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GOLD DEMAND FORECASTING IN MALAYSIA: A HYBRID NAR-ARIMA APPROACH

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Abstract: *This study investigates the demand for gold in Malaysia from 2010 to 2023, utilizing both nonlinear autoregressive (NAR) and autoregressive integrated moving averages (ARIMA) models to assess their predictive performance. Numerous global and domestic factors, such as market conditions, investor behavior, and economic fluctuations, influence gold demand, a critical economic indicator. We applied the NAR model, known for its ability to capture complex nonlinear relationships, and the ARIMA model, recognized for modelling linear trends, individually and in combination to forecast future gold demand. The results show that ARIMA performs well in capturing linear trends in the data, while NAR effectively captures nonlinear patterns. We proposed a hybrid NAR-ARIMA model that combines the strengths of both approaches, leading to enhanced forecast accuracy. The analysis highlights the effectiveness of this hybrid model in providing more reliable predictions, particularly for datasets exhibiting both linear and nonlinear behaviors. We then used the hybrid model to forecast gold demand in Malaysia up to 2030, providing valuable insights for policymakers, investors, and stakeholders in the gold market. These findings contribute to the growing body of literature on advanced time series forecasting techniques and their applicability to commodity demand forecasting.*

Keywords: *Gold Demand Malaysia, Time Series Forecasting, NAR Model, ARIMA Model, Hybrid Model.*

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Introduction

Forecasting time series data has always been a critical aspect of economic and financial analysis, as accurate predictions allow businesses and policymakers to make informed decisions. In the realm of commodity markets, particularly gold, demand is subject to both linear and nonlinear trends shaped by various global and domestic factors. Understanding these trends and their impact on gold demand is crucial for ensuring market stability and driving investment strategies. In recent years, advancements in modeling techniques have enabled more accurate forecasts, particularly through the application of nonlinear autoregressive (NAR) models and autoregressive integrated moving averages (ARIMA) models.

NAR models, a type of artificial neural network, are particularly useful in capturing complex, nonlinear relationships in time series data that traditional linear methods might miss. Various economic forecasting contexts, such as GDP growth and commodity demand, have successfully applied these models, which offer a flexible structure capable of adapting to fluctuating patterns. However, NAR models are computationally intensive and prone to overfitting without careful tuning, which poses challenges in model optimization and implementation (Ashour, Al-Dahhan, & Hassan, 2020; Ashour et al., 2023; Mubarak & Ashour, 2024).

However, due to their simplicity and capacity to capture linear relationships in stationary data, ARIMA models have long been a foundational tool in time series forecasting. ARIMA's strengths lie in its capacity to model trends, seasonal variations, and autocorrelations, making it a popular choice in predicting economic indicators such as inflation, GDP, and commodity prices. However, ARIMA models assume a linear relationship between variables, which limits their ability to capture the inherent complexities of time series data with nonlinear characteristics (Ashour, 2023; Hameed Ashour & Abbas, 2023a, 2023b).

Artificial Neural Networks (ANNs) have gained prominence in time series forecasting due to their ability to model complex, nonlinear relationships in data. Among these models, nonlinear autoregressive (NAR) models have been particularly effective in capturing the intricate dynamics often present in financial and economic data. According to Zhang (2003), NAR models handle nonlinearity that traditional linear models, such as ARIMA, struggle to represent. By utilizing past values in the time series as inputs to predict future values, NAR models excel in contexts where data exhibit irregularities and nonstationary behavior. Lawrence, Smith, and McDonald (2005) emphasized that NAR models are particularly useful for capturing cyclical and fluctuating patterns in time series data, making them ideal for applications such as forecasting GDP and commodity demand. Similarly, Fahad, Khan, and Malik (2018) demonstrated the effectiveness of NAR models in predicting global demand for commodities like gold, highlighting their ability to adapt to volatile economic conditions (Ferdiansyah et al., 2023a; Hossain et al., 2023; Lazcano et al., 2023; Semenoglou et al., 2023). Despite their advantages, NAR models are computationally intensive and can suffer from overfitting if not properly tuned. This makes the model selection process critical in ensuring accurate forecasts. Samarasinghe (2006) noted that, while NAR models offer superior accuracy in modeling nonlinear relationships, they require careful regularization techniques, such as dropout or early stopping, to avoid overfitting, especially in datasets with high variability. The reliance on a large amount of historical data for training also presents a challenge for NAR models, as it may not always be feasible in contexts with limited data availability.

