A NEURAL NETWORK TECHNIQUE BASED ON THE LEVENBERG-MARQUARDT METHOD FOR PREDICTING SHORT-TERM ELECTRICITY LOAD

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ABSTRACT

Short-term load forecasting (STLF) is pivotal for ensuring the reliable and efficient operation of power grid stations. Accurate predictions facilitate fault detection and enhance grid reliability by enabling effective energy transactions. This paper proposes a novel approach for STLF utilizing the Levenberg-Marquardt (LM) based Artificial Neural Network (ANN) technique. The model incorporates critical weather parameters and historical load data organized into seasonal time series to forecast electricity load for smart grids. By segmenting the data into weekdays and weekends and utilizing a three-year dataset, the model predicts week-ahead and day-ahead load demand at thirty-minute intervals. The Levenberg-Marquardt backpropagation algorithm optimizes the proposed model, which is evaluated using metrics such as Mean Absolute Percent Error (MAPE), Root Mean Squared Error (RMSE), R2, and R. Comparative analysis demonstrates superior performance, with MAPE and R2 scores of 1.5 and 0.98, respectively, indicating the efficacy of the LM-based ANN model in achieving enhanced accuracy and lower error rates compared to existing methods.

Keywords: STLF, ANN, Electricity Demand, Levenberg-Marquardt technique.

1. INTRODUCTION

Electric power load forecasting plays a crucial role in the strategic planning and operational decisions of power system management. It serves as a cornerstone for electric load generation, transmission, and distribution utilities, heavily influencing their infrastructure utilization. Accurate load forecasting is paramount for these utilities to ensure efficient, safe, and cost-effective operation of their systems [1, 2]. Load forecasting is commonly divided into four distinct categories: very short-term load forecasting (VSTLF), short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF) forecasting. These categories correspond to forecasting intervals of hourly, daily, weekly, and yearly durations, respectively [3]. Of all these categories, short-term load forecasting (STLF) stands out as the most crucial and demanding due to its immediate economic implications. Given the inability to store electrical energy and generate it instantaneously, there must be a delicate balance between electricity generation and consumer demand. Failure to accurately anticipate energy needs can lead to significant economic challenges for producers. For instance, energy companies incur substantial losses due to inaccuracies in load forecasting. To illustrate, a mere 1% overestimation in forecasted load can translate to a staggering $10 million increase in the operational costs of power plants [4]. Hence, it is imperative for power producers to ensure a harmonious balance in electricity generation, distribution, transmission, and consumption. Consequently, electrical companies necessitate a precise and effective short-term load forecasting system to achieve equilibrium between supply and demand, benefiting both producers and consumers alike [5]. Each approach has its drawbacks; classical methods, for instance, struggle with nonlinear data processing, while computational intelligence techniques may suffer from deficiencies in feature engineering and learning accuracy. To address these challenges, numerous machine-learning methods have emerged in recent years. Recognizing their crucial contribution to power management decision-making, these techniques have partially enhanced the accuracy of electric load forecasting [6]. For example, Boroojeni et al. [7]. Li et al. examined offline load data spanning various periods, such as daily, weekly, quarterly, and annually. They employed auto regressive and moving average (ARMA) components to analyze both seasonal and non-seasonal load sequences separately [8]. Taheri et al. investigated ensemble subsampled support vector regression (ESSVR) for short-term load forecasting

(STLF) and estimation [9]. Irfan et al. examined the application of long short-term memory (LSTM) networks to develop a model for forecasting short-term, medium-term, and long-term loads [10]. A DensetNet-121-based model was developed for week-ahead load forecasting, utilizing a support vector machine (SVM) ensemble to integrate multiple networks. Undoubtedly, these endeavors offer valuable insights into electric load forecasting. In addition to the aforementioned methods, achieving accurate electrical load forecasting while accounting for seasonal variations and the discrepancies between weekdays and weekends presents a formidable challenge. Load patterns can vary significantly between different weekdays, with Mondays and Fridays often exhibiting markedly different demand levels compared to Tuesdays and Thursdays due to their proximity to weekends. Moreover, a multitude of factors including time parameters (such as hours, days, months, and years), weather conditions, customer demographics, historical load data, regional expansions, and increased demand, exert significant influence on load requirements [11]. Recent research on short-term load forecasting (STLF) either overlooks the comprehensive consideration of weather conditions and temporal factors alongside historical load demand or falls short in terms of accuracy. Consequently, the importance of integrating weather parameters and addressing load demand fluctuations, including variations between weekdays, weekends, and throughout the day, underscores the need for a robust mapping between these influential factors and load disparities simultaneously.

