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ARIMA forecasting of primary energy demand by fuel in Turkey ☆

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Abstract

Forecasting of energy demand in emerging markets is one of the most important policy tools used by the decision makers all over the world. In Turkey, most of the early studies used include various forms of econometric modeling. However, since the estimated economic and demographic parameters usually deviate from the realizations, time-series forecasting appears to give better results. In this study, we used the Autoregressive Integrated Moving Average (ARIMA) and seasonal ARIMA (SARIMA) methods to estimate the future primary energy demand of Turkey from 2005 to 2020. The ARIMA forecasting of the total primary energy demand appears to be more reliable than the summation of the individual forecasts. The results have shown that the average annual growth rates of individual energy sources and total primary energy will decrease in all cases except wood and animal–plant remains which will have negative growth rates. The decrease in the rate of energy demand may be interpreted that the energy intensity peak will be achieved in the coming decades. Another interpretation is that any decrease in energy demand will slow down the economic growth during the forecasted period. Rates of changes and reserves in the fossil fuels indicate that inter-fuel substitution should be made leading to a best mix of the country's energy system. Based on our findings we proposed some policy recommendations.

Keywords: Primary energy demand; ARIMA forecasting; Turkey

1. Introduction

Energy demand forecasting is one of the most important policy tools used by the decision makers all over the world. This is true especially for energy emerging markets such as Turkey. Ediger (2003a) has shown that, although a medium consumer, Turkey's primary energy demand has grown rapidly during 1989–1999 and is expected to continue in the future. Turkey will certainly play a significant role in the world's energy sector during the first decades of the 21st century.

Similar to most countries forecasting is particulary carried out for demand side of the energy system in Turkey. Forecasting future energy production of the country is taken into consideration in publications such as Hepbaşlı et al. (2002), Öztürk et al. (2004), Öztürk and Hepbaşlı (2004), Ceylan et al. (2005a, b), and Ediger et al. (in press). Recently, in Ediger et al. (in press), we developed a decision support system for forecasting fossil fuel production by applying regression, Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving Average (SARIMA) methods to the historical data from 1950 to 2003 in a comparative manner. The method proposed in that study integrated the models obtained from each method by using some decision parameters related to goodness-of-fit or confidence interval, behavior of the curve, and reserves.

The studies on energy demand forecasting in Turkey dates back to 1960s. The tradition of energy forecasting by using simple regression techniques was initiated by the State Planning Organization (SPO). Similar studies later have been continued by the Ministry of Energy and Natural Resources of Turkey (MENR) and a number of academicians. These early forecasts consistently predicted much higher values than the consumptions that actually occurred. Later, starting from 1984, several econometric

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Table 1
Studies on forecasting energy demand in Turkey between 2002 and present

Reference	Method used	Data used	Forecasting for	Forecasted Years
Ediger and Tatlıdil (2002)	Winters' exponential smoothing method and cycle analysis	1950–1999	Primary energy demand	2000–2010
Sarak and Satman (2003)	Modeling based on degree-day (DD) concept	1990–1997	Natural gas demand by residential heating in Turkey	2000, 2005, 2010, 2015, 2020, 2023
Yumurtacı and Asmaz (2004)	Linear regression	1980–2002	Electricity demand of Turkey	2003–2050
Görücü and Gümrah (2004)	Multivariable regression model	1991–2001	Gas consumption for Ankara	2002 and 2005
Aras and Aras (2004)	First order autoregressive time series model	1996–2001	Natural Gas demand of Eskişehir	Model is established
Canyurt et al. (2004)	Genetic algorithm energy demand model (GAEDM)	1970–2001	Energy demand of Turkey	2002–2025
Ceylan and Öztürk (2004)	Genetic algorithm energy demand model (GAEDM)	1970–2001	Energy demand of Turkey	2002–2025
Öztürk et al. (2004)	Genetic algorithm exergy consumption (GAPEX)	1990–2000	Petroleum exergy demand	2001–2020
Haldenbilen and Ceylan (2005)	Genetic algorithm transport energy demand estimation (GATEDE)	1970–2000	Transport energy demand of Turkey	2001–2020
Ceylan et al. (2005a, b)	Genetic algorithm energy (GAEN) and exergy (GAEX) estimating models.	1990–2000	Energy and exergy consumption of Turkey	2001–2020
Görücü et al. (2004)	Artificial neural network (ANN)	1998–2001	Gas consumption for Ankara	2002 and 2005
Sözen et al. (2005)	Artificial neural-network (ANN)	1975–2003	Net energy consumption (NEC) of Turkey	Model is established

modeling techniques have been employed. Among them, the Model for Analysis of Energy Demand (MAED), which was used in energy planning and policy making by MENR, has been the most commonly applied one.

