Appl Intell
DOI 10.1007/s10489-016-0760-8

A study of ANFIS-based multi-factor time series models for forecasting stock index

You-Shyang Chen[1] · Ching-Hsue Cheng[2] · Chiung-Lin Chiu[3] · Shu-Ting Huang[2]

Abstract Despite the widespread use of time series models in stock index forecasts, some of these models have encountered problems: (1) the selection of input factors may depend on personal experience or opinion; and (2) most conventional time series models consider only one variable. Furthermore, traditional forecasting models suffer from the following drawbacks: (1) models may rely on restrictive assumptions (such as linear separability or normality) about the variables being analyzed; and (2) it is hard to define and select applicable input factors for artificial neural networks (ANNs) in particular, and the rules generated from ANNs are not easily understood. To address these issues, we propose a multi-factor time series model based on an adaptive network-based fuzzy inference system (ANFIS) for stock index forecasting. In the proposed model, stepwise regression was first applied for the objective selection of technical indicators and then combined with ANFIS to construct the forecasting model. We evaluated the performance of our proposed model against three other models, with transaction data from the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and the Hong Kong Hang Seng Index (HSI) stock markets from 1998 to 2006 as experimental data sets and the root mean square error (RMSE) as the evaluation criterion. The results show the superiority of the proposed combined model, which outperformed other models in terms of RMSE and profitability, with strategies for increasing long-term uses of stock index forecasts made on the TAIEX and the HSI.

Keywords Time series · Technical indicator · Adaptive network-based fuzzy inference system · Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) · Hang Seng Index (HSI)

1 Introduction

Identifying the best time to buy or sell a stock or index is a challenge. One must consider, particularly for stock indices, the numerous factors that could affect the stock price or index in stock markets. Thus, making accurate stock index forecasts is an interesting and important topic for parties such as stock investors, stock fund managers, financial analysts, dealers, and brokers. Each party attempts to make stock index forecasts either subjectively, based on their personal feelings/professional background, or objectively, with the assistance of stock analysis techniques/software. Although many techniques have been developed to improve stock index forecasts to date, there is still no model that is suitable across various types of data and applications. The development of a more efficient model for stock index forecasting continues to be a priority. Because investing in stock indices involves making predictions for the purpose of obtaining profits, even a slight improvement in forecasting accuracy may yield considerably better returns. Hence,

✉ You-Shyang Chen
ys_chen@cc.hwh.edu.tw

1 Department of Information Management, Hwa Hsia University of Technology, No. 111, Gongzhuan Rd., Zhonghe District, New Taipei City 235, Taiwan, Republic of China

2 Department of Information Management, National Yunlin University of Science and Technology, 123, University Road, Section 3, Douliou, Yunlin 64002, Taiwan, Republic of China

3 Department of Business Administration, Hwa Hsia University of Technology, No. 111, Gongzhuan Rd., Zhonghe District, New Taipei City 235, Taiwan, Republic of China

Published online: 24 February 2016

there is a continual demand for effective and efficient forecasting models to increase the profitability of stock market investments by reducing losses.

Several forecasting models based on time series approaches have been developed. First, the autoregressive integrated moving average (ARIMA) [1], based on conventional statistical methods, has been used extensively for the construction of forecasting models. Unfortunately, due to nonlinear issues associated with these statistical methods, variables must strictly obey the restrictive assumptions of linear separability or normal distribution [2]. To overcome these limitations, researchers have proposed computational intelligence techniques to address issues with nonlinearity in the field of stock forecasting. Kimoto et al. [3] developed a system to make predictions about the stock market using neural networks (NNs). Roh [4] integrated the NN technique with a time series model to forecast the volatility of stock price indices. Chen et al. [5] proposed a comprehensive fuzzy time series, which takes into consideration linear input/output relationships between recent periods of stock prices and nonlinear relationships on fuzzy logical relationships (FLR) of time series data. For nonlinear forecasting models, artificial neural networks (ANNs) prevail in well-known models for stock price forecasting [3–5]. Although ANNs have demonstrated robust and satisfactory results in application studies [6–8], the applicable input factors of ANNs are rarely identified and selected [9], and the rules generated from ANNs are not easily understandable [5]. Basically, ANNs are suitable on an environment with a deterministic setting [10]; in other words, ANNs retain the disadvantage of being incapable of modeling an uncertain input–output variable. Thus, an adaptive network-based fuzzy inference system (ANFIS), which is an advanced variety of ANN that is able to define the issues not dealt with by the ANNs, is of priority concern. To ascertain its benefits, the ANFIS-based model is the focus of this study. Nevertheless, the potential input factors that influence a stock index are complex and multiple, and negative factors can degrade forecasting performance. Thus, it is necessary to first select significant factors to improve the quality of the forecasting model. Attribute selection refers to the technique of selecting a subset of relevant factors (or attributes) to remove irrelevant or redundant factors. Doing so improves the performance of forecasting models and enables the building of robust learning models from a large set of factor-related data, which is clearly the case in the stock market.

Often, stock investors may make decisions that are subjective or not scientific. Two well-known methods—fundamental analysis and technical analysis— have typically been used to aid investors to make decisions more objectively and scientifically [11]. Briefly, technical analysis is preferred for short-run prediction, whereas fundamental analysis is widely used for intermediate- and long-term investment planning. In this study, we use technical analysis indictors as input factors to forecast stock indices for intermediate or long-term investment. Technical indicators constitute important tools in the analysis of patterns and trends in stock prices [12, 13]. Critically, the fluctuation of stock indices in the stock market involves time series, nonlinearity, and non-stationary signal processing, given the varied nature of factors and data characteristics. Thus, it is vital to develop an intelligent model to help investors make stock index forecasts. Although various forecasting models have been proposed, there have been four main drawbacks, as follows: (1) some of the previous work regarding the selection of important technical indicators as input factors has depended on subjective experiences or opinions; (2) conventional methods may entail restrictive assumptions, of linear separability or normality, regarding the variables used in the analysis; (3) most conventional time series models consider only one variable; and (4) input factors are not easy to identify and understand for ANNs that always accommodate the deterministic setting; however, stock markets are full of uncertainty in the real world. Given these limitations, we aim to establish a forecasting model that allows effective stock index forecasting. Thus, the objectives of this study are as follows. (1) Use stepwise regression to identify important technical indicators as input factors. (2) Integrate additional technical factors from the stock market to improve forecasting performance. (3) Build an ANFIS-based model for the development of intelligent systems to deal with uncertainty and to make stock index forecasts accurately. (4) Provide effective guidelines to help investors to time their buying/selling of stock indices.

The rest of this paper is organized as follows. Section 2 presents a review of the relevant literature. Section 3 provides the framework of the proposed model and introduces the major concepts and algorithm. Section 4 presents a verification of the proposed model based on real data and comparisons with other models. Finally, the conclusions of the study are drawn in Section 5.

2 Literature review

In this section, we discuss the related literature regarding technical indicators, time series models, subtractive clustering, and adaptive network-based fuzzy inference systems.

2.1 Technical indicator

Based on mathematical calculations, a technical indicator is a graphic representation of price action in relation to past trading price and/or volume behavior [14], which guides the trading decisions made in financial markets, such as stock markets. Typically, values obtained from a technical indicator are used to forecast probable prices or index changes (movements) [15], and trading decisions are made by applying simple rules based on the historical price and volume data. In particular, it is very important to understand that, by taking actions based on predictions about future development, the actions of market participants actually drive price movement. In addition, technical indicators help filter out the noise in price movements and constitute a good way to obtain an alternate view of the price. Based on prior research [12], the technical indicator has become one of the most popular methods that stock investors use to make forecasts about stock indices. In addition, researchers have focused on technical indicators to improve the investment return, given the highly nonlinear and uncertain nature of stock market processes [16, 17]. Technical indicators fill the knowledge gap of market information and are used to account for all the necessary factors in stock exchange formation [18]. Many types of technical indicators, such as volumes, oscillators, trend indicators, and Bill Williams, have been developed. Examples of technical indicators include moving averages (MA), moving average convergence/divergence (MACD), and relative strength index (RSI). Based on previous work [19], a list of important technical indicators is shown in Table 1.

