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Fusion ANFIS and Adaptive Expectation Model based on Multi-stock Volatility Causality for TAIEX Forecasting

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Abstract
Accurate stock price forecasting can be immensely helpful for investors, because more accurate predictions will bring more profit for investors. Stock market participants usually make their short-term investment decisions according to recent stock knowledge such as the analytical report before market opened, yesterday stock index volatility of other countries, and the price fluctuations in recent days. However, there are three major drawbacks in the conventional time series model: (1) the majority statistical methods rely upon assumptions for the variables; (2) most models do not consider the volatility of different country stock market; and (3) most forecasting models do not provide the predicting rule of stock price index. Based on these reasons above, this paper proposes a new model, using multi-stock volatility causality (Dow Jones (Dow Jones Industrial Average), NASDAQ (the largest US electronic stock market)) joining to fusion ANFIS models, to forecast Taiwan stock index. Furthermore, one-period and two-period adaptive expectation model are applied to the proposed model for enhancing the forecasting performance. To evaluate the forecasting performances, the proposed model is compared with two different models, Chen's model and Huarng's model. The experimental results indicate that the proposed model is superior to the listing methods in terms of RMSE (root mean squared error).
Keywords: Multi-stock, ANFIS, Adaptive Learning

Introduction

Stock market is one of challenging investment activities, because the shock of stock market is violent, forecasting what phenomenon will occur has been one of most challenging issues. High accurate predictions would generate huge profit by forecasting model. However, such forecasting procedure is difficult to understand because stock markets are influenced by psychological characteristics of investors and nonlinear relationships of various. Therefore, investors eagerly concern about forecasting accuracy, and it is more important how to build a higher accuracy forecasting model.

The dependence degree on a global economic system is very high in the commercial field of Taiwan and it is very huge that the impacts of world economic fluctuations to Taiwan. From the study of literature, Dickinson (Dickinson, 2000) proves that the influence of stock market in different counties is each other more or less. Thus, volatility of American stock index is utilized by proposed model in this study.

Recently, many researches have presented different methods to handle forecasting stock price problems based on statistical techniques or conventional time series models. Furthermore, the use of diverse market information such as technical indicators and news as model inputs is explored by researchers (Schumaker & Chen, 2009). These approaches have limitations because statistical methods require excessive assumptions. Nevertheless, dataming methods are vulnerable to learning complex patterns required in real trading.

According to the related work review above, there are three major drawbacks in those models: (1) most statistical methods depend on some assumptions about the variables used in the analysis; (2) most conventional time series models use only one variable in forecasting. However, many market variables should be considered in forecasting; and (3) most forecasting models do not offer the predicting rule of stock price index. Further, the forecasting rules are useful for investors to make investment strategy.

In order to solve the drawbacks above, this paper considers that the volatility of American stock indexes have important character to effect the volatility of TAIEX. Because the forecasting models utilize the relation between the volatility of American stock index and the volatility of TAIEX, the analytical results would proximate to the real world. Furthermore, a fuzzy inference system employing fuzzy if-then rules can model the qualitative features of human knowledge and can be suitable for human to use. In time-series research, adaptive expectation model (Kmenta, 1986) is a wise forecast model to represent a prediction approach for the future stock price. This model produces forecasts based on first-order linear relationship between recent two periods of stock prices. Additionally, recent stock information in these two days is usually utilized to make the short-term decisions by investors. Therefore, the linear relationships between recent periods of stock prices should be decomposed in forecasting process.

Based on the idea above, this paper proposes a new volatility model to forecast Taiwan stock index. Firstly, this paper calculates the volatility of NASDAQ stock index and Dow Jones stock index by equation (1)-(2). Then use the fuzzy inference system to forecast Taiwan stock index, it considers multi-stock index (NASDAQ stock index and Dow Jones stock index and TAIEX (t)) to forecast TAIEX (t+1). Secondly, to optimize the fuzzy inference system parameters by adaptive network, which can overcome the limitations of statistical methods. Thirdly, this study applies one-period and two-period adaptive expectation model to the proposed model for strengthen the forecasting performance.

