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COMPARATIVE ANALYSIS OF ARIMA, MLPNN AND HYBRID MODELS FOR FORECASTING NATURAL GAS SPOT PRICES FROM HENRY HUB

Forecasting natural gas spot prices is vital for effective planning and decision-making. This study compares ARIMA, MLPNN, and a hybrid ARIMA-MLPNN model using data from January 1997 to August 2024, evaluated by RMSE. Results show the hybrid model achieves the highest forecasting accuracy.

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The natural gas (NG) has a significant impact on the global energy market and is essential to the global economic system. Geopolitical tensions, wars, and developed industries have increased its demand globally in recent years, resulting in sustained growth over several decades (Mishra, 2012). Given that global policies prioritise clean energy and environmental impact, NG is thought to be the most environmentally friendly fossil fuel and represents a good transition from fossil fuels to entirely clean energy (Karabiber, Xydis, 2021). These characteristics have made it one of the most prevalent energy sources globally

The global trade in NG has grown in magnitude, making it the second most actively traded energy commodity after oil. The percentage of liquefied natural gas (LNG) that is traded globally is rising. globally after oil, with a rising share attributed to Liquefied Natural Gas (LNG) [1].

The natural gas price (NGP) volatility usually makes controlling production costs difficult and has an impact on energy policy. NGP are more uncertain due to a multitude of market factors, such as supply and demand, temperature, commodity substitution, and geopolitical risks, as the resource becomes more orientated towards the market (Zheng et al., 2023). The geopolitical risks that the gas market is susceptible to have been made evident by the conflict between Russia and Ukraine (Umar et al., 2022; Tang et al., 2023). As a result, it is now crucial to predict NGP accurately going forward. NGP are an important market indicator that have a big impact on industry demand and investment as well as national energy security. Therefore, increasing the accuracy of NGP forecasts is essential to help investors, decision-makers, and global energy markets (Sahed et al., 2020a)

Time series forecasting has been approached from many different angles, and over the past forty years, one of the most popular statistical approaches has been ARIMA models. These models' assumption of time series linearity, however, is a drawback because the majority of financial time series are currently non-linear (Aslanargun, 2007). For this reason, approaches based on machine learning techniques — like artificial neural networks (ANN) — have gained popularity as a way to improve forecasting performance (Alegado, Tumibay, 2020). One subtype of ANN is the multi-layer perceptron neural network (MLPNN). These models have been successfully employed to handle uncertainties, linearity, or non-linearity of systems across a wide range of disciplines including engineering, science, economics, medical diagnosis, signal processing, and control systems

However, no universal model is suitable for all applications. Therefore, forecasting accuracy can be improved by combining two different models and applying them to the same dataset rather than relying on a single model. Consequently, se-

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[1] The LNG industry in 2025. GIIGNL Annual Report, 2025. 76 p. URL: https://files.elfsightcdn.com/eafe4a4d-3436-495d-b748-5bdce62d911d/5a159954-fafb-4af9-a613-dca88e2a1736/GIIGNL-Livre-2025-20250610.pdf

veral studies have explored the application of hybrid techniques that leverage the advantages of two or more individual models. In 2003, G. Zhang proposed a hybrid ARIMA-ANN model (Zhang, 2003), which has been shown to offer flexibility in modeling nonlinearities and uncertainties. While each model has its strengths, hybrid approaches that combine linear and nonlinear methodologies can achieve superior forecasting accuracy by leveraging the advantages of each component. For example, in applications such as wind speed forecasting in three different regions of Mexico (Cadenas, 2010), short-term traffic flow forecasting (Zeng, 2008), and time series forecasting of exchange rates (Mucaj, 2017), this hybrid model outperformed both ARIMA and ANN models in one-step forecasting.

The purpose of this article is to evaluate and compare the forecasting performance of three different models, the statistical ARIMA model, the machine learning-based MLPNN model, and a hybrid ARIMA-MLPNN model. By applying these models to monthly natural gas spot price data covering the period from June 1986 to August 2024, the study aims to determine which model provides the highest predictive accuracy and robustness, especially under periods of market volatility and structural changes. The results are intended to support more informed and effective decision-making in energy pricing, planning, and investment, providing insights into the suitability of each model for future market predictions.

