FORECASTING TURKEY'S SECTORAL ENERGY DEMAND

MUSTAFA EFE OĞUZ

JUNE 2013

FORECASTING TURKEY'S SECTORAL ENERGY DEMAND

A THESIS SUBMITTED TO
THE BOARD OF GRADUATE PROGRAMS
OF
MIDDLE EAST TECHNICAL UNIVERSITY, NORTHERN CYPRUS CAMPUS

BY

MUSTAFA EFE OĞUZ

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE
DEGREE OF MASTER OF SCIENCE
IN
THE
SUSTAINABLE ENVIRONMENT AND ENERGY SYSTEMS PROGRAM

JUNE 2013

Approval of the Board of Graduate Programs

Prof. Dr. Erol Taymaz
Chairperson

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science

Assist. Prof. Dr. Ali Muhtaroğlu
Program Coordinator

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

Prof. Dr. Ramazan Sarı
Co-Supervisor

Assist. Prof. Dr. Tufan Ekici
Supervisor

Examining Committee Members

Assist. Prof. Dr. Tufan Ekici
Economics Department,
METU Northern Cyprus Campus

Prof. Dr. Ramazan Sarı
Business Administration Department,
Middle East Technical University

Assist. Prof. Dr. Ali Muhtaroğlu
Electrical and Electronics Engineering Department,
METU Northern Cyprus Campus

Assoc. Prof. Dr. Murat Sönmez,
Mechanical Engineering,
METU Northern Cyprus Campus

Dr. Hayriye Kahveci,
Political Science and International Relations Department,
METU Northern Cyprus Campus

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Mustafa Efe Oğuz

ABSTRACT

FORECASTING TURKEY'S SECTORAL ENERGY DEMAND

Oğuz, Mustafa Efe

Supervisor: Assist. Prof. Dr. Tufan Ekici
Co-Supervisor: Prof. Dr. Ramazan Sarı

JUNE 2013, 93 pages

This study forecasts the sectoral energy demand of Turkey in the agriculture, industry, transportation, residence and services sectors for 2023 by means of the ARIMA, Vector Autoregressive and Decomposition statistical methods, and their products are then combined to arrived at a composite, or ensemble forecast. Each of these methods has their own merits and compliments each other. Two scenarios are considered; either the use of entire, unedited data (scenario one), or the absence of the last 3 years of the data to remove the effects of the sudden changes observed at most recent years (scenario two). Finally, forecasts are combined and the results are discussed under the terms of current sectoral policies and strategies of Turkey. The overall analysis indicates that the energy demand is expected to increase by 25% in agriculture, 16.9% in industry, 30.6% in residence and services, 20.9% in transportation sector by 2023. The demand in agriculture sector is the lowest and does not exceed the 6000 ktoe level. Transportation sector's energy demand will be around 20000 ktoe, whereas industry sector demand around 36000 ktoe by the year 2023. The residence and services will have a slightly higher. demand on energy at 46000 ktoe.

Keywords: Energy Sectors, Energy Demand, Forecast, Statistical Methods

ÖZ

TÜRKİYE'NİN SEKTÖREL ENERJİ TALEBİNİN ÖNGÖRÜSÜ

Oğuz, Mustafa Efe

Tez Yöneticisi: Yrd. Doç. Dr. Tufan Ekici
Ortak Tez Yöneticisi: Prof. Dr. Ramazan Sarı

Haziran 2013, 93 sayfa

Bu çalışmada Türkiye'nin tarım, sanayi, ulaşım, konut ve hizmet sektörlerindeki.sektörel enerji talebinin tahmini üç farklı istatistiksel yöntem ile yapılmıştır. Daha sonra elde edilen tahminler biraraya getirilerek birleşik bir tahmin elde edilmiştir. Bu doğrultuda, ARIMA, VAR ve Decomposition yöntemleri kullanılmıştır. Bu çalışmada iki farklı senaryo uygulanmıştır. Birinci senaryo bütün (değiştirilmemiş) veriyi kullanır. İkinci senaryo ise verinin son üç yılını gözlenen ani değişimlerin etkileri kaldırmak için kullanmaz. Birleştirilen tahminler, Türkiye'nin mevcut sektörel politika ve stratejileri doğrultusunda tartışılmıştır. Analizlere göre enerji talebinin 2023 yılına kadar tarımda %25, sanayide %16.9, konut ve hizmetlerde %30.6 ve ulaştırma sektöründe %20,9 oranında artması beklenmektedir.

Anahtar Kelimeler: Enerji Talebi, Modelleme, Türkiye Enerjisi, Sektörler

To My Parents

&

Grandma, Rest in Peace

ACKNOWLEDGMENTS

The author wishes to express his deepest gratitude to his supervisor Assist. Prof. Dr. Tufan Ekici and co-supervisor Prof. Dr. Ramazan Sarı for their guidance, advice, criticism, encouragements and insight throughout the research.

The author would also like to thank Assoc. Prof. Dr. Murat Sönmez and Assist. Prof. Dr. Ali Muhtaroğlu for their valuable contributions.

The author would also like to thank Prof. Dr. Temel Oğuz for his suggestions and comments.

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CHAPTER 1

INTRODUCTION

The industrial revolution followed by technological advancement and the transition from a labor - based industry to machine (technology) - based industry led to an ever growing demand for energy, specifically in the form of coal and oil Therefore, energy became an indispensable source for modern economies. It is used in various areas and sectors such as residential, transportation and industrial. The residential sector consumes energy mostly in the form of electricity for heating, lighting, cooking and electronic supplies. Electricity therefore makes up the essential part of our modern daily life. Also, industry uses energy as an input to produce the goods and materials like plastics, steel and textiles that are the building blocks of the modern life.

Considering the fact that world population is increasing and predicted to reach 2.8 billion by the year 2040, energy demand will also be increasing. As the world becomes more technology oriented, the energy consumption and thus dependency on energy will continue to rise. The studies indicated that economic growth is connected with energy consumption which implies that energy consumption in growing or developing countries will be increasing steadily (Zhixin and Xin, 2011; Yildirim and Aslan, 2012). In conventional terms, demanding more energy implies a more tight dependence on fossil fuels like natural gas and oil which are however left with limited reserves. In addition to resource limitation, an expected increase in the fossil fuel prices undoubtedly introduce heavier burden to world economy. Also, fossil fuels release greenhouse gases (hereinafter referred to as GHG) which are harmful to the environment and the global climate change. All these reasons force countries to adopt new sustainable energy policies, and to find alternative ways to balance the energy demand in most efficient, cheapest and strategic way. They set up their strategic energy plans according to their geographical location, natural reserves, and the current capacity of the power plants. Furthermore, energy demand and energy policy are among the major factors in designing foreign policy and international relations of a country. International politics are largely manipulated by the benefits of energy sector and lobbies. In today's world, energy issues may even cause wars and crisis among countries.

It is essential to develop sustainable energy policies and strategies for any country for the proper allocation of different energy sources, particularly the widely available solar, wind, bioenergy and small hydropower sources. Sustainable energy policies are vital prerequisite for sustainable development of countries. Also, governments should be able to maintain a steady energy supply consistently to sustain the development targets and economical welfare. However, a reliable projection of the future of energy demand is needed in order to develop realistic policies and strategies. In this context, forecasting energy demand is crucial, and decisions based on forecasts may provide a better ability to foresee the uncertain future and the consequences or outcomes of decisions.. In short, the forecasting is to predict the future trends by minimizing the uncertainty and identifying and evaluating the risks. In this study, an example of the energy demand forecasting study is provided to assess the energy demand of Turkey for the next decade by performing demand analyses for various sectors and obtaining projections for 2023. Findings of the forecasts will be useful for policymakers while drafting energy policies for sustainable economic development of Turkey.

Turkey is a country with more than 70 million population, 1.3% of annual population growth rate and an average 5% economical growth rate over the last 30 years. According to the prediction by Yuksek et al. (2006) based on a long term annual data, only 29% of the Turkish electric energy demand can be met internally and the rest must be imported from other countries. The import dependency ratio may reach as high as 82% in 2020, as suggested by Sozen (2009). This situation is obviously not sustainable for Turkey's future economic growth and it is essential to reduce the level of foreign energy dependency. Turkey's changing economic structure also has a role in this growing energy demand. Turkish economy has historically been based on the agriculture, but more recently in the last 30 yearsservice and industrial sectors have grown substantially. Furthermore, Turkey is located in a very strategic position between Asia and Europe and the key country for Europe's energy security. It is geographically very close to the world's major oil and natural gas reserves. World's increasing energy demand puts pressure on oil and natural gas demand that is not a preferable situation for Turkey because of its dependency on the oil and natural gas imports, as well as its strategic position which may compel Turkey's international policies. In order to pursue the goal of sustainable development, Turkey needs to prepare alternative plans on energy production and consumption strategies. This is however only possible by forecasting the level of sustainability of its energy sources, and its future energy demand from various sources.

Assessing the current situation and forecasting the future energy potential and demand of Turkey are essential for developing sustainable energy policies that support the increasing energy demand. In this context, high foreign dependency in terms of energy is an important obstacle for obtaining a sustainable development. Investing primarily on oil and natural gas as the primary energy resources in Turkey may be politically a false decision-making because of their high foreign dependency (Yılmaz, 2007), and thus a risk for security of energy supply (Bolat, 2010), as well as their high cost (Toklu et. al., 2010). In order to reduce this burden, renewable energy resources seem to be the best alternatives. Tükenmez and Demireli (2012) also suggested renewable energy as the best alternative for Turkey because of limited fossil fuel resources and climate change Bilen et al. (2008) pointed to low marginal cost of renewable energy to provide electricity with respect to fossil fuels. Yüksel (2010), Oksay and Iseri (2011), and Kotcioğlu (2011), underlined Turkey's large potential on renewable energy and necessity of more efforts towards utilizing sustainable energy resources to reduce its foreign energy dependency, as a must in sustainable development and meeting growing energy demand. In the same fashion, Kaygusuz and Sarı (2003) underlined the potential of Turkey in renewable energy and a need for the governmental support to reduce the dependency on the fossil fuels. Soyhan (2009) stated inefficient use of large energy resources in Turkey, except for lignite and hydropower and therefore necessity for adoption of new policies for sustainable development and environmentally friendly energy production. Furthermore, Kaygusuz (2011) indicated solar energy as a good solution for Turkey in terms of meeting the growing energy needs. However, to make it commercially available, government needs to support and develop strategies. In addition, Demirbaş (2002) noted that state subsidies should be increased for encouraging enterprises to invest and increase energy efficiency and reduce the growth of energy consumption and imports. On the other hand, Ozyurt (2010) focused on environmental aspects of growing energy demand such as air quality and climate change. He emphasized the importance of the environment and suggested reducing the consumption of fossil fuels in energy and investing in its renewable alternatives. Alternatively, Tunç et. al. (2006) claimed Turkey must give importance to hydroelectric and nuclear plants due to their lower cost compared to others. Majority of the existing studies proposed renewable energy resources as a good alternative for sustainable economic development and should be invested to minimize the foreign dependency. However, there are some concerns about these renewable resources whether they can provide sufficient base load energy or additional support is needed by fossil fuel plants. This issue demands a more thorough analysis in order to set reliable targets and strategies for the future Turkish energy policy. On the other hand, the transition process to renewable energy requires a careful development of policies, strategies, regulations and laws.

Various forecasting methods and independent variables have been used to estimate energy demand of Turkey. Artificial Neural Network (ANN) is the most commonly used method. Sözen and Arcaklıoğlu (2007) developed three different models in order to estimate the future energy consumption of Turkey using the economic and energy data for 37 years (1968–2005). In the first model, installed capacity, generation, energy import and export were used as indicators, whereas the second and the third models used gross national product (GNP) and the gross domestic product (GDP), respectively, as the input layer of the network to estimate the net energy consumption as the output. The main purpose for the implementation of three different models was to be able to demonstrate the contributions of different economic indicators to the estimation of net energy consumption and the causality between the energy and economic indicators. The minimum deviation was obtained in Model 3 and the maximum deviation in Model 1 implying that the use of GDP or GNP in forecasting energy demand is expected to result in high confidence. Similarly, Hamzaçebi (2007) modeled net electricity energy consumption of Turkey on sectoral basis by an ANN model until 2020. Results provided that annual average net electricity consumption will increase until 2020 by 45.67% for industrial sector, 49.90% for residential sector, 3.65% for agriculture sector and 0.755% for transportation sector. The forecasted values for the industrial and transportation sector are higher than those provided by the Ministry of Energy and Natural Resources (MENR) projections, but lower in agriculture and residence. In addition, Hamzaçebi (2007) predicted a decreasing share of industrial sector contrary to an increasing share of residences. Agriculture and transportation sector shares had similar trends. Hamzacebi's predictions were close to the observed values.

Besides the ANN, various other statistical methods have also been used in energy forecasting. Table 1 provides a list of these studies in terms of their methods employed, the types of independent variables, the forecast types and periods. Among these examples, Canyurt et. al. (2004) modeled Turkey's future energy demand using the genetic algorithm method based on GDP, population and import and export figures. In their study, they assumed the average growth rates of GDP, population and import-export for 2002 - 2025 as 5%, 0.12% and 5% respectively. The results indicated their projection is significantly lower than those of the MENR and therefore the prediction was not accurate enough. Kavaklıoğlu et. al (2009) estimated electricity consumption using population, GNP and import and export variables for the period of 2007-2027. According to their findings, the electricity consumption will nearly double by rising to 279 billion Kwh by 2027. Employing the Autoregressive Integrated Moving Average (ARIMA) method to estimate the future primary energy demand of Turkey from 2005 to 2020, Ediger and Akar (2007) suggested that natural gas will remain to play a key element in energy diversity like coal, whereas the share of oil will be decreasing. Moreover, they forecasted a reduction in the average annual energy demand growth rate from 4.9% for 1950 - 2005 to 3.3% for 2005 - 2020. Total primary energy demand is predicted to reach at 143294 million tons of oil equivalent (mtoe).

Toksarı (2007) used Ant Colony Optimization method by selecting GDP, population, imports and exports as independent variables. Two forms of model was prepared and 3 different scenarios were proposed to estimate the future energy demand of Turkey which consisted of different assumptions on the average growth rates of GDP, population, imports and exports. The results underestimated the energy demand with respect to the MENR projections. Moreover, Yumurtacı and Asmaz (2004) estimated the electricity demand of Turkey to be approximately 1,173 billion kWh in 2050 by using the classic linear regression method with population, energy consumption increase per capita being as the only independent variable. The study also included an evaluation of the energy requirement for 2050 in the case of a complete use of the potential hydro-energy. Furthermore, Kucukali and Baris (2010) forecasted Turkey's short term gross annual electricity demand by using fuzzy logic approach. The results demonstrated the electricity demand growth mainly reflects the changing expectations of GDP. So, relatively short-term forecasts of Turkey’s electricity consumption according to the country’s economic performance will be more meaningful and it would provide more reliable data for the policy makers and investors. In this context, the electricity consumption growth rate is projected to be about 4% between 2010 and 2014.

There are similar studies performed for other countries. Among others, Pao (2006), Ekonomou (2010), AbuAl-Foul et. al. (2012) and Nasr et. al. (2002) all employed the ANN technique. Pao (2006) chose national income, GDP and consumer price index as the independent variables in order to estimate the future of electricity consumption in Taiwan for the forthcoming 2 years (24 months) using the monthly data. By adopting the linear and nonlinear ANN methods, surprisingly, it is found that economy indicators, GDP and Consumer Price Index CPI, have less effect on Taiwan’s electricity consumption than population and national income. The linear model is less efficient on estimating the high and low peaks regardless the amount of historical data. Also, the forecasting performance of ANN is higher than the other linear models due to the use of two sets of historical data provided a better fit with the actual data. Ekonomou (2010) forecasted an gradual increase in energy consumption of Greece using the ambient air temperature, installed power capacity, yearly electricity consumption per resident and GDP. AbuAl-Foul et. al. (2012) forecasted energy demand in Jordan for year 2025 using the support vector model that considered the GDP, population, exports, and imports as the input data for 1976 - 2008, and the energy consumption of 8349, 9269, and 10189 Ktoe as the output in years 2015, 2020, and 2025, respectively. Similarly, Nasr et al. (2002) examined the future of electricity consumption in Lebanon.

Bianco et. al. (2009) modelled electricity consumption of Italy using a regression analysis and population, GDP and GDP per capita chosen as the independent variables. According to their results, about 2% yearly increase in the total electricity consumption should be expected in the subsequent years. The price elasticity on domestic and non-domestic consumptions turned out to be quite limited, therefore there is no need to consider the electricity price as an independent variable for the forecast. In other words, the pricing policy cannot be used to promote an efficient use of electricity in Italy. Wang and Meng (2012) predicted the future energy consumption of Hebei province of China using the hybrid model of Neural Networks and ARIMA from 2009 to 2013. The results demonstrated that the energy consumption in Hebei province will continue to increase to 28856.26 million tons of standard coal, at the average annual growth rate of nearly 2.8%.

Alternative to the aggregate energy demand forecast models described above, the forecast models at sectoral level have also been proposed but at a much lower quantity. For example, Ireland Environmental Protection Agency (EPA) evaluated likely future trends on energy efficiency, renewable energy, climate change, air quality and security of energy supply. This is achieved by the model called HERMES developed by Ireland's Economic and Social Research Institute (ESRI) in which the fuel and electricity demand projections are calculated based on the macroeconomic projections using historical econometric time-series relationships. In other words, the energy forecasts were grounded by economic forecasts, principally sectorial GDPs. Similarly, New Zealand's Energy Outlook Report (2011) presented projections of the future energy supply, demand, prices and greenhouse gas emissions. This report presented detailed projections for the future energy demand in different sectors under two scenarios; the continuation of enacted government policies, such as the emissions trading scheme and its alternatives under changing macroeconomic variables such as economic growth (GDP), exchange rate, emissions price and oil price. Canadian National Energy Board Report (2011) forecasted the energy demand in the transportation, residential, commercial and industrial sectors for the year 2035 under either the most likely "reference" case and four alternative cases which are based on high and low prices, and fast and slow economic growth to 2035.

Shakouri and Kazemi (2011) forecasted energy demands of residential and commercial sectors of Iran for the period of 2011 to 2020. The study was specifically designed to assist decision makers for predicting the emerging energy demand in near-future among 13824 alternatives depending on different combinations of the external variables. An automated fuzzy decision-making (FDM) process determined the winner model for the energy demand of Iran residential and commercial sectors among the other remaining models. Kialashaki and Liesel (2013) estimated the energy demand of the residential sector in the United States by using both the ANN method and the multiple linear regression models. The study built the residential energy model on the basis of various independent variables such as resident population, gross domestic product, household size, median household income, cost of residential electricity cost of residential natural gas, and cost of residential heating oil. On the other hand, Lu et. al. (2009) forecasted the energy demand in Taiwan transportation sector by adopting the grey forecasting model to capture the development trends of the number of motor vehicles, vehicular energy consumption and CO_2 emissions in Taiwan during 2007–2025. An implication of the forecasting studies on total energy demand reported above is to choose a most appropriate model depending on the data availability, socio-economical and political expectations from the forecast results, and their reliability. Some researchers considered forecasting as an art rather than a science, But this may not be entirely correct based on the above criteria, unless choosing the methods and independent variables subjectively.

Forecasting the future energy demand is crucial in developing energy strategies of Turkey. In this respect, as documented in Table 1.1, most of the existing studies forecasted the total level of energy demand without providing details on the sectoral levels. The present study elaborates these studies by forecasting the future of energy demand at a sectoral level. The unique feature of this study is to be a first attempt to analyze and identify the future energy demand and supply of Turkey in sectoral levels based on three statistical methods. The analyses are performed using the Autoregressive Integrated Moving Averages (ARIMA), the Vector Autoregression (VAR) and the Decomposition methods first independently and then are combined together in order to obtain a final (ensemble) forecast. This approach is also unique in literature and may encourage similar new studies and may hopefully assist for developing energy policies for sustainable economic development .

This thesis consists of 5 sections. Description of the data and methods are given in section 2. The results are provided at section 3, followed by the discussion of results and conclusions in sections 4 and 5, respectively.

Table 1.1: Summary of studies around the world on energy forecasting

Authors	Methods used	Independent variables	Data used	Forecasting for	Forecasting period	Country
Bianco et al. (2009)	Regression models	Population, GDP, GDP per capita	1970-2007	Electricity consumption	2007-2030	Italy
Canyurt et al. (2004)	Genetic algorithm approach	GDP, population, import, export	1970-2001	Energy demand	2002-2025	Turkey
Ediger and Akar (2007)	ARIMA	-	1950-2005	Energy demand	2005-2020	Turkey
Ediger and Tatlıdil (2002)	Cyclic pattern analyses, Winter's exponential smoothing	-	1950-1999	Energy demand	2000-2010	Turkey
Ekonomou (2010)	ANN	Temperature, installed power capacity, GDP	2000-2008	Energy consumption	2008-2015	Greece
Hamzaçebi (2007)	ANN	Transportation, agriculture, residence, industry sector	1970-2004	Electricity consumption on sectoral basis	2003-2020	Turkey
Nasr et al. (2002)	ANN	Consumption, imports, degree days		Electricity consumption		Lebanon
Ozturk et al. (2007)	Genetic algorithm approach	GDP, population, import, export	1980-2001	Total and industrial electricity demand	2002-2020	Turkey
Pao (2006)	ANN	National income, GDP, CPI	1990-2001 (monthly)	Electricity consumption	January 2001-December 2002	Taiwan
Toksarı (2007)	Ant colony optimization	GDP, population, import, export	1970-2005	Energy demand	2006-2025	Turkey
Yumurtacı and Asmaz (2004)	Linear Regression	Population, energy consumption increase rates per capita	1980-2002	Electricity demand	2003-2050	Turkey

CHAPTER 2

MATERIAL AND METHODS

2.1. DATA

The main objective of the study is to forecast Turkish energy demand for different sectors using the available historical data. This section provides some information about the available data types and variables which could be used in forecasting process.

The most important data is sectoral energy consumption. This time series is available on various databases, but Turkish Republic Energy and Natural Resources Ministry's database provides the longest historical data for 1970 - 2006. .The more recent data for 2007-2010 are kindly provided by Mr. Adil Turkmen, the Ministry Employee.

The sectoral energy consumption data is sufficient for energy forecast analyses made by the ARIMA and Decomposition forecasting methods. Nevertheless, other independent data sets are necessary to add into model for the other forecasting method namely VAR. One of them is the changes in gross domestic product (GDP) that may affect the energy demand, as several studies suggested a direct relationship between GDP and energy consumption. Increase in GDP means increase in production of goods and services. Hence, more energy will be used in order to produce more. In this context, sectoral GDP of Turkey will be used in forecasting sectoral energy demand. On the other hand, sectoral employment is another data set added into the model. These data have been obtained from World

Bank's Database. Sectoral GDP is obtained for the period of 1960 - 2010, whereas the, sectoral employment is for 1988 - 2010.

