POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)

URL: http://dergipark.org.tr/politeknik

Short-term electric energy load forecasting of Ankara Region using artificial intelligence methods

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To cite to this article: Akman T., Yılmaz C. and Sönmez Y., “Short-term electric energy load forecasting of Ankara Region using artificial intelligence methods”, ***Journal of Polytechnic***, 26(4): 1517-1531, (2023).

Bu makaleye şu şekilde atıfta bulunabilirsiniz: Akman T., Yılmaz C. and Sönmez Y., “Short-term electric energy load forecasting of Ankara Region using artificial intelligence methods”, ***Politeknik Dergisi***, 26(4): 1517-1531, (2023).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.911634

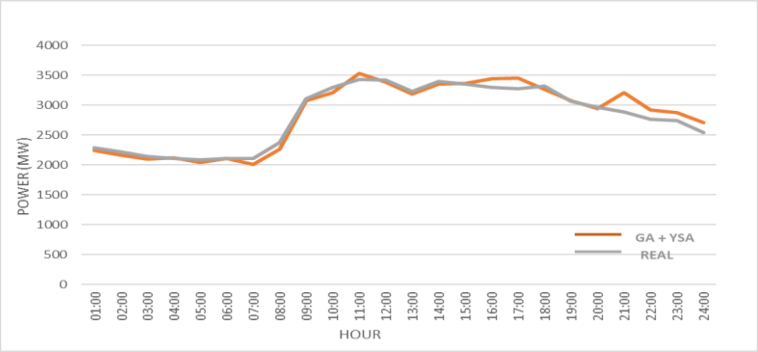
Short-term Electric Energy Load Forecasting of Ankara Region Using Artificial İntelligence Methods

Highlights

- *Yapay Sinir Ağlar/Artificial Neural Networks*
- *Güç sistemleri/Power systems*
- *Kısa Dönem Yük Tahmini/Short-Term Load Forecasting*
- *Genetik Algoritma/Genetic Algorithm*
- *Hibrit Tahmin Modeli/Hybrid Forecast Model*

Graphical Abstract

Çalışmada, yapay sinir ağları ve genetik algoritmaya dayalı kısa dönem elektrik yükü tahmini için adaptif hibrit sistem önerilmiştir./In this study, for short-term electric load forecasting based on artificial neural networks and genetic algorithm an adaptive hybrid system has been proposed.



Şekil. Gerçek ve tahmini yük eğrileri/ **Figure.**Actual and forecasting load curves

Aim

Önerilen model, Türkiye'de Ankara Bölgesi gerçek yük verileri kullanılarak test edilmiştir./The proposed model has been tested using actual load data of Ankara Region in Turkey.

Design & Methodology

Yapay sinir ağları ve genetik algoritmaya dayalı yük tahmini için adaptif hibrit sistem önerilmiştir../For load forecasting based on artificial neural networks and genetic algorithm an adaptive hybrid system has been proposed.

Originality

Özellikle doğrusal olmayan karmaşık problemler için oldukça iyi tahmin sonuçları elde edildiğinden, yük tahmini yapmak için genetik algoritma ile optimize edilmiş hibrit yapay sinir ağı modeli önerilmiştir./Hybrid artificial neural network model optimized with genetic algorithm has been proposed to perform load forecast since fairly good forecasting results are being obtained especially for non-linear complex problems.

Findings

Tahmin YSA tarafından yapılmıştır, YSA'nın her düğümü için en uygun aktivasyon fonksiyonunu seçmek için Genetik Algoritma kullanılır. Böylece ağ hatasının klasik YSA'ya göre daha da azaldığı gözlemlenmiştir./The actual forecast was made by ANN, Genetic Algorithm is used to select the most appropriate activation function for each node of ANN. Thus, it has been observed that network error decreased even more than classical ANN.

Conclusion

Sonuçlar hibrit YSA'nın klasik YSA'ya göre daha iyi sonuç verdiğini göstermektedir. Böylece yük tahmini için önerilen modelin doğruluğu artırılmıştır. Bu sonuçlar, önerilen modelin yük tahmininde klasik YSA'dan daha yüksek bir doğruluk oranına sahip olduğunu göstermiştir./The results show that hybrid ANN gives better result than classical ANN. So, the accuracy of the proposed model for load forecasting has been increased. These results showed that the proposed model has a higher accuracy rate than the classical ANN in the load forecasting.

Declaration of Ethical Standards

Bu makalenin yazarları çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler. The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Short-term Electric Energy Load Forecasting of Ankara Region Using Artificial İntelligence Methods

Research Article

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(Geliş/Received : 08.04.2021 ; Kabul/Accepted : 04.02.2022 ; Erken Görünüm/Early View : 16.12.2022)

ABSTRACT

While energy, which is an indispensable part of everyday life, maintains its importance and place in socio-economic structures of countries, importance of electricity energy, as an important component of energy, is increasing its gravity exponentially. Importance of electricity energy demand maintains its increasing trend in line with growing population, urbanization, industrialization, becoming widespread of technology and welfare. While meeting electricity energy demand, correct and effective load forecasting is needed in order to ensure operational safety without losing the stability of voltage, frequency and power flows within the limits determined under the real time conditions of electric power systems, operate and plan secure and low-cost electricity transmission systems and supply sustainable, reliable, high quality and affordable electricity to consumers. In recent years, use of the artificial intelligence models are quite common in many areas of the power system analysis and control, static and dynamic security analysis, dynamic load modelling and alarm processing and error diagnostics. Therefore, in this study, hybrid artificial neural network model optimized with genetic algorithm has been proposed to perform short-term load forecast since fairly good forecasting results are being obtained especially for non-linear complex problems. The proposed short-term load forecasting model has been tested by making 24 hours load forecasting using actual load data of Ankara Region in Turkey. The results obtained from the proposed model have been compared with classical ANN. In this study, for short-term electric load forecasting based on artificial neural networks and genetic algorithm an adaptive hybrid system has been proposed. Using artificial neural network based on Genetic Algorithm (GA) a new approach for short-term electric load forecasting has been developed. This proposed hybrid algorithm has been implemented for short-term load forecasting. In the proposed model, the actual forecast was made by ANN, Genetic Algorithm is used to select the most appropriate activation function for each node of ANN. Thus, it has been observed that network error decreased even more than classical ANN. The results show that hybrid ANN gives better result than classical ANN. So, the accuracy of the proposed model for short-term load forecasting has been increased. These results showed that the proposed model has a higher accuracy rate than the classical ANN in the short-term load forecasting.

Keywords: Short-term load forecasting, power systems, artificial neural networks, genetic algorithm, hybrid forecast model

1. INTRODUCTION

Energy in Turkey and in the world, is located at the beginning of the strategic development and security issues. Importance of energy demand maintains its increasing trend in line with growing population, urbanization, industrialization, becoming widespread of technology and welfare. Electric energy constitutes a large part of the energy. In the design and resource planning of electric power systems, by ensuring supply and environmental security, the meeting of the energy demand sustainably, reliably, with high quality and low cost has become the primary goals [1, 2, 3].

Load forecasting is one of the most important problems in the planning and control of electric energy systems. It provides important information for forecasting electricity energy demand, power distribution and planning; and thus, helps to control system operation risks such as demand fluctuations, changing reserve demand, susceptibility to failures. In addition, electricity energy demand is based on effective price offers in the free markets [4]. Therefore, load forecasting is the basis of almost all decisions made in the energy markets. Optimizing electricity prices according to short-term load estimation results helps electricity markets plan, establish, develop and operate efficiently, transparently, reliably by meeting the needs of the sector. Overestimated electricity demand, a large number of power supply units are activated and the system reaches unnecessary reserve levels and result in significant wasted investments in the construction of power facilities as well as excessive energy generation. On the contrary, underestimation may lead to insufficient reserve levels and unmet demand and lead the system to operate in an unprotected area at risk [5].

