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# *Forecasting Post-Crisis Volatility: An ARIMA Model Application to European Natural Gas Prices*

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***Abstract.*** Geopolitical upheavals and the ongoing energy transition have significantly heightened volatility in the European natural gas market, elevating the critical need for reliable price forecasts. Here, the autoregressive integrated moving-average (ARIMA) model is employed to forecast gas prices in Europe. To improve the reliability and generalization ability of the model, the dataset comprising daily closing prices of Dutch TTF Natural Gas Futures from January 1, 2023, to December 31, 2025, is incorporated into the model. Stationarity was ensured by applying the Augmented Dickey-Fuller (ADF) test and differencing where necessary. Model order (p, q) was selected by minimizing the Akaike Information Criterion (AIC). The ADF test shows that the original series is non-stationary; further, stabilized data sequences are obtained for the ARIMA model by differentiating the series. A reliable ARIMA(3,1,2) model was selected based on AIC minimization and validated through rigorous residual diagnostics. The study provides a validated statistical framework for short-term gas price forecasting. The model and its findings offer valuable quantitative insights for policymakers, traders, and risk managers navigating the post-crisis European gas market, supporting decisions related to security of supply, cost management, and investment.

***Keywords:*** ARIMA Model, TTF Natural Gas, Volatility Forecasting, Energy Markets, Post-Crisis Analysis

## 1. Introduction

### 1.1. Research background and significance

#### 1.1.1. Strategic importance of the European gas market

The European natural gas market occupies a pivotal position in the global energy system. With the EU advancing its "carbon neutrality" goal to 2050 and accelerating the energy transition, natural gas, as the cleanest fossil fuel, has become increasingly prominent as a transitional fuel in the energy mix. Europe is the largest player in global pipeline trade, responsible for 40% of global imports and 20% of exports [1]. In recent years, due to multiple factors, including geopolitical conflicts, changes in energy policy, and fluctuations in renewable energy, European natural gas market prices have exhibited unprecedented volatility.

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The Dutch Title Transfer Facility (TTF) has become a benchmark indicator for European natural gas prices, as it is the continent's most important virtual gas trading hub. TTF prices not only reflect the supply and demand for natural gas in Europe but also profoundly affect the global liquefied natural gas (LNG) trade flow and pricing mechanism. The work reported in this article used the Dutch TTF Natural Gas Futures (TFAc1) price as a benchmark for European natural gas prices to forecast European natural gas prices from January to June 2026, using daily closing prices of the futures.

#### 1.1.2. Economic implications of natural gas price volatility

To begin with, the escalated prices of gas have directly led to high inflation within Europe. Eurostat claims that in 2022, at the peak of consumption and growth, energy inflation in the eurozone was more than 40 percent, and the main factor was the price of natural gas [2]. As a result, European manufacturing has been exposed to poor competitiveness on the global market, especially the energy-intensive industries, which include chemicals, steel, and non-ferrous metals [3].

Secondly, being a major raw material in industries, an intermediate good, and a source of energy, natural gas price volatility has a direct effect on the cost base of the downstream industries. This has been the greatest impact of the power industry, where the majority of European countries have adopted marginal-cost pricing mechanisms, which base their electricity prices on natural gas prices, especially during the peak months of the year, resulting in the concomitant increase of electricity prices. This not only makes living more expensive for the residents but also poses a threat of disrupting the normal running of the industrial production.

Moreover, TTF natural gas futures have become a significant financial derivative worldwide [4]. Their price fluctuations significantly impact the pricing and risk management of energy financial products. As a result, price uncertainty increases hedging costs for market participants and affects the stability of energy finance markets.

In addition to the direct economic effects, fluctuation of the prices highlights the vulnerability of the European energy supply. In the background of a decrease in the number of Russian natural gas supplies, the role of LNG imports to Europe has become significantly high, and TTF prices have now become one of the crucial sources of information on the competition of LNG resources in the world market. However, proper price forecasting plays a vital role in obtaining energy sources, eliminating politics in importation policies, and facilitating the process of policy-making.

### 1.2. Literature review

The gas price forecasting in Europe is so tricky because of the interaction of various factors in various dimensions. The current literature singles out three key classes of influencing factors, and the highlight of the problem of European gas price predictions is the interaction of these factors. On the supply aspect, the flow of natural gas and liquid natural gas (LNG) supplied by the pipeline, geopolitical events, and unpredictable changes in regional inventory all combine to form the direct cause of price jolts [5]. At the demand side, market fundamentals are still being influenced by strong demand patterns in the seasonal and cycle variations in the macroeconomic cycles, as well as substitution effects caused by changes in the share of renewable energy generation. Besides that, there are market and financial reasons, including previous connections to oil prices through indexes, market fluctuations, and market speculations in the futures market, which contribute to the further improvement of the financial quality and volatility of the price series.

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Although the Autoregressive Integrated Moving Average (ARIMA) model has been widely used in energy price forecasting [6-9], there are still several key gaps in existing research on European gas prices: first, the lack of modelling according to extreme fluctuation data in the post-crisis period (2022-2025) is inherent, which incorporates the most unforeseen price volatility and structural changes to the market. Secondly, no systematic current up-to-date analysis of the ARIMA model predictive efficiency in the present complex market environment exists. Lastly, time-sensitive, strong, short-term forecasting tools, which should be explored in detail, are still needed in the market. These gaps will not only transform the theoretical analysis of the correlation between energy prices and extreme market conditions, but also offer some practical aids to the market participants to survive in the highly fluctuating European gas market.

