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Short-term prediction of Indonesian gold prices using a weighted Markov chain approach

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ABSTRACT

Gold is one of the most widely used investment assets because of its high economic value and relatively stable role during economic uncertainty. However, fluctuations in gold prices may affect investors' potential gains and losses, making price prediction important as a consideration in investment decision-making. This study applies the weighted Markov chain method to predict Indonesian gold prices using weekly gold price data from January 2019 to December 2020. The data were grouped into two state classifications, namely six states and ten states, to evaluate the effect of state formation on prediction accuracy. Transition probability matrices were constructed for each classification, while the weights were determined based on autocorrelation coefficients. Prediction accuracy was evaluated using the Mean Absolute Percentage Error (MAPE). The results show that the predicted gold prices tend to remain in the same state over the prediction period. In the six-state classification, the predicted price was in state 5 with an estimated value of Rp833,701 and a MAPE of 0.66%. In the ten-state classification, the predicted price was in state 9 with an estimated value of Rp847,580 and a MAPE of 1.67%. These results indicate that the weighted Markov chain method provides very good short-term prediction accuracy. However, for longer prediction periods, the predicted values tend to become constant and are less able to capture volatile movements in actual gold prices. Therefore, the weighted Markov chain method is more suitable for short-term gold price prediction than for long-term forecasting.

1. Introduction

Investment is an important financial activity that aims to allocate capital or assets in the present in order to obtain benefits in the future. In general, investment can be carried out through various instruments, ranging from financial instruments such as stocks, deposits, bonds, and mutual funds to real assets such as property, precious metals, and other valuable commodities. Each investment instrument has different characteristics in terms of return, liquidity, risk, and time horizon. Therefore, investors need to understand the behavior of the investment asset they choose, especially when the asset price tends to fluctuate over time [1, 2].

Among various investment instruments, gold is one of the most widely recognized and commonly used assets. Gold has long been considered a valuable asset because of its high economic value, durability, liquidity, and ability to maintain value over time. In many countries, including Indonesia, gold is not only used as jewelry but also as an investment instrument. Gold investment is relatively accessible because it can be started with small capital, is easy to sell or pawn, and is generally perceived as safer than several other investment instruments. In addition, gold is often viewed as a hedge against inflation and economic uncertainty because its price tends to increase when economic instability occurs [3–5].

The attractiveness of gold as an investment asset is also related to its role as a store of value. Unlike some financial assets that are strongly influenced by company performance, gold prices are affected by broader economic factors, such as global market conditions, inflation, exchange rates, interest rates, and investor sentiment. In the Indonesian context, gold prices are closely related to international gold prices and the exchange rate of the Indonesian Rupiah against the United States Dollar. This is because the international gold price is generally quoted in US dollars per troy ounce, while domestic gold prices are expressed in Rupiah per gram. As a result, changes in both world gold prices and exchange rates can cause fluctuations in Indonesian gold prices [6, 7].

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Fluctuations in gold prices create both opportunities and risks for investors. When gold prices increase, investors may gain profit from the difference between the buying and selling prices. However, when gold prices decline, investors may experience losses, especially if the decision to buy or sell gold is made without sufficient analysis. Therefore, the ability to estimate future gold price movements is important as a consideration in investment decision-making. Although no prediction method can provide perfectly accurate results, forecasting can help investors understand possible price tendencies and reduce uncertainty in making investment decisions [8–10].

Gold price prediction has become an important topic in financial and commodity market studies. Various quantitative methods have been developed and applied to predict gold prices, including statistical models, time series models, artificial intelligence methods, and stochastic models. Each method has its own advantages and limitations. Some models require long historical data and complex assumptions, while others are designed to capture short-term patterns based on recent data. In practice, the choice of prediction method depends on the characteristics of the data, the purpose of the prediction, and the expected prediction horizon [3, 11].

One method that can be used to predict dynamic changes in time series data is the Markov chain method. A Markov chain is a stochastic process in which the probability of a future state depends only on the present state and not on the sequence of past states. This characteristic is known as the Markov property. In the context of price prediction, the Markov chain approach can be used by classifying price data into several states and then estimating the probability of transition from one state to another. Through the transition probability matrix, the future state of a variable can be predicted based on the current state [12, 13].

