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Abstract. Turkey has an important geopolitical position with short distances to the regions of the largest natural gas reserves. It is a country that depends on importing this energy resource from Russia, Iran and Azerbaijan through pipelines, and LNG suppliers. Being very close to high demanding countries, Turkey has yet the chance to play an important role in transferring gas from reserves to the demand sites. That is why the natural gas market in Turkey can complete the liberalization by defining an international gas hub in the global gas trade system. In this respect, the pricing of large trading volumes will be an issue for the near future. This paper aims to underline the importance of hub pricing through structuring a virtual hub in Turkey. Hence, the current outlook of the global natural gas markets and Turkey's position in this business are presented in detail.

Keywords: Natural Gas Market, Hub Pricing, Gas Demand, Gas Transportation.

1 Introduction

The global need for natural gas has been increasing gradually. Countries maintain active relations to trade and meet the demand of this strategic resource. While there are many countries on the consumer side, there is imperfect competition on the producer side due to the limited number of countries. The most important issue would probably be setting the price of gas. Once seen as an undesirable and dangerous by-product of oil production, natural gas was flared into the atmosphere. In time, its market value was acknowledged. This is followed by a state-of-the-art pipeline network. Since it was not clear how to value natural gas when it was first started, it was associated with the prices of petroleum products. However, the increasing demand for gas, which has increased as of today, has enabled the gas to be recognized very well by the supply and demand points. This makes the pricing approach based on oil inadequate. For this reason, commercial centres have been established to measure the value of gas, especially in the

USA and Northern European countries. After all, the price of natural gas is determined by the balance of supply and demand as a result of commercial activities carried out in these centres.

Turkey is a natural gas import-dependent country. It responds to the domestic gas demand through oil-based long-term contracts. Turkey is close to the geographical area of rich natural gas reserves. With its growing economy, its thirst for natural gas is constantly increasing. Besides, given its geopolitical location, Turkey is close to countries that need gas, especially to Europe. All these could be seen as sufficient conditions to nominate Turkey as a strong gas-hub.

In 2019, Turkey has imported 35% of its total gas from Russia, 16% from Iran, 17% from Azerbaijan, 11% from Algeria, 5% from Nigeria, and 16% as spot LNG from primarily Qatar and other countries (EPDK, 2019). While natural gas imported from Russia, Iran, and Azerbaijan comes within the scope of long-term agreements over pipelines, it is taken as LNG from other countries. There is a long-term purchase agreement with Algeria and Nigeria in LNG purchases. Although it is accepted that the use of natural gas will reduce environmental problems like air pollution caused by coal and oil combustion, the high share of natural gas imports from several countries can be seen as a significant risk to Turkey (Biresselioglu et al., 2019). The 1.3 billion cubic meter agreement signed with Nigeria in 1995 expires in October 2021, and the 4.4 billion cubic meter agreement signed with Algeria in 1988 expires in October 2024. For gas coming from pipelines, a total of 10.6 billion cubic meters of agreement, covering Russian and Azeri gas, expires in 2021, the agreement for 16 billion cubic meters of Russian gas in 2025, and the agreement for 9.6 billion cubic meters of Iran gas in 2026. Following the end of the duration of the agreement, Turkey's natural gas trade will have significant flexibility. Thus, a period of opportunities will be entered to open up new resources and create a competitive market. In light of the agreements that will end, this study will prepare an infrastructure to create a trade centre by making predictions until 2025 in the natural gas market. Thus, in this study, two main scenarios have been identified in light of the current market structure in Turkey. In both cases, estimates of natural gas prices were made monthly until the end of 2025.

As the article contains the predictive and prescriptive analytics of Turkey becoming a Global Natural Gas Hub in terms of projections for gas prices, this study is the continuation of our initial article (Nalbant et al., 2020). Moreover, this current study meets a need to present the dynamic pricing structures that will precise the future scenarios for using Natural Gas to respond to the increasing power demand.

Scenario 1

In the early days of the natural gas industry, there were huge capital investments into gas field development and pipeline construction operations. Hence, the supplier had to carry these costs as a significant financial burden and risk. To mitigate total risk on the supplier, “take or pay” and destination clauses were introduced and agreed upon by both parties (Osicka, 2017). Turkey is also a country that is a net importer of natural gas. It realizes most of the gas it purchases through long term contracts with indexed pricing structure from neighbouring countries subject to conditions such as "take or pay". This scenario investigates how the price is affected under business as usual conditions. Using the time series methods, it is estimated what the gas import prices will be at the end of 2025.

Scenario 2

The second scenario estimates the price of Turkish imported gas as if there is a natural gas hub. We aim to analyse the dynamics of the prices that could be affected by many factors in the presence of such a natural gas hub. Once again, the estimation targets 2025.

Free market prices are determined by supply and demand forces. Therefore, assuming that Turkey is a trade hub, we analyse the impact on prices. Also, the factors that may affect the prices within a hub environment are identified.

Then, these factors were evaluated by Vector Autoregressive Analysis (VAR) and machine learning techniques. The results of medium-term forecasting were obtained by taking into consideration their effects on gas prices. Thus, Turkey's reference price based on supply and demand dynamics on a global scale has tried to be put forward.

