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Research Article

Prediction of Short-Term Electricity Consumption by Artificial Neural Networks Using Temperature Variables

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Abstract

Today, energy consumption is one of the most important indicators of countries' development levels. Energy, the most important input of social and economic development, is a necessary requirement for the increase of living standard and sustainable development. Electricity is one of the most preferred and consumed energy types because of easy use, easy transportation and clean energy. Electricity consumption varies depending on various social and economic variables such as population, economic growth and gross domestic product as well as on climatic variables such as temperature, precipitation and humidity. The electricity used for heating and cooling needs is bigger in electricity consumption. Weather conditions cause increase and decrease in electricity consumption. Temperature is the meteorological variable with the highest effect. As the comfort temperature gets away from the accepted temperature range, the electricity consumption also increases. The balance of electricity production and consumption is also important in terms of atmospheric disasters. In study, the relation of Turkish electricity consumption with temperature was examined between January 2012 and November 2016. In monthly and seasonal time periods, it was researched how the consumption was changed due to the temperature and how much it was changed and it was aimed to make a more consistent consumption estimation by adding as a temperature input to the consumption estimation model. In the study, short-term electricity consumption estimations were made by using Artificial Neural Network (ANN) method and data groups modeled by Levenberg-Marquardt backpropagation algorithm on MATLAB programing language. The temperature data is produced with a weighted average by consumption amount. The temperatures of 12 provinces with the largest share of consumption in Turkey are weighted according to their consumption rates. In the model weighting, the percentage of effect 1 day before is more than 1 week before and 1 week before is more than 1 year before. For this reason, deviations in the recent history more influence the model. Model results show that, error rates are considered to be reasonable. It is planned to establish the model on a regional basis for future work. When estimating regional electricity demand, a model can be developed by using different meteorological variables. It is predicted that rainfall data will increase the performance of estimates of the inclusion of temperature data in the Bosphorus region, which has a high population density and a high level of residential consumption.

Keywords: Temperature, Electricity Consumption, Annual Neural Network(ANN), Model, Turkey.

1. Introduction

Energy is a concept that has emerged from the industrial revolution as one of the most important human needs. The necessity of energy to make production clearly determines the energetic necessity of human being. Electric energy is a secondary energy source produced from primary energy sources such as wind, sun, coal. Due to the pollution of the environment and its easy use, many different areas such as industry, lighting, irrigation and dwelling are used. Meeting these requirements of different energy consuming centers is very difficult and requires significant investments. The most important criterion for ensuring sufficient energy is to make the right consumption estimate. Many different methods such as time series analysis and regression analysis, easy to use and artificial neural network method, which is highly preferred in recent years due to high consistency rate, are used for consumption estimation. In order for the electricity market to provide uninterrupted energy to users, it is necessary to estimate the electricity demand and price correctly. Electricity consumption forecasting is a very important process for the planning of the electricity industry and for the operation of energy systems. High accuracy estimates provide significant savings in operating and maintenance costs and contribute to the planning of future investments for sustainability [1]. Toros and Ark. (2014) emphasized the importance of countries moving to online payment systems depending on their production in order to encourage reducing imbalances between electricity generation and consumption. In addition, the development of smart devices for the operation of electric home appliances at the time of falling electricity prices will contribute to the more efficient use of energy resources as it will cause a serious decrease in electricity consumption. Naturally, efficient use of energy resources will have an impact in reducing meteorological disasters that threaten our earth [2].

Artificial intelligence-based algorithms have a great advantage as the relationship between electricity generation and

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the factors that affect the amount of consumption is not linear [3]. When the past electricity consumption data are analyzed, it is seen that the yield has seasonality. It is observed that short cycling electricity consumption is significantly influenced by day type (such as weekday, weekend, official holiday, religious days) and weather conditions. It is seen that meteorological variables such as temperature, precipitation and humidity are influential in the regional consumption of electricity and the meteorological variable which is the most effective is the temperature [4]. Slide. J. (1996) conducted regression and correlation analyzes to investigate the relationship between household electricity consumption in Hong Kong and economic factors and climatic factors. As a result of studying 23 years of economic data and energy data in the study, it is concluded that seasonal and annual domestic electricity usage changes depending on household income, household population, electricity price and cooling degree days [5]. Aneiros, G. and others (2015) developed two methods for estimating electricity demand and price one day later. These methods estimate the slope of price and demand for a day later using the slopes of past data. Hourly electricity demand and price data, maximum daily temperature and daily wind production data for Spain 2011-2012 are used in the study [6]. Daily, weekly and seasonal effects were observed in electricity consumption. Weekday and weekend consumption are different from each other.

