Load Forecasting Using Artificial Intelligence Neural Technique

Parminder Singh[1], Kanwardeep Singh[2]
[1]Department of Electrical Engineerring
Guru Nanak Dev Engineering College, Ludhiana-141006, Punjab
[2]Department of Electrical Engineerring
Guru Nanak Dev Engineering College, Ludhiana-141006, Punjab
Email: [1]parmindersardar@gmail.com, [2]kds97dee@gmail.com

***Abstract*—Electric load forecasting acts as a crucial device in the power grid that ensures system stability, keeps the system stable through significant disturbances, and optimizes energy source transmission. Load forecasting is one of the most common and critical steps in power system designing and implementation. There are a variety of methods commercially available for accurately predicting loads. However, these systems have several drawbacks, like high complexity, high learning rate, and time-consuming. To overcome these issues, a novel model called Bi-LSTM based on deep learning RNN architecture is proposed in this paper. The model starts making predictions using data that is available online or collected in the real world as input. The model uses a deep learning RNN-based Bi-LSTM prediction model to train itself based on these predictions. After the training is completed, the proposed method's output is evaluated and analyzed using MATLAB software. In terms of several parameters such as RMSE, max error, min error, and MAPE, the proposed model is compared to standard ENN, PSO-ENN models. Finally, the proposed Bi-LSTM model's power consumption is examined, and it is found to be stable and close to the desired performance. Hence, the proposed Bi-LSTM model is more effective, precise, and stable.**

Keywords: Load Forecasting, Artificial Intelligence, Electric Load Management, Deep Learning, Data Mining.

I. Introduction

Load forecasting is considered an important task in power systems for its utility. Based on existing/historical information, load forecasting helps to evaluate the electric load. It has the potential to manage and forecast energy usage trends, which aids in load control in future systems [1]. The distribution system and electric transmission currently have no significant energy storage. Electrical generation must meet the demand of electrical for optimum operations in the power system. To use the electrical infrastructure safely, economically, and efficiently, the transmission, generation, and generation utilities need a way to predict the electric node. Electric load forecasting methods are used by generation utilities to plan their generation services to fulfill the future demand load. To maximize power flow on the transmission network and minimize overloads and congestion, the transmission utilizes uses electric forecasting schemes. Forecasting electricity demand is regarded as one of the most important factors in the economic operation of power systems [2]. Factors like historical data, population growth, load density, geographical factors, etc. affect load forecasting.

Electric load forecasting can be divided into four subgroups on the basis of the time horizon: Very short-term load forecasting (VSTLF), short term load forecasting (STLF), mid-term load forecasting (MTLF), and long term load forecasting (LTLF). VSTLF entails forecasting a minute ahead of time, which is critical for real-time operations [3]. MTLF is a crucial stage in the planning and maintenance of electrical power systems. It is used in maintenance preparation and for the planning of power failures and major works [4]. This approach is generic and can be used to load any power system at an hourly rate. The first significant phase in the preparation of future requirements for power grid generation, transmission, and distribution facilities is long-term load forecasting. For more network planning and power system expansion, it is very relevant. Long-term forecasting usually runs from one year to ten years and is often complex because of future uncertainties, such as political factors, economic conditions, per capita growth, etc [5]. The STLF plays an important role in maintaining reliable, stable, and cost-effective operation of electricity systems. For basic functions like hydro-thermal coordination, unit commitment, safety assessment, and interchange assessment a comprehensive short-term load prediction has been needed. Load forecasting is nevertheless an essential milestone. Initially, as the loading sequence is complex and has several seasonal levels: not even just the load over the past hour but even the load over the past couple of hours; the load over the last couple of days, and other variables which affect each load at certain times [6]. On the contrary, STLF's excessively wide reserve

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potential contributes to increased maintenance costs. How the future pressure of historical data is predicted has remained a problem, in particular for extreme weather, holidays, and other special day load predictions. To overcome these challenges, several models have been developed in recent years to improve the accuracy of STLF predictions. The following section contains a detailed description of the different strategies proposed.

