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Machine Learning Based Short Term Load Estimation in Commercial Buildings

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Abstract

Nowadays, there are many problems with the electricity system, such as increasing consumption, short-time overload during the intra-day, environmental problems caused by fossil fuel, and foreign-source dependency. Therefore, it is necessary to meet these increasing energy needs, minimize environmental impacts, and develop cost optimization solutions. In order to meet these requirements, it is necessary for the network to have a more dynamic structure and to have real-time monitoring and control systems. Furthermore, to develop the aforementioned system, it is necessary to estimate the load of the users in the system. Therefore, the developed artificial neural network-based load estimation algorithm is capable of high accuracy load estimates, and high precision data were obtained for use in the demand side management system.

Keywords: "Short term load prediction, Machine Learning, Artificial Neural Network, Demand Side Management"

1. Introduction

According to reports from the United Nations (UN), the world population is rising rapidly. The rapid development of technology and the growth of the population increase the energy requirement. The increased energy demand is hardly met due to limited energy resources. The annual energy demand growth rate in Turkey is approximately four times the rate of increase in worldwide energy demand. In the projection reports, it is predicted that 2/3 of the energy efficiency potential in the world will not be used in the period until 2035. Energy sources used in Turkey about 3/4 are imported. According to the IEA report, energy supply in Turkey was 144 Mtoe, energy intensity per unit of GDP is about 4.5. In other words, some of the energy supplied is wasted before it is used. Therefore, it is necessary to meet the increasing energy demand, minimize the effects on the environment and develop cost-optimized solutions. In order to meet these requirements, the grid should be more dynamic, and there should be systems capable of real-time monitoring and control (Molavi, H., & Ardehali, M. M. 2016).

Smart grids are energy management systems that monitor and control all market participants' supply and consumption behavior. Smart grids collect information about producers and consumers using information and communication technologies and use this information to increase supply continuity, technical quality, and efficiency. In the smart grid, the measurements taken from generation, transmission, and distribution systems are collected in one or more control centers, and it is ensured that the system responds automatically or semi-automatically according to the instantaneous needs of the grid (Fujiwara, T., & Ueda, Y. 2018). Measuring devices with communication capability and communication infrastructure are the most important parts of the smart grid. Therefore, one of the most critical steps to create a smart grid is the continuous monitoring of the grid and electricity quality. With the widespread use of smart grids and the expansion of the technological infrastructure, energy demand forecasting applications have begun to be developed for systems that can be monitored (Bruno, S., Dellino, G., La Scala, M., & Meloni, C. 2018).

In Turkey, similar to the rest of the world, approximately 1/3 of the energy demand is consumed by buildings. In addition, the consumption of buildings increases during peak hours of energy consumption. Especially the high consumption of commercial buildings and the increase in energy demand during peak hours constitute an essential area for Demand Side Management (DSM) applications. Therefore, monitoring, and more importantly, accurately estimating energy consumption is essential for the efficient operation of DSM applications (Aghajani, G. R., Shayanfar, H. A., & Shayeghi, H. 2017). Electrical load estimation studies have started to be done primarily with statistical models and autoregressive methods in the literature. However, with the rapid spread of artificial intelligence techniques and the successful results of estimation algorithms, electricity consumption estimations have started to be made with neural networks.

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1.1. Related Work

Li, Ding, Zhao, Yi, and Zhang (2017) estimated the energy consumption in buildings with an extreme learning machine-based deep learning approach. The results obtained were compared with various machine learning methods and the developed model's success was demonstrated.

Mocanu, Nguyen, Gibescu, and Kling (2016) made 15-minute, hourly and weekly forecasts for buildings using Conditional Restricted Boltzmann Machine (CRBM) and Factored Conditional Restricted Boltzmann Machine (FCRBM) methods. It has been shown that the estimations made with the FCRBM method give better results than the estimations made with both CRBM and ANN, SVM, and RNN.

Berriel, Lopes, Rodrigues, Varejao, and Oliviera-Santos (2017) developed a system that estimates monthly energy consumption using three deep learning methods: deep fully connected network, convolutional neural network, and Long Term Short Memory (LSTM). It was determined that the best results were the estimations obtained with the LSTM model.