Friedrich L. and Afshari A. (2015) developed models for short-term electric charge estimation for Abu Dhabi. The methods they develop are methods based on statistics and artificial intelligence. Model constructions and, alternatively, both models are based on past load data and variables such as season, day type and weather. Among the meteorological variables related to the load in this model; Temperature, humidity, global solar radiation and wind have been examined and included in the model separately. This mathematical model was then compared with the artificial neural network model, which again uses the data of the same variables as input [7]. July 2009- June 2011 electricity consumption data was used in the study. In the transfer function (TF) model they developed, external variables were tested separately with the Akaike information criterion. The best transfer function structure was established with high related coefficients in the test result. In accordance with this structure, all variables are combined in the load model. To test the accuracy of the developed model, load estimates were taken from 1 hour to 1 week. The results are compared with the actual data and the consistency with MAPE (mean absolute error rate) method is measured.

Khwaja et al. (2016) developed a model using Boosted neural networks for estimating short-term electricity consumption in their study. The Boosted neural network (BooNN) consists of a series of repetitive artificial neural networks (ANN) combinations. At each iteration, the error between the estimated output of the ANN model trained in the previous iteration and the target output is minimized. This process is more successful when the size and variations of prediction errors are compared with a single ANN and packed neural networks (PNN). The hourly temperature and electricity consumption data of the New Pool area of the UK was used in the consumption forecasting model. In addition, while the model is being trained, dew point temperature, time of day, day of week, day of the week, variable indicating which day of the holiday, average electricity consumption before 1 day, electricity consumption data of the same hour 1 week ago are also added as model inputs. They have done many experiments with different algorithms to select the artificial neural network model that gives the best result. They have estimated the number of neurons to be 8 and have been estimated by different artificial neural network algorithms [3].

Azadeh et al. (2008) have made consumption forecasts with an artificial neural network approach for annual electricity consumption in the high energy consuming industrial sector in Iran and have obtained that the neural network model is more successful than the regression models. For the years 1979-2003, the high energy consuming industry set up a regression model with the artificial neural network model and the same data with the total monthly data of electricity consumption and multi-layer perceptron based variance analysis approach. Results were obtained as monthly training data between 1979-1999 and by testing the data of 2000-2003 with prediction. The artificial neural network algorithm is defined as back propagation. In order to compare the model results, the error rate was 0.99% for the artificial neural network and 7.5% for the regression model. It has been shown that artificial neural networks are reliable estimation methods for long-term electricity consumption prediction in the direction of these results [8].

In this study, it is examined how much electricity consumption of Turkey is affected by temperature changes. In monthly and seasonal time periods, it was researched how and in what way the consumption was changed due to the temperature and it was aimed to make a more consistent consumption estimation by adding as a temperature input to the consumption model. The electricity consumption forecasting model was developed by artificial neural network method, which has high fault tolerance and is thought to give more consistent results in learning ability and consumption prediction.

2. Data and Methodology

2.1 Study Area

Energy consumption in Turkey has increased rapidly in the last 30 years due to the increasing population, industrialization and living standards. The decline of agriculture, the development of industry and service sectors are among the reasons for the increase in energy consumption. Electricity can be transported by transmission and distribution networks to the areas where the energy is generated. However, since electricity cannot be stored, estimating electricity consumption is very important in terms of business and financial planning and sustainability. The most important criterion for ensuring sufficient energy is to make the right consumption estimate. Electricity consumption varies depending on various social and economic variables such as population, cost and gross domestic product, as well as on climatic variables such as temperature and rainfall. The determination of the factors affecting the electricity consumption and the high accuracy rate of the consumption forecast are very important for the energy market. It has been investigated how the electricity consumption of the 12 selected provinces is affected by the above factors. Istanbul is the most crowded and largest metropolis in terms of Turkey's population and Ankara and İzmir are the second and third cities in this context. Kocaeli is the busiest industrial city. Konya is the front plan of agriculture, Antalya and Mersin are the cities where tourism has come to the forefront. As shown in Figure 1, these figures are in different regions and represent different characters in terms of population, topography, social and economic variables.

