



Oil Consumption Forecasting using ARIMA Models: An Empirical Study for Greece

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ABSTRACT

Oil is considered one of the most widely used commodity worldwide and one of the most important goods for a country's productivity. Even if the effect of renewable energy sources tries to replace the consumption of fossil fuels, such as oil, nonetheless the level of worldwide oil consumption hasn't changed. Forecasting oil consumption plays an important role on the designing of energy strategies for policy makers. This paper aims at modeling and forecasting oil consumption in Greece using Box-Jenkins methodology during 1960-2020. Forecasting oil consumption was accomplished both with static and dynamic procedure, in and out-of-sample using various forecasting criteria. The results of our paper present a downturn in oil consumption for the following years due to two basic factors. The first is referred to Covid-19 pandemic where economic activity of the country decreased as well as business revenues. The second is the efforts made by the country to replace, oil consumption with other energy forms such as natural gas and mostly renewable sources like sun and wind. With these actions taken, the country – member of EU is consistent with the regulations signed to Kyoto protocol where there are commitments for CO₂ reduction emissions and improvement of energy use.

Keywords: Oil Consumption, ARIMA Model, Box-Jenkins Methodology, Forecasting, Greece

JEL Classifications: C52, C53, Q43, Q47

1. INTRODUCTION

Energy is one of the most important factors affecting modern human life. Its importance has increased in all sectors and trade activities and it is considered one of the fundamental inputs for economic growth. Energy can be produced from various sources such as oil, natural gas, coal, sun, wind, ocean waves and biofuels. According to International Energy Organization (IEA), global energy production sources consist of 36,1% oil, 18% coal, 26% natural gas, 5,8% biofuels and waste, 9,8% nuclear waste, 2,2% hydroelectric and 2,1% other sources. On the other hand, energy consumption is increasing as the total population, the standard of living, urbanization, industrialization and technology progress increase. Because of its leading role to economic growth, the aim of our paper is energy consumption and specifically oil consumption.

For many years, the impact of oil prices in various economic and financial variables is one of the issues that many researchers have dealt with. Even if the outbreak of renewable resources during the last years has replaced the consumption of fossil fuels, such as oil, still the level of oil consumption worldwide hasn't changed. The developed and industrialized countries are considered the largest oil consumers.

Oil is the most widely used commodity globally and one of the most important products for a country's productivity. Thus, it plays an important role in the economic activity both as an imported and exported good. The International Monetary Fund argues that shocks in oil prices affect stock markets, thus a country's economic activity, business income, inflation as well as monetary policy.

Oil is a commodity that is issued in all economic levels and a change in its future oil prices has an impact on the expected cash flows in

most companies, especially those which are dependent in a large extent to oil prices. Contrarily, oil price is affected by business cycles and moves according to growth or recession periods. Apart from economy's growth and the supply and demand forces in oil market, its price is elaborated also from speculative factors that seem to gain remarkable importance during the last years since oil has the characteristics of an investment product.

Oil consumption forecasting plays a vital role in the short and long run energy design for every country, both for policy makers and organizations in every country.

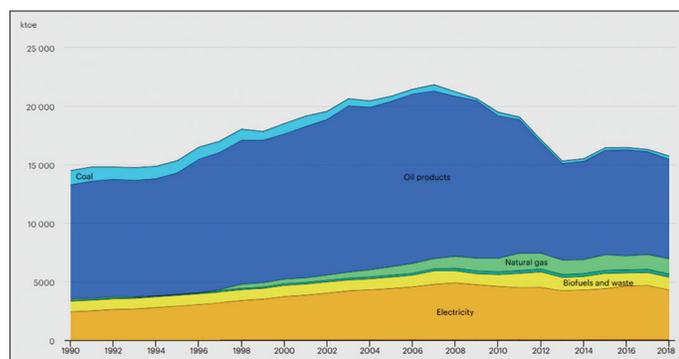
1.1. Energy Sector in Greece

From the beginning of 1990's until today, the energy sector of Greece is formed according to the demands of national economy, the progress of individual economic activities and the development of specific sectors, affecting consumers' habits and also european policies for energy, environment and growth.

In the total energy system, domestic final energy consumption was at 15,735 kilotons of oil equivalent (ktoe) in 2018, down 3.5% from 2017. Figure 1 depicts the share of the various fuels in final energy consumption over the period 1990-2018 for Greece. Oil products account for the largest share in final use consumption (54.2%), followed by electricity (27%), renewable energy sources (8.7%), natural gas (8.3%) and lignite (1.8%). The consumption of fossil fuels in final use, namely petroleum products, lignite and natural gas, decreased considerably in 2018 compared to consumption levels in 2007, falling by 36%. This reduction was to a large extent balanced by consumption of natural gas, the use of renewable energy sources and electricity. Indicatively, consumption of natural gas rose by approx. 54% to 1297 ktoe in 2018 as compared to 2007. Over the same period, the shares of oil products and lignite were reduced by 41% to 8493 ktoe and by 47% to 282 ktoe respectively (IENE, 2020).

In general, liquid fuels and petroleum products comprise an extremely dynamic sector of the economy, involved in all aspects of economic activity. According to the data of the Hellenic Petroleum Marketing Companies Association (SEEPE), internal market fuel sales rose slightly by 0.45%, from 6,655,720 tons in 2014 to 6,685,490 tons in 2018. It is worth noting that the drop in

Figure 1: Final energy consumption by type of fuel in Greece, 1990-2018



Source: IEA (International Energy Agency)

oil product consumption in 2018 as compared to 2017 (6,899,847 tons) was mainly due to a fall in consumption of heating oil and unleaded gasoline. The main feature of the domestic market for oil products is the lack of preventive control measures regarding the fuels in the market, so allowing scope for large-scale illegal activity (adulteration, smuggling) and problems in establishing rules of healthy competition; this impacts adversely the operation of healthy, law-abiding businesses, and ultimately public revenue.

