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Markov average-based weighted fuzzy time series model to predict PT Kimia farma Tbk stock price

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ABSTRACT

The COVID-19 pandemic impacted various activities in Indonesia, including the stock market. Despite the declining economic condition, people are increasingly interested in investing. Among other companies available on the Indonesia Stock Exchange, companies in the health sector have a particular appeal to potential investors, one of which is pharmaceutical companies. This research used a Markov Average-Based Weighted Fuzzy Time Series model applied to PT Kimia Farma Tbk stock price data. This model develops the previous Markov chain–Fuzzy Time Series model, which has not calculated the weights for recurring events and used the Sturgess rule to determine the interval length. In this research, each recurring event has given a different weight that provides different probability values for transitions from one state to another. The Average-Based method is used to determine the interval length that can reflect the fluctuation of the data used. The stock price prediction of PT Kimia Farma Tbk using this model is categorized as very accurate with a MAPE of 2.632%.

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INTRODUCTION

At the end of 2019, the world was shocked by the discovering of a new type of virus, SARS-CoV-2 (known as COVID-19), which was later designated as a pandemic by the World Health Organization (WHO). The spread of COVID-19 is still ongoing in Indonesia, impacting various activities, including the stock market. In their research, Liu et al. (2020) concluded that an increase in COVID-19 cases does diminish the country's stock performance. However, public interest in investment products has increased despite the declining economic condition. This is encouraged by public awareness to start investing and looking for additional income due to uncertain economic conditions (Otoritas Jasa Keuangan, 2021). During this pandemic, companies in the health sector have more attracted investors compared to other companies available on the Indonesia Stock Exchange (Utami & Aliyansah, 2020). This is also proven by Yunpeng et al. (2021) which expressed there is a trusting investor attitude toward the health sector industry, which plays a crucial part in preventing this unusual infectious disease. As a state-owned pharmaceutical company in Indonesia, PT Kimia Farma Tbk is currently responsible for handling this pandemic. The company's stock price tends to rise significantly after the news of the vaccine began to emerge so that it is considered interesting to analyze.

Stock price data is time-series data. Many methods can be used to analyze this type of data, but some methods require the satisfaction of basic assumptions. One method that can be used to analyze time-series data without requiring basic assumptions is the Fuzzy Time Series (FTS) (Aladag, 2012). FTS can handle uncertain and incomplete data well, even though it is done by ignoring basic assumptions.

FTS has been used in several previous researches. Susilowati and Sulistijanti (2018) predicted the number of inpatients using FTS, and Jatipaningrum et al. (2019) predicted the Rupiah exchange rate against the Dollar with FTS combined with the Markov chains method. The accuracy of the results obtained is satisfying enough. However, in the previous FTS, the determination of the partition interval length is only based on the number of data used and not considered to reflect the variation in the data. In their research, Sun and Li (2008) stated that the data fluctuation could be expressed as the absolute value of the difference between the two-consecutive data. Moreover, the previous FTS still ignores the repeated transitions that happened, whereas the higher the number of repetitions, the greater the probability of that event occurring again in the future (Yu, 2005).

This research discusses the Markov Average-Based Weighted Fuzzy Time Series Model, which developed the previous Markov FTS model. Mean Absolute Percentage Error is used to measure PT Kimia Farma Tbk stock price prediction accuracy obtained using this model.

METHOD

The two main differences raised in this research are the method to define the interval length and giving weight to the recurrence event of the FTS. The previous FTS used the Sturgess method, which only considers how much data is used for the research, and the interval length will adjust to the number of classes formed. This does not match Sun and Li (2008) who stated in their research that the calculation still cannot effectively reflect fluctuations in the data. Hence, this research uses the Average-Based method, which calculates the average difference between two consecutive data at times t and $t + 1$ and is considered to reflect the data's actual fluctuation.

Ignoring repeated transitions in FTS could result in data information loss. The event that keeps repeating is assumed to have the same opportunities to happen again in the future as events that only occur once. Therefore, the weighting procedure gives different probability values for each event (Yu, 2005). By considering these two things, the Markov Average-Based Weighted FTS Model is studied to complete the weaknesses that exist in the previous model.

The steps conducted as follows:

1. Determine the universal set U from the data used using the following equation:

$$U = [D_{min} - D_1 , D_{max} + D_2] \qquad (1)$$

   where D_{min} is the lowest data value, D_{max} is the highest data value, where D_1 and D_2 arbitrary positive numbers used for interval adjustment. (Tsaur, 2012).

