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Comparative Analysis of Moving Average Methods for Forecasting the Gold Price Volatility

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ABSTRACT
Forecasting gold prices is challenging due to high market volatility and uncertainty. This study compares moving average forecasting methods—Simple Moving Average (SMA), Double Moving Average (DMA), Exponential Moving Average (EMA), and Kaufman's Adaptive Moving Average (KAMA)—using daily gold price data from January 2014 to August 2024. Gold prices exhibited a notable upward trend, particularly after 2019, with a spike during the COVID-19 pandemic and subsequent increases driven by inflation and safe-haven demand. The results show KAMA achieves the lowest Root Mean Square Error (RMSE) of 25.2685 and Mean Absolute Percentage Error (MAPE) of 1.2108, offering superior forecasting of gold price changes in volatile markets. This suggests KAMA can improve trading strategies and investment decisions involving gold.

KEYWORDS
Gold Price Forecasting, Moving Average, KAMA, Volatility, Time Series.

1. INTRODUCTION

Gold prices are volatile and difficult to forecast. Moving average methods, such as the Simple Moving Average (SMA), Double Moving Average (DMA), Exponential Moving Average (EMA), and Kaufman's Adaptive Moving Average (KAMA), are commonly used to respond to these fluctuations.

The Simple Moving Average (SMA) calculates an average over a set period and indicates trends, but reacts slowly to rapid changes. The Double Moving Average (DMA) uses two SMAs to better capture market signals. The Exponential Moving Average (EMA) gives more weight to recent prices, making it more responsive than the SMA. Kaufman's Adaptive Moving Average (KAMA) quickly adjusts to volatility, capturing changing prices more effectively.

This study aims to evaluate and compare the effectiveness of different moving average methods in responding to gold price fluctuations, with a particular focus on identifying the most effective technique for managing price volatility and optimizing investment decision-making.

2. LITERATURE REVIEW

2.1 Simple Moving Average (SMA)

The Simple Moving Average (SMA) is one of the simplest and most widely used techniques in time series analysis. It calculates the arithmetic mean of a set of data over a specified time period. The primary function of the SMA is to smooth out short-term fluctuations, allowing long-term trends to be more clearly identified. Due to its simplicity and ability to reduce noise in the data, this method is considered a fundamental tool in many predictive models [1]. The formula for calculating the SMA is expressed as follows:

$$SMA_t = \frac{X_1 + X_2 + \ldots + X_t}{n} \tag{1}$$

where:
SMA_t = Simple Moving Average value in n^{th} period.
X_t = Actual value at a certain period t.
n = The number of time periods.

2.2 Double Moving Average (DMA)

The Double Moving Average (DMA) is an extension of the Simple Moving Average (SMA) that aims to smooth time series data and reduce the lag commonly associated with the SMA method. The DMA involves two stages of smoothing: the first stage calculates the SMA of the original data, while the second stage computes the SMA of the results obtained from the first smoothing process. According to Alexander [2], the DMA is more effective in identifying long-term trends than the SMA, as it can reduce noise and better adapt to rapid trend changes. The DMA formula, which involves two sequential moving average calculations, is presented in **Equation** (2) as follows:

$$DMA_t = \frac{SMA_1 + SMA_2 + \ldots + SMA_t}{n} \tag{2}$$

where:
SMA_t = Simple Moving Average value in n^{th} period.
DMA_t = Double Moving Average value in period t.
X_t = actual value at a certain t period.
n = The number of time periods.

The DMA provides clearer signals for trend changes because the data are smoothed twice, making it more responsive to changes than the SMA while still maintaining stability [3].