The short-term load forecasting generally covers the time from the hourly forecast to weekly. Short-term load forecast is highly relevant to many issues such as load flow analysis, power system studies, daily system operation and efficiency, within the generation, transmission and distribution systems of electrical energy. With a successful forecast, basic operating functions (such as hydrothermal coordination, economic

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distribution, fuel planning and maintenance of units) can be performed efficiently and reliably.

Short-term load forecasting is also a very important issue as it forms the basis for energy efficiency policies, energy operations and decision-making in energy markets. Decision makers in the energy sector need accurate forecasts because many of the decisions are necessarily based on forecasts of future demand. Forecasting in energy systems means meeting the energy demanded at the moment. Short-term load forecasting for electricity demand allows calculation of the electrical power reserve required to ensure energy supply and system security and reduce operating costs.

Various studies have been carried out in order to realize short-term load forecasting from past to present. In particular, the developments in artificial intelligence techniques and their success in modeling nonlinear systems have encouraged researchers to use these methods in load forecasting in recent years. Some of these studies are presented here.

Considering the markets and seasonal conditions of Turkey, Başoğlu and Bulut has developed a hybrid system that provides a high degree of accuracy in short-term electricity demand forecasts, in which artificial neural networks and expert systems are used together [6].

Fan and Hyndman proposed semi-parametric regression models to forecast the relationship between load demand and independent variables such as calendar and temperature. The proposed model was used to forecast electricity demand from the half-hour forecast to seven days for Australian National Electricity Market power systems [7].

Moturi and Kioko developed a model based on artificial neural network for short-term electric load forecasting, and evaluated the performance of the model to load forecasting a day ahead using actual load data from the National Electric Transmission Company of Kenya [8].

Senjyu et al. with an adaptive learning algorithm developed with artificial neural networks, and investigated the effect of temperature variation on load forecasting during the day. The accuracy of the proposed approach has been demonstrated by its application to the power system of the Okinawa Electric Company of Japan [9].

Adepoju et al. presented a study on short-term load forecasting using artificial neural networks for the Nigeria electrical power system [10].

Ceylan made short-term load forecasting of Gölbaşı Region by using multi-layer artificial neural network model and regression analysis method, which were trained with back propagation algorithm using actual power and temperature values of 2002 and 2003 [11].

Abdoos et al. proposed a new hybrid intelligent method for short-term electric load forecasting using the load and temperature values of similar days. He used support vector machines as a regression tool by identifying day types to improve the accuracy of forecast [12].

Chogumaira and Hiyama presented an artificial neural network based short-term load forecasting approach using the historical electricity prices and demand data for the Australian national electricity market [13].

Kaytez, using linear regression analysis, neural networks and support vector machines, has estimated that Turkey's electricity consumption [14].

Oğurlu, using mathematical modeling has estimated Turkey's peak load between the years 2010-2025 and the total electric energy demand. It is stated that load forecasting with a mathematical model is a useful and practical method [15].

Kargar and Charsoghi designed the time series ARIMA model and ANN model, using economic variables as input to estimate annual electricity consumption in Iran. When the designed network models are compared, it is stated that the ANN model gives results closer to the real values [16].

In these studies, researchers have successfully accomplished the solution of the complex nonlinear problem between load and temperature in short-term load forecast using ANN based models. Quite good forecasting results have been obtained with artificial neural networks, especially in complex nonlinear problems. However, the selection of the activation function used in the ANN model directly affects the success of solving the problem. This case can be remedied by using different activation functions in the training phase of the model, selecting the function that will produce results that are more successful. Thus, it becomes possible to create an ANN model independent of the problem. In this study, adaptive ANN model based on Genetic Algorithm (GA) is proposed. In the proposed model, GA optimizes the network by determining the activation function that each ANN node will use. The object here is to increase the solution success by making the network adaptive.

In this study, 24 hours short-term load forecasting for Middle Anatolia Load Dispatch Center (Ankara) Region was made with the proposed model. The actual data received from Turkish Electricity Transmission Co. was used to evaluate the performance of the model. Then, the results obtained were compared with the classical ANN. The results show that the proposed model has a lower error margin than the classical ANN.

In recent years, artificial neural networks are widely used in many areas of power system analysis and control, static and dynamic security analysis, dynamic load modeling, alarm processing and fault diagnosis. In short-term load forecasting, the complex nonlinear problem between load and temperature needs to be solved. For this reason, in the study, short-term load forecasting was made using a genetic algorithm (GA) based adaptive ANN model, since very good results were obtained especially in nonlinear complex problems.

2. LOAD FORECASTİNG

Demand for electricity is one of the most important indicators of economic development and social development. Meeting the electricity demand sustainably, reliably, quality and economically is among main objects of electricity system operators. Therefore, to meet the electricity demand on time by the system operators, electricity production and transmission development plans are made and those plans are very crucial. Load forecasting is needed for effective system planning and operation.

In the transmission system development plans, the main objectives are to keep the quality and continuity of energy supply at the highest level, to design an economic, easy to operate and open system for development, to use the existing facilities during their economic life and to finance them with transmission and distribution networks and realize those plans with minimum investment cost. The concept of load forecasting, which is the basis for estimating peak load and energy is based on forecasting the future condition by examining the prior conditions and data. The load forecasts are divided into various periods, generally short, medium and long-term load forecasting depending on the time planning studies.

2.1. Short-Term Load Forecasting

Short-term load forecasting generally includes forecasts to be made from an hour to one week. Short-term load forecasting is necessary for planning functions such as power generation coordination. This coordination can be used to create hourly schedules of the energy generating resources, and thus the operating cost of energy power systems is minimized. In addition, the forecasts made play an active role in the basic operating functions of energy power systems such as security analysis, economic dispatch, fuel planning and unit maintenance. Improving the accuracy of short-term load forecasting has a significant impact on power systems operations, as the operating economy and control of power systems are very sensitive to forecast errors. Depending on the type of power system, large forecasting errors can cause black outs, which can result in high operating costs.

Load Dispatch Centers should have an idea about load model in advance so that sufficient generation can be made to meet consumer needs. Short-term load forecasting is used to determine the peak value in the daily load curve and to determine when the generators will be activated and deactivated. Overestimation of the future peak load demand causes the extra power supply units to go into operation, leading to an unnecessary increase in system operating costs, and results in significant wasted investments in the construction of power facilities as well as excessive energy generation. On the contrary, underestimation may lead to insufficient reserve levels and unmet demand. In addition, the system can be operated in an unprotected area at risk and may cause black outs because system security cannot be ensured [17]. Considering the required periods for short-term load forecasting, it contains many different parameters compared with medium and long term load forecasting.

3. DEVELOPMENT OF ADAPTİVE HYBRİD SYSTEM BASED ON ARTİFİCİAL NEURAL NETWORK AND GENETİC ALGORİTHM FOR SHORT-TERM ELECTRİC ENERGY LOAD FORECASTİNG

Although artificial neural networks (ANN) are successful in solving nonlinear equations; if the model is not fully determined, it is hard to find the overall minimum point. Here, the most important factor is the proper determination of the activation function depending on the proposed model. Another important factor is the need for a big and flexible data set to develop an effective model with high forecast accuracy. Selection of the most appropriate activation function by using the ANN and Genetic Algorithm (GA), together with hybrid optimization methods is a solution that overcomes these disadvantages. This property provides an advantage to hybrid methods compared with the methods based on classical artificial intelligence methods. Optimization and forecast models based on hybrid algorithms are appropriate for all branches of the science. Especially, it provides great convenience in forecasting data for which experimental applications are difficult. Besides, a more accurate and quicker solution is obtained for optimization of hybrid algorithms with nonlinear systems.

The most common algorithms for describing short-term load forecasting parameters are algorithms based on artificial intelligence. In literature studies, different parameters have been used to obtain accurate forecast models with artificial neural networks, which has a back-propagation algorithm. In this study, for developing appropriate system different artificial neural network algorithms and hidden layers' number have been investigated and compared.

