



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

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### ABSTRACT

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

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### 1. Introduction

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

stock market investors, who utilize technical indicators to predict market fluctuations, how to select useful technical indicators to forecast stock price trends accurately is the key issue to make profit.

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

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

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

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

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

## 2. Preliminaries

### 2.1. Technical analysis

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

### 2.2. Subtractive clustering

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

output variable. The potential value  $P_i$  of data point is calculated by Eq. (1)

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

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

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

$$p_i = P_i - P_1^* \exp(-\beta \|W_i - W_1^*\|^2) \quad (2)$$

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

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

$$p_i = P_i - P_k^* \exp(-\beta \|W_i - W_k^*\|^2) \quad (3)$$

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

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

### 2.3. Adaptive-network-based fuzzy inference system

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

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

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

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

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

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

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

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

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

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

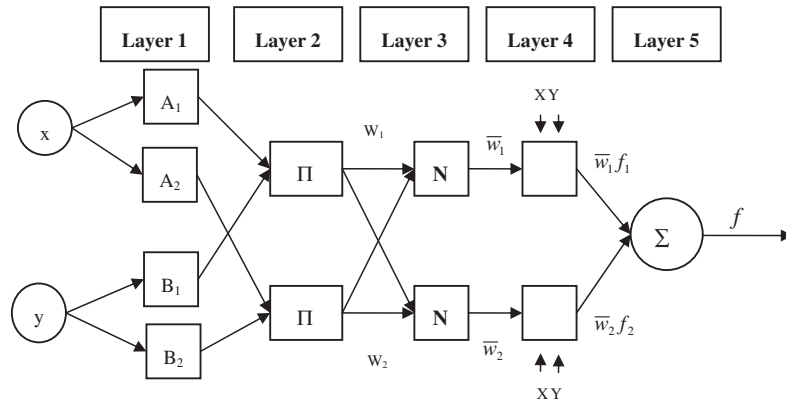


Fig. 1. The architecture of ANFIS network.

**Layer 3:** Every node in this layer is a square node labeled  $N$ . The  $i$ th node calculates the ratio of the  $i$ th rule's firing strength to the sum of all rules' firing strengths by Eq. (7). Output of this layer can be called normalized firing strengths

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

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

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

where  $p_i, q_i, r_i$  are the parameters.

**Layer 5:** The single node in this layer is a circle node labeled  $\Sigma$  that computes the overall output as the summation of all incoming signals (see Eq. (9))

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_{i=1}^2 w_i f_i}{\sum_{i=1}^2 w_i} = \text{overall output} \quad (9)$$

### 3. Proposed model

#### 3.1. Proposed concepts

As stated in Section 1, three major drawbacks were issued in past forecasting models to predict stock markets: (1) utility technical indicators to forecast future stock price based on personal experience and judgment is an subjective approach; (2) some prerequisites are necessary for conventional statistical forecasting models, such as statistical probability distribution (Chen, Chen, & Tseng, 2005); and (3) rule presentations of stock data are not produced from some data mining algorithms, and it is hard to explain the knowledge they learned (Trippi & Sieno, 1992) (i.e. the rules mined from ANN are not easily understandable). We argue that forecasting efficiency and applicability is diminished because of the drawbacks and, therefore, three methods are suggested in forecasting processes to refine past models as follows: (1) Use a correlation matrix to select useful forecasting factors from popular technical indicators, (2) EMPLOY the subtractive clustering method to granule the selected technical indicators and (3) utilize an adaptive-network-based fuzzy inference system (ANFIS) to extract forecasting rules from the linguistic dataset of technical indicators.

In the preprocessing phase of forecasting, three main procedures are contained as follows. Firstly, convert the dataset of the five daily fundamental stock quantities (maximum price, minimum price, opening price, closing price, and stock trading volume) into the dataset of popular technical analysis indicators (such as

moving average (MA), momentum (MTM), stochastic %K (%K), stochastic %D (%D), relative strength index (RSI), psychology line (PSY), Williams' percent range (%R), volume ratio (VR), volume (Volume), and accumulative ratio (AR)), which are commonly utilized by stock analysts and specialists.