### 1.3. Research framework

The ARIMA model was employed in this research to predict the price of gas in Europe. The data sample consists of closing prices of the Dutch TTF Natural Gas Futures on January 1, 2023, through December 31, 2025. This makes the ARIMA model still a basic tool in the prediction of energy prices because of its theoretical maturity and strong performance in stationary sequences [10]. On the data level, the study employed a dataset that spanned the past years of sudden market-related volatilities, hence providing better models of recent complex market conditions in the near future. To enhance the reliability and generalization capacity of the model, this study adopted a rather strict method of model construction at the methodological level. Finally, the practical value of this research was that it offered a better predictive instrument in the short term to policy makers, traders, and risk managers, and thus offered a timely quantitative aid to the supply security, cost control, and investment choice in the high-risk European natural gas market.

## 2. Methodology: ARIMA model framework and application

### 2.1. Theoretical foundations of the ARIMA model

To address the research gaps identified in Section 1.3, particularly the need for a robust and interpretable short-term forecasting tool, this study employed the Autoregressive Integrated Moving Average (ARIMA) model. This section delineates its theoretical underpinnings. ARIMA can be defined as a time series prediction model, and the main principle of its operation is to model time-dependent projections and random variations present in the past in order to forecast the events occurring in the future. A three-term model is known as autoregression, which incorporates the lags of a series to represent persistence, differential, which filters the series to smooth by removing trends and seasonality, and moving averages, which models prediction error in history to make the most optimal short-term adjustments [11]. Upon systematic combination of the above three components, ARIMA can offer a brief and efficient statistical prediction design to time-independent and time-dependent data. For an ARIMA model, its mathematical expression is based on $p, d, q$ , a stationary sequence after $d$-order difference $Y_t^{'}$ (where $Y_t^{'} = (1-L)^d Y_t$ , $L$ is a lagging operator)in the form of [10].

$$\left(1-\phi_1 L-\phi_2 L^2-\cdots-\phi_p L^p\right) Y_t^{'}=c+\left(1+\theta_1 L+\theta_2 L^2+\cdots+\theta_q L^q\right) \varepsilon_t \tag{1}$$

or equivalently expanded to the more common prediction equation [10].

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$$Y_t^{'} = c + \phi_1 Y_{t-1}^{'} + \phi_2 Y_{t-2}^{'} + \cdots + \phi_p Y_{t-p}^{'} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{2}$$

where:

$Y_t$ : observations of the original time series in $t$ ,

$Y_t^{'}$ : stable sequence after order $d$ ,

$L$ : lag operator( $L^k Y_t = Y_{t-k}$ ),

$p$ : the number of self-regression items,

$d$ : difference order (the minimum number of differences required to smooth the sequence),

$q$ : moving average item order,

$\phi_1, \ldots, \phi_p$ : autoregression coefficient,

$\theta_1, \ldots, \theta_q$ : moving average coefficient,

$c$ : c number,

$\varepsilon_t$ : the white noise error term with zero mean and constant variance.

### 2.2. Model implementation procedure

#### 2.2.1. Data preparation and stationarity testing

In this project, we are gathering the daily close price of the Dutch TTF Natural Gas Futures between January 1, 2023, and December 31, 2025. It performed a preliminary data analysis during the first step to check the stationarity of the sequences. In case the sequence had been identified as non-stationary, a first-order difference was computed. It is a loop: once the sequence is differentiated, the new sequence is retested with the loop being repeated until the stationarity point is met. The step is essential to stabilize the sequence and make it fit ARIMA modelling.

#### 2.2.2. Model recognition

The order (p, d, q) was calculated in this step. To examine the two major diagnostic diagrams, it was recognized as autocorrelation and partial autocorrelation functions. Through the analysis, the initial determination of the values of the features of p and q was achieved. The project tries to fit models with various (p, q) combinations and picks the model that achieves minimum AIC, which strikes the correct balance between model fit and model complexity and does not over-fit. Although BIC is stricter about model complexity, the adoption of AIC as the final model of choice was for the reason that AIC was interested in being up to date with prediction accuracy, which is the main aim of this forecasting study [12,13]. A grid search was based on the preliminary (p, q) points of the analysis of ACF, and the model was selected by minimizing the AIC criterion.

#### 2.2.3. Model estimation and diagnostic testing

Using the selected ARIMA (p, d, q) model, it was estimated using statistical software (R), and the coefficients of the AR and MA terms were calculated. This was followed by rigorous diagnostic testing to verify the model's adequacy. A good model with residuals should approximate white noise. The adequacy of the fitted model was rigorously assessed through residual diagnostics. The key criterion is that the residuals must exhibit properties of white noise: no significant autocorrelation, constant variance, and an approximate normal distribution. Afterwards, the Ljung-Box test was

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carried out to assess residual autocorrelation formally and to examine the residual plot for patterns or heteroscedasticity.

#### 2.2.4. Prediction and validation

After confirming the model to be statistically sufficient, out-of-sample prediction can be done using the model. The project operates on time-series cross-validation to introduce the simulations of actual real-time prediction. The data was divided into a training set and a retained set. This model was trained on the training set, and predictions were applied to the testing set. The source of the prediction was then rolled forward, and the procedure was repeated to create a series of predictions.