However, the conventional Markov chain method has limitations because it generally considers only the current state in predicting future states. In reality, financial and commodity price movements may still contain information from several previous periods. To overcome this limitation, the weighted Markov chain method can be applied. The weighted Markov chain extends the basic Markov chain approach by involving several previous transition steps and assigning weights to each step. These weights are usually determined based on the autocorrelation coefficient of historical data. Therefore, the weighted Markov chain method allows previous data patterns to contribute differently to the prediction process [10].

The weighted Markov chain method has been applied in several previous studies. Zhou (2015), for example, applied the weighted Markov chain method to predict stock prices in the Chinese sports industry and found that the weighted Markov chain produced lower prediction errors than the ordinary Markov chain. Abdullah (2016) also applied the weighted Markov chain method to predict the opening stock price of PT Indofood and showed that the method could provide good prediction results in several cases. In addition, Peng et al. (2010) applied the weighted Markov chain in the field of public health to analyze and predict infectious disease problems in Jiangsu Province, China. These studies indicate that the weighted Markov chain method can be used to model dynamic systems in different fields, including economics, finance, and health [6].

Although the weighted Markov chain method has been applied in stock price prediction and other dynamic systems, its application to Indonesian gold price prediction is still relevant to be further examined. Gold prices have specific characteristics because they are influenced by both global commodity prices and domestic exchange rate movements. Moreover, gold remains a popular investment asset among Indonesian investors. Therefore, a prediction model that is simple, interpretable, and suitable for short-term prediction may provide useful information for investors and researchers [5].

This study applies the weighted Markov chain method to predict Indonesian gold prices using weekly data from January 2019 to December 2020. The data consist of weekly gold prices that were converted into Indonesian Rupiah per gram based on international gold prices and exchange rates. In this study, the gold price data are classified into two different state groupings, namely six states and ten states. The purpose of using two state classifications is to examine how the number of states affects the prediction results and accuracy. After the states are formed, transition frequency matrices and transition probability matrices are constructed. The weights for the Markov chain are then calculated using autocorrelation coefficients, and the prediction results are evaluated using the Mean Absolute Percentage Error (MAPE) [7].

The main objective of this study is to apply the weighted Markov chain method in predicting Indonesian gold prices and to evaluate the accuracy of the prediction results. In addition, this study aims to compare the predicted gold prices with the actual gold prices in order to assess how well the method captures the movement of gold prices. The results of this study are expected to contribute to the application of stochastic methods in commodity price prediction and provide additional insight into the use of the weighted Markov chain method for short-term financial forecasting.

Based on the background above, this study focuses on two main research questions. First, how can the weighted Markov chain method be applied to predict Indonesian gold prices? Second, how accurate are the predicted gold prices compared with the actual gold prices? By answering these questions, this study is expected to provide a clearer understanding of the performance and limitations of the weighted Markov chain method in predicting gold price movements in Indonesia.

2. Materials and Methods

2.1. Study area and data collection

This study employed a quantitative approach using the weighted Markov chain method to predict Indonesian gold prices. The weighted Markov chain was selected because it can model dynamic changes in time series data by considering the probability of transition from one state to another. Unlike the ordinary Markov chain, the weighted Markov chain incorporates several previous transition steps by assigning different weights based on autocorrelation coefficients. Therefore, this method is suitable for examining short-term tendencies in gold price movements.

The main stages of this research consisted of data collection, data conversion, state classification, construction of transition frequency and transition probability matrices, calculation of autocorrelation coefficients and Markov weights, gold price prediction, and evaluation of prediction accuracy using the Mean Absolute Percentage Error (MAPE) [6, 14, 15].

The data used in this study were secondary data consisting of weekly gold prices from January 2019 to December 2020. The dataset covered 104 weeks, starting from 6 January 2019 to 27 December 2020. The data included international gold prices, which were obtained from Investing.com, and the exchange rate of the Indonesian Rupiah against the United States Dollar [4, 16].

Since international gold prices are commonly expressed in US dollars per troy ounce, the data were converted into Indonesian gold prices in Rupiah per gram. The conversion was conducted by using the following equation (1).

$$Indonesian\ Gold\ Price = \frac{World\ Gold\ Price}{31.1034768} \times Exchange\ Rate \quad (1)$$

where 31.1034768 represents the number of grams in one troy ounce. The converted values were then used as the main dataset for the prediction process.

