INTERNATIONAL HELLENIC UNIVERSITY

A Time Series Analysis: Electricity Demand in Turkey

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SCHOOL OF SCIENCE & TECHNOLOGY

A thesis submitted for the degree of

Master of Science (MSc) in Energy and Finance

DECEMBER 2019

THESSALONIKI – GREECE

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Dedication

This dissertation is dedicated to my beloved father, Mr. Nazım Meriç.

Abstract

This dissertation was written as a part of the MSc in Energy and Finance. The main aims of this study can be summarized as follows: a) to analyze the causal relationship between Turkish net electricity consumption and the GDP of the country, b) to forecast net energy consumption of Turkey for the next decade by using two appropriate Autoregressive Integrated Moving Average (ARIMA) models. The findings of this research indicate that there exists a significant unidirectional causality from GDP to electricity consumption, and both series are cointegrated. The estimated long-run income elasticity of demand for electricity in Turkey is found very high, i.e., 1,106. The results also indicate that the forecasts of the ARIMA(3,2,2) model are very close to the official consumption projections made by The Ministry of Energy and Natural Resources. Moreover, the ARIMA(13,2,0) model performance is superior to the ARIMA(3,2,2) model's one. It is predicted that net electricity consumption of Turkey in 2028 will be somewhere between 359.315 GWh and 367.553 GWh, which corresponds to a minimum 40% increase within ten years.

First of all, I would like to express my gratitude to my supervisor, Prof. Theodoros Panagiotidis. His enormous support and comprehensive guidance during my dissertation period gave me a big motivation to complete this study. I am exceptionally indebted to him, both personally and academically. I am extending my thanks to all academic staff at the IHU, especially to Prof. Theologos Dergiades, who has always shown me genuine support from the beginning of my study in Energy and Finance. My gratitude extends to my classmates, Ms. Konstantina Kovlaka, together with her beautiful family, and Mr. Evangelos Trilivas. My sincere thanks also go to the Jean Monnet Scholarship Programme, for giving me a chance to realize my dream by studying in an EU country. I am also very much thankful to my family and friends in Turkey for their great support during my stay in Greece. Last but not least, special thanks to Mr. Axiotis Giakzidis for giving me a lot of support and encouragement.

Asiyan Meric

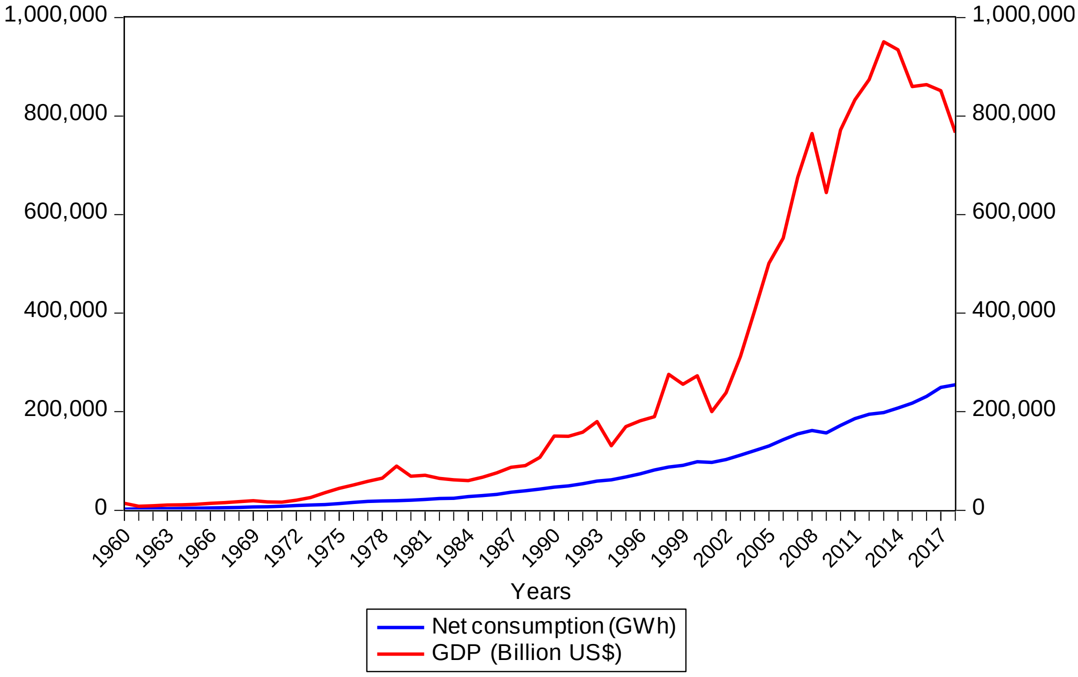
02/12/2019

Contents

1 Introduction

Turkey, as a natural bridge between Asia and Europe continents, has essential roles in both economic and political areas in the world. The country has one of the fastest developing economies in the world, with an average annual Gross Domestic Product (GDP) growth rate of 5,5% for years 2003-2018. According to the International Monetary Fund, the Turkish economy reached 13th rank globally last year, and it is expected to be located in 12th place among world economies in 2023. Moreover, with more than 82 million population, halves of which are under the age of 32, Turkey has also significantly remarkable labor force growth. Besides, the Helsinki European Council held on 10-11 December 1999 has opened a new era between Turkey and the European Union (EU) so that Turkey has been a candidate state to the union from that time. Looking at Figure 1, it is apparent that there exists a significant positive correlation between the net electricity consumption in Turkey and the Turkish GDP for the period of 1960-2018.

Figure 1: Time series plots for the net electricity consumption and GDP of Turkey, 1960-2018.



All these developments have also led to massive transformations and reforms in the energy markets of the country as well as the other sectors. Turkey's primary energy supply has doubled in the last 18 years. Expanding the economy along with population growth, has also affected the electricity sector of the country severely. As a natural consequence of all advancements, installed capacity and electricity consumption in Turkey have nearly tripled from 2002 to 2018. The country's electricity market has been restructuring via revolutionary privatization and liberalization programs since the beginning of the new millennium. The Turkish energy market has two main properties; these are increasing demand for energy and dependence on imports. Those factors are the main reasons for the fact that why the country continues in her efforts to enrich its national energy mix. At that point, it is worthy of mentioning the importance of electricity demand estimation in Turkey.

Electricity demand (consumption) forecasting has a crucial role in determining energy policies and making proper decisions for all market actors. Because of its non-storable characteristics, it also has a critical function within the context of the security of energy supply. The countries like Turkey, which are highly dependent on the external resources for power generation, should minimize the risks of energy-dependency through sustainable energy planning and revisions. In that manner, the importance of electricity demand estimations comes to light. Several studies have discussed this topic with alternative approaches and methodologies. Turkey's energy demand estimation has also drawn significant interest from researchers over recent years.

Furthermore, electricity consumption forecasts of Turkey are officially implemented by The Ministry of Energy and Natural Resources (MENR). However, these official projections have been mostly debated among scholars. The sum and the substance of it, the issue of Turkish energy consumption forecasts has been controversial and much-disputed subject within the field of time series. Most of the previous studies have been limited to convenience samples. To an extent to which electricity consumption of the country plays a role in Turkish GDP, or the opposite remains poorly understood. Causality is a term frequently used in the literature of Turkish electricity demand forecasting, but to date, there has been no consensus on this topic.

This prospective study is mainly designed to investigate the long-run economic relationship between electricity consumption and economic growth in Turkey and to make future consumption forecasts by modeling time series. Moreover, this dissertation sets out to assess the feasibility of official energy demand projections done by MENR. The specific aim of the study is to shine new light on the debates in the literature. To achieve all these aims, the data taken into account in this study are the most current ones. Therefore, this study is aimed to be designed for the most recent research in this field of the research area.

Specifically, the following issues will be addressed in this dissertation: Firstly, the stationarity of the time series of energy consumption and GDP and the existence of a long-run relationship between these series will be examined. Later on, according to the suitable VAR modeling, the results of the Granger causality analysis will be discussed together with Toda and Yamamoto model findings. Finally, appropriate ARIMA forecasting models will be determined, and their results for the energy consumption of Turkey will be compared with the official projections and between each other. All analyses in the study will be done via statistical software, i.e., EViews 9.

The remaining part of this dissertation proceeds as follows: The next part discusses the specific methods for energy demand forecasting in the literature. The third chapter is concerned with the structure of the Turkish electricity market from past to present. Chapter Four analyses the data gathered and addresses each of the research questions in turn. The purpose of the final part is to draw conclusions and to identify areas for further research.

2 Literature Review

According to Kumar and Jain (2010), forecasting energy demand forms a vital part of the energy policy of a country, more specifically, for a developing country whose energy demand is multiplying. In the literature, there are different techniques and approaches in forecasting electricity consumption of a country or country groups.

In a large-scale literature review consisting of 483 publications and reviews, 50 distinct forecasting methods for energy demand and supply are determined by Debnath and Mourshed (2018). As expected, the statistical methods are found more remarkable than the other ways of forecasting, namely computational intelligence, and mathematical programming. Moreover, Autoregressive Integrated Moving Average (ARIMA) method ranks first among statistical approaches in estimating energy demand. It is followed by linear regression, Autoregressive Moving Average (ARMA), and logistic regression. Moreover, cointegration is identified as a widely used technique to examine the relationship between analysed variables.

More precisely, the accuracy of time series econometric methods for forecasting electricity production in 106 developing countries for 1960-2012 is evaluated by a study conducted by Steinbuks (2019). This one of the most recent studies concludes that especially VAR and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models result in highly accurate short term (1-10 years) forecast predictions for the vast majority of examined countries. In this article, the author assumes that electricity production is co-determined by GDP (and population growth), mainly based on symmetric mean absolute percent error criterion. Moreover, another prominent finding of this study is the fact that econometric forecasts considerably surpass "*the simple heuristic rules*" used by assuming that the electricity production grows at some exogenous rate or is proportional to real GDP growth. Table 1 sums up some essential articles within the literature for the methods used in energy demand forecasting.

Table 1: Literature of the methods for energy demand forecasting in chronological order.

Author(s)	Country / Region	Methods used	Period examined / Level of data
Saab et al. (2001)	Lebanon	Autoregressive (AR), ARIMA and AR(1)/highpass filter model	From January 1970 to May 1999 / monthly
Mohamed and Bodger (2005)	New Zealand	Multiple linear regression	1965 - 1999 / annual
Pao (2006)	Taiwan	Artificial neural network (ANN), multiple log-linear regression, response surface regression with ARMA errors model	From January 1990 to December 2002 / monthly
Azadeh et al. (2007)	Iran	ANN, moving average (MA) and Analysis of Variance (ANOVA)	From April 1994 to January 2004 / monthly
Tso and Yau (2007)	Hong Kong	Stepwise regression, decision tree, and ANN	A two-phase survey carried out in the summer and winter of 1999 - 2000 / 1166 records
Amarawickrama and Hunt (2008)	Sri Lanka	Static Engle and Granger (EG), Dynamic EG, Fully modified ordinary least squares, Pesaran, Shin and Smith, Johansen and structured time series	1970 - 2003 / annual
Bessec and Fouquau (2008)	15 European countries	Logistic regression	1985 - 2000 / monthly
Bianco et al. (2009)	Italy	Linear regression	1970 - 2007 / annual
Ekonomou (2010)	Greece	ANN	1992 - 2004 / annual
Inglesi (2010)	South Africa	VAR	1980 - 2005 / annual
Narayan et al. (2010)	Australia	Unit root test	1973 - 2007 / annual
Taylor (2010)	Great Britain and France	Seasonal ARMA, an adaptation of Holt-Winters exponential smoothing and exponential smoothing method	From 2001 to 2006 / half-hourly observations
Yoo and Kwak (2010)	7 South American countries	Unit root test	From 1975 to 2006 / annual
Bakhat and Rosselló (2011)	Balearics Islands	Autoregressive Moving Average with Exogenous Inputs (ARMAX) and GARCH	From January 1995 to September 2007 / daily
Lee and Tong (2011)	China	ARIMA and genetic programming	1957 - 2007 / annual
Pao and Tsai (2011)	Brazil	Grey prediction method and ARIMA	1980 - 2007 / annual

Table 1 (cont.): Literature of the methods for energy demand forecasting in chronological order.

Author(s)	Country/ Region	Methods used	Period examined / Level of data
Kandananond (2011)	Thailand	ARIMA, ANN and multiple linear regression	1986 - 2010 / annual
Meng and Niu (2011)	China	Partial least squares regression	1990 - 2007 / annual
Adom and Bekoe (2012)	Ghana	Autoregressive distributed lag and partial adjustment	1975 - 2008 / annual
Barak and Sadegh (2016)	Iran	ARIMA and Adaptive Neuro Fuzzy Inference System (ANFIS)	1967 - 2012 / annual
Yang et al. (2016)	New South Wales	Neural Network, ANFIS, and Difference Seasonal Autoregressive Integrated Moving Average (SARIMA)	From 02.05.2011 to 03.07.2011 / half-hourly observations

Together with the Turkish energy market's radical transformation occurred in the past few decades, the studies for Turkish energy forecasting have shown increased parallel to this dramatic change. This context will be discussed in a more detailed manner in the following chapter of this study. According to Dilaver and Hunt (2011b), these researches could be categorized into threefold groups. The first category could be defined as "causality studies" that focus on the fact that whether there exists Granger causality between energy consumption and economic variables, mostly GDP. The second group of studies, i.e., "relationship studies," concerns the relationship between energy consumption and economic variables along with the magnitude of these relationships (mostly price and income elasticities for Turkish electricity demand). The final category, called "forecast studies," concentrate on forecasting future energy demand of the country by using different methods that will be mentioned below.

As one of the pioneering researches for Turkey in examining the causality between energy consumption and income could be considered as the study done by Soytaş et al. (2001). From 1960 through 1995, Johansen-Juselius Cointegration Methodology and VECM are applied to analyze this relationship. Moreover, it is concluded that energy consumption has both short- and long-term effects on GDP. In other words, a unidirectional causality that runs from energy consumption to income in Turkey exists. Contrary to that study, Lise and Van Montfort (2007) infer that causality runs unidirectionally from GDP to energy consumption, and both variables are co-integrated. With annual data on population, GDP, and total primary energy consumption in Turkey compromising the years 1970-

2003, the authors also conclude that the Environmental Kuznets Curve (EKC)[1] hypothesis is not a valid phenomenon for Turkey. Tatlıdil et al. (2009) analyze the relationship between the variables, as mentioned earlier, together with energy prices. Two-steps Autoregressive Distributed Lag framework is used to estimate the time-series equation. In connection with causality, similar results with Lise and Van Montfort's study (2007) are obtained.

A more exciting conclusion is drawn by the analysis of Yıldırım et al. (2014). In this research, the causal relations between economic growth and energy consumption of the Next 11 countries[2] except for Vietnam and Nigeria are analysed. The Granger causality test on the matter of energy-growth linkage is applied by using ARMA models. The three estimated VAR models include real GDP per capita, energy use per capita, and gross capital formation variables. The period of this study covers approximately 40 years for each examined country. The neutrality hypothesis claiming the fact that energy consumption does not affect economic growth and vice versa is found as "invalid" only for Turkey. In short, according to the findings of that analysis, there exists a one-way causal relationship from energy consumption to economic growth in Turkey. Another empirical study that deals with causality relation between energy consumption and economic growth (real Gross National Product) for Turkey is done by Erdal et al. (2008). Similar to the previous article, the neutrality hypothesis is rejected significantly in the case of Turkey, and it is claimed that there exists a bidirectional relationship between the two indicators. Further research on energy consumption-economic growth nexus for Turkey, by Kaplan et al. (2011), involves annual time series for energy consumption, real GDP, real energy prices, capital and labor data for the time-span of 1971-2006. Two-way causality, i.e., bidirectional between energy consumption and economic growth, is confirmed in this study once more.

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[1] EKC hypothesis assumes that there exits an inverted U-shaped connection between several pollutants and per capita income; specifically, environmental pressure increases until a certain level as income rises; later on, it starts to decrease. See Dinda (2004) for more information about EKC hypothesis.

[2] The Next 11 countries contain a group of eleven countries - namely Bangladesh, Egypt, Indonesia, Iran, Mexico, Nigeria, Pakistan, the Philippines, Turkey, South Korea and Vietnam. For further information, see the link available at: [https://energyeducation.ca/encyclopedia/N11_countries].

In the literature, different approaches, apart from the time-series analysis, have been applied in order to estimate electricity consumption in Turkey. In particular, Bilgili et al. (2012) apply linear and nonlinear regression models along with artificial neural network technique to estimate the residential and industrial energy usage of the country for years of 2008-2015. It is also encountered in the literature that Grey prediction with rolling mechanism approach (GPRM) is used to predict Turkey's energy consumption (Akay and Atak, 2007). Moreover, with the Optimized Grey Model, Hamzaçebi and Es (2014) forecast the amount of electricity consumption of Turkey by 2025 and also determine the electricity supply of the country. Also, forecasts of Turkey's electricity consumption on a sectoral basis until 2020 are explored by ANN in the study of Hamzaçebi (2007).

Additionally, Kankal et al. (2011) model GDP, population, import, and export amounts together with employment in order to forecast energy consumption in Turkey by modeling artificial neural network technique and regression analysis under different scenarios. Then, the authors compare the results with the official projections. Aside from those studies, by generating a forecasting model based on population and electricity demand per capita, Turkey's Vision 2023[3] energy targets are analyzed by Melikoğlu (2018). As distinct from those studies, Tutun et al. (2015) hold and argue that future electricity quantity is based not only on current net consumption but also on independent factors such as imports, exports, gross generation, and transmitted energy. To that end, to forecast future net electricity consumption, a new energy model is developed first by estimating independent factors using SARIMA and Nonlinear Autoregressive Artificial Neural Network (NARANN) methods. Afterward, LASSO-based Adaptive Evolutionary Simulated annealing (LADES) and Ridge-Based Adaptive Evolutionary Simulated Annealing (RADES) models are applied. Another approach in forecasting Turkey's short-term gross annual electricity demand is the analysis of Küçükali and Barış (2010). They apply fuzzy logic methodology, and contrary to many other models, only one parameter, i.e., GDP based on purchasing power parity, is used.

Besides, as an emerging market by having one of the most rapid economic growth rates in the world, Turkey's gross annual electricity demand is estimated by using time series,

[3] The centenary of the Republic of Turkey.

regression and fuzzy logic methods in the study of Yavuzdemir and Gökgöz (2015) and the results of forecasting approaches are compared on the basis of absolute relative errors. Considering a high correlation between GDP and electricity demand, the authors conclude that the time-series model has better forecasting performance than the other two modeling techniques. Over and above this, Kılıç and Özdemir (2018) estimate the energy demand and energy generation of Turkey as well as CO_2 emission potential as a function of population and GDP toward 2023 by using Long Range Energy Alternatives Planning model.

In the study of Bakırtaş et al. (2000), the long-run relationship between electricity consumption, income, and electricity price (all of them are in terms of per capita) is examined. Then electricity consumption for Turkey is reviewed by using the ARMA model to forecast for the years 2000-2010.

Erdoğdu (2007) uses quarterly time-series data, namely real electricity prices, real GDP per capita, and net electricity consumption per capita for the period 1984-2004. He concludes that cointegration analysis to model for Turkish electricity demand is appropriate. Then, ARIMA modeling is employed to forecast demand by assuming "*let the demand data speak itself*." Finally, its results are compared with current official projections, considered as highly overestimated the electricity demand in Turkey.

According to Ediger and Akar (2007), time-series forecasting shows better results, and both ARIMA and SARIMA models could be used adequately to estimate energy demand.

Dilaver and Hunt (2011a) identify Turkey's industrial energy demand as a function of industrial value-added, real industrial electricity price, and underlying energy demand trend for industrial electricity. The structural time series model estimates this demand function under three different scenarios. With very similar approach of the previously mentioned article, Turkey's aggregate electricity demand, defined by a function of GDP, real average electricity price and underlying energy demand trend for aggregate Turkish electricity, is forecasted by again using the structural time series method for annual data over the period of 1960-2008 in another study of Dilaver and Hunt (2011b).

Albayrak (2010) forecasts for energy production by fuel types and energy consumption by sectors via ARIMA modeling. The author finds it more representative and compares his findings with official projections and Erdoğdu's (2007) results.

In another research done by Boran (2014), it is presented the Box-Jenkins (BJ) method, identified as ARIMA (1,1,0) model, in order to forecast net electricity consumption in Turkey for the years 2009-2013. The data used in this study cover from 1970 to 2008.

Besides, Haliloğlu and Tutu (2018), distinct from the other studies on this topic, try to estimate Turkish energy demand daily. To achieve this aim, the SARIMA model, taking seasonality into account and in this way extending the ARIMA model, is used.

3 Turkish Electricity Market Structure

In this chapter, firstly, a brief history of the Turkish electricity market will be introduced. Then, an outlook for energy in the country will be demonstrated with some tables and graphs[4]. Later, the current status of the electricity market structure in Turkey will be mentioned. Finally, the methodology for the official energy demand forecast, and its results will be discussed.

