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A hybrid fuzzy time series model based on ANFIS and integrated nonlinear feature selection method for forecasting stock

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ABSTRACT

Forecasting stock price is a hot issue for stock investors, dealers and brokers. However, it is difficult to find out the best time point to buy or sell stock, since many variables will affect the stock market, and stock dataset is time series data. Therefore many time series models have been proposed for forecasting stock price; furthermore the previous time series methods still have some problems. Hence, this paper proposes a novel ANFIS (Adaptive Neuro Fuzzy Inference System) time series model based on integrated nonlinear feature selection (INFS) method for stock forecasting. Firstly, this study proposed an integrated nonlinear feature selection method to select the important technical indicators objectively. Secondly, it used ANFIS to build time series model and test forecast performance, then utilized adaptive expectation model to strengthen the forecasting performance. In order to evaluate the performance of proposed model, the TAIEX and HSI stock market transaction data from 1998 to 2006 are collected as experimental dataset and compared with other models. The results show that the proposed method outperforms the listing models in accuracy, profit evaluation and statistical test.

1. Introduction

Forecasting stock price has become an important issue for stock investors, dealers and brokers. Nevertheless, it is difficult finding out the best time point to buy or to sell stock, because many variables must take into consideration which may affect the stock market. Stock market is one of exciting and challenging monetary activities, individual investors, stock fund managers and financial analysts who attempt to forecast stock price based on their professional knowledge or consulting professionals. Although many techniques have been developed for forecasting stock price, building an efficient stock forecasting model is still an attractive issue since even the smallest improvement in prediction accuracy can have a positive impact on investments. Therefore, stock analysts strived to discover ways which can increase the profit from the stock market.

The fluctuation of stock price, often presented nonlinear and non-stationary, and investment itself is a kind of predicted behavior for more profits, however, to build an efficient stock forecasting model is not easy. From literature review, the variables selection will affect the forecast performance, and the inappropriate method will result in larger error such that the investors will face loss. Technical analysis has become an important approach for analyzing patterns and trends of stock price [2,43]. In previous studies, selected technical indicators such as input variables depended on personal experience and opinion. Therefore, this study proposed an integrated nonlinear feature selection (INFS) method to select important variables for forecasting stock index.

In time series models, the autoregressive integrated moving average (ARIMA, [4]) is extensively utilized for constructing a forecasting model. However, many statistical methods only deal with linear forecasting model and variables must obey statistical normal distribution [12]. In order to overcome the limitation, many researchers have proposed computational intelligence techniques for financial forecasting. Kimoto et al. [27] developed a prediction system for stock market by using neural network, Roh. [38] integrated neural network into time-series model for forecasting the volatility of stock price index. Chen et al. [11] proposed a comprehensive fuzzy time-series, in which variables have linear relationships between recent periods of stock prices and fuzzy logical relationships (nonlinear relationships) mined from time-series into forecasting processes.

In the past decades, artificial neural networks (ANN) have been explored by many researchers to develop a nonlinear model for stock forecast [11,31,38] and other applications. Even though ANN showed a great deal of experimental result in many studies, the applicable

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Table 1
The technical indicators are collected from the previous studies.

Indicator	Explanation
MA5	MA5 (moving average for 5 days) is the closing index of the current day [36].
MA10	MA10 (moving average for 10 days) is the closing index of the current day [36].
5BIAS	The difference between the closing value and MA5, which uses the stock price nature of returning back to average price to analyze the stock market [6].
10BIAS	The difference between the closing value and MA10, which uses the stock price nature of returning back to average price to analyze the stock market [6].
RSI	RSI compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset [6].
12PSY	PSY12 (psychological line for 12 days)$=(D_{up12}/12)*100$, D_{up12} means the number of days when price going up within 12 days [36].
10WMS%R	Williams %R 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's price to change direction before placing your trades [6].
MACD9	MACD shows the difference between a fast and slow exponential moving average (EMA) of closing prices. Fast means a short-period average, and slow means a long period one [6].
MO1	$\mathrm{MO1}(t)=\mathrm{price}(t)-\mathrm{price}(t-n), n=1$ [42].
MO2	$\mathrm{MO2}(t)=\mathrm{price}(t)-\mathrm{price}(t-n), n=2$ [42].
DIFN	$\mathrm{DIFN}(t)=\mathrm{TAIEX}(t)-\mathrm{NASDAQ}(t)$, NASDAQ stands for NASDAQ Composite Index.
DIFF	$\mathrm{DIFF}(t)=\mathrm{TAIEX}(t)-\mathrm{TAIFEX}(t)$, TAIFEX stands for Taiwan Futures Exchange.
DIFE	$\mathrm{DIFE}(t)=\mathrm{TAIEX}(t)-\mathrm{DowJonesIndex}(t)$.

input variables of ANN are hard to define and select [48] and the generated rules from ANN are not easily understandable [11].

In recent years, ANFIS system has been used widely to generate nonlinear models of processes to determine input–output relationships. Therefore, ANFIS is appropriate for forecasting nonlinear financial time series and generating meaningful rules for strategizing investment tactics. Many researchers also have applied prediction techniques for financial analysis [20,39,5]. Further, many hybrid forecasting techniques have been published recently [25,30,33,35,46]. Wei [46] proposed a hybrid time series adaptive network-based fuzzy inference system (ANFIS) model to forecast stock prices.

To sum up, previous studies have four main drawbacks as follows: (1) previous researches selected important technical indicators dependent on subjective experiences and opinions; (2) most conventional methods rely upon some assumptions about the variables used in the analysis, so it is limited to be applied to all datasets; (3) most conventional time series models considered only one variable to forecast stock price; and (4) the rules generated from ANN are not easy to understand. Therefore, the purpose of this paper is to propose a novel ANFIS (Adaptive Neuro Fuzzy Inference System) time series model based on integrated nonlinear feature selection (INFS) method for stock forecasting. The contributions are: (1) proposing an integrated nonlinear feature selection method to select the important technical indicators objectively, (2) using ANFIS to build time series model and test forecast performance, (3) utilizing adaptive expectation model to strengthen the forecasting performance, and (4) verifying the proposed model with good forecasting performance.