Natural gas is one of the most widely traded commodities and has a significant impact on various global activities. B. Soldo et al. (2014) categorised the literature up until the end of 2010 on forecasting NG consumption based on a variety of factors, including the year of publication, the forecasting horizon, the applied area, the frequency of data, the types of input data, and the forecasting tools utilised. J. Tamba et al. (2018) forecasted consumption by considering production, income elasticity, price increases, market volatility, and price hikes. H. Nguyen & I. Nabney (2010) used an MLP-based ANN model to forecast monthly NGP, with its accuracy slightly lower than the GARCH model. S. Hosseinipoor (2016) aimed to forecast future NGP in Indonesia using the ARIMA model. He found that GARCH (1,1) model was the best-fitting model, as it yielded the lowest mean square error. M. Akpinar & N. Yumusak (2016) forecasted a city's natural gas consumption using ARIMA, Holt-Winters, and time series decomposition, finding that ARIMA and Seasonal ARIMA models had the highest accuracy, improving with increased model complexity. A. Sahed et al. (2020b) compared a nonlinear autoregressive neural network (NAR) model with the ARIMA model for forecasting NGP, finding both models yielded similar results, but the NAR model was more suitable. On the other hand, many scholars employ ANN to forecast NGP, demand or consumption. S. Park & J. Kim (2014) used ANN for short-term NGP prediction, finding that a network with six inputs and ten hidden nodes minimized prediction error, making it the most effective model. J. Szoplik et al. (2015) used the MLP model to forecast NGP consumption in Szczecin, Poland, finding that the 22-36-1 MLP model effectively predicted daily and hourly NG consumption year-round. M. Ram et al. (2019) forecasted the monthly NGP in five European gas hubs and exchanges using ANN. The results demonstrated that ANN prediction is of a high degree of accuracy. C. Wang et al. (2019) forecasted long-term monthly spot NGP using the back-propagation neural network (BPNN) forecasting method. The numerical test results demonstrated that this method can provide accurate forecasting results. O. Karabiber & G. Xydis (2021) presented the most recent research on selecting the best predictive model for the day-ahead NG consumption based on ANN and ARIMA models as well as benchmark model's Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, and Seasonal components (TBATS) was the main goal of the work and the best model for prediction NGP. When it comes to hybrid models, M. Akpinar et al. (2017) developed one in order to forecasts NG demand. They demonstrate that their artificial bee colony trained ANN is more accurate than backpropagation trained ANN. In their comparison of a deep neural networks (DNN) forecasting results versus those of linear regression and ANN. M. Su et al. (2019) suggested using the autoregressive neural network (ARNN) to predict daily spot NGP. Through a cross-validation analysis, the mean squared error of the ARNN model was approximately 33% better than that of ARIMA. J. Li et al. (2021) proposed a hybrid model combining DBN, PSO, and VMD to forecast monthly Henry Hub NGP, outperforming traditional models and aiding investment strategy development. S. Gao et al. (2021) used a new class of hybrid models to assess how structural instability and regional features affect NGP forecasts. These models allowed for both abrupt and gradual changes in variance and mean, respectively. From January 1992 to December 2019, they made use of data from the US, EU, and Japanese markets. They established that allowing for distinct time-varying dynamics of the model parameters was essential for NGP forecasting. The models that allowed drastic changes in volatility and gradual changes in coefficients perform the best in forecasting for Japan and the EU, while the majority of forecasting gained for the US seem to have come from allowing gradual changes in volatility. B. Jin & X. Xu (2024) used a non-linear auto-regressive neural network model to forecast Henry Hub NGP, with results that can be integrated into policy or technical analysis. However, S. Sari-Hassoun et al. (2025) used a hybrid ARMA-GARCH-MLP and Prophet model to forecast weekly spot oil prices, with results aligning closely with the International Energy Agency (IEA) forecasts.

Despite the growing interest among researchers in forecasting natural gas prices, several critical gaps remain unaddressed. First, there is still no clear consensus on which modelling approach — statistical, machine learning, or hybrid — provides the most accurate and reliable forecasts under varying market conditions and timeframes. Second, only a limited number of studies have effectively integrated both linear and nonlinear models to fully capture the complex behavior of natural gas prices, particularly in the presence of structural breaks and prolonged volatility caused by global disruptions such as the COVID-19 pandemic and the Russia-Ukraine war. Third, empirical comparisons of ARIMA, MLPNN, and hybrid ARIMA-MLPNN models based on long-term datasets spanning over three decades are still rare, especially those that explicitly assess the models' robustness during recent periods of global instability.

DATA & METHODOLOGY

Data collection. To apply the theoretical aspects represented by the ARIMA, MLPNN and hybrid ARIMA-MLPNN model, we collected a dataset consisting of 459 observations of the monthly spot price of natural gas during the period of Juny 1986 to August 2024. The data are obtained from Index Mundi[2] and the data are in US Dollars per Million Metric British Thermal Unit.

