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Integration Model of Weighted Fuzzy Time Series, Relative Strength Index and Ichimoku Kinko Hyo in Gold Price Forecasting

(Case Study: Gold Price Analysis from April 2017 to 2023)

Dody Indra Sumantiawan[1*], Agus Fachrur Rozy[2] and Alya Fitri Syalsabilla[3]

[1]*Faculty of Science and Technology, Karangturi National University, Semarang, 50227, Indonesia*
[2]*Department of Statistics, Brawijaya University, Malang, 65145, Indonesia*
[3]*Department of Statistics, Sepuluh Nopember Institute of Technology, Surabaya, 60117, Indonesia*
[*]*dodyindrass@gmail.com*

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Abstract

Gold investment presents significant profit potential but is also associated with substantial risks, making gold price forecasting a critical challenge in financial market analysis. This study integrates Weighted Fuzzy Time Series (WFTS), Relative Strength Index (RSI), and Ichimoku Kinko Hyo (IKH) to enhance the accuracy of gold price predictions. WFTS is employed to address data uncertainty by modeling price movement patterns using fuzzy logic and historical weight-based data. RSI evaluates price fluctuations over a defined period to identify overbought or oversold conditions, while IKH identifies trends and key support and resistance levels. A comparative evaluation of WFTS and ARIMA across four standard error metrics demonstrates the superior performance of WFTS in gold price forecasting accuracy. WFTS achieves lower MAE (349.55 vs 355.05), smaller MSE (186,054.98 vs 188,203.37), lower RMSE (431.34 vs 433.82), and a more favorable MAPE (19.9% vs 20.0%) than ARIMA. With reduced absolute and squared errors, WFTS proves to be a more stable and reliable predictive model, offering greater effectiveness compared to ARIMA. The results indicate that WFTS forecasts an upward trend in gold prices, providing valuable insights for investors. IKH corroborates this trend through indicators such as the Conversion Line, Base Line, Lead Line A, and Lead Line B. Additionally, RSI calculations reveal an overbought signal between 2019 and 2021, suggesting potential selling opportunities. Furthermore, the gold price remained above the lower RSI threshold, indicating a probable price increase and offering investors profitable decision-making prospects.

Keywords: Gold price forecasting, Weighted Fuzzy Time Series (WFTS), Relative Strength Index (RSI), Ichimoku Kinko Hyo (IKH), ARIMA, Financial Market Analysis.

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1. Introduction

Gold investment holds significant potential for the future. Many people opt for this precious metal because it is widely recognized and easily accessible [1]. Additionally, gold prices tend to be stable and rarely decrease; in fact, they are currently experiencing a rapid increase. Gold investment is also highly liquid, making it suitable for addressing urgent financial needs [2]. Public sentiment towards gold plays a crucial role in influencing its price, emphasizing the need for accurate forecasting methods to facilitate effective gold investment planning in the future [3].

Forecasting methods can be categorized into two types: conventional and computational methods. Conventional methods are commonly used by researchers for forecasting because they are easy to understand and have numerous references that can serve as a foundation for conducting forecasts [4]. However, conventional methods have a limitation in that they require assumptions to model forecasting problems. This can lead to inflexibility in the forecasting process [5].

In certain cases, time series data tend to exhibit dynamic patterns of change due to the presence of trend, seasonal, and cyclical components, which cause variations in data over time. Consequently, a flexible method is needed to address the impact of temporal changes caused by trends and seasonality occurring in specific periods. One such method is the Weighted Fuzzy Time Series (WFTS) approach [8]. Another study focused on stock price forecasting using a multivariable fuzzy time series approach. The findings indicated that the proposed method achieved a Mean Absolute Percentage Error (MAPE) of 0.2284%, which is significantly lower than that of previous models, demonstrating an improvement in forecasting performance [9].

