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# Dynamic Load Forecasting in EV Charging Systems Using Deep Neural Networks

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***Abstract*— Load forecasting is crucial for efficient power system operations, particularly with the raising usage of electric vehicles (EVs) and fluctuating energy demands. However, traditional forecasting methods often fail to address the non-linear patterns and temporal dependencies in EV charging data, leading to inefficiencies in grid management and energy optimization. This study develops a deep learning-based algorithm using Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi LSTM) networks to enhance the accuracy of EV charging load predictions. A comprehensive dataset from EV charging stations in Palo Alto was preprocessed with outlier removal, temporal feature extraction, and normalization, while Principal Component Analysis (PCA) was applied for dimensionality drop. Results reveal that BiLSTM outperformed LSTM, achieving lower RMSE (0.1806) and MAE (0.1588) by effectively capturing bidirectional temporal patterns. Correlation analysis identified time-related variables as critical predictors, further improving forecast precision and scalability. This approach optimizes EV charging, integrates renewable energy, supports grid stability, and provides a robust solution for advancing energy management within the growing EV infrastructure, addressing the rising complexities of modern power systems.**

***Keywords*— *Load forecasting, EV charging, energy optimization, Bidirectional LSTM (BiLSTM), PCA.***

## I. INTRODUCTION

Optimal utilization of energy in EV charging systems is crucial for guaranteeing sustainability and meeting the difficulties of expanding EV adoption. Dynamic load forecasting is critical in managing energy supply and demand, especially in the face of fluctuating renewable energy sources and changing customer charging habits. Traditional forecasting approaches frequently fail to effectively predict load demand, resulting in inefficiencies, energy waste, and an increased reliance on conventional grids. Several research have used statistical models and machine learning techniques for load forecasting; however, these methods frequently fail to capture the complex, nonlinear linkages and temporal dependencies in EV charging needs. [1] introduced an EMD-AOA-DLSTM model for EV charging demand forecasting, showcasing effective predictions on the Georgia Tech dataset but needing broader validation. [2] explored time-series forecasting of monthly EV charging demand using Seq2Seq deep learning, showing superior multi-step prediction performance but limited by a small multi-region dataset. [3] focused on forecasting EV charging load using various models, highlighting renewable energy integration and optimization for grid management, but lacked focus on user behavior. [4] introduced an ICA-AOA-DLSTM model for EV charging demand forecasting with high accuracy (96.24%), but its reliance on a single dataset limits generalizability. [5] recommended a deep learning-based surveillance system for electric vehicle charging stations, demonstrating over 99% detection accuracy, but with limited focus on diverse cybersecurity threats. [6] focused on electricity load forecasting using CNNs and Transformers, integrating renewable energy sources to enhance grid efficiency and reduce CO2 emissions, but with limited regional application. [7] proposed a deep learning model with MPPI-based PCA for lithium-ion battery state of charge prediction, achieving high accuracy and efficiency, but with a limited dataset scope, requiring broader validation in EV battery management systems.

Recently, [8] presents a bi-objective model integrating queueing theory, deep learning, and NSGA-II for optimizing charging station location-capacity, reducing waiting time by 61.5% but with limited scalability for broader regional applications. [9] evaluated nine EV load forecasting methods using statistical deep learning across four datasets, offering insights into seasonal variations and market participation but highlighting challenges related to dataset-specific limitations. [10] explored machine and deep learning methods for SOC estimation in BEVs using dynamic simulation data, highlighting models like SVR, ANN, CNN, and LSTM, but with limited validation on diverse datasets. [11] introduced a deep learning model for EV energy consumption analysis, addressing dataset limitations and computational challenges through distributed cooperative learning, but with limited evaluation on rare event scenarios. [12] offered a deep learning model for predicting EV charging demand using T-LSTM-Enc and T-LSTM-Ori-TimeFeatures, improving forecasting and energy management efficiency but with limited dataset diversity affecting generalization. [13] presented a Spatial-Temporal Graph Convolutional Network integrating GCN and GRU to predict EV charging station availability, achieving 89% long-term forecasting accuracy, but with limited testing across diverse regions. [14] tackled EV load forecasting using CNN for traffic flow prediction, reducing forecasting losses by 20% through uncertainty modeling, but with limited exploration of real-time prediction scalability. Table I summarizes various application areas in EV systems, highlighting corresponding references and deep learning techniques used for tasks like demand forecasting, load prediction, SOC estimation, and station optimization.