This study seeks to create a comprehensive deep learning model for short-term load forecasting (STLF) to tackle the aforementioned challenges. The primary goal is to handle weather factors and fluctuations in load demand attributed to seasonal changes, weekdays, and weekends with improved precision and accuracy. To achieve this objective, an artificial neural network (ANN) is proposed, which takes into account historical load data.

In this context, we introduce an artificial neural network (ANN) designed to analyze historical load data categorized into winter and summer seasons. Each season is further divided into weekdays and weekends independently, with each weekday. Recognizing the dynamic nature of load profiles, characterized by temporal, seasonal, and day-to-day fluctuations, our model focuses on forecasting week-ahead electric load demand by predicting the load for each weekday intervals. This short-term prediction aims to enhance the interactivity of load forecasting, ensuring the reliable operation of power systems. To optimize the model's performance, we employ the Levenberg-Marquardt (LM) backpropagation algorithm, renowned for its effectiveness in training neural networks. We evaluate the proposed model using publicly available historical hourly load data from the Punjab power industry, conducting regression analysis across training, testing, and validation phases to assess its correlation with the target vector. Through its emphasis on accuracy and rapid convergence, the LM-based ANN model aims to significantly improve short-term load forecasting, thereby enhancing power grid management and operational efficiency.

The paper makes the following significant contributions:

1. Development of a technique that effectively handles historical load
2. Adoption of the LM backpropagation technique for optimizing the training process of our proposed model. Through extensive training, the model is equipped to forecast day-ahead and week-ahead load demand.
3. Validation of the proposed LM-based ANN model using historical load data. Empirical findings, including RMSE and MAPE values, demonstrate the model's superior accuracy and convergence rate in load forecasting.
4. Conducting regression analysis post-training to assess the model's performance in terms of the coefficient of determination (R2) and correlation (R) between actual and forecasted load demand.

2. RELATED WORK

In general, short-term load forecasting (STLF) encompasses predictions ranging from hourly to weekly intervals and plays a crucial role in the planning and management of power grid operations. Past studies suggest that statistical methods and machine learning models are commonly employed techniques for forecasting short-term electric load.

In recent years, short-term load forecasting (STLF) has witnessed significant advancements through various machine-learning techniques, which have demonstrated realistic prediction accuracy [12]. Among these techniques, regression stands out as one of the most prominent and straightforward models utilized thus far. Different forms of regression, including linear, multiple, and exponential, have been employed for load forecasting purposes. For instance, Jiang et al. [13] employed support vector regression to forecast short-term load based on historical data. Similarly, random forest regression has been utilized to model datasets from the Chinese Society of Electrical Engineering, yielding optimal prediction performance [14]. Abu-Shikhah et al. [15] implemented a multivariable regression approach incorporating three regression models—linear, polynomial, and exponential power-on Jordanian electric load data. Furthermore, Siami-Namini et al. [16] integrated Auto-Regressive Moving Average (ARMA) models with Auto-Regressive (AR) and Moving Average (MA) models for load forecasting purposes. Further, the findings indicate that the LSTM-based prediction was five to eight percent more accurate and robust than the ARIMA model's prediction.