This dataset was divided into a training phase and a testing phase for our models. The training phase covered the period from Juny 1986 to May 2016, while the testing phase was during Juny 2016 to August 2024. Python was used to perform the calculations.

The ARIMA Model. ARIMA models, introduced by Box and Jenkins in 1976, are among the most well-known methods for forecasting time series data (Dritsaki et al., 2021). ARMA models (*p, q*) consist of autoregressive AR(*p*) models of order *p*. The formula for an autoregressive process of order *p* (AR(*p*)) is represented as follow (Mahia, 2019):

$$Y_t = \mathrm{a}_t + \sum \theta_i y_{t-i} + \mu_t .$$

Moving average MA(*q*) models of order *q*. the MA(*q*) process can be expressed as follows:

$$Y_t = \mathrm{a}_t + \sum \theta_i \varepsilon_{t-i} .$$

When the series is not stationary, an additional component called the first differences of order *d* is incorporated, resulting in the ARIMA (*p, d, q*) model and the formula is as follows (Atique et al., 2019):

$$Y_t = \mathrm{a}_t + \sum_{i=1}^{p} \varnothing_i Y_{t-i} - \sum_{j=1}^{p} \theta_j \varepsilon_{t-j} + \varepsilon_t .$$

Multilayer Perceptron Neural Network model (MLPNN). It is a type of artificial neural network that has received significant attention from researchers due to its simplicity and successful applications in various fields (Nanda et al., 2023). It is considered one of the most widely used types for predicting time series. The network consists of an input layer (which performs no processing) and includes at least one hidden layer and one output layer. First, the input layer consists of data sets and *p* nodes connected to the hidden layer. In time series forecasting, MLPNN is provided with past delayed values of the actual data represented as an input vector (y_{t-1}, ... y_{t-p}). Then, the hidden layer is determined based on the specific study. At this stage, selecting the type of activation function is crucial, as it defines the relationship between the input and output layers (Ali et al., 2017). Commonly used activation functions include the sigmoid function, the hyperbolic tangent function, and the linear activation function. The formula for the hyperbolic tangent activation function is formulated as follow (Cifuentes et al., 2020):

$$\lambda(f) = \frac{2}{(1+e^{2n})} - 1.$$

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[2] *Index Mundi.* Accessed on 03/12/2025. URL: https://www.indexmundi.com/commodities/?commodity=natural-gas&months=360

Finally, the output layer, which comes after determining the activation function and the appropriate number of nodes in the hidden layer, the outputs of the neural network are used to predict future values of the time series. The function used for forecasting takes the following formula (Khashei, Hajirahimi, 2019):

$$Y_t = \mathrm{a}_0 + \sum_{j=1}^{n} \mathrm{a}_j f\left(\sum_{i=1}^{m} B_{ij} y_{t-1} + B_t\right)\varepsilon_t.$$

where m is the number of input points; n is the number of hidden nodes; $f(x)$ represents the activation function $\{\mathrm{a}_j, j = 0, 1, ..., n\}$ is the weight vector from the hidden layer to the output nodes; $\{B_{ij}, i = 1, 2, ..., m, j = 0, 1, ..., n\}$ represents the weights from the input layer to the hidden layer nodes.

The hybrid model. The hybrid model, proposed by G. Zhang (2003), combines a linear model with a nonlinear model to address the shortcomings that may arise when using either model alone (de Araújo Morais, da Silva Gomes, 2022). Relying on a single model can lead to errors or inaccurate results, whereas the hybrid model improves the accuracy of future forecasts and reduces these errors. It is also considered an effective tool for enhancing the quality of future forecasting (Skopal, 2015).

It is often assumed that a time series consists of both linear and nonlinear patterns. Based on this assumption, the series can be effectively represented as the combination of two distinct components: a linear structure and a nonlinear component. That can then be represented as follows (Ming et al., 2014):

$$y_t = L_t + N_t,$$

where L_t denotes the linear component and N_t denotes the nonlinear component. In brief, the proposed hybrid system methodology consists of two main steps (Xiao et al., 2014).