Ediger and Tatlıdil (2002) proposed a new technique of analyzing the cyclic patterns in the time-series data of annual additional amounts of energy consumption and compared the results with those of the Winters' exponential smoothing method. The paper also includes a comprehensive review and comparison of all previous energy demand forecasts done in Turkey.

Since Ediger and Tatlıdil (2002), various techniques have been applied in energy demand forecasting of Turkey, such as degree-day, linear and multivariate regression, autoregression, genetic algorithm, and artificial neural network (Table 1). Sarak and Satman (2003) modeled the natural gas demand for residential heating in Turkey based on degree-day (DD) concept, which was first applied by Durmayaz et al. (2000) and Gümrah et al. (2001) in Turkey. Later in 2004, linear regression, multivariable regression, and first-order autoregressive time series modeling were used by Yumurtacı and Asmaz (2004), Görücü and Gümrah (2004), and Aras and Aras (2004), respectively. Again in the year 2004, genetic algorithm model approach began to be used for forecasting energy and exergy consumptions by various authors such as Canyurt et al. (2004), Ceylan and Öztürk (2004), and Öztürk et al. (2004). In 2005, several versions of this methodology such as Genetic Algorithm Transport Energy Demand Estimation (GATEDE), Genetic Algorithm Energy (GAEN), Genetic Algorithm Exergy (GAEX) have been developed by Haldenbilen and Ceylan (2005) and Ceylan et al. (2005a, b). Finally, artificial neural-network (ANN) technique is used for energy demand forecasting by Görücü et al. (2004) and Sözen et al. (2005). A summary of the methods and data used and forecasting period in these studies are given in Table 1.

Among these studies, only four of them are associated with the primary energy demand in addition to Ediger and Tatlıdil (2002). Ceylan and Öztürk (2004), Canyurt et al. (2004), and Ceylan et al. (2005b) used genetic algorithm method whereas Sözen et al. (2005) used artificial neural network. Ceylan and Öztürk (2004) used three scenarios. Scenario 1 (GNP and population growth rates are taken as 5% and 0.12%, respectively) and Scenario 2 (GNP and population growth rates are taken as 4% and 0.14%, respectively) employ genetic algorithm in the form of linear and exponential whereas Scenario 3 employs polynomial curve fitting. Canyurt et al. (2004) used 5% of GDP growth rate and 0.12% population growth rate in two forms of non-linear equations such as exponential and quadratic. Ceylan et al. (2005b) used three forms of genetic algorithm methods such as linear, exponential, and mix. They accepted GDP growth rate as 5% and average annual population growth rate as 0.18%. Finally, Sözen et al. (2005) used artificial neural network in which economic, demographic, and energy data from 1975 to 2003 are used in two different methods to train the neural network.

As it is seen here most of these studies used various forms of econometric modeling. However, Ediger and

Tatlıdil (2002) has demonstrated clearly that the estimated economic and demographic parameters usually deviate from the realizations. For instance, GDP growth rates that are used in MAED applications are traditionally estimated much higher than actually realized. For the periods between 1985 and 1990, 1990 and 1995, and 1995 and 2000 years, MAED used the GNP growth rates of 6.0–7.0%, 7.0–8.0% and 7.0–7.5% in 1986; 6.4%, 6.8%, and 6.2% in 1990; and 5.7%, 4.8%, and 6.0% in 1994, respectively. But the realizations for the same periods have been around 4%, 3%, and 4%, respectively.