3.1 History of The Turkish Electricity Market

With a population of more than 80 million and a growing economy, the demand for energy in Turkey has increased over the last years. The country has the second highest electricity demand after China, and also it is in the first place in Europe[5.] However, Turkey is mainly dependent on external resources in order to meet its rising energy demand. Besides, the GDP of the country was improved from USD 150.676 billion in 1990 to USD 272.979 billion in 2000[6]. For the end of 2018, the GDP in Turkey was measured at USD 766.509. This steep growth in GDP was mainly considered as a result of high industrialization efforts that was driven by the manufacturing sector. On the other hand, many years after Turkey's application to join to the European Economic Community, the recognition of Turkey as a candidate for accession to the EU at the Helsinki European Council in December 1999 opened up a new period in the relations between Turkey and the EU. For both sides, Helsinki marks a new beginning and a process of mutual strategic

[4] The data used in this chapter were mainly derived from TEİAŞ's Electricity Statistics (Available at: https://www.teias.gov.tr/tr/turkiye-elektrik-uretim-iletim-istatistikleri), EMRA Annual Electricity Market Progress Reports (Available at: https://www.epdk.org.tr/Detay/Icerik/3-0-24/yillik-sektor-raporu) EMRA Monthly Electricity Market Reports (Available at: https://www.epdk.org.tr/Detay/Icerik/3-0-23-3/elektrikaylik-sektor-raporlar).

[5] Republic of Turkey Ministry of Energy and Natural Resources (http://www.enerji.gov.tr/en-US/Mainpage).

[6] The World Bank Statistics (https://data.worldbank.org/country).

transformation[7]. Hence, the significant increase in energy demand, together with industrialization and population growth, and Turkey's commitment to be a member of the EU have led to a significant change in the country's energy policy and its regulation.

In Turkey, remarkable progress has been accomplished in the liberalization and restructuring of electricity markets since the 1980s. The current structure of the Turkish electricity industry can be defined as a natural consequence of the long liberalization and privatization process. This action has led to not only the emergence of several private players in the market but also the restructuring of state-owned companies. Turkey's energy reforms can be divided into two phases: the opening of the private sector during the 1980s and 1990s; and market-based reforms since 2001 (IEA, 2016).

Up to 1983, the Turkish Electricity Authority (TEK), established in 1970, was operating as a monopoly for generation, transmission, distribution and rural electrification activities. However, TEK's monopoly position ended with the law enacted in 1984. And then the only authority in the electricity sector was split into two companies: The Turkish Electricity Transmission Company (TEİAŞ) and The Turkish Electricity Distribution Company (TEDAŞ). Those companies were acting as buyers of electricity from build-operate-transfer (BOT) and transfer of operational rights (TOOR) companies as well as autoproducers connected to the transmission and distribution grids, respectively (Dilli and Nyman, 2015).

One of the significant steps in Turkish electricity market reforms could be considered as Electricity Market Law No.4628 that entered into force in 2001[8]. This law would be the first step for the liberalization of generation and distribution activities in the country. Turkey's commitment to the accession to the EU was the main trigger of establishing the necessary legal framework with alignment with the EU legislation. In the same year, an independent administrative authority, i.e., the Energy Market Regulatory Authority (EMRA), was established under the law mentioned above. It is the only regulator in

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[7] Republic of Turkey Ministry of Foreign Affairs Directorate for EU Affairs (https://www.ab.gov.tr/index_en.php).

[8] Law No. 4628 was amended with Electricity Market Law No. 6446, entered into force on 30 March 2013.

Turkish energy markets, which are electricity, natural gas, oil, and LPG, together with market players. Its primary role is to perform the secondary regulatory and supervisory (auditing) functions. Besides these, EMRA has the decision body to approve tariffs. In order to provide a financially viable, stable, and competitive energy market as well as sustainable energy with good quality and low cost in a reliable and environmentally friendly manner, EMRA is also responsible for secondary legislation regarding the electricity market for effective implementation (Kölmek, 2012).

After that, liberalization process continued by unbundling TEİAŞ into three separate companies: Electricity Generation Company (EÜAŞ), Turkish Electricity Trading and Contracting Corporation (TETAŞ) and TEİAŞ in 2003 (Dilli and Nyman, 2015). This transformation mentioned above of the Turkish electricity market is summarized in Table 2.

Table 2: Old vs. new electricity market structure in Turkey (Kölmek, 2012).

	Old Structure	**New Structure**
Market	Monopolistic	Competitive
Tariffs	Non cost-reflective	Cost-reflective
Market Entrance	Bidding / Submission of feasibility studies	Licensing
Regulation	By the Ministry and related organizations	By the independent regulator (EMRA)
Role of State	Investment & Operation & Auditing	Auditing
Market risks borne by	The State	Market Participants
Private participation	Built-Own-Operate (BOO), BOT and TOOR with state guarantees	Privatization and new companies

3.2 An Outlook for Energy in Turkey

Having the 6th largest European electricity market, Turkey has almost tripled her installed capacity in the last 15 years (see Figure 2).

Figure 2: Annual development of Turkey's installed capacity, 1972-2018.

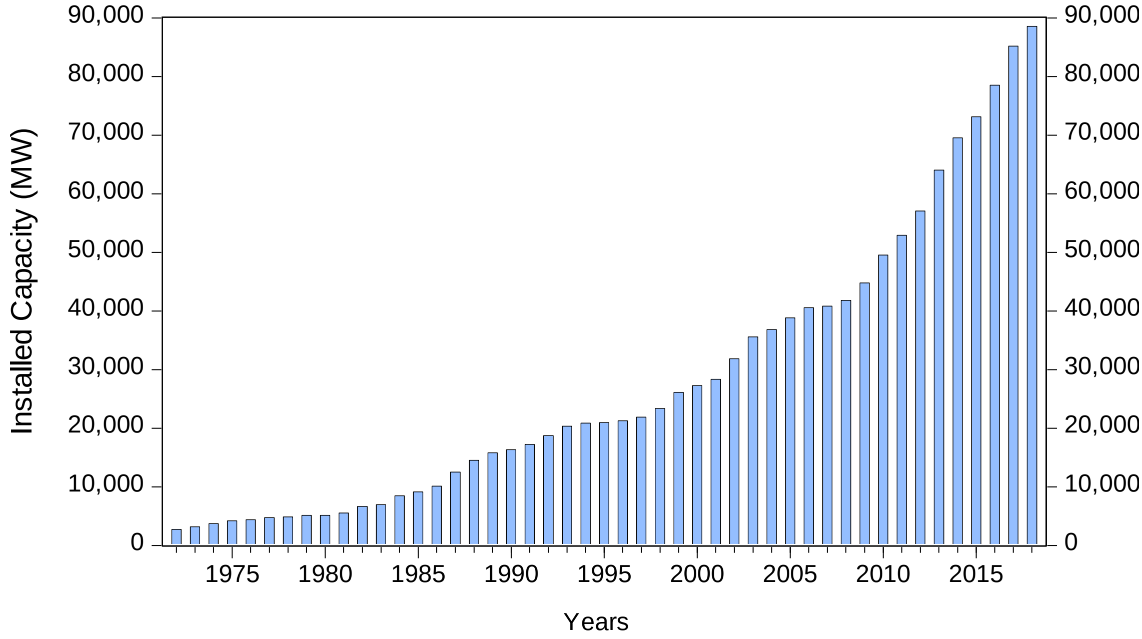
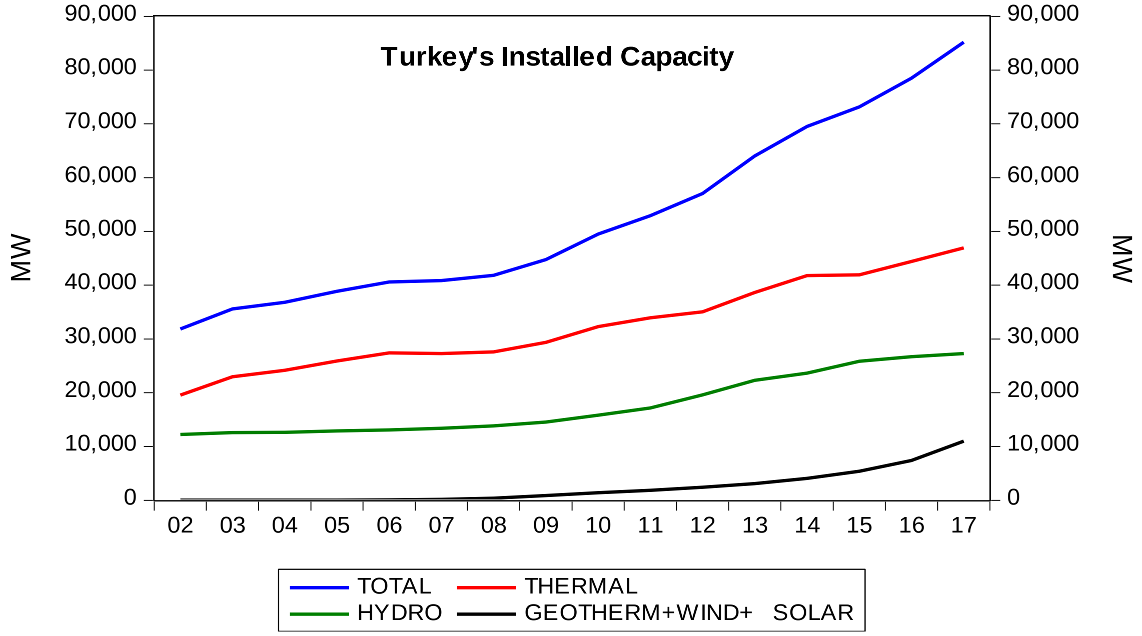


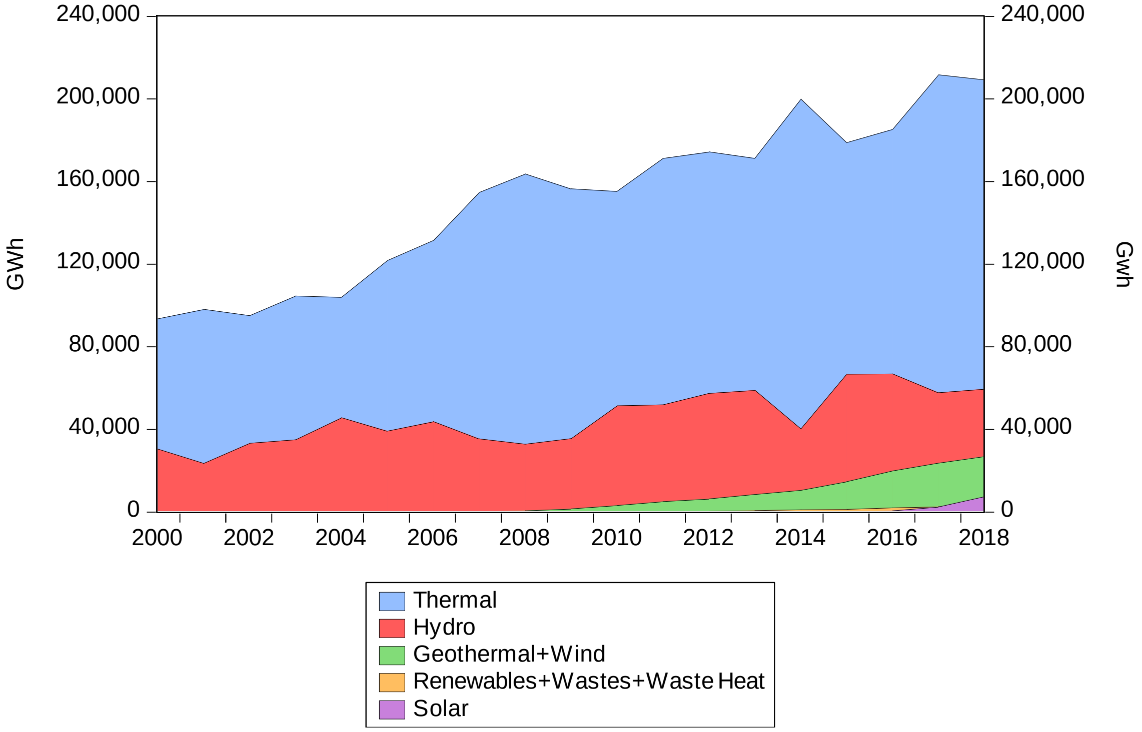
Figure 3 illustrates the annual development of Turkey's installed capacity by primary energy resources for years of 2006-2018.

Figure 3: Annual development of Turkey's installed capacity by resources, 2006-2018.



If the annual development of Turkey's gross electricity generation by primary energy resources presented in Figure 4 is examined, it could be observed that the share of thermal resources (namely hard coal, asphaltite, imported coal, lignite, fuel oil, diesel oil, LPG, naphtha, and natural gas) in energy generation has dominated the renewables over the years.

Figure 4: Annual development of Turkey's electricity generation by primary energy resources, 2000-2018.



At the end of 2018, total licensed installed capacity has reached to 83.187,05 MW, a 2,06% increase year-on-year. Installed capacity in 2018 by resources and their shares in total are shown in Table 3:

Table 3: Licensed installed capacity by resources in Turkey, 2018.

Resource Type	**Installed Capacity (MW)**	**Share (%)**
Natural Gas	25.731,93	30,93
Hydro (Dam)	20.534,80	24,69
Lignite	9.597,12	11,54
Imported Coal	8.938,85	10,75
Hydro (River)	7.748,90	9,32
Wind	6.942,27	8,35
Geothermal	1.282,52	1,54
Fuel Oil	709,21	0,85
Biomass	590,92	0,71
Solar	81,66	0,10
Naphtha	4,74	0,01
Other sources	1.024,13	1,21
Total	**83.187,05**	**100,00**

The share of the renewables (including hydro) in the total installed capacity was 43,26% in 2017, while this ratio increased to 44,70% in 2018. On the other hand, the ratio of the total conventional fossil fuel plants within the installed capacity was 56,74% in 2017; meanwhile, it was 55,30% in 2018.

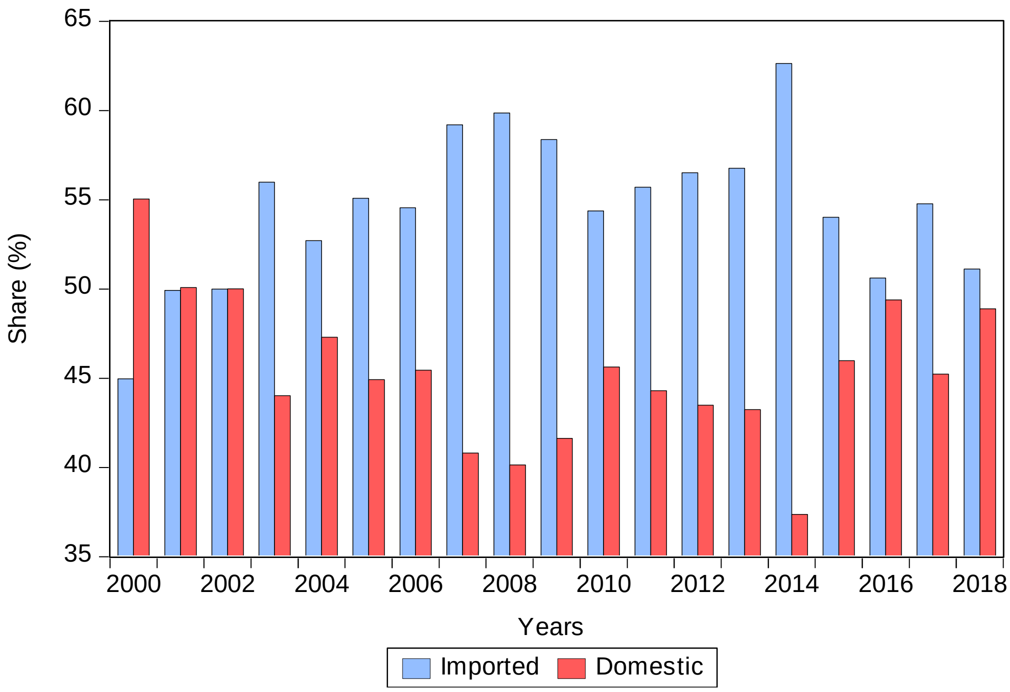
Licensed electricity generation in 2018 recorded as 295.442,15 GWh, which led to a 0,97% increase compared with the previous year. The table below illustrates the electricity generation in Turkey by resources for the years 2017 and 2018. The share of the renewables (including hydro) in total licensed electricity generation was 28,77% in 2017, while this ratio became 30,43% in 2018. Total electricity consumption reached 302.772,30 GWh in 2018, which was a rise of 3,69% year-on-year.

Table 4: Electricity generation by resources in Turkey, 2017-2018.

Resource Type	2017 (GWh)	Share (%)	2018 (GWh)	Share (%)
Natural Gas	108.837,19	37,20	91.227,14	30,88
Imported Coal	51.172,22	17,49	62.949,64	21,31
Hydro (Dam)	41.269,59	14,10	40.961,45	13,86
Lignite	40.581,02	13,87	45.055,29	15,25
Wind	17.859,86	6,10	19.891,37	6,73
Hydro (River)	17.124,40	5,85	18.975,98	6,42
Geothermal	5.969,48	2,04	7.611,58	2,58
Coal (others)	5.848,51	2,00	5.334,05	1,81
Biomass	1.939,72	0,66	2.410,00	0,82
Naphtha	1.008,83	0,34	0,98	0,00
Fuel Oil	957,86	0,33	957,98	0,32
Solar	24,56	0,01	65,56	0,02
Other sources	2,18	0,01	1,13	0,00
Total	**292.595,42**	**100,00**	**295.442,15**	**100,00**

Domestic and imported resources based on shares in Turkey's total electricity generation are demonstrated in Figure 5 below. As could be seen, the country has been highly demanded on imported resources to generate electricity.

Figure 5: Shares of domestic and imported resources for electricity generation in Turkey, 2000-2018.

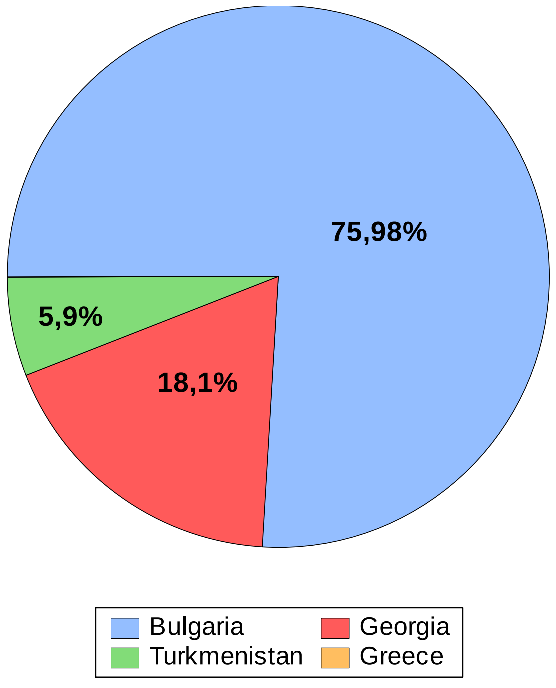


Unlicensed installed capacity in 2018 recorded as 5.310,57 MW. Solar (photovoltaic) energy consisted of 94,47% of this power. The unlicensed generation in 2018 was 8.212,41 GWh, which leads to a significant increase of 170,92% compared with 2017.

Moreover, the eligible consumer limit has been determined to be 1.600 kWh per annum for 2019 by EMRA, which corresponds to a theoretical market opening of almost 95%. This usage limit for electricity customers to become eligible to switch suppliers was 2.000 kWh for the year 2018. Just ten years ago, in 2009, customers who used more than 480.000 kWh of electricity per year would qualify as eligible customers.

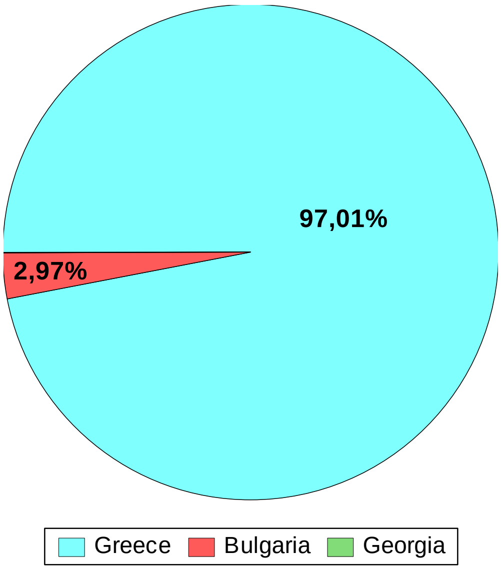
According to the data published by TEİAŞ, as shown in Figure 6 below, in 2017 Turkey imported total 2.728,3 GWh electricity from the following countries: Bulgaria (2.072 GWh; 75,98%), Georgia (493 GWh; 18,1%), Turkmenistan (160; 5,9%) and Greece (0,5 GWh; 0,02%). However, in 2016, Turkey imported a total of 6.330,4 GWh electricity from the following countries: Bulgaria (4.587 GWh; 73%), Georgia (1.039,3 GWh; 16%), Turkmenistan (635,8; 10%) and Greece (68 GWh; 1%).

Figure 6: The distribution of Turkey's imported electrical energy by countries, 2017.



On the other hand, in 2017, the country exported a totally of 3.303,7 GWh electricity to the following countries with these quantities (See Figure 7): Greece (3.204,9 GWh; 97,01%), Bulgaria (98 GWh; 2,97%) and Georgia (0,8 GWh; 0,02%). Turkey exported 1.451,7 GWh electricity to the following countries in 2016 as following quantities: Greece (1.443,7 GWh; 99,49%), Syria (4,3 GWh; 0,29%) and Bulgaria (3,1 GWh; 0,21%).

Figure 7: The distribution of Turkey's exported electrical energy by countries, 2017.



The most up-to-date data regarding the general view of the Turkish electricity market are shown in Table 5.

Table 5: General view of the electricity market in Turkey, August 2019.