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

Related Works

This section reviews related studies of different forecasting models on stock market, the ANFIS and Subtractive clustering (Subclust).

Different Forecasting Models on Stock Market

Stock market is one of the most dramatic activities. The market condition is changed in a second and the gain-loss is determined in a twinkling decision. Hence, many different methods are proposed by researches to deal with forecasting stock price issue. Firstly, the study of Dickinson (2000) shows that the stock price indexes in different countries would

influence with each other. Huarng et al (2007) have used the volatility of Dow Jones stock index and NASDAQ stock index to forecast Taiwan stock index.
Secondary, researchers have utilized various time series to handle financial forecasting, such as stock index forecasting. Engle (Engle, 1982) proposed the ARCH (Autoregressive Conditional Heteroscedasticity) model that has been used by many financial analysts and the GARCH (Bollerslev, 1986). Box and Jenkins (Box & Jenkins, 1976) proposed the autoregressive moving average (ARMA) model that combines a moving average process with a linear difference equation to obtain an autoregressive moving average model. Over the years, the many data mining techniques were applied to financial analysis. Huarng and Yu (Huarng & Yu 2006) apply the backpropagation neural network to establish fuzzy relationships in fuzzy time series for forecasting stock price. Chen and Chung (Chen & Chung, 2006) presented a new method to deal with the forecasting enrollments problem based on high-order fuzzy time series and genetic algorithms, where the length of each interval in the universe of discourse is tuned by using genetic algorithms. Kinoto et al (1990) developed a prediction system for stock market by using neural network. Nikolopoulos and Fellrath (Nikolopoulos & Fellrath, 1994) combined genetic algorithms and neural network to develop a hybrid expert system for investment advising. Kim and Han (Kim & Han, 2000) proposed genetic algorithms approach to feature discretization and the determination of connection weights for artificial neural networks (ANNs) to predict the stock price index. Roh (2007) integrated neural network and time series model for forecasting the volatility of stock price index. Further, machine learning (ML) and various statistical methods have applied market attributes to forecasting models (Altan & Karasu, 2019, Devpura et al., 2018, Karasu et al., 2020, Nguyen et al., 2015; Timmermann, 2008).

Subtractive Clustering

Subtractive clustering was developed by Chiu (1994), 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 ($i = 1,2,..., N$). $W_i = (x_i, y_i)$ 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 equation (4)

$$P_i = \sum_{j=1}^{N} e^{-\alpha \| W_i - W_j \|^2} \quad (4)$$

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

The data point with many neighboring data points is chosen as the first cluster center. To generate the other cluster centers, the potential P_i is revised of each data points W_i by equation (5)

$$p_i = p_i - p_1^* \exp(-\beta \| W_i - W_1^* \|^2) \quad (5)$$

where *β* 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 equation (5), the method selects the data point with the highest remaining potential as the second cluster center. For general equation, we can rewrite equation (5) as equation (6).

$$p_i = p_i - p_k^* \exp(-\beta \| W_i - W_k^* \|^2) \quad (6)$$

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, .., D)*. Then we define their membership functions. The spread is calculated according to *β*.

ANFIS: Adaptive-Network-based Fuzzy Inference System

Jang (1993) proposes Adaptive-Network-based Fuzzy Inference System (ANFIS), which is a fuzzy inference system, implemented in the framework of adaptive networks. For illustrating the system, this study assumes 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.