In this study, for short-term electric load forecasting based on artificial neural networks and genetic algorithm an adaptive hybrid system has been proposed. Using artificial neural network based on Genetic Algorithm (GA) a new approach for short-term electric load forecasting has been developed. This proposed hybrid algorithm has been implemented for short-term load forecasting. In the proposed model, the actual forecast was made by ANN, Genetic Algorithm is used to select the most appropriate activation function for each node of ANN.

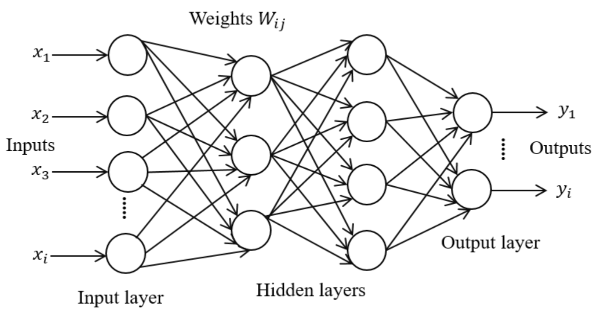

Figure 2. A multilayer feedforward artificial neural network

Thus, it has been observed that network error decreased even more than classical ANN. The results show that hybrid ANN gives better result than classical ANN. So, the accuracy of the proposed model for short-term load forecasting has been increased.

3.1. Classical ANN

ANN is one of the most effective methods in many processes like image diagnostic, classification, function forecasting and optimization. Thanks to this method, which simulate human neural system and brain learning skill many successful applications of these processes have been developed. ANN has a few network topology with different types of learning. Back propagation algorithm is most common network topology and is an effective type of algorithm for adjusting node weights [18, 19].

As seen in the general network topology of figure 2, an artificial neural network consists of an input layer, at least one hidden layer, an output layer, a range of propagation error, an activation function for each propagation error in layers and it also consists of layers containing weights that connect the nodes between the layers. To realize learning process known as generalized delta rule, initially random values are assigned to each weight and then input samples are transmitted in sequence to the network. In this feed forward process, outputs are calculated for each input sample. Then, an error signal is calculated by comparing the calculated outputs and the expected outputs. After that, these error signals are propagated backward from output to input layer to realize weight adjustments. This feed forward – back propagation repeats until total error value reaches to the expecting minimum value and then learning process is stopped. Assuming that A defines the input vector and B defines the expected output vector, for n inputs and m outputs A and B values below can be given as Eq.1 and 2.

$$\mathrm{A} = (\,\mathrm{a_1}, \mathrm{a_2}, \dots, \mathrm{a_n}\,) \tag{1}$$

$$\mathrm{B} = (\,\mathrm{b_1}, \mathrm{b_2}, \dots, \mathrm{b_m}\,) \tag{2}$$

In the training process, a range of input samples is given input layer and these are moved to hidden layer by weights. Each propagation error in hidden layer calculates the sum of the weighted inputs connected to it to calculate the net output. The net output of $i.$ propagation error on $j.$ layer is calculated as in Eq.3. In here, w_{ik}, $k.$ Is above the layer's, $i.$ is the weight value of the propagation error. Activation value is calculated as below depending on the activation function. The transfer functions used in this study are given in Table 1.

$$\mathrm{net_i^j} = \textstyle\sum_{\mathrm{k=0}}^{\mathrm{n}} \mathrm{w_{ik}}\,\mathrm{a_{ik}} \tag{3}$$

$$\mathrm{b_{net}} = \mathrm{f^k}(\mathrm{net_i}) \tag{4}$$

These activation values move to the output layer and the actual outputs of the network are calculated in the same way. Back propagation networks aim to minimize the error between the desired output b and the actual output b_{net}, of the network. The training of the network continues until this error value reaches to the minimum level.

Table 1. Activation functions used in Adaptive ANN

Function Number	Function Name	Mathematical Expression of Function
1	Linear	$f(x) = x$
2	Threshold	$f(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$
3	Logistic Sigmoid	$f(x) = \dfrac{1}{1 + e^{x}}$
4	Sine	$f(x) = \sin x$
5	Hyperbolic Tangent	$f(x) = \dfrac{1 - e^{-2x}}{1 + e^{-2x}}$
6	Radial Basis	$f(x) = e^{-x^2}$

3.2. Adaptive ANN

Unlike the classical ANN method, the adaptive ANN method has a heuristic search unit. ANN is optimized by genetic algorithm and is called adaptive ANN. The developed method is based on the hypothesis that neurons can respond to different characters. To accomplish this hypothesis, neurons in a network are designed to have different types of activation functions. The role of the heuristic search algorithm is to determine the function of each neuron to maximize network performance. In this study, genetic algorithm is used as a heuristic research unit. Six alternative transfer function used by each neuron in the network are determined by the genetic algorithm developed. These functions are given in Table 1 [20].

Genetic algorithms are successfully applied in various fields such as load flow analysis, trouble shooting, stability analysis, power system control and load forecasting. The obtained results are generally reliable, as the probability of error is low. This approach can also be used with a model of genetic neural network that can be adapted and learned. This indicates that the technique uses a numerical optimization approach. This means that genetic algorithms are robust and reliable. The main advantage of using genetic algorithms is that it includes all aspects of calculations such as instability, nonlinearity, robustness and uncertainty.

Genetic algorithms generally use enhanced genetic operators, which include variants of the reproduction, crossover and mutation operators. The use of appropriate operators is very important for the performance of genetic algorithms. Especially in the solution of complex problems, operators specially developed for the problem are needed. The characteristics of genetic algorithm parameters that significantly affect the performance of the algorithm used in this study are given.

Representation Mechanism: The coding used is the Binary coding technique.

Creation of the Initial Population: The initial population of the genetic algorithm was generated using a random number generator.

Conformity/Quality Evaluation: The technique used to determine the quality of the solutions greatly affects the performance of the genetic algorithm. In order not to adversely affect the development of the solutions, the normalization process was carried out in the conformity assessment unit.

Reproductive Operator: The reproduction operator is a genetic algorithm element that has the principle of increasing the survival of individuals with high quality and decreasing the number of individuals with low quality. In the developed method, this selection process is controlled by the objective function and the quality assessment processes. The higher quality solutions dominate the population, while the poor quality ones disappear over time.

Mutation Operator: The mutation operator performs the function of inverting the values of the bits according to the mutation rate, by simulating the genetic mutation event. Mutation plays an active role in the performance of the genetic algorithm by providing new, unseen, unexplored solution elements. Genetic algorithms that do not use mutation operators can perform well, but only by keeping the populations quite large.

Population Size: The first of the effects of the value chosen for this parameter on the performance of the genetic algorithm causes the population size to become too small and the research space to be undersampled. Thus, it becomes difficult to achieve controlled divergence and the research approaches a certain sub-optimal point. Second, when the overly high value is chosen for the population, a very long herd is needed for one generation of development. It is undesirable in the real-time problem application in this study.

Mutation Rate: The mutation operation allows new regions to be introduced into research. A high mutation rate diverges research too quickly, preventing population growth. The use of a very low mutation rate, on the other hand, reduces the divergence excessively, preventing full exploration of the search space. Therefore, the frequency of the mutation rate for the developed genetic algorithm has been very well controlled.

In this study, the genetic algorithm used aims to find the optimal combination of activation functions used by neurons in the two hidden layers of adaptive ANN. The objective function is given in Eq. 5. To achieve this, the cost function used for optimization is defined as the Root Mean Square Error (RMSE) value produced by ANN for each approach. The proposed genetic algorithm minimizes this error value by working in every approach in the learning process. The defined parameters of the genetic algorithm for using to minimize the RMSE value are given in Table 2.

$$\mathrm{Min}\ f = \frac{1}{2}\sum_t (y_t - a_t^L)^2 \tag{5}$$

Table 2. Defined parameters for the genetic algorithm

Number of individuals in the population	40
Termination criterion (generation)	50
Parental selection method	roulette wheel
Mutation coefficient	1
Mutation method	Bit inversion

Adaptive ANN selects a function, which gives the lowest error value from seven different transfer functions for the proposed model. Thus, it enables the development of a more accurate forecast model than the classical ANN.