Besides, the relationship between energy consumption and economic development in Turkey has not been clearly demonstrated yet (Ediger, 2004). Although an almost linear relationship exists between primary energy consumption and total GDP of Turkey during 1980–2000, the historical development of energy consumption and economic production demonstrates frequent fluctuations, evolving in a cyclic pattern (Ediger and Huvaz, 2006).

Reexamining the causal relationship between GDP, energy consumption, and employment, Soytaş and Sarı (2003) and Sarı and Soytaş (2004) suggested that the causality runs from energy consumption to GDP in Turkey. This indicates that in the long run decreasing energy consumption may harm economic growth in Turkey. However, others argued that there is no evidence of causality between energy consumption and GDP in Turkey (Altınay and Karagöl, 2004) and that consumption of different energy sources may have different effects on income in Turkey (Sarı and Soytaş, 2004).

In this study, we aimed at forecasting primary energy demand in Turkey by using trend fitting based on historical time-series. We used the ARIMA technique for this purpose. The consumption data for hard coal, lignite, asphaltite, petrocoke, wood, animal and plant remains, oil, natural gas, hydropower, geothermal heat and electricity, and solar cover the period between 1950 and 2004. One other important energy source, wind energy, is not taken into consideration since its time series data is not sufficient to apply ARIMA. The 1950–1969 data is obtained from WEC TNC (World Energy Council Turkish National Committee) (1990, Table VII.8 on p. 113), the 1970–2002 data from WEC TNC (2002, Table V.8 on p. 73) and the 2003–2004 data from MENR. The methodology will be discussed in the following section. In Section 3, the results will be discussed and compared with the previous studies. The final section includes the conclusions together with recommendations to the future studies and to the policy-makers.

2. Methodology

In this study we used the ARIMA technique to estimate the future primary energy demand of Turkey. For this the method is applied for time series data of each item and total primary energy, including hard coal, lignite, asphaltite, petrocoke, wood, animal and plant remains, oil, natural gas, hydropower, geothermal heat and electricity, and solar.

The ARIMA, which is one of the most popular models for time series forecasting analysis, has been originated from the autoregressive model (AR), the moving average model (MA) and the combination of the AR and MA, the ARMA models (Blanchard and Desrochers, 1984; Brown et al., 1984; Kamal and Jafri, 1997; Ho and Xie, 1998; Saab et al., 2001; Zhang, 2001; Ho et al., 2002). The ARIMA model can be used when the time series is stationary and there is no missing data in the within the time series. In the ARIMA analysis, an identified underlying process is generated based on observations to a time series for generating a good model that shows the process-generating mechanism precisely (Box and Jenkins, 1976). The ARIMA technique includes identification (Abdel-Aal and Al Garni, 1997; Chavez et al., 1999; Zhang, 2001), estimation (Abdel-Aal and Al Garni, 1997), and diagnostic checking (Abdel-Aal and Al Garni, 1997; Zhang, 2001; Brockwell and Davis, 2002). A good summary of the ARIMA method can be found in Ediger et al. (in press).

MINITAB statistical software package is used to establish the ARIMA model. To start applying ARIMA model, first autocorrelation (acf) and partial autocorrelation (pacf) functions should be determined. Moreover, acf and pacf provide a statistical summary at a particular lag. The maximum number of lags is determined simply by dividing the number of observations by 4, for a series with less than 240 based on Box and Jenkins method. Since the number of observations in this study is 55, the lag number is calculated as 14. Autocorrelation and partial autocortrelation graphs, which provides information about the AR and MA orders, are then drawn based on the specified lag numbers. Autoregressive (AR) process order is determined from the partial autocorrelation graph and similarly MA process order is determined from the autocorrelation graph.

The ARIMA procedure fits a model with a certain number of parameters and tests for the significance of the parameters. This means that it tests if the parameters are zero (null hypothesis, H_0) or different from zero (alternative hypothesis, H_a). Two statistics to test are conducted to test the significance of the parameters considered in the model which are T-statistics and P-value. The T statistic is not very informative by itself, but is used to determine the P-value. P-value is determined automatically by the software as 0.05 a-level corresponding 95% of confidence interval. If the P-value is less than this value, H_0 is rejected.