2.3 Exponential Moving Average (EMA)

The Exponential Moving Average (EMA) is a technical analysis method used to smooth time series data by assigning greater weight to the most recent observations. The EMA was developed as an alternative to the Simple Moving Average (SMA), which tends to respond more slowly to trend changes. According to Brown [4], the EMA is more responsive to changes in price or data values because the assigned weights decrease exponentially for older data, allowing for faster and more accurate trend identification. The formula for calculating the EMA is presented as follows

$$EMA_t = \alpha \times X_t + (1 - \alpha) \times EMA_{t-1} \tag{3}$$

where:
EMA_t = EMA value in period t.
X_t = actual value at a certain period t.
EMA_{t-1} = EMA value for the previous time period.
α = smoothing factor, with $\alpha = \frac{2}{n+1}$, where n is the number of time periods used to calculate the EMA.

2.4 Kaufman's Adaptive Moving Average (KAMA)

Kaufman's Adaptive Moving Average (KAMA) is a technical analysis method introduced by Perry J. Kaufman in 1988. KAMA is designed to adapt more effectively to changes in market volatility than conventional moving averages. It employs an adaptive approach that combines sensitivity to trend changes with the ability to smooth out insignificant price fluctuations. According to Kaufman [5], KAMA can reduce noise during periods of low volatility while remaining responsive to significant price movements. The KAMA calculation involves several steps, including determining the Efficiency Ratio (ER) and the Smoothing Constant (SC). The ER value can be calculated using the following **Equation** (4):

$$ER = \frac{Change}{Volatility} = \frac{|X_t - X_{t-n}|}{\sum_{i=0}^{n-1} |X_{t-i} - X_{t-i-1}|} \tag{4}$$

where:
$Change$ = the difference between the current price X_t and the previous period price (X_{t-i}).
$Volatility$ = the sum of absolute price changes over n periods.

Next is to calculate the Smoothing Constant (SC) value using the following equation **Equation** (5):

$$SC = \left[ER \times \left(\frac{2}{n+1} - \frac{2}{(n+1)^2}\right)\right] + \left(\frac{2}{n+1}\right)^2 \tag{5}$$

where n is the number of periods used to calculate the moving average. By using equations **Equation** (4) and (5), the KAMA value can be calculated using the following **Equation** (6) :

$$KAMA_t = KAMA_{t-1} + SC \times (X_t - KAMA_{t-1}) \tag{6}$$

where:
$KAMA_t$ = KAMA value in period t
X_t = actual value in period t
$KAMA_{t-1}$ = KAMA value ini period $t-1$.

2.5 Evaluations Metrics

In time series predictive analysis, particularly in financial contexts such as gold price forecasting, model evaluation plays a crucial role in assessing the performance of predictive models. Two commonly used and effective evaluation metrics for measuring prediction accuracy are the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). These metrics offer different perspectives on model performance and, when used together, provide a comprehensive understanding of the model's effectiveness in predicting historical data.

1. Root Mean Square Error (RMSE)

   The Root Mean Square Error (RMSE) is a metric used to measure the average magnitude of the squared errors. The RMSE is more sensitive to outliers because it assigns greater weight to larger errors. A smaller RMSE value indicates a lower prediction error rate and, consequently, better predictive accuracy. The RMSE formula is defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{X}_t - X_t\right)^2} \tag{7}$$

   where:
   $\hat{X}_t$ = prediction value at period t
   X_t = aktual value in period t.
   n = total number of observations/the number of periods.

   The RMSE is considered a robust metric because it provides an absolute measure of prediction error expressed in the same units as the original data, as noted by Chai and Draxler [6]. Furthermore, a smaller RMSE value indicates better model performance in representing the actual data.

2. Mean Absolute Percentage Error (MAPE)

   The Mean Absolute Percentage Error (MAPE) provides a different perspective on measuring prediction error, as it expresses error as a percentage relative to the actual value. The MAPE calculates the average absolute percentage error between the estimated and actual values, making it easier to interpret in practical and business contexts. A smaller MAPE value indicates that the model's predictions are more accurate, reflecting a relatively low error rate. The MAPE formula is defined in **Equation** (8):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{X}_t - X_t}{X_t}\right| \times 100\% \tag{8}$$

The Mean Absolute Percentage Error (MAPE) is particularly useful when an intuitive understanding of the magnitude of the error relative to the scale of the data is required. However, MAPE has a limitation when the actual value approaches zero, which can lead to unstable or undefined results. Nevertheless, MAPE remains one of the preferred metrics in many forecasting studies because it provides information that is easier for decision-makers to interpret [7].