Descriptive statistics of the variables are provided in the Table 2.1 below. ECRS, ECI, ECT and ECA stand for sectoral energy consumption in residence and services, industry, transportation and agriculture, respectively. Moreover, GDPS, GDPI and GDPA represent sectoral GDPs of services, industry and agriculture, respectively.

Table 2.1: Descriptive Statistics of Variables

	Minimum	***Maximum***	***Mean***	***Std. Deviation***
ECRS	8656,00	29466,00	16656,02	5229,067
ECI	4122,00	32466,00	15629,00	8751,876
ECT	3208,00	17284,00	9032,68	3918,990
ECA	510,00	5174,00	2151,85	1280,460
GDPS	34733702657	222749086796	104572872338	53423368726
GDPI	14069159243,40	122259190421,87	54444081077	30655032279
GDPA	17396362749	32124586195,39	23544080643	3780058996

Sectoral energy consumption data are expressed by tones of oil equivalent (toe) form. Sectoral GDPs are obtained in real US dollars with the year 2000 as the base year.. On the other hand, sectoral employment data is given in percentages of total employment. The figures below present characteristics of the data.

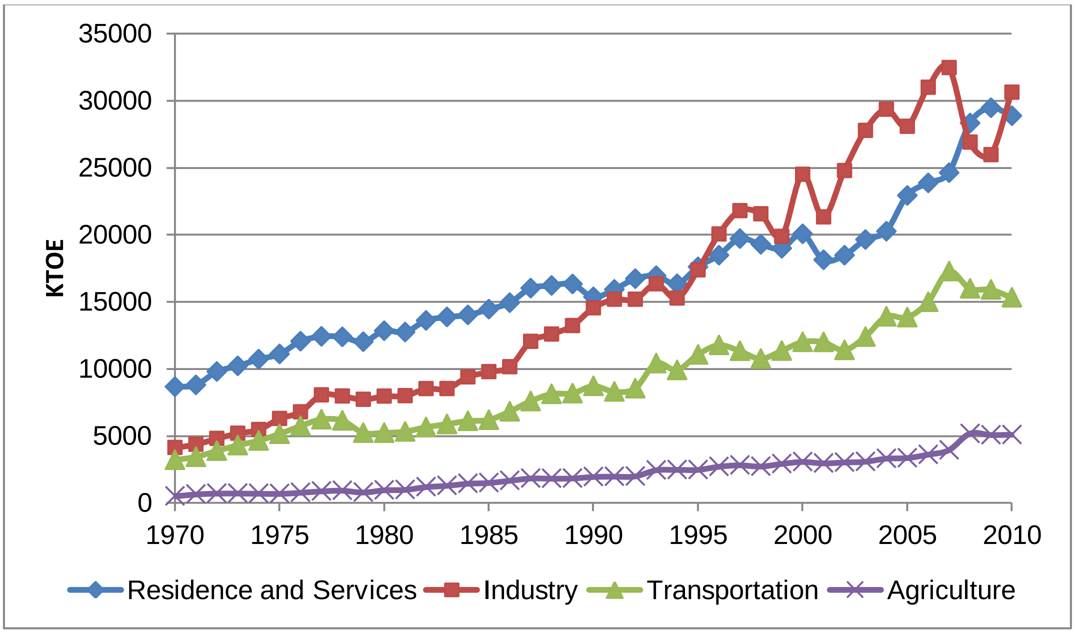

Figure 2.1: Changes in energy consumptions for various sectors; residence and services, industry, transportation and agriculture during 1970-2010.

As shown by the sectoral energy consumption curves in Figure 2.1, residence and services was the leading energy consumer, however, after 1995 industry became the leader in energy consumption. There is an increasing trend in agriculture and transportation sectors as well, and the rate of increase in consumption is higher in transportation than agriculture.

Figure 2.2 below presents the energy consumption shares of sectors. The share of residence and services was over 50%, but it decreased and industry now became as the highest share with roughly 40% during the last decade. Transportation's share remained steady around 20%, whereas the share of agriculture had a slight increasing trend from 3% to 6%.

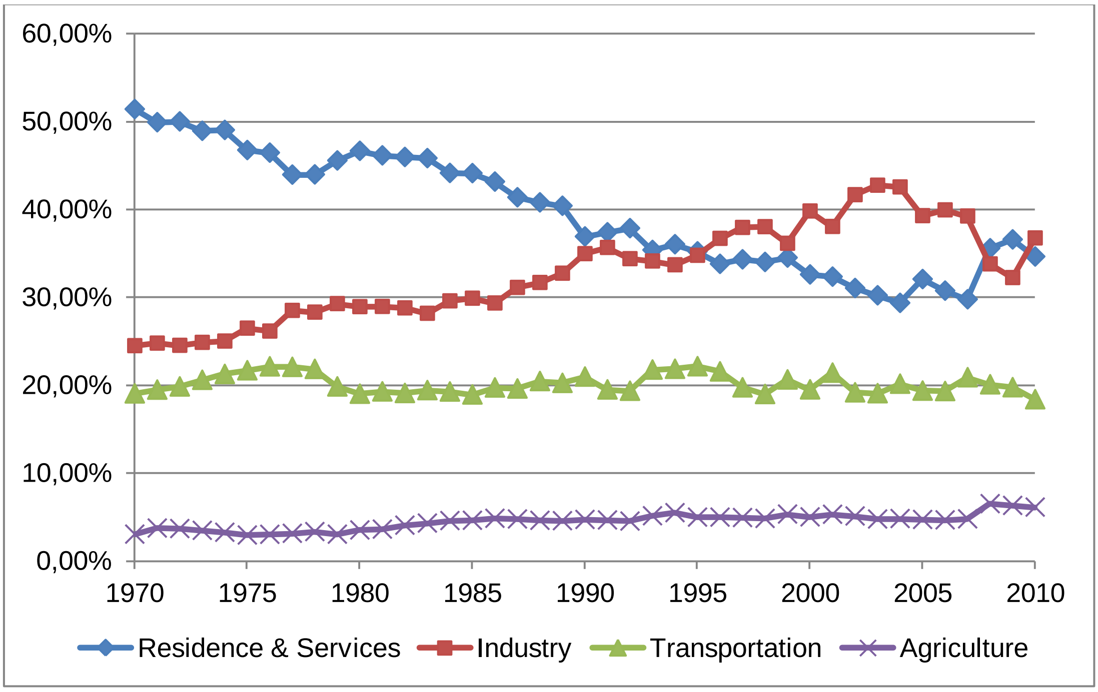

Figure 2.2: Shares of enegy consumption of different sectors during 1970-2010.

Figure 2.3 below shows the sectoral GDPs. It is clear that service sector has the biggest contribution to Turkey's GDP It increased rater steadily during 1980-2000 period by 100000 millions but experienced a sharp, four-fold increase in the subsequent decade. The industry sector has a similar trend of changes during these two distinct phases, rising from 40000 million to 160000 during theprevious decade. The agriculture has been the lowest contribution at all times, and experienced the slowest growth among sectoral GDPs that increased fron 20000 to 60000 only during the last decade. In spite of a modest growth in agricultural GDP, its share decreased constantly since the 1960s to almosy 10% at present (Figure 2.4). On the contrary, the share of services GDP is doubled during the last 50 years whereas the industry increased its share by 50% (Figure 2.4). Figures 2.3 and 2.4 clearly suggest the shift in Turkish economy from the agriculture to the services and industry sectors at an increasing rate starting by the early 1980s. On the other hand, in consistent with a large drop in the share of agriculture in the overall GDP its share in employment decreased by 10% during 1990-2000 and 20% afterwards (Figure 2.5). These losses appear to shift into the other sectors. For example the employment share of industry increased by 5-7% after 1990. The corresponding change in the services sector was around 20% during the same period. At present, half of the Turkish labor force appears to work for the services sector.

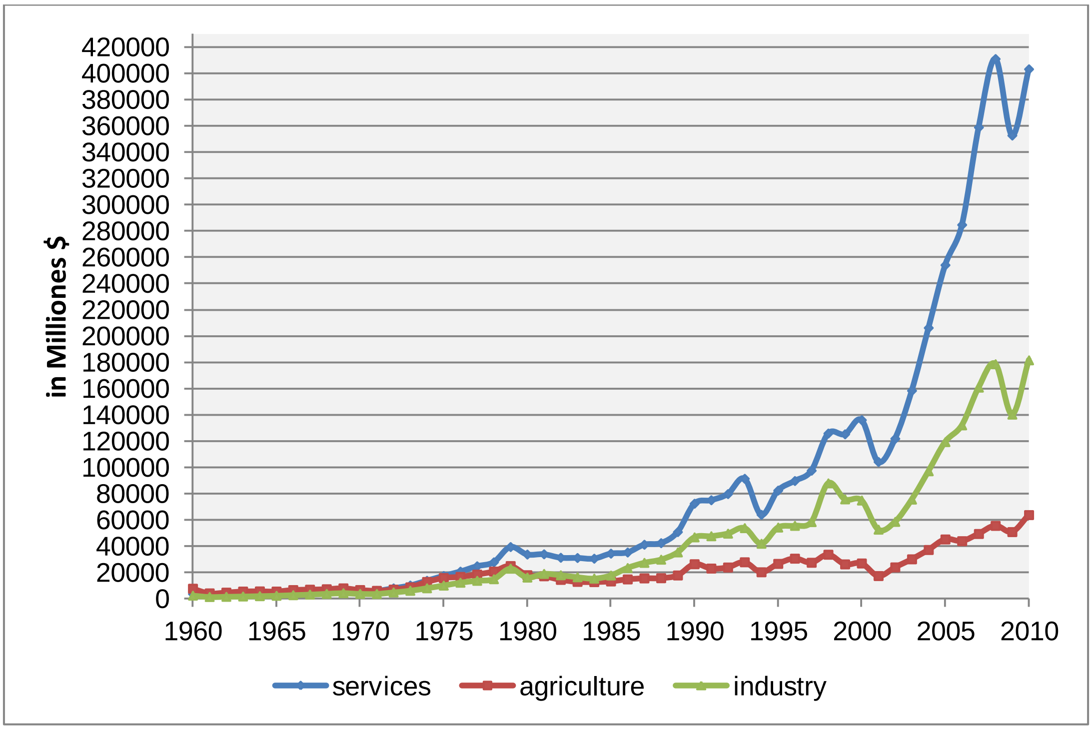

Figure 2.3: Changes in sectoral GDPs during 1960-2010 in Turkey.

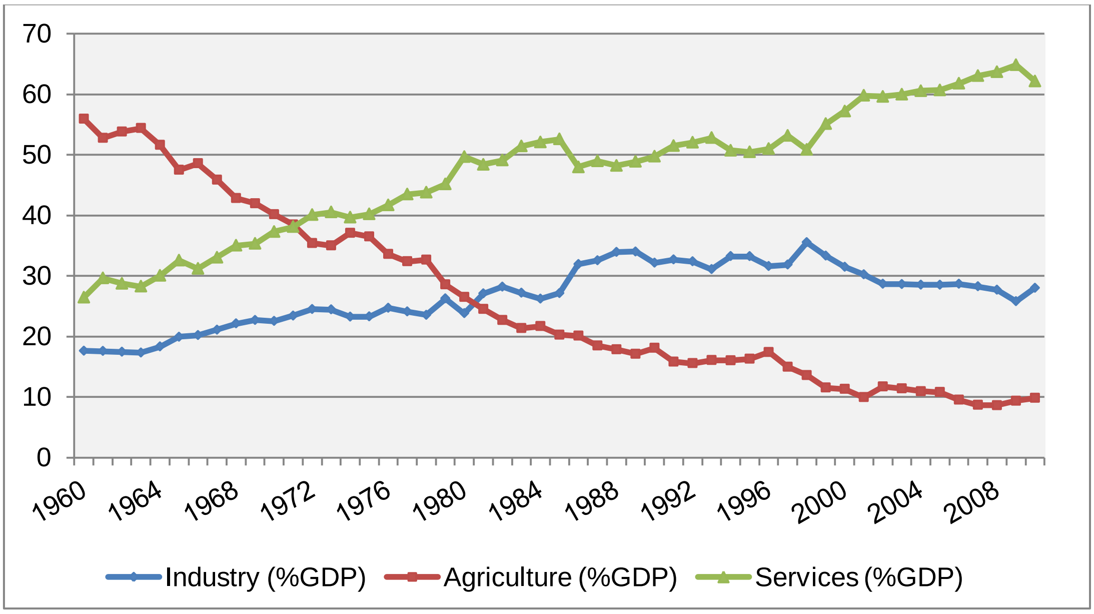

Figure 2.4: Changes in shares of the sectoral GDPs during 1960-2010 in Turkey.

2.2. METHODS

As described in the previous literature review section, different studies have implemented various types of forecasting methods using different variables. This chapter provides a brief documentation of the three different forecasting methods employed for the energy forecasting of Turkey; (i) Autoregressive integrated moving average (ARIMA), (ii) Decomposition, and (iii) Vector Autoregression (VAR), and synthesizing the results with the combinational approach. This section provides a brief explanation of each of these methods..

2.2.1) Autoregressive Integrated Moving Averages (ARIMA):

The Box-Jenkins methodology of ARIMA models is a technically sophisticated way of forecasting a variable. It is a univariate, or in other words, a single vector method. ARIMA forecasts future values by looking only at the past pattern of the time series without using other independent variables. It is formed as ARIMA(p,d,q) where p is the order of autoregressive terms, d is the number of differences and q is the number of moving average terms.

Autoregressive (AR) models were first introduced by Yule in 1926. Slutsky (1937) presented Moving Average (MA) schemes. However, Wold (1938) combined both AR and MA schemes to form ARMA for modeling all stationary time series. Box and Jenkins (1976) popularized the use of ARMA models. He provided guidelines for making the series stationary in both its mean and variance and suggested the use of autocorrelations and partial autocorrelation coefficients for determining appropriate values of p and q. A set of computer programs were developed in order to help users identifying appropriate values for p and q which made ARIMA as a widely used method.

The Box-Jenkins methodology of ARIMA models has some advantages over other time series methods. It provides more information from any other time series method while using a minimum number of parameters. It also allows for flexibility in the process of choosing the correct forecasting mode. It includes a process that allows us to examine a large variety of models in our search for the correct one. On the other hand, the only problem with ARIMA is the modeling which is difficult mathematically and requires a deep knowledge of the method. Therefore, it is not easy to build an ARIMA model without training in statistical analysis and a good knowledge of the methodology.

ARIMA is not using any other explanatory variables in forecasting process. Instead, it is based on its own past series which is called "white noise". White noise is essentially a purely random series of numbers. The numbers are normally and independently distributed. The observed time series start as a white noise and are transformed by the black box process into the series which are being tried to forecast. Finding a true black box is essential. If the black box is correctly specified, it is possible to obtain the forecast series from the white noise correctly.

In order to understand the logic behind the ARIMA, the autoregressive, integrated and moving average parts should be identified separately. A *moving average model (MA)* predicts Y_t as a function of the past errors in predicting Y_t. An MA model would take the following form:

$$Y_t = e_t + W_1 e_{t-1} + W_2 e_{t-2} + \dots\dots\dots + W_q e_{t-q}$$

where: e_t: The value at time t of the white noise series.

Y_t: The generated moving average time series

$W_{1,\,2,\,\dots,\,q}$: The coefficients (or weights)

$e_{t-1,\,t-2,\dots,\,t-q}$:Pevious values of the white noise series.

The order of moving average model (q) depends on the lag of white noise term (e_t). For instance, the model of $Y_t = e_t + W_1e_{t-1}$ is a MA(1) model, because it contains one lag of the white noise term. In order to decide the order of the model (or black box), autocorrelation and partial autocorrelation tools are used. Autocorrelation is the concept that the association between the values of the same variable at different time periods is nonrandom. If autocorrelation exists in a time series, there is correlation or mutual dependence between the values of the time series at different time periods. The correlation coefficient will always vary between -1 and 1. If it is equal to 1, there is a perfect positive correlation between the two series and as one increases so does the other. Its value of -1, on the other hand, indicates a perfect negative correlation, that is as one goes up, the other goes down. Moreover, the partial autocorrelation is the second tool that helps to identify the relationship between the current values and the past values of the original time series. The autocorrelation and partial autocorrelation correlograms provide us the information to determine the order of the models. The number of spikes in the autocorrelation function is the order of the MA model or the q.

Autoregressive models are also a part of the ARIMA. The equation of the AR models are similar to MA model. However, the dependent variable Y_t depends on its own previous values rather than the white noise series or residuals. The AR model is produced from a white noise series by using an equation of the form:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \dots\dots\dots + A_p Y_{t-p} + e_t$$

Where: Y_t: The moving average time series generated.

$A_1, A_2, \dots\dots, A_p$: Coefficients

$Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$: Lagged values of the time series (autoregressive)

e_t: White noise series

The order of the autoregressive model AR(p) depends on the lag of Y_t. For instance, $Y_t = A_1 Y_{t-1} + e_t$ is an AR(1) model, because there is only one lag of Y_t. And the same question rises again, how to determine the order of the model or black box (p)? The partial autocorrelation function is used in order to choose the correct AR model. The number of spikes gives the order of the model or p. To illustrate, if the partial autocorrelation correlogram presents only one significant spike, the model will be selected as AR(1).

As mentioned before, ARIMA (p,d,q) has three parts. So far, AR(p) and MA(q) parts are identified. The integrated part is also essential. The order of differences represents the letter "d" in the model. Generally we have been approaching our data as they were stationary. However, stationarity of the data should be examined because it affects the regressions. Stationarity is a key concept in time series processes. A time series is stationary when it has the following characteristics.

a) If its mean fluctuates around a constant long-run mean,
b) If it has a finite variance that is time-invariant,
c) If it has a theoretical correlogram that diminishes as the lag length increases.

Stationarity is important because if the series is non-stationary then all the typical results of the classical regression analysis are not valid. Regressions with non-stationary series may have no meaning. In this context, if the data is non-stationary it should be removed by taking differences which, at the end, identifies the order of differences (d).

2.2.2) Decomposition:

Decomposition is a linear model that splits a series into components in the form of Trend, Seasonality, Cyclical and Error, and determines their values, projects them forward and reassembles them to create a forecast. Decomposition methods usually try to identify two separate components of the basic underlying pattern that tend to characterize economics and business series, trend cycle and seasonal factors. The trend cycle represents long term changes in the level of series. On the other hand, the seasonal factor is the periodic fluctuations of constant length that is usually caused by known factors such as rainfall, month of the year, temperature, timing of the Holidays, etc. The decomposition model assumes that the data has the following form:

$$Y = T \times S \times C \times I$$

Y= The series to be forecast.

T= The long–term trend based on deseasonalized data. It is often called the centered moving-average trend (CMAT) since the deseasonalized data are centered moving averages (CMA) of the original Y values.

S = Seasonal indexes (SI). These are normalized average of seasonal factors that are determined as the ratio of each period's actual value y to the deseaonalized value (CMA) for that period.

C = The cycle component. The cycle factor (CF) is the ratio of CMA to CMAT and represents the gradual wavelike movements in the series around the trend line.

I = The irregular component. This is assumed equal to 1 unless the forecasters has reason to believe a shock may take place, in which case I could be different from 1 for all or part of the forecast period.

Decomposition provides an easy way to calculate seasonally adjusted data as a useful by-product. The process of de-seasonalizing the data has useful results. It allows to identify the underlying pattern in the data more clearly. Also, it provides measures of the extent of seasonality in the form of seasonal indexes. Seasonal adjustment allows reliable comparison of values at different points in time. It is easier to understand the relationship among economic or business variables once the complicating factor of seasonality has been removed from the data. Seasonal adjustment may be a useful element in the production of short term forecasts of future values of a time series.

In the process of de-seasonalizing the data, first the trend-cycle T_t is computed using a centered moving average. This removes the short-term fluctuations from the data so that the longer-term trend-cycle components can be more clearly identified. These short-term fluctuations include both seasonal and irregular variations. Therefore, an appropriate moving average (MA) can be used. The moving average should contain the same number of periods as there are in the seasonality that one wants to identify. For instance, in order to identify monthly or quarterly patterns MA(12) and MA(4) are used, respectively. The centered moving averages represent the deseasonalized data. The degree of seasonality, called seasonal factor (SF), is the ratio of the actual value Y_t to the deseasonalized value CMA_t.

Long term trend is also a part of the decomposition method. The long term movements or trend in a series can be described by a straight line or a smooth curve. The long term trend is estimated from the deseasonalized data for the variable to be forecasted. To find the long-term trend, we estimate a simple linear equation as

$$CMA = f(Time)$$

$$CMA = a + b(Time)$$

The method of least squares can be used to estimate a and b. These values can also be used to determine the trend equation. The trend equation can be used to estimate the trend value of the centered moving average for the historical and forecast periods. This new series is the centered moving-average trend (CMAT).

Moreover, another part of the decomposition, the cyclical component of a time series, is measured by a cycle factor (CF), which is the ratio of the centered moving average (CMA) to the centered moving average trend (CMAT). If the cycle factor is analyzed carefully, it may provide understanding of the likely future direction of the cycle movement.

$$CF = \frac{CMA}{CMAT}$$

As already mentioned, using multiplicative model a time series data can be decomposed into the product of four components. All of these components identified previously. All together, they constitute the decomposition model. Decomposition model has two different forms, additive and multiplicative. An additive model is appropriate if the magnitude of the seasonal fluctuation does not vary with the level of the series. In contrast, multiplicative model is more prevalent since most seasonal economic series have seasonal variation which increases with the level of the series.

$$Y_t = T_t + S_t + C_t + I_t \text{ (additive)}$$
$$Y_t = T_t\, S_t\, C_t\, I_t \text{ (multiplicative)}$$

2.2.3) Vector Autoregression (VAR)

The previous methods that are mentioned before were univariate or single vector methods. However, vector autoregression method is a multivariate method. It became popular by Sims (1980), who developed them as an alternative to simultaneous equations models, which do not focus on the dynamic structure of the variables. A VAR is a *n*-equation, *n*-variable linear model in which each variable is in turn explained by its own lagged values, plus current and past values of the remaining *n*-1 variables. This simple framework provides a systematic way to capture rich dynamics in multiple time series, and the statistical toolkit that came with VARs was easy to use and interpret.