In the case where seasonal components are included in the ARIMA model, the model is called as the SARIMA. The seasonal components are determined where the autocorrelation functions cut the confidence limits. In this study, different SARIMA models are applied to each item for various seasonal components ranging from order 1–5. The ARIMA forecasting gives results in three different options which are upper limits, lower limits, and forecasted values. Upper and lower limits provide a confidence interval of 95%, in other words any realization within the confidence limits will be acceptable. In this study we have taken the forecasted values and further calculations are done based on these data.

The accuracy of the fitted model is checked with the mean-square error (MS), which is a measure of accuracy of the fitted model. The MS is not very informative by itself, but it can be used to compare fits of different ARIMA models. For all measures, smaller values generally indicate a better fitting model.

3. Results and discussions

The mean-square errors of each model with different seasonal components are tabulated in Table 2. The MS values are meaningful within the same item. Since these numbers represent the goodness of each model within each item, smaller the number better the model will be. The results showed that seasonal order of 1 is suitable for each item except hard coal, natural gas; solar, and total, indicating the ARIMA model is suitable for them. On the other hand, hard coal gives better model fit in seasonal order of 3, natural gas in seasonal order of 2, solar energy in seasonal order of 4, and total in seasonal order of 5, indicating that the SARIMA model is suitable for them.

The ARIMA and SARIMA models constructed for each item will not be shown here. Instead, as an example, the result of forecasting for total primary energy is presented in Fig. 1. The graph includes the realizations from 1950 to 2004 and the forecast and upper and lower limits of the fifth-order SARIMA forecasting from 2005 to 2020.

The forecasted values for each item and for total from 2005 to 2020 is given in Table 3. As seen from the table, all but wood and animal–plant remains will still be increasing in the period from 2005 to 2020. However, the average annual rates will decrease in all cases. For the period between 1950 and 2004 the rate of increases are 8.3% for oil, 7.3% for lignite, 4.3% for hard coal, 59.8% for natural gas, 0.7% for wood, −0.2% for plant and animal remains, 18.3% for hydropower, 17.2% for petrocoke, 12.2% for geothermal heat, 32.6% for geothermal electricity, 29.0% for solar, and 259% for asphaltite and for the forecasted period between 2005 and 2020 the rates are expected to be 1.6%, 1.3%, 5.1%, 6.8%, −1.2%, −1.8%, 1.7%, 4.2%, 2.2%, 3.1%, 6.6%, 1.4%, and 3.3%, respectively. On the other hand, the average annual rate of total primary energy demand decreases from 4.9% between 1950 and 2005 to 3.3% between 2005 and 2020.

Studying the relationship between energy and economy, Ediger (2004) have shown that the industrialization in Turkey has not been completed yet and energy demand should be increasing faster than national income until the energy intensity of the country reaches to a peak. Therefore, the decrease in the rate of energy demand may be interpreted to indicate that the energy intensity peak will be achieved in the coming decades. However, a close relationship exists between energy and economy of Turkey and the average rate of change in GDP and primary energy consumption are 4.5 and 4.9, respectively (Ediger and Huvaz, 2006). Also, Soytaş and Sarı (2003) discovered causality from energy consumption to GDP in Turkey. Therefore, whether or not the decrease in energy consumption rate is related to energy intensity peak will depend on the future rates of GDP. If causality runs from energy consumption to GDP in the future and if the rates of energy consumption and GDP persist their past trends, any decrease in energy consumption is expected to slow down the economic growth during the foreacsted period.

The numbers in Table 3 demonstrates that the share of fossil fuels in sum of individual forecasts will increase from 87.6% in 2005 to 91.6% in 2020. The 4% increase in the share of fossil fuels in total shows that the fossil fuels will continue to be important in the future in Turkey similar to most of the other countries in the world. However, the

Table 2
Mean square errors (The smallest MS values are shown by bold numbers)

