Optimizing Electric Vehicle Energy Management Systems with a Hybrid LSTM-CNN Architecture

Ashish K Saxena

https://orcid.org/0009-0002-1647-9266

Prativa Pant Mishra

PhD in Information Technology Class of 2025 University of The Cumberlands

ABSTRACT

This study explores the integration of Electric Vehicles (EVs) into the global transportation network, emphasizing the role of advanced Energy Management Systems (EMS) in enhancing the efficiency, reliability, and sustainability of EVs. Despite significant strides in predictive modeling for energy consumption, current methodologies face challenges such as handling high-dimensional data and adapting to dynamic urban traffic conditions. To address these limitations, this research introduces a novel hybrid Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architecture designed to optimize energy consumption predictions by integrating both temporal and spatial data analyses. The proposed model demonstrates predictive superiority over existing models, validated through extensive experimentation with the comprehensive EV Energy Consumption and Speed Profiles Dataset (EVECS). This paper not only contributes to advancing predictive modeling capabilities within smart transportation systems but also lays the groundwork for future innovations in the sustainable integration of EVs into smart cities.

Keywords: CNN, Electric Vehicles, Energy Management Systems, LSTM, Predictive Modeling

I. INTRODUCTION

Electric vehicles (EVs) are rapidly becoming a significant part of the global transportation matrix, promising a more sustainable future. Central to their integration into smart cities and the reduction of the carbon footprint is the effective management of energy [1], [2]. The efficiency and reliability of EVs hinge on advanced Energy Management Systems (EMS) capable of optimizing energy consumption in real-time. Current methodologies, such as models that exclusively utilize Long Short-Term Memory (LSTM) networks or those combining LSTM with Gated Recurrent Units (GRU), have made considerable strides in predicting energy usage patterns [3]–[8]. However, these methods grapple with challenges such as high-dimensional data processing and the dynamic nature of urban traffic, often leading to less than optimal predictive performance.

Recent advancements in predictive modeling have significantly contributed to our understanding and capabilities in energy management. Notably, methodologies employing Long Short-Term Memory (LSTM) networks and those that harness the combined strengths of LSTM with Gated Recurrent Units (GRU) have marked considerable progress in forecasting energy usage patterns. Despite these advancements, such methods face inherent challenges, including the processing of high-dimensional data and adapting to the dynamic nature of urban traffic flows, which often compromise the predictive performance of these models. Studies such as Rajagukguk et al. [9] have underscored the efficacy of LSTM standalone models in handling time-series data, with hybrid models like CNN-LSTM further enhancing performance by integrating temporal and spatial data analyses. However, the longer training times of hybrid models indicate a trade-off between accuracy and efficiency. Model Predictive Control (MPC) strategies, as explored by Huang et al. [10], have also emerged as a viable approach, emphasizing the importance of prediction accuracy, design parameters, and solvers in optimizing the performance of hybrid electric vehicles (HEVs). In addressing the complexities of EV energy consumption, various strategies have been developed to predict or evaluate energy usage with increasing accuracy. The significance of hybridizing different energy resources to mitigate battery lifecycle degradation and extend the drive range has been discussed in the literature, pointing towards the necessity for innovative energy management techniques [11].

The application of AI techniques, particularly artificial neural networks (ANNs) and support vector machines (SVM), has been extensively reviewed by Ahmad et al. [12], highlighting their utility in forecasting electrical energy consumption with a potential for accuracy in EV energy management. Rahman et al. [13], explore hybrid renewable energy systems, demonstrating how ANNs facilitate precise energy predictions, essential for efficient EV operation. Varga et al. [14], tackle the critical issue of EV range prediction, presenting a comprehensive overview of the current challenges that underscore the complexity of accurate range estimation. Further, Panaparambil et al. [15], [16], examine hybrid source energy management strategies, shedding light on the integration of multiple energy sources to enhance EV performance. Tie and Tan and others [17]–[19], provide a systematic review of power and energy management strategies, emphasizing the need for sophisticated controls to optimize EV energy utilization. Lastly, Mahmud and Town [20], review computer tools for modeling EV energy requirements, highlighting the significance of simulation tools in understanding the impact of EVs on power distribution networks. Collectively, these papers contribute critical insights into the advancement of energy management systems for EVs the ongoing challenge of range prediction in the evolution of smart and efficient electric transportation solutions.

