International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2022, 12(6), 202-214.

Analysis of Precious Metal Price Movements Using Long Memory Model and Fuzzy Time Series Markov Chain

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Received: 28 July 2022 **Accepted:** 20 October 2022 **DOI:** https://doi.org/10.32479/ijeep.13531

ABSTRACT

Precious metals occur naturally and have a high resistance to corrosion or oxidation. These natural resources are used as investment instruments to protect wealth values, such as gold, silver, and palladium. Price movements need to be understood when investing, and it is achieved through a time series model that predicts future prices. Also, autoregressive fractional integrated moving average (ARFIMA) is used to model price movements with long memory effects, while fuzzy time series Markov chain (FTSMC) is employed for performing numerical approach. It was observed that gold price movement has a long memory effect; therefore, it is eligible to be formed into the ARFIMA model. However, the silver and palladium prices do not contain a long memory effect, which means their movements are only formed through the FTSMC numerical model. The ARFIMA modeling results show that the gold price long memory model has the best accuracy with the smallest error value and also demonstrates excellent goodness of fit. Furthermore, the gold price long memory model movement has long-term stability compared to other precious metals. This provides an investment advantage because it is a stable asset, easy to liquidate in cash, free of interest, has an emergency fund role, and protects wealth's value.

Keywords: Precious Metal, Long Memory, Fuzzy Time Series Markov Chain, Level of accuracy
JEL Classifications: C32, C58, C88, G23

1. INTRODUCTION

Precious metals are used extensively in energy fields, such as catalytic carbon dioxide reduction, petroleum cracking, and hydrogen energy production. Therefore, recycling strategies were optimized to promote coordinated energy and environmental development. Chen et al. (2021) found that the demand and consumption of this natural resource are increasing every year, thereby causing it to be expensive and valuable as an investment instrument. Gold is a well-known type of precious metal, which is widely used as jewelry and valuable property because it is soft and malleable. Furthermore, gold has been a popular and trusted investment instrument over time (Hillier et al., 2006; Blose, 2010; Baur and Lucey, 2010; Baur and McDermott, 2010; Hood and Malik, 2013; Reboredo, 2013; Ciner et al., 2013; Areal et al., 2015; Beckmann et al., 2015; O'Connor et al., 2015; Baur and McDermott, 2016; Hoang et al., 2016; Iqbal, 2017; Bekiros et al., 2017; Junttila et al., 2018; Tronzano, 2021). This is consistent with the discovery of Makala and Li (2021) that aside from being a valuable asset, gold is an investment instrument capable of protecting wealth because its value tends to be higher than other precious metals, such as platinum and palladium.

Aside from gold, silver is also one of the precious metals categorized as the earth's mineral product. It is characterized by a glossy white color, anti-corrosion, and soft nature. It is also often used as a material for jewelry, currency, home ornaments, and mirrors. Corbet and Connor (2021) found that pure silver must be mixed with other metal types because of its soft nature when forming another product. Another type of precious metal with a reasonably expensive price is Palladium (Maghyereh and Abdoh, 2022). It is a shiny white metal with the lowest melting strength compared to others and is very dense, not easily damaged by chemical compounds and physical impact.

The price of precious metals often changes over time; hence its probable future cost is predictable by observing the price movement patterns. Empirical predictions usually provide the community and investors with the basis for planning and decision-making to increase profits and prevent losses. A method used for predicting the price movement of precious metals is the time series model.

Khairuddin et al. (2016) stated that the time series method is used for time-ordered data. According to Wei (2019), the data has a repeating pattern in which the period in the past tends to reoccur in the present or future. The time series model analysis is meant to determine a pattern or regularity for modeling and identifying the component factors affecting the value in the time series (Marwan et al., 2021). Classic time series models include autoregressive integrated moving averages (ARIMA), time series regression, and exponential smoothing. The ARIMA model is a combination of autoregressive (AR) and moving average (MA), which represents stationary assumption (Yan et al., 2022). Granger (1980) discovered that the time series data showing a long memory pattern is seen in the autocorrelation function (ACF) plot, which slowly decreases for a longer period, while Monge and Infante (2022) modeled data with long memory effects using autoregressive fractionally integrated moving average (ARFIMA). Based on Hosking (1981), these models have long-term pattern properties that are traceable through their stationary by determining the differentiating coefficient of Geweke and Porter-Hudak (GPH). This is in line with Geweke (1983), who stated that the GPH method directly estimates the difference coefficient without knowing the AR and MA order values. The next long memory model development is the combination of ARFIMA and Poisson distribution to ensure non-negative credibility per period in the affine frequency risks prediction (Pinquet, 2020).

Furthermore, the numerical approach for the time series data is performed using the fuzzy time series (FTS) model (Severiano et al., 2021) and fuzzy logic concept in order to model applicants' numbers at a university (Cheng et al., 2008). Subsequently, several FTS methods have been proposed, such as the Chen model, Weighted, Markov, Stevenson Porter, and the multiple attribute fuzzy time series approach (Egrioglu et al., 2022). Tsaur (2012) analyzed the prediction accuracy of the Taiwan currency exchange rate with the US dollar by combining the FTS method and the Markov chain to obtain the largest probability using a transition probability matrix. The results showed that the Fuzzy time series Markov chain (FTSMC) method provides a fairly good accuracy compared to the FTS proposed by Cheng et al. (2008), Ramadani and Devianto (2020), as well as Sjofjan and Adli (2022). Further development by Zalan and Yaseen (2021) predicted the birth rates in Basra Province with the fuzzy-ARFIMA model and compared the result using the smallest value evaluation criteria of AIC, BIC, and Adjust R-squared.

Ramadani and Devianto (2020) forecasted bitcoin prices using three FTS methods, namely FTS-Chen, FTS-Segmented Chen, and FTSMC and discovered that the FTSMC has a better accuracy rate compared to other methods because it has the smallest MAPE value. Meanwhile, Lawal et al. (2020) examined the long memory effect of oil prices and exchange rates on Nigerian stocks and found that stock prices are driven by exchange rates and oil prices. Zaenurrohman et al. (2021) also conducted a literature study using Markov chains to predict currency exchange rates and inflation, followed by the use of the Chen and Hsu method for forecasting the Sharia Stock Exchange Index in the Jakarta Islamic Index.

The previous time series data modeling conducted showed that the ARFIMA model has good results than the ARIMA regarding long memory effect data. It is important to note that numerical modeling is mostly performed with the FTS method and its variations, but only a few compared the ARFIMA and FTSMC models when determining the best approach. Therefore, this current research employed the ARFIMA model as an extension of ARIMA for modeling the precious metals' monthly price movements. Furthermore, the proposed model is compared with the FTS approach, which is assessed with an accuracy level based on the value of MAE, RMSE, and MAPE. This study serves as a basis for future energy economy and investment policies.

2. MATERIALS AND METHODS

The precious metal prices used were the monthly data on gold, silver, and palladium prices from April 2017 to May 2022, which is about 62 datasets sourced from investing.com. Price movement detection was performed using the ARFIMA model for data with long memory effects, while the numerical approach was conducted with the FTSMC. In this section, ARFIMA and FTSMC's theories were explained as the steps used to form a time series model for the precious metal price movement.