Despite advancements in EV charging demand forecasting, challenges persist in capturing temporal dependencies, scalability, and generalization across diverse datasets. Existing models often struggle to integrate dynamic patterns effectively, limiting their applicability in real-world energy management scenarios.

The proposed study addresses these gaps by developing a deep neural network-based framework for dynamic load estimating in EV charging systems. Leveraging advanced temporal feature extraction and optimization techniques, it ensures precise demand prediction and energy management. The proposed solution is validated on diverse datasets, demonstrating scalability and accuracy in handling real-world charging demand variability, ultimately contributing to efficient and sustainable EV energy systems.

TABLE I. DL/ML TECHNIQUE USED IN EV LOAD FORECASTING APPLICATIONS

| Application Area | Ref. | DL Techniques |
|---|---|---|
| EV demand forecasting | [1] | EMD-AOA-DLSTM |
| Time-series forecasting | [2] | Seq2Seq, LSTM |
| Load prediction | [3] | KNN, Decision Trees |
| Demand forecasting | [2],[4] | ICA-AOA-DLSTM |
| Intrusion detection | [5] | DNN, LSTM |
| Load forecasting | [6] | CNN, Transformers |
| SOC prediction | [7] | PCA, LSTM |
| Station optimization | [8] | NSGA-II |
| DAM participation | [9] | CNN, KNN, SVM |
| SOC estimation | [10] | SVR, ANN, LSTM |
| Energy analysis | [11] | Deep Transfer Learning, MobileNet, EfficientNet |
| Demand prediction | [12] | T-LSTM-Enc, LSTM |
| Station availability | [13] | Spatial-Temporal GCN |

## II. METHODOLOGY

The proposed study focuses on forecasting EV charging loads to optimize charging grid operations using deep learning techniques, as illustrated in Fig. 1. The process begins with data collection, where features from EV charging stations are gathered, such as usage patterns and charging demand. In the data analysis phase, feature extraction and data processing are performed to identify nonlinear relationships within the dataset. The data that was processed is then divided into training and testing sets, with an LSTM and Bidirectional LSTM model used to estimate EV charging loads. Finally, in the evaluation and application phase, the predictions are analyzed, and insights are used to optimize the charging grid for improved efficiency and resource management. This end-to-end approach highlights the importance of leveraging deep learning algorithms to enhance grid performance and meet the growing demand for EV infrastructure.

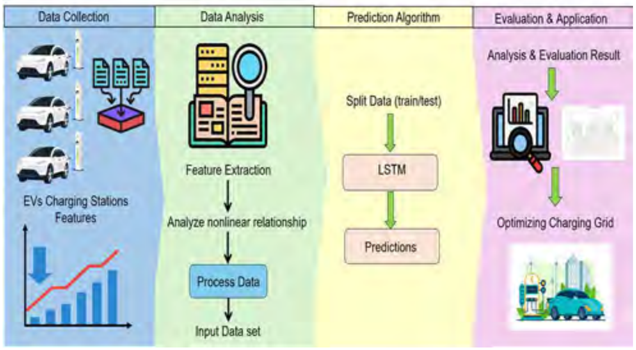


Fig. 1. Framework for EV Charging Load Forecasting.