The remaining section is organized as follows: Section 2 reviews the related literatures; Section 3 provides the framework of proposed models, and introduces the major concept and algorithm; Section 4 verifies the proposed model by two datasets and compares with other models. Finally, Section 5 represents conclusions.

2. Related works

This section briefly introduces technical indicator, time series model, subtractive clustering, adaptive network based fuzzy inference system, and adaptive expectation model.

2.1. Technical indicator

Technical indicator is forecasting the pattern of prices through the study of past stock data, primarily price and volume. For helping trade decisions in asset markets, these decisions are often generated by applying simple rules to historical price data. Technical indicator attempts to predict future stock price movements by analyzing the past sequence of stock price [37].

Analysts focus on the investor's psychology and response to certain price formation and price movements. The price depends on personal expectation which investors are willing to buy or sell. It is very important to understand that market participants anticipate future development and taking action, and their action drives the price movement. Since stock market process is highly nonlinear, many researchers have been focusing on technical indicator to improve the investment return [1,47].

A technical indicator consists in a formula that is normally applied to stock prices and volumes [19]. Technical indicator explores market information and to take into account all the necessary variables in the stock exchange information [6]. Technical indicator is one of the most popular methods in use by stock traders [2]. From the previous studies [40], the technical indicators are collected and illustrated in Table 1.

Murphy [34] summarizes the basis for technical indicator into the following three premises: (1) Market action discounts everything; (2) prices move in trends; (3) history repeats itself. Furthermore, the selection of technical and economic indicators to be used in the prediction system will depend on the following factors [15]:

(1) Availability: The data must be easily obtained.
(2) Sufficiency of the Historical Databases: There must be enough sample data for the machine learning and system testing process.
(3) Correlation of the Indicators to the Price: The data should have some relevancy to the price of the security (whether it is lagging, leading, coincidental or noise).
(4) Periodicity of the Data: The data must be available in a predictable frequency (daily, weekly, monthly, and annually).
(5) Reliability of the Data: The fast changing pace of today's global financial world and the increased in financial market volatility has resulted in difficulty to obtain reliable economic data.

2.2. Time series model

A time series is a collection of observations of well-defined data, which was obtained through repeated measurements over time. Time series analysis is a method for analyzing time series data to extract meaningful statistics and other data characteristics. Time series forecasting is to forecast future values based on previously observed values. Time series forecasting methods have

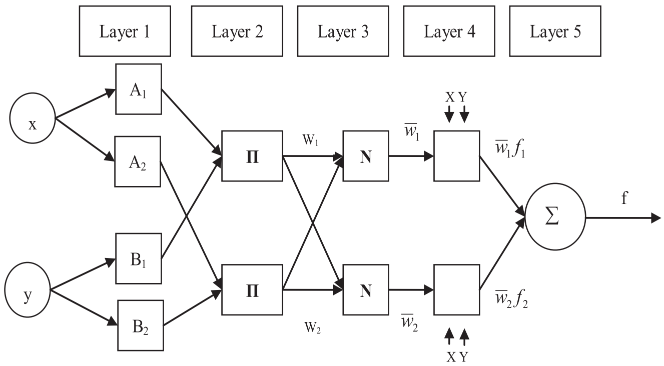

Fig. 1. The architecture of ANFIS network.

been applied in very wide areas including finance and business, computer science, physics, chemistry, and many interdisciplinary fields.

Many time series methods have been developed. Of conventional statistical methods, ARIMA [4] is utilized to construct a forecasting model. ARIMA models are organized from the autoregressive models (AR), the moving average models (MA) and the ARMA models which combine the AR with MA. ARIMA models can be used when the time series is stationary and there is no missing data [16]. ARIMA are linear predictions of the future values which are constrained in linear functions of past observations. In other words, ARIMA cannot be utilized to produce an accurate model for forecasting nonlinear time series.

Several classes of nonlinear models have been proposed in former study for overcoming the linear limitation of time series models. Many artificial intelligence methods such as the artificial neural network (ANN) and the support vector machines (SVM) have been successfully utilized to develop a nonlinear model for forecasting time series. These approaches usually forecast better results than the ARIMA model in nonlinear time series. Kimoto et al. [27] developed a prediction system for stock market by using neural network. Roh. [38] integrated neural network into time-series model for forecasting the volatility of stock price index. Li et al. [31] proposed a dynamic prediction model of surface movements based on SVM theory and times-series analysis, in order to study dynamic laws of surface movements over coal mines due to mining activities.

In recent years, many fuzzy time series methods have been proposed such as literature [10,11,49]. Some of these methods used fuzzy set theory, which needed complex matrix operations in fuzzy time series methods. In literature, many fuzzy time series forecasting methods were based on high-order fuzzy time series model, bivariate fuzzy time series model, and multivariate fuzzy time series model. Chen [10] presented a new method to forecast university enrollments based on fuzzy time series. Chen et al. [11] proposed a comprehensive fuzzy time-series, in which variables have linear relationships between recent periods of stock prices and fuzzy logical relationships (nonlinear relationships) mined from time-series into forecasting processes.

2.3. ANFIS: Adaptive Neuro Fuzzy Inference System

Fuzzy inference system is based on fuzzy if-then rules for human knowledge and inference procedure to perform qualitative description and analysis except for the lack of accurate quantitative analysis and correction of values. ANN has excellent self-learning ability and organizational skills, but ANN cannot deal with the qualitative knowledge and logical inference process.