Over the period 2005-2015, oil consumption in Greece recorded a sudden drop by one third due to the economic crisis of 2008 and the Greek financial crisis that ensued, especially after 2009. In recent years, however, oil consumption recovered, rising by 9% between 2013 and 2015, mainly in transport and to an extent in the residential sector.

In 2019, Greece moved from the last places at the top in terms of climate policy, as it now aims at phasing out all lignite power producing units by 2028 at the latest. This commitment was also included in the new NECP, while PPC's new business plan is even more ambitious, as it includes the closing down of all lignite units by 2023. Hence, Greece is among the 15 most advanced countries in the EU in this respect, which have already decided to fully phase out coal/lignite, and is the first lignite-producing EU member state that has set a firm decarbonisation date prior to 2030. Moreover, Greece is the 33rd country globally that enters into the international Powering Past Coal Alliance (Hellenic Republic Ministry of the Environment and Energy, 2019).

1.2. Treaty on Climate Change

Energy consumption is considered one of the most crucial issues for every country. The use of fossil fuels (coal, oil and gas) for industrialization and urbanization has been growing for more than three centuries leading to increased development of economies and technology advances worldwide. But, during the years the intensive use of fossil fuels resulted in environmental pollution and global warming. Such an increase in the global temperature has caused damage on nature, bringing about irreversible changes to many ecosystems and a consequent loss of biodiversity. Higher temperatures and adverse weather conditions have also resulted in huge costs for countries' economy and hamper their ability to produce food. During the last 20 years, it was imperative to endorse measures which will lead to energy saving both in national and international level. Drastic reduction of CO₂ emissions which destabilize earth's atmosphere and triggers climatic changes, energy thrift, improvement of energy efficiency and renewable energy sources are considered as urgent choices for many countries.

The Kyoto Protocol, which follows the United Nations Framework Convention on Climate Change (UNFCCC), is an international legal document signed for facing climate change. Kyoto Protocol was adopted on 11 December 1997. It is considered an obligation among industrialized countries to reduce the CO₂ emissions of greenhouse effect by 5.2% average in relation to the levels of 1990, during the first "commitment period," which covers the years from 2008 until 2012, and this has been applied since 2005 (UNFCCC, 1997). The European Community signed the Protocol

on 29 April 1998 which set binding obligations to reduce emissions and improve energy use. It is worth mentioning that European countries differ significantly in terms of resources, in economic and geographical size, in population and standard of living.

The Paris Agreement is a legally binding international treaty on climate change. It was adopted by 196 Parties in Paris, on 12 December 2015 and entered into force on 4 November 2016. Its goal is to limit global warming below 2, preferably to 1.5°C, compared to pre-industrial levels. To succeed in this long-term temperature goal, countries aim to reach global peaking of greenhouse gas emissions as soon as possible achieving a climate neutral world by mid-century. The Paris Agreement is a milestone in the multilateral climate change process because, for the 1st time, a binding agreement brings all nations into a common cause to undertake ambitious efforts to combat climate change and adapt to its effects (European Commission, 2016). According to Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), CO₂ emissions from fossil fuels should reach to zero by 2050-2070. This requires the abandonment of new investment in oil, lignite, coal and natural gas and the promotion of renewable energy sources. Nations have the means to limit climate change and build a more prosperous and sustainable future.

The rest of the paper is organized as follows: Section 2 describes literature review while Section 3 focuses on theoretical background. In Section 4, the data are presented and Section 5 the empirical results are provided. Section 6 focuses on the forecasting and in Section 7 conclusions are given.

2. LITERATURE REVIEW

In the literature, many researchers applied different methodologies such as multiple regression, exponential smoothing, ARIMA models, neural networks and more for the forecasting of energy consumption in various sectors.

Yuan et al. (2016) examined the forecasting of primary energy consumption for China creating two univariate models, ARIMA model and GM (1,1). In order to face the problems arised in the forecasting, the authors created a hybrid model for both models gaining better forecasts from the previous ones. The results of their paper showed that the growth rate of primary energy consumption for China from 2014 until 2020 will be larger but smaller than the first decade of the new century.

Barak and Sadegh (2016) for the forecasting of energy consumption in Iran, used ARIMA and ANFIS (Adaptive Neuro Fuzzy Inférence System) models. Due to various diversifications on both models, they created a hybrid ARIMA and ANFIS where the MSE criterion reduced to 0.026% from 0.058% in the two previous models.

Ozturk and Ozturk (2018) used annual data from 1970 to 2015 and ARIMA models to forecast energy consumption in Turkey. The results of their study showed that the energy consumption in Turkey will continue to increase until the end of 2040. Consumption in coal, oil, natural gas, renewable energy and total energy will continue to increase with an annual average rate

4,87%, 3,92%, 4,39%, 1,64% and 4,20%, respectively for the next 25 years.

Zhang (2016) used data from 2002 until 2014 and grey-extended SIGM model to forecast the annual consumption for the next 5 years in China. The results of the paper are better than those of classical grey GM, DGM and NDGM as well as those of the grey-extended SIGM model. At the same time, according to the FSIGM model, this paper predicts China's crude oil consumption for 2015-2020.

Godfred (2013) on his paper correlates energy consumption with per capita GDP increase for Ghana. Using S ARIMA (1,1,1) (0,1) model, he found that an increase on energy consumption annually by 1.21% has as a result the increase of per capita GDP by 5.5% annually for the period 2000-2008.