Current methodologies, predominantly based on Long Short-Term Memory (LSTM) networks or combinations of LSTM with Gated Recurrent Units (GRU), exhibit limitations in handling high-dimensional data and adapting to the dynamic nature of urban traffic, affecting predictive performance. Additionally, the extended training times required by hybrid models such as CNN-LSTM indicate a trade-off between accuracy and efficiency. Addressing the gaps identified in existing methodologies, this study proposes the development of a hybrid LSTM-CNN architecture designed to offer a multi-dimensional perspective on energy prediction and management for EVs. By synergizing temporal and spatial data analyses, this model aims to capture the intricate dynamics influencing EV energy consumption more accurately. Through the validation of our approach against existing models, this research not only demonstrates the predictive superiority of the hybrid LSTM-CNN model but also introduces novel datasets and experimental methodologies alongside comprehensive evaluation metrics. The outcome is a robust framework that advances predictive modeling capabilities and fosters innovation in smart transportation systems, thereby contributing to the sustainable evolution of urban mobility and energy management within the context of electric vehicles. The proposed hybrid LSTM-CNN architecture embodies a significant leap forward in enhancing the predictive accuracy of energy management systems, paving the way for future innovations in the realm of smart transportation systems and the sustainable integration of electric vehicles into the smart cities.

II. DEEP LEARNING METHODS

A. LSTM model.

The LSTM (Long Short-Term Memory) network is a type of recurrent neural network (RNN) capable of learning order dependence in sequence prediction problems. This is particularly useful in time series prediction where classical linear models fail to capture temporal dynamics. The detailed architecture of the LSTM model can be mathematically represented as follows:

a. LSTM Unit Architecture

An LSTM unit is composed of a cell (which contains the state of the network at a given time) and three regulating gates—input, output, and forget gates—that control the flow of information into and out of the cell. Let x_t be the input at time step t, and h_{t-1} be the output from the previous LSTM unit, then the LSTM transformations can be described by the following equations:

Forget Gate f_t: This gate decides what information is to be discarded from the cell state. It looks at h_{t-1} and x_t, and outputs a number between 0 and 1 for each number in the cell state C_{t-1}.

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

The input gate decides which values will be updated, and a tanh layer creates a vector of new candidate values, $\tilde{C}_t$, that could be added to the state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

The old cell state C_{t-1} is updated to the new cell state C_t. The previous state is multiplied by f_t, forgetting things we decided to forget earlier. Then we add $i_t * \tilde{C}_t$ for the new candidate values.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

The output gate decides what the next hidden state h_t should be. The hidden state contains information about previous inputs. The hidden state is also used for predictions.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Here, W terms denote weight matrices (e.g., W_f is the weight matrix for the forget gate), b terms denote bias vectors (e.g., b_f is the bias vector for the forget gate), and σ denotes the sigmoid function, which outputs a number between 0 and 1. The sigmoid function σ is defined as:

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{7}$$

The $*$ operator denotes element-wise multiplication. The tanh function outputs a number between -1 and 1 and is defined as:

$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{8}$$

b. Model Configuration

The configuration of the LSTM model, including the number of LSTM units (neurons) in each layer, the number of layers, and the connections between these units, will be tailored to the specific application of energy management in EVs. For instance, a model designed to predict energy consumption over short intervals might have fewer layers and units than one predicting over longer periods.

