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# Utilization of various time series models forecasting gold prices in Thailand

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## ABSTRACT

This work develops an interactive dashboard integrating various time series models to forecast gold prices in Thailand, enabling investors to make better decisions more efficiently and effectively manage their investments. The study used monthly data from 2009 to 2021, separated the data series into in- and out-samples, and found that the gold price dataset did not have an autoregressive conditional heteroskedasticity (ARCH) effect. The process consumed the autoregressive integrated moving average (ARIMA) best model without passing through the generalized autoregressive conditionally heteroskedastic (GARCH)/ARIMA best model. The highest-performance model for forecasting was the ARIMA (*1,1,1*) model. This research extends the implementation scope of previous research on gold price forecasting with developer fulfillment in Thailand by developing a business intelligence dashboard for users to utilize the predictions. The dashboard is interactive, allowing users to filter the data and predictions based on their needs. Integrating various time series models for forecasting gold prices in Thailand on a single dashboard will enable investors to make better decisions and manage their investments efficiently and effectively. The authors are also developing an automatic utilization script to further improve the dashboard usability.

**Keywords:** time series; business intelligence tool; forecasting; gold price; ARIMA; GARCH; ARCH

## 1. INTRODUCTION

Many countries have experienced financial failures and economic crises, causing fluctuations in the global stock market index and affecting investment and international capital flows (Copelovitch and Singer, 2020) in a normal situation. The COVID-19 pandemic caused a global economic recession, leading to increased interest in gold investments. Researchers worldwide have used various models, including the autoregressive integrated moving average (ARIMA) and generalized autoregressive conditionally heteroskedastic (GARCH) models, to predict gold prices, bearing mixed results depending on the region and data period. This study aims to identify the best-performing model for monthly gold price forecasting in Thailand to provide valuable insights for investors and businesses. Investors need a user-friendly user interface (UI) and better user experience (UX), and must know how to manage their portfolios to cope with risks and find the best value in return on investment. Nowadays, gold investment has gained attention due to its high long-term storage value, like another form of currency.

In terms of understanding relevant knowledge prior to investment choices, forecasting gold prices using different models is a popular subject of study for the industry and academic sectors. Based on the literature review of gold price forecasting studies, many authors have applied different models with various data types to analyze the gold prices in different countries (Table 1).

**Table 1.** International studies: comparison of data and predictive models between 2013 and 2022 and this research

| Author (year) | Country | Data | | | Models | | | BI |
|---|---|---|---|---|---|---|---|---|
| | | Daily | Monthly | Yearly | ARIMA | GARCH | Others | |
| Zhou et al. (2022) | International | | √ | | √ | | | – |
| Badge (2022) | India | | | √ | √ | | | – |
| Li et al. (2021) | USA | √ | | | | | VMD + ICSS + BiGRU | – |
| Chai et al. (2021) | USA | √ | | | | | ST, NN, BY | – |
| Surendra et al. (2021) | India | | | √ | √ | | | – |
| Syrris and Shenai (2021) | Europe | √ | | | √ | √ | | – |
| Makala and Li (2021) | International | √ | | | √ | | | – |
| Dhakan and Dalvadi (2022) | India | √ | | | √ | | | – |
| Yaziz et al. (2019) | Malaysia | √ | | | √ | √ | | – |
| Hasanah et al. (2019) | Indonesia | √ | | | √ | √ | | – |
| Tripathy (2017) | India | | √ | | √ | | | – |
| Unnikrishnan and Suresh (2016) | India | √ | | | √ | | | – |
| Guha and Bandyopadhyay (2016) | India | | √ | | √ | | | – |
| Ali et al. (2016) | USA | √ | | | √ | | | – |
| Ping et al. (2013) | Malaysia | √ | | | √ | √ | | – |
| Khan (2013) | USA | √ | | | √ | | | – |
| Proposed research | Thailand | | √ | | √ | √ | Note: Decision flow-based alternative, the best (ARIMA or GARCH) models | √ |

Li et al. (2021) offered a model to forecast the US gold price by creating a new hybrid approach from variational mode decomposition, iterated cumulative sums of squares, and bidirectional gated recurrent unit using the 2008–2019 test data. The strategy based on the proposed forecasting model can generate positive returns compared to other trading strategies and plans. Chai et al. (2021) also studied the daily gold prices in the US using a neural network (NN), a Bayesian structural time series, and STL-ETS to forecast the gold price for analysis. They found that the STL-ETS model can precisely fit the gold price return instability trend and the rise in the forecasting accuracy value. Ali et al. (2016) and Khan (2013) applied ARIMA to forecast the US daily gold price. For the ARIMA factors, they suggested the accuracy and most suitable model of ARIMA (*0,1,1*). Syrris and Shenai (2021) used daily data to forecast the gold prices in Europe by applying ARIMA and GARCH. Their findings revealed that GARCH models are required to apprehend the extreme volatility of the gold commodity, while ARIMA models establish the ability to apprehend the autoregressive process.

Another group of authors studied Indian gold price forecasting by applying the ARIMA model to different data types and defining the timing as daily, monthly, and yearly. Badge (2022) used the yearly gold price data (1964–2022), consequently finding an appropriate forecasting model in ARIMA (*1,1,1*). Surendra et al. (2021) investigated the Indian gold price forecast using yearly data by applying the ARIMA model (*0,2,3*). Tripathy (2017) and Guha and Bandyopadhyay (2016) used monthly data and the ARIMA model to forecast the Indian gold price, finding (*0,1,1*) and (*1,1,1*) suitable factors. Dhakan and Dalvadi (2022) used the daily data for 43 years to forecast the gold price in India, showing ARIMA (*25,1,25*) as a very accurate model with 0.46% forecast difference. Unnikrishnan and Suresh (2016) found ARIMA (*1,1,1*) to be the most appropriate model for forecasting the daily data of Indian gold prices.