Subject	**Unit**	**August 2019**	**January-August 2019 Period**
Licensed generation	MWh	26.513.226	196.457.019
Licensed installed capacity	MW	84.512	-
Maximum peak point	MW	45.324	45.324
Minimum peak point	MW	22.783	18.300
Unlicensed installed capacity	MW	5.761	-
Unlicensed generation bought as surplus	MWh	1.105.907	6.872.685
Gross unlicensed generation	MWh	1.116.162	6.968.030
Renewable Energy Support generation	MWh	6.132.995	58.982.786
Actual Consumption	MWh	26.421.503	195.379.501
Consumption Billed	MWh	19.975.814	152.356.150
Number of consumers	Number	44.550.819	-
Import	MWh	193.118	1.346.618
Export	MWh	175.865	1.970.865

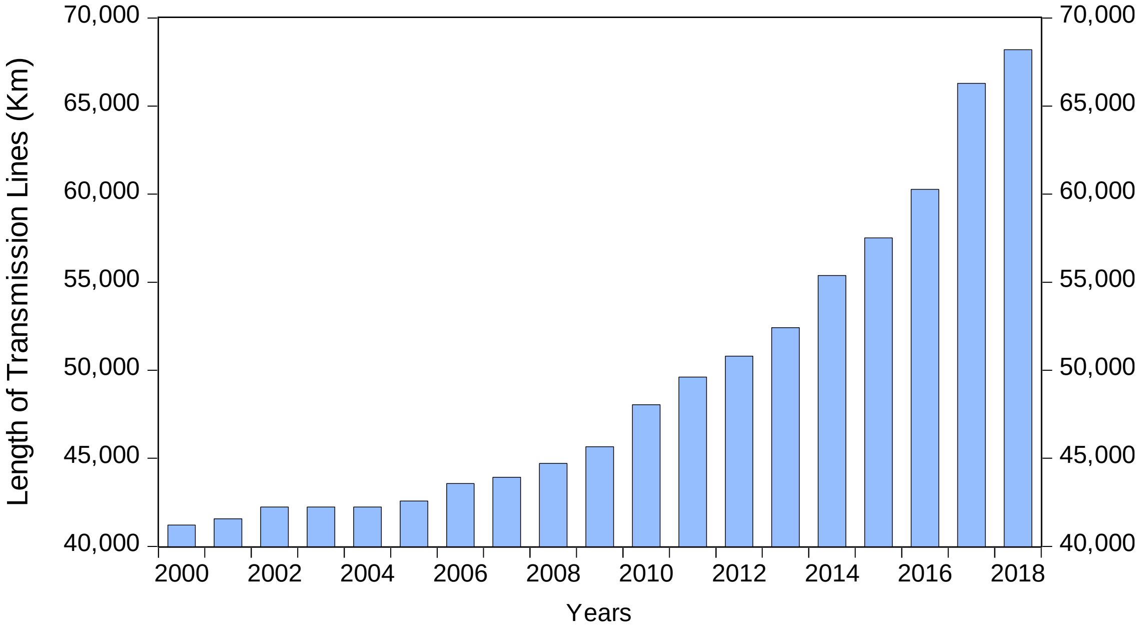
3.3 Current Status of Electricity Market Activities in Turkey

According to the legislation in force, electricity market activities in Turkey that are subject to licensing by EMRA are generation, transmission, distribution, wholesale, retail sale, market operating, import, and export.

Transmission activity is conducted only by TEİAŞ as a monopoly. The revision in Electricity Market Law in 2013 led to a new type of market operation license and Energy Market Operations Company (EPİAŞ) licensed in 2015. Today, TEİAŞ's responsibility for balancing the power market and the ancillary services market continues, while EPİAŞ functions in operating the day-ahead market and the intraday market (IEA, 2016).

At the end of 2018, there have been 1.161 substations and 2.265 transformers having 205.953 MVA total capacity in the transmission system. The length of the transmission lines in 2018 recorded at 68.204 km. The following figure shows the development of transmission lines in Turkey from 2000 to 2018.

Figure 8: The development of transmission lines in Turkey, 2000-2018.

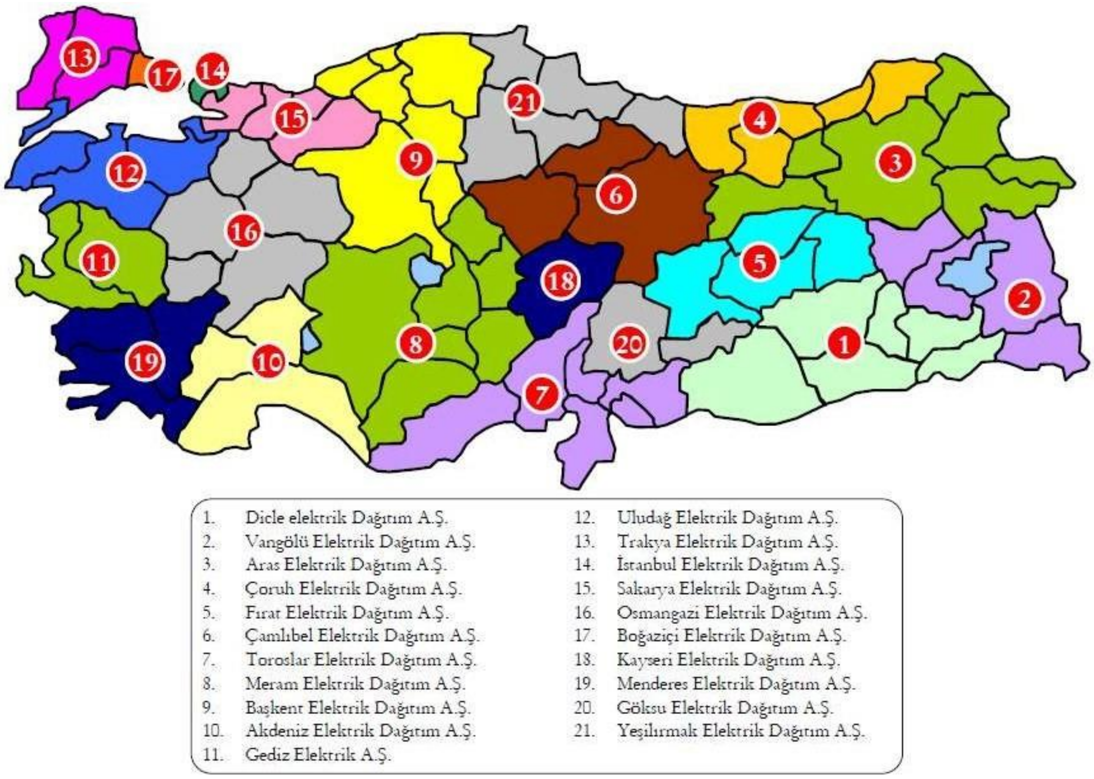


Moreover, in the previous year, 2,92 billion Turkish Liras investment (about 463 million Euros) was made by the transmission company. The loss ratio in the transmission system occurred 1,92% for the last year.

Apart from these, trial synchronous parallel operation between the Turkish Power System and ENTSO-E Continental Europe Synchronous Area (CESA) started on 18th September 2010. After that, the "Long Term Agreement," ensuring a permanent connection to the ENTSO-E, was signed between TEİAŞ and ENTSO-E on 15th April 2015. As a result of this, the Turkish electricity market has legally entered the way of integration with the European Internal Electricity Market. Besides, Turkey has become the first and sole observer member state of ENTSO-E since January 2016.

As shown in the following map, Turkey has been separated into 21 distribution regions.

Figure 9: Geographical coverage of distribution companies in Turkey[9].



Note: Elektrik Dağıtım A.Ş.=Electricity Distribution Co.

Although the state still owns the distribution network assets, the companies in distribution activity are all legally unbundled and privatized[10]. At the end of the year 2018, the number of customers using the distribution system recorded as 43,65 million by a 3% increase with respect to 2017. Moreover, the total line length was 1.164.170 km, 82% of which was accounted for overhead lines. Total consumed energy billed was 177,91 TWh, the highest losses occurred in Dicle, Vangölü, and Aras electricity distribution areas, with 54,94%, 49,16%, and 23,55% loss ratios, respectively. However, the lowest energy loss ratios were 4,2%, 4,37%, and 5,08% in Uludağ, Trakya, and Çamlıbel regions

[9] Republic of Turkey, The Ministry of Finance and Treasury, The Privatization Board of Turkey, Official Website (In Turkish): https://www.oib.gov.tr/.

[10] Republic of Turkey Prime Ministry Investment Support and Promotion Agency, Turkey’s Electricity Distribution Industry, http://www.turkey-japan.com/business/category5/category5_426.pdf

accordingly. There were 468.755 transformers, having 162.367 MVA power in the distribution system.

The state (EÜAŞ), private companies, and autoproducers execute generation activities in Turkey. According to the most up-to-date license holders' statistics, there are 1.629 generation plants and their distribution by resources together with installed capacity are shown in the table below.

Table 6: Licensed energy generation facilities by primary resources and installed capacities.

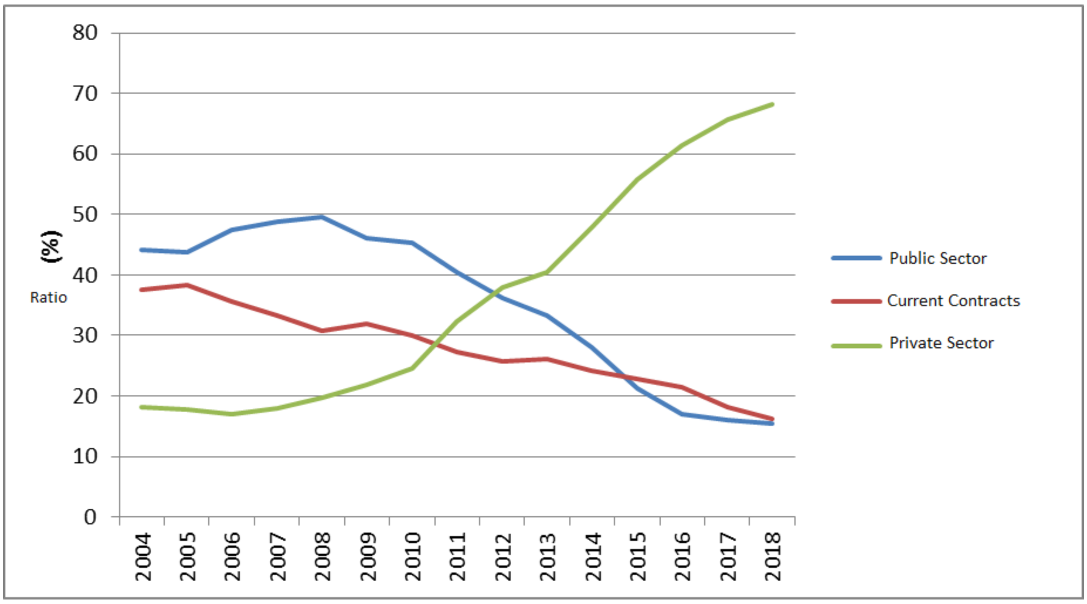
Plant Type	**Number of License holders**	**Installed Capacity (MWe)**
Solar	24	244,35
Thermal	416	63.094,519
Wind	244	10.219,419
Geothermal	57	1.673,783
Biomass	136	785,023
Hydro	752	32.500,354
Total	**1.629**	**108.515,448**

Pursuant to figures published in June 2019 Electricity Sector Report by EMRA, the following have been the main sources of electricity generation in Turkey (given as installed capacity and percentage, respectively): Natural gas: 26.269,01 MW (31,05%), Hydro (dam): 20.582,40 MW (24,33%), Lignite: 10.097,03 MW (11,93%), Imported coal: 8.938,85 MW (10,56%), Hydro (river type): 7.822,95 MW (9,25%), Wind: 7.147,15 MW (8,45%), Geothermal: 1.335,52 MW (1,58%), Biomass: 623,23 MW (0,74%), Solar: 81,66 MW (0,10%), Other sources (Fuel oil, naphtha, etc.): 1.710,67 MW (2,03%). Consequently, fossil fuels constitute almost 55% of electricity generation in Turkey. Natural gas is the major component in electricity generation, followed by hydro and coal. It should be noted here that the electricity generation mix in Turkey can change year on year, owing to the seasonality of hydro supply and the unavailability of old lignite plants.

Moreover, according to the latest figures, in 2018, the biggest share in electricity generation was the private sector, along with 68,23%. This ratio recorded as 65,68% in 2017. The share of the public sector in generation activity (including current contracts) was

34,32% in 2017, while this ratio was 31,77% by decreasing in 2018. Figure 10 shows the dramatic change in the distribution of the generation activity in Turkey between the public and private sectors over the years. Similarly, in 2016, the private companies accounted for 61,48% of electricity generation; however, as mentioned above, their contribution rose by 68,23% in the following year. Two main reasons could explain this increase: First of all, the new investments have been made mostly by private generation companies. Secondly, with the ongoing privatization, the ownerships of the public plants have been passed into the private sector.

Figure 10: The change in electricity generation in Turkey from the public to the private sector, 2004-2018.



EÜAŞ and private companies carry wholesale electricity market activities. Some crucial changes in the wholesale market have been seen to align with the EU Internal Market rules. The main mechanism, called Balancing Power Market (BPM), is now operated by the transmission company.

Besides, in order to decrease dependence on imported energy and to ensure security of supply, the Akkuyu Nuclear Power Plant, consisting of four units with a total capacity of 4.800 MW, has been planned to be constructed in cooperation with the Russian Federation by signing the intergovernmental agreement in 2010, and the first unit of the plant is scheduled to be in operation by 2023. In June 2017, EMRA granted the Akkuyu nuclear company a 49-year power generation license. Apart from that, detailed site investigation studies are underway for another nuclear power plant constructed in the northern part of Turkey. The Sinop Nuclear Power Plant is planned to have four units with a total capacity of 4.480 MW[11]. In the medium term, it is planned that the share of nuclear energy in the power generation of Turkey will be about 10%.

3.4 Official Electricity Demand Forecast

According to the Regulation Concerning Electricity Demand Forecast published in the official gazette, dated 07.05.2016 and numbered 29705, and prepared based on the 9th and 20th articles on Electricity Market Law no. 6446, TEİAŞ has been charged with submitting Turkey's Demand Forecasts Report to the EMRA by combining with the demand forecasts of the consumers that are directly connected to the transmission system together with the demand results of distribution companies. On the other hand, concerning the decree based on the 20th article on Electricity Market Law, namely "*Electrical Energy Demand Projection Report of Turkey covering the next twenty years shall be prepared and published by the Ministry once in two years by consultation with the Ministry of Development and the Authority*," MENR prepares the Electrical Energy Demand Projection Report of Turkey officially. In this projection study prepared for the next twenty years, in addition to the variables (economic growth rate, population, the number of households, the contribution of transportation sector on electricity consumption, domestic consumption, grid losses and efficiency) affecting directly electricity consumption, International Energy Agency's energy statistics of Turkey and the other countries evaluated as similar to Turkey, and sectoral GDP data on database of the World Bank are used. The models used in the study are as follows:

- Model 1: Econometric Model

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[11] Republic of Turkey Ministry of Energy and Natural Resources General Directorate for Nuclear Energy, https://nepud.enerji.gov.tr/en-US/Mainpage

- Model 2: ARIMA Model
- Model 3: Comparison Model
- Model 4: Regression Model
- Model 5: Flexibility Model

According to Lise (2019), demand forecasting and energy planning tools have been used at MENR on the ad-hoc basis. The fundamental models for energy demand are Model for Analysis of Energy Demand (MAED), Long-range Energy Alternatives Planning System (LEAP), and MedPRO.

The five models mentioned above are run with three scenarios, which are Scenario 1 – Low Scenario, Scenario 2 – Reference Scenario, and Scenario 3 – High Scenario. Then, 15 different demand series are obtained. The final demand forecasts are determined by weighting annually the model results based on scenarios. These forecasts are valid only for the Turkish electricity system and expressed in terms of gross demand, including network losses in transmission and distribution lines, as well as the internal usages by the power plants.

Table 7 illustrates the electrical energy demand projections of MENR for 2019-2039 (TEİAŞ, 2019). Considering the results shown in the table below, for the first 10-year forecasting period, i.e., 2019-2028, the annual average demand increase ratios have been estimated at 3,6%, 4,2%, and 4,8% for Scenario-1, Scenario-2, and Scenario-3 respectively. Meanwhile, for 2029-2039, MENR has forecasted the annual average demand increase ratios as the following: 2,4% (for Scenario-1), 2,8% (for Scenario-2), and 3,3% (for Scenario-3). In sum, 2,9%, 3,36%, and 3,84% are the projections for the annual average electricity demand increase ratios for the next 20 years from now on under three scenarios accordingly.

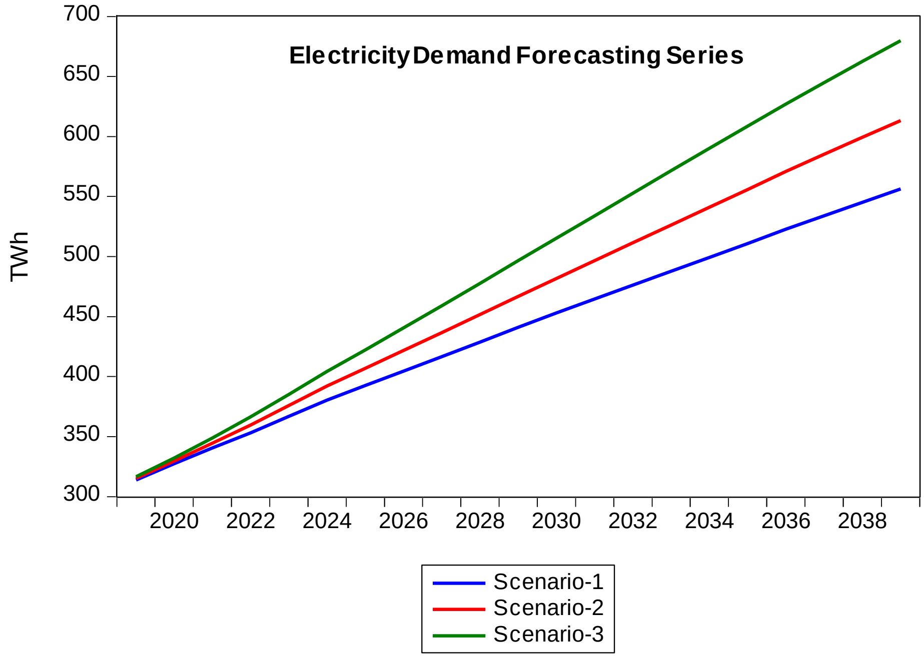
Table 7: MENR's electricity gross demand projections, 2019-2039.

Year	**S-1 (TWh)**	**S-2 (TWh)**	**S-3 (TWh)**	**S-1 (Change)**	**S-2 (Change)**	**S-3 (Change)**
2019	313,8	315,2	316,5	-	-	-
2020	327,3	329,6	332,1	4,30%	4,60%	4,90%
2021	340,5	344,4	348,7	4,00%	4,50%	5,00%
2022	353,2	359,6	366,4	3,70%	4,40%	5,10%
2023	366,8	375,8	385,2	3,80%	4,50%	5,10%
2024	380,4	392,1	404,3	3,70%	4,30%	5,00%
2025	392,6	406,9	422,3	3,20%	3,80%	4,50%
2026	404,6	421,8	440,7	3,10%	3,60%	4,30%
2027	416,6	436,6	458,9	3,00%	3,50%	4,10%
2028	428,8	451,7	477,6	2,90%	3,50%	4,10%
2029	441	466,8	496,6	2,90%	3,30%	4,00%
2030	453	481,7	515,4	2,70%	3,20%	3,80%
2031	464,6	496,7	534	2,60%	3,10%	3,60%
2032	476,3	511,6	552,9	2,50%	3,00%	3,50%
2033	487,8	526,4	571,6	2,40%	2,90%	3,40%
2034	499,3	541,0	590,2	2,30%	2,80%	3,30%
2035	510,8	555,7	608,5	2,30%	2,70%	3,10%
2036	522,7	570,8	627	2,30%	2,70%	3,10%
2037	534	585,3	644,9	2,20%	2,50%	2,90%
2038	545,1	599,4	662,5	2,10%	2,40%	2,70%
2039	556,3	613,4	679,9	2,10%	2,30%	2,60%

*S-1: Scenario-1, S-2: Scenario-2, S-3: Scenario-3.

The graph below shows the electricity demand estimation results of MENR for 2019-2039.

Figure 11: MENR's Turkish electricity gross demand projections for 2019-2039.



MENR's methodology and the forecasts are criticized in the literature frequently. For example, Akay and Atak (2007) claim that the GPRM approach performs better results than the official results of MENR in the comparison of electricity consumption values for both total and the industrial sector. According to the authors, since the MAED model uses too many indicators, the error effect on the results increases. Similarly, Hamzaçebi and Es (2014) assert that direct OGM (1,1) performs more accurate predictions than MENR's official results. Tutun et al. (2015) argue that the MAED simulation technique used by MENR gives forecasting results with high forecasting errors, more than a 10% error ratio for some years. Besides, MENR projections are found as overestimated by Erdoğdu (2007) and Kankal et al. (2011).

On the one hand, Hamzaçebi (2007) claims that the ANN technique for forecasting electricity consumption of Turkey gives better results than the MAED technique. However, this study does not claim that the ANN has always been superior to MAED forecasts. Küçükali and Barış's (2010) results computed by the fuzzy logic model have lower relative errors than MENR's forecasts. Alternatively, the results in the Ediger and Akar's (2007) research almost coincide with the MAED results for the years 2006-2007, but long-term ARIMA forecast gives an underestimation. Bilgili et al.'s (2012) ANN method based on the powerful scenario for the industrial sector gives lower forecasts of energy demand compared to the predictions of MENR; however, the ANN method gives higher forecasts of the energy demand than the data predicted by MENR for the residential sector. Our discussion and comments about official demand projections will be mentioned detailed in the next chapter of this study.