4. EXPERIMENTAL RESULTS

In this study, by developing similarity based mathematical model and forecasting the next 24 hours load, daily load curves have been obtained. At the same time, with the results obtained, the peak load value during the day has been also forecast. The suitability of the proposed approach has been demonstrated by the application to the actual load data of TEIAS. In the artificial neural network model created for Middle Anatolia Load Dispatch Center Region where the short-term load forecasting will be made, daily maximum and minimum temperature values to be used as input data are predominantly calculated in proportion to the effects to the load of Middle Anatolia Load Dispatch Center Region's provinces to the total load of the Region. If there are obvious differences between the daily load curves, a day type index is required for the short-term load forecasting model to be used in the study [21, 22, 23]. In this study the day type index is classified as follows:

1. Day Type: Monday Tuesday Wednesday Thursday
2. Day Type: Fridays
3. Day Type: Saturdays
4. Day Type: Sundays
5. Day Type: Eve, half day holidays (October 28, etc.)
6. Day Type: Single day holidays such as 23 April, 19 May, 1 January, 30 August

7. Day Type: Religious holidays

The proposed artificial neural network model is shown in Figure 3. There are 20 neurons, in this hidden layer of the network structure, which consists a single hidden layer. The 24 units obtained from the output layer of the proposed neural network are hourly power values from 01:00 to 00:00 for the day on which short-term load forecasting will be done.

Artificial neural networks are suitable for short-term load forecasting, as they provide very good forecasting results for solving complex nonlinear problems. In this study, a model that adapts to the seasonal changes and provides accurate short-term load forecasting for weekdays, weekends and other special days is proposed. This similarity based model forecasts the power load curve using similar day's data, similar to the weather of the forecast day. In addition, this developed model has the advantage of increasing the load forecasting accuracy by examining the load characteristics of other special days such as weekends or religious holidays. Generally, the load average of various similar days is taken to improve the accuracy of the load forecasting in the similarity based method.

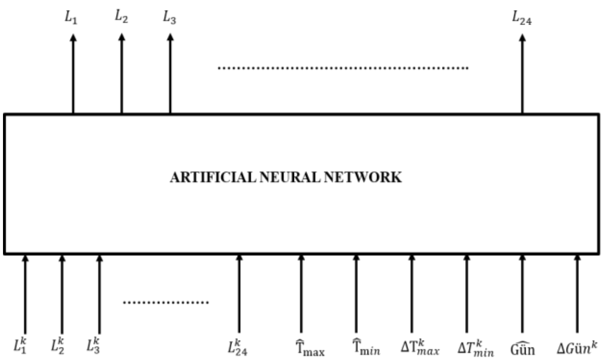

Figure 3. Artificial Neural Network Model

The input variables of the proposed neural network are 30 and are as follows:

L_n^k (n = 1~24)24 hours power values for the similar day,

Average maximum temperature $\hat{T}_{max}$ for the day to be forecast,

Average minimum temperature $\hat{T}_{min}$ for the day to be forecast,

Maximum temperature deviation between forecasting day and similar day ΔT_{max}^k

$$\Delta T_{max}^k = \hat{T}_{max} - \hat{T}_{max}^k \quad (6)$$

Minimum temperature deviation between forecasting day and similar day ΔT_{min}^k,

$$\Delta T_{min}^k = \hat{T}_{min} - \hat{T}_{min}^k \quad (7)$$

The type of day specified for the day to be forecast $\widehat{Gün}$, ($\widehat{Gün} = 1 \sim 7$),

Day type deviation between forecasting day and similar day $\Delta Gün^k$,

$$\Delta Gün^k = \widehat{Gün} - Gün^k \quad (8)$$

In Eq. 6, $\hat{T}_{max}^k$ is the maximum temperature for similar days. In equation 7, $\hat{T}_{min}^k$ is the minimum temperature for similar days. In Eq. 8, $Gün^k$ is the day type for similar days.

Table 3. is electric energy consumption (MWh) invoiced of the provinces included in Middle Anatolia Load Dispatch Center Region in the period of January 2018.

PROVINCES	Electric Energy Consumption (MWh)
ANKARA	1.315.789,65
KONYA	426.452,74
KAYSERİ	307.101,77
NİĞDE	79.208,57
YOZGAT	58.954,36
AKSARAY	56.635,63
KIRIKKALE	52.608,96
NEVŞEHİR	51.671,08
KARAMAN	49.973,23
KIRŞERHİR	33.748,66
GRAND TOTAL	2.432.144,65

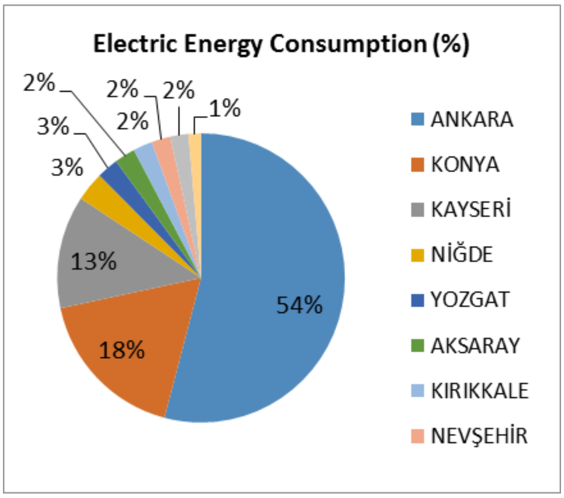

Figure 4. is percentage distribution (%-MWh) of electric energy consumption of the provinces included in Middle Anatolia Load Dispatch Center Region in the period of January 2018.

When the electric energy consumption of each of the provinces included in Middle Anatolia Load Dispatch Center Region in Table 3 and the consumption percentages in figure 4 are examined; it is observed that the effect of provinces other than Ankara, Konya and Kayseri provinces on total energy consumption is low enough to be neglected according to the percentages of energy consumption of Ankara, Konya and Kayseri provinces. Hereby, the temperature values of Ankara, Konya and Kayseri provinces are mainly used in the calculation of the maximum and minimum temperature values to be used in the load prediction of the Middle Anatolia Load Dispatch Center Region. Eq. 9 has been created according to the electric energy consumption of these provinces. All temperature data used in this study is the region temperature which has been calculated according to Eq. 9.

$$T = 0.64T_{Ank} + 0.21T_{Kon} + 0.15T_{Kay} \tag{9}$$

While creating Eq. 9, the total 15% consumption percentage of the provinces whose electric energy consumption are neglected; has been added proportionally to Ankara, Kayseri and Konya provinces' electric energy consumption percentages. Thus, the percentage of energy consumption of Ankara province, which is 54% in the region, increases to 64% when the provinces which have lower energy consumption percentage are neglected. As a result, when calculating the Middle Anatolia Load Dispatch Center Region temperature, the new temperature percentage for Ankara province is used as 0.64, the new temperature percentage for Kayseri province is used as 0.15 and the new temperature percentage for Konya province is used as 0.21. The details of these calculations are as follows:

Total temperature percentage of the provinces to be neglected in the region temperature calculation:

$$0.032+0.024+0.023+0.022+0.021+0.020+0.014=0.15 \tag{10}$$

Total temperature percentage of provinces included in the region temperature calculation:

$$0.54+0.18+0.13=0.85 \tag{11}$$

Temperature percentage of Ankara province in new condition:

$$0.54 + 0.15\frac{0.54}{0.85} \cong 0.64 \tag{12}$$

Temperature percentage of Konya province in new condition:

$$0.18 + 0.15\frac{0.18}{0.85} \cong 0.21 \tag{13}$$

Temperature percentage of Kayseri province in new condition:

$$0.13 + 0.15\frac{0.13}{0.85} \cong 0.15 \tag{14}$$

is calculated.

The daily maximum and minimum air temperature data of Ankara, Kayseri and Konya provinces from 01.01.2013 to 31.12.2019 were obtained from the General Directorate of Meteorology [24].