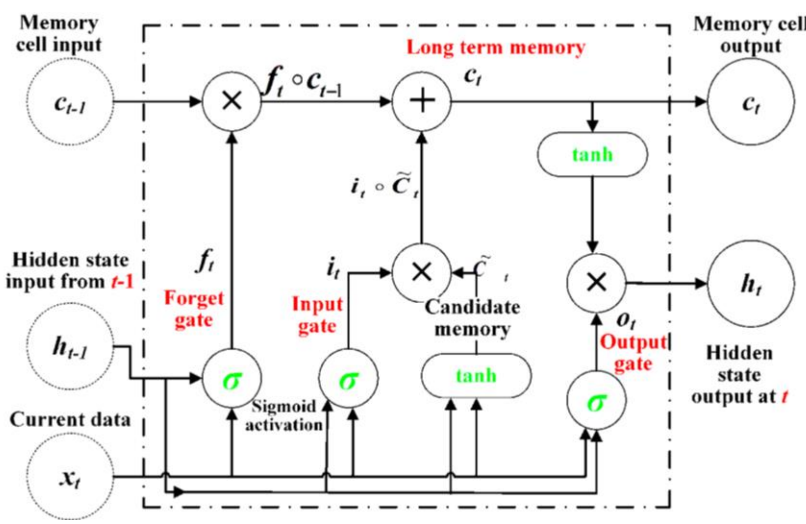


Figure 1. LSTM cell [21]

c. Training the LSTM Model

The model is trained using a set of input-output sequences from historical data, where the aim is to minimize a loss function, typically the Mean Squared Error (MSE) for regression problems. During training, the weights W and biases b of the model are adjusted through backpropagation over time (Backpropagation Through Time, or BPTT) and an optimization algorithm like Adam or RMSprop.

$$MSE = \frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2 \tag{9}$$

Where N is the number of training examples, y_t is the actual value, and $\hat{y}_t$ is the predicted value by the model. The learning rate, a hyper parameter, determines the step size at each iteration while moving toward a minimum of the loss function. The LSTM model's architecture, with its ability to capture both long-term dependencies and avoid the vanishing gradient problem, is uniquely suited for the time-series prediction challenges posed by EV energy management.

B. CNN model.

The Convolutional Neural Network (CNN) is a deep learning architecture widely used for image recognition and processing, which is well-suited to capture two-dimensional spatial information. In the context of energy management for electric vehicles (EVs), a CNN can process spatial data such as geographic maps, traffic heatmaps, or sensor data from the vehicle's surroundings.

a. CNN Architecture

A typical CNN architecture consists of several types of layers: convolutional layers, activation layers (usually ReLU), pooling layers, and fully connected (dense) layers. Below is a detailed breakdown:

This is the core building block of a CNN that does most of the computational heavy lifting. The convolutional layer applies a set of filters (kernels) to the input through a convolutional operation to create a feature map that highlights specific features in the input. For each filter, the convolution operation is defined as:

$$(I * K)(i, j) = \sum_{m} \sum_{n} I(i+m, j+n) K(m, n) \tag{10}$$

where I is the input image, K is the kernel, i and j are the spatial location coordinates on the image, and m and n are the corresponding coordinates on the kernel. After each convolution operation, an activation function is applied to introduce non-linear properties to the system. The Rectified Linear Unit (ReLU) is the most commonly used activation function in CNNs and is defined as:

$$ReLU(x) = \max(0, x) \tag{11}$$

Pooling (also known as subsampling or downsampling) reduces the dimensionality of each feature map while retaining the most important information. Max pooling, one of the most common pooling operations, takes the maximum value over a window of specified size. For example, a 2x2 max pooling operation would be defined as:

$$P(i, j) = \max_{m,n \in [0,1]} I(2i+m, 2j+n) \tag{12}$$

After several convolutional and pooling layers, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular neural networks. These layers are typically placed near the end of CNN architectures. The last fully connected layer often has a softmax activation function for multi-class classification problems, which outputs a probability distribution over the classes.

$$\text{Softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{13}$$

where z represents the input vector to the softmax function, i is the index of the current class, and K is the total number of classes.

