

A set of technical indexes affecting the stock price movement have been identified by Chang, P.-C., et al. (2004) There are seven technical indicators and raw data consisting of Stochastic, RSI, MACD, DMI, BIAS, foreign capital, and the suspension of margin purchase used as input variables in the research.

V. Empirical Results

V.1 Research Steps

1) Choose and define the data of inputs and outputs.

There are a lot of things that can influence stock prices; variables that have the highest correlation with stock prices should be used. This research used seven technical indicators and raw data to be input variables, then employed a selection strategy to find the optimal stock. After pre-processing the input data, the chosen ones were inputted into the neural networks model.

2) Choose the neural networks model.

Evaluate many NNs models' predicted performances and analyze their pros and cons. Then choose the optimal NNs model.

3) Choose the parameters.

Neural networks models have many parameters, including momentum learning rate, learning algorithm, transfer function, etc. There are important relationships among convergence with momentum, learning rate and learning algorithm and these can directly affect the accuracy; trial and error need to be employed to find the optimal parameters.

4) Artificial Neural Network's training and testing.

This research uses the BPN approach. If the value of mean square error (MSE) is diminished, it could mean ANN is trying to learn and find a linear/non-linear model. Overlearning is apt to bring about the problem of rigid learning. Too much precision network training can decrease the predicted accuracy.

5) Calculate accuracy and return.

According to the predicted result, calculate the returns of each stock.

In this section, the sample for the study includes seven stocks selected for performance comparisons using the BPN model. There are AUO, Epistar Corporation, Silicon Integrated System Corporation (SiS), D-Link Corporation (D-LINK), Foxlink Corporation (FOXLINK), Compal Corporation (COMPAL), and UMC Corporation (UMC) in Taiwan. The historic data cover from 2008/01/02 to 2011/05/31 in the Taiwan stock market. The training data is based on data from 2008/01/02 to 2010/12/31 and the test data is based on data from 2011/01/03 to 2011/05/31.

All of the stocks are subject to the same technical indicators as the input variables to the BPN. For technical indicators, there are 5-day RSI, MACD, 9-day %D, 60-day BIAS, 14-day DMI, foreign capital, and the suspension of margin purchase. The main purpose of the selections is to identify whether or not the set of indicators are able to outperform and beat the market by using the BPN methodology. If the proposed model is good enough, investors will also be able to make good trading decisions.

DOI: 10.0710/article-2

The parameter setting of the BPN includes numbers of input layers, hidden layers, output layers. These parameters are important because they will affect the system's performance if they are not properly adjusted. The final setup of the parameters for the BPN is listed in table1 after the experimental tests.

For these seven different stocks in the research, the rates of return by the BPN approach versus the buy and hold strategy are shown in table 2. The Taiwan stocks were applied in previous research by Chang, P.-C., et al. (2009) who used them in the PLR-BPN approach. Due to the input variables that could affect the BPN performance, the study would like to substitute the other input variables for the original ones. If the new input variables are good enough and the rates of return are better than the buy and hold strategy, investors can also make good trading decisions.

We also take into consideration the trading fees which are part of the trading strategy of buying or selling stocks. The trading strategy is more conservative and transaction costs consist of the commissions that come from buying and selling, the securities transaction tax, and the borrowing fee used by securities firms. To sum up, the transaction costs in this research is about 0.00665%.

In table 2, because each stock has different trading points, it means there is no standard to settle how many trading points a stock should make. All trading points depend on the results of the BPN approach. In table 2, the BPN column represents the returns of each stock; only three stocks have positive returns in the empirical results. The positive returns of Compal Corporation, Foxlink Corporation and Epistar Corporation are only 11.10%, 20.70% and 9.84% respectively. By contrast, other corporations' returns by the BPN approach are negative. However, comparing the returns by the BPN approach with the strategy of buying and holding, the performances of the BPN approach are obviously superior to the buy and hold strategy. There is only one stock with a positive return by the buy and hold strategy. In summary, although the empirical results show that the BPN approach could not make significant positive returns after a period of training, the approach is still superior to the buy and hold strategy. The result indicates that applying the BPN approach to forecasting the trading points of stocks are not significant enough or workable enough to offer investors a good reference tool to support their investment decisions.

VI. Conclusion

A considerable amount of research has been conducted to study the behavior of stock price movement. Investors are generally more interested in making profits by being provided information about how to make simple trading decisions such as buy/hold/sell rather than in learning how to determine the stock price itself. Consequently, a better approach is available by applying technical indicators; these can help decompose the historical data and then several of technical indices would be inputted to the BPN to train the connection weight of the model. The point is that a buy or a sell point of trading decision can be detected by the BPN.