Rahman, Srikumar, and Smith (2018) made hourly forecasts for a commercial building in Utah and residential campuses in Texas using the Recurrent Neural Network (RNN). The accurate estimation performance of the method has been demonstrated with the results obtained.

Chen et al. (2017) offered an SVR model to predict load forecasting for four large office buildings in eastern China. Hourly load predictions were compared with other SVR model baselines. It is shown that the developed SVR model has better results and is more stable in short-term load forecasting compared other seven forecasting models.

Yildiz, Bilbao, and Sproul (2017) estimated hourly and daily electricity consumption of a campus and a technology company building in Sydney. Obtained results were used to compare with MLR models and ML methods. The estimation results made by MLR, NN-LM, NN-BR, NARX-LM, NARX-BR, RT, and SVR methods were compared with RMSE, MAPE, MBE, and R2 metrics. It has been observed that ML methods give better results than MLR models.

Kuo and Huang (2018) estimated the electricity load demand of consumers in the US coastal areas for the next three days using the Deep energy method. The success of the Deep Energy method was compared with the SVM, RF, DT, MLP, and LSTM methods using MAPE and CV-RMSE metrics. Deep Energy method showed 10% more accurate performance compared to other methods.

Xu, Li, Xie, and Zhang (2018) predicted electrical load estimation of Albert area in Calgary, USA, and a service restaurant located in MT, USA. A hybrid model is developed using the ELM method to model shallow features and the LSTM method to extract deep patterns. The hourly consumption estimations of the hybrid model were compared with the SVR, ELM, and LSTM methods. It was demonstrated that the estimations of the hybrid model were more successful than other methods.

Kim, Moon, Hwang, and Kang (2019) estimated the 30-minute consumption of three industrial distribution complexes in South Korea. The method called RICNN was created by combining the RNN method with the 1-D inception module. When the developed method is compared with the MLP, 1-D CNN, and RNN methods, it has been seen that the 30-minute prediction performance gives better results than other methods.

Chitalia, Pipattanasomporn, Garg, and Rahman (2020) predicted hourly, and daily load predictions for five commercial buildings located one in Tailand; one in India; and three in the USA. The study indicated that there is a 20-45% improvement in estimations made with LSTM, LSTM-assisted attention, BiLSTM, and BiLSTM-attention models compared to the state-of-the-art models. Also, attention models obtained better results for most of the scenarios.

Bendaoud and Farah (2020) made hourly and daily load forecasts using the Convolutional Neural Network (CNN) method. In the study using real consumption data in Algeria, the data was not used as a one-dimensional input to the CNN method; instead, the data was used as a two-dimensional input. Comparisons with GBRT, RF, and SVR methods showed that the developed method gave successful results. A summary of the mentioned literature studies is given in Table 1.

Table 1. Review of building load forecasting studies

Reference	Prediction Method	Compared Method	Metric	Time Horizon
Chen et.al.	SVR	SVR (baseline models)	ME, MAE	Hourly
Chitalia et.al.	LSTM, LSTM w/att., BiLSTM, BiLSTM w/att.	LSTM, LSTM w/att., BiLSTM, BiLSTM w/att.	RMSE, MAPE, CV	Hourly, daily
Yildiz et.al.	MLR, NN-LM, NN-BR, NARX-LM, NARX-BR, RT, SVR	MLR models vs ML methods	RMSE, MAPE, MBE, R^2	Hourly, daily
Kuo et.al.	Deep Energy	SVM, RF, DT, MLP, LSTM	MAPE, CV-RMSE	Daily (next three days)
Xu et.al.	Hybrid model (ELM/ shallow features + LSTM/ extract deep patterns)	LSTM, ELM, SVR	MAE, MRE, RMSE	Hourly
Kim et.al.	RICNN	MLP, 1-D CNN, RNN	RMSE, MAPE	30 min.
Li et.al.	ELM	BPNN, GRBFNN, SVR, MLR	MSE, RMSE	30 min., 60 min.
Mocanu et.al.	CRBM, FCRBM	ANN, SVM, RNN	KOKH	15 min., 60 min., daily, weekly
Berriel et.al.	LSTM	DFC, CNN	MSE, RMSE, MdAPE	Monthly
Rahman et.al.	RNN	MLP	MSE	Hourly
Bendaoud et.al	CNN	GBRT, RF, SVR	RMSE, MAPE	15 min., daily

