Expert Systems with Applications 36 (2009) 6889–6898

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A neural network with a case based dynamic window for stock trading prediction

Pei-Chann Chang [a,*], Chen-Hao Liu [b], Jun-Lin Lin [a], Chin-Yuan Fan [c], Celeste S.P. Ng [a]

[a] Department of Information Management, Yuan Ze University, 135 Yuan-Tung Road, Chung-Li, Taoyuan, 32026 Taiwan, ROC
[b] Department of Digital Technology, KaiNan University, No. 1 Kainan Road, Luchu, Taoyuan County, 33810 Taiwan, ROC
[c] Department of Industrial Engineering and Management, Yuan Ze University, 135 Yuan-Tung Road, Chung-Li, Taoyuan, 32026 Taiwan, ROC

ARTICLE INFO

Keywords:
Stock forecasting
Trading points prediction
Back propagation network (BPN)
Case based reasoning (CBR)
Dynamic time window

ABSTRACT

Stock forecasting involves complex interactions between market-influencing factors and unknown random processes. In this study, an integrated system, CBDWNN by combining dynamic time windows, case based reasoning (CBR), and neural network for stock trading prediction is developed and it includes three different stages: (1) screening out potential stocks and the important influential factors; (2) using back propagation network (BPN) to predict the buy/sell points (wave peak and wave trough) of stock price and (3) adopting case based dynamic window (CBDW) to further improve the forecasting results from BPN. The system developed in this research is a first attempt in the literature to predict the sell/buy decision points instead of stock price itself. The empirical results show that the CBDW can assist the BPN to reduce the false alarm of buying or selling decisions. Nine different stocks with different trends, i.e., upward, downward and steady, are studied and one individual stock (AUO) will be studied as case example. The rates of return for upward, steady, and downward trend stocks are higher than 93.57%, 37.75%, and 46.62%, respectively. These results are all very promising and better than using CBR or BPN alone.

1. Introduction

The stock market has become the main outlet for investment recently in countries like Brazil, Russia, India and China (BRIC). The futures indicator, investment foundations, foreign capitals are diverse choices for investors. By observing the market, most of the investors in BRIC are individuals; few are consortiums with abundant fund. A lot of professional experts will analyze the stock market for consortiums to make a good trading strategy, but individual investors always lack experience of professional judgment. Based on this viewpoint, individuals usually lose their money in a vicious cycle. By observing this phenomenon, a comprehensive and professional technical analysis is needed for these nonprofessional investors. A good stock investing model is indispensable when individuals or consortiums want to buy/sell stocks.

However, predicting stock data with traditional time series analysis has been proven to be difficult. The time series forecasting in stock market is characterized by data intensity, noise, non-stationary, unstructured nature, high degree of uncertainty, and hidden relationships. Its behavior is more like a random walk. Traditionally, the analysis of stocks is divided into fundamental and technical analysis. According to the fundamental analysis, the prices of stocks depend on companies' profit, the macroeconomic and political environment, etc. Technical analysis assumes that all the needed information to predict future stock prices is incorporated into past stock prices, so in order to predict them one should analyze only historical data. Advanced trading technologies using machine intelligence belong to technical analysis. Actually, an artificial neural network may be more suitable for the task. Primarily no assumption about a suitable mathematical model has to be made prior to forecasting. Furthermore, a neural network has the ability to extract rule from large sets of data, which is often required for a satisfying description of a financial time series.

A neural network is able to work parallel with input variables and consequently handle large sets of data quickly. The principal strength with the network is its ability to find patterns (Chung, Fu, Ng, & Luk, 2004) and irregularities as well as detecting multidimensional non-linear connections in data. The latter quality is extremely useful for modeling dynamical systems, e.g., the stock market. Apart from that, neural networks are frequently used for pattern recognition tasks and non-linear regression.

This study develops a forecasting model, CBDWNN by integrating the case based dynamic window (CBDW) and the neural network for stock trading decision support which includes the following objectives: (1) screen out potential stocks (company) according to relative technical indicator. It is a very importance task, since selecting a good stock that will yield twice the result with half the effort. Even if the forecasting model is not a perfect one, the probability of investors to suffer from a setback will be quite small when a stock is in the arising trend. (2) develop an efficient and suitable forecasting model for making the buy/sell decisions more correctly. In addition, a case based dynamic

* Corresponding author. Tel.: +886 3 4352654; fax: +886 3 4559378.
E-mail address: iepchang@saturn.yzu.edu.tw (P.-C. Chang).

0957-4174/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2008.08.077

window (CBDW) is developed to assist the back propagation network in eliminating the false alarm for a buy/sell point.

The remainder of the paper is organized as follows: in Section 2, an introduction of financial time series forecasting models with ANN, CBR, and other artificial intelligence is given; in Section 3, the detail issues related to stocking trading are discussed; in Section 4, the development of the integrated system by integrating the neural network and CBR is presented; in Section 5, the experimental setup are explained in detail and the results are discussed; and finally, the conclusions are given in Section 6.

2. Literature review on financial time series forecasting

2.1. Time series forecasting

Time serial analysis performs better than other models as for the forecasting models with trendy and seasonal features. As mentioned in Qi and Zhang (2003), there has no general consensus on how to model the trends in time series data; thus, they used neural network to model their trend-influenced function. A fixed interval trend removal approach is used to successfully forecast the electricity demand (Infield & Hill, 1998).

Stock prices forecasting has been regarded as one of the most challenging applications of time series forecasting. A lot of numerous models have been depicted to provide the investors with more precise predictions. Three common risk factors are identified in Fama and French (1993), an overall market factor, and some factors related to firm size and book-to-market equity which seem to explain the average returns on stocks and bonds. Moreover, a stream of literatures (Chen, Yang, Dong, & Abraham, 2005; Fama & French, 1990; Keim & Stambaugh, 1986; LeBaron, 2001; Rozeff, 1984; Sheta & Jong, 2001) find out that macroeconomic variables such as short-term interest rates, expected inflation, dividend yields, yield spreads between long- and short-term government bonds, yield spreads between low- and high-grade bonds, lagged price–earnings ratios, and lagged returns have some power to predict stock returns.

2.2. Artificial neural network (ANN) for financial time series forecasting

ANN appear to be particularly suited for financial time series forecasting, as they can learn highly non-linear models, have general learning algorithms, can handle noisy data, and can use inputs of different kinds (see Armano, Marchesi, & Murru, 2005; Bhattacharyya, Pictet, & Zumbach, 2002; Chang, Hsieh, & Liao, 2005; Chang, Lai, & Lai, 2006; Chang & Wang, 2006; Chang, Wang, & Liu, 2007; Chien, Lin, Tan, & Lee, 1999; Refenes, Burgess, & Bentz, 1997 for a survey). Furthermore, complex non-linear models based on exponential GARCH processes (Bollerslev, 1986) show similar results (in terms of out-of-sample prediction performance) to those obtained by much simpler ANN based on multi-layer perception (MLP) architectures Campbell, Lo, & MacKinlay, 1997.

