10th International Scientific Conference ERAZ 2024 – Selected Papers
https://doi.org/10.31410/ERAZ.S.P.2024.97

Using Particular Time Series Algorithms to Model Natural Gas Indicators for the US

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Received: August 30, 2024
Revised: February 11, 2025
Accepted: February 26, 2025
Published: April 5, 2025

Keywords:
Seasonal autoregressive integrated moving average;
Time series;
Natural gas

Abstract: *Natural gas is a gaseous material that primarily consists of hydrocarbons. This is a primary component of energy resources and a fossil fuel. Its primary attribute is that it produces energy with great efficiency while generating negligible amounts of pollution. Natural gas is used in a wide range of industries. It is widely used as fuel for automobiles, to produce electricity, and for home heating. Because of its benefits, which include lower carbon emissions than other energy sources, natural gas is a desirable choice for both consumers and businesses. The purpose of this paper is to use the SARIMA (Seasonal Autoregressive Integrated Moving Average) model and the additive Holt-Winters model to forecast changes in natural gas prices in the United States and compare both models. These are a few of the most popular models for forecasting and time-series analysis.*

1. INTRODUCTION

This paper intends to forecast the natural gas prices over a months-long period using two fundamental time series models. It used the SARIMA model and the additive Holt-Winters model to forecast the evolution of natural gas prices in the United States. Time series that show seasonality can use this model without having to eliminate it. SARIMA is a seasonal component-based univariate time series model that is an extension of the ARIMA (Autoregressive Integrated Moving Average) model. Stated differently, the ARIMA model is transformed into a SARIMA model by incorporating seasonal elements. It is worth noting that in May 2021, in the United States, a cyber-attack occurred at one of the major fuel suppliers, three years after a similar event occurred in 2018. Then, in April, several US natural gas pipeline operators, including Energy Transfer Partners LP and TransCanada Corp., reported that a third-party electronic communications system had been compromised by a cyberattack. Five of the companies confirmed that he was responsible for service disruptions. While the cyber-attack did not disrupt gas supplies to US homes and businesses, it demonstrated how even minor attacks can have far-reaching consequences. The attack forced utilities to warn of widespread billing delays and made it difficult for analysts and traders to forecast a key government report on gas stocks.

Forecasting natural gas prices and energy consumption is an important policy tool for many decision-makers around the world (Bilgili & Pinar, 2023). It must be acknowledged that rising energy and natural gas prices, which are sometimes caused by inherent and unforeseeable events (such as war or pandemic), cause inflation to rise and economic growth to slow.

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The creation of models to forecast natural gas prices, yielding results consistent with socio-economic expectations, significantly aids in the formulation of policies and decisions conducive to sustainable development. This concept is crucial to comprehend and address, as it significantly influences the fulfillment of current needs without jeopardizing future generations' capacity to satisfy their requirements. This sustainable development aims to achieve a balance between economic advancement and the preservation of social and ecological equilibrium. Natural gas, energy, and natural resources are fundamental to development and survival; thus, it is essential to assess their prices to formulate policies and decisions that promote improved living standards and a robust economy.

2. LITERATURE REVIEW

In the recent literature, Gao et al. (2021) proposed a study of the markets in the United States, Japan, and the European Union through the perspective of the natural gas price, following its forecasting through a comparative approach that begins with the use of several models, such as time-varying coefficient with stochastic volatility models, Markov switching models, and hybrid models. The authors find reliable proof that models with time-varying covariance are critical for predicting gas prices throughout the three markets.

Peng (2023) used the MVMQ-CAViaR multiple market model to examine the impact of oil and natural gas prices on overnight risk in the HKD, RMB, and Yen markets. Proceeding in this manner, he concluded that the impact of oil price risk on the overnight risk of the three currencies is greater than that of natural gas prices. This can also be explained by the fact that oil is consumed more than natural gas.

