

# Electrical Load Short Term Prediction by Artificial Neural Network

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**Abstract:** Power generation facilities face a technical and economical challenge in the planning, operation, and management of electrical power systems. In the past, we have employed numerous techniques to forecast short-term electrical loads, but they have demonstrated several shortcomings, including their inability to accurately handle non-linear data. In order to forecast short-term electricity loads, we have created a novel artificial intelligence-based technique in this research study called the artificial neural networks (ANN) method. The neural network was trained, tested, and validated, and the predicted loads were produced by using the temperatures and historical data for peak loads in October 2023, which were represented by the highest electrical load for one day of the month and the temperature data per hour. We are researching and evaluating how electrical loads relate variables, meteorological conditions the results showed negligible mean square error (MSE) and exceptional realism and accuracy in determining future forecast values for this type of non-linear relationship compared to other forecasting methods.

**Keywords:** Artificial neural network; genericalgorithm; levenberg marquardt; short-term electric load forecasting

## 1. Introduction

Achieving accurate forecasts of the electrical load, including knowing the generated quantity, the importance of scheduling and periodic maintenance of stations, and storing future information on the expected performance of power plants to deal with changes are some of the most significant issues facing power plants due to the growing decline in oil reserves worldwide, the technical and economic challenges affecting the generation of electrical energy from multiple sources, such as solar and wind energy systems, and their high costs and health and safety precautions, such as in nuclear power reactors. in the rate of load. The load system is typically impacted by a wide range of elements, including pricing strategy, power tariffs, humidity, wind intensity, historical temperatures, and climatic and atmospheric conditions. Long-term forecasting factors include political activity, economic growth, industrial development level, and random changes in loads; the latter are largely dependent on the geographic area in which the electrical loads will be forecasted. Short-term load forecasting factors include daylight hours, temperature, relative humidity, population growth, and seasonal effects. Forecasting electric loads is an extremely difficult topic that calls for a great deal of modeling, problem framing, and statistical analysis. In electrical applications, short-term forecasting is a highly helpful tool for load flow analysis, system safety analysis, and power generation. Furthermore, it is extremely difficult to incorporate all of these components into forecasting models because the total electrical load system depends mostly on random variables and disturbances brought on by overloads or power outages. Thus, these approaches are examined and contrasted with the suggested approach in this research. The quantity of power needed to meet the demand is predicted using electric load forecasting. The electric load projections are divided into three groups according to the planning viewpoint of the necessary duration. Fuzzy logic and expert systems are two examples of long-, medium-, and short-term AI techniques that are necessary for the electric power system's optimal planning and operation (Sheikh & Unde, 2012; Olagoke et al., 2016). On the other hand, statistical models offer physical transparency in data interpretation and a respectable level of accuracy in STLF;

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however, they are less appealing than creative alternatives due to their associated restrictions, which include limited modeling and costly processing efforts (Olagoke et al., 2016). These projections vary in their nature as well; the absence of reliable long-term weather forecasts makes it impossible to anticipate the peak load of the following year with comparable accuracy (Feinberg & Genethliou, 2005). The biological nervous system serves as the foundation for the suggested mathematical and computer model, or ANN. It is made up of a linked network of artificial neurons and processes information using a connectionist computing paradigm. ANN has demonstrated a high degree of effectiveness in forecasting the behavior of large, complex, multivariate, nonlinear systems (Zhao et al., 1997).

## 1.2 Research Problem

The challenge of estimating the short-term electrical load and the anticipated and necessary demand from the energy system is the issue facing the current study. The results of a review of earlier studies on the usage of artificial neural networks for short-term electrical demand forecasting have been used to create a power technology training program for faculty of technology and education students.

- a. This study was also carried out because of certain deficiencies in the existing programs, such as the following:
  - The current preparation programs need to learn some of these skills
- b. Theoretical knowledge is prioritized over practical knowledge, which has a detrimental effect on students' academic performance.