II. Literature Survey

To predict short-term load consumption, researchers have conducted extensive research in this field. Some of them are listed here: Kang Ke et al. [7], based ona Gated recurrent unit (GRU) and stacked auto encoding, proposed a scheme to forecast short-term electrical load. Bo Sung Kwon et al. [8], suggested a deep neural network-based STLF with an LSTM layer. The features of input are divided into historical and prediction to implement the forecasting scheme to STLF. To design the relationships among past observed information, historical data is fed into the LSTM layer. E. Elattar, et al. [9], developed a unique hybrid forecasting algorithm. The developed approach is based on the MGOA (modified grasshopper optimization algorithm) and LWSVR (locally weighted support vector regression). WenJie Zhang et al. [10], to expand the length of load forecasting, reduce artificial debugging, and increase prediction precision for STLF, an integrated network architecture consisting of intelligent optimization algorithm, chaotic time series, LSTM, and self-organized routing, was suggested. Hasan-Al-Shaikh et al. [3], proposed a method for STLF by using a recurrent neural network (RNN) architecture called LSTM. S. Izudheen et al. [11], presented a Bayesian Neural Network model on the basis of historical load data and meteorological data for predicting load in a specified geographical area. Z. Xie et al. [12], developed a Fuzzy Neural Network-based Short-Term Power Load Forecasting Model with Enhanced Decision Tree. P. Borthakur et al. [13], proposed a hybrid technique based on data mining techniques for STLF. K. Chen et al. [14], proposed a deep residual network-based model for STLF. Zoran Janković et al. [15], proposed a modified method to select optimal similar days and its usage in STLF based ANN (artificial neural network).

From the literature survey, it was analyzed that electricity is one of the most important commodities in today's world. Based on the historical data of the electrical grid, load forecasting helps to assess potential electrical load. From the survey conducted it was analyzed that to estimate power load, many studies have been conducted in this field by several researchers in the last few years. The traditional approaches aimed to enhance the load forecasting accuracy by reducing the variations between predicted and actual load value. But these traditional approaches provided random outcomes, were time-consuming, had a low convergence rate, and have the potential to become stuck at a local minimum, particularly with complex issues. Hence, these shortcomings of the method contribute to an ineffective efficiency of the framework and inspired to design of a model so that the limitations can be overcome.

III. Problem Formulation

To overcome the issues related to traditional models, a novel scheme is developed. The proposed scheme is utilizing the deep learning algorithm, in which an artificial recurrent neural network (RNN) type BI-LSTM is considered for the training and prediction of the load. The Bi LSTM network is considered a modified version of the LSTM network. The reason behind using the Bi LSTM network over LSTM is that the Bi LSTM minimizes the complexity and time consumption. The Bi LSTM preserves the information from the future by using the two hidden states combined; information can be retrained from both past and future at any point in time. For sequence prediction, it resolves fixed sequence issues. The performance of the proposed Bi-LSTM and existing PSO-ENN is discussed below.

IV. Dataset Used

The proposed technique has used two datasets; the first one is a static dataset, while the second one is a real-time dataset. The main goal of the proposed research is to compare the output of current and proposed methods on both datasets. The standard dataset used is a portion of data from eastern Slovakia in 1999, which includes data on user power consumption in intervals. Table 1 shows the normal dataset. The real-time dataset, on the other hand, is obtained from the college on a regular basis. The main goal of gathering data from the real world is to see if the proposed model performs well as the inputs change. Table 2 shows the real-time dataset.

Table 1: Real Time Dataset of Load with Respect to Different Time Intervals

Dates	kWh	kVA	MDI	Pf	Net Reading
13.7.2020	265441.1	305857.5	47.14	0.862	712.3
14.7.2020	265692.6	306147.8	47.14	0.862	290.3
15.7.2020	265989.3	306487.6	47.14	0.862	339.8
16.7.2020	266270.1	306808.3	47.14	0.862	320.7

TABLE 2:.STANDARD DATASET OF LOAD WITH RESPECT TO DIFFERENT TIME INTERVALS

Time	0:30	1:00	21:00	21:30	22:00	22:30	23:00	23:30	0:00
User 1	751	735	751	629	629	641	625	616	650
User 2	651	646	651	635	632	643	639	621	653
User 3	666	659	666	619	624	623	617	613	623
User 4	624	628	624	647	644	640	617	614	641
User 5	624	649	624	637	622	631	622	619	634