In this study, the energy demand of a commercial building in Ankara is estimated, and the potential of commercial buildings for DSM applications is investigated. In this article, a hybrid short-term load forecast is presented by considering consumption data with a 10-minute time stamp, weather information (outdoor temperature), indoor temperature, lighting requirement time, time to be spent in daily overtime, and the number of people in the building between 2016-2018 The proposed model was developed by training with ANN, one of the machine learning algorithms, and the results obtained were evaluated with the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics, and their accuracy rates were determined. The frequency of historical data at high frequency, variables such as lighting and the number of personnel, and the use of the information such as overtime as parameters are the most important features of this article that distinguish it from other studies.

In the first part of the study, short-term electrical load estimation in commercial buildings is explained in light of the literature. The continuation of the work is organized as follows. In section II, the mathematical description of methods is introduced. Then, the proposed model is analyzed, the analysis results are discussed, and the simulation results are presented in section III. Finally, in section IV, conclusions are summarized, and future works are described.

2. Materials and Methods

2.1. Materials

The electrical load estimation problem has linear and non-linear characteristics due to its input parameters. Meanwhile, when considering the load consumption curves of commercial buildings, it is essential to organize the data by considering various cases such as weekdays - weekends, working hours - non-working hours, holidays - overtime. The input to be used in the model to be developed in the article is given in Table 2.

Weekdays, Weekends (Saturday - Sunday), Holiday (public and religious holidays), daily electric consumption, the previous day electric consumption, the previous week electric consumption, consumption on the same day of the previous year, the next day's consumption, the last 15 minutes' consumption, the previous day quarter-hourly consumption, the previous day quarter-hour consumption, are taken as input parameters for the past consumption prediction. In addition, outdoor temperature, indoor temperature, lighting requirement duration, overtime duration, and the number of people in the building are other input parameters. The lighting requirement duration parameter will be used for daily load forecasting but not for hourly load forecasting. The table containing the units of the variable is given in Table 3.

Data anomalies caused by measurement problems are solved by using filter in data preprocessing. The abnormality at the detected point is diagnosed by comparing it with the devices in the lower and upper layers. The missing lines were filled in by taking the average of the missing data in the previous and next time horizon and the data in the same time horizon.

Table 2. Variable for ANN

Variable	Abbreviation
Weekdays	Wd
Weekends	We
Holidays	H
The previous day electrical consumption	PDEC
The next day electrical consumption	NDEC
The previous week electrical consumption	PWEC
The previous hour electrical consumption	PHEC
The next hour electrical consumption	NHEC
The previous day hourly electrical consumption	PDHEC
The previous 10-min electrical consumption	P10EC
The previous day 10-min electrical consumption	PD10EC
The following 10 min. electrical consumption	F10EC

Table 3. Units of Variable

Input	Unit
Days of week	1-7
Temperature	°C
Electricity consumption	kWh
Number of people	-
Lighting requirement	Minutes
Overtime duration	Hour

2.2. Artificial Neural Network

Artificial neural networks are a model developed by being influenced by the human brain. Nerve cells communicate with each other and with synapses through electrical discharge events. The cells communicate with each other through their axons. In structures found in artificial neural networks, it combines the input information with an aggregate function filter it through the activation function, produces the necessary output and sends it to other nerve cells over network connections. The values of the connections that will communicate the artificial neural networks are expressed as weight values. They form a network by connecting to form 3 main layers, namely the input layer, hidden layers, and output layer, which are located on a parallel line. The number of hidden layers can be increased or decreased according to the network's structure. In the light of this information, the organized information given to the input layer is processed and weighted with various activation functions in the hidden layers and directed to the output layer. It can be briefly summarized the key points to be considered in order for the network to produce correct output for the given data: to organize the data correctly, to choose the proper activation function for the developed model, and to determine the network weights correctly (Salahat, 2017).

Training the network is the process of learning the correct weights required for predicting the network. These values, which are randomly assigned at the beginning, are changed during the training according to the learning rule of the network. Then, using these values in another network, the weights are changed again, aiming to find the optimum values. If these optimum values give correct answers to the data in the test set, the network is considered trained. Among the models developed for learning, networks such as LVQ, SOM, ART, and Elman are frequently used (Owda, Omoniwa, Shahid, & Ziauddin, 2014).