2 Background

In 1995, the efficiency of US Natural Gas markets was questioned. Also, the comparison of the New York Mercantile Exchange (NYMEX) price calculations were compared to the Kansas City Board of Trade (KCBOT) contracts, the second merchandiser in the USA. It was observed that the prices were getting apart in time (Herbert and Kreil, 1996). It is then seen that Henry Hub in Louisiana was not good enough in price forecasts for the USA and Canadian natural gas markets. Further econometric analysis showed that the difference is not only due to transportation costs. Pipelines and scarcity of the spot markets caused the need for more than one natural gas price in the USA and Canada. Hence, the confidence in future market price calculations got weaker in time. A cointegration analysis of USA, Japan, and Europe showed that local markets group in themselves (as pipe and LNG) but there is an evident dominance of existing long-term contracts and high impact of the traditional oil-index price formula (Siliverstovs, et al., 2005). Following the achievements of this study, a comparison of the price forecast performance of the markets and the economic models was studied. Wong-Parodi et al. (2006) compares the Short-Term Outlook Model of the US Energy Information office and the Henry Hub future market price forecasts statistically and demonstrates the success of the future market.

With the impact of increasing renewable energy investments, a new vision among the European researchers came up to have more integrated and more efficient energy markets with multiple hubs (Geidl et al., 2007). Agent-based control of multiple carriers would not only allow the reductions in market operations costs but also increase the mitigation of carbon emissions. Further analysis of multi-source multi-product energy markets has increased the need for multiple-hubs (Hemmes et al., 2007). It is only in the last decade that multi-hub dispatch management is analysed. Robustness of the energy dispatch and the impacts of the wind energy-optimized by using multi-agent systems is suggested as modern management of multiple hubs by Moeini-Aghtaie et al. (2014).

European policies to combine the energy markets have also encouraged the increasing research on multiple hubs. Causality among the European gas price time series at the points where cross-border connections of pipelines and trading occur at the same time was studied by Gianfreda et al. (2012) to analyse the possibilities of the integrated European energy market. The five markets that were studied in this study were not found at all related even the natural gas is imported from the very same countries. Italian and Dutch markets were relying on the German prices. In 2013, Germany made the critical policy change "energiewende" in favour of distributed energies which allowed bioenergy to influence the natural gas markets, hence 2 trading hubs are started (Burger and Weinmann, 2014).

European hubs have started influencing the other markets of the Globe. After the Fukushima explosion, Japan has also started discussing changes in the local energy market considering the regional price constructions based on energy security by the region (Tanaka, 2013). Shale gas discoveries in the USA have also strengthened the effectiveness of multiple hubs for energy security in the Globe, which is clearly shown by North American analysis of Kobek et al. (2015). Xunpeng (2016) studies the influences of Europe on East Asia and concludes that the hubs will not be successful unless the liberalization of the market is completed.

In the last five years, the European research is focused on combining the electricity markets and the heating markets in Europe. With the influence of this important change, more domestic conditions are studied like the impacts of infrastructure state and storage (Santibanez-Gonzalez, 2017). The new research trend is to study the influence of electric cars on natural gas prices as in Nikoobakht et al. (2020).

Prices formed in natural gas trade centres remain under the influence of more than one factor. Various methods are used to interpret how these factors affect, and at what levels prices are sensitive to these factors. For example, Mishra (2012) revealed the factors affecting natural gas prices and then estimates gas prices using ARIMA, which is one of the linear time series methods. Salehnia et al. (2013) used regression models to estimate Henry Hub short-term-spot natural gas market prices. This study is the first user of the Gamma test for the best selection of parameters in the calibration of models. After determining the factors affecting the prices occurring in the hub in the Netherlands, they developed a linear equation and tried to reveal the relationship between prices and related factors. Misund and Oglend (2016) used vector autoregressive analysis to investigate the causes of fluctuations in gas prices in England. In another Henry Hub-market price forecasting study, Ceperic et al. (2017) used neural networks and Support Vector Machine (SVM) machine-learning algorithms. Mulder et al. (2016) and Naderi et al. (2019) combined the statistical methods with the machine learning algorithms and conducted studies to estimate crude oil and gas prices. In this study, the authors introduced a new approach by trying methods such as genetic algorithm, artificial neural network (ANN), and ARIMA to achieve the optimum combination by using a meta-heuristic bat algorithm. Herrera et al. (2019) compared the performance of traditionally used econometric models in price estimates using neural networks and random forest models. As the outcome of the study, they argued that the random forest method was particularly successful in the monthly price estimate of energy commodities. Su et al. (2019) also discussed the performance of ANN in comparison to SVM, gradient boosting machines (GBM), and Gaussian Process Regression (GBR), and Henry Hub's performance in the monthly forecast of spot gas prices. Wang et al. (2020) compared the daily gas price estimation performance to the hybrid machine-learning model using the support vector regression (SVR) and long-term and short-term memory network (LSTM) models.

3 Methodology and Data

In the literature, it has been observed that studies for only gas price estimation are not very common. In general, it has been studied alongside other fossil fuels such as oil and coal or has been addressed in areas such as gas consumption, electricity generation, and electricity price estimation. Based on the estimated monthly average natural gas import prices between January 2011 and December 2019, and by using EViews 10 and R software, in the first scenario, the forecast was made using linear (ARIMA) and non-linear time series (TAR). Autoregressive moving averages models (ARIMA) are the time series estimation and forecasting method, also known as Box-Jenkins (1970) models. In these methods, the aim is simply to predict the future value of the variable from the past values of the series and past estimation errors. Threshold Autoregressive Regression model, which is one of the nonlinear time series methods, contain regime change information, unlike linear time series models. When the threshold variable takes different values, it provides different modelling and policy recommendations (Dodge, 2003).