Ichimoku Kinko Hyo (IKH), developed in the late 1960s, is a comprehensive technical analysis framework designed to provide insights into market trends, momentum, and potential support and resistance levels. The IKH framework comprises several key components, including the Tenkan-sen (conversion line), Kijun-sen (base line), Senkou Span A and B (leading spans forming the cloud), and Chikou Span (lagging span). Empirical research has assessed the profitability of IKH-based trading strategies across various financial markets. One such study analyzed these strategies in four major stock indices from 1995 to 2018 and four major currency pairs from 2003 to 2018 [10]. The results indicate that trading rules based on IKH exhibit varying degrees of profitability, suggesting that while IKH serves as a valuable analytical tool, its effectiveness is influenced by market conditions and the nature of the traded assets. Moreover, the ability of IKH to offer a comprehensive market perspective has contributed to its widespread adoption among traders and investors, particularly in Japan. Its flexibility enables its application across various financial markets and timeframes, assisting in the identification of trends, support and resistance levels, and optimal entry and exit points. In conclusion, although IKH provides a holistic approach to financial market analysis, its quantitative effectiveness varies across different markets and periods. Consequently, traders and analysts are encouraged to consider these variations and integrate IKH with complementary analytical tools to enhance decision-making processes [11].

The Relative Strength Index (RSI) is a momentum oscillator that measures the speed and magnitude of price movements on a scale from 0 to 100 [12]. Empirical studies have evaluated the effectiveness of RSI-based trading strategies across various financial markets. A study analyzing the daily exchange rate of the Swiss franc against the U.S. dollar found that applying the standard RSI thresholds (≤30 for buy signals and ≥70 for sell signals) did not generate profitable trading outcomes over the past decade; instead, it resulted in a slight loss. This finding suggests that traditional RSI thresholds may not be universally applicable across all markets and time periods [13]. Further research reveals that the performance of RSI-based strategies varies depending on the parameters used and specific market conditions. Adjusting the RSI period length and threshold levels can enhance the effectiveness of this indicator in certain contexts. Moreover, integrating RSI with other technical indicators or fundamental analysis has the potential to improve overall trading performance [14].

The WFTS model is a forecasting method that combines fuzzy logic with time series analysis [15]. In this model, time series variables are transformed into fuzzy sets, and fuzzy rules are applied to make forecasting decisions [16]. These decisions should consider technical indicators to enhance the reliability of the forecasts. One approach is to integrate the WFTS method with Ichimoku Kinko Hyo (IKH) and the Relative Strength Index (RSI) [17].

The integration process involving the Relative Strength Index (RSI) is conducted by comparing price increases and decreases over a specific period to provide signals indicating whether an asset's price is overbought (too high) or oversold (too low) [18][19]. By incorporating RSI into gold price forecasting, valuable insights into overbought and oversold conditions can be obtained, which can assist in making more informed forecasting decisions.

Meanwhile, the Ichimoku Kinko Hyo (IKH) method is a technical analysis system comprising several components, such as Tenkan Sen, Kijun Sen, Senkou Span A, Senkou Span B, and Chikou Span [19]. The IKH system provides information about price trends, support and resistance levels, as well as market momentum [20]. By integrating IKH into gold price forecasting, it becomes possible to identify long-term trends, determine key levels, and gain a more comprehensive understanding of gold price movements.

Based on the issues outlined in the background, this study aims to determine investment decisions by integrating three methods: Weighted Fuzzy Time Series (WFTS), Ichimoku Kinko Hyo (IKH), and the Relative Strength Index (RSI).

2. Research Method

Previous research has individually applied Weighted Fuzzy Time Series (WFTS), Relative Strength Index (RSI), and Ichimoku Kinko Hyo (IKH) in financial market analysis. However, there is limited research exploring the effectiveness of integrating these three methods for investment decision-making. The application of this integrated approach for gold price forecasting remains underexamined.

Most studies on WFTS have primarily focused on general time series forecasting, with only a few investigating its effectiveness in highly volatile markets, such as the gold market. The extent to which WFTS can adapt when combined with RSI and IKH remains insufficiently understood. Existing research also suggests that the standard RSI parameters (30 and 70) may not be universally effective across all markets, while the profitability of IKH-based strategies is highly contingent on specific market conditions. Therefore, further investigation is required to optimize RSI and IKH parameters when employed alongside WFTS.

Additionally, the majority of studies have examined RSI and IKH within stock and foreign exchange markets over specific time periods. However, their effectiveness in forecasting gold prices across various economic cycles (e.g., inflationary vs. non-inflationary periods) remains unexplored. Moreover, WFTS has rarely been directly compared with other forecasting models, such as ARIMA, LSTM, or GARCH, to assess its predictive performance.