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Autoregressive Integrated Moving Average (ARIMA) models, introduced by Box and Jenkins (1976), are among the most widely used in time series forecasting due to their simplicity and ability to model linear relationships. The design of ARIMA models captures the linear autocorrelations in a time series, rendering them highly effective when the data exhibits stationary behavior with consistent trends and patterns over time. Wang and Hu (2015) demonstrated the effectiveness of ARIMA models in forecasting key economic indicators such as GDP, inflation rates, and stock market prices. Their research emphasized that ARIMA's interpretability and ease of application make it a popular choice for practitioners, particularly in contexts where the data does not exhibit significant nonlinearity (Abdul et al., 2023; Ashour, 2022; Ashour & Alashari, 2022; Ferdiansyah et al., 2023b; Lazcano et al., 2023; Minu et al., 2010).

However, the assumption of linearity and stationarity in ARIMA models limits their ability to capture the nonlinear dynamics commonly observed in real-world time series data. Chong and Ahmad (2013) discussed these limitations, pointing out that ARIMA's inability to account for complex, nonlinear relationships reduces its accuracy in volatile markets, such as the demand for commodities like gold. Also, ARIMA relies on differencing to turn non-stationary data into stationary data, which can mean that important information about the underlying trends is lost, especially when the series has structural breaks or nonlinear shifts.

The literature has extensively explored the potential of hybrid models to overcome the limitations of both NAR and ARIMA. Khashei and Bijari (2011) were among the first to propose combining ARIMA's linear modeling capabilities with NAR's nonlinear adaptability in a hybrid approach. Their research found that hybrid models outperform stand-alone ARIMA or NAR models in capturing both linear and nonlinear patterns, particularly in datasets with complex trends and cyclical behavior. Similarly, Adhikari and Agrawal (2013) showed that the hybrid ARIMA-NAR model made commodity market forecasts much more accurate by breaking the time series into its linear and nonlinear parts. We used ARIMA to model the linear structure, and NAR to capture the remaining nonlinear residuals, resulting in a more comprehensive forecasting approach.

Babu and Reddy (2014) further supported the use of hybrid models, emphasizing their importance in financial markets, where both linear trends and nonlinear shocks are prevalent. Their study demonstrated that combining NAR and ARIMA leads to improved accuracy in long-term forecasts, especially in highly volatile markets. The hybrid approach allows the ARIMA model to handle the more predictable, linear aspects of the data, while the NAR model captures the irregular, nonlinear patterns that ARIMA may overlook. This synergy offers a powerful tool for improving the reliability of forecasts, particularly in the context of economic and financial time series (Ashour & Al-Dahhan, 2020, 2021; Jamal et al., 2021; Wirawan et al., 2019).

Building on this foundation, the present study applies both NAR and ARIMA models individually and in combination to forecast gold demand in Malaysia from 2010 to 2023. The study's goal is to find out if a hybrid NAR-ARIMA model can improve the accuracy of forecasts by considering both the linear and nonlinear parts of the data. By comparing the performance of the individual and hybrid models, this research contributes to the growing body of literature on the application of advanced forecasting techniques in commodity markets.

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Furthermore, the study extends the forecasting horizon to 2030, providing valuable insights for stakeholders in the gold market, including policymakers, investors, and industry leaders.