Apart from MENR's official forecasts, the short-term energy goals of the country are determined by 5-year development plans. Turkey's parliament ratified the 11th Development Plan for 2019-2023 on July 18, 2019. According to this plan, the goals of the energy sector are as follows:

Table 8: Developments and targets in Turkey's energy sector.

	2018	**2023**
Primary Energy Demand (Thousand Toe)	147.955	174.279
Electricity Demand (TWh)	303,3	375,8
Per capita Primary Energy Consumption (Thousand Toe per capita)	1,81	2,01
Per capita Electricity Consumption (kWh per capita)	3.698	4.324
Share of Natural Gas in Electricity Generation (%)	29,85	20,7
Share of Renewable Resources in Electricity Generation (%)	32,5	38,8
Electricity Generation by Domestic Resources (TWh)	150,0	219,5
Installed Power of Electricity (MW)	88.551	109.474

As can be seen from Table 8, electricity demand in the development plan is expected to be 375,8 TWh in 2023. This goal is the MENR's forecast under Scenario 2 – Reference Scenario.

4 A Time-Series Analysis of Turkish Electricity Demand

This chapter of the study starts with a summary of the data used in the analysis. After that, stationarity tests will be conducted in order to see whether the time-series have a unit root. Then, two types of cointegration tests will be run to detect the long-run relationship between variables. According to the result obtained in cointegration analysis, a suitable VAR model will be estimated, and its results will be discussed together with causality analysis. Then, appropriate ARIMA models will be found to forecast future electricity demand of Turkey. Finally, those projections will be compared with MENR's official estimations and between each other.

4.1 Data Overview

The data used for stationarity analysis, cointegration tests, and causality checks are the net electricity consumption in Turkey and the GDP of the country. The examined period covers from 1960 to 2018, i.e., a total of 59 observations, shown in Appendix-1. Turkey's annual GDP amounts in current USD were derived from the World Bank[12]; on the other hand, net electricity consumption data in terms of GWh were obtained from the Turkish Statistical Institute's (TurkStat) Energy Statistics database from 1960 to 2017. The data for 2018 were acquired from TEİAŞ's 2018 Turkey Electricity Consumption Statistics. It is worth mentioning that the TEİAŞ's database is harmonized with the TurkStat's one due to the Statistics Law of Turkey No. 5429. This law was enacted in 2005 in order to meet the EU norms and standards in the context of statistics.

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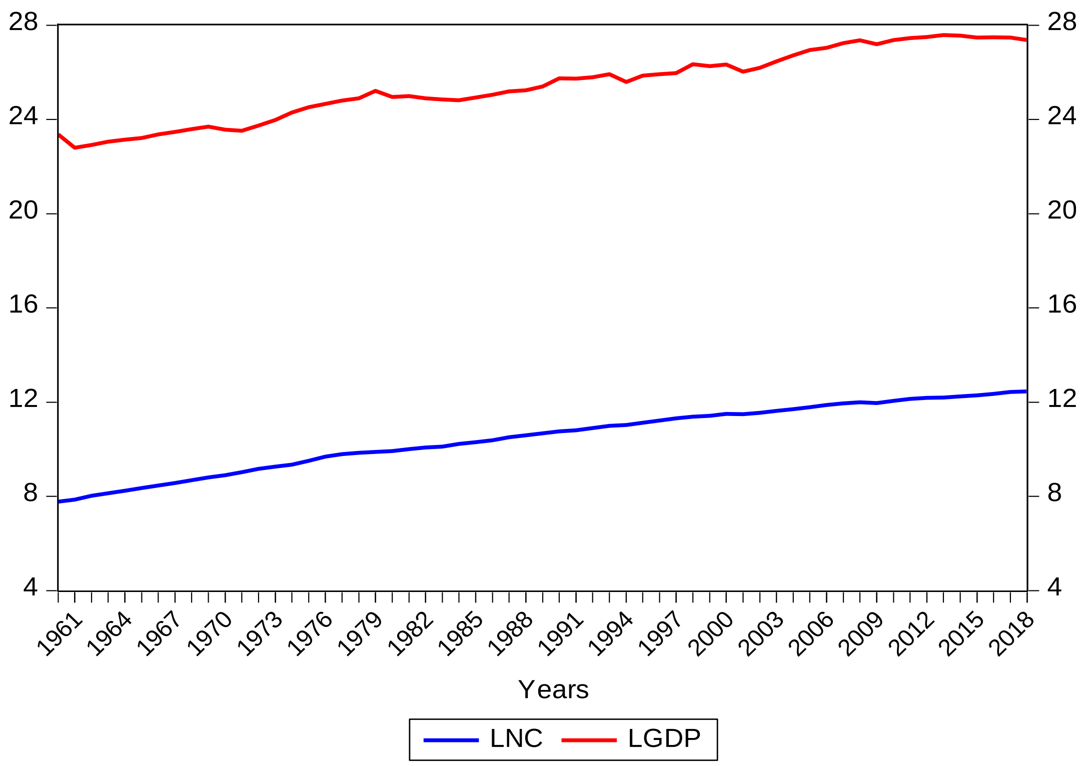
[12] GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Dollar figures for GDP are converted from domestic currencies using single year official exchange rates.

In order to observe the growth rate, it is preferred to examine the natural logarithms of the series. However, a more important effect of transforming series by logging is to straighten out the exponential growth patterns that many time series variables have and to obtain the more stabilized variance of series, which is the expected result of reducing heteroscedasticity. In this sense, Figure 12 shows the combined time series plot of natural logarithms for net electricity consumption (LNC) and natural logarithms for GDP (LGDP) in Turkey.

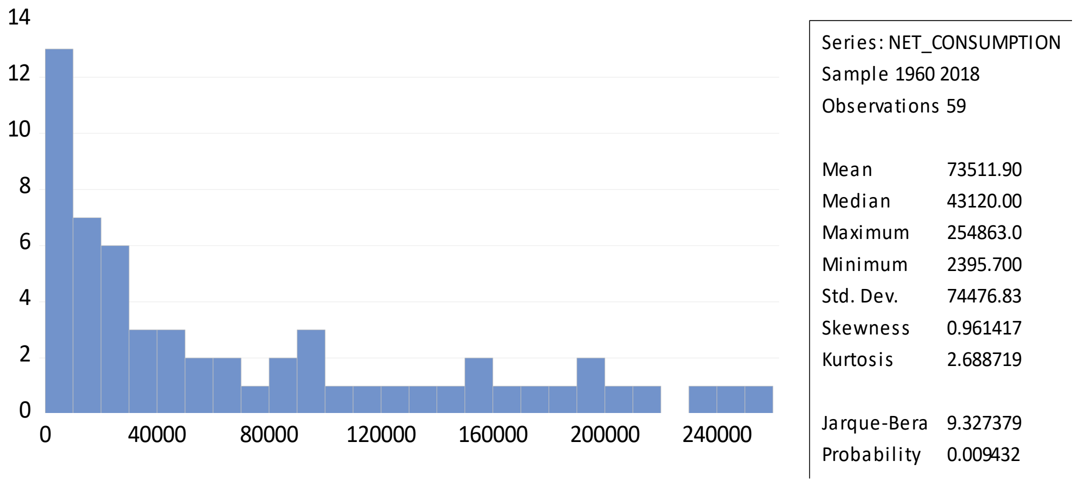
Figure 12: Combined time series plot of natural logarithms for LNC and LGDP, 1960-2018.



The first impression from the above figure and more generally from Turkey's electricity consumption and GDP data is the fact that both series tend to increase with time. However, there have been some fluctuations occasionally, specifically in the GDP series. Whether there exists a causal relationship between electricity demand and income is an important topic needed to be investigated. Nevertheless, the most significant issue examined is to answer the question of "*How will these series behave after the sampling period, stated in other words, in the future*?". These questions, together with others, will be discussed in the following sections of this chapter in a more detailed manner.

In order to provide basic information about the variables used in this study and to summarize the fundamental characteristics of the data set, descriptive statistics will be examined at this part. According to the results for the descriptive statistics of net electricity consumption in Turkey, shown in Figure 13, the distribution is positively skewed (0,9614), which could also be observed by the histogram, and the data are highly skewed. A distribution with kurtosis less than 3, like in this case, is called platykurtic. Compared to a normal distribution, its central peak is lower and broader, and its tails are thin. Jarque-Bera test for normality results that the observations are not normally distributed at the 0,05 level of significance (p-value=0,0094).

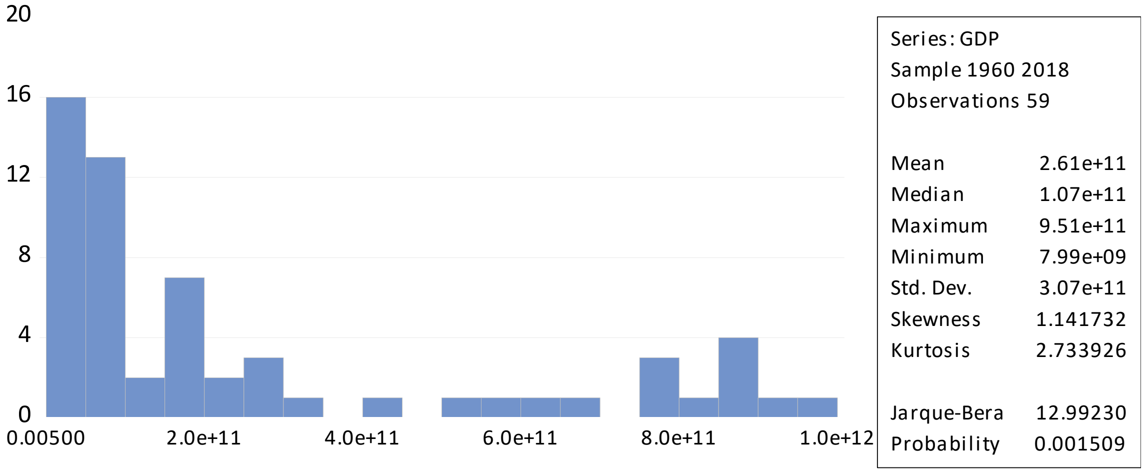
Figure 13: Histogram and descriptive statistics for net electricity consumption of Turkey.



Besides, it is observed that the minimum and maximum value of the annual electricity consumption of Turkey is very far from the average value. Furthermore, the standard deviation of data is too high. Since the examining period, as mentioned before, is the years of 1960-2018, those findings are the expected results of the series. With a long-time horizon, including a significant increase in population and high economic growth plus the other factors during this period, energy consumption has had a dramatic fluctuation towards upwards. Indeed, the population of the country was only 27 million in 1960, but it hit 82 million at the end of 2018, as stated in Eurostat's Demographic Statistics. Additionally, although the Turkish economy is experiencing a difficult period, nowadays, especially after 2000, Turkey's economic development performance is evaluated as impressive and leading to increased employment and incomes[13].

On the other side, Turkey's GDP has almost the same features as her net electricity consumption (See Figure 14).

Figure 14: Histogram and descriptive statistics for the GDP of Turkey.



Moreover, it is not surprising that there exists a high and positive ordinary (Pearson) correlation between the variables, namely LNC and LGDP (p-value=0.0000). The strength of a linear relationship is obtained as very strong with a correlation coefficient of 0,9866, almost near to the perfect correlation (See Table 9).

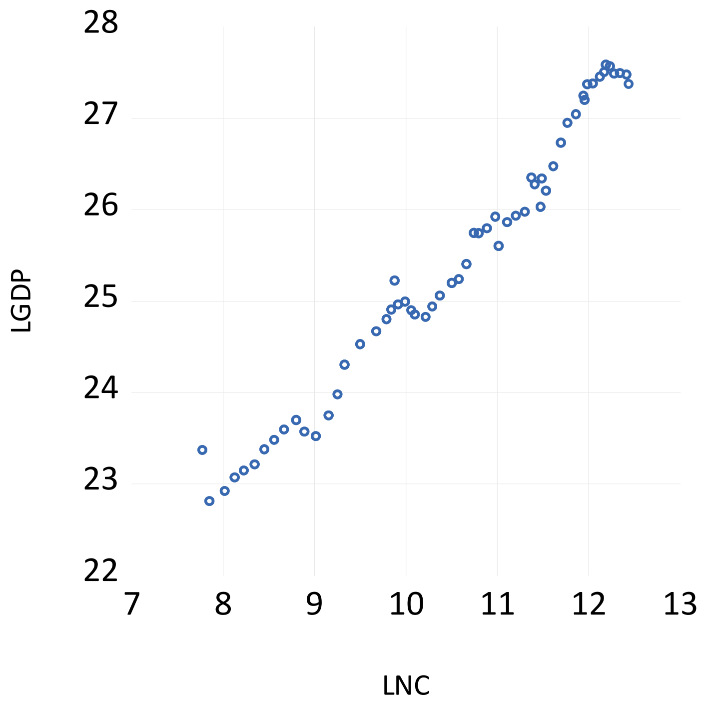
Table 9: Pearson correlation results for LNC and LGDP.

Correlation Probability	LNC	LGDP
LNC	1.000000	
p-value	-----	
LGDP	0.986645	1.000000
p-value	0.0000	-----

[13] The World Bank in Turkey, Available at: worldbank.org/en/country/turkey/overview

The scatterplot below (Figure 15) indicates the inferences obtained in the Pearson correlation analysis. It can be seen that as LNC values rise, so do the values for LGDP.

Figure 15: Scatterplot of LNC vs. LGDP.



It should be noted here that the Jarque-Bera normality tests for natural logarithms of both main variables are valid with respective p-values: 0,1373 and 0,1912. Furthermore, no matter how strong a negative or positive correlation between two variables exists, it cannot be deduced as the fact that there is also a causal relationship among them. As known, this is another type of analysis that will be shown later.

4.2 Methodology and Empirical Results of The Analyses

4.2.1 Stationarity Analysis

In time series analysis, it is considered that the series is stationary as a standard assumption. Because when the series is non-stationary, then it exhibits different behaviors with different data sets. Then, the behavior of the series cannot be generalized for the other periods such that this issue would be contradictory to the forecasting notion. In forecasting, the main aim is to find “something” that is desired to be the same later and to broaden “this thing” to the future. Meanwhile, shocks can lead to the series in a new path when a series exhibits non-stationary feature. Apart from these, invalidation of standard assumptions for asymptotic analysis could occur in the case of non-stationary.

Since stationarity is a required specification for univariate time series modeling, it is necessary for the series taken into account in this study to check whether they are stationary. In practice, there are three main approaches to examining stationary. The first is called the graphical method that might give an initial clue about the nature of the time series. When LNC and LGDP data are examined, as shown in Figure 12, it is difficult to draw a precise conclusion about the stationarity of the series. For instance, it is hard to claim that the variances of both series might differ before and after 1980. However, both plots show upward (increasing) trend structures on time, and the means and variances of the series may shift along the timeline. The graphical representation of LNC and LGDP do not exhibit mean-reversions. At that point, there is another method for detecting non-stationarity, i.e., autocorrelation function (ACF), formulated as follows:

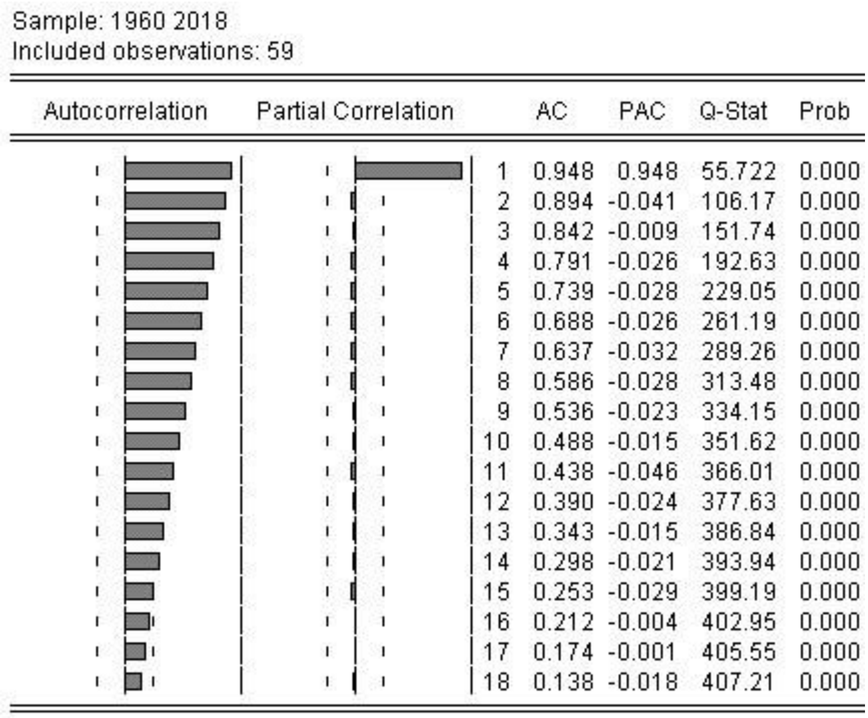
$$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{Covariance\ at\ lag\ k}{Covariance\ at\ lag\ 0}$$

The above formula belongs to the stochastic process; in other words, the population. Since only realizations could be observed in practice, the sample ACF is needed to be computed as:

$$\widehat{\rho_k} = \frac{\frac{\sum(Y_t - \overline{Y})(Y_{t+k} - \bar{Y})}{n}}{\frac{\sum(Y_t - \bar{Y})^2}{n}} = \frac{\widehat{\gamma_k}}{\widehat{\gamma_0}}$$

The plot of the sample ACF together with Partial ACF (PACF), i.e., correlogram, can give us an idea about the stationarity of series. The selection of the lag size is based on the rule of thumb by Gujarati (2003), stated as "*up to one-third to one quarter the length of the time series*." Since the number of observations in the data set is 59, the lag size can be selected from 15 to 20. It is assumed that 18 lags-choice is reasonable enough to examine correlograms. Figure 16 provides the correlogram of LNC up to 18 lags.

Figure 16: The correlogram for the logarithm of net electricity consumption up to 18 lags.


Sample: 1960 2018
Included observations: 59

Lag	AC	PAC	Q-Stat	Prob
1	0.948	0.948	55.722	0.000
2	0.894	-0.041	106.17	0.000
3	0.842	-0.009	151.74	0.000
4	0.791	-0.026	192.63	0.000
5	0.739	-0.028	229.05	0.000
6	0.688	-0.026	261.19	0.000
7	0.637	-0.032	289.26	0.000
8	0.586	-0.028	313.48	0.000
9	0.536	-0.023	334.15	0.000
10	0.488	-0.015	351.62	0.000
11	0.438	-0.046	366.01	0.000
12	0.390	-0.024	377.63	0.000
13	0.343	-0.015	386.84	0.000
14	0.298	-0.021	393.94	0.000
15	0.253	-0.029	399.19	0.000
16	0.212	-0.004	402.95	0.000
17	0.174	-0.001	405.55	0.000
18	0.138	-0.018	407.21	0.000

The third column of the output shows the lag length. In the fourth and fifth columns of Figure 16, the numerical values of the autocorrelation and partial autocorrelation coefficients at the lags from 1 to18 are illustrated respectively. From the above figure, it can be inferred that the autocorrelation function dies away very slowly. Moreover, up to lag numbered 15, ACFs are outside the 95% confidence intervals. Apart from this, only the first PACF emerges strongly significant. According to Brooks (2008), a given autocorrelation coefficient is classified as significant if it is outside a $\pm 1.96 \times 1/(N)^{1/2}$ confidence interval, where N is the number of observations. In our case, if the correlation coefficient is outside the interval of [-0.255, -0.255], then it could be implied that this coefficient is categorized as significant. So, it can be concluded that the first fourteen autocorrelation coefficients and only the first partial autocorrelation coefficient are significant under this rule. Since the first ACF coefficient is highly significant, the Ljung-Box joint test statistic rejects the null hypothesis of no autocorrelation at the 1% level for all numbers of lags considered (all p-values are 0). It could also be inferred that a mixed ARMA process could be an appropriate model; however, this will be discussed in the later parts of this chapter.

Similarly, the correlogram of LGDP up to 18 lags is shown in Figure 17.

Figure 17: The correlogram for the logarithm of Turkish GDP up to 18 lags.

Sample: 1960 2018
Included observations: 59

Lag	AC	PAC	Q-Stat	Prob
1	0.960	0.960	57.215	0.000
2	0.907	-0.193	109.16	0.000
3	0.852	-0.023	155.80	0.000
4	0.797	-0.028	197.35	0.000
5	0.742	-0.031	234.01	0.000
6	0.685	-0.053	265.87	0.000
7	0.631	0.011	293.44	0.000
8	0.578	-0.043	316.99	0.000
9	0.525	-0.020	336.83	0.000
10	0.475	-0.008	353.40	0.000
11	0.417	-0.147	366.43	0.000
12	0.359	-0.002	376.33	0.000
13	0.307	0.018	383.69	0.000
14	0.258	-0.008	389.01	0.000
15	0.216	0.039	392.83	0.000
16	0.181	0.030	395.56	0.000
17	0.150	0.003	397.49	0.000
18	0.123	-0.011	398.81	0.000

From the figure above, similar inferences can be made as it has been done for the correlogram of LNC. Up to lag numbered 15, the autocorrelation functions are outside the 95% confidence intervals. Only the first partial autocorrelation emerges strongly significant.

Based on the rule of thumb by Brooks, it can be deduced that the first fourteen autocorrelation coefficients and only the first partial autocorrelation coefficient are significant.