A major weakness of MLP, from a time series forecasting perspective, is the absence of an internal state, making it difficult to capture the dynamics of the given data series. Even if standard MLP can still be used (Castiglione, 2001), due to their simplicity and flexibility, a variety of more complex architectures with some form of internal memory has been proposed (see Campolucci, Uncini, Piazza, & Rao, 1999 for a survey). In particular, Recurrent ANN (RANN) has proved capable of outperforming stateless architectures in financial time series forecasting (Giles et al., 1997). Nevertheless, it is well known (LeBaron & Weigend, 1997) that out-of-sample results have a strong dependence on the time period used to train the network. In other words, ANN trained on data belonging to a specific period perform reasonably well only if the test period is relatively similar to the one used for training.

Back propagation neural (BPN) network is applied (Kimoto & Asakawa, 1990) to predict the stock price then determine buying and selling time for Tokyo Stocks. They used six input indicators, vector curve, interest rate, New York Dow-Jones average, turnover, foreign exchange rate and a teaching data, to successfully predict the stock price. The Mean Absolute Percentage Error (MAPE) of their BPN was 0.98; it was a very accurate forecasting result.

2.3. Case based reasoning (CBR)

CBR is one of the emerging paradigms for designing intelligent systems. It shows significant promise for improving the effectiveness of complex and unstructured decision making. It solves new problems by adopting previously successful solutions to analogous problems. In general, the problem-solving life cycle in a CBR system consists essentially of the following four parts:

- Retrieving: similar previously experienced cases whose problem is judged to be similar.
- Reusing: the cases by copying or integrating the solutions from the cases retrieved.
- Revising: or adopting the solution(s) retrieved as an attempt to solve the new problem.
- Retaining: the new solution once it has been confirmed or validated.

A structured model with multiple stages is proposed and it consists of four phases of problem-solving (training, test, adjusting and prediction), and three types of external input data (training, testing and generalization). The integrated model combined three methods: discriminate analysis, neural network and case based forecasting and it was applied in bankruptcy prediction. This integrated approach produces higher prediction accuracy than individual models.

A computer model employing a case based reasoning (CBR) to provide intelligent support to construction negotiations is presented (Li, 1996) and this model has been implemented in the MEDIATOR, a computer program that utilizes previous cases as a basis for addressing new problems. In contrast to conventional expert systems (ESs) that use compiled knowledge in problem-solving, the system selects similar cases to help in solving a given negotiation problem.

An intelligent fault Diagnosis Company combining CBR and ANN methods is studied on-line (Jha et al., 1999) to find out the knowledge from the customer service database. The collected knowledge was run by CBR to retrieve suitable malfunction and repairing cases. Cases studied in that research have shown that the hybrid case based reasoning and neural network approach to on-line intelligent fault diagnosis had higher accuracy than the conventional CBR.

Case based reasoning (CBR), artificial neural network (ANN) and rule induction (RI) of machine learning methods (Carolyn, Gada, Martin, Keith, & Chris, 2000) are applied to build software effort prediction systems, and compare the prediction systems in terms of three factors: accuracy, explanatory value and configurability. They showed that ANN methods had superior accuracy and that RI methods were least accurate. However, this view was somewhat counteracted by problems with explanatory value and configurability.

In summary, integrating CBR and ANN is a practicable and useful way to model a more accurate forecasting system. Therefore, a case based window search method will be constructed in this research to further improve the results from ANN.

3. Problem statements

This research mainly focuses on predicting the buy/sell points of individual stock price. The first stage is to select the target individual stock from 700 listed stocks in Taiwan stock market. The data of each individual stock can be obtained from the on-line data base “TEJ, Taiwan Economic Journal”.

To select a most profitable stock, different sets of criteria have been proposed by researchers and personal investors. In the following, some stock selecting criteria are described:

- CapitalInvestors can measure the scale of the company by this viewpoint. According to the experts' experience, choosing a company with small to medium capital size is a better choice when investing. Company with large capital size, the variation range of stock price is small. On the other hand, small capital stocks lack liquidity.
- SalesBy observing this indicator, investors may know how the company operates. If the sales achieve a new high level, it will be a good candidate for investing in this specific stock.
- ProfitThe “Earnings per Share, EPS” will be seemed as the profit of a company, it is a seasonal result.
- Transaction volumes
  This is a very important indicator when choosing a valuable stock. No matter looking for a short-term or a long term stock, the quantity of transaction implies the stock is popular or not.
- Marginal account
  When long buy is at high level, it is a warning signal. That means lots of individual investors have this stock, however, corporation had this stock earlier than individuals. And then the corporation will sell this stock in a few days, so the stock price will drop. Also, the short sell is another important indicator when choosing a stock.

A lot of technical indicators of stock price have been developed; this study will apply the following familiar indicators:

- Moving average, MA
  Apply the n period MA to forecast the stock price in the future.
- BIASIf the BIAS is positive, the investing market is optimistic, otherwise, the market is pessimistic.
- Stochastic line, KD
  The KD indicator is composed of two smooth moving average

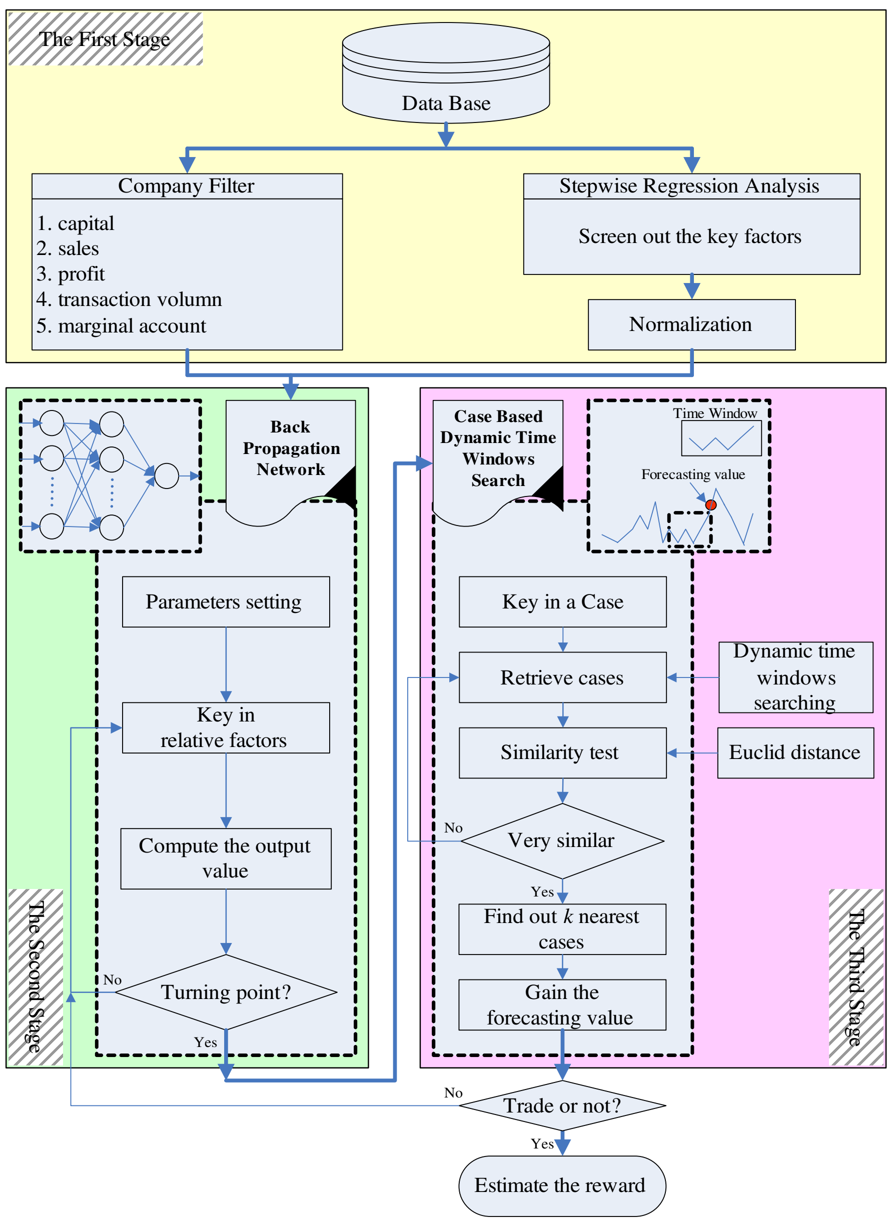

Fig. 1. The procedure of investing decision support system.