2.2. State classification

Before applying the weighted Markov chain method, the gold price data were classified into several states. State classification was conducted to transform continuous gold price data into discrete categories, as required in the Markov chain approach.

In this study, two classification scenarios were used. The first scenario divided the gold price data into six states, while the second scenario divided the data into ten states. These two scenarios were applied to examine whether different numbers of states affected the prediction results and prediction accuracy. [17, 18]. The formation of states was based on the mean and standard deviation of the Indonesian gold price data. The mean was calculated as equation (2).

$$\bar{x} = \frac{x_1 + x_3 + \cdots + x_n}{n} = \frac{\sum_{t=1}^{n} x_t}{n} \qquad (2)$$

where x_t represents the gold price at time t, and n is the number of observations. The standard deviation was calculated as:

$$S = \sqrt{\frac{\sum_{t=1}^{n}(x_t - \bar{x})^2}{n-1}} \qquad (3)$$

where S denotes the standard deviation of the gold price data. Based on the mean and standard deviation, each weekly gold price was assigned to one of the predetermined states. This process produced a sequence of states representing the movement pattern of Indonesian gold prices.

2.3. Construction of transition frequency and probability matrix

After the gold price data were classified into states, a transition frequency matrix was constructed. The transition frequency matrix records the number of transitions from one state to another in consecutive periods. If the gold price moves from state i at time t to state j at time $t+1$, then the frequency of transition from state i to state j increases by one. This process was applied to the entire sequence of weekly gold price states [3, 6, 16]. The transition frequency matrix can be expressed as equation (4).

$$F = \begin{bmatrix} f_{11} & f_{12} & f_{13} & \cdots & f_{1m} \\ f_{21} & f_{22} & f_{23} & \cdots & f_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{m1} & f_{m2} & f_{m3} & \cdots & f_{mm} \end{bmatrix} \qquad (4)$$

where f_{ij} represents the frequency of transition from state i to state j, and m represents the number of states. The transition probability matrix was obtained from the transition frequency matrix. The probability of transition from state i to state j was calculated by dividing the transition frequency from state i to state j by the total frequency of transitions from state i. The transition probability is given by equation (5).

$$P_{ij} = \frac{f_{ij}}{\sum_{j=1}^{m} f_{ij}}, \qquad (5)$$

where P_{ij} is the probability of transition from state i to state j, and f_{ij} is the corresponding transition frequency. The transition probability matrix is written as equation (6).

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} & \cdots & P_{1j} \\ P_{21} & P_{22} & P_{23} & \cdots & P_{2j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{i1} & P_{i2} & P_{i3} & \cdots & P_{ij} \end{bmatrix} \qquad (6)$$

Each row of the matrix represents the probability distribution of future states given the current state. Therefore, the sum of each row is equal to one [19–21].

2.4. Weighted Markov chain model

The weighted Markov chain method extends the ordinary Markov chain by considering several previous transition steps. In this study, predictions were made by involving up to five previous steps, namely $K=1, 2, 3, 4$, and 5. The purpose of using several previous steps was to determine the most suitable lag structure for predicting future gold prices [3, 6, 16]. The weight for each lag was calculated using the autocorrelation coefficient. The autocorrelation coefficient for lag k is given by equation (7).

$$r_k = \frac{\sum_{t=1}^{n-k}(x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^{n}(x_t - \bar{x})^2} \qquad (7)$$

where r_k is the autocorrelation coefficient at lag k, xt is the gold price at time t, $xt+k$ is the gold price at time $t+k$, and x⁻ is the mean of the gold price data. The weight for each lag was then calculated as equation (8).

$$\omega_k = \frac{|r_k|}{\sum_{\ell=1}^{K}|r_\ell|}, \quad k = 1,2,\ldots,K \qquad (8)$$

where ω_k is the weight for lag k, and K is the maximum number of previous steps used in the prediction process. The use of absolute autocorrelation values ensures that all weights are non-negative and proportional to the strength of the relationship between current and previous observations [6, 14, 15]. After the weights were obtained, the weighted transition probability was calculated as equation (9).

$$\hat{P}_{ij} = \sum_{k=1}^{K} \omega_k P_{ij}^{(k)}, \qquad (9)$$

where $\hat{P}_{ij}$ is the weighted transition probability from state i to state j, ω_k is the weight for lag k, and $P_{ij}^{(k)}$ is the k-step transition probability. The predicted state was determined by selecting the state with the highest weighted transition probability see equation (10).

$$\hat{X}_{t+1} = arg\max_{j}\{\hat{P}_{ij}\} \qquad (10)$$

The predicted gold price was then represented by the corresponding price value of the predicted state.

