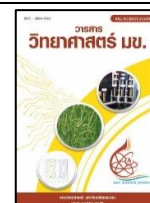




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การพยากรณ์ราคาทองคำแท่งรายวันในประเทศไทยโดยใช้เทคนิค โครงข่ายประสาทเทียมแบบถดถอยอัตโนมัติไม่เป็นเชิงเส้นร่วมกับปัจจัยภายนอก Daily Gold Bar Price Forecasting in Thailand Using Nonlinear Autoregressive Network Technique with Exogenous Factors

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บทคัดย่อ

งานวิจัยนี้พัฒนาตัวแบบพยากรณ์ราคาทองคำแท่งรายวันในประเทศไทยโดยใช้แบบจำลอง NARX และเปรียบเทียบกับแบบจำลอง ARIMAX การศึกษาใช้ข้อมูลทองคำแท่งรายวันในช่วงปี ค.ศ. 2015 - 2024 และตัวแปรภายนอก ได้แก่ ราคาทองคำโลก อัตราแลกเปลี่ยนสกุลดอลลาร์สหรัฐและราคาน้ำมันโลก ดำเนินการทดลองโดยแบ่งช่วงเวลาในการศึกษา 3 ช่วง ได้แก่ปี ค.ศ. 2015 - 2019 ค.ศ. 2020 - 2024 และ ค.ศ. 2015 - 2024 เพื่อศึกษาประสิทธิภาพของการทำนายราคาทองคำเมื่ออนุกรมเวลามีความผันผวนแตกต่างกัน โดยแต่ละช่วงเวลาข้อมูลถูกแบ่งตามลำดับวันเป็นชุดข้อมูลสำหรับการฝึกฝน 90% ของข้อมูลทั้งหมดและที่เหลือ 10% เป็นชุดข้อมูลสำหรับทดสอบตัวแบบ ผลการศึกษาพบว่า แบบจำลอง NARX มีประสิทธิภาพสูงกว่าแบบจำลอง ARIMAX ในทุกช่วงเวลาประเมิน ซึ่งชี้ให้เห็นว่าแบบจำลองที่ไม่เป็นเชิงเส้นสามารถเรียนรู้ความสัมพันธ์เชิงซ้อนระหว่างตัวแปรได้ดี มีความเหมาะสมในการพยากรณ์ราคาทองคำแท่งรายวันในประเทศไทยโดยมีความแม่นยำในการพยากรณ์สูงกว่าแบบจำลอง ARIMAX โดยการพยากรณ์ราคาทองคำแท่งในช่วงปี ค.ศ. 2020 - 2024 แบบจำลอง NARX ให้ค่า RMSE และค่า MAPE เท่ากับ 486.17 และ 0.93 ตามลำดับ ส่วนราคาทองคำแท่งในปี ค.ศ. 2015 - 2019 ซึ่งมีความผันผวนของราคาทองคำต่ำ แบบจำลอง NARX ให้ประสิทธิภาพดีกว่าโดยค่า RMSE และ MAPE เท่ากับ 144.14 และ 0.36 ตามลำดับ

ABSTRACT

This research developed a daily gold bar price forecasting model in Thailand using the NARX model and compares it with the ARIMAX model. This study uses daily gold bar price data from 2015 to 2024, along with exogenous variables such as global gold prices, USD exchange rates, and global oil prices. The experiments were conducted by separating the dataset into three periods: 2015 - 2019, 2020 - 2024, 2015

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- 2024, to evaluate forecasting performance under different levels of time-series volatility. For each period, the dataset is split in a chronological order into training dataset using 90% of the whole dataset and using the rest for testing. The results show that the NARX model outperformed the ARIMAX model in forecasting accuracy throughout all evaluation periods. This finding suggests that nonlinear models can capture complex relationships between input variables and are more suitable for forecasting gold prices in Thailand. For the gold bar price datasets spanning 2020 to 2024, which exhibited high volatility, the NARX model yielded the lower RMSE and MAPE of 486.17 and 0.93, respectively. While the forecasting of gold bar price spanning 2015 to 2019, which exhibited low volatility, the NARX model also provided the better performance with RMSE and MAPE of 144.14 and 0.36, respectively.