3. THEORETICAL BACKGROUND

3.1. ARIMA Models

ARIMA are theoretically the most frequently used models for the forecasting of short run forecasts of time series. ARIMA models became popular from Box and Jenkins (1976) and predict the future values of a time series as a linear combination of its past values and the lags of forecast errors named innovations. An ARIMA (p, d, q) model has three parameters. AR parameter (p) represents the order of autoregressive procedure, parameter (d) represents the order of difference on the time series and MA parameter (q) represents the order of moving average process. The ARIMA forecasting equation for a stationary time series is a linear equation like regression where the predictors consist of the lags of dependent variable as well as the lags of forecast errors. Thus, the form of ARIMA equation will be (Dritsaki and Dritsaki, 2020):

$$\left(1 - \sum_{i=1}^p \phi_i L^i\right) (1-L)^d (y_t - \mu) = \left(1 - \sum_{j=1}^q \vartheta_j L^j\right) e_t \quad (1)$$

where

$$\phi_p(L) = 1 - \sum_{i=1}^p \phi_i L^i \text{ and } \vartheta_q(L) = 1 - \sum_{j=1}^q \vartheta_j L^j \text{ are polynomials in}$$

terms of L of degree p and q.

y_t is the time series, and e_t is the random error at time period t, with μ is the mean of the model.

dis the order of the difference operator.

$\phi_1, \phi_2, \dots, \phi_p$ and $\vartheta_1, \vartheta_2, \dots, \vartheta_q$ are the parameters of autoregressive and moving average terms with order p and q respectively.

L is the difference operator defined as $\Delta y_t = y_t - y_{t-1} = (1-L)y_t$.

3.2. The Box-Jenkins Methodology

The Box-Jenkins approach consists of the following steps:

- Data preparation for series stationarity

For series stationarity we use time plots, the estimation of linear trend, auto correlation function (ACF) as well as unit root tests. If the levels of series are non-stationary, we proceed with second differences.

- Model identification

ARIMA model identification is referred to the determination of the parameters p, d, q . First, the number of d differences is determined in order the series to be stationary. To determine the order of ARMA (p, q), the function of autocorrelation (ACF) and partial autocorrelation (PACF) of the stationary series is used. Parameter p of autoregressive operator is determined by the partial autocorrelation coefficient and parameter q of the moving average operator is determined by the autocorrelation coefficient. The limits $\pm \frac{2}{\sqrt{n}}$ for non-stationarity on both functions are used so

we obtain a number of ARMA (α, β) models where $0 < \alpha < p$, and $0 < \beta < q$. For the optimum model we use the Akaike (AIC) and Schwartz (SIC) criteria.

- Estimation model

Model estimation is done with Maximum likelihood methodology. We maximize the probability by iterating Marquardt and Berndt-Hall-Hausman algorithms using derivatives, optimum step and a convergence criterion for the change in the norm of the parameter vector from one iteration to the next.

- Diagnostic checking of the model

With diagnostic checking, we investigate if the estimated model is acceptable and statistical significant, in other words if it “best” fits the data. The diagnostic testing of the model consists of Ramsey specification test (1969) (RESET test), normality test (Jarque and Bera, 1980 test), autocorrelation test (Ljung and Box, 1978 statistic), ARCH (squared residuals’ and Ljung and Box, 1978 test, Engle, 1982 test).

- Forecasting.

One of the main goals of the analysis on time series models is forecasting. Forecasting can be static and dynamic. Static forecasting is known as a one-step ahead forecast and uses the actual lagged values of time series Y for the forecasts. The dynamic forecasting is known as multi-step ahead forecast and uses the actual lagged value of Y variable to measure the first predicted value. After, it uses the first predicted values in order to calculate the second one and so on (Dritsaki, 2015).

If s is the first observation for forecasting, then we have the following equation:

$$\hat{Y}_s = c(1) + c(2)Y_{s-1} \tag{2}$$

where Y_{s-1} is the actual value of the last observation of the sample and \hat{Y}_s is the first predicted value. For the next predicted values, we use the equation below:

$$\hat{Y}_{s+k} = c(1) + c(2)Y_{s+k-1} \tag{3}$$

where \hat{Y}_{s+k-1} are the lagged predicted values

The accuracy of the forecasting depends on forecasting error. Furthermore, the following statistical measures are used:

The mean absolute error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i| \tag{4}$$

where

Y_i is the actual value.

\hat{Y}_i is the predicted value

The root of mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2} \tag{5}$$

Theil’s U statistics (1961).

$$U_1 = \frac{\left[\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \right]^{1/2}}{\left[\frac{1}{n} \sum_{i=1}^n Y_i^2 \right]^{1/2} + \left[\frac{1}{n} \sum_{i=1}^n \hat{Y}_i^2 \right]^{1/2}} \tag{6}$$

$$U_2 = \frac{\left[\sum_{i=1}^{n-1} \left(\frac{\hat{Y}_{i+1} - Y_{i+1}}{Y_i} \right)^2 \right]^{1/2}}{\left[\sum_{i=1}^n \left(\frac{Y_{i+1} - Y_i}{Y_i} \right)^2 \right]^{1/2}} \tag{7}$$

4. DATA

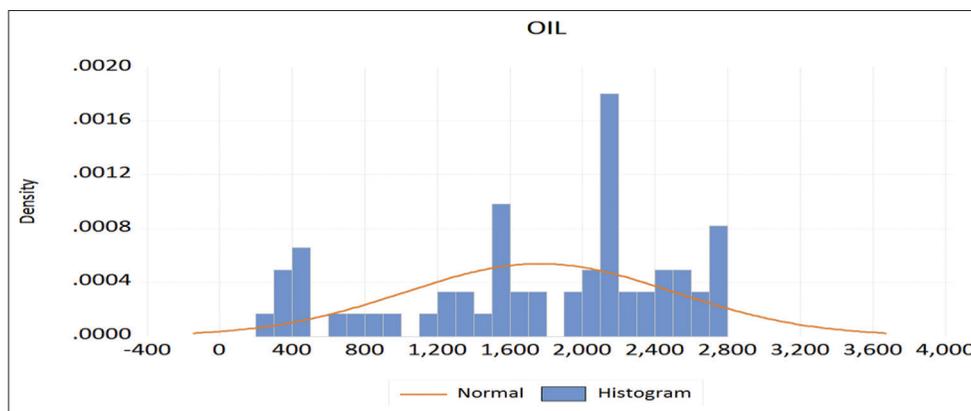
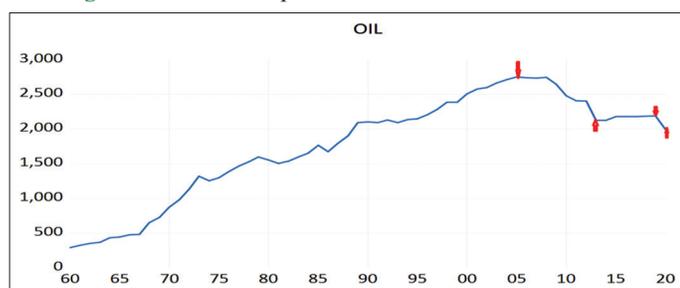
For the empirical analysis of the paper, the oil consumption (in kilotons) in Greece was used covering the period 1960-2020, in total of 61 annual observations. The data derived from World Bank. E-Views 11 econometric software was used for the construction of ARIMA models.