For the second scenario in which we assume that Turkey is a natural gas hub, following Mulder et al. (2016), the study investigates the correlation between gas prices and various independent variables for the relevant periods using the vector autoregressive (VAR) model. Vector autoregression is an econometric model that generalizes univariate AR models and provides development and interdependence between multiple time series (see Enders, 2003). Stacking Regressor is a machine learning method for forming linear combinations of different predictors to give improved prediction accuracy. The idea is to use cross-validation data and least squares under non-negativity constraints to determine the coefficients in the combination (Breiman, 1996). Moreover, the model is also used to forecast the prices in this scenario.

Data for monthly natural gas import prices for 108 months from January 2011 to December 2019 are taken from Beyazgül (2016). The day ahead markets in Turkey form and announce natural gas prices in TL/MWh (EPIAS, 2020c), therefore, this study uses $/MWh as the price unit for average monthly prices, which allows the validation and correction of the data. Figure 1 provides the time plot. According to this graph, it is clear that the decrease in imported gas prices in 2015 increased again after 2016 when it bottomed out. The reason for this decrease is that Brent oil prices, which were at the level of $ 110 in June 2014, declined rapidly to $ 50 in early 2015 and to $ 27 in early

2016. With this decrease in oil prices, natural gas prices and import amount started to decrease rapidly in late 2014.

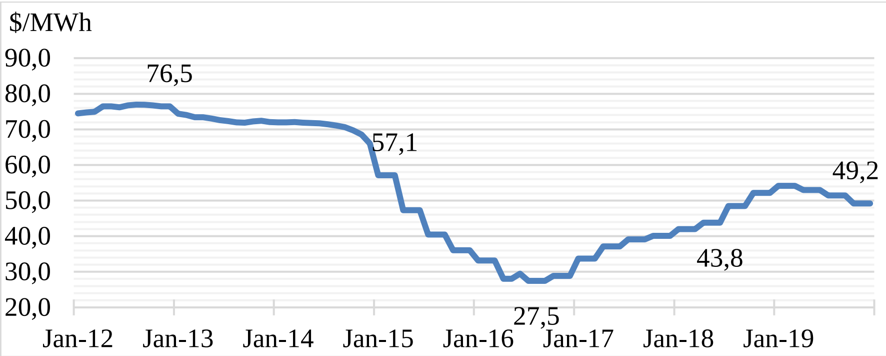

Fig. 1. Time plot of imported gas price in Turkey.

A review of the literature survey allowed the determination of the criteria that can have an impact on natural gas prices. These are briefly presented below.

Oil Price ($/Barrel): Since oil prices have an important effect on gas trade in the world, Brent oil prices are included in the analysis. For example, Serletis and Rangel-Ruiz (2004) found that there are a common trend and cycle in prices after the liberalization of the oil and gas markets in the USA. Asche et al. (2006), in their study, state that the existence of a single market for the major energy sources in England can be mentioned, and the prices in this market are determined by global oil prices. The monthly values of this variable for the years 2011-2019 are taken from the US Energy Information Administration (EIA) website (EIA, 2020a).

Coal Price ($/Ton): Both the domestic and imported coal are still important inputs for the power market, i.e., coal is a close substitute for natural gas. Bachmeir and Griffin (2006) stated that there may be a weak cointegration between oil, natural gas, and coal prices, which is why it is not acceptable to have a single energy market for major sources around the world, but it can be claimed when evaluated in a very long term. Besides, Manzur and Seiflou (2011) found that there is a long-term relationship between crude oil, natural gas, and coal prices in the US energy market, but natural gas prices have no deterministic effect on oil prices in the short term. Coal price data are taken from Turkey's largest coal importer with a monthly Reuters database for Colombia's coal prices over the years 2011-2019.

Carbon Emission (€/ton): Emission Trade Scheme (ETS) aims to force industries that cause pollution by utilizing the CO_2 trade system to buy carbon credits to create an effective tax for carbon emission, and thus, encourage industries to adopt cleaner technologies. The objective is to limit global warming to 2°C, develop energy efficiency, increase the roles of renewable energy sources, strengthen the carbon market, and provide a transparent and competitive domestic energy market (Kocaslan, 2011). Unfortunately, there is no active carbon market yet established in Turkey. However, in the medium-term due to carbon market's expected existence, this variable is included. Meanwhile, since there are no reliable prices yet in Turkey, European carbon emission prices between the years 2011-2019 are included in the analysis (Business Insider, 2020).

Heating Degree Days (HDD): Demand for natural gas in Turkey, especially because of the intensity of household consumption, is increasing in the cold season (Energy Market Regulatory Authority - EPDK, 2017). The values of Heating Degree Days (HDD) were compiled from the calculations and data published regularly by the Turkish State Meteorological Service (MGM, 2020) for each province on an annual and monthly basis. These values were calculated monthly for Turkey for the years 2011-2019.

Herfindahl-Hirschman Index (HHI): Herfindahl-Hirschman index (HHI) is widely used to demonstrate the degree of competition in a market. HHI is an indicator for understanding the depth of the market and is calculated by the formula $\boldsymbol{HHI} = \sum_{i=1}^{n} S_i^2$ (Mulder et al., 2016). Here, S_i, represents the country i's market share in total gas imports, and n represents the total number of countries in which imports are realized. Therefore, it is an indicator of a market structure and also points to the measurement of the effective power of firms in the markets. This variable, when long-term contracts and spot market purchases are concerned, reveals how many different countries Turkey imports natural gas from and in what volumes. Especially considering the diversity of supply alternatives in a gas trading hub is very critical. To include this variable in the multivariate time series analysis, monthly natural gas sector reports published by EPDK (2020) have been examined one by one, and the list and import amounts of the countries imported in the relevant month have been compiled. Finally, with the help of the specified formula, the Herfindahl-Hirschman index value was calculated monthly for the years 2012-2019.