#### 2.2.5. Result integration and interpretation

The project understands the short-term momentum and shock persistence inherent in the price series by interpreting the significance of the estimation coefficients. At the same time, the model's advantages and limitations were clearly discussed. Ultimately, the prediction results were closely tied to the economic and geopolitical realities of the European gas market.

### 2.3. Model justification and limitations

#### 2.3.1. Rationale for model selection

The ARIMA model was chosen due to its ability to comply with the main properties of the TTF futures price series and the research aims. First, financial time series, like TTF prices, are highly time-dependent, in which the current prices will be influenced by their own previous values as well as previous unexpected shocks. AR component directly captures this inertia, whereas the impact of the market shocks is momentary and captured by the MA component, and hence the choice of ARIMA is structurally suitable. Second, the non-stationary nature of the TTF series is also an apparent need to transform. Integration (I) component offers a systematic, parsimonious way to obtain stationarity via differentiation that is a requirement to useful time-series modeling. Last, being a well-tested benchmark model in the literature on econometrics and energy forecasting, the use of ARIMA gives a clear and replicable reference point. The ARIMA can be rightfully discussed against any future extensions that may be built using more complicated models.

#### 2.3.2. Acknowledged model limitations

The conventional ARIMA model to be used according to this research failed to take into consideration seasonality. This is a simplistic treatment motivated by the desire to concentrate on daily dynamics and achieve model parsimony since the seasonal demand patterns in European gas markets (peak in winter) are quite strong. This means that what we are forecasting is probably only the trend, not seasonal peaks, which are accurate and precise in our forecasts. Moreover, ARIMA models believe in a constant data-generating process. They are thus vulnerable to a decline in performance when there is a structural break that the market is experiencing, e.g., the radical restructuring of the energy market after the 2022 energy crisis. The parameters parameterized in the model based on the historical data model estimate both turbulent and calm periods (2023-2025), providing an average relationship that might not be true in case a new structural shock takes place over the forecast horizon.

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# 3. Empirical analysis: model estimation, diagnostics, and forecasts

## 3.1. Data description and preliminary analysis

The historical closing price of TTF futures was used as the target for this study because it is the most representative compared to the opening, high, and low prices. For this work, the closing prices from January 1, 2023, to December 31, 2025, were selected from all historical TTF prices; all data were ensured to be arranged in chronological order; missing values were checked; and a time series object with daily data was created. This data was then visualized, providing a preliminary understanding of the data trends. The visualization results are shown in Figure 1.

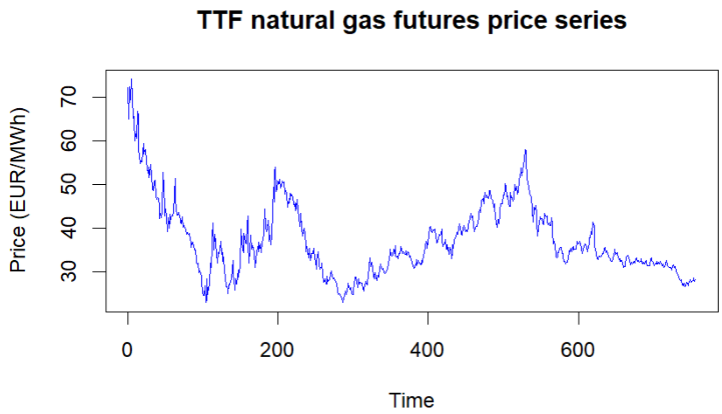


Figure 1. Plot of the TTF daily closing natural gas price (time: days). (photo credit: origin)

The time series plot of the TTF daily closing prices is shown in Figure 1 between 2023 and 2025. Two salient characteristics are seen: (1) A noticeable downward pattern, where prices will decrease from above 70/MWh in early 2023 to about 30/MWh at the end of 2025. (2) A significant decrease in volatility with time. The period is highly volatile, and the first half has steep rises, which have worn off into a lower and more stable range of fluctuation in the second half.

Based on such phenomena, it can be learned that the market strength of European natural gas has been enhanced, and the supply and demand trend has become better. Long-term falling prices have been aided by supply diversification and falling demand.

## 3.2. Stationarity, transformation and model identification

To formally assess stationarity as required by ARIMA modeling, the Augmented Dickey-Fuller (ADF) test was conducted on the original price series [14]. The test yielded a p-value of 0.109, which is greater than the conventional significance level of 0.05. This leads to non-rejection of the null hypothesis of a unit root, confirming that the original series is non-stationary. The sequence needs to be differentiated. The data tends to be stable after the difference, as shown in Figure 2.