## 1.3 Research GAP

The research gap in this study is to conduct comprehensive comparisons of common methods for short-term forecasting of electrical loads. The existing research has focused on a comparison between traditional statistical methods and machine learning-based algorithms for short-term load forecasting. According to the findings of this study, the artificial neural network method is one of the most accurate methods for short-term electrical load forecasting.

The paper claims the following contributions:

- a. Studying the relation(s) between the system's parameters, such as peak loads and temperature, to improve the method of forecasting and comparing the results with conventional
- b. Comparison between the actual load data and results obtained from the outputs of the trained neural network
- c. The proposed neural network model does not need a certain number of variables or a specific type of relationship, whether linear or non-linear, considering the relationship between electrical loads and temperatures

## 2. Methodology

### 2.1 Data Collection and Preparation

There are two types of forecasting methodologies: traditional methods and AI-based methods. STLF researchers are interested in a variety of neural network models. Along with Srinivasan, Liew, and Chen, Park Hambali et al. (2016) was among the first researchers to employ the ANN technique for STLF Srinivasan et al. (1991) out of the other AI techniques now in use. For forecasting based on back propagation, Hwang, Tzeng, and Chen employed an ANN, which outperformed traditional techniques. Moturi & Kioko (2013) We employed a supervisory functional ANN technique to forecast three substations in Taiwan. The performance of a supervised ANN-based model for STLF was evaluated by Christopher and Francis Chen et al. (1996) using actual load data from Kenya's national grid power system. In this research, an accurate ANN-based method for STLF is proposed.

Berikut tambahan satu paragraf lanjutan yang tetap konsisten secara akademik dan menguatkan kontribusi penelitian:

In addition to conventional ANN approaches, recent developments in AI-based forecasting have introduced hybrid and optimized models to further enhance prediction accuracy (Lipu, 2021). These approaches integrate ANN with optimization algorithms, statistical techniques, or other machine learning models to overcome limitations such as overfitting and sensitivity to input variability (Abdolrasol et al., 2021). For instance, hybrid models combining ANN with techniques such as genetic algorithms or fuzzy logic have shown improved performance in handling nonlinear and complex load patterns. Moreover, the increasing availability of high-resolution load data and computational power has enabled the development of more robust and adaptive forecasting systems. Therefore, this study not only builds upon the strengths of traditional ANN models but also considers the need for improved accuracy, generalization capability, and reliability in STLF applications.

### 2.2 The First Cluster

Neural network training has advantages in terms of its weights and starts. It can produce previously unanticipated novel models. When data inputs are approximations, neural networks' robustness can guard against inaccuracies. In the learning stage, approximately 70% of the total data must be involved.

### 2.3 The Second Cluster

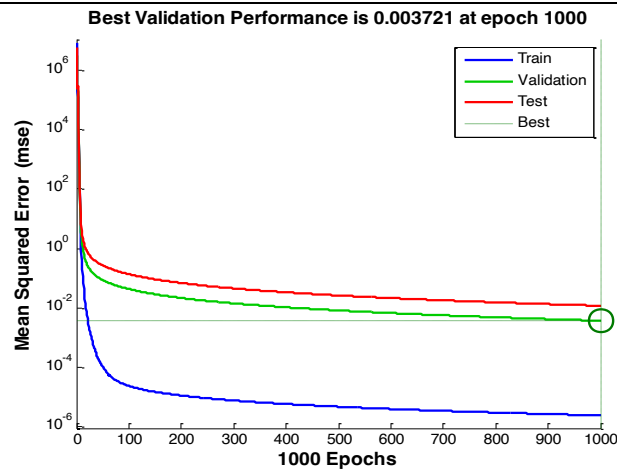
Network Validation of the network's performance is after it is trained to determine if it can make accurate predictions using this data. By comparing the calculated outputs with the actual outputs that were input into the network, the verification group can determine whether the model produces the expected outputs or not. There may be a potential and acceptable error. With a change in the set of learning parameters, the validation set requires approximately 15% of the total data to perform the Check process.