4.1. Similar Day Choosing

Similar day is selected from the set of thirty days before the day to be forecast and within sixty-one days from the thirty days before and after the same day of previous year. If there is a change in the day which will be predicted, similar days are chosen in the same way. A period of ninety-one days in total is examined to select a similar day. A similar day is selected for both the day to be forecast and days in the training set.

In this study, weight factors and Euclidean norm are used to evaluate the similarity between the forecasted day and the previous days investigated. Evaluation based on the Euclidean norm is useful for understanding the similarity by using a statement based on the concept of norm. Based on the Euclidian norm, similar days are chosen corresponding to the day to be forecast. Thus, a decrease in the Euclidian norm, results in a better evaluation of the similar day. The correlation coefficient between the weather data and the load was investigated before applying the Euclidean norm. According to the examination, it is realized that there is a high correlation between maximum temperature, minimum temperature and load. Therefore, similar days corresponding to the day to be forecast have been selected according to the Euclidean norm and formed by using the maximum and minimum temperature. Meanwhile, similar days are selected from the day type corresponding to the day type of the day to be forecast [25].

In general, the Euclidean norms with the weighting factors of Eq. 15 are used for the selection of similar days to be used in the study:

$$D = \sqrt{\hat{w}_1 \Delta T_{max}^2 + \hat{w}_2 \Delta T_{min}^2 + \hat{w}_3 \Delta Gün^2} \tag{15}$$

$$\Delta T_{max} = \hat{T}_{max} - T_{max}^n \tag{16}$$

$$\Delta T_{min} = \hat{T}_{min} - T_{min}^n \tag{17}$$

$$\Delta Gün = \widehat{Gün} - Gün^n \tag{18}$$

$\hat{T}_{max}$ and $\hat{T}_{min}$ in Eq. 16 and 17 are the average maximum and minimum temperatures for the day to be forecast. T_{max}^n and T_{min}^n are respectively maximum and minimum temperatures of previous days which have been investigated. In Eq. 18, $\widehat{Gün}$ is the day type of the day to be predicted, $Gün^n$ is the day type of the day to be investigated. $\hat{w}_i$ ($i = 1, 2$) is the weight factor. Weight factor $\hat{w}_i$ is determined by least squares method based on multiple regression model.

$$L_{max} = \hat{w}_0 + \hat{w}_1 T_{max} + \hat{w}_2 T_{min} + \hat{w}_3 Gün \tag{19}$$

In Eq. 19, $\mathrm{L_{max}}$ is the peak power value during the day, $\mathrm{T_{max}}$ is maximum temperature, $\mathrm{T_{min}}$ is minimum temperature and Gün is the day type values used in this study. $\hat{w}_i$ ($i = 0{\sim}3$) is the weight factor.

Weight factors are used to show how the load factor affects maximum power and to determine the similar day in the face of Euclidean norm. Eq. 19 is analyzed for ninety-one days. By solving this ninety-one equations based on multiple regression model, $\hat{w}_i$ ($i = 0{\sim}3$) weights can be calculated. By putting up these values in Eq. 15, D values are calculated for a period of ninety-one days analyzed. The day with the smallest value is selected as the similar day for the day to be forecast. This means the smaller the results of the Euclidean norm, the better the choice of similar days will be determined [26].

It is very important to normalize the input and output variables of the network before network training to achieve a good result and shorten the calculation time. In this study, all input variables in the data set used to train the network have normalized using learning interval data within the limits between (0.1 - 0.9) values, so that the minimum normalization value will be 0.1 and the maximum normalization value will be 0.9 [27,28].

In the multilayer artificial neural network model created for this study, max-min normalization was used, due to using logarithmic sigmoid activation function. In addition, all properties associated with the data are retained without any deviation. Training and forecasting processes for the proposed artificial neural network are listed as follows:

1. Determining the learning range of the network
2. Selection of similar days for a learning day: N similar days are selected for a learning day. The proposed network is trained using N similar days for a learning day.
3. Training the back propagation algorithm for each day of the learning interval: The proposed network is trained throughout the day of learning, in the same way as in step 2.
4. Training the back propagation algorithm with 1000 iterations in a given range: The proposed network is trained by repeating the learning set 1000 times.
5. Selecting similar days for the day to be forecast
6. Entering network parameters for load forecasting
7. Load forecasting: The input variables described in step 6 are used by the trained network. Thus, short-term load forecasting is obtained.

The simulation program has been implemented using C# language in Microsoft Visual Studio integrated development environment. The back propagation algorithm has been used according to the method explained during the 24 hours load forecasting. The network was tested at different weights to find out how stable the random values are. Weights are determined by random small values. When choosing these values, it is seen that the performance of the network varies. Weights increase or decrease the network performance. These weights are adjusted by selecting from 0.05 to 0.1. The learning variables of the network obtained by trial and error are given in Table 4. After the training of the network, the functions determined by the nodes in the layers of the ANN by GA have been presented in Table 5. Which functions the numbers given in Table 5 belong to is shown in Table 1.

Table 4. Artificial Neural Network Variable Parameters

Learning Speed	0.02
Momentum	0.015
Iteration	1000
Number of Hidden Layers	1
Number of Neurons in Hidden Layer	20
Sigmoid Function Coefficient	1

Table 5. Activation functions specified by GA for hidden layer nodes for nodes of the proposed network structure

Node Number	Function Number	Node Number	Function Number
1	3	11	6
2	2	12	3
3	1	13	2
4	5	14	1
5	5	15	4
6	3	16	2
7	6	17	2
8	1	18	2
9	1	19	6
10	5	20	4

In the hidden layer of the network proposed in Table 5, numbers of activation functions of the nodes determined as a result of optimization by GA are given. Hyperbolic tangent activation function number 5 is used as standard in the exit layer of the network. As a result of the optimized training of the network, the fitness function's value given in Eq. 5 was obtained as 0.024.

Load forecasting performance has been calculated as the mean absolute percentage error (MAPE). Absolute error is measured in percent and defined in Eq. 20 as follows:

$$MAPE\ (\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{|H_A^i - H_F^i|}{H_A} \times 100 \qquad (20)$$

In Eq. 20, H_A is defined as the actual load value, H_F is defined as the forecast load value, N is defined as the total number of hours and i is defined as the hour index.

After the training was carried out according to these network data, a total of 9 days whose dates are specified in Table 6 were used to test the effectiveness of the proposed algorithm. Classic ANN for each test data and MAPE values obtained from GA-ANN algorithm proposed in the study are presented in Table 6. When the table 6 is examined, it is seen that the GA-ANN model for 8 test data greatly reduces the error value and makes a closer approach to reality. However, in the test data of 23.04.2018, the classical ANN realizes a forecasting with lower error value than the proposed algorithm.

Table 6. Simulation Results

Days Tested	ANN MAPE (%)	GA + ANN MAPE (%)
28.05.2018	17,5108	5,788481
15.05.2018	12,56611	6,871812
14.02.2018	15,50986	2,699343
09.08.2018	16,53364	7,061283
15.06.2018	21,46847	9,960938
29.09.2018	39,50391	34,59648
21.10.2018	5,652136	5,085615
20-24.08.2018	29,34922	1,42763
23.04.2018	5,520896	10,03819

To see the trend of the results obtained from the proposed network model, weekly load curves are plotted according to the actual and forecasting results. As it can be clearly seen from the graphs, the error between the load curves of the forecasting days and the actual load curves is lower than the one in the conventional ANN. This shows that the proposed network model produces stronger results for the short-term load forecasting. The graphics of the results obtained are given in the appendix.

5. RESULTS

The load forecasting model is a critical decision support tool for the safe and economic operation of the electric system. One of the first decisions to be made is to select an appropriate model by examining the factors that may affect the load forecasting in the region. In addition, for short-term load forecasting the power system should be known in detail. Thus, the optimum method can be selected for the specified power system [29].