The training of a CNN involves using backpropagation and an optimization algorithm such as SGD (Stochastic Gradient Descent), Adam, or RMSprop to minimize a loss function, typically cross-entropy for classification tasks.

$$\text{Cross-Entropy}(y, \hat{y}) = -\sum_{i} y_i \log(\hat{y}_i) \tag{14}$$

where y is the binary indicator (0 or 1) if the class label i is the correct classification, and $\hat{y}$ is the predicted probability of the class label i.

C. Integration

In the context of energy management for electric vehicles (EVs), the integration of Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) models are designed to address the interplay between the temporal dynamics of vehicle energy consumption and the spatial factors influencing it, such as urban environment features and traffic conditions. Through a sequential architecture, this integration effectively processes and analyzes complex, multi-dimensional data for accurate prediction of EV energy needs. Initially, data preprocessing and feature extraction tasks prepare temporal data—historical energy consumption rates, driving speeds, and State of Charge (SoC) levels for the LSTM model, and spatial data—traffic heat maps, road types, and weather conditions, including images or sensor data capturing the vehicle's immediate environment, for the CNN model. The LSTM model then delves into the temporal data sequence to discern patterns in energy usage over time, leveraging its capacity to remember long-term dependencies to forecast future energy needs. Concurrently, the CNN model evaluates spatial data to identify critical environmental factors impacting energy consumption, such as traffic congestion and road gradients. Subsequently, features extracted by both models are amalgamated into a comprehensive feature vector that encapsulates the temporal and spatial dimensions of the EV's energy management challenge. This vector is then utilized in a series of dense layers to predict the EV's forthcoming energy requirements, enabling the determination of optimal energy utilization strategies, including route planning and charging schedules. This integrated approach not only enhances the accuracy of energy predictions but also supports the development of more efficient and reliable energy management systems for EVs, catering to the nuanced demands of smart urban mobility.

III.LSTM-CNN MODEL

This section introduces the architecture of the proposed LSTM-CNN hybrid model and details the experimentation process undertaken to validate its efficacy in managing energy within electric vehicles (EVs).

A. Model Architecture and Training

The LSTM-CNN model architecture is designed to leverage the temporal predictive power of LSTM networks alongside the spatial feature extraction capabilities of CNNs. The LSTM layers are configured to interpret the sequential data, capturing the time-dependent nuances of EV energy usage. These layers help to predict future energy requirements based on past consumption patterns, which are crucial for route planning and battery management. Following the LSTM layers, the CNN layers process the spatial aspects of the data, such as road topology, traffic density, and urban layouts, to contextualize the energy consumption within the physical environment of the EV. The integration of these two networks is expected to produce a composite model that comprehensively understands both time series and spatial data. Caption: Figure Y: Architecture of the LSTM-CNN Hybrid Model for Predictive Energy Management in Electric Vehicles.

The architecture depicted in Figure Y outlines a sophisticated hybrid model combining Long Short-Term Memory (LSTM) networks with Convolutional Neural Network (CNN) layers, tailored for predictive energy management in electric vehicles (EVs). The model harnesses LSTM layers to interpret sequential temporal data, analyzing energy consumption patterns, driving speeds, and battery states of charge (SoC) over time. This temporal analysis is used for predicting future energy demands, thereby aiding in the planning of efficient routes and the scheduling of battery charging. Simultaneously, the CNN layer processes spatial data, such as GPS trajectories, traffic patterns, and information pertaining to urban infrastructure. This layer applies convolutional operations to capture spatial dependencies and contextual features within the physical environment of the EV. The use of a ReLU activation function ensures non-linear transformation, while the pooling layer reduces the dimensionality of the spatial feature maps, emphasizing the most salient features. The combined outputs of the LSTM and CNN layers are then integrated into a cohesive feature vector through a process of feature fusion. This composite vector, carrying rich temporal and spatial information, is passed through successive dense layers—Dense Layer 1 and Dense Layer 2—designed to further synthesize the features and make intricate predictions regarding the EV's energy consumption. The architecture culminates in the final predictive output, offering insights into energy consumption predictions, optimized routing, and charging schedules.

