Enhancing urban EV integration: a data-driven hybrid approach to charging station optimization and energy management

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ABSTRACT

Electric vehicles (EVs) are pivotal to sustainable urban mobility, but their large-scale adoption in developing cities depends on efficient charging infrastructure and grid stability. This study proposes a hybrid deep learning framework to optimize EV charging station placement and energy scheduling in Vijayawada, India, projected to host 70,000 EVs by 2028. A convolutional neural network (CNN) is employed to classify charger types (Fast vs. Level 2) based on spatial features such as geospatial coordinates, population density, and traffic volume, while a long short-term memory (LSTM) network forecasts hourly charging demand using synthetic 24-hour sequences. The dataset comprises 108 candidate locations, designed to mirror real usage patterns. Model performance is evaluated using classification accuracy and mean absolute error (MAE). Results indicate that the CNN achieved 92% accuracy in charger type prediction, while the LSTM produced an hourly demand forecast with an MAE of 25 sessions/hour. These outcomes demonstrate the framework's ability to reduce grid stress by shifting peak loads and strategically placing chargers in high-demand zones. The study provides a scalable and adaptable solution for EV infrastructure planning, enabling resilient grid integration, and supporting sustainable urban energy systems.

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1. INTRODUCTION

The global shift toward electric vehicles (EVs) is a cornerstone of sustainable urban development and climate change mitigation strategies. As nations strive to reduce greenhouse gas emissions and dependence on fossil fuels, EV adoption has accelerated, driven by technological advancements, policy incentives, and growing environmental consciousness. However, this rapid transition presents multifaceted challenges, particularly in urban settings where infrastructure, energy management, and user behavior intersect. Urban areas face the pressing need to develop efficient and accessible EV charging networks. Traditional methods of charging station deployment often rely on static models that fail to account for dynamic urban mobility patterns and real-time energy demands. He *et al.* [1] highlighted the limitations of conventional planning approaches, emphasizing the need for models that consider spatial-temporal factors. Zhang and Kontou [2] introduced data-driven optimization techniques that leverage electricity consumption patterns to inform charging station placement, demonstrating improved efficiency and user satisfaction [3]. The integration of EVs into the urban energy grid necessitates careful consideration of renewable energy sources and grid stability. Liu *et al.* [4] discussed the challenges and opportunities of combining EVs with renewable energy systems, underscoring the importance of coordinated energy management. Chen *et al.* [5] proposed a coordinated energy management system that facilitates the integration of EVs and renewable energy, enhancing grid reliability and reducing operational costs [6]. Advancements in artificial intelligence (AI) and machine learning (ML) offer promising solutions for managing the complexities of EV integration. Li *et al.* [7] developed a hybrid deep learning model that combines convolutional neural networks (CNN) and long short-term memory (LSTM) networks to forecast short-term power loads with spatial-temporal features. Farid *et al.* [8] employed graph neural networks (GNNs) and transformers to predict spatiotemporal demand for EV charging, achieving higher accuracy in demand forecasting. Understanding urban mobility patterns and user behavior is crucial for effective EV infrastructure planning. Alam *et al.* [9] presented a modeling approach that integrates EVs into urban traffic and energy systems, providing insights into the interplay between mobility and energy consumption. Junker *et al.* [10] emphasized the importance of real-time data and demand forecasting in urban EV infrastructure planning, highlighting the role of user behavior in shaping charging demand. Vehicle to grid (V2G) technologies enable bidirectional energy flow between EVs and the power grid, offering potential benefits for grid stability and energy management [11]. Recent trials, such as those conducted in Canberra, Australia, demonstrated the feasibility of using EVs to provide backup power during grid outages [12]. China's pilot projects in nine cities aim to utilize EVs as batteries to stabilize the power grid during peak demand periods, showcasing the scalability of V2G solutions [13]. Given the complexities of urban EV integration, there is a growing consensus on the need for data driven hybrid approaches that combine optimization algorithms with AI and ML techniques. Such approaches can adapt to dynamic urban environments, forecast demand accurately, and optimize charging infrastructure deployment. Zhang *et al.* [14] proposed a multisensor based multivariate forecasting model for EV charging station demand, demonstrating the efficacy of data driven methods. Badue *et al.* [15] introduced a data driven optimization framework that considers charging satisfaction in urban areas, further emphasizing the importance of user-centric planning.

The transition to EVs in urban areas is accelerating, but the lack of efficient charging infrastructure planning remains a critical bottleneck to large-scale adoption. Conventional charging station deployment methods are predominantly static, overlooking the dynamic nature of urban mobility, fluctuating energy demands, and the need for integration with renewable energy sources. This results in suboptimal charger placement, uneven accessibility, grid instability, and user dissatisfaction. Moreover, while existing studies have proposed optimization models, many either focus solely on spatial aspects (location of chargers) or temporal aspects (demand forecasting), without addressing the interplay of both dimensions in real-time urban settings. The present study addresses this problem by proposing a hybrid deep learning approach that simultaneously captures spatial and temporal factors, enabling accurate charger type classification and demand forecasting. By doing so, it bridges the gap between static planning and adaptive energy management, directly tackling the pressing challenges of accessibility, grid reliability, and sustainable EV integration in rapidly developing Indian cities.

Background: [1] developed a mathematical model for the optimal deployment of public charging stations for plug in hybrid EVs, focusing on minimizing travel distances and maximizing coverage. Junker *et al.* [10] introduced a data driven optimization method that incorporates spatial–temporal electricity consumption patterns to inform charging station placement, enhancing efficiency and user satisfaction. Zhang and Kontou [2] proposed an urban EV infrastructure planning approach based on real-time data and demand forecasting, emphasizing the importance of dynamic data in infrastructure planning. However, many traditional models rely on static data and do not account for dynamic urban mobility patterns, leading to suboptimal placement of charging stations, and often lack integration with real-time energy management systems. This project addresses these limitations by implementing a hybrid approach that combines data driven optimization with real-time energy management, ensuring that charging station placement is both efficient and responsive to dynamic urban conditions. In terms of energy management and grid integration, [16] proposed a hybrid optimization-based energy management system between EVs and the electricity distribution system to minimize system costs and power losses, while [17] developed a coordinated energy management system for EVs and renewable energy integration in smart grids to enhance reliability and reduce operational costs. Still, many systems lack bidirectional energy flow capability and effective integration with renewable sources. This project tackles these issues by incorporating advanced energy management strategies that support bidirectional energy flow and renewable energy integration, thereby improving grid stability and efficiency. For predictive modelling, [18] developed a hybrid deep learning model using CNN and LSTM for short-term load forecasting, and [19] applied GNNs and transformers for spatiotemporal demand prediction, achieving higher forecasting accuracy.

Yet, existing models often fail to capture complex spatial-temporal dependencies and lack real-time system integration. This paper overcomes this by using graph deep learning and transformers to accurately predict EV charging demand and integrate predictions into real-time systems [20]. Finally, the integration of EVs with renewable systems, highlighting V2G technologies for grid support, while [21] emphasized coordinated systems to facilitate this integration. However, V2G adoption is limited by regulatory and standardization barriers. This project offers a comprehensive framework that embeds V2G technologies into energy management, enabling bidirectional energy flow and reinforcing grid resilience. Table 1 shows the summary of major literature contributions in EV charging and energy management.