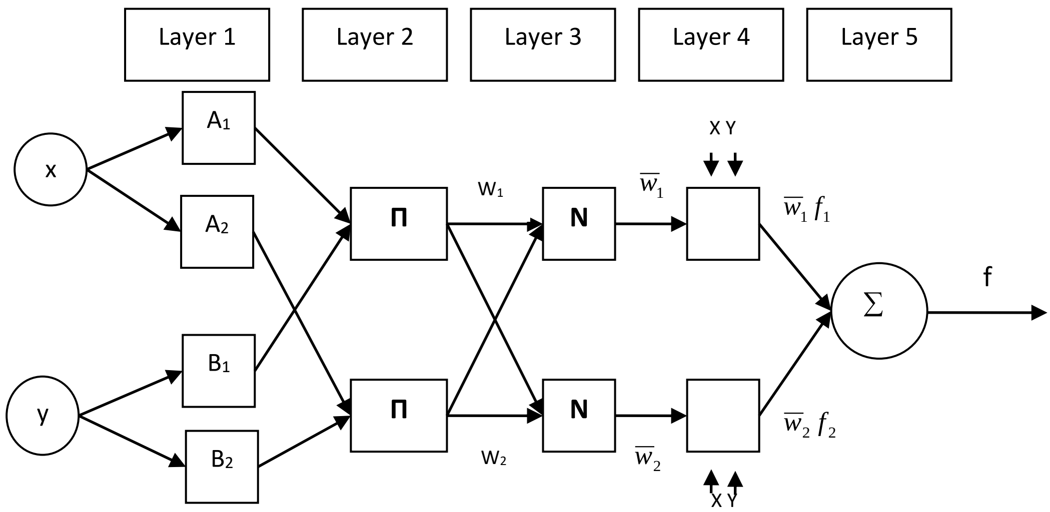

Fig. 1 The architecture of ANFIS network

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 $f_1 = p_1 x + q_1 y + r_1$

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 *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 equation (7)). $O_{1,i}$ 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 equation (8)) with maximum equal to 1 and minimum equal to 0.

$O_{1,i} = \mu A_i(x)$ for i=1, 2 (7)

$$\mu A_i(x) = \frac{1}{1+[(\frac{x-c_i}{a_i})^2]^{bi}} \quad (8)$$

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 Π which multiplies the incoming signals and sends the product out by equation (9).

$O_{2,i} = w_i = \mu A_i(x) \times \mu B_i(y)$ for i=1, 2 (9)

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 equation (10). Output of this layer can be called normalized firing strengths.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad \text{for } i=1, 2 \quad (10)$$

Layer 4: Every node i in this layer is a square node with a node function (see equation (11)). Parameters in this layer will be referred to as consequent parameters.

$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i + q_i + r_i)$ (11)

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 (see equation (12))

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_{i=1} w_i f}{\sum_{i=1} w_i} = \text{overall output} \quad (12)$$

Proposed Model

Based on discussion on research purpose in section 1, this paper pvovides a new volatility model to forecast Taiwan stock index. Firstly, this paper calculates the volatility of NASDAQ stock index and Dow Jones stock index by equation (13)-(14). Then this study adopts the fuzzy inference system to forecast Taiwan stock index, it considers multi-stock index (NASDAQ stock index and Dow Jones stock index and TAIEX (t)) to forecast TAIEX (t+1). Secondly, to optimize the fuzzy inference system parameters by adaptive network, which can overcome the limitations of statistical methods. Thirdly, we utility one-period and two-period adaptive expectation model to the proposed model for promoting the forecasting performance. Then, the overall flowchart of the proposed model is shown as Fig 2.