lines, K line and D line. Both ranges of these indicators are between 0 and 100; investors may depend on this to judge the buy/sell points.

- Relative strength indicator, RSIRSI is a strength indicator computed as rise rate over fall rate in a time period. If the value is positive, the stock is worthy to invest.
- Moving average convergence and divergence, MACDMACD is based on the MA; it is much easier to find out the stock price fluctuation.
- William, WMS%R
  This is an indicator of stock overbuy or oversell, it can also measure the peak or trough of the stock price in a time period.
- Volume of transaction
  This indicator is also an important one. If a stock without large volume of transaction, it's not a good investing target.
- The variation rate of technical indicators
  This study focuses on predicting the buy/sell decision point instead of the stock price, so the variation of some technical indicators need to be considered too, i.e. *K*, D and WMS%R.

4. Development of a stock trading support system

The principal motivations for the CBDWNN approach in stock prediction are: (1) stock data is highly complex and hard to model; therefore a non-linear model is beneficial; (2) a large set of interacting input series is often required to explain a specific stock, which suites neural networks.

The main purpose of this study is to develop a stock selection decision support system for investors and there are three stages in this system, (1) screening out the outstanding stocks and the important factors; (2) using back propagation network (BPN) to predict the turning points (wave peak and wave trough) of stock price; (3) adopting case based dynamic windows (CBDW) to improve the results from BPN. The procedure of the investing decision support system is shown as (Fig. 1).

4.1. Back propagation network

The BPN and the supervised learning, i.e., learned by samples, are chosen to train the forecasting process. After learning (or training), the trained weight can be used for the prediction of future occurrences. The BPN is an ANN using back propagation algorithm and is one of the popular ANNs, which has been widely applied to many scientific and commercial fields for non-linear analysis and prediction. The structure of BPN contains three layers: input, hidden, and output layers as shown in Fig. 2.

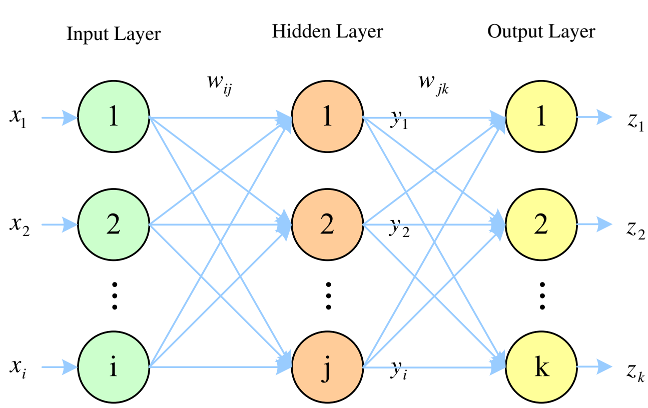

Fig. 2. The structure of back propagation neural network.

Each layer contains *I*, *J* and *K* nodes denoted respectively by circles. The node is also called neuron or unit. The neurons are connected by links, denoted by arrows in Fig. 2, and those arrows represent numerical weights. The w_{ij} is denoted as numerical weights between input and hidden layers and so is w_{jk} between hidden and output layers as also shown in Fig. 2. The processing or the computation is performed in each node in the hidden and output layers. As for the number of layers and number of nodes, they will be further decided using design of experiment.

The back propagation learning algorithm is composed of two procedures: (a) a feed forward step and (b) a back propagation weight training step. These two separate procedures will be explained in detailed as follows:

4.1.1. Feed forward

Assume that each input factor in the input layer is denoted by x_i, y_j and z_k represent the output in the hidden layer and the output layer, respectively. And, y_j and z_k can be expressed as follows:

$$y_j = f(X_j) = f\left(w_{oj} + \sum_{i=1}^{I} w_{ij} x_i\right) \tag{1}$$

and

$$z_k = f(Y_k) = f\left(w_{ok} + \sum_{j=1}^{J} w_{jk} y_j\right) \tag{2}$$

where the w_{oj} and w_{ok} are the bias weights for setting threshold values, *f* is the activation function used in both hidden and output layers, and X_j and Y_k are the temporarily computing results before applying activation function *f*. In this study, a sigmoid function (or logistic function) is selected as the activation function. Therefore, the actual outputs y_j and z_k in hidden and output layers, respectively, can be also written as

$$y_j = f(X_j) = \frac{1}{1 + e^{-X_j}} \tag{3}$$

and

$$z_k = f(Y_k) = \frac{1}{1 + e^{-Y_k}} \tag{4}$$

The activation function f introduces the non-linear effect to the network and maps the result of computation to a domain (0, 1). This sigmoid function is differentiable. The derivative of the sigmoid function in Eqs. (3) and (4) can be easily derived as

$$f' = f(1 - f) \tag{5}$$

4.1.2. Back propagation weight training

The error function is defined as

$$E = \frac{1}{2}\sum_{k=1}^{K} e_k^2 = \frac{1}{2}\sum_{k=1}^{K} (t_k - z_k)^2 \tag{6}$$

where t_k is a predefined network output (or desired output or target value) and e_k is the error in each output node. The goal is to minimize *E* so that the weight in each link is accordingly adjusted and the final output can match the desired output. To get the weight adjustment, the gradient descent strategy is employed. In the link between hidden and output layers, computing the partial derivative of *E* with respect to the weight w_{jk} produces

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial Y_k}\frac{\partial Y_k}{\partial w_{jk}} = -e_k \frac{\partial f(Y_k)}{\partial Y_k} y_j = -e_k f'(Y_k) y_j = -\delta_k y_j \tag{7}$$

where

$$\delta_k = e_k f'(Y_k) = (t_k - z_k) f'(Y_k) \tag{8}$$

The weight adjustment in the link between hidden and output layers is computed by

$$\Delta w_{jk} = \alpha \cdot y_j \cdot \delta_k \tag{9}$$

where α is the learning rate, a positive constant between 0 and 1. The new weight herein can be updated by the following:

$$w_{jk}(n+1) = w_{jk}(n) + \Delta w_{jk}(n) \tag{10}$$

where n is the number of iteration. Similarly, the error gradient in links between input and hidden layers can be obtained by taking the partial derivative with respect to w_{ij}

$$\frac{\partial E}{\partial w_{ij}} = \left[\sum_{k=1}^{K} \frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial Y_k}\frac{\partial Y_k}{\partial y_j}\right] \cdot \frac{\partial y_j}{\partial X_j} \cdot \frac{\partial X_j}{\partial w_{ij}} = -\Delta_j x_i \tag{11}$$

where

$$\Delta_j = f'(X_j) = \sum_{k=1}^{K} \delta_k w_{jk} \tag{12}$$

The new weight in the hidden-input links can be now corrected as

$$\Delta w_{ij} = \alpha \cdot x_i \cdot \Delta_j \tag{13}$$

and

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) \tag{14}$$

Training the BPN with many samples is a very time-consuming task. The learning speed can be improved by introducing the momentum term η Usually, η falls in the range [0, 1]. For the iteration n, the weight change Δw can be expressed as

$$\Delta w(n+1) = \eta \times \Delta w(n) + \alpha \times \frac{\partial E}{\partial w(n)} \tag{15}$$