2.1. Autoregressive Fractionally Integrated Moving Average (ARFIMA)

The steps in forming a time series model with data containing long memory effects are modeled into ARFIMA as follows:

Step 1. Check the stationary data for homogeneity of variance. When the data is not stationary, data transformation was performed to obtain a rounded value (λ). For example, when data X_t is not stationary with respect to variance, it is transformed by the formula $T(X_t)=(X_t^{\lambda-1}/\lambda$, where λ represents the transformation parameter. The data is considered stationary when parameter λ=1 goes through the rounded value process (Wei, 2019).

Step 2. Create an ACF plot of the transformed data to identify whether the data contains a long memory effect or not.

Step 3. Estimate the differentiating parameters using the Geweke and Porter-Hudak method with the following formula (Geweke, 1983):

$$\hat{d}_{GPH}=\frac{\sum_{j=1}^{m}\left(x_j-\bar{x}\right)\left(y_j-\bar{y}\right)}{\sum_{j=1}^{m}\left(x_j-\bar{x}\right)^2} \quad (1)$$

Where $I(\lambda_j)$ is the periodogram with m Fourier frequency $\lambda_j=\frac{2\pi j}{T}$ for $j=1,2,\ldots,m$ and T represents the observational data number.

Meanwhile, x_j is observational data and defined by the value $y_j = \ln I(\lambda_j)$.
Step 4. Differentiate the transformed data using the value of $\hat{d}_{GPH}$.
Step 5. Identify the ARFIMA model to determine the combination of its parameters by plotting ACF and PACF from differentiating data. The ACF plot shows the order of MA(q), while that of PACF describes the order of AR(p).
Step 6. Parameter estimation and significance test of ARFIMA model. After obtaining all the candidate models, the next step is estimating each model's parameters, followed by the significance test. The model was considered feasible for usage when the parameters were significant, with a significance level of α = 5%.
Step 7. Choose the best ARFIMA model with the smallest Akaike information criterion (AIC) value.
Step 8. Test the assumptions of the best ARFIMA model residues, which include non-autocorrelation and normality tests.
Step 9. Determine the best ARFIMA model equation and its interpretation.

2.2. Fuzzy time series Markov Chain (FTSMC)

The main difference between FTS and time series models is the variable values employed in modeling. For example, a fuzzy set of real numbers were applied in FTS to a certain universal set. The fuzzy set was interpreted as a class of numbers with the same limit, and the modeling stages are as follows:
Step 1. Collect historical data and define the universal set U. The first step is determining the minimum (D_{min}) and maximum (D_{max}) values of the historical data. It is important to note that the values of D_1 and D_2 are independently determined since the two number values are positive real numbers. In addition, D_1 and D_2 values aim to facilitate the formation of intervals, while the universal set U is denoted as follows:

$$U = [D_{min} - D_1, D_{max} + D_2] \quad (2)$$

Step 2. Determine the number and length of the intervals. The universal set U is partitioned into intervals by using the Sturges rule:

$$n = 1 + 3{,}322 \log N, \quad (3)$$

where N is the number of historical data. Then the next interval length l was determined using the formula

$$l = \frac{[(D_{max} + D_2) - (D_{min} - D_1)]}{n} \quad (4)$$

which the intervals u_n are determined by

$$u_n = [B + (n-1)l; \mathrm{B} + nl] \quad (5)$$

where $B=D_{min}-D_1$.

Step 3. Determine the fuzzy set for the entire universe set U using the following rules:
1. If the historical data (Y_t) represents u_i, then u_i membership degree is 1, u_{i+1} is 0.5, and others are 0
2. If the historical data (Y_t) denotes u_i, 1 < i < n, then the membership degree of u_i is 1, u_{i-1} and u_{i+1} are 0.5, while others are 0
3. If the historical data (Y_t) is u_n, then the membership degree of u_n is 1, u_{n-1} is 0.5, and others are 0.

Therefore, the fuzzy set for the entire universe set U is expressed as follows:

$$A_1 = \frac{1}{u_1}, \frac{0.5}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \ldots, \frac{0}{u_{n-1}}, \frac{0}{u_n},$$
$$A_2 = \frac{0.5}{u_1}, \frac{1}{u_2}, \frac{0.5}{u_3}, \frac{0}{u_4}, \ldots, \frac{0}{u_{n-1}}, \frac{0}{u_n}$$
$$A_3 = \frac{0}{u_1}, \frac{0.5}{u_2}, \frac{1}{u_3}, \frac{0.5}{u_4}, \ldots, \frac{0}{u_{n-1}}, \frac{0}{u_n}$$
$$A_{n-1} = \frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \ldots, \frac{1}{u_{n-1}}, \frac{0.5}{u_n}$$
$$A_n = \frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \ldots, \frac{0.5}{u_{n-1}}, \frac{1}{u_n} \quad (6)$$

Step 4. Fuzzification of historical data. This is a data identification process in fuzzy sets. If the historical data collected is included in u_i, then the data is fuzzified into A_i.
Step 5. Determine the fuzzy logical relationship (FLR) and fuzzy logical relationship group (FLRG).

Definition 1. According to Cheng (2008), when F(t)=A_i and F(t–1)=A_j, then the relationship between F(t) and F(t–1) is called a fuzzy logical relationship (FLR), represented by $A_i \rightarrow A_j$, where A_i is the left-hand side (LHS) and A_j is the right-hand side (RHS) of the FLR. When two FLRs have the same fuzzy set (LHS $A_i \rightarrow A_{j1}, A_i \rightarrow A_{j2}$), they are categorized into a fuzzy logical relationship group (FLRG) $A_i, A_{j1} \rightarrow A_{j2}$.

Step 6. Create a Markov transition probability matrix. The transitional probability for that state is written as follows (Tsaur, 2012):

$$P_{ij} = \frac{M_{ij}}{M_i}, \text{for } i, j = 1, 2, 3, \ldots, n \quad (7)$$

The transition probability from state A_i to state A_j is P_{ij}, while the amount of data from the state A_i is M_i and the transition times from state A_i to state A_j is M_i. Therefore, the transition probability matrix **R** from a state space is written as follows:

$$\boldsymbol{R} = \begin{bmatrix} P_{11} & P_{12} & \ldots & P_{1n} \\ P_{21} & P_{22} & \ldots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \ldots & P_{nn} \end{bmatrix} \quad (8)$$

Step 7. Calculate the initial modeling results based on the probability matrix obtained in the previous step using the following rules:

Rule 1. If the FLRG of A_i changes to the empty set ($A_i \rightarrow \phi$), then the modeling result of F(t) is m_i, with the mean value of u_i satisfying

$$F(t) = m_i \quad (9)$$

Rule 2. If the FLRG of A_j does transitions from one state to another one $A_i \rightarrow A_k$ with P_{ij}=0 and P_{ik}=1,$j \neq k$, then the modeling result of F(t) is m_k with the mean value of u_k satisfying

$$F(t) = m_k P_{ik} = m_k \quad (10)$$

Rule 3. If the FLRG from A_j is transited from one-to-many (i.e $A_j \rightarrow A_1, A_2, \ldots A_n$, j=1,2,…,n) and the data set X(t–1) as in the state A_j at time t–1, then the result of modeling F(t) is as follows:

$$F(t) = m_1 P_{j1} + m_2 P_{j2} + .. + m_{j-1} P_{j(j-1)} + X(t-1) P_{jj} + m_{j+1} P_{j(j+1)} + .. + m_n P_{jn} \quad (11)$$

Where $m_1, m_2.., m_{j-1}, m_{j+1}.., m_n$ is the midpoint of $u_1, u_2.., u_{j-1}, u_{j+1}.., u_n$ and m_j is substituted for X(t–1) to have the information from the state A_j at t-1.

