ISSN No:-2456-2165

Forecasting Indonesia Stock Exchange (IDX) Composite Using Fuzzy Time Series Methods

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Abstract:- The main objective of this research is to propose forecasting model of stock exchange (IDX) composite index using a weighted fuzzy time series (WFTS) model. The Mamdani inference system has been applied with the fuzzy model by using centroid defuzzification. After the models have been executed and verified, the performance of WFTS model has been compared with the conventional fuzzy time series (FTS) model using root mean square error (RMSE). The results showed that WFTS models had better performance than the conventional FTS models. The RMSE values achieved from WFTS and FTS models for training data sets were 0.314 and 0.4443, and for testing data 0.3246 and 0.4351, respectively. Finally, it is recommended that optimization techniques should be employed with the proposed type of models to improve their performance.

Keywords:- *Forecasting Model; Fuzzy Time Series; Weighted Fuzzy Time Series; Stock Exchange Composite.*

I. INTRODUCTION

An index of all stocks listed by the Indonesia Stock Exchange is called Indonesia Stock Exchange (IDX) Composite. According to Ibnu Khajar [1], there are over 400 companies trade listed in Indonesia stock market. Indonesia Stock Exchange is based in Jakarta, the capital of Indonesia. Indonesia Investments Stock Market Update section contains a daily analysis concerning the performance of the Indonesia Stock Exchange. Recently, foreign investors have high affected to Indonesia Stock Exchange (IDX) due to the small number of domestic investors, which can be a risk to the economy. Domestic investors prefer to invest in risk-free assets such as bank deposits due to they were not familiar with the stock market and concerned about the risks (risk-averse type of investor). Hence, it is significant to provide useful information to the domestic investors and convince them to get involved in the stock exchange. In 2009, the approximately 300,000 investors (only about 0.1% of the country's total population) were much fewer in proportion than in other Asian countries e.g., Singapore (approximately 1.26 million investors or 30% of total population), and Malaysia (around 3 million people or 12.8% of total population).

A numeric prediction approximates the value of something in the future based on past scientific data analysis, particularly by using statistical methods. Predictions are vital in many areas including the financial field. The financial predictions can be provided to the investor for decision making to buy or sell the stocks in the market. After predictions are available, the informed actions taken based on them may decrease significant losses. For instance, an international company can make short-term financing and investment decisions, capital budgeting decisions, long-term financing decisions and judgments that influence its profits based on expected changes in currency exchange rates.

In order to stabilize the economy and make the IDX not so strongly dependent on foreign investors, Indonesian government need to increase the number of domestic investors by educating and providing them with useful information. Currently, the most of Indonesian investors are risk-averse investors. Fitting data with mathematical models enables simulations predicting future trends, and thereby gaining useful information for the domestic investors. The predictions of the stock exchange composite must consider several aspects, such as time, patterns and relationships in the data, and the precision or reliability of predictions. This investigation proposes a fuzzy time series models to predict the future IDX composite in order to make it easier for the market participants to decide their economic activities. Later on, the performance of fuzzy time-series models in predicting IDX composite will be investigated.

Fuzzy time-series method has been proposed by Song and Chissom [2, 3] to predict the enrollment count to a university. It is a dynamic process that used linguistic values as observations. Chen [4] adopted the Song and Chissom method to illustrate the process to forecast the university enrollment, and later on it was further adopted by Yu [5]. In 2012, Lee [6] adopted the Song and Chissom method to deal with seasonal data. Suhartono and Lee [7] also presented forecasting seasonal method and data trend analysis. A'yun et al. [8] proposed the weighted fuzzy time series model to forecast Trans Jogja's passengers. Rubio et al. [9] applied the weighted fuzzy time series method to forecast the portfolio returns. Lastly, Septiarini et al. [10] presented the wavelet fuzzy model to forecast the exchange rate of IDR to USD.

II. METHODOLOGIES

A. Fuzzy Time Series Method

Fuzzy time series has been adopted from fuzzy systems for dealing with time series data. The general procedures to build forecasting model with fuzzy time series are as follows:

1) Define the universe of discourse (U) of fuzzy set
2) Define fuzzy set
3) Choose the membership function of fuzzy set
4) Determine the fuzzy relationships
5) Defuzzification and forecasting/predicting
6) Evaluate performance

The preliminary definitions used in fuzzy time series method are described below.