Other studies focused on applying ARIMA and GARCH as the forecasting models for the gold prices of Malaysia and Indonesia. Yaziz et al. (2019) and Ping et al. (2013) used daily data to find the most suitable model by applying ARIMA and GARCH to forecast Malaysian gold prices. Yaziz et al. (2019) discovered ARIMA (*0,1,0*)-GARCH (*1,1*) with t-innovations as the ideal models for forecasting the daily Malaysian gold price. Ping et al. (2013) disclosed that GARCH (*1,1*) is a more suitable model for forecasting these prices when compared with ARIMA (*1,1,1*). Hasanah et al. (2019) studied the daily gold price in Indonesia by applying ARIMA and GARCH, as well. Their results showed that ARIMA (*3,0,3*)-GARCH (*1,1*) is the most suitable model.

The gold price forecasting in the international market was also studied. Makala and Li (2021) used the daily data from 1979 to 2019 to analyze the ARIMA model with the best root mean square error (RMSE) and mean absolute percentage error (MAPE). Zhou et al. (2022) used the ARIMA model as the best-performing model among all mainstream machine learning models, to predict gold and Bitcoin.

Khashei and Bijari (2011) proposed a novel hybrid ARIMA-ANN model to improve the forecasting accuracy by identifying and magnifying the linear structure in data using the ARIMA model, capturing the underlying data-generating process, and performing a prediction using an ANN. Their experimental results showed that the proposed model outperforms the traditional hybrid and individual models.

ARIMA and GARCH models in Table 1 were chosen over others in this work because ARIMA solved the problem in several previous studies, and GARCH is a popular alternative. This study also includes a BI component, different from global research. The BI tool complements the data-driven implementation loop by enabling the delivery of the data output to nontechnical users.

Table 2 shows that previous studies on gold price forecasting in Thailand focused on finding the most accurate forecasting model, and no one implemented a dashboard to allow users utilize the predictions and enhance user experience through visualization. This study extended its scope by developing a BI dashboard, using Tableau, for users based on the most accurate forecasting model for the gold price forecasting in Thailand.

**Table 2.** Comparison of studies related to Thailand gold forecasting between 2013 and 2022

| No. | Author (year) | Years | Country | Data time | Models | | | Implementation method |
|---|---|---|---|---|---|---|---|---|
| | | | | | ARIMA | ARCH | Others | |
| 1 | Goganutapon (2020) | 8 years | Thailand | **Monthly** | √ | | | – |
| 2 | Siriratanapaisalkul (2022) | 30 years | Thailand | **Daily** | √ | | Linear regression analysis, ANN, SVM, Holt-Winters | – |
| 3 | Sopipan (2018) | 3 years | Thailand | **Daily** | √ | √ | EGARCH, GJR-GARCH | – |
| 4 | Keerativibool and Na-laed, (2013) | 5 years | Thailand | **Monthly** | √ | | Holt's method, damped | – |
| 5 | Our work (2022) | 10 years | Thailand | **Monthly** | √ | √ | | BI: Tableau |

In this study, researchers studied the gold price forecasting in Thailand using daily and monthly data by applying ARIMA, GARCH, and other models. The range of data collection was between 3 and 30 years. Goganutapon (2020) applied ARIMA for the monthly forecasting of gold prices in Thailand to find the most suitable model for gold price forecasting and determine the most appropriate forecasting period. The study found that ARIMA (*0,1,0*) provides the best model performance, and a three-month period is the best option for gold price forecasting in Thailand. Sopipan (2018) applied the ARIMA-GARCH model to forecast the daily gold price in Thailand, finding that the ARIMA (*2,0,2*)-GARCH-t models provide a lower cumulative return compared to ARIMA (*2,0,2*)-GARCH-GED and ARIMA (*2,0,2*)-GARCH-N models. Our study extracted a 10-year gold price dataset and used ARIMA and ARIMA/GARCH alternative with BI: Tableau for the implementation step, consequently completing the data life cycle in publish to end-user usage.

The main objective of this study is to identify the best-performing forecasting models for monthly gold prices in Thailand. The time series models ARIMA and GARCH are used for data analysis using the R programming language. This study provides results of the monthly gold price forecasting model that could offer relevant information to stores and distributors, helping them make decisions and manage their investments more efficiently and effectively. The end user does not necessarily know R code and increase the better UX|UI without self-programming while using or browsing the forecasting results.

## 2. MATERIALS AND METHODS

Figure 1 shows the detailed procedures for the gold price forecasting performed in this work. Data Collection involved collecting the gold price data in Thailand from 2009 to 2021. The data stationarity was then tested with the unit root test. If the data were stationary, the ARIMA model was used to analyze the data. If the data were not stationary, the process of data differencing was included, and differencing was redone until the data became stationary. ARIMA was then used to analyze the data. Subsequently, the "ARCH-LM test" was performed to test the data ARCH. If the data had the ARCH effect, the GRACH model was used for the forecasting. If the data did not have this effect, ARIMA was employed to forecast the model. Next, the best result was determined by the model performance. Finally, the most effective model was used to develop data visualizations using BI for investors and entrepreneurs.