Industry Index: According to the EPDK report, the industry sector realizes 21.69% of the total gas consumption (EPDK, 2019). Acaravcı and Reyhanoğlu (2013) emphasized that there is a long-term relationship between energy prices and variables of BIST-100 index, oil prices, natural gas prices, and industrial production index. The industry sector is also accepted as a variable within the scope of this analysis since it is a very important indicator in the development of the country's economy and a significant factor in the demand fluctuations of gas. The industrial production index (2015 = 100) for this purpose has been taken monthly from the Turkstat (2020) database for 2011-2019, free of season and calendar effects.

Natural Gas Storage Amount (Sm3): Natural gas storage facilities serve as a very important supply source. Because, firstly, when the demand is very high, it will contribute to the supply security by providing sufficient gas supply to the network, and secondly, it will provide an abundance of gas to trade the gas in the free market. These facilities are usually filled in summer periods for use in the winter months. While the amount of gas stored above the seasonal normal decreases the prices in a gas hub, the storage below the seasonal normal has an increasing effect on the prices (Mulder et al., 2016). The total amount of gas stored in Turkey has been compiled monthly for the 2011-2019 period from EPDK (2020) monthly reports.

Hydroelectric Energy Production (GWh): Turkey is a country with an important source of hydrology. Due to the energy supply security in the country, both reservoir and run of river type power plants are actively used for electricity generation. According to TEIAS Installed Capacity Report-2019, Turkey's total installed capacity by the end of 2019 is 91,267 MW. Hydroelectric Power Plants (HEPPs) with a total of 682 plants constitute 31% of this installed power (TEIAS, 2019a). According to TEIAS, a total of 304,251.6 GWh of electricity was generated at the end of 2019, 29% by hydroelectric plants with a total production of 58 450 GWh (TEIAS, 2019b). This variable was included in the analysis since the production performance of hydroelectric power plants can directly affect the working order of the gas power plants and as a natural consequence, it may change the demand for gas. Historical production data of HEPPs were compiled by reviewing both EPIAS (2020a) and related sector reports monthly for 2011-2019.

Wind Energy Production (GWh): Increasing investments in renewable energy suggest that it can help alleviate the threat of high gas prices in the short and long-term. Increasing renewable energy distribution by replacing gas-fired production is expected to reduce natural gas demand and consequently put downward pressure on gas prices (Wiser and Bolinger, 2007). Wind energy investment in Turkey has gained pace especially since 2007. With the commissioning of an average capacity of 700 MW each year, a total of 7,591.2 MW wind power plant (WPP) installed power was reached at the end of 2019 (TEIAS, 2019a). Again, according to the data published by TEIAS, the contribution of WPPs to electricity production in 2019 was around 7% (TEIAS, 2019b). In 2017, a capacity of 3000 MW was allocated to investors through tenders and two other tenders were held within the scope of the "2 GW of renewable resource areas" study. For all these reasons, it has been found appropriate to include WPPs as a renewable energy source in this study. The past production data of WPPs were compiled by reviewing both EPIAS (2020a) and related sector reports monthly for 2011-2019.

Solar Power Generation (GWh): By diversifying natural gas and oil suppliers, increasing the use of alternative renewable energy sources such as wind and solar energy, it can be possible both to reduce foreign dependency on oil and natural gas and to reduce energy costs (Gokırmak, 2017). The first tender for the realization of the licensed stations for solar energy in Turkey took place in 2014. Following this, Solar Power Plant (SPP) investments gained great momentum with the unlicensed electricity generation plants, which were initiated so that investors can meet their internal consumption primarily. As of the end of 2019, the total SPP installation, which was almost non-existent before 2014, contributed approximately 3% to the electricity generation of the country with 6.901 power plants and total installed power of 5.995.2 MW. Following its strategic goals, Turkey allocated a 1 GW solar power capacity in the first quarter of 2017. Based on the expanding pattern of solar power capacity both in and out of the country, this parameter is also taken as a variable. Data on SPP production was compiled from the related sources published (production data for 2011-2019 were reviewed monthly from both EPIAS (2020b) and related industry reports).

Natural Gas Price in the Importer Country ($ per Million Metric): De Vany and Walls (1993) indicated that natural gas prices in different markets are integrated. Opening the access to pipelines leads to increased competition and thus, makes the prices converge to each other. According to EPDK reports, Russia is Turkey’s biggest natural gas provider. Therefore, natural gas prices in this market should be also in the model (the data for the 2011-2019 period is retrieved from the Russian Natural Gas Monthly Price Reuters database).

4 Scenario Analysis

Analysis based on Scenario 1: This scenario investigates how the price is affected under business as usual conditions. Before starting the analysis of natural gas prices with time series, firstly, logarithmic transformation was applied to the variable to ensure the variance stationary, and secondly, its stationarity was examined by unit root tests. Based on the results of the unit root tests, the first-degree difference was found to be stationary according to 5% (Augmented Dickey-Fuller: -2.13 and Phillips-Perron Test: -11.02). Accordingly, the logarithmic differentiation state of the variable is used. Next, the correlogram of this variable was examined to switch to ARIMA modelling over this value (see Figure 2).