### 2.4 The Third Cluster

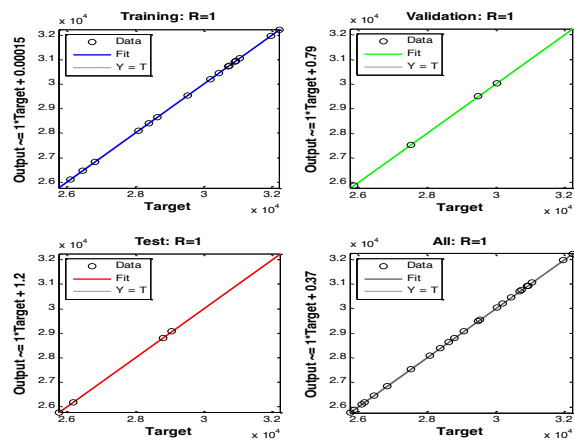
The model then requires the remaining aggregate data to be tested, with a 15%

**Table1.** Network parameters

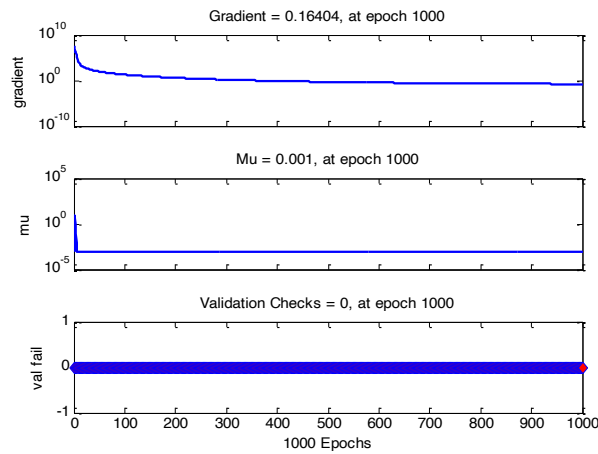
Network parameters	
Transfer function used in the hidden layer	Sigmoid
Training algorithm	Levenberg-Marquardt (train)
Network topology	multi-layer feed-forward neural network
Number of epochs	1000
Transfer function used in the output layer	Sigmoid function
Number of hidden layers	4
Input variables	Electrical loads and the temperture for 24 hours



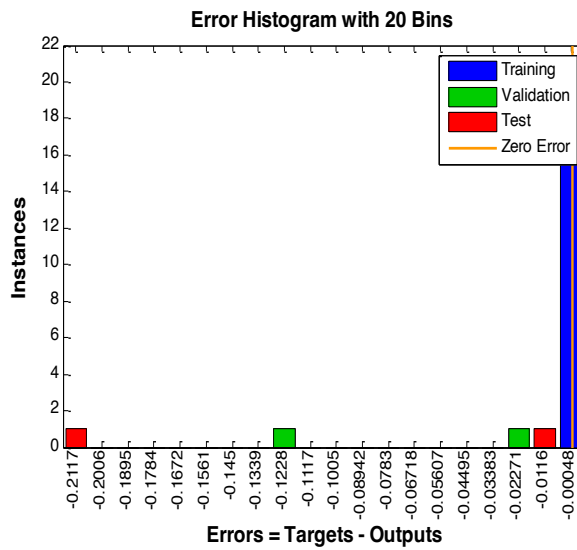
**Figure 1.** Performance Plot for Peak load October 2023