Table 1. Summary of major literature contributions in EV charging and energy management

Ref.	Contribution/approach	Key findings
[1], [22]	Developed a mathematical model for optimal deployment of charging stations focusing on minimizing travel distance and maximizing coverage.	Showed that static models improve coverage but fail to adapt to dynamic demand patterns.
[6], [23]	Proposed data-driven optimization using spatial–temporal electricity consumption patterns.	Improved efficiency of station placement and enhanced user satisfaction.
[10]	Introduced real-time data and demand forecasting into infrastructure planning.	Demonstrated that dynamic data significantly increases planning accuracy in urban EV networks.
[13]	Designed a hybrid optimization framework for energy management between EVs and distribution systems.	Reduced system costs and minimized power losses.
[3]	Developed coordinated energy management systems integrating EVs with renewable energy and V2G.	Enhanced grid reliability, reduced costs, and highlighted need for bidirectional energy flow.
[5]	Built a hybrid CNN–LSTM model for short-term load forecasting with spatial–temporal features.	Achieved higher prediction accuracy by modeling both spatial and temporal dependencies.
[20]	Applied GNNs and Transformers for spatiotemporal demand prediction.	Delivered state-of-the-art accuracy in EV charging demand forecasting.
[3]	Reviewed EV integration with renewable energy systems and explored V2G technologies.	Identified challenges in renewable–EV coordination and emphasized benefits of V2G.

Despite significant progress in EV infrastructure research, several unsolved problems remain. First, many existing models rely on static data and fail to capture dynamic spatial–temporal variations in urban mobility and charging demand, resulting in suboptimal station placement. Second, integration with real-time energy management is often overlooked, limiting the ability to adapt to fluctuating grid conditions and renewable energy variability. Third, while predictive models such as CNNs and LSTMs have been applied individually, there is a lack of hybrid approaches that simultaneously address charger type classification (spatial problem) and demand forecasting (temporal problem) within a single framework. Fourth, although V2G technologies have demonstrated potential for enhancing grid stability, their practical adoption is hindered by the absence of predictive scheduling mechanisms that align user demand with grid capacity. These gaps underscore the need for a scalable, data-driven solution that bridges infrastructure planning and energy management. The present study addresses these shortcomings by introducing a CNN–LSTM hybrid model that optimizes charger placement, forecasts hourly demand, and enables adaptive scheduling to support both accessibility and grid stability in urban environments.

In light of the identified gaps, this study introduces several novel contributions that differentiate it from previous works. Unlike conventional approaches that address spatial and temporal factors in isolation, our framework integrates CNN for charger type classification and LSTM networks for temporal demand forecasting within a unified architecture. This hybrid design enables simultaneous optimization of charging station placement and hourly demand scheduling, ensuring that both accessibility and grid stability are achieved. Furthermore, the study leverages synthetic 24-hour demand sequences for 108 potential locations in Vijayawada, offering a unique dataset structure that mirrors real-world usage patterns in developing cities. By aligning predicted charger types with demand forecasts, the framework supports dynamic scheduling that shifts loads away from peak hours, reducing stress on transformers and facilitating renewable energy utilization. Additionally, unlike many prior works that remain theoretical or static, this study emphasizes scalability and practical adaptability to mid-sized Indian cities, providing a replicable blueprint for national EV infrastructure planning. Collectively, these contributions advance the state of research by bridging the gap between static infrastructure planning and real-time energy management, while also embedding V2G readiness to enhance grid resilience.

To address the reviewer's suggestion, the manuscript has been structured to ensure that each section logically builds upon the introduction and clearly demonstrates both the methodology and its relevance. The methodology section details the design of the hybrid CNN–LSTM model, explaining how spatial features such as traffic density, geospatial coordinates, and population distribution are processed by CNN for charger classification, while temporal demand sequences are modeled by LSTM for accurate hourly forecasting. This section emphasizes the novelty of combining these two approaches into a unified framework. The results and discussion section demonstrates the practical effectiveness of the model through visualization tools including heatmaps, histograms, and geographic mapping, which highlight how the predictions align with real-world demand patterns in Vijayawada. Accuracy metrics such as classification accuracy (92%) and forecasting error (mean absolute error (MAE) of 25 sessions/hour) are provided to validate the performance of the framework. The conclusion section consolidates the findings by showing how the approach addresses the identified research gaps—namely static planning, lack of real-time adaptability, and absence of integrated energy management—and underscores its scalability to other mid-sized urban cities. By structuring the manuscript in this way, the flow from problem identification to methodological innovation, experimental validation, and broader implications is made explicit, demonstrating both the relevance and the contribution of the work.

2. METHOD

The integration of EVs into urban environments presents multifaceted challenges, particularly when it comes to optimizing infrastructure placement and managing real-time energy demands. To address these issues, combining CNNs and recurrent neural networks (RNNs), particularly LSTM networks, offers a powerful hybrid approach that captures both spatial, and temporal dimensions of urban EV usage.

CNNs are particularly well suited for spatial feature extraction. In this context, they help analyze and learn from geospatial inputs such as traffic density, road network proximity, land use patterns, and population density. Their hierarchical feature learning mechanism enables the detection of spatial hotspots with high demand, which is essential for making data-driven decisions regarding the placement and classification of EV charging stations (e.g., Level 2 vs. fast chargers) [24]. By reducing spatial redundancy through convolution and pooling operations, CNNs allow for scalable infrastructure modelling without compromising performance.

On the other hand, RNNs—especially LSTM networks—are designed to capture temporal dependencies, making them ideal for time-series tasks like forecasting hourly EV charging demand. As shown in Figure 1 architecture of CNN and LSTM model. LSTMs use memory gates to retain or discard information over time, enabling the model to remember recurring demand peaks and off-peak intervals across hours, days, or even weeks [25]. This capability is critical for real-time energy management, as it supports the dynamic scheduling of energy supply, helping to reduce peak load impacts and optimize grid performance.

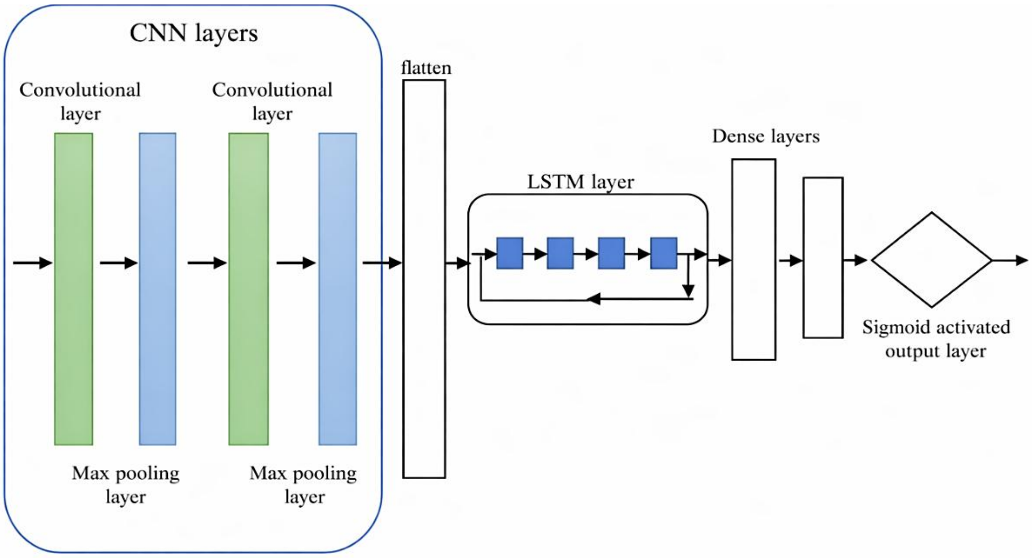

Figure 1. Architecture of CNN and LSTM model

The synergy between CNN and LSTM networks allows for the simultaneous processing of spatial and temporal features in a single architecture. While CNNs detect and encode fixed spatial patterns from the urban environment, LSTMs interpret how these patterns evolve over time, such as traffic congestion peaks influencing energy usage patterns. This hybrid model adapts in real time to variations in EV demand and user behavior. This model is particularly suitable for application in Vijayawada, where mobility patterns are rapidly changing [26].