คำสำคัญ: ราคาทองคำแห่งประเทศไทย การพยากรณ์ราคาทองคำแท่ง ARIMAX NARX ตัวแปรภายนอก

Keywords: Thailand Gold Bar Price, Gold Bar Price Forecasting, ARIMAX, NARX, Exogenous Variables

INTRODUCTION

The popularity of gold as an investment has grown in recent years, largely due to its consistently rising price since 2021. Despite the sustained upward trend, gold prices have shown high fluctuations due to evolving global economic uncertainties. However, gold continues to maintain its position as a safe-haven asset and remains highly interested by investors worldwide. In 2024, the global gold market reached the highest price of \$2,790 per ounce and continued to rise throughout the year. At the beginning of 2025, gold analysts anticipate that gold prices will remain strong, continuing their upward trend since it has already increased by 25% in the first half of the year compared to the year 2024 that prices have risen by 27% over the entire year (Prachachat Business, 2025). This demonstrated its status as a trusted investment asset, regardless of market conditions. In addition, the rise of gold prices is driven by several factors such as stagnant economic outlook, the trade war, the Federal reserve's interest rate policies and ongoing geopolitical tensions in the Middle East, etc (Prachachat Business, 2024). Moreover, gold prices are influenced by various internal and external factors such as internal factors include market demand, supply of gold and important (Saengarun *et al.*, 2024), external factors consist of the U.S. dollar exchange rate, inflation rate, and interest rate, which directly affect investment decisions and economic forecasts. Consequently, these factors underscore gold's appeal as a stable and reliable asset during times of financial crisis and market volatility. In Thailand, gold investment depends on cultural and consumer behaviors in which gold is a decoration and represents stability, wealth, and family heirloom. In Thailand, gold investment is influenced by several factors, including global gold prices (Khangphukhieo *et al.*, 2017; Kumari *et al.*, 2023; Saengarun *et al.*, 2024), the exchange rate of the Thai baht per US dollar (Limkulsawat, 2009; Kulram, 2020), and inflation in the current economic climate in Thailand and worldwide (Saweta *et al.*, 2022).

In this paper, we study the forecasting of gold bar prices in Thailand, and we also investigate the previous studies published since 2017 until 2024, the finding show that most of the studies are mostly adopted ARIMA approaches. Moreover, they focus on monthly gold bar prices and do not incorporate

exogenous factors into the gold bar price forecasting models. Limkulsawat (2009) aimed to compare the accuracy of gold price forecasting between daily and monthly data from 1990 to 2007 using the ARIMA model. Their results demonstrated that forecasting models built from daily data provided higher accuracy compared to those based on monthly data. In addition, the daily forecasting models had lower RMSE, AIC, and U-Theil values, indicating improved predictive performance. Their study suggested that gold price fluctuations are more effectively captured using high-frequency data, as it reflects short-term market dynamics better than aggregated monthly data (Limkulsawat, 2009). Saweta *et al.* (2022) compared the effectiveness of the ARIMA and ARIMAX models in forecasting gold jewelry prices from January 2012 to April 2023. The ARIMA model used historical gold prices as the primary variable for forecasting, while the ARIMAX model incorporates additional exogenous variables. This study found that the ARIMA (1,1,0) model for forecasting purchased and selling gold jewelry prices provided more accurate results compared to the ARIMAX (0,1,0) model. The ARIMA model achieved a MAPE of 2.040%, MAE of 447.450, and RMSE of 581.305, while the ARIMAX model showed slightly higher errors with an MAPE of 2.498%, MAE of 551.811, and RMSE of 733.32. The study concludes that the ARIMA (1,1,0) model is more effective for forecasting both the purchase and selling prices of gold jewelry, given its lower error values and better overall performance. In addition, the data mining techniques are investigated and compared the efficiency of the statistical models. Siriratanapaisakul (2022) developed forecasting models using gold price data spanning from January 2, 1990, to December 31, 2020, over 30 years, and focused on Box-Jenkins (ARIMA), Holt-Winters, Artificial Neural Networks (ANN), Linear Regression, and Support Vector Machine (SVM). The results showed that the Box-Jenkins model (ARIMA(0,1,1)) outperformed the other models and achieved the lowest RMSE, making it the most suitable for forecasting gold prices. The results also found that SVM model had a lower MAE, but a higher RMSE compared to Box-Jenkins, indicating that Box-Jenkins was the most consistent and accurate model for predicting gold prices.