In terms of the natural gas and energy markets, the recent literature contains numerous studies on the development of machine learning models for forecasting such indicators. These models include the following: nonlinear autoregressive neural network (Jin & Xu, 2024), neural networks (Herrera et al., 2019; Pei et al., 2023), support vectors regressions (Su et al., 2019; Čeperić et al., 2017), regression trees (Mouchtaris et al., 2021), boosting (Su et al., 2019), Gaussian process regressions (Mouchtaris et al., 2021).

To sustain a balance between natural gas demand and supply, a model that makes an efficient prediction must be identified because most countries must maintain a stable economy without incurring significant losses. To overcome the limitations of single models, Gao et al. (2023) proposed a hybrid model based on the Choquet integral for NGC forecasting time series. Before combining models, the prediction problem requires a decision support model to evaluate model performance effectively during model selection. Additionally, the proposed model uses LSTM, GHW, and SARIMA to collect information in time series. Interactions between models are introduced to improve model stability, particularly in the context of incidents. The efficacy of the model is demonstrated using datasets of natural gas consumption in the United States.

Su et al. (2025) analyze the characteristics and laws governing natural gas price fluctuations, turning points, and the scope of influence in Asia-Pacific natural gas markets. Japan/Korea Maker natural gas spot price time series has been transformed into a visibility graph network of natural gas prices and a visibility graph network of natural gas price fluctuations. The findings show that time series changes in Asia-Pacific natural gas prices are not random, but have long-term persistence, with it taking approximately 314 days to erase the historical memory of the natural gas price time series.

In addition, concerning natural resources, Guo et al. (2023) present methods associated with artificial intelligence to evaluate the most effective forecasting strategy for the price of crude oil futures in China. The processing of historical data, volatility, and non-linear characteristics is accomplished through the use of machine learning. They estimate the forecasting effects of RNN, LSTM, GRU, SVR, MLP, CNN, and BP models on China crude oil futures, respectively, by using daily data from March 26, 2018, to February 28, 2023. These periods span from March 26, 2018, to February 28, 2023. Using many different evaluation tests, we can demonstrate that the GRU model is superior to other models in terms of the accuracy of its forecasts and its overall performance for the price of crude oil futures in China.

Mati et al. (2023) investigate the performance of three models, namely the Autoregressive Integrated Moving Average (ARIMA), the Threshold Autoregressive Moving Average (TARMA), and the Evidential Neural Network for Regression (ENNReg), in forecasting the price of Brent crude oil. This is an important economic variable that has a significant impact on the economy of the entire world. The analysis suggests incorporating the impact of the war can significantly improve the forecasting accuracy of the models, with the ENNReg model exceeding the other models during the war.

Chaturvedi et al. (2022) compare the performance of four time-series models for predicting total and increased monthly energy demand in India. The existing trend-based model from India's Central Energy Authority (CEA) is compared to Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Long Short Term Memory Recurrent Neural Network (LSTM RNN), and Facebook (Fb) Prophet models. Using 108 months of training data to predict 24 months of unseen data, the CEA model predicts monthly overall demand for energy with low root-mean-square error (RMSE 4.23 GWh) and mean absolute percentage error (MAPE, 3.4%), but significantly underestimates monthly peak energy demand. Also, researchers used various energy methods to forecast depending on the type, quality, and length of time resolution of the available data. ARIMA is the most general and commonly utilized time-series model for predicting future energy consumption (Akpinar & Yumusak, 2016; Al-Musaylh et al., 2018; Deb et al., 2017). Some studies rely on the fact that it is useful to combine hybrid approaches, integrating various prediction models in order to attain more versatility and prediction accuracy than a single model (Barassi & Zhao, 2018; Kim & Cho, 2019; Wang et al., 2012).

Meira et al. (2022) propose a new approach for forecasting natural gas consumption using ensembles. It combines Bootstrap Aggregation (Bagging), univariate time series forecasting, and modified regularization schedules. A novel version of Bagging is introduced, which employs Maximum Entropy Bootstrap (MEB) and an updated regularization routine to keep the data generation process within the group of data.

