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A Study of Load Demand Forecasting Models in Electricity using Artificial Neural Networks and Fuzzy Logic Model

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ABSTRACT

Since load time series are very changeable, demand forecasting of the short-term load is challenging based on hourly, daily, weekly, and monthly load forecast demand. As a result, the Turkish Electricity Transmission Company (TEA) load forecasting is proposed in this paper using artificial neural networks (ANN) and fuzzy logic (FL). Load forecasting enables utilities to purchase and generate electricity, load shift, and build infrastructure. A load forecast was classified into three sorts (hourly, weekly and monthly). Over time, forecasting power loads with artificial neural networks and fuzzy logic reveals a massive decrease in ANN and a progressive increase in FL from 24 to 168 hours. As illustrated, fuzzy logic and artificial neural networks outperform regression algorithms. This study has the highest growth and means absolute percentage error (MAPE) rates compared to FL and ANN. Although regression has the highest prediction growth rate, it is less precise than FL and ANN due to their lower MAPE percentage. Artificial Neural Networks and Fuzzy Logic are emerging technologies capable of forecasting and mitigating demand volatility. Future research can forecast various Turkish states using the same approach.

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1. INTRODUCTION

Turkish Electricity Transmission Company (TEİAŞ) is responsible for power production, transmission and distribution to its users throughout Turkish. TEİAŞ provide electricity load for all residents in Turkey with constant, consistent and cost-effective electricity transport while keeping environmentally sensitive and supporting efficient resource use proudly and effectively [1]. The main objective of the demand support model forecasting is to decide whether a demanding series requires applying a classification model, a statistical or judgmental approach for forecasting demand [2]. The products are first classified according to their product life cycle status.

The classifications in the stage of the launch increase [3]; these grades have no representative historical demand data that is required for statistical estimates [4].

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To create a classification model for forecasting mature goods, we use the findings of the first question of the study. The main benefit of the forecast is that it offers valuable knowledge to different stakeholders used to make future decisions—the art of estimating in a far future while anticipating/projecting for short periods [5]. The end cannot be forecast correctly. Mistakes marginalize the future forecast. Particularly when forecasting, there is a marginal error; which is widened.

Senthil Kumar et al. [6] developed net energy using Artificial neural networks (ANN) equations to calculate potential energy consumption levels in Turkey using an artificial nerve network technique. Hasheminia and Niaki [7] defined and implemented a new artificial wave forecasting network, a recurrent network with an updated algorithm. Yama and Lineberry [8] have presented an intelligent hybrid system that combines autoregressive built-in average moving models and ANN for demand

forecasting. Scholars examined the application of advanced machinery training techniques, including neural networks, new neuro networks and super-port vector machines, to forecast distorted demand at the end of the supply chain. Sharma [9] used fuzzy neural networks (FNN) with initial weights created by a genetic algorithm to learn fuzzy rules for promotion obtained by marketing experts. Mounce et al. [10] updated the changing FNN and took a weighted factor in determining the value of each element between these various rules. Also, Pezeshki and Mazinani [11] had an intelligent Fuzzy neural forecasting decision support system available.

Demand forecasting of electric loads is essential to assist power companies to plan and managing efficiently. The precise short-term load forecast is challenging since the load time series has high uncertainty levels [12]. Depending on the horizon to be considered, electricity load forecasts are classed into long-term and short-term [13]. Forecasts for short-term load cover hourly, every day, weekly and monthly forecasts; they are thoroughly covered in literature and covered in many publications. Several research papers have been produced to apply Artificial Neural Networks (ANN). Yao et al. [14] utilized a heterogeneous ANN for load prediction in the short-term forecast challenge. They also discussed the uses of minimum historical evidence to determine neural weights. Aksoy et al. [15] employed the ANN to anticipate the hourly temperatures for electricity utilities. The ANN for forecasting has also been described in the Greek power system.