The goal of this study is to make gold demand predictions more accurate and reliable in Malaysia by using both the NAR (Nonlinear Autoregressive) and ARIMA (Autoregressive Integrated Moving Average) models, both alone and together, from 2010 to 2023. Researchers are looking at how well these models work against each other to see if a hybrid NAR-ARIMA model can make better predictions by combining the data's linear and nonlinear changes more skillfully. This method not only tries to address the difficulties inherent in the gold market but also to deliver practical insights that might help policymakers, investors, and industry leaders. Furthermore, the study extends the forecasting period to 2030, therefore enhancing strategic planning and decision-making in commodities markets.

Method

Nonlinear Autoregressive (NAR) Models

Time series forecasting widely employs artificial neural networks (ANN) because of their capacity to capture complex patterns. Among these, the nonlinear autoregressive (NAR) model is particularly well suited for modeling time series data. Unlike traditional linear methods, NAR models can represent intricate relationships between past and future values, making them ideal for data with nonlinear trends.

A NAR model predicts future values for a time series based on its own past values. The model is defined as (Abbas et al., 2020; Derbentsev et al., 2019; Munim et al., 2019)

$$y_t = f(y_{t-1}, y_{t-2}, \dots \dots y_{t-p} + \epsilon_t) \qquad (1)$$

where f is a nonlinear function estimated by the neural network, and p indicates the number of lags. The NAR model's nonlinearity allows it to adjust to various time series structures, capturing fluctuations and irregularities that linear models might overlook.

The NAR model's neural network structure includes input, hidden, and output layers. It processes past values through hidden layers using activation functions like sigmoid, generating forecasts through the output layer. While NAR models can be very accurate, they require careful tuning to avoid overfitting, such as adjusting the number of hidden layers and using techniques like dropout or early stopping during training(Ashour, 2022; Ashour & Al-Dahhan, 2021).

NAR models are particularly valuable in economic and financial forecasting. For instance, NAR models excel in forecasting Saudi Arabia's GDP growth, better capturing cyclical economic patterns than linear models. Similarly, in forecasting global demand for commodities like gold, NAR models can account for complex, non-linear relationships between economic factors, offering more precise forecasts.

Despite their advantages, NAR models have challenges, including computational intensity and a reliance on large datasets for effective training. Their complexity also makes them prone to overfitting if not properly managed. However, when applied to careful model design and

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regularization, NAR models can provide powerful insights and accurate forecasts for complex time series data(Ashour, Al-Dahhan, & Hassan, 2020; Ashour et al., 2023; Mubarak & Ashour, 2024).

ARIMA Models in Time Series Forecasting

Autoregressive Integrated Moving Average (ARIMA) models are very important in time series analysis and forecasting because they are good at finding linear relationships in data that change over time. ARIMA combines three components—autoregression (AR), integration (I), and moving average (MA)—to model the past values and forecast future trends. Its simplicity and interpretability make it a popular choice for economic and financial applications, where understanding the structure of time series data is essential(Hossain et al., 2023; Semenoglou et al., 2023).

ARIMA models are defined by three parameters: (p, d, q). The parameter p tells us how many delayed observations were used in the autoregressive part, d tells us how much differencing was used to get stationarity, and q tells us how many delayed forecast errors were used in the moving average part. Differencing, a key feature of ARIMA, helps in transforming a non-stationary series into a stationary one, which is crucial for accurate forecasting (Abdul et al., 2023; Ashour & Al-Dahhan, 2020, 2021).

The strength of ARIMA lies in its ability to capture trends and autocorrelation structures in time series data. By analyzing the autocorrelation function (ACF) and the partial autocorrelation function (PACF), analysts can determine appropriate values for p and q, ensuring the model accurately represents the underlying data. The integration step (d) is particularly important when dealing with economic indicators that exhibit trends over time.
Despite its strengths, ARIMA has limitations. It assumes a linear relationship between variables and may struggle with capturing nonlinearity and abrupt shifts in time series. Additionally, the model requires careful transformation of data due to its reliance on stationarity. Nonetheless, ARIMA remains a foundational tool in time series analysis, offering a balance of simplicity and predictive power that makes it an essential starting point in many forecasting tasks(Ashour, Al-Dahhan, & Hassan, 2020; Ashour & Al-Dahhan, 2020; Wirawan et al., 2019).