4.2. Principles for deciding the trading signals/output value

The training procedure of BPN is highly related to the prediction performance, the factors screen process is also a necessary step before implementing the training stage. When screening the relative factors (dependent variables), the output variable (independent variable) needs to be given first. If the wrong or worse output variable feed into the BPN, the results generated by testing stage will be worthless. Therefore, the better output variable is selected, the more relative input variables are screened out, and the higher prediction accuracy is achieved. Traditionally, the output variable (buy/sell points) of training stage was determined by the real turning points, but it is not correct. Many experts tried to describe the stock trend by calculating the technical index. In this paper, the output variable (buy/sell signal) will be generated by experts' experience which will be predefined as the sell, hold or buy decision for each set of inputs. The principle decision making process for each stock in daily trading is based on the KD and William (WMS%R) indicators. Then the input variables will be screened out by using stepwise regression analysis for each outstanding stock. Those variables $(X_1, X_2, \ldots, X_n)$ are the most relative factors of the output variable.

- KD indicator

When the KD indicators are in high level (reaching 80) and the D indicator crosses the K indicator from upper side to lower one, the experts suggest selling the stock. On the contrary, when the KD indicators are in low level (reaching 20) and the D indicator crosses the K indicator from lower side to upper one, the experts suggest buying the stock, although, the KD indicators can easily determine the points of buy/sell.

The N-day KD of the tth trading day is defined below:

$$\mathrm{RSV}_t = \frac{C_t - L_n}{H_n - L_n} \times 100\% \tag{16}$$

$$K_t = \mathrm{RSV}_t \times \frac{1}{3} + K_{t-1} \times \frac{2}{3} \tag{17}$$

$$D_t = K_t \times \frac{1}{3} + D_{t-1} \times \frac{2}{3} \tag{18}$$

where RSV_t is the Raw Stochastic Value of the tth trading day, H_n, L_n are the highest and lowest stock prices during the latest N trading days, and C_t is the closing price of the tth trading day. If the values of K_t and D_t are over an upper bound, it means the difference between L_n and C_t is large and the stock price is overvalued. Therefore, we can wait for a short trading signal to sell the stock. Conversely, if the values of K_t and D_t are under a lower bound, it means that the difference between L_n and C_t is small and the stock price is undervalued. We can wait for a long trading signal to buy the stock. The upper bound and lower bound are heuristic values and stock dependent. The accuracy of forecasting result will decrease when KD is sustained less than 20 or greater than 80. Based on this, the William indicator should be adopted to assist the turning point decision.

- WMS%R indicator

The WMS%R indicator was proposed by Larry Williams in 1973. The N-day WMS%R of the tth trading day is

$$\mathrm{WMS\%}R_t = \frac{H_n - C_t}{H_n - L_n} \times 100\% \tag{19}$$

where H_n, L_n are the highest and lowest stock prices during the latest N trading days, and C_t is the closing price of the tth trading day. If the value of $\mathrm{WMS\%}R_t$ is over a threshold, then the difference between H_n and C_t is large and the stock price is undervalued. We can wait for a long trading signal to buy the stock. Conversely, if the value of $\mathrm{WMS\%}R_t$ is under a threshold, then the difference between H_n and C_t is small and the stock price is overvalued. We can wait for a short trading signal to sell the stock.

This study investigates some principles to judge the trading signals/Output value. The WMS%R will be adopted to assist the KD intersection for judging the points of buy/sell. The principle is shown as following:

- When KD intersection occurred at the low level (less than 20) and the smooth value of WMS%R is 100%, it is a buying point. The output value will be 0 in this study.
- When KD intersection occurred at the high level (greater than 80) and the smooth value of WMS%R is 0%, it is a selling point. The output value will be 1 in this study.
- If the signal of buy/sell doesn't change, the output value will inherit from the previous output value (that means hold).

Table 1
The output value for the training stage in BPN

Date	WMS%R	K	D	Buy/sell point	Output value
2006/1/1	21	79.21	69.14	–	–
2006/1/2	0	86.14	74.81	Sell	1
2006/1/3	76	57.43	69.02	–	1
2006/1/4	87	38.29	58.77	–	1
2006/1/5	88	17.02	37.46	–	1
2006/1/6	100	11.34	28.76	Buy	0
2006/1/7	61	40.9	32.8	–	0
2006/1/8	39	73.73	52.62	–	0
2006/1/9	36	88.33	71.16	–	0
2006/1/10	42	69.99	70.77	–	0
2006/1/11	20	79.21	69.14	–	0

4.3. Illustration of generating the trading signals

To illustrate the working principle, (Table 1), Figs. 3 and 4 are shown as follows:

By the observation from Fig. 3, the intersection occurred between date 2 and 3; while in Fig. 4, the WMS%R of date 2 is 0%. That implies the date 2 is a selling point; on the contrary, the date 6 is a buying point. In (Table 1), the output value from the training stage for BPN is preset as "−111100000". That means the 2nd day is the selling point, and no investing decision will be made from days 3 to 5. The 6th day is the buying point, and also there will be no selling signal from days 7 to 11. The forecasting procedure of BPN will be shown as in Fig. 5.

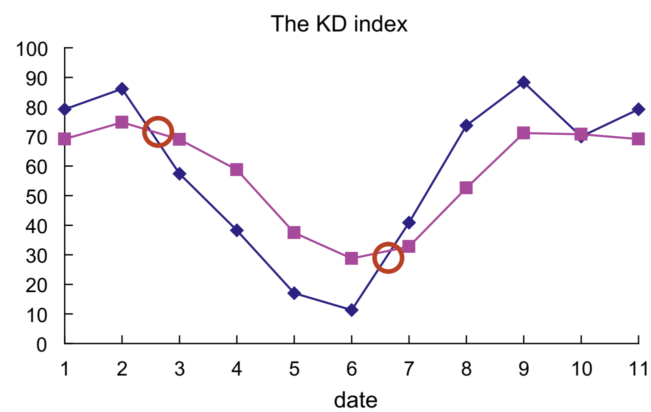

Fig. 3. KD indicator.