Definition 1 (proposed byZadeh [11])
Let $U = \{u_1, u_2, \dots, u_m\}$ be the universe of discourse. A fuzzy set A of the universe of discourse U is defined by its membership function, $\mu_A: U \to [0,1], \mu_A(u)$ is the degree of membership of the element $u \in U$ in the fuzzy set A.

Definition 2 (proposed by Song and Chissom [2,3])
Supose $Y(t)$ is a subset of real numbers, for $t = \cdots, 0, 1, 2, \dots$ being the universe of discourse in which the fuzzy sets $A_i(t)$ defined, $i = 1,2, \dots, m$. Let $F(t)$ be a collection of fuzzy sets $A_i(t)$, $i = 1,2, \dots, m$ then $F(t)$ is called fuzzy time series on $Y(t)$.

Definition 3 (proposed by Chen [4])
Let $F(t)$ be a fuzzy time series. If for any time, $F(t) = F(t - 1)$ and $F(t)$ only has a finite count of elements, then $F(t)$is called a time-invariant fuzzy time series. Otherwise, it is called a time-variant fuzzy time series.
As stated by Definition 3, the data in this study has to be preprocessed to stationary pattern.

Definition 4 (proposed by Song and Chissom [2,3])
Let $F(t-1) = A_i$ and $F(t) = A_k$, for $t = 1,2, \dots, N$ and $i, k = 1,2, \dots, m$. The relationship between two consecutive observations, $F(t-1)$ and $F(t)$, is denoted by $F(t-1) \to F(t)$ or by $A_i \to A_k$, where A_i is called the left-hand side and A_k the right hand side of the fuzzy logical relationship (FLR).

Definition 5 (proposed by Huarng [12])
Suppose that there are several fuzzy logical relationship with the same left-hand side, that is, $A_i \to A_{k1}, A_i \to A_{k2}$, and so on. They can be collected into a fuzzy logical group (FLG) by putting all their right-hand sides together which has same in left-hand sides as the right-hand side of the fuzzy logical group, such as $A_i \to A_{k1}, A_{k2}, \dots$.

Definition 6 (proposed by Singh and Borah [13])
Let $F(t)$ be the fuzzy time series on the universal set, for $= \cdots, -2, -1, 0, 1, 2, \dots$. If $F(t)$is caused by $F(t-1), F(t-2), \dots$ and $F(t-n)$, then the n-order fuzzy logical rule can be expressed as $F(t-n), \dots, F(t-1) \to F(t)$, where $F(t)$ is the forecasting component.

In this research, the forecasting performance of fuzzy time series model will be compared with weighted fuzzy time series model.

B. Weighted Fuzzy Time series Method

Weighted fuzzy time series is a method for establishing the fuzzy forecast by assigning weights to fuzzy relationships (FLR) or fuzzy rules. The FLR will be taken from the original time series data by considering the temporality of each one-to-one FLR, while the fuzzy relationship group (FLG) makes it possible to normalize the weights. The procedures to build the forecasting model using weighted fuzzy time series are described below:

1) State the universe of discourse (U) and intervals for observations
2) Define fuzzy sets
3) Fuzzification
4) Establish fuzzy relationships
5) Establish fuzzy relationship groups
6) Forecasting
7) Defuzzification
8) Assigning weights to fuzzy relationships
9) Calculate results
10) Evaluate the performances

C. Data and Implementations

The Indonesia stock exchange (IDX) composite data used in this study was collected from the website «www.yahoofinance.com» for the period of December 7th, 2015, to September 21st, 2016. The total number of observations is 200. The collected data were divided into training data (150 exemplars) and testing data (50 exemplars). Fig. 1 shows a plot of the original IDX data. As mentioned earlier, the data used for forecasting with FTS and WFTS have to be stationary. To obtain stationary data, these data need to be differenced between consecutive days. Fig. 2 shows the differences in the IDX data used for fuzzy time series modeling.

