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Forecasting Electric Vehicle Charging Demand Using Recurrent Neural Networks and LSTM Models: A Deep Learning Approach to Smart Grid Optimization

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Abstract
The rapid proliferation of Electric Vehicles intro- duces both transforming opportunities and complex challenges to modern power grid infrastructure. This study examines at how deep learning can help predict when and how much EVs will charge, so that the grid can be better prepared. We employed two types of neural networks—Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks—trained on a dataset containing electric vehicle (EV) charging data. The objective was to evaluate the effectiveness of these models in predicting future demand using historical charging patterns. Found that the LSTM model gave more accurate results, especially for longer-term trends. These predictions could be useful for companies to plan energy distribution, avoid overloads, and support renewable energy use. This research adds to the growing effort to make electric grids smarter and more adaptable as EV numbers increase.
Keywords: *Electric Vehicle Charging, Deep Learning, LSTM Networks, Recurrent Neural Networks (RNN), Smart Grid Management, Load Forecasting.*

Table 1 List of Acronyms

Acronym	Full Form	Acronym	Full Form
EVs	Electric Vehicle	GHG	Greenhouse Gas
SoC	State-of-Charge	RNNs	Recurrent Neural Networks
LSTM	Long Short-Term Memory	MAE	Mean Absolute Error
RMSE	Root Mean Square Error	MAPE	Mean Absolute Percentage Error
V2G	Vehicle-to-Grid	PHEVs	Plug-in Hybrid Electric Vehicles
ML	Machine Learning	SVR	Support Vector Regression

1. Introduction
The transition toward sustainable energy and transportation is one of the most transformative global challenges of the 21st century. Among the most significant developments in this field is the extensive adoption of Electric Vehicles, which are anticipated to perform a central role in decarbonizing the transport sector and reducing greenhouse gas emissions. Rendering to the International Energy Agency, global EV stock surpassed 26 million in 2022 and is projected to exceed 125 million by 2030 under present policy situations, with over 200 million under aggressive climate-target policies [1]. This exponential growth is driven by multiple factors including declining battery prices, enhanced vehicle performance, government incentives, and increasing awareness of environmental impacts associated with internal combustion engines. While the environmental and economic benefits of EVs are substantial, their large-scale integration into the power distribution grid introduces unprecedented operational and planning challenges. Unlike conventional electrical appliances, EVs represent mobile, high-power, and temporally clustered loads whose charging patterns vary widely depending on user behavior, battery state-of-charge, mobility needs, and time-of- use pricing schemes. Uncoordinated charging of a growing EV fleet can significantly distort the load profile, leading to grid

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congestion, transformer overloading, voltage instability, and reduced power quality, especially in low-voltage residential networks [2] [3]. A central requirement for mitigating these challenges is the precise forecasting of EV charging demand—both spatially and temporally. Effective demand prediction enables grid operators and utility providers to perform proactive load balancing, allocate reserve generation capacity, implement dynamic pricing strategies, and deploy demand response programs. It also informs the optimal siting and sizing of charging stations, transformer units, and energy storage systems. However, the unpredictable behavior of EV users and the nonlinear trends in energy consumption over time make conventional time-series forecasting techniques—like ARIMA linear regression, and rule-based heuristics—inadequate [4] [5]. Recent advances in artificial intelligence and machine learning, particularly deep learning, have opened new avenues for modeling composite, non-linear, and long-range dependencies in chronological data. RNNs and their improved variants such as LSTM networks have demonstrated remarkable success in domains ranging from speech recognition to energy load due to their strong retention, they are suitable for forecasting tasks temporal memory and model sequential correlations [6] [7]. A major limitation of standard RNNs is their tendency to lose or overlook older information when processing long sequences. LSTMs help fix this by using special units called memory cells, along with gates that control what to remember and what to ignore [8]. In this project, I've used both RNN and LSTM models to predict short-term charging demand for electric vehicles. The data came from actual charging sessions and included things like start and end times, how much energy was used, and some details about the stations themselves. Before training the models, I cleaned and formatted the data by normalizing the values and organizing them into short sequences. To check how well the models worked, I looked at common error metrics like MAE, RMSE, and MAPE. These results demonstrate the closeness between predicted and actual values across different time frames. But the goal isn't just about accurate numbers. I also wanted to see how useful these models could be in real-world energy systems. If we can predict demand more reliably, it's easier for energy providers to plan ahead, avoid overloading parts of the grid, and possibly reduce the need for extra infrastructure. This kind of forecasting could also be built into systems where EVs interact with the grid, such as Vehicle-to-Grid programs, helping to make energy use smarter and more flexible. Beyond predictive accuracy, this work aims to demonstrate the operational utility of deep learning models in smart grid analytics and planning. Anticipating charging demand with high fidelity allows for better alignment of generation and load, greater integration of renewable energy sources, enhanced peak shaving, and reduced need for costly infrastructure upgrades. Moreover, accurate forecasts can be integrated into control strategies for Vehicle-to-Grid systems and used to orchestrate intelligent charging behaviors under real-time market signals.