Step 8. Calculate the adjusted value in the model in order to correct the error caused by the biased Markov chain matrix. Therefore, the modeling adjustment value (D_t) is needed for correcting the error using the following rules:

a. When state A_i changes with A_j, then state A_i at t–1 is F(t-1)=A_i. For a transition up to the state A_j at *t,* ($i<j$), the adjustment value of D_t is D_{t1} =(l/2).
b. When state A_i moves to A_j, state A_i at time t–1 as F(t–1)= A_i, during the transition down to state A_j at *t*,($i>j$) showed the adjustment value of D_t is D_{t1} =(l/2)
c. When state A_i at time *t*-1 is F(t-1)=A_i and there is a forward transition jump to state A_{i+s} at t, 1≤s≤n-i, then the adjustment values of D_t and D_{t2} =(l/2)s, where s is the number of forwarding transition jumps
d. When state A_i at time t-1 is F(t-1)=A_i and there is a backward transition jump to state A_{i-v} at t, 1≤v≤i, then the adjustment value of D_t is D_{t2}=–(l/2)v, where v is the number of backward transition displacement jumps.

Step 9. Determine the final modeling result by summing the initial value with those adjusted. The general form of the final modeling result F'(t) is expressed as follows

$$F'(t) = F(t) \pm D_{t1} \pm D_{t2}. \quad (12)$$

2.3. Modeling Accuracy

Error calculation is a strategy for determining the obtained model's accuracy. It is used to examine how closely the modeling data matches the actual ones. According to Kumar et al. (2022), a small value generated from the error size represents a better model. The mean absolute percentage error (MAPE) was used to measure the accuracy of each modeling method using the following formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|X_t - \hat{X}_t\right|}{X_t} \times 100\% \quad (13)$$

The MAPE accuracy criteria are as follows:

a. The modeling accuracy is very good when the MAPE value is <10%
b. The modeling accuracy is good when the MAPE value is 10–20%
c. The modeling accuracy is sufficient when the MAPE value is 20–50%
d. The modeling accuracy is not accurate when the MAPE value is >50%.

The next accuracy was measured with the root mean square error (RMSE) and mean absolute error (MAE) using the following formula

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(X_t - \hat{X}_t)^2} \quad (14)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|X_t - \hat{X}_t\right| \quad (15)$$

Where X_t is the actual data and $\hat{X}_t$ is the modeled data.

3. RESULTS AND DISCUSSION

In this section, the process of modeling the precious metal price movement was discussed based on the target model and its stages. Subsequently, the model was described using the ARFIMA and FTSMC approaches.

3.1. ARFIMA Model Approach to Precious Metal Prices

3.1.1. Detection of gold price movement model with ARFIMA

The initial step taken in identifying the gold price movement model was to plot the monthly gold price data shown in Figure 1.

Figure 1 shows that the pattern of gold price data for each period fluctuates and has an upward trend. The highest point in the monthly gold price occurred in July 2020, and since the data does not fluctuate around the median and variance values, it does not move toward any side. For a time series data to be stationary toward variance, the first data transformation stage was conducted by determining the rounded value (λ). The transformation parameter formula utilized showed a λ value of –0.7042. It was concluded that the data was not stationary regarding variance; therefore, the second stage of transformation was performed, and the value obtained was 1. This means that the gold price data is stationary toward variance. The data was also investigated to observe whether it contains a long memory effect by plotting a stationary ACF against the variance as shown in Figure 2.

Based on Figure 2, the data decreases slowly over time and is not stationary toward the mean value. The data is made stationary by differentiating the value of *d,* which has been estimated using the Geweke Porter-Hudak (GPH) method with a value of $\hat{d}_{GPH}$= $\hat{d}_{GPH}$= 0.3269. Since $\hat{d}_{GPH}<0.5$, the data is concluded to have a long memory effect and has the ability to be modeled with ARFIMA. The next is identifying the ARFIMA model by looking at the ACF and PACF plots based on Figures 3 and 4.

Figure 3 shows that the significant value of the ACF coefficient reaches lag 12, then based on Figure 4, the PACF coefficient was significant only at lag 1. All possible ARFIMA model was formed by combining the maximum lag of 1 for the p parameter and lag of 12 for the q with d value of 0.3269. These parameters were estimated for each candidate model by conducting a significance test whose values are shown in Table 1.

The model was considered significant when its probability value was small at 0.05, therefore ARFIMA (0,0.3269,1), ARFIMA (0,0.3269,2), ARFIMA (0,0.3269,3), ARFIMA (0,0.3269,5), and ARFIMA (1,0.3269,0) was significant and useful. The next step

Table 1: The optimal parameters of autoregressive fractional integrated moving average (*p,d,q*)

Model	Φ_1	θ_1	θ_2	θ_3	θ_4	θ_5
ARFIMA (0,0.3269,1)		<2.22 e^{-16}				
ARFIMA (0,0.3269,2)		1.0544 e^{-11}	1.8864 e^{-8}			
ARFIMA (0,0.3269,3)		5.9055 e^{-11}	5.8110 e^{-7}	0.0005		
ARFIMA (0,0.3269,5)		1.3547 e^{-9}	0.0001	0.0006	0.0058	0.0242
ARFIMA (1,0.3269,0)	<2.22 e^{-16}					