Figure 1: Cities which data are used

2.2. Data

Hourly temperature data was used in the estimation of electricity consumption in Turkey, officially announced by Turkish Electricity Enterprises Corporation, hourly electricity consumption values between January 2012 and November 2016, and provincial basis of the same turn obtained from General Directorate of Meteorology. Considering the data, two different periods were chosen, summer and winter, and the demand for these periods was estimated. Winter Season: Training period: 01.01.2012 - 31.12.2015 Forecast period: 01.01.2016-31.01.2016 during these periods. Summer period: Training period: 01.07.2012 - 31.07.2016, Forecast period: 01.08.2016-31.08.2016. These evaluations were made at intervals.

2.3 Methodology

Turkey's electricity consumption is affected by temperature changes. In monthly and seasonal time periods, it was researched how and in what way the consumption was changed due to the temperature and it was aimed to make a more consistent consumption estimation by adding as a temperature input to the consumption model. The Levenberg-Marquardt algorithm is a predominant algorithm with fast and stable convergence for nonlinear functions. It is a suitable training algorithm especially for small and medium sized data groups in ANN area [9].

Within the scope of the study, short-term electricity consumption estimations were made by using the Levenberg-Marquardt backpropagation data model which is modeled by ANN method on MATLAB programing language. The study period was January 2012-November 2016. Turkey's hourly consumption data and hourly temperature data are used for these years. The temperature data is produced with a population weighted average. The temperatures of 12 provinces with the largest share of consumption in Turkey are weighted according to their consumption rates. In the model 38 interlayer artificial neural networks were found to give the best results. When estimates are established with this structure, the consumption of the hottest and coldest August and January months for 2016 is estimated according to the monthly average. In addition to model temperature and electricity consumption, the day effect was also included as input. Using the same network structure and algorithm, temperature data and only electricity consumption data and total electricity consumption were estimated. In the study, the Levenberg-Marquardt backpropagation ANN algorithm and Equation 1 and 2, X input series including 8 and 12 different input datasets were used. And a single output data set, F forecast, was obtained

$$X_{1input} = [G_1, TG_1, G_2, TG_2, H_1, TH_1, Y_1, TY_1, T_{holiday}, HG, Sa] \quad (1)$$

$$X_{2input} = [G_1, G_2, H_1, Y_1, T_{holiday}, HG, Sa] \quad (2)$$

G_1: Electricity consumption value for the same hour of one day before

TG_1: Temperature value for the same hour of one day before

G_2: Electricity consumption value for the same hour of two day before

TG_2: Temperature value for the same hour of two day before

H_1: Electricity consumption value for the same hour of one week before

TH_1: Temperature value for the same hour of one week before

Y_1: Electricity consumption value for the same hour of one year before

TY_1: Temperature value for the same hour of one year before

Tholiday: Bank holiday

HG: Days of the week (Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, Saturday)

Sa: Time [1:24]

In the model in which X_1 is used, the temperature data is set as a model input in the same groups as the consumption data. In the ANN structure created by this data group, there are 11 data groups in the input section. 2-layer model with 38 hidden layers and 1 output layer has been designed. X_2 in the model in which the input is used, the consumption tax is placed as a model entry. In the ANN structure created by this data group, there are 7 data groups in the input section. 2-layer model with 38 hidden layers and 1 output layer has been designed.

