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An Efficient Deep Learning Framework for Household Electric Power Consumption Forecasting

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***Abstract*— The increasing variation in residential electricity demand has created a need for accurate and efficient household electric power consumption forecasting for improved energy management and reliable operation of modern electrical distribution systems. Household electricity consumption is highly dynamic and nonlinear due to changes in appliance usage, consumer activities, seasonal conditions, and other influencing factors, making accurate forecasting challenging using conventional approaches. In this research, an efficient deep learning framework based on Bidirectional Long Short-Term Memory (BiLSTM) is developed for forecasting household electric power consumption. The Household Electric Power Consumption dataset is first preprocessed through missing-value handling, normalization, and feature selection to improve the quality of electrical load data. The processed data are then divided into training and testing sets, and the BiLSTM model is trained to learn temporal relationships within historical household electricity consumption patterns. The developed framework is implemented using Python Spyder 3.7 and evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared (R^2) metrics. The experimental results achieve an MSE of 0.35, RMSE of 0.59, and R^2 of 0.47, demonstrating the capability of the BiLSTM model to capture important temporal characteristics of residential electrical demand. The developed framework can support household energy management, peak-load planning, demand-side management, and intelligent smart-grid applications.**

Keywords: Household Electricity Consumption, Electric Load Forecasting, BiLSTM, Deep Learning, Smart Energy Management.

I. INTRODUCTION

The increasing demand for electricity in residential areas has made household electric power consumption forecasting an important research area in modern electrical engineering. Residential electricity demand changes continuously according to appliance operation, occupancy, time of day, weather conditions, seasonal variations, and consumer activities. Accurate forecasting of household power consumption can help consumers and electricity providers understand future demand and make appropriate decisions related to energy utilization. It can also support residential load scheduling, peak-demand management, energy conservation, and efficient operation of distribution systems. With the increasing deployment of smart meters, detailed household electricity consumption data are becoming available at shorter time intervals, creating new opportunities for accurate load forecasting [1].

Household electric power consumption forecasting refers to the prediction of future electrical demand using previously recorded household electricity consumption and related influencing parameters. Depending on the forecasting requirement, predictions may be performed for very-short-term, short-term, day-ahead, or longer periods. For residential applications, short-term and day-ahead forecasting are particularly useful because household demand can vary significantly within a single day. Accurate forecasting can provide information about expected load during peak and off-peak periods and can therefore assist in efficient electricity scheduling. It is especially important in modern residential environments where the simultaneous operation of multiple electrical appliances can produce considerable variations in household power demand [2].

The residential load profile is considerably different from relatively predictable industrial or commercial loads. Household electricity consumption is strongly influenced by individual consumer behavior and appliance usage patterns. For example, the operation of air conditioners, refrigerators, water heaters, washing machines, cooking appliances, and water pumps can cause significant changes in electrical demand. The timing and duration of appliance operation may also differ from one household to another. As a result, household electricity consumption generally contains nonlinear, irregular, and time-dependent characteristics. These characteristics make accurate prediction more difficult and require forecasting methods capable of learning complex relationships within historical electrical load data [3].

Weather and seasonal conditions are also important factors affecting household electricity consumption. During hot periods, increased use of air-conditioning and cooling equipment can substantially increase residential electrical demand, while heating appliances can produce higher consumption during colder periods. Temperature, humidity, and seasonal changes can therefore influence both the magnitude and timing of household electricity demand. In addition, variations between weekdays and weekends can produce different consumption profiles because household occupancy and daily activities are different. Consequently, an effective household power forecasting model should be capable of identifying temporal and seasonal characteristics present in the electrical load data [4].

Traditional forecasting approaches have been widely used for predicting electricity demand and include statistical techniques such as autoregressive models, moving-average

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models, regression methods, and other time-series approaches. These methods can perform effectively when the load pattern is relatively stable and its statistical characteristics remain consistent over time. However, household electricity consumption often contains nonlinear relationships and sudden changes that may not be adequately represented by conventional mathematical models. The increasing complexity of residential load profiles has therefore encouraged researchers to investigate intelligent data-driven forecasting approaches that can learn electrical consumption patterns directly from historical measurements [5].