Due to the complexity of the market, load forecasting in the electrical market is difficult. The instant nature of power, the complicated design of the market and frequent regulatory interventions make this complex. Artificial intelligence is a relatively recent research topic that grows in quality [16]. Computer intelligence is commonly used to refer to fuzzy parts of the system, swarm intelligence, progressive computer systems and artificial neural networks [12]. One of the area's most often employed in electricity prediction is ANNs. Artificial neural networks have gained greater attention because of their evident design, straightforward execution, and good performance [17].

Following the research in demand forecasting, several contributions address the impact of ANN and FL on short-term load forecasting, which aid the impact, benefits, and prospects (see Table 1). As a result, this study substantially contributes by anticipating demand using artificial neural networks and fuzzy logic approaches and comparing them to conventional methods. In addition, the study is made by the valuable techniques of Artificial Neural Network algorithms for forecasting demand. Since they can handle non-linear data and capture subtle functional correlations between empirical data, even when the underlying relationships are unknown or difficult to express, applying fuzzy logic

TABLE 1. Comparison of Contribution

Previous studies	Present study
Previous studies addressed the impact, challenges, and importance of ANN and FL on short-term forecasting [18-23].	This study substantially contributes by anticipating demand using artificial neural networks and fuzzy logic approaches and comparing them to conventional methods. In addition, the study is made by the valuable techniques of Artificial Neural Network algorithms for forecasting demand. Also, the MAPE indicated that ANN and FL are accurate and consistent compared to the regression method. This study showed that ANN and FL have a minimal error percentage compared to the regression analysis.

and artificial neural networks in demand forecasting will overcome many constraints encountered in the workplace. Also, the MAPE indicated that ANN and FL are accurate and consistent compared to the regression method. This study showed that ANN and FL have a minimal error percentage compared to the regression analysis. Therefore, demand forecasting of load using artificial neural network (ANN) and fuzzy logic (FL) from the Turkish Electricity load is proposed in this study.

In general, both methods and procedures are critical for accurate estimation; yet, there is a dearth of research on load forecasting methodologies. The study is classified into five broad categories based on requirements from the journal. The paper is structured as follows. Section 1, the background of the study. Section 2, the methodology of the research paper. Section 3 presented the data analysis, while section 4 presented the interpretation of the data and general discussion. The final section presented the conclusion and recommendation of the research paper.

2. METHODOLOGY

2. 1. Data Collection and Pre-processing Collecting data is the first step in creating a forecast. The amount of data necessary varies depending on the complexity of the underlying function that we are trying to approximate. The number of neurons in the neural network directly impacts the choice of the data set. A neural network is trained using pre-processed data to make forecasting easier. It is possible to perform data pre-processing, such as normalization, non-linear transformations and feature extraction.

Normalization is the first and most crucial stage in pre-processing of data. As a result, the neural network will be better able to retrieve meaningful information during training. For the most part, there are two ways to normalize data. Standardize the data to fall into a standard range - usually harmful to positive.

2. 2. Simulation of Real-Time Forecasts
Although in actuality, these variables might be dependent on forecasts, actual weather data collected at the Fort Collins Weather Station [24] for the test day is utilized to model weather-related variables in the network. Regarding weather-predicting accuracy, [24] suggests that further research in this area may be warranted.

2. 3. Artificial Neural Network
Artificial neural network undertakes calculations to replicate the learning processes of the human brain, which consists of a parallel-distributed structure of neurons that uses the gained knowledge to match inputs to outputs and make the "map" of the inputs to outputs available for usage. They are modelled after their namesakes in the brain and built to allow them to be adaptable [24]. An incomplete understanding of the brain's mechanism of neural information processing led to a variety of ANN models. An overview of ANN models for time-series forecasting is provided in the next section.

As one of the most often used ANN architectures for prediction algorithms, the multilayer perceptron (MLP) is renowned for its ability to adapt to complicated patterns [24]. Layers in MLPs comprise three layers: an input or input-output-output layer.