2.5. Prediction procedure and accuracy evaluation

The prediction procedure was carried out separately for the six-state and ten-state classifications. The steps were as follows. First, the weekly Indonesian gold prices were classified into states based on the predetermined state intervals. Second, the transition frequency matrix was constructed from the sequence of observed states. Third, the transition probability matrix was calculated from the transition frequency matrix. Fourth, the autocorrelation coefficients were computed for several lags. Fifth, the Markov weights were calculated using the autocorrelation coefficients. Sixth, the weighted transition probabilities were obtained by combining the transition probabilities with their corresponding weights. Finally, the future state was predicted by selecting the state with the highest weighted transition probability.

The initial prediction was conducted for several values of K, namely $K=2, 3, 4$, and 5. The prediction results were then compared with the actual gold prices to determine which value of K produced the most accurate prediction. After the best value of K was identified, the prediction was extended to several forecasting periods [19–21].

The accuracy of the prediction results was evaluated using the Mean Absolute Percentage Error (MAPE). MAPE measures the average percentage difference between actual values and predicted values. Mathematically, MAPE is defined as follows equation (11).

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

where: Y_t = represents the actual Bitcoin price at time t, $\hat{Y}_t$ = denotes the forecasted Bitcoin price at time t, and n = the total number of forecasting observations.

The interpretation of MAPE values was based on the following criteria: a MAPE value of less than or equal to 10% indicates very good prediction accuracy; a value between 10% and 20% indicates good prediction accuracy; a value between 20% and 50% indicates moderate prediction accuracy; and a value greater than 50% indicates poor prediction accuracy.

The overall research procedure can be summarized as follows. The study began with the collection of weekly world gold price data and exchange rate data. The world gold prices were then converted into Indonesian gold prices in Rupiah per gram. After that, the Indonesian gold prices were grouped into six-state and ten-state classifications. For each classification, transition frequency and transition probability matrices were constructed. Autocorrelation coefficients were then calculated to obtain the Markov weights. The weighted Markov chain model was applied to predict future gold price states, and the prediction results were compared with actual gold prices using MAPE. Through this procedure, the study evaluated not only the ability of the weighted Markov chain method to predict Indonesian gold prices but also the effect of different state classifications on prediction accuracy [14, 22, 23].

3. Results and discussion

3.1. Overview of gold price data

The data used in this study consisted of weekly Indonesian gold prices from 6 January 2019 to 27 December 2020. A total of 104 observations were used to construct the weighted Markov chain model. The gold price data were obtained by converting international gold prices into Indonesian Rupiah per gram using the exchange rate of the Indonesian Rupiah against the United States Dollar.

The descriptive analysis showed that Indonesian gold prices experienced an increasing trend during the observation period. At the beginning of the period, the gold price was approximately Rp612,041 per gram, while at the end of the period it reached Rp860,271 per gram. This movement indicates that gold prices changed considerably during the two-year period, although some short-term movements occurred within relatively close price ranges.

The mean value of Indonesian gold prices during the observation period was Rp750,427, while the standard deviation was Rp111,031. The standard deviation was smaller than the mean, indicating that the weekly gold price data were distributed around the average value and did not show extremely wide dispersion. However, the standard deviation still suggests that there was meaningful variation in gold prices, which makes prediction relevant for investment analysis.

In this study, the gold price data were grouped into two state classifications. The first classification consisted of six states, while the second consisted of ten states. These two classifications were used to examine whether the number of states affected the prediction results and prediction accuracy.

3.2. State classification of Indonesian gold prices

The classification of gold prices into states is an important step in applying the Markov chain method because the method requires discrete states. The continuous gold price data were therefore transformed into several intervals based on the mean and standard deviation. For the six-state classification, the Indonesian gold prices were divided into the following intervals in Table 1.