On Table 1, the descriptive statistics of oil consumption in Greece are presented.

From the above table, we can see that the average annual oil consumption is 1763.7 kilotones with the largest consumption to be recorded in year 2005 with 2753 kilotones. The series is

Table 1: Descriptive statistics of oil consumption

Mean	Max.	Min.	Std. dev.	Skew.	Kur.	J-B	Obs.
1763.7	2753.0	289.06	744.07	-0.612	2.253	5.226 (0.073)	61

Diagram 1: Histogram and graph of normal distribution function**Diagram 2:** Oil consumption for Greece from 1960 until 2020

left skewed and leptokurtic while all data series follow normal distribution.

On the following Diagram 1, the histogram together with the graph of normal distribution is depicted.

Most of the data series follow a normal distribution as it is shown from the above Diagram 1.

5. EMPIRICAL RESULTS

5.1. Testing for Stationarity

- Time plots

On Diagram 2, the progression of oil consumption for Greece is showed for the examined period.

From Diagram 2 we can see that oil consumption in Greece exhibits an upward trend for a long time period until 2005 and a decline follows until 2013 due to economic crisis and memorandums. As light increase followed until 2019 while on 2020 a decrease was recorded due to Covid-19 crisis worldwide. In other words, we conclude that the movement of oil consumption is a random walk model.

- Linear trend model.

On the following table, the estimation of the variable in relation to time for the determination of the existence of trend is presented together with the Diagram 3 of actual and estimated values of the examined variables.

Based on the results on Table 2 and Diagram 3, we can see that there is a trend on the estimated model (prob<5%). Thus, this series is characterized as non-stationary.

- Graph on auto correlation coefficients.

Afterwards, we test for stationarity through the auto correlation correlogram.

The autocorrelation coefficients on Diagram 4 decay slowly denoting that the series is non stationary. Moreover, the value of the first auto correlation coefficient is large and positive meaning that the series is non stationary.

- First differences on series.

We apply again the previous tests so that we can detect the existence of stationarity of the series on first differences. Diagram 5 shows oil consumption on first differences.

We notice that the behavior of oil consumption presents significant fluctuations. This is a possible indication for mean stationarity.

Afterwards, we test for stationarity with the autocorrelation correlogram on first differences.

The autocorrelation coefficients decay quickly from the above Diagrams 6 and this denotes that the series is stationary.

- Unit root tests

The confirmation of series stationarity is conducting also with Dickey and Fuller (1979; 1981) and Phillips and Perron (1998) unit root tests.

The results on Table 3 confirm that the series is stationary on first differences.

- Model Identification:

The identification of ARIMA model is referred to the determination no f , p , d , q parameters. First, the number of differences d is

determined in order to change the series in a stationary series. The determination of parameter d was employed using autocorrelation coefficients and confirmed with unit root tests. Afterwards, from the results of Diagram 7 the parameters p and q are determined compared with the critical value $\pm \frac{2}{\sqrt{n}} = \pm \frac{2}{\sqrt{61}} = \pm 0.256$. So, we

get a number of ARMA (α, β), where $0 < \alpha < p$, and $0 < \beta < q$. From the values of partial autocorrelation only the value $p=2$ is larger than critical value and from the values of autocorrelation coefficients $q=1$ is larger than critical value. Using the above values, we choose the best ARMA (p, q) model from the smallest values of AIC, SC, and Sigma SQ criteria as well as the largest of $A_j R^2$ from the Table 4.

The results from Table 4 show that according to AIC, SC, Sigma SQ, and $A_j R^2$, the most suitable model is ARIMA (1,1,1).

Using the automatic ARIMA forecasting procedure with EViews, we find all models' alternatives.

From Figure 2, we select the best ARMA(p, q) model from the smallest values of AIC criterion. According to Figure 2, the ARMA (0,1) (0,0) model is the most appropriate. Due to the fact that its coefficients are not statistical significant, we obtain ARMA (1,1) (0,0) as the most appropriate.

- Estimation and Diagnostic tests of the model

Diagram 3: Actual, fitted and residuals plot

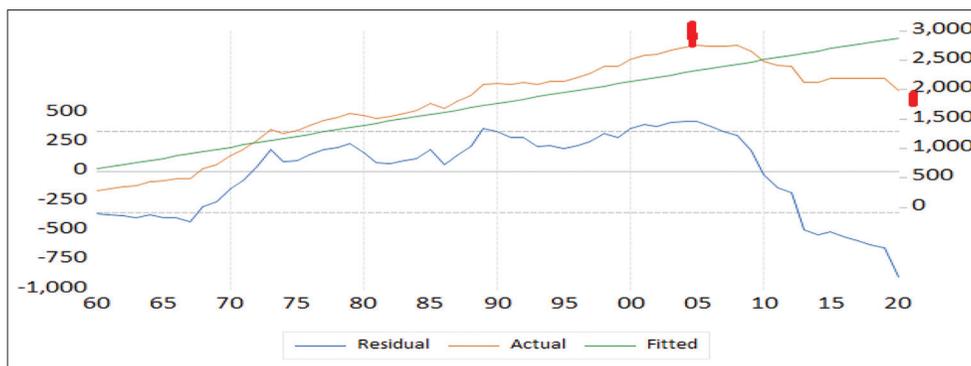


Diagram 4: Autocorrelation and partial autocorrelation correlogram of oil consumption