ANFIS [24] combined the fuzzy inference system with ANN, which means the fuzzy inference system based on neural network; it can improve model for uncertainty and imprecision of system process capability, while self-learning and organizational capacity, be able to adjust the parameters of the model.

ANFIS networks have been successfully applied to forecast tasks, rule-based process controls, patterns recognition problems and so on. From the previous study, Cheng and Wei [13] proposed a new model, which incorporated one step-ahead concept into ANFIS to build a fusion ANFIS model and enhanced forecasting for electricity loads by adaptive forecasting equation. Chang et al. [7] proposed a hybrid adaptive network-based fuzzy inference system model that is based on AR and volatility to forecast stock price problems of the Taiwan exchange capitalization weighted stock index (TAIEX). For illustrating the system, it is assumed that the fuzzy inference system under consideration has two inputs x, y, and one output z. The architecture of ANFIS is shown in Fig. 1.

Suppose that the system consists of 2 fuzzy if-then rules based on Takagi and Sugeno's type [41]:

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 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 Eq. (1)). $O_{i,i}$ 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 (as Eq. (2)) with maximum equal to 1 and minimum equal to 0.

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

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

where a_i, b_i, c_i are the parameters, and b_i is a positive value and c_i 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. (3):

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \text{for } i = 1, 2 \tag{3}$$

Layer 3: Every node in this layer is a square node labeled N. The i-th node calculates the ratio of firing strength of the i-th rule to the sum of firing strengths of all rules by Eq. (4). Output of this layer is called normalized firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \text{for } i = 1, 2 \tag{4}$$

Layer 4: Every node i in this layer is a square node with a node function (as Eq. (5)), parameters in this layer will be referred to as consequent parameters.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{5}$$

where p_i, q_i, r_i are the parameters.

Layer 5: The single node in this layer is a circle node labeled $\sum$ that computes the overall output as the summation of all incoming signals (as Eq. (6)).

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_{i=1} w_i f}{\sum_{i=1} w_i} \tag{6}$$

2.4. Adaptive expectation model

In time series forecasting, the adaptive expectation model [28] has been shown to be a reasonable forecast model for forecasting future stock price, the forecast is generated by the last one-period stock price and the correction of last one-period forecasting error (see Eq. (7)).

$$P(t+1) = P(t) + h_0 * \varepsilon(t) \tag{7}$$

where $P(t+1)$ is the forecasting stock index at time $t+1$, $P(t)$ is the real stock index at time t, h_0 is the adaptive parameter for $\varepsilon(t)$, and $\varepsilon(t)$ is forecasting error at time t.

3. Proposed model

From literature review, there are four drawbacks about time series forecasting model: (1) previous researches selecting important technical indicators depend on subjective experiences and opinions; (2) most conventional methods rely upon some assumptions about the variables used in the analysis, so it is limited to be applied to all datasets; (3) most conventional time series models considered only one variable to forecast stock index; and (4) the rules generated from ANN are not easy to understanding.

Based on the above reasons, this study proposes a novel time-series model which incorporates the reasonable selected technique indicators into ANFIS method, and using adaptive expectation model [28] to strengthen forecasting performance. At first, the proposed integrated nonlinear feature selection method is used to choose technical indicators. Subsequently, investor's knowledge is represented by fuzzy if-then rules, then all fuzzy if-then rules are built in fuzzy inference system. And ANFIS method can optimize the fuzzy inference system parameters by adaptive network, which can overcome the limitations of statistical methods, finally, using adaptive expectation model to enhance forecasts. In order to verify the forecast accuracy of proposed model, this study is compared with other models. The research process of proposed model is shown in Fig. 2.

3.1. Proposed algorithm

For easily understanding the proposed model, this study proposes an algorithm to step by step introduce the proposed model. The proposed algorithm contains three phases with six steps as follows.

Phase 1: Data Preprocessing: This phase contains two steps as step 1 and step 2.

Step 1: Transform data into technical indicators

This step transforms the daily basic variable (open, close, highest, lowest price and volume) into technical indicators [6] such as moving average (MA), psychology line (PSY), relative strength index (RSI), BIAS, Williams Overbought/Oversold Index (WMS%R), and so on. Besides, this study also considers other indicators [40]: (1) the exchange rate for NT dollars to US dollars, (2) momentum of stock price, (3) the difference between TAIEX with NASDAQ and (4) the difference between TAIEX with TAIFEX. The details of technical indicator have been listed in Table 1.

Step 2: Select important indicators by proposed integrated non-linear feature selection

After transforming data into technical indicators, this study proposed the integrated non-linear feature selection to select the important indicators. The proposed integrated non-linear feature selection method can rank the important indicator of different

