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Improving an Expert-Supported Dynamic Programming Algorithm and Adaptive-Neuro Fuzzy Inference System for Long-Term Load Forecasting

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Abstract: Load forecasting is very important to manage the electrical power systems. Load forecasting can be analyzed in three different ways as short-term, medium-term and long-term. Long-term load forecasting (LTLF) is in need to plan and carry on future energy demand and investment such as size of energy plant. LTLF is affected by energy consumption, national incoming per year, rates of civilization, increasing population rates and moreover economical parameters. Some of the forecasting models use mathematical formulas and statistical models such as correlation and regression analysis. In this study, a new effective expert-supported dynamic programming algorithm (ESDP) has been improved. Additionally, adaptive neuro-fuzzy inference system (ANFIS) and mathematical modeling (MM) are used to forecast long term energy demand. ANFIS is one of the famous artificial intelligence and has widely used to solve forecasting problems in literature. In addition to numerical inputs, ANFIS has linguistics inputs. The results obtained from ESDP, ANFIS and MM are compared to show availability. In order to show error levels mean absolute percentage error (MAPE) and mean absolute error (MAE) are used. The obtained results show that the proposed algorithms are available.

Keywords: *ANFIS, Dynamic programming, Electrical load forecasting, ENPEP, MAED.*

1. Introduction

Electricity energy consumption is a vital input for technical, social and economic development of a country. Therefore, development and analysis of energy policy options are of prime importance [1]. One of the conditions of reliable operation of the power system is load forecasting. Load forecasting is important for all participants in electric energy generation, transmission, distribution, market and customers. Load forecasting can be divided into short-term, mid-term and long-term forecasting. Short-term, mid-term and long-term load forecasts are range from an hour to one week, one week to one year and one year to decades, respectively [2, 3]. For short-term load forecasting (STLF) several factors should be considered, especially such as time, weather and renewable sources. Allocation of generation groups can be planned during the day by STLF. The medium-term and LTLF take into account the historical load, weather, the number of customers in different categories and other factors [4]. Many LTLF techniques have been proposed used for resource planning and utility expansion in the last 30 years [1-15, 21-35].

Many software packages have been made for safety and quality of energy systems management. [36-37]. Today, nearly 90 countries, the full version of Energy and Power Evaluation Program (ENPEP) or some sub-modules are used in energy planning. Model for Analysis of Energy Demand (MAED) is an ENPEP module. MAED forecasts long-term energy demand based on deterministic approach according to different scenarios. In Turkey, energy consumption projections are made by Ministry of Energy and Natural Resources of Turkey (MENR). Since 1984, MENR prepares energy demand forecasts by using MAED. MAED requires several types of data related to social, economical and demographical structure of country [5,6]. In particular, the electricity price, population growth, employment, climate change, technological developments, price of electrical appliances, etc. are used for electrical load forecasting. Many researchers have studied on forecasting of Turkey's electricity energy demand and peak load using different methods [7-12]. In these studies, in particular neural networks (NN), genetic algorithms (GA) and MM are used. The use of NN is an alternative method that is becoming an efficient technique to solve the electrical load forecasting. There are researches that treat this problem using the back-propagation algorithm [13]. This algorithm is considered on the specialized literature a benchmark in precision. However, the convergence is slow, although there are some adaptations to improve the performance. The idea is to use a NN that combines good results with a faster processing [14]. Neuro-fuzzy modeling refers to the way of applying various learning techniques developed in the NN literature to fuzzy modeling or a fuzzy inference system (FIS) [15]. Neuro-fuzzy system, which combine NN and fuzzy logic have recently gained a lot of interest in research and application. A specific approach in neuro-fuzzy development is the ANFIS, which has shown significant results in modeling nonlinear functions [16]. Auto-Regressive Integrated Moving Average (ARIMA) is widely used for forecasting short-term, medium-term and long-term demands [17]. Time series load forecasting model of ARIMA which incorporates the knowledge of expert operators is carried out by using a linear combination of the past values of the variable [18].

