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Forecasting Regional Electricity Demand for Turkey

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ABSTRACT

Electricity demand forecasting is important for planning in the different segments of the electricity sector. In this study, the main aim is to forecast regional electricity demand by using time series, panel data and spatial panel data models and compare their forecasting performance. As in 2004, 21 regional monopolistic distribution companies were established by the implementation of Strategy Paper, this study employs data on these regions between 1986 and 2013. The results show that forecasts obtained by using pooled panel data model are on average better than the ones obtained by using other models based on root mean squared error evaluation criterion.

Keywords: Regional Electricity Demand, Forecasting, Spatial Interaction
JEL Classifications: C53, Q47, R12

1. INTRODUCTION

Accurate forecasts of electricity consumption are essential for the well-planned development of the electricity sector. Forecasts of future electricity consumption are employed by many decision makers such as energy suppliers, independent system operators, financial institutions and other participants in the electricity market and different segments of the sector, such as, generation, transmission, distribution and trade, for various purposes, for example, for the decision-making related to capital investment in generation, transmission and distribution and operational decisions related to plant availability requirements, purchasing decisions on fuel, tariffs and revenue calculations and marketing and manpower issues (Rhys, 1984; Feinberg and Genethliou, 2005).

Therefore, in this study, our aim is to compare the forecasting performance of various models using regional level data for Turkey over the period from 1986 to 2013. Our region definition is based on the strategy paper published in 2004. According to this Strategy Paper, 21 regional monopolistic distribution companies were planned to be established. These companies were established and their privatization was completed in year 2013. After the period of Turkish Electricity Authority (TEK), since 1984 the private sector participation was allowed into the distribution segment by the enactment of Law No. 3096 (Atiyas and Dutz, 2005). Restructuring process proceeded by the vertical unbundling of TEK in 1993, introduction of Electricity Market Law No. 4628 in 2001, further unbundling of the activities, establishment of Energy Market Regulatory Authority, enactment of Electricity Market Law No. 6446 in 2013, and lastly, the revision of the Electricity Market Law in 2016. Between the years 2001 and 2016, many other regulations and legislation were introduced related to important issues as nuclear power plants, energy efficiency, and renewable energy power plants. The main aims of this restructuring process characterized by the liberalization in supply as well as demand side can be summarized as follows; satisfying investment requirements and improving efficiency (Özkıvrak, 2005), introducing competition to all the segments except transmission and distribution in a regulated environment, ensuring supply security and low-cost and environmentally friendly electricity to consumers (Electricity Market Law No. 6446, 2013). This study restricts the attention to the distribution segment of the sector. Law No. 4628 states that distribution activities are performed by regional distribution companies based on their licenses. By the implementation of the Strategy Paper issued in 2004 with the High Planning Council Decision No. 2004/3 (dated 17.3.2004), 21 regional distribution monopoly companies were established and by 18th December 2012, privatization of the 12 distribution regions were completed by the method of operation rights issuance, and other 8 distribution regions were also privatized in 2013.

Figure 1 shows the regions served by each distribution companies. Distribution companies could also obtain retail sales licenses to

Figure 1: Regions of electricity distribution companies

engage in retail activities. However, by the Decree of Energy Market Regulatory Board in 2012, the retail sale and distribution activities were agreed to be performed under the separate legal entities beginning from 2013, January. Distribution companies are responsible for the provision of electricity distribution and connection services to all the users without discrimination, the purchase and provision of ancillary services, planning investment, performing investments for renewal, replacement, and capacity expansion, and preparation of demand forecasts. In the previous law (No. 4628), private distribution companies were allowed to engage into the generation activities only if separate accounts were kept; however, in the new Electricity Market Law (No.6446), activity of the distribution companies is restricted by distribution activity only.

The progression in the restructuring process necessitates different planning methods as well as forecasting techniques. On the other hand, recent trends in the energy sector planning show the importance of regional level planning in addition to the national level. Therefore, because of this restructuring process, especially the establishment of regional distribution companies and their need for forecasts of future electricity requirements, in this study, the focus is on the forecasting of regional electricity demand. Moreover, as also discussed by Zellner and Tobias (2000), forecasting performance can be improved by using disaggregated data on the economic series under consideration (Ohtsuka and Kakamu, 2013). In order to forecast electricity demand, this study employs different models and compares their forecasting performance: ARIMA model, pooled panel data model, fixed effects panel data model, pooled spatial lag and spatial error models, spatial lag and spatial error panel data models with fixed effects.