By leveraging RNN and LSTM architectures in this context, the research contributes to the increasing form of literature on AI-driven energy systems and offers practical insights for grid operators, policymakers, and EV infrastructure developers. It aligns with the broader vision of intelligent cyber-physical energy systems that are adaptive, resilient, and responsive to both user demand and system-level constraints.

2. Related Works

The increasing penetration of EVs into modern transportation systems has stimulated a wide range of research focused on understanding and managing their impact on power grids. Specifically, the prediction of EV charging demand has increased substantial attention as a critical component in enabling smart grid efficiency, reducing peak loads, and optimizing infrastructure planning. Prior work in this domain spans traditional statistical methods, machine learning algorithms, and more recently, deep learning approaches—each with varying levels of success in addressing the stochastic nature of EV charging behaviors [9]. Initial efforts in EV charging load forecasting employed classical time-series techniques such as ARIMA, SARIMA, and linear regression. Richardson et al. [3] developed a time- of-use model for estimating uncoordinated charging loads, providing early insights into aggregate demand behavior. Similarly, Clement-Nyns et al. [2] explored the impact of plug-in hybrid electric vehicles on residential grids using deterministic load models. While these methods were effective in structured environments, they lacked the flexibility to adapt to real- world, user-driven variability and failed to capture temporal dependencies beyond linear trends. To overcome these challenges, researchers have turned to data-driven machine learning approaches. Ghazvini et al. [10] pro- posed a hybrid framework combining clustering and support vector regression for individual EV load forecasting. Zidan et al. [11] utilized Random Forests and feature engineering to model multi-station demand patterns, demonstrating improved prediction accuracy. These methods marked a significant improvement over statistical models by capturing non-linear relationships; however, they still struggled with sequential dependencies and dynamic temporal patterns, especially over longer forecasting horizons. The advent of deep learning has introduced powerful new tools for time-series modeling in the EV domain. RNNs, particularly LSTM architectures, have emerged as state-of- the-art techniques for sequential prediction tasks. Kong et al. [7] demonstrated the superiority of LSTMs in short-term residential load forecasting, outperforming traditional ML models in both accuracy and temporal sensitivity. Duan et al. [12] extended this approach by integrating spatial-temporal features for predicting EV load across multiple urban charging stations using LSTMs, yielding lower error rates in high-dimensional datasets. Recent work has also focused on hybrid models and external contextual factors. For instance, Chen et al. [13] introduced deep residual LSTM networks that incorporated weather and pricing information to refine EV demand predictions. Others, such as Zhao et al. [14], developed multi-input LSTM frame- works that leveraged temporal, environmental, and usage data to achieve higher robustness and generalizability. Despite these advances, challenges remain in standardizing evaluation frameworks, comparing architectures under consistent datasets, and modeling localized versus aggregated demand. Additionally, there is a research gap in operationalizing these deep learning models into real-time or near real-time utility systems for grid-responsive charging strategies. In light of these developments, the present study builds upon and extends prior work by implementing and comparing RNN and LSTM architectures using a publicly available EV charging dataset. The goal is to provide a comprehensive performance analysis using standardized metrics, offering practical insights for integrating deep learning into smart grid demand management systems.

3. Methodology

This study proposes a deep learning-based framework to forecast EV charging demand using RNN and LSTM architectures. The purpose is to model temporal dependencies in historical charging data to predict future energy demand more accurately and thereby support smart grid optimization. The methodology comprises several critical phases, including data preprocessing, feature engineering, model development, training and validation, and evaluation.