Secondly, select the essential technical indicators from the popular indicators with "a correlation matrix", that can examine the relationship degree to the future price. The selection approach employs a statistical method, Pearson correlation with two-tailed tests, to select useful technical analysis indicators from popular indicators. The Pearson's correlation coefficient is usually signified by a symbol of " $r$ ". The statistical significance of " $r$ " is tested with a  $t$ -test. The hypotheses for the  $t$ -test are described as  $H_0 : r = 0$ , and  $H_1 : r \neq 0$ . If a lower  $p$ -value for the test (i.e.  $p \leq 0.05$ ) is generated, it means that there is a confident evidence to reject the null hypothesis ( $H_0$ ) and accept the alternative hypothesis ( $H_1$ ). For example, the future stock index is related with MA-5, MTM-5, %K-5, %D-5, RSI-5, PSY-5, %R-5, VR-5, volume, and AR-5 significantly (the marker "\*\*" in the last column in Table 6) (Cheng et al., 2010).

Lastly, subtractive clustering method (Chiu, 1994) is suggested to discretize the dataset of the selected technical indicators into the dataset of granule (linguistic) values. The main advantage to use discretization method in preprocessing raw dataset is that the data dimension of database can be reduced and simplified, and using discrete features are usually more compact and shorter than using continuous ones (Liu, Hussain, Tan, & Dash, 2002).

In model building process, a fuzzy inference system (FIS) implemented in the framework of adaptive networks, named as ANFIS, is suggested to generate forecasting rules from complex and high dimension of stock dataset. "Fuzzy inference" is the process to formulate the mapping from given inputs to an output based on fuzzy logic algorithm. The mapping provides a basis from which decisions can be made, or patterns discerned. Fuzzy inference systems have been successfully applied in many fields such as data classification, decision analysis, expert systems, and computer vision. Besides, FIS also plays an important role in the application systems base on fuzzy logic (i.e. electronic control systems), and such systems perform crisp nonlinear mapping, which is specified in the form of fuzzy rules encoding expert or common-sense knowledge about the problem at hand. In the proposed model, ANFIS is served as a basis for constructing a set of fuzzy *if-then* rules with appropriate choice of membership functions to generate the stipulated input-output pairs. In particular, the learning algorithm of ANFIS combines gradient decent and least-square methods to result in efficient hybrid training for system identification. The least square method is the major driving force to make the ANFIS operations converge fast, while the gradient decent method serves to generate

basis membership functions for the least-square method. The error rate for training data set propagates backward from the output toward the input so that the premise parameters are updated to make that the error measure is minimized for each input–output pair by the gradient decent method. The other advantage for ANFIS system prediction is that fewer trials and simpler architecture are required, compared to neural networks (NN), which require extensive trials in order to achieve the model optimization. Therefore, in this paper, the proposed model employs ANFIS as the basis for rule extraction to avoid the limitations of statistical methods (data need obey some mathematical distribution), and produce “if-then” rules that can model the qualitative aspects of human knowledge to be applicable for investors.

3.2. Proposed algorithm

To implement the proposed concepts, this paper proposes a hybrid model, which uses a correlation matrix as forecasting factor (named as “conditional features” in the proposed model) selection method, subtractive clustering as discretization method, and ANFIS as rule extraction method, to forecast stock market. The overall framework of the proposed model is illustrated as Fig. 2 and three major phases are provided. To detail the proposed model, each process of the proposed model is described as follows.

Step 1: Collect experimental datasets

In this step, a specific period of stock data including five daily fundamental stock quantities (maximum price, minimum price, opening price, closing price, and stock trading volume) should be collected as experimental datasets. One-year period of stock data is defined as one unit of experimental dataset. Ten-month period

of the stock data, from January to October, is defined as training data and the remaining period, from November and December, is used for testing.