By addressing these research gaps, this study seeks to improve forecasting accuracy and enhance investment decision-making in the gold market through the integration of WFTS, RSI, and IKH, while also evaluating their applicability in financial market analysis.

This study utilizes monthly gold price data from April 2017 to 2023. The data, collected as secondary time series data, is sourced from www.yahoo.finance.com. In this case study, the proposed methodology integrates the Weighted Fuzzy Time Series (WFTS) model with technical indicators such as the Relative Strength Index (RSI) and Ichimoku Kinko Hyo to forecast monthly gold prices over the specified period. This approach allows the incorporation of historical information and technical factors to produce more accurate gold price predictions. The WFTS concept is employed to model trends in the actual data by transforming it into fuzzy numbers. The Ichimoku Kinko Hyo method, integrated with WFTS, is utilized to identify future trend patterns. Meanwhile, the RSI method facilitates decision-making for investors in gold trading, providing guidance on buy-and-sell transactions. This integrated approach aims to leverage both historical data analysis and technical indicators to enhance the accuracy of monthly gold price forecasts and provide actionable insights for investors. The research steps are outlined as follows:

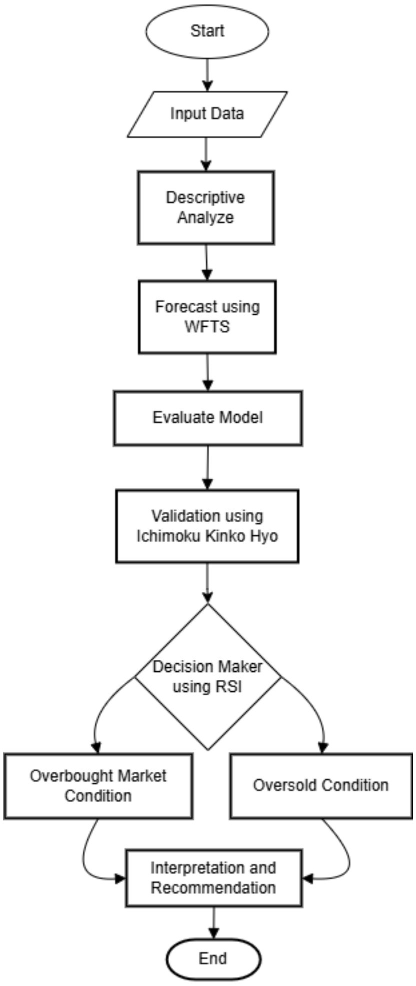

Fig. 1 Research Flowchart

2.1 Forecasting Method

According to Heizer et al. (2015), forecasting is the art and science of predicting future events [7]. Additionally, Rusdiana (2014) emphasizes that forecasting is a critical activity in developing a company's production strategy [13]. Fahmi (2014) further explains that forecasting can be conducted using both qualitative and quantitative approaches to achieve accurate results [6]. Effective forecasting must meet certain criteria. Rusdiana (2014) identifies key criteria for effective forecasting. First, the accuracy of forecasting is evaluated by comparing the forecasted results with actual outcomes. If the forecast significantly overestimates or underestimates reality, it is considered suboptimal. Second, the consistency of forecasting is determined by the relatively small magnitude of forecasting errors.

2.2 Weighted Fuzzy Time Series (WFTS)

The algorithm in the Weighted Fuzzy Time Series (WFTS) method differs from the traditional Fuzzy Time Series (FTS) method, particularly in the defuzzification process. The steps of the algorithm are as follows [8]:

1. Define the universe of discourse U.
2. Divide the universe of discourse U into intervals with equal class divisions.
3. Determine the fuzzy sets within the universe of discourse U.
4. Establish the fuzzy logical relationships.
5. Group the fuzzy logical relationships.
6. Perform defuzzification by assigning weights to parameters $A_{j1,}, A_{j2}, \ldots, A_{jk}$ denoted as $w_1, w_2, \ldots, w_k$ as in Eq. (1)

$$w_i = \frac{w_i}{\sum_{h=1}^{k} w_i} \quad (1)$$

With $w_1 = 1$ and $w_i = c^{i-1}$ to $c \geq 1$ and $2 \leq i \leq k$. Then a matrix transformation form is carried out, as in Eq. (2)

$$w(t) = \left[\frac{1}{\sum_{h=1}^{k} w_i}, \frac{c}{\sum_{h=1}^{k} w_i}, \ldots, \frac{c^{k-1}}{\sum_{h=1}^{k} w_i}\right] \quad (2)$$