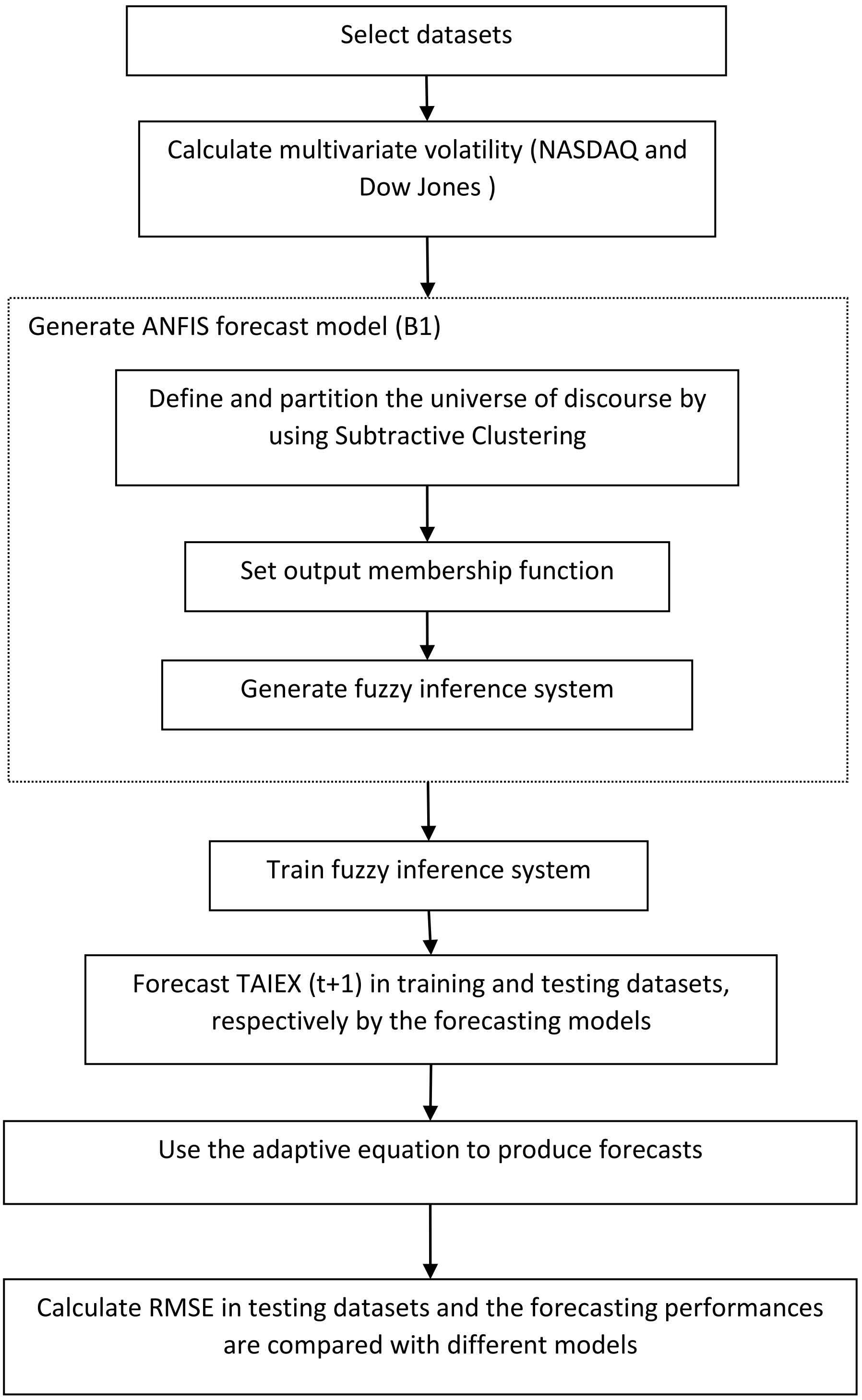

Fig. 2 Flowchart of the proposed procedure

For easy comprehension, this section uses some numerical data as the example step by step shows the main concept in proposed algorithm.

Step1: Select data set
In this section, this study choses 2000-year TAIEX which contains 271 transaction days as an example to illustrate the proposed model. The training data are selected from January to October and the remainder data (from November and December) are used for testing.
Step 2: Calculate multivariate volatility (NASDAQ stock index and Dow Jones stock index)
In this section, we define two variables namely (1) the NASDAQ (*N)* and (2) the Dow Jones (*D*), and calculate the volatility of the two variables by equation (13)-(14). Table 1 lists the differences in the variables NASDAQ and Dow Jones. From Table 1, some data under the NASDAQ and Dow Jones are empty; because of there were no transactions on those days. For this reason, this paper fills in the last volatility as the differences.