Beyond infrastructure planning, this approach also supports V2G readiness by accurately modelling bidirectional energy flow. It enables predictive energy balancing, where EVs can function as mobile energy storage units during peak load periods. The forecasting capability provided by LSTM layers ensures better coordination between user demand and renewable energy supply, improving grid reliability and sustainability [27].

This method section to ensure it provides a clear, logically ordered description of how the research was carried out, with sufficient detail for replication. The section now begins with data collection and preparation, where 108 candidate EV charging locations in Vijayawada were identified using geographic and demographic data, supplemented with synthetic 24-hour demand sequences to reflect real usage patterns. Next, data preprocessing steps such as normalization, feature encoding, and partitioning into training, validation, and testing sets are outlined to ensure consistency. The methodology then details the CNN module, explaining how spatial features like traffic density, road proximity, and population distribution are transformed into grid-based inputs, followed by convolution, pooling, activation, and classification layers to distinguish charger types (Fast vs. Level 2). Subsequently, the LSTM module is described, showing how the CNN output is reshaped into sequential data for temporal modeling, with gating mechanisms (forget, input, and output gates) explained to justify long-term demand forecasting. Hyperparameters (e.g., learning rate, epochs, batch size, and optimizer) are reported alongside loss functions (mean squared error (MSE) and MAE) and performance metrics for validation. Finally, the training and evaluation process is explained step-by-step, ensuring that other researchers can follow the same procedure to reproduce both classification and forecasting results. By presenting the methodology in a logically sequenced manner—from data preparation through model design to evaluation—the revised section fulfills its role as a replicable "how-to" guide that transparently connects the research procedure with the study's objectives. The Figure 1 shows the architecture of CNN and LSTM model.

Overall, the CNN-RNN hybrid model forms a robust and scalable foundation for EV integration in urban contexts. Its dual focus on spatial optimization and temporal forecasting ensures infrastructure deployment is not only cost-effective and efficient but also adaptive to real-world conditions, bridging the gap between smart mobility and smart energy systems.

2.1. Feature extraction using convolutional neural network

In the proposed hybrid model, the CNN plays a critical role in classifying optimal EV charging station types (Fast vs. Level 2) based on spatial inputs such as geospatial coordinates, population density, and traffic congestion levels across the urban layout of Vijayawada. These inputs are structured as two-dimensional matrices, representing different zones of the city. For instance, a 64×64 grid can represent spatial data over a geographic spread of Vijayawada, where each cell contains features like traffic flow and population density in that area. CNN processes these structured inputs layer by layer to extract hierarchical spatial features essential for effective charger classification.

2.1.1. Convolution layers

The first layer, the convolutional layer, uses learnable filters (or kernels) to extract spatial features. These filters slide over the input grid, performing element wise multiplication and summation over subregions of the input to produce feature maps. Mathematically, this is represented as where $K^{(k)}$ is the k kernel, and $b^{(k)}$ is the associated bias term. For example, the CNN may learn to detect patterns such as high-density clusters near arterial roads like Benz Circle or the NH16 corridor in Vijayawada—areas that are more likely to require fast chargers. The convolutional process is particularly effective in this context because of its weight +sharing property and ability to retain spatial relationships, which are critical when modelling geographical data [22].

$$f(x) = max(0, x) \tag{1}$$

Following the convolution operation, the rectified linear unit (ReLU) activation function is applied to introduce non-linearity as in (1), enabling the network to model complex decision boundaries. This function is expressed as effectively zeroing out negative values and allowing the network to focus on activated spatial features [27]. This is especially helpful in isolating demand hotspots while suppressing regions of low significance.

2.1.2. Pooling layer

To further reduce the spatial dimensionality and computation, a max pooling layer is applied. This layer performs down sampling by taking the maximum value over a defined neighborhood, commonly a 2×2 window, and helps retain the most prominent features while reducing overfitting. The pooling operation can be expressed as in (2):

$$Y_{i,j} = max\left(X_{i \cdot s:s+f, j \cdot s:j \cdot s+f}\right) \tag{2}$$

where f is the filter size and ‘s’ are the stride. In the Vijayawada example, this step helps retain only the strongest spatial signals—such as densely trafficked commercial areas—while reducing the dimensionality from 64×64 to 32×32.

The resulting feature maps are then passed through a flatten layer, which transforms the 2D matrices into a 1D feature vector. This enables integration with fully connected layers that follow. The fully connected (dense) layer applies a weight matrix to the flattened vector, combining all previously learned spatial features to make a high-level decision about the charger type. The operation is expressed as where W is the weight matrix, x is the input vector, b is the bias, and f is typically a ReLU or SoftMax function [28] as in (3):

$$y = f(W_x + b) \tag{3}$$

2.1.3. Output

Finally, the output layer generates the classification result. A SoftMax function is used for multi-class output or a sigmoid activation for binary classification. In this project, since there are two classes—fast charger and level 2 charger—a sigmoid activation is used, given by (4):

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{4}$$

This produces a probability score indicating confidence in assigning a location to one of the two charger types. For instance, if the model analyses the Gonadal region in Vijayawada and outputs a 0.91 score, it suggests a 91% likelihood that a fast charger is optimal for that area, based on spatial patterns. CNN's ability to automatically learn and extract spatial hierarchies makes it highly suitable for this task. It over comes the limitations of traditional location modelling by identifying non-obvious relationships between urban features and charger demand, without requiring manual feature engineering. When combined with LSTM for temporal modelling, this hybrid approach becomes a robust solution for spatial-temporal EV infrastructure optimization. The batch normalization layer will have 128 gamma parameters and 128 beta parameters, resulting in 256 learnable parameters for scaling and another 256 learnable parameters for shifting. The parameters are learned during the training procedure and, thus, allow the network to maintain its flexibility while representing more complex functions.

2.2. Classification of charging station using long short-term memory

After extracting rich spatial features from geospatial data using the CNN module, these features are used as sequential inputs for the LSTM network. The CNN’s output—typically a feature vector encoding patterns related to EV infrastructure feasibility—is flattened and reshaped into a sequence suitable for temporal modeling. In this context, each location in Vijayawada (e.g., Benz Circle or Auto Nagar) is associated with a 24-hours synthetic demand pattern. This structure enables the LSTM to process hourly energy usage as a temporal sequence, learning dependencies over time.