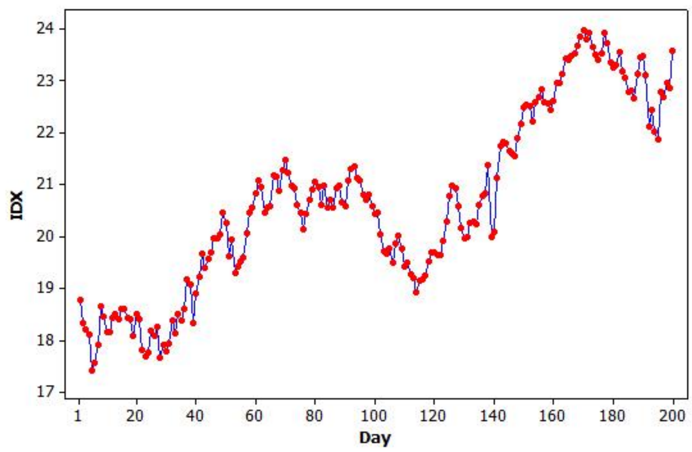

Fig. 1. The 200 daily exemplars of IDX data

ISSN No:-2456-2165

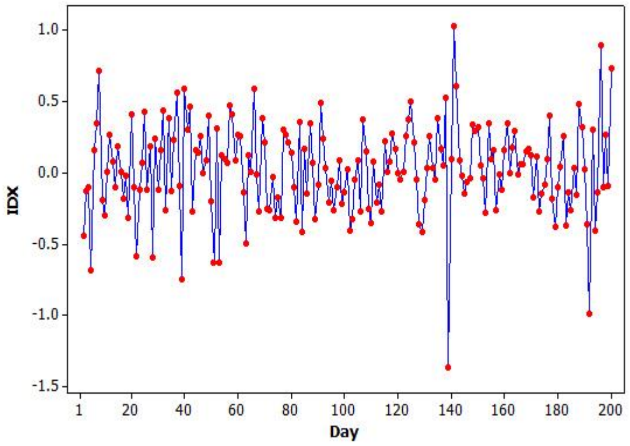

Fig. 2. Differences between consecutive days in the IDX data

1) Implementing Fuzzy Time Series Model

The processes for constructing the forecasting IDX model using fuzzy time series are described as the following.

Step1. Define the universe of discourse (U) of fuzzy set

Based on stationary data, the smallest and largestvalues give the values are range between -1.37 and 1.029. So, the universal of discourse can be defined as$U = [-1.7127, 1.0290]$. According to Chen [4] and Song and Chissom [2,3], the universe of discourse has been divided into seven equal intervals as shown below:

$$u_1 = [-1.7127, -1.0273], u_2 = [-1.37, -0.6846],$$
$$u_3 = [-1.0273, -0.3419], u_4 = [-0.6846, 0.0009],$$
$$u_5 = [-0.3419, 0.3436], u_6 = [0.0009, 0.6863], \text{and}$$
$$u_7 = [0.3436, 10290].$$

Step 2. Define fuzzy set

As stated in Step 1, there are seven intervals then it can be referred into fuzzy set $A_1, A_2, A_3, A_4, A_5, A_6,$ andA_7. In this study fuzzy set is defined as follow:

$$A_1 = \frac{\mu_{A1}}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_2 = \frac{0}{u_1} + \frac{\mu_{A2}}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_3 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{\mu_{A3}}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_4 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{\mu_{A4}}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_5 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{\mu_{A5}}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{\mu_{A6}}{u_6} + \frac{0}{u_7}$$
$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{\mu_{A7}}{u_7}$$

To determine membership of u_1, u_2, $u_3, u_4, u_5, u_6,$ and u_7 into $A_1, A_2, A_3, A_4, A_5, A_6,$ andA_7 use triangular membership function as follows:

$$\mu_{A1}(x) = \begin{cases} 0 & x \le -1.7127 \text{ or } x \ge -1.0273 \\ \dfrac{x + 1.7127}{0.3427} & -1.7127 \le x \le -1.37 \\ \dfrac{-1.0273 - x}{0.3427} & -1.37 \le x \le -1.0273 \end{cases}$$

$$\mu_{A2}(x) = \begin{cases} 0 & x \le -1.37 \text{ or } x \ge -0.6846 \\ \dfrac{x + 1.37}{0.3427} & -1.37 \le x \le -1.0273 \\ \dfrac{-0.6846 - x}{0.3427} & -1.0273 \le x \le -0.6846 \end{cases}$$

$$\mu_{A3}(x) = \begin{cases} 0 & x \le -1.0273 \text{ or } x \ge -0.3419 \\ \dfrac{x + 1.0273}{0.3427} & -1.0273 \le x \le -0.6846 \\ \dfrac{-0.3419 - x}{0.3427} & -0.6846 \le x \le -0.3419 \end{cases}$$