The model's training framework is encapsulated on the right-hand side of the architecture. This framework consists of a feedback loop, where the predicted outcomes are recursively fine-tuned through backpropagation, guided by a predefined loss function and optimized using advanced algorithms. This iterative learning and validation process is critical for refining the model's parameters and enhancing its predictive accuracy, ensuring robustness and reliability in real-world applications. The overall architecture is shown in Figure 2.

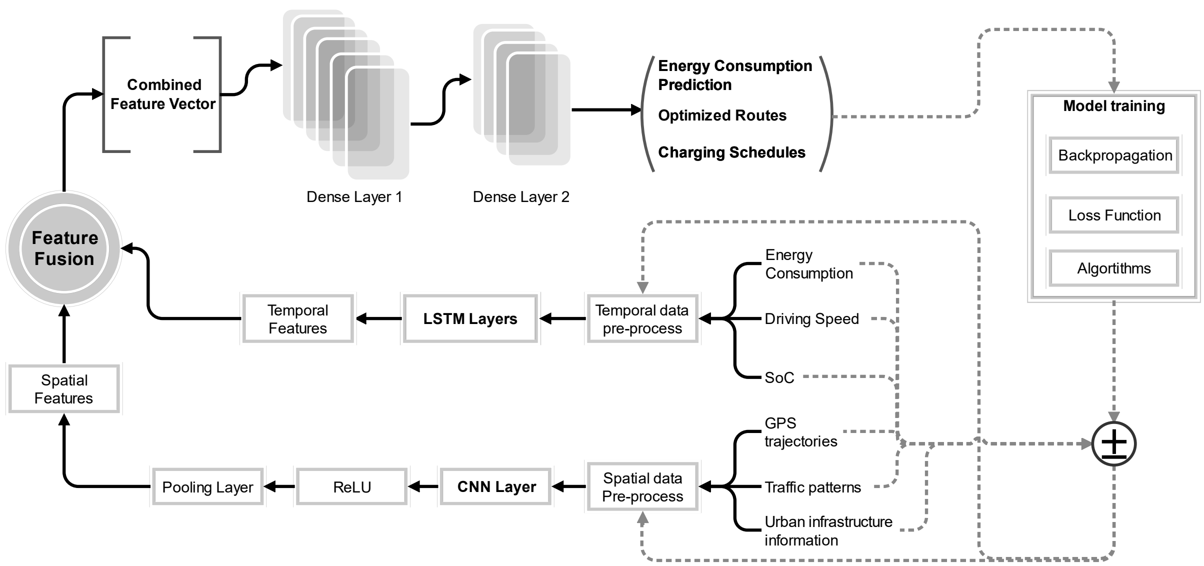


Figure 2. Architecture of the LSTM-CNN Hybrid Model for Predictive Energy Management in Electric Vehicles.

B. Dataset Description:

The experiments described in this study leverage the EV Energy Consumption and Speed Profiles Dataset (EVECS) a comprehensive dataset that meticulously records various aspects critical to understanding and predicting energy consumption patterns in electric vehicles (EVs) [22]. This dataset stands as an invaluable resource for training the proposed LSTM-CNN model due to its rich, multi-dimensional nature, encompassing a wide array of data points collected from real-world EV usage. EVECS encompasses historical data on EV energy consumption, integrating it with GPS trajectories, traffic patterns, and urban infrastructure information. Specifically, it includes data from two electric vehicle models: the Renault Zoe Q210 2016 and the Renault Kangoo ZE 2018. These vehicles were equipped with data loggers connected to the Controller Area Network (CAN) bus, enabling the collection of detailed information such as high-voltage battery current, voltage, State of Charge (SoC), and instantaneous speeds. Furthermore, the dataset is enriched with GPS tracks and altitude data obtained through a GPS logger mobile application, providing precise information on the vehicles' routes and the topographical characteristics of their environment.

The EVECS dataset provides the necessary temporal and spatial data required for training the LSTM component of the model to recognize and predict energy consumption patterns over time. Concurrently, the CNN component utilizes the spatial data to identify and learn the significance of various environmental and infrastructural factors affecting energy consumption. By training the LSTM-CNN model on this dataset, the research aims to develop a predictive model capable of accurately forecasting EV energy requirements, thereby facilitating more efficient energy management strategies for electric vehicles operating in urban environments.