Machine learning techniques have provided an alternative approach for household electric power consumption forecasting. Models such as artificial neural networks, support vector machines, decision trees, random forests, and gradient-based methods can identify relationships between historical electricity consumption and future demand. These approaches can incorporate multiple input variables and can model nonlinear relationships that are difficult to represent using conventional statistical techniques. However, residential electricity consumption is fundamentally a time-series problem in which previous load conditions can influence future demand. Therefore, forecasting methods must not only identify nonlinear relationships but also effectively preserve important temporal information from historical electrical load sequences [6].

Deep learning techniques have become increasingly relevant for household electricity forecasting because of their ability to automatically learn complex patterns from large-scale sequential data. Recurrent Neural Networks (RNNs) are particularly suitable for electrical load forecasting because they are designed to process sequential information. Long Short-Term Memory (LSTM) networks further improve this capability by using memory mechanisms that allow important information to be retained over longer sequences. This characteristic is useful for household electricity forecasting because residential load may exhibit relationships across different time intervals, such as hourly, daily, and weekly consumption patterns. Deep learning models can therefore provide a suitable framework for learning the temporal characteristics of household electrical demand [7].

Among advanced deep learning approaches, Bidirectional Long Short-Term Memory (BiLSTM) networks provide an extended architecture for sequential data analysis. A BiLSTM network processes sequence information in both forward and backward directions, allowing the model to obtain a broader representation of the relationships present within the available input sequence. For household electric power consumption forecasting, this capability can help in extracting meaningful temporal characteristics from historical load data. By learning complex dependencies within electricity consumption sequences, BiLSTM can provide an effective approach for forecasting future household demand. Its application is particularly relevant when residential load profiles contain nonlinear fluctuations and varying consumption patterns [8].

Another important consideration in household electricity forecasting is the quality and preparation of electrical consumption data. Smart-meter datasets may contain missing measurements, abnormal values, noise, and variations in measurement intervals[9]. If such problems are not appropriately addressed, they can negatively affect the learning capability of forecasting models. Data preprocessing techniques such as missing-value treatment, normalization, feature selection, and appropriate data partitioning are therefore important components of a reliable household load forecasting framework. Proper preprocessing can improve data consistency and allow deep learning models to learn the underlying electrical consumption patterns more effectively [10].

II. METHODOLOGY

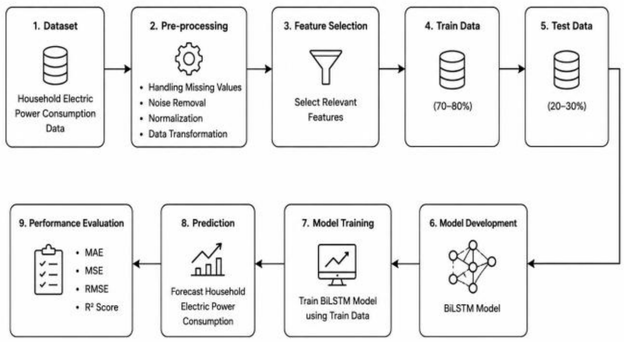

Figure 1: Flow chart

The proposed framework follows a systematic sequence for forecasting household electric power consumption using a BiLSTM-based deep learning model. The complete process starts with the collection of household electrical consumption data and proceeds through data preprocessing, feature selection, training and testing data preparation, BiLSTM model development, model training, power consumption prediction, and final performance evaluation. Each stage is designed to improve the reliability of the forecasting process and to enable the model to learn the temporal characteristics of residential electrical load.

1. Household Electric Power Consumption Dataset

The first stage involves collecting historical household electric power consumption data. The dataset contains time-based measurements of household electricity usage, which provide the basis for learning residential load patterns. Depending on the available dataset, parameters such as global active power, global reactive power, voltage, global intensity, and sub-metering values can be used as input variables. Since electricity consumption is a time-series phenomenon, the chronological order of the measurements is preserved during the forecasting process.

Let the household electrical dataset be represented as:

$D = \{X_1, X_2, X_3, ..., X_t\}$

where X_t represents the electrical measurements recorded at time t. The objective of the proposed framework is to learn the relationship between historical measurements and future household power consumption.