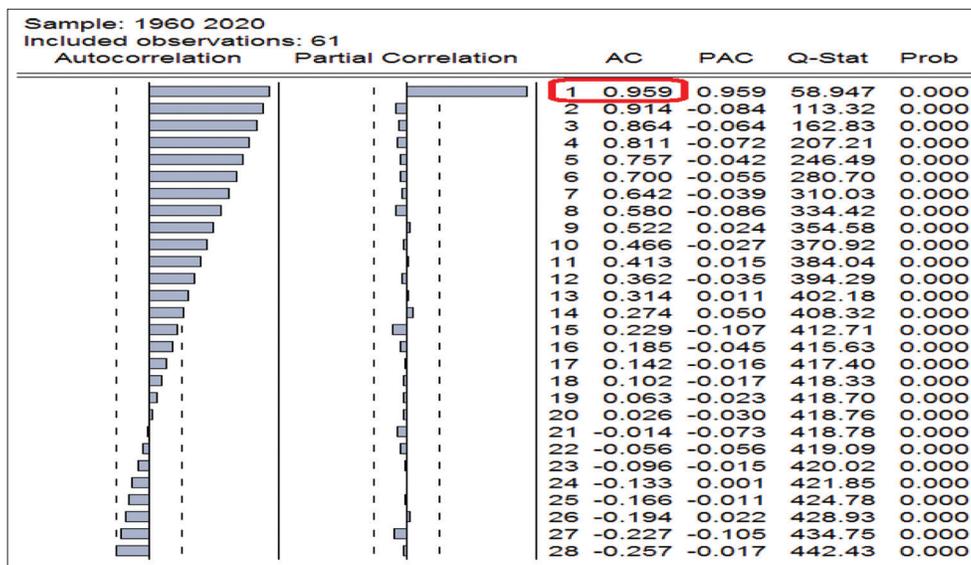


Table 2: Estimation of oil consumption

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	647.9274	87.49797	7.405056	0.0000
TREND	37.19374	2.515390	14.78647	0.0000
R-squared	0.787494	Mean dependent var.	1763.740	
Adjusted R-squared	0.783893	S.D. dependent var	744.0742	
S.E. of regression	345.9004	Akaike info criterion	14.56242	
Sum squared resid	7059178	Schwarz criterion	14.63163	
Log likelihood	-442.1537	Hannan-Quinn criter.	14.58954	
F-statistic	218.6397	Durbin-Watson stat	0.061234	
Prob (F-statistic)	0.00000			

Since the most suitable model is ARIMA (1,1,1) the estimation will occur with Maximum Likelihood approach. We maximize the probability by iterating algorithms Marquardt and Berndt-Hall-Hausman, using derivatives optimum step size and a convergence criterion for the change in the norm of the parameter vector from one iteration to the next.

The following Table 5 provides results of the estimation of ARIMA (1,1,1) model.

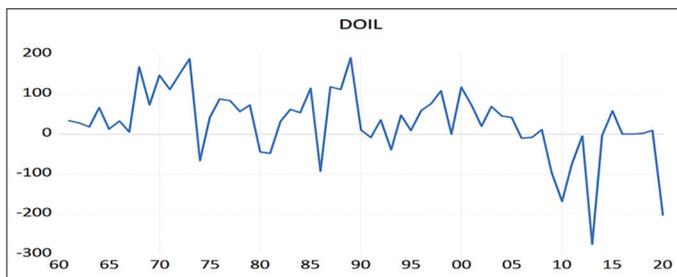
The results on Table 5 show that the coefficients are statistically significant in 1% level of significance.

The estimation occurred with Maximum Likelihood methodology using BHHH algorithm and the inverse matrix OPG. The results come up after 14 iterations. The coefficient for the estimation of error variance (volatility) is statistical significant in 1% level of significance.

Afterwards, we exhibit inverted AR Roots and inverted MA Roots for model's stationarity.

Figure 3 shows that the inverted AR Roots and inverted MA Roots of the model are within the unit circle meaning that the process is

Diagram 5: Oil consumption on first differences



stationary. So, we can use the ARIMA (1,1,1) model for diagnostic tests.

Next, we examine model specification with Ramsey RESET test.

The results from Table 6 display that the ARIMA (1,1,1) model has correct specification (prob>5%) on both F distribution and LR likelihood ratio.

Following, we examine the autocorrelation of model's residuals.

As the coefficients of autocorrelation and partial autocorrelation of the residuals are within the limits, we conclude that there is

Table 3: Summary table of Augmented Dickey–Fuller and Phillips-Perron unit root tests

Variable	ADF		P-P	
	C	C, T	C	C, T
OIL	-2.784 (0)	0.933 (0)	-2.346[4]	0.614[3]
DOIL	-5.061 (0)*	-6.155 (0)*	-5.369[4]*	-6.157[2]*

*, ** and *** show significant at 1%, 5% and 10% levels respectively. The numbers within parentheses followed by ADF statistics represent the lag length of the dependent variable used to obtain white noise residuals. The lag lengths for ADF equation were selected using Schwarz Information Criterion (SIC). Mackinnon (1996) critical value for rejection of hypothesis of unit root applied. The numbers within brackets followed by PP statistics represent the bandwidth selected based on Newey and West (1994) method using Bartlett Kernel. C=Constant, T=Trend

Table 4: Comparison of the model through AIC, SIC, Sigma SQ, Aj R²

ARIMA model (p, d, q)	Criteria			
	SigmaSQ	AdjR ²	AIC	SC
(1,1,0)*	6511.6	0.054	11.72	11.82
(2,1,0)^	6282.4	0.071	11.71	11.85
(1,1,1)*	6085.6	0.100	11.68	11.82
(2,1,1)^	6083.7	0.084	11.72	11.89
(0,1,1)^	6681.3	0.029	11.74	11.85