### 2.1 Data management

The data management procedures involved data processing before forecasting with the ARIMA and GARCH models. The machine specifications included an AMD Ryzen 7 5800H processor with Radeon Graphics 3.20 GHz, an installed RAM of 32.0 GB (31.9 GB usable) with a 64-bit operating system (OS), and the Windows 11 OS. The R version 3.6.3 program was used as the programming software.

#### 2.1.1 Data preparation

The monthly gold price data expressed in Thai baht from January 2009 to December 2020 were collected to fit the model. The forecasting dataset contained six observations from January to June 2021. Figure 2 shows the time series plot of the gold price data from January 2009 to December 2020, which depicts an upward trend and a non-seasonal pattern.

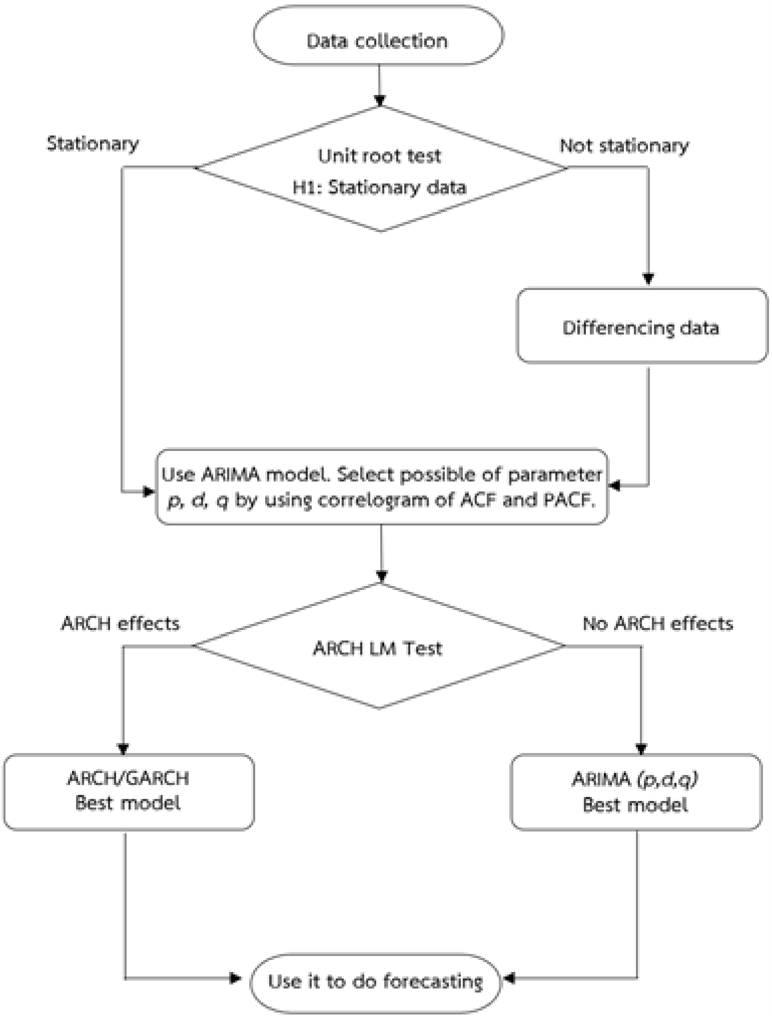


**Figure 1.** Study procedures for forecasting the gold price data in Thailand

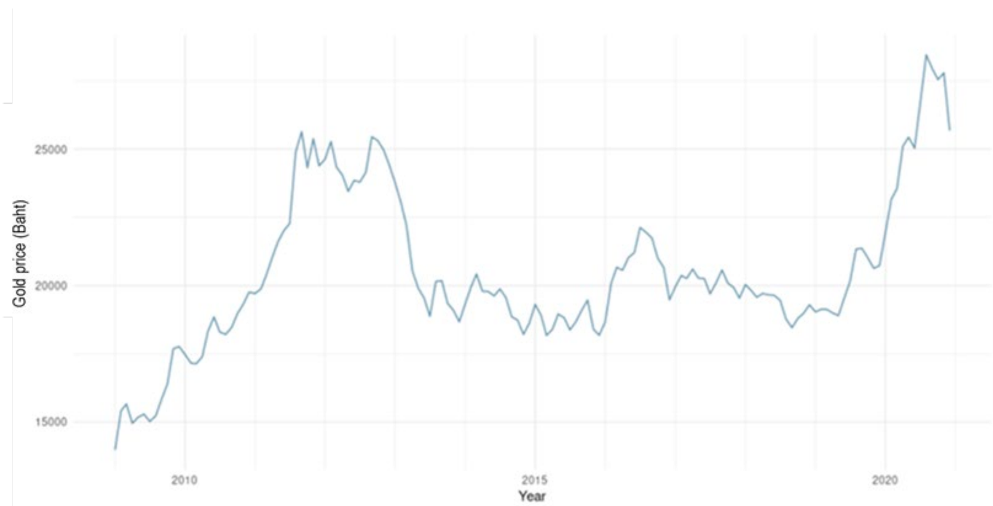


**Figure 2.** Exploratory data analysis of the monthly gold price data from January 2009 to December 2020
Source: http://www.taradthong.com

The correlograms of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) in Figure 3 shows that the series decreased very slowly and remained above the significance range denoted by the dotted blue lines. Table 3 presents the results of the augmented Dickey-Fuller (ADF) unit root test used to confirm more precisely the series stationarity. According to the test, the $p$–value (0.4213) was greater than the significance level (alpha = 0.05), indicating that the gold price series data were non-stationary. Therefore, the trend and the seasonality of the gold price series must be eliminated before a time series model is created, which can be achieved through differencing.