Artificial neural networks are grouped under two main headings: feedforward networks and recurrent networks, depending on the information flow and the weighting of the network.

2.2.1 Feedforward Networks

Feedforward neural networks are the most basic form of ANN. Data only move forward to the hidden and output layers in such networks. Due to the memoryless nature of the system, this network is called a "static network". While the weights of the feedforward links can be changed during training thanks to the weight adjustment algorithm, it is not possible to change the feedforward link weights (Mena, Rodríguez, Castilla, & Arahal, 2014).

2.2.2 Recurrent Networks

In recurrent neural networks, there is a structure in which feedback is made to the hidden layers and input layers before the outputs in the output layer and hidden layers. Since this type of neural network has a dynamic memory structure, the output of the neurons does not depend on the input values valid for that situation. Because of this structure, recurrent networks are suitable for prediction applications. At the same time, recurrent networks provide successful results in estimating time series (Chernykh, Chechushkov, & Panikovskaya, 2014). NARX network structure is given in Figure 1.

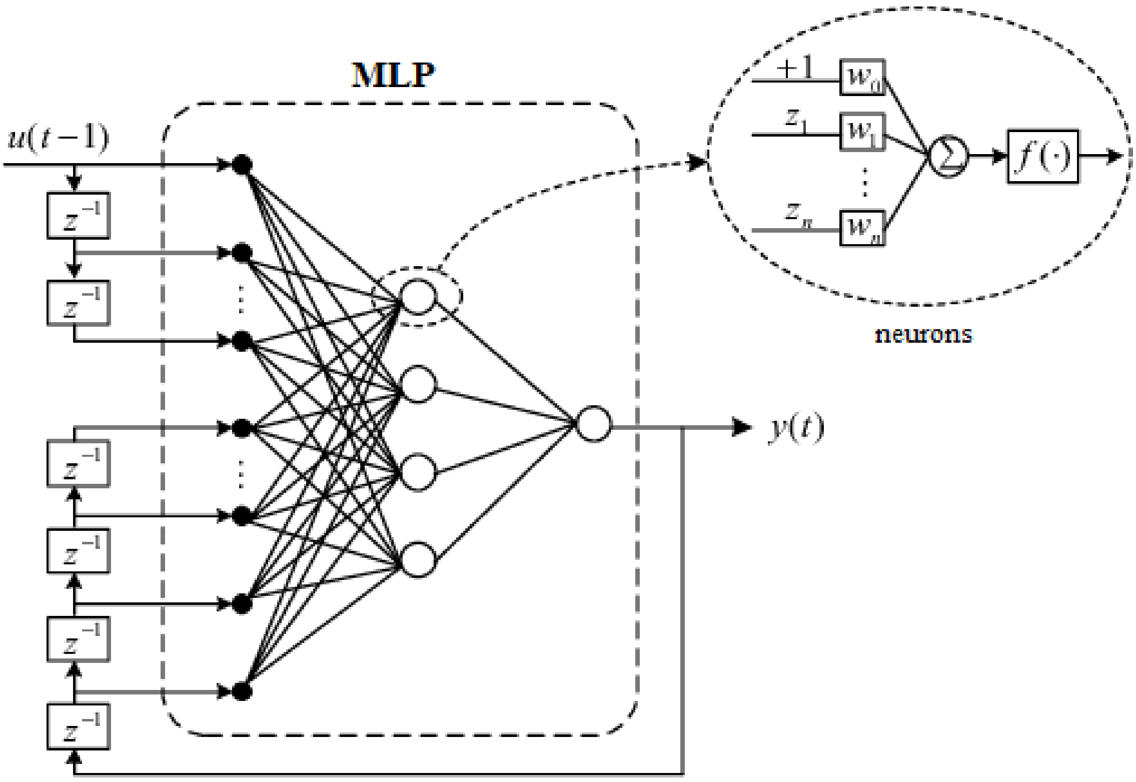

Figure 1. NARX network structure (Huang et al. 2017)

2.2.3 Prediction Assessment Metrics

It is very vital to measure the success of the prediction mechanism in the prediction model to be developed. In the literature, metrics such as Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE), Mean Squared Error (MSE), and Root Mean-Square Error (RMSE) are used to measure the prediction success of machine learning algorithms. . The results obtained from these metrics enable measurement of the model's success by comparing the predictions of the developed model with the actual values.