2. Divide U into several partitions following the Average-Based method steps below:
   a. Determine the length of the initial interval (l^1)

$$l^1 = \frac{1}{2}\left(\frac{\sum_{t=1}^{N-1}|Y(t+1) - Y(t)|}{N-1}\right) \quad (2)$$

   with N is the number of data used.

   b. According to l^1, determine the base for the interval length based on Table 1.

Table 1. Interval Length Base

Range	Base
0.1 – 1.0	0.1
1.1 – 10	1
11 – 100	10
101 – 1000	100

(Sun & Li, 2008)

   c. Rounding l^1 according to the basis obtained from Table 1 and get the length of the final interval used (l).

   d. Divide U into several partitions with interval length l.

3. Determine the fuzzy set A_i for the universal set U, with:

$$A_i = \begin{cases} \frac{1}{u_1} + \frac{0,5}{u_2} & ,i = 1 \\ \frac{0,5}{u_{i-1}} + \frac{1}{u_i} + \frac{0,5}{u_{i+1}} & ,2 \leq i \leq k-1 \\ \frac{0,5}{u_{k-1}} + \frac{1}{u_k} & ,i = k \end{cases} \quad (3)$$

4. Data fuzzification
   Fuzzification is a process of mapping numerical values into fuzzy sets (Díaz-Cortés et al., 2017). If the observation data is the element of the interval u_i, then the data is fuzzified to the A_i fuzzy set.

5. Define Weighted Fuzzy Logical Relationship (Weighted FLR)
   Let $w_{i,j}$ be the weight of the transition from state i to state $j, w_{i,j} = \varphi$ where φ is the T^{th} repetition of transition i to another state.

6. Establish Fuzzy Logical Relationship Group (FLRG)
   Assume there are Weighted FLRs, a transition from a state i as follow:

$$A_i \to A_1$$
$$A_i \to A_2$$
$$\vdots$$
$$A_i \to A_k$$

   In that case, they can be grouped into an FLRG as $A_i \to A_1, A_2, \dots, A_k$ (Khuat & Le, 2017)

7. Construct a Markov chain transition probability matrix with its element is calculated by:

$$p_{i,j} = \frac{\sum w_{i,j}}{\sum_{j=1}^{k} \sum w_{i,j}} \quad (4)$$

   where $\sum w_{i,j}$ is the sum of the transition weight from state i to state j while $\sum_{j=1}^{k} \sum w_{i,j}$ is the total weight of the transition from state i to state j according to the FLRG that has been formed.

8. Defuzzification by observing the following rules:
   Rule 1: If FLRG of state A_i is one to one $(A_i \to A_j)$, with A_i is a state on $t-1$, then:

$$Y^*(t) = [m_j][p_{i,j}] \quad (5)$$

   Rule 2: If FLRG of state A_i is one to many (e.g:$A_i \to A_1, A_2, \dots, A_k$, $i = 1,2, \dots, k$) and $Y(t-1)$ is a data on the previous time $(t-1)$, then:

$$Y^*(t) = [m_1, m_2, \dots, Y(t-1), \dots, m_k] \begin{bmatrix} p_{i,1} \\ p_{i,2} \\ \vdots \\ p_{i,i} \\ \vdots \\ p_{i,k} \end{bmatrix} \quad (6)$$

where $Y^*(t)$ is the result of defuzzification or the initial prediction value and m_j is the median of the interval class j.

9. Adjusting the predicted value by observing these following rules:
   Rule 1: If state A_i communicate with its own state $(A_i \leftrightarrow A_i)$ and experiences an increasing transition for $i < j$ or a decreasing to state A_j at time t, the adjustment value can be measured by:

$$D_1(t) = \pm \frac{l}{2} \quad (7)$$

   where the value will be positive when $i < j$ and negative for $i > j$.

   Rule 2: If state A_i is a state at time $t-1$ and experience the increasing transition to the state of $A_{i \pm v}$ at time t, then:

$$D_2(t) = \pm \frac{l}{2} v \quad (8)$$

10. Calculate the final prediction result $\hat{Y}(t)$ considering these points below:

    - If FLRG of state A_i is one to many and A_{i+1} can be reached from state A_i with $A_i \leftrightarrow A_i$, then:

$$\hat{Y}(t) = Y^*(t) + D_1(t) + D_2(t) \quad (9)$$

    - If FLRG of state A_i is one to many and $A_{i \pm j}$ can be reached from state A_i but A_i is not communicated with its own state, then:

$$\hat{Y}(t) = Y^*(t) \pm D_2(t) \quad (10)$$

11. Measure the prediction accuracy using MAPE

$$\text{MAPE} = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{Y(t) - \hat{Y}(t)}{Y(t)} \right| \times 100\% \quad (11)$$

The accuracy level of the prediction results based on the MAPE value can be seen in Table 2.