### A. Dataset and Preprocessing

The dataset for the proposed study encompasses EV charging session data from the Palo Alto area, collected between July 29, 2011, and December 31, 2020, sourced from the City of Palo Alto Open Data platform. It includes critical attributes such as charging start and end times, energy consumption, day of the week, weekday versus weekend indicators, and cumulative daily energy consumption. Preprocessing involved removing outliers in energy consumption using the Interquartile Range (IQR) method, filtering data by a specified split date, and converting timestamps to datetime objects for temporal analysis. The dataset was resampled to hourly intervals by distributing total session energy proportionally across hourly slots, aggregated by summing energy for each interval, and enriched with features like the day of the week, binary weekday indicators, and year, month, and day attributes to capture temporal trends. Missing values were addressed through interpolation, either replacing them with zeros or using linear methods for continuity. Numerical features were normalized to a [0, 1] scale, and dimensionality was reduced using Principal Component Analysis (PCA) to improve computational efficiency and mitigate overfitting. The processed data was saved in CSV format, categorized by dataset type, ensuring a clean and robust dataset ready for predictive modeling.

### B. Principal Component Analysis

Principal Component Analysis (PCA) is a popular reduction of dimensionality method that converts data with multiple dimensions into less-dimensional space while preserving the most important information. It functions by determining principal components, which are orthogonal vectors that indicate the directions of greatest variance in the data. The proposed study proceeds by standardizing the features to guarantee that they are on the same scale, eliminating greater magnitudes from dominating the investigation. A covariance matrix is then generated to represent the relationships between attributes and how they change together. This matrix yields eigenvectors and related eigenvalues, which are used to calculate the directions and magnitudes of variance. The major components are determined by ranking eigenvectors according to their eigenvalues, and the data is projected into the subspace formed by these components. This modification simplifies the way data is presented and analyzed while keeping important patterns in the dataset.

### C. Performance Metrics for Model Evaluation

By analyzing the outcome of deep learning models, especially for regression tasks utilizing Long Short-Term Memory (LSTM) networks, several error measures must be considered. These metrics measure the model's forecasting reliability and accuracy in comparison to the actual values in the training and testing datasets. MSE, MAE, and RMSE are the three most common error measurements used in this context.

*1. Mean Squared Error (MSE)*

MSE estimates the average squared variance between the actual ($y_{act}$) and predicted values ($y_{pre}$), which amplifies larger errors due to the squaring, as shown in eq (1) [2]. It is useful when the goal is to penalize larger deviations from the actual values, and a lesser MSE directs a better model fit.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{act} - y_{pre})^2 \tag{1}$$

*2. Mean Absolute Error (MAE)*

MAE in eq (2) compares the average of the absolute variances between the actual ($y_{act}$) and predicted values ($y_{pre}$) [3]. Unlike MSE, it is unable to square the errors, making it less susceptible to outliers. It offers an additional straightforward estimate of the average error magnitude.

$$MAE = \frac{1}{n}\sum_{i=1}^{N} | \, y_{act} - y_{pre}| \tag{2}$$

*3. Root Mean Squared Error (RMSE)*

RMSE is the square root of the MSE, offering an error metric in the identical units as the predicted values ($y_{pre}$). Like MSE, it is sensitive to large errors, but taking the square root makes it more interpretable in the original data context, also depicted in eq (3) [6]. Lower RMSE values indicate more accurate predictions.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{act} - y_{pre})^2} \tag{3}$$

*D. Proposed Deep Learning Algorithms*

The proposed work uses advanced deep learning algorithms, notably LSTM and BiLSTM, to effectively predict dynamic load patterns in EV charging systems. These models were chosen because of the way they identify temporal interdependence and increase forecast accuracy by assessing both historical and upcoming trends.

*1. Long Short-Term Memory (LSTM)*

LSTM is a kind of recurrent neural network (RNN) intended to overcome the vanishing gradient issue in conventional RNNs, enabling the modeling of long-term correlations in sequential data. It achieves this through memory cells and gating mechanisms: The input gate regulates the addition of new data, the forget gate determines what data to discard, and the output gate decides what to share about the cell state. These gates are governed by specific equations, where the input gate ($i_t$) computes the contribution of new input using weights ($W_{xi}, W_{hi}, W_{ci}$) and biases ($b_i$); the forget gate ($f_t$) modulates memory retention; the cell state ($c_t$) is updated by combining previous cell states and new input information; and the hidden state ($h_t$) represents the output after applying activation functions as mentioned in eq (4-10) [13]. This mechanism allows LSTM to selectively retain critical long-term dependencies while discarding irrelevant data, making it ideal for time series estimation, speech detection, and processing natural languages issues. Fig. 2 depicts the flow of data through the LSTM gates, demonstrating its ability to manage sequential dependencies effectively.

