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A GA-weighted ANFIS model based on multiple stock market volatility causality for TAIEX forecasting

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ABSTRACT

Stock market forecasting is important and interesting, because the successful prediction of stock prices may promise attractive benefits. The economy of Taiwan relies on international trade deeply, and the fluctuations of international stock markets will impact Taiwan stock market. For this reason, it is a practical way to use the fluctuations of other stock markets as forecasting factors for forecasting the Taiwan stock market. In this paper, the proposed model uses the fluctuations of other national stock markets as forecasting factors and employs a genetic algorithm (GA) to refine the weights of rules joining in an ANFIS model to forecast the Taiwan stock index. To evaluate the forecasting performances, the proposed model is compared with four different models: Chen's model, Yu's model, Huarng's model, and the ANFIS model. The results indicate that the proposed model is superior to the listing methods in terms of the root mean squared error (RMSE).

1. Introduction

A lack of natural resources and a relatively small domestic market have made Taiwan dependent on foreign trade. Therefore, Taiwan needs to find other ways to obtain resources, the only way is through trade with other countries. Since the US economy still dominates the world market, the US still plays the leading role. Trends and movement in the US stock market can influence the world. So we can see that the relationship between the volatility of American stock market and the volatility of TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) is very close. Additionally, Hong Kong has a very dynamic and open economy which exerts a tremendous influence on other economies in the Pacific basin area. Thus, the economic volatility of Hong Kong influences the Taiwan stock market. Under such circumstances, the impacts of world, it is very high that the economic fluctuation of USA and Hong Kong impact on Taiwan. Dickinson [14] found that stock markets influence each other in different countries. The significance of volatility causality in a multi-nation stock market is an important indicator for forecasting stock price movement within another stock market. Thus, we employ the volatility causality in multi-nation multi-stock market forecasting in this paper.

Undoubtedly, 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. Observed volatility in stock market prices arises from the fact that required rates of return are themselves highly volatile, driven by cyclical and other short-term fluctuations in aggregate demand [2]. Conventional time-series models have been applied to forecasting problems, such as Engle [15], who proposed the ARCH (p) (Autoregressive Conditional Heteroscedasticity) model. To refine the ARCH model, Bollerslev [4] proposed the GARCH (Generalized ARCH) model, and then Box and Jenkins [5] proposed the autoregressive moving average (ARMA) model and the ARIMA model. Autocorrelation (AR) is the correlation (relationship) between members of time series of observations, such as weekly share prices or interest rates. More technically, autocorrelation occurs when residual error terms from observations of the same variable at different time periods are correlated (related). AR, a popular and important method in conventional time-series models, has been applied to time-series forecasting problems. However, the AR technique has limited capabilities for modeling time series data, and more advanced nonlinear methods, including neural networks, have been frequently applied with success [8].

Further, fuzzy methods have been employed to stock price forecasting. Song and Chissom [27] first proposed the original model of the fuzzy time-series; then, Huarng proposed distribution-based and average-based length to approach this issue [18]. In addition, Chen proposed a new method [10], in which the length of linguistics intervals is tuned by using genetic algorithms, and Yu [32] proposed a weighted fuzzy time-series method to forecast the TAIEX. Cheng et al. [11] proposed a methodology that incorporates trend-weighting into the fuzzy time-series model. However, the models mentioned above have been limited to one variable

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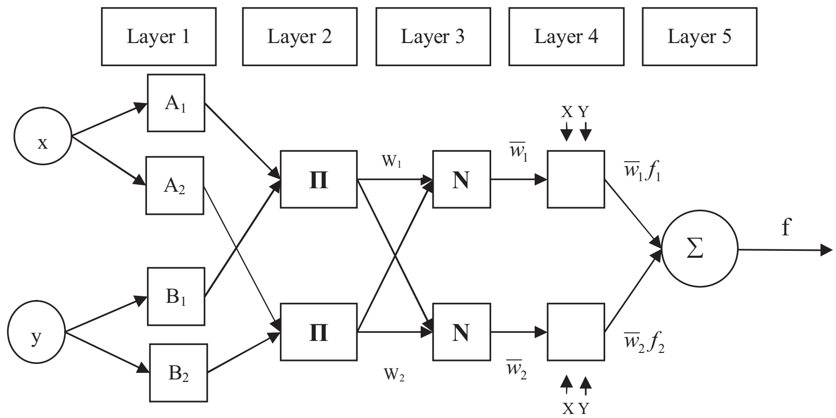