ARFIMA: Autoregressive fractional integrated moving average

Figure 1: Plot of gold price monthly data

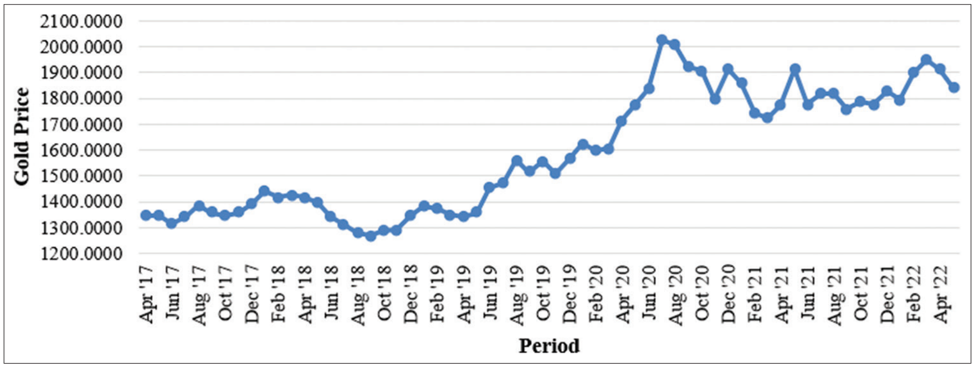


Figure 2: ACF plot of static gold price data against variety

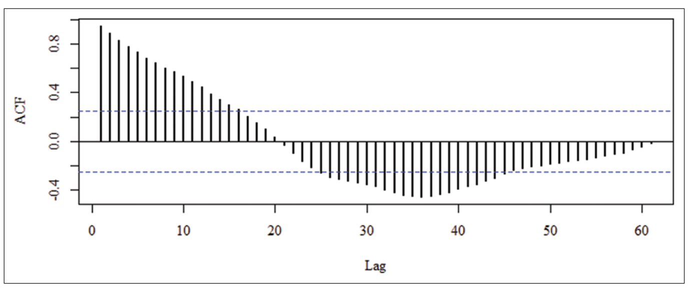


Figure 3: ACF plot of gold price data

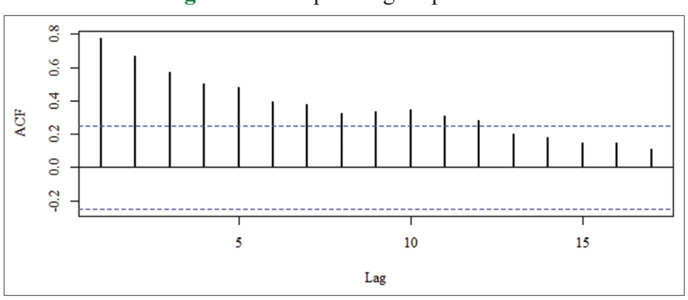
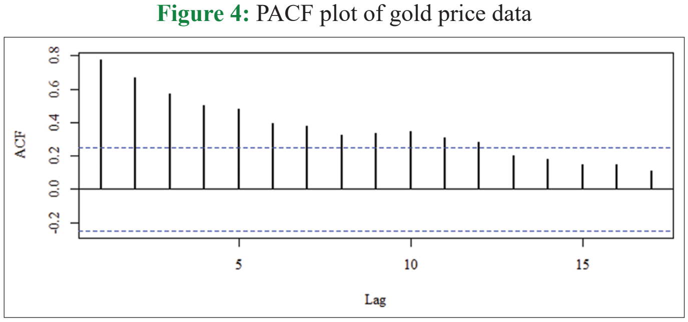


Figure 4: PACF plot of gold price data



is selecting the best model by comparing the AIC values for each model presented in Table 2.

Based on the comparison of AIC values in Table 2 for the five models, the ARFIMA (1,0.3269,0) has the smallest AIC value among other models and was regarded as the best. The residual assumption test of the ARFIMA (1,0.3269,0) is shown in Table 3.

Table 3 shows that the obtained P-value of the non-autocorrelation test was >0.05, meaning that there is no correlation between residues. In the normality test, the obtained P < 0.05 was ignored because time series data fluctuates rapidly. Therefore, the ARFIMA (1,0.3269,0) model was regarded as the best model using the following equation:

$$(1-B)^{0.3269} X_t = 0.8511 X_{t-1} + \varepsilon_t \tag{16}$$

In Figure 5, the modeling result was close to the actual data, as seen from the line that coincides with the outcome. It is therefore concluded that the ARFIMA was able to model gold price data appropriately.

3.1.2. Detection of silver price movement model with ARFIMA

The initial step taken when identifying the model for the silver price movement was the plotting of monthly price data as shown in Figure 6.

It was observed from Figure 6 that the pattern of silver price data for each period fluctuates and has an upward trend. The highest point in the price occurred in August 2020, and since the silver price data does not fluctuate around the mean and variance, it is not stationary toward the mean or variance. To make the time series data stationary toward variance, the first data transformation process was performed by determining the value of λ. The data processing result shows a value of –1.4456 but was not stationary toward variance. Meanwhile, the second stage produced a λ value of 1, indicating that the silver price data was stationary toward variance. A further examination was performed to confirm whether the model contains a long

Figure 5: Graph of gold price actual data and modeling results

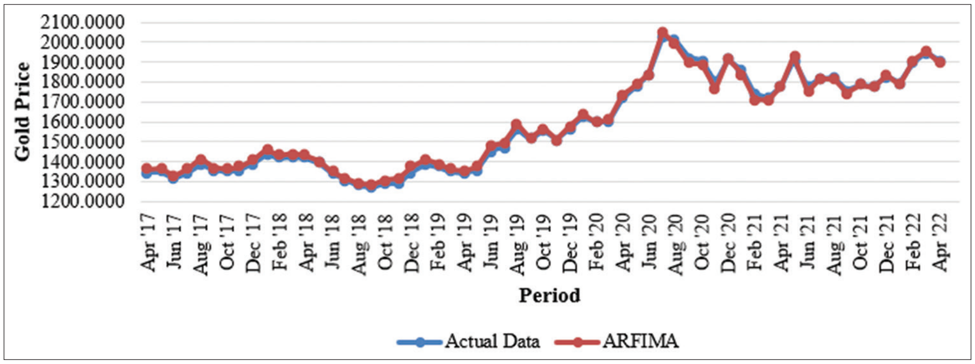


Figure 6: Monthly data plot of silver prices

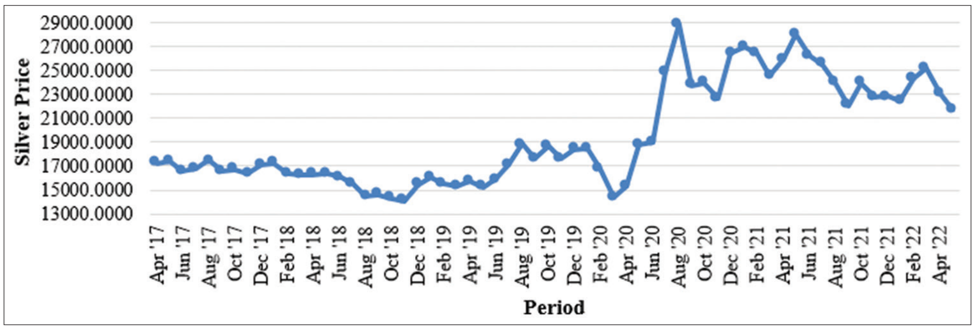


Table 2: Comparison of akaike information criterion value of autoregressive fractional integrated moving average (*p,d,q*)

Model	AIC
ARFIMA (0,0.3269,1)	−1051.429
ARFIMA (0,0.3269,2)	−1068.362
ARFIMA (0,0.3269,3)	−1075.692
ARFIMA (0,0.3269,5)	−1079.753
ARFIMA (1,0.3269,0)	−1092.959

AIC: Akaike information criterion, ARFIMA: Autoregressive fractional integrated moving average

Table 3: The residual assumption test of autoregressive fractional integrated moving average (1,0.3269,0)

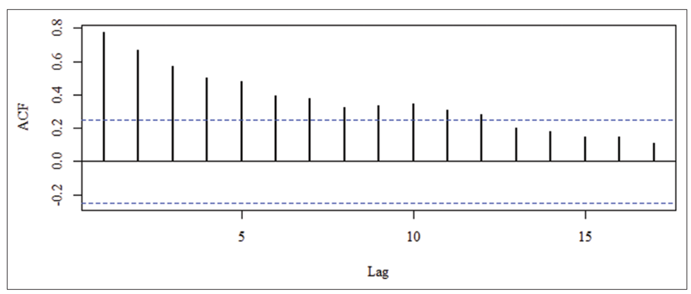
Residual assumption	Non-autocorrelation	Normality
P	0.6453	0.0445

ARFIMA: Autoregressive fractional integrated moving average

memory effect or not by plotting ACF against variance as shown in Figure 7.