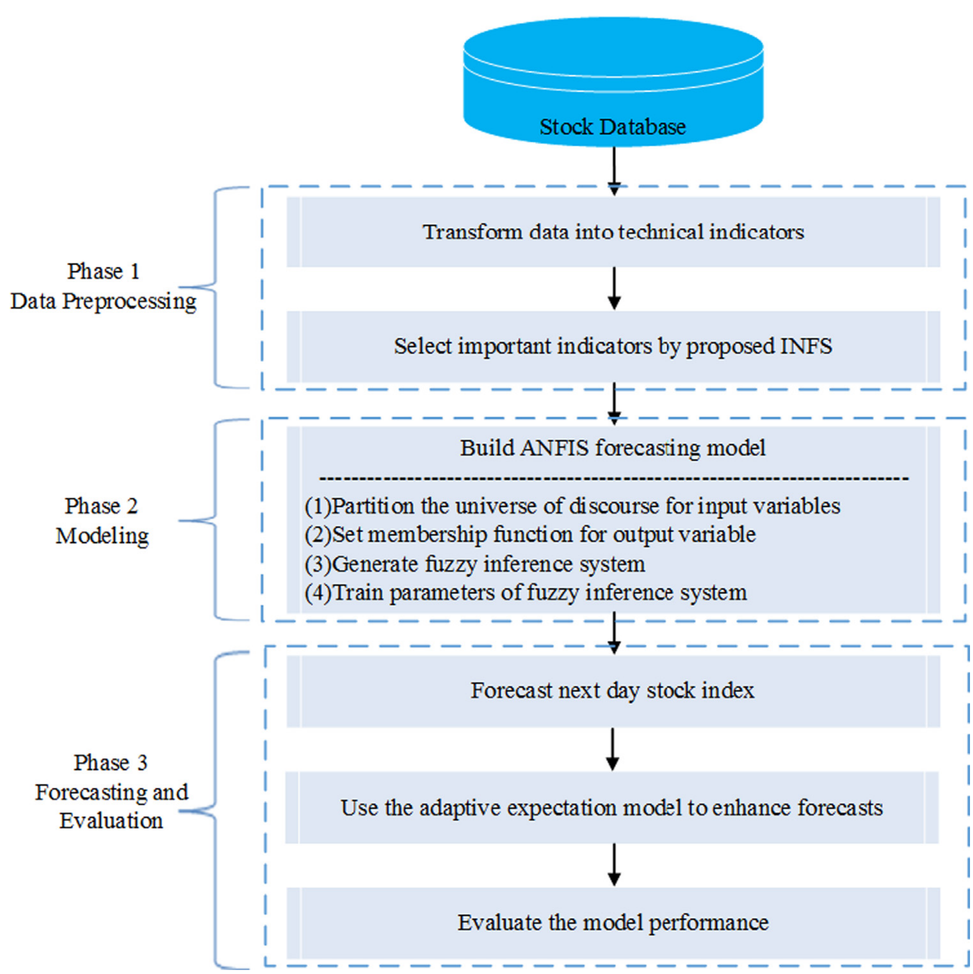

Fig. 2. The procedure of proposed model.

non-linear feature selection methods; this paper used three non-linear feature selection methods to select the important indicators, which are general regression neural network (GRNN, [29]), and gene expression programming (GEP, [18]), supportive vector regression (SVR, [3]). The proposed integrated non-linear feature selection method is introduced as follows.

(1) Input the technical indicators and dependent variable into three feature selection methods to select the important indicators, respectively.
(2) Use $\frac{W_i}{\max\{W_i\}} \times 100$ to normalize the value of importance degree for the selected indicators, where W_i is the value of important degree for ith selected indicator.
(3) Rank the orderings of the selected indicators by normalized value, for each feature selection method has its rank. The biggest normalized value assigns the first, the second normalized value gives the second,…, etc.
(4) Integrate the rank of the three feature selection methods by summing the value of rank on each selected indicator, the smallest value of rank is first selected indicator, the second value of rank is second selected indicator,…, etc.

Table 2
ANFIS computational environment.

Programming language	MATLAB R2015
ANFIS architecture	3-3-3
The number of Membership function	3 (high, middle, low)
The number of Rules	27

Table 3
The selected indicators by INFS for TAIEX.

Year	Variable1	Variable2	Variable3
1998	MA10	MA5	DIFN
1999	MA10	DIFN	MA5
2000	MA5	MA10	DIFN
2001	MA5	DIFN	DIFF
2002	MA10	MA5	DIFN
2003	MA5	DIFN	MA10
2004	DIFN	MA5	MA10
2005	MA10	MA5	DIFN
2006	MA10	DIFN	MA5

Table 4
The partial results of adaptive forecasts for TAIEX 2002-year.

Date	$P(t)$	$D(t)$=Initial forecast	$\varepsilon(t)=P(t)-D(t)$	$P(t+1)=P(t)+h_0{}^*\varepsilon(t)$
2002/1/2	5600.05			
2002/1/3	5526.32	5590.78	−64.46	$5526.32+h_0{}^*-64.46$
2002/1/4	5638.53	5538.94	99.58	$5638.53+h_0{}^*99.58$
2002/1/7	5834.89	5659.98	174.90	$5834.89+h_0{}^*174.90$
2002/1/8	5810.08	5810.49	−0.42	$5810.08+h_0{}^*-0.42$
2002/1/9	5865.54	5832.05	33.48	$5865.54+h_0{}^*33.48$
⋮	⋮		⋮	⋮

Phase 2: Modeling: The step 3 introduces the detailed description in the following.

Step 3: Build ANFIS forecasting model

This step introduces the ANFIS forecasting model in Step 3.1 to Step 3.4, and the ANFIS method uses subtractive clustering [14] to partition the universe of discourse for input variables, and then generates the fuzzy inference system. The sub-steps of Step 3 are described as follows:

Step 3.1: Partition the universe of discourse for input variables.

Firstly, we define each universe of discourse for variables according to the minimum and maximum value in each variable. Secondly, partition the universe of discourse by subtractive clustering using Gaussian membership function [14]. There are many clustering methods to create fuzzy inference system in ANFIS, however, Chiu's subtractive clustering has the advantage of avoiding the explosion of the rule set and dimensionality reduced, and subtractive clustering has recently been applied for extracting fuzzy models for nonlinear processes.

Step 3.2: Set membership function for output variable.

This step uses linear type membership function for output variables. For example, in 2002-years TAIEX dataset, there are three inputs X_{t-1}, Y_{t-1} and Z_{t-1} and three linguistic intervals partitioned by subtractive clustering in each input variable. Therefore, a typical rule in a Sugeno fuzzy model is described as follows:

If $x(X_{t-1})=A_i, y(X_{t-1})=B_i$ and $z(X_{t-1})=C_i$

then $f_i(X_t)=p_i x+q_i y+r_i z+s_i$.