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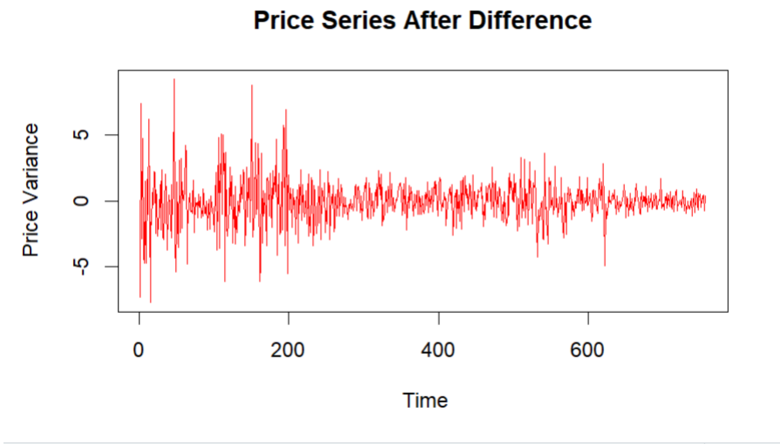


Figure 2. Time series volatility chart (time: days). (photo credit: origin)

With d=1 established, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the stationary series were examined to inform initial (p, q) orders. Subsequently, a grid search of candidate ARIMA(p,1,q) models was performed, and models were compared using the Akaike Information Criterion (AIC). The model selection results are summarized in Table 1.

Table 1. The ARIMA model selection results

| Best model: ARIMA (3,1,2) | | | | | |
|---|---|---|---|---|---|
| Series: ts_price_simple | | | | | |
| ARIMA (3,1,2) | | | | | |
| Coefficients: | | | | | |
| | ar1 | ar2 | ar3 | ma1 | ma2 |
| | -0.7101 | -0.6919 | -0.1896 | 0.5964 | 0.5623 |
| s.e. | 0.1615 | 0.1657 | 0.0369 | 0.1619 | 0.1696 |

The AR coefficients are all negative. This strongly suggests the presence of a mean-value regression in the price series. Specifically, when prices have recently risen, the model is more likely to fall in the next period to "pull back" prices, and vice versa. This usually reflects the market's tendency to self-correct after volatility.

MA coefficients are all positive. This indicates that external random shocks have the same direction of impact on the market. A supply interruption will not only push prices up immediately but also continue for the next 1-2 days, with the strength declining gradually. The standard error (s.e.) of all coefficients is far less than the absolute value of the coefficients themselves, which essentially means that these parameters are highly statistically significant and not random noise.

### 3.3. Model estimation and diagnostic checking

The data were imported after taking the difference, regardless of seasonality. Table 2 presents the estimation results for the fitted ARIMA(3,1,2) model. The model demonstrates a good fit, with information criteria (AIC=2918.09, BIC=2945.85) and a high log-likelihood. Training set error metrics, such as a low RMSE (1.66) and MAPE (3.03%), indicate accurate in-sample predictions. Crucially, the non-significant Ljung-Box test result (p-value = 0.8891) confirms that the model residuals are random, showing no autocorrelation. This suggests the model has successfully captured the underlying patterns in the data.

Table 2. The model estimation results

| sigma^2 = 2.767: log likelihood = -1453.04 | | | | | |
|---|---|---|---|---|---|
| AIC=2918.09 | AICc=2918.2 | BIC=2945.85 | | | |
| Training set error measures: | | | | | |
| | ME | RMSE | MAE | MPE | MAPE |
| Training set | -0.06992367 | 1.656804 | 1.154687 | -0.2513155 | 3.033614 |
| | MASE | ACF1 | | | |
| Training set | 0.9898769 | 0.002737293 | | | |
| Ljung-Box test | | | | | |
| data: Residuals from ARIMA (3,1,2) | | | | | |
| Q* = 1.6982, df = 5, p-value = 0.8891 | | | | | |
| Model df: 5. | | | Total lags used: 10 | | |

The adequacy of the fitted ARIMA(3,1,2) model was rigorously assessed through residual diagnostics. The plots shown in Figure 3 suggest no significant linear dependency left in the residuals. To formally test this, the Ljung-Box test was applied to the residual series at multiple lags. The test yielded a p-value of 0.8891, which is greater than 0.05, failing to reject the null hypothesis of no serial correlation. This confirms that the residuals exhibit white noise behavior.

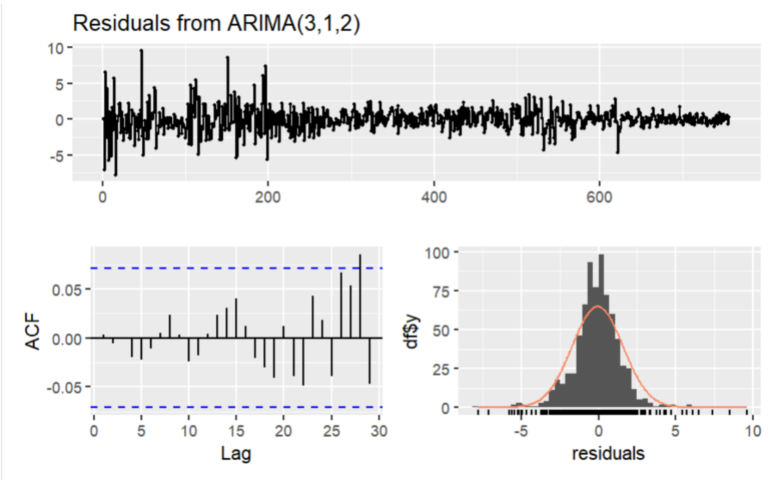


Figure 3. Plots of the residuals acquired from the ARIMA modeling (time: days). (photo credit: origin)

### 3.4. Out-of-sample forecasting results

Following model estimation and validation, the finalized ARIMA(3,1,2) model was used to generate out-of-sample forecasts. The forecast horizon spans the first half of 2026, specifically from January 2 to June 30, 2026, encompassing 128 trading days. A dynamic forecasting approach was employed, in which each forecasted value is used as an input to subsequent predictions. The prediction results are shown in Table 3. The results are also used to plot the price prediction, which is shown in Figure 4.