3. METHODOLOGY

In essence, seasonally adjusted ARIMA models have the same structure as non-seasonally adjusted ones, with the exception that, in the case of SARIMA, all factors will take into account multiple lags of order s, where s is the number of seasons (Banaś & Utnik-Banaś, 2021). As a result, SARIMA models are classified as ARIMA (p, d, q) x (P, D, Q) models, with the first part representing the non-seasonal component and the second, capitalized, the seasonal. They have the following meanings:

- p → the autoregressive term;
- d → the term regarding the integration order;
- q → the term moving average;

- P → the number of autoregressive seasonal terms (SAR);
- D → the number of seasonal differences;
- Q → the number of seasonal moving average terms (SMA).

Before determining whether or not a series exhibits seasonality, it is necessary to decide whether or not the series is stationary, as the majority of series in the economy are not stationary. Thus, we can use one of the following methods: graphical analysis (of the schedule and correlogram), evolution of the autocorrelation function (ACF) and partial autocorrelation (PACF), Bartlett, Box Pierce and Ljung Box tests, Dickey-Füller test. Another important test is the Hegy test, which determines whether or not the unit root exists in the series. Its assumptions are:

$$\begin{cases} H_0:\ \pi_i = 0 \\ H_1:\ \pi_i < 0 \end{cases}$$

If π_i are not equal to zero, the null hypothesis H_0 is rejected and H_1 is accepted, indicating that the series is stationary.

Once the series has been analyzed for stationarity, it will be possible to identify the seasonality of the relevant model. The first step is to determine whether a seasonal difference is required in addition to or instead of a non-seasonal difference by analyzing the model's graphs, the autocorrelation function, and the partial autocorrelation function and identifying all existing combinations of non-seasonal differences of order 0 or 1 and seasonal differences of order 0 and 1. When identifying them, it is also important to consider whether the seasonal component is strong and stable over time, in which case the seasonal difference should be used so that the chosen model can still make accurate forecasts. An important rule in this step is to avoid using more than one seasonal difference or more than two differences in total (seasonal and non-seasonal).

The next step is to adjust the autocorrelation for the seasonal period. If this is positive, a SAR term is added to the model as a variant; if it is negative, a SMA term is used. The value is positive when no seasonal difference is made, indicating that the seasonal pattern is unstable, and negative when a seasonal difference is used for a stable and logical model. In this situation, avoid using more than one or two seasonal parameters (SAR+SMA) in the same model, as this will result in data overfitting and/or estimation issues.

Long-term forecasts typically employ linear time series models, such as ARIMA and exponential smoothing methods, which forecast based on historical data. For exponential smoothing methods, the forecasts are weighted averages of the observations, with informational weight decreasing as the series becomes out of date. Holt-Winters is one example of such a method.

The Holt-Winters method, also known as triple exponential smoothing, estimates behavior, trend, and seasonality using a weighted moving average. As a result, there will be three parameters, one for each smoothing, and the method will have two models: additive and multiplicative. An additive model is suitable for a series in which the seasonal pattern's amplitude is not influenced by the average level of the series. This type of series is characterized by additive seasonality. Given the fluctuating nature of seasonality in the data series, this model will be employed for forecasting purposes.

The equations for the additive model are as follows, where a_t, b_t, s_t Represent the standardized estimates of behavior, trend, and seasonality, and α, β, γ denote the smoothing parameters:

$$a_t = \alpha\left(x_t - s_{t-p}\right) + (1-\alpha)(a_{t-1} + b_{t-1}) \quad (1)$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \quad (2)$$

$$s = \gamma(x_t - a_t) + (1-\gamma)s_{t-p} \quad (3)$$

These parameters highlight the significance of differentiating between old and new data, as well as the exponential decay of information weight based on data age (Alonso-Brito et al., 2021).

4. DATA

The data source is The U.S. Energy Information Administration (EIA) - Short-Term Energy Outlook. The EIA is the primary statistical agency in charge of gathering, analyzing, and disseminating information about energy in economic and environmental contexts. The analyzed time horizon spans from January 1, 1981, to February 1, 2021. This period was chosen because it marked the start of oil price deregulation, with the Reagan administration allowing US producers to raise prices to market levels. The forecast horizon spans the next 24 months. Nominal prices were converted to comparable prices using the consumer price index, which was then logarithmized to work with returns for higher forecast accuracy.