Energy source	Seasonal component				
	1	2	3	4	5
Hardcoal	554,855	859,998	**487,219**	580,981	n/a
Lignite	**371,921**	430,044	425,943	428,738	435,371
Asphaltite	**4,518**	5,584	n/a	n/a	n/a
Petrocoke	**64,415**	n/a	n/a	n/a	n/a
Wood	**7,473**	7,873	8,402	8,269	n/a
Animal and Plant	**10,644**	13,977	13,375	11,968	n/a
Oil	**1,020,049**	1,586,948	1,119,171	1,227,784	n/a
Natural Gas	646,567	**305,101**	n/a	n/a	n/a
Hydrolic	**105,484**	111,213	108,652	153,973	150,884
Geothermal Electricity	**120.49**	n/a	n/a	n/a	n/a
Geothermal Heat	**215.33**	221.26	247.62	n/a	n/a
Solar	72.59	62.589	74.149	**45.143**	73.081
Total	3,979,060	3,359,960	3,659,938	3,667,651	**2,840,285**

n/a: Not applicable.

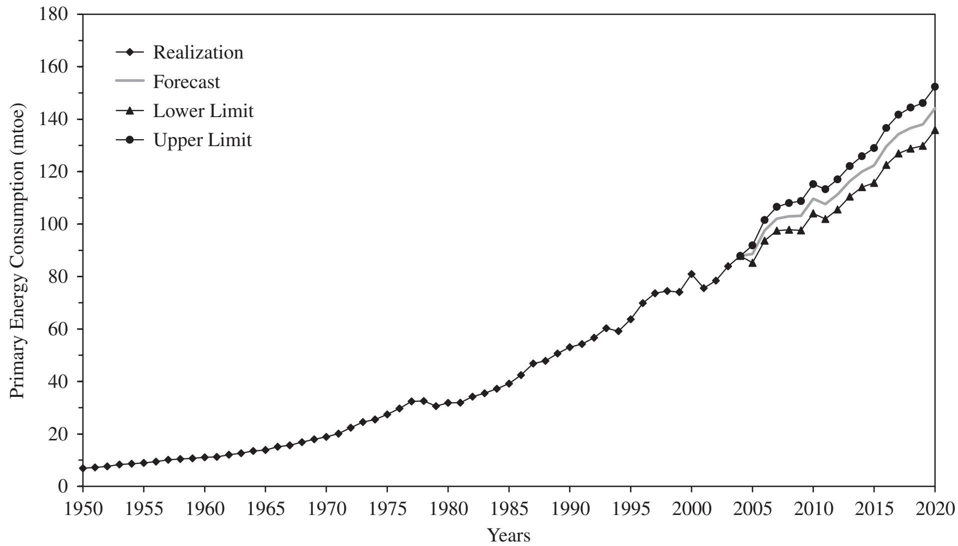

Fig. 1. SARIMA modelling for the primary energy demand of Turkey.

Table 3
Forecasted values for each item and total primary energy from 2005 to 2020

Years	Oil	Natural gas	Hardcoal	Lignite	Wood	Hydro-power	Petrocoke	Plant-An. remains	Geothermal heat	Solar	Asphaltite	Geothermal electricity	Primary energy
2005	33.613	22.319	10.923	9.326	4.176	3.870	1.512	1.189	0.840	0.408	0.261	0.083	88.332
2006	34.169	24.155	13.375	9.348	4.049	3.972	1.599	1.145	0.850	0.455	0.226	0.086	97.225
2007	34.725	26.569	10.667	9.387	3.945	4.037	1.683	1.082	0.871	0.485	0.255	0.089	101.544
2008	35.300	28.378	12.390	9.490	3.855	4.109	1.768	1.034	0.886	0.521	0.260	0.093	102.499
2009	35.891	30.854	14.701	9.608	3.781	4.180	1.852	0.985	0.910	0.558	0.264	0.096	102.612
2010	36.493	32.872	15.665	9.744	3.718	4.251	1.937	0.953	0.930	0.601	0.269	0.099	109.050
2011	37.096	35.534	14.571	9.887	3.665	4.322	2.021	0.932	0.956	0.642	0.274	0.102	107.004
2012	37.694	37.698	17.071	10.036	3.622	4.393	2.106	0.919	0.977	0.678	0.278	0.106	110.673
2013	38.284	40.512	14.609	10.187	3.586	4.464	2.190	0.911	1.002	0.721	0.283	0.109	115.713
2014	38.872	42.839	16.240	10.340	3.557	4.535	2.275	0.906	1.024	0.775	0.288	0.112	119.470
2015	39.462	45.814	18.617	10.493	3.534	4.606	2.359	0.903	1.048	0.817	0.293	0.115	121.823
2016	40.055	48.300	19.457	10.648	3.516	4.677	2.444	0.902	1.070	0.862	0.297	0.118	128.949
2017	40.650	51.434	18.560	10.803	3.502	4.748	2.528	0.900	1.093	0.909	0.302	0.122	133.611
2018	41.245	54.079	21.109	10.958	3.492	4.819	2.613	0.900	1.115	0.963	0.307	0.125	135.881
2019	41.839	57.373	18.874	11.113	3.485	4.890	2.697	0.900	1.138	1.013	0.311	0.128	137.217
2020	42.431	60.178	20.429	11.268	3.480	4.961	2.782	0.899	1.161	1.060	0.316	0.131	143.294
Aver.%	1.6%	6.8%	5.1%	1.3%	−1.2%	1.7%	4.2%	−1.8%	2.2%	6.6%	1.4%	3.1%	3.3%