Artificial Neural Networks (ANN) are extensively utilized for various types of load forecasting, serving as a versatile and valuable method for pattern classification [17-19]. Researchers in [20] examined the efficacy of deep residual networks for short-term load forecasting (STLF) and found them to be well-suited for this task, offering reasonable prediction accuracy compared to long-term load forecasting (LTLF). Elgarhy et al. [21] asserted that an enhanced ANN technique outperformed conventional ANN methods. By leveraging 10 years of historical electric load data, they successfully forecasted short-term load for New England, demonstrating a reduction in ambiguity. Additionally, deep neural networks (DNN) have emerged as a recent approach for load forecasting [22,23]. For instance, Deep Neural Networks (DNN) have been applied in short-term load forecasting (STLF) and probability density forecasting. Researchers in [24] conducted experiments using electricity consumption data from three Chinese cities, demonstrating superior performance of the DNN model compared to random forest and gradient boosting approaches. In another study [25], various types of recurrent neural networks (RNNs) were employed to predict hourly load for residential consumers. The findings revealed that the prediction accuracy of Long Short-Term Memory (LSTM)-based RNNs surpassed that of simple RNNs. Hossen et al. [26] utilized Google's TensorFlow platform to train machine learning models for the Iberian electric market, considering differences between weekends and weekdays to forecast load. Similarly, researchers in [27-29] utilized LSTM networks, renowned for their recurrent nature, to predict STLF for small regions, achieving notable accuracy. It is evident that electricity consumption is significantly influenced by weather and other environmental factors [4]. While the techniques described above often involve a single model with rapid convergence, they may suffer from inadequate forecast accuracy, failing to meet the required standards.

Researchers have increasingly explored the combination of classical models and deep learning techniques to develop hybrid models, yielding significant improvements in forecast accuracy, particularly for time series data in power system applications. For instance, Eapen et al. [30] utilized neural networks with backpropagation to mitigate predictive inaccuracies, introducing a hybridized neural network model with two phases of backpropagation. Testing the model on hourly electric load data demonstrated notable accuracy. Similarly, Zhang et al. [31] proposed a hybrid model for short-term load forecasting (STLF) incorporating empirical mode decomposition, ARIMA, and wavelet neural network (WNN) techniques. Evaluation based on historical load data from the Australian and New York electricity markets revealed enhanced prediction accuracies compared to existing methods. Additionally, researchers in [32] advocated a hybrid model integrating signal decomposition and correlation analysis techniques for STLF. Another hybrid model introduced in [33], based on Long Short-Term Memory (LSTM) networks, considered climate factors alongside historical load demands from various states in the USA, claiming improved load predictions. Massaoudi et al. [34] devised a stacked generalization approach combining a light gradient boosting machine (LGBM), extreme gradient boosting machine (XGB), and multilayer perceptron (MLP) for STLF. Simulation results demonstrated the superior accuracy of the proposed model compared to existing approaches.

Various researchers have made significant efforts to predict short-term load forecasting (STLF); however, there is still a lack of standardized and accurate forecasting models that can be universally applied across different scenarios. STLF poses challenges due to numerous influencing factors affecting electricity load beyond historical demand, including day, weekdays or weekends, climate conditions, social variables. In this paper, we address these challenges and aim to enhance forecasting accuracy by proposing a novel hybrid STLF model.

3. THE PROPOSED LM-BASED ANN TECHNIQUE

For precise load forecasting, the data undergoes initial preprocessing to ensure cleanliness. The outcomes of this preprocessing process are then transferred to the proposed Levenberg-Marquardt (LM)-based Artificial Neural Network (ANN) model for training. An adaptive learning algorithm is employed for model training, leveraging past load data to determine the optimal weights. Once trained, the model is validated, and short-term load demand for the following day is forecasted.

3.1 Basic Error Back Propagation algorithm

The SBP algorithm has become the standard algorithm used for training multilayer perceptron as treated in the literature. It is a generalized least mean squared (LMS) algorithm that minimizes a criterion (performance function) which equals to the sum of the squares of the errors between the actual and the desired outputs. This criterion is

$$\mathrm{Ep} = \sum_{\mathrm{j}=1}^{nl} (e_{1\mathrm{j}}^{[L]})^2$$

Where the nonlinear error signal is $e_{1j}^{[L]} = d_j^{[L]} - y_j^{[L]}$; $d_j^{[L]}$ and $y_j^{[L]}$ are respectively the desired and the current outputs for the jth unit. P denotes the pth pattern, nl is the number of the output units. The gradient descent method is given by:-

$$\Delta W_{\mathrm{ji}}^{[s]} = -\mu \frac{\partial Ep}{\partial W_{\mathrm{ji}}^{[s]}}$$