In this study, ESDP, ANFIS and MM are used to solve energy consumption and peak demand forecasting problems from 2015 to 2030 for Turkey. In particular, some of the causes of the energy crisis are lack of accurate and timely investment planning. Therefore, this study is intended to provide more accurate

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information for the investment planning.

2. The ANFIS Structure Used for LTLF

Numerous researchers have proposed different methods to forecast electricity load. Load forecasting can be categorized into two main groups: statistical methods and artificial intelligence methods. Statistical methods may be considered time series analysis, end-user models, econometric forecasting and regression analysis. Artificial intelligence methods may be considered artificial neural network, fuzzy logic, ANFIS, GA, expert systems and etc. The ANFIS is capable of dealing with uncertainty and complexity in the given data set and thus provides better solution and estimation with this valuable commodity [19]. In this study, due to faster convergence and smaller size training set, ANFIS is intended for use. ANFIS was presented by R.Yang in 1993 [20]. ANFIS is widely used in engineering applications many kinds of nonlinear problems [21, 22].

ANFIS structure used can be explained in five stages:

Stage 1: This layer can be called as fuzzification layer. Used parameters in this stage is called premise parameters and re-arranged according to output error in every loop. These parameters are membership grades of a fuzzy set and input parameters in this layer.

Stage 2: A fixed node labeled Π whose output is the product of all the incoming signals can be computed. Every output of the stage 2 affects the triggering level of the rule in the next stage. Trigger level is called firing strength and Π norm operator is called AND operator in fuzzy system.

Stage 3: This layer can be called as normalization layer. For this layer, all firing strengths are re-arranged again by considering own weights.

Stage 4: Defuzzication, this layer is a preliminary calculation of the output for real world. This layer has adaptive nodes and it is expressed as functions and if ANFIS model is Sugeno type then is valid calculation styles turn to linear approach. This type is called first order Sugeno type [23].

Stage 5: Summation neuron; this layer is a fixed node, which computes the overall output as the summation of all incoming signals. ANFIS Learning Ability; ANFIS has two times error correction ability in one loop. This correction is processed through backward and forward. For the backward correction, the antecedent parameters are tuned while the consequent parameters are kept fixed. Least square estimator arranges the parameters to minimize the squared error.

In this study, data set is not normalized to obtain real response from ANFIS structure. Natural condition of data set has been kept and used low ANFIS rule structure to obtain fast response. ANFIS setting are configured as range of influence 0.5, squash factor 1,25, reject ratio 0.15, and accept ratio is 0.5. Range of influence and squash factor are increased to obtain low level ANFIS rule structure and to decrease training cycles.

3. Expert-Supported Dynamic Programming (ESDP) for LTLF

Dynamic Programming (DP) with respect to time can be performed forecasting problem solving. In particular, DP is used in solving the problems of load forecasting. The coefficients proposed new algorithm actuated by DP makes it possible to intervene following experts are available to improve the accuracy of these solutions. Expert systems should be able to estimate the socio-economic situation of the region made a very good level of analysis. Proposed dynamic programming algorithm with expert coefficients solution method was developed. Load forecasting problem is solved with an ESDP. The proposed ESDP algorithm steps are given below:

Step 1 Start
Step 2 Read time-dependent variables (population, income, etc.)
Step 3 Calculate the rate of change of variable
Step 4 Determining the amount of activity
Step 5 Take the weight coefficients (from the expert)
Step 6 Calculate the energy consumption
Step 7 If n=last number then go to step 9
Step 8 n= n+1, go to step 2
Step 9 Compose consumption, stop.

4. Mathematical Modelling for LTLF

Proposed mathematical model uses economic data, social data and projections prepared for the future. In this study, the peak load demand, consumption of total energy, income, population, population projections and income projections were used to forecast. Data used for LTLF and peak load demand forecasting are given in Table 1 and Table 2. As a result, between 2015 and 2030, peak load demand and total energy consumption has been forecasted.