2. 4. The Fuzzy Logic Systems
Weekday and weekend parameters of both fuzzy logic systems were intended to be identical [25]. The fuzzy logic system's input and output sets used symmetrical Gaussian distributed membership functions, with variables and parameterized throughout the evolutionary algorithm parameterization loop [26]. There are no discontinuous spots in the Gaussian distribution where the optimization may fail [24].

2. 5. Mean Absolute Percentage Error (MAPE)
Error metrics explain that the gap between actual and expected values is successful if the model's performance is measured in terms of the difference between the actual and anticipated values. Due to the magnitude of this quantity's impact on model performance and dependability, forecasting's primary objective is to minimize it. Some error measures can be used to evaluate the model's performance. The MAPE error is the most frequently encountered among neural network researchers [12]. There are 24 forecast points in this example, and n is the number of forecast points. Calculating the most significant error across 24 hours also allows it to determine the amount of energy consumed during that period as represented by the area spanned by the load profile curve and the forecasting accuracy, referred to as the "magnitude of peak hour [24].

2. 6. Forecasting Load
In order to calculate the projected load profile, the ANN calculates the average of three load profiles. When the weights are initialized, this is done to reduce the random effects of the initialization. They are 24-hour periods with no precedent in the network, meaning that the network has never been exposed to a day like a forecast. The training and validation data sets are based on the data before the forecasting date [24].

3. SIMULATION RESULTS

The above Figure 1 shows the prediction of electricity loads using artificial neural networks and fuzzy logic at various hours, and we can see a sharp decline for ANN and an abrupt decline for FL from the 24 hours to 168 hours' horizon. The above analysis compares artificial neural networks (ANN) and fuzzy logic (FL) at various week hours. We can see that both ANN and FL show a better forecast.

The above Figure 2 reveals that regression shows a higher growth in electricity load prediction than FL and ANN from the first week of the Year, Sunday to Saturday. The electricity load consumption in Figure 2 was based daily for domestic, commercial, or industrial.
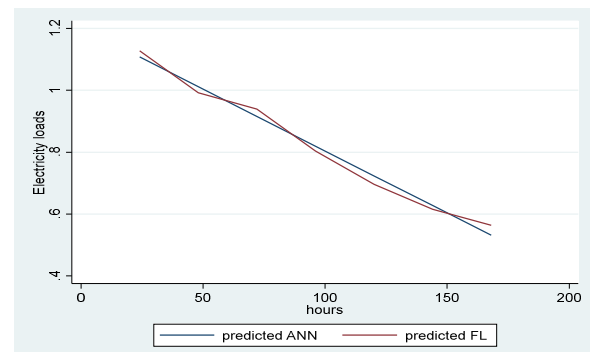

Figure 1. Load forecast demand using artificial neural network (ANN), fuzzy logic (FL)
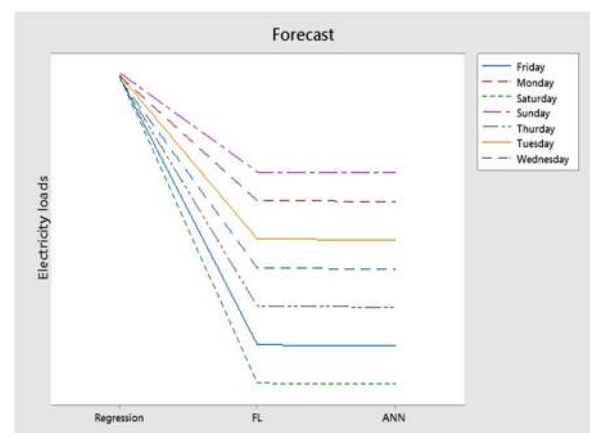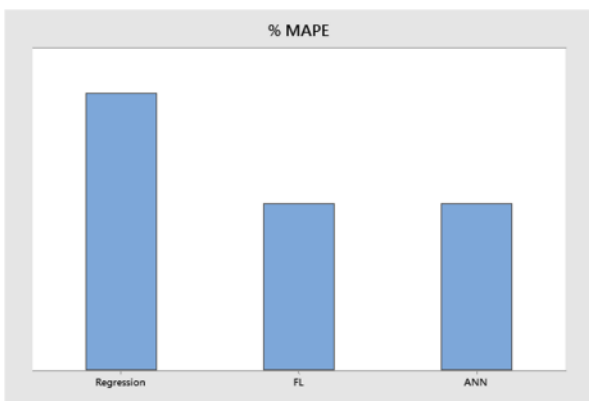