The literature review highlights two important insights: 1) not many studies have incorporated exogenous factors into the daily gold bar price forecasting models, 2) daily gold price forecasting tends to provide higher accuracy than monthly gold price forecasting. Therefore, this study aims to address that gap by developing and comparing models for forecasting gold bar prices, using daily data, and incorporating relevant exogenous variables to assess their impact on predictive performance. Furthermore, this study aims to evaluate the factors influencing gold bar prices and to examine whether the volatility of gold price datasets impacts the performance of the models. Moreover, we aim to compare performance the NARX model with the ARIMAX model for daily gold bar prices forecasting.

RESEARCH METHODOLOGY

The data used in this study are secondary time-series data recorded by the Gold Traders Association (2024), the World Gold Council, the Bank of Thailand (2024) and the Organization of Petroleum Exporting Countries (2024), during January 1, 2015, to December 31, 2024. Data sets employed in this study are listed below:

- Thai Gold Bar Prices refers as TG (Baht per Baht-weight) were collected from the Gold Traders Association, for a total of 3,094 records.

- Global Gold Prices refers as GG (US dollars per ounce) were collected from the World Gold Council, for a total of 2,553 records.

- USD Exchange Rate refer as UR (Baht per US dollar) were collected from the bank of Thailand (BOT) website, for a total of 2,609 records.

- Global Crude Oil Price refers as GO (US dollars) were collected from the organization of petroleum exporting Countries (OPEC), for a total of 2,579 records.

Because our forecasting study requires daily data from January 1, 2015, to December 31, 2024, we encountered gaps in variables that do not update every day. For example, Thai gold bar prices remain unchanged on Sundays (resulting in missing values for those days). To address these discontinuities, we applied forward-fill imputation by filling a missing value with the last observed value, as commonly adopted in financial time-series studies (Ribeiro and Castro, 2022; Hyndman and Athanasopoulos, 2021). However, the forward filling creates flat pattern in the market holiday that may have an impact on short-term price dynamic such as sudden changes in the price (after the market holidays).

Three forecasting techniques are employed, ARIMA, ARIMAX and NARX, and they are described as follows:

1. Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX)

ARIMA model capture autocorrelation structures of a target series, whereas the ARIMAX model extends the ARIMA framework by incorporating external (exogenous) variables that are expected to influence the target series. The ARIMA and ARIMAX models are typically expressed as ARIMA (p, d, q) and ARIMAX (p, d, q), where:

p is the number of lag observations in the AR model,

d is the degree of differencing (how many times has the series been differenced)

q is the size of the moving average window.

X represents the external or explanatory variables (Herman, 1939; Box and Jenkin, 1994).

The ARIMA equation is as follows:

$$Y_t = \varepsilon_t + \sum_{i=1}^p \varphi_i Y_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i}$$

The ARIMAX equation is as follows:

$$Y_t = \varepsilon_t + \sum_{i=1}^p \varphi_i Y_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \sum_{i=1}^b \eta_i X_{t-i}$$

where Y_t is the target variable at time, X_{t-i} are lagged exogenous variables, φ_i and θ_i are autoregressive and moving average coefficients, respectively. ε_t is a white noise error term and η_i represents the influence of exogenous factors.