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i) \tag{4}$$

$$f_t = \sigma(W_i h_{t-1} + U_f x_t + b_f) \tag{5}$$

$$o_t = \sigma(W_0 h_{t-1} + U x_t + b_o) \tag{6}$$

$$C_t = tanh(W h_{t-1} + U x_t + b) \tag{7}$$

$$C_t = f_t o (c_{t-1} + i_{t-1} o \, c_t) \tag{8}$$

$$h_t = o_t o \tanh(c_t) \tag{9}$$

$$y_t = h_t \tag{10}$$

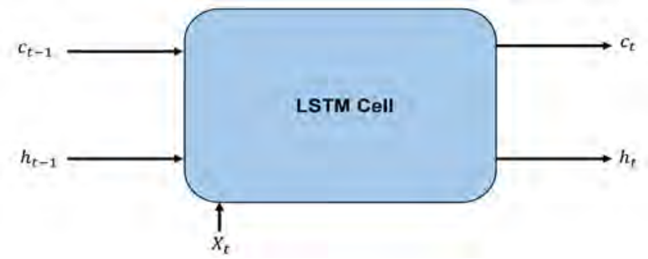


Fig. 2. LSTM cell structure with input, output, and hidden state representations.

*2. Bidirectional LSTM (BiLSTM)*

BiLSTM is an extension of LSTM that processes sequences in both forward and backward directions, allowing the model to incorporate both historical and future background. It employs two LSTM layers, with one processing the sequence ahead and the other analyzing it backward. The outputs from both layers are concatenated to enhance feature representation. The BiLSTM computations involve equations similar to LSTM, with independent forward and backward passes as shown in eq (11), eq (12) and eq (13) [9]. These equations define the input, forget, and output gates, cell state updates, and hidden state computations, ensuring effective sequence modeling. Fig. 3 describes the bidirectional mechanism, highlighting how both directions contribute to better sequential understanding.

$$\underset{h_t}{\rightarrow} = LSTM_{forward}(X_t) \tag{11}$$

$$\underset{h_t}{\leftarrow} = LSTM_{backward}(X_t) \tag{12}$$

$$h_t = \underset{h_t}{\rightarrow} \oplus \underset{h_t}{\leftarrow} \tag{13}$$

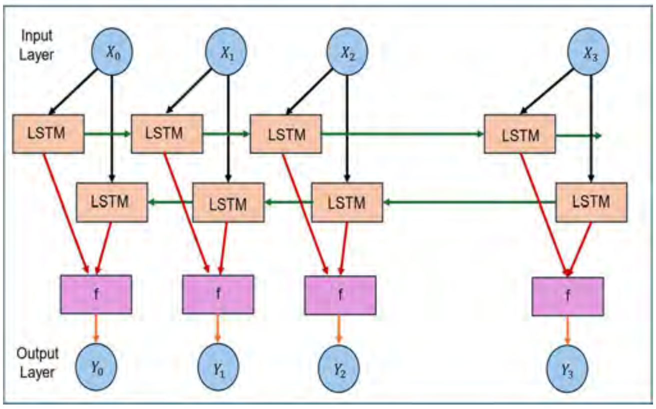


Fig. 3. Architecture of a bi-directional LSTM (Bi-LSTM) algorithm.

## III. Result Analysis And Discussion

### A. Correlation Matrix Analysis

Fig. 4 highlights the relationships among key input features used in the proposed LSTM and BiLSTM models for forecasting EV charging loads. Strong positive correlations are evident between features like charging demand and time-related variables, indicating their significant contribution to forecasting accuracy. On the other hand, features with weak or near-zero correlations, such as certain environmental factors, show limited influence on the target variable. The provided analysis supports the necessity of focusing on highly correlated variables while excluding less impactful ones to improve model performance. By leveraging this understanding, the LSTM and BiLSTM models can be optimized for better accuracy and efficiency in predicting EV charging loads.