The mathematical models to forecast total energy consumption ($F_E(x)$) and peak load demand ($F_P(x)$) using Table 1 data are given in (1) and (2). Equations (1) and (2) by curve fitting method using between the years of 2001-2014 data were created. Peak load and energy consumption values from 2015 until 2030 were calculated according to the Eq. (1) and (2).

$$F_E(x) = -391742 + 98{,}758 \text{ x (income)} + 6{,}281 \text{ x (population)} \quad (1)$$

$$F_P(x) = -65789 + 15{,}549 \text{ x (income)} + 1{,}034 \text{ x (population)} \quad (2)$$

Projection data used by Turkish Electricity Transmission Company (TETC) are given in Table 2. Economic growths are assumed 3%, 6% and 10%, respectively to estimate S1, S2 and S3. In this study, S2 were used.

Table 1. Data for load forecasting

Years	*Peak (MW)*	*Energy (GWh)*	*Income (₺/month)*	*Population (x1000)*
2001	19612	126871	1049	65135
2002	21006	132553	1099	66009
2003	21729	141151	1142	66873
2004	23485	150018	1233	67734
2005	25174	160794	1320	68582
2006	27594	174637	1394	69421
2007	29249	190000	1441	70256
2008	30517	198085	1440	71079
2009	30982	200137	1498	71897
2010	33392	210434	1501	73722
2011	36122	229319	1584	74724
2012	39011	239838	1618	75627
2013	42132	246356	1645	76667
2014	1713	1821	1998	77358

Table 2. Projection Data

Years	*Monthly income per person (₺)*			*Population (x1000)*
	S1	*S2*	*S3*	
2015	1790	1948	2198	78101
2016	1871	2068	2417	78825
2017	1955	2199	2659	79546
2018	2043	2374	2925	80257
2019	2135	2594	3218	80954
2020	2231	2643	3539	81635
2021	2331	2776	3893	82293
2022	2436	2910	4283	82933
2023	2546	3043	4711	83566
2024	2660	3177	5182	84276
2025	2780	3310	5700	84993
2026	2994	3538	6092	85715
2027	3233	3861	6481	86444
2028	3368	4109	6863	87178
2029	3609	4574	7218	87919
2030	3865	5046	7584	88667

5. Experimental Results

Peak load demand forecasting of the ANFIS, ESDP and MM are presented together in Figure 1. The values found by MM are lower than others. The main reason is, after the year 2019 according to S2 scenario, growth rate of income is fall. But according to S3 scenario, growth rate of income is rise.

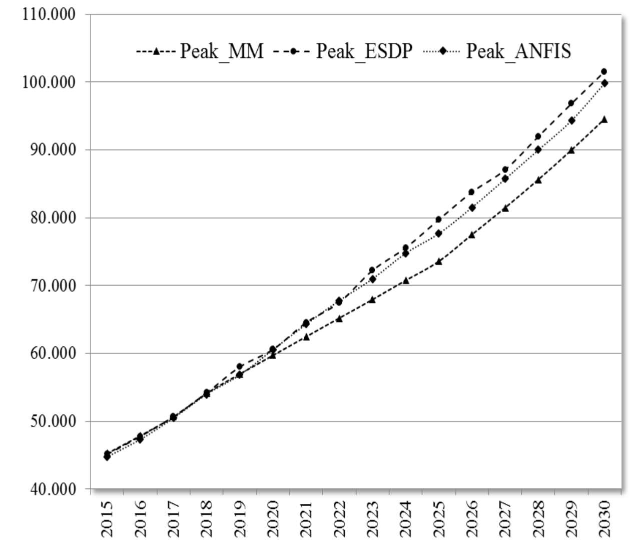

Figure 1. Peak Load Demand Forecasting

Energy consumption forecasting by MAED [24], ESDP, ANFIS and MM are presented together in Figure 2. MAED data and peak forecasting results obtained from ESDP, ANFIS and MM for comparison are given in Table 3. According to Table 3 the data obtained by MAED have been more accurately predicted by ANFIS. But it must be noted that unfortunately MAED data is far from the actual data. ESDP results were much closer to the actual data.