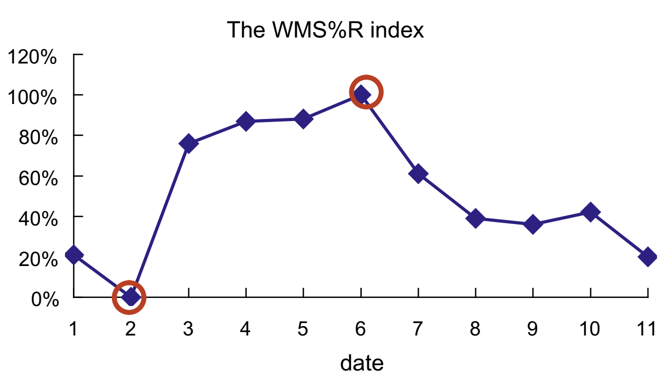

Fig. 4. WMS%R indicator.

Table 2
The buy/sell points from BPN

Date	Output from BPN	Buy/sell point
2006/1/12	0.699899	–
2006/1/13	0.624224	–
2006/1/14	0.599974	–
2006/1/15	0.477695	Buy
2006/1/16	0.819345	Sell
2006/1/17	0.669645	–
2006/1/18	0.589442	–
2006/1/19	0.319328	Buy
2006/1/20	0.361134	–
2006/1/21	0.624334	Sell
2006/1/22	0.457972	Buy

In the testing stage, the output value will be a continuous value between 0 and 1, and the 0.5 will be the boundary point. When the next output value decrease through 0.5, the buying point occurs; on the other hand, the selling point exists. For example, there are 11 testing data as shown in Table 2.

The main purpose of this study is to predict the right turning points so as to maximize the investing revenue. If simply using the BPN to predict the turning points, the transaction frequency will be high. When the number of turning points is large, the investors will lose a lot of transaction fee. That is the reason why CBR is applied as a dynamic window search to assist the BPN to fine tune the trading decision. By changing the period of dynamic windows, CBR will help to identify similar scenario from the previous stock data and apply this scenario to project the future change of the stock price thus make a better trading decision.

4.4. Case based dynamic windows

The case based dynamic window will be applied to search the most similar scenario from the previous stock data and predict

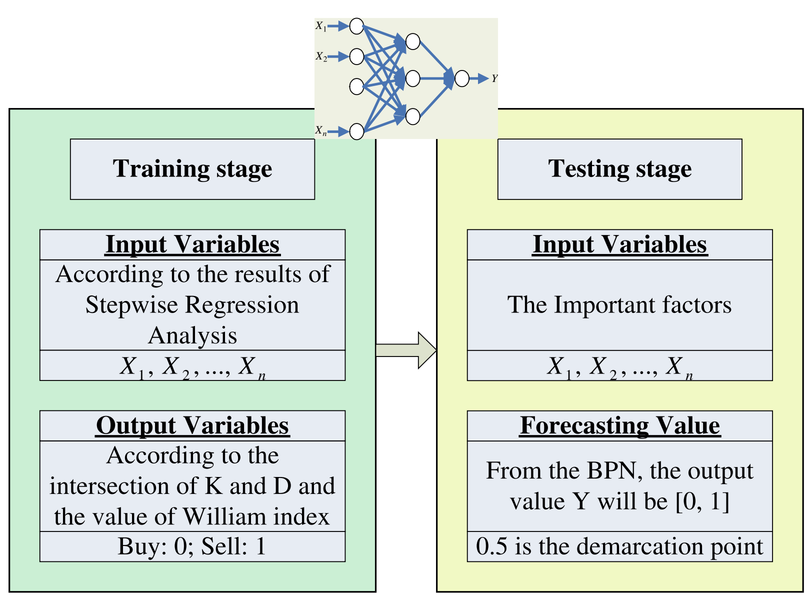

Fig. 5. The BPN training and testing procedure.

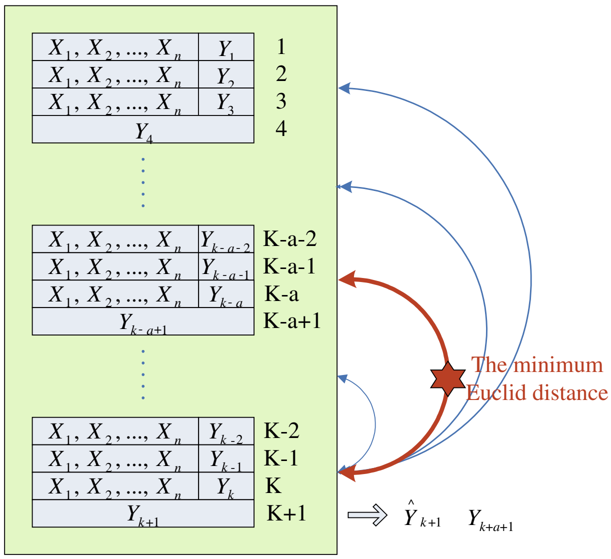

Fig. 6. The three-period dynamic time windows search.

the stock price fluctuation of the next day according to the adaptation of these similar patterns. The dynamic window search will be illustrated as in Fig. 6.

In (Fig. 6), X_i is the ith input variable, for $i = 1, 2, \ldots, n$;

Y_k is stock price fluctuation in percentage ($-7\% \sim +7\%$, the standard of Taiwan) of day k. By calculating the shortest Euclid distance between the current data pattern, i.e., three day stock price fluctuation, and the previous stock price fluctuation in the past three months, the average stock price fluctuation of the next day Y_{k-a+1} will be applied to predict value of $\hat{Y}_{k+1}$.

The detailed procedures of the case based dynamic window search are described as follows:

1. Determine the length of the searching time period
   When the number of time period (n) is small, that represent it is a short period forecasting model. This parameter is determined by investors or experts.
2. Case retrieve
   When the time period is determined, the dynamic time windows search will be processed. If an investor wants to forecast the stock price fluctuation of the next day, by using mapping process, the most similar time window can be found. Supposed that today is the 17th day, the time period is 3, the most similar time window is the 6th one (days 6–8), then the value of day 9 is the forecasting value of day 18.
3. Threshold test
   In this study, more than one case will be reused. If the similarity coefficient is over the threshold, the case will be retrieved from the stock data. All these similar cases retrieved with similarity coefficient over the threshold value will be applied to adapt these old solutions into the next day's price change.
4. Case reuse
   In this stage, the weighted average of those outperform cases will be the forecasting stock price fluctuation. If there are m suitable cases, the fluctuation will be

$$\hat{Y}_k = \sum_{i=1}^{m} W_i Y_i \tag{20}$$

$$W_i = d_i \Big/ \sum_{i=1}^{m} d_i \tag{21}$$

where $\hat{Y}_k$ is the forecasting result of the day k; W_i is the weight of the case i; d_i is the Euclid distance of the case i; Y_i is the real stock price fluctuation of the day i.