$$\mu_{A4}(x) = \begin{cases} 0 & x \le -0.6846 \text{ or } x \ge 0.0009 \\ \dfrac{x + 0.6846}{0.3427} & -0.6846 \le x \le -0.3419 \\ \dfrac{0.0009 - x}{0.3427} & -0.3419 \le x \le 0.0009 \end{cases}$$

$$\mu_{A5}(x) = \begin{cases} 0 & x \le -0.3419 \text{ or } x \ge 0.3436 \\ \dfrac{x + 0.3419}{0.3427} & -0.3419 \le x \le 0.0009 \\ \dfrac{0.3436 - x}{0.3427} & 0.0009 \le x \le 0.3436 \end{cases}$$

$$\mu_{A6}(x) = \begin{cases} 0 & x \le 0.0009 \text{ or } x \ge 0.6863 \\ \dfrac{x - 0.0009}{0.3427} & 0.0009 \le x \le 0.3436 \\ \dfrac{0.6863 - x}{0.3427} & 0.3436 \le x \le 0.6863 \end{cases}$$

$$\mu_{A7}(x) = \begin{cases} 0 & x \le 0.3436 \text{ or } x \ge 1.0290 \\ \dfrac{x - 0.3436}{0.3427} & 0.3436 \le x \le 0.6863 \\ \dfrac{1.0290 - x}{0.3427} & 0.6863 \le x \le 1.0290 \end{cases}$$

In this study, triangular membership function has been chosen for input and output fuzzy sets as shown in Fig. 3.

ISSN No:-2456-2165

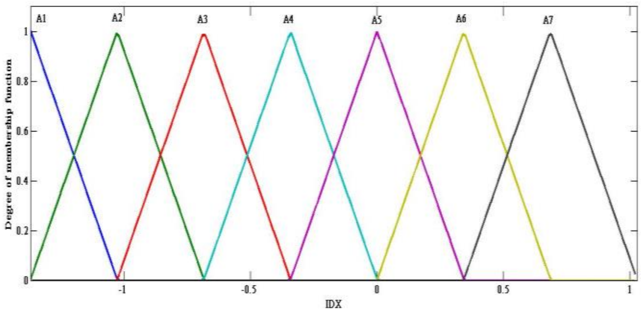

Fig. 3. Triangular membership functions of input and output fuzzy sets

Fig. 4.

Step3. Determine the fuzzy relationships (rules)

The fuzzy rules are established by training data and conducted based on fuzzy logic, $F(t-1) \rightarrow F(t)$ or by $A_i \rightarrow A_k$, referring to Definition 2.4. In this study, there are 17 rules after eliminating similar cases, shown in Table I.

No	A_i	A_k
1	A1	A5
2	A1	A6
3	A3	A5
4	A3	A6
5	A4	A3
6	A4	A4
7	A4	A5
8	A4	A6
9	A5	A1
10	A5	A3
11	A5	A4
12	A5	A5
13	A5	A6
14	A6	A1
15	A6	A4
16	A6	A5
17	A6	A6

TABLE I. FUZZY RULES

Step4. Defuzzification and forecasting

After defuzzification of the stationary data was obtained, the results had to be converted to the original data form. The forecasting results will then be compared with the original data to evaluate prediction performance.

Step5. Evaluate the performance of the model

In order to evaluate the performance of model, the root mean square rrror (RMSE) has been applied to measure the accuracy of forecasting results.

2) Implementing Weighted Fuzzy Time Series Model

The processes for building the forecasting IDX model using weighted fuzzy time series are detailed as the following.

Step 1. Define the universe of discourse and intervals for observations

According to the problem domain, the universe of discourse for observations $U = [starting, ending]$, is defined. Then the universal discourse is $U = [-1.37, 1.1732]$. The lower bound of U (-1.37) is the minimum value in interval u_1, while the upper bound (1.1732) maximum is in interval u_8, as shown in Table II. The length of fuzzy sets intervals is determined by standard deviation of stationary data, which is σ = 0.3179.