2. Data Pre-processing

Raw household electricity data may contain missing measurements, noise, abnormal values, and different numerical ranges. Therefore, preprocessing is performed before supplying the data to the BiLSTM model. Missing values are handled appropriately, while noisy or abnormal observations are identified and treated to improve data quality. Data normalization is also performed because electrical parameters such as voltage, current, active power, and reactive power may have significantly different numerical ranges.

For normalization, the Min-Max normalization technique can be expressed as:

$$X' = (X - X_{min}) / (X_{max} - X_{min})$$

where X is the original value, Xmin and Xmax are the minimum and maximum values of the corresponding parameter, and X' is the normalized value. This converts the input values into a common range, generally between 0 and 1, and helps the BiLSTM model learn more efficiently.

3. Feature Selection

After preprocessing, relevant electrical features are selected for forecasting. Feature selection is important because unnecessary or less informative variables may increase model complexity without providing significant forecasting information. The selected features can represent important characteristics of household electrical demand, such as active power, reactive power, voltage, current, and other available consumption-related parameters.

The forecasting problem can therefore be represented as:

$Y(t+1) = f[X(t), X(t-1), X(t-2), ..., X(t-n)]$

where Y(t+1) represents the household electric power consumption to be forecasted, X(t) represents the current electrical measurements, and n represents the number of previous time steps considered by the model.

4. Training Data

The processed dataset is divided into training and testing subsets. In the proposed framework, approximately 70–80% of the data are used for training, as shown in the flowchart. The training dataset contains historical household electricity measurements that are used to learn the temporal relationship between previous and future electrical demand.

The training data are arranged into sequential input samples so that the BiLSTM model can learn the relationship between previous household load conditions and the corresponding future consumption. Maintaining the correct time sequence is important because randomly mixing time-series observations can lead to unrealistic forecasting conditions.

5. Test Data

The remaining 20–30% of the dataset is used as test data. These observations are not used during the model-training stage. Instead, they are used after training to evaluate how effectively the developed BiLSTM model can forecast previously unseen household electricity consumption. The separation of training and testing data provides an independent basis for evaluating the forecasting capability of the proposed framework. A general representation is:

$D = Dtrain \cup Dtest$

where Dtrain represents the training dataset and Dtest represents the testing dataset.

6. BiLSTM Model Development

The core component of the proposed framework is the Bidirectional Long Short-Term Memory (BiLSTM) model. BiLSTM is selected because household electricity consumption contains important temporal dependencies. For example, electricity consumption at a particular time can be related to consumption during previous hours, previous days, and recurring daily patterns.

A conventional LSTM processes a sequence primarily in one temporal direction, whereas BiLSTM uses two LSTM components to process the sequence in forward and backward directions. The general BiLSTM representation can be expressed as:

$h_t = [\rightarrow h_t, \leftarrow h_t]$

where $\rightarrow h_t$ represents the forward LSTM hidden state and $\leftarrow h_t$ represents the backward LSTM hidden state. The combined representation provides the model with richer sequential information for forecasting household electric power consumption.

7. Model Training

In this stage, the BiLSTM model is trained using the prepared training data. The model learns the relationship between historical electrical consumption patterns and the target household power consumption. During training, the model parameters are continuously adjusted to minimize the difference between the actual and predicted electrical power values.

The basic prediction error can be represented as:

$e_t = Y_t - \hat{Y}_t$

where Y_t is the actual household electric power consumption and $\hat{Y}_t$ is the predicted value.

The model attempts to minimize this error during the training process. Through repeated training iterations, the

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BiLSTM learns temporal patterns associated with residential electricity demand.

8. Household Electric Power Consumption Prediction

After completing the training process, the trained BiLSTM model is applied to the test data to forecast household electric power consumption. The model receives historical electrical measurements as input and generates the corresponding predicted power consumption.

The forecasting relationship can be represented as:

$$\hat{Y}(t+1) = \text{BiLSTM}[X(t), X(t-1), ..., X(t-n+1)]$$

where $\hat{Y}(t+1)$ represents the predicted household electric power consumption for the next time interval. The predicted values can subsequently be compared with the actual electrical consumption values available in the test dataset.

9. Performance Evaluation

The final stage evaluates the forecasting performance of the BiLSTM framework using MAE, MSE, RMSE, and R^2 Score. These metrics provide different perspectives on the accuracy of household electric power consumption forecasting.