Step 2: Data transformation and select essential technical indicators

In this step, several popular technical indicators (moving average (MA), momentum (MTM), stochastic %K (%K), stochastic %D (%D), relative strength index (RSI), psychology line (PSY), Williams’ percent range (%R), volume ratio (VR), volume (Volume), and accumulative ratio (AR)) are generated from five fundamental quantities (opening price, the highest price, the lowest price, closing price, and trading volume) (Kim, Min, & Han, 2006; Richard & Julie, 1999). Table 1 demonstrates the partial five fundamental quantities of the TAIEX and Table 2 demonstrates partial instances of technical indicators transformed from five fundamental quantities. In the proposed model, the technical indicators are used as conditional features, and the future stock index, is used as decision feature. In order to select the useful technical indicators that are highly related to the future stock index (defined as the price fluctuation at next day), a “correlation matrix” is employed as conditional feature selection method to select essential technical indicators from popular indicators.

Step 3: Define and partition the universe of discourse for input variables by subtractive clustering

Step 3.1: Define each universe of discourse for each input variable (conditional feature) with the minimum and maximum value of each variable ( $TIA(t)$ ,  $TIB(t)$ ).

Step 3.2: Partition the universe of discourse by subtractive clustering method (Chiu, 1994) (Gaussian membership function).

Step 4: Set the type of membership function for output variable

In this step, set linear type membership function for output variables. For example, three linguistic intervals are partitioned by subtractive clustering in each input variable. Take a typical rule from a Sugeno fuzzy model as example to describe output variable as follows:

$$\text{If } x(TIA(t)) = A_i \text{ and } y(TIB(t)) = B_i \\ \text{Then } f = p_i x + q_i y + r_i$$

where  $x(TIA(t))$  and  $y(TIB(t))$  are linguistic variables;  $A_i$  and  $B_i$  are the linguistic values (high, middle, low),  $f_i$  denotes the  $i$ th output value,  $p_i$ ,  $q_i$ ,  $r_i$ , are the parameters ( $i = 1, 2, 3$ ).

Step 5: 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 ( $A_i$ ,  $B_i$ ) from input membership functions are used as the if-condition part, and the output membership functions ( $f_i$ ) is the then part. Two typical rules extracted from the TAIEX of year 2000 are demonstrated as follows:

Rule 1:

$$\text{if } x_1(MA-5(t)) = L_{MA-5,low} \text{ and } x_2(RSI-5(t)) = L_{RSI-5,low} \text{ and } \dots \\ \text{and } x_7(AR-5(t)) = L_{AR-5,low} \\ \text{then } f_{low}(TAIEX_{t+1}) = P_{MA-5,low}x_1 + P_{RSI-5,low}x_2 + \dots + P_{AR-5,low}x_7 + r_{low}$$

Rule 2:

$$\text{if } x_1(MA-5(t)) = L_{MA-5,high} \text{ and } x_2(RSI-5(t)) = L_{RSI-5,high} \text{ and } \dots \\ \text{and } x_7(AR-5(t)) = L_{AR-5,high} \\ \text{then } f_{high}(TAIEX_{t+1}) = P_{MA-5,high}x_1 + P_{RSI-5,high}x_2 + \dots + P_{AR-5,high}x_7 + r_{high}$$

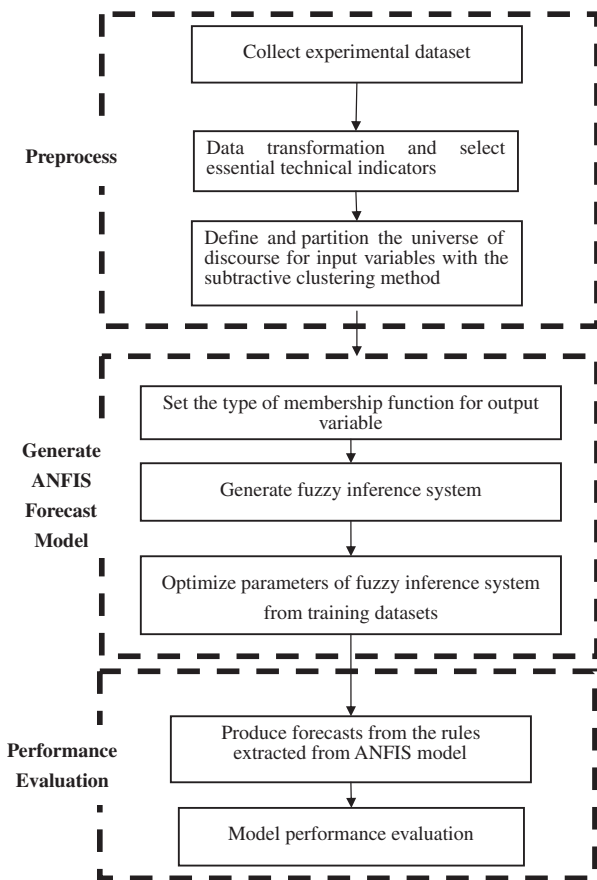


Fig. 2. The framework of proposed model.