The idea underlying forecasting with a vector autoregression model (VAR) is first to summarize the dynamic correlation patterns among observed data series and then use this summary to predict likely future values for each series. Mathematically, a VAR expresses the current value of each of *m* series as a weighted average of the recent past of all the series plus a term that contains all the other influences on the current values. A VAR can be written compactly as

$$y_t = \text{n} + B_1\, y_{t-1} + \ldots + B_p\, y_{t-p} + u_t,$$

where y_t denotes the m x 1 vector of variables included in the VAR for month *t.* Notice that the m x 1 error vector u_t measures the extent to which y_t cannot be determined exactly as a linear combination of the past values of y with weights given by the constant coefficients v and B_l , $l = 1, \ldots, p$. Uncertainty about the value of u_t arises because the numbers of lagged observations of y to be included in the VAR, p, along with the values of the coefficients are unknown and hence will have to be estimated from the available data. The uncertainty about u_t is made operational by assuming that u_t is a random vector having a zero mean and uncorrelated with lagged values of y_t. The VAR(p) process is stable, when it generates stationary time series, implying that the equation returns to an equilibrium after a shock.

The lag length for the VAR(p) model may be determined using model selection criteria. The general approach is to fit VAR(p) models with orders p = 0, ..., p-max and choose the value of p which minimizes some model selection criteria. The three most common information criteria are the Akaike (AIC), Schwarz-Bayesian (BIC) and Hannan-Quinn (HQ).

The Multivariate Least Square (MLS) can be assessed to estimate the coefficients. As the explanatory variables are the same in each equation, MLS is equivalent to the Ordinary least squares estimator applied to each equation separately. The question of lag order selection can be solved by using a F-test, testing if the additional explained sum of squares is significant.

It is not uncommon to find that VAR models freely fitted to data of the type used here have many estimated coefficients whose standard errors are large. Perhaps they are large because the coefficients are actually zero as indicated. Alternatively, the data might not be rich enough to provide sufficiently precise estimates of nonzero coefficients. If the parameters are too imprecise, then the situation is serious because it has been observed that large estimation uncertainty can lead to poor forecasts.

The vector autoregressive (VAR) model is a general framework used to describe the dynamic interrelationship among stationary variables. So, the first step in time-series analysis should be to determine whether the levels of the data are stationary. Usually, if the levels of your time series are not stationary, the first differences will be. When the time series are not stationary then the VAR framework needs to be modified to allow consistent estimation of the relationships among the series. The vector error correction (VEC) model is just a special case of the VAR for variables that are stationary in their differences. The VEC can also take into account any cointegrating relationships among the variables. In short, if the variables *are* I(1) and cointegrated, then the system of equations is modified to allow for the cointegrating relationship between the I(1) variables. Introducing the cointegrating relationship leads to a model known as the vector error correction (VEC) model.

The VEC has cointegration relations built into the specification so that it restricts the long-run behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the *error correction* term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments.

Forecasts can be calculated by using VEC models. Obtained VEC models can be solved for a period (the period that is wanted to forecasted). Results will present the future values of the series. The results section below explains the forecasting process in details.

CHAPTER 3

RESULTS

This section provides the results of the forecasts of three methods; decomposition, ARIMA and VAR, respectively.

3.1.DECOMPOSITION FORECAST:

This section will provide the forecast results and assumptions in the process of forecasting Turkish sectoral energy demand by decomposition method. The properties of the method are presented in the previous sections. However, some necessary details will be given in this section.

Multiplicative decomposition method is used in decomposing the data into trend, cycle and irregular terms. ARIMA method is selected and used in projecting the values of the coefficients. Moreover, moving averages MA(3) is used in determining the cyclical and irregular terms. Quadratic trend equations have given better fit. However, the order of the trend equation affects the forecast. Therefore both second

Table 3.1: Decomposition Forecast Results for Different Sectors

Sector	Scenario	Forecast (2023)	Projected Change	MAPE(%)
Agriculture	*1A*	7442,554	2353,55	6,341
	1B	9333,787	4244,79	7,540
	2A	5933,533	844,534	6,466
	2B	4301,753	-787,247	5,897
Industry	*1A*	48270,02	17642,07	6,715
	1B	35397,87	4769,82	7,827
	2A	57266,35	26638,35	6,347
	2B	65208,27	34580,27	5,807
Transportation	*1A*	23302,45	7974,45	7,153
	1B	23447,84	8119,84	7,147
	2A	22648,7	7320,7	6,925
	2B	22305,4	6977,39	6,943
Residence & Services	*1A*	37643,81	8805,81	4,479
	1B	58011,04	29143,04	4,070
	2A	29526,73	658,729	4,076
	2B	44273,66	15405,66	3,685

and third order trend equations are used. In order to indentify the forecasts with different ordered trends, the names "A" and "B" are given for second order trend and third order trend, respectively. Decomposition method applied under these terms on both forecast scenarios. As a result, 4 different forecast scenarios are obtained. The results of these different forecast scenarios are provided in the table below. The table also provides the mean absolute percentage error (MAPE) and the amount of the projected change in the energy demand. Forecasts which have MAPEs around 6% can be considered as reasonable.

3.1.1.Agriculture:

The first scenario, 1A, based on a second order trend equation, projected an increase in energy demand by 2353,55 ktoe and has an error by 6,341%. The trend equation used is given below.

$$y = 1{,}9902x^2 + 19{,}101x + 594{,}44$$

$$R^2 = 0{,}9617$$

Scenario 1B used third order equation. It forecasted an increase of 4244,79 ktoe in 13 years which is nearly doubled the projection of Scenario 1A. It has a trend equation of :

$$y = 0{,}0698x^3 - 2{,}406x^2 + 93{,}849x + 317{,}2$$

$$R^2 = 0{,}9668$$

Moreover, Scenario 2A forecasted agricultural energy demand with a second order trend equation which is given below. It forecasted that the increase will be by 844,534 ktoe by the year 2023. The forecast has an error of 6,466%.

$$y = 0{,}8636x^2 + 55{,}49x + 403{,}87$$

$$R^2 = 0{,}9851$$

The last scenario, 2B, used 3rd order trend curve. On contrast to other forecasts, it projected a decrease by 787,247 ktoe. Moreover, the lowest MAPE in agriculture is obtained in Scenario 2B.

The Figure 3.1 below presents the graphs of forecasts of 4 different scenarios.

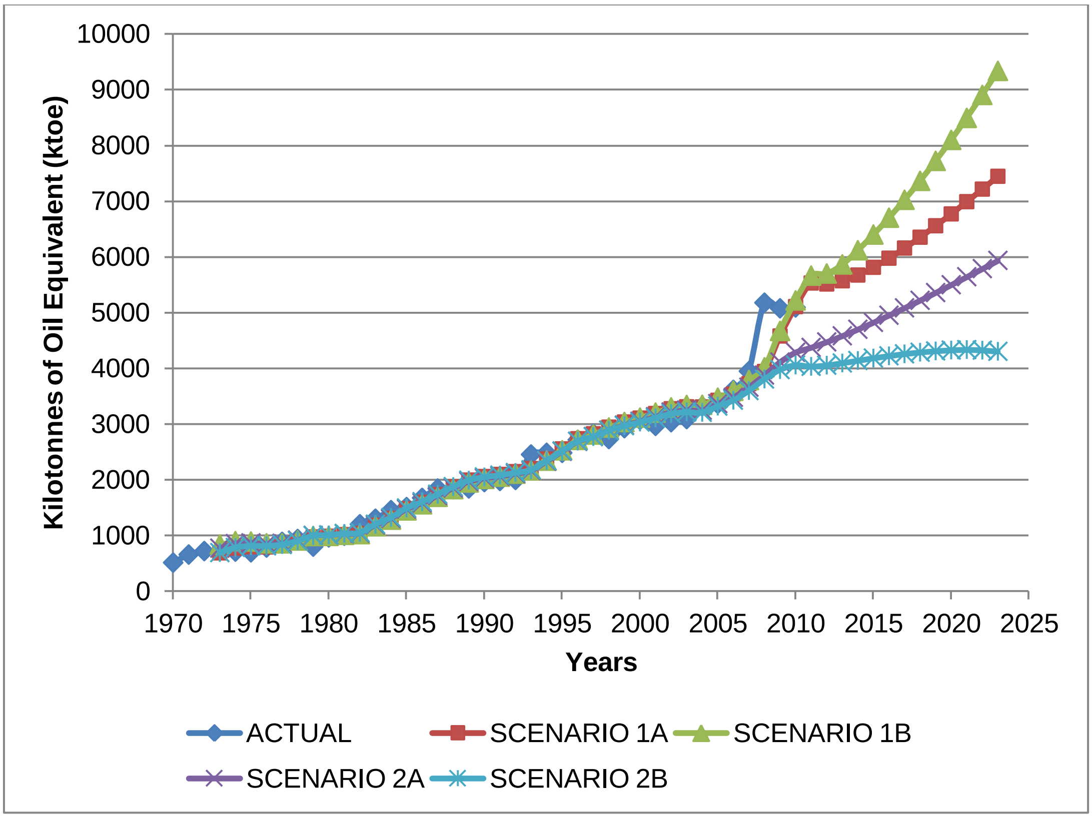

Figure 3.1: Agricultural Energy Consumption Forecast by Decomposition Method

The forecast scenarios provides very different results in agriculture sector. Scenarios 1A and 1B reflects the rapid increase in demand at 2008. Therefore, both scenarios obtained higher results compared to Scenario 2. Forecast of Scenario 1B seems to be very high. Under current agricultural policies and growth in agricultural production, it is not realistic to expect such an increase in just 13 years. On contrast, Scenario 1A is reasonable with more realistic increase in demand. It also has an acceptable MAPE.

Furthermore, Scenario 2 without the rapid increase in year 2008 presents very different results from Scenario 1. Scenario 2A projected the increase in demand will continue in same rate. However, Scenario 2B projected the opposite. According to 2B, energy demand will no longer increase. It will start to move along the 4000 ktoe.

3.1.2.Industry*:*

The first scenario, 1A, projected an increase in the industrial energy demand by 17642,07 ktoe with an error by 6.715%. The equation below represents the trend which is used in forecasting.

$$y = 9{,}6249x^2 + 305{,}51x + 3621{,}1$$
$$R^2 = 0{,}9632$$

Scenario 1B used 3rd order trend equation that presented below. It forecasted the change will be 4769,82 ktoe by 2023. It has a forecast error by 7,827% which can be considered as not desirable.

$$y = -0{,}462x^3 + 38{,}73x^2 - 189{,}37x + 5456{,}7$$
$$R^2 = 0{,}968$$

Furthermore, Scenario 2A projected the future energy demand by using 2nd order trend equation. According to findings, energy demand will increase by 26638,35 ktoe. The forecast error is 6,347%.

$$y = 16{,}495x^2 + 83{,}191x + 4787{,}5$$
$$R^2 = 0{,}9851$$

The last forecast scenario, 2B, forecasted the biggest increase compared to other scenarios. The projected increase will be 34580,27 ktoe. A third order trend curve is used in this scenario and an error of 5.807% obtained. Figure 3.2 below shows the forecast curves of different scenarios.

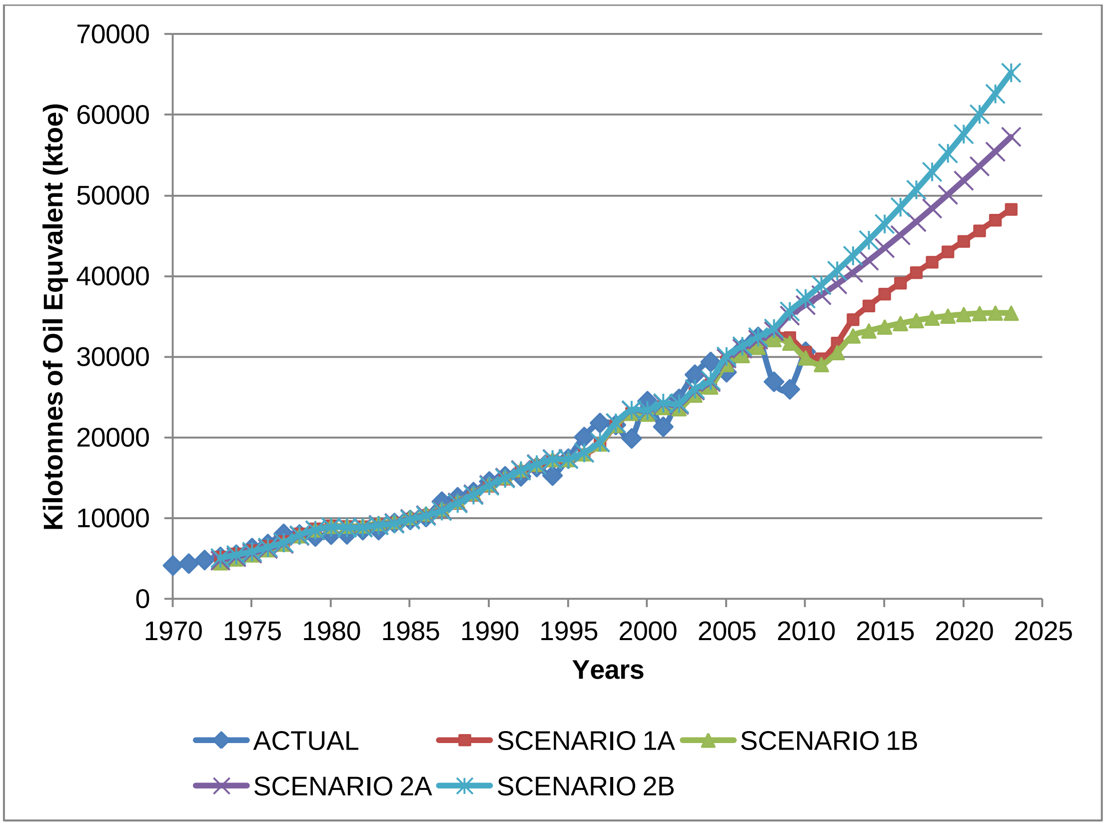

Figure 3.2: Industrial Energy Consumption Forecast by Decomposition Method

The forecasts indicate very different results like agriculture forecasts. Both of the first scenarios reflects the immediate decrease in 2008. The main reason of this rapid decrease is the economic crises that caused a recession in industrial production. Scenario 1A predicts an increase to 50000 ktoe while Scenario 1B presents the increase will be limited and there won't be significant increase in industrial energy demand over the next 13 years.

On the other hand, 2nd scenarios are cleaned from the effects of economic crises in 2008. Therefore, the forecasts give higher projections. The scenarios predicted the demand close, however, Scenario 2B has higher projection. Also, the lowest MAPE is belong to Scenario 2B.

3.1.3.Transportation:

The same scenarios also applied to transportation sector. The first scenario, 1A, projected a change by 7974,45 ktoe with an error of 7,153%. It used the trend equation which is given below.

$$y = 4{,}2061x^2 + 141{,}78x + 3611{,}6$$
$$R^2 = 0{,}9659$$

The scenario 1B forecasted an increase by 8119,84 ktoe. It has 7,147% MAPE. Moreover, it used a 3rd order trend equation that is presented below.

$$y = 0{,}0053x^3 + 3{,}8726x^2 + 147{,}45x + 3590{,}6$$
$$R^2 = 0{,}9659$$

On the other hand, Scenario 2A forecasted demand by using a 2nd order trend equation. The error is calculated as 6,925%. According to results, there will be an increase in energy demand by 7320,7 ktoe.

$$y = 3{,}6491x^2 + 157{,}38x + 3541{,}8$$
$$R^2 = 0{,}9635$$

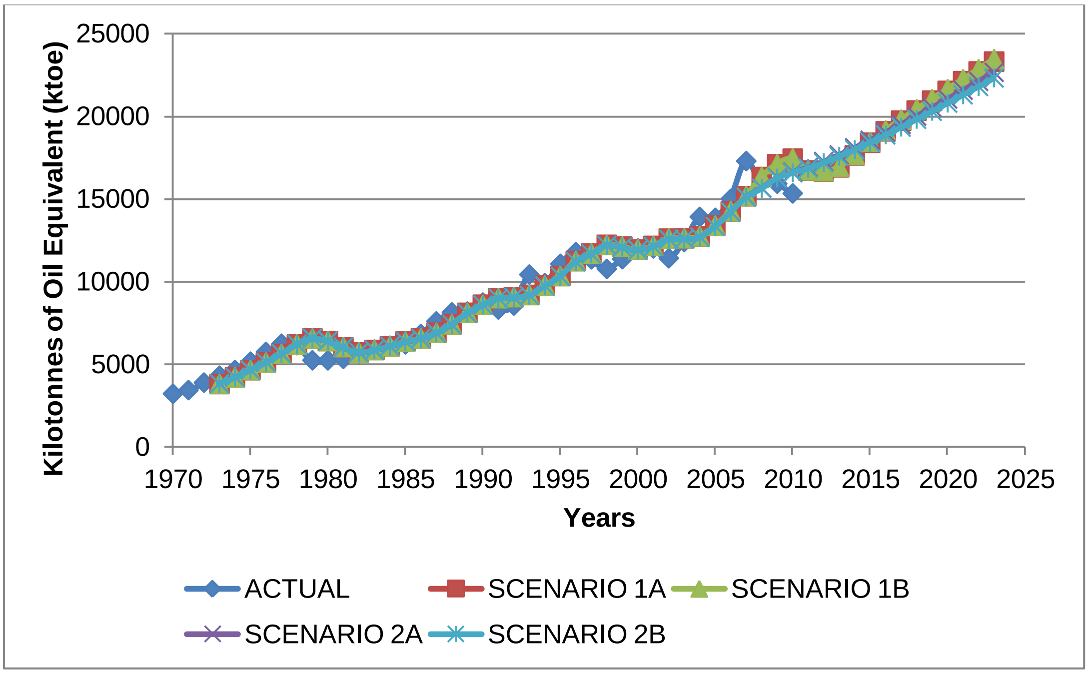

Figure 3.3: Energy Demand Forecast by Decomposition Method in Transportation Sector

The last scenario of transportation sector, 2B, calculated an increase by 6977,39 ktoe. A third order trend curve is used in this scenario and an error of 6,943% obtained. The results of the forecasts are provided in the Figure 3.3 above.

The energy demand curve of transportation sector is wavy. There are cycles in data. As the figure illustrates, the four forecast scenarios are very close to each other. The only significant difference is the little cycle in the first scenarios (1A, 1B) in the year 2010. Moreover, the errors, MAPEs are very close. It is very difficult to distinguish a scenario between them.

3.1.4.Residence and Service:

The first scenario, 1A, based on a second order trend equation, projected an increase in energy demand by 8805,81 ktoe and has an error by 4,479%. The trend equation used is given below.

$$y = 7{,}0185x^2 + 119{,}66x + 10065$$
$$R^2 = 0{,}9303$$

Scenario 1B used third order equation. It forecasted an increase of 29143,04 ktoe in 13 years which is far more than the projection of Scenario 1A. It has a trend equation of :

$$y = 0{,}7595x^3 - 40{,}832x^2 + 933{,}27x + 7047{,}6$$
$$R^2 = 0{,}9667$$

Furthermore, Scenario 2A forecasted an increase by 658,7288 ktoe with an error of 4,026%. It used 2nd order trend equation that is given below.

$$y = 1{,}3398x^2 + 303{,}63x + 9099{,}2$$
$$R^2 = 0{,}9517$$

The last Scenario 2B has the lowest MAPE which is only 3,685%. The results indicate that there will be an increase in energy demand by 15405,66 ktoe in 13 years. The Scenario used 3rd order trend equation in this calculations.

$$y = 0{,}4402x^3 - 24{,}411x^2 + 710{,}58x + 7691{,}4$$
$$R^2 = 0{,}9645$$

Figure 3.4 below identifies the forecast results of different scenarios.

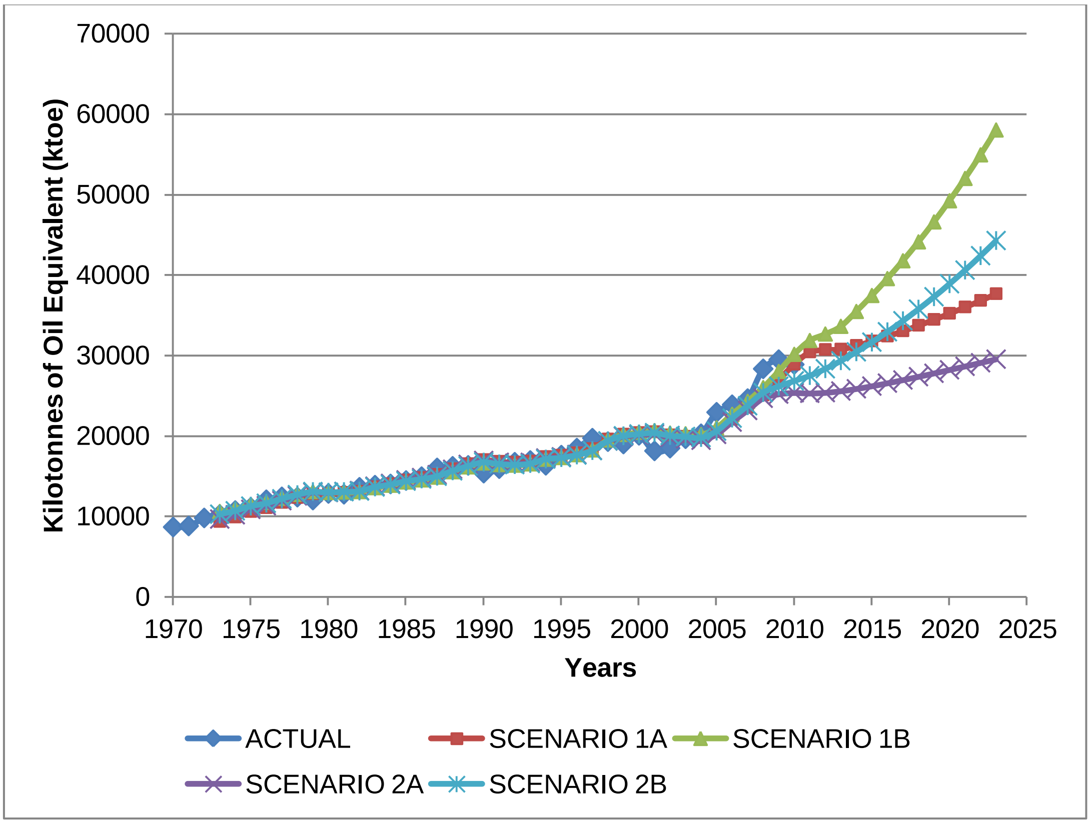

Figure 3.4: Energy Demand Forecast by Decomposition Method in Residence and Service Sector

Like agriculture and industrial sectors, residence and services sector also provides very different results for different scenarios. The most interesting results is obtained by Scenario 2A. As a result of the cleaning the rapid increase in 2008, it forecasted that the energy demand will be on 30000 ktoe level. However, it is only 658,7288 ktoe more than the observed amount in 2010. On the other hand, Scenario 2B states the increase will continue with an increasing rate and energy demand will reach to 45000 ktoe level. This scenario also provided the lowest MAPE.