5. RESEARCH RESULTS

The case study was developed with the help of the *RStudio* software. For the first time, the data set was divided into two parts: the training set, which contains 75% of the observations (January 1981 - December 2012), and the test set, which contains 25% of the observations (January 2013 - February 2021), with an out-of-sample forecast horizon of 24 months.

The analysis of Figure 1 shows that the series fluctuates in its evolution: it has an upward trend until 1985, then decreases until 2000, and finally reaches a maximum in 2008. Thus, the series is not stationary.

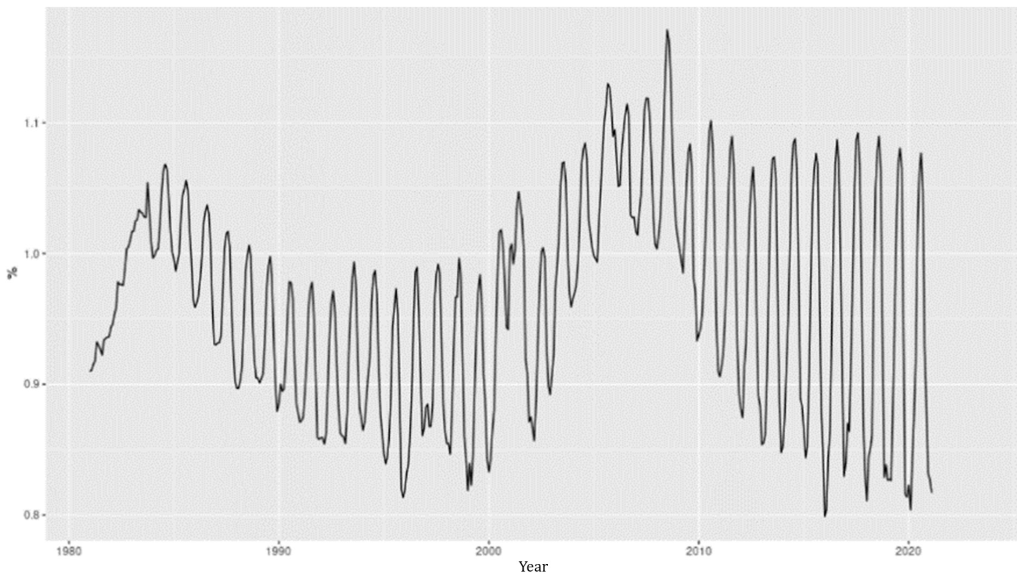

Figure 1. The evolution of the price of natural gas in the period 1981 – 2021

Source: Own processing

To be certain about stationarity, we will use the Augmented Dickey-Fuller (ADF) root test. Analyzing the ADF test results, which are summarized in Table 1, we can conclude that the series exhibits stochastic non-stationarity, with probabilities exceeding the 10% significance threshold. The null hypothesis is accepted, implying that the series admits a unit root, and thus the time series is first-order integrated, i.e. non-stationary.

Table 1. Augmented Dickey-Fuller (ADF) test results

	Critical values τ	τ_{calc}	Likelihood
Trend & Intercept			
Threshold 1%	-3.982988	-2.445024	0.3556
Threshold 5%	-3.421983		
Threshold 10%	-3.133816		
Statistically insignificant coefficient for deterministic trend			
Intercept			
Threshold 1%	-3.447770	-2.364803	0.1526
Threshold 5%	-2.869113		
Threshold 10%	-2.570871		
None			
Threshold 1%	-2.571210	-0.099602	0.6488
Threshold 5%	-1.941680		
Threshold 10%	-1.616127		

Source: Own processing

From Figure 2 it follows that the price of natural gas is higher in the summer and lower in the winter, indicating that the analyzed series is seasonal.