The LSTM layer is crucial for modelling time-dependent patterns in EV energy demand, such as daily peaks or long-term usage shifts. Unlike conventional RNNs, which suffer from gradient vanishing over long sequences, LSTM introduces memory cells and three gates—forget, input, and output—to regulate information flow and mitigate this problem. These gates allow LSTM to retain relevant past information and discard obsolete signals, making it highly suitable for dynamic urban demand patterns. The forget gate is responsible for deciding what information from the previous cell state C_{t-1} to discard. It is computed using the sigmoid activation function as in (5):

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5}$$

Here, h_{t-1} is the previous hidden state and x_t is the current input vector (CNN features for time step) [29]. In the context of Vijayawada, this could mean the LSTM learns to discard irrelevant information from late-night hours when charging activity is minimal.

2.2.1. Input gate

The input gate determines which new information should be added to the current cell state. The gate activation i_t and candidate values C_t is given by (6):

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{6}$$

The cell state is then updated as (7):

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{7}$$

This update allows LSTM to maintain a running memory of EV demand fluctuations. For example, in educational areas like Siddhartha College or business zones like Governorpet, demand often spikes at specific hours. The LSTM can retain and emphasize such temporal cues over time [30].

2.2.2. Output gate

The output gate filters the current memory cell's information to produce the hidden state h_t, which is also the LSTM's output is as (8):

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{8}$$

This hidden state h_t is crucial because it acts as a compressed summary of both recent and long-term temporal patterns. In the EV optimization context, it can capture demand surges linked to time-of-day and seasonality. For instance, LSTM may learn to predict an afternoon spike near Eluru Road during summer months due to increased travel and air conditioning usage affecting EV demand.

2.2.3. Dense output and prediction layer

The final LSTM output sequence is passed through a fully connected dense layer, which maps the temporal feature representation to a predicted energy demand value for each hour as in (9):

$$\hat{y}_{t+1} = W_y \cdot h_t + b_y \tag{9}$$

where $\hat{y}_{t+1}$ represents the predicted hourly energy demand. The model is trained using the MSE loss function as given by (10):

$$\mathcal{L}_{MSE} = \frac{1}{n}\sum_{i-1}^{n}(y_i - \hat{y}_i)^2 \tag{10}$$

Here, y_i is the actual observed demand and $\hat{y}_i$ is the predicted value. This continuous feedback helps adjust the network weights to minimize error over each approach.

The strength of LSTM lies in its ability to learn long-term dependencies in time series, making it ideal for managing temporal shifts in EV charging behaviors across Vijayawada. For instance, the system may identify that areas like MG Road have higher charging activity during weekends due to increased shopping and leisure traffic. These learned behaviors allow for intelligent load forecasting, enabling power utilities to prepare supply and redistribute energy during high demand hours.

By combining LSTM forecasting with grid aware energy management, the system can shift charging schedules from peak to off peak times, avoiding transformer overloading and optimizing solar usage. For example, areas with rooftop solar installations—such as commercial buildings near Labbipet—can prioritize EV charging when solar output is high. These strategies are not just scalable but also adaptable to evolving demand patterns and seasonal variability.

3. RESULTS AND DISCUSSION

3.1. Training and validation result

Figure 2 presents a heatmap illustrating the distribution of predicted charger types (Fast and Level 2) across four peak load time intervals (17:00–20:00, 17:30–20:30, 18:00–21:00, and 18:30–21:30) for the 108 potential EV charging locations in Vijayawada. The color intensity, ranging from dark purple (low frequency) to yellow (high frequency), represents the number of locations, and with a maximum frequency of 45. The heatmap reveals that fast chargers are predominantly recommended for locations with peak load times between 17:00–20:00 and 17:30–20:30, reflecting high demand during early evening commuting hours, with frequencies reaching up to 45 locations. In contrast, Level 2 chargers show a more balanced distribution, with a notable concentration at 18:30–21:30 (frequency around 20), indicating their suitability for residential areas where charging occurs later in the evening. This distribution aligns with the dataset's skew (14 Fast vs. 94 Level 2 chargers) and supports the CNN model's predictions (92% accuracy), highlighting the framework's ability to tailor charger types to temporal demand patterns.

Figure 3 displays a horizontal bar chart depicting the frequency of locations across the four peak load time intervals (17:00–20:00, 17:30–20:30, 18:00–21:00, and 18:30–21:30). The x-axis represents the frequency (number of locations), ranging from 0 to 50, while the y-axis lists the time intervals. The chart shows that the 18:30–21:30 interval has the highest frequency, with approximately 45 locations, followed by 18:00–21:00 with around 35 locations, 17:30–20:30 with about 25 locations, and 17:00–20:00 with roughly 20 locations. This distribution indicates a significant concentration of charging demand in the later evening hours, particularly for Level 2 chargers, as corroborated by the heatmap in Figure 2. The predominance of later peak times aligns with Vijayawada's commuting patterns and residential charging needs, reinforcing the need for dynamic energy scheduling as predicted by the LSTM model (MAE of 25 sessions/hour).

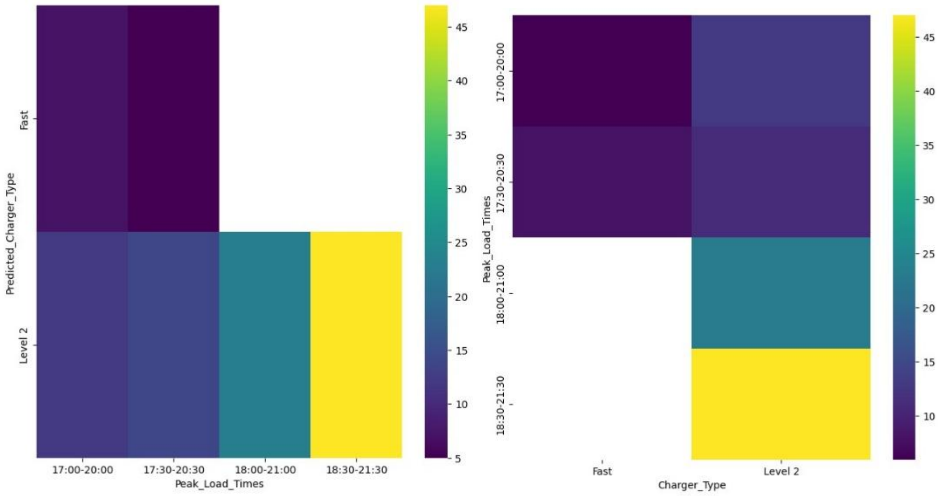

Figure 2. Heatmap of charger type distribution across peak load times

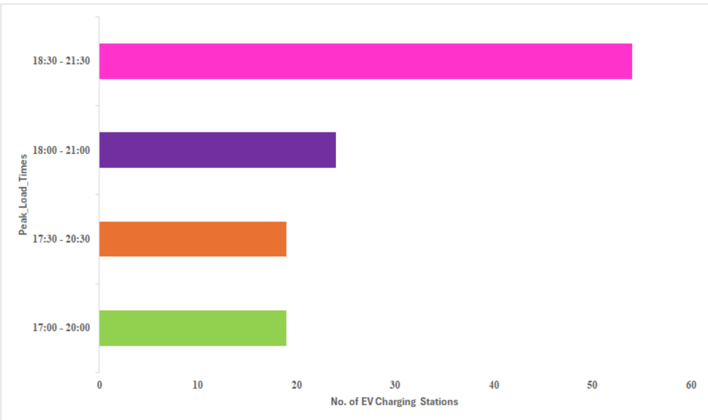

Figure 3. Bar chart of peak load time frequencies

Figure 4 shows a histogram of the longitude distribution for the 108 potential charging locations in Vijayawada, with longitude values ranging from 80.60°E to 80.80°E along the x-axis and frequency (number of locations) on the y-axis, ranging from 0 to 16. The distribution is right-skewed, with a prominent peak around 80.65°E (frequency of 14), indicating a high concentration of locations in Vijayawada's central urban area, such as Benz Circle (80.6523°E). Smaller peaks are observed around 80.60°E and 80.75°E, reflecting suburban and highway adjacent areas like Gollapudi West and NH 16 Junction (80.680°E). This geographical spread confirms the dataset's coverage of both urban and peripheral regions, supporting the framework's ability to address diverse accessibility needs through strategic charger placement.