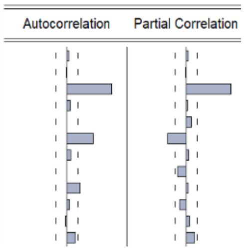

Fig. 2. Correlogram of imported gas prices

After this step, the data set is divided into training and test data set (last 8 months). In Figure 2, we see significant values of up to 6 delays according to autocorrelation and partial autocorrelation values. Based on this, the ARIMA (6,1,6) model was executed and the most suitable model was determined as the following ARIMA (3,1,6) according to the Information Criteria and coefficient significance. Coefficients are shown in table 1. According to the results in Table 1, imported gas prices are affected by their pre-3-period values and shocks up to 6-period.

Table 1. ARIMA (3,1,6) model[1]

Sample:2011M02 2019M04
Included observations: 99

DLOG(Imported Gas Price)	Coefficient	Std. Error
Constant	0.0005	0.011
Ar(3)	0.31***	0.10
Ma(3)	0.78***	0.11

[1] The correlogram of the residual square obtained from this model was examined and ARCH-LM (nR^2 (6) = 3.43) test was performed. No conditional heteroscedasticity was found as a result of the test.

Ma(6)	0.59***	0.08

**** Significant at 1%.*
*** Significant at 5%.*
** Significant at 10%.*
R^2: 0.69, Akaike: -4.32, Schwarz -4.20, HQ: -4.28
Residuals are white noise.

Training and test sample performance of this model is presented in Table 2.

Table 2. Performance measures of ARIMA (3,1,6)

	RMSE	MAE	MAPE
Training	1.23	0.69	1.44
Test	0.99	0.68	1.37

Since gas prices are determined indexed to oil, there is a serious correlation with oil prices. Therefore, especially the increase in oil prices until the end of 2018 is reflected in gas prices. Given the serious factors such as sudden shocks, uncertainties in prices, political risks, and supply capacity in the global oil market, the course of oil prices may remain open to serious changes. Since these contracts will be affected by these fluctuations, imported gas prices will also be seriously affected. For this reason, this effect can be examined by establishing nonlinear time series models. For this purpose, Threshold Autoregressive Models (TAR) were applied and nonlinearity was confirmed by the Bai Perron test (F: 10.44, significant at 5%). The model results are given in Table 3. According to Table 3, if the value of oil prices is below $ 47.7 / Barrel 6 months ago, the increases and decreases in natural gas prices are fast. If the price of oil is realized at $ 47.7 / Barrel and above 6 months ago, natural gas prices tend to increase rapidly[2].

Table 3. Results of TAR model

DLOG (Imported Gas Price)
Included observations: 93 after adjustments
Selection: Trimming 0.15, Sig. level 0.05
Threshold variable: OIL PRICE (-6)

Variable	Coefficient	Std. Error
OIL PRICE (-6) < 47.7 -- 14 observations		
C	0.003	0.007
DLOG(Imported Gas Price)(-3)	0.93***	0.16

[2] After this step, the estimation of ESTAR and LSTAR models was made, but only 1 model had a significant threshold. Achieving the high slope parameters of the threshold in this model indicated that the model converged to the TAR model. Besides, this model's Sum of Squared Residuals and information criteria indicate that the TAR model is better. In this case, it can be said that the regime change in gas prices is sharp rather than smooth. Therefore, only the results of the TAR model are included in this study.

DLOG(Imported Gas Price)(-6)	-0.83***	0.17
47.7 <= OIL PRICE (-6) -- 79 observations		
C	-0.005***	0.00
DLOG(Imported Gas Price)(-3)	0.93***	0.11
DLOG(Imported Gas Price)(-6)	-0.11	0.11

**** Significant at 1%.*
*** Significant at 5%.*
** Significant at 10%.*
R^2: 0.74, Akaike: -4.50, Schwarz -4.33, HQ: -4.43
Residuals are white noise.

In order to forecast in this model, the forecasting value of Oil Prices must be determined in the model. For this reason, a separate model was estimated by using the Imported Gas Price (-4) as a threshold variable for the forecasting. Training and test sample performance of this model was obtained as in Table 4.

Table 4. Performance measures of TAR model

	RMSE	MAE	MAPE
Training	1.18	0.64	1.29
Test	1.00	0.88	1.81

Although the training sample performance of this model is better than the ARIMA model, out of sample (test) performance is lower.

Analysis Based on Scenario 2: In this scenario, the price was analysed considering Turkey as an international natural gas hub. Therefore, the aforementioned variables Oil Price ($/Barrel), Coal Price ($/Ton), Carbon Emission (€/Ton), Heating Degree Days (HDD), Herfindahl-Hirschman Index (HHI), Industry Index, Natural Gas Storage Amount (Sm3), Hydroelectric Power Generation (GWh), Wind Power Generation (GWh), Solar Power Generation (GWh), Natural Gas Price in Importer Country ($ per Million Metric) are included in the analysis of the estimation of gas prices.

After taking the logarithm for variance stability, we control for seasonality. These are followed by seasonal smoothing of the Heating Degree Days (HDD), Herfindahl-Hirschman Index (HHI), Natural Gas Storage Amount (Sm3), Hydroelectric Energy Production (GWh), Wind Energy Production (GWh) and Solar Energy Production (GWh) variables. Finally, unit root tests are performed for all the variables. The result of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests show that all variables were I (1) (see Table 5).