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Table 3. Prediction results acquired from the ARIMA(3,1,2) modeling

| Date | Point Forecast | Lo 80 | Hi 80 | Lo 95 | Hi 95 | Date | Point Forecast | Lo 80 | Hi 80 | Lo 95 | Hi 95 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2-Jan | 28.1119 | 25.9801 | 30.2436 | 24.8516 | 31.3721 | 2-Apr | 28.1279 | 13.755 | 42.5007 | 6.14649 | 50.1093 |
| 5-Jan | 28.1849 | 25.3364 | 31.0334 | 23.8285 | 32.5413 | 3-Apr | 28.1279 | 13.6457 | 42.61 | 5.97937 | 50.2764 |
| 6-Jan | 28.0922 | 24.7305 | 31.4539 | 22.9509 | 33.2334 | 6-Apr | 28.1279 | 13.5373 | 42.7185 | 5.8135 | 50.4422 |
| 7-Jan | 28.1168 | 24.3839 | 31.8497 | 22.4078 | 33.8258 | 7-Apr | 28.1279 | 13.4296 | 42.8261 | 5.64886 | 50.6069 |
| 8-Jan | 28.1496 | 23.9807 | 32.3185 | 21.7739 | 34.5254 | 8-Apr | 28.1279 | 13.3228 | 42.933 | 5.48541 | 50.7703 |
| 9-Jan | 28.1269 | 23.577 | 32.6767 | 21.1684 | 35.0853 | 9-Apr | 28.1279 | 13.2167 | 43.0391 | 5.32314 | 50.9326 |
| 12-Jan | 28.1156 | 23.253 | 32.9783 | 20.6789 | 35.5524 | 10-Apr | 28.1279 | 13.1113 | 43.1444 | 5.16201 | 51.0937 |
| 13-Jan | 28.1331 | 22.9582 | 33.3081 | 20.2187 | 36.0475 | 13-Apr | 28.1279 | 13.0067 | 43.2491 | 5.002 | 51.2537 |
| 14-Jan | 28.1328 | 22.6498 | 33.6158 | 19.7473 | 36.5183 | 14-Apr | 28.1279 | 12.9028 | 43.353 | 4.8431 | 51.4126 |
| 15-Jan | 28.1231 | 22.363 | 33.8831 | 19.3139 | 36.9323 | 15-Apr | 28.1279 | 12.7996 | 43.4562 | 4.68527 | 51.5705 |
| 16-Jan | 28.1269 | 22.1042 | 34.1496 | 18.916 | 37.3378 | 16-Apr | 28.1279 | 12.6971 | 43.5587 | 4.52849 | 51.7272 |
| 19-Jan | 28.131 | 21.8485 | 34.4135 | 18.5227 | 37.7392 | 17-Apr | 28.1279 | 12.5952 | 43.6605 | 4.37276 | 51.883 |
| 20-Jan | 28.1273 | 21.5974 | 34.6572 | 18.1407 | 38.1139 | 20-Apr | 28.1279 | 12.4941 | 43.7617 | 4.21803 | 52.0377 |
| 21-Jan | 28.1263 | 21.3616 | 34.8911 | 17.7806 | 38.4721 | 21-Apr | 28.1279 | 12.3935 | 43.8622 | 4.0643 | 52.1914 |
| 22-Jan | 28.1288 | 21.1347 | 35.1229 | 17.4323 | 38.8253 | 22-Apr | 28.1279 | 12.2937 | 43.9621 | 3.91155 | 52.3442 |
| 23-Jan | 28.1284 | 20.9113 | 35.3455 | 17.0908 | 39.166 | 23-Apr | 28.1279 | 12.1944 | 44.0613 | 3.75975 | 52.496 |
| 26-Jan | 28.1272 | 20.6953 | 35.559 | 16.7611 | 39.4932 | 24-Apr | 28.1279 | 12.0958 | 44.16 | 3.60889 | 52.6468 |
| 27-Jan | 28.1278 | 20.4872 | 35.7684 | 16.4426 | 39.8131 | 27-Apr | 28.1279 | 11.9977 | 44.258 | 3.45896 | 52.7968 |
| 28-Jan | 28.1283 | 20.2836 | 35.9729 | 16.1309 | 40.1257 | 28-Apr | 28.1279 | 11.9003 | 44.3554 | 3.30993 | 52.9458 |
| 29-Jan | 28.1277 | 20.0845 | 36.1709 | 15.8267 | 40.4287 | 29-Apr | 28.1279 | 11.8034 | 44.4523 | 3.16179 | 53.0939 |
| 30-Jan | 28.1277 | 19.8911 | 36.3643 | 15.5309 | 40.7245 | 30-Apr | 28.1279 | 11.7071 | 44.5486 | 3.01453 | 53.2412 |