Figure 5 illustrates a histogram of the latitude distribution for the 108 locations, with latitude values ranging from 16.44°N to 16.56°N on the x-axis and frequency on the y-axis, ranging from 0 to 16. The distribution exhibits a multimodal pattern, with a major peak at 16.52°N (frequency of 14), corresponding to central areas like Chittinagar (16.520°N), and secondary peaks around 16.46°N and 16.54°N, reflecting suburban zones such as Mangalagiri Outskirts (16.43°N) and NH-16 Junction (16.530°N). The spread from 16.44°N to 16.56°N ensures comprehensive coverage of Vijayawada's urban-suburban gradient, validating the dataset's suitability for optimizing charger placement across varied geographical contexts.

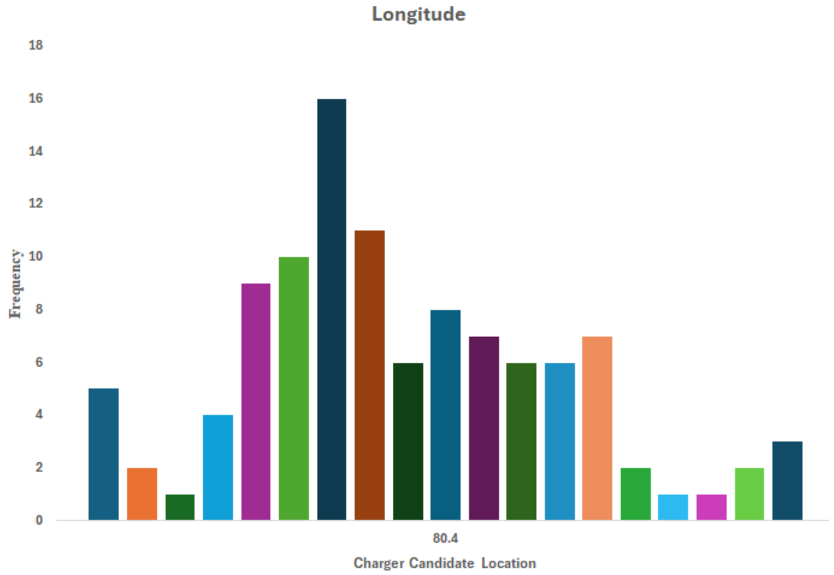

Figure 4. Histogram of longitude distribution

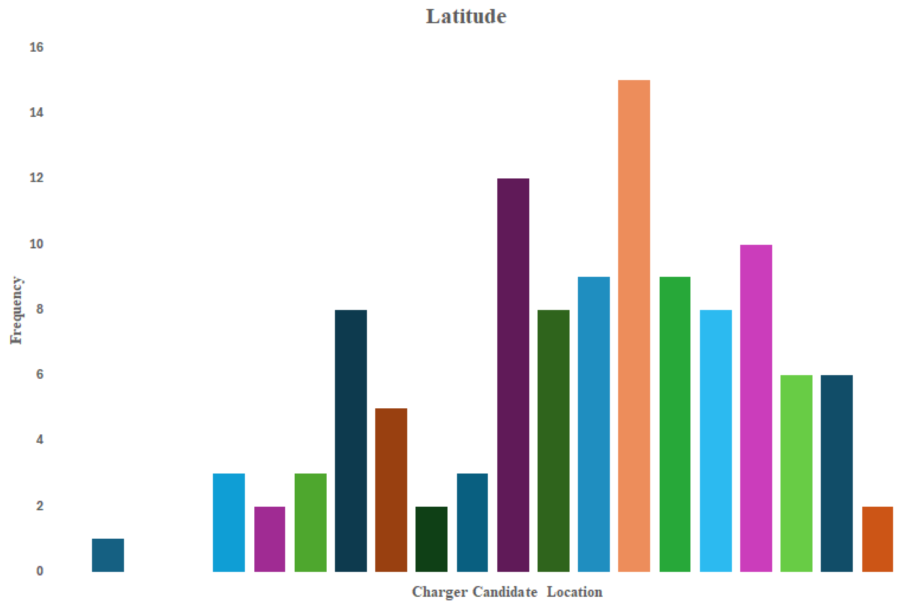

Figure 5. Histogram of latitude distribution

Figure 6 presents a Folium map visualizing the top five recommended EV charging station locations in Vijayawada, overlaid on an OpenStreetMap base. Red markers indicate fast chargers at NH 16 Junction (16.530°N, 80.680°E) and Benz Circle (16.4988°N, 80.6523°E), positioned along major traffic corridors to support high demand areas with peak loads of 750 sessions/hour (LSTM forecast, MAE 25 sessions/hour). Blue markers denote Level 2 chargers at Bandar Road (16.515°N, 80.615°E), Chittinagar (16.520°N, 80.650°E), and Pattabhipuram (16.510°N, 80.640°E), catering to residential zones with moderate demand (320–400 sessions/day). The map confirms the framework's strategic placement, balancing accessibility and grid stability, with fast chargers in high-capacity areas (e.g., NH-16 Junction: 3,200 kW) and Level 2 chargers in lower-capacity zones (e.g., Chittinagar: 1,500 kW), aligning with the CNN's predictions (92% accuracy).