**Table 3.** ADF test for the gold price series

| Dickey-Fuller statistic | $p$–value |
|---|---|
| −2.3727 | 0.4213 |

Figure 4 depicts the time series plot of the first-order difference gold price data. After the first differencing, the ADF test of the differenced series showed a statistically significant $p$–value of 0.02499, indicating that the first-order differenced gold price series became stationary. Therefore, the ACF and PACF graphs of the differenced time series were used to select the model. The correlogram patterns of the ACF and the PACF in Figure 5 were plotted to identify the orders of the AR and moving average (MA) terms in the ARIMA model. Figure 5(a) illustrates the ACF of the first-difference gold price series, while Figure 5(b) demonstrates its PACF from January 2009 to December 2020.

## 2.2 Model application and evaluation

This study aimed to fit and forecast the monthly gold price in Thailand using two popular techniques: ARIMA and GARCH. The methodology is presented below.

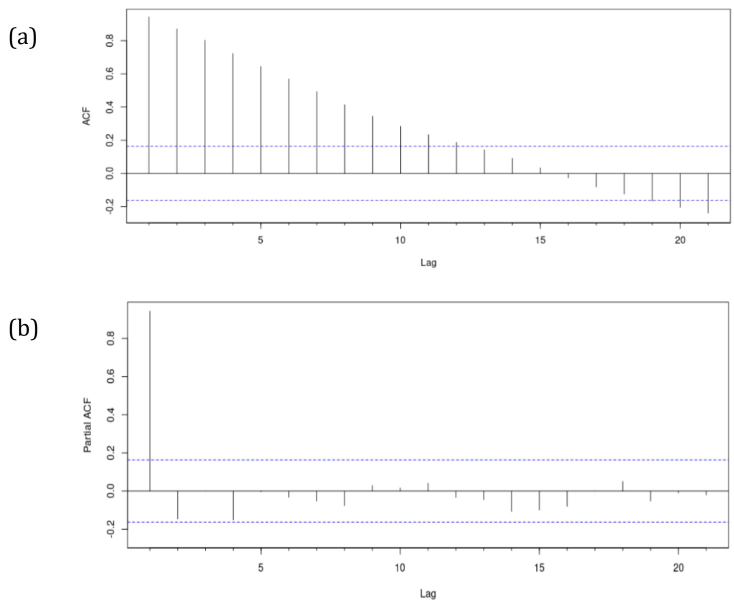


**Figure 3.** (a) Autocorrelation function (ACF) and (b) partial autocorrelation function (PACF) of the monthly gold price data from January 2009 to December 2020

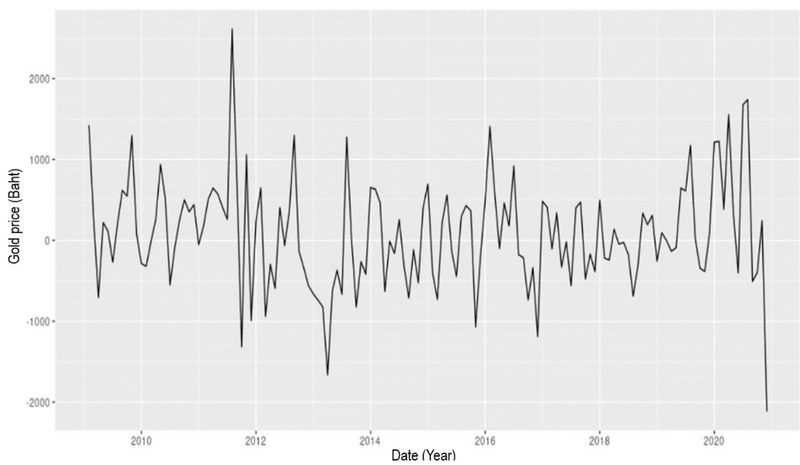


**Figure 4.** First-order differenced series of the monthly gold price from January 2009 to December 2020

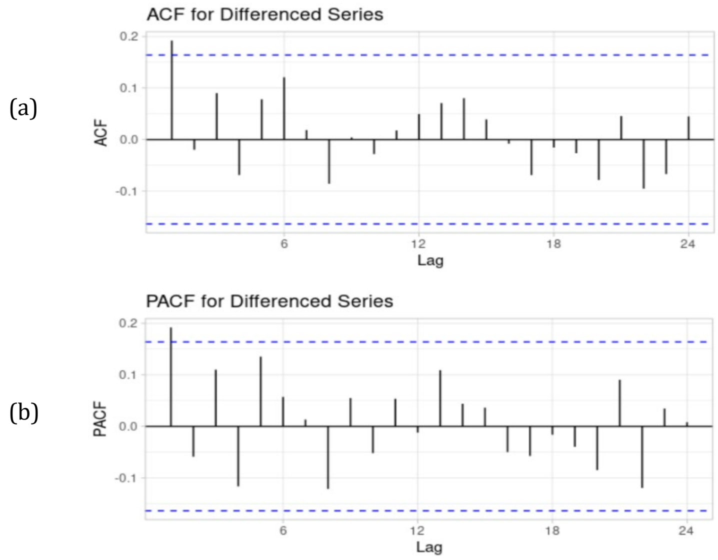


**Figure 5.** (a) ACF of the first-difference gold price series from January 2009 to December 2020 and (b) its PACF from January 2009 to December 2020

### 2.2.1 Autoregressive integrated moving average

ARIMA is a popular model in Box-Jenkins modeling that is designed for stationary and nonseasonal time series. Equation 1 shows that ARIMA (*p, d, q*) has three parameters, namely *p*, *d*, and *q*, which represent the degrees of the autoregressive (AR), integrated (I), and MA terms, respectively (Kleiner, 1977).