Table 1
Classification of gold prices across six states

State	Gold Price Interval
State 1	(X < 639,395)
State 2	(639,395 \leq X < 694,911)
State 3	(694,911 \leq X < 750,427)
State 4	(750,427 \leq X < 805,943)
State 5	(805,943 \leq X < 861,459)
State 6	(X \geq 861,459)

The six-state classification provides wider price intervals, while the ten-state classification provides more detailed intervals (Table 2). A larger number of states may give more specific price categories, but it may also reduce the transition frequency in each state. This can affect the stability of the transition probability matrix.

Table 2
Classification of gold prices across ten states

State	Gold Price Interval
State 1	(X < 639,395)
State 2	(639,395 \leq X < 667,153)
State 3	(667,153 \leq X < 694,911)
State 4	(694,911 \leq X < 722,669)
State 5	(722,669 \leq X < 750,427)
State 6	(750,427 \leq X < 778,185)
State 7	(778,185 \leq X < 805,943)
State 8	(805,943 \leq X < 833,701)
State 9	(833,701 \leq X < 861,459)
State 10	(X \geq 861,459)

After the gold price data were classified into states, the next step was to construct the transition frequency matrix. The transition frequency matrix shows how often the gold price moved from one state to another in consecutive weeks. For the six-state classification, the transition frequency matrix was obtained as follows matrix below.

$$F = \begin{bmatrix} 22 & 1 & 0 & 0 & 0 & 0 \\ 0 & 12 & 4 & 0 & 0 & 0 \\ 0 & 3 & 17 & 2 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 13 & 2 \\ 0 & 0 & 0 & 0 & 3 & 19 \end{bmatrix}$$

Based on this matrix, most transitions occurred within the same state. For example, state 1 remained in state 1 for 22 transitions, state 3 remained in state 3 for 17 transitions, state 5 remained in state 5 for 13 transitions, and state 6 remained in state 6 for 19 transitions. This indicates that weekly gold prices tended to remain in the same price category rather than moving sharply to another category. The transition probability matrix for the six-state classification was:

$$\boldsymbol{P} = \begin{bmatrix} 0,9565 & 0,0435 & 0 & 0 & 0 & 0 \\ 0 & 0,7500 & 0,2500 & 0 & 0 & 0 \\ 0 & 0,1364 & 0,7727 & 0,0909 & 0 & 0 \\ 0 & 0 & 0,2500 & 0,2500 & 0,2500 & 0,2500 \\ 0 & 0 & 0 & 0,0625 & 0,8125 & 0,1250 \\ 0 & 0 & 0 & 0 & 0,1364 & 0,8636 \end{bmatrix}$$

The matrix shows that the highest transition probabilities are generally located on the diagonal. This means that the probability of remaining in the same state was higher than the probability of moving to a different state. For instance, when the price was in state 5, the probability of remaining in state 5 in the next period was 0.8125. Similarly, when the price was in state 6, the probability of remaining in state 6 was 0.8636. For the ten-state classification, the transition frequency matrix was:

$$\boldsymbol{F} = \begin{bmatrix} 22 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 5 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 6 & 4 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3 & 15 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 7 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 2 & 19 \end{bmatrix}$$

In the ten-state classification, several states had fewer observations and fewer transitions. This is because the price intervals were narrower than those in the six-state classification. As a result, some states had limited transition information [20, 21, 25]. This condition may affect prediction stability because the transition probabilities are estimated from relatively small frequencies. The transition probability matrix for the ten-state classification was:

$$\boldsymbol{P} = \begin{bmatrix} 0,9565 & 0,0435 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0,8333 & 0,1667 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0,6 & 0,4 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0,1579 & 0,7895 & 0,05\,26 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0,3333 & 0,6667 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0,3333 & 0 & 0,3333 & 0 & 0 & 0,3333 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0,2 & 0 & 0,2 & 0,6 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0,1818 & 0,6364 & 0,1818 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0,0455 & 0,0909 & 0,8636 \end{bmatrix}$$

3.3. Autocorrelation coefficients and Markov weights

The weighted Markov chain method requires weights for each transition step. These weights were calculated based on the autocorrelation coefficients of the historical gold price data. In this study, autocorrelation coefficients were calculated for five lags, namely k=1,2,3,4, and 5 [16, 26, 27]. The autocorrelation coefficients were in Table 3.