In both models, the estimation of the parameters p (Autoregressive: AR) and q (Moving Average: MA) are required, and we employed the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to estimate p and q . When identifying AR and MA orders, we first inspect both the ACF and PACF across all lags to ensure that the final few spikes (e.g., lags 36 - 40 in a 0 - 40 plot) lie close to zero. If not, the series may not exhibit AR or MA structure. For model identification, an AR (p) order is suggested when the PACF exhibits significant spikes up to lag p , while the ACF shows a gradual decay. Conversely, an MA (q) order is indicated when the ACF displays significant spikes up to lag q while the PACF gradual decay. Although the ACF and PCF provide initial guidance for selecting p and q , the final model specification should be evaluated using AIC and BIC. In this study, the value of p and q were varied from 1 to 10, and the model with the lowest AIC were selected. In our preliminary study, we found that the assumptions of heteroskedasticity and normality of the residuals were violated, thus we took square root of Y_t to transform the target variable.

2. Nonlinear Autoregressive with Exogenous Inputs (NARX)

The NARX model is a nonlinear neural network used for time series forecasting, integrating past values of both the target variable and exogenous inputs. It captures complex temporal dependencies through feedback connections, making it suitable for dynamic systems influenced by exogenous factors u . NARX model is formulated as:

$$Y_t = f(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}, u_{t-1}, u_{t-2}, \dots, u_{t-p})$$

Where the next value of the dependent output signal Y_t is regressed on previous values of the output signal and previous values of an exogenous input signal. The NARX architecture is depicted in Figure 1, and the NARX model can be implemented by using a feedforward neural network to approximate the function f .

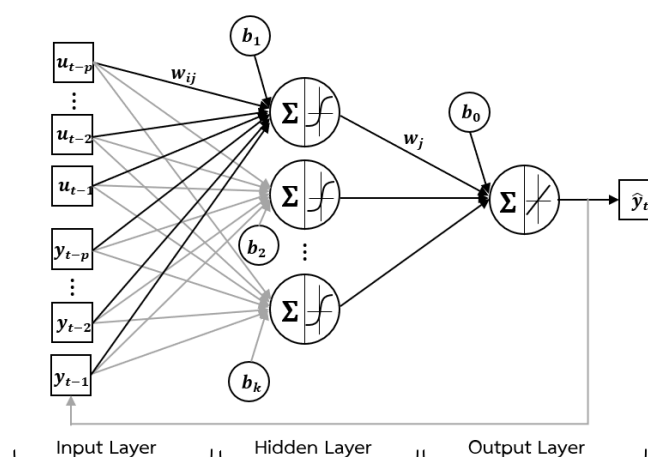


Figure 1 NARX architecture

The multi-step forecasting is a closed-loop architecture in such a way that the model predicts the one-step ahead future value using the historical value of the target variable and exogenous variables. Then, the predicted value is fed back into the network as a past value to predict the next step ahead, and the forecasting process repeats until the desired number of future steps has been reached. However, because the future values of the exogenous variables are required to forecast the target variable, therefore, the future value of the exogenous variables from the test set are provided to the model for forecasting Y_t . Since the predicted values of the target variable are used to generate subsequent step-ahead forecasts, the forecast errors accumulate over longer horizon.

3. Experimental setup

This study conducts six experiments according to the forecasting techniques and the datasets which are described in Table 1.

Table 1 Dataset splitting for three periods

Model	Training Period	Testing Period
Model_2015-2024	1 Jan 2015 - 31 Dec 2023 (3,287 days)	1 Jan 2024 - 31 Dec 2024 (366 days)
Model_2015-2019	1 Jan 2015 - 1 Jul 2019 (1,644 days)	2 Jul 2019 - 31 Dec 2019 (183 days)
Model_2020-2024	1 Jan 2020 - 1 Jul 2024 (1,644 days)	2 Jul 2024 - 31 Dec 2024 (183 days)

For the NARX model, we employed `nnetar()` in forecast package in R (Hyndman and Khandakar, 2008; Hyndman *et al.*, 2025), The models were estimated using ten independent training runs, during which the lagged inputs (p) using the default which is the optimal number of lags according to AIC. The number of hidden nodes (size) were also determined by the default which is half of the number of input variables including the exogenous variables, but the number of repeats is set to five. The final model of NARX_2015–2024 and NARX_2020-2024 yielded $p = 1$ and $\text{size} = 2$, while Model_2015-2019 yielded $p = 4$ and $\text{size} = 4$.