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + \varepsilon_t \qquad (1)$$

where $y_t$ is the observed value at time *t*; $\varepsilon_t$ is a random error at time *t*; and $\varphi_1, \varphi_2, \ldots, \varphi_p$ are the autoregressive parameters.

The MA($q$) model of $y_t$ is defined in Equation 2.

$$y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \qquad (2)$$

where, $\theta_1, \theta_2, \ldots, \theta_q$ are the MA parameters.

ARIMA (*p, d, q*) can be represented using the general format in Equation 3.

$$(1 - \sum_{i=1}^{p} \varphi_i B^i)(1 - B)^d y_t = (1 + \sum_{j=1}^{q} \theta_j B^j)\, \varepsilon_t \qquad (3)$$

where, $B^j y_t = y_{t-j}$ is the backward shift operator.

The Box–Jenkins methodology comprises the four following steps: model identification, parameter estimation, diagnostic checking, and forecasting.

### 2.2.2 Generalized autoregressive conditional heteroskedasticity

The GARCH model is used in the time series analysis to model data with heteroskedasticity, which means that the error term variance varies over time. The model assumes that the error term follows an autoregressive MA process, indicating that the error term at any given time is modeled as a linear combination of the previous error terms and shocks. The standard notation used for this model is GARCH (*p, q*), where the parameters are substituted with specific values from the ARIMA model or the base parameter GARCH (*1,1*). The GARCH model comprises two components with the following parameters:

AR($p$) = variance of the residuals
MA($q$) = GARCH process error

Let $R_t = \sigma_t \varepsilon_t$. The variance equation of the GARCH(*p,q*) model is defined as per Equation 4 (Chatfield, 1977).

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (4)$$

where, $\varepsilon_t \sim iid\ N(0,1)$; $\alpha_i$ is the coefficient of parameter ARCH; $\beta_j$ is the coefficient of parameter GARCH; $\sigma_t^2$ is the variance of residual of time *t*; $\alpha_0 > 0$; and $0 < \alpha_i + \beta_j < 1$. The GARCH orders, *p* and *q*, are assisted in identification by the ACF and the PACF of the residuals.

### 2.2.3 Model evaluation

A time series dataset of six observations for the gold prices was used to generate the forecasts. The forecast accuracy was assessed using the evaluation criteria commonly employed in previous literature, specifically the RMSE and the MAPE. The RMSE equation shows the RMSE measuring the deviation between the forecasted and actual values. A smaller RMSE indicates less error and a better fit of the model to the actual data. The RMSE is expressed in Equation 5.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\widehat{Y}_t - Y_t\right)^2} \qquad (5)$$

where *n* is the amount of data, and $\widehat{Y}_t$ and $Y_t$ are the forecast and actual values at time *t*, respectively.

The MAPE is a precision measurement tool used to determine the statistical appropriateness of a time series model. It is calculated as a percentage. Lower values indicate a higher accuracy. The MAPE is determined as per Equation 6.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\frac{|Y_t - \widehat{Y}_t|}{Y_t} \quad (6)$$

The measurement criteria are as follows (Lewis, 1982): MAPE less than 10% is very accurate; MAPE between 10 and 20% is high accuracy; MAPE between 20 and 50% is medium accuracy; and MAPE over 50% is little accuracy.

## 3. RESULTS AND DISCUSSION

The ARIMA order was ascertained herein by examining the ACF and PACF plots of the stationary time series.

Figure 5 illustrates that the ACF and PACF plots of the first-order difference series exhibit a stable time series after conversion.

The ARIMA model order was determined by analyzing the ACF and PACF plots of the first-order difference series exhibiting a stable time series (Figure 5). The next step involved examining the heteroskedasticity problems using the stationarity of the first-order differenced series.

The ($p$, $q$) specifications considered herein were (*1,0*), (*0,1*), and (*1,1*) based on the ACF and PACF plots cutting off after lag 1. The best-fit model was selected using the Akaike information criterion (AIC) values. Table 4 lists the parameter coefficients and AIC values. The ARIMA (*1,1,1*) model was selected as the best-fit model with the lowest AIC value and a significant parameter coefficient. Model diagnostic checking was performed to investigate the properties of the ARIMA (*1,1,1*) residuals, including zero mean and no serial correlation.

**Table 4.** Parameter coefficient and AIC values of the ARIMA models

| No | Model | Parameter | Parameter estimation | *p*–Value | AIC | Note |
|---|---|---|---|---|---|---|
| 1 | ARIMA (*1,0,0*) | ar1 | 0.9862 | 0 | 2,296.08 | Significant |
| 2 | ARIMA (*1,0,1*) | ar1 | 0.9714 | 0 | 2,289.17 | |
| | | ma1 | 0.3016 | 0.003 | | |
| 3 | ARIMA (*1,1,1*) | ar1 | −0.6881 | 0 | 2,261.52 | Significant |
| | | ma1 | 0.9405 | 0 | | |
| 4 | ARIMA (*2,0,0*) | ar1 | 1.2242 | 0 | 2,290.23 | Significant |
| | | ar2 | −0.2473 | 0.004 | | |
| 5 | ARIMA (*2,0,1*) | ar1 | 0.3015 | 0.001 | 2,284.19 | Significant |
| | | ar2 | 0.6675 | 0 | | |
| | | ma1 | 0.9385 | 0 | | |
| 6 | ARIMA (*2,1,1*) | ar1 | −0.6429 | 0 | 2,262.49 | Insignificant |
| | | ar2 | 0.0933 | 0.3092 | | |
| | | ma1 | 0.9539 | 0 | | |
| 7 | ARIMA (*0,0,2*) | ma1 | 1.3644 | 0 | 2,450.68 | Significant |
| | | ma2 | 0.6649 | 0 | | |
| 8 | ARIMA (*1,0,2*) | ar1 | −0.7653 | 0 | 2,290.14 | Insignificant |
| | | ma1 | 1.0677 | 0 | | |
| | | ma2 | 0.1088 | 0.306 | | |
| 9 | ARIMA (*1,1,2*) | ar1 | −0.7653 | 0 | 2,262.64 | Insignificant |
| | | ma1 | 1.0677 | 0 | | |
| | | ma2 | 0.1088 | 0.348 | | |