Mean Squared Error (MSE) defines how close the estimates are to the actual value. It always produces positive-valued results and shows that models with MSE values close to zero are more successful. The formula for the MSE metric is given below.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - f(x_i))^2 \tag{1}$$

In this equation, $f(x_i)$ represents the i-th value estimate of the model, and y_i represents the i-th real value.

Root Mean Squared Error (RMSE) expresses the standard deviation of the calculated errors between the forecast and the actual values. It expresses how close that data is to the truth around a line that expresses the correlation between the RMSE forecast data and the actual values. The RMSE value varies between 0 and ∞. A zero RMSE indicates that the estimated value is the same as the actual value. As this value moves away from zero, it is understood that the error in the estimation values increases. The formula for the RMSE metric is given below.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {e_i}^2} \tag{2}$$

As can be understood from the equation, it is summed up by taking the squares of the inputs entering the model separately. The RMSE value can be calculated by taking the square root of the total.

Mean Absolute Error (MAE) determines the difference between two continuous variables. MAE measures the error by drawing a line that best expresses the input data and calculating the horizontal and vertical distances between the actual data and these values. Since the MAE value is easy to interpret, it is preferred in time series applications. The MAE value varies between 0 and ∞. Models with MAE values close to zero show better prediction success. The equation of the MAE metric is shown below.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{3}$$

Mean Absolute Percent Error (MAPE) is another MAE-based metric. MAPE is used to measure the accuracy of such applications because it is more successful in predicting time series models. It usually expresses accuracy as a percentage and is defined by the following equation:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{|e_i|}{|A_i|} \tag{4}$$

Here e_i: represents the difference between the estimated value and the actual value. A_i is the actual value, n is the number of operations. The absolute value in this calculation is added up for each predicted point in time and divided by n by the number of fitted points. Multiplying by 100 makes it a % error.

3. Proposed Model

In order to develop a realistic and highly accurate model with the recurrent multilayer ANN model, two years of data covering the years 2017-2018 were collected in a commercial building in Ankara. In order to obtain reliable estimation results, it is very important that the data have a 10-minute timestamp.

The developed model allowed to increase the number of hidden layers. Adding the number of hidden layers increases the predictive power in some cases and complexity in other cases, making the model difficult to work. It has been tried to determine the optimum number of hidden layers by doing many experiments. At the same time, MSE, RMSE, MAE, MAPE metrics, whose equations were given in the previous section, were used to test the success of the developed model. Estimates were made by dividing our study into two parts, hourly and 10-minute. The results and discussions regarding the estimations will also be made in the following subsection. The developed ANN-based load prediction model flowchart is given in Figure 2.