RESULTS AND DISCUSSION

In this paper, the ARIMAX is used as a baseline method, which required the stationary assessment. We employed Unit Root Test or stationarity test by using Augmented Dickey-Fuller (ADF Test) method to check whether the variables used for analysis are stationary time series. The results of Unit Root Test at 0.05 level of significance, found that all variables are non-stationary as TG-Sqrt, TG, GG, UR, GO had a p -value of 0.992, 0.997, 0.994, 0.275, and 0.236, respectively. Moreover, all variables exhibited ADF statistics above the Dickey–Fuller critical values at the 1%, 5%, and 10% significance level. Therefore, all variables require further differencing before fitting the ARIMA and ARIMAX models. After first differencing, each ADF test statistic lies well below the Dickey–Fuller critical values, and all variables has p -value < 0.001 , therefore, the differencing parameter $d = 1$. The results show that the ARIMAX (2,1,0) is suitable for ARIMAX_2015-2024 and ARIMAX_2015-2019, while ARIMAX(1,1,1) is suitable for ARIMAX_2020-2024 model.

We conducted nine experiments for the ARIMA, ARIMAX, and NARX models using same datasets as described in Table 1. We set the same parameter of all NARX models as described in the experimental setup. Figure 2 - 3 show the forecasting results for Thai gold bar prices for 2015 - 2019 and 2020 - 2024 period. Figure 2 shows the NARX_2015-2019 forecasted values and actual values are almost identical throughout the testing period. However, Figure 3 shows that ARIMAX_2020-2024 model is unable to accurately track the rapid gold bar price increasing whereas NARX model demonstrates an improved ability to follow the general direction of price changes, particularly during the peaks and subsequent declines in late 2024. Nonetheless, all ARIMAX models are capable of short-term forecasting under relatively stable market conditions. However, when the market became more volatile all ARIMAX models perform less effectively, showing their limitations during periods of sudden changes in gold bar prices.