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

Step 3.3: Generate fuzzy inference system.

Firstly, from Step 3.1, we can get the linguistic intervals as input membership functions and the output membership functions are set by Step 3.2. Secondly, generate fuzzy if-then rules, where the linguistic values (A_i, B_i, C_i) from input membership functions are

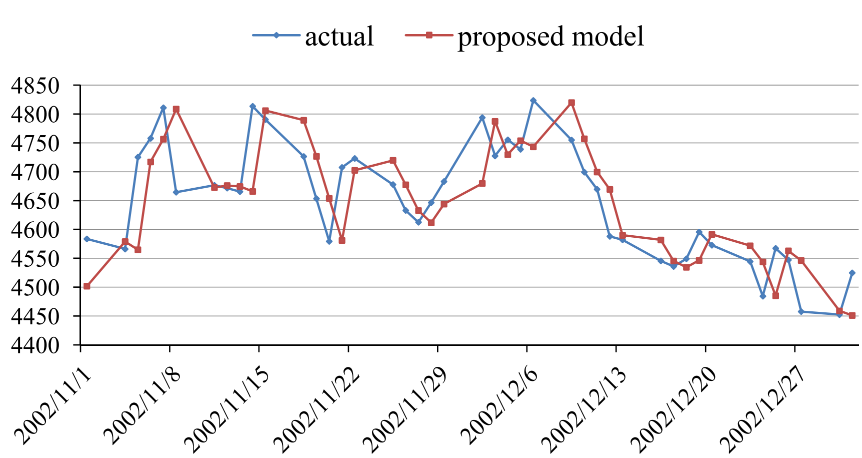

Fig. 3. Forecasting results for TAIEX from 2002/11/01 to 2002/12/31.

used as the if-condition part, and the output membership functions ($f_i(X_t)$) are the then part. Three generated rules (the number of rules is the same as the number of linguistic intervals) are described as follows:

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 parameters of fuzzy inference system.

In this step, we employ the least-squares method and the back-propagation gradient descent method for training the forecasting model. This study sets epoch as 100 (the process is executed for the predetermined fixed number of iterations unless it terminates while the training error converges) for the training stopping criterion, and then obtains the optimal parameters for the selected output membership function.

Phase 3: Forecasting and Evaluation: This phase contains three steps as step 4 to step 6.

Step 4: Forecast next day stock index.

The FIS parameters of the forecasting model is determined when the stopping criterion reaches from Step 3, then the training forecasting model is used to forecast next day stock index for testing datasets.

Step 5: Use the adaptive expectation model to enhance forecasts.

Use adaptive expectation model [28] to enhance forecasts by Eq. (7). In order to strengthen the forecasting performance, this step trains the adaptive parameter (h_0) under minimal root mean square error (RMSE) (as Eq. (8)) for training data. And set 0.001 as the iterated step between −0.07 and 0.07 to obtain optimal adaptive parameter (h_0).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{t=1}^{n}(y_t - \hat{y}_t)^2} \quad (8)$$

Table 5
The selected variables by INFS for HIS.

Year	Variable1	Variable2	Variable3
1998	MA5	5BIAS	DIFN
1999	MA5	5BIAS	MO1
2000	MA5	5BIAS	10BIAS
2001	MA5	5BIAS	10WMS%R
2002	MA5	5BIAS	10BIAS
2003	MA5	5BIAS	DIFN
2004	MA5	5BIAS	10WMS%R
2005	MA5	5BIAS	DIFF
2006	MA5	5BIAS	DIFF

Table 6
The partial results of adaptive forecasts for HSI 2002-year.

Date	$P(t)$	$D(t)$=Initial forecast	$\varepsilon(t)=(t)-D(t)$	$P(t+1)=P(t)+h_0{}^*\varepsilon(t)$
2002/1/2	11,350.85			
2002/1/3	11,423.52	11,351.45	72.07	$11{,}423.52 + h_0{}^*72.07$
2002/1/4	11,702.15	11,442.88	259.27	$11{,}702.15 + h_0{}^*259.27$
2002/1/7	11,892.64	11,715	177.64	$11{,}892.64 + h_0{}^*177.64$
2002/1/8	11,713.71	11,803.75	−90.04	$11{,}713.71 + h_0{}^* - 90.04$
2002/1/9	11,440.72	11,688.91	−248.19	$11{,}440.72 + h_0{}^* - 248.19$
2002/1/10	11,256.07	11,389.03	−132.96	$11{,}256.07 + h_0{}^* - 132.96$
2002/1/11	11,166.46	11,175.51	−9.05	$11{,}166.46 + h_0{}^* - 9.05$
⋮	⋮		⋮	⋮

Table 7
The results of proposed model (TAIEX testing dataset).

Training	Testing	h_0	RMSE
1998/01 ~ 1998/10	1998/11 ~ 1998/12	0.011	121.18
1999/01 ~ 1999/10	1999/11 ~ 1999/12	0.07	112.11
2000/01 ~ 2000/10	2000/11 ~ 2000/12	−0.022	132.19
2001/01 ~ 2001/10	2001/11 ~ 2001/12	0.015	113.23
2002/01 ~ 2002/10	2002/11 ~ 2002/12	−0.041	65.83
2003/01 ~ 2003/10	2003/11 ~ 2003/12	−0.025	57.62
2004/01 ~ 2004/10	2004/11 ~ 2004/12	0.03	54.33
2005/01 ~ 2005/10	2005/11 ~ 2005/12	0.056	54.81
2006/01 ~ 2006/10	2006/11 ~ 2006/12	−0.07	56.31

Table 8
The results of proposed model (HSI testing dataset).