C. Data Processing and Prediction Mechanism:

a. Stage One - Temporal Data Analysis with LSTM

The first stage of data processing involves the LSTM layers, which are specialized in handling sequential data that is time-dependent. The LSTM units receive input in the form of historical energy consumption patterns and vehicle diagnostic readings. Due to the LSTM's architecture, which includes mechanisms like forget and input gates, the network can learn from long-term sequences without losing significant information over time. This ability allows it to recognize patterns in energy usage and to forecast future requirements based on historical trends.

b. Stage Two - Spatial Data Analysis with CNN

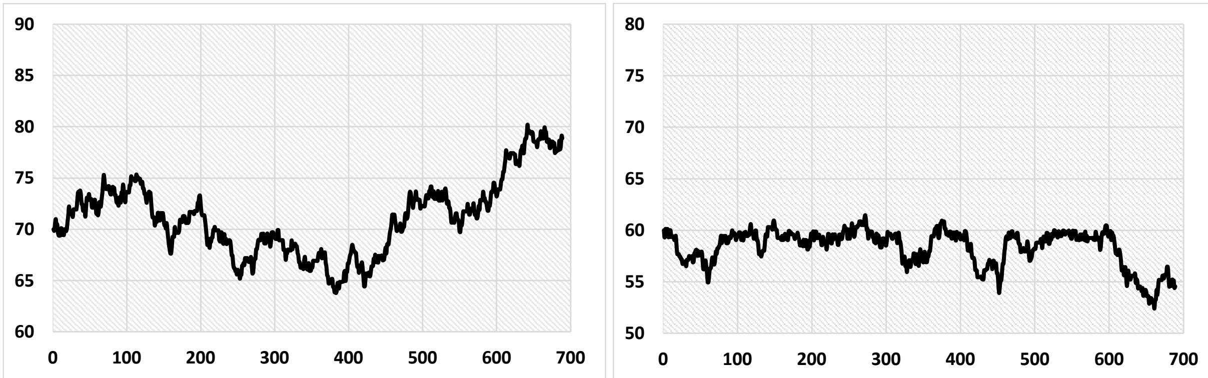
The second stage utilizes a CNN layer to process spatial information. This may encompass a variety of inputs, such as real-time traffic condition updates and Geographic Information System (GIS) data, which includes the topography and layout of the urban environment. The CNN excels at extracting meaningful features from spatial input due to its convolutional filters, which can identify patterns like traffic densities and road types that directly impact energy consumption.

c. Prediction Mechanism

Upon completing the two distinct stages of data analysis, the model proceeds to the prediction phase. The LSTM and CNN outputs are fused into a combined feature set that captures both the temporal dynamics and spatial context of the EV's operation. Leveraging this integrated data representation, the model applies dense layers to distill the features into predictions about future energy demands. These predictions include estimations of required energy for upcoming routes, identification of energy-efficient paths, and potential schedules for battery charging, thus optimizing the vehicle's energy utilization. This advanced data processing and predictive mechanism of the LSTM-CNN model positions it as a potent tool in the realm of smart energy management systems for electric vehicles, where accuracy in predicting energy demands translates into substantial efficiency gains.

IV. RESULTS AND DISCUSSION

The results section of the study offers a comprehensive analysis of the predictive performance of the LSTM-CNN model in the context of electric vehicle (EV) energy management. The figures presented provide visual insights into the relationship between actual energy metrics and the predictions made by the proposed model, as well as a baseline rule-based (RB) model for comparison.



(a) (b)

Figure 3. Comparative Analysis of Energy Variables in an Electric Vehicle. (a) Trajectory of battery voltage over time, illustrating potential charging events and energy accumulation. (b) Fluctuations in State of Charge (SoC) voltage, indicating energy management dynamics in response to operational activities.