According to the correlograms above, it is observed that when the lag size increases, each corresponding autocorrelation coefficient decrease gradually; however, even after ten lags, it has high values. It is expected in stationary series that almost all autocorrelation coefficient is near to zero. In other words, they should be inside the confidence interval limits so that the hypothesis having zero value cannot be rejected. Those facts might be clues to the matter that both time series are non-stationary. Silvia et al. (2014) state this fact as a natural consequence of non-stationarity of many macroeconomic series, exhibiting trending behavior or having the non-stationary mean, which results in not being mean-reverting.

However, these two approaches, in order to detect stationarity, namely graphical method and correlogram, can be considered as figural ways. Consequently, it is needed a formal hypothesis testing procedure to examine for a unit root. In order to test the unit root of the series $\{Y_t\}$, where $\{Y_t\}$ is an AR(1) process; the formula below is considered:

$$d(Y_t) = \delta Y_{t-1} + u_t$$

When the null hypothesis $H_0 \colon \delta = 0$ fails to be rejected, then a unit root exists; in other words, the time series is non-stationary. The most common test for unit root is known as the Augmented Dickey-Fuller (ADF) test. In this approach, the test statistic can be estimated by using three different formulas that existed in EViews. Practically, the test equation among those named "trend and intercept" will be selected for unit root test, and this equation is formulated as follows:

$$d(Y_t) = c(1)Y_{t-1} + c(2) + c(3)@TREND + u_t$$

The null hypothesis is described as $H_0 \colon c(1) = 0$, which indicates that the time series is non-stationary. If H_0 is rejected, then it is concluded that Y_t is a stationary time series around a deterministic trend in the case of a random walk with drift around a stochastic trend.

Output 1 shows the results of the Augmented Dickey-Fuller (ADF) test for LNC based on the trend and intercept model. The test statistic obtained as -0,9974 is less negative than the critical values at all three levels of significance, so it can be concluded that the null hypothesis of a unit root in the LNC series can fail to be rejected. The remainder of the output shows the intermediate test equation used to calculate the ADF statistic. It is observed that the trend coefficient is not statistically significant (p-value=0,9362), which indicates that the LNC series has no trend.

Output 1: The ADF test results for LNC with trend and intercept.

Null Hypothesis: LNC has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.997495	0.9362
Test critical values:	1% level	-4.124265	
	5% level	-3.489228	
	10% level	-3.173114	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNC)
Method: Least Squares
Sample (adjusted): 1961 2018
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNC(-1)	-0.024149	0.024210	-0.997495	0.3229
C	0.315403	0.195786	1.610961	0.1129
@TREND("1960")	0.000593	0.001966	0.301784	0.7640

R-squared	0.338720	Mean dependent var	0.080466
Adjusted R-squared	0.314674	S.D. dependent var	0.039895
S.E. of regression	0.033027	Akaike info criterion	-3.932669
Sum squared resid	0.059992	Schwarz criterion	-3.826095
Log likelihood	117.0474	Hannan-Quinn criter.	-3.891156
F-statistic	14.08604	Durbin-Watson stat	1.743227
Prob(F-statistic)	0.000011		

Since the trend was found as insignificant, then we have to estimate the model with an intercept. The results of the intercept model are illustrated in Output 2.

Output 2: The ADF test results for LNC with intercept.

Null Hypothesis: LNC has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.342688	0.0000
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNC)
Method: Least Squares
Sample (adjusted): 1961 2018
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNC(-1)	-0.016907	0.003164	-5.342688	0.0000
C	0.257196	0.033357	7.710341	0.0000

R-squared	0.337625	Mean dependent var	0.080466
Adjusted R-squared	0.325797	S.D. dependent var	0.039895
S.E. of regression	0.032757	Akaike info criterion	-3.965497
Sum squared resid	0.060091	Schwarz criterion	-3.894448
Log likelihood	116.9994	Hannan-Quinn criter.	-3.937822
F-statistic	28.54431	Durbin-Watson stat	1.752414
Prob(F-statistic)	0.000002		

Based on the intercept model, the null hypothesis of being non-stationary is rejected at the 5% level of significance with a p-value of 0,000. If the constant term is checked, the intercept term is statistically significant. So, we have a stochastic trend with constant. Such kind of data can be stationary only by using the Difference Stationary Process that will be discussed later.

In addition to the ADF test, the Phillips–Perron (PP) test could be used to assess the null hypothesis of a unit root in a univariate time series. The test results are shown in Output 3. Similar to the ADF test's result, the null hypothesis cannot be rejected with the p-value of 0,9365, which means that the time series of LNC is non-stationary.

Output 3: The PP test results for LNC with trend and intercept.

Null Hypothesis: LNC has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.995594	0.9365
Test critical values:	1% level	-4.124265	
	5% level	-3.489228	
	10% level	-3.173114	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.001034
HAC corrected variance (Bartlett kernel)	0.001024

Phillips-Perron Test Equation
Dependent Variable: D(LNC)
Method: Least Squares
Sample (adjusted): 1961 2018
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNC(-1)	-0.024149	0.024210	-0.997495	0.3229
C	0.315403	0.195786	1.610961	0.1129
@TREND("1960")	0.000593	0.001966	0.301784	0.7640

R-squared	0.338720	Mean dependent var	0.080466
Adjusted R-squared	0.314674	S.D. dependent var	0.039895
S.E. of regression	0.033027	Akaike info criterion	-3.932669
Sum squared resid	0.059992	Schwarz criterion	-3.826095
Log likelihood	117.0474	Hannan-Quinn criter.	-3.891156
F-statistic	14.08604	Durbin-Watson stat	1.743227
Prob(F-statistic)	0.000011		

Similarly, the ADF and PP tests for LGDP with trend and intercept fail to reject the null hypothesis at the 5% level of significance with the p-values of 0,2012 and 0,0774 respectively, so that the series of LGDP is also non-stationary (See Output 4).

Output 4: The ADF and PP test results for LGDP with trend and intercept.

Null Hypothesis: LGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.805806	0.2012
Test critical values:	1% level	-4.124265	
	5% level	-3.489228	
	10% level	-3.173114	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LGDP)
Method: Least Squares
Sample (adjusted): 1961 2018
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP(-1)	-0.268995	0.095871	-2.805806	0.0069
C	2.704549	0.952422	2.839655	0.0063
@TREND("1960")	0.009883	0.003599	2.746078	0.0081

R-squared	0.125617	Mean dependent var	0.029975
Adjusted R-squared	0.093821	S.D. dependent var	0.074271
S.E. of regression	0.070701	Akaike info criterion	-2.410375
Sum squared resid	0.274925	Schwarz criterion	-2.303800
Log likelihood	72.90088	Hannan-Quinn criter.	-2.368862
F-statistic	3.950756	Durbin-Watson stat	1.466859
Prob(F-statistic)	0.024934		

Null Hypothesis: LGDP has a unit root Exogenous: Constant, Linear Trend Bandwidth: 3 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.294195	0.0774
Test critical values:	1% level	-4.124265	
	5% level	-3.489228	
	10% level	-3.173114	
*MacKinnon (1996) one-sided p-values.			
Residual variance (no correction)			0.004740
HAC corrected variance (Bartlett kernel)			0.006668

If the second part of the ADF test's output above is examined, it will be observed that the trend coefficient is significant. This result is also valid for the PP test. With non-stationary series having a significant trend, we can conclude that the data has a deterministic trend. Trend Stationary Process or Difference Stationary Process techniques can be used to have it stationary.

4.2.2 Cointegration Tests

As previously mentioned, the linear combination of non-stationary variables has the possibility of producing a spurious regression. Nevertheless, errors tend to disappear and become zero when there exists a long-run relationship between them. If a linear combination of non-stationary variables is stationary, then the set of variables in question is defined as cointegrated. In other words, there is a long-term (equilibrium) relationship between them. In fact, Brooks (2008) notes that although many time series are non-stationary, they can move together long-term, implying that they are bound by some relationship over time.

This study considers two cointegration tests for non-stationary series in the literature, namely Engle-Granger and Johansen Cointegration Tests. The fundamental difference between them can be summarized as the fact the former is a single-equation methodology, whereas the latter is a systems technique involving estimation of more than one equation[14].

a) Engle-Granger Cointegration Test

The idea behind the Engle-Granger Test is the fact that for the bivariate case, based on two variables, say Y_t and X_t; it is needed to check residuals of the regression model described as

$$Y_t = \beta_0 + \beta_1 X_t + u_t$$

in order to see whether they are stationary. By estimating a static long-run equation, the regression results are obtained as in Output 5 below.

Output 5: Long-run equation results for the LNC regressed on LGDP.

Dependent Variable: LNC
Method: Least Squares
Sample: 1960 2018
Included observations: 59

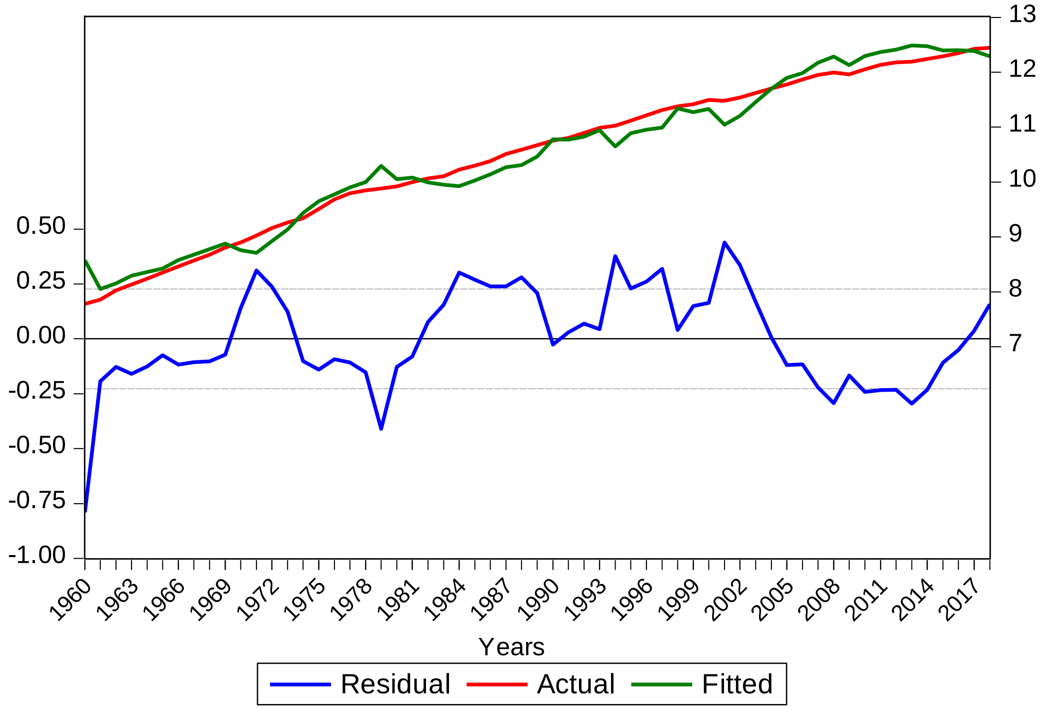
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-13.13067	0.517286	-25.38378	0.0000
LGDP	0.928974	0.020313	45.73186	0.0000

R-squared	0.973469	Mean dependent var	10.48700
Adjusted R-squared	0.973003	S.D. dependent var	1.383835
S.E. of regression	0.227374	Akaike info criterion	-0.091133
Sum squared resid	2.946834	Schwarz criterion	-0.020708
Log likelihood	4.688409	Hannan-Quinn criter.	-0.063641
F-statistic	2091.403	Durbin-Watson stat	0.426968
Prob(F-statistic)	0.000000		

[14] Solutions to the end of chapter questions of Brooks' *Introductory Econometrics for Finance*, Available at: http://www.cambridge.org/features/economics/brooks/Solutions.html

The time series graphs of the actual and fitted (predicted) values, together with the regression residuals, are presented in Figure 18.

Figure 18: Actual, fitted, and residual graphs of the regression model.



When examined in the regression output, it can be noted that the time series regression equation with a high degree of fit, as measured by the coefficient of determination R^2 (0,9734) or the adjusted $\bar{R}^2$ (0,9730). However, the Durbin-Watson statistic has an extremely low value of 0,4269 compared with these two coefficients. Besides, the t-statistic values (-25,3837 and 45,7318) have significantly higher values to reject the related null hypotheses for the significance of the model coefficients. As stated by Granger and Newbold (1974), those findings may recall us spurious regression.

By running the Engle-Granger Test in EViews, we get the following results presented in Output 6. According to these results, the null hypothesis stating that the series are not cointegrated fails to be rejected at the 5% level of significance. Consequently, the evidence suggests that the LNC and LGDP series are not cointegrated.

Output 6: Statistical results for the Engle-Granger cointegration test.

Series: LNC LGDP
Sample: 1960 2018
Included observations: 59
Null hypothesis: Series are not cointegrated
Cointegrating equation deterministics: C
Automatic lags specification based on Schwarz criterion (maxlag=10)

Dependent	tau-statistic	Prob.*	z-statistic	Prob.*
LNC	-4.182479	0.0078	-18.44342	0.0521
LGDP	-3.965460	0.0140	-17.88970	0.0596

*MacKinnon (1996) p-values.

Intermediate Results:

	LNC	LGDP
Rho - 1	-0.317990	-0.308443
Rho S.E.	0.076029	0.077782
Residual variance	0.016890	0.020033
Long-run residual variance	0.016890	0.020033
Number of lags	0	0
Number of observations	58	58
Number of stochastic trends**	2	2

**Number of stochastic trends in asymptotic distribution

b) Johansen Cointegration Test

Although the Engle-Granger test for cointegration is straightforward to perform and to interpret its results intuitively, it is incapable of detecting more than one relationship cointegrated. Moreover, it is not possible to test the hypothesis for the cointegrating vector with this test. Therefore, the Johansen approach is regarded as a superior technique than the Engle-Granger method for cointegration testing.

Before conducting the Johansen cointegration test, we should check whether the series are I(1). A series is defined as I(1) if it is non-stationary in level but stationary in its first differences. If the time series $\{Y_t\}$ has a unit root as in our case, then the first differences model shown as $d(Y_t) = Y_t - Y_{t-1} = u_t$, where $Y_t = Y_{t-1} + u_t$ is taken into consideration to test the unit root of a process.

LNC series was obtained as non-stationary at level according to the unit root tests performed above. When the series of LNC in first differences (hereafter DIFF_LNC) is tested for stationary, as presented in Output 7 and Output 8, it is founded that the null hypothesis of having unit root is rejected at the 5% level of significance (both p-values are obtained as 0,0000), which means that DIFF_LNC is a stationary series.

Output 7: The ADF test results for the first-differences of LNC.

Null Hypothesis: DIFF_LNC has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.688092	0.0000
Test critical values:	1% level	-4.127338	
	5% level	-3.490662	
	10% level	-3.173943	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DIFF_LNC)
Method: Least Squares
Sample (adjusted): 1962 2018
Included observations: 57 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFF_LNC(-1)	-0.892902	0.133506	-6.688092	0.0000
C	0.110515	0.018513	5.969586	0.0000
@TREND("1960")	-0.001290	0.000318	-4.059941	0.0002

R-squared	0.454112	Mean dependent var	-0.000930
Adjusted R-squared	0.433894	S.D. dependent var	0.043716
S.E. of regression	0.032892	Akaike info criterion	-3.939983
Sum squared resid	0.058421	Schwarz criterion	-3.832454
Log likelihood	115.2895	Hannan-Quinn criter.	-3.898194
F-statistic	22.46071	Durbin-Watson stat	1.828975
Prob(F-statistic)	0.000000		

Output 8: The PP test results for the first-differences of LNC.

Null Hypothesis: DIFF_LNC has a unit root Exogenous: Constant, Linear Trend Bandwidth: 4 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.649994	0.0000
Test critical values:	1% level	-4.127338	
	5% level	-3.490662	
	10% level	-3.173943	
*MacKinnon (1996) one-sided p-values.			
Residual variance (no correction)			0.001025
HAC corrected variance (Bartlett kernel)			0.000849

Similar to the unit root tests mentioned above, since the calculated Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test statistic (0,0392) is less than the asymptotic critical values at all levels as tabulated below, we fail to reject the null hypothesis stating that the DIFF_LNC series is stationary.

Output 9: The KPSS test results for the first-differences of LNC.

Null Hypothesis: DIFF_LNC is stationary Exogenous: Constant, Linear Trend Bandwidth: 3 (Newey-West automatic) using Bartlett kernel		
		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.039256
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		
Residual variance (no correction)		0.001053
HAC corrected variance (Bartlett kernel)		0.001042

When we examine the time series plot and correlogram of DIFF_LNC, we will encounter a very different pattern than those of LNC (See Figure 19 and Figure 20).

Figure 19: Time series plot of DIFF_LNC.

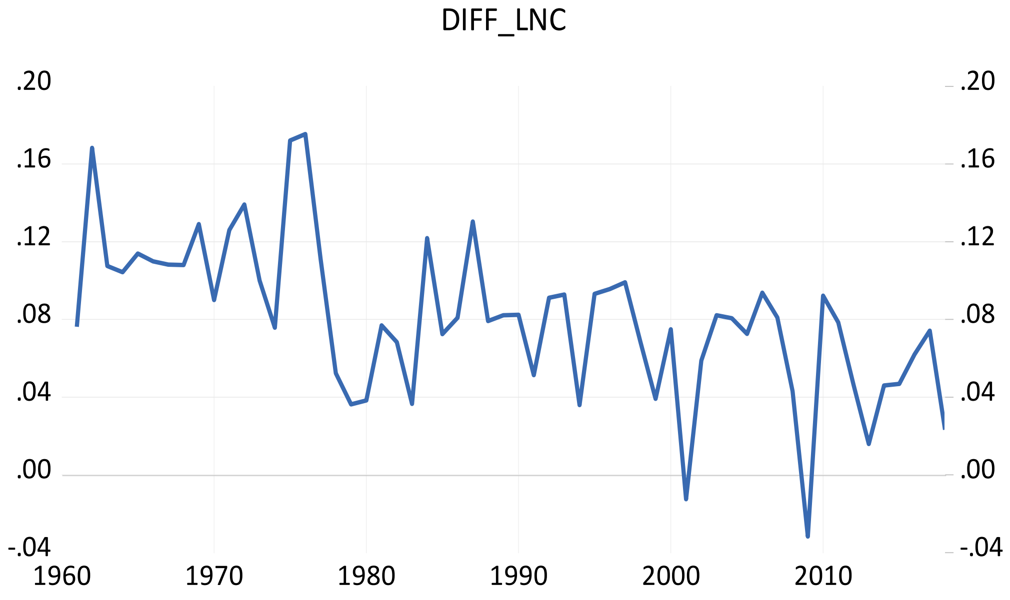
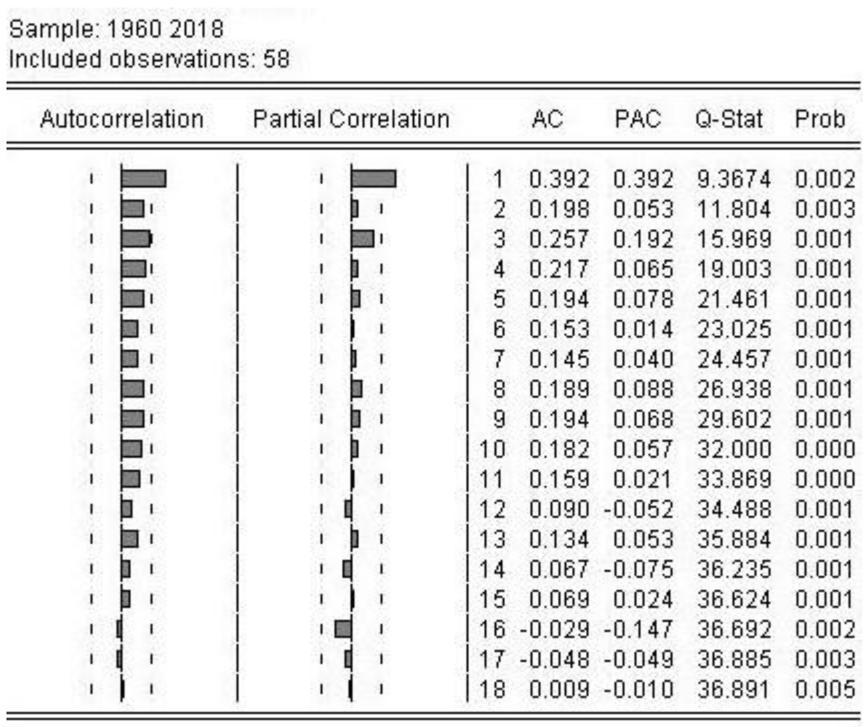


Figure 20: The correlogram for DIFF_LNC up to 18 lags.



Sample: 1960 2018
Included observations: 58

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.392	0.392	9.3674	0.002
		2	0.198	0.053	11.804	0.003
		3	0.257	0.192	15.969	0.001
		4	0.217	0.065	19.003	0.001
		5	0.194	0.078	21.461	0.001
		6	0.153	0.014	23.025	0.001
		7	0.145	0.040	24.457	0.001
		8	0.189	0.088	26.938	0.001
		9	0.194	0.068	29.602	0.001
		10	0.182	0.057	32.000	0.000
		11	0.159	0.021	33.869	0.000
		12	0.090	-0.052	34.488	0.001
		13	0.134	0.053	35.884	0.001
		14	0.067	-0.075	36.235	0.001
		15	0.069	0.024	36.624	0.001
		16	-0.029	-0.147	36.692	0.002
		17	-0.048	-0.049	36.885	0.003
		18	0.009	-0.010	36.891	0.005

Similarly, since the LGDP series was found as non-stationary as expected, we should test the unit root in the first differences. In this case, the ADF test statistic shown in Output 10 is more negative than the critical values at all levels, and the p-value is less than 0,05; hence, the null hypothesis of having a unit root in the first differences is convincingly rejected. That means the series for the logarithm of GDP in the first differences (hereafter DIFF_LGDP) is stationary.