In the literature, there are many studies for the electricity demand forecasting. These studies have employed different methods which were classified by Rhys (1984) and Feinberg and Genethliou (2005) as follows: (1) Projection and statistical interpretation of past trends, (2) econometric methods, (3) end-use models, (4) combination of econometric methods and end-use approach. These methods are mostly employed for medium and long-term forecasting. Different methods are also developed for short term forecasting, for example, similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic and expert systems. Detailed explanation of each method and the review of studies employing different methods can be found in Rhys (1984), Feinberg and Genethliou (2005), Singh et al. (2013), Suganthi and Samuel (2012), Tutun et al. (2015) and Günay (2016). Moreover, some studies forecast electricity demand at the regional level, for example, Ohtsuka et al. (2010), Wang et al. (2012) and Ohtsuka and Kakamu (2013), Arisoy and Ozturk (2016). Among these studies, Wang et al. (2012) follows decomposition approach for forecasting the electricity demand of Australia's regions based on historical half-hourly electricity demand data over the period from 2002 to 2011. They analyze the decomposed electricity demand series using regression and statistical methods. Lastly, they forecast annual average electricity demand and peak electricity demand up to 2020 by employing Monte Carlo simulation. On the other hand, Ohtsuka et al. (2010) and Ohtsuka and Kakamu (2013) forecast regional electricity demand in Japan using spatial autoregressive ARMA (SAR-ARMA) model. In both studies, data sets cover the monthly electricity consumption of 9 regions served by different companies including the period between 1992 and 2003. In the former study, the forecasting performance of SAR-ARMA(1,1) model is compared with univariate ARMA(1,1) model with aggregated data and their findings show that SAR-ARMA model is superior to ARMA model in forecasting electricity demand for Japan. However, from the comparison of SAR-ARMA(1,1) model with VAR(1) model, the latter study obtains the following result that VAR(1) model outperforms the SAR-ARMA(1,1) model in forecasting the electricity demand which is explained by the misspecification of the weight matrix employed in SAR-ARMA(1,1) model.

For Turkey, there are various forecasting studies for electricity demand employing different methods. However, at the regional level, there are only few studies. For example, Çakmak (2014) forecasts the electricity consumption for the provinces of Turkey using random effects, fixed effects and dynamic panel data models and data between 1999 and 2011. Another study was performed jointly by Transmission Company of Turkey (TEİAŞ) and Marmara Research Center (TÜBİTAK-MAM) considering the transformation centers and using trend curves. Their region definition is based on the share of province's electricity consumption out of total consumption of Turkey

Table 1: Some recent studies forecasting net total electricity consumption for Turkey

Study	Method	Time period	Frequency of data	Independent factors/variables	Forecast period
Tutun et al. (2015)	LADES and RADES models	1990-2010	Monthly data	Transmitted energy, gross generation, imports and exports	2011-2020
Kaytez et al. (2015)	LS-SVM	1970-2011	Annual data	Gross electricity generation, installed capacity, total subscribership and population	
Hamzacebi and Es (2014)	Optimized grey model	1945-2010	Annual data		2013-2025

LADES, RADES, and LS-SVM are abbreviations for LASSO-based adaptive evolutionary simulated annealing, ridge-based adaptive evolutionary simulated annealing, and least squares support vector machines, respectively