7. Calculating the forecasting value by multiplying the midpoint values with the weighting matrix. as in Eq. (3)

$$\hat{\hat{F}}(t) = M(t) \times w(t)^T = [m_{j1}, m_{j2}, \ldots, m_{jk}] \text{x} [w_1', w_2', \ldots, w_k']^T \quad (3)$$

$$= [m_{j1}, m_{j2}, \ldots, m_{jk}] \text{ x } \left[\frac{1}{\sum_h^k w_h}, \frac{c}{\sum_h^k w_h}, \ldots, \frac{c^{k-1}}{\sum_h^k w_h}\right]^T$$

2.3 Relative *Strenght Index* (RSI)

The RSI, also known as the Relative Strength Index, is an indicator commonly used to identify overbought and oversold conditions, as stated by Martin (2014). RSI has a specific function, which is to measure the speed of price changes. In this context, price movements are assumed to be elastic or capable of moving within a certain range from the current price before changing direction. In the Relative Strength Index (RSI), there are two extreme zones: the upper extreme zone, where the RSI value is above the 70 level, and the lower extreme zone, where the RSI value is below the 30 level.

2.4 Ichimoku *Kinko Hyo* (IHK)

Ichimoku Kinko Hyo consists of several components or indicators, each with different functions. These components are Tenkan Sen (or Conversion Line), Kijun Sen (or Base Line), Chikou Span (or Lagging Span), Senkou Span A, and Senkou Span B [5]. The Tenkan Sen line, also known as the Conversion Line, is calculated using the formula. as in Eq. (4)

$$\frac{(Highest\ High\ 9\ period + Lowest\ Low\ 9\ period)}{2} \quad (4)$$

The Tenkan Sen line is used for a 9-period calculation. The 9 periods referred to here mean that if a daily chart is used, the calculation is based on the last 9 days, and if an hourly chart is used, the calculation is based on the last 9 hours. The Kijun Sen line, also known as the Base Line, is calculated using the same formula as the Tenkan Sen but with a longer calculation period. as in Eq. (5)

$$\frac{(Highest\ High\ 26\ period + Lowest\ Low\ 26\ period)}{2} \quad (5)$$

The Kijun Sen line is used for a 26-period calculation. This period approximately represents one month of trading, as when Ichimoku Kinko Hyo was introduced, the number of working days in Japan was 6 (six) days per week.

The next two indicators or lines are Senkou Span A (also known as Leading Span A) and Senkou Span B (also known as Leading Span B). These two lines form the Kumo, or cloud, by shading or filling the area between them. The equation used to calculate Senkou Span A is as follows. as in Eq. (6)

$$\frac{Tenkan\ Sen + Kijun\ Sen}{2} \quad (6)$$

Senkou Span A is used to calculate the value for the next 26 periods. This means that, for example, on a daily chart, the Tenkan Sen and Kijun Sen values from today will be used to calculate the Senkou Span point for the 26th day from now. The final indicator, Senkou Span B, which will be used in conjunction with Senkou Span A, is calculated based on the following formula. as in Eq. (7)

$$\frac{(Highest\ High + Lowest\ Low)}{2} \quad (7)$$

Based on the calculation formula, it is evident that Senkou Span B takes into account volatility over a relatively long period. For instance, when using a weekly chart, it considers volatility over the past 52 weeks or the last year. This line represents the component with the longest period compared to other elements of Ichimoku. Similarly to Senkou Span A, on a daily chart, the calculation result from today will be used to determine the Senkou Span B point for the 26th day ahead. The logic behind using a 26-period forward timeframe is that current prices can influence future price movements.