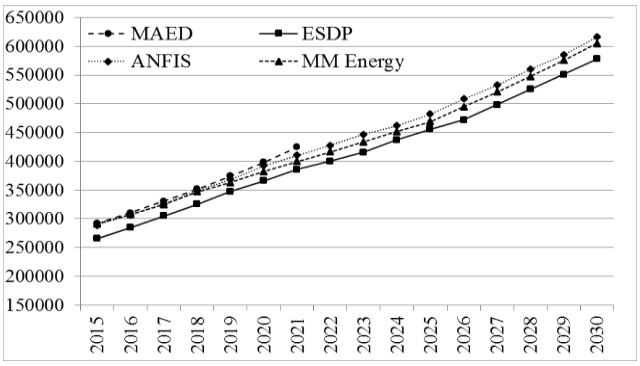

Figure 2. Energy Consumption Forecasting

Table 3. Peak Load Comparisons (MW)

Years	*MAED [24]*	*MM*	*ANFIS*	*ESDP*
2015	44955	45.257	44.756	45.150
2016	47870	47.871	47.329	47.800
2017	50965	50.654	50.482	50.700
2018	54230	54.110	53.994	54.200
2019	57685	56.972	56.843	58.050
2020	61340	59.718	60.575	60.609
2021	65440	62.466	64.320	64.570
2022	67520	65.211	67.814	67.540
2023	71300	67.934	71.000	72.250
2024		70.752	74.782	75.590
2025		73.561	77.683	79.750
2026		77.522	81.540	83.803
2027		81.467	85.732	87.102
2028		85.612	90.015	92.000
2029		89.969	94.356	96.850
2030		94.547	99.876	101.578

The values found by Unler [6] are lower than others due to the projection data for 2006-2025 are used. The total annual energy consumptions for Turkey for the years 2010 and 2011 are 210434 and 229319, respectively. Even, these values were above the values forecasted by MAED. Here is clearly seen that in Turkey's rapid economic development. Thus, the importance of planning is understood. It is so difficult to make energy forecasting. Energy forecasting is not only to find numbers but also to give direction to the future.

More data types in order to increase the success of the mathematical modeling should be used. At the same time as the projection data must be forecasted correctly. According to MAPE values, ANFIS performs the forecasting better than MM. MAPE values obtained from ANFIS and MM to estimate the total energy consumption are 1.558 and 1.865, respectively. When the successes of both methods are compared it is clearly seen that the difference is not much. Besides, MM can be applied more easily.

The energy consumption forecasting values obtained from different studies are given in Table 4.

Table 4. Energy Consumptions Comparisons (GWh)

Years	*MAED [24]*	*ESDP*	*ANFIS*	*MM*
2015	291790	265475	288743	291191
2016	310730	284673	307021	307589
2017	330800	304789	326251	325055
2018	352010	325466	348765	346804
2019	374430	347821	368659	362908
2020	398160	365987	392670	382025
2021	424780	385723	410067	399293
2022	438300	400234	427642	416546
2023	462850	415672	446928	433657
2024		437367	461567	451352
2025		455720	482036	468986
2026		472098	508238	494816
2027		498453	532306	520303
2028		525398	559825	547103
2029		550717	584912	575283
2030		577935	616238	604915

Some conditions are required small numbers and small quantities. In this case mean absolute error (MAE) and its derivatives may lead misunderstanding or may not explain correctly. MAE is one of the simplest ways to evaluate any success and depends on mean of difference among observations and real values [25,26]. MAE is shown in equation 3.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_{im} - x_{ip}\right| \tag{3}$$

where x_{im} is the i^{th} measured value and x_{ip} is the forecasted value.