Murphy [22] noted three premises underlying the technical indicator. (1) **Market action discounts everything**: The

Table 1 Technical indicators from previous studies

Indicator	Description
MA5	The MA (moving average) is used to emphasize the direction of a trend and to smooth out price and volume fluctuations. MA5 (5-day moving average) $= \frac{P_c + P_{c-1} + \cdots + P_{c-4}}{5}$, and P_c is the closing index of the current day [20].
MA10	MA10 (10-day moving average) $= \frac{P_c + P_{c-1} + \cdots + P_{c-9}}{10}$, and P_c is the closing index of the current day [20].
BIAS5	BIAS (bias to moving average) is an enveloped moving average indicator, and it consists of a moving average plus and minus a percent deviation. BIAS5 refers to the difference between the closing value and MA5, which uses the tendency for stock prices to return to the mean to analyze the stock market [18].
BIAS10	BIAS10 is the difference between the closing value and MA10, which uses the tendency for stock prices to return to the mean to analyze the stock market [18].
RSI	RSI (relative strength index) measures the velocity and magnitude of directional price movements and compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset or stock market [18].
PSY12	PSY12 (12-day psychological line) = $(D_{up12}/12)$*100, D_{up12} refers to the number of days on which the price has gone up within 12 days [20]. PSY is a technical indicator and is the ratio of the number of rising periods over the total number of periods; it can reflect the buying power in relation to the selling power.
WMS%R10	WMS%R10 or called Williams%R10 (10-day Williams overbought/oversold index) is usually plotted using negative values. For the purpose of analysis and discussion, simply ignore the negative symbols. It is best to wait for the security price to change direction before placing your trades [18].
MACD9	MACD (moving average convergence/divergence) displays trends that follow characteristics and display momentum characteristics. MACD9 is the difference between fast and slow exponential moving averages (EMA) of closing prices for 9 days. Fast refers to a short-range average, and slow refers to a long-period one [18].
MO1	$MO1(t) = price(t) - price(t-n), n = 1$ [21]. MO (momentum) measures how much a securities price has changed over a given time span and displays the rate-of-change of a stock price.
MO2	$MO2(t) = price(t) - price(t-n), n = 2$ [21].
DIFN	$DIFN(t) = TAIEX(t) - NASDAQ(t)$, NASDAQ: NASDAQ Composite Index.
DIFT	$DIFT(t) = TAIEX(t) - TAIFEX(t)$, TAIFEX: Taiwan Futures Exchange Index.
DIFD	$DIFD(t) = TAIEX(t) - DJIA(t)$, DJIA: USA Dow Jones Industrial Average Index.

price action is assumed to reflect shifts in demand and supply, which is the basis for all economic and fundamental analyses, with everything that affects the market price ultimately reflected in the market price itself. (2) **Prices follow trends**: Almost all technical systems that aim to identify trends and trading are based on the assumption that a trend in motion is more likely to continue than to reverse. (3) **History repeats itself**: This premise is derived from the study of human psychology, which does not typically change over time. A behavioral perspective allows the identification of chart patterns that recur over time, revealing traits of a bullish or bearish market psychology. In particular, the selection of technical indicators to be used in prediction models will depend on the following factors [23]: (1) The availability of the data, (2) the sufficiency of the historical databases for machine learning and the system testing process, (3) the relevance of the indicators to the price, (4) the periodicity of the data (daily, weekly, monthly, and annually), and (5) the reliability of the historical data on financial market volatility.

2.2 Time series model

A time series is a continuous set of observations of well-defined data items obtained through repeated measurements over time. Time series analysis is a type of computational analysis used to extract meaningful statistical outcomes and characteristics of the data. Time series forecasting, in turn, applies time series analysis to the prediction of future values based on previously observed values. In practice, time series forecasting models have numerous applications across many areas, including finance, business, computer science, physics, chemistry, and interdisciplinary fields.

The development of time series forecasting models [24] has continued over several decades. Initially, Box and Jenkins [1] integrated traditional statistical methods, autoregressive models (AR), moving average (MA), and ARMA (a combination of AR and MA) models to create the ARIMA method for stock index forecasting. The linear ARIMA model is used when the time series data are stationary with no missing data [25] and constrained as linear functions of past observations. In other words, ARIMA represents an unsatisfactory solution in nonlinear time series for forecasting systems. To overcome the linear limitation of time series models, artificial intelligence (AI) nonlinear models have been designed, such as the ANNs and support vector machines (SVMs), which have been successfully used to develop nonlinear models for forecasting time series data [26]. First, ANNs perform well in dealing with raw data, where fuzzy logic uses linguistic information to justify the reasoning ability. Second, a main advantage of the ANNs technique is that it does not require information about the complex nature under consideration to be explicitly described in mathematical form [27]. Generally, ANNs have some advantages when compared with other methods for classification, based on their low classification error rates, robustness to noise, and are best with numerical data [28]. Third, SVMs are capable of handling the uncertainties in the model inputs and have probabilities outputs and can have good generalization ability, especially for small sample data; the SVMs thus successfully solve the over-learning problem in the ANNs. Furthermore, Li et al. [29] proposed a dynamic prediction model of surface movements based on the theory of SVMs and time series analysis to study dynamic laws in coal-mining activities. Obviously, the above nonlinear time series approaches yield better results than the linear ARIMA model.

Recent years have seen the proposal of various fuzzy time series methods that apply classical fuzzy set theory to complex matrix operations. Subsequently, Chen [30] presented a new fuzzy time series method to forecast university enrollments and Chen et al. [5] proposed a comprehensive fuzzy time series for forecasting processes. Fuzzy time series forecasting methods include high-order fuzzy time series models, bivariate fuzzy time series models, and multivariate fuzzy time series models. Moreover, Jha and Sinha [31] used the feed-forward time-delay neural network (TDNN) model to process agricultural price forecasting for the potential methods on time series prediction.

2.3 Subtractive clustering

Subtractive clustering— a type of fuzzy clustering— serves to estimate both the number and initial locations of cluster centers, with each data point assumed to be a potential cluster center. The method calculates the likelihood for each data point to define the cluster center based on the density of the surrounding data points [32]. The subtractive clustering algorithm is as follows.

(1) Consider N data points of a set T in a $D-$dimensional hyper-space for each data point $W_i (i = 1, 2, \ldots, N)$. For the $W_i = (x_i, y_i)$, x_i denotes the input variables, and y_i is the output variable. A potential value P_i of the data point is calculated by (1):

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

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

(2) Choose the data point with as many neighboring data points as the first cluster center. To generate other cluster centers, the potential P_i is revised at each data point W_i by (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, which has measurable reductions in potential, W_1^* is the first cluster center, and P_1^* is its potential value.

(3) Based on (2), the data point with the highest remaining potential is selected as the second cluster center. Thus, (2) can be rewritten as (3) as follows.

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

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

(4) Finally, the subtractive clustering method yields q cluster centers and D corresponding spreads S_i, $i = (1, \ldots, D)$. Next, the membership functions (MF) are defined and the spread is calculated based on β.