**Table 1**  
The partial five fundamental quantities for the TAIEX of year 2000.

Date	Opening price	Highest price	Lowest price	Closing price	Volume
2000/01/04	8644.91	8803.61	8642.50	8756.55	3,902,921
2000/01/05	8690.60	8867.68	8668.02	8849.87	4,602,396
2000/01/06	8876.59	9023.99	8863.91	8922.03	4,811,126
⋮	⋮	⋮	⋮	⋮	⋮
2000/10/27	5991.83	6003.38	5805.17	5805.17	2,068,108
2000/10/30	5644.26	5666.96	5615.90	5659.08	566,113
2000/10/31	5530.80	5626.03	5502.67	5544.18	1,837,995

**Table 2**  
The partial instances of technical indicators transformed from fundamental quantities.

Date	MA-5( <i>t</i> )	RSI-5( <i>t</i> )	K-5( <i>t</i> )	D-5( <i>t</i> )	R-5( <i>t</i> )	PSY-5( <i>t</i> )	AR-5( <i>t</i> )	TAIEX( <i>t</i> + 1)
2000/01/04	8384.68	100	96.46	88.16	0	1	3.72	8849.87
2000/01/05	8537.95	100	97.64	91.32	0	1	4.81	8922.03
2000/01/06	8678.47	100	98.42	93.68	0	1	4.86	8845.47
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2000/10/27	5874.07	65.98	66.88	67.65	63.76	0.6	1.30	5659.08
2000/10/30	5869.70	48.45	44.58	59.96	100	0.4	1.46	5544.18
2000/10/31	5794.81	17.98	29.72	49.88	100	0.2	1.13	5425.02

where  $x_1(MA-5(t)), x_2(RSI-5(t)), \dots, x_7(AR-5(t))$  are linguistic variables,  $L_{MA-5,i}, L_{RSI-5,i}, \dots, L_{AR-5,i}$ , are the linguistic values,  $p_{MA-5,i}, p_{RSI-5,i}, \dots, p_{AR-5,i}, r_i$ , are the parameters,  $f_i(TAIEX_{t+1})$  denotes the *i*th output value, (*i* = 1 denotes “low”; *i* = 2 denotes “high”).

Step 6: Optimize fuzzy inference system parameters from training datasets

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

Step 7: Produce forecasts from the rules extracted from ANFIS model

The FIS parameters for ANFIS model are determined when the stopping criterion is reach from step 6, and then the extracted rules are used to forecast the corresponding testing dataset. The partial parameters for the extracted rules from the TAIEX of year 2000 are demonstrated as follows:

$$P_{MA-5,low}, P_{RSI-5,low}, \dots, P_{AR-5,low}, r_{low} = 0.9904, 5.071, \dots, -103.4, 268.8$$

$$P_{MA-5,high}, P_{RSI-5,high}, \dots, P_{AR-5,low}, r_{high} = 0.9992, -4.155, \dots, 45.32, 202.7$$

With the rules and determined parameters, the forecast for the future stock index at time, *t* + 1, can be produced by the forecasting rule if the present conditional attributes match the rule of *if*-part.

**Table 3**  
The performance comparisons for three forecasting models (TAIEX).

Model	Year						Average	Standard deviation
	2000	2001	2002	2003	2004	2005		
Chen's model (1996)	176	148	101	74	83	66	108	44
Yu's model (2005)	191	167	75 <sup>a</sup>	66 <sup>a</sup>	79	69	108	39
Proposed model	147 <sup>a</sup>	66 <sup>a</sup>	83	69	76 <sup>a</sup>	65 <sup>a</sup>	84 <sup>a</sup>	31 <sup>a</sup>

<sup>a</sup> The best performance among three models.