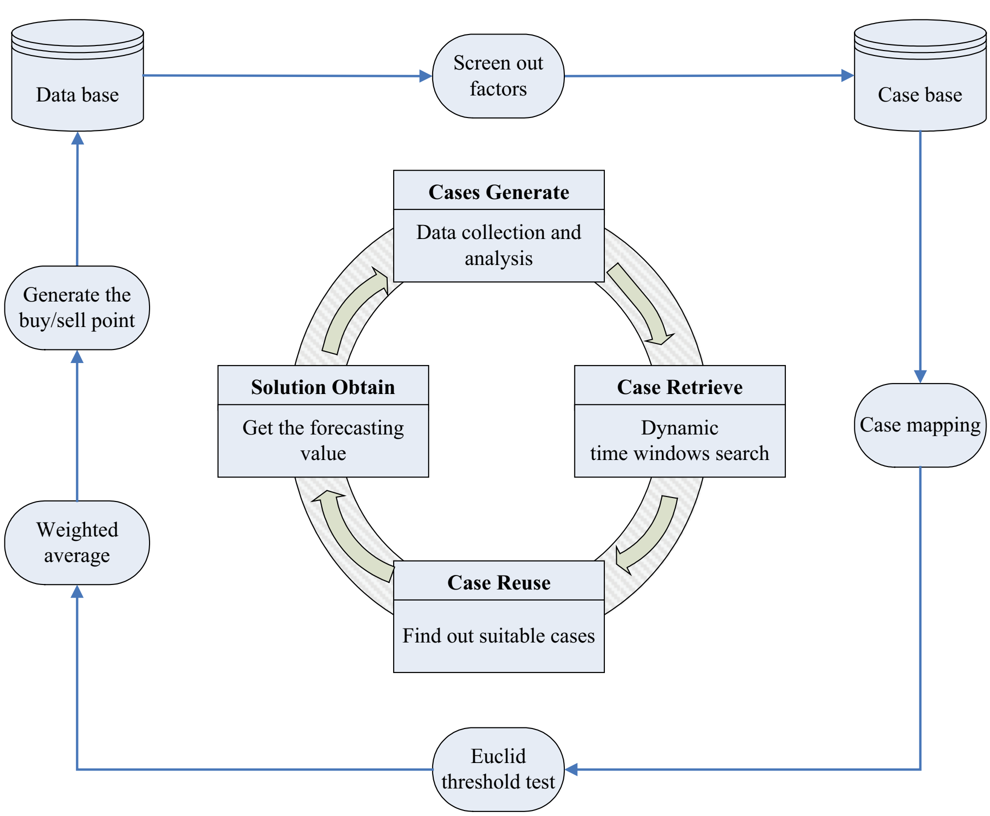

Fig. 7. The framework of the case based dynamic time windows search.

Table 3
The buy/sell points from CBDW assisted BPN

Date	Output of BPN			Output of CBDW (%)	Final decision
2006/1/12	0.699899	–	–	−3.27	–
2006/1/13	0.624224	–	–	−5.66	–
2006/1/14	0.599974	–	–	−1.45	–
2006/1/15	0.477695	0	Buy	3.73	Buy
2006/1/16	0.819345	1	Sell	−2.64	Sell
2006/1/17	0.669645	1	–	−3.58	–
2006/1/18	0.589442	0	–	−0.49	–
2006/1/19	0.319328	1	Buy	0.18	Buy
2006/1/20	0.361134	0	–	2.45	–
2006/1/21	0.624334		Sell	6.12	–
2006/1/22	0.457972	0	Buy	0.03	–

The detailed procedure of case based dynamic window search will be shown in Fig. 7.

By integrating the BPN and CBDW; the buy/sell points can be generated effectively. From the results of BPN, if the buy/sell point occurred then apply the CBDW to search the data base including the past 6 month stock information. Accordingly, the CBDW will retrieve similar pattern of the past stock fluctuation information and forecast the average stock price fluctuation in the next day. If the result of CBDW in checking the turning point is the same as the prediction from BPN, the turning point occurred and is reconfirmed. The results were shown in Table 3.

By integrating the BPN and CBDW, the buy/sell points can be further reduced, and some profitless turning points can be avoided.

5. Numerical examples

In this section, nine different stocks are choosing as the instances. Three of them are during upward trend (AU Optronics Corp. (AUO), Epistar Corp. (EPISTAR), Green Point Corp. (GP) as shown in Fig. 8), three are downward trend (Silicon Integrated System Corp. (SiS), SENAO International Corp. (SENAO), D-Link Corp. (D-LINK) as shown in Fig. 9), and others are steady (Foxlink Corp. (FOXLINK), Compal Corp. (COMPAL), UMC Corp. (UMC) as shown in Fig. 10). The main purpose of instance selection is that we want to emphasis the importance of stock screening. However, even the down trend stock is selected; investors can also make good trading decision. In the following, the stocks screening process will be introduced first. And then the different factors were selected according to different stocks. The results of on stock (AUO) will be showed in detailed, and the overall comparison of all instances will be represented in the last paragraph.

5.1. Stocks Screening

A stock screening procedure is the most important step if an investor wants to earn a profit. In this study, the variation of monthly sales, Earning per Shares (EPS), weekly trading volumes etc will be applied as key factors to identify potential stocks for investment. The rules of thumb are monthly sales increasing gradually and even breaking the historic records, EPS monthly increasing, and the daily trading volumes over the 5-day average volumes. From June 15, 2005 to September 15, 2005, two stocks are screened out from the following filter.

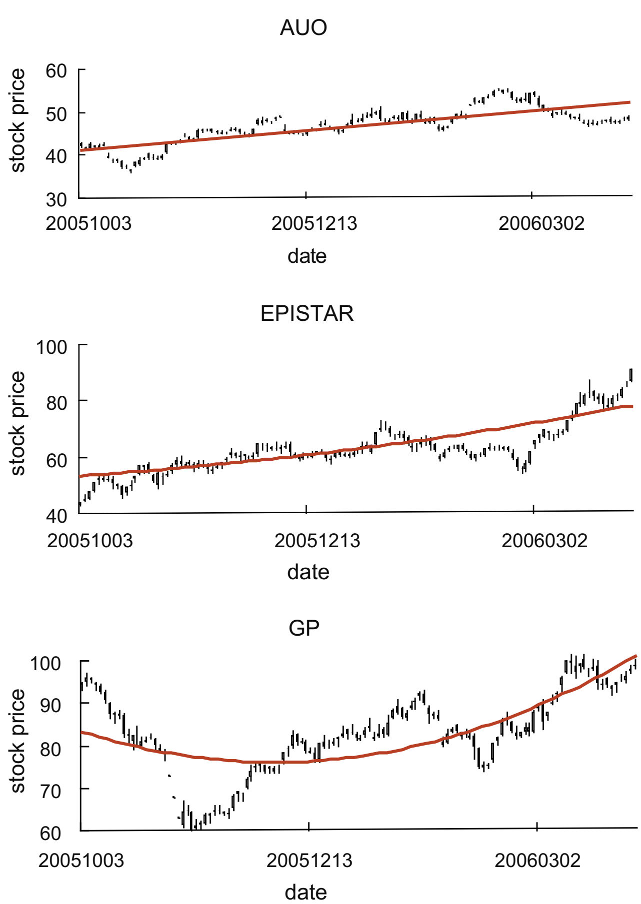

Fig. 8. Three upward trend stocks this paper selects.