and also regions of distribution companies. Other electricity consumption forecasting studies for Turkey are performed using aggregate time series data (Regional Level 0) and various methods covering the different time periods with different time frequencies. One can refer to Kankal et al. (2011), Çakmak (2014), Tutun et al. (2015), Oğurlu and Çetinkaya (2016) and Günay (2016) for the review of some forecasting studies performed for Turkey using only time series data. In general, studies employ AR(I)MA model (Bakırtaş et al., 2000; Erdoğdu, 2007), S-curve trend model (Ercan and Genç, 2004), curve fitting (Tunc et al., 2006), artificial neural network (Hamzaçebi and Kutay, 2004; Hamzaçebi, 2007; Bilgili, 2009; Kavaklioglu et al., 2009; Sozen et al., 2011; Günay, 2016), projection based on population increase and energy consumption increase rates per capita (Yumurtacı and Asmaz, 2004), genetic algorithm approach (Ozturk and Ceylan, 2005; Ozturk et al., 2005), grey prediction with rolling mechanism approach (Akay and Atak, 2007), error correction models (Küçükbahar, 2008), regression model with seasonal latent variables (Sumer et al., 2009), ant colony optimization approach (Toksari, 2009), adaptive neuro fuzzy inference system (Demirel et al., 2010), fuzzy logic approach (Kucukali and Barış, 2010), support vector machines (SVM) (Küçükdeniz, 2010; Kavaklioglu, 2011), structural time series technique (Dilaver and Hunt, 2011), optimized grey modeling (Hamzacebi and Es, 2014), LASSO-based adaptive evolutionary simulated annealing and ridge-based adaptive evolutionary simulated annealing models (Tutun et al., 2015), and least squares SVM (Kaytez et al., 2015).

Table 1 summarizes the information on some recent forecasting studies for Turkey. In Turkey, official electricity demand projections are performed by Ministry of Energy and Natural Resources (ETKB) using model for analysis of energy demand module of Energy and Power Evaluation Program under three different scenarios, low, base and high growth considering macroeconomic targets. But according to some studies, these projections overestimate the electricity consumption (Erdoğdu, 2007; Ediger and Tatlıdil, 2002; Madlener et al., 2005; Hamzaçebi, 2007; Akay and Atak, 2007). Therefore, in order to obtain accurate forecasts for electricity consumption, it is important to develop and employ different models and methods and compare their forecasting performances. The organization of the paper is as follows; after the introduction, section 2 discusses the methodological issues. Sections 3 and 4 give information on the data employed in the analysis and present the results of estimation and forecast evaluation, respectively. Last section concludes and makes suggestions for future studies.

2. METHODOLOGY

In this study, methodology is based on the study of Kholodilin et al. (2008). They forecast regional gross domestic product considering spatial interdependencies. This study also employs spatial panel data models. For the comparison purposes, panel data models and linear ARIMA model are considered for each region. Because of economic and social interactions among the regions, one needs to account for spatial interdependencies. According to Tobler (1970), although there is a relation among everything, there appears to be a stronger relation between the near things compared to distant ones, which is called first law of geography (Anselin, 1992). This implies that neighboring relations should be included into the analysis while studying at the regional level. Also, as a methodological issue, ignoring spatial interactions may cause the estimates to be biased, inefficient and inconsistent based on the type of the spatial effects. Following Kholodilin et al. (2008), this study considers the following models given by (a)-(h) in equations (1)-(9) under different assumptions where Y is the first difference of per capita net electricity consumption;

a. Linear ARMA (p,q) model for each region i (Model 1):

$$Y_{it} = \beta_{i0} + \alpha_i t + \sum\nolimits_{j=1}^{p} \beta_{ij} Y_{it\text{-}j} + \varepsilon_{it} + \sum\nolimits_{k=1}^{q} \delta_{ik} \varepsilon_{it\text{-}k} \quad (1)$$

Where, $\varepsilon_{it} \sim \text{Niid}(0, \sigma_i^2)$, i = 1,2,…,20 and t = 1,2,…,28 are subscripts for regions and time periods. These models allow for different coefficients and variances for each region. The determination of AR and MA lag orders, i.e., p and q, and inclusion of trend are based on model selection criterion, AIC, taking the maximum p and q as 4.[1] As per capita net electricity consumption series is nonstationary and I(1) except only for region 1 in which it is I(2) based on KPSS unit root test, before the estimation of the model, the first difference and for region 1 second difference of the series are taken.

b. Linear AR(1) model for each region i (Model 2):

$$Y_{it} = \beta_{0i} + \beta_1 Y_{it-1} + \varepsilon_{it} \quad (2)$$

Where, $\varepsilon_{it} \sim \text{Niid}(0, \sigma_i^2)$, i = 1,2,…,20; t = 1,2,…,28. Same AR model structure is assumed while allowing for different coefficients and variances for each region.