**Table 4**  
Paired *t*-test for performance difference between Chen's and the proposed model.

Statistics	Variable 1 (Chen's model)	Variable 2 (proposed model)
Mean	108	84.333
Variation	1963.6	988.667
Observations	6	6
Assumed difference of mean	0	
Degree	5	
<i>t</i> -statistic	1.911	
<i>p</i> value ( <i>T</i> ≤ <i>t</i> ): one-tail	0.057	
α	0.1	
Critical value: one-tail	1.475884037	

Step 8: Model performance evaluation

Root Mean Square Error (RMSE) is employed as performance indicator for the proposed model, which is defined by Eq. (10).

$$RMSE = \sqrt{\frac{\sum_{t=1}^n |actual\ stock\ index(t+1) - forecast(t+1)|^2}{n}} \quad (10)$$

where *actual stock index* (*t* + 1) denotes actual stock index at time *t* + 1, *forecast* (*t* + 1) denotes the prediction for future stock index at time *t* + 1, and *n* denotes the total amount of forecasts.

**4. Model verification**

To verify proposed model, six-year period of the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), from 2000 to 2005, is selected from Taiwan Stock Exchange Corporation

**Table 5**  
Paired *t*-test for performance difference between Yu's and the proposed model.

Statistics	Variable 1 (Yu's model)	Variable 2 (proposed model)
Mean	107.833	84.333
Variation	3116.967	988.667
Observations	6	6
Assumed Difference of mean	0	
Degree	5	
<i>t</i> -statistic	1.363	
<i>p</i> value ( $T \leq t$ ): one-tail	0.116	
$\alpha$	0.1	
Critical value: one-tail	1.476	

(TWSE) <http://www.twse.com.tw/>. One-year period of stock data is defined as one unit of experimental dataset. Ten-month period of the stock data, from January to October, is defined as training data and the remaining period, from November and December, is used for testing (Chen, 1996; Yu, 2005). To examine the superior of the proposed model, two fuzzy time-series models, Chen (1996) and Yu (2005) models, are used as comparison model. The experimental results consist of 18 forecasting performance values for three forecasting models with six units of experimental dataset, and the performance data are listed in Table 3. From Table 3, it is shown that proposed model win 4 out of 6 testing datasets and outperforms the other two fuzzy time-series models in RMSE. Additionally, the proposed model bears the smallest average and variation of RMSE.

To verify the performance improvement, the paired *t*-test is used to examine the performance difference between two forecasting models. From Table 4 (paired *t*-test for Chen's and the proposed models), it is concluded that the proposed model outperforms Chen's model significantly with  $\alpha = 0.1$ . However, from Table 5

(paired *t*-test for Yu's and the proposed models), the performance evidence does not confirm the superior of the proposed model statistically but numerically. Although the proposed model surpasses Chen's significantly ( $\alpha = 0.1$ ) but Yu's, smaller RMSE still makes the proposed model valuable because less forecasting error avoids larger profit loss for common investors.

## 5. Findings and conclusions

This paper has proposed a new hybrid model, which employs technical indicators as forecasting factors and three novel methods (correlation matrix, subtractive clustering, and ANFIS) in forecasting processes, to promote prediction performance in stock market. From the experimentation and forecasting results, three findings are given in this paper in the followings.

- (1) Experimental results (Table 3) have shown that the proposed model outperforms two listing fuzzy time-series models (Chen's and Yu's models) numerically in RMSE. It can be explained by that the employing useful technical indicators as forecasting factors, which are highly related to the future stock index, can promote forecasting accuracy. Besides, we argue that the ANFIS model can efficiently reduce forecasting error because the forecasting rules are optimal in training dataset.
- (2) From Table 3, it is clear that the proposed model bears smaller performance variation (standard deviation = 31) performs more stably than the two listing models (Chen's = 44; Yu's = 39). The main reason we argue is that the back-propagation architecture of ANFIS model can produce optimal forecasting rules in training dataset to make the forecasts for the future stock index more reliable.