2.5 Evaluation Metrics

Evaluation metrics are statistical measures used to quantify the accuracy and reliability of a predictive model (Hodson, 2022). These metrics help in comparing different models, identifying errors, and improving forecasting accuracy. The choice of evaluation metrics depends on the nature of the data and the objective of the prediction The formula for MAE is (Robeson & Willmott, 2023):

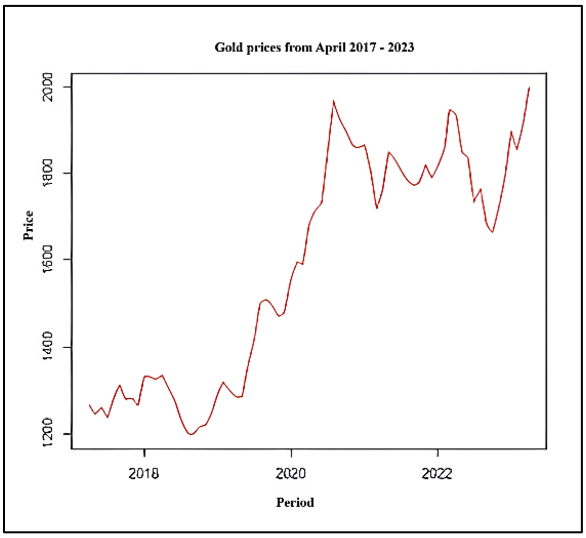

Fig. 2 The actual gold price data spanning from April 2017 to April 2023.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (8)$$

where n is the number of observations, y_i represents the actual values, and $\hat{y}_i$ denotes the predicted values. Since MAE does not square the errors, it provides a more interpretable measure of average error but does not heavily penalize large deviations. Mean Squared Error (MSE) formula is (Ahmar, 2023):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (9)$$

Although MSE provides a smooth error surface for optimization purposes, its values are in squared units of the original data, which can make interpretation more challenging. To address this, Root Mean Squared Error (RMSE) takes the square root of MSE, bringing the error value back to the same unit as the original data. RMSE is particularly useful when large errors should be penalized, but the interpretation of the error value needs to be more intuitive. The RMSE formula is given by (Hodson, 2022):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (10)$$

Unlike MAE, RMSE emphasizes larger errors, making it more sensitive to outliers. Another commonly used metric is Mean Absolute Percentage Error (MAPE), which expresses errors as a percentage of actual values. This makes MAPE useful for comparing performance across datasets with different scales. The formula for MAPE is (Ahmar, 2023):

Table 1. Descriptive statistics for gold prices from April 2017 to April 2023

Descriptive Measure	Value
Number of Observations	73
Minimum	1,198.39 USD
Maximum	1,999.77 USD
Range	801.38 USD
Median	1,664.45 USD
Mean	1,581.98 USD
Standard Error	30.75 USD
Variance	69,016.544 USD
Standard Deviation	262.70 USD

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \qquad (11)$$

MAPE provides a clear, percentage-based interpretation of error magnitude, but it has limitations when dealing with actual values close to zero, as it can lead to disproportionately high error values.In summary, MAE provides a simple interpretation of prediction errors, MSE and RMSE penalize larger errors more heavily, and MAPE is useful for p ercentage-based comparisons but may struggle with small actual values. Each metric serves different purposes depending on the characteristics of the dataset and the importance of penalizing large errors.

3. Result and Discussion

3.1 Descriptive Statistics

In the initial stage, descriptive statistical analysis is conducted to identify data patterns and provide a general overview of gold prices. Data patterns can be observed through visualizations derived from the actual gold price data spanning from April 2017 to April 2023. The plot of gold prices can be seen in Fig. 2.

Based on Fig.2, it can be observed that there was an extreme increase during the period from 2019 to 2020. The highest price reached was 1999.77 USD. Meanwhile, an extreme decrease occurred from 2022 to early 2023. The generated visualization is not sufficient to determine data patterns, and descriptive parameters are needed to provide a detailed depiction of the data patterns, as shown in Table. 1.

Based on the provided results, it can be generalized that the data consists of 73 observations with a range of values between 1,198.39 and 1,999.77. The median of the data is 1,664.45, while the mean is 1,581.98. The standard error of 30.75 reflects the uncertainty in the mean estimate, while the standard deviation of 262.70 indicates the level of variation in the data from the mean. The variance of 69,016.544 illustrates the extent to which the data is dispersed around the mean.