gradual increase in the share of fossil fuels in total will come from mostly the interaction between oil and natural gas in Turkey since the coal's share in total fluctuates between 21.2% and 24.7% (Fig. 2). From 2005 to 2030, the share of oil will decrease from 38.7% to 28.9% while that of natural gas will increase from 25.7% to 41.1%, indicating that 9.8% decrease in oil's share will be compensated by the 15.4% increase in natural Gas's share. The natural gas curve which, has already cut the coal curve around 2000, is expected to cut the oil curve in 2012. Similar results have previously been demonstrated in electricity generation of Turkey by Ediger (2003b).

Additionally, the highest rate of increase will be recorded in the future in natural gas. This indicates, although rate of increase will decrease from 59.8% to 6.8%, natural gas will continue to be a key element of the Turkish energy system in the future. The cumulative graph of realized and forecasted primary energy demand from 1950 to 2020 given in Fig. 3 demonstrates how important natural gas demand will be in the future keeping in mind that it is met almost completely by imports. In this context, the decrease in both average rates and share in total in oil can be considered reasonable since its domestic production meets only about 10% of the demand. On the other hand, lignite,

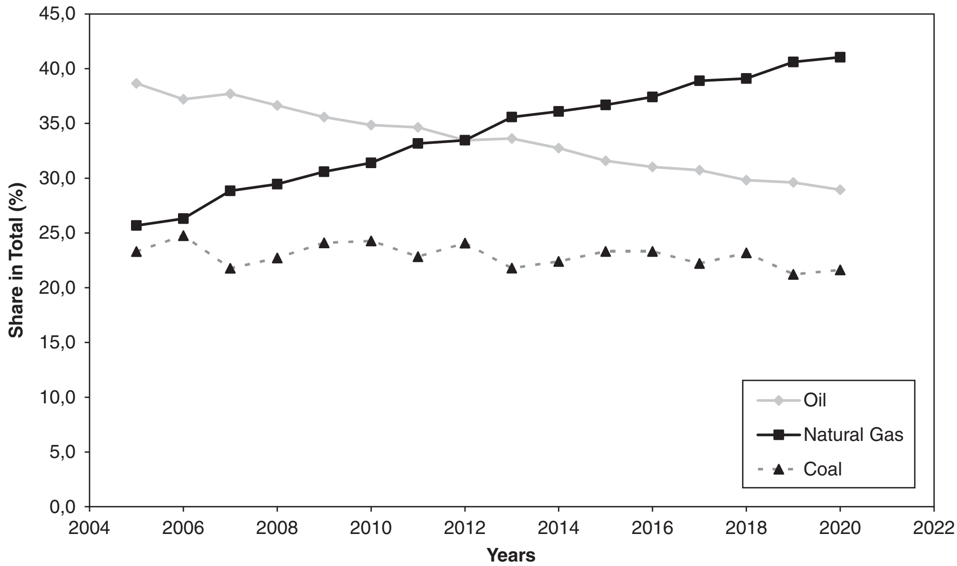

Fig. 2. Future trends of oil, natural gas and coal.