3. METHODOLOGY

3.1 Research Design

This study employs a quantitative approach to compare the effectiveness of four moving average methods—Simple Moving Average (SMA), Double Moving Average (DMA), Exponential Moving Average (EMA), and Kaufman's Adaptive Moving Average (KAMA)—in forecasting gold prices. The purpose of this comparative study is to identify the most effective method for gold price forecasting based on predictive performance.

3.2 Data dan Data Source

The data used in this study consist of daily gold prices obtained from Yahoo Finance [8]. The dataset includes the closing prices of gold from January 2, 2014, to August 30, 2024.

3.3 Data Analysis Techniques

The data processed using the moving average approach are analyzed using four methods—SMA, DMA, EMA, and KAMA—to evaluate the effectiveness of each in forecasting gold prices. The RMSE and MAPE metrics are employed to measure the accuracy of each model. The analysis procedure is outlined as follows:

1. Moving Average Calculation This study applies the Simple Moving Average (SMA), Double Moving Average (DMA), Exponential Moving Average (EMA), and Kaufman's Adaptive Moving Average (KAMA) methods based on the available gold price data.

2. Comparison of Predictions with Actual Prices The forecasted results from each method are compared with the actual gold prices to assess their predictive performance.

3. Model Accuracy Evaluation The RMSE and MAPE are used to evaluate the accuracy of each forecasting method. RMSE measures the average magnitude of prediction errors, whereas MAPE expresses the error as a percentage relative to the actual values.

4. Comparative Analysis The RMSE and MAPE results from the four methods are compared to determine the most effective forecasting technique. Lower RMSE and MAPE values indicate a higher level of predictive accuracy.

4. RESULT & DISCUSSION

4.1 Data Description

The data used in this study consist of daily gold prices (GC=F) from January 2, 2014, to August 31, 2024, obtained from Yahoo Finance. The dataset contains 168 observations, including the opening, closing, high, and low prices for each trading day. In this analysis, the primary focus is on the closing price, which serves as the basis for calculating moving averages and conducting forecasts.

Figure 1 illustrates the movement of daily gold prices over the past decade, from January 1, 2014, to August 30, 2024, showing a significant upward trend, particularly since 2019. During the 2014–2018 period, gold prices remained relatively stable, ranging between USD 1,000 and USD 1,400. However, beginning in 2019, gold prices experienced a sharp increase, reaching a peak in 2024 at over USD 2,500. A notable surge occurred during the COVID-19 pandemic in 2020, when gold served as a safe-haven asset amid global uncertainty [9]. After a decline in 2021, prices rose steadily again through 2024, driven by inflation and strong demand for gold as a hedge asset, as reported by the World Gold Council [10]. This upward trend provides an overview of market direction in 2024, which is relevant for further analysis using the moving average prediction methods applied in this study—SMA, DMA, EMA, and KAMA.