1 The forecasting is performed by Eviews 9 using the Automatic ARIMA Forecasting command.

c. Pooled panel data model (Model 3):

$$Y_{it} = \beta_{0i} + \beta_1 Y_{it-1} + \varepsilon_{it} \quad (3)$$

Where, $\varepsilon_{it} \sim \text{Niid}(0, \sigma^2)$, i = 1,2,…,20; t = 1,2,…,28. The coefficients and variances are assumed to be same across regions.

d. Panel data model with spatial fixed effects (Model 4):

$$Y_{it} = \beta_{io} + \beta_1 Y_{it-1} + \varepsilon_{it} \quad (4)$$

Where, $\varepsilon_{it} \sim \text{Niid}(0, \sigma^2)$, i = 1,2,…,20; t = 1,2,…,28. Only intercepts are allowed to vary among the regions.

e. Pooled spatial lag model (Model 5):

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \rho \sum_{j=1}^{20} W_{ij} Y_{jt} + \varepsilon_{it} \quad (5)$$

Where, $\varepsilon_{it} \sim \text{Niid}(0, \sigma^2)$, i = 1,2,…,20; t = 1,2,…,28. We assume that coefficients and variances are same across regions but account for spatial interdependence among regions through endogenous interaction effects. Here, w_{ij}'s, are the weights formed by considering the neighboring relations. Throughout the analysis, binary (queen) contiguity weight matrix is employed which is shown below in equation (6);

$$w_{ii} = 0 \text{ for all i and } w_{ij} = \begin{cases} 1, & \text{if two regions are contiguous to each other} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

f. Pooled spatial error model (Model 6):

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \varepsilon_{it}$$

$$\varepsilon_{it} = \rho \sum_{j=1}^{20} w_{ij} \varepsilon_{jt} + u_{it} \quad (7)$$

Where, $u_{it} \sim \text{Niid}(0, \sigma^2)$, i = 1,2,…,20; t = 1,2,…,28. The coefficients and variances are assumed to be same across regions but the model accounts for spatial interdependence among regions through correlated effects.

g. Spatial lag panel data model with fixed effects (Model 7):

$$Y_{it} = \beta_{0i} + \beta_1 Y_{it-1} + \rho \sum_{j=1}^{20} w_{ij} Y_{jt} + \varepsilon_{it} \quad (8)$$

Where, $\varepsilon_{it} \sim \text{Niid}(0, \sigma^2)$, i = 1,2,…,20; t = 1,2,…,28. Intercepts are allowed to vary among the regions and the model allows for spatial interdependence among regions through endogenous interaction effects.

h. Spatial error panel data model with fixed effects (Model 8):

$$Y_{it} = \beta_{0i} + \beta_1 Y_{it-1} + \varepsilon_{it}$$

$$\varepsilon_{it} = \rho \sum_{j=1}^{20} w_{ij} \varepsilon_{jt} + u_{it} \quad (9)$$

Where, $u_{it} \sim \text{Niid}(0, \sigma^2)$, i = 1,2,…,20; t = 1,2,…,28. The model allows intercepts to vary among the regions and spatial interdependence among regions through correlated effects.

The order of ARIMA (p, d, q) model is determined based on Box-Jenkins methodology. In the estimations of Models 2 and 3, least squares estimation method is employed, and for others, maximum likelihood estimation method is used. The models are estimated for the periods between 1986 and 2010 and forecasting performances are compared between 2011 and 2013. Further, using the model which has better forecasting performance, the per capita electricity consumption and electricity consumption are forecasted for the period between 2014 and 2018. Next section gives information on the data and presents the empirical results.

3. DATA AND EMPIRICAL RESULTS

3.1. Data

Province (NUTS-3) level net electricity consumption and population data between the periods 1986 and 2013 are obtained from Statistical Institution of Turkey (TURKSTAT) database. These values are net consumption values, i.e. it does not include the technical and nontechnical losses. The data is arranged considering the region definitions given in Strategy Paper published in 2004 for each 21 distribution companies. In the definitions, for İstanbul province, there are two distribution companies, one for Anatolia part and the other for Europe part. But in the data, there is no separate information for these two companies. Therefore, the arranged data includes the per capita net electricity consumption (pcec) of 20 regions over the period from 1986 to 2013. Table 2 shows the descriptive statistics for per capita electricity consumption of each region for the period between 1986 and 2013. Highest average level of per capita electricity consumption is observed in the region in which TREDAŞ is responsible for electricity distribution, second highest is recorded by SEDAŞ's region. Overall average per capita electricity consumption is realized as 1,396688 MWh/capita for the period under consideration.