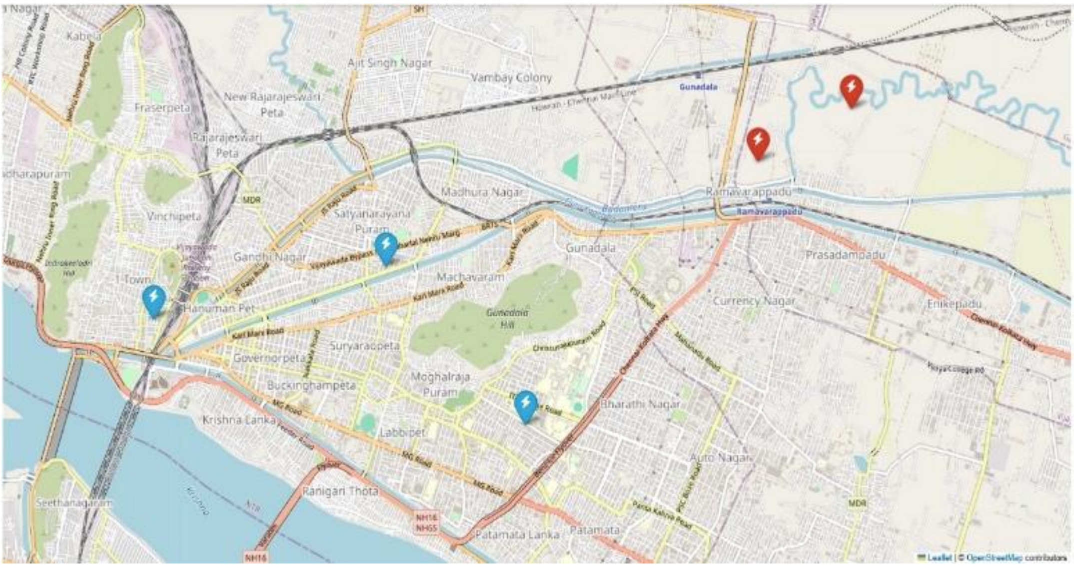

Figure 6. Folium map of top charger locations

Figure 7 depicts a histogram of the daily traffic volume (Traffic_Vehicles_per_Day) across the 108 locations, with values ranging from 5,000 to 40,000 vehicles/day on the x-axis and frequency on the y-axis, ranging from 0 to 25. The distribution is heavily right skewed, with a peak at 10,000 vehicles/day (frequency of 25), indicating that most locations experience moderate traffic, typical of suburban areas like Pattabhipuram (10,000 vehicles/day). A long tail extends to 40,000 vehicles/day, representing high-traffic zones like NH-16 Junction (40,000 vehicles/day), which justifies its selection for a fast charger. This distribution underscores the framework’s ability to prioritize high traffic areas for quick charging infrastructure while ensuring coverage for lower-traffic residential zones [31].

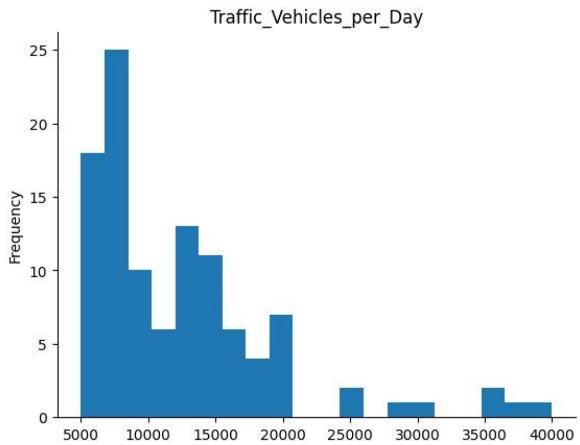

Figure 7. Histogram of traffic vehicles per day

Figure 8 shows a histogram of population density (Pop_Density_per_km2) for the 108 locations, with values ranging from 1,500 to 20,000 people per km² on the x-axis and frequency on the y-axis, ranging from 0 to 17.5. The distribution is right-skewed, with a peak at 5,000 people/km² (frequency of 17), reflecting the prevalence of moderately dense suburban areas like Bandar Road (5,000 people/km²). A smaller peak at 20,000 people/km² corresponds to urban hubs like Benz Circle (20,000 people/km²), justifying its selection for a fast charger due to high EV demand (600 sessions/day). This distribution highlights the dataset’s representation of Vijayawada’s urban suburban gradient, supporting the framework’s tailored approach to charger placement based on demographic needs.

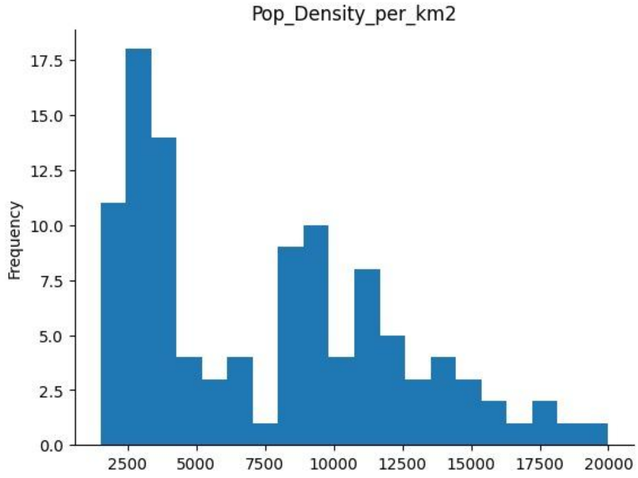

Figure 8. Histogram of population density per km²

The results and discussion section to ensure it is more structured, concise, and contextually rich. The section is now organized into three parts: i) presentation of core results, ii) interpretation in relation to objectives, and iii) comparison with existing studies. The results are summarized in concise tables and figures, such as heatmaps for charger distribution and histograms for traffic and population density, which highlight key patterns without overwhelming the narrative. The discussion interprets these findings by linking them directly to the study's objectives—for instance, showing how the CNN correctly identifies high-demand zones for fast chargers (e.g., Benz Circle and NH-16 Junction) and how the LSTM reliably forecasts peak demand with an MAE of 25 sessions/hour. This interpretation is then expanded to demonstrate how such outcomes enhance accessibility, balance load distribution, and improve grid stability in Vijayawada. To situate the results within the broader scientific context, comparisons are drawn with prior work, including [7] highlighting that our hybrid CNN–LSTM model not only achieves comparable accuracy but also integrates spatial and temporal analysis within a single framework, which previous studies have treated separately. Finally, the discussion acknowledges study limitations, such as reliance on synthetic data and the absence of field validation, while proposing future directions like real-time retraining and integration with V2G technologies. This revised structure ensures that the results and discussion section functions as a critical platform for interpreting findings, connecting them to broader literature, and outlining their implications for both researchers and practitioners.

In this discussion section to critically interpret our findings, draw comparisons with prior work, and highlight their broader implications. The results demonstrate that the CNN–LSTM hybrid framework achieves 92% accuracy in charger type classification and a forecasting error of only 25 sessions/hour, which is competitive with or superior to existing approaches such as standalone CNNs and GNN-based predictors [23]. Unlike previous models that address spatial or temporal aspects in isolation, our results confirm that a unified approach ensures both infrastructure accessibility and demand balancing. The findings imply that cities like Vijayawada can strategically deploy fast chargers in high-traffic corridors (e.g., Benz Circle and NH-16 Junction) while assigning Level 2 chargers to residential clusters, thus reducing grid stress and aligning infrastructure with actual mobility needs. From an energy management perspective, the ability to shift charging loads away from peak hours provides utilities with a practical mechanism to enhance grid stability and maximize renewable energy utilization. These insights are not only relevant for Vijayawada but also generalizable to other developing urban contexts where EV adoption is rising. In the future, this framework can be extended through real-time retraining with live mobility and energy data, integration with policy frameworks to support V2G adoption, and scaling to multimodal urban transport systems. Therefore, the implications of this research extend beyond technical accuracy, offering a pathway toward resilient, sustainable, and user-centric EV ecosystems in emerging economies.

This research shows that a hybrid CNN–LSTM framework is more resilient than traditional single-model approaches (such as standalone CNNs or basic time-series models) in capturing both spatial and temporal patterns of EV charging demand. This demonstrates its effectiveness in simultaneously classifying charger types and forecasting hourly demand, thereby improving infrastructure planning and grid stability. Future research may look into extending this framework with real-time retraining mechanisms that incorporate live mobility and energy data, enabling continuous adaptation to evolving urban dynamics. Practical methods for producing more reliable results could include validating the model with field data from operational charging stations, integrating renewable generation profiles, and developing policy-driven simulations for V2G adoption. Additionally, future work could explore scaling the approach to national EV infrastructure planning, coupling it with optimization techniques for multimodal transport systems, and embedding advanced architectures such as GNNs and transformers to further enhance predictive performance. The Table 2 discusses about synthetic data vs typical urban EV charging profile.