2.4 Adaptive network-based fuzzy inference system

Based on fuzzy if-then rules for knowledge discovery and inference procedures, the fuzzy inference system (FIS) enables qualitative description and analysis but does not offer accurate quantitative analyses or auto-correction of values. In contrast, ANNs [33] offer excellent self-learning ability and organizational skills but cannot deal with qualitative data and logical inference. ANFIS [34] combines the FIS and ANN to improve both the capability of the system and the ability to process uncertain and imprecise data via self-learning and the organizational capacity to adjust the parameters of the models. ANFIS has been successfully applied to tackle classification tasks, rule-based process controls, and pattern recognition problems. Cheng et al. [35] proposed a fusion ANFIS model based on multi-stock volatility causality for addressing stock price forecasting problems in Taiwan. Chang et al. [36] proposed a hybrid adaptive network-based FIS model based on the AR and volatility to forecast the stock price of the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX). Khalaj and Khalaj [37] used an ANFIS-based model for predicting the layer thickness of duplex coating of steel specimens and showed a strong potential. Ocak and Ertunc [38] proposed an ANFIS-based method for the prediction of the fetal state from the fetal heart rate and the uterine contraction signals obtained from cardiotocogram recordings. Deneme [39] presented a development of an ANFIS model for estimating the modal damping ratio of impact-damped flexible beams. Uçar et al. [40] used the Sugeno-type ANFIS and rough sets to predict the existence of mycobacterium tuberculosis. The architecture of ANFIS is shown in Fig. 1.

A demonstration of this system begins with two inputs, x and y, and the output z. Next, based on Takagi and Sugeno's type [41], the system consists of two fuzzy if-then rules as follows:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$,
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$.

The node in the formation of the *i-th* position of the *k-th* 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 (4)). $O_{1,i}$ is the membership function of A_i and specifies the degree to which the given x satisfies the quantifier A_i. The bell-shaped membership function is usually selected as the input membership function with a maximum of 1 and a minimum of 0 (see (5)).

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

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

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

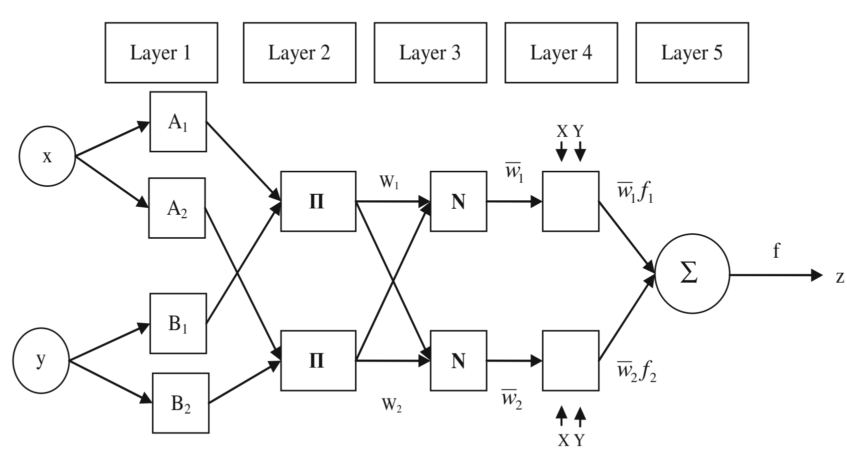


Fig. 1 The architecture of the ANFIS network

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

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

Layer 3: Every node i in this layer is a square node labeled N. The *i-th* node calculates the ratio of the firing strength of the *i-th* rule to the sum of firing strengths of all rules by (7). The output of this layer is referred to as the normalized firing strength.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \text{ for } i = 1, 2 \tag{7}$$

Layer 4: Every node i in this layer is a square node with a node function (see (8)). Its function parameters in this layer will be referred to as consequent parameters.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \tag{8}$$

where p_i, q_i, and r_i are all function parameters.

Layer 5: The single node in this layer is a circle node, labeled Σ, which computes the summation of all incoming signals as the overall output (see (9)).

$$\text{Overall output } = O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_{i=1} w_i f}{\sum_{i=1} w_i}. \tag{9}$$

Although merging the ANNs with the FIS has resulted in the development of intelligent systems for the ANFIS, the performance of AI techniques is highly related with the specific context, the specific data, or the specific field of application [42]. As for the classification performance of the ANFIS compared to ANNs, FIS, and SVMs, it is very difficult to objectively compare different approaches if there are no arbitral output values of the system from earlier literature [43]; thus, two directions are defined. First, Mahjoobi et al. [44] compared the results of ANNs, FIS, and ANFIS in a wave prediction problem in Lake Ontario. They demonstrated that ANFIS could provide more accurate results than FIS and ANNs and showed the superiority of ANFIS. Thus, ANFIS mostly has more advantages than those of ANNs and FIS from previous studies. Second, from the study by Ali et al. [43] under the context of a QOS case, the ANFIS, ANNs, and FIS have close values for mean square error (MSE), but SVMs have a greater value of MSE; the ANFIS and ANNs have a positive aspect of zero flatness; the implementation complexity for the ANFIS, ANNs, and FIS is moderate; however, the computation time is greater and implementation is more difficult for the SVMs than the other three methods. In general, it can be concluded that the accuracy of the ANFIS, ANNs, and SVMs is nearly the same and they show promising results. However, case by case, some papers show the evidence of the superiority of SVMs over ANFIS and ANNs. In this study, it can be concluded with certainty that the superiority of ANFIS is shown by the evidence that it has the main advantage of providing fuzzy if-then rules to model the quantitative aspect of human knowledge and reasoning processes. Conclusively, the ANFIS-based model has more advantages than ANNs, FIS, and SVMs in knowledge discovery and reasoning representation in the fields of application.

3 The proposed model

In this section, we present details of the methodology concerning the concept and algorithm of the proposed model. Typically, a methodology comprises the theoretical analysis of quantitative or qualitative techniques associated with an application field of study and principles addressed to a branch of knowledge. Thus, five elements, namely, subjects, apparatus, measures, data, and techniques, are identified in this study. First, for the subjects, the problem of weighted stock indexes from the Taiwan and Hong Kong financial markets is addressed. Second, this study presents a hybrid model to solve such a problem. Third, various measures of technical indicators are regarded as input variables. Fourth, the daily transaction data of the Taiwan and Hong Kong stock indexes are collected. Last, an ANFIS-based time series model is incorporated with multiple factors and technical indicators to benefit practitioners, researchers, and other decision makers.

3.1 Concept of the proposed model

To overcome the drawbacks of traditional statistics methods and specific nonlinear models, we have developed a variation on the time series forecasting model that incorporates multiple factors and technique indicators into the ANFIS method to improve the stock index forecasting performance of the proposed model. Importantly, ANFIS has a high speed of training, the most effective learning algorithm and is simple in terms of its structure [45]. Furthermore, ANFIS has advantages of intelligent forecasting, such as producing easily understood decision rules for human knowledge, a well-compatible input and output for mapping stock data, no requirement for prior information on stock nonlinear and non-stationary characteristics, and having low time complexity. From the limited literature, the knowledge gap regarding the identification of ANFIS-based models and factors of classification models related to stock index forecasting remains to be further filled and identified from time to time; thus, this study aims to fill the gaps for the proposed model. The model consists of three phases. First, we conducted stepwise regression to identify potential technical indicators with the largest partial correlation coefficient of independent variables to dependent variables. Second, we transformed investor knowledge into fuzzy if-then rules, which are aggregated to form the

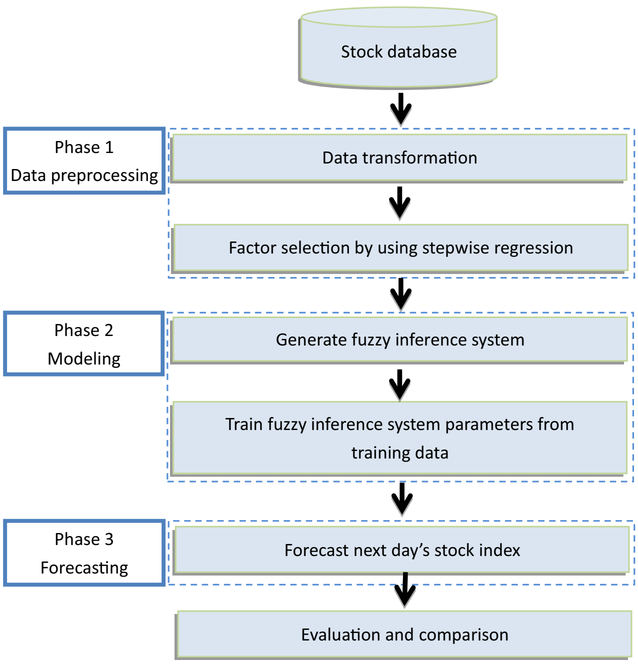


Fig. 2 Research flowchart of the proposed model

FIS. Finally, the ANFIS method optimizes FIS parameters using adaptive networks. To verify the forecasting performance of the model, the forecasting results of our model are compared with other forecasting models, with the root mean square error (RMSE) as the evaluation criterion. The research procedures are shown in Fig. 2.