Table 2: Descriptive statistics

Distribution company	Mean	Maximum	Minimum	SD
BAŞKENT EDAŞ	1.381	2.392	0.704	0.528
SEDAŞ	2.894	5.232	1.169	1.152
MERAM EDAŞ	1.177	2.450	0.654	0.579
ARAS EDAŞ	0.467	0.997	0.162	0.260
ÇORUH EDAŞ	0.757	1.658	0.308	0.423
FIRAT EDAŞ	0.919	1.823	0.333	0.396
TREDAŞ	2.998	5.518	0.784	1.648
OSMANGAZİ EDAŞ	1.520	2.926	0.590	0.705
YEDAŞ	0.823	1.721	0.269	0.462
ÇEDAŞ	0.701	1.524	0.230	0.411
ULUDAĞ EDAŞ	2.187	3.716	0.866	0.918
GEDİZ EDAŞ	2.384	3.819	0.954	0.845
İSTANBUL	1.685	2.398	0.922	0.482
AKEDAŞ	1.286	2.670	0.474	0.723
AKDENİZ EDAŞ	1.533	2.892	0.491	0.791
AYDEM EDAŞ	1.436	2.646	0.443	0.707
DİCLE EDAŞ	0.675	1.118	0.385	0.250
VAN GÖLÜ EDAŞ	0.234	0.882	0.051	0.237
TOROSLAR EDAŞ	1.529	2.874	0.803	0.608
KCETAŞ	1.347	2.301	0.495	0.606
All	1.397	5.518	0.051	1.017

Table 3: Pesaran (2004) cross-sectional dependence (CD) Test and Pesaran (2007) panel unit root (CIPS) test

Test	Pcec	Δpcec
Pesaran (2004) CD test	69.714***	
Pesaran (2006) CIPS test	−2.355	−3.107***

*, **, ***show the statistical significance of test statistic at 10%, 5% and 1%

Table 4: Moran's I statistic for pcec[1]

Years	Moran's I	Z value
1986	0.5894	4.4327***
1990	0.5555	4.2709***
1995	0.5496	4.2530***
2000	0.6525	4.9301***
2005	0.5525	4.3230***
2013	0.4231	3.3953***

[1]***Shows statistical significance at 1% significance level

In Table 3, Pesaran (2004) cross-sectional dependence test is also shown for the panel data of per capita electricity consumption covering the regions of 20 distribution companies over the period from 1986 to 2013 and indicates that in the per capita electricity consumption panel data series, there is evidence of cross-sectional dependency. Therefore, in order to test for unit root, Pesaran (2007) panel unit root (CIPS) Test is employed (Table 3). Test indicates that pcec series is I(1). While estimating the Models 3-8, first difference of the series is taken. In addition, the results show that there is evidence of spatial interactions among the regions of Turkey, as Moran's I statistic (Table 4) and Figure 2 indicate the evidence of spatial effects. Therefore, one needs to consider the spatial interdependency in the electricity consumption estimation and forecasting.

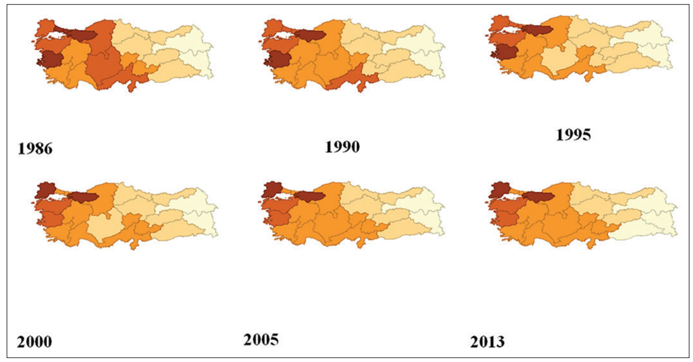
3.2. Empirical Results

This section first presents the estimation results and then results related to the forecasting evaluation of different models. Table 5 presents the estimation results for Model 2 and panel data models over the period from 1986 to 2013.[2] Results show that when the fixed effects are included into the models, AR coefficients become statistically significant. Also, in the models with fixed effects, AR coefficients are found to be very similar to each other. Findings indicate that the intercept terms are statistically significant in all the models.