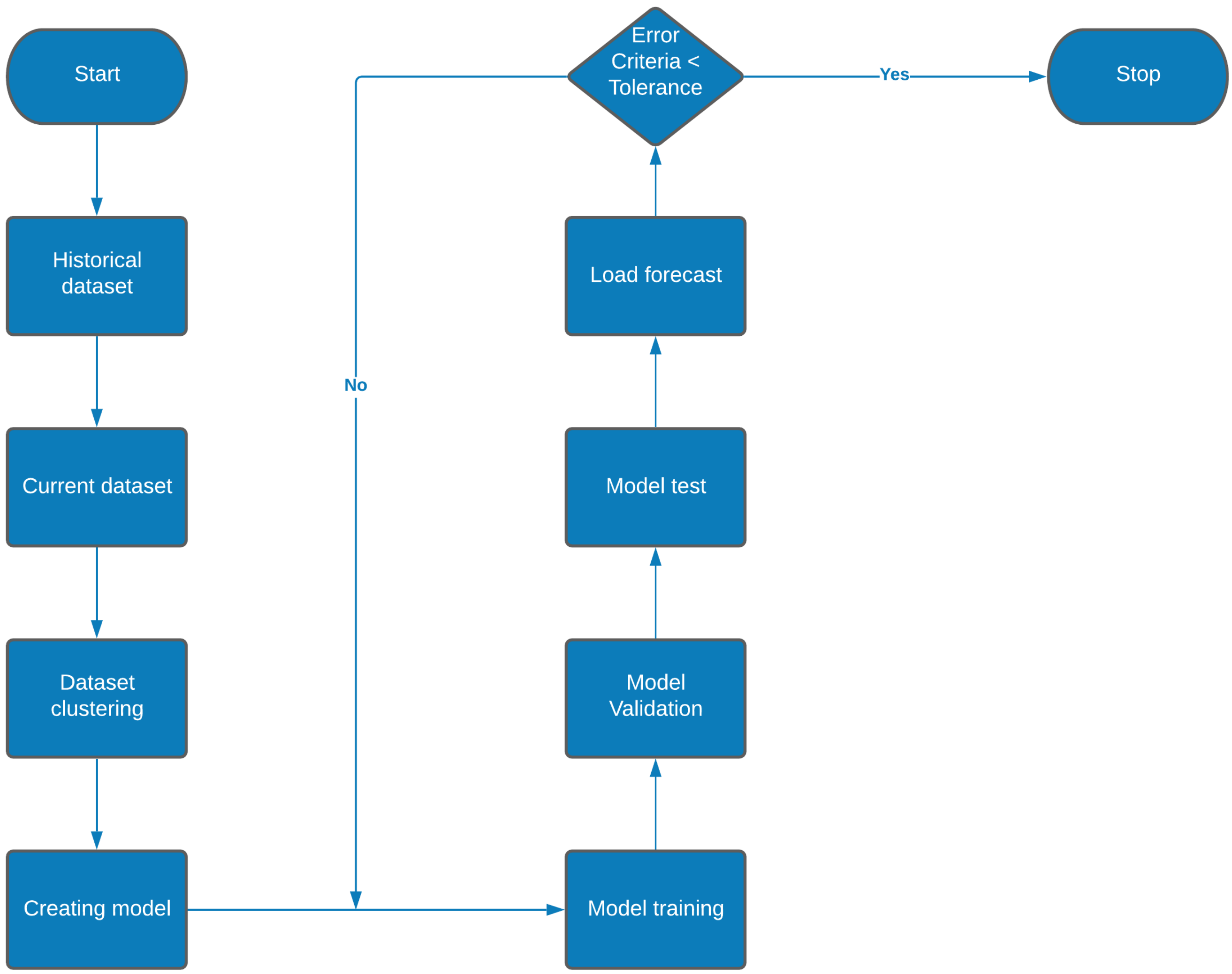

Figure 2. ANN-based load prediction model flowchart

3.1 Hourly ANN Prediction Model

In the hourly ANN prediction model, dataset was trained using 17520 pieces of data. 70% of this data amount was used as a training dataset, 15% as a test dataset, and 15% as a validation dataset. In order to develop a realistic and highly accurate model with the recurrent multilayer ANN model, two years of data covering the years 2017-2018 were collected in a commercial building in Ankara. In order to obtain reliable estimation results, it is very important that the data have a 10-minute timestamp. Hourly load prediction results with prediction metrics are given in Table 4. Regression plots for the hourly ANN model are given in Figure 3.

Table 4. Hourly prediction results

	Weekdays	Weekends	Holidays
MSE	0,2488	1,1312	0,0379
RMSE	0,4988	1,0636	0,1947
MAE	0,4735	0,8416	0,2401
MAPE	6,5937	9,1724	3,3611