Table 5. Results of unit root tests

Variables	ADF		PP	
	Level (None)	First Difference (None)	Level (None)	First Difference (None)
Imported Gas Price ($/Barrel)	-0.70	-2.13**	-0.28	-11.02***

Oil Price ($/Barrel)	-0.53	-8.07***	-0.51	-7.87***
Coal Price ($/Ton)	-0.24	-7.94***	-0.21	-8.07***
Carbon Emission (€/ton)	0.01	-7.42***	0.13	-7.12***
Heating Degree Days (HDD)	0.53	-9.72***	-0.66	-45.22***
Herfindahl-Hirschman Index (HHI)	1.10	-9.09***	0.39	-19.08***
Industry Index	2.50	-15.58***	2.00	-15.19***
Natural Gas Storage Amount (Sm3)	0.08	-9.78***	0.17	-10.17***
Hydroelectric Energy Production (GWh)	0.16	-15.94***	0.37	-19.23***
Wind Energy Production (GWh)	3.31	-11.64***	2.64	-17.57***
Solar Power Generation (GWh)	0.03	-5.49***	0.06	-5.49***
Natural Gas Price in the Importer Country ($ per Million Metric)	-0.73	-9.08***	-0.71	-9.20***

**** Significant at 1%.*
*** Significant at 5%.*
** Significant at 10%.*

After this step, lag length criteria were firstly determined to examine whether these variables affect imported gas prices. According to Schwarz and Hannan Quin criteria, the appropriate lag length is 1, and according to the Akaike information criterion is 7. Since the number of data is not very large, Schwarz and Hannan Quin criteria were preferred and it was decided to continue with 1 lag.

Afterwards, an appropriate short-term equation was established and variables that affect gas prices were determined by the stepwise method. Natural Gas Price ($ per Million Metric), Industry index and oil prices in Russia affect short-term natural gas prices (R^2: 0.13). Thus, Vector autoregressive analysis (VAR) continued with these variables. The lag length criteria specific to these variables have also been determined. Following this, the appropriate delay number was determined as 4 and 6, respectively, based on the Schwarz and Hannan Quin criteria, and based on the Akaike information criteria. The analysis was continued with the length of 4 lags and the results are presented in Table 6.

Table 6. Results of VAR model[3]

Sample (adjusted): 2011M06 2019M04
Included observations: 95

	Imported Gas Price	Oil Price	Natural Gas Price in the Importer Country_ Russia	Industry Index
Imported Gas Price (-1)	-0.11	-0.85**	-0.59**	0.03
	(0.11)	(0.34)	(0.27)	(0.09)

[3] All variables are in logarithmic differences.

Imported Gas Price (-2)	-0.09	0.02	-0.07	-0.03
	(0.07)	(0.21)	(0.17)	(0.05)
Imported Gas Price (-3)	0.66***	0.43**	0.03	0.11**
	(0.06)	(0.20)	(0.16)	(0.05)
Imported Gas Price (-4)	0.09	0.47	0.60**	-0.10
	(0.10)	(0.30)	(0.24)	(0.08)
Oil Price (-1)	0.12***	0.36***	0.29***	0.02
	(0.04)	(0.11)	(0.08)	(0.02)
Oil Price (-2)	-0.04	-0.01	-0.02	0.02
	(0.04)	(0.12)	(0.10)	(0.03)
Oil Price (-3)	0.09**	-0.22*	0.17*	-0.04
	(0.04)	(0.12)	(0.09)	(0.03)
Oil Price (-4)	0.07*	0.13	0.15	0.01
	(0.04)	(0.13)	(0.10)	(0.03)
Natural Gas Price in the Importer Country_Russia (-1)	-0.01	-0.05	0.27**	-0.02
	(0.05)	(0.14)	(0.11)	(0.03)
Natural Gas Price in the Importer Country_Russia (-2)	0.09**	0.16	-0.11	-0.02
	(0.05)	(0.14)	(0.11)	(0.04)
Natural Gas Price in the Importer Country_Russia (-3)	0.05	-0.24	0.15	-0.01
	(0.05)	(0.15)	(0.12)	(0.04)
Natural Gas Price in the Importer Country_Russia (-4)	0.04	0.24	-0.04	0.002
	(0.05)	(0.15)	(0.12)	(0.04)
Industry Index(-1)	-0.13	0.44	0.44	-0.48***
	(0.15)	(0.45)	(0.36)	(0.11)
	Imported Gas Price	Oil Price	Natural Gas Price in the Importer Country_ Russia	Industry Index
Industry Index(-2)	0.06	0.51	0.42	-0.12
	(0.17)	(0.50)	(0.40)	(0.13)
Industry Index(-3)	-0.16	0.02	0.21	-0.08
	(0.17)	(0.50)	(0.40)	(0.13)
Industry Index(-4)	-0.29**	0.39	-0.22	0.08
	(0.15)	(0.45)	(0.35)	(0.11)
Constant	0.002	-0.009	-0.006	0.006***
	(0.003)	(0.009)	(0.008)	(0.002)
R-squared	0.75	0.25	0.35	0.32
Adjusted	0.70	0.10	0.21	0.18

R-squared				
Log likelihood	220.89	115.51	137.64	247.28
Akaike AIC	-4.29	-2.07	-2.54	-4.85
Schwarz SC	-3.84	-1.62	-2.08	-4.39

Standard Errors are in parentheses
**** Significant at 1%.*
*** Significant at 5%.*
** Significant at 10%.*

Table 7 presents the predictive performances of gas prices depending on the training and test sample that are based on the VAR model results.