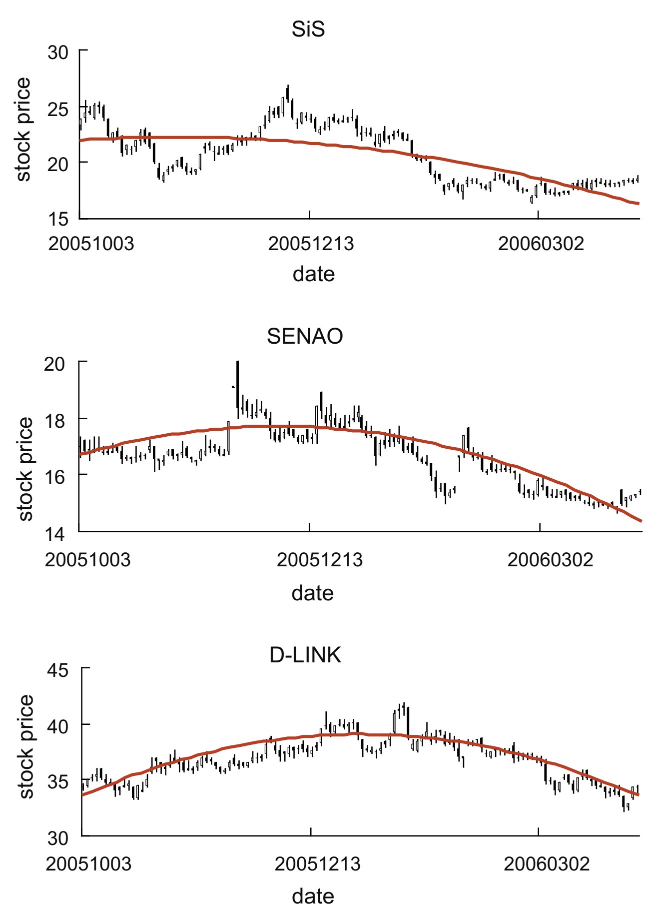

Fig. 9. Three downward trend stocks this paper selects.

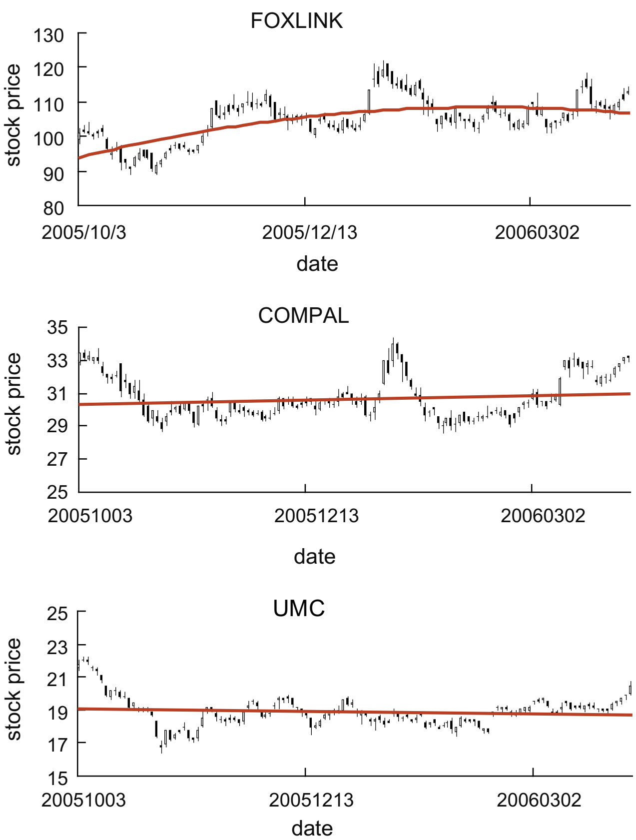

Fig. 10. Three steady trend stocks this paper selects.

1. Capital > 20,000,000 NT dollars.
2. Monthly sales is increasing and even breaking the historic high record.
3. EPS in this year is greater than the last year, and is a positive value.
4. Volume of transaction is in the rank of the first 50 positions.
5. Long buy decrease and short sell increase.

The stocks screened out from the above filters are AU Optronics Corp (AUO), Epistar Corp. (EPISTAR), and Green Point Corp. (GP). AUO is a world-leading manufacturer of large-size thin film transistor liquid crystal display (TFT–LCD) panels, which are currently the most widely used flat panel display technology. EPISTAR focuses on developing, manufacturing and marketing high brightness Light Emitting Diode (LED) products, which is widely used in areas such as fax machine, scanner lighting, LCD back lighting, etc. GP is a well-known manufacturer of mobile phone parts, mobile communication parts, battery charger parts, etc. All of these three stocks were in upward trend during the testing period.

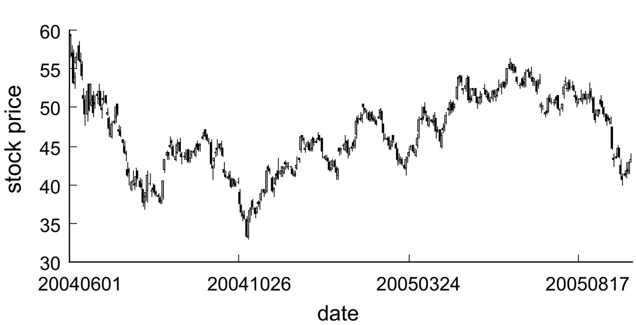

Fig. 11. The historical stock price of AUO.

5.2. Factors selecting

In this study, the important factors will be screened out by using stepwise regression analysis for each individual stock. For AUO, the variation of D, WMS%R indicator, and the variation of WMS%R are the most relative factors to the experts' buy/sell points. For EPISTAR, the variation of D indicator, WMS%R indicator, and the variation of WMS%R are the most relative factors to the experts' buy/sell points. For GP, 10 days Moving Average (10MA) and WMS% R indicator are the most relative ones.

5.3. Comparison of CBR, BPN and the CBDWNN

The training data is collected from September 1, 2004 to August 31, 2005; testing data is from September 1, 2005 to December 31, 2005. This section takes the AUO as an illustration example. The historical stock prices of AUO from June 1, 2004 to September 30, 2005 are shown as (Fig. 11).

5.3.1. Forecasting results from CBR

The trading decision points for AUO during the forecasted period using CBR are listed in Table 4, the total revenue is 65.70%.

5.3.2. Forecasting results from BPN

The best parameters of the BPN for the stock AUO were chosen from a set of experimental designs as shown in the (Table 5).

The trading decision points for AUO during the forecasted period using BPN are listed in Table 6, the total revenue is 71.47%.

Table 4
The forecasting buy/sell points for AUO using CBR

Buy/sell date	Buying price	Selling price
2005/10/19–2005/11/22	36.05	45.05
2005/11/24–2005/12/06	44.20	45.60
2005/12/23–2006/01/04	45.85	48.00
2006/01/25–2006/02/21	46.45	54.70
2006/03/23–2006/03/24	47.30	48.10
2006/03/27–2006/03/31	47.60	48.80

Table 5
The best parameter setting of BPN for the stock AUO

Node of input layer	3
Node of hidden layer	3
Node of output layer	1
Momentum	0.4
Learning ratio	0.5
Learning rule	Delta-rule
Transfer function	Sigmoid
Learning times	50,000

Table 6
The forecasting buy/sell points for AUO by using BPN

Buy/sell date	Buying price	Selling price
2005/10/03–2005/10/11	41.90	42.30
2005/10/19–2005/11/22	36.05	45.05
2005/11/24–2005/12/06	44.20	45.60
2005/12/15–2005/12/21	46.15	45.55
2005/12/23–2006/01/04	45.85	48.00
2006/01/10–2006/01/11	48.00	49.85
2006/01/25–2006/02/21	46.45	54.70
2006/03/23–2006/03/24	47.30	48.10
2006/03/27–2006/03/31	47.60	48.80