^Model with coefficients non statistical significant. *1%significance

Diagram 6: Autocorrelation and partial autocorrelation correlograms of oil consumption on first differences

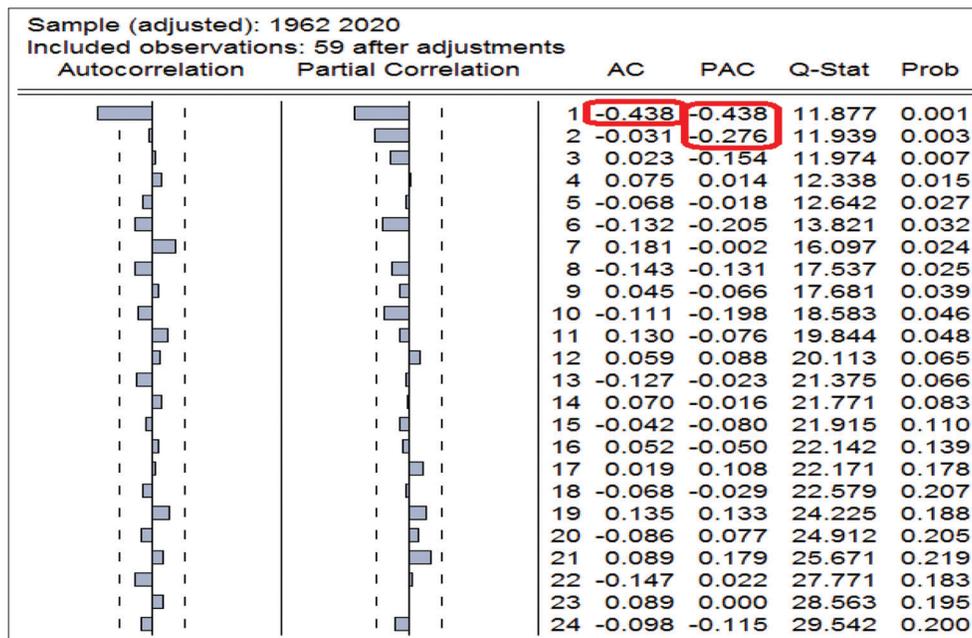


Figure 2: Automatic ARIMA model estimation choice

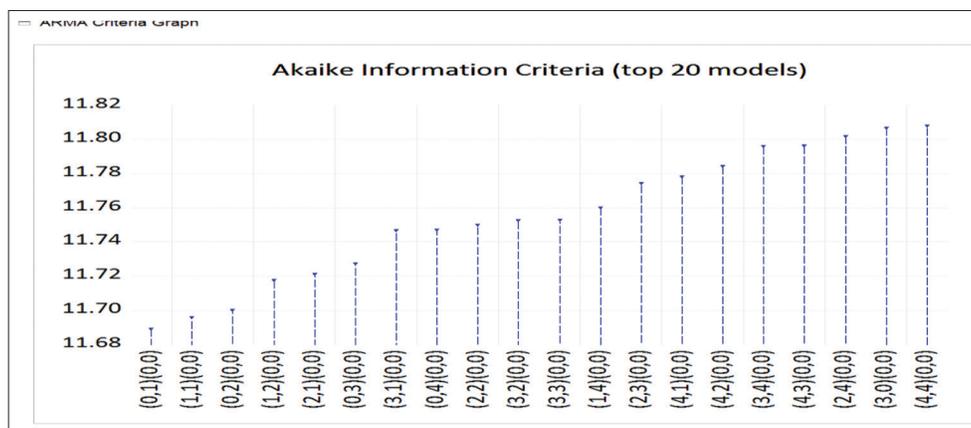
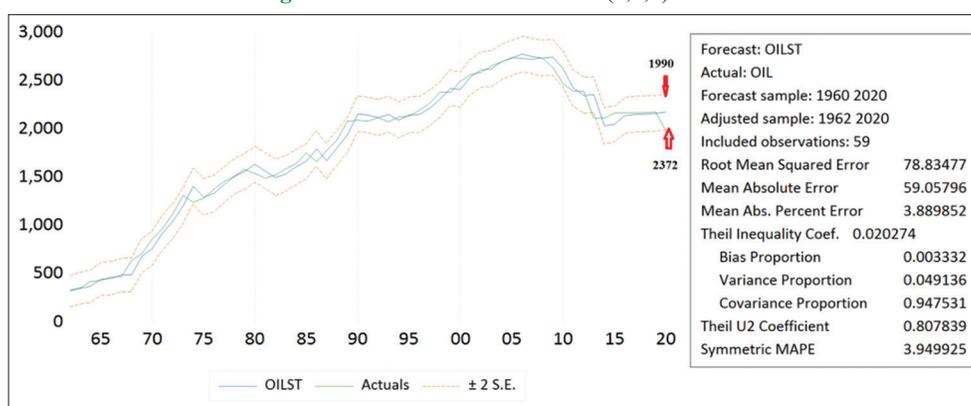


Figure 3: Inverted roots of ARIMA (1,1,1) model



independence between the residuals of the ARIMA (1,1,1) model in 5% level of significance (no autocorrelation).

The following Diagram 8 exhibits the test of conditional autocorrelation.

Autocorrelation and partial autocorrelation coefficients' on squared residuals are within the limits ± 0.256 so we can claim that there is no autoregressive conditional heteroscedasticity on the residuals of ARIMA (1,1,1) model in 5% level of significance (no ARCH effect).

The diagnostic tests of the model have no issues thus we can proceed with forecasting.

6. FORECASTING

On the following Table 7 we exhibit the evaluation criteria of static and dynamic forecasting of the model for the period 1960-2020.