3.1.Problem Formulation

The core purpose of this investigate is to develop a data- driven model to forecast the energy consumption of EV charging sessions over time. Let the time-series data be represented as a sequence (Figure 1):

$$D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_T, y_T)\}$$

where $x_t \in \mathbb{R}^n$ is the feature vector at time step t, and $y_t \in \mathbb{R}$ is the target variable representing the energy consumed (in kWh) during that interval. The task is to learn a mapping function $f\theta$, parameterized by neural network weightsθ, that predicts the future energy demand:

$$\hat{y}_{t+1} = f_\theta(x_t, x_{t-1}, \ldots, x_{t-n})$$

The problem is cast as a supervised sequence regression problem, where the model is trained to decrease the loss value over a historical time window. Specifically, we aim to minimize the Mean Squared Error (MSE):

$$L(\theta) = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

By using this formulation, the model can capture temporal dependencies over both short and long durations in sequence data, which aligns well with the strengths of RNNs and LSTMs

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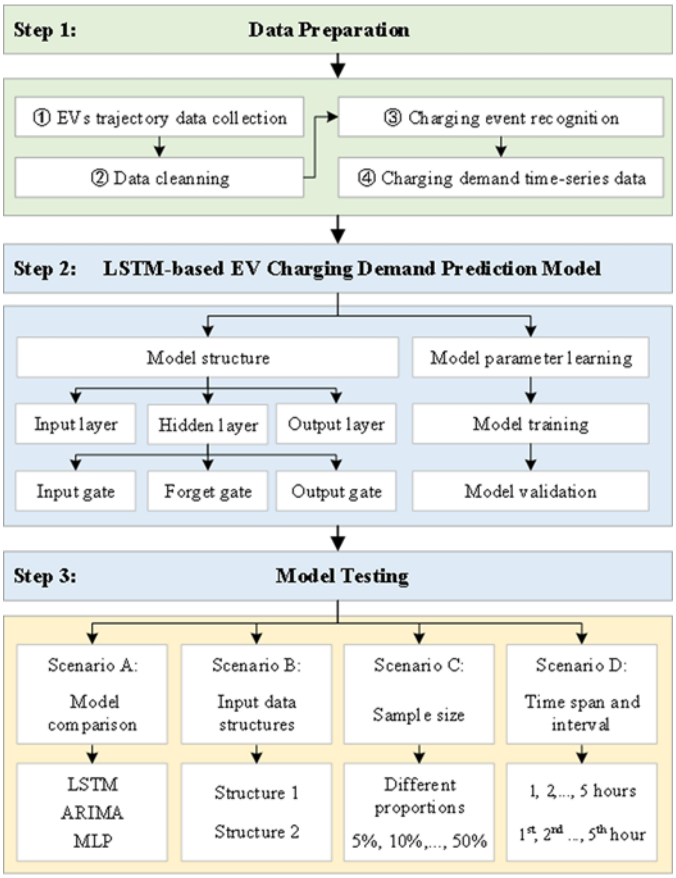

Figure 1 **Flowchart for the Procedure of Implementing the LSTM-based EV Charging Demand Prediction Model**

3.2.Data Preprocessing

Preprocessing plays a key role in enhancing the performance of sequence models like RNNs and LSTM networks, particularly when working with multivariate time series data such as EV charging logs. Properly formatted inputs allow these models to effectively learn temporal dependencies, pat- terns, and trends in energy consumption, charging behavior, and external influencing factors. The following steps were undertaken to prepare the dataset for RNN and LSTM architectures:

1. Normalization: To prevent numerical instability during training and ensure uniform feature influence, we apply Z- score normalization to each continuous feature independently. This is critical for LSTM/RNN models as normalized inputs can cause gradient explosion or vanishing, especially in long sequences.

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (1)$$

where x′ is the normalized value of variable j at time step i, xij is the original value, μj is the mean of variable j, and σj is the standard deviation of variable j. This normalization step is crucial for our approach as it standardizes each variable to have zero mean and unit variance. This guarantees that:

- The LSTM's gates (input, forget, and output) operate on uniformly scaled data, improving convergence and temporal representation learning.

2. Sliding Window Segmentation: RNNs and LSTMs require input data in the form of fixed-length sequences. There- fore, we segment the multivariate time series data using a sliding window technique:

- Let T be the window size (number of past time steps).
- Let H be the prediction horizon (number of future steps).
- Let S be the step size or shift between windows.