Figure 2. Comparison of Load forecast demand for the first week of the Year using artificial neural network (ANN), fuzzy logic (FL) and Multiple Linear Regression
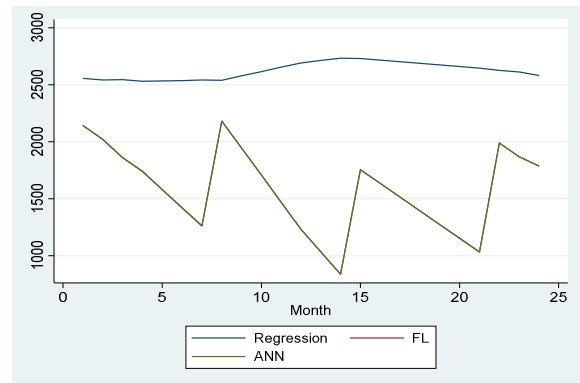
The domestic is a people dwelling place. Commercial consumers are businesses and industries that require a more considerable volume of supplies than residential clients do. The load, however, are predicted by residential vs commercial, with the latter being the more prevalent.

Figure 3 illustrate significant discrepancies between the three models. As shown from Figure 3, fuzzy logic and ANN approaches are more accurate and dependable than regression methods. According to statistical, qualitative characteristics such as MAPE, Figure 3 indicated that ANN and FL model were more potent than the regression model in predicting load. Compared to the MLR model, the selected ANN and FL model could predict load for training, validation, and testing stages with a per cent gain in R^2. Additionally, the ANN and FL model is clearly defined compared to the MLR model by considering the relatively similar values of statistical parameters such as the median or similar distribution for the actual values (Figure 3). Additionally, a graphical representation of the actual values by the ANN, FL and MLR models shown on a graph (Figure 3) can aid in predicting load.

A short-term load forecasting model for consumption was built using ANN and FL and then compared with regression (Figure 4). The study forecasted Turkey's electricity consumption using ANN and FL techniques; regression has the highest growth (Figure 4). This figure illustrates how an ANN and FL model improved short-term electrical load predictions. The suggested ensemble technique has lower variance and bias than regression. According to the findings, the regression shows the highest growth compared to FL and ANN in Figure 4. The above, Figure 5 shows the forecast with FL and ANN with Regression as a standard method, and this indicates that regression has the highest growth and highest mean absolute percentage error (MAPE) compared to FL and ANN. Although we can see that regression has the highest forecast growth but has lower precision

Figure 4. Comparison of Load forecast demand for months using artificial neural network (ANN), Fuzzy Logic (FL) and Multiple Linear Regression
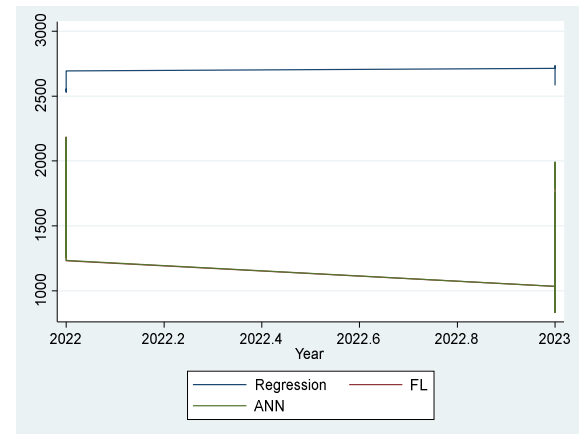
Figure 5. Comparison of Load forecast demand for months using artificial neural network (ANN), Fuzzy Logic (FL) and Multiple Linear Regression

compared to FL and ANN, both FL and ANN models keep lower MAPE per cent.