Figure 3 comprises two sub-figures, (a) and (b), each depicting the behavior of different energy-related variables over time. Sub-figure (a) shows a progressive increase in battery voltage over sequential time steps, illustrating a scenario that could reflect a cumulative charging process or an increase in stored energy due to regenerative braking. In contrast, sub-figure (b) portrays a more stable pattern in the State of Charge (SoC) voltage, indicating a balanced state between energy consumption and charging events over the observed period.

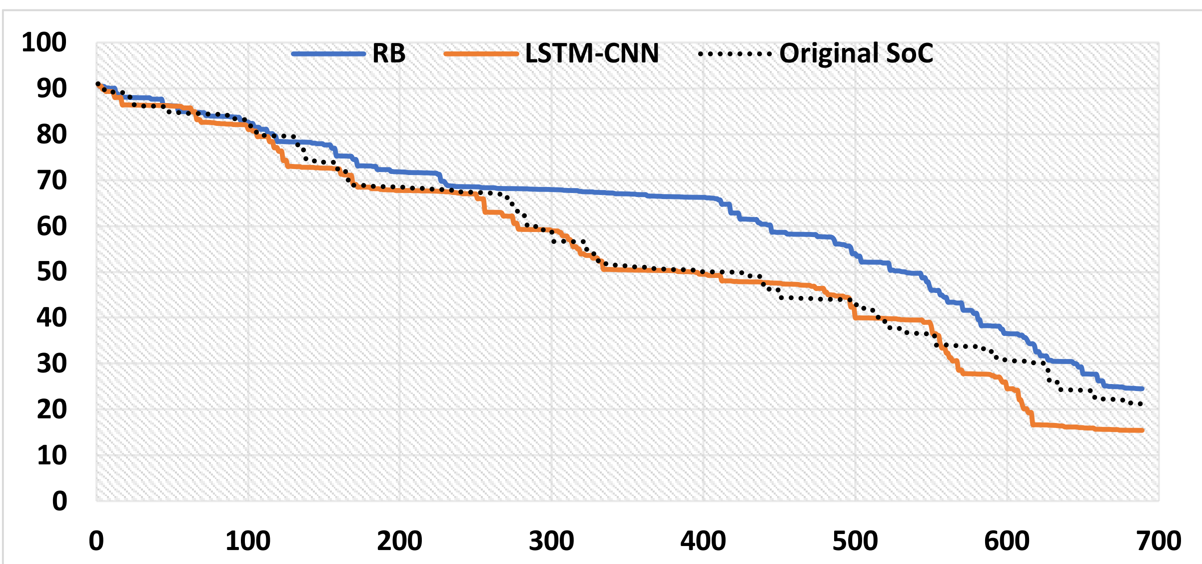


Figure 4. Comparative SoC Profiles Predicted by Different Models

Figure 4 presents a side-by-side comparison of the SoC profiles as predicted by the LSTM-CNN model, a rule-based (RB) model, and the actual SoC recorded from the EV. The graph reveals that while both the RB and LSTM-CNN models follow the trend of the original SoC profile, the LSTM-CNN model demonstrates a closer alignment with the actual data points, especially during rapid changes in SoC levels. This suggests that the LSTM-CNN model is more adept at capturing the complex temporal dynamics of EV energy consumption and regeneration.