V. METHODOLOGY

The proposed system is analyzed in the MATLAB simulation software. This section provides a detailed description of how the proposed method works. At first, to start the process, the input data readings are loaded in the proposed system with two different datasets. One dataset is static that is collected from the internet and another one is collected on a real-time basis to check the efficiency of the proposed system. Once the data is loaded in the system, the next step is to initialize the prediction model in which different parameters like the number of iterations, learning function, training and validation data, etc. Then to train the network in the next step, the training data is defined. A training input and targets are given to the network and after this, the network starts training itself. In the proposed work, the deep learning-based RNN-BI-LSTM model is utilized. The reason behind using Bi-LSTM instead of LSTM is discussed here.

A. Bi-LSTM

Bidirectional LSTMs are indeed a type of LSTM that can be used for boosting the performance of the model in sequence classification issues.To classify text Bi-LSTM acts as a sequence processing model that combines the convolutional layers and bidirectional recurrent neural networks (BRNN) into a single model. At each step of time, this structure enables the networks to provide information backward and forward. What distinguishes this method from unidirectional is that, unlike the LSTM that runs backward, information from the future is preserved, while using the two hidden states combined, information can be retrained from both past and future at any point in time. Therefore, Bi-LSTMs provide a greater understanding of the context and increase the amount of input data that could be utilized by the network. The BRNN performs a mechanism in which the neurons of a regular RNN are split into bidirectional forms. One is for negative time direction or backward states, and another is for positive time direction or forward states.

The reverse direction states' inputs are unrelated to the outcomes of these two states. The BiLSTM structure is depicted in fig.1. The past and future input data can be utilized by using two-time directions, while standard RNN needs delays for future data. In the Bi-LSTMforward state neurons functions as a unidirectional LSTM framework. When neurons are not linked in both networks, network training is conducted by using a standard unidirectional LSTM.

Following the training phase, the network is tested, and after receiving the predicted outcome, the proposed Bi-LSTM model performance is measured and evaluated in terms of performance parameters such as RMSE, Max error, Min error, and MAPE to determine its efficiency. And finally, the load is estimated by the given model, which has a high level of accuracy as compared to conventional approaches.

VI. RESULTS AND DISCUSSION

LSTM and current PSO-ENN methods on two datasets, the standard dataset, and the real-time dataset, in terms of RMSE, max error, min error, and MAPE.

Phase 1: Evaluation of the proposed Bi-LSTM and existing PSO-ENN methods for the standard dataset.

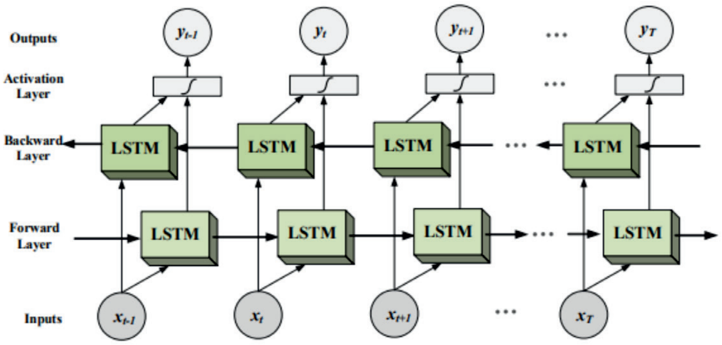

Fig. 1: The Basic Structure of BiLSTM

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Then to test and analyze the performance of the proposed Bi-LSTM on a standard dataset in terms of RMSE, max error, min error, and MAPE after the performance of the current PSO-ENN method have been analyzed for the standard dataset. In addition, the proposed Bi-LSTM method's output is compared to that of the current and conventional PSO-ENN and ENN approaches. Table 3 illustrates the basic values for RMSE, max and min errors, and MAPE.