Where $W_{ji}^{[s]}$ is the weight of the ith unit in (s-1)th layer to the jth layer. The steps of the algorithm are summarized as-

1. Compute the error signals for the output layer from

$$e_{1\mathrm{j}}^{[L]} = f'(u_{\mathrm{j}}^{[L]}) e_{1\mathrm{j}}^{[L]}$$

2. Compute the error signals from the hidden layers, i.e. for s=L-1 to one, from

$$e_{1\mathrm{j}}^{[L]} = f'(\, u_{\mathrm{j}}^{[s]}) \sum_{r=1}^{n_{s+1}} e_{\mathrm{r}}^{[s+1]} w_{\mathrm{rj}}^{[s+1]}$$

3. Update the weighs according to the following equation:

$$w_{\mathrm{ji}}^{[s]}(k+1) = w_{\mathrm{ji}}^{[s]}(k) - \mu \mathrm{e}_{\mathrm{j}}^{[s]} \mathrm{y}_{\mathrm{i}}^{[s-1]}$$

Where μ is the learning coefficient and *f'* is the first derivative of *f*.

This is the basic algorithm based on the gradient descent for training the neural network. A form of training algorithm is proposed to be used for this study and is discussed in the following subsection.

3.2 Levenberg Marquardt Algorithm

Levenberg Marquardt Algorithm also abbreviated as LMA treated in the literature, and in this algorithm the performance function is

$F(w) = e^T e$ ………………….. *(1)*

where w=[w1, w2, ……., wN] consists of all weights of the network, e is the error vector comprising the error for all the training examples.

When training with the LM method, the increment of weights can be obtained as follows-

$\Delta w = [\ J^T J + \mu\beta\ ]\ J^T e$ …………. (2)

Where J is the Jacobian matrix and μ is the learning rate, which is to be updated depending on the outcome. In particular μ is multiplied by the decay rate β (1 > β > 0) whenever F(w) decreases, whereas μ is divided by β whenever F(w) increase in a new step.

The standard LM algorithm can be illustrated in the following pseudo-code

1. Initialize the weights and parameter μ (μ=0.1) is appropriate
2. Compute the sum of the squared error over all inputs F(w)
3. Solve equation(2) to obtain the increment of the weight Δw
4. Re-Compute the sum of squared error F(w)
5. Using w+Δw as the trail w and judge

If trail F (w) < F (w) in the step 2 THEN

w=w+Δw

μ= μ*β (β=0.1)

go back to step 2

ELSE

μ = μ /β

go back to step 4

END IF

3.3 Methodology for Electricity Demand Prediction

Conducting research typically involves a systematic process that consists of several steps. The first step is identifying a research question or problem to investigate, which is followed by conducting a thorough literature review to identify existing knowledge gaps and refine the research question. The next step is developing a hypothesis, which is a tentative explanation for the phenomenon being studied. After the hypothesis has been developed, the study design is developed, which involves selecting a sample, defining the variables to be measured, and selecting appropriate data collection methods. Once the study design has been finalized, data is collected and analyzed using appropriate statistical or qualitative methods. The results of the analysis are then interpreted in light of the research question and hypothesis, and conclusions and recommendations are drawn based on the findings. The research findings are communicated through written reports, presentations, or other forms of communication, such as academic journals or conference presentations. Finally, the research is evaluated to assess its validity and reliability, which may involve peer review, replication studies, or meta-analysis. Overall, conducting research involves a systematic approach that requires careful planning, execution, and evaluation to produce credible and reliable results. The steps that are proposed to be followed are shown in below Fig. 3-1.