$$\mathrm{diff}(N(t)) = N(t) - N(t-1) \quad (13)$$

$$\mathrm{diff}(D(t)) = D(t) - D(t-1) \quad (14)$$

Table 1
Differences in variables

Date	NASDAQ	diff(*N*(*t*))	Dow Jones	diff(*D*(*t*))
2000/1/3	4131.15		11357.51	
2000/1/4	3901.69	-229.46	10997.93	-359.58
2000/1/5	3877.54	-24.15	11122.65	124.72
2000/1/6	3727.13	-150.41	11253.26	130.61
2000/1/7	3882.62	155.49	11522.56	269.3
2000/1/8		155.49		269.3
2000/1/9		155.49		269.3
2000/1/10	4049.67	167.05	11572.2	49.64
2000/1/11	3921.19	-128.48	11511.08	-61.12
2000/1/12	3850.02	-71.17	11551.1	40.02
2000/1/13	3957.21	107.19	11582.43	31.33
2000/1/14	4064.27	107.06	11722.98	140.55
2000/1/15		107.06		140.55
2000/1/16		107.06		140.55
2000/1/17		107.06		140.55
2000/1/18	4130.81	66.54	11560.72	-162.26
2000/1/19	4151.29	20.48	11489.36	-71.36
2000/1/20	4189.51	38.22	11351.3	-138.06
2000/1/21	4235.4	45.89	11251.71	-99.59
2000/1/22		45.89		-99.59
2000/1/23		45.89		-99.59
2000/1/24	4096.08	-139.32	11008.17	-243.54
2000/1/25	4167.41	71.33	11029.89	21.72
2000/1/26	4069.91	-97.5	11032.99	3.1

2000/1/27	4039.56	-30.35	11028.02	-4.97
2000/1/28	3887.07	-152.49	10738.87	-289.15
2000/1/29		-152.49		-289.15
2000/1/30		-152.49		-289.15
2000/1/31	3940.35	53.28	10940.53	201.66

Step 3: Generate ANFIS forecast model (see B1 block of Fig2)

The ANFIS forecast model is from Step 3.1 to Step 3.3, and the proposed ANFIS method uses Subtractive Clustering 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: Define and partition the universe of discourse for input variables by using Subtractive Clustering

Firstly, we define each universe of discourse for three variables (*TAIEX (t), diff(N(t)*), *diff(D(t)*)) according to the minimum and maximum value in each variable. Secondly, partition the universe of discourse into three linguistic intervals by using Subtractive Clustering (Chiu 1994) (Gaussian membership function).

Step 3.2: Set the type of membership function for output variables
In this section, we set Lineal type membership function for output variables. A typical rule in a Sugeno fuzzy model has the form as follows:

If x (*TAIEX (t)*) = A_i , y (*diff(N(t)*)) = B_i and z (*diff(D(t)*)) = C_i , then f_i = p_i x + q_i y + r_i z+ s_i
Where x (*TAIEX (t)*), y (*diff(N(t)*)), z (*diff(D(t)*)) are linguistic variables, A_i , B_i , C_i are the linguistic labels (high, middle, low), f_i denotes the *i-th* output value, p_i , q_i , r_i , 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 used as the if-condition part and the output membership functions (f_i) as the then part.

Step 4: Train fuzzy inference system parameters from training datasets
In this section, this study employ a combination of the least-squares method and the backpropagation gradient descent method for training four types of forecasting models, and use FIS membership function parameters to emulate a given training datasets. This paper sets epoch as 50 (the process is executed for the predetermined fixed number (50) 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 5: Forecast TAIEX (t+1) in training and testing datasets, respectively by the forecasting models

Firstly, the FIS parameters of the forecasting models are determined when the stopping criterion is reach from step 6, then the training forecasting model are used to forecast *T (t+1)* for the target training and testing datasets, respectively.

Step 6: Use the adaptive equation to produce forecasts

From step 5, the forecast *T (t+1)* in training and testing datasets are obtained. Then, this study use two-period adaptive equation (15) and the one-period adaptive equation (16) to produce forecasts, respectively.

$$Forecast\ (t+1) = p(t) + \alpha(Forecast\ (t+1) - P(t)) + \beta(Forecast\ (t) - P(t-1)) \quad (15)$$

$$Forecast\ (t+1) = p(t) + \alpha(Forecast\ (t+1) - P(t)) \quad (16)$$

The two-period adaptation model is defined in Eq. (15), where α, β are the adaptive parameters, range from -1 to1 (exclude 0) with the stepped value, 0.001, to adapt the forecasts with the minimal RMSE in the training dataset by equation (17).

$$\text{RMSE} = \sqrt{\sum_{t=1}^{n} |\ actual\ (t) - forecast\ (t)\ |^2 \Big/ n} \quad (17)$$

Where actual (t) denotes the real TAIEX value, forecast (t) denotes the predicting TAIEX value and *n*is the number of data.