**Table 6**  
Correlations of technical indicators for TAIEEX.

	MA-5	MTM-5	%K-5	%D-5	RSI-5	PSY-5	%R-5	VR-5	Volume	AR-5	Price fluctuation	
MA-5	Pearson correlation Sig. (2-tailed)	1 .000	.741*** .000	.753*** .000	.472*** .000	.797*** .000	.818*** .000	-.835*** .000	.676*** .000	1.000*** .000	.251*** .000	.169*** .009
MTM-5	Pearson correlation Sig. (2-tailed)	.741*** .000	1 .000	.903*** .000	.714*** .000	.880*** .000	.889*** .000	-.713*** .000	.861*** .000	.741*** .000	.299*** .000	.112 .088
%K-5	Pearson correlation Sig. (2-tailed)	.753*** .000	.903*** .000	1 .000	.860*** .000	.835*** .000	.836*** .000	-.781*** .000	.768*** .000	.753*** .000	.223*** .001	.133** .042
%D-5	Pearson correlation Sig. (2-tailed)	.472*** .000	.714*** .000	.860*** .000	1 .000	.713*** .000	.705*** .000	-.424*** .000	.585*** .000	.472*** .000	.074 .260	.134** .041
RSI-5	Pearson correlation Sig. (2-tailed)	.797*** .000	.880*** .000	.835*** .000	.713*** .000	1 .000	.973*** .000	-.619*** .000	.791*** .000	.797*** .000	.232*** .000	.152** .020
PSY-5	Pearson correlation Sig. (2-tailed)	.818*** .000	.889*** .000	.836*** .000	.705*** .000	.973*** .000	1 .000	-.627*** .000	.796*** .000	.818*** .000	.269*** .000	.128** .047
%R-5	Pearson correlation Sig. (2-tailed)	-.835*** .000	-.713*** .000	-.781*** .000	-.424*** .000	-.619*** .000	-.627*** .000	1 .000	-.594*** .000	-.835*** .000	-.232*** .000	-.126** .049
VR-5	Pearson correlation Sig. (2-tailed)	.676*** .000	.861*** .000	.768*** .000	.585*** .000	.791*** .000	.796*** .000	-.594*** .000	1 .000	.676*** .000	.367*** .000	.109 .097
Volume	Pearson correlation Sig. (2-tailed)	1.000*** .000	.741*** .000	.753*** .000	.472*** .000	.797*** .000	.818*** .000	-.835*** .000	.676*** .000	1 .000	.251*** .000	.169*** .009
AR-5	Pearson correlation Sig. (2-tailed)	.251*** .000	.299*** .000	.223*** .001	.074 .260	.232*** .000	.269*** .000	-.232*** .000	.367*** .000	.251*** .000	1 .000	.137** .035
Price fluctuation	Pearson correlation Sig. (2-tailed)	.169*** .009	.112 .088	.133** .042	.134** .041	.152** .020	.128** .047	-.126** .049	.109 .097	.169*** .009	.137** .035	1

Note: MA-5 denotes that the value of the indicator is calculated using 5 periods of fundamental stock quantities (maximum price, minimum price, opening price, closing price, and stock trading volume) from present day to previous 4 day; and the values of other indicators (MTM-5, %K-5, %D-5, RSI-5, PSY-5, %R-5, VR-5 and AR-5) are produced in the same way.

- (3) The proposed model can produce fewer forecasting rules to forecast stock market. In the experimentation using the TAIEX as datasets, only two rules are generated by the proposed model. In the forecasting processes, the subtractive clustering method is utilized to granule conditional attributes (technical indicators) and it reduces probably the amount of FIS rules.

Additionally, from the forecasting rules generated by the proposed model, two advantages are discovered:

- (1) Reasonable and understandable rules, “if-then” rules, produced by ANFIS can model the qualitative aspects of human knowledge.
- (2) The forecasting rules based on objective stock data rather than subjective human judgments can provide stock investors objective suggestions (forecasts) to make decisions.

In the future works, the model can be verified by other stock market such as China, Japan and Hong Kong. Besides, there are two suggested approaches to refine the proposed model to improve forecasting performance: (1) validate the generated rules by financial experts or stock analysts to improve accuracy; and (2) apply other data discretization methods in preprocessing phase to evaluate the performance variation.

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