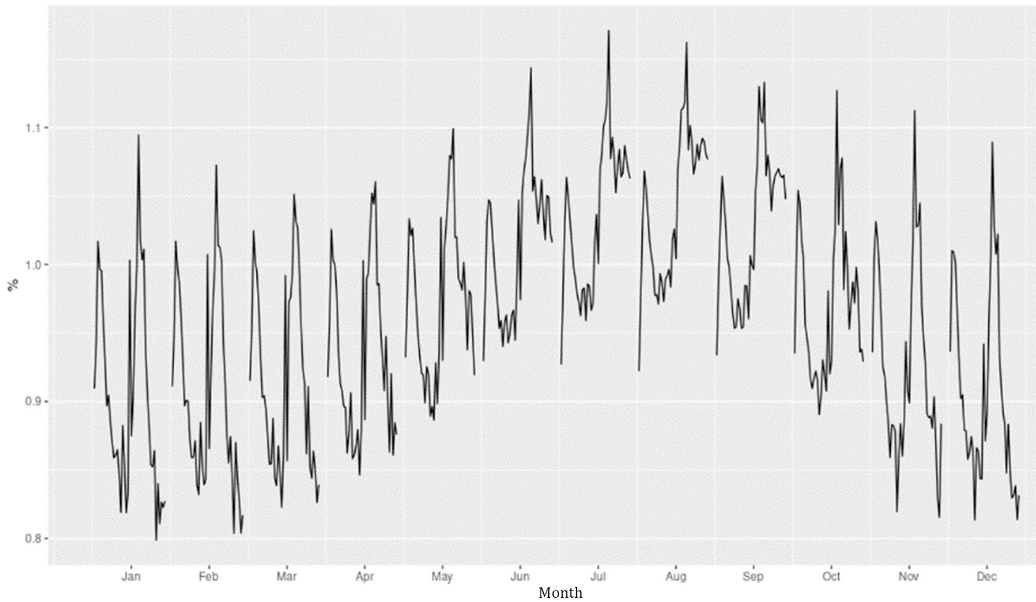

Figure 2. Chart of averages by season

Source: Own processing

Due to the presence of seasonal patterns in the data, we utilized the SARIMA model to predict future values for the specified period. To eliminate non-stationarity, we conducted the HEGY (Seasonal Unit Root Test) to determine whether non-seasonal or seasonal differentiation should be applied. This analysis determines if the series exhibits a seasonal unit root and if there is a peak at any seasonal frequency in its spectrum, excluding the zero frequency.

Based on the information presented in Figure 3, the first value is considered statistically insignificant (p-value > 0.1). Therefore, we cannot reject the presence of a unit root in the series, and we acknowledge that the series does have a unit root. Similarly, because the first frequency is insignificant and the probability exceeds the significance threshold, the presence of the seasonal unit root cannot be discounted. To be stationary, the analyzed series must have both a seasonal and non-seasonal difference.

```
        HEGY test for unit roots

data:  training

        statistic p-value
t_1       -1.6843  0.4185
t_2       -6.0976       0 ***
F_3:4      1.2123  0.3122
F_5:6      9.1131   1e-04 ***
F_7:8     49.7465       0 ***
F_9:10    46.7663       0 ***
F_11:12   72.2071       0 ***
F_2:12    229.155       0 ***
F_1:12   210.4974       0 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Deterministic terms: constant
Lag selection criterion and order: fixed, 0
P-values: based on response surface regressions
```

Figure 3. The HEGY test for determining the existence of unit roots

Source: Own processing

Analyzing the graphs in Figure 4 reveals that the series is now stationary. We also identified an SMA(1) process because the coefficient on the seasonal lag on ACF is significant and the partial autocorrelation function coefficients decrease slowly with seasonal lags.