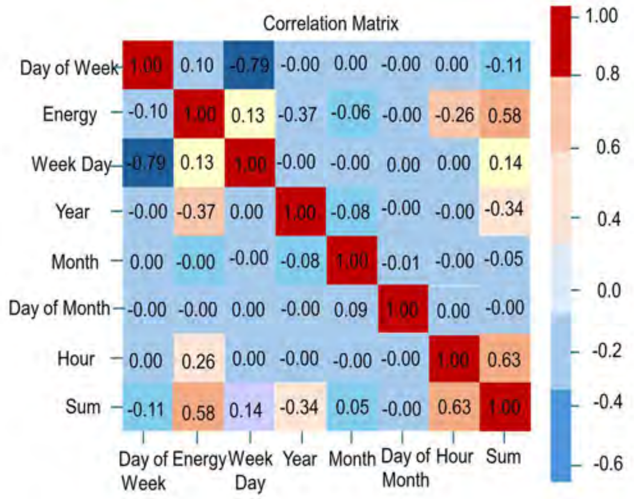


Fig. 4. Correlation matrix of input features for EV charging load forecasting.

### B. Model Performance and Evaluations

Fig. 5 illustrates the LSTM model's performance in forecasting EV charging loads using the test dataset. The predicted results nearly match the actual data, demonstrating the model's ability to capture temporal dependencies effectively. Minor differences between predicted and actual values show areas for additional refinement while demonstrating the LSTM model's dependability. The graphic validates the model's capacity to generalize effectively on previously unreported data, demonstrating its usefulness for projecting EV charging needs in real-world scenarios.

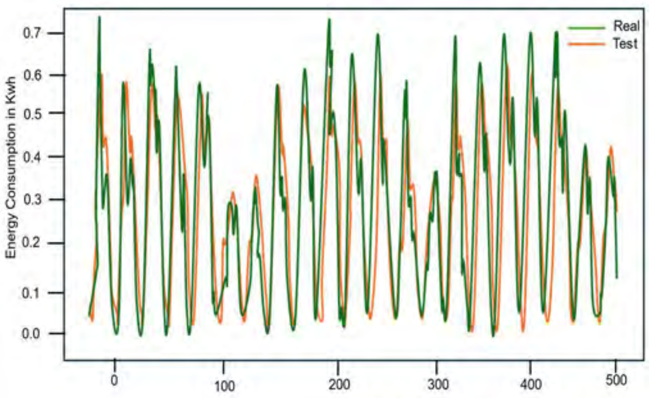


Fig. 5. LSTM Model Predictions on Test Dataset.

Fig. 6 displays how the BiLSTM model's estimates compare to the actual values on the test dataset. The values that are expected nearly match the actual data points, demonstrating the model's great accuracy in identifying bidirectional temporal patterns and dealing with complicated data relationships. The lower error margins demonstrate the BiLSTM model's enhanced capacity to analyze input sequences both forward and backward, resulting in improved generalization and prediction dependability. This visualization verifies the BiLSTM model's ability to provide consistent and exact EV charging load forecasting, highlighting the possibilities for practical usage in dynamic energy management.

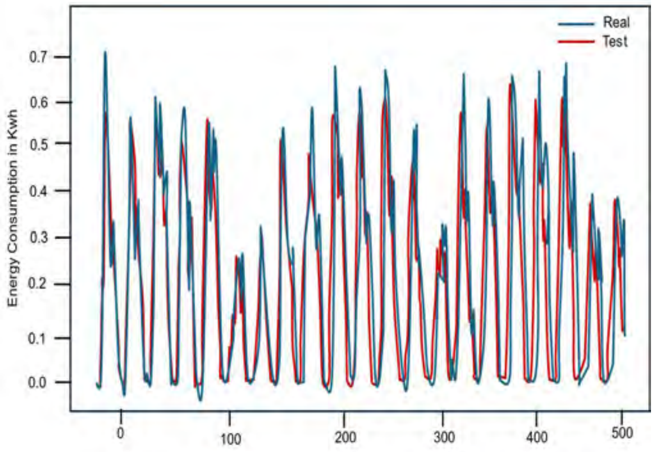


Fig. 6. BiLSTM model predictions on test dataset.