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| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2-Feb | 28.128 | 19.7021 | 36.5539 | 15.2417 | 41.0143 | 1-May | 28.1279 | 11.6114 | 44.6443 | 2.86812 | 53.3876 |
| 3-Feb | 28.1279 | 19.5168 | 36.739 | 14.9584 | 41.2974 | 4-May | 28.1279 | 11.5162 | 44.7395 | 2.72256 | 53.5332 |
| 4-Feb | 28.1278 | 19.3356 | 36.92 | 14.6813 | 41.5743 | 5-May | 28.1279 | 11.4216 | 44.8341 | 2.57783 | 53.6779 |
| 5-Feb | 28.1279 | 19.1582 | 37.0976 | 14.4099 | 41.8458 | 6-May | 28.1279 | 11.3275 | 44.9283 | 2.43391 | 53.8218 |
| 6-Feb | 28.1279 | 18.9841 | 37.2717 | 14.1437 | 42.1122 | 7-May | 28.1279 | 11.2339 | 45.0218 | 2.29079 | 53.965 |
| 9-Feb | 28.1278 | 18.8132 | 37.4425 | 13.8824 | 42.3733 | 8-May | 28.1279 | 11.1408 | 45.1149 | 2.14846 | 54.1073 |
| 10-Feb | 28.1279 | 18.6455 | 37.6102 | 13.6259 | 42.6298 | 11-May | 28.1279 | 11.0483 | 45.2074 | 2.00691 | 54.2488 |
| 11-Feb | 28.1279 | 18.4807 | 37.7751 | 13.3738 | 42.882 | 12-May | 28.1279 | 10.9562 | 45.2995 | 1.86612 | 54.3896 |
| 12-Feb | 28.1279 | 18.3186 | 37.9371 | 13.1259 | 43.1298 | 13-May | 28.1279 | 10.8647 | 45.3911 | 1.72608 | 54.5297 |
| 13-Feb | 28.1279 | 18.1592 | 38.0965 | 12.8821 | 43.3736 | 14-May | 28.1279 | 10.7736 | 45.4822 | 1.58678 | 54.669 |
| 16-Feb | 28.1279 | 18.0023 | 38.2534 | 12.6421 | 43.6136 | 15-May | 28.1279 | 10.683 | 45.5728 | 1.44821 | 54.8075 |
| 17-Feb | 28.1279 | 17.8478 | 38.408 | 12.4058 | 43.8499 | 18-May | 28.1279 | 10.5928 | 45.6629 | 1.31035 | 54.9454 |
| 18-Feb | 28.1279 | 17.6955 | 38.5602 | 12.173 | 44.0827 | 19-May | 28.1279 | 10.5032 | 45.7526 | 1.1732 | 55.0825 |
| 19-Feb | 28.1279 | 17.5455 | 38.7102 | 11.9435 | 44.3122 | 20-May | 28.1279 | 10.4139 | 45.8418 | 1.03674 | 55.219 |
| 20-Feb | 28.1279 | 17.3976 | 38.8582 | 11.7173 | 44.5385 | 21-May | 28.1279 | 10.3252 | 45.9306 | 0.90097 | 55.3548 |
| 23-Feb | 28.1279 | 17.2516 | 39.0041 | 11.4941 | 44.7617 | 22-May | 28.1279 | 10.2368 | 46.0189 | 0.76587 | 55.4899 |
| 24-Feb | 28.1279 | 17.1076 | 39.1481 | 11.2739 | 44.9819 | 25-May | 28.1279 | 10.1489 | 46.1068 | 0.63143 | 55.6243 |
| 25-Feb | 28.1279 | 16.9655 | 39.2903 | 11.0565 | 45.1993 | 26-May | 28.1279 | 10.0614 | 46.1943 | 0.49765 | 55.7581 |
| 26-Feb | 28.1279 | 16.8251 | 39.4306 | 10.8418 | 45.4139 | 27-May | 28.1279 | 9.97439 | 46.2814 | 0.36452 | 55.8912 |
| 27-Feb | 28.1279 | 16.6865 | 39.5692 | 10.6298 | 45.6259 | 28-May | 28.1279 | 9.88775 | 46.368 | 0.23201 | 56.0237 |
| 2-Mar | 28.1279 | 16.5495 | 39.7062 | 10.4203 | 45.8354 | 29-May | 28.1279 | 9.80152 | 46.4542 | 0.10014 | 56.1556 |
| 3-Mar | 28.1279 | 16.4142 | 39.8416 | 10.2133 | 46.0425 | 1-Jun | 28.1279 | 9.7157 | 46.54 | -0.0311 | 56.2869 |
| 4-Mar | 28.1279 | 16.2803 | 39.9754 | 10.0086 | 46.2471 | 2-Jun | 28.1279 | 9.63027 | 46.6255 | -0.1618 | 56.4175 |