Both of the first scenarios, 1A and 1B, reflects the sudden increase in the demand in 2008. Still, the rate if increase is lower in Scenario 1A. Therefore, Scenario 1B calculated the highest energy demand. Also, it has lower MAPE than 1A.

3.2. ARIMA (Box Jenkins) FORECAST:

Based on Box Jenkins methodology of ARIMA, available data is analyzed and some projections about the futures of sectors obtained. The major findings of the forecasting analyses are explained below.

Forecasts are based on 2 different scenarios as in the case of the decomposition model. The first scenario considers the ARIMA forecast based on the 40 years of data which can be considered as the appropriate in order to apply ARIMA. In the scenario 2, the effects of rapid increase in the last 3 years are eliminated by removing the data of those years, and therefore the data include only 37 observations.

In literature, selecting a true model for ARIMA is considered as an art, not science. Different ordered models provide various results. However, textbooks suggest looking into autocorrelation and partial autocorrelation functions can be a guide for deciding for appropriate model. The number of spikes in ACF and PACF functions gives the order of AR(p) and MA(q). Moreover, the results of the unit root tests provide the order of I(d). Unit root tests are applied for testing whether the data is stationary or not. If the data is not stationary it should be converted by differentiating. Stationarity is important because if the series is non-stationary then all the assumptions of the classical regression analysis are not valid. We used augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP), Elliott et al. (1996) Dickey-Fuller GLS detrended (DF-GLS) and Point Optimal (ERS-SPO), Kwiatkowski et al. (1992) (KPSS), and Ng and Perron's (2001) MZa (NP). The details of the methodology is provided in methods section.

Based on this knowledge, unit root tests are applied to data. The results of the stationarity/unit root tests are reported in Table 1 for the levels and the first differences.

Results of the unit root tests state that the data is stationary in first differences. Therefore, I(1) or I(2) can be used as the integrated part of the ARIMA model. Autocorrelation and partial autocorrelation functions are obtained according to the integration of the data, which is in this case I(2). Statistical software ForecastX and Eviews provide ACF and PACF and calculate the future values based on data's own past. The results of the forecast for different sectors are presented in details below.

Table 3.2: Unit root tests										
Levels										
	ADF		**DF-GLS**		**PP**	**KPSS**	**ERS-PO**		**NP-Z**	
	Statistic	*Lag*	*Statistic*	*Lag*			*Statistic*	*Lag*	*Statistic*	*Lag*
intercept										
ECA	1.314	0	2.061	0	2.121	0.7844	113.19	0	2.986	0
ECI	1.687	6	-0.589	7	0.512	0.764	1702.4	6	-48.8***	7
ECRS	1.457	7	2.018	0	1.056	0.777	1212.1	7	3.117	0
ECT	0.403	0	0.655	0	0.403	0.778	90.624	0	1.248	0
intercept & trend										
ECA	-1.189	0	-1.397	0	-1.191	0.162	19.465	0	-4.657	0
ECI	-1.181	6	-1.446	7	-3.157	0.182	113.43	6	-24.4***	7
ECRS	-0.837	0	-2.335	3	-1.091	0.135	19.213	0	-361.8**	3
ECT	-2.630	0	-2.648	0	-2.648	0.150	8.747	0	-10.210	0
First Differences										
	ADF		**DF-GLS**		**PP**	**KPSS**	**ERS-PO**		**NP-Z**	
	Statistic	*Lag*	*Statistic*	*Lag*			*Statistic*	*Lag*	*Statistic*	*Lag*
intercept										
ECA	-6.0667***	0	-6.145***	0	-6.067***	0.315	1.241***	0	-20.2***	0
ECI	-1.961	6	-1.921	6	-8.096***	0.204	0.834***	1	-45.7***	1
ECRS	-3.638**	6	-5.410***	0	-5.645***	0.222	1.432***	0	-18.9***	0
ECT	-6.452***	0	-6.423***	0	-6.453***	0.049***	1.406***	0	-19.6***	0
intercept & trend										
ECA	-3.078	9	-6.499***	0	-6.636***	0.088	5242.6	9	-19.40**	0
ECI	-4.484***	5	0.409	9	-8.687***	0.165**	657.1	5	1.437	9
ECRS	-3.928**	6	-4.133***	6	-5.720***	0.105	222.84	6	-0.210	6
ECT	-6.360***	0	-6.465***	0	-6.380***	0.049	4.822**	0	-20.07**	0

Superscripts ***, ** and * represent significance at 1%, 5%, and 10%, respectively. ADF, DF-GLS, PP, KPSS, ERS-PO, NP-Za refer to Dickey–Fuller, Dickey–Fuller GLS detrended, Phillips–Perron, Kwiatkowski–Phillips–Schmidt–Shin, Elliot–Rothenberg-Stock point optimal, and Ng-Perron Za, respectively. Lag lengths are determined by Akaike Information Criterion (AIC).

3.2.1.Agriculture:

This subsection explains the details of the forecast results of the agricultural sector in Turkey. The ACF and PACF for scenario 1 are given as follows.

Table 3.3: ACF and PACF for Agriculture - Scenario 1

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
****| . |	****| . |	1	-0.486	-0.486	9.9407	0.002
. | . |	.**| . |	2	-0.005	-0.315	9.9417	0.007
. | . |	.**| . |	3	-0.039	-0.284	10.010	0.018
. |*. |	. | . |	4	0.151	-0.028	11.054	0.026
.**| . |	. *| . |	5	-0.192	-0.183	12.782	0.026
. |*. |	. *| . |	6	0.119	-0.071	13.465	0.036
. *| . |	. *| . |	7	-0.070	-0.116	13.711	0.057
. | . |	.**| . |	8	-0.015	-0.189	13.722	0.089
. |*. |	. | . |	9	0.109	0.018	14.360	0.110
. *| . |	. *| . |	10	-0.147	-0.184	15.556	0.113
. |*. |	. *| . |	11	0.084	-0.085	15.958	0.143
. | . |	. | . |	12	0.017	-0.034	15.976	0.192

There is only one significant spike in PACF which suggests AR(1) model is used. Moreover, ACF has also only one spike indicating that MA(1) can be used in ARIMA model. Furthermore, the data is integrated in 2nd order level suggests ARIMA(1,2,1) model to be used. However, for the sake of comparison, other models are also applied such as ARIMA(2,2,2) or ARIMA(3,2,2). The models are run by ForecastX and the results are provided in Figure 3.5. The Mean Absolute Percentage Errors (MAPE) of models are also listed in Table 3.4.

Table 3.4: MAPE's of ARIMA models for Agriculture - Scenario 1	
Model	*MAPE*
ARIMA(1,2,1)	6.84%
ARIMA(2,2,2)	6.70%
ARIMA(3,2,1)	6.29%
ARIMA(3,2,2)	5.97%

Table 3.5 below provides the ACF and PACF of Scenario 2. The 3 significant spikes in ACF means MA(3) as the model to be used. Similarly, PACF also has 3 spikes. In that case, ARIMA model of (3,2,3) is the suggested as the likely model. These arguments imply different models may be applied as we describe below for comparison of their results.

Table 3.5: ACF and PACF for Agriculture - Scenario 2

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
****| . |	****| . |	1	-0.473	-0.473	8.7458	0.003
. *| . |	****| . |	2	-0.185	-0.527	10.130	0.006
. |**. |	.**| . |	3	0.264	-0.213	13.021	0.005
. |* . |	. |**. |	4	0.121	0.214	13.646	0.009
***| . |	. *| . |	5	-0.413	-0.159	21.156	0.001
. |**. |	. *| . |	6	0.229	-0.090	23.539	0.001
. |* . |	. |* . |	7	0.195	0.146	25.339	0.001
***| . |	. *| . |	8	-0.357	-0.094	31.561	0.000
. |* . |	. | . |	9	0.106	-0.013	32.125	0.000
. | . |	***| . |	10	0.033	-0.327	32.184	0.000

. |* . |	. |* . |	11	0.102	0.092	32.758	0.001
.**| . |	. | . |	12	-0.266	-0.048	36.784	0.000

The results of ARIMA(3,2,3) and ARIMA(2,2,1) and ARIMA(1,2,1) models are provided in Figure 3.6 and , their MAPEs are listed in Table 3.6 below.

Table 3.6: MAPE's of ARIMA models for Agriculture - Scenario 2

Model	*MAPE*
ARIMA(1,2,1)	4.21%
ARIMA(2,2,1)	4.14%
ARIMA(3,2,3)	3.77%
ARIMA(4,2,1)	4.14%

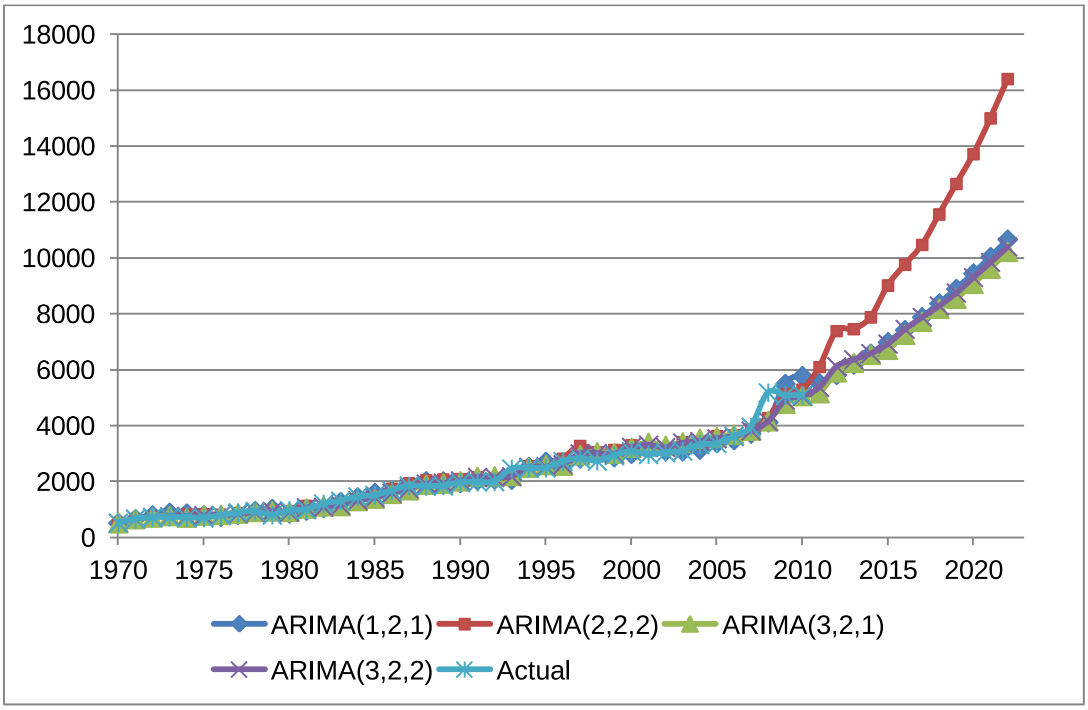

Figure 3.5: Agricultural Forecast Results under Scenario 1

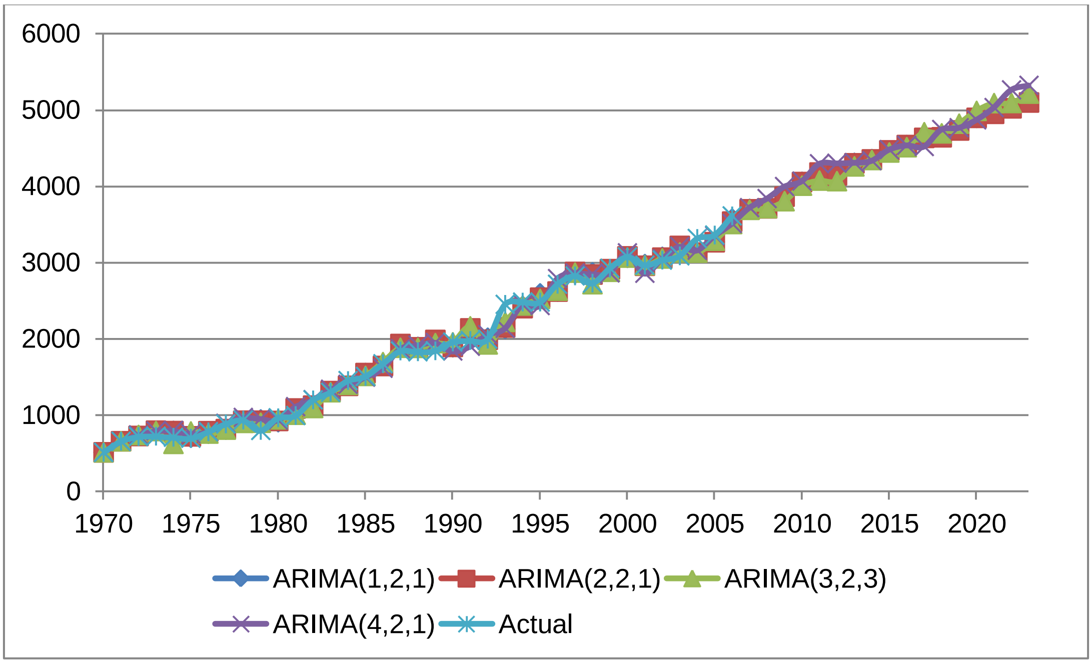

Figure 3.6: Agricultural Forecast under Scenario 2

The Figure 3.5 indicates very small differences between the models except the ARIMA(2,2,2), for the case of the scenario 1. The latter forecasts an increase to 16000 ktoe during 2023. On the other hand, all the other 3 models forecast the energy demand around 10000 ktoe in 2023. The difference, which is more than current agricultural demand of Turkey, can be considered as quite high. On the other hand, the suggested model, ARIMA(1,2,1), has the highest error when it compared to others. The lowest MAPE is for ARIMA(3,2,2) and it forecasts agricultural energy demand very close to other two models. The results of these two models are indeed distinguishable.

The Figure 3.6 shows the same forecasts results under the scenario 2 that tries to remove the effect of sudden demand increase in 2007. When this effect is removed, the forecast results become more realistic. All models forecast the agricultural energy demand around 5000 ktoe by the year 2023. The increase in agricultural demand will continue almost linearly without any expansion or high increase. The lower MAPE (3.77%.) is calculated by ARIMA(3,2,3) model,. A forecast with an error around 4% can be considered as very good forecast.

3.2.2.Industry:

In this subsection, the energy demand forecast of industrial sector of Turkey will be examined. The Table 3.7 provides the ACF and PACF.

Table 3.7: ACF and PACF for Industry - Scenario 1

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
***| . |	***| . |	1	-0.426	-0.426	7.6346	0.006
. *| . |	***| . |	2	-0.132	-0.383	8.3911	0.015
. | . |	.**| . |	3	0.063	-0.256	8.5654	0.036
. |*. |	. | . |	4	0.169	0.050	9.8699	0.043
.**| . |	. *| . |	5	-0.207	-0.106	11.883	0.036
. *| . |	***| . |	6	-0.139	-0.340	12.821	0.046
. |*** |	. |*. |	7	0.373	0.088	19.785	0.006
.**| . |	. *| . |	8	-0.245	-0.157	22.870	0.004
. | . |	. *| . |	9	-0.001	-0.076	22.871	0.006
. |*. |	. |*. |	10	0.144	0.129	24.014	0.008
. | . |	. | . |	11	-0.005	0.003	24.015	0.013
. *| . |	. | . |	12	-0.142	-0.012	25.203	0.014

The suggested model will be decided by looking into ACF and PACF results. The ACF has one spike which is in observation 1. That means MA(1) will be chosen as moving averages part of the model. Moreover, PACF has 3 spikes in observation

1,2 and 6, respectively. Therefore, as the autoregressive part, AR(3) will be selected. In this case, ARIMA(3,2,1) is obtained as the suggested model. As in the case of the analysis for the agriculture sector, other models are predicted in order to get a comparison. Figure 3.7 below presents the forecasts of different ARIMA models. Table 3.8 below provides the MAPEs of the predicted models.

Table 3.8: MAPE's of ARIMA models for Industry - Scenario 1

Model	*MAPE*
ARIMA(1,2,1)	6.29%
ARIMA(2,2,2)	6.33%
ARIMA(3,2,1)	6.39%
ARIMA(3,2,2)	6.35%

Table 3.8 clearly presents that there are no big difference in MAPEs. This situation can be verified by looking into Figure 3.7. The forecasts are very close to each other. In other words, different ARIMA models predicts the industrial demand will be around 50000 ktoe by the year 2023.

Table 3.9 gives the ACF and PACF of the scenario 2 for the industrial energy demand forecast. The original data contains the effects of the Turkish industrial economic crisis in 2008 which are, however, are eliminated in the scenario 2. The results of this revised data set are provided in Figure 3.8.

Table 3.9: ACF and PACF for Industry - Scenario 2

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*****| . |	*****| . |	1	-0.629	-0.629	15.059	0.000
. |* . |	***| . |	2	0.144	-0.416	15.869	0.000

. *| . |	***| . |	3	-0.068	-0.404	16.056	0.001
. |* . |	. *| . |	4	0.153	-0.146	17.037	0.002
. *| . |	. *| . |	5	-0.171	-0.175	18.295	0.003
. | . |	***| . |	6	0.010	-0.360	18.300	0.006
. |**. |	. | . |	7	0.206	-0.035	20.260	0.005
. *| . |	. |* . |	8	-0.166	0.094	21.579	0.006
. | . |	. |* . |	9	0.004	0.096	21.580	0.010
. | . |	. | . |	10	0.005	0.044	21.581	0.017
. | . |	. | . |	11	0.047	-0.019	21.702	0.027
. *| . |	. *| . |	12	-0.096	-0.117	22.220	0.035

The ACF in Table 3.9 has one spike which is in the observation one. On the other hand, PACF contains 4 significant spikes. Therefore, ARIMA(4,2,1) model can be selected as the suggested model. Similar to previous sections, other models are also calculated as a comparison. Table 3.10 provides the MAPEs of the forecasts.

Table 3.10: MAPE's of ARIMA models for Industry - Scenario 2

Model	*MAPE*
ARIMA(1,2,1)	5.52%
ARIMA(2,2,1)	5.53%
ARIMA(3,2,3)	5.51%
ARIMA(4,2,1)	5.55%

Figure 3.8 presents very similar results as in the case of the Scenario 1. The forecasts are very close to each other. However, the Scenario 2 predicts generally higher industrial demands that will reach to 80000 ktoe by the year 2023. Energy demand is increasing with an increasing rate. The main reason for the large

difference of about 30000 ktoe between the scenarios may be explained by less fluctuations in demand data for the Scenario 2 as compared to the Scenario 1.

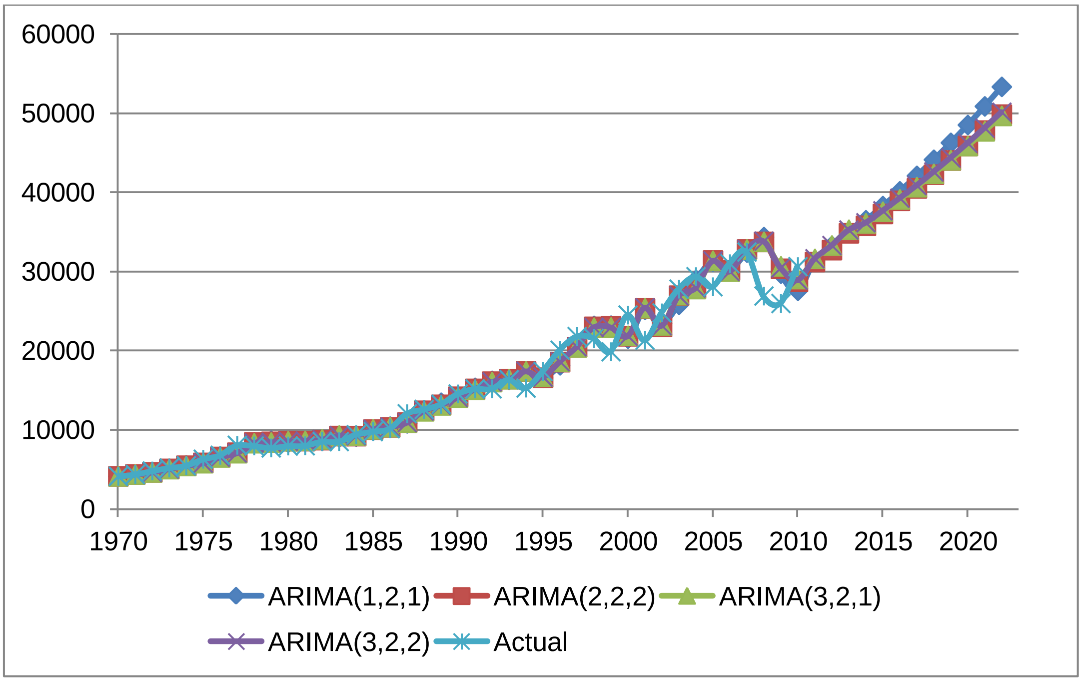

Figure 3.7: Industrial Forecast under Scenario 1

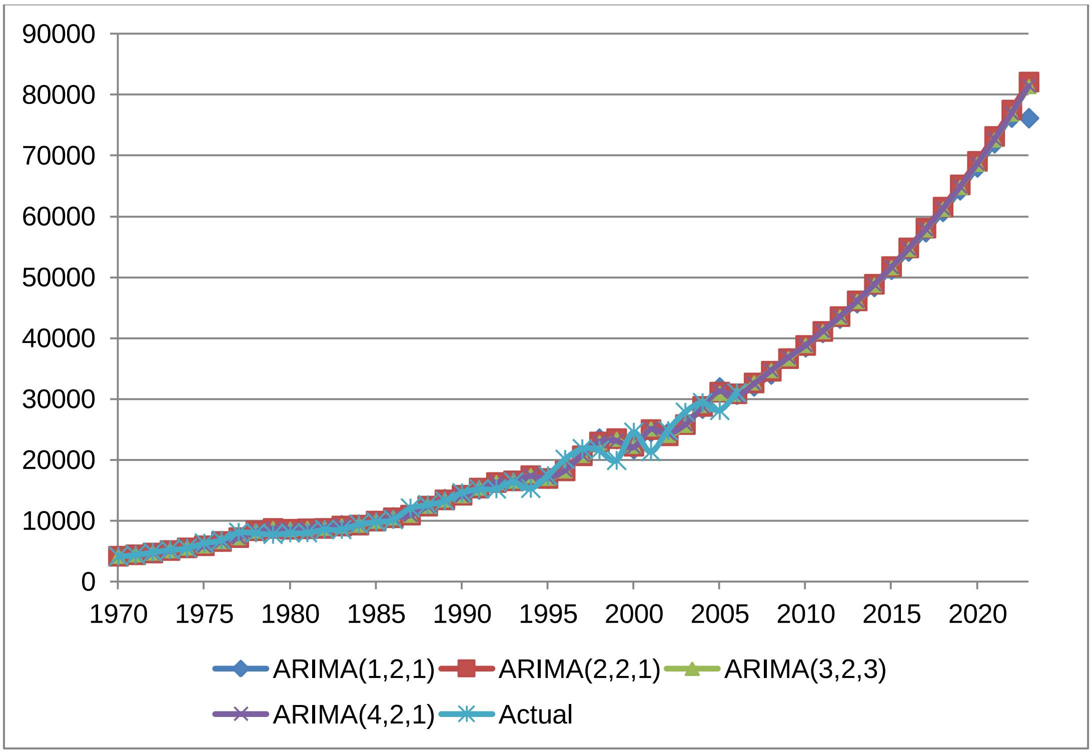

Figure 3.8: Industrial Forecast under Scenario 2

3.2.3.Residence and Services:

Similar to previous sectors, 2 scenarios are also applied for this sector. The Table 3.11 below presents the ACF and PACF for Scenario 1.