The results in Table 5 relate to the Ljung-Box test for the ARIMA (*1,1,1*) residuals.

**Table 5.** Ljung-Box test for the ARIMA (*1,1,1*) residuals

| **Null hypothesis: uncorrelated** | |
|---|---|
| Ljung–Box statistic = 11.607 | *p*–Value = 0.965 |

Figure 6(a) illustrates the graph of the residuals for ARIMA (*1,1,1*). It displays the ACF correlogram showing no significant correlation. The residual time plot was close to zero. Figure 6(b) depicts the ACF and the PACF of the standardized ARIMA (*1,1,1*) residuals, with the histogram showing normally distributed residuals. The normality assumption of the standardized residuals for all models was verified by conducting the Shapiro-Wilk test.

After obtaining the ARIMA parameters (i.e., $p$ = 1 and $q$ = 1), the combinations of ARIMA (*1,1,1*) and {GARCH (*1,1*), GARCH (*0,1*), GARCH (*1,0*)} were explored for the modeling process. The ARCH-LM test was performed before implementing the GARCH model to examine the presence of ARCH effects. The results in Table 6 indicate the absence of ARCH effects.

**Table 6.** ARCH-LM test

| **Null hypothesis: No ARCH effects** | |
|---|---|
| Chi–squared statistic = 0.44549 | *p*–Value = 0.5045 |

(a)

(b)

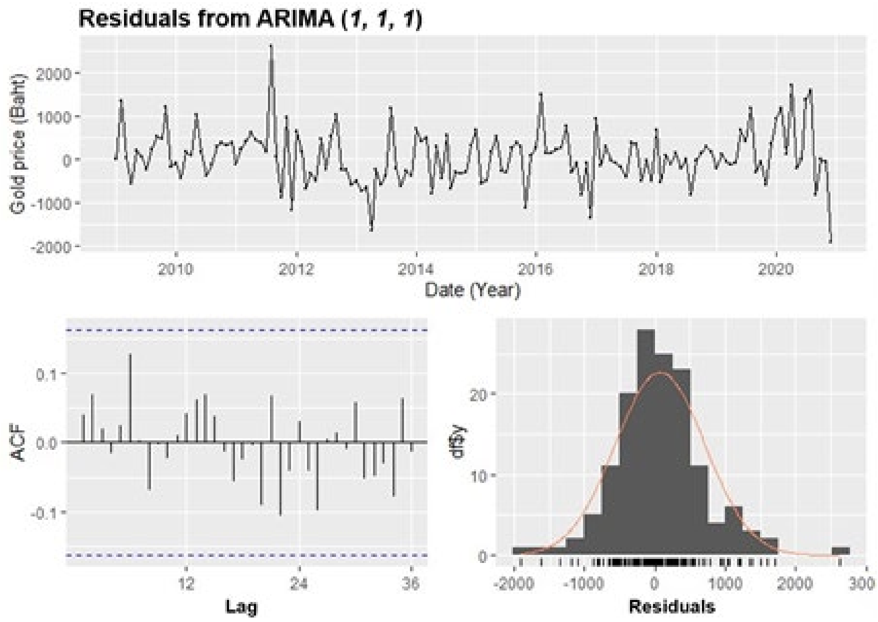


**Figure 6.** (a) Graph of ARIMA (*1,1,1*) residuals and (b) ACF and PACF of the standardized ARIMA (*1,1,1*) residuals

However, the objective was to examine various GARCH models using the generalized error distribution to ensure their suitability in series representation. Their performances and forecast accuracies were compared. Table 7 presents the forecast evaluations for the proposed models.

The forecast accuracies of the ARIMA (*1,1,1*), GARCH (*1,1*), GARCH (*0,1*), and GARCH (*1,0*) models were assessed using the MAPE and the RMSE (Table 7). The findings indicated that the ARIMA (*1,1,1*) model was the most accurate model for the gold price prediction in Thailand, yielding the lowest MAPE of 3.76126 and the RMSE of 1,325.531. The GARCH (*1,0*) model had a slightly lower MAPE of 3.761561 and an RMSE of 1,349.719. Thus, the ARIMA model is displayed in the visualization herein for those interested in gold investment.