From the results of Table 7, all the statistical criteria conclude that Static Forecast provides better results for forecasting than the Dynamic Forecast for the ARIMA (1,1,1) model.

On the Figure 4, the trend of actual and predicted values in oil consumption with static forecasting is featured concerning the in-sample period from 1960-2020.

Table 5: Estimation of ARIMA (1,1,1) model

Variable	Coefficient	Std. Error	T-Statistic	Prob.
AR (1)	0.914696	0.113684	8.045983	0.0000
MA (1)	-0.698697	0.191814	-3.642580	0.0000
SIGMASQ	6123.907	940.4168	6.511908	0.0000
R-squared	0.140641	Mean	28.35100	
Adjusted R-squared	0.110489	S.D.	85.12884	
S.E. of regression	80.28834	Akaike info criterion	11.66522	
Sum squared resid	367434.4	Schwarz criterion	11.76994	
Log likelihood	-346.9567	Hannan-Quinn criter.	11.70618	
Durbin-Watson stat	1.885325			
Inverted AR Roots	0.91			
Inverted MA Roots	0.70			

Table 6: Ramsey RESET test

Omitted variables: Squares of fitted values			
Specification: D (OIL) AR (1) MA (1)			
Distribution	Value	df	Probability
t-statistic	0.304680	56	0.7617
F-statistic	0.092830	(1,56)	0.7617
Likelihood ratio	0.134664	1	0.7136

Diagram 7: Correlograms of autocorrelation and partial autocorrelation of the residuals on ARIMA (1,1,1) model

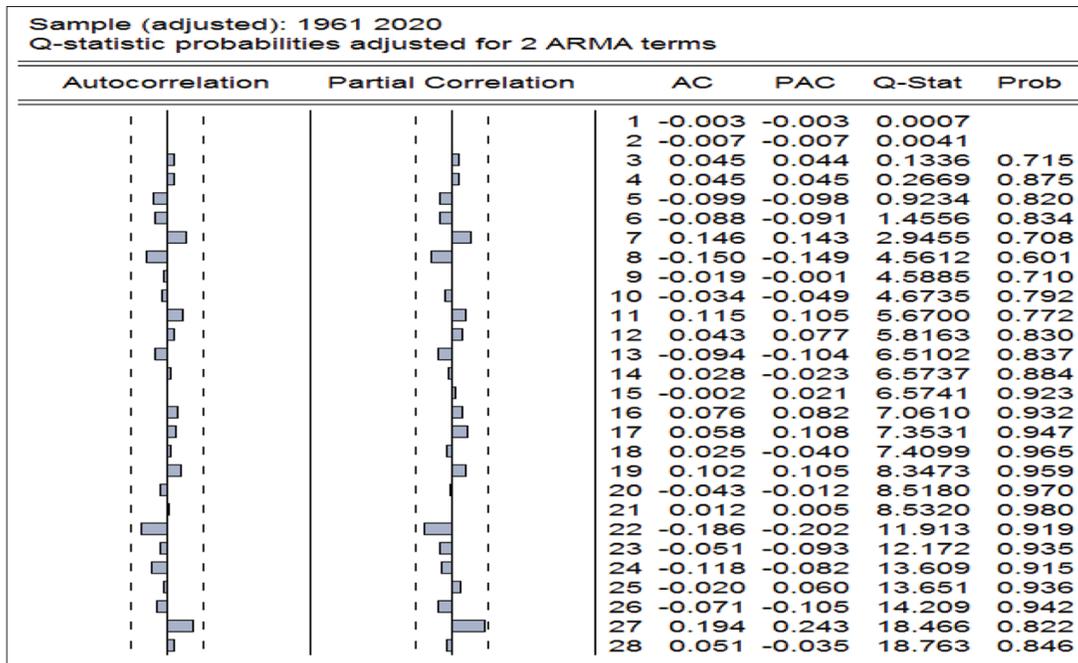


Diagram 8: Correlograms of autocorrelation and partial autocorrelation of the squared residuals on ARIMA (1,1,1) model

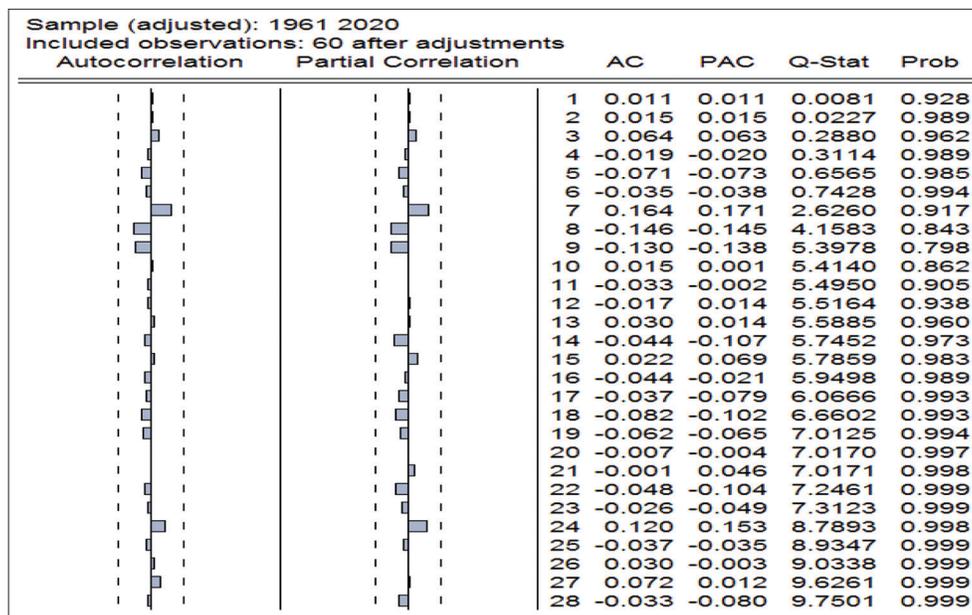
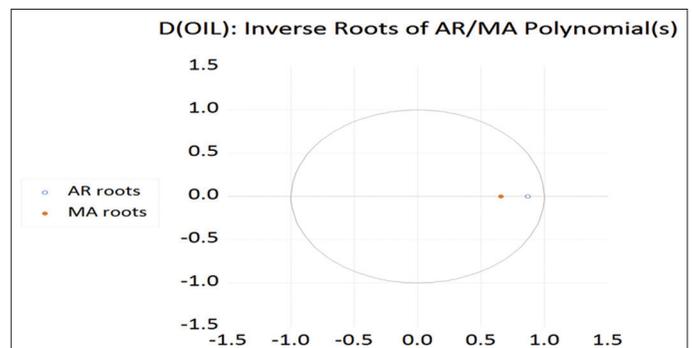