Recent years have seen a surge in interest in short-term power load forecasting, and the literature has numerous intriguing examples. Accurate load forecasting is critical for both power plants and manufacturing operations. Exogenous variables like weather, consumption time, day type, seasonal effects, and economic or political changes substantially affect the load consumption pattern. These methods have been modified to provide more precise approximations, necessitating the employment of a variety of methodologies.

The figures illustrate that non-linear linkages between input variables and load may impair ANN, FL, and MLR models. A comparison of ANN, FL, and MLR models demonstrated the critical importance of selecting the appropriate model to forecast load. ANN-based load forecasting can be enhanced on the Turkish market by using a more extensive training dataset and more detailed feature sets. The most critical aspect of developing an

Figure 3. Comparison of MAPE (%) Load forecast demand using artificial neural network (ANN), Fuzzy Logic (FL) and Multiple Linear Regression

effective system for anticipating electric load is selecting the appropriate input parameters. We studied the effect of these variables on the test subjects' performance. We studied the effects of these factors on the performance of load forecasting using ANN and FL then compared the results to those obtained using Regression analysis. The Turkish market's hourly load data are derived from EPIAS. We computed hourly lagged load statistics using this data, including the previous hour's load, the load at the same hour the previous day, the same hour the previous week, and the average load for the last 24 hours. As the air temperature rises, the load increases to levels more significant than those experienced during the coldest temperatures. We evaluated the accuracy of our power load forecasting models using data from the deregulated Turkish market [27].

Fuzzy logic and artificial intelligence optimization techniques and approaches are extensively applied [18, 20, 21, 28, 29]. These fuzzy models have been enhanced and adjusted here with the assistance of specialists. The specialists directly impacted the system's ability to succeed due to their skill and breadth of knowledge. The knowledge base, ruleset, and rule count all develop in lockstep with the size of the input variable and membership function. As a result, the fuzzy model must be modified regardless of whether classical or artificial intelligence approaches are utilized [26].

This paper constructs a short ANN, FL, and Regression load predictors model. The first two forecasts and ANN and FL were done, while the second part compared ANN and FL with Regression. The performance may be improved by more intricate structures, such as the combination structure presented by Emeç and Akkaya [30].

In Turkey, electricity is generated by fossil fuel-fired power stations that rely heavily on natural gas. Turkey is forced to import petroleum and natural gas due to domestic resources. This reliance on imported energy directly affects power generation. Forecasting future electricity use is a significant issue in Turkey regarding planning electricity generation. Incorrect prediction of electricity usage will result in either a power shortfall or an oversupply of electricity. A power deficit will result in unhappiness and disharmony in the household and industrial sectors. The economy will suffer adversely due to the industrial sector's disarray. Excess electricity output will also cost the country money because it would produce more than is required [18].

Model for Analysis of Energy Demand (MAED) anticipates energy consumption based on various criteria about the country's economic, technological, social, and demographic characteristics. The MAED approach is not considered reliable for forecasting Turkey's electricity consumption. Because the assumptions utilized in MAED forecasts mirror the MENR's aims, anticipated figures are typically greater than actual energy consumption. As a result, providing updated electricity consumption predictions for Turkey has remained a priority over the years. MLR is used to decide which independent factors will anticipate future electricity usage using artificial neural networks. MLR is applied after the independent and dependent variables have been transformed logarithmically. Incorporating logarithmic transformation into the MLR allows the connection between the independent and dependent variables to remain non-linear while preserving the linear model [22,31,32].