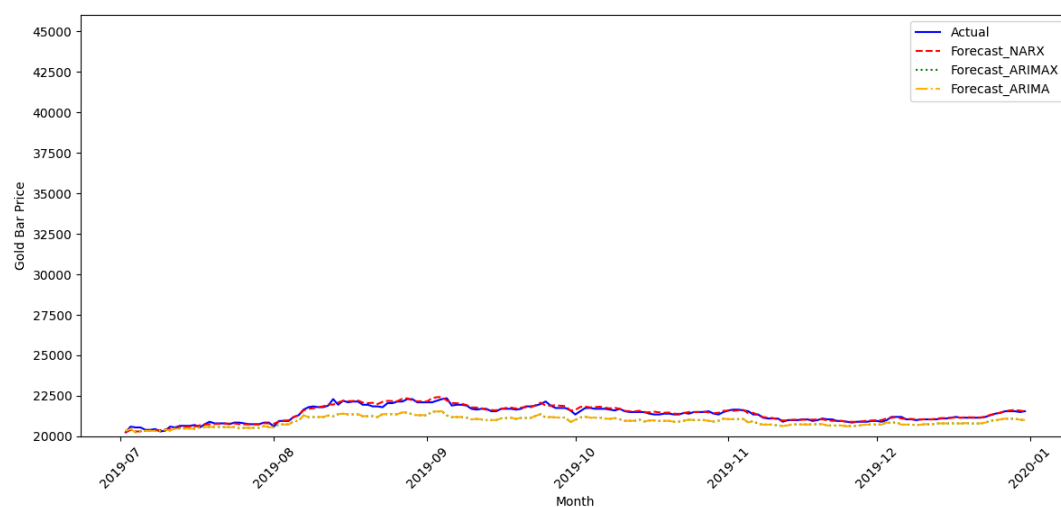


Figure 2 Model_2015-2019 models forecasted values vs actual values

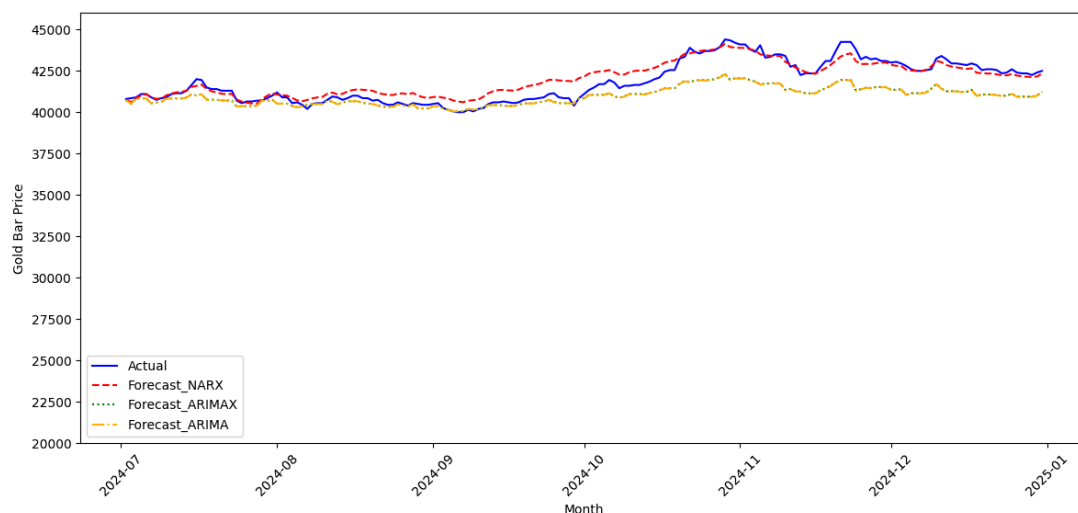


Figure 3 Model_2020-2024 models forecasted values vs actual values

The results of the coefficients of explanatory variables in the ARIMAX models show that it is sufficiently evident that both Global Gold Price and USD Exchange Rate have a statistically significant impact on Thai gold bar prices (p -value < 0.001). However, the relation between gold bar prices and global crude oil price varies between the models. Table 2 and 4 show that the global crude oil price is statistically significant ($p < 0.05$) for the ARIMAX_2015-2024 and ARIMAX_2020-2024 model. Conversely, ARIMAX_2015-2019 model, which is based on data during 2015 - 2019, shows that global crude oil price has no significant effect (p -value = 0.590) as shown in Table 3. The Ljung–Box test p -values (Prob(Q)) of ARIMA and ARIMAX models during 2015 - 2024, 2015 - 2019, 2020 - 2024 are 0.98, 0.99, 0.88, 0.95, 0.93, 0.91, respectively. These relatively large p -values indicate no significant autocorrelation in the residuals at 0.05 level of significance. However, the Jarque–Bera normality test p -values (Prob(JB)) of ARIMA and ARIMAX models are all below 0.001 (p -values are extremely small and close to zero), this means that the residuals are not normally distributed. Furthermore, the heteroskedasticity test of ARIMA_2015-2024 and ARIMAX_2015-2024 models yield the p -values (Prob(H)) of 0.19 and 0.06, the p -values > 0.05 means the variance of the residuals is constant at 0.05 level of significance. However, the Prob(H) of models during 2015 - 2019 and 2020 - 2024 are all below 0.05, this could potentially affect the reliability of confidence intervals and forecast accuracy.