It was observed from Figure 7 that the data slowly decreases over time. The test result also showed that the data was not stationary toward the mean value. To make the data stationary toward the mean, the value of d was differentiated using the Geweke Porter-Hudak (GPH) method, and a value of $\hat{d}_{GPH}$ = 0.7991 was obtained. Since the value of $\hat{d}_{GPH}$ = >0.5, it was concluded that the data has no long memory effect and is unable to identify the ARFIMA model. In the next stage, the silver price movement formed through the FTSMC numerical approach was observed.

Figure 7: ACF plot of stationary silver price data against variety



3.1.3. Palladium price movement model detection with ARFIMA

The initial step taken to identify the palladium price movement model is to plot the monthly palladium price data as shown in Figure 8.

Based on Figure 8, the pattern of palladium price data for each period fluctuates and has an upward trend. The highest price point occurred in April 2021. Since the palladium price data does not fluctuate around the mean and variance, it is termed as not stationary toward the mean or variance. To make the time series data stationary toward variance, the first transformation stage was performed by determining the value of λ, which is 0.4341. It was concluded that the data was not stationary toward variance; hence the second stage was conducted, and a λ value of 1 was obtained. This means that the palladium price data was stationary toward variance. The model was further checked; perhaps it contains a long memory effect or not by plotting the stationary ACF against variance as shown in Figure 9.

According to Figure 9, the data decreases slowly over time and the test result showed that the data was not stationary toward the

Figure 8: Plot of monthly data on palladium prices

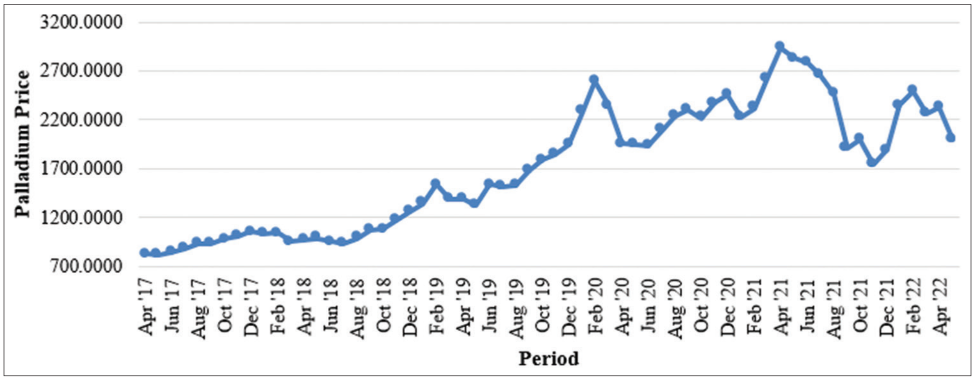
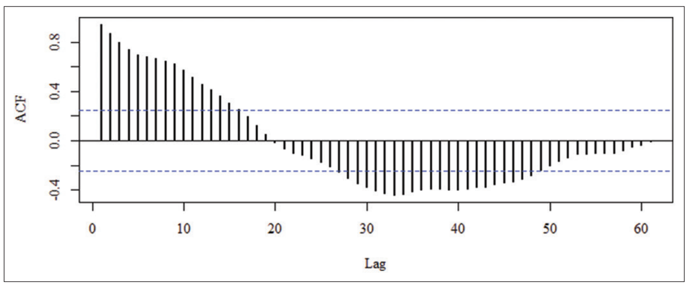


Figure 9: ACF plot of stationary palladium price data against variety



mean value. For it to be stationary toward the mean, the data was differentiated with the value of d which has been estimated using the Geweke Porter-Hudak (GPH) method with a score of $\hat{d}_{GPH} = 0.8203$. Since $\hat{}_{GPH}$ .5, it was concluded that the data has no long memory effect and is unable to identify the ARFIMA model. The next stage was to observe the palladium price movement formed by the FTSMC approach.

3.2. FTSMC Model Approach to Precious Metal Prices

3.2.1. Gold price movement model with FTSMC approach

The first step is setting the value of D_{min}=1268.7 and D_{max}=2026.9, followed by determining the values of D_1=0.7 and D_2=0.1. The universal set U is expressed as follows:

$$U = \left[D_{min} - D_1, D_{max} + D_2\right] = \left[1268.000, 2027.000\right] \quad (17)$$

The universal set U was partitioned into several parts with n intervals using the following Sturges formula:

$$n = 1 + 3,322 \log 62 = 6.9543 \approx 7 \quad (18)$$

Also, the length of the interval was determined using the formula below:

$$l = \frac{[(D_{max} + D_2) - (D_{min} - D_1)]}{n} = \frac{[(2026.900 + 0.100) - (1268.700 - 0.700)]}{7} = 108.428 \quad (19)$$

The universal set was defined as follows:

$$u_1 = \left[1268.000;1376.429\right], u_2 = \left[1376.429;1484.857\right], u_3 = \left[1484.857;1593.286\right],$$

$$u_4 = \left[1593.286;1701.714\right], u_5 = \left[1701.714;1810.143\right], u_6 = \left[1810.143;1918.571\right], u_7 = [1918.571;2027.000] \quad (20)$$

Then the fuzzy set for each linguistic variable was obtained as follows:

$$A_1 = \frac{1}{u_1} + \frac{0.5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$

$$A_2 = \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$

$$A_2 = \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$

$$A_3 = \frac{0}{u_1} + \frac{0.5}{u_2} + \frac{1}{u_3} + \frac{0.5}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$

$$A_4 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0.5}{u_3} + \frac{1}{u_4} + \frac{0.5}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$

$$A_5 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0.5}{u_4} + \frac{1}{u_5} + \frac{0.5}{u_6} + \frac{0}{u_7}$$

$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0.5}{u_5} + \frac{1}{u_6} + \frac{0.5}{u_7}$$

$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0.5}{u_6} + \frac{1}{u_7} \quad (21)$$

After the linguistic variables were defined, the next step was the fuzzification process, which focused on determining the linguistic interval of the actual data. For example, the actual value of gold price in April 2017 was 1347.1, meaning that the data was in the linguistic interval and variable of u_1 and A_1, respectively. Table 4 shows the fuzzification process conducted.

Linguistic variables have been defined in each table for the actual data. It was observed that the data was in a fuzzy set; hence the next stage is determining the relationship between fuzzy sets through fuzzy logic relations (FLR) and fuzzy logic relations group (FLRG) according to Definition 1. Tables 5 and 6 show the results obtained.