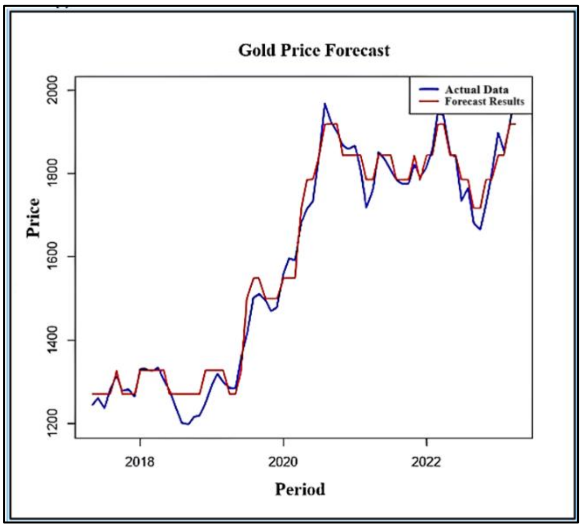

Fig. 3 Gold Price Forecasting WFTS Method

3.2 Gold Price Forecasting with WFTS

The forecasting conducted using the WFTS method is based on the midpoint values and estimated weights. The forecasting results are shown in Fig. 3.

Based on the forecasting results shown in Fig. 3, it can be concluded that the future price trend indicates an upward trajectory. This is evidenced by the red line, which aligns with the movement of the actual data. The depiction of this trend can serve as a basis for investors in making decisions about gold investments. Subsequently, forecast validation is conducted to trengthen the explanation of the trend produced by the WFTS method using the Ichimoku Kinko Hyo method.

3.3 Trend Validation using Ichimoku Kinko Hyo

Ichimoku Kinko Hyo can be utilized as a technical indicator in technical analysis to assist in asset price forecasting, trend identification, and generating trading signals. In this study, it is employed to validate the results of the WFTS method. The visualization produced from forecasting using the Ichimoku Kinko Hyo method is as Fig. 4.

From Figure 4 (Graph Gold Price Trend Ichimoku Kinko Hyo Method), it can be concluded that the Ichimoku Kinko Hyo (IKH) method provides trend signals for gold prices through its five main components: Conversion Line, Base Line, Lead Line A, Lead Line B, and the position of the price relative to these components. Based on Table 2 (Ichimoku Kinko Hyo Component Descriptive), the distribution of values for each component is as follows: The Conversion Line (Tenkan-sen) ranges from 1244.558 to 1863,269 to 1863.269, with an average of 1583.6956. The Base Line (Kijun-sen) has a range of 1274.848 to 1834.499, with the same average of 1583.6956. The Lead Line A (Senkou Span A) varies from 1268.933 to 1840.255, maintaining an average

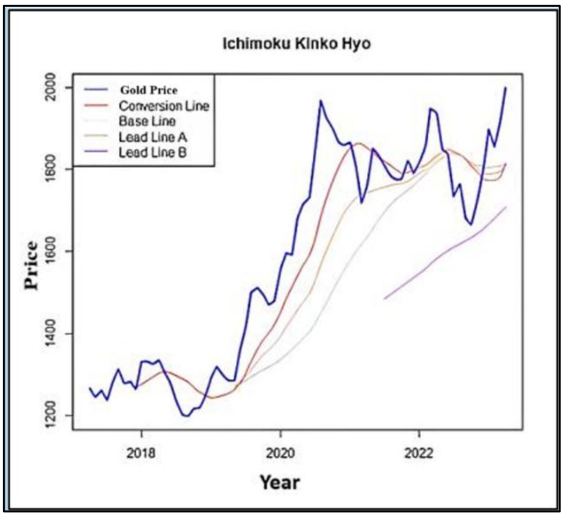

Fig. 4 Graph Gold Price Trend Ichimoku Kinko Hyo Method

Table 2. Ichimoku Kinko Hyo Component Descriptive

Component	Min	Max	Mean
Conversion Line	1244.558	1863.269	1583.6956
Base Line	1274.848	1834.499	1583.6956
Lead Line A	1268.933	1840.255	1583.6956
Lead Line B	1485.824	1708.088	1583.6956

Table 3. Trend Confirmation

Trend Confirmation	Date
Weak Bullish	1-May-19
Bullish	1-Sep-19
	1-May-21
	1-Oct-21
Strong Bullish	1-Jan-20
	1-Jul-20
	1-Mar-22
Neutral	1-Aug-22
Bearish	1-Jan-23

of 1583.6956. Meanwhile, the Lead Line B (Senkou Span B) has a minimum value of 1485.824 and a maximum of 1708.088, with an average also at 1583.6956. These values indicate that Lead Line B tends to be higher than the other components, signifying stronger support and resistance levels compared to Lead Line A.