Fig. 1. The architecture of the ANFIS network.

application [33]. Further, Chang et al. [6] applied an ANFIS-based adaptive expectation model to forecast the stock index, and Chang et al. [7] proposed a hybrid ANFIS model based on AR and volatility for TAIEX forecasting. Recently, soft computing methods have been applied in many research fields [22–25,30]. The advances in soft computing techniques offer useful tools in forecasting noisy environments, like stock markets, capturing their nonlinear behavior. One of the soft computing methods, GA, which is usually the preferred solution to the optimization problems, performs genetic operations, such as selection, crossover, and mutation. GA provides near-optimal solutions for an evaluation (fitness) function in optimization problems. For this reason, this paper uses GA to optimize the weight of rules in ANFIS.

As mentioned above, there are two major drawbacks in these models: (1) most statistical methods rely upon some assumptions about the variables used in the analysis; so, it is limited to be applied to all datasets [21]; and (2) most conventional time-series models utilize only one nation's stock data for input variable in forecasting. However, financial analysts should consider many market variables in forecasting. For this reason above, forecasting models should utilize more variables to improve forecasting accuracy [33].

In order to reconcile the drawbacks above (there is a reference [7] backing the described volatility relationship between indexes), this paper considers that the volatility of American stock indexes and Hong Kong play an important role to affect the volatility of TAIEX. Because the forecasting models utilize the relation between the volatility of the American stock index and of TAIEX and the relation between the volatility of the Hong Kong index and of TAIEX, the analytical results would approximate the real world. Further, Chang et al. [7] proposed model which is based on an AR model and the volatility of TAIEX (momentum) causality, joining to a fusion ANFIS procedure, to forecast stock price problems in Taiwan, and the model of Chang et al. outperforms the listing methods. Therefore, the AR method is applied to enhance our proposed model. Third, the proposed model, employing fuzzy if-then rules (in the ANFIS method), can model the qualitative aspects of human knowledge and can be applicable for humans. Finally, the proposed model refines the forecasting accuracy of the proposed model by weighted rule method, in which the weight of rules is optimized using GA.

Based on the concept above, this paper proposes a novel model to forecast the Taiwan stock index. First, this paper calculates the volatility of the NASDAQ stock index and Hang Seng stock index by Eqs. (10) and (11). Second, this paper tests the lag period of TAIEX to build the AR method. Using the fuzzy inference system to forecast the Taiwan stock index, it considers a multi-stock index (NASDAQ stock index and Hang Seng stock index) to forecast TAIEX ($t+1$), where t denotes the tth day, $t+1$ denotes next day, and TAIEX (t) denotes TAIEX stock price at t day. Third, optimize the fuzzy inference system parameters by an adaptive network, which can overcome the limitations of statistical methods (data need to obey some mathematical distribution). Finally, the weighted rule model in which weights of rules are optimized using GA is applied to the proposed model for refining forecasting accuracy.

This rest of the paper is organized in the following. Section 2 describes related studies; Section 3 briefly presents the proposed model; Section 4 describes the experiments and comparisons; and Section 5 is the findings and discussions. Finally, the conclusions of the study are in Section 6.

2. Related works

This section reviews related studies of the adaptive network-based fuzzy inference system (ANFIS), subtractive clustering (Subclust), and genetic algorithm.

2.1. Subtractive clustering

Chiu [12] 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 hyper-space, where each data point W_i ($i=1, 2, \ldots, N$). $W_i=(x_i, y_i)$, where x_i denotes the i-th 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 $||\cdot||$ 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 point 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 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 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.