Output 10: The ADF test results for the first-differences of LGDP.

Null Hypothesis: DIFF_LGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.450704	0.0000
Test critical values:	1% level	-4.127338	
	5% level	-3.490662	
	10% level	-3.173943	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DIFF_LGDP)
Method: Least Squares
Sample (adjusted): 1962 2018
Included observations: 57 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFF_LGDP(-1)	-0.998278	0.118130	-8.450704	0.0000
C	0.053125	0.018420	2.884028	0.0056
@TREND("1960")	-0.000614	0.000528	-1.161285	0.2506

R-squared	0.574661	Mean dependent var	0.003470
Adjusted R-squared	0.558908	S.D. dependent var	0.098803
S.E. of regression	0.065620	Akaike info criterion	-2.558688
Sum squared resid	0.232520	Schwarz criterion	-2.451159
Log likelihood	75.92261	Hannan-Quinn criter.	-2.516899
F-statistic	36.47875	Durbin-Watson stat	1.991944
Prob(F-statistic)	0.000000		

The results of the PP and KPPS tests for the same series, evidenced in Output 11 and Output 12, are consistent with the ADF test result. The obtained p-value for the PP test was 0,0000 which is less than the level of significance. Moreover, KPSS test statistic value, i.e., 0,07353, is less than all asymptotic critical values at all levels.

Output 11: The PP test results for the first-differences of LGDP.

Null Hypothesis: DIFF_LGDP has a unit root Exogenous: Constant, Linear Trend Bandwidth: 1 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.455093	0.0000
Test critical values:	1% level	-4.127338	
	5% level	-3.490662	
	10% level	-3.173943	
*MacKinnon (1996) one-sided p-values.			
Residual variance (no correction)			0.004079
HAC corrected variance (Bartlett kernel)			0.004061

Output 12: The KPSS test results for the first-differences of LGDP.

Null Hypothesis: DIFF_LGDP is stationary Exogenous: Constant, Linear Trend Bandwidth: 1 (Newey-West automatic) using Bartlett kernel		
		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.073538
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		
Residual variance (no correction)		0.005419
HAC corrected variance (Bartlett kernel)		0.005415

According to all unit root tests performed, namely ADF, PP, and KPSS tests, it can be concluded that the DIFF_LGDP series is integrated of order one, I(1). The time series plot and correlogram of DIFF_LGDP have a much more contrary pattern than those of

LGDP (see Figure 21 and Figure 22). The ACFs and PACFs at all 18 lags are not statistically different from zero at the 5% level of significance.

Figure 21: Time series plot of DIFF_LGDP.

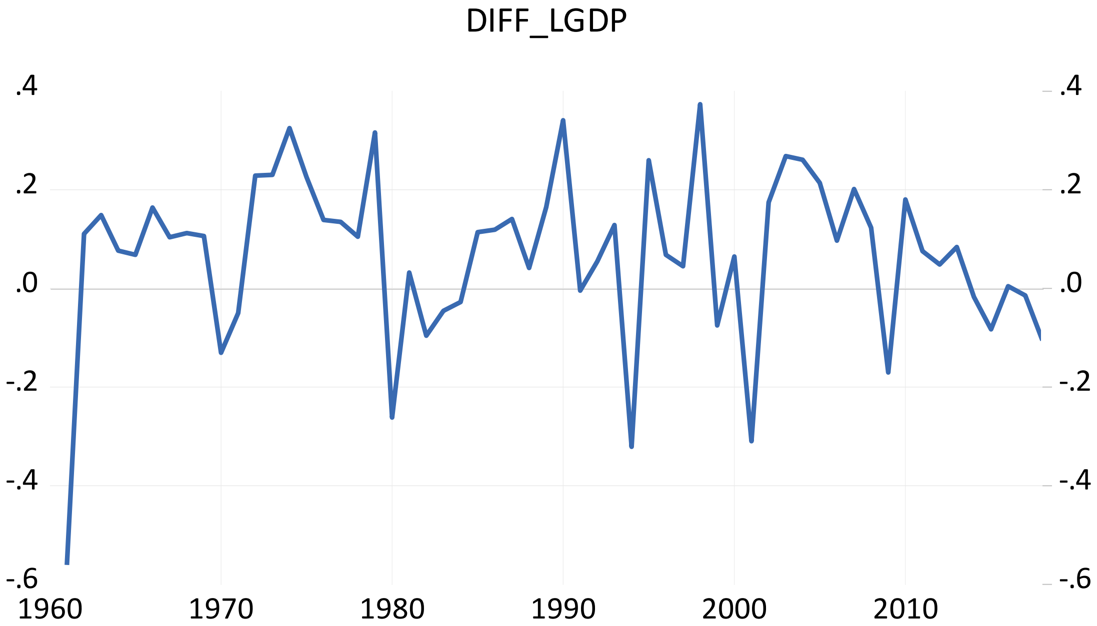
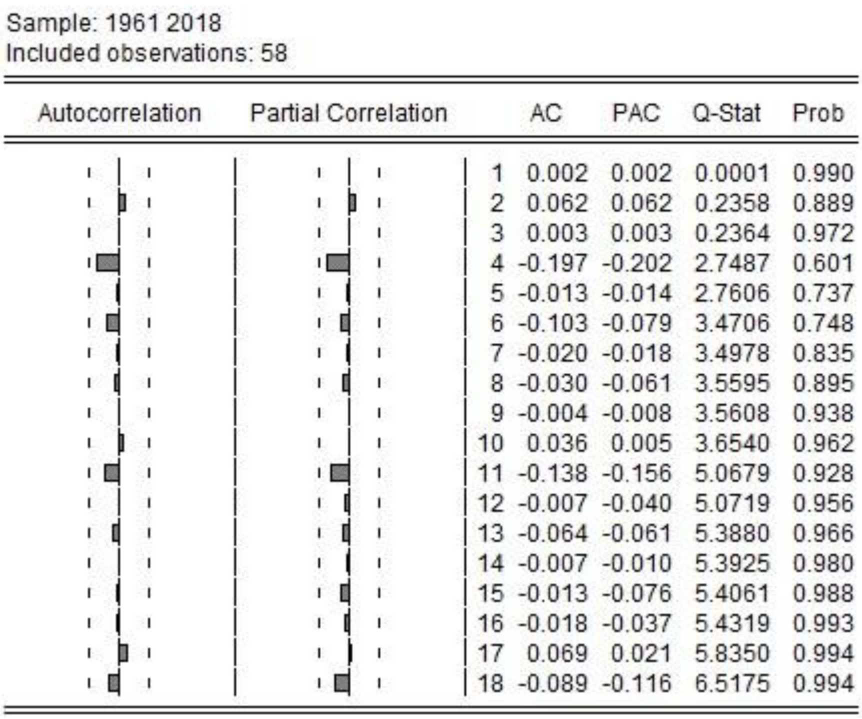


Figure 22: The correlogram for DIFF_LGDP up to 18 lags.


Sample: 1961 2018
Included observations: 58

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.002	0.002	0.0001	0.990
		2	0.062	0.062	0.2358	0.889
		3	0.003	0.003	0.2364	0.972
		4	-0.197	-0.202	2.7487	0.601
		5	-0.013	-0.014	2.7606	0.737
		6	-0.103	-0.079	3.4706	0.748
		7	-0.020	-0.018	3.4978	0.835
		8	-0.030	-0.061	3.5595	0.895
		9	-0.004	-0.008	3.5608	0.938
		10	0.036	0.005	3.6540	0.962
		11	-0.138	-0.156	5.0679	0.928
		12	-0.007	-0.040	5.0719	0.956
		13	-0.064	-0.061	5.3880	0.966
		14	-0.007	-0.010	5.3925	0.980
		15	-0.013	-0.076	5.4061	0.988
		16	-0.018	-0.037	5.4319	0.993
		17	0.069	0.021	5.8350	0.994
		18	-0.089	-0.116	6.5175	0.994

Since it has been satisfied that both series, namely LNC and LGDP, are I(1), now we can continue to the Johansen cointegration test. However, before the test, we need to determine the appropriate lag length of the model. Based on the information criteria of Sequential Modified LR Test (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ) statistics, the sufficient lag order was found as 1 lag (see Output 13).

Output 13: Statistical results of lag order selection criteria for the VAR model of {LNC, LGDP}.

VAR Lag Order Selection Criteria
Endogenous variables: LNC LGDP
Exogenous variables: C
Sample: 1960 2018
Included observations: 51

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-71.55396	NA	0.061343	2.884469	2.960227	2.913418
1	134.2948	**387.4800***	**2.24e-05***	**-5.031168***	**-4.803894***	**-4.944320***
2	135.2561	1.734070	2.53e-05	-4.912002	-4.533213	-4.767256
3	140.6087	9.235982	2.40e-05	-4.965048	-4.434743	-4.762403
4	143.6079	4.939876	2.51e-05	-4.925802	-4.243981	-4.665258
5	145.1001	2.340658	2.78e-05	-4.827455	-3.994119	-4.509013
6	147.3555	3.360978	3.01e-05	-4.759039	-3.774187	-4.382698
7	150.9236	5.037369	3.10e-05	-4.742103	-3.605735	-4.307864
8	152.1445	1.627802	3.51e-05	-4.633117	-3.345233	-4.140979

To perform the Johansen Cointegration test, firstly, we will look at test summary results for all 5 options, which are no trend, restricted constant, unrestricted constant, restricted trend, and unrestricted trend. The following conclusions can be drawn from the test results (see Output 14): Model 5 (the level data have a quadratic trend and cointegrating equations have linear trends) seems to be the best model with 2 cointegrating equations.

Output 14: The Johansen cointegration test summary results.

Sample: 1960 2018
Included observations: 58
Series: LNC LGDP
Lags interval: No lags

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	2	2	2	2
Max-Eig	1	2	2	2	0

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	82.12982	82.12982	130.6543	130.6543	144.3676
1	143.8809	145.6085	145.7136	146.9593	152.3713
2	144.8198	153.6390	153.6390	154.9071	154.9071
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	-2.832063	-2.832063	-4.436354	-4.436354	-4.840262
1	-4.823479	-4.848570	-4.817710	-4.826183	-4.978322*
2	-4.717926	-4.953071	-4.953071	-4.927829	-4.927829
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	-2.832063	-2.832063	-4.365304	-4.365304	-4.698163*
1	-4.681379	-4.670945	-4.604561	-4.577509	-4.694123
2	-4.433727	-4.597822	-4.597822	-4.501531	-4.501531

Based on the results from both trace test and maximum eigenvalue test (see Output 15), there are two cointegration equations between the series LNC and LGDP at the 0,05 level of significance. In other words, the two series tend to move closer together over time, and it is not expected to drift arbitrarily in the long-run. Moreover, in the long run, any increase in LGDP has a positive impact on LNC on average, ceteris paribus. If the economic growth in Turkey increases by 1%, the net electricity consumption in the country will also increase by about 1,106%. Furthermore, the normalized cointegrating coefficient for LGDP is statistically significant, with a t-statistic value of -4,103.

Output 15: Statistical results for the Johansen cointegration test.

Sample (adjusted): 1961 2018
Included observations: 58 after adjustments
Trend assumption: Quadratic deterministic trend
Series: LNC LGDP
Lags interval (in first differences): No lags

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.241180	21.07890	18.39771	0.0206
At most 1 *	0.083725	5.071417	3.841466	0.0243

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.241180	16.00749	17.14769	0.0727
At most 1 *	0.083725	5.071417	3.841466	0.0243

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LNC	LGDP
-3.977206	4.401904
4.396915	1.819324

Unrestricted Adjustment Coefficients (alpha):

D(LNC)	-0.008176	-0.008060
D(LGDP)	-0.083131	0.002496

1 Cointegrating Equation(s): Log likelihood 152.3713

Normalized cointegrating coefficients (standard error in parentheses)

LNC	LGDP
1.000000	-1.106783
	(0.26971)

Adjustment coefficients (standard error in parentheses)

D(LNC)	0.032518
	(0.01684)
D(LGDP)	0.330631
	(0.07921)

The null hypothesis of no cointegration is rejected against the alternative stating the fact that there exists a cointegrating relationship in the model. In short, it may be concluded from the Johansen cointegration test performed that the series LNC and LGDP are cointegrated, which means they share a common stochastic drift. Based on these findings, i.e., cointegrated non-stationary series, the VECM model of {LNC, LGDP} can be applied. Nevertheless, since this model and its findings are out of scope for the aims of this study, such kind of analysis is left for other research.

4.2.3 Causality Checks

As discussed before, positive economic growth is expected to affect the energy consumption of the country and vice versa. However, there is no consensus on the causal relationship between these variables in the literature. Since the optimal lag length was found as 1, Granger Causality/Block Exogeneity Tests option in EViews is not allowed. This procedure requires at least one lag in the lag specification. On the other hand, according to the pairwise Granger causality test results presented in Table 10, the null hypothesis that DIFF_LGDP is not a Granger-cause of DIFF_LNC is rejected at the 5% significance level based on the F-statistics value of 5,9293 and p-value of 0,0182. Notably, an increase in the GDP of Turkey will lead to a rise in the net electricity consumption of the country. When GDP increases, it will indicate a positive economic condition in the country. This motivation indicates that as the economic growth expands, it will directly result in an increase in the demand for electricity, more generally for energy, at the same time. Kahsai et al. (2012) describe this causal relationship as the fact that there can be several ways of energy consumption affected by the rise in GDP. To them, with an increase in GDP, households can spend their additional income on further energy services. Apart from these, in the production system, there can also be an extra demand for energy inputs as a result of growth in GDP. When this increase occurs, the distribution in energy services is expected to reach remote regions within the country, and consequently, that is likely to increase energy demand.

However, the null hypothesis that DIFF_LNC is not a Granger-cause of DIFF_LGDP is failed to reject at the 5% level of significance according to the F-statistics value of 1,4051 and p-value of 0,2411. So, it can be inferred from the Granger causality test that there exists significantly unidirectional Granger causality from DIFF_LGDP to DIFF_LNC, and thereby past values of DIFF_LGDP are able to help predict future values of DIFF_LNC, but since DIFF_LNC is not a Granger-cause of DIFF_LGDP the past values of the former are not helpful in forecasting the latter.

Table 10: Granger causality test results.

Null Hypothesis:	Obs	F-Statistic	Prob.
DIFF_LGDP does not Granger Cause DIFF_LNC	57	5.92923	0.0182
DIFF_LNC does not Granger Cause DIFF_LGDP		1.40510	0.2411

Alternatively, no matter the economic series are cointegrated and/or integrated at the same orders, a procedure developed by Toda and Yamamoto, called as augmented Granger causality could be used to test causality. For this test, two pieces of information are needed to implement. Those are the optimal lag length (*k*) and the maximum order of integration for the system (*d(max)*). VAR lag order selection option in EViews resulted that the optimal lag length is 1 for the VAR model with endogenous variables of LNC and LGDP. What we know from unit root tests is that the maximum order of integration for each of the time series was also found as 1.

Then, a level VAR was estimated with a total of $k + d(max) = 2$ lags for exogenous variables. The test results were obtained as follows:

Table 21: Granger's causality test results based on Toda and Yamamoto for the augmented VAR model.

Dependent variable: LNC

Excluded	Chi-sq	df	Prob.
LGDP	3.035866	1	0.0814

Dependent variable: LGDP

Excluded	Chi-sq	df	Prob.
LNC	0,305133	1	0.5807

More surprisingly, a long-run causal relationship based on Toda and Yamamoto level VAR model also shows that since the p-value is 0,0814, there is unidirectional causality from LGDP to LNC at the 10% level of significance. The estimated coefficient of lagged LGDP in the augmented level VAR model is statistically different from zero as a group. On the other hand, the opposite of this causality that runs from energy consumption to income in Turkey is not valid (p-value=0,5807).

4.2.4 ARIMA Modeling

One of the main aims of econometric analysis can be considered as predicting the future values of the time series. As discussed in the literature review part of this study, there are different methods to forecast energy demand. Exponential smoothing, regression, and ARIMA models are the most encountered ones. ARIMA models have the advantage of being less sensitive to the underlying assumptions of the nature of the data fluctuations than many other systems. In this forecasting approach, also known as the BJ method, the main point is to explain the econometric series with its past values and stochastic error terms by aiming to describe the autocorrelations in the data. Moreover, MENR's forecasting technique includes ARIMA models together with other methods. Since one of the purposes of this study is to visualize the future energy demand of Turkey by forecasting and to compare the findings with the official projections, it has been determined that ARIMA modeling fits the data to develop electricity consumption forecast in Turkey.

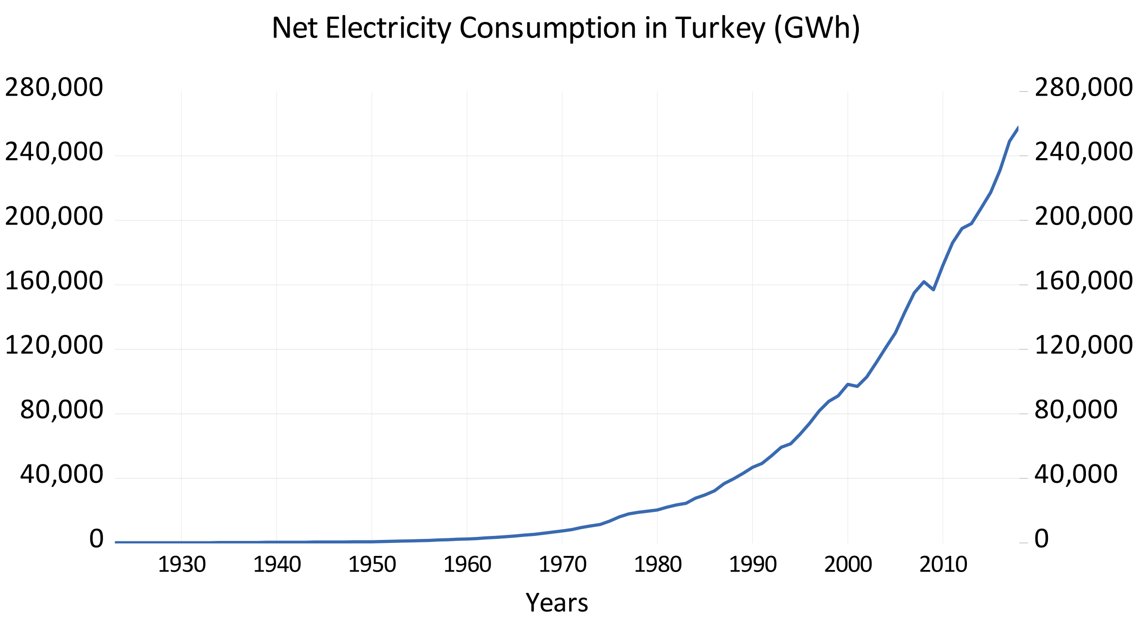
Before making the forecast, it would be suitable to mention that although the data period taken into consideration in the previous parts of this analysis is from 1960 to 2018 due to the lack and inadequacy of Turkey's GDP data before 1960, in this section the data for annual net electricity consumption of Turkey will cover the years of 1923-2018, totally 96 observations. Furthermore, the data itself in GWh units (See Appendix 2) will be used. In other words, there will be no transformation into the natural logarithms as made in the former part. From 1923 through 2017, Turkstat's Energy Statistics database and for the year of 2018, TEİAŞ's Turkey 2018 Electricity Consumption Statistics were used to obtain this data.

ARIMA modeling consists of four simple steps: (a) Identification of the model to be used, (b) Estimation of the model, (c) Engagement for diagnostic checking to confirm that whether the model is suitable, (d) Forecast the series. Now we will handle those steps with the Turkish net energy consumption series.

Foremost, how the appropriate ARIMA model could be identified will be discussed. This identification phase is described as "*an art rather than a science*," because selection from several possible alternative models may require judgment and knowledge of the data. In fact, intuition may be required to reach the best solution among many choices. With the same data set, different people might come up with unlike ARIMA models as best fitting.

The graph for the net electricity consumption of Turkey from 1923 to 2018 shows that there exists a trending upwards, and visually this series seems non-stationary, as expected.

Figure 23: Net electricity consumption in Turkey, 1923-2018.



The correlogram of the series (see Figure 24) shows significant ACFs that are outside the standard error bounds and decline very slowly. From lag 1 to lag 20, the lags are very significant. On the other hand, PACF at the first lag is very significant, but just after lag

1, it drops dramatically. To sum up, the energy consumption series of Turkey exhibits non-stationary behavior.

Figure 24: The correlogram of net electricity consumption in Turkey up to 32 lags.