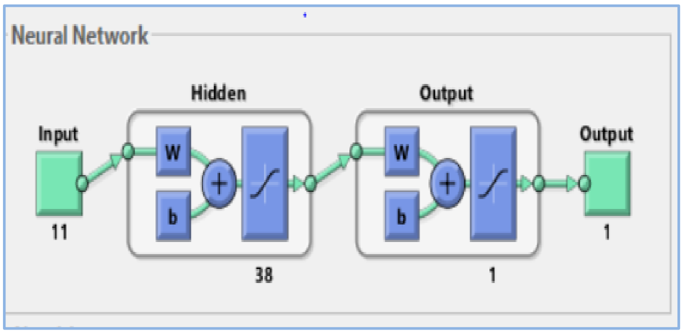

Figure 2: Model schema view

Performance factor in the study; F forecast data has been interpreted with the interpretation of MAPE values against F test data. The Mean Absolute Percentage Error (MAPE) expresses the error change in percent of the actual data. This allows for easy interpretation between the predicted and tested data set. It is also desirable that the MAPE be close to 0% as much as possible. In Equation 3, Xt is the estimated value of real and Ft is the estimated value, and m is the numerical quantity subject to the MAPE calculation. Predictability indicates a degree of accuracy when estimating a time series. When using the time series method, we can see the difference between the mean absolute percent error (MAPE) and the expected range and predicted value [10].

$$\text{MAPE}=\frac{\sum_{t=1}^{m}\left|\frac{Xt-Ft}{Xt}\right|}{m}(100)=\frac{\sum_{t=1}^{m}\left|\frac{et}{Xt}\right|}{m}(100) \quad (3)$$

The MAPE values used to determine the prediction performance is calculated according to Equation 4.

$$\text{MAPE}=\frac{\sum_{t=1}^{m}\left|\frac{Ftest-Ftahmin}{Ftest}\right|}{m}(100)=\frac{\sum_{t=1}^{m}\left|\frac{et}{Ftest}\right|}{m}(100) \quad (4)$$

Two months' total electricity consumption forecast for January 2016 and August 2016 was made with two different models. In order to measure the consistency of models;

A) Daily average MAPE,

B) Hourly average MAPE values are calculated separately.

3. Results

In the scope of this study, a model was established in which the temperature is included to make a short-term estimate of the demand for electricity with higher accuracy. Models were checked for performance when they received or did not receive temperature data as input.

For the electricity demand forecast, the January and August months, the lowest and highest temperatures for the winter and summer periods, were selected as an example. The effect of temperature on electricity consumption is mostly seen during people's need for warming and cooling. For this reason, the hottest and coldest month of the year is taken as an example. January 2016 was used as the training data set for January 2012-December 2015, and it was used as the test data for January 2016. August 2016 was used as test data in the model in which January 2012-July 2016 was used as training data set. The average absolute percent error (MAPE) is also calculated for the performance measurement. X1 is the model in which the temperature data is used, and X2 is the model in which the temperature data is not used. During the winter season (Table 1), the X1 model was more successful than the X2 model in daily and hourly averages. In the summer period (Table 2), the X1 model is more successful than the X2 model in daily and hourly average. Compared to the two periods, the X_1 model is lower than the summer period MAPE value winter. The model produced more consistent estimates in August. However, when you look at the X_2 model, it is seen that the model was more successful in January, and the hourly and daily error rate increased in August.

Table 1: Winter time hourly and daily average table

Input X_1		***Input X_2***	
Hourly	Daily	Hourly	Daily
1,94%	1,34%	2,20%	1,81%

Table 2: Summer time hourly and daily average table

Input X_1		***Input X_2***	
Hourly	Daily	Hourly	Daily
1,62%	1,04%	2,76%	2,08%

Based on these results, it is predicted that the effect of temperature on electricity consumption is higher in summer. The use of air conditioning for summer cooling needs directly leads to an increase in electricity consumption. However, since the heating requirement in winter is high for natural gas and coal, the use of electric heaters and air conditioners is low for heating needs. Thus, the direct effect of temperature on electricity consumption is decreasing. In the transition seasons, it is thought that the model will work close to performance in these periods as the temperatures are close to the comfort temperature. The consistency of the X_1 model is close to that of the X_2 model in the spring.

The need for electricity depends on the warmth of the large residence group. Residential electricity consumption accounts for 24.76% of total electricity consumption in Turkey (Figure 3). When regional electricity consumption is considered in some cases, the model will be more successful in regions where population density is particularly high for the residential group. In Turkey, the industrial group has the biggest share with 40.87% in total electricity consumption (Figure 3).