In this study, an adaptive hybrid system model based on artificial neural networks and genetic algorithm is proposed for short-term load forecasting of Middle Anatolia Load Dispatch Center (Ankara) Region. Classical ANN uses the predefined activation function to calculate output neurons. The developed adaptive model dynamically updates this function for each layer. In this developed model, genetic algorithm was used as a heuristic search unit to define the optimal combination of activation function of neurons. The developed model was applied to the test data and the results were compared with the classical ANN. The performance of the developed model is calculated as mean absolute percent error (MAPE). The calculations verify that the developed adaptive hybrid model performs better than the classical ANN. Thus, it has suggested that the proposed model gives realistic results for short-term load forecasting and is in the correct tendency.

The proposed approach is of great benefit since it is experimentally easier, simpler and cost effective. It is possible to improve the accuracy of the forecasts by using real time data accurately and completely. In addition, the accuracy of the forecasts can be improved by adding more temperature and parameter information to the model. It is necessary to develop new techniques to reduce the uncertainty of forecasts. It is suggested that different learning algorithms and other support vector machine learning techniques will be used in the future.

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS’ CONTRIBUTIONS

Tuğba AKMAN: Performed the experiments and analyse the results. Wrote the manuscript.

Cemal YILMAZ: Performed the experiments and analyse the results.

Yusuf SÖNMEZ: Performed the experiments and analyse the results.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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Appendix

The graphics of the results obtained are given below.