Table 7: Evaluation criteria of forecasting ARIMA (1,1,1)

Criteria	Dynamic forecast	Static forecast
RMSE	1525.321	78.83477
MAE	1371.491	59.05796
MAPE	68.70311	3.889852
Theil	0.639231	0.020274
Bias Proportion	0.808469	0.003332
Var. Proportion	0.190127	0.049136
Cov. Proportion	0.001403	0.947531
Theil U2 coef.	9.260582	0.807839
SymmetricMAPE	110.2998	3.949925

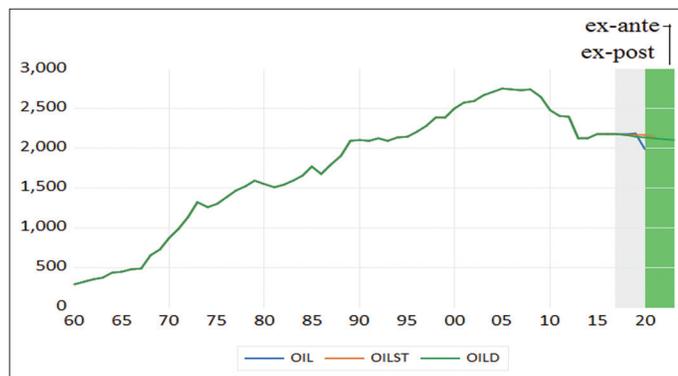
Figure 4: Actual and predicted value of Greece oil consumption from 1960 to 2020



From the Figure 4 we notice that the width of confidence interval for the year 2020 is between 1990-2372.

Table 8: Static and dynamic forecast of Greece oil consumption

Year	Actual (OIL)	Static forecast (OILST)	Dynamic forecast (OILD)
Ex-post forecast			
2018	2183.45	2168.19	2165.45
2019	2198.45	2173.96	2152.69
2020	1990.12	2167.76	2141.47
Ex-ante forecast			
2021		2152.45	2129.12
2022			2117.54
2023			2106.01

Figure 5: Static and dynamic forecast of oil consumption

On Table 8 the forecasted results are shown. The period 2018-2020 was used as a forecast for in-the-sample, whereas the forecast for out-of-sample covers the period 2021-2023.

The results on Table 8 show the increase of oil consumption for Greece with the static forecasting for the year 2020, while the dynamic forecasting exhibit a slight decrease of oil consumption for the years 2021-2023. On the following Figure 5, the trend of static and dynamic forecasting is presented.

The oil consumption seems to have a slight downturn for the years 2021-2023.

7. CONCLUSION

Energy is regarded as a significant material basis for global economic and social growth. The production and consumption of oil may lead or prevent economic growth. Imbalances on supply/demand oil market are becoming more apparent due to the increasing use of renewable energy sources. Low use of oil, irrational consumption structure, pollution and other issues can limit the growth of industrialized countries. With the industrialization of the countries, urbanization and the increase of energy consumption, environmental restrictions will rise in most countries. Arrangements between energy and economic growth should be made that will lead to a sustainable economic development and society worldwide.

The prediction of demand and oil consumption is an important part of growth strategies. The increasing consumption of sustainable energy in Greece and also the structural changes that are taking

place account for the new energy policy applied in Greece abiding by the rules and criteria addressed from the European Union.

This paper aimed at modeling and forecasting oil consumption for Greece using Box-Jenkins methodology during the period 1960-2020. The results of the paper shown that according to AIC, SC, Sigma SQ, and AjR^2 criteria, the most suitable model is ARIMA (1,1,1) for estimation and forecasting of oil consumption. The estimation of ARIMA (1,1,1) model was accomplished with Maximum Likelihood approach. We maximized likelihood by iterating Marquardt and Berndt-Hall-Hall-Hausman algorithms using derivatives, optimum step size and a convergence criterion for the change in the norm of the parameter vector from one iteration to the next. Forecasting was attained with static and dynamic procedure in and out-of-sample using all the forecasting criteria. The results presented a sharp drop in oil consumption in the following years because of two basic factors. The first one is due to coronavirus crisis that hit the economic activity of the country and the second one are the efforts made by replacing oil consumption with other energy forms.

International Energy Agency (IEA) on the recent Oil Market Report (2021) points out that the rebalancing of the oil market remains fragile in the early part of 2021 as measures to contain the spread of Covid-19, with its more contagious variants, weigh heavily on the near-term recovery in global oil demand. IEA predictions for economic growth and oil demand increase depend in a large scale on progress in distributing and administering vaccines, and the easing of travel restrictions in the world's major economies.

The outbreak of Covid-19 added more uncertainty to the perspective of oil market outlook and oil consumption in the beginning of the forecasting period which covers the years 2021-2023. In the year 2020, oil consumption has shrunk for the first time after the economic crisis and memorandums in Greece. However, the situation remains volatile until global pandemic will disappear. The potentials for the oil market and oil consumption will depend on how quickly the Greek government will take action to constrain pandemic. This uncertain situation is leading to two possible scenarios. The first one, the pessimistic scenario, is the delay to constrain the virus. The second, the optimistic, refers to the coronavirus infections to the global population so that the countries can recover and economic activity will start again.

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