Fig. 7 depicts a assessment between the true values (actual EV charging load) and the predictions made by the LSTM and BiLSTM models on the test dataset. The actual values are represented alongside the predicted values from the LSTM (red line) and BiLSTM (green line) models. Both models capture the overall trends and shapes in the data, but the BiLSTM model predictions (green) appear to align more closely with the true values compared to the LSTM model. The graphical analysis suggests that the BiLSTM's bidirectional nature allows it to process information more effectively, improving prediction accuracy. Minor deviations between the predicted and actual values indicate areas for further refinement. It also validates the BiLSTM model's superior performance in forecasting EV charging loads over the LSTM model.

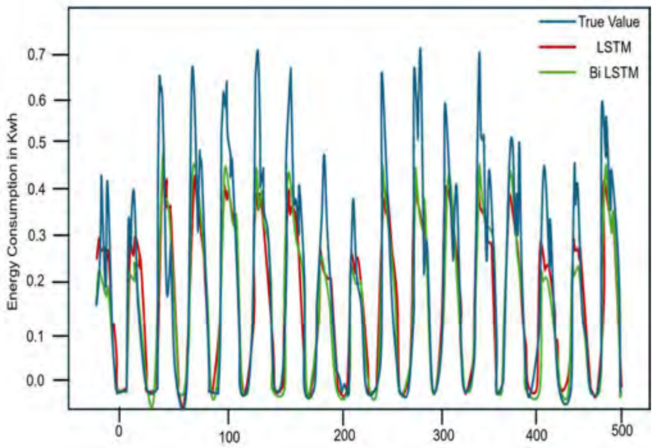


Fig. 7. Comparison of LSTM and BiLSTM predictions with actual values on test dataset.

Table II presents the performance metrics of the testing data, comparing the RMSE and MAE for LSTM and BiLSTM models. The BiLSTM model demonstrates superior performance, achieving a lower RMSE of 0.1806 and MAE of 0.1588 compared to the LSTM's RMSE of 0.2882 and MAE of 0.2354. These findings demonstrate BiLSTM's improved capacity for interpreting complicated temporal connections by processing data in both forward and backward orientations, resulting in more accurate predictions. The significant reduction in error metrics validates BiLSTM as a more robust model for the given dataset, ensuring greater reliability in forecasting tasks.

TABLE II. PEFORMANCE MATRICS OF TESTING DATA

| Metrics | RMSE | MAE |
|---|---|---|
| LSTM | 0.2882 | 0.2354 |
| Bi LSTM | 0.1806 | 0.1588 |

## IV. CONCLUSION

The proposed study addresses the increasing necessity for precise load forecasting in EV charging systems, which is essential for managing energy demand amid rising EV adoption and the incorporation of renewable energy sources. By leveraging LSTM and BiLSTM models, the research achieves notable improvements in forecasting accuracy and efficiency. Rigorous preprocessing techniques, including outlier removal, normalization, and dimensionality drop using PCA, ensure the dataset's reliability and usability. The findings demonstrate that Bi-LSTM outperforms LSTM in capturing temporal dependencies and bidirectional patterns, achieving superior performance metrics such as RMSE and MAE. The model capability to handle the complex and dynamic characteristics of EV charging data. Additionally, the analysis of feature importance and correlations identified key predictive variables, further enhancing the interpretability and accuracy of the forecasts. The proposed framework not only improves the efficiency of EV charging operations but also facilitates the integration of renewable energy, thereby reducing reliance on conventional power grids and contributes significantly to the field of energy management systems by providing a scalable solution for real-world applications, aiding the transition toward a more workable and competent EV infrastructure. Future research could focus on expanding datasets and incorporating additional features to achieve broader generalization.

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