Table 3
Autocorrelation coefficient value

Lag (k)	1	2	3	4	5
(r_k)	0.97079	0.94417	0.91244	0.88642	0.68254

The values show that the gold price data had strong positive autocorrelation, especially from lag 1 to lag 4. This means that gold prices in one week were strongly related to prices in the previous weeks. The autocorrelation value decreased as the lag increased, indicating that more recent observations had a stronger relationship with current gold prices than older observations. The weights for the weighted Markov chain were calculated from these autocorrelation coefficients. The resulting weights were presented in Table 4.

Table 4
The Markov chain weights for each k

Lag (k)	*(K=1)*	*(K=2)*	*(K=3)*	*(K=4)*	*(K=5)*
1	1.0000	0.50695	0.34335	0.26140	0.21213
2	-	0.49305	0.33394	0.25423	0.20632
3	-	-	0.32271	0.24569	0.19938
4	-	-	-	0.23868	0.19370
5	-	-	-	-	0.18848

The distribution of weights shows that the first lag had the largest contribution in all values of K. However, the differences between weights were not very large for $K=2$, $K=3$, and $K=4$. This indicates that the recent several weeks still contributed meaningfully to the prediction process.

The strong autocorrelation values support the use of the weighted Markov chain method because the method relies on the relationship between current and previous states. However, high autocorrelation can also cause the prediction results to remain in the same state, especially when the transition probability matrix is dominated by diagonal values.

3.4. Prediction results based on the weighted Markov chain

The prediction process was conducted using the weighted Markov chain model for both state classifications. The prediction was initially performed for five weeks after the training period, namely week 105 to week 109. The actual gold prices for these five weeks were compared with the predicted states.

For the six-state classification, the gold price in week 104 was in state 5. Based on the transition probability matrix and the weighted Markov chain calculation, the predicted gold price for week 105 was also in state 5 for all values of K. The same result occurred for weeks 106 to 109. Thus, the model consistently predicted state 5 during the five-week prediction period.

For the ten-state classification, the prediction results also showed a similar pattern. The model predicted that the gold price would be in state 9 from week 105 to week 109 for all values of K. This indicates that both classifications produced stable predicted states during the short-term prediction period. The comparison between actual and predicted states is presented in Table 5.

Table 5
Comparison of predicted gold prices in Indonesia with actual data

Week	Actual Price	Actual State in Six-State Case	Predicted State in Six-State Case	Actual State in Ten-State Case	Predicted State in Ten-State Case
105	833,403	5	5	8	9
106	831,678	5	5	8	9
107	842,999	5	5	9	9
108	838,176	5	5	9	9
109	822,129	5	5	8	9

The six-state classification produced predicted states that matched the actual states for all five weeks. In contrast, the ten-state classification matched the actual state only in weeks 107 and 108, while weeks 105, 106, and 109 were predicted as state 9 although the actual state was state 8. This result suggests that the six-state classification performed better in terms of state prediction for the five-week prediction period.

The predicted state was then converted into a representative price using the median value of the corresponding state interval. In the six-state classification, the predicted state was state 5, with a representative price of Rp833,701. In the ten-state classification, the predicted state was state 9, with a representative price of Rp847,580.

These results show that the weighted Markov chain model produced stable predictions. This stability is caused by the structure of the transition probability matrix, where the highest probabilities are mostly located on the diagonal. In other words, the model tends to predict that the future state will remain the same as the current or recent dominant state.

3.5. Prediction accuracy based on MAPE

Prediction accuracy was evaluated using the Mean Absolute Percentage Error. Since the predicted states were the same for all values of K, the MAPE calculation was conducted once for each state classification [28, 29]. For the six-state classification, the predicted gold price was Rp833,701. Based on the actual gold prices from week 105 to week 109, the MAPE was calculated as follows:

$$MAPE = \frac{1}{n}\sum_{t-1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t} \times 100\%$$

$$= \frac{1}{5}\left[\left(\frac{|833403 - 833701|}{833403}\right) + \left(\frac{|831678 - 833701|}{831678}\right) + \left(\frac{|842999 - 833701|}{842999}\right) + \left(\frac{|838176 - 833701|}{838176}\right) + \left(\frac{|822129 - 833701|}{822129}\right)\right] \times 100\%$$