Interval	Min	Mid	Max
u_1	**-1.37**	-1.2111	-1.0521
u_2	-1.0521	-0.8932	-0.7342
u_3	-0.7342	-0.5753	-0.4163
u_4	-0.4163	-0.2574	-0.0984
u_5	-0.0984	0.0606	0.2195
u_6	0.2195	0.3785	0.5374
u_7	0.5374	0.6964	0.8553
u_8	0.8553	1.0143	**1.1732**

TABLE II. INTERVALS OF FUZZY SETS

Step 2. Define fuzzy sets for observations

Each linguistic observation or fuzzy set $A_i$is defined by the interval u_i.There are 8 interval fuzzy sets, and the following are their membership functions.

$$A_1 = \frac{1}{u_1} + \frac{0.5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_2 = \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_3 = \frac{0}{u_1} + \frac{0.5}{u_2} + \frac{1}{u_3} + \frac{0.5}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_4 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0.5}{u_3} + \frac{1}{u_4} + \frac{0.5}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_5 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0.5}{u_4} + \frac{1}{u_5} + \frac{0.5}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0.5}{u_5} + \frac{1}{u_6} + \frac{0.5}{u_7} + \frac{0}{u_8}$$
$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0.5}{u_6} + \frac{1}{u_7} + \frac{0.5}{u_8}$$
$$A_8 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0.5}{u_7} + \frac{1}{u_8}$$

Step 3. Fuzzifying all observations

In fuzzification we convert all the numeric data into fuzzy sets. Since the data size is quite big, Table III shows only some examples of fuzzification based on the membership functions in Step 2.

Date	Data	Fuzzy sets
8/12/2015	-0.44	A_3
9/12/2015	-0.129999	A_4
10/12/2015	-0.100001	A_4
…	…	…
20/9/2016	-0.09	A_5
21/9/2016	0.729999	A_7

TABLE III. FUZZIFYING

Step 4. Establishing fuzzy relationships

Fuzzy relationships has been established from training data, and can be written as:

$$F(t-1) \rightarrow F(t) \text{ or } A_i \rightarrow A_k .$$

The training data gave in total 148 fuzzy relationships (fuzzy rules).

Step 5. Establishing fuzzy relationship groups

Fuzzy relationship groups (FLRGs) can be defined from the fuzzy relationships that have the same fuzzy sets in their left-hand sides (LHSs) by placing all their RHSs together as on the RHS of the FLRG shown in Table IV.

Group	LHS	RHS
1	$\boldsymbol{A_1}$	A_5
2	A_2	A_7
3	A_3	$A_4, A_5, A_4, A_6, A_6, A_5, A_5, A_5, A_4$
4	A_4	$A_4, A_4, A_3, \ldots$
5	A_5	$A_5, A_6, A_6, \ldots$
6	A_6	$A_6, A_7, A_5, \ldots$
7	A_7	A_4, A_5, A_6, A_5, A_5
8	A_8	A_7

TABLE IV. FUZZY RELATIONSHIP GROUPS

Step 6. Forecasting

If $F(t-1) = A_i$, then the forecasting of $F(t)$ is defined by using the following rules:

Rule 1: If $A_i \rightarrow \emptyset$, the forecast of $F(t) = A_i$.

Rule 2: If $A_i \rightarrow A_{j1}, A_{j2}, \ldots, A_{jk}$, the forecast of $F(t) = A_{j1}, A_{j2}, \ldots, A_{jk}$

For example according to Group 3 of FLRGs in Table IV, If $F(t-1) = A_3$, then the forecasting of $F(t) = A_4, A_5, A_4, A_6, A_6, A_5, A_5, A_5, A_4$.

Step 7. Defuzzifying

Suppose the forecast $F(t)$ is $A_{j1}, A_{j2}, \ldots, A_{jk}$. The defuzzified matrix is equal to a matrix of the midpoints of $A_{j1}, A_{j2}, \ldots, A_{jk}$ as in

$$M(t) = [m_{j1}, m_{j2}, \ldots, m_{jk}]$$

where $M(t)$ is the defuzzified forecast of $F(t)$.

Continuing with the previous example, the corresponding defuzzified forecast of A_3 is

$$M(t) = [m_4, m_5, m_4, m_6, m_6, m_5, m_5, m_5, m_4]$$

Step 8. Assigning weights to fuzzy relationships

Suppose the forecast of $F(t)$ is $A_{j1}, A_{j2}, \ldots, A_{jk}$. The corresponding weights for $A_{j1}, A_{j2}, \ldots, A_{jk}$, denoted by $w_1, w_2, \ldots, w_k$, will be directly defined. The matrix weight $W(t) = [w'_1, w'_2, \ldots, w'_k]$ should satisfy a normalization condition:

$$\sum_{h=1}^{k} w'_h = 1$$

which is achieved as follows:

$$W(t) = [w'_1, w'_2, \ldots, w'_k] = \left[\frac{w_1}{\sum_{h=1}^{k} w_h}, \frac{w_2}{\sum_{h=1}^{k} w_h}, \ldots, \frac{w_k}{\sum_{h=1}^{k} w_h}\right] = \left[\frac{1}{\sum_{h=1}^{k} h}, \frac{2}{\sum_{h=1}^{k} h}, \ldots, \frac{k}{\sum_{h=1}^{k} h}\right]$$

where w_h is the weight for A_{jh}.