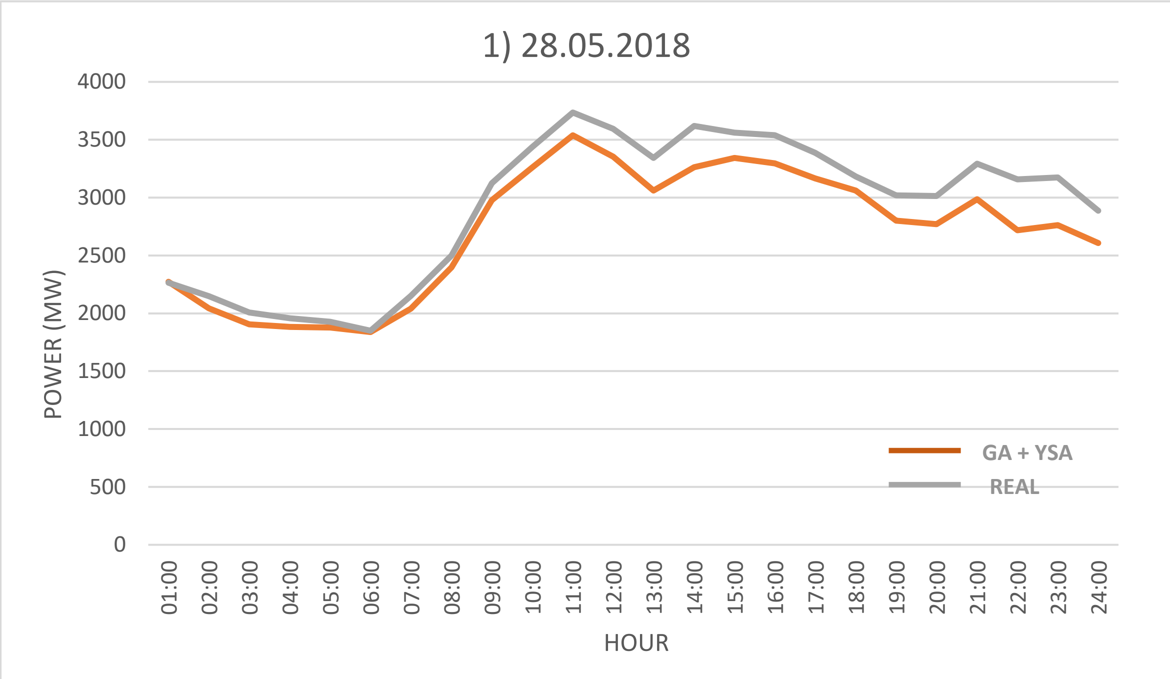

Figure 5. Actual and forecasting load curves for 28.05.2018

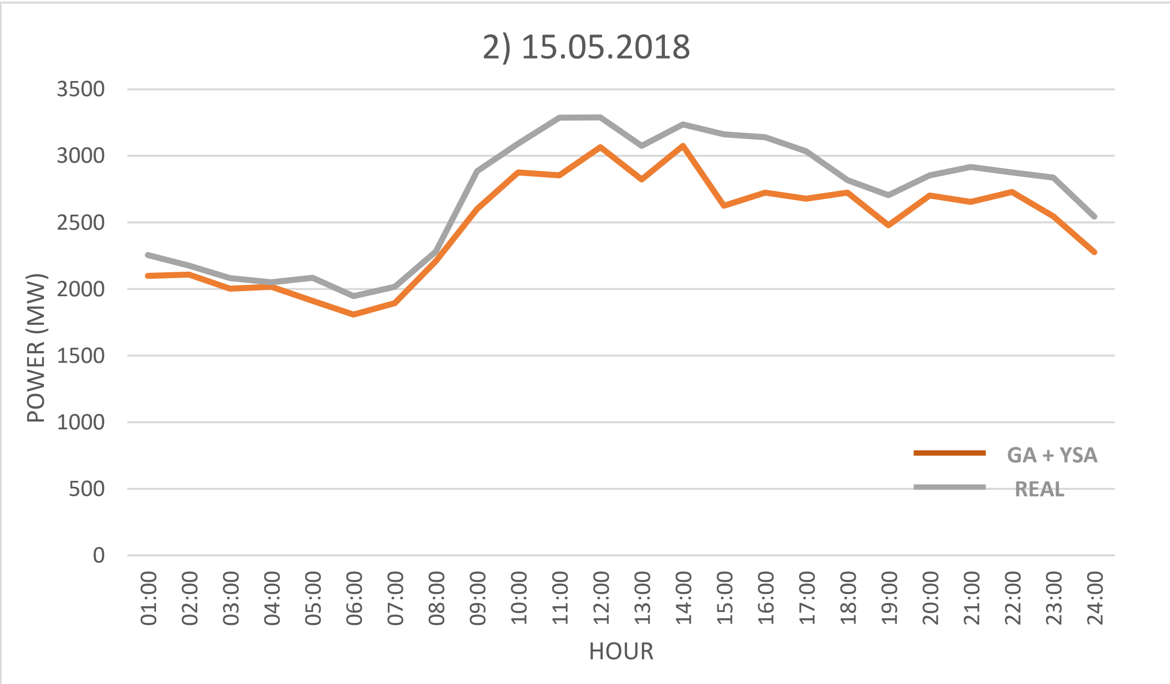

Figure 6. Actual and forecasting load curves for 15.05.2018

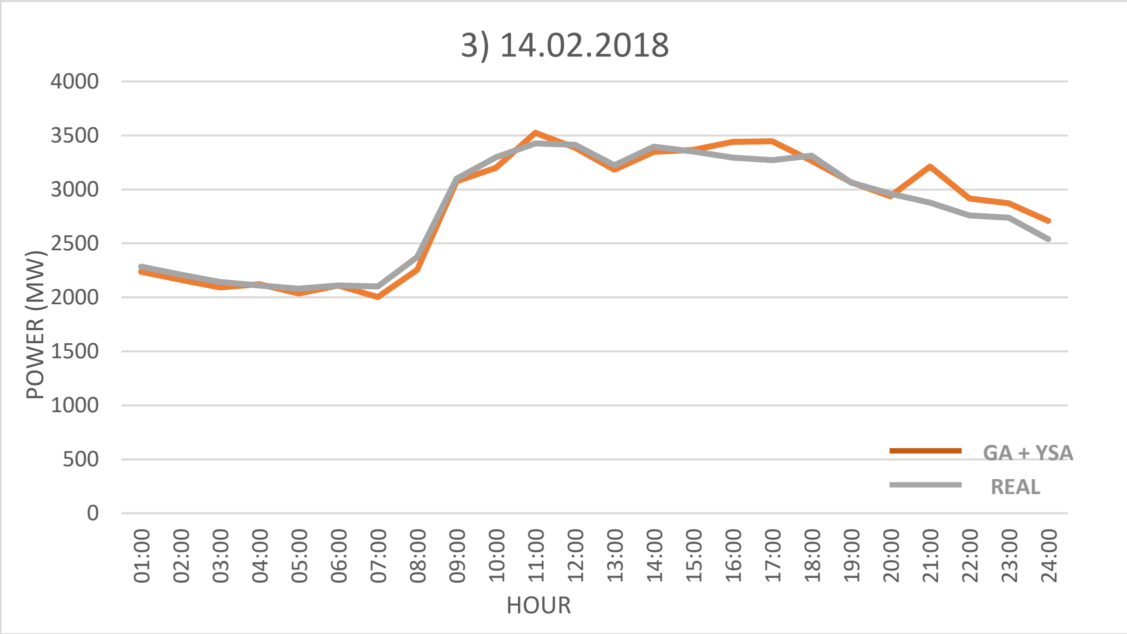

Figure 7. Actual and forecasting load curves for 14.02.2018

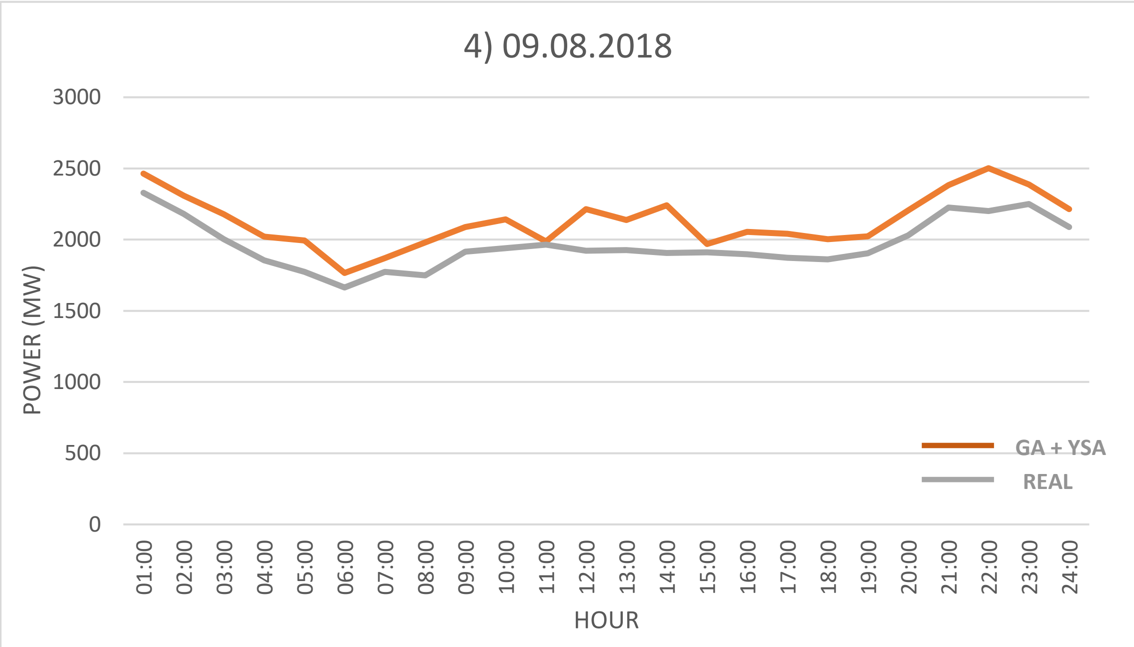

Figure 8. Actual and forecasting load curves for 09.08.2018

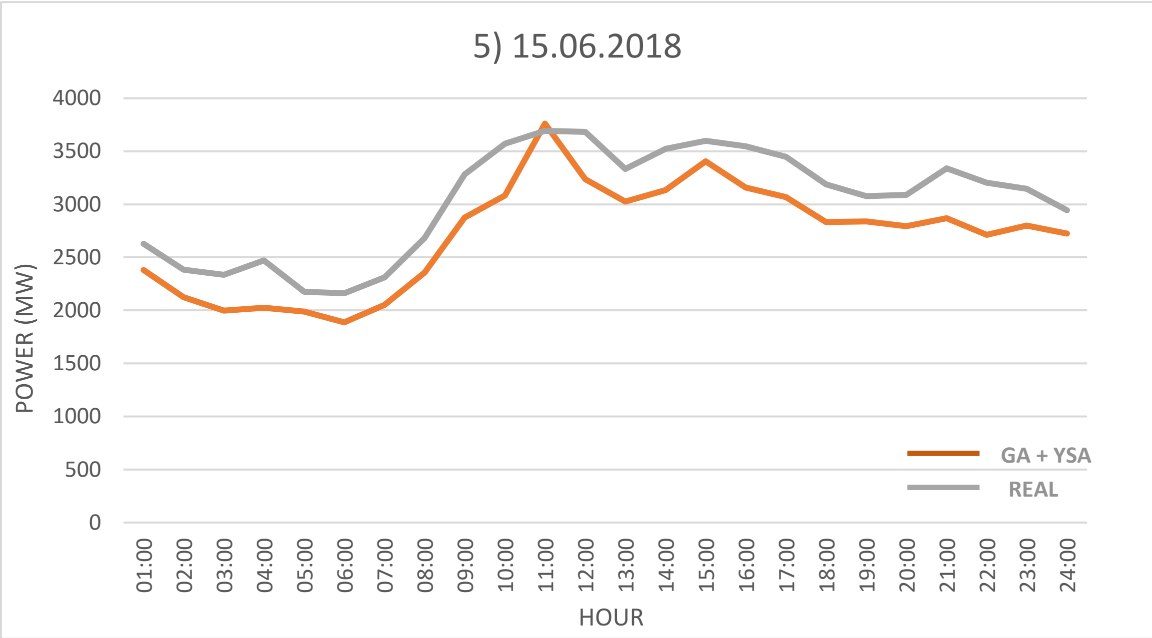