3.2 The proposed algorithm

The computational algorithm used in the proposed model to address stock indices is implemented step by step.

Step 1: Transform the relevant stock index data into pre-selected technical indicators.
This step transforms the daily transaction values of basic variables (i.e., open, close, highest, lowest prices, and trading volume) into the pre-selected technical indicators [18], such as the MA, PSY, RSI, BIAS, WMS%R, MACD, and other potential indicators [19] including the momentum of stock price, the difference between the TAIEX and NASDAQ (National Association of Securities Dealers Automated Quotation) composite index, the difference between the TAIEX and Taiwan Futures Exchange (TAIFEX) index, and the difference between TAIEX and the exchange rate of NTD (new Taiwan dollar) to USD (the United States dollar). These technical indicators are listed in Table 1.

Step 2: Select the important indicators using stepwise regression.
Run stepwise regression to identify the largest partial correlation coefficients of the dependent variable. Stepwise regression is a semi-automated process of building a forecasting model by successively adding relevant variables or removing irrelevant variables based on the t-statistics of the estimated coefficients. The procedure results in the selection of important indicators.

Step 3: Build ANFIS forecasting model.
This step uses subtractive clustering [32] to partition the universe of discourse of input variables from training data sets and generate the FIS to construct the ANFIS-based forecasting model. The process is divided into four sub-steps, as follows:

Step 3.1: Partition the universe of discourse for input variables.
First, define the universe of discourse based on the minimum and maximum values of each input variable from training data sets. Next, partition the universe of discourse by subtractive clustering [32] (Gaussian membership function).

Step 3.2: Set membership function to output variables.
This step uses a linear membership function to output variables. For example, for a 2002-year TAIEX data set, three inputs X_{t-1}, Y_{t-1}, and Z_{t-1} are defined, and the three input variables are partitioned into three linguistic intervals by subtractive clustering. Therefore, a typical rule in the fuzzy forecasting model in Takagi and Sugeno [41] is described as follows:

$$\begin{aligned} \text{If } x(X_{t-1}) &= A_i, \\ y(X_{t-1}) &= B_i, \text{ and} \\ z(X_{t-1}) &= C_i, \text{ then} \\ f_i(X_t) &= p_i x + q_i y + r_i z + s_i. \end{aligned}$$

where $x(X_{t-1})$, $y(X_{t-1})$, and $z(X_{t-1})$ are three linguistic variables, A_i, B_i, and C_i are the three linguistic values (such as low, middle, and high), $f_i(X_t)$ denotes the i-th output value, and all p_i, q_i, r_i, and s_i are the function parameters ($i = 1, 2, 3$). The first three parameters p_i, q_i, and r_i are the

Table 2 Selected factors based on stepwise regression from the TAIEX data set

Year	Factor1	Factor2	Factor3
1998	MA5	DIFN	DIFT
1999	MA5	BIAS5	DIFD
2000	MA5	BIAS5	WMS%R10
2001	MA5	BIAS5	DIFT
2002	MA5	BIAS5	RSI
2003	MA5	BIAS5	WMS%R10
2004	MA5	BIAS5	DIFT
2005	MA5	BIAS5	WMS%R10
2006	MA5	BIAS5	PSY12

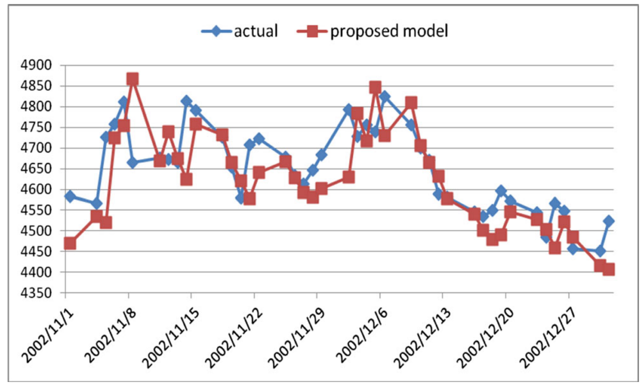


Fig. 3 Forecasting results for a TAIEX sub-data set from 2002/11/01 to 2002/12/31

coefficient of x, y, and z for the output function, respectively, and the last one s_i is a constant term of the output function.

Step 3.3: Generate the FIS.

After Steps 3.1 and 3.2, the resultant linguistic intervals are used as the membership functions of the input and output variables, respectively. Next, generate fuzzy if-then rules, where the linguistic values (A_i, B_i, and C_i) (e.g., low, middle, and high) from the membership functions of the input variables are used as the *if* condition, and the membership functions ($f_i(X_t)$) of the output variables constitute the *then* outcome. The 'three' generated rules for the 'three' linguistic intervals are described below.

Rule 1 (Low): If $x(X_{t-1}) = A_{low}$, $y(X_{t-1}) = B_{low}$, and $z(X_{t-1}) = C_{low}$, then $f_{low}(X_t) = p_{low}x + q_{low}y + r_{low}z + s_{low}$.

Rule 2 (Middle): If $x(X_{t-1}) = A_{middle}$, $y(X_{t-1}) = B_{middle}$, and $z(X_{t-1}) = C_{middle}$, then $f_{middle}(X_t) = p_{middle}x + q_{middle}y + r_{middle}z + s_{middle}$.

Rule 3 (High): If $x(X_{t-1}) = A_{high}$, $y(X_{t-1}) = B_{high}$, and $z(X_{t-1}) = C_{high}$, then $f_{high}(X_t) = p_{high}x + q_{high}y + r_{high}z + s_{high}$.

Step 3.4: Train the function parameters of the FIS.

This step employs the least-squares (LS) method and the back-propagation gradient descent method to train the function parameters of the generated

Table 3 The generated forecasts for a TAIEX sub-data set in 2002

Date	Practice(t)	Forecast($t+1$)
2002/1/2	5600.05	5590.78
2002/1/3	5526.32	5538.95
2002/1/4	5638.53	5659.99
2002/1/7	5834.89	5810.50
2002/1/8	5810.08	5832.06
2002/1/9	5865.54	5892.39
2002/1/10	5871.28	5884.34
2002/1/11	5687.59	5688.76
2002/1/14	5611.86	5583.86
2002/1/15	5592.74	5571.51
⋮	⋮	⋮

Table 4 Selected factors based on stepwise regression from the HSI data set

Year	Factor1	Factor2	Factor3
1998	MA5	BIAS5	DIFN
1999	MA5	BIAS5	MO1
2000	MA5	BIAS5	BIAS10
2001	MA5	BIAS5	WMS%R10
2002	MA5	BIAS5	BIAS10
2003	MA5	BIAS5	DIFN
2004	MA5	BIAS5	WMS%R10
2005	MA5	BIAS5	DIFT
2006	MA5	BIAS5	DIFT

Table 5 The generated forecasts for an HSI sub-data set in 2002

Date	Practice(t)	Forecast($t+1$)
2002/1/2	11350.85	11351.45
2002/1/3	11423.52	11442.88
2002/1/4	11702.15	11715.0
2002/1/7	11892.64	11803.75
2002/1/8	11713.71	11688.91
2002/1/9	11440.72	11389.03
2002/1/10	11256.07	11175.51
2002/1/11	11166.46	11105.16
2002/1/14	11209.43	11153.86
2002/1/15	11013.59	10986.47
⋮	⋮	⋮

FIS. The training process is executed for the predetermined number of iterations unless the process terminates early as training error accumulates. Thus, set 100 epochs for the termination criterion of this training process for it to obtain the optimal parameters for the selected membership function of output variables. As a result, the ANFIS-based forecasting model is built.