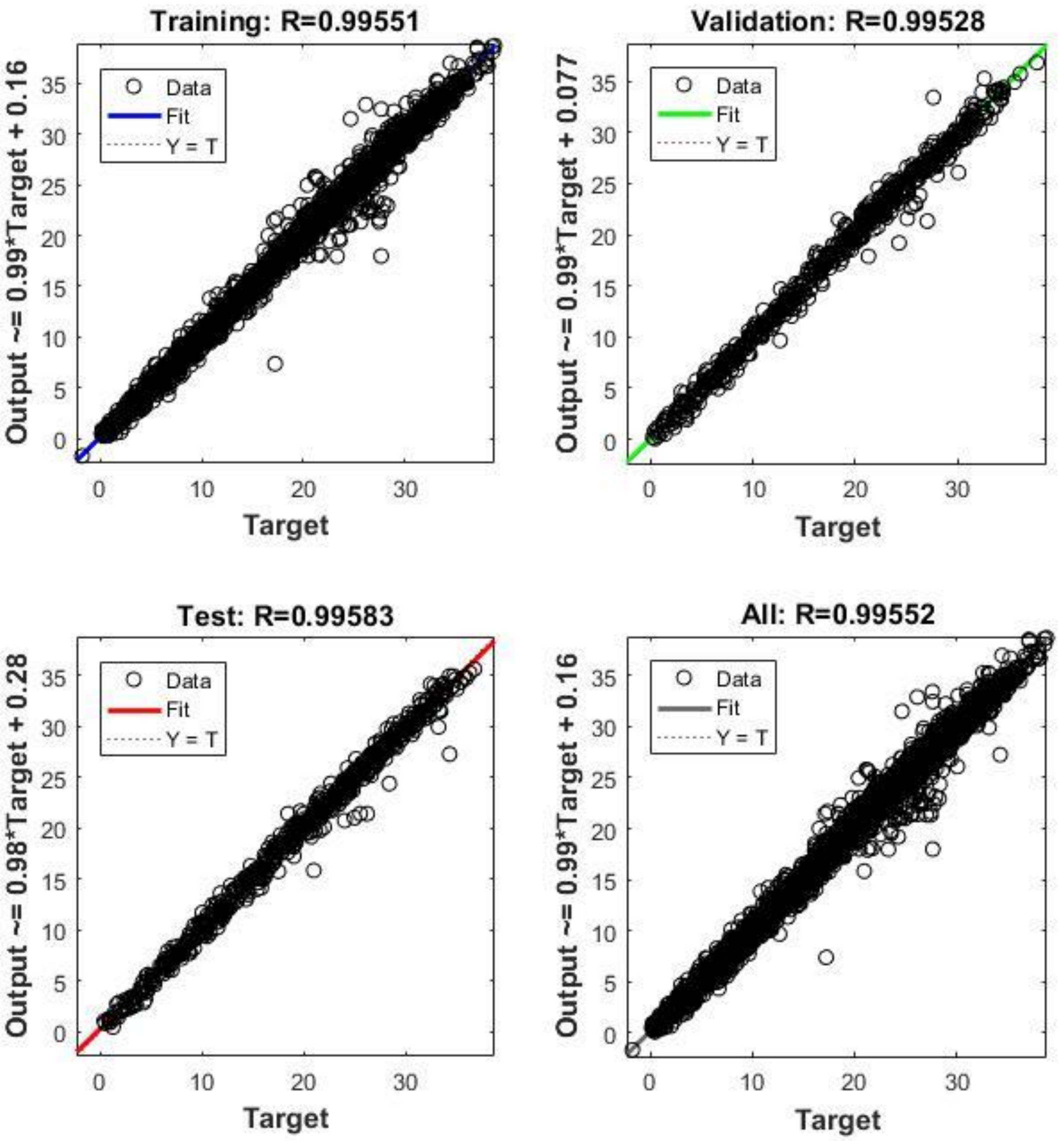

Figure 3. Regression plots for hourly ANN model

3.2 10 Minutes ANN Prediction Model

In the 10-minute ANN prediction model, the dataset was trained using 51840 pieces of data. 70% of this data amount was used as a training dataset, 15% as a test dataset, and 15% as a validation dataset. The estimation results were evaluated under three main headings: working days, weekends, and holidays. 10 minutes load prediction results with prediction metrics are given in Table 5. Regression plots for 10 minutes ANN model are given in Figure 4.