Referring to Table 3 (Trend Confirmation), the trend direction of gold prices is validated based on price movement patterns relative to the Ichimoku Kinko Hyo components. The Weak Bullish trend on May 1, 2019, suggests an initial upward movement, likely indicated by the price crossing above the

Conversion Line but still near the Base Line. The Bullish trend observed on September 1, 2019, May 1, 2021, and October 1, 2021, is confirmed when the price remains above the Base Line, and Lead Line A surpasses Lead Line B, indicating a more stable uptrend. The Strong Bullish trend on January 1, 2020, July 1, 2020, and March 1, 2022, further strengthens this bullish momentum, with prices consistently above the Base Line and Lead Line A rising further above Lead Line B, confirming a dominant upward trend. The Neutral trend on August 1, 2022, suggests market uncertainty or consolidation as prices hover around the Base Line. However, by January 1, 2023, a Bearish trend emerges as prices drop below the Base Line, signaling a downward movement in gold prices.

In conclusion, Figure 4 confirms that the Ichimoku Kinko Hyo method effectively analyzes gold price trends, with each component providing crucial insights into market direction. Table 2 highlights that Lead Line B consistently holds higher values than Lead Line A, indicating stronger long-term resistance levels. Table 3 illustrates that the period 2020-2022 was dominated by bullish and strong bullish trends, whereas early 2023 marked a transition into a bearish phase. By utilizing this method, investors and traders can identify potential trading opportunities based on ongoing trends and possible trend reversals.

3.4 Determining Investment Decisions with RSI

Investment decisions derived from the RSI (Relative Strength Index) calculations may differ depending on the investment strategy and individual preferences. The RSI calculation results are presented and visualized in Fig. 5

Based on Figure 5, it can be observed that the green line represents the upper limit of the highest price of gold that can be reached within a certain period. The green line indicates the overbought phenomenon that occurred between 2019 and 2021. This suggests that during this period, investors were considering selling the gold they held. Additionally, from Fig. 3, it can be seen that the price of gold did not surpass the red line or the lower boundary. The red line represents the oversold condition, indicating that the price dropped below the 30-level and then began to rise, which can be considered a buy signal. Both of these boundaries can serve as a basis for investors to consider entering a buy position or closing any existing sell positions.

3.4 Evaluation Model

Evaluation is essential to assess the predictive performance of a model. By comparing different forecasting approaches, it becomes possible to determine which method provides more accurate and reliable predictions. In this section, the performance of the Weighted Fuzzy Time Series (WFTS) model is evaluated against the ARIMA model using four commonly used error metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results are shown in Table 4.

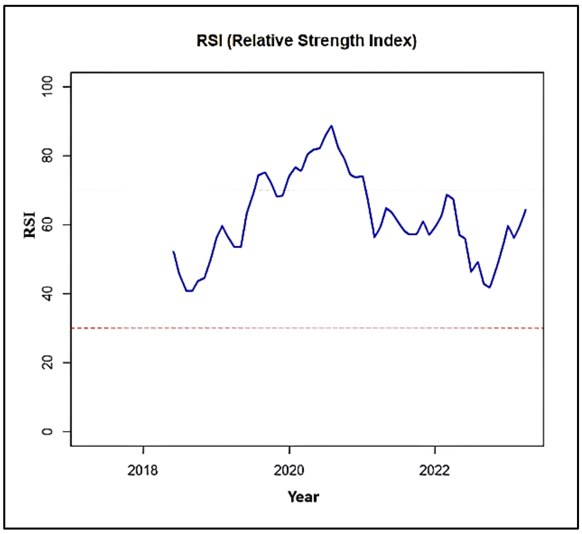

Fig. 5 Gold Price Relative Strength Index Chart

Table 4. Evaluation Model

Metrics	WFTS	ARIMA
MAE	349.55	355.05
MSE	186054.98	188203.37
RMSE	431.34	433.82
MAPE	19.9%	20%