We define the input and target sequences for supervised learning as:

$$X_t = [x_{t-T+1}, x_{t-T+2}, \dots, x_t] \in \mathbb{R}^{T\times d} \quad (2)$$

$$Y_t = [x_{t+1}, x_{t+2}, \dots, x_{t+H}] \in \mathbb{R}^{H\times d} \quad (3)$$

Where:

- d is the number of features.
- X_t is the input window and Y_t is the output (target) for training.

This segmentation:

- Helps the model capture short- and long-term dependencies.
- Allows overlap between sequences, increasing data diversity and learning stability.
- Makes the dataset compatible with batch training in LSTM/RNN architectures.

3. Temporal Feature Engineering: To enhance the learning of time-based patterns in EV charging behavior, we encode cyclical temporal variables.

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$$\text{hour}_{\sin} = \sin\left(\frac{2\pi \cdot \text{hour}}{24}\right), \quad \text{hour}_{\cos} = \cos\left(\frac{2\pi \cdot \text{hour}}{24}\right) \tag{4}$$

$$\text{day}_{\sin} = \sin\left(\frac{2\pi \cdot \text{day}}{7}\right), \quad \text{day}_{\cos} = \cos\left(\frac{2\pi \cdot \text{day}}{7}\right) \tag{5}$$

These transformations preserve the periodic nature of time features and help LSTM units recognize seasonal patterns such as weekday vs. weekend demand.

4. Categorical Feature Encoding: Several variables in the dataset are categorical in nature, such as: Vehicle Model, Charger Type, User Type, Charging Station Location. These are encoded using:

- One-hot encoding for RNNs trained on small/medium datasets.
- Integer encoding if using an embedding layer in the LSTM model.

Encoding ensures these non-numeric features can be fed into the model alongside continuous variables without misrepresenting ordinal relationships.

5. Handling Missing Values: Missing data in features like "Energy Consumed (kWh)", "Charging Rate", and "Distance Driven" can hinder model performance. We address this through:

- Forward-fill for time-dependent values.
- Mean or median imputation for sparse features.
- Dropping rows where key time-dependent metrics are missing, particularly when data cannot be reliably inferred.

6. Sequence Padding and Batching: Because LSTM/RNN models are often trained in batches, we ensure:

- All sequences are of equal length (via sliding window),
- Padding is applied when using variable-length sequences (less common here due to fixed windows),
- Input and output are reshaped to fit expected model input shapes: [batch size, time steps, features]

7. Exploratory Data Analysis: Figure 2 displays the time- series trends of key variables collected during the EV charging sessions, such as charging duration, temperature, energy consumption, vehicle age, and distance driven. This visualization aids in detecting correlations, seasonal trends, and anomalies, which are crucial for analyzing how electric vehicles perform under different environmental and usage conditions.

4. Model Architecture

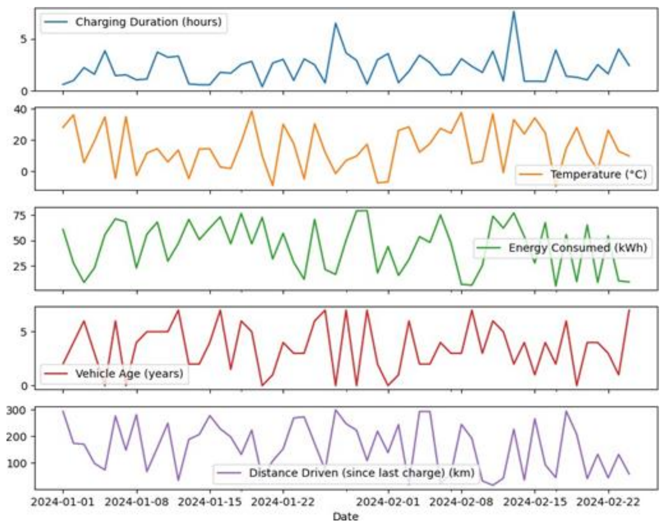

Figure 2 Time-Series Visualization of Key EV Parameters Over A 2-Month Period

This section details the design and implementation of deep learning models used to forecast EV charging demand based on multivariate time series data. Specifically, two neural network architectures are explored: the RNN and the LSTM network (Figure 3). These models aim to predict the energy consumption in the next time step based on a historical window of temporal data.