**Table 7.** Gold price forecasting from January 2021 to June 2021

| Month | ARIMA (*1,1,1*) | GARCH (*1,1*) | GARCH (*0,1*) | GARCH (*1,0*) |
|---|---|---|---|---|
| Jan 2021 | 25,341.23 | 25,038 | 24,785 | 25,597 |
| Feb 2021 | 25,573.66 | 25,018 | 24,601 | 25,542 |
| Mar 2021 | 25,413.72 | 24,998 | 24,430 | 25,488 |
| Apr 2021 | 25,523.78 | 24,978 | 24,269 | 25,433 |
| May 2021 | 25,448.04 | 24,958 | 24,118 | 25,378 |
| Jun 2021 | 25,500.16 | 24,938 | 23,977 | 25,324 |
| **RMSE** | **1,325.531** | **1,679.117** | **2,249.468** | **1,349.719** |
| **MAPE** | **3.76126** | **4.931737** | **7.301315** | **3.761561** |

Accurate gold price prediction is important for investors because gold is a reliable asset, especially during an economic crisis. The ARIMA (*1,1,1*) model can help investors make informed investment decisions by providing insights into potential price trends. However, modeling approaches must still be explored and refined to improve the forecasting performance. Figure 7 displays a graph of the actual and forecasted data of ARIMA (*1,1,1*).

As end user, the investors can use all the forecasting models from this research by a BI tool like Tableau (Figure 8).

The system processes in this work can be summarized to gather data sources from the official Thai gold price website. The data are presented in columns. The data was prepared, modeled, and evaluated following the procedures in Section 2. The results presented in Section 3 were filtered to transform them into the model view (Figure 7). The BI was used to utilize various time series models and perform visualization and design to make the dashboard interactive while user-filtering the dashboard. Figure 8(a) depicts a dashboard with the Tableau of gold prices from January 2009 to December 2020. Figure 8(b) shows a dashboard of the gold prices forecasted by the ARIMA model. As shown in the overview of the system processes in Figure 9, the end users are the investors. BI plays a vital role in the post-prediction phase of the ML, helping businesses to interpret, operationalize, monitor, report, and enhance their ML models. The results highlight that the time series models produce complex outputs that can be difficult for decision-makers to understand and interpret. BI tools can help visualize these outputs in clear and concise ways, such as using date and model filtering, charts, graphs, and other visual elements, enabling decision-makers to quickly grasp the implications of the model's predictions and make informed decisions.