Table 3.11: ACF and PACF for Residence and Services - Scenario 1

Autocorrelation	Partial Correlation	obs	AC	PAC	Q-Stat	Prob
***| . |	***| . |	1	-0.419	-0.419	7.3851	0.007
. *| . |	***| . |	2	-0.150	-0.395	8.3552	0.015
. |* . |	. | . |	3	0.254	0.002	11.229	0.011
.**| . |	. *| . |	4	-0.220	-0.186	13.442	0.009
. |*. |	. |*. |	5	0.167	0.095	14.760	0.011
. | . |	. | . |	6	-0.027	0.005	14.795	0.022
.**| . |	***| . |	7	-0.317	-0.330	19.819	0.006
. |** |	. *| . |	8	0.246	-0.187	22.952	0.003
. | . |	. *| . |	9	-0.006	-0.112	22.955	0.006
. *| . |	. *| . |	10	-0.121	-0.101	23.760	0.008
. |*. |	. | . |	11	0.136	-0.038	24.822	0.010
. | . |	. | . |	12	-0.056	0.023	25.007	0.015

ACF in Table 3.11 has 2 spikes which are in the observations 1 and 8 respectively, indicating that MA(2) is selected for the moving averages part. On the other hand, PACF contains 3 significant spikes and therefore AR(3) is selected as autoregressive part. As a result, ARIMA(3,2,2) is suggested as the primary model. The results are given in Figure 3.9 and the MAPEs of the forecasts are listed in Table 3.12. Moreover, Table 3.13 presents the ACF and PACF for the Scenario 2. It can be identified that there is only one spike in ACF which refers to MA(1). On

PACF, there are 2 spikes and thus AR(2) indicating that ARIMA(2,2,1) model is suggested.

Table 3.12: MAPE's of ARIMA models for Residence and Services - Scenario 1

Model	*MAPE*
ARIMA(1,2,1)	3.61%
ARIMA(2,2,2)	3.55%
ARIMA(3,2,1)	3.79%
ARIMA(3,2,2)	3.55%

Table 3.13: ACF and PACF for Residence and Services - Scenario 2

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
****| . |	****| . |	1	-0.515	-0.515	10.358	0.001
. | . |	***| . |	2	0.014	-0.341	10.366	0.006
. |* . |	. *| . |	3	0.109	-0.088	10.859	0.013
.**| . |	.**| . |	4	-0.224	-0.287	13.008	0.011
. |**. |	. | . |	5	0.232	-0.037	15.390	0.009
. *| . |	. *| . |	6	-0.168	-0.154	16.677	0.011
. *| . |	.**| . |	7	-0.073	-0.316	16.929	0.018
. |* . |	.**| . |	8	0.168	-0.229	18.304	0.019
. | . |	. *| . |	9	-0.057	-0.127	18.468	0.030
. | . |	. *| . |	10	0.006	-0.179	18.470	0.048
. |* . |	. *| . |	11	0.075	-0.064	18.774	0.065
. *| . |	. *| . |	12	-0.099	-0.085	19.334	0.081

The results of the suggested model ARIMA(2,2,1) and their comparison with the other models are provided in Figure 3.10. On the other hand, Table 3.14 below presents the MAPEs of the forecasts.

Table 3.14: MAPE's of ARIMA models for Residence and Services - Scenario 2

Model	*MAPE*
ARIMA(1,2,1)	3.53%
ARIMA(2,2,1)	3.10%
ARIMA(3,2,3)	3.13%
ARIMA(4,2,1)	3.41%

MAPEs of the both scenarios are lower than 4% which can be considered as very good. However, the scenario 2 provides slightly lower errors. In terms of forecasts, two scenarios result in very different results. In the Scenario 1, all the alternative ARIMA models lead to different results for the year 2023. The suggested model have the lowest MAPE and predicts the energy demand in residence and service sector to reach at 50000 ktoe by 2023. On the other hand, ARIMA(1,2,1) predicts the lowest which is about 40000 ktoe. On the contrary, the models in the Scenario 2 forecast nearly the same amounts with very small changes for the year 2023. The suggested model, ARIMA(2,2,1) has the lowest MAPE.

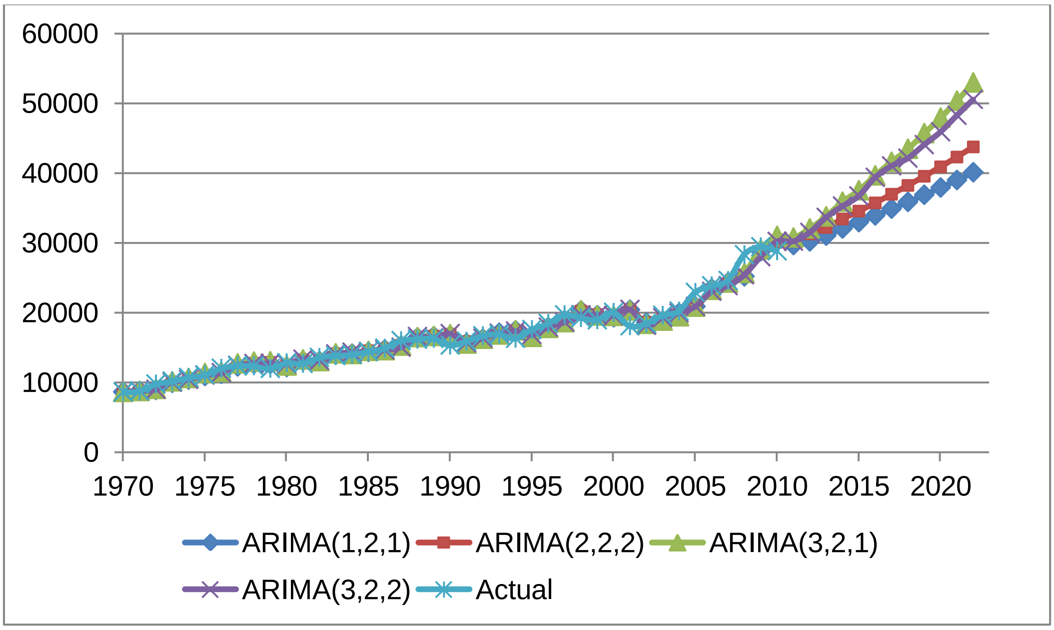

Figure 3.9: Residence and Services Forecast under Scenario 1

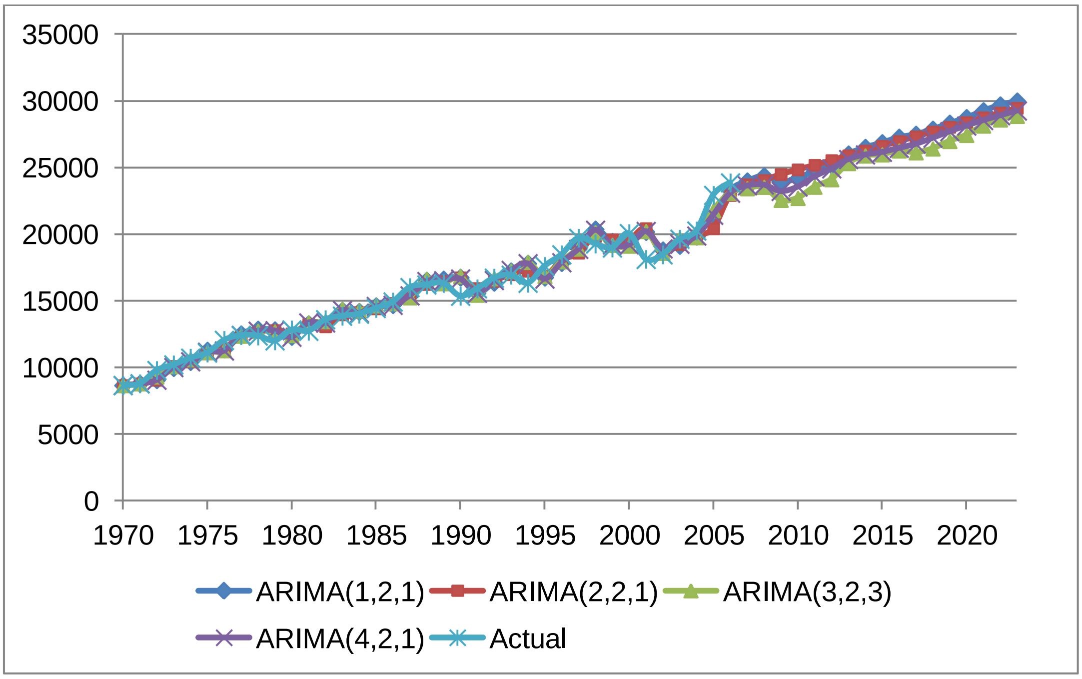

Figure 3.10: Residence and Services Forecast under Scenario 2

4.2.4.Transportation:

The ACF and PACF for the energy demand forecast of transportation sector of Turkey is given Table 3.15.. There are two significant spikes in PACF which mean AR(2) model is suggested. Moreover, ACF has also two spikes. Therefore MA(2) can be used in ARIMA model. Based on this knowledge ARIMA(2,2,2) is obtained. However, in order to compare different results, other models are also applied such as ARIMA(1,2,1) or ARIMA(3,2,2). The model results are provided in Figure 3.11. The MAPEs of models are also listed in Table 3.16.

Table 3.15: ACF and PACF for Transportation - Scenario 1

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>***| . |</td><td>***| . |</td><td>1</td><td>-0.445</td><td>-0.445</td><td>8.3410</td><td>0.004</td></tr>
<tr><td>.**| . |</td><td>****| . |</td><td>2</td><td>-0.227</td><td>-0.530</td><td>10.562</td><td>0.005</td></tr>
<tr><td>. |** |</td><td>. *| . |</td><td>3</td><td>0.326</td><td>-0.112</td><td>15.284</td><td>0.002</td></tr>
<tr><td>. *| . |</td><td>. | . |</td><td>4</td><td>-0.068</td><td>-0.025</td><td>15.497</td><td>0.004</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>5</td><td>-0.154</td><td>-0.075</td><td>16.609</td><td>0.005</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>6</td><td>0.048</td><td>-0.182</td><td>16.723</td><td>0.010</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>7</td><td>0.048</td><td>-0.172</td><td>16.839</td><td>0.018</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>8</td><td>0.069</td><td>0.084</td><td>17.086</td><td>0.029</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>9</td><td>-0.180</td><td>-0.076</td><td>18.804</td><td>0.027</td></tr>
<tr><td>. | . |</td><td>.**| . |</td><td>10</td><td>-0.030</td><td>-0.276</td><td>18.854</td><td>0.042</td></tr>
<tr><td>. |** |</td><td>. *| . |</td><td>11</td><td>0.233</td><td>-0.121</td><td>21.946</td><td>0.025</td></tr>
<tr><td>. *| . |</td><td>. | . |</td><td>12</td><td>-0.087</td><td>0.049</td><td>22.394</td><td>0.033</td></tr>
</table>

Table 3.16: MAPE's of ARIMA models for Transportation - Scenario 1	
Model	*MAPE*
ARIMA(1,2,1)	5.46%
ARIMA(2,2,2)	5.56%
ARIMA(3,2,1)	5.57%
ARIMA(3,2,2)	5.54%

Table 3.17 below provides the ACF and PACF of the scenario 2. It can be inferred that there is only one significant spike in ACF that means as a model of MA(1). On the other hand, PACF has 2 spikes. In that case, ARIMA model of (2,2,1) is the suggested model. As in the previous case, the method is applied to different models in order to compare their results.

Table 3.17: ACF and PACF for Transportation - Scenario 2

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
***| . |	***| . |	1	-0.421	-0.421	6.7468	0.009
.**| . |	****| . |	2	-0.253	-0.523	9.2625	0.010
. |**. |	.**| . |	3	0.249	-0.223	11.777	0.008
. | . |	. *| . |	4	-0.010	-0.148	11.781	0.019
. | . |	. | . |	5	-0.057	-0.038	11.920	0.036
. | . |	. *| . |	6	-0.039	-0.112	11.986	0.062
. | . |	. *| . |	7	0.039	-0.099	12.058	0.099
. |* . |	. | . |	8	0.088	0.041	12.429	0.133
. *| . |	. | . |	9	-0.137	-0.054	13.365	0.147
. *| . |	.**| . |	10	-0.071	-0.214	13.629	0.191
. |**. |	. | . |	11	0.264	0.038	17.394	0.097
.**| . |	. *| . |	12	-0.224	-0.181	20.224	0.063

The results of the suggested model ARIMA(2,2,1) and the other models ARIMA(3,2,3) and ARIMA(1,2,1) are provided in Figure 3.12. Their MAPEs of the forecasts are listed in Table 3.18.

Table 3.18: MAPE's of ARIMA models for Residence and Services - Scenario 2

Model	*MAPE*
ARIMA(1,2,1)	5.09%
ARIMA(2,2,1)	5.24%
ARIMA(3,2,3)	5.18%
ARIMA(4,2,1)	5.27%

The results of the forecasts under two different scenarios are very different. The main reason is the small temporal fluctuations in the energy demand data for transportation sector. These fluctuations cause lower quality forecasts. Moreover, eliminating the last 4 years of the data changes considerably the forecasts.

In the first scenario, the models, except ARIMA(3,2,1), forecast the energy demand around 24000 ktoe by 2023 (Figure 3.11). However, ARIMA(3,2,1) projects a very different energy demand that is around 16000 ktoe. On the contrary, the scenario 2 forecasts that the energy demand in transportation sector will increase to more than 30000 ktoe. According to the suggested model, ARIMA(2,2,1), the demand will reach nearly 35000 ktoe (Figure 3.12). This huge increase suggests doubling of the energy demand during the next 13 years.

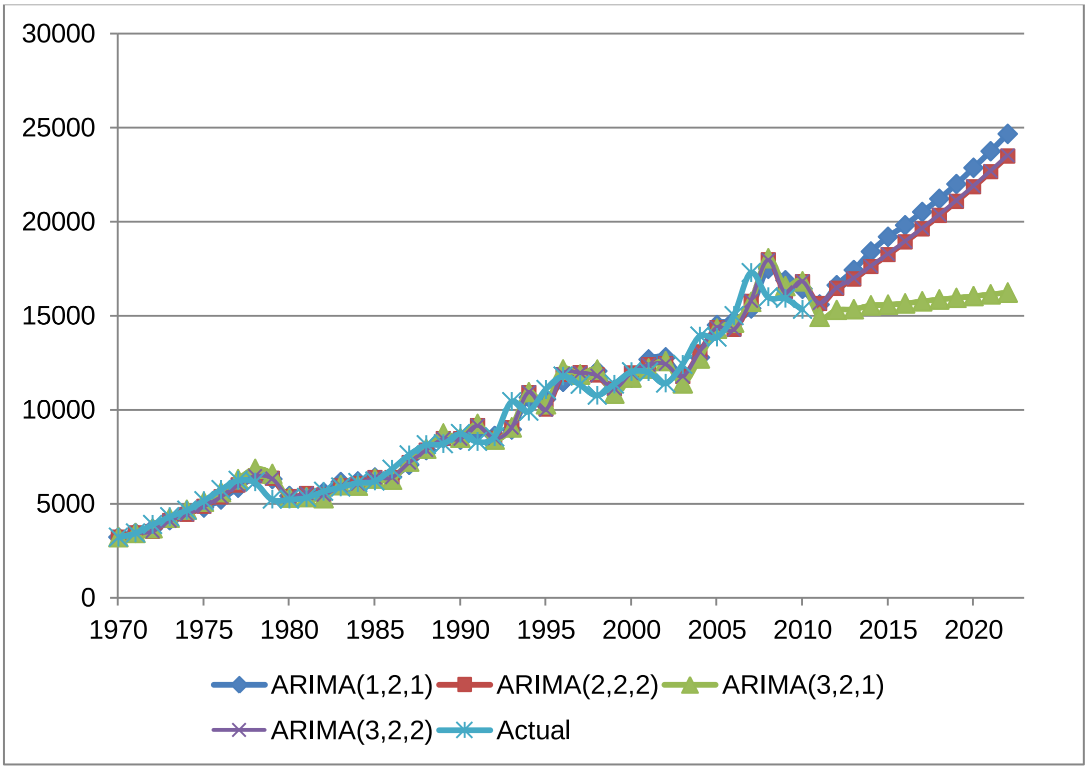

Figure 3.11: Transportation Forecast under Scenario 1

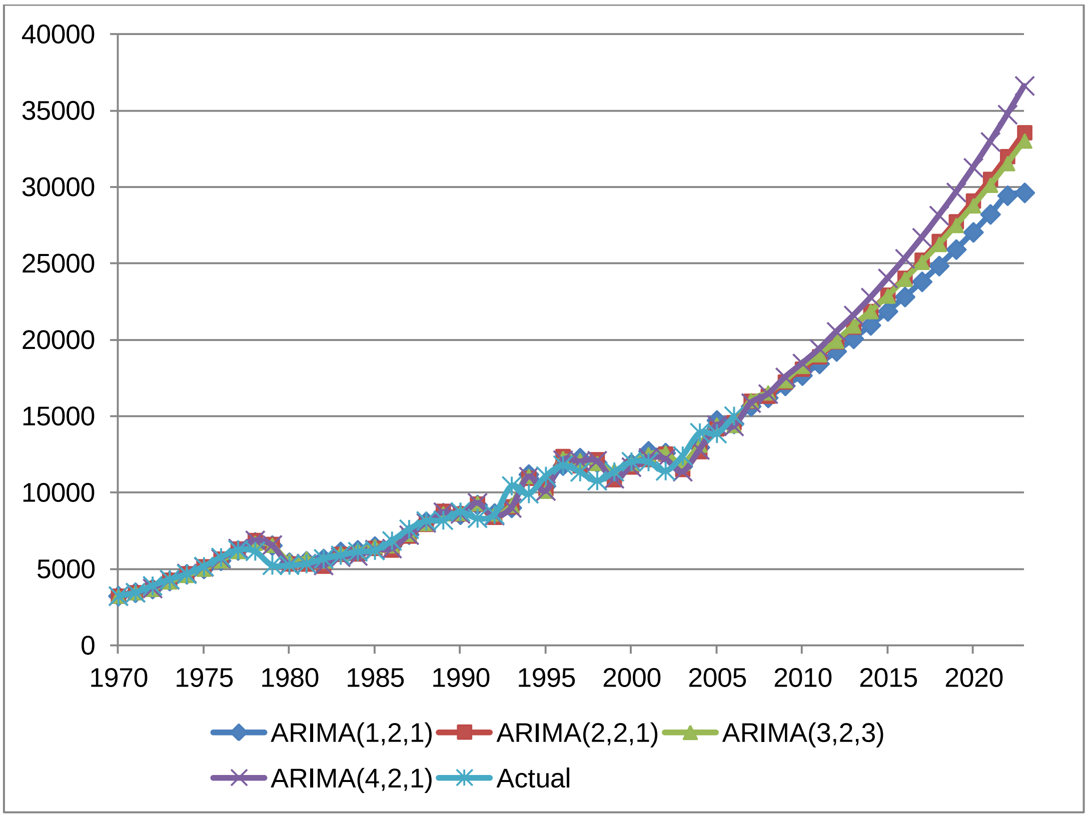

Figure 3.12: Transportation Forecast under Scenario 2

3.3.VECTOR AUTOREGRESSION (VAR) FORECAST:

The same two scenarios also are also forecasted by VAR methodology. We recall that the previous two methods (ARIMA and Decomposition) are the univariate methods. In other words, they forecast the future values based on their own past without adding other variables. On the contrary, VAR is a multivariate method. In VAR, new variables are added in order to obtain a forecast which is based on a theory. In this study, effects of sectoral GDP and aggregate GDP on sectoral energy consumption is investigated while the sectoral energy demand is obtained.

The existing studies that examined the relationship between energy consumption and GDP showed that countries with high GDP consumed more energy (Soytas and Sarı, 2003). Based on this knowledge, GDP's of each sector are added as a variable in VAR model. On the other hand, the total GDP is also added as a variable to the model considering the fact that aggregate GDP may provide a broader picture of the economic performance. Moreover, the sectoral GDP's are dependent to aggregate GDP. In other words, using only sectoral GDP's in the model can lead in inaccurate results because one sector's performance can be related to other sectors or factors. They justify the use of both sectoral and aggregate GDP's in the model.

The forecasts are obtained using the statistical software Eviews. Vector Error Correction Model (VECM) is used in order to eliminate all of the errors of the data such as autocorrelation, cointegration. First, the variables are created as a VAR model. Then this VAR model converted to a VECM. However, before applying this model it is necessary to determine an appropriate lag length in the VAR since the model is sensitive to the choice of the number of lagged terms.

Similar to previous sections, two different scenarios are considered. Tables given below document the estimation results of the VECM for the sectors for the scenarios.

3.3.1.Agriculture:

Table 3.18 gives the estimation results of the VECM of the agriculture sector for the scenario 1. The top part of the table indicates the cointegration tests that are applied during the error correction process. Moreover, the numbers within the brackets () and the square brackets [] specify the standard errors and t-statistics, respectively. GDP_AGR, SEC_AGR and GDPCAP refer to the agricultural GDP, the agricultural energy demand, and the GDP per capita, respectively. There are three different equations in the model and they are listed in a matrix form.

The appropriate lag length determined by the tests is 2 in agriculture sector. As the estimation output, Table 3.19 shows all 3 variables are lagged 2 times. When this model is solved for the years 2011 - 2023 the forecasted values are calculated. Figure depicts the forecast results for the Turkish agricultural sector.