Table 7. Performance measures of VAR model

	RMSE	MAE	MAPE
Training	1.11	0.82	1.66
Test	1.30	1.01	1.97

Assuming that Turkey hosts a natural gas hub, we use machine learning to analyse how the determinants that affect natural gas prices may potentially shape these prices. In this context, more than one machine learning algorithm has been studied and the price estimation has been made by using Stacking Regressor as a result of the evaluations. Stacking (or Stacked Regression) is an ensemble machine learning algorithm. It uses a meta-learning algorithm to learn how to best combine the predictions from two or more base machine learning algorithms. The idea is to use cross-validation data and least squares under non-negativity constraints to determine the coefficients in the combination (Breiman, 1996). The 3 independent variables selected as a result of the work done in the previous section constitute the input of the study to be described in this section. Therefore, Brent-oil price with natural gas prices, industry index (IND) reflecting the economic development level of the country, and Russian natural gas price are included in the analysis.

The 88-month values of the 3 independent variables were selected for the analysis between January 2012 and April 2019 were used to complete the training process of the algorithm. Then, the forecast performance of the algorithm was examined by considering the 8 months' test values between May 2019 and December 2019. Forecasting performances of gas prices according to the training and test sample obtained according to this algorithm are given in Table 8.

Table 8. Performance measures of Stacking Regressor

	RMSE	MAE	MAPE
Training	1.94	1.68	4.09
Test	2.17	1.81	3.55

In this context, for the oil prices (till the end of 2021), we take the monthly estimates of the Short-Term Energy Outlook (STEO) presented by EIA (2020c). For the period up to 2025, the 2050 projection data presented in the Energy Outlook 2020 by EIA were used (2020b). For the industry index and Russian gas prices, we use the forecast values obtained in the previous section.

4.1 The impact of COVID-19 Pandemic

The outbreak of COVID-19, which started in Wuhan, China in the last months of 2019, affected the world dramatically. The World Health Organization declared COVID-19 as a global pandemic on 11th of March, 2020 (WHO, 2020). This is followed by a series of restrictions, such as banning international travel, temporary shutdowns, lockdowns and/or home office working, etc., all widely implemented by the governments and businesses. Due to these developments, there were serious fluctuations in foreign exchange and commodity prices, while oil prices also dropped sharply.

Our study has been prepared based on the data realized as of the end of 2019. However, the effects of this pandemic on a global scale have been tried to be examined as a subsection. Our prediction study with machine learning was also rerun with the realizations of the first quarter of 2020. To do so, oil prices from the end of 2021 were compiled from the EIA's May STEO (EIA, 2020b), and for the period from 2022 to 2025, oil prices were compiled from Deloitte's (2020) first-quarter report. The estimates made by the aforementioned institutions have added value to our study as they have a pandemic effect in line with the actual data and the latest prices.

For the industry index, both the realized up to March and afterwards the results obtained by the time series method; and for the Russian gas price, the actual results up to April and then the results obtained by the time series method were used. According to the performance of our Stacking Regressor algorithm, a serious decrease in natural gas prices is observed in 2020 with the effect of the pandemic. It is anticipated that the effects of this decline will only begin to disappear after 2021 and will reach the normal level after 2023 (see figure 3).

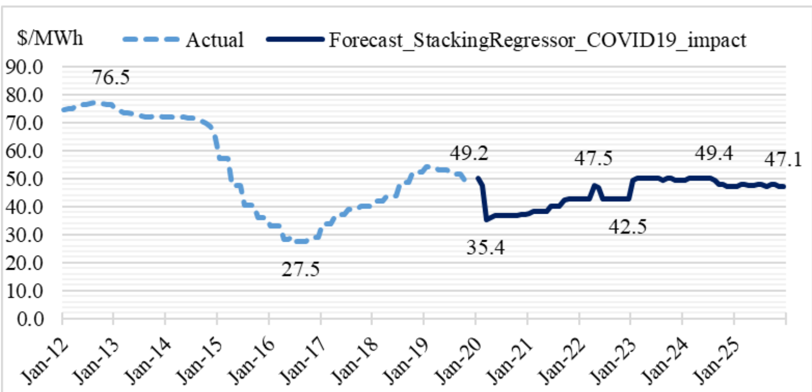

Fig. 3. Forecasts of the Covid effect.

5 Comparison of Scenarios and Discussion

Natural gas prices in Turkey were examined under two scenarios: (i) the current commercial structure (or business as usual), and (ii) assumption of a natural gas hub. In Scenario 1, ARIMA and TAR have estimated the prices based on time series. In Scenario 2, the relationship between supply and demand factors and their effects on prices are examined. Also, the results of the VAR and machine learning studies are obtained. The natural gas price estimation values calculated under both scenarios are shown in Figure 4.

Monthly prices realized during the period from January 2011 to December 2019, and the estimated prices using "ARIMA, TAR, VAR, and Stacking Regressor" between January 2020 and December 2025 were obtained as shown in Figure 4. While the ARIMA forecast under Scenario 1 estimates prices at \$ 44 / MWh by the end of 2025, the VAR analysis estimates under Scenario 2 shows a downward trend to \$ 37 / MWh at the end of 5 years. On the other hand, with the results of machine learning, which is also within the scope of Scenario 2, it is predicted that it will move to reach the level of \$ 48 / MWh at the end of the forecast period. Furthermore, in this analysis in which the effect of COVID-19 is also analysed, although serious decreases of prices in the short term are expected, it is predicted that after 2023 this effect will start to disappear altogether.