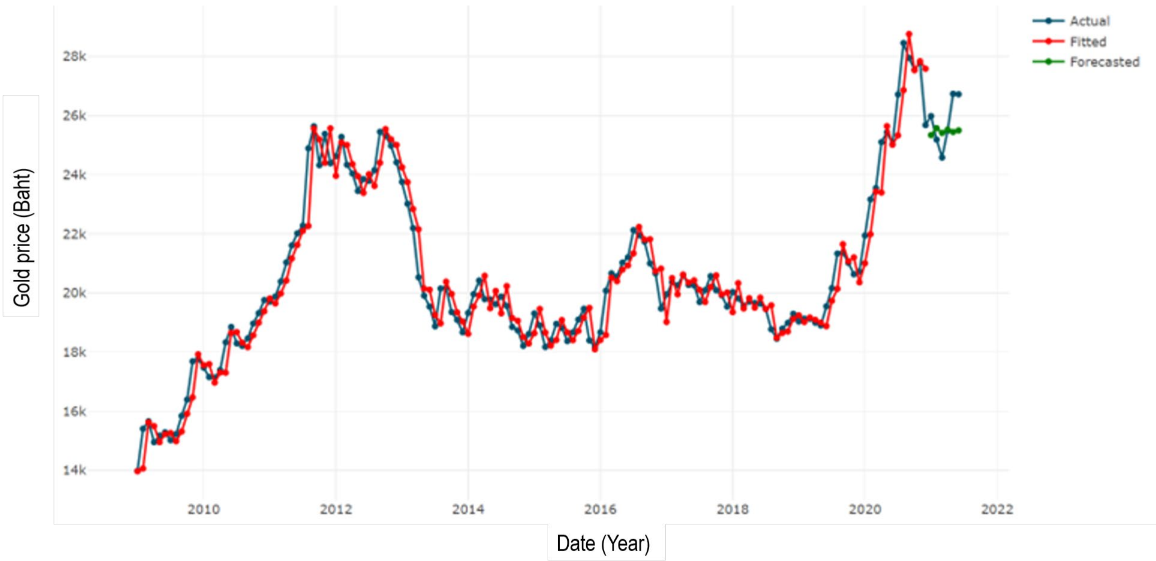


**Figure 7.** Actual and forecasted data of ARIMA (*1,1,1*)

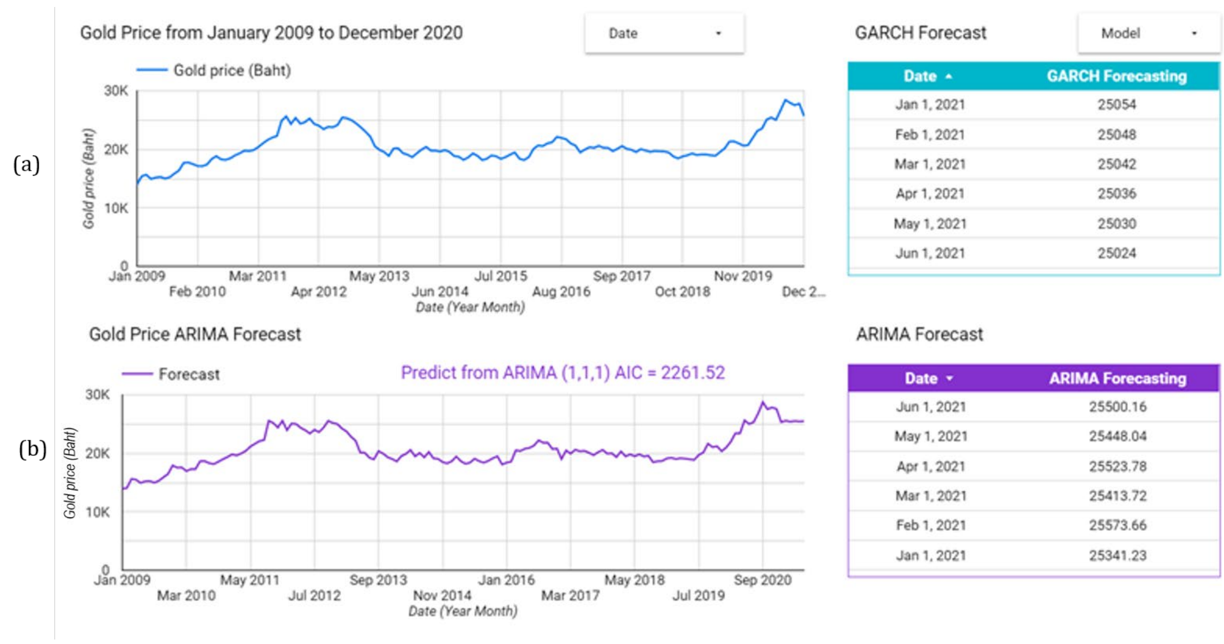


**Figure 8.** (a) Dashboard with the Tableau of gold prices from January 2009 to December 2020 and (b) dashboard with the Tableau of gold prices forecasted by the ARIMA model

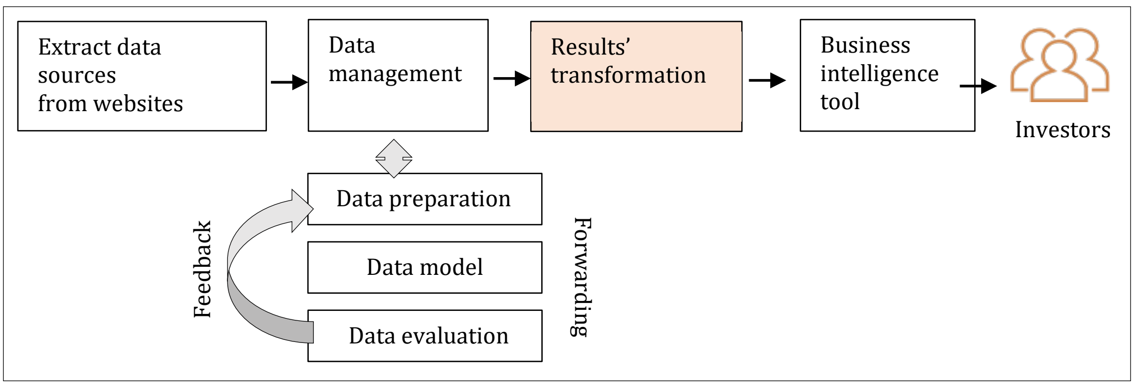


**Figure 9.** System processes for the utilization of various time series models forecasting the gold prices in Thailand

The future work will apply an automatic utilization script from all steps before being represented by BI. The various time series models more efficiently forecasting the gold prices in Thailand in one dashboard would effectively assist investors in final decision-making and investment management.

Platforms like https://www.tradingview.com/ currently represent the gold prices in Thailand, allowing users to view real-time and historical gold prices on a web application. This study aimed to develop a dashboard displaying the gold price forecasts in Thailand using models that were previously studied and tested for accuracy.

## 4. CONCLUSION

A 10-year gold price dataset taken from an official Thai website and a managing dataset was analyzed and various time series predictive modeling techniques were used. After collecting the 10-year monthly data, it was cleaned, transformed, and loaded for use in the experiment by the decision flow along with data life cycle activities. Analysis of the results shows that the ARIMA (*1,1,1*) model is the most effective model. Its MAPE and RMSE were the lowest in various testing parameters. Even though the GARCH (*1,0*) model had slightly better MAPE and RMSE scores, the ARIMA (*1,1,1*) model showed larger parameter coefficients and returned a lower AIC value. The resulting model was confirmed to be better at dealing with patterns and trends in this gold price dataset. The implementation phase is very important and is represented into an interactive BI tool delivering the data product to end users. This Tableau BI dashboard allows investors, learners, and end users to explore by range of date/year, compare the results of different forecasting models without coding from the developer, and browse from the editor's terminal. It also facilitates data-driven decision-making and efficient investment management, including the data gathering, preparation, modeling, and evaluation steps of the research methodology. This provides a transparent and reproducible approach to this research. In the future, it is planned to automate utilization to improve the efficiency and accessibility of the forecasting process. Future research could investigate the inclusion of external factors that may influence gold prices to further improve the gold price forecast accuracy. Incorporating economic indicators, global political events, interest rates, and other macroeconomic factors into forecasting models could help to more effectively capture the impact of these factors on gold prices. Additionally, the forecast horizon can be extended to a longer term (e.g., quarterly or yearly predictions). Analyzing longer-term trends can provide additional insights into the behavior of gold prices over extended periods, which will be valuable for long-term investors.

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## APPENDIX

| Acronym | Explanation |
|---|---|
| ACF | Autocorrelation function |
| ADF | Augmented Dickey-Fuller |
| ARCH | Autoregressive conditional heteroskedasticity |
| ARCH-LM | Autoregressive conditional Heteroskedasticity-Lagrange multiplier |
| ARIMA | Autoregressive integrated moving average |
| BI | Business intelligence |
| GARCH | Generalized autoregressive conditionally heteroskedastic |
| PACF | Partial autocorrelation function |