In the first step, the ARIMA model is applied to forecast the linear component of the future values. The residuals, which represent the portion of the data not explained by the ARIMA model, are then extracted. These residuals are calculated as follows:

$$\hat{e}_t = y_t - \hat{L}_t.$$

In the second step, the residuals reflecting the nonlinear patterns in the data are modelled using artificial neural networks (ANN), since the ARIMA model is not capable of capturing the nonlinear structure inherent in the time series. According to study of L. Wang et al. (2013), the final forecasted is calculated as follows:

$$\hat{y}_t = \hat{L}_t - \hat{N}_t.$$

Performance and Evaluation of the Models. In order to evaluate the performance of the forecasting model, three metrics were used to measure forecasting accuracy and compare the performance of different ARIMA and hybrid models: root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) (Chicco et al., 2021).

$$RMSE = \sqrt{\frac{1}{2}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2};$$

$$MAE = \frac{1}{n}\sum_{i=1}^{N}\left|y_t - \hat{y}_t\right|;$$
$$R^2 = 1 - \frac{SSR}{SST}.$$

EMPIRICAL RESULTS AND DISCUSSION

Statistics description. Table 1 presents the descriptive statistics of the data. The average price is 1.366 US dollars per million metric units, with a maximum value of 4.049 and a minimum of 0.294. The median price stands at 1.177, indicating that half of the observations are below this value. The standard deviation is 0.851, reflecting a moderate degree of dispersion around the mean. The kurtosis value is 2.153, which is less than the benchmark value of 3, indicating that the distribution is platykurtic, or flatter than a normal distribution. Meanwhile, the skewness is 0.591, suggesting a positive skew, meaning the distribution has a longer right tail.

ARIMA model estimation. In order to implement the ARIMA model for time series forecasting, it is crucial to follow a systematic approach that ensures the robustness and accuracy of the model. To achieve this, the time series data are divided into two distinct stages, which are training and testing stage. 367 observations are allocated to the training stage, which served as the foundational dataset for building of the three model parameters. The remaining 92 observations were reserved for the testing stage, which was later used to evaluate the models out-of-sample forecasting ability and validate its predictive performance.

At training stage, and before applying the Box-Jenkins (B-J) methodology, it is essential to verify one of the fundamental assumptions of the ARIMA modelling process, which is the stationarity of the time series. A stationary series is characterized by constant statistical properties over time (mean, variance, and autocorrelation structure). This condition is necessary, because the ARIMA model assumes the underlying data-generating process is stationary to produce reliable forecasts.

Figure 1 below illustrates the evolution of natural gas prices over the study period, showing noticeable fluctuations in price movements. It also illustrates how the data was divided into training and testing phases.

In order to verify whether the time series under study is stationary or non-stationary, this paper employs both the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Both tests provide a more robust assessment, as the ADF test has a null hypothesis of non-stationarity (presence of a unit root), while the KPSS test assumes stationarity under the null hy-

Table 1. **Results of Descriptive Statistics**

Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis
1.366	1.177	4.049	0.294	0.851	0.591	2.153

Source: was compiled by the authors by Python.

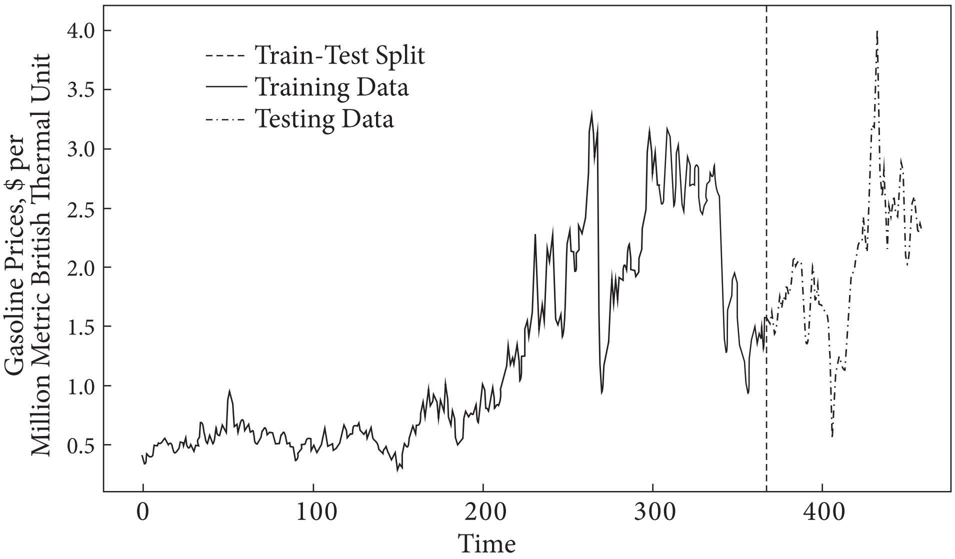

Fig. 1. Evolution of Natural Gas Prices
Source: done by authors using Python.