Mean absolute percentage error (MAPE) is used to support of MAE results. MAPE, shown in equation 4, has no unit and very common in energy forecasting applications [27,28].

$$MAPE = 100 \times \frac{1}{n}\sum_{i=1}^{n}\frac{\left|x_{im} - x_{ip}\right|}{x_{im}} \tag{4}$$

where x_{im} is the i^{th} measured value and x_{ip} is the forecasted value. MAPE and MAE values for total energy consumption and peak load demand forecasting were calculated using data from the year of 2014 to 2021 due to MAED data used by TETC are available until 2023 [24]. Error levels for MAE and MAPE are given in table 5. According to MAE and MAPE values, peak load demand was estimated to be more accurate from energy consumption. While the minimum MAPE for ESDP is calculated as 1.027, the maximum MAPE for MM is calculated as 1.255. MAE value calculated for ESDP is lower than calculated for ANFIS and MM. In this case both energy consumption forecasting and peak load demand forecasting more reliable by ESDP according to ANFIS and MM. Errors for MM, ANFIS and ESDP are given in Figure 3.

Table 5. MAE and MAPE Comparisons

	MM		*ANFIS*		*ESDP*	
	Peak	*Energy*	*Peak*	*Energy*	*Peak*	*Energy*
MAE	756	7219	577	5597	556	4919
MAPE	1.255	1.865	1.048	1.558	1.027	1.456

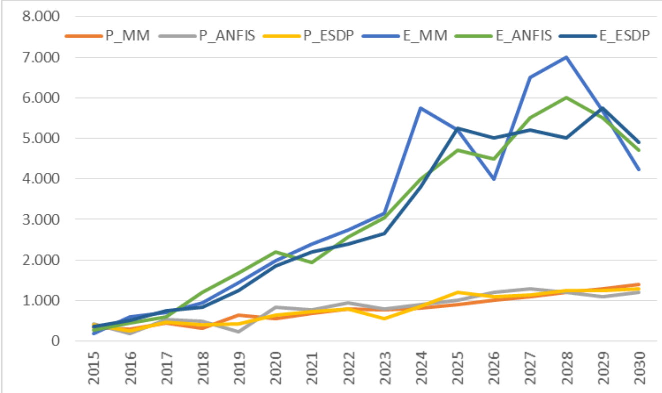

Figure 3. Errors for MM, ANFIS and ESDP

6. Conclusion

LTLF is one of the famous power system problems in literature and has no linear correlation among the input variables. Among the variables used to LTLF also affect each other, therefore, difficult study to make an accurately LTLF. This study is one of the latest studies used Turkey electrical data. The more LTLF is making accurately, the more planning and investment are obtained accurately. This study is intended to benefit the national economy. Therefore, ESDP, ANFIS and MM are used to evaluate real energy demand through the years. Especially, in 2020 about 400 TWh, in 2030 about 600 TWh of energy consumed are seen in all three approaches. Thus emerges the target of investment planning. Proposed method based on ANFIS is extended and created by background data. Data structure was windowed as six parts from last four years, present year and future year. After data turned to new time series ANFIS structure is used to evaluate. ANFIS has low error level especially for the future years load forecasting. Average forecasting error is 5597 GWh, although energy demands vary from 288743 to 616238 GWh. Average forecasting error is 577 MW, although peak load demands vary from 44756 to 99876 MW. ANFIS structure and settings can be changed in future studies for LTLF. After the changes, success of the study should be evaluated by calculating MAE and MAPE. Proposed MM finds easier and faster solution. However, forecasting success is lower than ANFIS and ESDP. Average energy consumption forecasting error is 7219 GWh. Average peak load forecasting error is 756 MW. Need to increase the number of input data in order to increase the success of the MM. Considering with results which obtained in this study, we can say to use the proposed ANFIS structure is more suitable and more accurate than MM. When electricity consumption between 2001 and 2014 and looking at the development of the country; ESDP has achieved more close to real results. Unfortunately, the most important result here is that the actual data to the remote MAED data. As a result, the proposed ESDP algorithm is available for electrical load forecasting.

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