$$= \frac{1}{5}\,[(0{,}0004) + (0{,}0024) + (0{,}0110) + (0{,}0053) + (0{,}01408)] \times 100\%$$

$$= 0{,}66\%.$$

The resulting MAPE for the six-state classification was 0.66%. For the ten-state classification, the predicted gold price was Rp847,580. The MAPE was calculated as:

$$MAPE = \frac{1}{n}\sum_{t-1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t} \times 100\%$$

$$= \frac{1}{5}\left[\left(\frac{|833403 - 847580|}{833403}\right) + \left(\frac{|831678 - 847580|}{831678}\right) + \left(\frac{|842999 - 847580|}{842999}\right) + \left(\frac{|838176 - 847580|}{838176}\right) + \left(\frac{|822129 - 847580|}{822129}\right)\right] \times 100\%$$

$$= \frac{1}{5}\,[(0{,}0170) + (0{,}0191) + (0.0054) + (0{,}0112) + (0{,}0310)] \times 100\%$$

$$= 1{,}67\%.$$

The resulting MAPE for the ten-state classification was 1.67%. Based on the MAPE criteria, both results indicate very good prediction accuracy because the MAPE values were below 10%. However, the six-state classification produced a lower MAPE than the ten-state classification. This indicates that, for the data used in this study, the six-state classification provided more accurate short-term predictions.

The MAPE values for different prediction periods are presented in Table 6.

Table 6
27 Percentage error values for different values of *n*

Prediction Period	Six-State Classification	Ten-State Classification
5 weeks	0.66%	1.67%
13 weeks	2.45%	3.90%
26 weeks	2.18%	3.01%
48 weeks	2.15%	2.89%

The table shows that the MAPE values remained below 10% for all prediction periods. This means that the weighted Markov chain method had very good prediction accuracy based on the MAPE criterion. Nevertheless, the six-state classification consistently produced lower error values than the ten-state classification.

This finding suggests that using more states does not always improve prediction accuracy. Although the ten-state classification provides more detailed price intervals, it also produces fewer observations in each state. As a result, the estimated transition probabilities may become less stable. In contrast, the six-state classification provides wider intervals, allowing more observations in each state and producing a more stable transition probability structure.

3.6. Comparison between actual and predicted gold prices

The comparison between actual and predicted gold prices showed an important characteristic of the weighted Markov chain model. The actual gold prices fluctuated from week to week, while the predicted prices remained constant during the prediction period (Fig 1). For the six-state classification, the predicted price remained at Rp833,701. For the ten-state classification, the predicted price remained at Rp847,580. Meanwhile, the actual gold prices changed each week, with values of Rp833,403, Rp831,678, Rp842,999, Rp838,176, and Rp822,129 during the first five weeks of prediction.

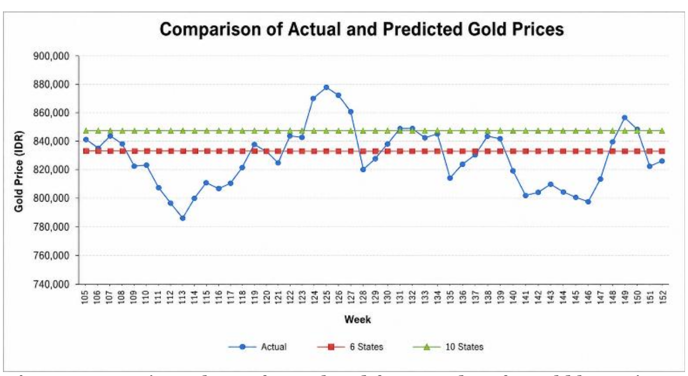

Fig. 1. Comparison chart of actual and forecast data for gold bar prices

This result indicates that the weighted Markov chain method was able to provide accurate short-term predictions when the actual prices remained close to the predicted state interval. However, the method was less able to capture weekly fluctuations in actual gold prices. This is because the Markov chain approach predicts states rather than exact continuous values. When the predicted state does not change, the representative predicted price also remains constant.