Table 2. **Results of the Stationarity Tests**

t-Statistic	Prob	Lags Used	Decision	*t*-Statistic	Prob	Lags Used	Decision
At level				*First Difference*			
ADF							
–1.325	0.618	8	Non-stationary	–9.722 *	0	7	Stationary
KPSS							
2.373 **	0.010	11	Non-stationary	0.039	0.1	2	Stationary

Notes: * and **— refer to the significance level at 1, 5 and 10%.
Source: done by authors using Python.

pothesis (the opposite of ADF). The results of these two complementary tests are presented in Table 2.

The results presented in Table 2 reveal the outcomes of the stationarity tests. At the level, the ADF test shows a statistic of –1.325 with a *p*-value of 0.618, meaning that the series is non-stationary, as the null hypothesis of a unit root cannot be rejected. Similarly, the KPSS test produces a statistic of 2.37 with a *p*-value of 0.01, indicating the rejection of the null hypothesis of stationarity. However, in the first difference, both tests assume that the series becomes stationary. The ADF test indicates a statistic of –9.722, with a *p*-value of 0, suggesting that we cannot reject the alternative hypothesis, rather we accept it. The KPSS test shows a statistic of 0.039 with a *p*-value of 0.1, indicating that the null hypothesis of stationarity cannot be rejected, rather it is accepted.

After ensuring the stationarity of the series, the ARIMA model for the time series data was determined using the Akaike Information Criterion (AIC). In this study, various combinations of the parameters p and q were compared to determine the optimal lag order. As a result, the best model selected is ARIMA (2, 1, 1), with an AIC value of –374.808. Regarding the residual tests, the Jarque-Bera test indicates that the residuals are normally distributed (p-value = 0.96). The heteroskedasticity test shows evidence of constant variance (p-value = 0.255), while the Durbin-Watson statistic is 2.45, indicating the absence of first-order autocorrelation in the residuals.

The MLPNN Model estimation. The following steps outline the procedure adopted in developing and evaluating the MLPNN model. The first one is the data standardization, which is about to standardize data to ensure that all input features were scaled within a uniform range, thus improving the convergence of the learning algorithm and preventing dominance by features with larger numeric ranges. The normalization process was carried out using the min-max scaling technique, expressed by the following formula

$$x_{\text{scaled}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}.$$

This transformation maps the input data to a range between 0 and 1, which is particularly beneficial when using activation functions that are sensitive to the scale of input data. The second phase is the data partitioning, which indicates that the time series dataset was divided into two separate subsets to facilitate model training and validation. 360 observations were allocated to the training phase, and to train the neural network by adjusting its internal parameters (weights and biases) through an iterative learning process. The remaining 99 observations were allocated to the testing phase, which was used to evaluate the model generalization ability and assess its predictive performance on previously unseen data. The third step is the network structure determination, which shows the identification of the most appropriate architecture for the MLPNN model with testing several configurations. The selection of input neurons was based on the concept of time delay embedding, which helps capture the temporal dependencies in the time series data. A time delay of 2 was adopted, resulting in 2 inputs neurons being used in each case. This means that the model used two previous time steps to predict the next value in the series.

Furthermore, three configurations of the hidden layer were evaluated by varying the number of neurons, which are 5, 10, and 20 neurons. These configurations were chosen to analyse the impact of the network's complexity on its predictive performance. Increasing the number of neurons generally allows the model to capture more complex patterns, but it also increases the risk of overfitting if not properly managed. Besides, the hidden layer utilized the Rectified Linear Unit (ReLU) activation function, which is widely recognized for its computational efficiency and effectiveness in addressing the vanishing gradient problem. ReLU introduces nonlinearity into the model, enabling it to learn complex relationships in the data. Then, RMSE, MAE, and RI are used to assess the predictive performance of the network and determine the best configuration.

