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A hybrid model based on ANFIS and adaptive expectation genetic algorithm to forecast TAIEX

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A R T I C L E I N F O

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A B S T R A C T

Technical analysis is one of the useful forecasting methods to predict the future stock prices. For professional stock analysts and fund managers, how to select necessary technical indicators to forecast stock trends is important. Traditionally, stock analysts have used linear time series models for stock forecasting. However, the results would be in doubt when the forecasting problems are nonlinear. Further, stock market investors usually make short-term decisions based on recent price fluctuations, but most time series models only use the last period of stock prices in forecasting. In this paper, the proposed hybrid model utilizes an adaptive expectation genetic algorithm to optimize adaptive network-based fuzzy inference system (ANFIS) for predicting stock price trends, and four proposed procedures are included in the hybrid model for forecasting: (1) select essential technical indicators from popular indicators by a cited paper (Cheng et al., 2010); (2) use subtractive clustering to partition technical indicator values into linguistic values based on an objective data discretization method; (3) employ fuzzy inference system (FIS) to build linguistic rules from the linguistic technical indicator dataset and optimize the FIS parameters by adaptive network; and (4) refine the proposed model using the adaptive expectation model, which optimizes parameter by genetic algorithm. The effectiveness of the proposed model is verified with performance evaluations and root mean squared error (RMSE), and a 6-year period of TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) is selected as the experimental datasets. The experimental results have shown that the proposed model is superior to the three listing forecasting models (Chen's model, Yu's model, and Cheng et al.'s model) in terms of RMSE.

1. Introduction

In stock markets, there are complex factors that will influence stock markets and nonlinear relationships, which are contained among different periods of stock prices for investors to forecast the future stock trends with difficulty. Therefore, many forecasting methods have been employed in predicting stock prices since the first stock market was opened. Further, financial analysts and stock fund managers attempt to predict price activity in the stock market on the basis of either their professional knowledge or with the assistance of stock analyzing tools. If more accurate predictions are given, myriad profit will be made. Therefore, stock analysts have perennially strived to discover ways to predict stock prices accurately. However, forecasting stock returns is difficult, because market volatility needs to be captured in a used and implemented model. Accurate modeling requires, among other factors, consideration of phenomena that are characterized.

Many conventional numeric forecasting models by financial researchers have been proposed, such as Engle's (1982) autoregressive conditional heteroscedasticity (ARCH) model, Bollerslev's (1986) generalized ARCH (GARCH) model, Box and Jenkins's (1976) autoregressive moving average (ARMA) model, and the autoregressive integrated moving average model (ARIMA).

Further, many researchers have been focusing on technical analysis to improve the investment return (Azo, 1994; Chi et al., 2003; Kimoto et al., 1990), because technical analysis methods are one of the major analysis approaches for investors to make investment decisions. A technical analysis method is one of the major analysis techniques in stock markets 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, coming from the mathematic formulas based on stock price and volume, can be applied to predict the future price fluctuation and also provide for investors to determine the timing of buying or selling stocks (Chi et al., 2003).

In the evolution of time series models, many researchers have applied data mining techniques in financial analysis. In 1990, Kimoto et al. (1990) developed a prediction system for stock markets by using neural networks. The following researchers, Nikolopoulos and Fellrath (1994), have combined genetic algorithms (GAs) and neural networks to develop a hybrid expert system for investment decisions. Kim and Han (2000) have proposed a genetic algorithm approach to feature

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discretization and the determination of connection weights for artificial neural networks (ANNs) to predict the stock price index. Huarng and Yu (2006) have applied backpropagation neural networks to establish fuzzy relationships in fuzzy time series for forecasting stock price. Roh (2007) has integrated neural networks and time series models for forecasting the volatility of a stock price index.

From the literature above, there are four major drawbacks found in these forecasting methods and models: (1) stock market analysts and fund managers apply various technical indicators to forecast stock markets based on their personal experiences, which might give wrong judgments on market signals; (2) for most statistical methods, there are some assumptions about the variables used in the analysis, and they cannot be applied to these datasets, which do not follow the statistical distributions; (3) artificial neural network (ANN) is a black-box method, and the rules mined from the methods are not easily understandable; and (4) stock market investors usually make short-term decisions based on recent price fluctuations, but most time series models use only the last period of stock price in forecasting.

To improve the past forecasting models, a thoughtful model should be able to overcome these drawbacks contained in past models and offer good methodology to be used and realized easily by investors. In time series research, the adaptive expectation model (Kmenta 1986) is a reasonable forecast model. Stock market investors usually make their short-term decisions based on recent stock information, such as the latest market news or price fluctuations. Furthermore, Chen et al. (2008) proved that the price patterns in the Taiwan and Hong Kong stock markets are short-term. Therefore, for stock price forecasting, we claim that the linear relationships between recent periods of stock prices should be included in forecasting models (Chen et al., 2007; Cheng et al., 2006). To consider the linear relationships between recent periods, we apply an adaptive expectation model to the proposed model for enhanced forecasting performance. Further, genetic algorithms, which are usually the preferred solution to the optimization problems, perform genetic operations, such as selection, crossover, and mutation. Genetic algorithms provide near-optimal solutions for an evaluation (fitness) function in optimization problems. For this reason, this paper uses a GA to optimize the parameter of the adaptive expectation model.

Therefore, this paper proposes a hybrid forecasting model to refine past models in stock price forecasting, and there are four processes provided in the forecasting model: it (1) selects essential technical indicators from a citation paper (Cheng et al., 2010); (2) uses subtractive clustering to discretize condition features (technical indicators); (3) applies a fuzzy inference system (FIS) to produce rules from the linguistic values of technical indicators and employs an adaptive network to optimize FIS parameters to improve forecasting accuracy; and (4) refines the forecasting accuracy of the proposed model by the adaptive expectation model, which optimizes parameters using a genetic algorithm.

In an empirical study, this paper employs a stock index as the experimental datasets. From the model verification, it is shown that the proposed processes are effective in improving forecasting accuracy, and based on the evidence, stock analysts or investors can employ the refined processes proposed in this paper to improve their forecasting tools or models.

The rest of this paper is organized as follows. Section 2 introduces the related works. Section 3 demonstrates the proposed model and algorithm. Section 4 describes the model verification. Conclusions are finally drawn in Section 5, as well as findings, conclusions, and recommendations for future research.

2. Related works

This section reviews related works of technical analysis, subtractive clustering, ANFIS, and genetic algorithms.

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 looking for particular configurations that are supposed to have a predictive value. Analysts focus on the investor psychology and investor response to certain price formations 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 that their action drives the price movement. Since stock market processes are highly nonlinear, many researchers have been focusing on technical analysis to improve the investment return (Allen and Karalainen, 1999; Azo, 1994; William et al., 2002).

2.2. Subtractive clustering

Chiu (1994) developed subtractive clustering, one of the fuzzy clustering methods, to estimate both the number and initial locations of cluster centers. Consider a set T of N data points in a D-dimensional hyperspace, 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 a 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 $\|.\|$ 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 for each data point W_i by Eq. (2)

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

where β is a positive constant defining the neighborhood that 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 a general equation, we can rewrite Eq. (2) as Eq. (3).

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

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

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

2.3. ANFIS: adaptive network-based fuzzy inference system

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