Table 3.19: VECM for Agriculture - Scenario 1:

Cointegrating Eq:	CointEq1		
GDP_AGR(-1)	1.000000		
SEC_AGR(-1)	-1262511. (693801.) [-1.81970]		
GDPCAP(-1)	-2541714. (1007742) [-2.52219]		
C	-1.36E+10		
Error Correction:	D(GDP_AGR)	D(SEC_AGR)	D(GDPCAP)

CointEq1	-0.747482	1.26E-07	5.50E-08
	(0.27720)	(7.2E-08)	(3.9E-08)
	[-2.69651]	[1.75702]	[1.42636]
D(GDP_AGR(-1))	-0.142585	-1.34E-07	-2.42E-08
	(0.25080)	(6.5E-08)	(3.5E-08)
	[-0.56851]	[-2.06643]	[-0.69471]
D(GDP_AGR(-2))	0.172061	-4.45E-08	-6.56E-10
	(0.19061)	(4.9E-08)	(2.7E-08)
	[0.90269]	[-0.90213]	[-0.02475]
D(SEC_AGR(-1))	-330331.6	0.044974	-0.020486
	(717013.)	(0.18541)	(0.09970)
	[-0.46071]	[0.24257]	[-0.20548]
D(SEC_AGR(-2))	-527215.0	0.190587	0.057374
	(732033.)	(0.18929)	(0.10178)
	[-0.72021]	[1.00685]	[0.56368]
D(GDPCAP(-1))	-2894102.	0.673964	-0.120628
	(1281329)	(0.33133)	(0.17816)
	[-2.25867]	[2.03413]	[-0.67708]
D(GDPCAP(-2))	-799909.4	0.565944	-0.079404
	(1491617)	(0.38570)	(0.20740)
	[-0.53627]	[1.46730]	[-0.38286]
C	6.38E+08	56.57122	83.69239
	(2.3E+08)	(59.7776)	(32.1434)
	[2.76077]	[0.94636]	[2.60372]
R-squared	0.557613	0.259149	0.165640
Adj. R-squared	0.454389	0.086284	-0.029044
F-statistic	5.401991	1.499140	0.850814

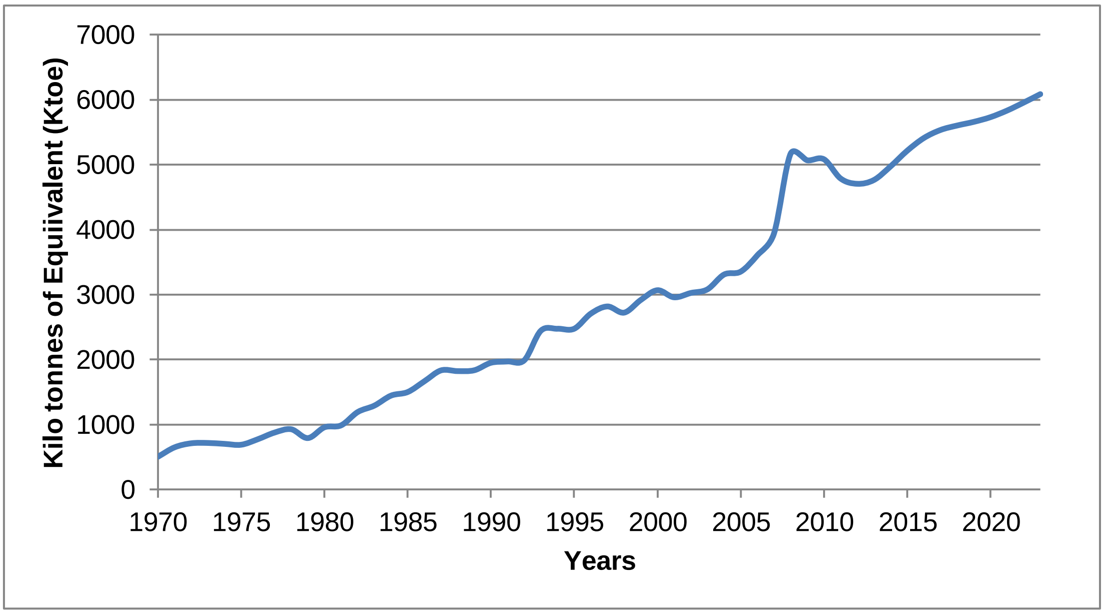

Figure 3.13: The agricultural energy demand changes predicted using the VAR method for the first scenario.

According to the results of Scenario 1, the effects of sudden increase in 2008 will no longer continue and the demand will decrease temporally below 5000 ktoe range, but start increasing again to 6000 ktoe level at 2023.

The estimation outputs for the Scenario 2 are given in Table 3.20. The appropriate lag length is determined as 1. If the VECM below is solved for 2023, the forecast results shown in Figure 3.14 are obtained. According to Figure 3.14, this scenario does not produce the temporal increase at 2008 and instead the agricultural demand continues linearly up to ~5200 ktoe by 2023.

Table 3.20: VECM for Agriculture - Scenario 2:

Cointegrating Eq:	CointEq1
SEC_AGR(-1)	1.000000
GDP_AGR(-1)	-5.09E-07 (1.4E-07) [-3.64467]

GDP(-1)	9.38E-09		
	(7.7E-09)		
	[1.21544]		
C	8591.565		

Error Correction:	D(SEC_AGR)	D(GDP_AGR)	D(GDP)
CointEq1	-0.185021	1102934.	-2602299.
	(0.06927)	(502183.)	(3526701)
	[-2.67098]	[2.19628]	[-0.73788]
D(SEC_AGR(-1))	-0.114986	-990186.9	17392430
	(0.16975)	(1230596)	(8642158)
	[-0.67740]	[-0.80464]	[2.01251]
D(GDP_AGR(-1))	-4.53E-08	-0.338295	-0.162817
	(2.6E-08)	(0.18794)	(1.31986)
	[-1.74878]	[-1.80001]	[-0.12336]
D(GDP(-1))	2.96E-09	-0.035792	-0.050222
	(3.6E-09)	(0.02580)	(0.18120)
	[0.83257]	[-1.38715]	[-0.27716]
C	100.4660	6.31E+08	4.58E+09
	(29.9458)	(2.2E+08)	(1.5E+09)
	[3.35493]	[2.90803]	[3.00609]
R-squared	0.220060	0.525021	0.135544
Adj. R-squared	0.119422	0.463734	0.024002
F-statistic	2.186660	8.566517	1.215179

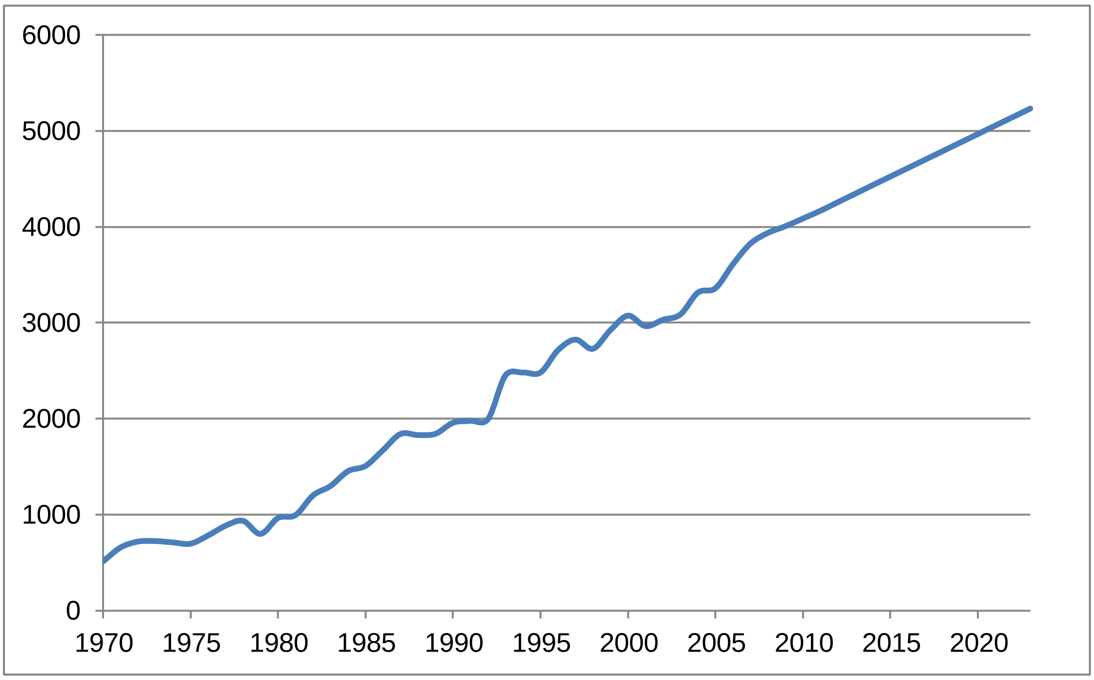

Figure 3.14: The agricultural energy demand changes predicted using the VAR method for the second scenario.

3.3.2.Industry:

Table 3.21 provides the estimation outputs of the VECM for the industrial sector. The lag length tests suggest the presence of 2 lags in the model. When the model is solved for 2023, the the forecast for the first scenario is shown in Figure 3.15. It indicates that the energy demand in industrial sector will increase to more than 35000 ktoe by 2023, however this increase is not a linear but comprises some fluctuations. As expected, effects of the economic crisis in 2008 are evident. According to results, there won't be any sudden changes in demand over next 13 years.

Table 3.21: VECM for Industry - Scenario 1:

Cointegrating Eq:	CointEq1	CointEq2	
GDP_IND(-1)	1.000000	0.000000	
SEC_IND(-1)	0.000000	1.000000	
GDPCAP(-1)	-40727518	-12.38691	
	(3707909)	(1.16497)	
	[-10.9840]	[-10.6328]	
C	6.05E+10	18754.89	
Error Correction:	**D(GDP_IND)**	**D(SEC_IND)**	**D(GDPCAP)**
CointEq1	-0.524345	-1.44E-07	-5.99E-09
	(0.21090)	(9.6E-08)	(5.7E-09)
	[-2.48618]	[-1.49183]	[-1.04292]
CointEq2	1356957.	0.299974	0.034286
	(704334.)	(0.32129)	(0.01920)
	[1.92658]	[0.93367]	[1.78617]
D(GDP_IND(-1))	-0.108168	-4.63E-08	1.74E-09
	(0.27867)	(1.3E-07)	(7.6E-09)
	[-0.38815]	[-0.36418]	[0.22851]
D(GDP_IND(-2))	0.758866	1.93E-08	1.44E-08
	(0.31094)	(1.4E-07)	(8.5E-09)
	[2.44057]	[0.13639]	[1.69954]
D(SEC_IND(-1))	-125890.8	-0.438506	-0.016419
	(759158.)	(0.34629)	(0.02069)
	[-0.16583]	[-1.26628]	[-0.79358]
D(SEC_IND(-2))	-1321828.	-0.407060	-0.049048
	(660239.)	(0.30117)	(0.01799)
	[-2.00204]	[-1.35159]	[-2.72586]
D(GDPCAP(-1))	-10432508	-1.796429	-0.096713
	(6971929)	(3.18029)	(0.19001)
	[-1.49636]	[-0.56486]	[-0.50900]
D(GDPCAP(-2))	-10062911	-3.912280	-0.029188
	(7148779)	(3.26096)	(0.19483)
	[-1.40764]	[-1.19973]	[-0.14982]
C	3.08E+09	1608.696	75.84658

	(9.5E+08)	(434.838)	(25.9795)
	[3.23216]	[3.69953]	[2.91948]
R-squared	0.335870	0.323523	0.311435
Adj. R-squared	0.152662	0.136909	0.121486
Sum sq. resids	4.35E+20	90486868	322992.6
S.E. equation	3.87E+09	1766.419	105.5352
F-statistic	1.833267	1.733645	1.639571

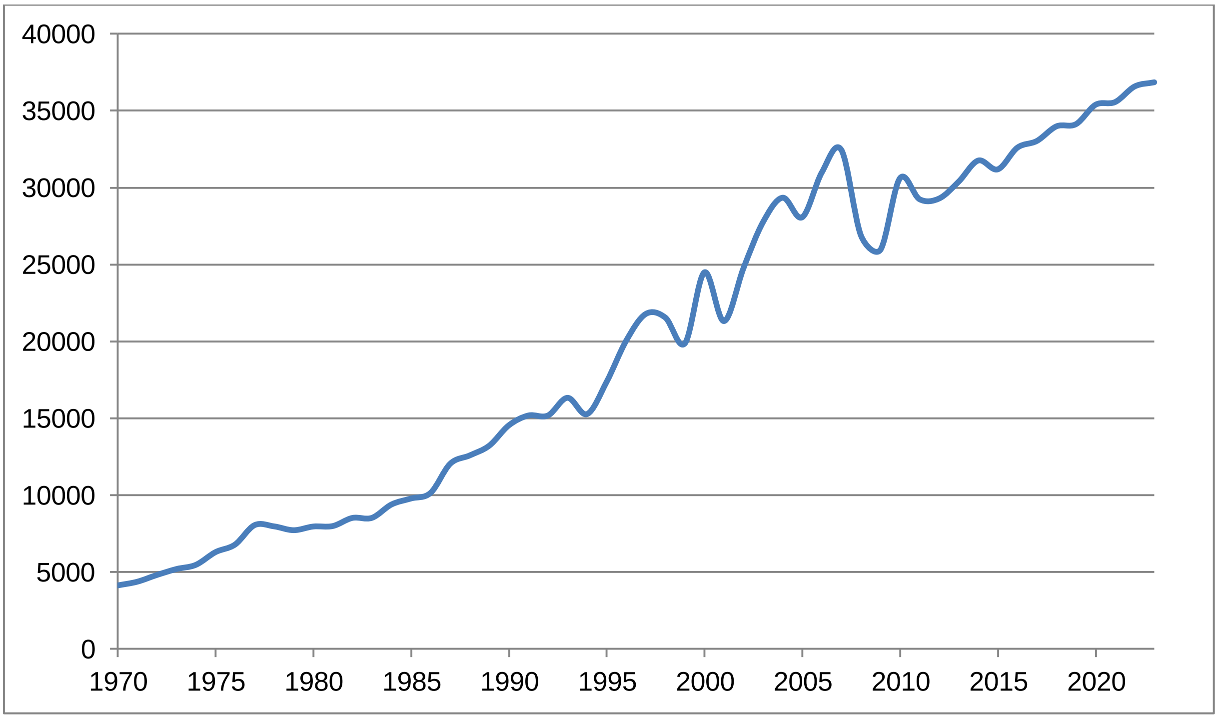

Figure 3.15: The industry sector energy demand changes predicted using the VAR method for the first scenario.

Furthermore, Table 3.22 provides the VECM estimations for Scenario 2. According to lag tests, appropriate lag length is 3 for this model. When this model is solved for the years 2011 - 2023 the forecasted changes are shown Figure 3.17 for the Turkish industrial sector. Figure 3.16 presents very interesting results for Scenario 2. and suggests that the demand will not constantly increase but experience large temporal increases and decreases at the interannual time scale. However, at the end, 2023, the demand will exceed the 45000 ktoe level which is roughly 10000 ktoe higher than the previous scenario.

Table 3.22: VECM for Industry - Scenario 2:

Cointegrating Eq:	CointEq1		
SEC_IND(-1)	1.000000		
GDP_IND(-1)	-4.12E-07		
	(6.2E-08)		
	[-6.63599]		
GDP(-1)	3.53E-08		
	(2.8E-08)		
	[1.27703]		
C	956.6654		
Error Correction:	**D(SEC_IND)**	**D(GDP_IND)**	**D(GDP)**
CointEq1	-0.337699	624496.0	-1726933.
	(0.30477)	(750112.)	(1139117)
	[-1.10805]	[0.83254]	[-1.51603]
D(SEC_IND(-1))	-0.638448	-1219469.	-1193481.
	(0.33575)	(826360.)	(1254906)
	[-1.90157]	[-1.47571]	[-0.95105]
D(SEC_IND(-2))	0.567860	835363.7	384791.3
	(0.43743)	(1076638)	(1634977)
	[1.29816]	[0.77590]	[0.23535]
D(SEC_IND(-3))	0.055406	-121717.4	2203911.
	(0.40888)	(1006362)	(1528257)
	[0.13551]	[-0.12095]	[1.44211]
D(GDP_IND(-1))	3.38E-08	0.505274	0.323343
	(1.4E-07)	(0.34107)	(0.51795)
	[0.24374]	[1.48142]	[0.62427]
D(GDP_IND(-2))	-4.26E-07	-0.195045	-0.622843
	(1.9E-07)	(0.46523)	(0.70649)
	[-2.25470]	[-0.41925]	[-0.88160]
D(GDP_IND(-3))	-2.21E-07	-0.087390	-1.398120
	(2.2E-07)	(0.53122)	(0.80671)
	[-1.02468]	[-0.16451]	[-1.73311]

D(GDP(-1))	5.03E-08	0.020434	-0.079626
	(5.4E-08)	(0.13241)	(0.20108)
	[0.93527]	[0.15433]	[-0.39600]
D(GDP(-2))	-3.72E-08	-0.101526	-0.057011
	(6.3E-08)	(0.15558)	(0.23626)
	[-0.58923]	[-0.65257]	[-0.24131]
D(GDP(-3))	2.00E-07	0.239523	0.661742
	(7.4E-08)	(0.18294)	(0.27781)
	[2.68514]	[1.30930]	[2.38200]
C	914.2335	1.43E+09	5.06E+09
	(591.555)	(1.5E+09)	(2.2E+09)
	[1.54548]	[0.97941]	[2.28858]
R-squared	0.467552	0.343926	0.461186
Adj. R-squared	0.225530	0.045710	0.216270
F-statistic	1.931858	1.153280	1.883039

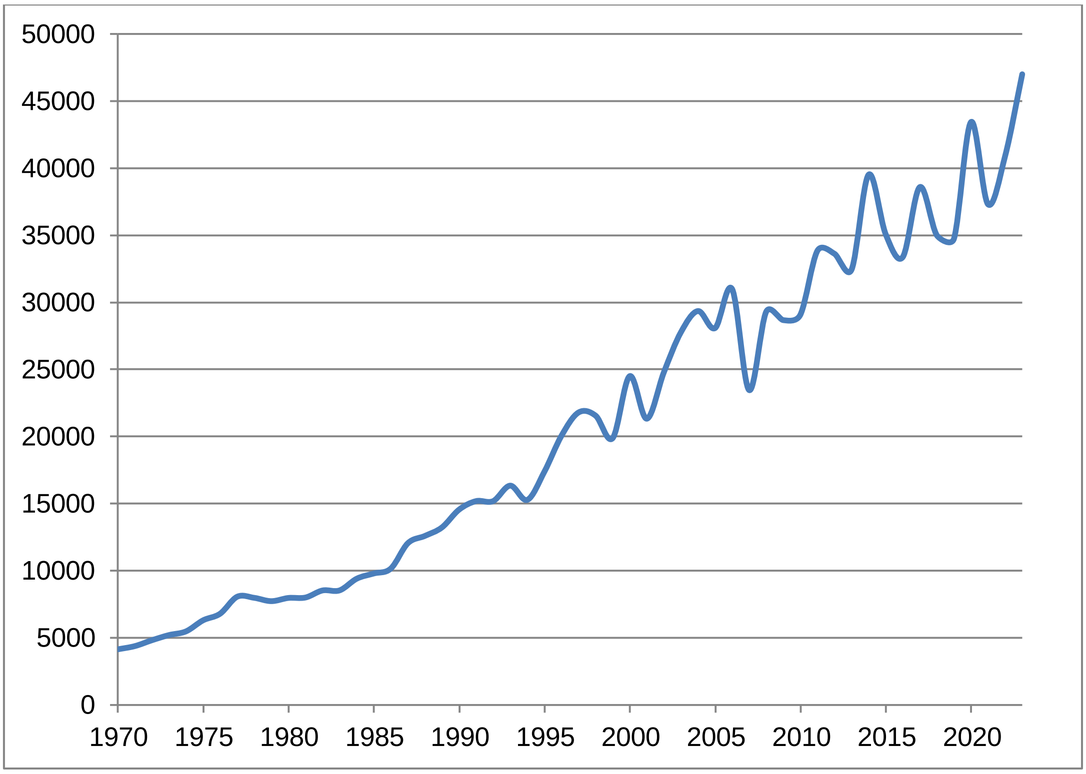

Figure 3.16: The industry sector energy demand changes predicted using the VAR method for the second scenario.

3.3.3.Transportation:

The only difference of the VAR method used for this sector is to exclude the sectoral GDP as a variable because the data we compiled did not include GDP values for the transportation sector's. Therefore, the GDP and GDP per capita is used instead of sectoral GDP. The estimation outputs of the VECM is given in Table 3.23 for the first scenario. The lag length tests indicate that there is only one lag in the model. As a result, a smaller model is obtained and resulted in the forecast for the first scenario as shown in Figure 3.17. The increasing trend in the demand curve at 2002 - 2007 period up to 17000 ktoe decreases to 15000 ktoe level at 2010. The demand is expected to increase gradually in a linear form afterwards. The energy demand will stay under 20000 ktoe level by 2023.