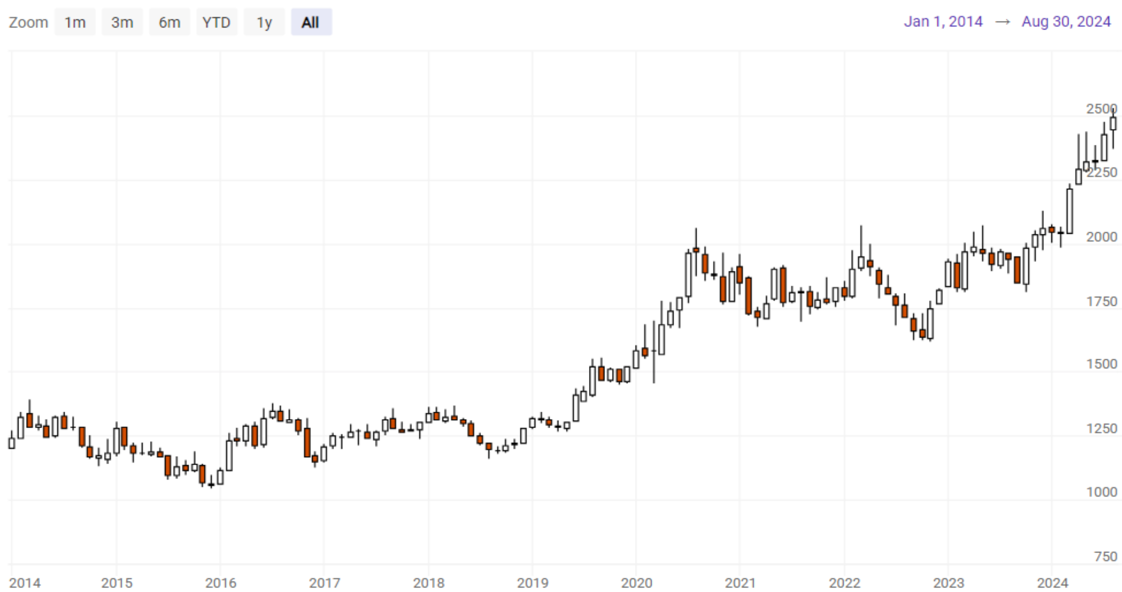


Figure 1. Daily Gold Price Plot (GC=F) January 2, 2014 – August 31, 2024

4.2 Moving Average and Actual Value Analysis

This study applied four moving average methods: the Simple Moving Average (SMA), the Double Moving Average (DMA), the Exponential Moving Average (EMA), and Kaufman's Adaptive Moving Average (KAMA). Each method has distinct characteristics in capturing gold price movements and exhibits varying levels of responsiveness to price changes. A comparison between the daily gold closing prices and the results of each moving average analysis is presented in **Figure 2**.

A comparison of the four moving average methods presented in **Figure 2** reveals differences in their responsiveness to daily gold price fluctuations. The KAMA, with its ability to adapt to market volatility, provides the most accurate predictions in responding to rapid price changes. Meanwhile, the SMA and DMA are more suitable for analyzing stable long-term trends, with the DMA offering greater stability but being less sensitive to short-term price fluctuations than the SMA.

The EMA lies between these two approaches, providing a balance between responsiveness to price changes and smoothness in mitigating fluctuations. These findings indicate that the choice of an appropriate moving average method largely depends on the analytical objectives and the characteristics of the data being examined.

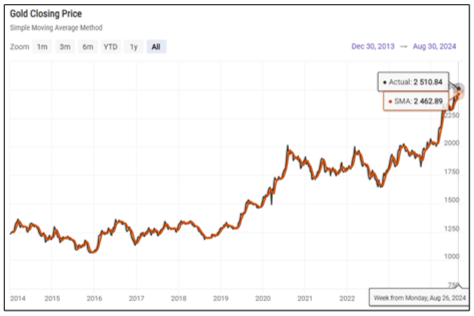
4.3 Model Accuracy Evaluation

To ensure the accuracy and effectiveness of each moving average method in capturing gold price fluctuations, a model performance evaluation is required. In this study, the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are employed as the primary evaluation metrics. By using these two metrics, model performance can be objectively assessed to identify the most reliable moving average method for addressing gold price volatility. The results of the model accuracy calculations are presented in **Table 1**.