Table 2. MAPE Accuracy Level

MAPE	Accuracy
< 10%	Very Accurate
11% – 20%	Good
21% – 50%	Make Sense
> 50%	Not Accurate

(Klimberg et al., 2010).

RESULTS AND DISCUSSION

The data used in this research is the stock price of PT Kimia Farma Tbk from March 09, 2020, to May 31, 2021, collected from the Indonesia Stock Exchange official site (https://www.idx.co.id).

Table 3. PT Kimia Farma Tbk Stock Price

No.	Date	Stock Price (Rupiah)
1	09/03/2020	740
2	10/03/2020	830
3	11/03/2020	770
4	12/03/2020	695
5	13/03/2020	720
6	16/03/2020	675
7	17/03/2020	630
8	18/03/2020	630
9	19/03/2020	600
10	20/03/2020	670

No.	Date	Stock Price (Rupiah)
11	23/03/2020	835
⋮	⋮	⋮
201	12/01/2021	6.975
202	13/01/2021	6.500
203	14/01/2021	6.050
204	15/01/2021	5.650
205	18/01/2021	5.275
⋮	⋮	⋮
283	11/05/2021	2.640
284	17/05/2021	2.580
285	18/05/2021	2.610
286	19/05/2021	2.550
287	20/05/2021	2.530
288	21/05/2021	2.420
289	24/05/2021	2.370
290	25/05/2021	2.420
291	27/05/2021	2.420
292	28/05/2021	2.430
293	31/05/2021	2.600

The number of data used (N) is 293, with the highest stock price was on January 12, 2021, and the lowest stock price can be seen on the 9th data (March 19, 2020). Thus, from the data above, we get $D_{max} = 6.975$ and $D_{min} = 600$. Using $D_1 = 0$ and $D_2 = 25$, obtained the universal set $U = [600, 7.000]$. The interval length determination was carried out using the *Average-Based* method. Using Equation (2), we obtained the initial interval length $l^1 = 50,667$. This value is in the interval of 11–100, hence according to Table 1, base 10 is used to determine the final interval length (l) and got $l = 50$.

Furthermore, U is partitioned with the interval length of each class is 50. Thus, there are 128 partition classes as follows.

$$
\begin{array}{ll}
u_1 = [600\,,650] & \vdots \\
u_2 = [650\,,700] & u_{122} = [6.650\,,6.700] \\
u_3 = [700\,,750] & u_{123} = [6.700\,,6.750] \\
u_4 = [750\,,800] & u_{124} = [6.750\,,6.800] \\
u_5 = [800\,,850] & u_{125} = [6.800\,,6.850] \\
u_6 = [850\,,900] & u_{126} = [6.850\,,6.900] \\
u_7 = [900\,,950] & u_{127} = [6.900\,,6.950] \\
u_8 = [950\,,1.000] & u_{128} = [6.950\,,7.000]
\end{array}
$$

The next step is determining the fuzzy sets using Equation (3). The number of fuzzy sets formed is 128, as much as the number of partitions formed in the previous step. The fuzzy set formed is as follows.

$$A_1 = \frac{1}{u_1} + \frac{0,5}{u_2}$$
$$A_2 = \frac{0,5}{u_1} + \frac{1}{u_2} + \frac{0,5}{u_3}$$
$$A_3 = \frac{0,5}{u_2} + \frac{1}{u_3} + \frac{0,5}{u_4}$$
$$A_4 = \frac{0,5}{u_3} + \frac{1}{u_4} + \frac{0,5}{u_5}$$
$$A_5 = \frac{0,5}{u_4} + \frac{1}{u_5} + \frac{0,5}{u_6}$$
$$A_6 = \frac{0,5}{u_5} + \frac{1}{u_6} + \frac{0,5}{u_7}$$
$$A_7 = \frac{0,5}{u_6} + \frac{1}{u_7} + \frac{0,5}{u_8}$$
$$A_8 = \frac{0,5}{u_7} + \frac{1}{u_8} + \frac{0,5}{u_9}$$
$$\vdots$$
$$A_{124} = \frac{0,5}{u_{123}} + \frac{1}{u_{124}} + \frac{0,5}{u_{125}}$$
$$A_{125} = \frac{0,5}{u_{124}} + \frac{1}{u_{125}} + \frac{0,5}{u_{126}}$$
$$A_{126} = \frac{0,5}{u_{125}} + \frac{1}{u_{126}} + \frac{0,5}{u_{127}}$$
$$A_{127} = \frac{0,5}{u_{126}} + \frac{1}{u_{127}} + \frac{0,5}{u_{128}}$$
$$A_{128} = \frac{0,5}{u_{127}} + \frac{1}{u_{128}}$$

After the fuzzy set is formed, the stock price data is fuzzified and the weighting process is carried out for each repetition that occurs in each fuzzy set. Table 4 shows the results of fuzzification and weighting for each transition.