Table 3.23: VECM for Transportation - Scenario 1:

Cointegrating Eq:	CointEq1		
SEC_TRANS(-1)	1.000000		
GDP(-1)	-9.56E-08		
	(3.4E-08)		
	[-2.79061]		
GDPCAP(-1)	6.758525		
	(2.91840)		
	[2.31584]		
C	-15132.38		
Error Correction:	D(SEC_TRANS)	D(GDP)	D(GDPCAP)
CointEq1	-0.134739	916048.3	0.007688
	(0.06919)	(614469.)	(0.01113)
	[-1.94738]	[1.49080]	[0.69054]
D(SEC_TRANS(-1))	-0.067215	1701936.	0.033988
	(0.16453)	(1461196)	(0.02647)
	[-0.40852]	[1.16476]	[1.28383]
D(GDP(-1))	2.13E-07	-0.708195	-1.56E-08

	(1.1E-07)	(0.97489)	(1.8E-08)
	[1.94028]	[-0.72644]	[-0.88541]
D(GDPCAP(-1))	-9.592019	26215609	0.658014
	(5.83891)	(5.2E+07)	(0.93949)
	[-1.64278]	[0.50556]	[0.70039]
C	-202.9180	7.24E+09	98.09546
	(264.436)	(2.3E+09)	(42.5482)
	[-0.76736]	[3.08110]	[2.30552]
R-squared	0.161296	0.148391	0.088354
Adj. R-squared	0.062625	0.048202	-0.018898
F-statistic	1.634686	1.481111	0.823797

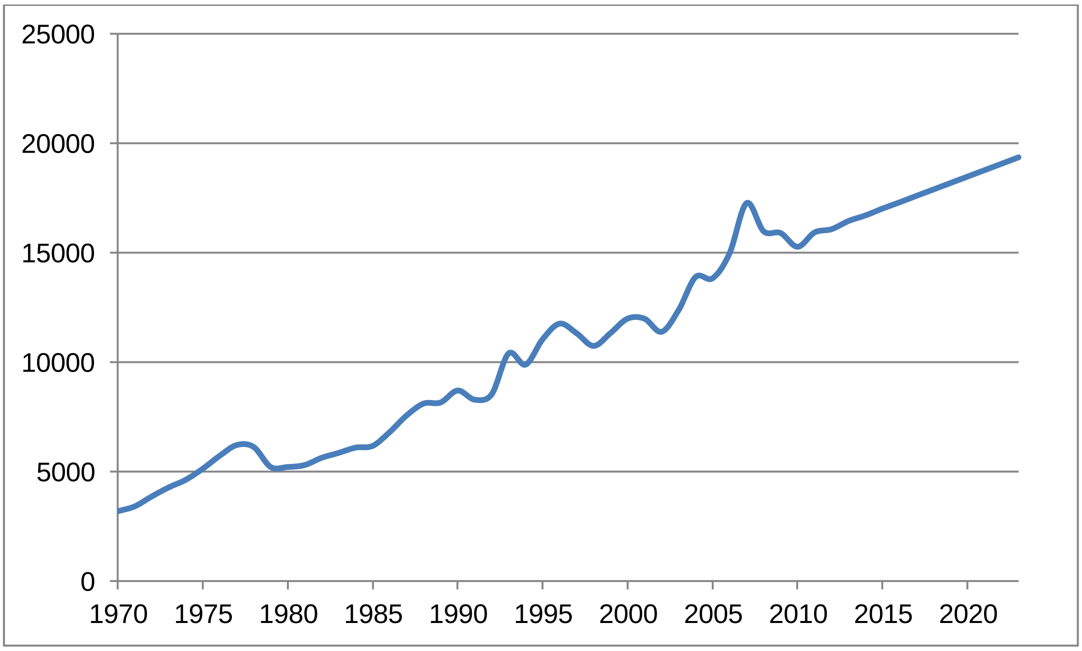

Figure 3.17: The transportation sector energy demand changes predicted using the VAR method for the first scenario.

On the other hand, the second scenario provides different results. The Table 3.24 below gives the estimation outputs for the Scenario 2. Lag length is decided by appropriate tests as 1. Figure 3.18 below provides the forecast. On contrary to the first scenario , there is no a temporal decrease in energy demand at the end of 2000's. The scenario removes the part where the energy demand is decreasing, and yields a more steep increase suggesting more demand that nearly reach at 25000 ktoe level. This is approximately 5000 ktoe larger than predicted by the first scenario.

Table 3.24: VECM for Transportation - Scenario 2:

Cointegrating Eq:	CointEq1		
SEC_TRANS(-1)	1.000000		
GDP(-1)	-5.33E-08		
	(3.0E-08)		
	[-1.75103]		
GDPCAP(-1)	3.870057		
	(2.42718)		
	[1.59447]		
C	-12047.01		
Error Correction:	D(SEC_TRANS)	D(GDP)	D(GDPCAP)
CointEq1	-0.090392	1457188.	0.017610
	(0.06683)	(585758.)	(0.01144)
	[-1.35263]	[2.48769]	[1.53868]
D(SEC_TRANS(-1))	0.035864	-801747.8	-0.006049
	(0.18896)	(1656315)	(0.03236)
	[0.18979]	[-0.48406]	[-0.18690]
D(GDP(-1))	2.04E-07	-1.479397	-2.89E-08
	(1.2E-07)	(1.01080)	(2.0E-08)
	[1.76533]	[-1.46359]	[-1.46317]
D(GDPCAP(-1))	-9.004681	62114620	1.268681
	(5.80035)	(5.1E+07)	(0.99337)
	[-1.55244]	[1.22172]	[1.27715]
C	-144.5222	9.24E+09	135.8123
	(278.086)	(2.4E+09)	(47.6251)
	[-0.51970]	[3.78936]	[2.85170]
R-squared	0.128964	0.217720	0.102784
Adj. R-squared	0.012826	0.113416	-0.016845
F-statistic	1.110437	2.087356	0.859188

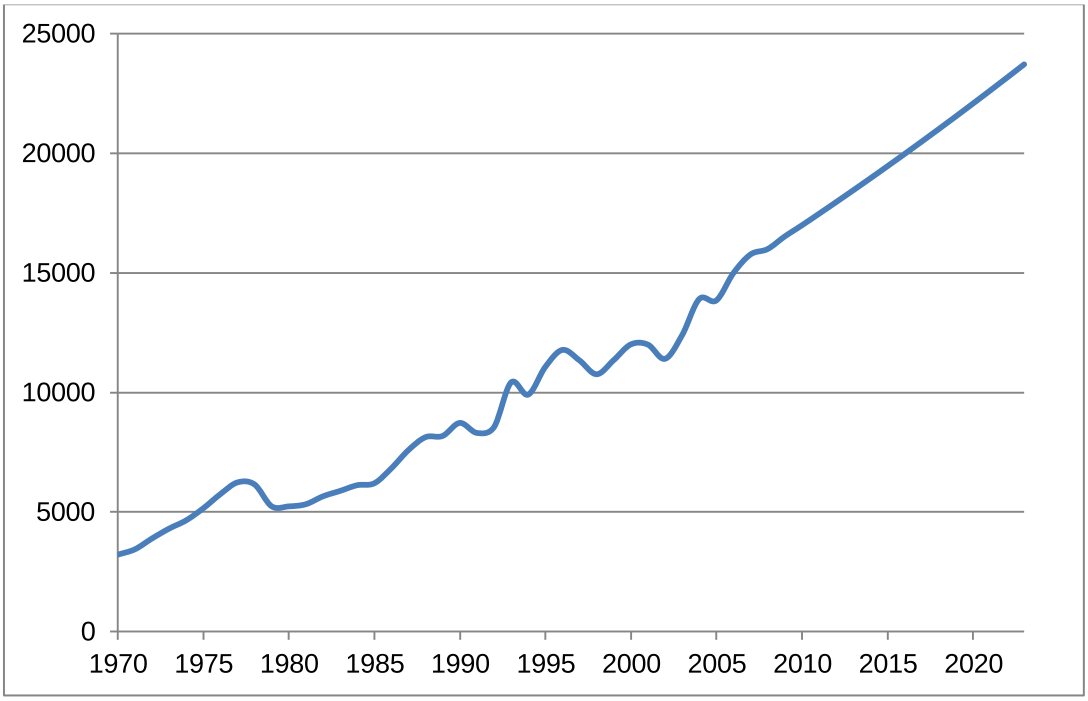

Figure 3.18: The transportation sector energy demand changes predicted using the VAR method for the second scenario.

3.3.4.Residence and Services:

Table 3.25 below provides the estimation outputs of the VECM. Lag length is decided as 3 by applying necessary lag tests for the first scenario. Therefore, the model obtained has more variables compared to other models. The results are provided in Figure 3.19 which shows that the energy demand will be on the 30000 ktoe level by 2020 and it represents almost the same level achieved at 2008 following the pronounced increasing trend starting by the early 2000's. However, the results indicate a gradual decrease to 27000 ktoe level during 2015 and a gradual increase to 31000 ktoe at 2023.

Table 3.25: VECM for Residence and Services - Scenario 1:

Cointegrating Eq:	CointEq1		
SEC_RS(-1)	1.000000		
GDP_SERV(-1)	3.73E-09		
	(1.9E-08)		
	[0.19391]		
GDPCAP(-1)	-6.759788		
	(1.20111)		
	[-5.62796]		
C	1763.955		
Error Correction:	**D(SEC_RS)**	**D(GDP_SERV)**	**D(GDPCAP)**
CointEq1	0.030981	-3935712.	0.013278
	(0.27338)	(1279051)	(0.03487)
	[0.11333]	[-3.07706]	[0.38078]
D(SEC_RS(-1))	-0.213237	3199906.	-0.061263
	(0.38161)	(1785442)	(0.04868)
	[-0.55879]	[1.79222]	[-1.25858]
D(SEC_RS(-2))	-0.392572	4275106.	0.026979
	(0.33870)	(1584680)	(0.04320)
	[-1.15906]	[2.69777]	[0.62448]
D(SEC_RS(-3))	-0.095799	144096.7	-0.007271
	(0.44218)	(2068856)	(0.05640)
	[-0.21665]	[0.06965]	[-0.12891]
D(GDP_SERV(-1))	6.04E-08	-0.393633	7.94E-09
	(4.8E-08)	(0.22441)	(6.1E-09)
	[1.25872]	[-1.75408]	[1.29792]
D(GDP_SERV(-2))	9.68E-08	-0.251160	-2.13E-09
	(5.8E-08)	(0.27200)	(7.4E-09)
	[1.66469]	[-0.92337]	[-0.28680]
D(GDP_SERV(-3))	4.64E-08	0.288903	6.78E-09
	(5.9E-08)	(0.27707)	(7.6E-09)
	[0.78385]	[1.04270]	[0.89801]
D(GDPCAP(-1))	-0.708813	-18563603	0.028660
	(2.08575)	(9758665)	(0.26605)
	[-0.33984]	[-1.90227]	[0.10773]

D(GDPCAP(-2))	2.260566	-25140488	-0.326202
	(1.87786)	(8786000)	(0.23953)
	[1.20380]	[-2.86143]	[-1.36183]
D(GDPCAP(-3))	2.037185	-12878960	0.121917
	(2.28075)	(1.1E+07)	(0.29092)
	[0.89321]	[-1.20691]	[0.41907]
C	-269.1004	5.77E+09	48.19861
	(367.011)	(1.7E+09)	(46.8143)
	[-0.73322]	[3.35808]	[1.02957]
R-squared	0.347584	0.466835	0.262684
Adj. R-squared	0.096654	0.261771	-0.020899
F-statistic	1.385185	2.276539	0.926302

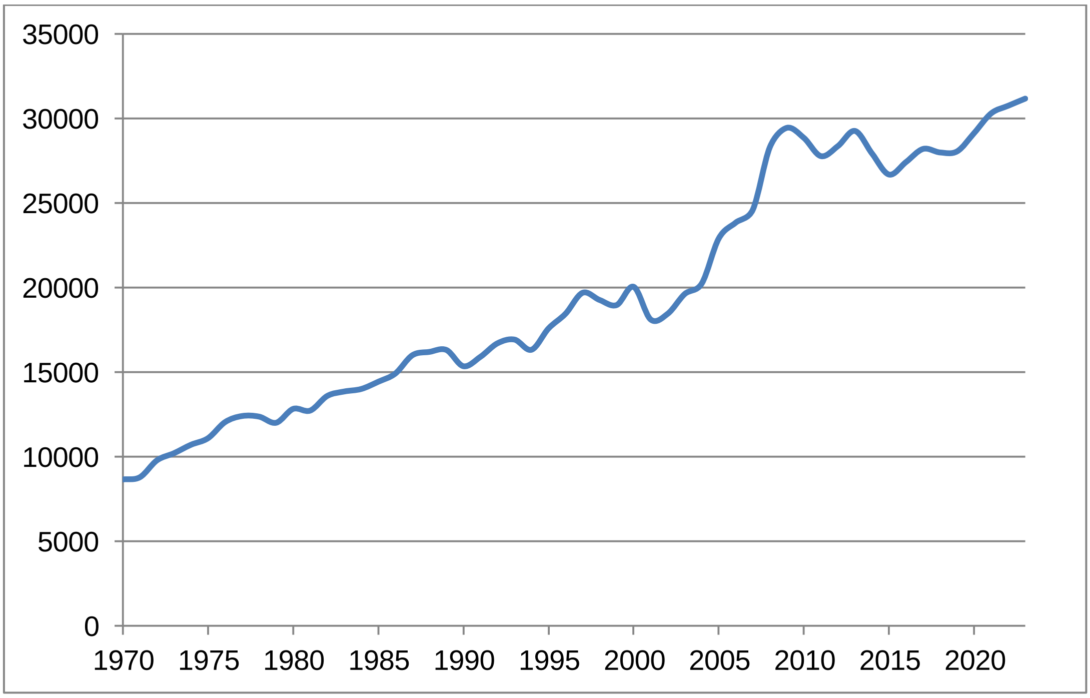

Figure 3.19: The residence and services sector energy demand changes predicted using the VAR method for the first scenario.

Conversely, as shown by Table 3.26 and Figure 3.20 the second scenario yields different results as compared to the previous scenario 1. Lag length is decided by appropriate tests as 1. This scenario instead suggests a continuous linear increase up to 42000 ktoe level by 2023. This is almost 10000 ktoe higher than what the first scenario suggested.

Table 3.26: VECM for Residence and Services - Scenario 2:

Cointegrating Eq:	CointEq1		
SEC_RS(-1)	1.000000		
GDP_SERV(-1)	-8.47E-08 (1.3E-07) [-0.64954]		
GDP(-1)	-8.46E-08 (9.6E-08) [-0.88571]		
C	2462.922		
Error Correction:	**D(SEC_RS)**	**D(GDP_SERV)**	**D(GDP)**
CointEq1	-0.073600 (0.03651) [-2.01609]	-849364.8 (166781.) [-5.09269]	-574168.0 (273430.) [-2.09987]
D(SEC_RS(-1))	0.276035 (0.25623) [1.07731]	3772639. (1170574) [3.22290]	394848.4 (1919101) [0.20575]
D(GDP_SERV(-1))	-2.22E-08 (4.6E-08) [-0.48193]	-0.563316 (0.21073) [-2.67313]	0.177992 (0.34549) [0.51519]
D(GDP(-1))	-7.30E-08 (2.9E-08) [-2.50748]	-0.302272 (0.13304) [-2.27207]	-0.230879 (0.21811) [-1.05855]
C	801.8590 (238.319) [3.36465]	6.80E+09 (1.1E+09) [6.24462]	6.07E+09 (1.8E+09) [3.40120]

R-squared	0.205267	0.484845	0.227624
Adj. R-squared	0.102721	0.418373	0.127962
F-statistic	2.001702	7.294005	2.283971

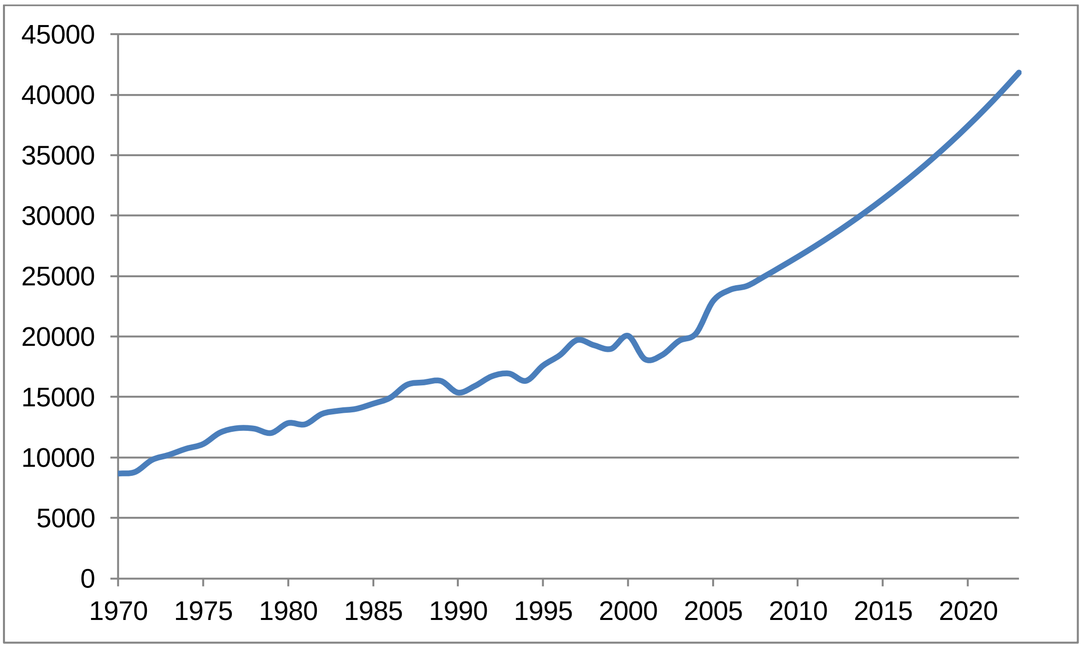

Figure 3.20: The residence and services sector energy demand changes predicted using the VAR method for the second scenario.

CHAPTER 4

DISCUSSION

As stated in Introduction, good and reliable forecasts on the future energy demand is crucial in developing energy strategies and for setting up right policies and regulations for a sustainable future in Turkey. In this context, the aim of this study is to forecast the future energy demand of Turkey in sectoral level. The present study extends previous ones that focused on the energy demand forecasting for the total level of energy demand without providing details on the sectoral levels. This is the first attempt to analyze and identify the future energy demand and supply of Turkey in sectoral levels using three alternative methods. In this regard, energy demands for the agriculture, industry, residence and services, and transportation sectors are forecasted for the next 10 years, up to 2023. Among three methods are used, the ARIMA and the Decomposition methods forecasted sectoral energy demands based on the data's own past and therefore they are uni-variate methods. On the other hand, the VAR multivariate method employes other independent variables such as the aggregate GDP and the sectoral GDP. Below, we discuss the findings of the energy demand forecasts according to the current sectoral policies, regulations and strategies by combining the individual forecasts to arrive at an "emsemble" forecast for each sector.

Combining the forecasts obtained by using two or more methods to produce a final forecast minimizes the effects of biases of the independent forecasts. Giving a particular weight to a specific forecasting method can be a way to reduce the bias. In the present study, the final forecast for each sector is obtained by combining the individual forecast provided by three methods with their pre-assigned weights. The weights are decided by a regression model in which the actual (observed energy demand) is used as the dependent variable and the forecasted values (fitted values) of the three methods as the independent variables. The regression model calculates the relationship between these variables and thus assigns the weights of the forecasting methods as their contributions to the ensemble forecast. By definition, the sum of these weight must be equal to unity, and it is confirmed by the computations. This procedure is applied to all four sectors, indicating that each sector may have different weights for the corresponding combined forecast. In most of the sectors, the VAR method acquired the highest weights which means that the VAR method provided the most accurate forecasts due to its multivariate character. On the other hand, the Decomposition method is generally used for the quarterly data for eliminating the seasonal effects. However, the seasonal contribution is already absent in our yearly data. Moreover, the ARIMA method is particularly successful and provides good results for relatively long time series with more than 50 data. Because our data contains 40 observations from 1970 to 2010, the ARIMA and the Decomposition methods give rise to smaller weights with respect to the VAR method. An alternative approach for combining forecasts is simply to take averages of all three forecasts. In this case, equal weights will be assumed for the forecasts.

4.1. Agriculture:

Agriculture was the most important sector for Turkish economy once. Its contribution to the Turkish GDP was about 43% in 1923. This rate decreased to 24% by 1980 because of setting the new economic strategies towards an open market economy. The agricultural employment that was over 70% before 1980 reduced to 30% at the begining of 2000s. Agriculture started to contribute lower to Turkish income and the farmers and employees moved to urban areas and started to work on the services sector. Now the imports of Turkish agriculture is higher than the exports. This economic transformation hindered a notable increase in the agricultural energy demand. However, after 2000s, Turkish government imposed the direct income supports in order to increase the domestic agricultural production and to reduce the imports. Moreover, rural development supports was also aiming at the restructuring of agricultural production policy. In the light of these, it can be stated that the energy demand in agriculture sector will increase as shown in Figure 4.1 by the combined forecast. This increase is almost linear at a rate 100 ktoe per year. As the figure states there is no big differences between the estimations, lthough the decomposition method forecasted a higher increase than the others. The following formula is used in combining forecasts. The VAR forecast has the biggest weight, and the ARIMA acquired a negative weight indicating that the ARIMA forecast was not accurate with respect to the other two models.

Combined Forecast = 0.944(Decomposition) -1.912(ARIMA) + 1.99(VAR)

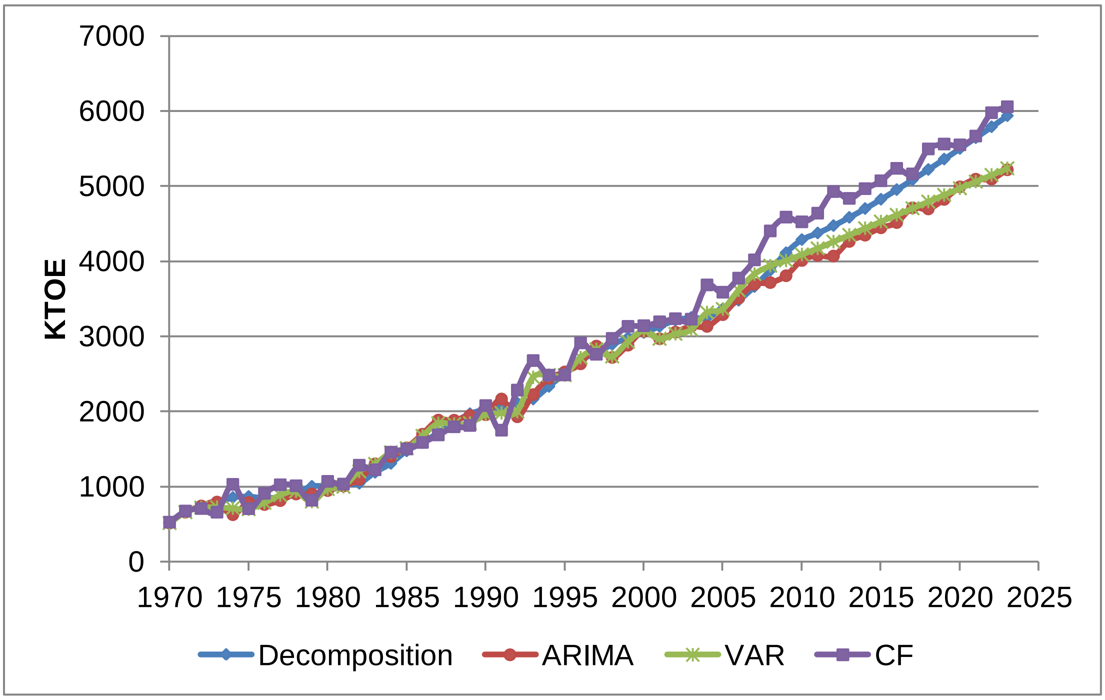

Figure 4.1: Combined Forecast result for the Agricultural Energy Demand

As the figure indicates, the energy demand is forecasted as 6000 ktoe in 2023. It is obvious that the sharp increase in 2008 is temporary and the demand will not continue to increase in that rate. Therefore, the first scenario is not taken account in the combined forecast. The second scenario is selected for all methods in the process of calculating the combined forecast.