Table 3: Specific Values for Different Parameters

S. No.	Parameters	ENN	PSO-ENN	Bi-LSTM
1	RMSE	21.496	6.6606	2.8785
2	Max error	31.988	13.198	12.198
3	Min error	10.197	0.26067	0.26067
4	MAPE%	2.8805	0.696	0.2502

Table 3 shows that the RMSE value obtained for the standard dataset in the ENN, PSO-ENN is about 21.496 and 6.6606, respectively, whereas the RMSE value acquired for the suggested Bi-LSTM when applied to the standard dataset is just 2.8785. Furthermore, in the conventional ENN and PSO-ENN, the maximum and minimum errors are 31.988, 13.198, and 10.197, 0.26067, respectively. The max-error and min-error acquired in the proposed Bi-LSTM, on the other hand, are very low, i.e. about 12.198 and 0.26067. In addition, the MAPE value is used to assess the efficiency of the PSO-ENN, ENN, and proposed model. MAPE is 2.8805 and 0.696 for traditional ENN and PSO-ENN, respectively, while it is just 0.2502 for the proposed Bi-LSTM model. The power consumption of the proposed Bi-LSTM is compared to the standard ENN and PSO-ENN methods as illustrated in Fig.4.

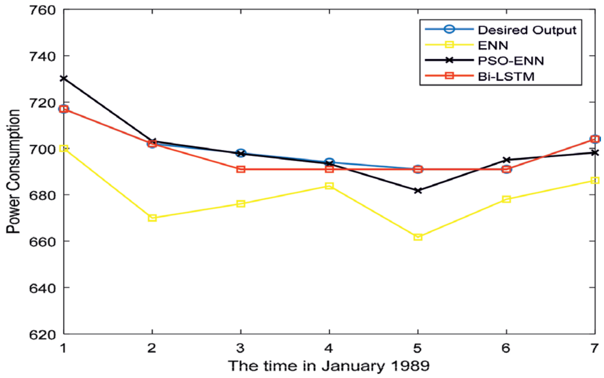

Fig. 2: Power Consumption in the Proposed and Traditional Model

Conventional ENN, PSO-ENN models is shown in Fig.2. The power consumption line of the proposed Bi-LSTM is almost constant and does not fluctuate much, as shown in the graph. In contrast to the proposed method, the power consumption graph in conventional ENN and PSO-ENN systems has high fluctuations and does not effectively predict the load.The proposed Bi-LSTM effectively predicts the loads with a standard dataset, according to the graphs and tables.

Phase 2: the comparison of the proposed Bi-LSTM approach with the current ENN and PSO-ENN methods for a real-time dataset is illustrated in table 2.

In terms of RMSE, Max error, min error, and MAPE, the proposed Bi-LSTM approach is compared to the ENN, PSO-ENN, and Bi-LSTM model for real-time datasets, as represented in figure Fig.3.

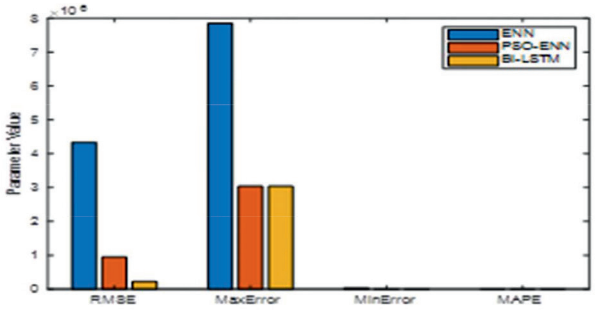

Fig. 3: Comparison Graph of ENN, PSO-ENN, and Bi-LSTM

In terms of RMSE, max error, min error, and MAPE, Fig. 3 depicts a comparison graph of the standard ENN, PSO-ENN, and proposed Bi-LSTM for a real-time dataset. The output of the proposed Bi-LSTM model is more effective as the rate of errors is lower, as seen in the graph. This aids the proposed model's ability to accurately predict load. Table 4 shows the basic value obtained for the traditional ENN, PSO-ENN, and proposed Bi-LSTM.