In order to evaluate the forecasting performance of the models, first the Models 1-7 are estimated for the period between 1986 and 2010[3] and then, the per capita electricity demand is forecasted over the period from 2011 to 2013. The forecasting performances of different models are compared as shown in Table 6 based on root mean squared error evaluation criterion. Forecasts obtained by using pooled panel data model are on average better than the others. This finding is in line with the principle of parsimony.

Further, by using the pooled panel data model, the per capita electricity consumption is forecasted for the period between 2014 and 2018 and forecasts are shown in Figure 3. In Figure 3, forecasts are shown on the graph including the actual values for the period before 2014. Figure 3 shows that per capita electricity consumption increases in all the regions and this signals a need for the distribution capacity expansion for all the regions which are under the responsibility of different distribution companies.

Figure 2: Electricity consumption per capita of Turkey for different years (classified based on natural breaks)



Here, our conclusion is based on per capita values. However, for the determination of the electricity consumption forecasts, one needs population forecasts for each region over the same period considering the possibility of migration. Then, by using this information, one can forecast the value of the investment requirements for distribution capacity expansions for each region. Therefore, in the last step of the analysis, population forecasts are obtained by employing ARIMA models for each region, separately.[4] By using per capita net electricity consumption and population forecasts, forecasts of electricity consumption are calculated for each region over the period from 2014 to 2018 which are shown in Figure 4.[5]

Table 7 shows the comparison of the forecasts for total net electricity consumption with actual values and forecast of one recent study for Turkey. As official forecasts are performed for gross electricity consumption, the comparison will lead to misleading conclusions. Therefore, the forecasts are compared with the ones obtained by other recent studies using net electricity consumption data. However, some studies did not provide their forecast values, therefore, the results are compared with only one study. The comparison shows that the forecasts of this study is lower than the ones obtained by Hamzacebi and Es (2014)[6] but more close to the actual values realized in 2014 and 2015. This difference between the studies can be related to the time period considered, level of disaggregation of the data, method and forecast horizon.

4. CONCLUSION

The aim of the study is to compare the forecasting performance of various models for the regional electricity demand forecasting. The study employs panel data on per capita electricity consumption covering 20 regions defined by the classification of the provinces

2 Estimation results for ARIMA models can be available upon request.
3 Estimation results can be available upon request.
4 The forecasting is performed by Eviews 9 using the Automatic ARIMA Forecasting command. The results can be available upon request.
5 The results can be available upon request.
6 Detailed information related to this study is given in Table 1.

Table 5: Estimation results (1986-2013)[1]

Δpcec	Model 2[2]	Model 3	Model 4[3]	Model 5	Model 6	Model 7[3]	Model 8[3]
Constant	0.063***	0.074***	0.074***	0.049***	0.077***	0.046**	0.077***
		(13.7215)	(15.6864)	(7.06679)	(9.1537)	(2.16736)	(3.45986)
AR (1)	0.019169	0.002829	−0.100**	−0.00039	−0.00123	−0.104***	−0.129***
		(0.06389)	(−2.2246)	(−0.0096)	(−0.0281)	(−2.6161)	(−3.0050)
W×Δpcec				0.355***		0.393***	
				(6.98052)		(8.03436)	
W×ε					0.358***		0.402***
					(7.05044)		(8.23298)
R^2	0.066045	0.000008	0.097679	0.1151	−0.0001	0.2389	0.1063

[1]Models are described in the methodology section. [2]Median values are given for Model 2 in the table. Minimum value for AR coefficient (constant term) is−0.87 (0.025), maximum is 0.68 (0.185). For R^2, minimum and maximum values are 0.000155 and 0.58, respectively. [3]In order to save space, the coefficients on dummy variables are not presented. T-statistics are given in parenthesis. The statistical significance of coefficients are shown by *, **, ***at 10%, 5% and 1% significance levels