The monthly fuzzy set relationship was analyzed in Table 5. Furthermore, the relationship was represented with $A_i \rightarrow A_j$, where A_i was at the *left-hand side* (LHS) and A_j was at the right-hand side (RHS) of the FLR. The above fuzzy set relationship showed

Table 4: Data fuzzification

t	Month	Actual data	Fuzzy data
1	April 17	1347.1	A_1
2	May 17	1348.5	A_1
3	June 17	1314.0	A_1
⋮	⋮	⋮	⋮
60	March 22	1949.2	A_7
61	April 22	1911.7	A_6
62	May 22	1842.1	A_6

Table 5: Fuzzy logic relations

t	Month	FLR
1	April 17-May 17	$A_1 \rightarrow A_1$
2	May 17-June 17	$A_1 \rightarrow A_1$
3	June 17-July 17	$A_1 \rightarrow A_1$
⋮	⋮	⋮
60	March 22-April 22	$A_7 \rightarrow A_6$
61	April 22-May 22	$A_6 \rightarrow A_6$
62	May 22-June 22	$A_6 \rightarrow \emptyset$

FLR: Fuzzy logic relation

Table 6: The fuzzy logic relations group

Serial number	FLRG
1	$A_1 \rightarrow 14A_1, 4A_2$
2	$A_2 \rightarrow 3A_1, 6A_2, A_3$
3	$A_3 \rightarrow 4A_3, A_4$
4	$A_4 \rightarrow 2A_4, A_5$
5	$A_5 \rightarrow 5A_5, 6A_6$
6	$A_6 \rightarrow 5A_5, 3A_6, 2A_7$
7	$A_7 \rightarrow 2A_6, 2A_7$

FLRG: Fuzzy logic relations group

that the FLR was in a group. The purpose of this phase was to relate the fuzzy set on the left-hand side with those at the right. Consequently, the transition probability matrix R was obtained using the fuzzy logic relationship group.

$$R = \begin{bmatrix} \frac{14}{18} & \frac{4}{18} & \cdots & 0 \\ \frac{3}{10} & \frac{6}{10} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{2}{4} \end{bmatrix} \quad (22)$$

The model can be calculated below. For example, when $t = 2$, the modeling value is as follows:

$$F(2) = \frac{3}{10} * m_1 + \frac{6}{10} * X(1) + \frac{1}{10} * m_3 = 1365.6650 \quad (23)$$

After obtaining the probability matrix, the initial modeling value was calculated using the **R** matrix above. Table 7 shows the initial modeling values.

The next step after obtaining the initial modeling value was the adjustment value calculation. Table 8 shows the adjustment values.

After obtaining the adjustment value, the final modeling value was calculated by summing the initial scores with that of adjustments. Table 9 shows the final modeling values.

Table 7: Results of preliminary modeling of gold prices with the fuzzy time series Markov chain model

t	Month	Actual data	Initial modeling value
1	April 17	1347.1	
2	May 17	1348.5	1365.6650
3	June 17	1314.0	1366.7539
⋮	⋮	⋮	⋮
60	March 22	1949.2	1842.7314
61	April 22	1911.7	1906.7785
62	May 22	1842.1	1846.0314

Table 8: Gold price adjustment results with the fuzzy time series Markov chain model

t	Month	Actual data	Adjustment value
1	April 17	1347.1	
2	May 17	1348.5	0
3	June 17	1314.0	0
⋮	⋮	⋮	⋮
60	Marcch 22	1949.2	54.2142
61	April 22	1911.7	−54.2142
62	May 22	1842.1	0

Table 9: Final modeling results of gold price using fuzzy time series Markov chain model

t	Month	Actual data	Final modeling value
1	April 17	1347.1	
2	May 17	1348.5	1365.6650
3	June 17	1314.0	1366.7539
⋮	⋮	⋮	⋮
60	March 22	1949.2	1896.9457
61	April 22	1911.7	1852.5642
62	May 22	1842.1	1846.0314

Furthermore, the actual data and the final modeling value are graphically presented as follows:

Figure 10 shows that the results of the FTSMC model are almost close to the actual data. In other words, the difference between the actual and the modeled data was not too much. Overall, the data from the FTSMC model is good modeling.

3.2.2. Silver price movement with FTSMC model approach

The first step is setting the values of D_{min}=14094 and D_{max}=28860. Then, the values D_1=0 and D_2=0 are determined, while the universal set U is as follows:

$$U = [D_{min} - D_1, D_{max} + D_2] = [14904 - 0,\ 28860 + 0] = [14904, 28860] \quad (24)$$

The universal set U was partitioned into several parts with equal intervals (n), using the following Sturges formula:

$$n = 1 + 3,322 \log 62 = 6.9543 \approx 7 \quad (25)$$

Then, the length of the interval was determined using the formula:

$$l = \frac{[(D_{max} + D_2) - (D_{min} - D_1)]}{n} = \frac{[(28860 + 0) - (14904 - 0)]}{7} = 2109.4290 \quad (26)$$

The next step is defining the universal set, and it is determined as follows:

$$u_1 = [14094;16203.43], u_2 = [16203.43;18312.86], u_3 = [18312.86;20422.29], u_4 = [20422.29;22531.71], u_5 = [22531.71;24641.14], u_6 = [24641.14;26750.57], u_7 = [26750.57;28860] \quad (27)$$

Furthermore, the fuzzy set for each linguistic variable was obtained as follows:

$$A_1 = \frac{1}{u_1} + \frac{0.5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_2 = \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_3 = \frac{0}{u_1} + \frac{0.5}{u_2} + \frac{1}{u_3} + \frac{0.5}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_4 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0.5}{u_3} + \frac{1}{u_4} + \frac{0.5}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_5 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0.5}{u_4} + \frac{1}{u_5} + \frac{0.5}{u_6} + \frac{0}{u_7}$$
$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0.5}{u_5} + \frac{1}{u_6} + \frac{0.5}{u_7}$$
$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0.5}{u_6} + \frac{1}{u_7} \quad (28)$$

The next step after defining the linguistic variables was the fuzzification process to determine the linguistic interval of the actual data. For example, the actual value of the silver price data in April 2017 was 17191. This means that the linguistic interval variable was in u_2 and A_2, respectively. Table 10 shows the fuzzification process performed.

The linguistic variables defined in each table showed that the actual data are represented as a fuzzy set. Furthermore, the relationship between the fuzzy sets was determined with the FLR through the same process of gold price data, as shown in Table 11.

Table 11 shows the monthly fuzzy set relationship expressed by $A_i \rightarrow A_j$, where A_i is the *left-hand side* (LHS), and A_j is *right-hand side* (RHS) of FLR. With the use of the fuzzy logic relationship group, the transition probability matrix R was obtained as follows,

$$R = \begin{bmatrix} \frac{13}{15} & \frac{1}{15} & \cdots & 0 \\ \frac{2}{18} & \frac{13}{18} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix} \quad (29)$$

The following is the calculation of the modeled output. For example, the modeling value of $t = 2$ gives,

$$F(2) = \frac{2}{18} * m_1 + \frac{13}{18} * X(1) + \frac{3}{18} * m_3 = 17326.8412 \quad (30)$$

The probability matrix is obtained by calculating the initial modeling value using the R matrix above. Table 12 shows the initial modeling value:

The next step after obtaining the initial modeling value is to calculate the adjustment value as shown in Table 13.

Furthermore, the final modeling value was calculated by adding the initial modeling value with that of adjustment. Table 14 shows the final modeling value.