Figure 9. Actual and forecasting load curves for 15.06.2018

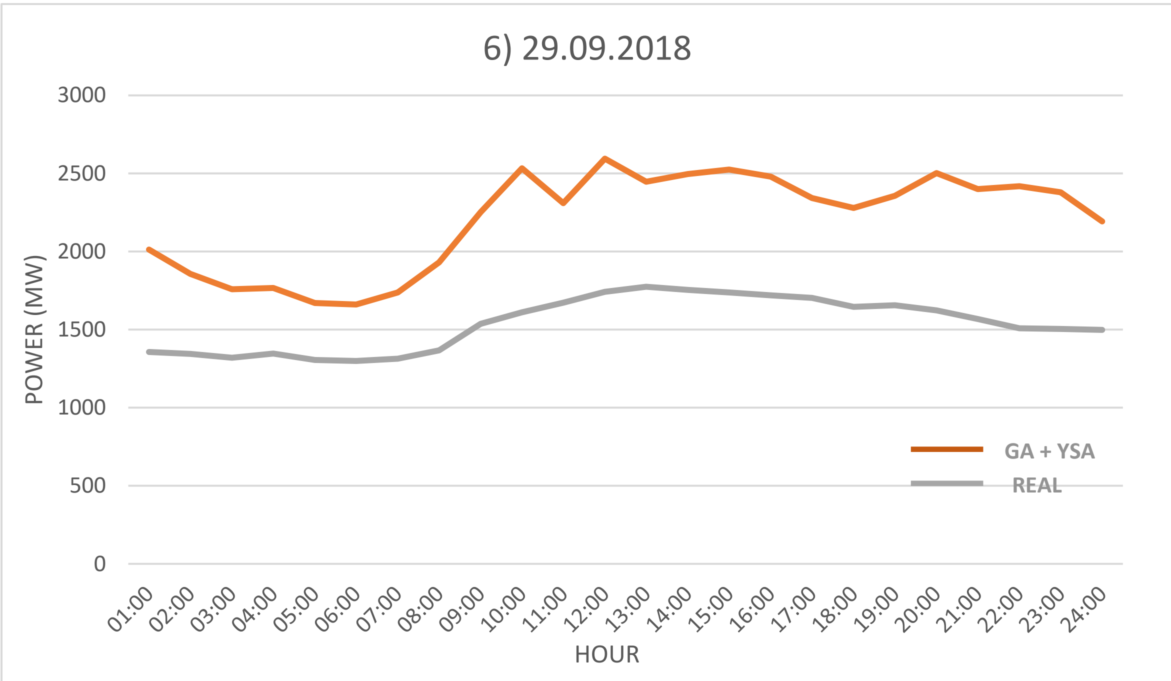

Figure 10. Actual and forecasting load curves for 29.09.2018

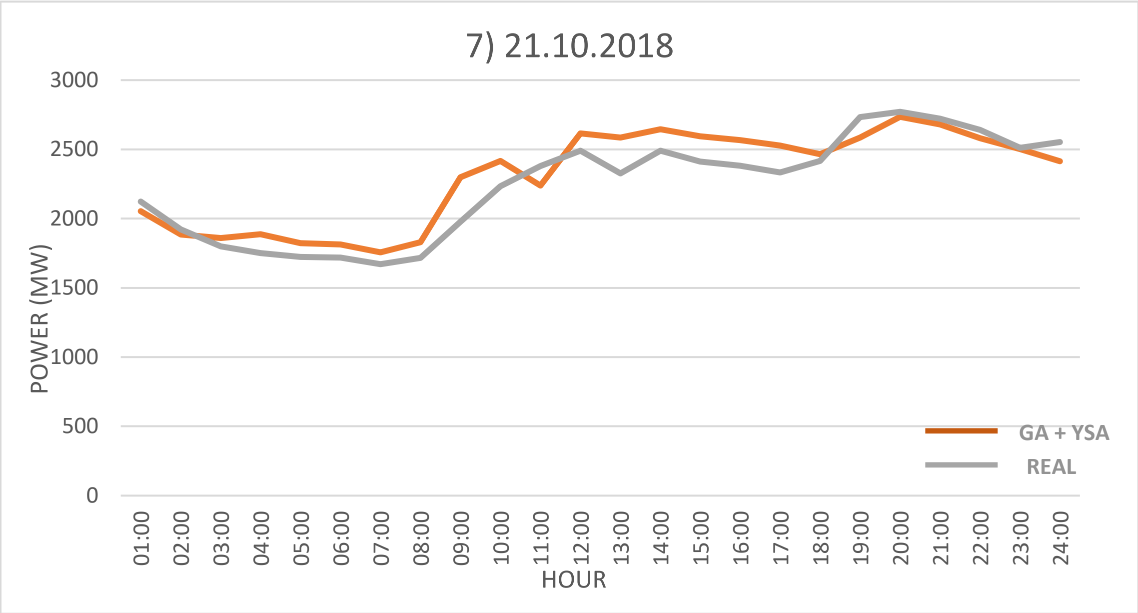

Figure 11. Actual and forecasting load curves for 21.10.2018

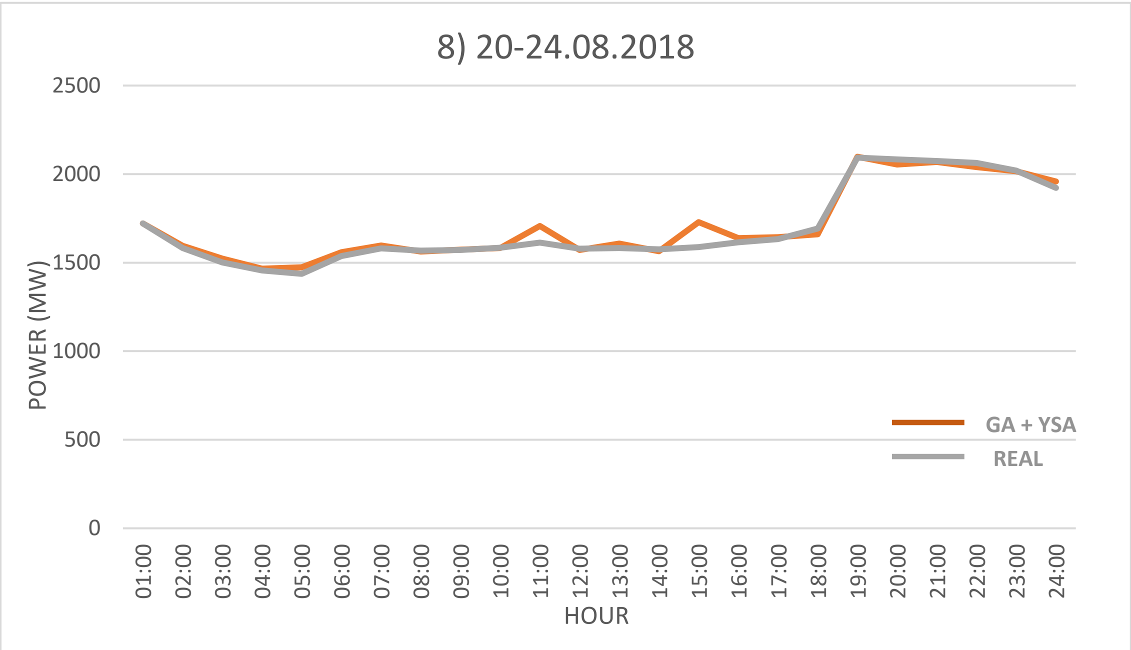

Figure 12. Actual and forecasting load curves for dates covering the feast of sacrifice 20-24.08.2018

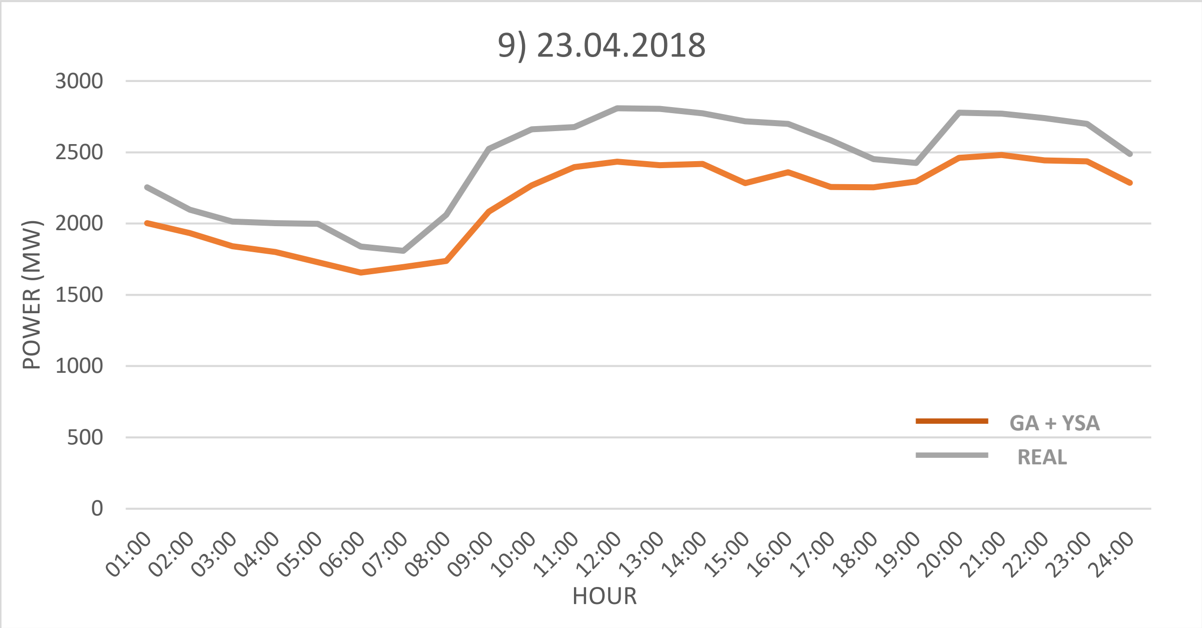

Figure 13. Actual and estimated load curves for 23.04.2018