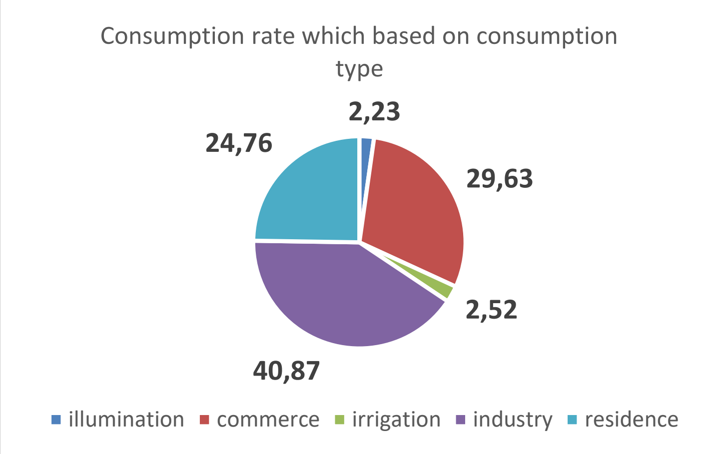

Figure 3: Consumption rate which based on consumption type in 2015 [11].

Considering the working profile of the industrial group, it is predicted that the temperature will affect at low level. Since the model is highly related to the smaller group of households and Turkey estimates the total electricity consumption, the performance difference between the X1 and X2 models is not very high. As a development, we can see the direct effect of the temperature and the difference between the two models, even if we set the model only with the data of the residential electricity consumption. In the model, the day type was used as input. The results were analyzed according to the days of the week. Table 3 shows the average daily MAPE values for the X_1 and X_2 model for the August day type.

Table 3: Average daily MAPE by day type of August X1 and X2 models

Day	**X_1 MAPE**	**X_2 MAPE**
Monday	1,062%	1,027%
Tuesday	1,033%	5,274%
Wednesday	0,808%	1,303%
Thusrday	0,424%	0,637%
Friday	1,260%	1,631%
Saturday	1,630%	2,339%
Sunday	1,081%	1,980%

In Figure 4, the average daily MAPE values of the X_1 and X_2 models for August are compared. On Monday, the models performed very close to each other while X_2 performed better than X_1 at 0.04%. Looking at the other days, it is seen that X_1 has lower MAPE value per day. In the chart, the forecast of Tuesday's X_2 model shows that the MAPE average is very high. The reason for this is that on August 30, 2016, it will coincide with Tuesday. In the model, August 30 has a distinct day type as a public holiday. However, the artificial neural network has a limited number of data to be learned because there are few official holidays in hand when making weight assignments. It is much easier to assign the right weight to today as it is on Tuesday with data on it. This result shows us that the model has a higher error rate on special days. Although the X_1 performs better on August 30th, it has a fatal error above the average. When looking at the graph in general, the error rates are low because weekday days show similar profiles, but it is higher than other days due to the changing consumption on weekends. The average daily MAPE values for the X_1 and X_2 model for the August day type are given in Table 4.

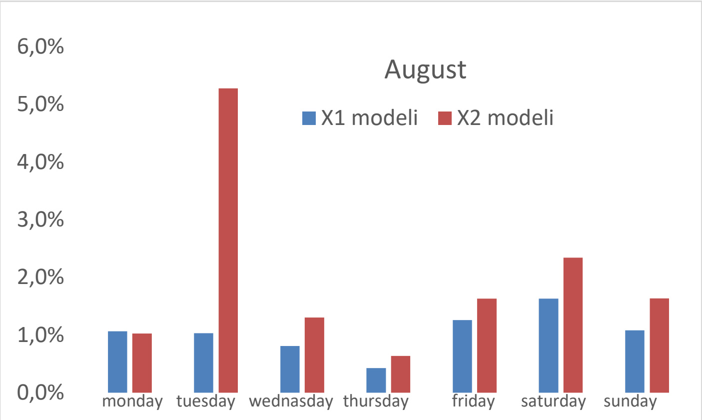

Figure 4: MAPE values of X_1 and X_2 models on the days of August days

Table 4 shows the average daily MAPE values for the X_1 and X_2 model for the January day type. Figure 5 compares the average daily MAPE values of the X_1 and X_2 models for days on a daily basis. On Thursday the average MAPE X_2 model is less than X_1. For other days, the X_1 model was more successful. The day with the highest error rate on both models has been Saturday. The highest error rates were observed on Friday, January 1 and Saturday, January 2, when looking at daily errors. Parallel to August results, on weekdays the error was less and the error of the weekend models rose.