After obtaining the final modeling value, the actual data and the final modeling value are graphically presented as follows:

Table 10: Data fuzzification

t	Month	Actual data	Fuzzy data
1	April 17	17191	A_2
2	May 17	17368	A_2
3	June 17	16568	A_2
⋮	⋮	⋮	⋮
60	March 22	25133	A_6
61	April 22	23085	A_5
62	May 22	21688	A_4

Table 11: Fuzzy logic relations

t	Month	FLR
1	April 17-May 17	$A_2 \rightarrow A_2$
2	May 17-June 17	$A_2 \rightarrow A_2$
3	June 17-July 17	$A_2 \rightarrow A_2$
⋮	⋮	⋮
60	March 22-April 22	$A_6 \rightarrow A_5$
61	April 22-May 22	$A_5 \rightarrow A_4$
62	May 22-June 22	$A_4 \rightarrow \emptyset$

FLR: Fuzzy logic relation

Table 12: Silver price initial modeling using the fuzzy time series Markov chain model

t	Month	Actual data	Initial modeling value
1	Apr 17	17191	17326.8412
2	May 17	17368	17454.6746
3	Jun 17	16568	16876.8968
⋮	⋮	⋮	⋮
60	Mar 22	25133	23898.2571
61	Apr 22	23085	25615.4489
62	May 22	21688	23385.8571

Table 13: Silver price adjustment with the fuzzy time series Markov chain model

t	Month	Actual data	Adjustment value
1	Apr 17	17191	
2	May 17	17368	0
3	Jun 17	16568	0
⋮	⋮	⋮	⋮
60	Mar 22	25133	1054.7142
61	Apr 22	23085	−1054.7142
62	May 22	21688	−1054.7142

Figure 10: Graph of gold price actual data and FTSMC modeling results

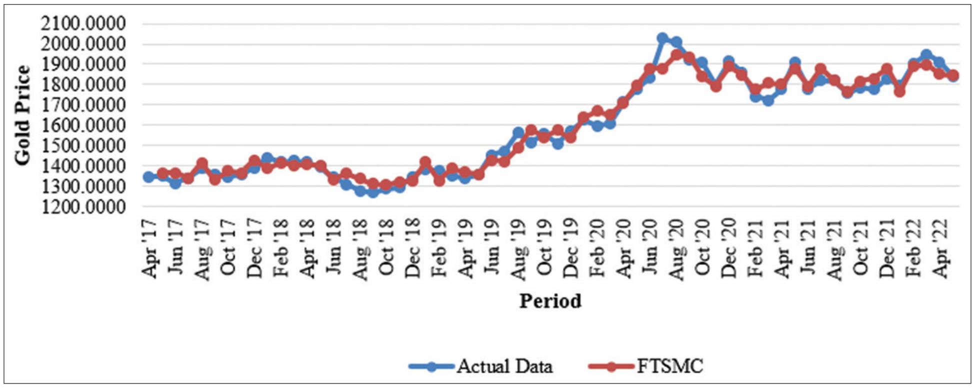


Figure 11: Graph of silver price actual data and modeling results

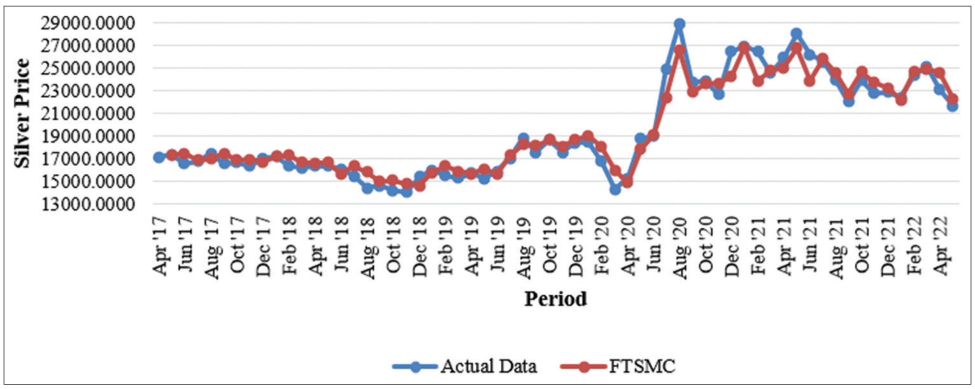


Table 14: Silver price final modeling with fuzzy time series Markov chain model

t	Month	Actual data	Final modeling value
1	April 17	17191	
2	May 17	17368	17326.8412
3	June 17	16568	17454.6746
⋮	⋮	⋮	⋮
60	March 22	25133	24952.9714
61	April 22	23085	24560.7346
62	May 22	21688	22331.1428

Based on Figure 11, the model results using FTSMC are almost close to the actual data. In other words, the difference between the actual and the modeled data was not too much. Therefore, the data from the FTSMC model results were good in modeling.

3.2.3. Palladium price movement with FTSMC model approach

The first step is setting the values of D_{min}=817 and maximum D_{max}=2935.5, followed by determining the value of D_1=0 and D_2=0. The universal set U is expressed as follows:

$$U=\left[D_{min}-D_1,D_{max}+D_2\right]=\left[817-0,2935.5+0.5\right]$$
$$=\left[817,2936\right] \quad (31)$$

The universal set U is partitioned into several parts with equal intervals (n), using the following Sturges formula:

$$n=1+3,322\log 62=6.9543\approx 7 \quad (32)$$

Furthermore, the length of the interval is determined using the formula below:

$$l=\frac{[(D_{max}+D_2)-(D_{min}-D_1)]}{n}$$
$$=\frac{[(2935.5+0.5)-(817-0)]}{7}=302.7143 \quad (33)$$

The next step is defining the universal set; hence the following were obtained:

$$u_1=\left[817.0000;1119.7140\right],u_2=\left[1119.7140;1422.4290\right],$$
$$u_3=\left[1422.4290;1725.1430\right],u_4=\left[1725.1430;2027.8570\right],$$
$$u_5=[2027.8570;2330.5710],u_6=[2330.5710;2633.2860],$$
$$u_7=[2633.2860;2936.0000] \quad (34)$$

The next step is determining the fuzzy set for each linguistic variable as follows:

$$A_1=\frac{1}{u_1}+\frac{0.5}{u_2}+\frac{0}{u_3}+\frac{0}{u_4}+\frac{0}{u_5}+\frac{0}{u_6}+\frac{0}{u_7}$$

$$A_2=\frac{0.5}{u_1}+\frac{1}{u_2}+\frac{0.5}{u_3}+\frac{0}{u_4}+\frac{0}{u_5}+\frac{0}{u_6}+\frac{0}{u_7}$$

$$A_3=\frac{0}{u_1}+\frac{0.5}{u_2}+\frac{1}{u_3}+\frac{0.5}{u_4}+\frac{0}{u_5}+\frac{0}{u_6}+\frac{0}{u_7}$$

$$A_4=\frac{0}{u_1}+\frac{0}{u_2}+\frac{0.5}{u_3}+\frac{1}{u_4}+\frac{0.5}{u_5}+\frac{0}{u_6}+\frac{0}{u_7}$$

$$A_5=\frac{0}{u_1}+\frac{0}{u_2}+\frac{0}{u_3}+\frac{0.5}{u_4}+\frac{1}{u_5}+\frac{0.5}{u_6}+\frac{0}{u_7}$$

$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0.5}{u_5} + \frac{1}{u_6} + \frac{0.5}{u_7}$$

$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0.5}{u_6} + \frac{1}{u_7} \quad (35)$$

After the linguistic variables are defined, the next step is the fuzzification process to obtain the linguistic interval of the actual data. For example, the actual value of palladium price data in April 2017 is 823.5, indicating that it is in the linguistic interval and variable u_1 and A_1, respectively. Table 15 shows the fuzzification process performed.

Linguistic variables have been defined in each table for the actual data, which are contained in a fuzzy set. The next stage is determining the relationship between the fuzzy sets using the FLR as employed in the previous gold and silver prices. Table 16 shows the results obtained.