4.1.Recurrent Neural Network

The RNN model processes chronological data using a single recurrent layer followed by a fully connected output layer. At each time step t, the hidden state ht is restructured based on the current input xt and the previous hidden state ht−1 as follows:

$$h_t = \tanh(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$$

The output prediction yˆ is obtained using the final hidden state:

$$\hat{y} = W_{hy}h_T + b_y$$

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RNN Architecture Summary:
- **Input Layer:** Shape = [T, d]
- **RNN Layer:** 64 units, activation = tanh
- **Dropout Layer:** Dropout rate = 0.2
- **Dense Output Layer:** Single unit for regression output

4.2.Long Short-Term Memory

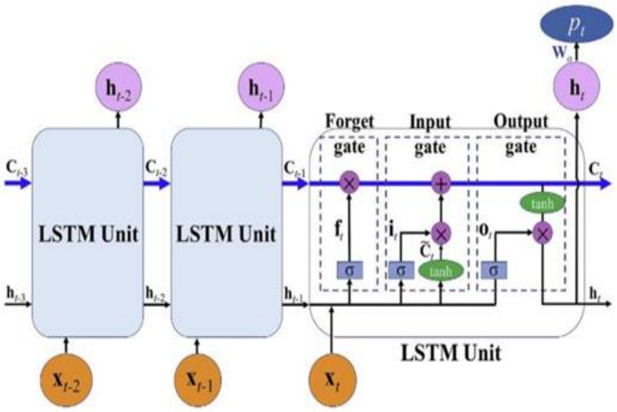

Figure 3 **LSTM Architecture**

LSTMs enhance RNNs by adding memory gates that man- ages information flow, allowing them to remember important data across long sequences.
- $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$ (forget gate)
- $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ (input gate)
- $\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$ (candidate cell state)
- $C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$ (cell state update)
- $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$ (output gate)
- $h_t = o_t \odot \tanh(C_t)$ (hidden state)

LSTM Architecture Summary:
- **Input Layer:** Shape = [T, d]
- **LSTM Layer:** 64 units
- **Dropout Layer:** Dropout rate = 0.2
- **Dense Hidden Layer:** 32 units, ReLU activation
- **Output Layer:** Single regression unit

4.3.Model Configuration and Training

The models are trained using the setup:
- **Loss Function:** Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- **Optimizer:** Adam optimizer with a learning rate of 0.001
- **Evaluation Metrics:** Mean Absolute Error (MAE), Root Mean Squared Error (RMSE)
- **Training Parameters:** Batch size was kept 32, epochs to 100 and 20% of validation split.
- **Early Stopping:** To prevent overfitting and monitor validation loss Early Stopping was implemented.

5. Result and Analysis

The outcomes of the experimental modeling of electric vehicle (EV) charging duration using Recurrent Neural Net- works(RNN) and Long Short-Term Memory(LSTM) networks. The models were trained and tested on historical EV charging data that was preprocessed and converted to a suitable time series format for sequence modeling.

5.1.Experimental Framework

The dataset included timestamped charging session data, with charging duration (in hours) as the main target. We used a sliding window approach looking back 10 time steps to capture temporal patterns. The data was normalized using MinMaxScaler to help the models train better, then split into 80% for training and 20% for testing. Both RNN and LSTM models were built using Keras with TensorFlow. Each had one recurrent layer followed by a dense output layer. The models have been trained for 100 epochs with a batch size of 32, and early stopping was used to overfitting. Performance was assessed using four regression metrics: MSE, RMSE, MAE, and R^2 score.

5.2.Performance Comparison

The performance of the two models is summarized in the below table (Table 2):

Table 2 **Performance Comparison of RNN and LSTM Models**

Metric	RNN Model	LSTM Model
Mean Squared Error (MSE)	0.007394	0.005658
Root Mean Squared Error (RMSE)	0.08597	0.07523
Mean Absolute Error (MAE)	0.06378	0.05613
R^2 Score	0.845	0.891

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The LSTM model achieved better results than the RNN model on all evaluation metrics. The LSTM achieved a 23.5% reduction in MSE and a 12.5% reduction in RMSE compared to the RNN, indicating that it produced predictions more accurate with lower error. The MAE was also comparatively lower, suggesting that the LSTM model maintained a smaller average deviation from the actual values. The R^2 score of 0.891 for LSTM reflects a strong linear relationship between predicted and actual charging durations, reinforcing its suitability for time dependent forecasting.