Following previous example, the weight matrix is determined as:

$$W(t) = \left[\frac{1}{1+2+\cdots+9}, \frac{2}{1+2+\cdots+9}, \ldots, \frac{9}{1+2+\cdots+9}\right] = \left[\frac{1}{45}, \frac{2}{45}, \frac{3}{45}, \frac{4}{45}, \frac{5}{45}, \frac{6}{45}, \frac{7}{45}, \frac{8}{45}, \frac{9}{45}\right]$$

Step 9. Calculating results

In weighted fuzzy time series model, the final forecast is defined as:

$$\widehat{A_i} = M(t) \times W(t)^T = M(t) \times [w'_1, w'_2, \ldots, w'_k]^T = M(t) \times \left[\frac{1}{\sum_{h=1}^{k} h}, \frac{2}{\sum_{h=1}^{k} h}, \ldots, \frac{k}{\sum_{h=1}^{k} h}\right]^T$$

where

$\times$ is the matrix product operator

$M(t)$ is $1 \times k$ matrix

$W(t)^T$ is $k \times 1$ matrix

The final forecasting of previous example is $\widehat{A_3} = M(t) \times W(t)^T = [m_4, m_5, m_4, m_6, m_6, m_5, m_5, m_5, m_4]$

$$\times \left[\frac{1}{45}, \frac{2}{45}, \frac{3}{45}, \frac{4}{45}, \frac{5}{45}, \frac{6}{45}, \frac{7}{45}, \frac{8}{45}, \frac{9}{45}\right]^T = 0.0323$$

Table V shows the forecasting result for all fuzzy sets as crisp sets.

$F(t-1)$	$F(t)$
A_1	0.0606
A_2	0.6964
A_3	0.0323
A_4	-0.0055
A_5	0.0639
A_6	0.0223
A_7	0.1029

TABLE V. FORECASTING RESULTS

III. RESULTS

After all the fuzzy time series models have been constructed, their performances were evaluated with both training and testing data portions of the IDX composite. Fig. 4 compares the forecast from fuzzy time series model to the original data within the training set. The similar comparison within test data is shown in Fig. 5.

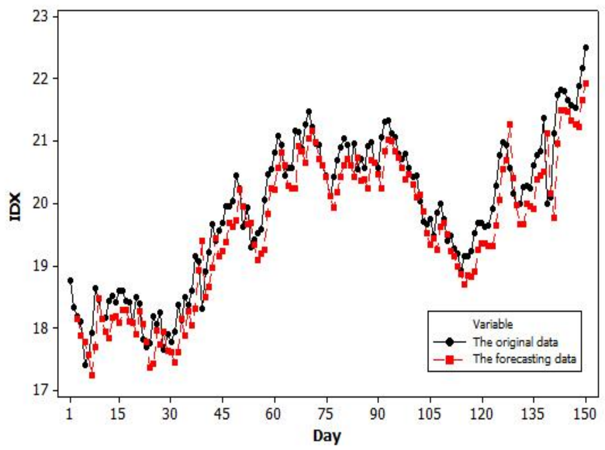

Fig. 5. The plot of training data and forecasting result from FTS (i.e., model fit)

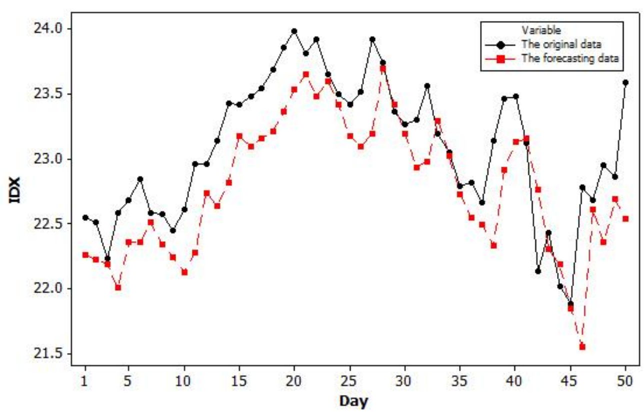

Fig. 6. The plot of original testing data and forecasting result from FTS (i.e., test of prediction in previously unseen data)

Fig. 6 compares the forecasting results from weighted fuzzy time series model to original data in the training set. The similar comparison within testing data is shown in Fig. 7.