Table 7
The forecasting buy/sell points for AUO by using the CBDWNN

Buy/sell date	Buying price	Selling price
2005/10/03–2005/10/11	41.90	42.30
2005/10/19–2005/11/09	36.05	45.80
2005/11/17–2005/11/21	45.00	46.05
2005/11/24–2005/12/05	44.20	49.00
2005/12/14–2006/01/03	45.85	50.00
2006/01/25–2006/02/20	46.45	55.20
2006/03/23–2006/03/24	47.30	48.10
2006/03/27–2006/03/31	47.60	48.80

Table 8
The rate of return by CBR, BPN and the CBDWNN

Company		Rate of return (%)		
		CBR	BPN	CBDWNN
Upward	AUO	65.70	71.47	96.59
	EPISTAR	204.42	213.57	282.49
	GP	67.08	66.18	93.57
Steady	FOXLINK	38.25	36.93	73.46
	COMPAL	31.35	24.3	37.75
	UMC	26.54	33.45	78.46
Downward	SiS	39.32	53.17	65.20
	SENAO	31.90	34.73	46.62
	D-LINK	21.49	37.55	51.48

5.3.3. Forecasting results from the CBDW model

The time window of CBDW are decided using the set of experiments and the size is decided as 5. The trading decision points for AUO during the forecasted period using the CBDWNN are listed in Table 7, the total revenue is 96.59%.

5.3.4. Results comparison

The CBDWNN in this study is outperforming other two methods, i.e., CBR and BPN from the final result in Table 8.

6. Conclusion

In this study, an integrated system by combining dynamic time windows, CBR, and Neural Network for stock trading prediction is developed and there are three stages in the CBDWNN system; (1) screening out the potential stocks and the important influential factors; (2) using a back propagation network (BPN) to predict the buy/sell points (wave peak and wave trough) of stock price; (3) adopting case based dynamic windows (CBDW) to further improve the forecasting results from BPN. The empirical results show that the proposed model, CBDWNN can reduce the false alarm of buying or selling decisions.

Nine individual stocks will be the testing targets, the rates of return of upward trend stocks are higher than 93.57%, the steady are higher than 37.75%, and the downward are higher than 46.62%. According to the observation of the numerical results, the most important thing of the decision support system is the first stage, screen out a valuable stock. The revenue of the upward trend stock is the highest ones when comparing with the steady or downward stock; that's why the stock screening process is necessary. However, all of the results are very satisfactory. Even when the trend is downward, the CBDWNN still can make good trading decisions which represents the model is very informative and robust for average investors.

References

Armano, G., Marchesi, M., & Murru, A. (2005). A hybrid genetic-neural architecture for stock indexes forecasting. *Information Sciences, 170*, 3–33.

Bhattacharyya, S., Pictet, O. V., & Zumbach, G. (2002). Knowledge-intensive genetic discovery in foreign exchange markets. *Transaction on Evolutionary Computation, 6*(2), 169–181.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedaticicty. *Journal of Econometrics, 52*, 307–327.

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). *The econometrics of financial markets*. Princeton, New Jersey: Princeton University Press.

Campolucci, P., Uncini, A., Piazza, F., & Rao, B. D. (1999). On-line learning algorithms for locally recurrent neural networks. *Transactions on Neural Networks, 10*(2), 253–271.

Carolyn, M., Gada, K., Martin, L., Keith, P., & Chris, S. (2000). An investigation of machine learning based prediction systems. *The Journal of Systems and Software, 53*, 23–29.

Castiglione, F. (2001). Forecasting price increments using an artificial neural network. *Advances in Complex Systems, 4*(1), 45–56.

Chang, P. C., Hsieh, J. C., & Liao, T. W. (2005). Evolving fuzzy rules for due-date assignment problem in semiconductor manufacturing factory. *Journal of Intelligent Manufacturing, 16*(5), 549–557.

Chang, P. C., Lai, C. Y., & Lai, K. R. (2006). A hybrid system by evolving case-based reasoning with genetic algorithm in wholesaler's returning book forecasting. *Decision Support Systems, 42*, 1715–1729.

Chang, P. C., & Wang, Y. W. (2006). Fuzzy Delphi and back-propagation model for sales forecasting in PCB industry. *Expert Systems with Applications, 30*(4), 715–726.

Chang, P. C., Wang, Y. W., & Liu, C. H. (2007). The development of a weighted evolving fuzzy neural network for PCB sales forecasting. *Expert Systems with Applications, 32*(1), 86–96.

Chen, Y. H., Yang, B., Dong, J., & Abraham, A. (2005). Time-series forecasting using flexible neural tree model. *Information Sciences, 174*, 219–235.

Chien, T. W., Lin, C., Tan, B., & Lee, W. C. (1999). A neural networks-based approach for strategic planning. *Information & Management, 35*(6), 357–364.

Chung, F. L., Fu, T. C., Ng, V., & Luk, R. W. P. (2004). An evolutionary approach to pattern-based time series segmentation. *Transaction on Evolutionary Computation, 8*(5), 471–489.

Fama, E., & French, K. (1990). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics, 25*, 23–49.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3–56.

Giles, C. L., Lawrence, S., & Tsoi, A. C. (1997). Rule inference for financial prediction using recurrent neural networks. In *Proceedings of IEEE/IAFE conference on computational intelligence for financial engineering (CIFE)* (pp. 253–259).

Infield, D. G., & Hill, D. C. (1998). Optimal smoothing for trend removal in short term electricity demand forecasting. *IEEE Transactions on Power Systems, 13*(3), 1115–1120.

Jha, G., Hui, S. C., & Foo, S. (1999). A hybrid case-based reasoning and neural network approach to online intelligent fault diagnosis. In *Proceeding third international ICSC symposia on intelligent industrial automation and soft 39 computing* (pp. 376–381).

Keim, D., & Stambaugh, R. (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics, 17*, 357–390.

Kimoto, T., & Asakawa, K. (1990). Stock market prediction system with modular neural network. *IEEE International Joint Conference on Neural Network*, 1–6.

LeBaron, B. (2001). Empirical regularities from interacting long- and short-memory investors in an agent-based stock market. *IEEE Transaction on Evolutionary Computation, 5*(5), 442–455.

LeBaron, B., & Weigend, A. S. (1997). A boo strap evaluation of the effect of data splitting on financial time series. *IEEE Transactions on Neural Networks, 9*, 213–220.

Li, H. (1996). Case-based reasoning for intelligent support of construction negotiation. *Information & Management, 30*(5), 231–238.

Qi, M., & Zhang, G. P. (2003). Trend time series modeling and forecasting with neural networks. *Computational Intelligence for Financial Engineering, IEEE International Conference*, 331–337.

Refenes, A. P. N., Burgess, A. N., & Bentz, Y. (1997). Neural networks in financial engineering: A study in methodology. *IEEE Transactions on Neural Networks, 8*(6), 1222–1267.

Rozeff, M. (1984). Dividend yields are equity risk premiums. *Journal of Portfolio Management, 11*, 68–75.

Sheta, A. F., & Jong, K. D. (2001). Time-series forecasting using GA-tuned radial basis functions. *Information Science, 133*, 221–228.