Sample: 1923 2018
Included observations: 96

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.946	0.946	88.534	0.000
		2	0.890	-0.040	167.78	0.000
		3	0.839	0.019	239.03	0.000
		4	0.792	0.003	303.17	0.000
		5	0.746	-0.013	360.72	0.000
		6	0.701	-0.013	412.13	0.000
		7	0.655	-0.041	457.46	0.000
		8	0.609	-0.016	497.15	0.000
		9	0.568	0.007	532.00	0.000
		10	0.531	0.016	562.80	0.000
		11	0.488	-0.073	589.19	0.000
		12	0.446	-0.018	611.50	0.000
		13	0.408	0.001	630.32	0.000
		14	0.373	0.007	646.25	0.000
		15	0.340	-0.005	659.66	0.000
		16	0.309	0.000	670.92	0.000
		17	0.282	0.007	680.38	0.000
		18	0.255	-0.008	688.23	0.000
		19	0.226	-0.043	694.48	0.000
		20	0.199	-0.010	699.38	0.000
		21	0.171	-0.020	703.06	0.000
		22	0.145	-0.009	705.75	0.000
		23	0.121	-0.002	707.65	0.000
		24	0.100	-0.004	708.94	0.000
		25	0.079	-0.001	709.78	0.000
		26	0.059	-0.018	710.25	0.000
		27	0.041	-0.005	710.48	0.000
		28	0.023	-0.008	710.55	0.000
		29	0.006	-0.011	710.56	0.000
		30	-0.010	-0.009	710.57	0.000
		31	-0.025	-0.009	710.66	0.000
		32	-0.040	-0.010	710.90	0.000

To make the series stationary, instead of observing correlograms of the first and if needed, second differenced data (hereafter DNC and SDNC, respectively), we will use a more formal way, i.e., unit root tests. The summary of three different unit root tests conducted for both first and second differenced time series is illustrated in Table 12. Consequently, the second-differenced series was found as stationary.

Table 32: Unit root test statistics values for DNC and 2DNC series.

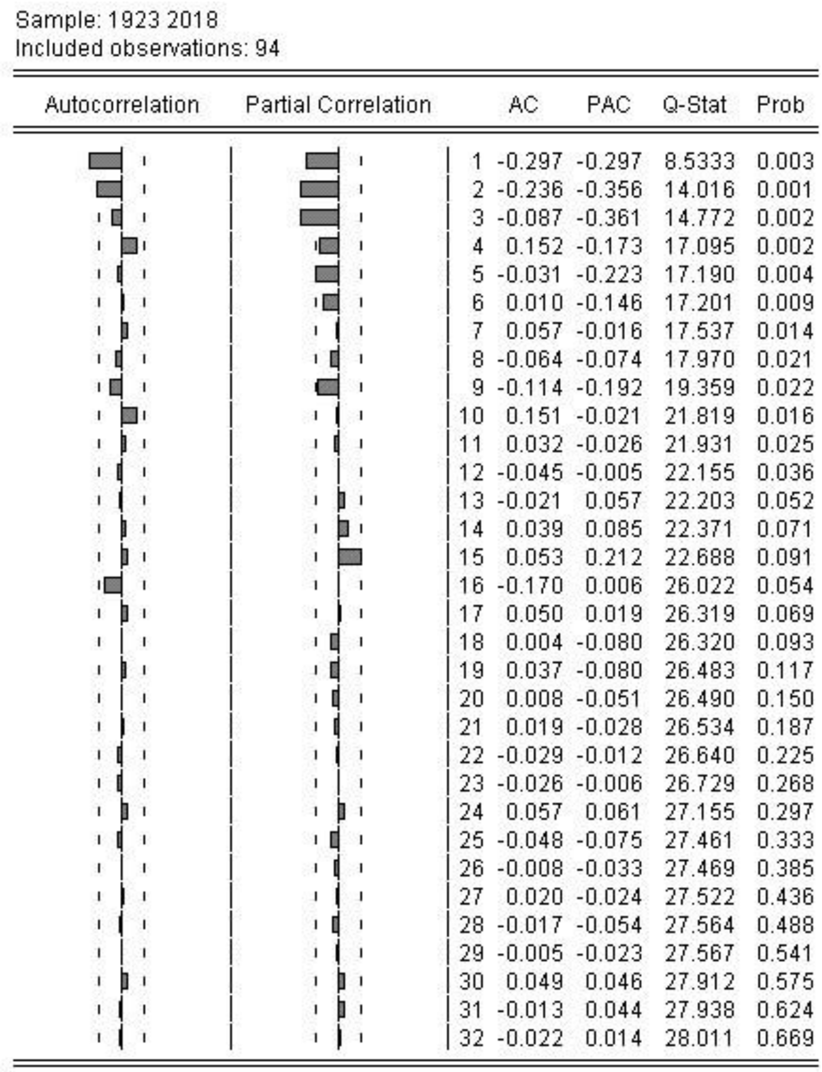
	ADF	PP	KPSS
DNC	-0,6100*	-6,9940*	0,4147**
SDNC	-9,2709**	-29,95**	0,1194*

* Not significant at the 5% level of significance.

** Significant at the 5% level of significance.

If we observe the similarities between ACF and PACF for the second-differenced series' correlogram shown in Figure 24, we will see that both functions show a rapid decline, which is a very different pattern from the correlogram of the series itself. Only the 1st lag for ACF seems significant, and for PACF at the 1st, 2nd, and 3rd lags are statistically different from zero. Since both ACFs and PACFs show almost the same pattern, this process might be called ARIMA.

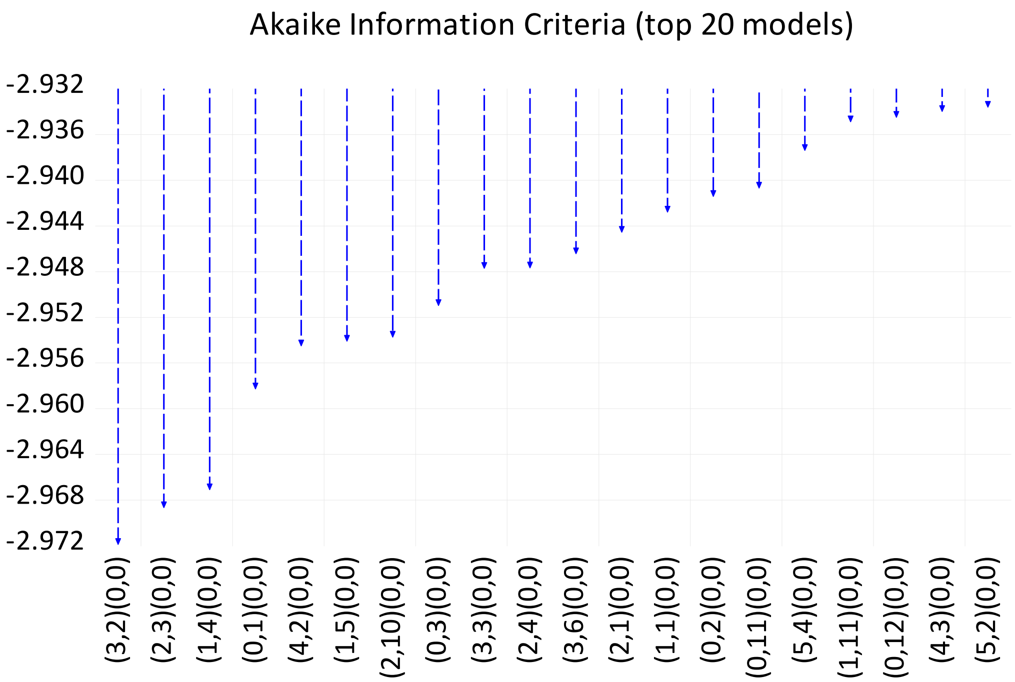
Figure 25: The correlogram of the SDNC series up to 32 lags.


Sample: 1923 2018
Included observations: 94

Lag	AC	PAC	Q-Stat	Prob
1	-0.297	-0.297	8.5333	0.003
2	-0.236	-0.356	14.016	0.001
3	-0.087	-0.361	14.772	0.002
4	0.152	-0.173	17.095	0.002
5	-0.031	-0.223	17.190	0.004
6	0.010	-0.146	17.201	0.009
7	0.057	-0.016	17.537	0.014
8	-0.064	-0.074	17.970	0.021
9	-0.114	-0.192	19.359	0.022
10	0.151	-0.021	21.819	0.016
11	0.032	-0.026	21.931	0.025
12	-0.045	-0.005	22.155	0.036
13	-0.021	0.057	22.203	0.052
14	0.039	0.085	22.371	0.071
15	0.053	0.212	22.688	0.091
16	-0.170	0.006	26.022	0.054
17	0.050	0.019	26.319	0.069
18	0.004	-0.080	26.320	0.093
19	0.037	-0.080	26.483	0.117
20	0.008	-0.051	26.490	0.150
21	0.019	-0.028	26.534	0.187
22	-0.029	-0.012	26.640	0.225
23	-0.026	-0.006	26.729	0.268
24	0.057	0.061	27.155	0.297
25	-0.048	-0.075	27.461	0.333
26	-0.008	-0.033	27.469	0.385
27	0.020	-0.024	27.522	0.436
28	-0.017	-0.054	27.564	0.488
29	-0.005	-0.023	27.567	0.541
30	0.049	0.046	27.912	0.575
31	-0.013	0.044	27.938	0.624
32	-0.022	0.014	28.011	0.669

For the estimation phase of ARIMA modeling, the "Automatic ARIMA Forecasting" option in EViews was used to determine the appropriate ARIMA model specification. It should be noted that the version of EViews 9 allows the maximum order of the AR and MA terms of the ARIMA model up to 12 lags. From among 169 estimated models, the software selected a suitable ARIMA model as ARIMA (3,2,2) for the net electricity consumption series of Turkey with a minimum AIC value of -2,9715. Figure 26 illustrates the ARIMA criteria graph for the top 20 models. As discussed before, there cannot be an exact or perfect ARIMA model. Since parsimonious models produce better results than over-parametrized ones, the first model used for forecasting Turkish electricity consumption has been determined as ARIMA (3,2,2) model.

Figure 26: ARIMA criteria graph for the top 20 models.



In the phase of diagnostic checking, the correlogram of residuals for the selected ARIMA model should be examined. The graph for ACF and PACF of the ARIMA residuals comprises lines showing 2 standard errors from both sides of zero, and any value of these functions passing standard errors are statistically significant, which means that the model is not explained all autocorrelation in the data. In other words, the residuals estimated from the ARIMA model are not purely random. As presented in Figure 27, all ACF and PACF values are not statistically significant. So, there is no need to re-estimate the model.

Figure 27: The correlogram of the residuals from ARIMA (3,2,2) up to 32 lags.

Sample: 1923 2018
Included observations: 94
Q-statistic probabilities adjusted for 5 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.030	-0.030	0.0892	
		2	0.012	0.011	0.1024	
		3	-0.102	-0.102	1.1376	
		4	0.062	0.056	1.5209	
		5	-0.028	-0.024	1.6026	
		6	0.029	0.017	1.6905	0.194
		7	0.024	0.038	1.7522	0.416
		8	-0.014	-0.022	1.7740	0.621
		9	0.004	0.011	1.7757	0.777
		10	0.234	0.241	7.6395	0.177
		11	0.081	0.092	8.3578	0.213
		12	0.034	0.045	8.4887	0.291
		13	0.023	0.078	8.5465	0.382
		14	0.015	0.011	8.5706	0.478
		15	0.028	0.045	8.6574	0.565
		16	-0.129	-0.136	10.594	0.478
		17	0.075	0.045	11.260	0.507
		18	0.051	0.070	11.574	0.563
		19	0.098	0.070	12.737	0.547
		20	0.081	0.065	13.542	0.560
		21	0.063	0.032	14.031	0.596
		22	0.004	0.002	14.033	0.665
		23	-0.021	-0.034	14.091	0.723
		24	0.028	0.002	14.190	0.772
		25	-0.054	-0.090	14.574	0.800
		26	-0.029	0.007	14.684	0.838
		27	0.002	-0.011	14.685	0.875
		28	0.005	-0.050	14.688	0.905
		29	0.018	-0.024	14.732	0.928
		30	0.055	-0.006	15.161	0.938
		31	-0.000	-0.047	15.161	0.954
		32	-0.020	-0.071	15.220	0.966

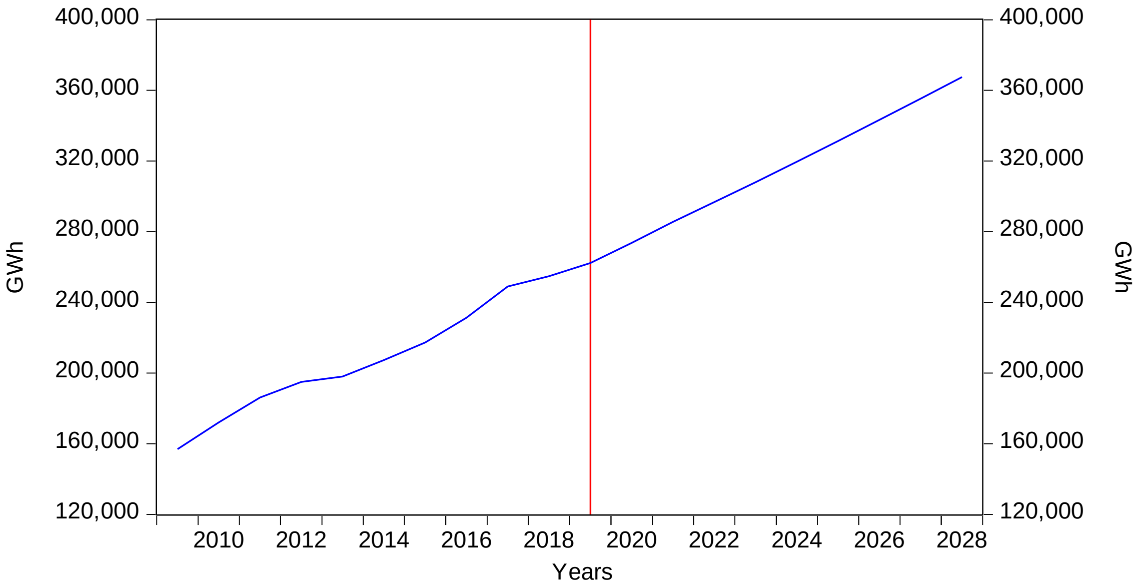
Finally, the net electricity consumption of Turkey is forecasted, as shown in Table 13, according to the selected ARIMA model for the next decade. The energy demand in the country is likely to continue with an annual mean rate of 3,73% for the period 2019-2028, and it is forecasted to reach 367.553 GWh in 2028, which will lead to a 44,2% increase in net consumption compared with the value in 2018. It should be noted that there was a 44,7% increase in net electricity consumption of Turkey from 2009 to 2018, and the average annual change percentage of these ten years accounted for as 4,69%.

Table 13: Net electricity consumption forecasts for Turkey from the ARIMA(3,2,2) model, 2019-2028.

Years	**Forecasted consumption amount (GWh)**	**Annual Change (%)**
2019	262.345	2,94
2020	273.645	4,31
2021	285.540	4,35
2022	296.800	3,94
2023	308.003	3,77
2024	319.560	3,75
2025	331.378	3,70
2026	343.318	3,60
2027	355.368	3,51
2028	367.553	3,43

The energy demand forecast for Turkey with the selected ARIMA model is also illustrated in the following graph.

Figure 28: Actual and forecasted net electricity consumption for Turkey, 2009-2028.



At that part of the study, we will compare the obtained results with official projections for the energy demand of Turkey done by MENR. However, before interpreting the results, it is needed to find MENR's net electricity demand projections. As presented in the previous section, official demand forecasts are based on gross electricity consumption. Therefore, the conversion of those forecasts into the net electricity values seems to be necessary in order to make relevant conclusions. Net consumption is calculated as the difference between gross consumption and the losses (grid losses and the electricity that is used by power plants themselves, i.e., internal usage). For this aim, the data covering of 2007-2017 (the data for the year 2018 has been unavailable up to this study's texting) was taken into account[15]. All the data with related calculations are shown in Table 14.

Table 14: Total losses and their shares in gross electricity demand of Turkey, 2007-2017.

Years	**(a) Gross Demand (GWh)**	**(b) Supply (GWh)**	**(c)=(a)-(b) Internal Usage (GWh)**	**(d) Grid Losses (GWh)**	**(e) = (c)+(d) Total Losses (GWh)**	**(f)= [(e)/(a)]*100 Percentage of total losses in gross demand**
2007	190.000,20	181.781,80	8.218,40	26.646,60	34.865,00	18,3
2008	198.085,20	189.429,10	8.656,10	27.481,50	36.137,60	18,2
2009	194.079,10	185.885,50	8.193,60	28.991,40	37.185,00	19,2
2010	210.434,00	202.272,30	8.161,70	30.221,70	38.383,40	18,2
2011	230.306,30	218.468,90	11.837,40	32.369,40	44.206,80	19,2
2012	242.369,90	230.580,40	11.789,50	35.657,00	47.446,50	19,6
2013	246.356,60	235.179,70	11.176,90	37.134,50	48.311,40	19,6
2014	257.220,10	244.706,10	12.514,00	37.331,10	49.845,10	19,4
2015	265.724,40	253.840,50	11.883,90	36.528,30	48.412,20	18,2
2016	279.286,40	266.829,50	12.456,90	35.611,70	48.068,60	17,2
2017	296.702,10	283.682,10	13.020,00	34.659,50	47.679,50	16,1

Hence, the average of total losses for the period of 2007-2017 was accounted for 18,5% of the gross electricity consumption in Turkey. This obtained percentage value is assumed as the same for the following ten years. With this assumption, Table 15 provides the

[15] TEİAŞ, Annual development of installed capacity gross generation supply and net consumption per capita in Turkey, Available at: http://www.teias.gov.tr/sites/default/files/2018-10/46.xls; Annual development of electricity generation - consumption and losses in Turkey, Available at: http://www.teias.gov.tr/sites/default/files/2019-03/56%2893-2017%29.xls

comparison between official demand forecasts by considering only Scenario 2 – Reference Scenario and the projections from the appropriate ARIMA model found in this study.

Table 15: The comparison of the results from the ARIMA (3,2,2) model and MENR's forecast, 2019-2028.

Years	**MENR's forecasts for gross electricity consumption (GWh)**	**MENR's forecasts for net electricity consumption (GWh)**	**Forecasted net electricity consumption (GWh)**	**Absolute value of difference**
2019	315.200	256.888	262.345	5.457
2020	329.600	268.624	273.645	5.021
2021	344.400	280.686	285.540	4.854
2022	359.600	293.074	296.800	3.726
2023	375.800	306.277	308.004	1.727
2024	392.100	319.562	319.560	2
2025	406.900	331.624	331.378	246
2026	421.800	343.767	343.318	449
2027	436.600	355.829	355.368	461
2028	451.700	368.136	367.553	583

The main inference from the comparison table above, official projections fall behind the suggested ARIMA modeling for many years. Nevertheless, there is no significant difference between these two forecast values. Surprisingly, most of the forecasts fit each other very well, especially for the year 2024 and later. The average annual deviation from the MENR's projections in terms of absolute differences is found as 2.253 GWh. Official forecasts will be underestimated for the years of 2019 and 2024-2028 period if the selected ARIMA model results are accepted as correct.

Indeed, when the MENR's previous demand forecasts are examined, it could be observed that official forecasts and actual consumption values have been very precisely estimated in the last years, especially for the short-term forecasts seem to be too accurate. For instance, according to the 10-Years Demand Forecasting Report for the period 2017-2026[16], the following projections for gross electricity consumption were made for the year 2017 under three different scenarios, respectively: 278.057 GWh, 284.553 GWh, and 289.926 GWh. Moreover, the percentage of total losses in gross demand in 2017 accounted for 16,1%. So, with this projection perspective, the forecasted net electricity consumption of Turkey would be 233.567 GWh, 238.739 GWh, and 243.247 GWh under three scenarios, which are Low, Reference, and High Scenario respectively. The actual net electricity consumption of that year realized as 249.023 GWh. Similarly, official gross electricity consumption forecasts for 2018 were 301.512 GWh, 304.425 GWh, and 307.212 GWh for the scenarios mentioned above[17]. With the same assumption for the share of total losses in gross consumption, the official forecasts for net electricity consumption would be 252.968 GWh, 255.412 GWh, and 257.750 GWh. Nonetheless, what we know from official energy consumption statistics that the net electricity consumption of Turkey in 2018 was announced as 258.210 GWh. As can be observed, the forecasted amount under the high scenario is so accurate that only -5.776 GWh deviation in 2017 and just -460 GWh deviation in 2018.

Table 16 provides MENR's demand projections with actual demand values and the deviation ratios according to the demand realization from 2004 to 2017 with some gaps in the period (TEİAŞ, 2017). What stands out in this table is that in the past, the accuracy ratios of the official demand projections were so low even for the short-term forecasts. Consistent with the literature of that period, this study also found that the MENR's future projections for electricity demand in the past were highly overestimated. Nevertheless, it has also been observed that there have been significant improvements in Turkish official demand forecasting in terms of accuracy and precision during recent years.

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[16] TEİAŞ, 10-Years Demand Forecasting Report 2017-2026, In Turkish, Available at: https://www.teias.gov.tr/sites/default/files/2017-06/10Y%C4%B1ll%C4%B1kTalepTahminleriRaporu2016%282%29.pdf

[17] TEİAŞ, 10-Years Demand Forecasting Report 2018-2027, In Turkish, Available at: https://www.teias.gov.tr/sites/default/files/2018-02/Taleprapor_2017.pdf

Table 16: Official demand projections of Turkey with actual demand values and the deviation ratios, 2004-2017.

		Forecasts* (Deviation Ratios**)								
Year	**Actual Demand***	**2004**	**2008**	**2010**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
2005	160,8	160,5 (-0,2)								
2006	174,6	176,4 (1,0)								
2007	190,0	190,7 (0,4)								
2008	198,1	206,4 (4,2)	204 (3,0)							
2009	194,1	223,5 (15,1)	219 (12,8)							
2010	210,4	242,0 (15,0)	236,2 (12,3)	210,4						
2011	230,3	262,0 (14,3)	253,8 (10,7)	219,5 (-4,3)						
2012	242,4	283,5 (17,0)	272,8 (12,5)	235,9 (-2,7)	244 (0,7)					
2013	246,4	306,1 (23,3)	293,2 (18,1)	253,6 (2,1)	262 (5,5)	255,5 (2,9)				
2014	257,2	330,3 (28,4)	315,1 (22,5)	272,7 (6,0)	281,8 (9,6)	271 (5,4)	256,7			
2015	265,7	356,2 (34,1)	338,7 (27,5)	293,1 (10,3)	303,1 (14,1)	287,3 (8,1)	271,5 (2,2)	268,8 (1,2)		
2016	279,3		363,7 (30,2)	314,8 (12,7)	325,9 (16,7)	302,7 (8,4)	287,3 (2,9)	284,6 (1,9)	273,5 (-2,1)	
2017	294,9		390,6 (32,4)	338,1 (14,6)	350,3 (18,8)	318,7 (8,1)	302,7 (2,6)	301,2 (2,1)	285,3 (-3,3)	284,6 (-3,5)

* Expressed in TWh.