Step 4: Test stock index on next day.
The trained ANFIS-based forecasting model is used to test (or forecast) the stock index on the next day after testing the data sets.

Step 5: Evaluate the performance of the model.
To evaluate the forecasting performance of the proposed model, the RMSE (see (10)) is employed as the evaluation criterion in testing the data sets, and the proposed model is compared against three other forecasting models (developed by Chen [30], Chen and Chen [46], and Yu [47], respectively), which are selected given their strong performance in stock index forecasting.

$$\textbf{RMSE} = \left(\frac{1}{n}\sum_{t=1}^{n}(y_t - \tilde{y}_t)^2\right)^{\frac{1}{2}} \tag{10}$$

where y_t denotes the real stock index value at time t, $\tilde{y}_t$ denotes the forecasting stock index value at time t, and n is the number of sample data.

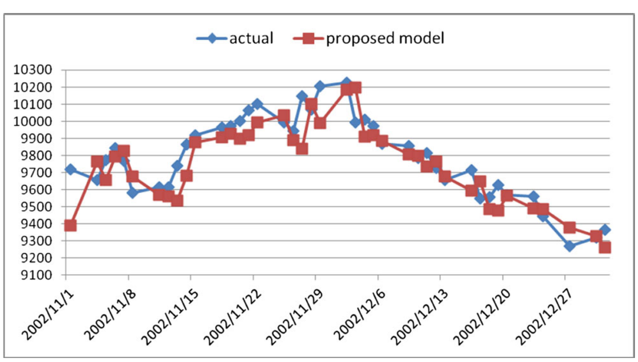


Fig. 4 Forecasting results for the HSI sub-data set from 2002/11/01 to 2002/12/31

Table 6 Forecasting performance for the TAIEX data set

Training	Testing	RMSE
1998/01∼1998/10	1998/11∼1998/12	147.59
1999/01∼1999/10	1999/11∼1999/12	115.58
2000/01∼2000/10	2000/11∼2000/12	180.03
2001/01∼2001/10	2001/11∼2001/12	133.59
2002/01∼2002/10	2002/11∼2002/12	81.11
2003/01∼2003/10	2003/11∼2003/12	77.31
2004/01∼2004/10	2004/11∼2004/12	56.44
2005/01∼2005/10	2005/11∼2005/12	55.97
2006/01∼2006/10	2006/11∼2006/12	77.03

4 Experiments and comparisons

To evaluate the forecasting performance of the proposed model, we used two experimental data sets, the TAIEX and the Hong Kong Hang Seng Index (HSI), and a set of technical indicators, as shown in Table 1. The performance of the proposed model is compared against that of the models developed by Chen [30], Chen and Chen [46], and Yu [47], respectively.

4.1 The TAIEX data set

The experimental TAIEX data set contains the transaction data of the TAIEX stock index between 1998 and 2006.

Table 7 Forecasting performance for the HSI data set

Training	Testing	RMSE
1998/01∼1998/10	1998/11∼1998/12	310.28
1999/01∼1999/10	1999/11∼1999/12	372.97
2000/01∼2000/10	2000/11∼2000/12	256.61
2001/01∼2001/10	2001/11∼2001/12	298.39
2002/01∼2002/10	2002/11∼2002/12	118.27
2003/01∼2003/10	2003/11∼2003/12	132.67
2004/01∼2004/10	2004/11∼2004/12	111.92
2005/01∼2005/10	2005/11∼2005/12	154.67
2006/01∼2006/10	2006/11∼2006/12	191.0

Table 8 Performance comparisons for the TAIEX data set

Testing	RMSE			
	Chen's model [30]	Chen and Chen's model [46]	Yu's model [47]	The proposed model
1998/11∼1998/12	152.14	143.75	141.56[a]	147.59
1999/11∼1999/12	190.11	96.04[a]	112.99	115.58
2000/11∼2000/12	353.0	213.91	175.63[a]	180.03
2001/11∼2001/12	165.31	142.39	134.39	133.59[a]
2002/11∼2002/12	139.64	82.35	91.43	81.11[a]
2003/11∼2003/12	103.96	94.48	68.07[a]	77.31
2004/11∼2004/12	82.32	194.87	72.34	56.44[a]
2005/11∼2005/12	86.12	58.89	62.52	55.97[a]
2006/11∼2006/12	215.64	129.77	83.92	77.03[a]

[a]The best performance among the four models

Given that the training period occurred in the first ten months of each year and the testing period in the final two months of the same year, there are nine sub-data sets from 1998 to 2006. To demonstrate the proposed model using examples, we randomly selected data for the 244 transactions in TAIEX in 2002. First, stepwise regression revealed three important technical indicators (MA5, BAIS5, and RSI) in 2002. Table 2 lists the important technical indicators from the TAIEX data set in 1998–2006. Second, the technical indicators were used as input factors for testing the trained ANFIS-based forecasting model to generate the forecasts (or forecasting values) shown in Table 3. The testing (forecasting) results of the TAIEX sub-data set from testing period 2002/11/01 to 2002/12/31 are shown in Fig. 3, with an RMSE of 81.11.

4.2 HSI data set

To further validate the proposed model, we tested the model based on an additional data set: the HSI transaction data collected from the Hong Kong stock market in the same period (1998–2006). Similar to the TAIEX, there are also nine sub-data sets in the HSI given that the training period occurred in the first ten months of each year and the testing period occurred in the final two months of the same year. The 247 daily transaction data in 2002 are used as examples to verify the proposed model. First, stepwise regression revealed three important technical indicators (MA5, BIAS5, and BIAS10) in 2002. Table 4 presents the important technical indicators from the HSI data set in 1998–2006. Second, the three technical indicators were used as input factors to

Table 9 Performance comparisons for the HSI data set

Testing	RMSE			
	Chen's model [30]	Chen and Chen's model [46]	Yu's model [47]	The proposed model
1998/11∼1998/12	279.67	270.08	250.47[a]	310.28
1999/11∼1999/12	491.85	389.64	269.03[a]	372.97
2000/11∼2000/12	315.13	281.47	341.80	256.61[a]
2001/11∼2001/12	261.70[a]	367.30	281.46	298.39
2002/11∼2002/12	183.45	79.36[a]	138.90	118.27
2003/11∼2003/12	337.82	197.90	172.87	132.67[a]
2004/11∼2004/12	280.24	205.31	139.82	111.92[a]
2005/11∼2005/12	117.70	183.69	112.60[a]	154.67
2006/11∼2006/12	270.39	198.72	185.93[a]	191.0

[a]The best performance among the four models

Table 10 Wilcoxon test on the three models for the TAIEX data set in 1998–2006

Method	1998	1999	2000	2001	2002	2003	2004	2005	2006	Total
The proposed model vs. Chen's model [30]	0	1	1	1	1	1	1	1	1	8
The proposed model vs. Chen and Chen's model [46]	0	−1	1	1	0	1	1	0	1	4
The proposed model vs. Yu's model [47]	0	0	0	0	1	−1	1	1	1	3
Chen and Chen's model [46] vs. Chen's model [30]	1	1	1	1	1	1	−1	1	1	7
Chen and Chen's model [46] vs. Yu's model [47]	0	1	−1	−1	1	−1	−1	1	−1	−2
Chen's model [30] vs. Yu's model [47]	−1	−1	−1	−1	−1	−1	−1	−1	−1	−8

test the trained ANFIS-based forecasting model to generate the forecasts shown in Table 5. The forecasting results from the HSI sub-data set in 2002/11/01 to 2002/12/31 are shown in Fig. 4, with an RMSE of 118.27.

4.3 Comparisons

In the same way, we extrapolated the analysis across all TAIEX and HSI sub-data sets in the 1998–2006 period. The results of the proposed model, in terms of RMSE, are presented for the TAIEX and HSI sub-data sets in Tables 6 and 7, respectively.