Then, we can use the adaptive parameters to forecast the target testing dataset.

Step 7: Calculate RMSE in testing datasets and the forecasting performances are compared with different models

Calculate RMSE values in testing datasets by equation (17). Then the RMSE is taken as evaluation criterion to compare with different models.

Experiments and Comparisons

To verify the proposed model, the experimentation, using the TAIEX from 1997 to 2003 (7 sub-datasets) is implemented. The sub-datasets for previous 10-month are used for training and those from November to December are selected for testing.

After experiments, this study generates 7 forecasting performance for the 7 testing sub-datasets. Then, this paper compares the performances of the proposed procedure with the conventional fuzzy time series model, Chen's (Chen 1996) model. Furthermore, to examine whether the proposed procedure surpasses the latest fuzzy time series model combined backpropagation neural network, the performances of Huarng's (Huarng & Yu 2006)) model which chooses the neural network to establish fuzzy relationships in fuzzy time series are compared with the proposed procedure. The forecasting performances of Chen's model, Huarng's model and the two proposed approaches (adapt one-period, adapt two- period) in the 7 testing sub-datasets are listed in the Table 2. From Table 2, results show that the proposed procedure outperforms the performances of listing model.

Table 2
The performance comparisons of different models (TAIEX)

Models	Year						
	1997	1998	1999	2000	2001	2002	2003
Chen's model [5]	154	134	120	176	148	101	74
Huarng's model [11]	141	121	109	152	130	84	56
Proposed approach (adapt one-period)	130	113	102 [a]	138 [a]	120 [a]	64	46 [a]
Proposed approach (adapt two-period)	128 [a]	111 [a]	102 [a]	138 [a]	120 [a]	63 [a]	46 [a]

[a] The best performance among four models

Discussions

After verification and comparison, the proposed method outperforms the listing methods. However, some opinions can be further discussed in this section. Taiwan is a viable member of the international economic society and the dependence degree on a global economic system is very high; therefore, the impacts of world economic fluctuations to Taiwan are very high, too. Therefore, this paper would explore whether proposed forecasting methods considering the volatility of USA stock index are better than other forecasting models. According to Table 2, it is evidence that the proposed model is superior to the listing methods in terms of RMSE. The main reason is that the proposed model takes into account multi-stock volatility causality with ANFIS learning for TAIEX forecasting.

Conclusions

Proposed model, based on multi-stock volatility causality joining to fusion ANFIS procedure and adaptive expectation model, is utilized to forecast stock price problems in Taiwan; furthermore, the proposed model is compared with two different models, Chen's model and Huarng's model, to evaluate the results. This proposed model mainly employs input variables of stock index (e.g., Dow Jones, NASDA, and TAIEX) to forecast the TAIEX in the next trading day for investors. To illustrate the proposed model, three practical collected stock index datasets from USA and Taiwan stock markets, Dow Jones, NASDA, and TAIEX, are employed in this empirical experiment, which all consist datum from 1997 to 2003 (7 years in total). Each dataset including data of 7 years is spilt into 7 sub datasets based on year, respectively. Sub dataset of each year for the first 10-month, January to October, is used for training and the last 2-month, November to December, is used for testing. From Table 2, the experimental results of three datasets indicate that the proposed model outperforms the listing models in terms of RMSE. Moreover, the results of this paper are useful and feasible for future researches, decision makers and stock investors. Major conclusions are summarized in Table 3.

Table 3
The major conclusions of this paper

Item	Contents
Findings	1. The parameters of output function in ANFIS are not equal to 0. This means fluctuation of USA stock indexes have effected TAIEX. 2. Experimental results indicate that a two-period adaptive model could reduce forecasting error more beneficially than a one-period adaptive model.
Contributions	1. Investors can utilize proposed model to dig out the advanced mark of investment with benefits in stock market. 2. Results of this paper are useful and feasible for future researches, decision makers and stock investors.

For following research, researchers can use other stock datasets such as South Korea, Hong Kong, and Japan is to further validate the proposed model.

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