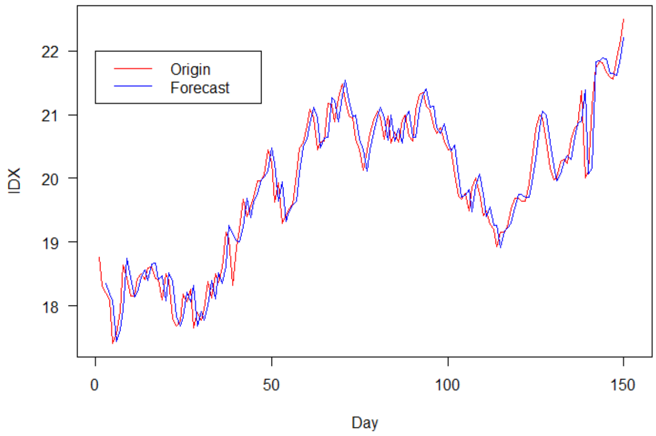

Fig. 7. The plot of original training data and forecasting result of WFTS (i.e., model fit)

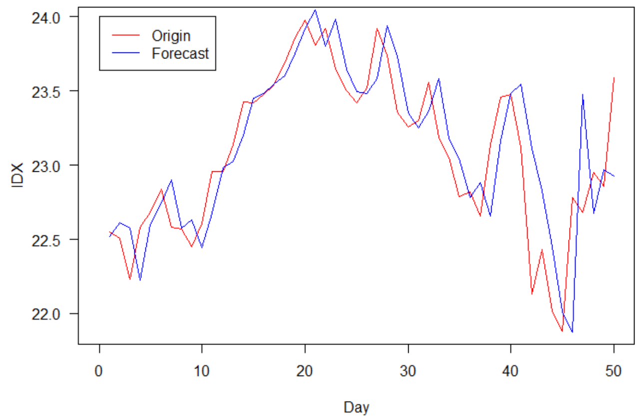

Fig. 8. The plot of original testing data and forecasting result of WFTS (i.e., model prediction for previously unseen data)

Table VI shows the forecasting results of conventional and weighted fuzzy time series along with the original data. The plot forecasting results from conventional and weighted fuzzy time series models of training and testing data sets are shown in Fig. 8 and 9, respectively.

No	Original Data	FTS	WFTS
1	22.55	22.264	22.5223
2	22.51	22.225	22.6139
3	22.23	22.185	22.5739
4	22.58	22.004	22.2245
5	22.68	22.358	22.6023
6	22.84	22.355	22.7439
7	22.58	22.511	22.9039
8	22.57	22.337	22.5745
9	22.45	22.245	22.6339
10	22.61	22.124	22.4445
11	22.96	22.281	22.6739
12	22.96	22.738	22.9823
13	23.14	22.634	23.0239
14	23.43	22.816	23.2039
15	23.42	23.178	23.4523
16	23.48	23.095	23.4839
17	23.54	23.155	23.5439
18	23.69	23.215	23.6039
19	23.86	23.362	23.7539
20	23.98	23.53	23.9239
21	23.81	23.654	24.0439
22	23.92	23.479	23.8045
23	23.65	23.594	23.9839
24	23.50	23.416	23.6445
25	23.42	23.172	23.4945
26	23.52	23.095	23.4839
27	23.92	23.195	23.5839
28	23.74	23.699	23.9423
29	23.36	23.421	23.7345
30	23.26	23.189	23.3545
31	23.30	22.935	23.2545
32	23.56	22.975	23.3639
33	23.19	23.292	23.5823
34	23.05	23.019	23.1845
35	22.79	22.723	23.0445
36	22.82	22.547	22.7845
37	22.66	22.495	22.8839
38	23.14	22.331	22.6545
39	23.46	22.917	23.1623
40	23.48	23.134	23.4823
41	23.12	23.155	23.5439
42	22.13	22.76	23.1145
43	22.43	22.303	22.8264
44	22.02	22.184	22.4523
45	21.88	21.849	22.0145
46	22.78	21.553	21.8745
47	22.68	22.609	23.4764
48	22.95	22.355	22.6745
49	22.86	22.687	22.9723
50	23.59	22.535	22.9239