The tendency of the prediction to remain constant is closely related to the transition probability matrix. Since the diagonal elements of the matrix were dominant, the model assigned a high probability to the same state in the following period. Therefore, once the model predicted a particular state, it tended to continue predicting the same state for the next periods. This characteristic has two implications. First, the weighted Markov chain method is useful for short-term prediction when the price movement is relatively stable and remains within the same state interval. Second, the method has limitations for longer-term forecasting or for periods with high volatility because it may fail to capture changes in price direction and magnitude.

The results of this study show that the weighted Markov chain method can be applied to predict Indonesian gold prices, particularly for short-term prediction. The method produced very low MAPE values, especially in the six-state classification. The five-week prediction produced a MAPE of 0.66% for the six-state case and 1.67% for the ten-state case. These results indicate that the predicted prices were close to the actual prices during the short-term prediction period.

However, the prediction results also show that the weighted Markov chain method tends to produce constant values when the predicted state does not change. This occurred in both classifications. In the six-state classification, the predicted state remained in state 5, while in the ten-state classification, the predicted state remained in state 9. As a result, the predicted gold price remained unchanged for the prediction period.

This finding confirms that the weighted Markov chain method is more appropriate for identifying the likely future state of gold prices rather than predicting exact weekly price movements. The method is effective in estimating the price range, but it is less sensitive to short-term fluctuations within the same state interval. Therefore, when the actual price changes but remains within the same state, the model still produces the same predicted value.

The comparison between the six-state and ten-state classifications also provides an important insight. The six-state classification produced better accuracy than the ten-state classification. This may be because the six-state classification has wider intervals, which makes the model more robust in classifying price movements. In contrast, the ten-state classification uses narrower intervals, causing small changes in gold prices to be classified into different states. Although this provides a more detailed classification, it may also increase prediction error when the model predicts a neighboring state.

Another important point is that the transition probability matrices showed high probabilities of remaining in the same state. This suggests that gold price movements in the observed weekly data had strong persistence. The autocorrelation coefficients also supported this finding, with values above 0.88 for lags 1 to 4. This means that gold prices in recent weeks were strongly related to prices in previous weeks.

Nevertheless, strong persistence can make the model less responsive to sudden changes. If gold prices move sharply due to external factors such as changes in global market conditions, exchange rates, inflation, monetary policy, or economic uncertainty, the weighted Markov chain model may not immediately capture those changes. This is because the model relies mainly on historical state transitions and does not include external explanatory variables.

Therefore, although the MAPE values indicate very good prediction accuracy, the interpretation of the results should be made carefully. The low MAPE values show that the predicted prices were numerically close to actual prices during the evaluation period. However, the graphical comparison shows that the model did not fully follow the fluctuating pattern of actual gold prices. This means that the method is suitable for short-term range-based prediction but may not be sufficient for detailed forecasting of weekly price movements.

Overall, the results demonstrate that the weighted Markov chain method is simple, interpretable, and useful for short-term prediction of Indonesian gold prices. The method can provide investors with an estimated price range that may help in short-term investment considerations. However, for longer prediction periods or more volatile market conditions, the method should be combined with other forecasting approaches or additional variables to improve its ability to capture price fluctuations.

4. Conclusion

This study applied the weighted Markov chain method to predict Indonesian gold prices using weekly data from January 2019 to December 2020. The data were grouped into six-state and ten-state classifications, and prediction accuracy was evaluated using MAPE. The results show that the method produced very good short-term prediction accuracy. The six-state classification predicted the gold price in state 5 with a representative value of Rp833,701 and a MAPE of 0.66%, while the ten-state classification predicted the gold price in state 9 with a representative value of Rp847,580 and a MAPE of 1.67%.

The six-state classification produced lower prediction errors than the ten-state classification for all evaluation periods. This indicates that a larger number of states does not necessarily improve prediction accuracy. Although the weighted Markov chain method provided very good MAPE values, the predicted prices tended to remain constant, while the actual prices were more fluctuating. Therefore, the method is suitable for short-term range-based prediction but has limitations in capturing detailed price volatility, especially for long-term forecasting. Future research may improve the model by incorporating external factors such as exchange rates, inflation, interest rates, and global gold price movements.

CRediT authorship contribution statement

Mirnawati: Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **T. Murdani Saputra:** Writing – review & editing, Investigation. **Ikhsan Maulidi**: Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fajri Farid:** Formal analysis, Writing – review & editing, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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