To reexamine the forecasting performance of the proposed model, this study compares the proposed model with two other similar fuzzy time series models developed by Chen [30] and Yu [47], respectively. Furthermore, this study further adds a later study, by Chen and Chen [46], for a comprehensive comparison. The comparison results (in terms of RMSE) for the TAIEX and HSI data sets are presented in Tables 8 and 9, respectively.

Table 8 shows that, based on the RMSE as the evaluation criterion, the proposed model provides the best performance in five TAIEX sub-data sets (2001, 2002, and 2004–2006), with the model developed by Chen and Chen [46] performing the best in 1999 and the model developed by Yu [47] performing the best in 1998, 2000, and 2003. Likewise, Table 9 shows that the proposed model provides the best performance in three HSI sub-data sets (2000, 2003, and 2004), with the model developed by Chen and Chen [46] performing the best in 2002, the model developed by Chen [30] performing the best in 2001, and the model developed by Yu [47] performing the best in 1998, 1999, 2005, and 2006.

The Wilcoxon signed-rank test is a non-parametric test developed to analyze data from studies that include two repeated measures or related independent samples to assess whether their population mean ranks differ when the populations are not necessarily normally distributed [48]. In this study, we reject the null hypothesis when the Wilcoxon statistic exceeds or equals the critical value for a two-tailed test with a significance level of 0.05. Tables 10 and 11 summarize the results of the Wilcoxon test under the proposed model with the three listed models in the TAIEX and HSI data sets, respectively. In Tables 10 and 11, the values 1, 0, and −1 indicate that the first method outperformed, performed equally to, or underperformed the other method in having a 95 % confidence interval for a two-tailed test, respectively. The Wilcoxon results are based on the column 'Total' and reported in five directions from Tables 10 and 11. (1) Based on the TAIEX and HSI data from 1998 to 2006, the proposed model outperforms the models developed by Chen [30] and Chen and Chen [46]. (2) Based on the TAIEX data from 1998 to 2006, the proposed model outperforms the model developed by Yu [47], and the proposed model yields comparable results with Yu [47] in the HSI data from 1998 to 2006. In particular, regarding the comparable results, it is thus necessary to further conduct a profitability measurement in the next subsection. (3) Chen and Chen's model [46] has a better forecasting performance than Chen's model [30] in both the TAIEX and HSI data. (4) Chen and Chen's model [46] has a worse forecasting performance than Yu's model [47] in the TAIEX and HSI data.

Table 11 Wilcoxon test on the three models for the HSI data set in 1998–2006

Method	1998	1999	2000	2001	2002	2003	2004	2005	2006	Total
The proposed model vs. Chen's model [30]	−1	1	1	1	1	1	1	−1	1	5
The proposed model vs. Chen and Chen's model [46]	−1	0	1	1	−1	1	1	1	0	3
The proposed model vs. Yu's model [47]	−1	−1	1	−1	1	1	1	−1	0	0
Chen and Chen's model [46] vs. Chen's model [30]	0	1	1	−1	1	1	1	−1	1	4
Chen and Chen's model [46] vs. Yu's model [47]	−1	−1	1	−1	1	−1	−1	−1	−1	−5
Chen's model [30] vs. Yu's model [47]	−1	−1	1	1	−1	−1	−1	0	−1	−4

Table 12 Profitability comparisons for the TAIEX data set

Testing	Profitable unit			
	Chen's model [30]	Chen and Chen's model [46]	Yu's model [47]	The proposed model
1998/11∼1998/12	191.68	−107.44	−64.0	295.16
1999/11∼1999/12	−1045.76	274.52	−1126.5	334.34
2000/11∼2000/12	−348.82	1024.18	512.40	−239.66
2001/11∼2001/12	−1161.98	−675.72	−789.0	319.96
2002/11∼2002/12	576.62	−348.06	−287.72	609.0
2003/11∼2003/12	−460.97	104.29	−343.87	−381.41
2004/11∼2004/12	532.67	189.57	−400.93	218.95
2005/11∼2005/12	468.25	18.55	−157.91	−54.65
2006/11∼2006/12	−375.87	−663.67	−456.23	−383.43
Total	−1624.18	−183.78	−3113.76	718.26[a]

[a]The best performance among the four models

(5) Yu's model [47] outperforms Chen's model [30] in the TAIEX and HSI data.

4.4 Findings

Based on the empirical results above, we present three observations, as follows:

(1) **Economic crisis**: Table 8 shows that all four models performed more poorly in their TAIEX forecasts in 2000 than in other years. This finding can be attributed to the blows sustained by the Taiwan stock market from the bursting of the dot-com bubble [49] and the Taiwan Presidential Election in 2000. For this period, the proposed model performed better than the two comparison models and yields comparable results to those of the model developed by Yu [47] from Table 10. Similarly, Table 9 shows that the proposed model performed better than the three other models in 2000, when the stock market in Hong Kong suffered the negative impact of the dot-com bubble burst [49]. The above examples suggest that, relative to the other models, our model may be more suitably applied to a negative stock market environment.

(2) **Factor selection**: According to Tables 10 and 11, the proposed model mostly performs better in terms of RMSE than the other three models, which consider only a single variable (factor). In contrast, our proposed model first selects important factors objectively by stepwise regression then considers multiple important factors by integrating the ANFIS technique to improve the forecasting performance. Tables 2 and 4

Table 13 Profitability comparisons for the HSI data set

Testing	Profitable unit			
	Chen's model [30]	Chen and Chen's model [46]	Yu's model [47]	The proposed model
1998/11∼1998/12	243.51	−218.11	−627.55	498.99
1999/11∼1999/12	−2030.72	−1548.16	890.78	2302.20
2000/11∼2000/12	506.85	2457.65	−1734.99	1006.19
2001/11∼2001/12	1178.60	−688.54	−639.32	378.70
2002/11∼2002/12	10.72	137.48	399.04	−369.36
2003/11∼2003/12	−288.77	975.77	999.83	1163.47
2004/11∼2004/12	−25.49	−713.99	−697.67	−575.13
2005/11∼2005/12	571.57	196.41	−482.61	209.21
2006/11∼2006/12	358.21	931.91	1312.75	1146.55
Total	524.48	1530.42	−579.74	5760.82[a]

[a]The best performance among the four models

show that the most frequently important indicator factors are MA5 and BIAS5 in both the TAIEX and HSI data sets. In other words, this information clearly indicated that MA5 and BIAS5 strongly influence the daily forecasts of future TAIEX and HSI transaction data.

(3) **Profitability measurement**: In the context of the stock market, while the accuracy of forecasting models is important, examining the profitability of forecasting models is even more crucial for investors because the profitability of investments is a key piece of information. Therefore, we propose a profitable unit equation and the rules of selling/buying time to compare against the listing models. The profitable unit equation is defined as (11), and the best selling and buying rules are formatted as (12) and (13). The profitable unit results are shown in Tables 12 and 13 for the TAIEX and HSI data sets, respectively. Given that stock investments are typically made on the long term and investors often consider long-term goals, forecasting models should also focus on long-term investing profitability. Obviously, the proposed model has significantly the best profitable results under the long-term investing strategy for both the TAIEX and HSI data sets from Tables 12 and 13. In summary, the forecasting performance in terms of profitability is ranked simultaneously in the proposed model → Chen and Chen's model [46] → Chen's model [30] → Yu's model [47] in both the TAIEX and HSI data sets.

$$\text{Profitable unit} = \sum_{t_s=1}^{p}(A(t+1) - A(t)) + \sum_{t_b=1}^{q}(A(t) - A(t+1)), \qquad (11)$$

where $A(t)$ represents the real index at time t, $A(t+1)$ represents the real index at time $(t+1)$, p represents the total number of days for selling, q represents the total number of days for buying, t_s represents the *t-th* day for selling, and t_b is the *t-th* day for buying.

$$\textbf{Selling rule}: \text{ If } forecast(t+1) - actual(t) > 0, \text{ then sell stock on the next day.} \qquad (12)$$

$$\textbf{Buying rule}: \text{ If } forecast(t+1) - actual(t) < 0, \text{ then buy stock on the next day.} \qquad (13)$$

5 Conclusion

In the learning applications of stock and index investments, the investment risk is inseparable from the expected return and is an inherent part of the investment profits. To escape from the investment risk, the long-term profitability becomes a priority concern to interested parties over time, particularly in technical indicator investors. The motivation for this study was thus to propose an instrument for financial applications, which addresses the problem of weighted stock indexes in order to lower the investment risk and reap the investment benefit, to make sure of investing profitability with strategies for increasing long-term uses, and to highlight the advantage of minimal forecasting-RMSE simultaneously for interested parties. In detail, we present an ANFIS-based time series model that incorporates multiple factors and objectively selected technical indicators into a trained ANFIS model to maximize forecasting performance. The daily transaction data of the stock index in the Taiwan and Hong Kong stock markets during the 1998–2006 period were used to test the performance of the model. The empirical results show that our model is effective in improving forecasting performance for both the TAIEX and HSI data sets. Critically, the proposed model offers better forecasting performance (in terms of RMSE and profitability) than the three other fuzzy time series models examined in this work.