Combining Model

In time series forecasting, combining different models can often yield more accurate and robust predictions than using a single model alone. A common hybrid approach involves integrating nonlinear autoregressive (NAR) models with autoregressive integrated moving average (ARIMA) models. This combination leverages the strengths of both models ARIMA's ability to capture linear trends and structures and NAR's capacity to model complex, nonlinear linear relationships. This synergy makes hybrid models especially effective in forecasting economic and financial data that exhibit both linear and nonlinear patterns.

Typically, the hybrid approach separates a time series into linear and nonlinear components, modeling them separately before combining the forecasts. We use ARIMA to capture the linear structure of the time series, including trends or seasonal patterns. We then model the residuals from the ARIMA model using an NAR model, which may contain nonlinear aspects not captured by ARIMA. We obtain the final forecast by combining the outputs of both models,

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which provides a more comprehensive representation of the time series. Mathematically, this can be expressed as (Abdul et al., 2023; Ferdiansyah et al., 2023a, 2023b):

$$y(t) = \hat{y}\,ARIMA(t) + \hat{y}NAR9t) + e(t) \qquad (2)$$

where: $\hat{y}$ ARIMA(t) represents the forecasted value from the ARIMA model.
$\hat{y}$NAR(t) is the forecasted nonlinear residual from the NAR model.
e(t) is the remaining error term.

This mixed structure is helpful because the ARIMA model does a decent job of detecting linear trends and seasonality in the data, while the NAR model adjusts to any nonlinear patterns that are still present in the residuals.

The NAR+ARIMA hybrid approach can offer significant improvements in forecast accuracy, but it comes with challenges. The process of fitting and combining two models is more complex and computationally intensive than using a single model. It also requires expertise in model selection and parameter tuning for both ARIMA and NAR. However, when applied properly, this approach provides a powerful forecasting tool that balances interpretability with flexibility, making it valuable for analyzing complex time series data(Ferdiansyah et al., 2023b; Jamal et al., 2021; Minu et al., 2010).

Accuracy in computing errors

To assess the accuracy of time series forecasts and ensure the efficacy of statistical models, it is essential to evaluate key error rates. The root mean square error (RMSE) and the mean absolute percentage error (MAPE) are the most significant metrics. To calculate the root mean squared error (RMSE), we compute the square root of the mean squared differences (MSD) between the actual and predicted values. This provides insight into the magnitude of prediction errors in units corresponding to the original data. This measure proves to be highly effective when dealing with significant errors. Conversely, MAPE facilitates the comprehension and comparison of diverse measurements by offering an estimate of the mean absolute percentage error between actual and projected values. Corporate environments, where an accurate relative error estimate is essential, also find it beneficial. Numerous studies indicate that these indicators provide a comprehensive assessment of forecasting models. This facilitates the identification of necessary modifications and guarantees precise and dependable forecasts across several sectors, including healthcare, financial services, and supply chain management. We can express this numerically in the following way: The two most critical error metrics for evaluating the efficacy of statistical models and the precision of time series forecasts are the mean absolute percentage error (MAPE) and the root mean square error (RMSE) (Alayham et al., 2018; Ashour et al., 2022; Semenoglou et al., 2023). To get the root mean squared error (RMSE), we take the square root of the mean squared differences (MSD) between the actual and projected values(Ashour, Al-Dahhan, & Al-Qabily, 2020; Munim et al., 2019; Wirawan et al., 2019). This gives us an idea of how big the prediction mistakes are in units that match the original data. All agree that this measure works wonders when it comes to punishing big mistakes. In contrast, MAPE makes it simpler to understand and compare various metrics by providing an estimate of the mean absolute percentage error between the actual and anticipated values. Corporate settings, where precise relative error estimation is crucial, also consider it helpful. The financial industry, healthcare, and supply chain management are just a few of the