Mean Absolute Error (MAE):

$$MAE = (1/N)\ \Sigma\ |Y_i - \hat{Y}_i|$$

MAE represents the average absolute difference between actual and predicted electricity consumption. A lower MAE indicates better forecasting performance.

Mean Squared Error (MSE):

$$MSE = (1/N)\ \Sigma(Y_i - \hat{Y}_i)^2$$

MSE gives greater importance to larger forecasting errors because the errors are squared.

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{[(1/N)\ \Sigma(Y_i - \hat{Y}_i)^2]}$$

RMSE represents the square root of the average squared forecasting error and is expressed in the same scale as the target variable.

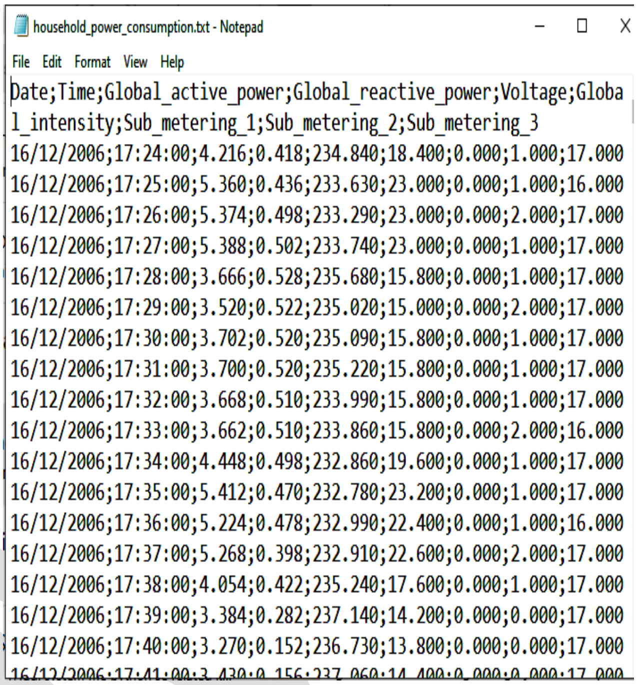
R^2 Score:

$$R^2 = 1 - [\Sigma(Y_i - \hat{Y}_i)^2 / \Sigma(Y_i - \bar{Y})^2]$$

where $\bar{Y}$ represents the mean of the actual household electricity consumption values. A higher R^2 value indicates that the model explains a greater proportion of the variation in the observed electrical load.

III. Simulation Results

The simulation results are performed using the python software.


household_power_consumption.txt - Notepad
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Date;Time;Global_active_power;Global_reactive_power;Voltage;Global_intensity;Sub_metering_1;Sub_metering_2;Sub_metering_3
16/12/2006;17:24:00;4.216;0.418;234.840;18.400;0.000;1.000;17.000
16/12/2006;17:25:00;5.360;0.436;233.630;23.000;0.000;1.000;16.000
16/12/2006;17:26:00;5.374;0.498;233.290;23.000;0.000;2.000;17.000
16/12/2006;17:27:00;5.388;0.502;233.740;23.000;0.000;1.000;17.000
16/12/2006;17:28:00;3.666;0.528;235.680;15.800;0.000;1.000;17.000
16/12/2006;17:29:00;3.520;0.522;235.020;15.000;0.000;2.000;17.000
16/12/2006;17:30:00;3.702;0.520;235.090;15.800;0.000;1.000;17.000
16/12/2006;17:31:00;3.700;0.520;235.220;15.800;0.000;1.000;17.000
16/12/2006;17:32:00;3.668;0.510;233.990;15.800;0.000;1.000;17.000
16/12/2006;17:33:00;3.662;0.510;233.860;15.800;0.000;2.000;16.000
16/12/2006;17:34:00;4.448;0.498;232.860;19.600;0.000;1.000;17.000
16/12/2006;17:35:00;5.412;0.470;232.780;23.200;0.000;1.000;17.000
16/12/2006;17:36:00;5.224;0.478;232.990;22.400;0.000;1.000;16.000
16/12/2006;17:37:00;5.268;0.398;232.910;22.600;0.000;2.000;17.000
16/12/2006;17:38:00;4.054;0.422;235.240;17.600;0.000;1.000;17.000
16/12/2006;17:39:00;3.384;0.282;237.140;14.200;0.000;0.000;17.000
16/12/2006;17:40:00;3.270;0.152;236.730;13.800;0.000;0.000;17.000
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Figure 2: Dataset