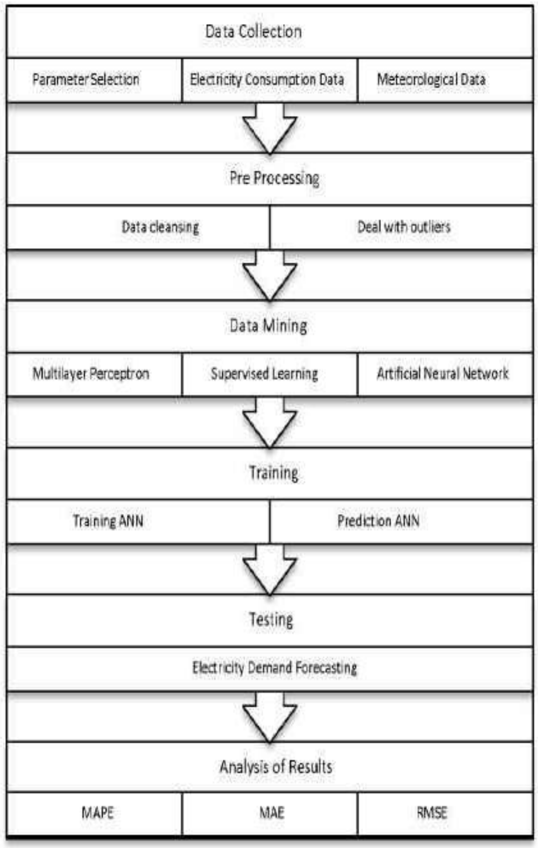

Fig 3-1 Methodology for electricity demand prediction

4 Testing and Result Analysis Results

The results of testing on a test data on a sample of 259 tuples are recorded. The plot between the Actual Demand values (shown in red) and the predicted demand values (shown in blue) is drawn. Same trend is followed by both the predicted as well as actual outputs.

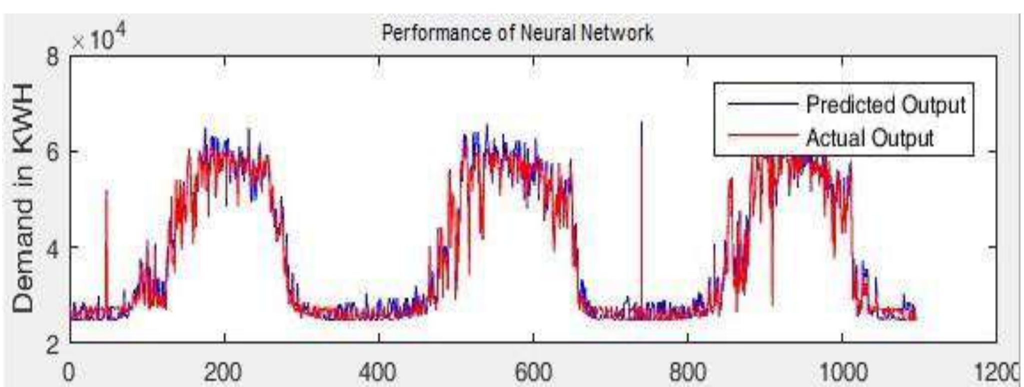

Fig. 4-1 Variation between the predicted demand and the actual demand

Analysis of results –The Mean Absolute Error of around 0.03 was observed and Mean absolute percentage error of 3.54 % was observed. It also shows Mean Absolute Scaled Error of 0.99.

Table 4-1 Performance of ANN on whole date

Mean Actual Error	**1513.085135**
Mean Absolute Scaled Error	**0.996153846**
Mean Squared Error	**5766370.301**
Root Mean Squared Error	**2401.326779**
Mean Absolute Percentage Error	**3.542181533**
Mean Absolute Error	**0.035421815**

The LM-based ANN model, as proposed, is trained to predict forthcoming load demands with satisfactory precision.

4.1 Best Results

The figure 4-2 illustrates the performance of the proposed LM-based ANN model in forecasting load demand for the winter season. The blue line represents the actual load demand, while the red line depicts the predicted load demand by our model. It is evident that our model achieves the highest accuracy, closely matching the actual load demand throughout the forecasting period. This indicates the effectiveness of our approach in accurately predicting short-term load demand.