Table 2 Coefficients of ARIMAX_2015-2024 model

Variable	Coefficient	Std Err	z-value	p -value
Global Gold Price	0.020	<0.001	67.145	<0.001
USD Exchange Rate	1.204	0.054	22.404	<0.001
Global Crude Oil Price	0.011	0.004	2.841	0.004

Table 3 Coefficients of ARIMAX_2015-2019 model

Variable	Coefficient	Std Err	z-value	p -value
Global Gold Price	0.028	0.001	41.696	<0.001
USD Exchange Rate	1.168	0.075	15.555	<0.001
Global Crude Oil Price	-0.004	0.007	-0.539	0.590

Table 4 Coefficients of ARIMAX_2020-2024 model

Variable	Coefficient	Std Err	z-value	p -value
Global Gold Price	0.018	<0.001	43.812	<0.001
USD Exchange Rate	1.310	0.083	15.833	<0.001
Global Crude Oil Price	0.018	0.006	2.961	0.003

Table 5 Performance forecasting of All models

Model	RMSE	MAPE (%)
ARIMA_2015-2024 (p=5, d=1, q=4)	6,893.93	15.05
ARIMAX_2015-2024 (p=2, d=1, q=0)	3,679.80	8.01
NARX_2015-2024	2,019.01	4.37
ARIMA_2015-2019 (p=2, d=1, q=7)	490.07	2.05
ARIMAX_2015-2019 (p=2, d=1, q=0)	494.16	2.06
NARX_2015-2019	144.14	0.36
ARIMA_2020-2024 (p=2, d=1, q=0)	1,129.28	2.03
ARIMAX_2020-2024 (p=1, d=1, q=1)	1,119.72	2.01
NARX_2020-2024	486.17	0.93

Table 5 indicates that the ARIMA models yield higher RMSE and MAPE compared with the ARIMAX models during 2015 - 2024. However, for the periods 2015 - 2019 and 2020 - 2024, the errors of the ARIMA and ARIMAX models are no significant differences. Moreover, ARIMAX_2015-2019 model provides the lower RMSE value of 494.16 and the MAPE of 2.06, while ARIMAX_2015-2024 and ARIMAX_2020-2024 models yield higher RMSE of 3,679.80 and 1,119.72. Furthermore, ARIMAX_2015-2024 model has the highest RMSE of 3,679.80 and MAPE of 8.01, this may be due to a sharp upward trend in gold bar prices after the year 2020.

In addition, the results show that the NARX_2015–2019 model achieved lowest RMSE and MAPE, with the value of 144.14 and 0.36, respectively. This suggest that the stability of the gold bar prices, resulting in higher predictive accuracy when using both models, as illustrated in Figure 2. However, when the NARX model is applied to the extended dataset (2015 - 2024), their error rate increased significantly with the NARX_2015–2024 model yielded RMSE of 2,019.01 and MAPE of 4.37. This indicates that the NARX model struggled to capture the sharp upward trend and high volatility that occurred in later years.

Furthermore, the NARX_2020-2024 model gave a lowest RMSE and MAPE with value of 486.17 and 0.93, respectively. Both NARX_2020_2024 and ARIMAX_2020-2024 models provided the lower RMSE and MAPE than those which are trained on 2015 - 2024 dataset. This suggests that NARX model may be more suitable for short-term training datasets, especially when dealing with highly volatile datasets, as illustrated in Figure 3.

CONCLUSIONS

This study compared the forecasting performance of ARIMAX and NARX models for daily Thai gold bar prices using RMSE and MAPE across three different training periods (2015 - 2019, 2015 - 2024, and 2020 - 2024). The results show that the ARIMAX models demonstrated higher error levels than NARX in all datasets. The NARX_2015–2019 model achieved the lowest RMSE 144.14 and MAPE 0.36, indicating that it provided the most accurate forecasts when the gold market was relatively stable and less volatile. Similar to the NARX_2015–2019 model, ARIMAX_2015–2019 model performed moderately well under more stable

market conditions as indicated by the RMSE of 494.16 and MAPE values of 2.06. When the models were applied to the high volatile dataset, the NARX_2020–2024 models exhibited slightly better adaptability to recent price movements (RMSE = 486.17, MAPE = 0.93) than the ARIMAX_2020-2024. This reinforces the idea that while ARIMAX can effectively capture linear and seasonal components, it underperforms when price volatility increases. However, NARX model still showed a lagged response during sudden market fluctuations. Future work should consider hybrid modeling approaches to enhance responsiveness to market shocks. Additionally, adding external indicators other could further improve forecasting precision.

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