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A hybrid model based on adaptive-network-based fuzzy inference system to forecast Taiwan stock market

Liang-Ying Wei [b,*], Tai-Liang Chen [a], Tien-Hwa Ho [b]

[a] Department of Information Management and Communication, Wenzao Ursuline College of Languages, 900 Mintsu 1st Road, Kaohsiung 807, Taiwan
[b] Information Management, Yuanpei University, 306 Yuanpei Street, Hsin Chu 30015, Taiwan

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ABSTRACT

In recent years, many academy researchers have proposed several forecasting models based on technical analysis to predict models such as Engle (1982) and Cheng, Chen, and Wei (2010). After reviewing the literature, two major drawbacks are found in past models: (1) the forecasting models based on artificial intelligence algorithms (AI), such as neural networks (NN) and genetic algorithms (GAs), produce complex and unintelligible rules; and (2) statistic forecasting models, such as time series, require some basic assumptions for variables and build forecasting models based on mathematic equations, which are not easily understandable by stock investors. In order to refine these drawbacks of past models, this paper has proposed a model, based on adaptive-network-based fuzzy inference system which uses multi-technical indicators, to predict stock price trends. Three refined processes have proposed in the hybrid model for forecasting: (1) select essential technical indicators from popular indicators by a correlation matrix; (2) use the subtractive clustering method to partition technical indicator value into linguistic values based on an data discretization method; (3) employ a fuzzy inference system (FIS) to extract rules of linguistic terms from the dataset of the technical indicators, and optimize the FIS parameters based on an adaptive network to produce forecasts. A six-year period of the TAIEX is employed as experimental database to evaluate the proposed model with a performance indicator, root mean squared error (RMSE). The experimental results have shown that the proposed model is superior to two listing models (Chen's and Yu's models).

1. Introduction

For participants in stock market, technical analysis method is one of major analysis techniques in stock market forecasting that has the ability to forecast the future price direction by studying past market data, primarily stock price and volume. The technical analysis method has assumed that stock price and volume are the two most relevant factors in determining the future direction and behavior of a particular stock or market, and the technical indicators, come from the mathematic formula based on stock price and volume, can be applied to predict the future price fluctuation and also provided for investors to determine the timing of buying or selling the stocks (Chi, Peng, Wu, & Yu, 2003). For stock analysts and fund managers, using technical indicators to analyze stock market is a practical way, but it is hard to apply this technique for common investors because there are too many technical indicators to be considered as forecasting factors and most of popular indicators are usually not understandable. Therefore, for those stock market investors, who utilize technical indicators to predict market fluctuations, how to select useful technical indicators to forecast stock price trends accurately is the key issue to make profit.

In academy research, many time-series models was advanced by financial researchers to model stock market based on historical stock data, such as autoregressive conditional heteroscedasticity (ARCH) model by Engle (1982), ARCH (GARCH) model by Bollerslev (1986), autoregressive moving average (ARMA) model, and the autoregressive integrated moving average model (ARIMA) by Box and Jenkins (1976). As the arising of intelligent algorithms in recent years, many researchers have applied soft computing (Zadeh, 1994) algorithms in time-series model for financial forecasting. Kimoto, Asakawa, Yoda, and Takeoka (1990) developed a prediction system for stock market by using neural network. Nikolopoulos and Fellrath (1994) have combined genetic algorithms (GAs) and neural network (NN) to develop a hybrid expert system for investment decisions. Kim and Han (2000) proposed an approach based on genetic algorithms to feature discretization and the determination of connection weights for artificial neural networks (ANNs) to predict the stock price index. Huarng and Yu (2006) applied a backpropagation neural network to establish

* Corresponding author.
E-mail addresses: g9523808@yuntech.edu.tw, lywei@mail.ypu.edu.tw (L.-Y. Wei), 97007@mail.wtuc.edu.tw (T.-L. Chen), howa@mail.ypu.edu.tw (T.-H. Ho).

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fuzzy relationships in fuzzy time series for forecasting stock price. And, Roh (2007) has integrated neural network and time series model for forecasting the volatility of stock price index.

After reviewing the past models, three major drawbacks are found: (1) stock market analyst and fund managers apply various technical indicators to forecast stock market based on personal experience, which might give wrong judgments on market signals; (2) for some statistical models, specific assumptions are required for observations, and those models cannot be applied to the datasets that do not follow the statistical assumptions; and (3) some soft computing algorithms, such as neural networks (NN) and genetic algorithms (GAs), contain complex computation procedures like black-box, and the rules mined from these algorithms are not easily understandable for common invertors.