Training	Testing	h_0	RMSE
1998/01 ~ 1998/10	1998/11 ~ 1998/12	0.039	201.18
1999/01 ~ 1999/10	1999/11 ~ 1999/12	0.003	235.68
2000/01 ~ 2000/10	2000/11 ~ 2000/12	0.04	249.28
2001/01 ~ 2001/10	2001/11 ~ 2001/12	−0.054	157.97
2002/01 ~ 2002/10	2002/11 ~ 2002/12	−0.01	105.6
2003/01 ~ 2003/10	2003/11 ~ 2003/12	0.058	124.15
2004/01 ~ 2004/10	2004/11 ~ 2004/12	−0.014	103.28
2005/01 ~ 2005/10	2005/11 ~ 2005/12	0.035	101.66
2006/01 ~ 2006/10	2006/11 ~ 2006/12	−0.019	192.52

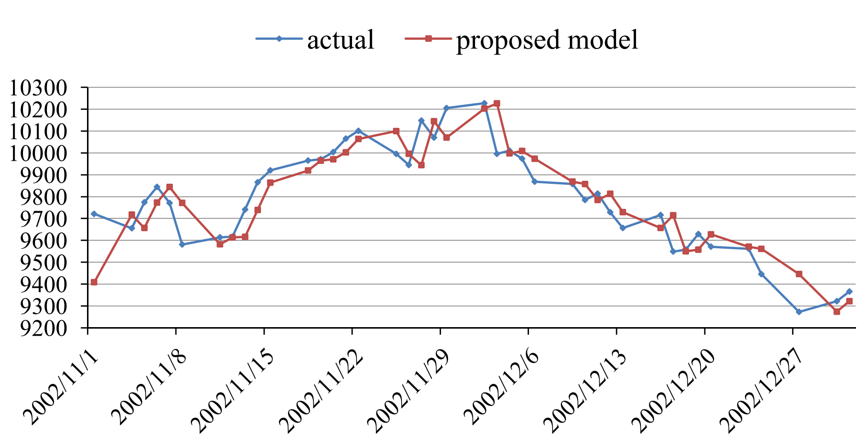

Fig. 4. Forecasting results for HSI from 2002/11/01 to 2002/12/31.

Table 9
The results of comparisons for the TAIEX dataset.

Testing	RMSE				
	Chen [10]	Yu [50]	INFS+ANFIS	INFS+SVR	Proposed
1998/11 ~ 1998/12	152.14	141.56	147.59	117.28[a]	121.18
1999/11 ~ 1999/12	190.11	112.99	115.58	118.91	112.11[a]
2000/11 ~ 2000/12	353	175.63	180.03	148.52	132.19[a]
2001/11 ~ 2001/12	165.31	134.39	133.59	110.76[a]	113.23
2002/11 ~ 2002/12	139.64	91.43	81.11	70.38	65.83[a]
2003/11 ~ 2003/12	103.96	68.07	77.31	59.22	57.62[a]
2004/11 ~ 2004/12	82.32	72.34	56.44	53.07[a]	54.33
2005/11 ~ 2005/12	86.12	62.52	55.97	54.72[a]	54.81
2006/11 ~ 2006/12	215.64	83.92	77.03	63.22	56.31[a]

[a] The best performance among 5 models.

Table 10
The results of comparisons for the HIS dataset.

Testing	RMSE				
	Chen [10]	Yu [50]	INFS+ANFIS	INFS+SVR	Proposed
1998/11 ~ 1998/12	279.67	250.47	310.28	216.39	201.18[a]
1999/11 ~ 1999/12	491.85	269.03	372.97	285.05	235.68[a]
2000/11 ~ 2000/12	315.13	341.8	256.61	254.16	249.28[a]
2001/11 ~ 2001/12	261.7	281.46	298.39	158.53	157.97[a]
2002/11 ~ 2002/12	183.45	138.9	118.27	108.98	105.6[a]
2003/11 ~ 2003/12	337.82	172.87	132.67	126.86	124.15[a]
2004/11 ~ 2004/12	280.24	139.82	111.92	113.21	103.28[a]
2005/11 ~ 2005/12	117.7	112.6	154.67	99.49[a]	101.66
2006/11 ~ 2006/12	270.39	185.93[a]	191	189.41	192.52

[a] The best performance among 5 models.

Table 11
The results of Theil's test for the TAIEX dataset.

Testing	Theil's *U* Statistic				
	Chen [10]	Yu [50]	INFS+ANFIS	INFS+SVR	Proposed
1998/11 ~ 1998/12	0.0143	0.0134	0.0106	0.0084[a]	0.0087
1999/11 ~ 1999/12	0.0149	0.0106	0.0074	0.0076	0.0072[a]
2000/11 ~ 2000/12	0.0339	0.0207	0.0170	0.0140	0.0124[a]
2001/11 ~ 2001/12	0.0233	0.0189	0.0139	0.0115[a]	0.0117
2002/11 ~ 2002/12	0.0155	0.0124	0.0087	0.0076	0.0071[a]
2003/11 ~ 2003/12	0.0106	0.0076	0.0065	0.0050	0.0049[a]
2004/11 ~ 2004/12	0.0076	0.0080	0.0048	0.0045[a]	0.0046
2005/11 ~ 2005/12	0.0078	0.0065	0.0045	0.0044[a]	0.0044
2006/11 ~ 2006/12	0.0156	0.0077	0.0052	0.0042	0.0038[a]

[a] The best performance among 5 models.

where y_t denotes the real stock index, $\hat{y}_t$ denotes the forecasting stock index and n is the number of data.

Step 6: Evaluate the model performance.