Table 4. Fuzzification and Transition *W*eighting

No.	Date	Stock Price (Rupiah)	Fuzzification	Transition	Weight
1	09/03/2020	740	A_3		
2	10/03/2020	830	A_5	$A_3 \rightarrow A_5$	1
3	11/03/2020	770	A_4	$A_5 \rightarrow A_4$	1
4	12/03/2020	695	A_2	$A_4 \rightarrow A_2$	1
5	13/03/2020	720	A_3	$A_2 \rightarrow A_3$	1
6	16/03/2020	675	A_2	$A_3 \rightarrow A_2$	2
7	17/03/2020	630	A_1	$A_2 \rightarrow A_1$	2
8	18/03/2020	630	A_1	$A_1 \rightarrow A_1$	1
⋮	⋮	⋮	⋮	⋮	⋮
291	27/05/2021	2.420	A_{37}	$A_{37} \rightarrow A_{37}$	2
292	28/05/2021	2.430	A_{37}	$A_{37} \rightarrow A_{37}$	3
293	31/05/2021	2.600	A_{41}	$A_{37} \rightarrow A_{41}$	4

From the fuzzification outcomes, establish FLRG based on the transition that occurs in each state. The FLRG formed are as follow.

$$
\begin{gathered}
A_1 \rightarrow A_1, A_2 \\
A_2 \rightarrow A_1, A_3, A_5 \\
A_3 \rightarrow A_2, A_5 \\
A_4 \rightarrow A_2 \\
A_5 \rightarrow A_4, A_9 \\
A_9 \rightarrow A_{15} \\
A_{11} \rightarrow A_{11}, A_{12}, A_{13} \\
\vdots \\
A_{96} \rightarrow A_{118} \\
A_{102} \rightarrow A_{94} \\
A_{110} \rightarrow A_{102} \\
A_{118} \rightarrow A_{128} \\
A_{119} \rightarrow A_{110} \\
A_{128} \rightarrow A_{119}
\end{gathered}
$$

To construct a Markov chain transition probability matrix **P**, calculate the probability values for each state i transitions to state j using Equation (4) Below is the calculation of $p_{i,j}$:

- Since A_1 transitions to A_1 and A_2, thus:

$$p_{1,1} = \frac{\sum w_{1,1}}{\sum_{j=1}^{2} \sum w_{1,j}} = \frac{3}{6}$$
$$p_{1,2} = \frac{\sum w_{1,2}}{\sum_{j=1}^{2} \sum w_{1,j}} = \frac{3}{6}$$

- Since A_2 transitions to A_1,A_3 and A_5, thus:

$$p_{2,1} = \frac{\sum w_{2,1}}{\sum_{j=1}^{5} \sum w_{2,j}} = \frac{2}{6}$$
$$p_{2,3} = \frac{\sum w_{2,3}}{\sum_{j=1}^{5} \sum w_{2,j}} = \frac{1}{6}$$
$$p_{2,5} = \frac{\sum w_{2,5}}{\sum_{j=1}^{5} \sum w_{2,j}} = \frac{3}{6}$$

- Since A_3 transitions to A_2 and A_5, thus:

$$p_{3,2} = \frac{\sum w_{3,2}}{\sum_{j=1}^{5} \sum w_{3,j}} = \frac{2}{3}$$
$$p_{3,5} = \frac{\sum w_{3,5}}{\sum_{j=1}^{5} \sum w_{3,j}} = \frac{1}{3}$$
$$\vdots$$

and so on, until we obtained all elements values for the 128x128 matrix **P**.

$$
\mathbf{P} = \begin{bmatrix}
1/2 & 1/2 & 0 & 0 & 0 & 0 & \cdots \\
1/3 & 1/6 & 0 & 1/2 & 0 & 0 & \cdots \\
0 & 2/3 & 0 & 1/3 & 0 & 0 & \cdots \\
0 & 1 & 0 & 0 & 0 & 0 & \cdots \\
0 & 0 & 0 & 1/3 & 0 & 0 & \cdots \\
0 & 0 & 0 & 0 & 0 & 0 & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots
\end{bmatrix}
$$

From the matrix **P** above, it can be seen that there are some $p_{i,j}$ with a value of 0. It means that no transition occurs from state i to state j.