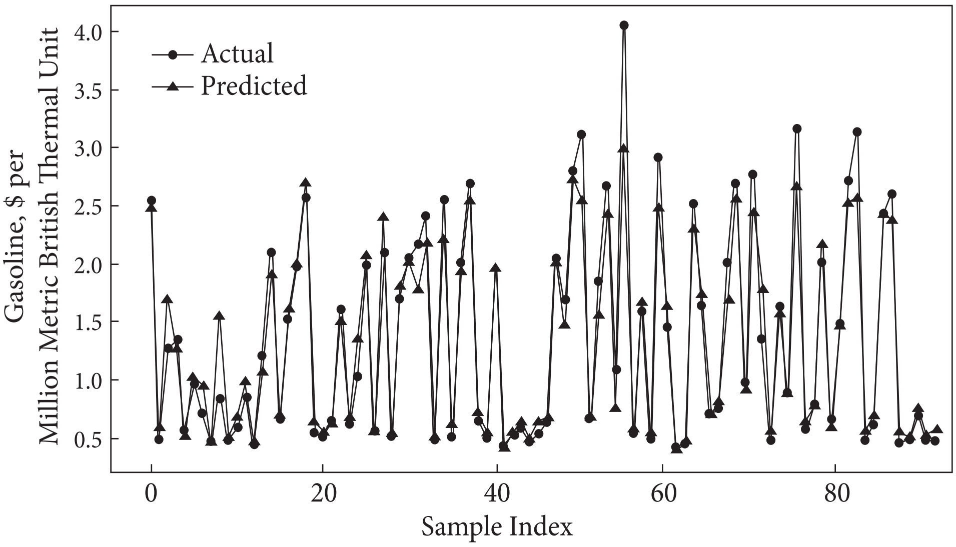

Fig. 2. Comparison of actual and predicted values using a MLPNN model with 10 hidden neurons
Source: done by authors using Python

The results of the evaluation indicate that the model's structure, comprising two input neurons, a hidden layer with 10 neurons activated by the ReLU function, and a single output neuron with a linear activation function, proved to be the most effective configuration according to the evaluation criteria applied, thus the MLPNN model is written as MLPNN (2, 10, 1). Figure 2 below shows the comparison between the actual and predicted values of a MLPNN model consisting of 10 hidden neurons. This configuration provided a good balance between model complexity and generalization capability.

The Figure 2 indicates that the predicted values closely follow the general trend of the actual data. Although there are some discrepancies, particularly in data where the actual values exhibit sharp fluctuations or extreme peaks, the model demonstrates an overall good performance in approximating the observed data. This is consistent with the statistical evaluation metrics obtained for this configuration, where RMSE is 0.328, MAE is 0.272, and RI is 0.866. These results confirm the model's effectiveness in capturing the underlying patterns of the data and its suitability for time series prediction tasks. In summary, the MLPNN model, with its carefully selected architecture and parameters demonstrates strong predictive capabilities in forecasting. The model's structure, comprising two input neurons, a hidden layer with 10 neurons activated by the ReLU function, and a single output neuron with a linear activation function, proved to be the most effective configuration according to the evaluation criteria applied.

The hybrid model estimation. The residual series, which capture the linear unexplained components, was extracted following the estimation of the ARIMA (2, 1, 1) model. In order to estimate the nonlinear structure that ARIMA was unable to capture, this residual series was then used as input data for the MLPNN model.

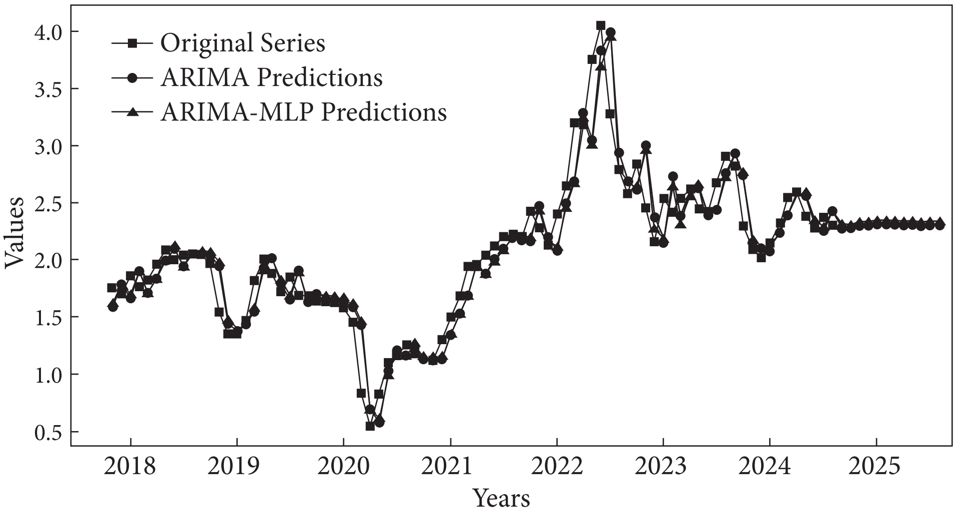

Fig. 3. Graphical representations NGP with original series, ARIMA model and hybrid model
Source: done by authors using Python

Then, to identify the most effective neural network structure, several MLPNN architectures were tested and rigorously evaluated based on the RMSE, MAE and RI criterions. Therefore, the architecture of neural network structure was selected according to these criterions, and the optimal one demonstrates superior predictive accuracy and generalization capability. The optimal ARIMA-MLPNN (hybrid model) architecture selected is composed of two neurons as input layer, 64 nodes in the first hidden layer, and 32 nodes in the second hidden layer, while in the output layer, there is only one single neuron.