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many areas that might benefit from precise and dependable forecasts made possible by these measures, which allow for a thorough review of forecasting models. According to various studies, one can express this mathematically in the following ways(Abdul Hameed Ashour et al., 2022; Ahmed et al., 2020; Anbalagan et al., 2020; Lazcano et al., 2023):

$$MAPE = \frac{\sum \left|\frac{wt}{Zt}\right|}{n} * 100 \qquad (3)$$

$$RMSE = \sqrt[2]{\frac{\sum \quad Wt}{n}} \qquad (4)$$

Where:
Z_t: original data
W_t= error

Result
Table 1 indicates gold demand in Malaysia. From this data we can see a trend in gold demand in Malaysia from 2010 to 2023, highlighting significant fluctuations influenced by various economic factors. The demand increased from 16.72 tons in 2010, reaching a peak of 26.58 tons in 2013, likely driven by economic uncertainty that led investors to seek gold as a haven. A downward trend followed until 2017, stabilizing between 2016 and 2019, indicating a period of economic adjustment. The COVID-19 pandemic in 2020 resulted in a sharp decline in demand to 13.07 tons, reflecting reduced economic activity and consumer spending. The subsequent recovery in 2021, reaching 14.86 tons, suggests a partial economic rebound. In 2022, demand further improved to 18.53 tons, but a slight decline to 16.59 tons in 2023 suggests ongoing market adjustments influenced by factors such as inflation, economic policies, and global gold price volatility. This analysis underscores the dynamic nature of gold demand, shaped by both global and domestic economic conditions.

Table 1: Annual Gold Demand in Malaysia (2010-2023), Measured In Tons. (Source: World Gold Council)

Year	Gold Demand (tons)
2010	16.72368
2011	19.79205
2012	19.57238
2013	26.57862
2014	24.75564
2015	20.37178
2016	17.7577
2017	17.54824
2018	18.917
2019	17.605
2020	13.0731
2021	14.86175
2022	18.53279
2023	16.592

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The performance of NAR is presented in figure 1. As shown in the figure demonstrates strong learning capabilities in the initial epoch, with the training error decreasing significantly. This rapid reduction in training error indicates that the model is quickly capturing patterns from the data, which is a positive sign of its learning effectiveness. Notably, the best validation performance is achieved early at Epoch 1, with an MSE of 1.1092. Achieving such a strong validation performance early on highlights the model's potential for quick and efficient learning, which is promising for forecasting tasks.

While the validation and test errors remain stable after the first epoch, this stability reflects a model that is consistent in its predictions without further degradation in performance. To harness this early success, implementing early stopping would ensure the model retains its optimal performance without overfitting. Additionally, this result highlights the robustness of the model during the initial training phases, offering an excellent foundation for further fine-tuning and optimization. With minor adjustments, the NAR model can be further enhanced to improve generalization and maintain its efficiency.

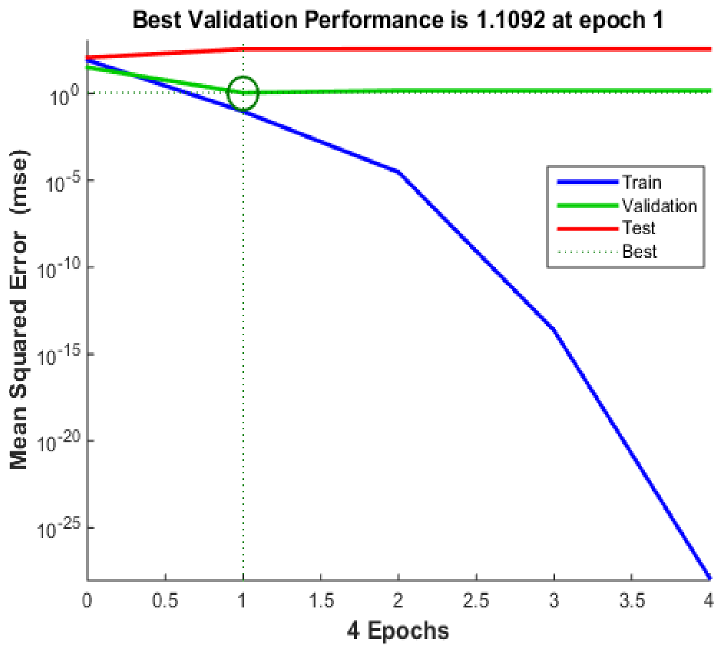

Figure 1: NAR Performance

Table 2:Provides the Results of Estimating the Best Diagnostic Model.