Table 6: RMSE[1] criterion for different models[2] (3-step ahead forecast)

Forecasts	Model 1	Model 2	Model 3*	Model 4	Model 5	Model 6	Model 7	Model 8
Static forecast	0.11508	0.11536	0.105197	0.105199	0.62509	0.62278	0.64107	0.63496

[1]RMSE is given by the following expression: $\text{RMSE} = \sqrt{\sum_{i=1}^{n} (y_i - y_{fi})^2 / n}$ where, n is forecast horizon, y_i and y_{fi} denote the actual and forecasted values, respectively. [2]Models are described in the Methodology section in detail

Table 7: Comparison of Forecasts with actual values and forecasts of some recent studies for period between 2014 and 2018 (GWh)

Study	2014	2015	2016	2017	2018
Actual values	207233.2	216233.2			
This study	205621.6	213030.9	220656.9	228307.2	235971
Hamzacebi and Es (2014)	221098	224723	236078	252829	270920

Figure 3: Forecasts of per capita electricity consumption values for regions of electricity distribution companies for the period 2014-2018 using model 2. (1) BAŞKENT EDAŞ, (2.) SEDAŞ, (3) MERAM EDAŞ, (4) ARAS EDAŞ, (5) ÇORUH EDAŞ, (6) FIRAT EDAŞ, (7) TREDAŞ, (8) OSMANGAZİ EDAŞ, (9) YEDAŞ, (10) ÇEDAŞ, (11) ULUDAĞ EDAŞ, (12) GEDİZ EDAŞ, (13) İSTANBUL, (14) AKEDAŞ, (15) AKDENİZ EDAŞ, (16) AYDEM EDAŞ, (17) DİCLE EDAŞ, (18) VAN GÖLÜ EDAŞ, (19) TOROSLAR EDAŞ, (20) KCETAŞ