Outcomes of ARIMA, MLPNN and ARIMA-MLPNN models. Table 3 describes the comparison among three forecasting model as follow.

According to result from Table 3, it shows that ARIMA-MLPNN has the lowest value of RMSE and MAE, while it has the highest value of R^2, meaning that the hybrid model is the optimal model for forecasting data in this case. This outcome establishes that the hybrid model provides more stable predictions and a stronger ability to explain variance in the data. This suggests that this model effectively captured underlying patterns in the time series, making it a reliable option for accurate and consistent forecasting. Moreover, both the ARIMA model and the hybrid ARIMA-MLPNN model proved to be superior compared to MLPNN. The ARIMA model is ideal for minimizing large forecast errors, while the hybrid model provides a well-balanced performance, combining the strengths of both ARIMA and MLPNN to achieve stable and accurate predictions.

Table 3. **Comparison between ARIMA, MLPNN and hybrid models**

Models	RMSE	MAE	R_2
ARIMA	0.2194	0.1587	0.8742
MLPNN	0.2269	0.1432	0.8354
ARIMA-MLPNN	0.2127	0.1379	0.8861

Source: done by authors using Python.

Figure 3 shows three graphical representations, which are NGP (original series), NGP forecasted with ARIMA and NGP forecasted with hybrid model.

Figure 3 shows several results of the GNP original series, GNP with ARIMA model and GNP with ARIMA-MLPNN model designed on three curves. It displays that both models follow a general trend of the original series (represented in green). The blue dots represent the forecasted series generated by the ARIMA model, while the orange dots represent the forecasted series of the hybrid model. However, the hybrid model appears more stable, especially in the recent periods (2024-2025), indicating its ability to capture non-linear patterns better than ARIMA. Nevertheless, the differences between the two models remain limited, reflecting similar performance in most periods, but the hybrid model potentially provide more accurate forecasts during sharp fluctuations.

The following Table 4 presents the predicted values obtained from both models for the four months of 2024 and the eight months of 2025. The results indicate that there is no significant difference between the forecasted data generated by both models.

According to the results, NGP will rise from September 2024 to February 2025 because of the high demand for natural gas during winter time and high energy power for heating and people's needs, but it will fall from March 2025 to August 2025 because of lower demand.

Since 2023, NGP has decreased due to high storage levels, imports of liquid natural gas, particularly from the United States, decreased demand, and mild winters, which result in less demand for heating in Asia and Europe. Moreover, the conflict between Russia and Ukraine, as well as some geopolitical tension in the Middle East, necessitates the study and forecasting of fossil fuel sources like NGP. As a result, the price of NGP will fluctuate and destabilise a number of nations, particularly the rentier states. However, in 2024, NGP increased in emerging market and developing economies, and the demand for NGP worldwide hit a new all-time high. This result was due to ongoing economic growth, emerging market and developing economies in Asia accounted for about 40% of the additional petrol demand in 2024.

Discussion of Findings and Contribution. The previous outcomes confirm the superior forecasting performance of the hybrid ARIMA-MLPNN model across

Table 4. **ARIMA and ARIMA-MLP results predictions**

Date	ARIMA	ARIMA-MLP	Date	ARIMA	ARIMA-MLP
Sep 2024	2.2812	2.3080	Mar 2025	2.3128	2.3434
Oct 2024	2.2869	2.3175	Apr 2025	2.3120	2.3426
Nov 2024	2.2988	2.3294	May 2025	2.3114	2.3420
Dec 2024	2.3078	2.3384	Jun 2025	2.31112	2.34170
Jan 2025	2.3122	2.3428	Jul 2025	2.31106	2.34168
Feb 2025	2.3133	2.3439	Aug 2025	2.31110	2.34172

Source: prepared by the authors.

all evaluated metrics (RMSE, MAE, R^2). This superiority stems from its capacity to capture both the linear dependencies (via ARIMA) and the complex, nonlinear patterns (via MLPNN, particularly in residuals), a crucial advantage in volatile natural gas markets. This finding directly addresses the identified lack of consensus in the literature regarding optimal forecasting approaches, providing robust evidence for hybrid methodologies. Our integration of linear and nonlinear models further bridges a significant research gap, rigorously demonstrating their combined benefits in capturing the intricate behavior of NGP, especially amidst structural breaks and prolonged volatility from global disruptions like the COVID-19 pandemic and the Russia-Ukraine war.