The BPN model was tested on seven stocks in the Taiwan stock market. Although the empirical results show that the BPN approach could not achieve significant positive returns after a period of training, the approach is still superior to the buy and hold strategy. Only three corporations had positive returns; other corporations' returns are negative. In summary, the result indicates that applying the BPN approach to forecasting the trading points of stocks is better than the strategy of buying and holding. However, as stated earlier, the BPN is still not significant enough or workable enough to offer investors a good reference tool that they can use to support investment decisions.

In the future, predictions can be further improved by incorporating other forecasting models or by providing a better forecasting model other than BPN. There are listed as follows:

1)*A different forecasting model*
There are various forecasting models other than the BPN model in the literature. It is essential to study the behavior of these models when they are applied to predicting a stock's trading point. Future researchers could focus on different types of forecasting models such as ANN, RNN, FNN, and GA, etc, that are likely to improve the accuracy of a stock trading decision.

2)*Different input variables*
According to the research, different input factors could obviously affect the experimental result. Choosing appropriate input factors is essential. If future researchers pay careful attention to choosing the right input variables, trading decisions are likely to become more productive.

References

Brock, W., Lakonishok, J., LeBarn, B., (1992) Simple Technical Trading Rules and the Stochastic Properties of Stock Returns, the Journal of Finance, vol.47, Issue 5, 1731-1764.

Chang, P.-C., Wang, Y.-W., and Yang, W.-N., (2004), An Investigation of the Hybrid Forecasting Models for Stock Price Variation in Taiwan, J. Chin. Inst. Ind. Eng., vol.21, No. 4, pp. 358-368.

Chen, W.-H. and Shih, J.-Y., (2006) Comparison of Support-vector Machines and Backpropagatio Neural Networks in Forecasting The Six Major Asian Stock Markets, Int. J. Electronic Finance, vol. 1, No. 1.

Choudhry, R. and Garg, K., (2008) A Hybrid Machine Learning System for Stock Market Forecasting, World Academy of Science, Engineering and Technology 39.

Chang, P.-C., Fan, C.-Y., and Liu, C.-H., (2009) Integrating a Piecewise Linear Representation Method and a Neural Network Model for Stock Trading Points Prediction, IEEE Transactions on Systems, Man, and Cybernetics—Part C: Applications and Reviews, vol. 39, No.1.

Fernandez-Blanco, P., Bodas-Sagi, D., Soltero, F., and Hidalgo, J.-I., (2008) Techical Market Indicators Optimization using Evolutionary Algorithms.

Graham, R., (2004) Neural Networks for Real-time Path Finding in Computer Games, ITB J., vol. 9, pp. 223-230.

Khajanchi, A., Artificial Neural Networks: The Next Intelligence.

Kryzanowski, Galler and Wright, (1993) Using Artifical Neural Networks to Pick Stocks, Financial Analysts Journal, pp. 21-27.

Kim, K.-J. and Han, I., (2000) Genetic Algorithms Approach to Feature Discretization in Artificial Neural Networks for the Prediction of Stock Price Index, Expert Syst. Appl., vol.19, pp. 125-132.

Lane, G.-C., (1984) Lane's Stochastics, Technical Analysis of Stocks and Commodities magazine; 2: 87-90.

Lee, C.-H. and Park, K.-C., (1992) Prediction of Monthly Transition of The Composition Stock Price Index Using Recurrent Backpropagation, Int. Conf. on Artificial Neural Networks, Brighton, UK, pp. 1629-1632.

Li, E.-Y., (1994) Artificial Neural Networks and Their Business Applications, Information & Management 27, pp.303-313.

DOI: 10.0710/article-2

Liao, G.-C. and Tsao, T.-P., (2006) Application of Fuzzy Neural Networks and Artificial Intelligence for Load Forecasting, IEEE Trans. Evol. Comput., vol. 10, no. 3, pp. 330-340, Jun.

Marijana Z. MS, (1998) Neural Network Applications in Stock Market Predictions-A Methodology Analysis.

Roman, J. and Jameel, A., (1996) Backpropagation and Recurrent Neural Networks in Financial Analysis of Multiple Stock Market Returns, Proceedings of the 29th Annual Hawaii International Conference on System Sciences.

Schoeneburg, E., (1990) Stock Price Prediction Using Neural Networks: A Project Report, Neurocomputing, vol. 2, pp. 17-27.

Stawicki, S. -P., (2007) Application of Financial Analysis Techniques to Vital Sign Data: a Novel Method of Trend Interpretation in the Intensive Care Unit, OPUS 12 Scientist, vol. 1, No.1.

Tang, Y., Xu, F., Wan, X., and Zhang, Y.-Q., (2002) Web-based Fuzzy Neural Networks for Stock Prediction.

Tsai, C.-F. and Wang, S.-P., (2009) Stock Price Forecasting by Hybrid Machine Learning Techniques.

Wong, W.-K., Manzur, M., and Chew, B.-K., How Rewarding Is Technical Analysis? Evidence from Singapore Stock Market, NUS, Department of Economics Working Paper No. 0216.