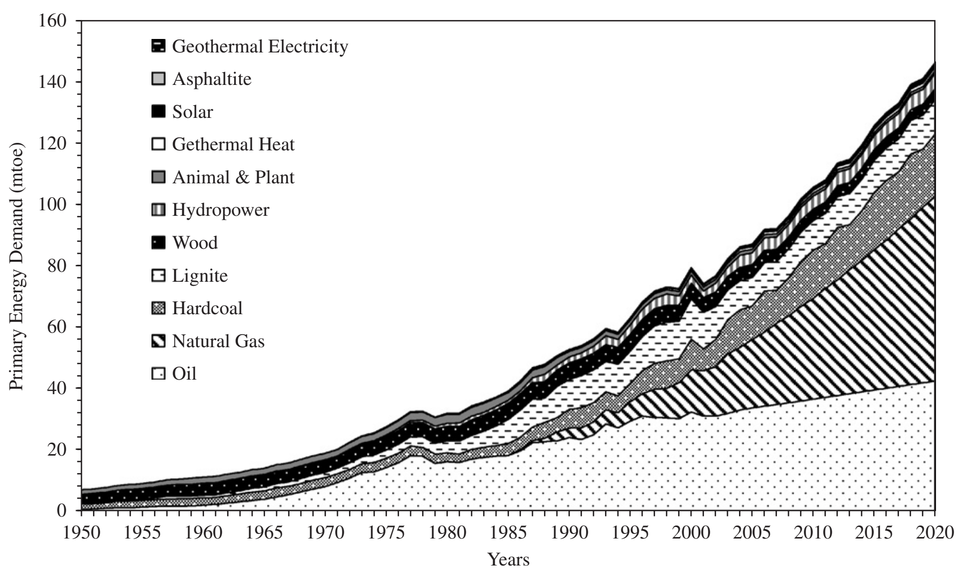

Fig. 3. Cumulative graph of realized and forecasted primary energy demand from 1950 to 2020.

which is the richest energy source of the country, will decrease to only 1.3%. Therefore, an interfuel substitution within fossil fuels should be made leading to a best mix of the country's energy system. For instance, Çamdalı and Ediger (in press) showed that a reduction of 1.663 billion US $ in fossil fuel cost can be made possible by giving more emphasis on domestic production particularly of oil, lignite, and hard coal. Additionally, modern renewable energy sources should be emphasized.

The ARIMA forecasting of total primary energy consumption values and the summation of the ARIMA and SARIMA forecasting of each item are also compared (Fig. 4). As it is clearly seen in the figure, the ARIMA forecasting of total primary energy consumption values are higher than the summation of the ARIMA and SARIMA forecasting of each item for the period between 2005 and 2010. It is just the reverse for the period between 2011 and 2020. The difference between the two is minimum in 2009 with a value of 83,000 toe and maximum in 2007 with a value of 8.830 million toe. Considering that the ARIMA forecasting is expected to give better results for short-terms than long-terms and that during summmation the errors involved in each forecasting are also summed up, the ARIMA forecasting of the total primary energy demand appears to be more reliable than the summation of the individual forecasts.

Finally, the results of the ARIMA forecasting of the total primary energy demand are compared with the most recent MAED application (Table 4). It is obvious that in the years 2006 and 2007 the low and high limits of this