TABLE VI. THE FORECASTING RESULTS OF TEST DATA

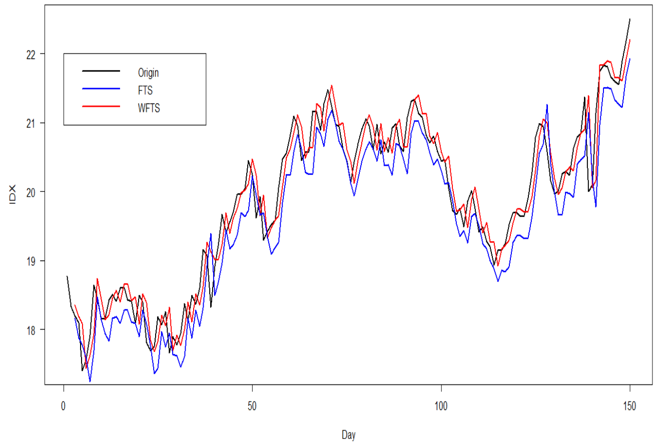

Fig. 9. The plot of original training data and forecasting results (model fits)

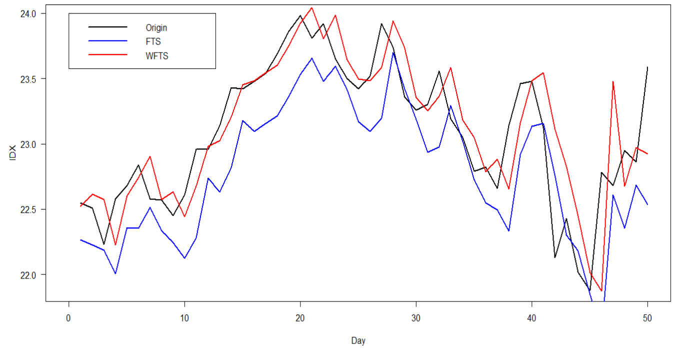

Fig. 10. The plot of original test data and forecasting results (actual predictions)

The root mean squared error (RMSE) was applied to quantitate the performances of the alternative models.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{s}(actual(t) - forecast(t))^2}{s}}$$

where
s is the number of forecasted data.
t is time step (day).

Table VII shows the evaluation results for both the models within training and testing data sets.

Forecasting Model	RMSE	
	Training Data	Testing Data
FTS	0.4443	0.4351
WFTS	**0.3142**	**0.3246**

TABLE VII. THE RMSES FOR FUZZY TIME SERIES AND WEIGHTED FUZZY TIME SERIES MODELS BY PARTITION OF DATA. SMALLER RMSE IS BETTER.

ISSN No:-2456-2165

IV. CONCLUSIONS AND DISCUSSION

The aims of this study were to present the brief concepts of fuzzy sets and systems and the fuzzy time series method (FTS), and to propose a forecasting model for stock exchange (IDX) composite using weighted fuzzy time series method (WFTS). The procedures for creating an FTS model are to define the universe of discourse (U), define fuzzy sets, determine fuzzy rules, assign weights to fuzzy rules, establish fuzzy logical relationship groups (FLRGs), fuzzification, fuzzy inferencing, defuzzification, and calculating the forecasting results.

In this study, the performance of WFTS model was been compared with a conventional FTS model using root mean square error (RMSE). The results showed that WFTS model had better performance than the conventional FTS. The RMSE values achieved by WFTS and FTS models (as shown in Table 7) within training data were 0.314 and 0.4443 and within test data 0.3246 and 0.4351, respectively.

This application case study assessed only the Indonesia Stock Exchange (IDX) composite index, so the model type comparison did not provide a general conclusion. To improve the accuracy of prediction, further study may need to consider other factors that influence the IDX composite, such as changes in a country's financial policy, interest rates, political changes in the country, and others unpredictable factors. Finally, the performance of a proposed model could be compared with various other types of time series models.

ACKNOWLEDGMENT

This research was supported by the Faculty of Science and Technology, Prince of Songkla University, Pattani Campus, Thailand under SAT-ASEAN project. This work is also (partially) funded by the Centre of Excellence in Mathematics, Commission on Higher Education, Thailand. Finally, the authors would like to thank the reviewers for their helpful suggestions.

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