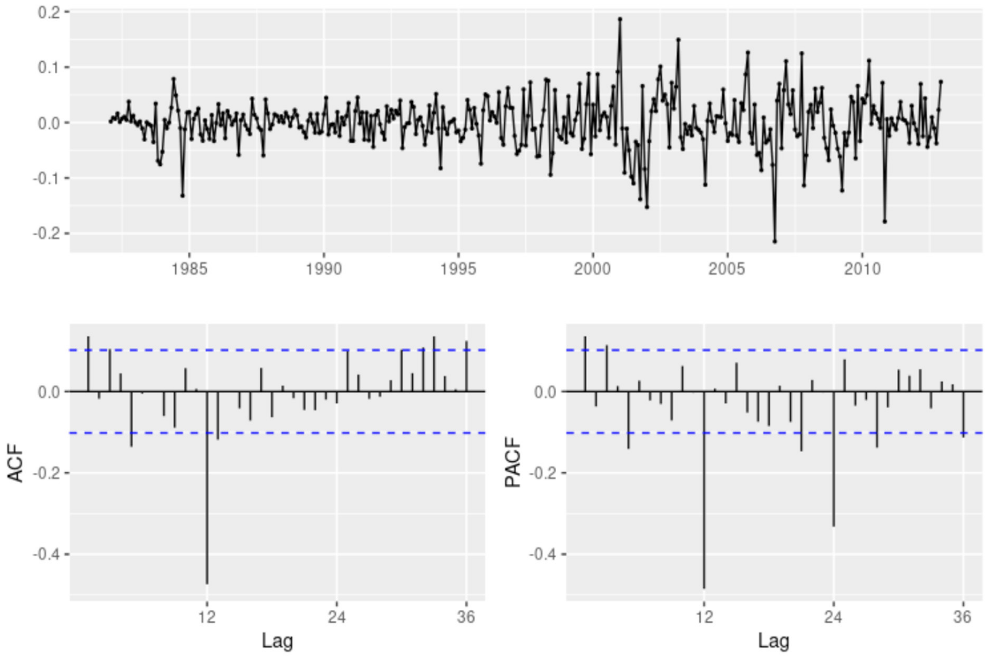

Figure 4. Stationary time series

Source: Own processing

For the non-seasonal component, the authors tested several models: SARIMA(1,1,1)(0,1,1), SARIMA(1,1,0)(0,1,1), SARIMA(0,1,1)(0,1,1), and SARIMA(2,0,0)(0,1,1). Considering that the first model has insignificant coefficients and Auto-Arima proposed a model with no non-seasonal differentiation, we compared models 2 and 3.

As can be seen in Table 2, The optimal model is SARIMA(1,1,0)(0,1,1) due to lower values for AIC, AICc, and BIC in the first model compared to the second.

Table 2. Performance indicators for each of these models

Model/Criteria	AIC	AICc	BIC
SARIMA(1,1,0)(0,1,1)	-1400.88	-1400.81	-1389.13
SARIMA(0,1,1)(0,1,1)	-1400.13	-1400.06	-1388.38

Source: Own processing

Finally, the forecast was made on the test set, and the results are provided in Figure 5.

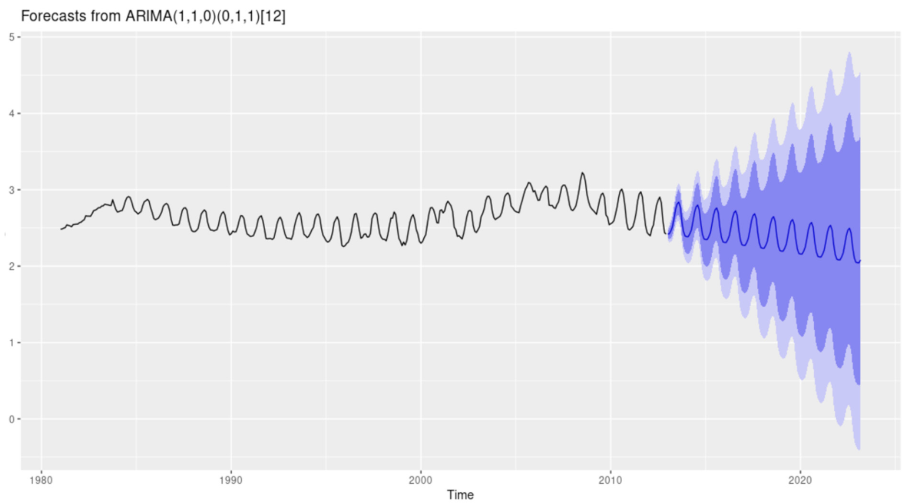

Figure 5. Natural gas prices forecast with SARIMA model
Source: Own processing

Regarding the Holt-Winters additive model, the results on the forecast horizon can be found in Figure 6.