Artificial neural networks (ANNs) have been used to forecast short-term demand. ANNs are mathematical or computational representations of biological neural networks that take structure and function into account. It comprises a network of artificial neurons that utilizes a connectionist algorithm to process information. Each artificial neural network is built on a single artificial neuron [6]; the neuron must adhere to only three rules: multiplication, addition, and activation. As a result, all input values are multiplied by a unique weight at the artificial neuron's entry site. The sum function is essential to the artificial neuron. Calculate the sum of all weighted inputs and biases. A transfer function, or activation function, is the sum of previously weighted inputs and biases that have passed through the exit of the artificial neuron [32].

From Monday to Sunday, the days of the week were allocated number values ranging from 1 to 7. The 'weekdays' are denoted by the number 1 and the 'weekends' by the number 0. Additionally, the hours of the day were allocated numbers ranging from 1 to 24, indicating 1 am to 12midnight. Adjustments to the network were now made till the optimal performance was obtained. The number of epochs, hidden layers, activation functions, and network design, among other parameters, can be modified to obtain the optimal network. Training is essentially a matter of trial and error. The activation function was the sigmoid transfer function [33-35].

Fuzzy set theory is a generalization of classical set theory. In classical set theory, an element is either a member of or not a member of a given set. As a result, the degree of membership in that set is its crisp value [26]. However, in fuzzy set theory, an element's degree of membership can be modified continually from the realm of discourse, a fuzzy set maps to the near interval 0, 1. In fuzzy sets, a membership function can represent the continuous character of data. Fuzzy set theory is a critical component of artificial intelligence (AI) and has many applications in load forecasting. For instance, it can model standard linguistic variables imprecise or ambiguous on a cognitive level. Load forecasting is fraught with uncertainty due to variations in parameters such as temperature, humidity, rainfall, wind speed, air pressure, and solar radiation about the load, and its value cannot be predicted mathematically. As a result, a fuzzy logic approach will be the most appropriate way to apply

in these circumstances [20]. Therefore, fuzzy logic is utilized to map the highly non-linear relationship between meteorological characteristics and their impact on peak demand each month of the year (membership functions). The two parameters, temperature, and humidity are employed as inputs to the fuzzy logic model in this paper, whereas load is used as an output [36].
MLR is more trustworthy than FNN, fuzzy logic, and ANN approaches. This article suggests three distinct STLF approaches: ANN, Fuzzy Logic, and Fuzzy Neural Network. The load data for the ISO New England power utility are compared to those using the multiple linear regression approach. The figures demonstrate that the more recent fuzzy logic, ANN, and FNN algorithms surpass the previous MLR strategy. We have rephrased this for clarity, but the relationship between preceding one-week and two-day time-lag loading is likely more substantial [21,29,31,33,37-39].

The electrical load is affected by the calendar effect, consumption, electricity pricing, weather, and currency. These factors have the following effects: Demand is influenced by the calendar, which includes working hours, holidays, and national or religious festivals. Consumption is directly related to demand in both the industrial and household sectors. Electricity prices are affected by both production and trade. The current weather conditions may affect electricity usage. These four weather measures are sometimes regarded as the most affectionate because they need the usage of air conditioners or electric heaters. Currency changes also affect cross-border electricity trade agreements and industrial costs [38,40].

From a utilitarian viewpoint, ANN, as a black-box technique, can lower the entrance barrier for engineers interested in load forecasting, as it does not require advanced statistical knowledge or an understanding of systems. On the other hand, an ANN-based method does not provide a systematic means for engineers to improve their understanding of the system or their knowledge of its load consumption [41]. From this advantage point, the MLR methodology offers an advantage over the ANN approach: the many impacts, such as holiday and weekend effects, can be detected and modelled transparently and methodically. They analyzed using multiple linear regression (MLR) and artificial neural networks (ANN). They employed seven independent variables to forecast energy use over time; multiple linear regression was used to analyze the proposed models. By analyzing all possible combinations of the seven independent and dependent variables, 27 equations were constructed. Three models were chosen as the best for predicting future energy use, and these three models were combined in an ANN to do so. They created the ANN using back-propagation training with a feed-forward multilayer perceptron neural network [27,32,35,42].
An error-based comparison was performed between the proposed model and the classical back propagation-