For evaluating forecast performance, the RMSE and Theil's U Statistic (as Eq. (9)) are employed as evaluation criterion in testing data, and compare with other models: (1) Chen's model (1996), (2) Yu's model (2005), (3) INFS+ANFIS model and (4) INFS+SVR model. In Eq. (8), a smaller RMSE value indicates the model with good accuracy. In Eq. (9), U value is between 0 and 1, the U value close to 0 indicates the model with good accuracy.

$$U = \frac{\sqrt{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}}{\sqrt{\sum_{t=1}^{n} {y_t}^2} + \sqrt{\sum_{t=1}^{n} {\hat{y}_t}^2}} \tag{9}$$

where y_t denotes the actual stock index, $\hat{y}_t$ denotes the forecasting stock index.

Table 12
The results of Theil's test for the HIS dataset.

Testing	Theil's *U* Statistic				
	Chen [10]	Yu [50]	INFS+ANFIS	INFS+SVR	Proposed
1998/11 ~ 1998/12	0.0166	0.0164	0.0152	0.0106	0.0098[a]
1999/11 ~ 1999/12	0.0200	0.0123	0.0122	0.0093	0.0077[a]
2000/11 ~ 2000/12	0.0125	0.0144	0.0085	0.0084	0.0083[a]
2001/11 ~ 2001/12	0.0128	0.0155	0.0134	0.0071	0.0071[a]
2002/11 ~ 2002/12	0.0107	0.0085	0.0061	0.0056	0.0054[a]
2003/11 ~ 2003/12	0.0146	0.0083	0.0054	0.0052	0.0051[a]
2004/11 ~ 2004/12	0.0101	0.0060	0.0040	0.0041	0.0037[a]
2005/11 ~ 2005/12	0.0046	0.0050	0.0052	0.0033[a]	0.0034
2006/11 ~ 2006/12	0.0089	0.0071	0.0050	0.0050[a]	0.0051

[a] The best performance among 5 models.

4. Experiments and comparisons

In order to verify the forecasting performance of the proposed model, this study chooses the TAIEX and HSI as experimental datasets. And Chen's model (1996), Yu's model (2005), INFS based on ANFIS (INFS+ANFIS) and INFS based on support vector regression (INFS+SVR) are used as compared models. For overcoming "curse of dimensionality", this paper utilized feature selection and subtractive clustering to reduce computational complexity, the detailed ANFIS computational environment is listed in Table 2.

4.1. TAIEX datasets

The TAIEX experimental dataset is practically collected from Taiwan Stock Exchange in year 1998 to 2006. For each year, the training period is the first ten months and the testing period is the last two months. For detailed illustration of proposed model, the 2002-year TAIEX index with 244 transaction data is employed as an example. Firstly, three important technical indicators (MA10, MA5 and DIFN) are selected by INFS as shown in Table 3. Secondly, the technical indicators are used as input variables for ANFIS forecasting model to generate the initial forecasts as shown in Table 4. Finally, the initial forecasts (2002/01 ~ 2002/10) are retrained by adaptive expectation model to find the optimal parameter (h_0) as shown in Table 4. From the results of adaptive forecasting, the best result is RMSE = 95.45 when $h_0 = -0.041$.

After obtaining the best adaptive parameter, the new forecasts are computed by Eq. (10) for testing data (2002/11 ~ 2002/12). The forecasting result of TAIEX from 2002/11/01 to 2002/12/31 is shown in Fig. 3, and the RMSE is 65.83 (as Table 7).

4.2. HIS datasets

In order to verify proposed model in different datasets, the HSI dataset is practically collected from year 1998 to 2006. For each year, the training period is the first ten months and the testing period is the last two months. Similarly, the 2002-year HSI index with 247 transaction days is employed as an example to illustrate the proposed model. Firstly, three important technical indicators (MA-5, 5BIAS and 10BIAS) are selected by INFS as shown in Table 5. Secondly, the technical indicators are utilized as input variables for ANFIS forecasting model to generate the initial forecasts (see Table 6). Finally, the initial forecasts of training data (2002/01 ~ 2002/10) are fed into adaptive expectation model to find the optimal parameter (h_0); the detailed processes are listed in Table 6. The best training result is RMSE = 130.03 when $h_0 = -0.01$.

From adaptive expectation model, the best parameter can be used to forecast HSI index for testing data (2002/11 ~ 2002/12).

Table 13
The results of profitability comparisons for the TAIEX dataset.

Testing	Profitable unit				
	Chen [10]	Yu [50]	INFS+ANFIS	INFS+SVR	Proposed
1998/11 ~ 1998/12	191.68	−64	−107.44	440.12	295.16
1999/11 ~ 1999/12	−1045.76	−1126.5	274.52	−484.74	334.34
2000/11 ~ 2000/12	−348.82	512.4	1024.18	−428.04	−239.66
2001/11 ~ 2001/12	−1161.98	−789	−675.72	535.16	319.96
2002/11 ~ 2002/12	576.62	−287.72	−348.06	−302.72	609
2003/11 ~ 2003/12	−460.97	−343.87	104.29	−36.53	−381.41
2004/11 ~ 2004/12	532.67	−400.93	189.57	486.95	218.95
2005/11 ~ 2005/12	468.25	−157.91	18.55	147.21	−54.65
2006/11 ~ 2006/12	−375.87	−456.23	−663.67	−826.25	−383.43
Total	−1624.18	−3113.76	−183.78	−468.84	718.26

Table 14
The results of profitability comparisons for the HIS dataset.