To improve the past forecasting models, this paper proposes a hybrid forecasting model to refine past models in stock price forecasting. The proposed model utilizes technical indicators as forecasting factors and an intelligent inference system as forecasting algorithms that can offer understandable rules for common investors. Three main processes are provided in the model as follows: (1) selects essential technical indicators from popular indicators with a "correlation matrix"; (2) use the subtractive clustering method (Chiu, 1994) to granule the dataset of essential technical indicators into linguistic stock dataset and apply a fuzzy inference system (FIS) to extract non-linear relationships (rules) among the linguistic stock dataset; and (3) employ an adaptive network to optimize FIS parameters to improve forecasting accuracy and produce understandable forecasting rules.

To verify the performance of the proposed model, this paper employs a six-year period of the TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) as experimental dataset, and two fuzzy time-series models (Chen, 1996; Yu, 2005) as comparison models.

2. Preliminaries

2.1. Technical analysis

Technical analysis is an attempt to predict future stock price movements by analyzing the past sequence of stock prices (Pring, 1991) and it relies on charts and look for particular configurations that are supposed to have predictive value. Analysts focus on the investor psychology and investor response to certain price formation and price movements. The price at which investors are willing to buy or sell depends on personal expectation. If investors expect the security price to rise, they will buy it; if investors expect the security price to fall, they will sell it. These simple statements are the cause for a major challenge in setting security prices, because they refer to human expectations and attitudes (Pring, 1991). As some people say securities never sell for what they are worth but for what people think they are worth. It is very important to understand that market participants anticipate future development and take action now and their action drive the price movement. Since stock market processes are highly nonlinear, many researchers have been focusing on technical analysis to improve the investment return (Allen & Karalainen, 1999; Azo, 1994; William, Russell, & James, 2002).

2.2. Subtractive clustering

Chiu (1994) developed the subtractive clustering, one of the fuzzy clustering, to estimate both the number and initial locations of cluster centers. Consider a set T of N data points in a D-dimensional hyper-space, where each data point W_i $(i = 1, 2, \ldots, N)$ $W_i = (x_i, y_i)$ where x_i denotes the p input variables and y_i is the output variable. The potential value P_i of data point is calculated by Eq. (1)

$$P_i = \sum_{j=1}^{N} e^{-\alpha \|W_i - W_j\|^2} \tag{1}$$

where $\alpha = 4/r^2$, r is the radius defining a W_i neighborhood, and $\|\cdot\|$ denotes the Euclidean distance.

The data point with many neighboring data points is chosen as the first cluster center. To generate the other cluster centers, the potential P_i is revised of each data points W_i by Eq. (2)

$$p_i = p_i - p_1^* \exp(-\beta \|W_i - W_1^*\|^2) \tag{2}$$

where β is a positive constant defining the neighborhood which will have measurable reductions in potential. W_1^* is the first cluster center and P_1^* is its potential value.

From Eq. (2), the method selects the data point with the highest remaining potential as the second cluster center. For general equation, we can rewrite Eq. (2) as Eq. (3)

$$p_i = p_i - p_k^* \exp(-\beta \|W_i - W_k^*\|^2) \tag{3}$$

where $W_k^* = (x_k^*, y_k^*)$ is the location of the kth cluster center and P_k^* is its potential value.

As the end of the clustering process, the method obtains q cluster centers and D corresponding spreads S_i, $i = (1, \ldots, D)$. Then we define their membership functions. The spread is calculated according to β.

2.3. Adaptive-network-based fuzzy inference system

Adaptive-network-based fuzzy inference system (ANFIS) was proposed by Jang (1993), which is a fuzzy inference system, implemented in the framework of adaptive networks. For illustrating the system, we assume the fuzzy inference system which consists of five layer of adaptive network with two inputs x and y and one output z. The architecture of ANFIS is shown as Fig. 1.

Then, we suppose that the system consists of 2 fuzzy if-then rules based on Takagi and Sugeno's type (Takagi & Sugeno, 1983):

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$.

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$.

The node in the ith position of the kth layer is denoted as $O_{k,i}$, and the node functions in the same layer are of the same function family as described below:

Layer 1: This Layer is the input layer and every node i in this layer is a square node with a node function (see Eq. (4)). $O_{1,i}$ is the membership function of A_i, and it specifies the degree to which the given x satisfies the quantifier A_i. Usually, we select the bell-shaped membership function as the input membership function (see Eq. (5)) with maximum equal to 1 and minimum equal to 0

$$O_{1,i} = \mu A_i(x) \quad \text{for } i = 1, 2 \tag{4}$$

$$\mu A_i(x) = \frac{1}{1 + [(\frac{x - c_i}{a_i})^2]^{bi}} \tag{5}$$

where a_i, b_i, c_i are the parameters and b is a positive value and c denotes the center of the curve.

Layer 2: Every node in this layer is a square node labeled Π which multiplies the incoming signals and sends the product out by Eq. (6)

$$O_{2,i} = w_i = \mu A_i(x) \times \mu B_i(y) \quad \text{for } i = 1, 2 \tag{6}$$