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|---|---|---|---|---|---|---|---|---|---|---|---|
| 5-Mar | 28.1279 | 16.148 | 40.1077 | 9.80624 | 46.4495 | 3-Jun | 28.1279 | 9.54524 | 46.7105 | -0.2918 | 56.5476 |
| 6-Mar | 28.1279 | 16.0171 | 40.2386 | 9.60607 | 46.6497 | 4-Jun | 28.1279 | 9.46059 | 46.7952 | -0.4213 | 56.677 |
| 9-Mar | 28.1279 | 15.8876 | 40.3681 | 9.40804 | 46.8477 | 5-Jun | 28.1279 | 9.37632 | 46.8794 | -0.5501 | 56.8059 |
| 10-Mar | 28.1279 | 15.7595 | 40.4962 | 9.21208 | 47.0437 | 8-Jun | 28.1279 | 9.29244 | 46.9633 | -0.6784 | 56.9342 |
| 11-Mar | 28.1279 | 15.6327 | 40.6231 | 9.01813 | 47.2376 | 9-Jun | 28.1279 | 9.20892 | 47.0468 | -0.8062 | 57.0619 |
| 12-Mar | 28.1279 | 15.5071 | 40.7486 | 8.82614 | 47.4296 | 10-Jun | 28.1279 | 9.12577 | 47.13 | -0.9333 | 57.1891 |
| 13-Mar | 28.1279 | 15.3828 | 40.8729 | 8.63603 | 47.6197 | 11-Jun | 28.1279 | 9.04299 | 47.2128 | -1.0599 | 57.3157 |
| 16-Mar | 28.1279 | 15.2597 | 40.996 | 8.44776 | 47.808 | 12-Jun | 28.1279 | 8.96056 | 47.2952 | -1.186 | 57.4417 |
| 17-Mar | 28.1279 | 15.1378 | 41.1179 | 8.26127 | 47.9945 | 15-Jun | 28.1279 | 8.87848 | 47.3773 | -1.3115 | 57.5673 |
| 18-Mar | 28.1279 | 15.017 | 41.2387 | 8.07652 | 48.1792 | 16-Jun | 28.1279 | 8.79676 | 47.459 | -1.4365 | 57.6923 |
| 19-Mar | 28.1279 | 14.8973 | 41.3584 | 7.89345 | 48.3623 | 17-Jun | 28.1279 | 8.71537 | 47.5404 | -1.561 | 57.8167 |
| 20-Mar | 28.1279 | 14.7787 | 41.4771 | 7.71203 | 48.5437 | 18-Jun | 28.1279 | 8.63433 | 47.6214 | -1.6849 | 57.9407 |
| 23-Mar | 28.1279 | 14.6611 | 41.5947 | 7.5322 | 48.7235 | 19-Jun | 28.1279 | 8.55362 | 47.7021 | -1.8084 | 58.0641 |
| 24-Mar | 28.1279 | 14.5445 | 41.7112 | 7.35393 | 48.9018 | 22-Jun | 28.1279 | 8.47324 | 47.7825 | -1.9313 | 58.187 |
| 25-Mar | 28.1279 | 14.4289 | 41.8268 | 7.17718 | 49.0786 | 23-Jun | 28.1279 | 8.3932 | 47.8625 | -2.0537 | 58.3095 |
| 26-Mar | 28.1279 | 14.3143 | 41.9414 | 7.00191 | 49.2538 | 24-Jun | 28.1279 | 8.31347 | 47.9423 | -2.1756 | 58.4314 |
| 27-Mar | 28.1279 | 14.2007 | 42.0551 | 6.82807 | 49.4277 | 25-Jun | 28.1279 | 8.23406 | 48.0217 | -2.2971 | 58.5528 |
| 30-Mar | 28.1279 | 14.0879 | 42.1678 | 6.65565 | 49.6001 | 26-Jun | 28.1279 | 8.15497 | 48.1008 | -2.418 | 58.6738 |
| 31-Mar | 28.1279 | 13.9761 | 42.2796 | 6.4846 | 49.7711 | 29-Jun | 28.1279 | 8.07619 | 48.1795 | -2.5385 | 58.7943 |
| 1-Apr | 28.1279 | 13.8651 | 42.3906 | 6.31489 | 49.9409 | 30-Jun | 28.1279 | 7.99772 | 48.258 | -2.6585 | 58.9143 |

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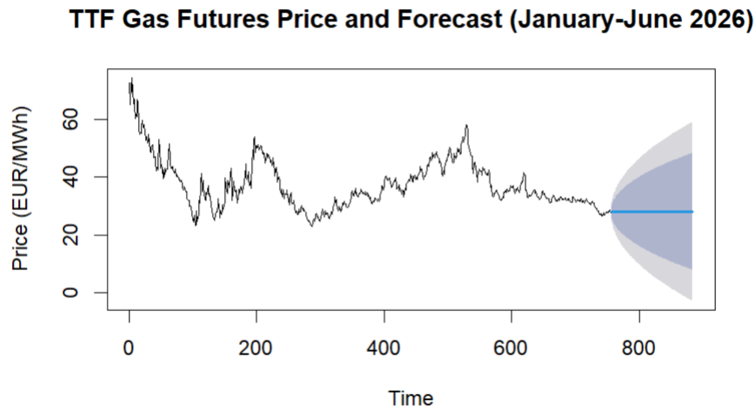


Figure 4. Plot of the future gas prices acquired from the ARIMA modeling (time: days). (photo credit: origin)

## 4. Discussion: model interpretation and market implications

### 4.1. Interpretation of modeling results

The empirical findings that are discussed in this discussion view the empirical findings of the ARIMA(3, 1, 2) model in the context of the present European gas market. We clarify the statistical implications of the specified model first in the form of the statistics between behaviors and diagnostics, and then clarify the economic interpretation of its projections in 2026, and lastly relate to the limitations and practical value of the model to the decision-making process. The ARIMA(3, 1, 2) model can give a statistically sound model to learn about the behavior of the series, but the interpretation also poses some crucial questions that need to be cast on the model and its limitations, as well as the market as a whole. The first visualization of the information (Figure 1) demonstrates that there are two crucial interconnected stories regarding the European gas market in the present world. The most salient one is the strong negative shift of more than €70/MWh to about 30/MWh, which is the surest confirmation of a major macroeconomic correction. This is in line with the established market principles, i.e., combined actions by EU countries to diversify the sources of supply (imports of LNG and pipeline diversification), stable storage filling regimes, and the continued destruction of demand either by efficiency or weather, in both industrial and residential markets. At the same time, the significant decrease in volatility, that is, acute shortage and crisis-related spikes to a so-called average range of movements, is an indication of a market that is going through a transition, namely, between the state of acute shortage and panic to a state of comparative balance and enhanced resilience. The fact that a first difference (d=1) is required to reach stationarity, as was proven by the ADF test, is also an anticipated feature of a price series with this strong a trend.