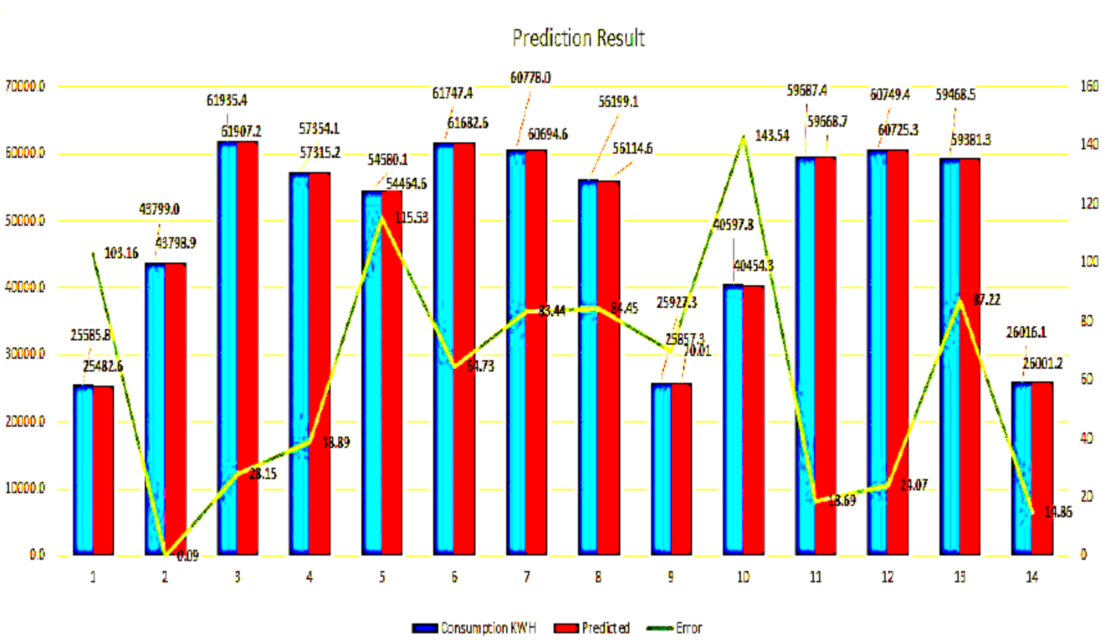

Fig. 4-2 Predication Results with LM-based ANN model

Correlation and coefficient of determination are statistical concepts that are often used to describe the relationship between two variables in a dataset, particularly in the context of linear relationships. In addition, below Table 4.2 offers valuable insights Correlation and coefficient of determination of NN and Regression and serves as a basis for further discussion and analysis. Tt has been clearly shown that the prediction using neural networks technique is significantly better than the regression technique for prediction.

Table 4-2 Correlation and coefficient of determination of NN and Regression

Techniques	R	R Square
Neural Network	0.77	0.60
Regression	0.69	0.48

Moreover, Table 4.3 Testing of Neural Network vs Regression based results and comparison of Neural Network and Regression, performance metrics. Null hypothesis (H0) = There is no significance difference between neural network and Regression based results.

Table 4-3 Testing of Neural Network vs Regression based results

Cases	N	Mean	Std. Deviation	Std. Error ean	t-Test	p-Value
Error ABS(NN)	**1096**	**7351.24**	**9469.40**	**286.03**	**3.62**	**0.000***
Error ABS REG	**1096**	**8906.02**	**10607.65**	**320.42**		
* **Result is Significant as p-value < 0.05**						

5. CONCLUSION

This paper proposed an LM-based ANN model to forecast short-term electricity load. We take time and weather data with historical load demand simultaneously as input to the LM-based ANN model due to the great impact of meteorological parameters on the next day's load. In the above table 4-3, it shows that mean and standard deviation of Neural Network are 7351.24 and 9469.40 respectively, whereas mean of regression based technique and standard deviation are 8906.02 and 10607.65 respectively. The t-test value between neural network and regression based technique result is 3.62 and p-value is 0.000, which is less than 0.05. Therefore, we reject the null hypothesis that there is no significant difference between neural network results and regression based technique for electricity consumption prediction. It elaborate that neural network results are significantly better than regression based technique for electricity consumption prediction. Power load prediction is essential for an effective energy system operation and scheduling.

Conflict of Interest:

The authors declare that they have no conflict of interest.

Dataset Availability Statement:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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