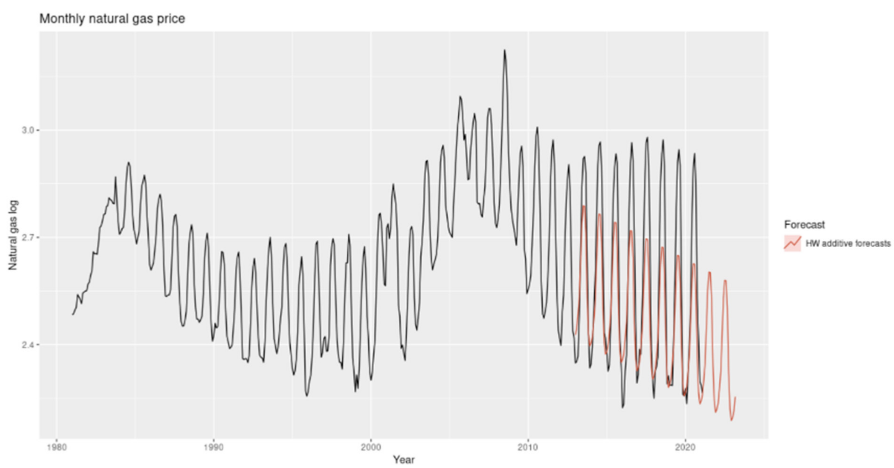

Figure 6. Holt-Winters additive model for gas prices forecast
Source: Own processing

Considering that both models presented in the article provide a forecast in line with realistic and economic expectations but have different accuracy, a final decision on the best model for forecasting natural gas prices will be made based on forecast accuracy indicators, with a conclusion to be formulated in this regard. Table 3 depicts the forecast performance indicators for the two models for the test set.

Table 3. Forecast performance measurement indicators

Model/Indicators	ME	RMSE	MAE	MPE	MAPE	MASE
SARIMA(1,1,0)(0,1,1)	0.2331	0.2471	0.2331	8.9121	8.9121	2.8605
Holt-Winters	0.1419	0.1790	0.1419	5.2316	5.2316	1.7419

Source: Own processing

6. FUTURE RESEARCH DIRECTIONS

Future research directions may include the use of other specific time series models (for example, VAR/VECM to analyze the impact of natural gas prices on electricity or oil prices). In addition, a hybrid model can be developed to overcome the limitations imposed by a single model and improve forecast accuracy. Such trends have been identified in the literature.

7. CONCLUSION

Summarizing all of the considerations presented in this article, the goal of the research is to forecast the price of natural gas in the US market, taking into account the importance of this indicator and the outcomes that decision-makers seek when developing policies and strategies, as well as selecting an optimal model that best captures expectations and socioeconomic reality. The overall goal of the research was to estimate results that will provide adequate support for decision-making to meet the high standard of living incorporated into the concept of sustainable development.

To perform the analysis, two-time series models, SARIMA and the Holt-Winters additive model, were used, with seasonality taken into account. The models were applied to monthly data from January 1981 to February 2021, with a forecast horizon of 24 months. Considering that the two final models chosen for the forecast have different accuracies, the forecast accuracy indicators for both models were compared on the test sets, with the Holt-Winters additive model emerging as the most suitable for forecasting, with the six indicators in Table 3 having lower values for this model. Beyond selecting the best model based on performance indicators, the article's two models can contribute to estimating the price of natural gas following economic expectations over a 24-month time horizon, which should not be too long to obtain a more accurate forecast. This also helps to support sustainable development because there are no unexpected fluctuations in gas prices over the forecasted time horizon, which would destabilize the economy and, implicitly, development.

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