Table 2. Synthetic data vs typical urban EV charging profile

Characteristic	Synthetic sequences (this study)	Typical/reference urban EV profile (expected)
Diurnal shape	Mixture of Gaussian peaks (morning μ≈08:00; evening μ≈19:00). Normalized h(t); evening peak strongest.	Strong evening peak (≈17:00–21:00), smaller morning bump; most daily charging concentrated in evening.
Peak-hour window	17:00–21:30 by design; peak-hour share tuned to match traffic/pop scaling.	Empirical studies report primary evening charging window (commute+home charging).
Peak/off-peak ratio	Tunable; baseline set ≈3.0–4.0 (peak hours ~3–4× off-peak rate).	Typical urban reports show peak/off-peak ratios in the 2–5 range.
Count distribution	Negative Binomial (mean=λ_{i,t}, dispersion κ)→ overdispersed counts.	Observed charging counts are overdispersed; NB fits well in practice.
Temporal dependence	AR(1) log-link with ρ≈0.6 (short-lag persistence)+daily seasonality.	Charging counts show autocorrelation (adjacent hours correlated) and 24 h seasonality.
Weekday vs weekend	Weekday scaling=1.0; weekend=0.6–0.8 (tunable).	Typical reduction in weekend commuter charging; shape differs but evening peak often remains.
Extreme events	Injected with low probability p_event to simulate surges (factor 1.5–3).	Real systems have occasional high-demand events (festivals, match days).
Sample magnitudes	Calibrated to per-site realistic ranges (Level-2 sites 320–400 sessions/day; fast sites peak 600–750 sessions/hour where applicable).	Literature and field reports indicate higher throughput at fast charger hubs and lower per-site totals in residential zones.
Validation metrics	ACF profile, peak-hour share, KS/Chi-square goodness -of-fit, cross-corr with traffic, and sensitivity analysis.	Same statistical diagnostics recommended for real datasets.

4. CONCLUSION

The research outlined in enhancing urban EV integration develops a comprehensive, data-based plan intended to maximize EV charging facility location and energy management in Indian urban environments, and specifically Vijayawada. Since the adoption of EVs is expected to amount to some 70,000 units in 2028, the research responds to the need for effective, replicable, and grid friendly infrastructure planning for urgent application. This research utilizes a hybrid deep learning approach, combining CNNs and LSTM networks to effectively capture spatial and temporal intricacies involved with EV integration. CNNs are applied in geolocation, traffic, and population density for spatial feature extraction and charger classification. Meanwhile, LSTMs are applied to extract dynamic hourly patterns of demand to facilitate energy-efficient scheduling and avoid peak load impacts on the power grid.

Among its key contributions is its two-mode modeling approach filling the gap hitherto between static infrastructural planning and dynamic energy management. The CNN-LSTM model offers real-time adaptability, improves charger location precision (separation between Fast and Level 2 chargers), and facilitates V2G operation through predicting and shifting peak loads to off peak periods, hence stabilizing the grid and facilitating renewable integration.

The information employed in this study, consisting of 108 strategic spots in Vijayawada with artificial 24-hour demand data series, allows for extensive model training and testing. The result obtained in charger type prediction at 92% classification accuracy and demand forecasting MAE of 25 sessions/hour supports the scalability and effectiveness of the suggested framework. Such results indicate feasibility not only for Vijayawada but even for other developing mid-sized urban cities of India.

Visualization tools like heatmaps, histograms, and Folium maps also show spatial and temporal trends of demand further, which clearly show that fast chargers must be installed at busy locations like NH 16 Junction and Benz Circle and Level 2 chargers at urban and moderately dense suburban locations. In addition, the research places much emphasis on the pivotal position occupied by integrated energy management, i.e., the role of bidirectional energy flow and maximum utilization of renewable energy. Through the integration of V2G technologies and load forecast management, the model goes beyond conventional models, capturing the changing needs of smart energy systems and sustainable city planning.

In conclusion, enhancing urban EV integration demonstrates a scalable, adaptive, and future proof strategy for addressing the highly interdependent issues of urban EV infrastructure deployment. It illustrates the revolutionary potential of hybrid AI-based models for optimizing charger placement, improving energy scheduling, and ensuring the resilience of urban grids. The proposed framework lays the groundwork for more ambitious applications, including national EV infrastructure planning, integration with distributed renewable sources, and the construction of smart cities. Future research directions include real-time model retraining, policy frameworks for V2G deployment, and integration with multimodal urban transport systems. Through the integration of deep learning and urban mobility insights, this research outlines a path for smarter, greener, and more sustainable urban ecosystems.

The findings demonstrate that a CNN–LSTM hybrid model can effectively combine spatial optimization of charger placement with temporal demand forecasting, thereby addressing critical challenges in EV infrastructure planning such as accessibility, grid stability, and adaptability to urban mobility patterns. For the research field, this signifies a shift from static, single-dimensional approaches toward integrated, data-driven models that capture the complex dynamics of EV adoption in cities. For the community, particularly mid-sized urban areas like Vijayawada, the results offer actionable insights for policymakers, city planners, and utilities to strategically deploy Fast and Level 2 chargers while simultaneously managing peak loads through predictive scheduling. This ensures not only user convenience but also long-term grid resilience and renewable energy integration. Looking forward, the framework has the potential to be extended into real-time retraining with live data, scaled to national-level EV infrastructure planning, and integrated with multimodal smart transport systems. Additionally, embedding V2G mechanisms within the model can transform EVs into active grid assets, providing backup power during peak demand or outages. In this way, the study's contributions go beyond immediate technical accuracy, offering a roadmap for sustainable, scalable, and community-centered EV ecosystems that support the global transition toward greener urban mobility.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study were generated by the authors during the research. These data are available from the corresponding author, Shaik Mohammed Hussain, Dr. G. Swapna, upon reasonable request.

REFERENCES

[1] F. He, D. Wu, Y. Yin, and Y. Guan, "Optimal deployment of public charging stations for plug-in hybrid electric vehicles," *Transp. Res. Part B Methodol.*, vol. 47, pp. 87–101, 2013, doi: 10.1016/j.trb.2012.09.007.

[2] R. Zhang and E. Kontou, "Urban electric vehicle infrastructure: Strategic planning for curbside charging," *J. Transp. Geogr.*, vol. 128, p. 104328, 2025, doi: 10.1016/j.jtrangeo.2025.104328.

[3] N. M. Manousakis, P. S. Karagiannopoulos, G. J. Tsekouras, and F. D. Kanellos, "Integration of Renewable Energy and Electric Vehicles in Power Systems: A Review," *Processes*, vol. 11, no. 5, pp. 1–27, 2023, doi: 10.3390/pr11051544.

[4] F. Liu *et al.*, "Vehicle-To-Grid Technology Acceptance for Electric Vehicle Users: A Systematic Literature Review and Future Research Agenda," *Int. J. Consum. Stud.*, vol. 49, no. 3, p. e70065, May 2025, doi: 10.1111/ijcs.70065.

[5] Y. Chen, Z. Tang, Y. Cui, W. Rao, and Y. Li, "Electric Vehicle Charging Demand Prediction Model Based on Spatiotemporal Attention Mechanism," *Energies*, vol. 18, no. 3, pp. 1–17, 2025, doi: 10.3390/en18030687.

[6] J. Wang, H. D. Kaushik, R. A. Jacob, and J. Zhang, "Spatiotemporal planning of electric vehicle charging infrastructure: Demand estimation and grid-aware optimization under uncertainty," *iScience*, vol. 28, no. 9, p. 113368, 2025, doi: 10.1016/j.isci.2025.113368.