Yan, W. and Clack, C.-D, Evolving Robust Solutions for Hedge Fund Stock Selection in Emerging Markets, GECCO'07, London, England, United Kingdom, ACM 978-1-59593-697-3/07/0007.

Authors

Chuan-Wen Chiang
Associate Professor, Department of Industrial Management, Lunghwa University of Science and Technology, Taiwan

Jun-Biao Lin*
Associate Professor, Department of Money and Banking, National Kaohsiung First University of Science and Technology, Taiwan, jblin@ccms.nkfust.edu.tw

Chin-ming Chen
Associate Professor Department of Money and Banking National Kaohsiung First University of Science and Technology, Taiwan

Yi-Ting Lin
Graduate student Department of Money and Banking National Kaohsiung First University of Science and Technology, Taiwan

*Corresponding author

International Research Journal of Applied Finance ISSN 2229 – 6891
Vol. VII Issue – 10 October, 2016 www.irjaf.com
DOI: 10.0710/article-2

Figure 1 Model of neural network

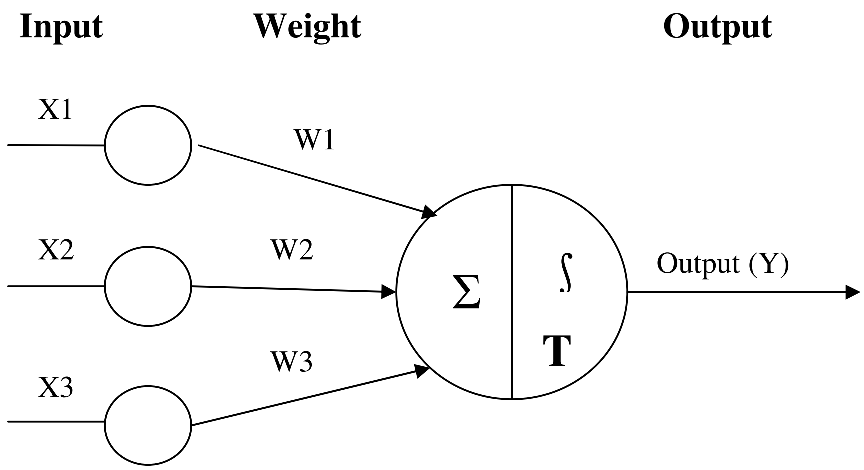
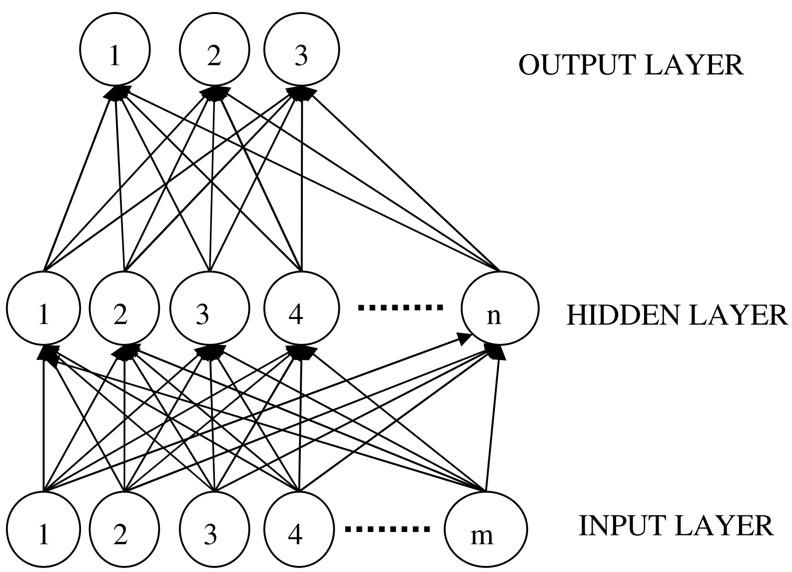


Figure 2 Structure of backpropagation neural network



DOI: 10.0710/article-2

TABLE 1 Parameters Setup for BPN

PARAMETER	***BEST***
Number of nodes in Input layer	7
Number of nodes in hidden layer	8
Number of nodes in output layer	3
Number of learning times	5000
Transfer function	Sigmoid

TABLE 2 Rates of Return by BPN approach versus Buy & Hold strategy

STOCKS	***INPUT TECHNICAL INDEX***	***TRADING POINT***	***BPN***	***BUY AND HOLD***
COMPAL	5RSI, MACD, 9 %D, 60BIAS, 14DMI, foreign capital, and the suspension of margin purchase	15	11.10%	-10.55%
UMC		11	-3.47%	-8.64%
D-LINK		3	-4.80%	-13.29%
AUO		13	-6.22%	-22.41%
FOXLINK		9	20.70%	10.15%
SIS		22	-11.03%	-26.45%
EPISTAR		87	9.84%	-9.09%