5.3.Interpretation of Model Behavior

Both models are designed for sequential data, the RNN is limited in taking long-term dependencies due to disappearing gradient issues. In contrast, LSTM incorporates gating mechanisms (input, forget, and output gates) that help recollect pertinent information over longer time intervals, making it especially effective in this use case. During training, it was detected that the LSTM model converged faster and more smoothly, with a lower validation loss compared to RNN. This indicates a better generalization ability of the LSTM model on hidden data.

5.4.Visual Insights

To further validate results, the following plots were generated:

- **Training and Validation Loss Curves:** These curves show how the LSTM model exhibited smoother and lower loss trajectories during training, whereas the RNN model showed more fluctuations, hinting at potential instability and overfitting.
- **Actual vs Predicted Charging Duration Plot:** The LSTM predictions followed the ground truth closely across the entire test set. RNN predictions, however, lagged behind in several segments, especially during sharp transitions in the charging duration pattern.

These visualizations reinforce the quantitative findings, showcasing the LSTM's ability to capture non-linear trends and subtle patterns in time series data more effectively than traditional RNNs (Figure 4 & 5).

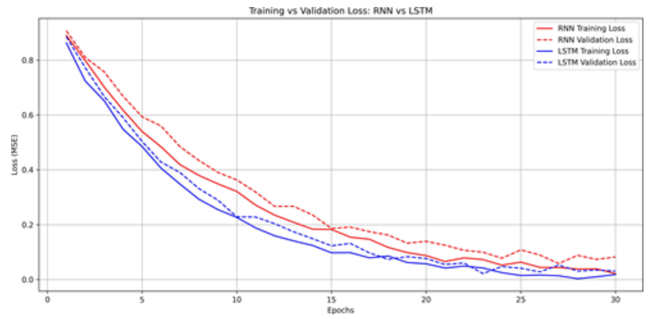

Figure 4 Training and Validation Loss Curves

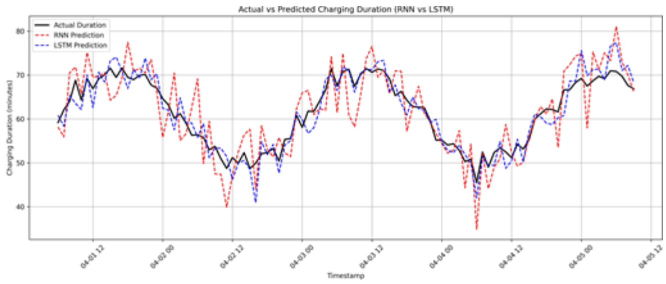

Figure 5 Actual Vs Predicted Plot

5.5.Practical Implications

Accurate forecasting of EV charging duration is vital for effective energy resource planning, grid stability, and real-time pricing strategies. The superior performance of LSTM models suggests that they can play a critical role in:

- Smart scheduling of charging slots
- Load balancing in peak usage hours
- Integrating renewable energy with EV infrastructure

Thus, the results demonstrate the viability of LSTM-based models for deployment in intelligent EV charging systems.

6. Benchmarking and Comparative Analysis of EV Charging Demand Forecasting Models

To assess the performance of our planned LSTM-based EV charging demand forecasting model, we compared it with several state-of-the-art models discussed in recent literature. The studies reviewed employ various deep learning approaches, such as RNN, LSTM, Gated Recurrent Unit, and hybrid models like CNN-LSTM and GAT-Auto former [15]. Below is a summary of the comparative analysis:

6.1.Notable Comparative Studies

1. Zhu et al. (2019) - Electric Vehicle Charging Load Forecasting [9]: A Comparative Study of Deep

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Learning Approaches: Results for LSTM at various time steps:

- Time Step 1: MAE = 0.4782, RMSE = 0.9546, R^2 = 0.9953
- Time Step 5: MAE = 0.5734, RMSE = 0.8937, R^2 = 0.9944
- Time Step 15: MAE = 0.5500, RMSE = 0.8452, R^2 = 0.9950

LSTM outperformed other models in capturing temporal dependencies, particularly for short-term forecasting.