The study's use of an extended dataset spanning over three decades (June 1986 to August 2024) significantly enhances the empirical validity and fills a crucial void, as comprehensive comparisons of ARIMA, MLPNN, and hybrid models on such long, volatile series are rare. Our findings align with G. Zhang (2003) and subsequent studies that advocated for hybrid ARIMA-ANN models, but our unique contribution lies in validating their robustness over an unprecedented period of global instability and geopolitical shocks, an aspect less explored previously (e.g., Su et al., 2019). The demonstrated robustness of the hybrid model offers valuable practical implications. For policymakers, it supports more effective energy policy formulation and risk management. For investors and market participants, this reliable predictive tool can lead to more informed trading decisions and enhanced national energy security in an increasingly uncertain global energy landscape marked by supply chain disruptions and geopolitical uncertainties.

CONCLUSION

This paper successfully investigated natural gas spot price (NGP) forecasting using ARIMA, Multi-Layer Perceptron Neural Network (MLPNN), and a hybrid ARIMA-MLPNN model, spanning data from January 1997 to August 2024. The empirical results definitively show that the hybrid ARIMA-MLPNN model is optimal, achieving the lowest RMSE and MAE, and the highest R^2. This model's superior performance, particularly in capturing both linear and nonlinear patterns, proved crucial for accurate forecasting in a volatile market characterized by recent global disruptions. The study also provided NGP predictions, indicating a rise from September 2024 to February 2025 due to winter demand, followed by a decrease from March 2025 to August 2025.

Accurate NGP forecasting is vital for effective planning and decision-making in the energy sector. This paper makes several key recommendations. First, for sustainable energy management, it is crucial to deploy optimal forecasting models like the hybrid ARIMA-MLPNN into real-time systems. Second, future research should explore more advanced hybrid approaches, potentially integrating deep learning techniques such as Long Short-Term Memory (LSTM) or Convolutional Neural Networks (CNN) to enhance prediction accuracy. Finally, incorporating external factors like economic indicators, policy changes, and climate variables is essential to further improve model performance, especially given the susceptibility of prices to weather events, supply disruptions, and geopolitical shocks like the Russia-Ukraine conflict and non-linear market dynamics.

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ПОРІВНЯЛЬНИЙ АНАЛІЗ МОДЕЛЕЙ ARIMA, MLPNN І ГІБРИДНОЇ МОДЕЛІ ДЛЯ ПРОГНОЗУВАННЯ СПОТОВИХ ЦІН НА ПРИРОДНИЙ ГАЗ ВІД HENRY HUB

Метою цього дослідження є прогнозування спотових цін на природний газ за допомогою трьох підходів до моделювання: ARIMA (авторегресійна інтегрована модель ковзних середніх), нейронної мережі типу багатошарового перцептрона (MLPNN) і гібридної моделі ARIMA-MLPNN. Аналіз ґрунтується на щомісячних даних з червня 1986 р. по серпень 2024 р. Ураховуючи волатильність цін на газ, спричинену геополітичною напруженістю і динамікою ринку, підвищення точності прогнозу має вирішальне значення для планування й розроблення політики. Модель ARIMA, придатну для лінійних закономірностей, і модель MLPNN, ефективну для опрацювання нелінійних зв'язків, було оцінено разом з гібридною моделлю, яка інтегрує обидва підходи для усунення їх індивідуальних обмежень.

Для оцінювання моделей використано статистичні показники ефективності: середньоквадратичну похибку (RMSE), середню абсолютну похибку (MAE) і коефіцієнт детермінації (R^2). Результати показали, що гібридна модель ARIMA-MLPNN перевершує обидві окремі моделі, забезпечуючи вищу точність прогнозування і краще реагуючи на структурні зміни в даних. Гібридна модель продемонструвала надзвичайно високу ефективність протягом останніх періодів, що характеризуються глобальною нестабільністю, підтверджуючи свою стійкість у опрацюванні як лінійних, так і нелінійних компонентів часових рядів.

Підкреслено важливість застосування гібридних методів прогнозування в економіці енергетичного сектору, особливо для ухвалення стратегічних рішень в умовах невизначеності. Результати дослідження показують, що поєднання традиційних статистичних моделей з машинним навчанням розширює прогностичні можливості, що робить гібридну модель ARIMA-MLPNN надійним інструментом для прогнозування цін на природний газ.

***Ключові слова**: ухвалення рішень; прогнозування спотових цін на природний газ; авторегресійні інтегровані моделі ковзних середніх; модель нейронної мережі типу багатошарового перцептрона; гібридна модель.*

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