** In terms of percentages.

From this point forth, it is also considered as necessary in such kind of analysis to run another ARIMA model and compare its results with the other appropriate ARIMA model, i.e., ARIMA (3,2,2). As mentioned before, the automatic ARIMA forecasting tool in EViews can allow users up to 12 lags for AR and MA components. However, in Erdoğdu's (2007) article on this topic, which is very highly cited, the suitable ARIMA model to forecast electricity demand of Turkey is suggested as ARIMA(13,2,0). The data used in this study covered 1923-2004, a total of 82 observations for the net electricity demand of Turkey. The table below indicates the author's net energy consumption forecasts at that period and the actual consumption quantities for the years 2005-2014. As can be observed, used ARIMA modeling fitted very well to the data to explain its future behavior. During those years, MENR's projections for electricity demand was significantly overestimated. For those reasons, it has also been decided to model the data with ARIMA(13,2,0) model and then to discuss its results.

Table 17: The comparison of the forecasts from the ARIMA(13,2,0) model and actual data, 2005-2014.

Years	**Forecasted net electricity consumption by Erdoğdu (2007) (GWh)**	**Actual net electricity consumption (GWh)**	**Absolute value of difference**
2005	129.311	130.263	952
2006	132.631	143.071	10.440
2007	138.134	155.135	17.001
2008	146.365	161.948	15.583
2009	145.144	156.894	11.750
2010	155.667	172.051	16.384
2011	156.010	186.100	30.090
2012	158.150	194.923	36.773
2013	169.210	198.045	28.835
2014	160.090	207.375	47.285

Since the model was selected as ARIMA(13,2,0), the next phase of modeling is diagnostic checking. When we examine the ACFs and PACFs of the residuals from the estimated model, it can be seen that there exists a reasonable fitting to the data. All the functions are statistically significant; there is no lag outside the limits (see Figure 29).

Figure 29: The correlogram of the residuals from the ARIMA (13,2,0) up to 32 lags.

Sample: 1923 2018
Included observations: 94
Q-statistic probabilities adjusted for 13 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.024	-0.024	0.0570	
		2	-0.056	-0.056	0.3608	
		3	-0.007	-0.010	0.3655	
		4	-0.020	-0.023	0.4050	
		5	0.028	0.026	0.4842	
		6	0.110	0.110	1.7283	
		7	0.034	0.044	1.8490	
		8	0.003	0.017	1.8497	
		9	0.026	0.034	1.9210	
		10	0.170	0.181	5.0315	
		11	0.081	0.097	5.7401	
		12	0.071	0.093	6.3014	
		13	0.010	0.030	6.3133	
		14	0.014	0.038	6.3366	0.012
		15	0.106	0.113	7.6186	0.022
		16	-0.094	-0.124	8.6381	0.035
		17	0.064	0.036	9.1242	0.058
		18	0.097	0.067	10.240	0.069
		19	0.079	0.079	10.983	0.089
		20	0.011	-0.026	10.997	0.139
		21	0.111	0.079	12.515	0.130
		22	-0.016	-0.019	12.547	0.184
		23	-0.053	-0.072	12.909	0.229
		24	0.058	0.009	13.339	0.272
		25	-0.105	-0.188	14.773	0.254
		26	-0.047	-0.068	15.066	0.303
		27	0.041	-0.047	15.287	0.359
		28	-0.017	-0.083	15.329	0.428
		29	0.003	-0.078	15.330	0.501
		30	0.062	0.002	15.868	0.533
		31	-0.030	-0.046	15.997	0.593
		32	-0.014	-0.051	16.024	0.656

Since the residuals are found to be random, the final step of the modeling, i.e., forecasting, can be discussed. What can be observed from Table 18 is the fact that there is almost no meaningful difference between the forecasted values for net electricity consumption from 2019 to 2028 by ARIMA(13,2,0) model and the official projections for the same next 10-year term. The average annual deviation from the MENR’s projections in terms of absolute differences is found at 7.078 GWh.

Table 18: The comparison of the results from the ARIMA(13,2,0) model and MENR's forecasts, 2019-2028.

Years	**MENR's forecasts for net electricity consumption (GWh)**	**Forecasted net electricity consumption (GWh)**	**Absolute value of difference**
2019	256.888	252.390	4.498
2020	268.624	263.161	5.463
2021	280.686	283.277	2.591
2022	293.074	294.600	1.526
2023	306.277	300.143	6.134
2024	319.562	308.701	10.861
2025	331.624	320.393	11.231
2026	343.767	331.724	12.043
2027	355.829	348.219	7.610
2028	368.136	359.315	8.821

At that point, since we have two 'powerful' ARIMA models, it would be better to evaluate their forecasting performances and to choose the 'optimal' or, more optimistically, to find 'best' forecasting results between these models or the combination of them. Table 19 gives the forecast results of two ARIMA models, together with the absolute differences between them. As it can be observed, forecasts from the ARIMA(3,2,2) model overestimates the net electricity consumption of Turkey for the next ten years. The average annual deviation from the ARIMA(13,2,0) model in terms of absolute differences is found at 8.159 GWh.

Table 19: The comparison of the forecasts from the ARIMA(3,2,2) model and the ARIMA(13,2,0) model, 2019-2028.

Years	ARIMA(3,2,2)	ARIMA(13,2,0)	Absolute value of difference
2019	262.345	252.390	9.955
2020	273.645	263.161	10.484
2021	285.540	283.277	2.263
2022	296.800	294.600	2.200
2023	308.004	300.143	7.861
2024	319.560	308.701	10.859
2025	331.378	320.393	10.985
2026	343.318	331.724	11.594
2027	355.368	348.219	7.149
2028	367.553	359.315	8.238

If we turn back to a more technical way of comparison of the two ARIMA models, it should be noted that this evaluation is mainly based on comparing the forecast values to actual values over a forecast period. In order to make this quality assessment, each of forecast evaluation series (SNCF for ARIMA(3,2,2) and SNCF2 for ARIMA(13,2,0)) now includes actual data from 1923 to 2009, inclusive and forecast data from 2010 to 2018. Evaluation sample that was set to 2014-2018 will give us 5-years forecasts to evaluate, and the training sample was chosen from 2010 to 2013. Output 16 provides summary information about the forecast evaluation analysis.

Output 16: Evaluation of forecasts from ARIMA(3,2,2) and ARIMA(13,2,0) models.

Forecast Evaluation
Sample: 2014 2018
Included observations: 5
Evaluation sample: 2014 2018
Training sample: 2010 2013
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
SNCF	6.029412	0.0912
SNCF2	0.124598	0.7474

Diebold-Mariano test
(HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	1.275347	0.2712	0.8644	0.1356
Sq Error	1.223867	0.2882	0.8559	0.1441

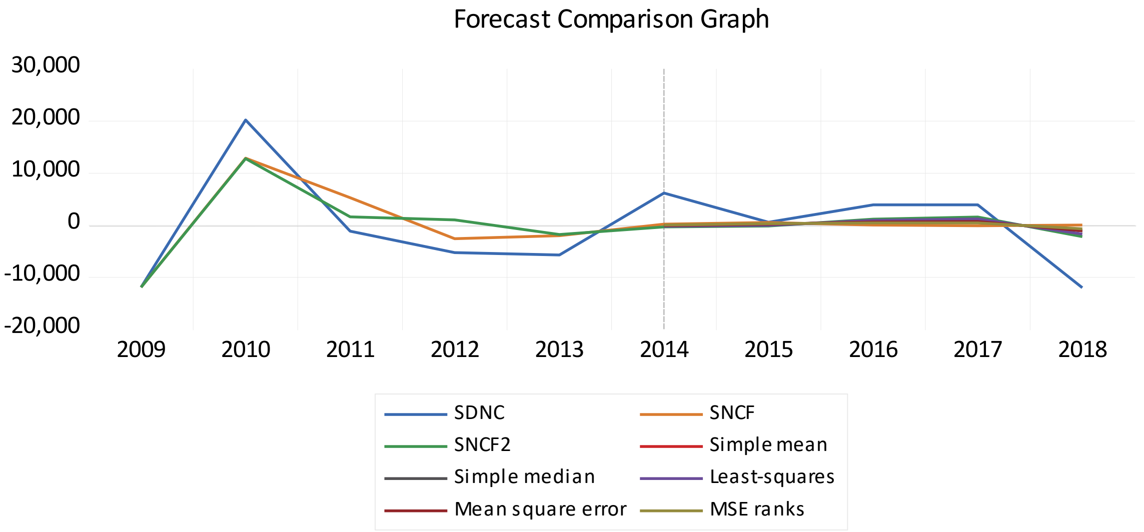
Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
SNCF	6497.445	5183.271	80.79296	157.0795	0.953667	1.038250
SNCF2	5529.267	4439.292	87.58763	146.3381	0.704539	0.756661
Simple mean	5993.005	4811.281	84.19029	148.6329	0.834108	0.896959
Simple median	5993.005	4811.281	84.19029	148.6329	0.834108	0.896959
Least-squares	5721.243	4597.803	86.13996	153.2177	0.756692	0.816290
Mean square error	5998.565	4815.537	84.15142	148.6555	0.835724	0.898571
MSE ranks	6157.107	4935.278	83.05785	149.9159	0.881659	0.943968

The results from combination tests indicate that the null hypothesis of "*Forecast i includes all information contained in others*" fails to be rejected for both models' forecasts at the 5% level of significance. If a single forecast contains all information contained in the other forecast like in our case, that forecast could be considered as good as a combination of both forecasts. This assessment was found as valid for both forecasts. When the forecasting performance of the two models is compared by the Diebold-Mariano (DM) test, the following conclusions can be drawn: According to the DM test based on absolute error loss, since the obtained test statistic of 1,27 is less than 1,96; the null hypothesis claiming the fact that "*Both forecasts have the same accuracy*" cannot be rejected at the 5% level of significance. Otherwise stated, the observed difference between the forecasting performance of the ARIMA(3,2,2) model and the ARIMA(13,2,0) model is not significant.

Similarly, the DM test based on squared-error loss result infers the same conclusion. In the evaluation statistics part of the output, the shaded areas show the forecast or averaging method that exhibits the best under each of the evaluation statistics, which are Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE) and Theil Inequality Coefficients (Theil1 and Theil2). The trimmed mean averaging method could not be calculated due to insufficient data. As the results examined, based on RMSE, MAE, SMAPE, Theil1 and Theil2 criteria, ARIMA(13,2,0) model's performance surpasses ARIMA(3,2,2) model's one as well as the other 5 averaging approaches, namely simple mean, simple median, least squares, mean square error (MSE), and MSE ranks. The graph below illustrates a visual comparison of all methods together with the actual values over a training period of 2010-2013 and the evaluation period of 2014-2018.

Figure 30: Forecast Comparison Graph.



* SDNC is the second-order difference of Turkish net electricity consumption series.

In short, both ARIMA models in question perform very well in order to forecast net electricity consumption in Turkey. However, Erdoğdu's approach in 2007 is thought of as still standing methodology in this research area. The forecast evaluation analysis has also shown us that based on MAPE, the ARIMA(3,2,2) model would able to give more accurate forecasts than any forecasting methods by itself.

Finally, it is worth mentioning that although ARIMA models are one of the most popular and powerful linear models in time series forecasting, what is known from its theoretical background is that the forecasts are determined only by the past behavior of the series in this modeling. In the last 25 years, the Turkish economy encountered three crises in 1994, 2001 and 2008, the final of which is considered exceptional and has had more negative effects on the financial sector than the others. Such kind of possible fragility in the country's economy could result in dramatic changes in actual electricity consumption. Since the unidirectional causal relation from GDP to net electricity consumption is another known fact from this study, any instability in economic growth is expected to affect the energy consumption of the country directly. Therefore, the results and the conclusions of the forecasting methodology should be reviewed under these assumptions.

5 Conclusions

This dissertation aimed at two main research topics: First, to investigate the long-run relationship between net electricity consumption and economic growth measured by GDP in Turkey. Secondly, to model the electricity consumption by the ARIMA technique, to make forecasts, and compare findings from the models with official projections. Since the data in this analysis included the most up-to-date observations, it was also intended to contribute to the literature by analyzing the latest data.

After a short outlook for the data comprising the years from 1960 to 2018, it was observed that there was a high positive correlation between Turkish net electricity consumption and income. The unit root tests also showed us that both series were non-stationarity. After that, two cointegration tests were conducted, namely Engle-Granger and Johansen, and it was concluded that there was a cointegration between energy consumption and the GDP of Turkey. This implies that both series have a long-run equilibrium relationship. Although there is a possibility of diverging for those series in the short run, net electricity consumption and economic growth will not wander apart without bound in the long run. The long-run response of energy consumption to the GDP change in Turkey is remarkably very high. When the income increases by 1%, the electricity demand in Turkey will also rise to 1,106% in the long run. Besides, it was observed that there was a significantly unidirectional Granger causality from the GDP of Turkey to the net electricity consumption of the country. However, the opposite causality was not valid in the case of Turkey. Surprisingly, a similar conclusion could be drawn by the Toda and Yamamoto approach to explaining the causal relationship between two series.

The second part of the analysis in this dissertation composed of ARIMA modeling to make future forecasts for electricity consumption of Turkey for the years 2019-2028. To achieve this, the data set for the net electricity consumption were enlarged from 1923 to 2018, including a totally of 96 observations. As expected, the time series itself was found as non-stationary at level, but it was identified as stationary at the second differences. The software's automatic ARIMA forecasting option gave us the ARIMA(3,2,2) model as the most appropriate for the net electricity consumption series of Turkey with a minimum

AIC value of -2,9715. The other suitable models after ARIMA(3,2,2) were found as ARIMA (2,2,3), ARIMA(1,2,4) and ARIMA(0,2,1) models. According to the forecast results of ARIMA(3,2,2), it was observed that Turkish net electricity consumption was prone to increase in the next decade as in the past years, with an average annual increase ratio of 3,73%. It is expected to reach 308.003 GWh in 2023 and 367.553 GWh in 2028. It was also conclusively shown that the annual average rate of Turkish energy demand increase in the following ten years would be less than the same ratio for the last decade.

In order to see whether there exists a meaningful distinction between the available ARIMA model's forecasts and MENR's ones, a crucial assumption was made. Because official electricity consumption predictions are based on gross demand, which contains internal usage of the power generators and grid losses as well as energy supply. Hence, the average of the two losses for the previous eleven years was calculated, and it was assumed that this ratio would also be valid for the next ten years. When the results from the ARIMA (3,2,2) model and official forecasts were compared, it was seen that there were no significant differences between them. In fact, in the year 2024, the forecast absolute difference between those two projections was found as only 2 GWh, and the following years after that time, this difference was obtained less than 500 GWh.

Furthermore, official projections, especially in recent years, were evaluated as very accurate to foresee the future electricity consumption of Turkey such that the deviation ratios were within in the range of [-3,5%,2,2%].

Apart from these, another model's performance, i.e., the ARIMA(13,2,0) model, was taken into account. This model was suggested in one of the most cited and seminal articles on this topic, dated 2007. As in the ARIMA(3,2,2) model, the forecasted values for net electricity consumption of Turkey covering the period of 2019-2028 by ARIMA(13,2,0) model were found very close to the official projections for the same next 10-year term. The average annual deviation from the official estimations in terms of absolute differences was 7.078 GWh.

When two appropriate ARIMA models compared, firstly, we tested the null hypothesis of stating, "*forecaster is as good as the combination of forecasts*." For both models, the null hypothesis failed to be rejected. Besides, when the fact that whether two competing forecasts had equal predictive accuracy was tested, it was found that two models executed better than the naïve forecast used as a benchmark, based on both absolute error and squared error. Also, the ARIMA(13,2,0) model's performance was found superior to the ARIMA(3,2,2) model by checking forecast data of both series from 2010 to 2018.

For further study in this context could consider other time series such as electricity price, the population of the country as well as the GDP. Moreover, further tentative and appropriate ARIMA models could be taken into account for better forecasting performance. Instead of using only one model, other averaging methods like simple mean, simple median, or MSE ranks approach could be tested to forecast energy consumption of the country, and their performances might be compared.

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Appendix-1

Years	GDP of Turkey (current USD)	Net Electricity Consumption in Turkey (GWh)	Years	GDP of Turkey (current USD)	Net Electricity Consumption in Turkey (GWh)
1960	13.995.067.817,51	2.396	1998	275.768.693.191,09	87.705
1961	7.988.888.888,89	2.585	1999	255.884.300.638,53	91.202
1962	8.922.222.222,22	3.059	2000	272.979.390.333,74	98.296
1963	10.355.555.555,56	3.406	2001	200.251.925.227,88	97.070
1964	11.177.777.777,78	3.781	2002	238.428.125.942,40	102.948
1965	11.966.666.666,67	4.237	2003	311.823.003.788,62	111.766
1966	14.100.000.000,00	4.729	2004	404.786.739.602,81	121.142
1967	15.644.444.444,44	5.269	2005	501.416.301.536,12	130.263
1968	17.500.000.000,00	5.870	2006	552.486.912.921,99	143.071
1969	19.466.666.666,67	6.679	2007	675.770.112.179,99	155.135
1970	17.086.956.521,74	7.308	2008	764.335.657.637,62	161.948
1971	16.256.619.963,80	8.289	2009	644.639.901.973,70	156.894
1972	20.431.095.406,36	9.527	2010	771.901.768.870,08	172.051
1973	25.724.381.625,44	10.530	2011	832.523.680.908,06	186.100
1974	35.599.913.836,43	11.359	2012	873.982.246.611,95	194.923
1975	44.633.707.242,76	13.492	2013	950.579.413.122,56	198.045
1976	51.280.134.554,29	16.079	2014	934.185.915.386,10	207.375
1977	58.676.813.687,37	17.969	2015	859.796.872.677,61	217.312
1978	65.147.022.485,79	18.934	2016	863.721.648.068,81	231.204
1979	89.394.085.658,20	19.633	2017	851.549.231.502,62	249.023
1980	68.789.289.565,74	20.398	2018	766.509.088.837,58	254.863
1981	71.040.020.140,44	22.030			
1982	64.546.332.580,76	23.587			
1983	61.678.280.115,50	24.465			
1984	59.989.909.457,84	27.635			
1985	67.234.948.264,60	29.709			
1986	75.728.009.962,79	32.210			
1987	87.172.789.528,33	36.697			
1988	90.852.814.004,99	39.722			
1989	107.143.348.667,09	43.120			
1990	150.676.291.094,21	46.820			
1991	150.027.833.333,33	49.283			
1992	158.459.130.434,78	53.985			
1993	180.169.736.363,64	59.237			
1994	130.690.172.297,30	61.401			
1995	169.485.941.048,04	67.394			
1996	181.475.555.282,56	74.157			
1997	189.834.649.111,26	81.885			

Appendix-2

Years	Net Electricity Consumption in Turkey (GWh)		Years	Net Electricity Consumption in Turkey (GWh)		Years	Net Electricity Consumption in Turkey (GWh)
1923	41,3		1960	2.395,7		1997	81.885,0
1924	41,3		1961	2.585,4		1998	87.705,0
1925	41,9		1962	3.059,3		1999	91.202,0
1926	60,6		1963	3.406,3		2000	98.296,0
1927	63,4		1964	3.780,7		2001	97.070,0
1928	81,4		1965	4.236,8		2002	102.948,0
1929	88,9		1966	4.728,9		1999	91.202,0
1930	96,7		1967	5.269,2		2000	98.296,0
1931	106,0		1968	5.870,1		2001	97.070,0
1932	117,5		1969	6.679,0		2002	102.948,0
1933	136,2		1970	7.307,8		2003	111.766,0
1934	157,7		1971	8.289,3		2004	121.142,0
1935	199,6		1972	9.527,3		2005	130.263,0
1936	206,8		1973	10.530,1		2006	143.071,0
1937	257,7		1974	11.358,7		2007	155.135,0
1938	279,9		1975	13.492,0		2008	161.948,0
1939	316,8		1976	16.079,0		2009	156.894,0
1940	359,3		1977	17.969,0		2010	172.051,0
1941	377,6		1978	18.934,0		2011	186.100,0
1942	372,5		1979	19.633,0		2012	194.923,0
1943	395,7		1980	20.398,0		2013	198.045,0
1944	429,9		1981	22.030,0		2014	207.375,0
1945	459,0		1982	23.587,0		2015	217.312,0
1946	487,0		1983	24.465,0		2016	231.203,7
1947	541,2		1984	27.635,0		2017	249.022,6
1948	585,7		1985	29.709,0		2018	254.863,0
1949	633,9		1986	32.210,0			
1950	678,8		1987	36.697,0			
1951	764,0		1988	39.722,0			
1952	878,5		1989	43.120,0			
1953	1.012,5		1990	46.820,0			
1954	1.191,5		1991	49.283,0			
1955	1.347,3		1992	53.985,0			
1956	1.544,8		1993	59.237,0			
1957	1.757,0		1994	61.401,0			
1958	1.961,5		1995	67.394,0			
1959	2.170,5		1996	74.157,0			