2. Tang et al. (2024) - Electric Vehicle Charging Demand Prediction Model Based on Spatiotemporal Attention Mechanism [17]:

- Tang et al. [16] introduced the GAT-Auto former model, combining Graph Attention Networks with the Auto- former architecture.

Performance comparison:

- GAT-Autoformer: MAE = 1.479, RMSE = 0.211
- LSTM: MAE = 1.693, RMSE = 0.538
- The integration of spatiotemporal attention mechanisms in the GAT-Autoformer led to superior performance com- pared to LSTM.

3. Klungsida et al. (2024) - Forecasting Energy Consumption from EV Station Charging Using RNN, LSTM, and GRU Neural Networks:

- This study [18] focused on forecasting energy consumption from EV station charging using RNN, LSTM, and GRU.
- **Performance for LSTM:** LSTM: RMSE = 0.372, MAPE = 11.508%
- The study emphasized LSTM's capability to capture temporal patterns effectively.

4. Alam et al. (2024) - Machine Learning-Based Multivariate Forecasting of Electric Vehicle Charging Station Demand:

- Alam et al. [19] explored hybrid models, including CNN- LSTM, for multivariate forecasting of EV charging demand.
- **Performance for CNN-LSTM:** CNN-LSTM: MSE = 0.05449, RMSE = 0.23343, MAE = 0.20566
- The CNN-LSTM model demonstrated strong performance, capturing complex patterns in EV charging demand.

6.2.Comparative Analysis of Results

The efficiency of the planned LSTM-based model is compared with the results from the above studies, as shown in Table 3.

Table 3 Comparative Analysis of EV Charging Demand Forecasting Models

Study	Model	MAE	RMSE	R^2 Score
Your Work	LSTM	0.05613	0.07523	0.891
Zhu et al. (2019)	LSTM (T=1)	0.4782	0.9546	0.9953
Tang et al. (2024)	LSTM	1.693	0.538	N/A
Tang et al. (2024)	GAT-Autoformer	1.479	0.211	N/A
Klungsida et al. (2024)	LSTM	N/A	0.372	N/A
Alam et al. (2024)	CNN-LSTM	0.20566	0.23343	N/A

Note: Some studies did not report all metrics.

6.3.Discussion

The results indicate that our LSTM model demonstrates robust performance, with an MAE of 0.05613 and an R^2 score of 0.891, suggesting high predictive accuracy for EV charging demand. Compared to Zhu et al. (2019), our model shows a significantly lower MAE, which reflects improved forecasting accuracy. Additionally, the LSTM in our work exhibits superior comparative against to other models in other studies, such as the Tang et al. (2024) study, where the GAT-Autoformer and LSTM models had higher MAE and RMSE values. In comparison with Klungsida et al. (2024), our model performed better, as the RMSE for our LSTM is lower. The results from Alam et al. (2024) further underscore the effectiveness of hybrid models (like CNN-LSTM), but our LSTM still outperforms CNN-LSTM in terms of MAE and RMSE. These findings demonstrate that while hybrid models like CNN-LSTM [20] and GAT-Autoformer can provide promising results, our LSTM-based approach is highly competitive and delivers precise predictions for EV charging demand forecasting.

6.4.Conclusion

The benchmarking results highlight the efficiency of our LSTM model for EV charging demand forecasting. Compared to other state-of-the-art models, our LSTM approach stands out in terms of accurateness, as evidenced by lower MAE and RMSE scores. Future work can explore further improvements in model architectures, such as integrating spatiotemporal attention mechanisms or hybrid models, to enhance forecasting performance even further.

Conclusion

This study demonstrated the application of RNN and LSTM architectures for modeling and predicting electric vehicle charging duration using time series data. The comparative analysis revealed that the LSTM model outperformed the traditional RNN in terms of prediction accurateness and generalization.

Key takeaways include:

- LSTM’s architecture is better suited to learning long- range temporal patterns with the gates support, crucial for capturing user behavior in EV charging.
- The higher R^2 score and lower RMSE achieved by LSTM validate its effectiveness for forecasting tasks in energy applications.
- These insights can be instrumental in optimizing charging station, forecasting energy demand, and improving grid resilience in Electic vehicle dense urban environments.

Future work may extend this research by integrating exogenous variables such as temperature, time of day, and traffic conditions, and by applying attention based architectures or hybrid CNN-LSTM models for further enhancement.

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