trained ANN model [43]. The suggested technique outperforms standard neural networks in terms of energy demand prediction. MENR (Ministry of Energy and Natural Resources) estimates were lower in both instances [36,44]. The word "primary energy" refers to an unaltered type of energy. Two examples are coal and natural gas. Logarithmic regression was used to generate the model, and t- and F-tests were used to validate it [24]. Additionally, he forecasted Turkey's PEC from 2010 to 2025 using three different growth rates for the CP and GDP.

Over two-thirds of the energy consumed in the United States is generated by electricity. Additionally, there are additional articles devoted to Turkey's electricity consumption predictions. There is a correlation between meteorological conditions and electrical consumption in short-term projections. The long-term electricity consumption of Turkey is calculated by Senthil Kumar et al. [6] using a recurrent neural network (RNN) and a three-layered feed-forward back-propagation network (FFBPN). Finally, the RNN is the most effective structure. The authors have forecasted Turkey's electricity demand for 2008-2014.

3. CONCLUSION

Load forecasting aids an electric utility in purchasing and generating power, load shifting, and infrastructure development. Demand forecasting is critical in a deregulated energy industry. Load forecasting has three categories—load projection for one hour to one week. Short term load forecasting can help predict load flows and minimize overloading. The daily load peak forecast is fundamental in dispatching tasks. ANN and FL short-term load forecasting models usually rely on endogenous information, generally in the active power. The proposed techniques in this study were used to forecast the load for Turkey electricity. These two methods yield a minimal MAPE value compared to regression. Artificial Neural Networks and Fuzzy logic are recent technologies that predict and reduce actual and forecasted demand. There was no historical data for the load forecast for the selected years. As a result, the data was forecasted for these two years. Therefore, future studies should investigate the other new technologies to forecast; future studies can also forecast for different states in Turkey using the same techniques.

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Persian Abstract

چکیده

از آنجایی که سری های زمانی بار بسیار متغیر هستند، پیش بینی تقاضای بار کوتاه مدت بر اساس تقاضای پیش بینی بار ساعتی، روزانه، هفتگی و ماهانه چالش برانگیز است. در نتیجه، پیش‌بینی بار شرکت انتقال برق ترکیه (TEA) در این مقاله با استفاده از شبکه‌های عصبی مصنوعی (ANN) و منطق فازی (FL) پیشنهاد شده است. پیش‌بینی بار، شرکت‌های برق را قادر می‌سازد تا برق بخرند و تولید کنند، تغییر بار و زیرساخت بسازند. پیش‌بینی بار به سه دسته (ساعتی، هفتگی و ماهانه) طبقه‌بندی شد. با گذشت زمان، پیش‌بینی بارهای توان با شبکه‌های عصبی مصنوعی و منطق فازی، کاهش شدید ANN و افزایش تدریجی FL را از ۲۴ ساعت به ۱۶۸ ساعت نشان می‌دهد. همانطور که نشان داده شد، منطق فازی و شبکه های عصبی مصنوعی از الگوریتم های رگرسیون بهتر عمل می کنند. این مطالعه بالاترین نرخ رشد و میانگین درصد خطای مطلق (MAPE) را در مقایسه با FL و ANN دارد. اگرچه رگرسیون بالاترین نرخ رشد پیش‌بینی را دارد، اما به دلیل درصد MAPE پایین‌تر از FL و ANN دقیق‌تر است. شبکه های عصبی مصنوعی و منطق فازی فناوری های نوظهوری هستند که قادر به پیش بینی و کاهش نوسانات تقاضا هستند. تحقیقات آتی می تواند کشورهای مختلف ترکیه را با استفاده از همین رویکرد پیش بینی کند.