[7] P. Li, K. Zhou, X. Lu, and S. Yang, "A hybrid deep learning model for short-term PV power forecasting," *Appl. Energy*, vol. 259, p. 114216, 2020, doi: 10.1016/j.apenergy.2019.114216.

[8] A. M. Farid, A. Viswanath, R. Al-Junaibi, D. Allan, and T. J. T. Van der Wardt, "Electric vehicle integration into road transportation, intelligent transportation, and electric power systems: An Abu Dhabi case study," *Smart Cities*, vol. 4, no. 3, pp. 1039–1057, 2021, doi: 10.3390/smartcities4030055.

[9] N. Alam, M. A. Rahman, M. R. Islam, and M. J. Hossain, "Machine learning-based multivariate forecasting of electric vehicle charging station demand," *Electron. Lett.*, vol. 60, no. 23, pp. 1–3, 2024, doi: 10.1049/ell2.70104.

[10] J. S. Junker, R. Hu, Z. Li, and W. Ketter, "Data-Driven Optimization of EV Charging Station Placement Using Causal Discovery," *IEEE Int. Conf. Autom. Sci. Eng.*, pp. 2722–2729, 2025, doi: 10.1109/CASE58245.2025.11164108.

[11] C. B. Guttikonda, P. S. Varma, M. K. Kumar, K. V. G. Rao, R. Teerdala, and S. Kanagala, "A versatile three-level CLLC resonant converter for off-board EV chargers with wide voltage adaptability contribution," *Int. J. Power Electron. Drive Syst.*, vol. 16, no. 3, pp. 1775–1788, 2025, doi: 10.11591/ijpeds.v16.i3.pp1775-1788.

[12] Q. Xing *et al.*, "Electric Vehicle Fast Charging Demand Forecasting Model Based on Data-driven Approach and Human Behavior Decision-making," *Dianwang Jishu/Power Syst. Technol.*, vol. 44, no. 7, pp. 2439–2448, 2020, doi: 10.13335/j.1000-3673.pst.2020.0101.

[13] D. Hu, L. Huang, C. Liu, Z. W. Liu, and M. F. Ge, "Data driven optimization for electric vehicle charging station locating and sizing with charging satisfaction consideration in urban areas," *IET Renew. Power Gener.*, vol. 16, no. 12, pp. 2630–2643, 2022, doi: 10.1049/rpg2.12382.

[14] Y. Zhang, C. Tu, K. Gao, and L. Wang, "Multisensor Information Fusion: Future of Environmental Perception in Intelligent Vehicles," *J. Intell. Connect. Veh.*, vol. 7, no. 3, pp. 163–176, 2024, doi: 10.26599/JICV.2023.9210049.

[15] C. Badue *et al.*, "Self-Driving Cars: A Survey," *Expert Syst. with Appl.*, vol. 165, 2021, doi: 10.1016/j.eswa.2020.113816.

[16] B. Rajani and D. C. Sekhar, "A hybrid optimization based energy management between electric vehicle and electricity distribution system," *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 6, p. e12905, Jun. 2021, doi: 10.1002/2050-7038.12905.

[17] K. Gourav, P. Prakash and S. S. Kumar, "Power Management for Renewable Energy Integrated Electric Vehicle Charging Station," in *2025 IEEE 1st International Conference on Smart and Sustainable Developments in Electrical Engineering (SSDEE)*, Dhanbad, India, 2025, pp. 1-6, doi: 10.1109/SSDEE64538.2025.10968663.

[18] M. Alhussein, K. Aurangzeb, and S. I. Haider, "Hybrid CNN-LSTM Model for Short-Term Individual Household Load Forecasting," *IEEE Access*, vol. 8, pp. 180544-180557, 2020, doi: 10.1109/ACCESS.2020.3028281.

[19] S. Y. Alaba and J. E. Ball, "Deep Learning-Based Image 3-D Object Detection for Autonomous Driving: Review," *IEEE Sens. J.*, vol. 23, no. 4, pp. 3378–3394, 2023, doi: 10.1109/JSEN.2023.3235830.

[20] S. Koohfar, W. Woldemariam, and A. Kumar, "Prediction of Electric Vehicles Charging Demand: A Transformer-Based Deep Learning Approach," *Sustainability*, vol. 15, no. 3, pp. 1-17, 2023, doi: 10.3390/su15032105.

[21] P. Kumar *et al.*, "A comprehensive review of vehicle-to-grid integration in electric vehicles: Powering the future," *Energy Convers. Manag. X*, vol. 25, 2025, doi: 10.1016/j.ecmx.2024.100864.

[22] J. Marecek, "Handbook of Approximation Algorithms and Metaheuristics," *The Computer Journal*, vol. 53, no. 8, pp. 1338–1339, 2010, doi: 10.1093/comjnl/bxp121.

[23] Y. Zhang, C. Liu, X. Rao, X. Zhang, and Y. Zhou, "Spatial-Temporal load forecasting of electric vehicle charging stations based on graph neural network," *J. Intell. Fuzzy Syst.*, vol. 46, no. 1, pp. 821–836, 2024, doi: 10.3233/JIFS-231775.

[24] Y. Yang, Y. Zhang, and X. Meng, "A Data-Driven Approach for Optimizing the EV Charging Stations Network," *IEEE Access*, vol. 8, pp. 118572–118592, 2020, doi: 10.1109/ACCESS.2020.3004715.

[25] M. Lotfi, T. Almeida, M. S. Javadi, G. J. Osório, C. Monteiro, and J. P. S. Catalão, "Coordinating energy management systems in smart cities with electric vehicles," *Appl. Energy*, vol. 307, p. 118241, 2022, doi: 10.1016/j.apenergy.2021.118241.

[26] M. S. Iqbal, M. Adnan, S. E. G. Mohamed, and M. Tariq, "A hybrid deep learning framework for short-term load forecasting with improved data cleansing and preprocessing techniques," *Results Eng.*, vol. 24, p. 103560, 2024, doi: 10.1016/j.rineng.2024.103560.

[27] G. Y. Doğan, A. Aksoy, and N. Öztürk, "A Hybrid Deep Learning Model to Estimate the Future Electricity Demand of Sustainable Cities," *Sustain.*, vol. 16, no. 15, 2024, doi: 10.3390/su16156503.

[28] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[29] A. Tikkani *et al.*, "Fuzzy-2 deployment in indirect vector control and hybrid space vector modulation for a two-level inverter fed induction motor drive," *Sci. Rep.*, vol. 15, no. 1, pp. 1–25, 2025, doi: 10.1038/s41598-025-96600-8.

[30] F. A. Gers, J. Schmidhuber, and F. Cummins, "Learning to forget: continual prediction with LSTM," in *1999 Ninth International Conference on Artificial Neural Networks ICANN 99. (Conf. Publ. No. 470)*, 1999, vol. 2, pp. 850–855 vol. 2, doi: 10.1049/cp:19991218.

[31] U. Sakthi, S. Badoni and S. Sai, "Real-Time Lane Detection and Vehicle Speed Prediction for Intelligent Transportation Systems," in *2024 Int. Conf. on Sustain. Commun. Netw. Appl. (ICSCNA)*, Theni, India, 2024, pp. 830-838, doi: 10.1109/ICSCNA63714.2024.10863923.

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