Table 5. 10 minutes prediction results

	Weekdays	Weekends	Holidays
MSE	0,6116	0,8926	0,2630
RMSE	0,7821	0,9448	0,5129
MAE	0,6427	0,7769	0,4344
MAPE	8,8962	10,660	6,0174

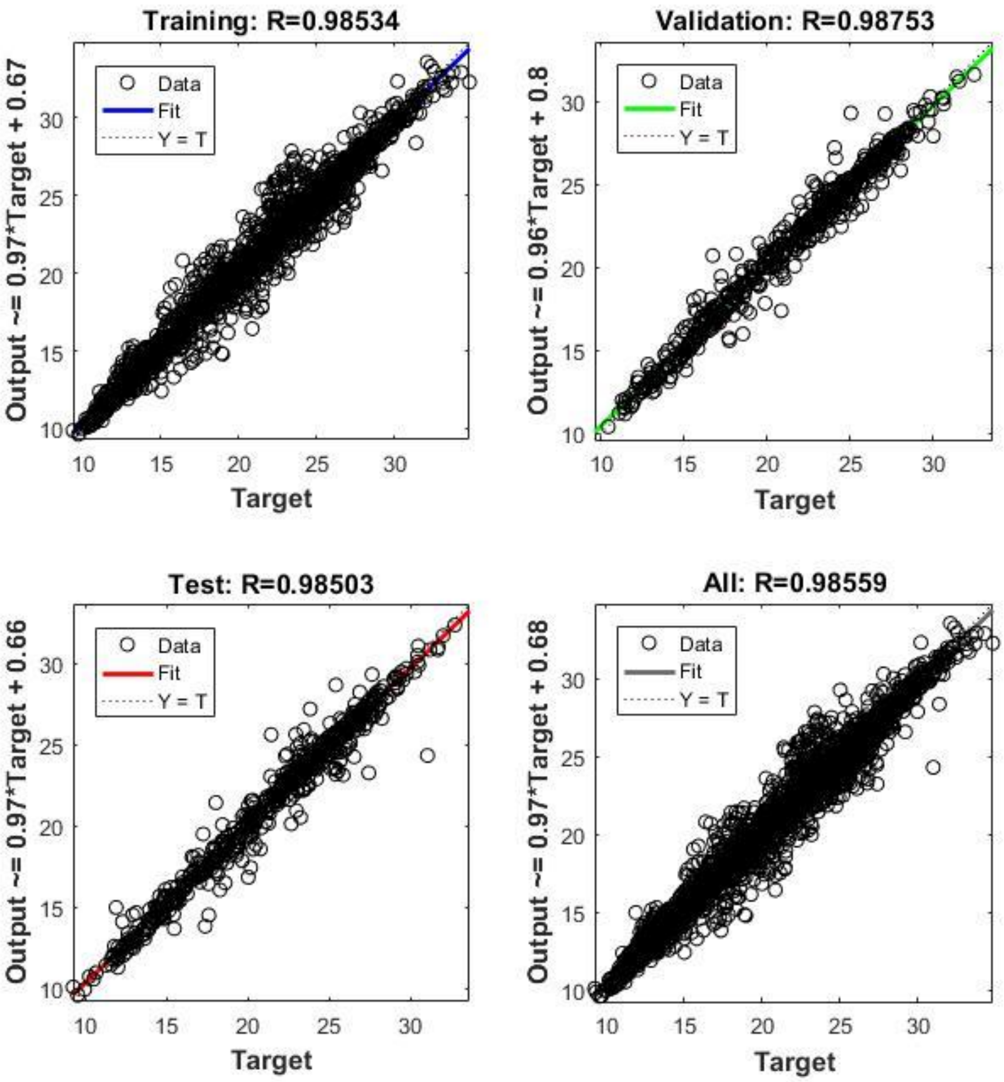

Figure 4. Regression plots for 10-min. ANN model

4. Conclusion and Future Works

This article uses a recurrent multilayer ANN method for short-term electrical load estimation in commercial buildings. The prediction model developed with this new approach has produced very successful results in terms of prediction assessment metrics. The most substantial aspect of the developed model is that increasing the variety and frequency of data works seamlessly with the optimum number of hidden layers in a simple structure and produces satisfactory results. This is because one of the most important parameters for estimation algorithms is data frequency. Therefore, the frequency of data used in the study and the input parameters such as illumination duration and the number of people, which are essential features that distinguish this study from other studies, are the most critical factors that increase the accuracy of the results obtained.

The success achieved in the prediction results by increasing the number of layers in the multilayer ANN model paves the way for more successful results using deep learning methods. In future studies, electric load estimation can be made using deep learning methods. In addition, it is thought that various optimization algorithms can be used to determine the most appropriate number of layers in such applications. In addition, ultra-short term load estimation studies can be made by using similar methods.

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