Table 4: A Specific Value of Parameters for a Real-Time Dataset

S. No.	Parameter	ENN	PSO-ENN	Bi-LSTM
1	RMSE	4.3335e+06	9.5364e+05	2.2045e+05
2	Max error	7.8569e+06	3.0319e+06	3.0319e+06
3	Min error	39551	50.098	50.098
4	MAPE%	1384.6	274.16	11.153

Table 4 shows that the RMSE value for the real-time dataset in conventional ENN and PSO-ENN is around 4.3335e+06 and 9.5364e+05, respectively, while the value for RMSE acquired when applied to the standard dataset in the proposed Bi-LSTM is only 2.2045e+05. Furthermore, in the standard ENN and PSO-ENN, the maximum error is 7.8569e+06 and 3.0319e+06, respectively. While the proposed Bi-LSTM approach achieves a maximum error value of 3.0319e+06. The conventional ENN and PSO-ENN have minimum errors of 39551 and 50.098, respectively. The proposed Bi-LSTM achieves the same minimum error as the PSO-ENN, i.e. 50.098. In addition, the MAPE value is used to assess the efficiency of the PSO-ENN, ENN, and proposed model. MAPE is 1384.6 and 274.16 for traditional ENN and PSO-ENN, respectively, while it is just 11.153 for the proposed Bi-LSTM model. The power consumption of the suggested Bi-LSTM is compared to the standard ENN and PSO-ENN methods for real-time datasets based on these findings, as represented in Fig.4.

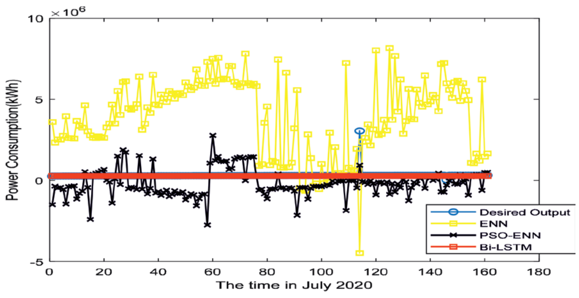

Fig. 4: Power Consumption in Traditional ENN, PSO-ENN, and Bi-LSTM

The power consumption graph for the real-time dataset is shown in Fig.4. The blue line represents the desired quality. In traditional ENN and PSO-ENN methods, the yellow and black colors reflect the power consumption. The red-colored line depicts the output of the proposed Bi-LSTM. The graph shows that both conventional ENN and PSO-ENN models have a lot of fluctuation, which affects the system's accuracy. The power consumption of the proposed Bi-LSTM model, on the other hand, remains constant and similar to the desired input value, implying that the proposed Bi-LSTM can more accurately predict loads. The proposed Bi-LSTM is a more reliable, stable, and accurate method to predict load forecasting with high precision, according to the graphs and tables.

VII. Conclustion

The suggested Bi-LSTM model was created to reduce uncertainty and improve forecasting accuracy. For this, BI-LSTM is utilized which is an advanced variant of LSTM. In the MATLAB software, the proposed model's output is evaluated and simulated. The results of the simulations were obtained for two datasets: a standard dataset and a real-time dataset. The RMSE values for conventional ENN and PSO-ENN are 21.496 and 6.6606, respectively, while the RMSE value for the proposed model is just 2.8785. MAPE is 2.8805 and 0.696 in traditional ENN and PSO-ENN, respectively, whereas it is just 0.20502 in the proposed Bi-LSTM form. Finally, the power usage of ENN, PSO-ENN, and Bi-LSTM is examined, with the proposed Bi-LSTM proving to be more accurate and efficient for standard datasets. In terms of RMSE, max error, min error, and MAPE, the performance of the proposed Bi-LSTM is compared to that of the standard ENN and PSO-ENN models for real-time datasets. Conventio+nal ENN, PSO-ENN, and proposed Bi-LSTM models have RMSE values of 4.3335e+06, 9.5364e+05, and 2.2045e+05, respectively. Moreover, the min error obtained for traditional ENN and PSO-ENN is 39551 and 50.098, respectively, while the proposed Bi-min LSTM's error is the same as that of PSO-ENN, i.e. 50.098. Finally, the MAPE value is determined, which is 1384.6 and 274.16 for standard ENN and PSO-ENN models, respectively, and 11.153 for the proposed Bi-LSTM model. The proposed Bi-LSTM method's power consumption is a steady line, indicating that it is more accurate and effective.

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