Nevertheless, the forecast may vary and can be realistic if the agricultural conditions are affected by the extreme climatic and/or economic conditions. For example, floods or long droughts can affect negatively the agricultural production and hence the energy consumption.

4.2. Industry:

Throughout the five-year development plans implemented since 1963, "industry based growth" has been one of the main objectives of Turkey. However, the industrialization strategies adopted and economic policies followed have shown great differences before and after 1980. While an import substitution policy had been implemented until 1980, after 1980, significant efforts has been made towards establishing the principles and fundamentals of a open market economy by the introduction of export-oriented industrialization. The reforms made significant contribution to the adaptability to internal and external impacts and created a dynamism in economy. Considerable increases were recorded in the industrial value added, in the volume of exports and the share of manufacturing industry in exports. The share of industry in GDP reached 30% in 2000 and 29% in 2002 with respect its share around 25% in 1980.

Turkey set the main target of long-term industrial policies as to provide sustainable economic growth and to increase the competitiveness of the economy. Another objective is to increase the exports by improving competitiveness of the goods via a transitional phase from the labor intensive to the technology intensive production.

The policies and strategies indicates the investments will increase in industry and these technology based investments will also increase the energy demand. On the other hand, with the current growth rates of the Turkish economy, more energy will be needed in order to meet the growing industrial demand. In this respect, the combined industrial energy demand forecast suggest an increase to 37000 ktoe level at 2023. It suggests an increase of nearly 10000 ktoe within 13 years. Expecting much higher increase is not realistic under the current industrial policies and strategies, and there is no sign of any large boom in industry that needs more aggressive investment policies and effective regulations.

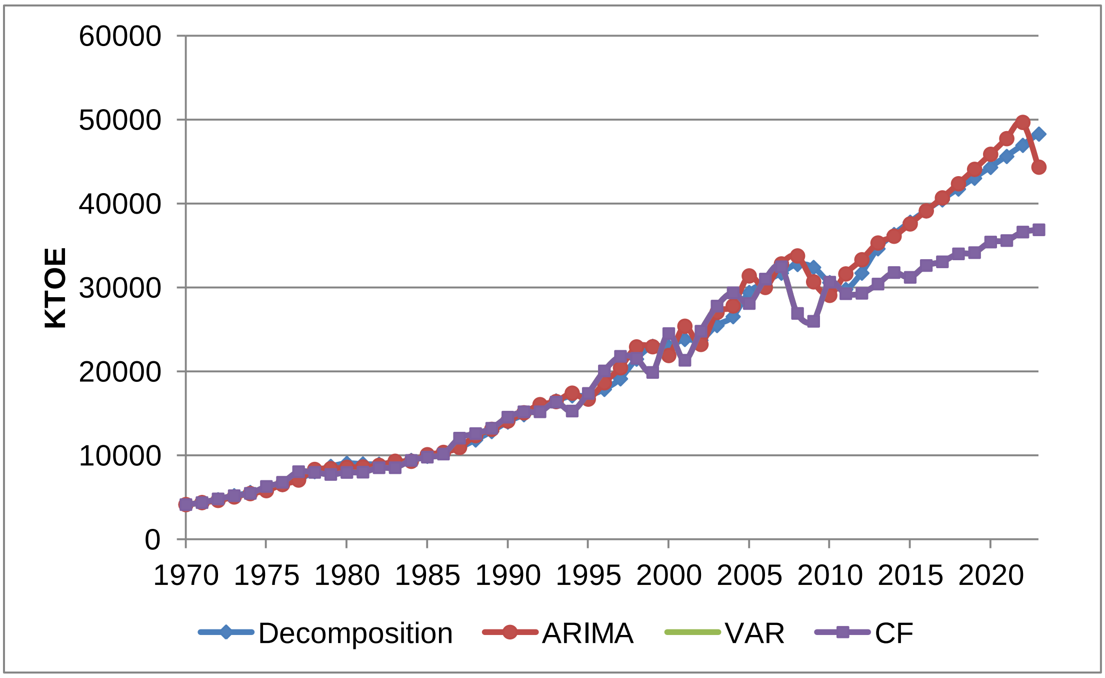

Figure 4.2: Combined Forecast Result of Industrial Energy Demand

The following formula is used for the combined forecast.

$$\text{Combined Forecast} = 0.018(\text{Decomposition}) + 0.053(\text{ARIMA}) + 0.93(\text{VAR})$$

The coefficient of VAR is close to unity which means VAR forecast is the most accurate one and has a better fit to the data, while the others have negligible contributions, as depicted in Figure 4.2 in which the Combined Forecast is almost identical with the one provided by the VAR method.

The second scenario in the forecasting process is not suitable for industry, since it eliminated the effects of economic crisis in 2008 by removing these particular years from the estimations. However, the industrial crisis in 2008 still affects the energy demand curve. Therefore in the process of obtaining the combined forecast, the scenario 1A from the Decomposition method, the scenario 1 from the VAR method and the scenario 1 under the ARIMA(3,2,1) are selected. The forecasts of ARIMA and Decomposition methods are close to each other and slightly higher that the VAR prediction.

Turkish economy experienced two major economic crisis during 2000s. Both crisis damaged the economic productivity and growth. Also, it reduced the energy consumption. The forecasts obtained in this study is expected to fail if such a crisis happens in the future.

4.3. Transportation:

Its geographical position puts Turkey in a very strategic position. Turkey is the bridge for carrying the goods and products between Europe and Middle East or Asia. This makes the transportation industry crucial for the economic development of the region. The Customs Union agreement between Turkey and EU in 1996 and potential EU membership are important opportunities encouraging new investments in the transportation industry.

Road transport is the major transportation type in Turkey. At present 95% of passengers and 90% of goods are conveyed by the highway transport (Export Promotion Center of Turkey, 2009). Still the investments are continuing in this area. İzmir - İstanbul highway is under construction and the government invests considerable amount of money for better road conditions.

Turkish railways is relatively old. However, the high-speed inter-city lines between Ankara-Istanbul, Ankara-Izmir and Istanbul-Bulgaria are under construction and the high-speed lines connecting Ankara-Konya and Ankara-Eskişehir are under the operation. The Marmaray (the Rail Tube Tunnel under Bosphorus in Istanbul) Project which has been under construction for several years is planned to finish at 2013.

Turkey has a competitive advantage in maritime transport since it is surrounded by the Mediterranean, the Aegean, and the Black Seas, together with the straits of the Dardanelles and the Bosphorus on its three sides. Marine transport is mostly handled by İstanbul, İzmit, Izmir, Mersin and Samsun ports.

Turkish airways sector is growing fast and the private enterprises are blooming in the market as more people started using the air transportation. There are 45 airports, 16 of which serve for the international flights. In addition, the construction of new airports are underway. Also, a reasonable budget is allocated for modernization of the current airports.

The transportation sector therefore appears to be important in Turkish economy. With the modernization of the existing facilities and new investments, the transportation sector may become even more strategic, and energy demanding. The combined energy demand curve shown in Figure 4.3 suggests an increase to 20000 ktoe by 2023. With the expected developments in the sector, the forecast can't be considered as high, and the Turkish transportation sector may have enough potential to exceed the 20000 ktoe consumption level after 2020.

In the process of combining forecasts the following weights are assigned and the following formula is used.

Combined Forecast = 0.028(Decomposition) + -0.000205(ARIMA) + 0.998(VAR)

The scenario 2A in the decomposition, the scenario 1 in the VAR and the scenario 1 and ARIMA(1,2,1) are used for combining this forecast. However, contributions of the decomposition and ARIMA forecasts are totally negligible and the ensemble forecast is controlled by the VAR method.

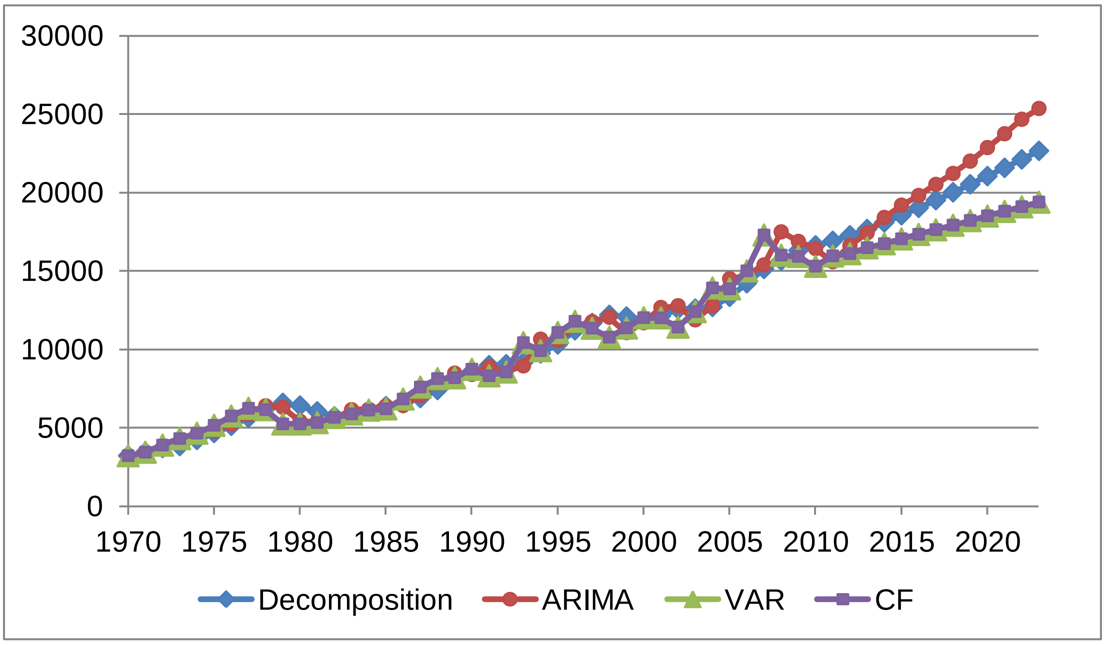

Figure 4.3: Combined Forecast Result of Transportation's Energy Demand

However, the unbalanced and complex political situation in Middle East due to the internal war in Syria, the conflicts between the central government in Iraq and the Northern Iraq Kurdish community, the US - Iran crisis, and the Turkey-Israel relations may be critical factors affecting the trade capacity of Turkey. They have a potential to introduce an indirect effect on the forecast of the transportation sector. Another important factor that may affect the future projections is the adoption of the fuel saving technologies and possibility of using energy efficient fuels and the electric motors. These developments may reduce the energy consumption; but when the next 13 years of the forecast period is considered, their effect is expected to be not high and should not introduce a major error in the forecast.

4.4. Residence and Services:

In the sectoral energy demand data that is provided by Turkish Energy and Natural Resources Ministry, the residence and services are taken into account together. The effects of population and technology is important for the residential energy demand. The population of Turkey is increasing constantly. More population means more consumers for the energy. Together with the technological advancements, the residential energy demand is increasing significantly as electrical tools are becoming more and more an indispensible part of our lives. They also consume significant amount of energy and increase the demand.

As a developing country, Turkey has been going through a wide-scale urbanization as a result of the rapid industrialization since 1950's. The increase in the population and migration from the rural to urban areas triggered rapid growth in the cities. Based on this, the real estate and the building construction emerged as a new industry. Today, the construction sector is one of the biggest contributors to the economical growth. At present, the new trend is the construction of smart buildings where everything is connected to electricity and thus more energy consumption. On the other hand, the green buildings that produce their own energy and are desinged for the lowest energy consumption are an emerging new field in the construction sector. For the moment, these buildings are expensive and it is not common in Turkey. To sum up, these new advancements in the construction technology are expected to regulate the energy demand in a complex way. For example, as the smart buildings will increase the energy consumption the green buildings will reduce the consumption. Moreover, The new urban renewal process imposed by the Turkish government plans to replace thousands of buildings with the modern ones. This transformation process implies a large energy consumption. It can be therefore concluded that the residential energy demand will continue to increase due to the new investments and consumers in the sector.

The service sector also consumes a major part of the energy in education, finance, tourism, communications, health care, utilities, wholesale and retail trade as they are the biggest contributors to Turkey's GDP. The investments are increasing notably in these fields. The tourism sector has been one of the most important drivers behind Turkey’s economic development over recent decades. In 2009, combined with the travel sector, the industry generated TL 95.3 billion of economic activity (approximately 10.2% of Turkey’s GDP). The Ministry of Culture and Tourism has issued the “Tourism Strategy for Turkey – 2023” to set a framework and roadmap for investors considering investment in Turkey. Within this framework, the government wishes to make maximum use of the country’s tourism potential and provides various forms of support.

All these investments imply more energy consumption and thus an increasing energy demand. Figure 4.4 below provides the results of the combined forecast together with the individual contributions from the scenario 2B of the decomposition method, the scenario 1 of the ARIMA(2,2,2) method and the scenario 2 from the VAR method. The combined forecast implies a linear trend of increase as in the other sectors at an approximate rate of 1000 ktoe per year. The weights of three methods contributing to in the combined forecast is given by

$$\text{Combined Forecast} = -0.44(\text{Decomposition}) + 0.77(\text{ARIMA}) + 0.686(\text{VAR}).$$

It suggests that the decomposition method provided an adverse contribution to the combined forecast. This contribution is mostly compensated by the ARIMA forecast, leaving the VAR method for the main contributor.

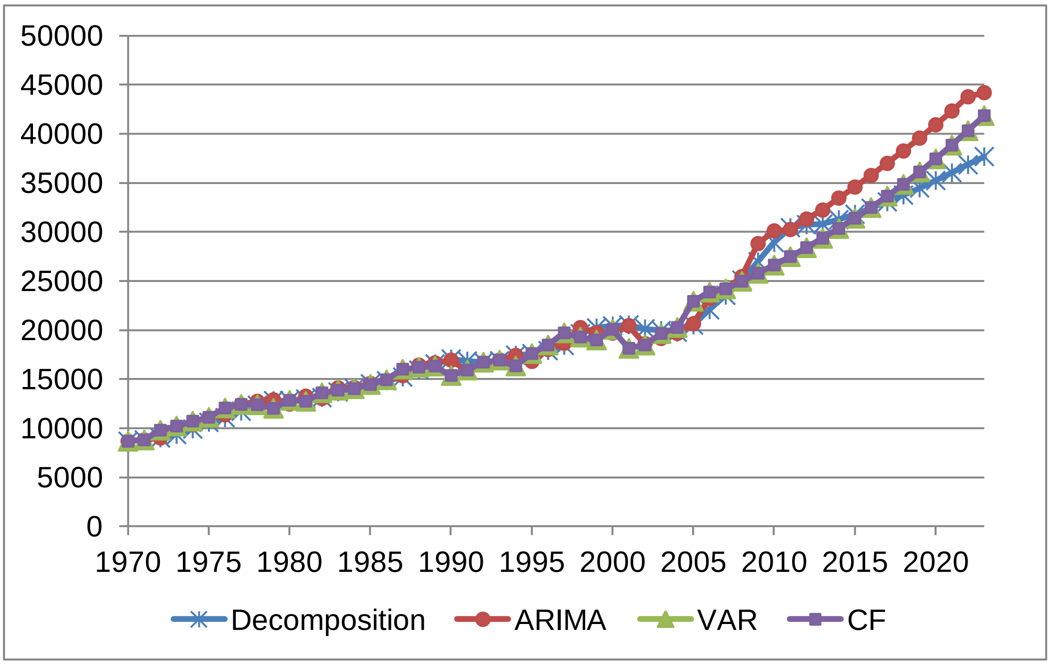

Figure 4.4: Combined Forecast Result of Residence and Services Energy Demand

CHAPTER 5

CONCLUSIONS

Energy is one of the most critical commodities in today's world. Countries' international relations and strategies are based on the energy benefits and it is very important to set sustainable development policies based on effective energy consumption and production strategies. In this regard, countries give importance to energy forecasts in order to foresee their likely future energy demands. Investing on the renewable energy sources can also be a way to avoid the import dependency, to support economic growth, and to reduce unemployment. European Union adopted targets and strategies for 2020 in order to increase the share of renewable energy sources in energy demand and to reduce the carbon emissions. Consistently with this strategy, European countries started to increase the investments on renewable energy. For example, Sweden currently meets 47.9% of its energy by renewable sources and invests considerable efforts for developing alternative renewable sources, such as using ethanol as an alternative source of energy. Even although Spain is facing economic crisis, its investments in renewable energy continues to increase its share to 20% by 2020 in consistent with the EU Targets. In this regard, countries set policies and strategies in order to increase the share of renewable sources in energy consumption.

In Turkey, the nuclear energy is considered as a solution to meet the growing domestic energy demand. Nuclear energy is often identified by energy experts to be an ideal "base supply" to provide for non-instantaneous electricity demand. On the other hand, it is not the most cost efficient and sustainable means to provide electricity. In addition, there are many concerns about nuclear energy due to the disastrous accidents that happen from time to time, the last example being the Fukushima accident following the local earthquake on 11 March 2011. Carefully planned and systematic investments on different renewable energy sources such as solar, wind and geothermal energies can help to decrease Turkey's import dependency just as well as the nuclear option, and contribute to a healthier and safer sustainable development. It can also contribute to the economic growth and creation of new job opportunities. Sectoral energy demand forecasts can be used to develop more informed strategies on such energy investments in Turkey. This study thus attempted to forecast the sectoral energy demand of Turkey as an elaboration to the existing non-sectoral or integrated estimations. Agriculture, industry, residence and services and transportation were selected as the sectors to be studied for the energy demand forecasts up to the year 2023.

The forecasts were performed by three different methods including the decomposition, the ARIMA and the VAR, and their product were then combined to arrive at a composite, or ensemble forecast. While the former two methods are based on the univariate approach, the VAR employs a multivariate approach by considering the sectoral GDP and total GDP as additional independent variables. The forecasts were obtained under two different scenarios. The first scenario uses the entire, unedited data, whereas the second scenario eliminates last 3 years of the data to remove the effects of sudden changes observed in the most recent years.

The results suggested an increase in the energy demand for all sectors, as expected and shown in Figure 5.1. The demand in agriculture sector is the lowest and does not exceed the 6000 ktoe level. The forecast can be considered as realistic. However, it may vary if the agricultural conditions are affected by the extreme climatic and/or economic conditions. Transportation sector's energy demand will be around 20000 ktoe. With the expected developments in the sector, the forecast can't be considered as high, and the Turkish transportation sector will have enough potential to consume more than 20000 ktoe after 2020. On the other hand, the energy demand on residence and services will reach at 46000 ktoe. This number may be even higher because of the fast growing capacity of this sector. The industry sector will have a demand around 36000 ktoe by the year 2023. Expecting much higher increase in energy demand is not realistic under current industrial policies and strategies, and there is no sign of any large boom in industry that needs more aggressive investment policies and effective regulations.

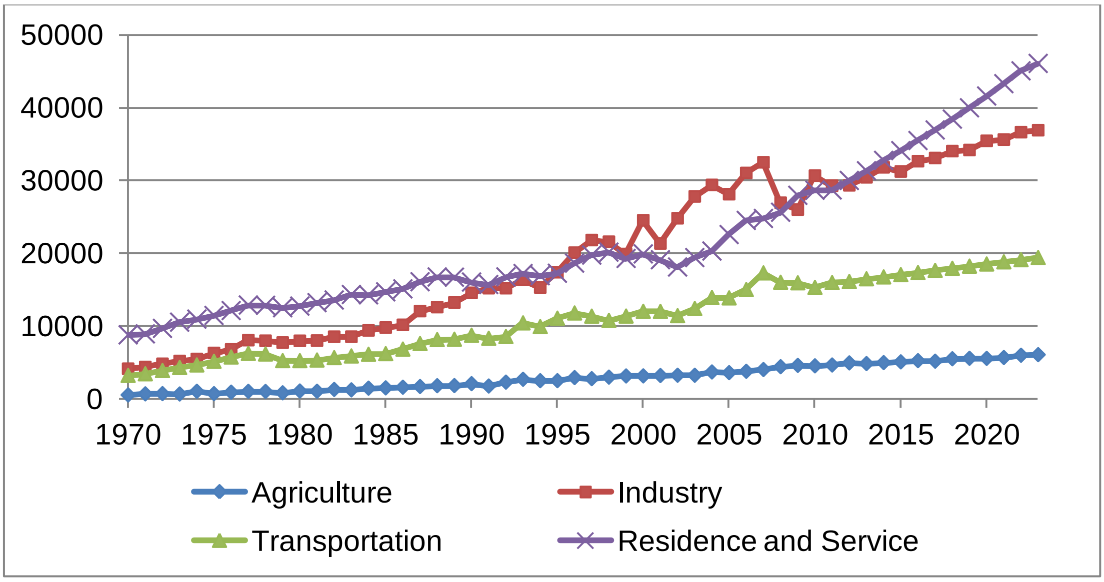

Figure 5.1: Combined energy demand forecasts of all sectors

The forecasts reveal an increase of energy demand in all the sectors in response to population increase and the current rate of economical development. However, Turkey produces only 29% of the energy consumed. The rest is imported from other suppliers. The official strategy papers and reports clearly state the sustainable development of Turkey as the main target. The import dependency of the energy however conflicts with this target, and demands development of new policies and strategies. For example, the sector with the steepest energy demand slope is the industry, where most of the energy-consuming activity occurs during day time when the solar resource is available. If new industry establishments are encouraged and supported to invest in local PV farms, this policy can potentially enrich efficient distributed energy generation and decrease the demand on inefficient electricity distribution across long distances. Similarly the second steepest demand belongs to the residential and services sector, where most of the demand is typically in the mornings, evenings and weekends. Local wind farms can be encouraged for such areas. On the other hand, the agricultural energy consumption of Turkey is the least to worry due to its low capacity as compared to the other sectors. Nevertheless, new investments on agriculture machinery in order to increase the production efficiency can cause some additional energy demand. Demand-side management approaches can be taken aggressively to balance energy demands across different sectors wisely, and effectively provide for the same demand with less supply. Many such policy examples can be provided for the beneficial application of the sectoral energy forecasts provided in this thesis.

In conclusion, a new composite method has been utilized for the first time in this thesis toward accurately forecasting the energy demand in Turkey until 2023. Based on this analysis, energy demand will increase in all sectors of Turkey, but at a higher rate in some sectors compared to others. With the high energy import dependency, sector specific sustainable energy strategies and plans become more important. Informed investments in renewable or domestic energy sources and advanced demand-side management strategies are enabled as a result of the forecasts delivered in this thesis.

CHAPTER 6

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