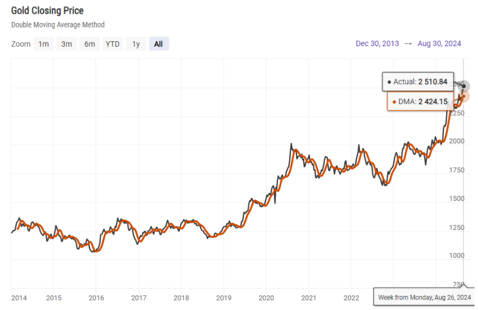
Table 1. Comparison of RMSE and MAPE Values in Various Moving Average Methods

Method	RMSE	MAPE
SMA	35.1058	1.6990
DMA	51.5815	2.5101
EMA	29.7283	1.4299
KAMA	25.2685	1.2108

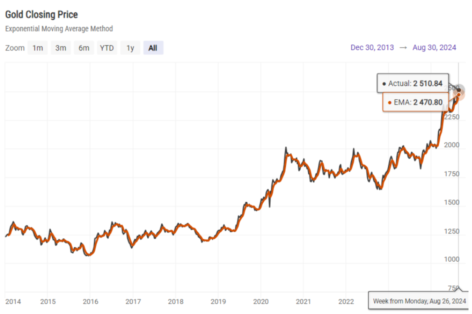
Based on the evaluation results, the KAMA method produced the lowest RMSE and MAPE values 25.2685 and 1.2108, respectively indicating the highest level of accuracy in predicting gold prices, both in terms of absolute and percentage errors.



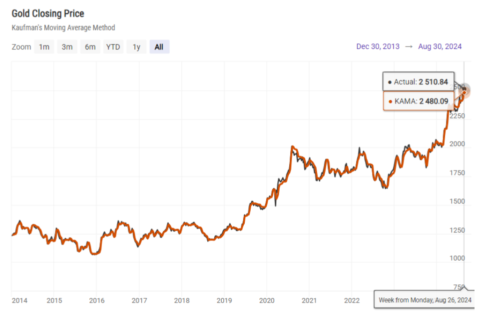
(a) Comparison of Daily Gold Closing Prices with Simple Moving Average (SMA) Calculations



(b) Comparison of Daily Gold Closing Prices with Double Moving Average (DMA) Calculations



(c) Comparison of Daily Gold Closing Prices with Exponential Moving Average (EMA) Calculations



(d) Comparison of Daily Gold Closing Prices with Kaufman's Adaptive Moving Average (KAMA) Calculation

Figure 2. Comparison of Daily Gold with the 4 Methods

The EMA method also performed well, with an RMSE of 29.7283 and a MAPE of 1.4299, although its performance was slightly inferior to that of KAMA. Conversely, the SMA and DMA methods showed higher RMSE and MAPE values, with the DMA producing an RMSE of 51.5815 and a MAPE of 2.5101, indicating a substantially larger prediction error and lower efficiency in handling gold price volatility.

The continued rise in gold prices, particularly since 2019, along with the significant surge in 2020 due to the COVID-19 pandemic, suggests that KAMA is more effective in capturing dynamic changes in volatile markets. The analysis using KAMA indicates that the upward trend in gold prices is expected to persist in the coming months, based on patterns observed in previous periods. Although KAMA demonstrates a high degree of accuracy, external factors such as global economic conditions, inflation, and monetary policy still need to be considered to further enhance the precision of future forecasts [11].

Future research could explore hybrid approaches by integrating other analytical techniques such as ARIMA [12], artificial neural networks [13], or machine learning models [14, 15] to improve the accuracy of gold price predictions. Additionally, sensitivity testing of KAMA to variations in market periods and data samples could be conducted to evaluate its robustness under broader market conditions.

5. CONCLUSION

Based on the analysis of the four moving average methods, the evaluation results indicate that Kaufman's Adaptive Moving Average (KAMA) performed best in predicting gold prices, with an RMSE of 25.2685 and a MAPE of 1.2108. These findings suggest that KAMA provides predictions with the lowest error rate compared to the other methods, making it the most effective approach for capturing and managing gold price volatility.

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