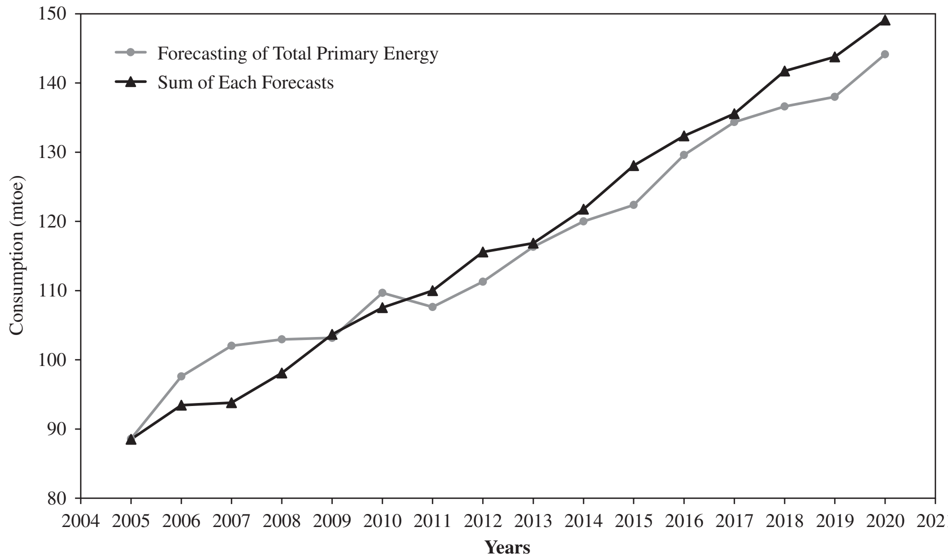

Fig. 4. Comparison of ARIMA forecasting of total primary energy consumption values and the summation of the ARIMA and SARIMA forecasting of each item.

Table 4
Comparison of the results with MAED (2005) (in million toe)

		2005	2006	2007	2008	2009	2010	2015	2020
MAED	Low	93.302	92.615	98.001	104.215	110.096	116.300	151.225	194.220
	High	93.302	100.014	105.193	111.072	118.354	125.592	169.493	222.121
This study	Low	85.256	93.675	97.482	97.878	97.604	104.090	115.736	135.896
	High	91.924	101.520	106.565	108.043	108.740	115.235	129.005	152.385
Difference	Low	8.046	−1.060	519	6.337	12.492	12.210	35.489	58.324
	High	1.378	−1.506	−1.372	3.029	9.614	10.357	40.488	69.736

study almost coincides with the MAED results. However, for the long-term ARIMA forecast gives an underestimation when compared with the MAED. The differences between lower and upper limits starts with 6.337 and 3.029 million toe in 2008 and reaches to 58.324 and 69.736 million toe in 2020, respectively.

4. Conclusions

The major conclusion reached in this study is that although all but wood and animal–plant remains will still be increasing the average annual growth rates of individual energy sources and total primary energy will decrease in all cases in the forecasted period between 2005 and 2020. The average annual rate of total primary energy demand decreases from 4.9% between 1950 and 2005 to 3.3% between 2005 and 2020.

The decrease in the growth rate of energy consumption may be interpreted that the energy intensity peak will be achieved in the coming decades provided that GDP increases faster than energy consumption. This will depend largely on economic performance of the country. However, any decrease in energy consumption may also be expected to slow down the economic growth in the future, depending on the causality from energy consumption to GDP. Therefore, the best policy recommadation will be to decrease the energy requirements without sacrifying economic development. This may be achieved by significant structural shifts in the economy from agricultural to manufactural based one and from high to low energy-intensive sectors by scientific and technological advancements, and by a move from less efficient fuel to more efficient one.

However, the forecasting results show that fossil fuels will continue to play a major role in the future energy mix of Turkey. Also, within the fossil fuels, the leading fuel, oil will be replaced by natural gas in 2012 and natural gas's share will reach to 41.2% in the energy mix in 2020. This will make the Turkish energy system depended more on natural gas than on other fuels. The natural gas demand is, however, met almost completely by imports.

On the other hand, the lowest rate of increase will be in lignite, which is the richest energy source of the country. Therefore, we recommend that inter-fuel substitution should be made towards decreasing dependence on imported fuels by employing more indigenous sources. Efficiency and environmental aspects of the fuels should also be considered in determining the best mix of the country. Therefore, great emphasis should be given also on the exploitation of other domestic energy sources, including renewable energy sources such as hydropower, geothermal, wind, and solar, of which the country has a significant potential. Diversification will certainly increase the energy security of Turkey, which appears to be one of the most significant aspects of the Turkish energy system in the 21st century.

We also concluded that the ARIMA forecasting of the total primary energy demand appears to be more reliable than that of the summation of the individual forecasts. While making forecasts of each time series separately and adding them up to obtain an overall picture of the energy demand, the errors involved in each step is also summed up which results a greater error. Finally, the ARIMA and SARIMA models can efficiently be used for forecasting of energy demand.

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