**Figure 2.** Regression Plot for Peak load October 2023



**Figure 3.** Training State Plot for Peak load October 2023



**Figure 4.** Error Targets – Outputs for Peak load October 2023

The figure 4 presents a histogram of the error distribution for the model, divided into three datasets: training (blue), validation (green), and test (red), with the orange line indicating zero error (error = 0). Most of the training data are highly concentrated near the zero-error line, indicating that the model produces very small errors on the training dataset. The validation and test data are also distributed around zero, although in smaller quantities, suggesting that the model has good generalization capability. Overall, the concentration of errors around zero indicates that the model performs accurately and consistently in making predictions. The figure illustrates the error histogram of the model across training, validation, and test datasets. The blue bars (training data) are sharply concentrated around zero error, indicating that the model fits the training data very well with minimal deviation. The green (validation) and red (test) bars are also located close to zero, although more sparsely distributed, which suggests that the model maintains good predictive performance on unseen data. The presence of the zero-error reference line further highlights that most prediction errors are very small. Overall, this distribution demonstrates that the model achieves high accuracy with stable and reliable performance across all datasets.

The figure 4 shows the distribution of prediction errors for the model using training, validation, and test datasets. The majority of the errors, particularly from the training set (blue), are tightly clustered around zero, indicating a high level of accuracy in fitting the data. The validation (green) and test (red) datasets also exhibit errors close to zero, suggesting that the model performs consistently well on new, unseen data. The zero-error reference line emphasizes that

most deviations are minimal. Overall, the pattern of this histogram reflects a well-trained model with good generalization and low prediction error.

**Table 2.** Actual load and Forecasted load October 2023

Hours	Actual Load (MW)	Forecasted Load (MW)
1	28385	28385
2	27520	27520.02
3	26830	26830
4	26105	26105
5	25755	25755.22
6	25875	25875.12
7	26180	26180.01
8	26455	26455
9	28080	28080
10	28800	28800
11	29065	29064.99
12	29530	29530
13	30030	30030
14	30710	30710
15	30935	30935
16	30750	30750
17	30450	30450
18	31970	31970
19	32230	32230
20	31055	31055
21	30915	30915
22	30205	30205
23	29500	29500
24	28640	28640

### 3. Results and Discussion

Gaining an advantage over the current artificial neural network approach is the primary goal of this research. The network behavior is explained throughout training, validation, and testing and is depicted in the performance plot. At 1000 epochs, the desired performance was achieved (number of iterations). The mean square error (MSE) versus multiple epochs where the mean square error decreased during the learning process is displayed. Used the function maps to preprocess the data collection before training and validation. This function permits a zero mean and a unity standard deviation for the inputs and targets. One of the most promising methods for a neural network model was demonstrated for the prediction field, according to current studies. Highly accurate data on day-level temperatures and electrical loads were recorded, and then previous procedures were implemented.

- a. exceptional realism and accuracy in determining future forecast values along with electricity loads. This indicates that the efficiency and efficacy of precise electrical load prediction are increased by the application of neural networks.
- b. Fast access to the intended outcomes since the neural network approach connects the electrical load data, completing the prediction process and this emphasizes how important it is to have a database used since it makes the neural network model more efficient.
- c. The suggested neural network model does not require a particular number of variables or a particular type of relationship, either linear or non-linear, and it permits the addition of numerical elements of variables.

### 4. Conclusion

In This paper was designed, and the implementation of a neural network has been done manually, analogous to a biological process in which the neural network specifies the input and output for data provided by the Egyptian Electric Power Distribution Company, covering time periods of one hour to twenty-four hours. For the peak times for actual loads, through training, testing, and validation, the model enables overcoming the non-linear relationship between temperatures and historical loads by utilizing Using the Levenberg-Marquardt back propagation algorithm, the weights of the load input were divided, and the output values were fed back into the input. The network was trained following the computation. The results of the work confirmed the effectiveness of ANN in short-term electric load forecasting. With an estimated error of 0, this confirms the high accuracy of the results of the study. The suggested technique is

characterized by both standard statistical models and predictions generated. The suggested design offers a great deal of accuracy in each of the three situations. Learn, verify, and test, and the forecasting procedure under study offers a chance to maximize benefits. The research experiment achieved high performance and consistent results.

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### **Conflict of Interest**

The authors declare no conflicts of interest

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