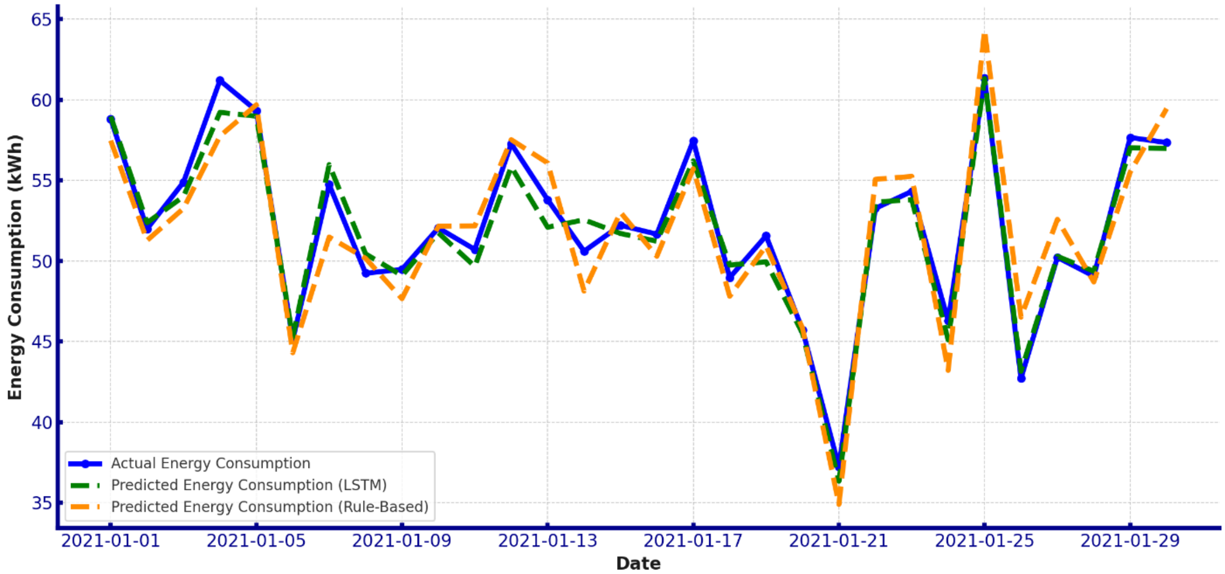


Figure 5. Energy Consumption Predictions vs. Actual Data

In Figure 5, the actual energy consumption of the EV is plotted against the predicted consumption using both LSTM and RB methods over a span of dates. The graph shows that the LSTM predictions closely track the actual energy consumption pattern, while the RB model exhibits some deviations. The precise tracking by LSTM underlines the model's strength in time-series forecasting, emphasizing its capability in handling the intricate variability in energy usage that a simple rule-based model might not capture effectively. The discussion deduced from these figures centers on the LSTM-CNN model's capability to handle both spatial and temporal data to provide accurate energy consumption predictions. The model's temporal component (LSTM) effectively captures patterns and dependencies across time, while its spatial component (CNN) extracts relevant features from environmental data, contributing to the robustness of the predictions. These results affirm the potential of the LSTM-CNN model to significantly optimize energy management strategies, which is imperative for enhancing the operational efficiency and sustainability of EVs in smart cities. The synergy between LSTM and CNN in capturing the intricate spatial-temporal patterns in energy usage demonstrates the effectiveness of the proposed model over traditional RB approaches. The empirical evidence provided by the figures substantiates the model's applicability in real-world scenarios, indicating its readiness to contribute meaningfully to the advancements in EV energy management systems.

V. CONCLUSION

The integration of electric vehicles (EVs) into the global transportation network is a step towards a sustainable future, addressing the urgent need for a reduction in carbon emissions and enhanced energy efficiency. This study has explored the energy management systems (EMS) for EVs, highlighting the strides the application of advanced predictive modeling techniques like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). Despite notable advancements, existing methodologies encounter challenges in handling high-dimensional data and adapting to the dynamic nature of urban traffic, underscoring a critical gap in predictive performance. Addressing these challenges, the development of a hybrid LSTM-CNN architecture presents a novel approach to energy prediction and management for EVs. This architecture leverages the temporal analysis capabilities of LSTM networks with the spatial data processing strength of CNNs, offering a solution that enhances predictive accuracy and efficiency. Key areas of interests for future research include optimizing the model to reduce training times while maintaining high predictive accuracy, integrating real-time data streams to improve responsiveness to dynamic urban environments, and exploring scalability to handle more complex datasets. Additionally, efforts will be directed towards the development of advanced energy management strategies based on the model's predictions, aiming for dynamic optimization of EV route planning and charging schedules. Further research will also investigate the model's potential in user-centric design, incorporating user preferences and behavior patterns to personalize energy management solutions.

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