Overall, the main contribution and significance of this study therefore is three-fold, as concerns various aspects of academic learning and explanation of the practical applications, including its methodological/managerial contribution and significance, and the novel contribution of relevance to both practitioners and academics, respectively, as follows:

(1) **Methodological contribution and significance**: This study was conducted to propose an improved technique for an ANFIS-based multi-factor time series model to be applied to mine hidden knowledge for stock index forecasting from the TAIEX and HSI data sets when compared to most of the related works in Section 2. The proposed model reflected a new architecture and trial in the stock market field for interested parties and obtained a satisfactory result. In particular, our research on previous studies indicates that the practical application of the proposed model to identify objectively the selection of key technical indicators in various years and then to combine these with ANFIS to construct a forecasting model has still rarely been undertaken using real-life data sets describing the stock index fields in Taiwan and Hong Kong. This study fills the knowledge gaps and sheds light on the importance and significance of these factors, providing the rationale for the proposed model. Thus, this study has a contribution and significance in methodological terms from the academic learning point of view.

(2) **Managerial contribution and significance**: Generally, from the standpoint of the implied empirical results, this study offers the following five values in terms of its management contribution and significance.

First, various key technical indicators were identified in the different years and were discovered and characterized in the two experimental data sets. The proposed model is thus a useful tool to help investors objectively focus on the resources to identify the key technical indicators to satisfy the need for excellent indicator selection, which is required for knowledge discovery and performance assessment, especially in complex stock market domains. Second, in the context of strong financial markets under the specific constraint of the market limits of various countries, the proposed model is still more effective than the three other listed models, and performs well in the circumstances here of experimenting on a period of economic crisis. The positive effect of the application of the proposed model is significant. Third, in real-life management applications, the proposed model yields the advantage of minimum RMSE in the cases of overnight information in the examples and thus has the potential to obtain maximum investment profits and minimum risk losses on long periods for interested parties. Fourth, the proposed model is also resistant to the conditions and effects of a severe stock fluctuation. Last, interested parties can adopt various perspectives during their evaluations to use the proposed model for stock index forecasting. For example, increased investing benefits can restore the organizational reputations of fund managers significantly; for investors, the long-term profitability thereby provides a means of simplifying investment strategy when analyzing investment portfolio management.

(3) **Novel contribution to both practitioners and academicians**: The proposed model demonstrated its strength with promising results in the application fields of the stock market. The proposed model makes a novel contribution for both practitioners and academics to solve the problems of time series models for forecasting the stock index, as follows: (a) For practitioners, it employs the rule-based fuzzy logic used in fuzzy knowledge and reasoning processes to direct investors to forecast up/down cases of stock prices (or the index). (b) For practitioners, it also offers useful knowledge-based references to direct investors to time their stock index buying/selling behaviors accurately. (c) For researchers, it utilizes the Wilcoxon test to show that the proposed model outperforms the other listed models. (d) For researchers, it also has a multi-factor ANFIS-based time series model with the advantage of ANFIS providing an if-then rule, and this is superior to both ANNs and SVMs. (e) For both practitioners and researchers, it objectively integrates and selects the core technical indicators from the stock market to improve the forecasting performance. (f) For both practitioners and researchers, the proposed model calculates the real profitability of the listed models, thus demonstrating its superiority and strength.

Furthermore, this work can be extended in several future directions:

(1) In terms of factor selection, non-quantitative factors (such as breaking news, macroeconomic policies, and significant regulations) can be added to train the model.
(2) Apply the proposed model to different areas of forecasting, such as the forecasting of electric loads, tourism demand, and Information and Communication Technology (ICT) products.
(3) Consider using other AI techniques, such as genetic algorithms (GA) and particle swarm optimization (PSO), to optimize the proposed model.

Acknowledgments The authors would like to thank the Ministry of Science and Technology of the Republic of China, Taiwan, for financially supporting this research under Contract Nos. NSC 102-2410-H-146-003 & MOST 103-2221-E-146-003-MY2. In particular, the author cordially thanks the Editor-in-Chief, associate editor, and anonymous referees for their useful comments and suggestions, which led to significant improvement in the presentation and quality of this study.

References

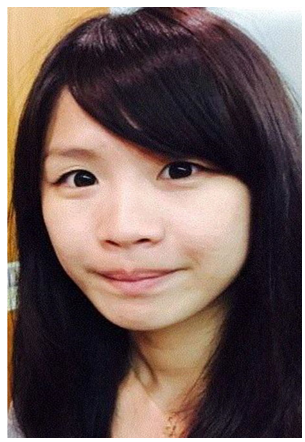
1. Box GEP, Jenkins GM (1976), Time series analysis: forecasting and control. Holden-Day, San Francisco
2. Chen YS (2013) Modeling hybrid rough set-based classification procedures to identify hemodialysis adequacy for end-stage renal disease patients. Comput Biol Med 43(10):1590–1605
3. Kimoto T, Asakawa K, Yoda M, Takeoka M (1990) Stock market prediction system with modular neural network. In: Proceedings of the international joint conference on neural networks, San Diego, pp 1–6
4. Roh TH (2007) Forecasting the volatility of stock price index. Expert Syst Appl 33(4):916–922
5. Chen TL, Cheng CH, Teoh HJ (2008) High-order fuzzy time-series based on multi-period adaptation model for forecasting stock markets. Phys A 387(4):876–888
6. Chen MY, Chen DR, Fan MH, Huang TY (2013) International transmission of stock market movements: an adaptive neuro-fuzzy inference system for analysis of TAIEX forecasting. Neural Comput Appl. doi:10.1007/s00521-013-1461-4
7. Kankal M, Yüksek Ö (2013) Artificial neural network for estimation of harbor oscillation in a cargo harbor basin. Neural Comput Appl. doi:10.1007/s00521-013-1451-6