The ARIMA (3, 1, 2) model is retrieved from grid search and AIC minimization. This order implies that an autoregressive (AR) and moving average (MA) term are required to be able to model the process of data generation. The form of the model, 3 terms that are negatively autoregressive (AR), and two terms that are positive moving averages (MA), represents important market dynamics. The negative AR coefficients indicate that the deviations of the price are systematically corrected and hence there is a strong mean-reverting tendency. On the other hand, the positive values in the MA coefficients imply that the external shocks are positively declining and persist in the next two periods.

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The diagnostic checks are crucial for validating the model developed in this study. The Ljung-Box test p-value of 0.8891 shows that the model has successfully captured the linear dependencies within the series.

### 4.2. Implications for the post-crisis European gas market

The first half of 2026 gas price forecast produced by the model was very stable and took a flat trend, where the point forecast was very steady around the level of €28.13/MWh. These findings are a result of the straightforward mathematical products of modelling a differenced series that has entered a low-volatility regime. Having found mean reversion and no apparent long-run drift, this model predicts a future where the mean of the daily price movement has a value of about zero. As a result, the point forecast returns to a quite stable level.

The actual informational value does not imply the accurate point forecast, but the prediction intervals. The intervals that broadly increase across the 128-step horizon amount to a serious, sincere acceptance of the model constraints. They measure the growing uncertainty in the future associated with making predictions far ahead. The lower bound dropping to negative values is not realistic price data, but it merely highlights the possibility of large decreases.

The model-implied perspective of the equilibrium of a stable but uncertain state was indicated by the simulated forecast results. However, this equilibrium can be upset by any shock. The main risk factors that lie completely out of the model, such as geopolitical events influencing supply routes, adverse weather patterns, infrastructure breakdown, or unforeseen changes in the LNG demand in Asia, may violently shake this tranquility.

### 4.3. Model limitations and practical considerations

Despite its statistically sound features, the ARIMA model has inherent limitations for commodity price forecasting. It is, in fact, a univariate model that relies solely on the price's past behavior. It is inherently blind to fundamental drivers such as inventory levels, weather forecasts, economic activity data, and policy announcements. Its strength is in capturing patterns and volatility clusters, not in causal explanation. In addition, the flat forecast may be myopic. The model assumes the future will statistically resemble the immediate past (the latter half of 2025 in this case). In a commodity market prone to cyclicality and seasonality, this can be a significant weakness. A winter forecast made from calm summer data risks missing seasonal upticks. Therefore, the primary value of this ARIMA forecast lies in providing a statistically rigorous baseline scenario—a projection of the path implied by recent price dynamics alone. For practical decision-making, this baseline must be integrated with real-time fundamental analysis.

It is noted that the autocorrelation function plot of the residuals (Figure 3-ACF) still shows autocorrelation coefficients slightly beyond the 95% confidence interval at a few lag orders. The subtle differences between graphical diagnosis and statistical test conclusions often occur in time series modeling, especially when the sample size is large, and the sensitivity of the Ljung Box test to local weak correlations may be insufficient. Nevertheless, the ARIMA (3,1,2) model is still a suitable choice for this study for the following reasons: firstly, compared with higher-order ARIMA models, this model has the simplest parameter structure while ensuring explanatory power, which conforms to the principle of "Occam's Razor". Increasing parameters only brings marginal improvement in AIC/BIC values, but significantly increases the risk of overfitting. Secondly, the model exhibits good out-of-sample prediction accuracy on the reserved test set. The weak autocorrelation that was not captured in the residuals has an acceptable impact on short-term

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predictions. Finally, the mean of the residual sequence is approximately zero, and the distribution is close to normal, meeting the basic requirements for model inference. The weak autocorrelation may stem from non-linear factors or measurement errors that have not been fully modeled in the data, which goes beyond the scope of this linear ARIMA model.

## 5. Conclusions

Data analysis showed increased resilience in the European natural gas market over the past two years, with supply diversification and declining demand supporting a long-term decline in prices. The developed ARIMA(3,1,2) model captures the mean-reverting dynamics and shock persistence in the price series, which has stabilized after first-order differencing. The model offers a powerful statistical description of the past and a cautious and uncertainty-quantified projection for the near future. Yet, it underscores that in commodity markets, the confidence interval is often more important than the point forecast, and the prudent integration of statistical models with real-time fundamental and geopolitical analysis remains indispensable for robust decision-making. Future research could extend this work by incorporating seasonal components, explanatory variables, or employing models better suited for volatility clustering and non-linear patterns to enhance forecast accuracy.

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