Testing	Profitable unit				
	Chen [10]	Yu [50]	INFS+ANFIS	INFS+SVR	Proposed
1998/11 ~ 1998/12	1097.03	−1625.97	221.03	360.91	−475.35
1999/11 ~ 1999/12	−1628.32	−1242.94	−1609.98	−3725.44	2421.12
2000/11 ~ 2000/12	1869.57	−1698.99	606.99	−1202.73	−344.57
2001/11 ~ 2001/12	933.42	−633.66	−1192	289.54	−133.58
2002/11 ~ 2002/12	−237.42	867.26	496.06	646.18	660.04
2003/11 ~ 2003/12	428.15	−144.21	519.73	1025.83	429.31
2004/11 ~ 2004/12	50.17	−376.17	−653.01	−1143.17	1017.01
2005/11 ~ 2005/12	836.55	283.45	372.51	373.23	−769.05
2006/11 ~ 2006/12	1143.01	−936.15	299.23	584.03	−234.47
Total	4492.16	−5507.38	−939.44	−2791.62	2570.46

The forecasting result is shown in Fig. 4, and the result is RMSE = 105.6 (see Table 8).

4.3. Comparisons

After illustrating proposed model by small dataset, this section uses two complete datasets to extend experiments and comparisons, the practically collected two datasets are from 1998 to 2006. The experimental results are listed in Tables 7 and 8 respectively.

In order to show the accuracy of proposed model, this study compares the proposed model with other models. The first type is fuzzy time series model including Chen's model (1996) and Yu's model (2005), since ANFIS combine the characteristic of fuzzy inference system with artificial neural network. The second type is time series model including INFS+ANFIS model and INFS+SVR model. The reason why uses SVR to compare with proposed model: (1) SVR [44] is that the support vector machines (SVMs) extended to solve nonlinear regression estimation problems. (2) The idea of SVR is based on the computation of a linear regression function in a high dimensional feature space where the input data are mapped via a nonlinear function [3]. (3) SVR has been applied in various fields such as electric loads forecasting [17,21,8], financial forecasting [23,26,32] and tourism demand forecasting [22,9].

Finally, the comparison result of RMSE is listed as in Tables 9 and 10. The comparison table for TAIEX shows that the proposed model is the best performance in 5 testing datasets (1999, 2000, 2002, 2003 and 2006) and the RMSE is smaller than other models. Furthermore, the compared results for HIS shows that the proposed model shows the best performance in 7 testing datasets (from 1999 to 2004).

The comparison result of Theil's *U* Statistic is listed as in Tables 11 and 12. The comparison table for TAIEX shows that the proposed model shows the best performance in 5 testing datasets (1999, 2000, 2002, 2003 and 2006) and the Theil's *U* Statistic is smaller than other models. Furthermore, the compared results for HIS show that the proposed model shows the best performance in 7 testing datasets (from 1999 to 2004).

4.4. Findings

From the empirical results, there are three findings provided as follows:

(1) Important indicators

According to Tables 9 and 10, the proposed model under the criteria of RMSE is better than the fuzzy time series models [10,50]. Since these models only consider one variable. However, the proposed model considers multi-variables to improve forecasting accuracy and utilize proposed INFS to select variables objectively. From Tables 3 and 5, the most frequently chosen variables are MA5, DIFN and MA10 in TAIEX and HIS are MA5 and 5BIAS. Thus, we can confirm that the technical indicators of MA5 and 5BIAS have great influence on forecasting TAIEX and HSI.

(2) Adaptive expectation

From Tables 9 and 10, the proposed model under the spread of RMSE show the volatility for TAIEX dataset is smaller than the HSI dataset. Since Taiwan policy has limited $\pm 7\%$ volatility for every share. However, there is no policy limitation in Hong Kong and the performance of proposed model in HIS is better than TAIEX. In other words, the proposed model fits more in high volatility market. Furthermore, all models have a bad forecasting result in the 2000-year TAIEX due to the impact of the dot-com bubble event [45] and the Taiwan Presidential Election. However, the result shows that the RMSE of proposed model is smaller than other models. Thus, we can confirm the proposed model employs the adaptive expectation model that can effectively lower the

RMSE within the proposed model in the all testing periods and raise forecasting performance.

(3) Profitability

In order to prove that the proposed model not only has good forecast ability, but also has higher profit. This finding proposes a profitable unit equation and the rules of selling and buying to compare with the listing models. The profitable unit equation is defined as Eq. (10).

$$\text{Profitable unit} = \sum_{ts=1}^{p} (A(t+1)-A(t)) + \sum_{tb=1}^{q} (A(t)-A(t+1)) \tag{10}$$

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 represents the t-th day for buying.

And the selling and buying rules are defined as:

Selling rule:

If forecast $(t+1)-$actual $(t)>0$ then the next day to sell stock

Buying rule:

If forecast$(t+1)-$actual $(t)<0$ then the next dayto buy stock

The results of profitable unit are shown in Tables 13 and 14. Stock investment usually looks at long-term goals, and therefore the stock forecasting should focus on long-term investment profitability. Based on the result of profitable unit, the proposed model has the best result in TAIEX. Furthermore, the proposed model has better total profitable unit than listing models in HSI except the Chen's model (1996).

5. Conclusion

This study proposed a novel time-series model which used proposed ANFS method to select the reasonable variables into the ANFIS model, and utilized adaptive expectation model to strengthen forecasting performance. This study proposed an INFS method to select three important technical indicators, and utilized the selected technical indicators as input variables for ANFIS forecasting model to generate the initial forecasts. Finally, using the adaptive expectation model to enhance forecasts. The experimental results show that the proposed model can effectively improve accuracy of forecasting, and the proposed model outperforms the listing models in TAIEX and HSI dataset. From three finding in Section 4.4, the proposed model has better total profitability and accuracy than the listing models because proposed model extracts three important variables and subtractive clustering to reduce computational complexity, and employs adaptive expectation theory to get the best forecast. In future work, several related issues could be extended as follows:

(1) In selected variables method, the proposed model can consider the other variables more to train model such as non-quantitative breaking news, macroeconomic policies and regulations.
(2) Apply to different fields such as electric loads forecasting, tourism demand forecasting, and so on.
(3) Consider other artificial intelligence techniques to optimize the proposed model such as genetic algorithm, particle swarm optimization, and so on.

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