8. Rezaeianzadeh M, Tabari H, Arabi Yazdi A, Isik S, Kalin L (2013) Flood flow forecasting using ANN, ANFIS and regression models. Neural Comput Appl. doi:10.1007/s00521-013-1443-6
9. Yao JT, Tan CL, Poh HL (1999) Neural networks for technical analysis: a study on KLCI. Int J Theoretical Appl Finance 2(2):221–241
10. Windecker RC (2013) Stochastic artificial neurons and neural networks. In: 2013 international joint conference on neural networks, Dallas, Texas
11. Oppenheimer HR, Schlarbaum GG (1981) Investing with Ben Graham: an ex ante test of the efficient markets hypothesis. J Financ Quant Anal 16(3):341–360
12. Tsai CF, Lin YC, Yen DC, Chen YM (2011) Predicting stock returns by classifier ensembles. Appl Soft Comput 11(2):2452–2459
13. Atsalakis G, Valavanis K (2009) Surveying stock market forecasting techniques – Part II: soft computing methods. Expert Syst Appl 36(3):5932–5941
14. Gorgulho A, Neves RF, Horta N (2011) Applying a GA kernel on optimizing technical analysis rules for stock picking and portfolio composition. Expert Syst Appl 38(11):14072–14085
15. Pring MJ (1991) Technical analysis. McGraw-Hill, New York
16. Allen F, Karalainen R (1999) Using genetic algorithms to find technical trading rules. J Financ Econ 51:245–271
17. William L, Russell P, James MR (2002) Forecasting the NYSE composite index with technical analysis, pattern recognizer, neural network, and genetic algorithm: a case study in romantic decision support. Decis Support Syst 32:361–377
18. Chang PC, Liao TW, Lin JJ, Fan CY (2011) A dynamic threshold decision system for stock trading signal detection. Appl Soft Comput 11(5):3998–4010
19. Su CH, Cheng CH, Tsai WL (2013) Fuzzy time series model based on fitting function for forecasting TAIEX index. Intel J Hybri Infor Technol 6:111–121
20. Park JI, Lee DJ, Song CK, Chun MG (2010) TAIFEX and KOSPI 200 forecasting based on two-factors high-order fuzzy time series and particle swarm optimization. Expert Syst Appl 37(2): 959–967
21. Tanaka YM, Tokuoka S (2007) Adaptive use of technical indicators for the prediction of intra-day stock prices. Physica A 383(1):125–133
22. Murphy JJ (1986) Technical analysis of the futures market: a comprehensive guide to trading methods and applications. New York Institute of Finance (NYIF), New York, pp 2–4
23. Clarence N, Tan W (1999) A hybrid financial trading system incorporating chaos theory, statistical and artificial intelligence/soft computing methods. In: Queensland Finance Conference, School of Information Technology, Bond University, Queensland
24. Adhikari R (2015) A mutual association based nonlinear ensemble mechanism for time series forecasting. Appl Intell 43(2):233–250
25. Ediger V, Akar S (2007) ARIMA forecasting of primary energy demand by fuel in Turkey. Energy Policy 35(3):1701–1708
26. Bas E, Egrioglu E, Aladag CH, Yolcu U (2015) Fuzzy-time-series network used to forecast linear and nonlinear time series. Appl Intell 43(2):343–355
27. Haykin S (1999) Neural networks: a comprehensive foundation, 2nd ed. Upper Saddle River, 536 New Jersey
28. Ravi A, Kurniawan H, Thai PNK, Ravi Kumar P (2008) Soft computing system for bank performance prediction. Appl Soft Comput 8:305–315
29. Li PX, Tan ZX, Yan LL, Deng KH (2011) Time series prediction of mining subsidence based on a SVM. Min Sci Technol 21(4):557–562
30. Chen SM (1996) Forecasting enrollments based on fuzzy time-series. Fuzzy Sets Syst 81(3):311–319
31. Jha GK, Sinha K (2014) Time-delay neural networks for time series prediction: an application to the monthly wholesale price of oilseeds in India. Neural Comput Appl 24(3–4):563–571
32. Chiu SL (1994) Fuzzy model identification based on cluster estimation. J Intel Fuzzy Syst 2(3):267–278
33. Nazemi A, Abbasi B, Omidi F (2015) Solving portfolio selection models with uncertain returns using an artificial neural network scheme. Appl Intell 42(4):609–621
34. Jang JS (1993) ANFIS: adaptive-network-based fuzzy inference systems. IEEE Trans Syst Man Cybern 23(3):665–685
35. Cheng CH, Wei LY, Chen YS (2009) Fusion ANFIS models based on multi-stock volatility causality for TAIEX forecasting. Neurocomputing 72(16–18):3462–3468
36. Chang JR, Wei LY, Cheng CH (2011) A hybrid ANFIS model based on AR and volatility for TAIEX forecasting. Appl Soft Comput 11(1):1388–1395
37. Khalaj G, Khalaj MJ (2014) Application of ANFIS for modeling of layer thickness of chromium carbonitride coating. Neural Comput Appl 24(3–4):685–694
38. Ocak H, Ertunc HM (2013) Prediction of fetal state from the cardiotocogram recordings using adaptive neuro-fuzzy inference systems. Neural Comput Appl 23(6):1583–1589
39. Deneme IO (2013) Estimation of modal damping ratio of impact-damped flexible beams using ANFIS. Neural Comput Appl 23(6):1669–1676
40. Uçar T, Karahoca A, Karahoca D (2013) Tuberculosis disease diagnosis by using adaptive neuro fuzzy inference system and rough sets. Neural Comput Appl 23(2):471–483
41. Takagi T, Sugeno M (1983) Derivation of fuzzy control rules from human operator's control actions. In: Proceeding of the IFAC symposium on fuzzy information, knowledge representation and decision analysis, pp 55–60
42. Kattan MW, Cooper RB (2000) A simulation of factors affecting machine learning techniques: an examination of partitioning and class proportions. Omega - Int J Manage S 28:501–512
43. Ali S, Abbadeni N, Batouche M (2012) Multidisciplinary computational intelligence techniques: applications in business, engineering, and medicine. IGI Global Publishing, Pennsylvania
44. Mahjoobi J, Shahidi AI, Kazeminezhad MH (2008) Hindcasting of wave parameters using different soft computing methods. Appl Ocean Res 30(1):28–36
45. Vairappan C Tamura H Gao S Tan Z (2009) Batch type local search-based Adaptive Neuro-Fuzzy Inference System (ANFIS) with self-feedbacks for time-series prediction. Neurocomputing 72:1870–1877
46. Chen SM, Chen CD (2011) TAIEX forecasting based on fuzzy time series and fuzzy variation groups. IEEE Trans Fuzzy Syst 19(1):1–11
47. Yu HK (2005) Weighted fuzzy time-series models for TAIEX forecasting. Phys A 349(3–4):609–624
48. Wilcoxon F (1945) Individual comparisons by ranking methods. Biometrics Bull 1(6):80–83. http://sci2s.ugr.es/keel/pdf/algorithm/articulo/wilcoxon1945.pdf
49. Weale PR, Amin HL (2003) Bursting the dot.com 'Bubble': a case study in investor behavior. Technol Anal Strateg Manage 15(1):117–136

You-Shyang Chen, He is now an associate professor of department of information management in Hwa Hsia Institute of Technology and majors in Information Management. He was ever a practitioner in the field of financial industry and manufacturing industry over 20 years. He received the Bachelor's degree in Industry Management from National Taiwan University of Science and Technology in 1988, and the Master's degree and Ph.D. degree in Information Management from National Yunlin university of Science & Technology in 2006 and 2009, respectively. His major research interests are financial analysis, medical management, soft computing, fuzzy time series, expert system, rough set theory, and behavior analysis. He has published over 100 journal and conference papers.

Chiung-Lin Chiu, She was awarded her Ph. D. degree from Department of Accounting and Information Technology at National Chung Cheng University, Taiwan in 2012. She is currently an assistant professor of Business Administration at Hwa Hsia University of Technology. Her research publications have appeared in Expert Systems with Applications, Social Behavior and Personality, Contemporary Accounting, and so on. Other works have been presented in a variety of conference proceedings. Her current research has focused on financial accounting, capital market, and intellectual capital.

Ching-Hsue Cheng, Professor, he received the Bachelor's degree in Mathematics from Chinese Military Academy in 1982, the Master's degree in Applied Mathematics from Chung-Yuan Christian University in 1988, and the Ph.D. degree in System Engineering and management from National Defense University in 1994. He is now professor of information management department in National Yunlin University of Science and Technology. His research is mainly in the field of fuzzy logic, fuzzy time series, soft computing, reliability, and data mining. He has published more than 200 papers (include 114 significant journal papers).



Shu-Ting Huang, She received the degree of Master of Information Management from National Yunlin University of Science and Technology in 2013. She is a practitioner in the field of Taiwan's industry now. Her main fields of research are fuzzy time series, data analysis, and data mining.