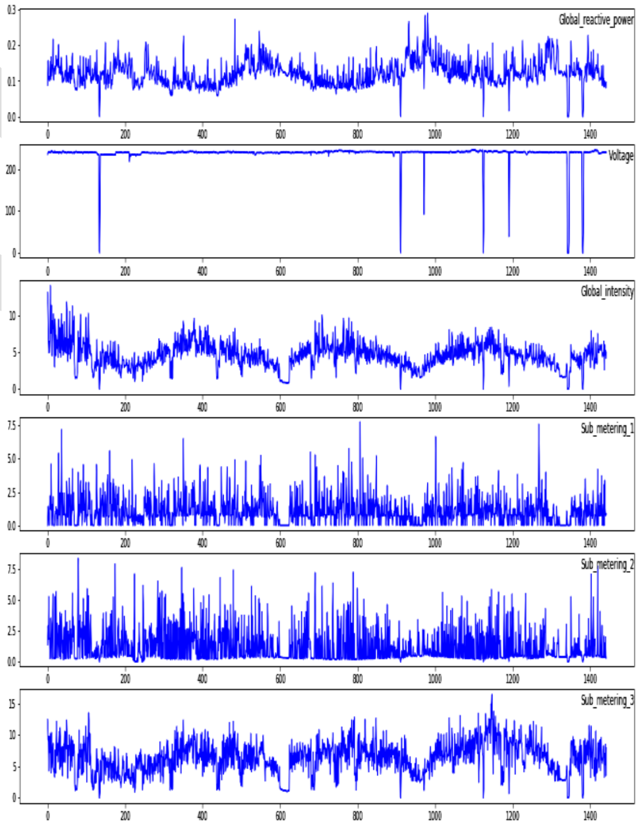

Figure 3: Prediction

Figure is 3 is showing prediction performance of the propped model. The first subplot illustrates the variation of Global Reactive Power over the observation period.

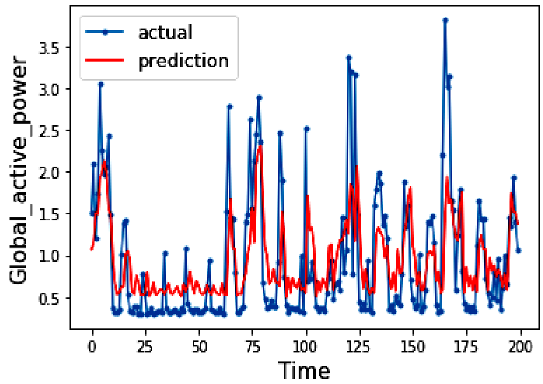

Figure 4: Original dataset in .csv file

The figure 4 is showing prediction performance, the actual and prediction performance is closely related that means the proposed model gives the maximum true prediction.

Table 1: Result Comparison

Sr. No.	Parameter	Previous Work [1]	Previous Work [2]	Proposed Work
1	Method	XGBoost	Random Forest	**BiLSTM**
2	MSE	0.370	0.378	**0.35**
3	RMSE	0.608	0.615	**0.59**
4	R-Squared	NA	NA	**0.47**

IV. CONCLUSION

The study presents an efficient BiLSTM-based deep learning framework for household electric power consumption forecasting, with the objective of accurately learning the temporal and nonlinear characteristics of residential electrical load. The proposed framework includes household electricity data preprocessing, relevant feature selection, training and testing data separation, BiLSTM model development, forecasting, and performance evaluation using MAE, MSE, RMSE, and R^2 metrics. The experimental results achieved an MSE of 0.35, RMSE of 0.59, and R^2 of 0.47, demonstrating that the developed BiLSTM model is capable of capturing important variations in household electricity consumption and generating useful forecasting results. The framework can support residential energy management, peak-load planning, demand-side management, energy scheduling, and smart-grid operation. Overall, the findings confirm that BiLSTM provides a suitable deep learning approach for household electric power consumption forecasting, while future improvements can focus on incorporating additional electrical and environmental parameters, optimizing the network architecture, and improving forecasting accuracy under rapidly changing residential load conditions.

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