Table 2: ARIMA Model Parameters

	Estimate	SE	t	Sig.
Constant	18.441	1.67	11.043	0
AR Lag 1	0.558	0.237	2.356	0.036

The diagnosis of the ARIMA model is conducted by analyzing the autocorrelation and partial autocorrelation patterns illustrated in Figure 2.

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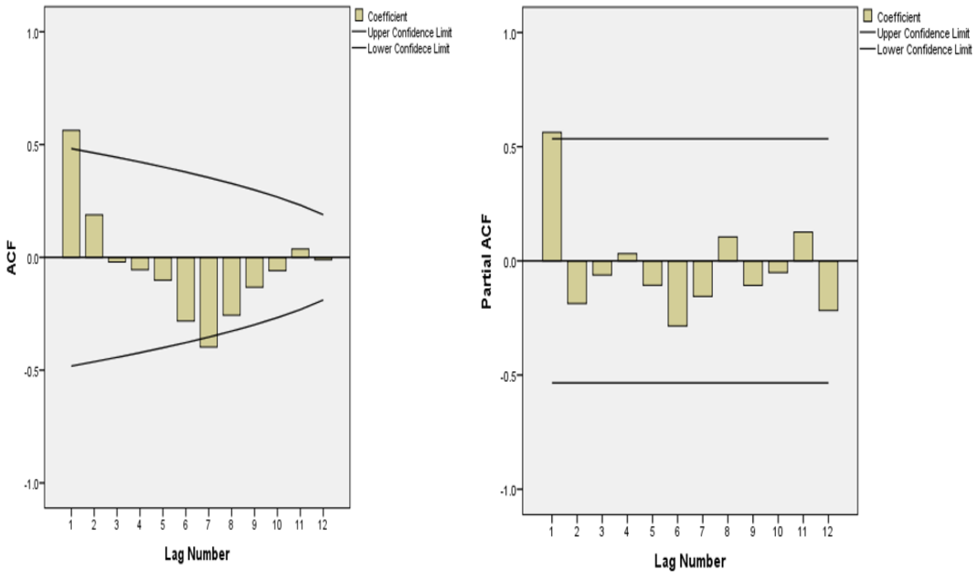

Figure 2: The Autocorrelation and Partial Autocorrelation for Time Series

ARIMA (1, 0, 0) is the best-identified model for the data, suggesting that an autoregressive term of order 1 can effectively model the time series without the need for differencing (d = 0) or a moving average component (q = 0). This implies that the series is stationary, with no long-term trend or need for further transformations. At lag 1, the autoregressive component captures the data's dependencies, where past observations influence current values.

The significance of the AR coefficient (estimated at 0.558) indicates that the first lag has a meaningful impact on future predictions, and the constant term (18.441) contributes significantly to the overall forecast. The absence of a moving average term and no need for differencing simplifies the model, allowing it to capture the underlying linear patterns in the data with fewer parameters. This makes ARIMA (1, 0, 0) an efficient and interpretable model, providing reliable forecasts without overcomplicating the structure. Thus, it balances accuracy and simplicity, making it a robust choice for time series forecasting in this context.

The differences between NAR and ARIMA are highlighted in Table 3.