The fuzzy set relationship per month was expressed by $A_i \rightarrow A_j$, where A_i is the *left-hand side* (LHS) and A_j is the *right-hand side* (RHS) of FLR. With the use of fuzzy logic relationship group, the transition probability matrix R is obtained as follows,

$$R = \begin{bmatrix} \frac{18}{19} & \frac{1}{19} & \cdots & 0 \\ 0 & \frac{4}{6} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{3}{4} \end{bmatrix} \quad (36)$$

The following is the calculation of the modeled output. When $t = 2$, the modeling value is,

$$F(2) = \frac{4}{6} * X(1) + \frac{2}{6} * m_3 = 847.0564 \quad (37)$$

The probability matrix obtained is proceeded by calculating the initial modeling value using the **R** matrix above. Table 17 shows the initial modeling value:

After obtaining the initial modeling value, the adjustment value was calculated and the result is shown in Table 18.

Furthermore, the final modeling value was calculated by adding the initial modeling score with that of adjustment. Table 19 shows the final modeling value.

The actual modeling value was presented graphically after obtaining final modeling value as follows:

According to Figure 12, the model results using FTSMC are almost close to the actual data. This also means that the difference between the actual and the modeled data is not too much; hence the results were considered to be good for modeling.

3.3. Accuracy Level and Model Output Analysis

After the modeling, the MAE, RMSE, and MAPE values were calculated to determine the accuracy level. The following is a table of accuracy levels:

Table 15: Fuzzification data

t	Month	Actual data	Fuzzy data
1	April 17	823.5000	A_1
2	May 17	817.0000	A_1
3	June 17	841.5000	A_1
⋮	⋮	⋮	⋮
60	March 22	2261.5800	A_5
61	April 22	2320.5000	A_5
62	May 22	1999.5300	A_4

Table 16: Fuzzy logic relations

T	Month	FLR
1	April 17-May 17	$A_1 \rightarrow A_1$
2	May 17-June 17	$A_1 \rightarrow A_1$
3	June 17-July 17	$A_1 \rightarrow A_1$
⋮	⋮	⋮
60	March 22-April 22	$A_5 \rightarrow A_5$
61	April 22-May 22	$A_5 \rightarrow A_4$
62	May 22-June 22	$A_4 \rightarrow \emptyset$

FLR: Fuzzy logic relation

Table 17: Palladium price initial modeling with fuzzy time series Markov chain model

t	Month	Actual data	Initial modeling value
1	April 17	823.5000	
2	May 17	817.0000	847.0563
3	June 17	841.5000	840.8984
⋮	⋮	⋮	⋮
60	March 22	2261.5800	2295.1514
61	April 22	2320.5000	2292.2428
62	May 22	1999.5300	2324.9761

Table 18: Palladium price adjustment results with the fuzzy time series Markov chain model

t	Month	Actual data	Adjustment value
1	April 17	823.5000	
2	May 17	817.0000	0
3	June 17	841.5000	0
⋮	⋮	⋮	⋮
60	March 22	2261.5800	−151.3571
61	April 22	2320.5000	0
62	May 22	1999.5300	−151.3571

Table 19: Palladium price final modeling with fuzzy time series Markov chain model

t	Month	Actual data	Final modeling value
1	April 17	823.5000	
2	May 17	817.0000	847.0563
3	June 17	841.5000	840.8984
⋮	⋮	⋮	⋮
60	March 22	2261.5800	2143.7942
61	April 22	2320.5000	2292.2428
62	May 22	1999.5300	2173.6190

Based on Table 20, the model of ARFIMA for gold price data has smaller model accuracy than all FTSMC models for precious metal prices. For example, its MAPE value was 2.93%, indicating a very good accuracy since the MAPE value is <10%. In other words, it means gold has a long memory effect, unlike silver and palladium. Gold is considered more stable as the medium of

Figure 12: Graph of palladium price actual data and modeling results

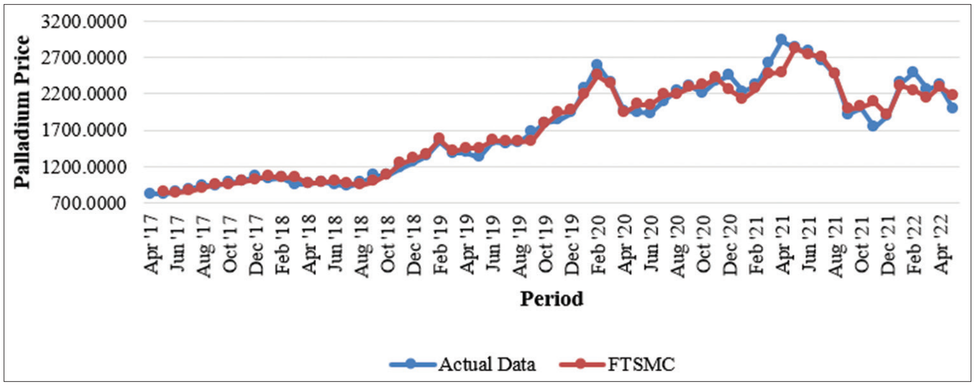


Table 20: Modeling accuracy

Model	MAE	RMSE	MAPE
ARFIMA gold price	48.3721	61.5666	2.9347
FTSMC gold price	55.4569	176.3437	3.7295
FTSMC silver price	981.5496	2374.6861	5.1878
FTSMC palladium price	79.3442	147.0130	5.3015

MAE: Mean absolute error, RMSE: Root mean square error, MAPE: Mean absolute percentage error, ARFIMA: Autoregressive fractional integrated moving average, FTSMC: Fuzzy time series Markov chain

exchange because it is correlated with previous data, but silver and palladium have a weak correlation with the previous ones. It is important to note that the FTSMC also models precious metal data properly, indicating that it is crucial in modeling precious metal time series data.

Gold price movements with a long memory data effect provide an investment advantage because it serves as an asset that tends to be stable, easy to liquidate in cash, free of interest, has a role as an emergency fund, and protects wealth's value. In addition, its stable nature due to the effect of long memory data makes gold an alternative long-term investment even though it incurs administrative and custody costs in the process. Meanwhile, the price movements of silver and palladium do not have a long memory data effect. This is presumably because their prices are not affected by the economy. As one of the basic materials for jewelry, price movements of silver and palladium are momentarily influenced by demand.

4. CONCLUSION

Precious metal is one of the most important assets in investment. Its price movements serve as a guide for investors when planning and making decisions to increase profits and prevent losses. Gold has a long memory effect, as shown by the ACF plot, which slowly decreases over time, but silver and palladium prices do not have a long memory effect. These data were implemented with a long memory effect by ARFIMA and the FTSMC model for a numerical approach to predict the price movement; both techniques were close to the actual data, as evidenced by each model's accuracy value. When the ARFIMA was used to model gold price movement data, the smallest error values were obtained as measured by MAE, RMSE, and MAPE, making it a better approach compared to others. Also, the gold price movement has long-term stability when compared to the other two precious metals because the gold price contains a long memory effect. This stability was maintained by gold during and after an economic crisis. These findings need to be used by capital market practitioners as a basis for developing portfolio strategies in order to consider the long-memory nature of the gold price movement when making investment decisions.

5. ACKNOWLEDGMENT

The authors are grateful to Indonesia Universitas Terbuka for their support with contract number B/212/UN31.LPPM/PT.01.03/2022. The authors are also thankful to the reviewers for their valuable input in perfecting this paper.

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