Table 4: Average daily MAPE by day type of January X_1 and X_2 models

Days	**X_1 MAPE**	**X_2 MAPE**
Monday	1,50%	1,87%
Tuesday	1,36%	1,79%
Wednesday	0,75%	1,10%
Thusday	0,95%	0,62%
Friday	0,79%	1,89%
Saturday	2,01%	2,94%
Sunday	1,86%	2,11%

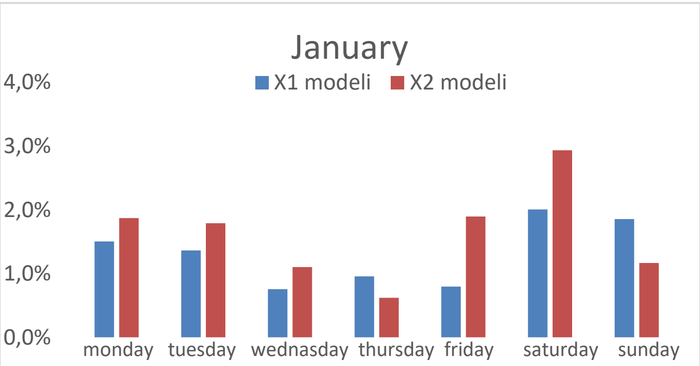

Figure 5: MAPE values of X_1 and X_2 models in the days of January

The study presents a model for forecasting electricity demand, which is very important for today's electricity markets and is very effective in terms of economic and financial performance of market participants. When the model results are evaluated, the error rates are considered to be reasonable. For future work, it is planned to establish the model on a regional basis. When estimating regional electricity demand, a model can be developed by using different meteorological variables. It is predicted that rainfall data will increase the performance of estimates of the temperature data, which is felt in the Bosphorus region, which has a lot of population density and dwelling consumption.

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References

[1] Almeshaiei ve H. Soltan, A methodology for Electric Power Load Forecasting, Alexandria Engineering Journal, no. 50, p. 137–144, 2011.

[2] H. Toros, R. Ayaz, A. Ajder, A. Durusu ve H. Yıldırım, Online Load Shifting Of Electricity Production-Consumption For Reducing Environmental Hazard, *European Journal of Science and Technology (EJOSAT),* cilt 1, no. 2, pp. 39-42, 2013.

[3] A. S. Khwaja, X. Zhang,, A. Anpalagan and B. Venkatesh, Boosted neural networks for improved short-term electric load forecasting, *Electric Power Systems Research*, p. 431–437, 2017.

[4] J. Moral-Carcedo ve J. PerezüGarcia, Temperature effects on firms' electricity demand: An analysis of sectorial differences in Spain, *Applied Energy*, no. 142, p. 407–425, 2015.

[5] J. C. Lam, «Climatic and economic influences on residential electricity consumption,» *Energy Conversion and Management*, cilt 39, no. 7, pp. 623-629, 1998.

[6] G. Aneiros, J. Vilar ve P. Raña, Short-term forecast of daily curves of electricity demand and price, *Electrical Power and Energy Systems*, no. 80, pp. 96-108, 2016.

[7] L. Friedrich ve A. Afshari, Short-term forecasting of the Abu Dhabi electricity load using,» *Energy Procedia*, no. 75, pp. 3014-3026, 2015.

[8] A. Azadeh, S. F. Ghaderi ve S. Sohrabkhani, Annual Electricity Consumption Forecasting By Neural Network İn High Energy Consuming İndustrial Sectors of Iran, *Energy Conversion and Management*, no. 49, p. 2272–2278, 2008.

[9] S. Yıldız, Türkiye Elektrik Piyasası Kısa Dönemli Referans Fiyat Tahmini,, İTÜ, Enerji Enstitüsü, İstanbul, 2015.

[10] J. Boylan, « Toward a More Precise Definition of Forecastabilitiy,» Business Forecasting, SAS Institute Inc., Cary, North Carolina, USA.

[11] EPDK, Elektrik Piyasası 2015 Yılı Piyasa Gelişim Raporu, T.C. Enerji Piyasası Düzenleme Kurumu (EPDK), Ankara, Türkiye., 2016.