Table 3: Result Of Accuracy Error

Method Criteria	NAR	ARIMA
RMSE	5.5	3
MAPE	7.5	11.1

Table 3 shows that both the NAR and ARIMA models are better at making predictions than each other. These models may work better together for reliability and efficiency. The ARIMA model does a better job of lowering the absolute prediction mistakes, as shown by its lower root mean squared error (RMSE). The NAR model, on the other hand, does better when measuring mean absolute percentage error (MAPE). This implies that it produces more precise percentage-based predictions when comparing errors to actual numbers. Therefore, rather than relying solely on one model, a hybrid approach that integrates the strengths of both models could potentially improve prediction accuracy. ARIMA is adept at dealing with data that has stable changes and linear trends. NAR, on the other hand, can find irregular relationships that ARIMA might miss. To make forecasts more accurate overall, this kind of mixed approach might help cut down on both absolute mistakes and relative percentage errors. Decision: One type is not "better" than the other. Instead, data type and projection goals determine the choice. ARIMA is better for forecasts that want to minimize precise mistakes, while NAR is better for predictions that want to maximize accuracy based on percentages. Combining the two models could yield the best results, ensuring high accuracy in various measures.

To enhance the robustness of the prediction outcomes, a concurrent model integrating both the NAR and ARIMA methodologies was used. The combined methodology enhances accuracy by significantly reducing prediction errors.

The forecast for gold demand in Malaysia for 2030 using the combing model (NAR+ARIMA), is shown in Table 4.

Table 4: Forecast Value

Year	Forecast
2024	17.40969
2025	17.86586
2026	18.12035
2027	18.26232
2028	18.34153
2029	18.38571
2030	18.41036

Table 4 shows that the numbers for expected gold demand in Malaysia from 2024 to 2030 show a slow but steady rise. The model says that demand will rise steadily, starting at 17.41 tonnes in 2024 and ending at 18.41 tonnes in 2030. This shows that demand will keep going up over the next few years, even though the growth isn't very fast.

Several factors, including a potential economic rebound, growing investor interest in gold as a stable asset, and shifts in the global economy that frequently boost demand for safe-haven goods like gold, predict the growth. Increases each year are pretty small, running from about 0.03 to 0.47 tonnes. This is due to the expectation of steady, long-term growth rather than significant fluctuations.

Economic forecasts indicate that despite global uncertainty, rising pressures, and economic policies that impact gold as an investment, things will gradually improve. This gradual rise in gold demand fits with these predictions. Also, as Malaysia's economy grows, more people may want to buy and trade in gold, which could cause the price to go up.

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The prediction shows that Malaysians will want to buy gold in the future, thanks to factors in both the Malaysian and world economies. Forecasts for steady growth up to 2030 give lawmakers, investors, and market players useful information for making plans based on the stable demand for gold in the coming years.

Conclusion

This study analyzed the demand for gold in Malaysia from 2010 to 2023, revealing significant fluctuations driven by various economic factors, including global market conditions, investor sentiment, and the COVID-19 pandemic. The demand peaked in 2013, followed by a decline and subsequent recovery in the post-pandemic period. We applied forecasting models, specifically the NAR and ARIMA, to the data to evaluate their predictive accuracy. The ARIMA (1, 0, 0) model was found to effectively capture the linear patterns in the data, while the NAR model showed strength in capturing nonlinear relationships.

A comparison between the two models highlighted their strengths. ARIMA performed better in terms of minimizing absolute errors, as evidenced by a lower RMSE, whereas NAR excelled in percentage-based accuracy with a lower MAPE. Given these complementary strengths, a hybrid approach combining both models was proposed to further enhance the reliability of forecasts. This combination leverages ARIMA's capacity to handle linear trends and NAR's ability to capture nonlinear patterns, providing a more comprehensive and accurate forecasting framework.

We then employed the combined NAR-ARIMA model to forecast Malaysia's gold demand up to 2030. The forecast predicts a steady increase in demand, reaching 18.41 tones by 2030. This integrated approach offers a robust tool for decision-makers, providing more reliable insights into future trends in gold demand, which are crucial for policymakers, investors, and industry stakeholders in planning for the future of Malaysia's gold market.

Authors' Contribution

Ashour, M. A. H. and Abbas, R. A conceived and planned the Application. Ashour, M. A. H. planned and carried out the Application. Ashour, M. A. H., contributed to the interpretation of the results. Abbas, R. A. took the lead in writing the manuscript. All authors provided critical feedback and helped shape the research, analysis and manuscript.

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