The evaluation results indicate that the WFTS model outperforms the ARIMA model in all four metrics. The MAE for WFTS is 349.55, which is slightly lower than the 355.05 obtained by ARIMA, suggesting that WFTS has a smaller average absolute error. Similarly, the MSE value for WFTS (186,054.98) is lower than that of ARIMA (188,203.37), indicating that the squared errors in the WFTS model are less pronounced. This trend continues with the RMSE, where WFTS records a value of 431.34 compared to ARIMA's 433.82, further confirming its superior predictive accuracy. Lastly, the MAPE for WFTS is 19.9%, marginally better than ARIMA's 20%, suggesting that the WFTS model provides more precise percentage-based error predictions. These findings highlight the effectiveness of the WFTS model in handling forecasting tasks compared to the conventional ARIMA approach.

4. Conclusions

The forecasting analysis using the Weighted Fuzzy Time Series (WFTS) method demonstrates a strong predictive capability for gold price trends. The results indicate an upward trajectory, validated by the Ichimoku Kinko Hyo method, which confirms trend direction, support, and resistance levels. Additionally, the Relative Strength Index (RSI) provides insights into market conditions, identifying overbought and oversold periods that influence investment decisions. The evaluation of predictive accuracy further supports the effectiveness of the WFTS model, which outperforms the ARIMA model in terms of MAE, MSE, RMSE, and MAPE, reinforcing its suitability for forecasting financial time series data.

Future research can explore several areas to enhance forecasting accuracy and decision-making strategies. One potential improvement is the development of hybrid models by integrating WFTS with deep learning techniques such as Long Short-Term Memory (LSTM) networks or other artificial intelligence-based models to improve predictive performance. Additionally, incorporating macroeconomic indicators like inflation rates, interest rates, and geopolitical factors could refine gold price predictions and provide a more comprehensive analysis. Another avenue for advancement is the implementation of real-time forecasting systems that dynamically adapt to market fluctuations, ensuring more responsive and up-to-date predictions. Furthermore, integrating risk assessment models such as Copula-based approaches could enhance the ability to quantify and manage uncertainties in gold price movements. Lastly, expanding the comparative analysis to include machine learning models like XGBoost or ensemble techniques could provide a more thorough benchmarking of forecasting performance. By pursuing these improvements, future studies can contribute to the development of more robust and accurate forecasting models, aiding investors and policymakers in making more informed financial decisions.

5. Wisdom Recommendation

Based on the conclusions from the research conducted, the policy recommendations are defined as follows:

1. Enhancement of Investor Understanding
   The government and financial institutions can make efforts to improve investor understanding of the use of the Weighted Fuzzy Time Series Integration Model, Relative Strength Index, and Ichimoku Kinko Hyo in gold price forecasting analysis. This can be achieved through the provision of guides, training, and educational resources that assist investors in understanding the forecasting tools and methods used.
2. Development of Investment Guidelines
   The government and financial market regulators may consider developing investment guidelines that outline the use of forecasting tools in investment decision-making. These guidelines should emphasize the importance of considering other factors and understanding the limitations of forecasting models when making informed investment decisions.
3. Effective Supervision and Regulation
   The government and financial market regulators must maintain strict oversight of forecasting practices and the use of complex forecasting models. Effective regulations can help prevent market manipulation and ensure that investors do not overly rely on forecasting results.

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Author information

Dody Indra Sumantiawan is a lecturer in Programming and Machine Learning at the Faculty of Science and Technology, Karangturi National University, Semarang. He earned his Bachelor of Computer Science degree from Dian Nuswantoro University, Semarang, and his Master of Computer Science degree from Diponegoro University. His research interests include data science, machine learning, data mining, and artificial intelligence.
Email: dodyindrass@gmail.com

Agus Facrur Rozy is a researcher in Machine Learning and Optimization Techniques. He obtained his Bachelor of Mathematics degree from Udayana University and his Master of Statistics degree from Brawijaya University. He is also an online tutor at Universitas Terbuka. His research interests include machine learning, optimization techniques, and fuzzy logic.
Email: agus.rozy@yahoo.com

Alya Fitri Syalsabilla is a graduate student in the Master's Program in Statistics at the Sepuluh Nopember Institute of Technology. She earned her Bachelor of Statistics degree from Brawijaya University. Her research interests include spatial-temporal statistics, computational statistics, and advanced statistical methods. Email: alyaaaaasy@gmail.com

Additional Information