The defuzzification process calculates the initial prediction value using Equations (5) and (6). After calculating the prediction adjustment value by Equations (7) and (8), then obtained the final prediction results calculate following Equation (9) or (10). The results of defuzzification and the final prediction result can be seen in Table 5.

Table 5. Defuzzification and Final *P*rediction *R*esult

t	Date	$Y(t)$	Fuzzification	$Y^*(t)$	$D(t)$	$\hat{Y}(t)$	$\left\|\frac{Y(t)-\hat{Y}(t)}{Y(t)}\right\|$
1	09/03/2020	740	A_3				
2	10/03/2020	830	A_5	725	0	725	0,127
3	11/03/2020	770	A_4	942	0	942	0,223
4	12/03/2020	695	A_2	675	0	675	0,029
5	13/03/2020	720	A_3	742	0	742	0,030
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
290	25/05/2021	2.420	A_{37}	2.358	0	2.358	0,025
291	27/05/2021	2.420	A_{37}	2.498	0	2.498	0,032
292	28/05/2021	2.430	A_{37}	2.498	0	2.498	0,028
293	31/05/2021	2.600	A_{41}	2.503	100	2.603	0,001

To predict the stock price for 02–07 June 2021, consider the fuzzification of the previous data $(t = 293)$. Follow the defuzzification process until obtained the initial prediction value $Y^*(t)$. Do the same steps as before to gain the final prediction result $\hat{Y}(t)$. Table 6 shows the prediction stock price and the error with the actual prices. The comparison of the two can be seen in Figure 1.

Table 6. Prediction for 02 – 07 June 2021

t	Date	$Y^*(t)$	Fuzzification	$D(t)$	$\hat{Y}(t)$	$Y(t)$	$\left\|\frac{Y(t)-\hat{Y}(t)}{Y(t)}\right\|$
294	02/06/21	2.599	A_{40}	-25	2.574	2.600	0.01
295	03/06/21	2.575	A_{40}	0	2.575	2.600	0.01
296	04/06/21	2.575	A_{40}	0	2.575	2.590	0.006
297	07/06/21	2.575	A_{40}	0	2.575	2.500	0.03

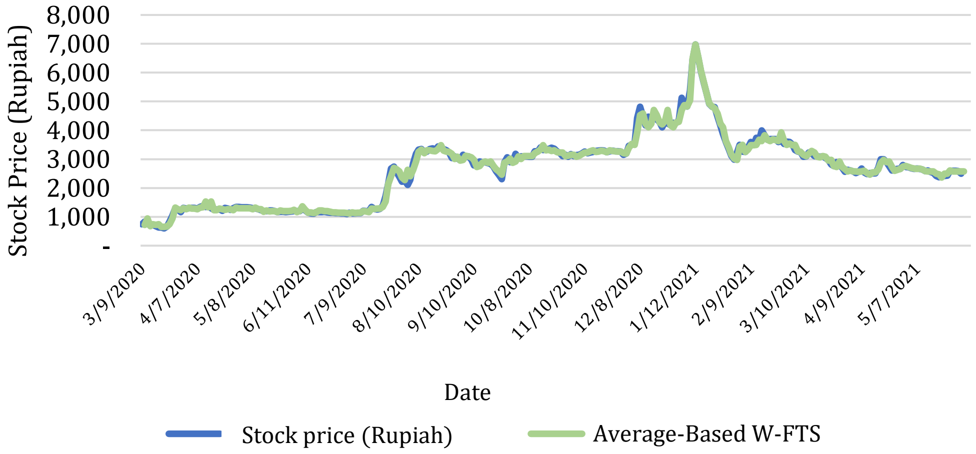

Figure 1. Comparison of Prediction Results Using Markov Average-Based Weighted FTS with Actual Stock Prices

From Figure 1, it can be seen that the two lines almost match each other and the pattern is nearly identical. It means the prediction results obtained are close to the actual value with a relatively small error. To be more specific, the MAPE value is calculated to see the accuracy of the Markov Average-Based Weighted FTS model in predicting the stock price of PT Kimia Farma Tbk. Using the prediction data from March 09, 2020 - June 07, 2021, the MAPE obtained is 2.632% and categorized as very accurate.

CONCLUSIONS AND SUGGESTIONS

The weight calculation in the Markov Average-Based Weighted Fuzzy Time Series model is carried out by considering the repeated transitions from a state $\boldsymbol{i}$ to another state. The Average-Based method is utilized to define the interval length based on the value of half the average difference between two consecutive data. Using this model, PT Kimia Farma Tbk stock price prediction obtained has a MAPE of 2.632%, which was classified as very accurate.

Further research is suggested to develop an R software script to help the calculation process, which is still done manually.

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