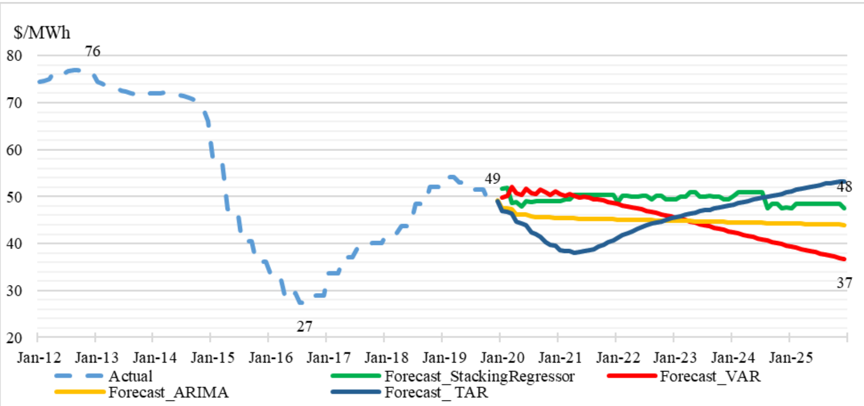

Fig. 4. Forecasts of the two scenarios.

According to Scenario 1, under the conditions where oil-indexed pricing continues, ARIMA showed that future prices will continue to decrease. However, future volatility and potential thresholds in oil prices will likewise be reflected in natural gas prices, and hence, the result of TAR model is more acceptable for this scenario. Also, considering the market prices formed under Scenario 2, although the short-term price increases were seen in the VAR analyse, prices were generally in the direction of decreasing; Stacking Regressor application shows more stable prices. As a result of the statistical analysis, the predictive dynamics of the VAR analysis is provided by using the historical values of the relevant variables. Predicted prices resulted from the Stacking Regressor application considers the impact of future projections of the variables affecting gas prices. Therefore, the prices obtained using machine learning will be taken as the basis for Scenario 2.

6 Conclusion and Recommendations

It is observed in the literature that the medium-term and long-term energy price forecasts are studied mainly using the regressors and the time series analysis. This study is motivated to present the effect of a possible hub construction in the Turkish natural gas market. Hence, two scenarios are constructed to analyse the natural gas prices in the middle term of 2020-2025. The first one is “As Is”, hence the time series gives reliable predictions. The second scenario assumes the existence of a hub and the impacts of oil price, coal price, renewable energy usage, competition index, industry index, carbon emissions, gas storage capacities, heating days are considered as well as the time series on prices.

Currently, Turkey imports natural gas mainly from Russia with bilateral contracts indexed to the oil prices. This allows BOTAS, the state company importing natural gas to determine the price without allowing the market balance of the demand and supply. Scenario 1 is structured using these facts and a time series analysis of 8 years is made using ARIMA and TAR methods to forecast prices for the years 2020, 2021, 2022, 2023, 2024, and 2025. Yet, forecasts with ARIMA show a linear trend after a small descent in parallel to the oil prices, whereas TAR shows continuous price drops but after mid-2021, it is expected to increase.

Scenario 2 with the hub does not have market prices since such a market does not exist in Turkey but assumes that the historical import prices are the market prices. The impacting criteria are analysed using the VAR and Stacking Regressor algorithms to achieve monthly price forecasts for the period 2020-2025. This method shows steep drops in prices down to $37/MWh. Although VAR is well known to show the impacts of different criteria on the dependent variable, and therefore it is very strong in short term forecasts, the results demonstrate the weakness of these methods in medium-term forecasts. Both impacts of different criteria and the time series on the natural gas price are considered only by the Stacking Regressor implementation. This is why medium-term price forecasts for scenario 2 are more reliable and realistic to have almost stable results dropping from $49 to $ 47.6 when Stacking Regressor is used.

With the COVID19 shocks the Globe lived in the last three months, we studied the COVID19 effect in the forecasts. Stacking Regressor is used as the most reliable method and showed the decrease of prices in short term dropping down to $35.6, but recovering prices and finding almost the same figures over $47 at the end of 2025.

All the price analysis run for Scenario 2 showed correlation with Russian gas prices, oil prices, and industry index. Correlation with the oil prices is clear due to the input of bilateral contracts. However, the analysis revealed that there is a significant level of correlation not only with oil prices but also with IND and Russian gas prices. All the different levels of correlations with other criteria show that the natural gas price forecasts should not only be based on time series analysis but either direct or indirect impacts of the nine criteria studied should always be taken together in Turkey.

Analysis for constructing the Hub in Turkey shows the most realistic predictions for the future. Even with the impact of COVID19, Turkey seems more secure if the hub is constructed. There is a continuing strategical plan to create a Natural Gas Market similar to the Power Market and the law is announced but the market is not yet established (EPDK, 2018). It would be wise to consider the natural gas storage options and international hub construction before the market is structured.

Turkey is a continuously developing country with geopolitical importance. As industrialization grows energy markets will have strategic importance. Turkey does not have natural gas reserves and depends on the importation of the resource. A potential natural gas hub constructed in Turkey will make the country stronger in import strategies and might influence the energy security of the European Natural Gas market. This study is giving a foresight for the natural gas prices in Turkey in case a hub is created. Achievements of this study will support the energy decision-makers and Natural Gas policies in Turkey.

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