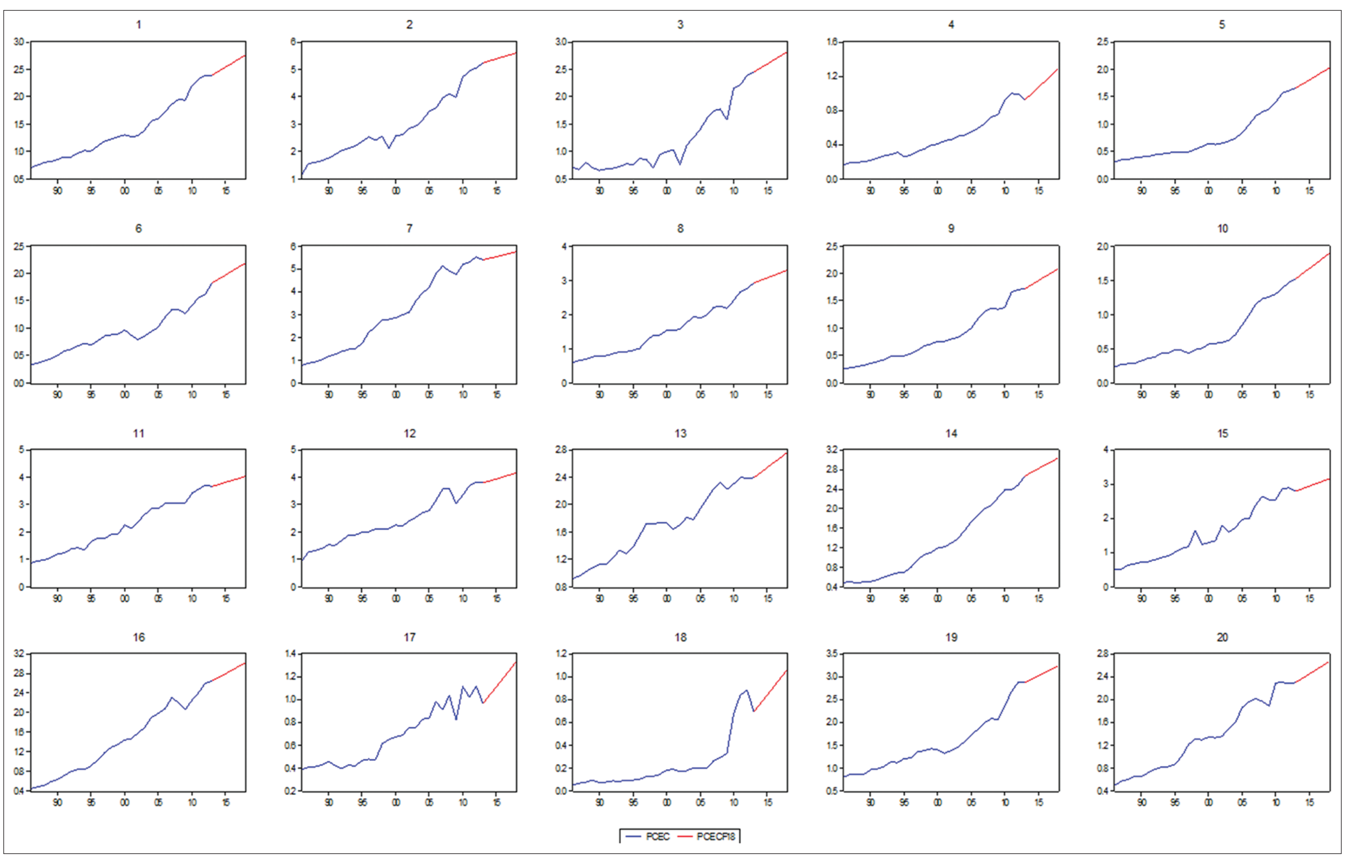
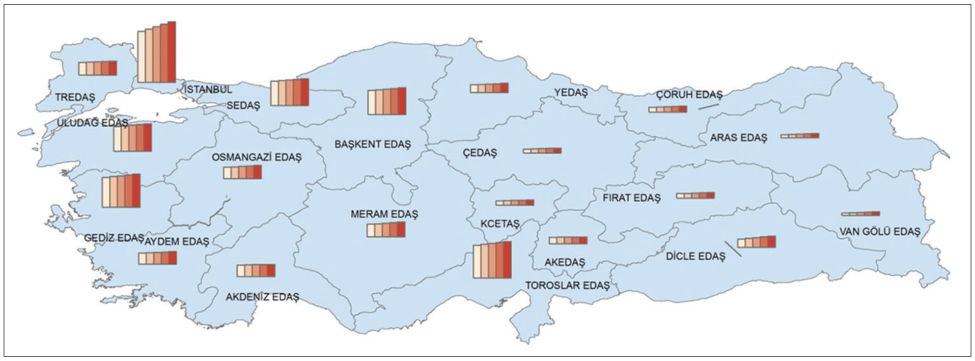


Figure 4: Forecasted values of net electricity consumption (GWh) for regions of electricity distribution companies over the period between 2014 and 2018 using Model 2



under the responsibility of same distribution companies over the period from 1986 to 2013 for Turkey. Results show that forecasts obtained by using pooled panel data model outperform the other forecasts using other models, such as ARIMA model, fixed effects panel data model, pooled spatial lag and spatial error models, spatial lag and spatial error panel data models with fixed effects. Therefore, the study concludes that while forecasting the regional electricity demand for Turkey, one can pool the data assuming homogeneity among regions. However, this result is only valid under the region definition considered as well as spatial weight matrix employed. Also, other technological and economic factors affecting electricity demand and explaining regional differences should be included into the analysis based on the availability of data. In addition, in this study, annual data is employed, but as a future study, by using high frequency data, the accuracy of forecasts can be improved.

Moreover, after choosing the best model, electricity demand is forecasted for the period between 2014 and 2018. Forecasts indicate that electricity consumption continue to increase which necessitates for generation, transmission and distribution capacity expansions for all the regions. On the other hand, the investment requirements on centralized electricity generation can decline by implementing energy efficiency applications and spreading out the use of distributed generation technologies which however, can increase the needs for transmission and distribution capacity expansions, especially for smart grid technologies. Lastly, as distributed generation technologies mostly use renewable energy, they will also contribute to the attempts for reducing the severe environmental impacts of power plants based on conventional technologies.

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