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Using Machine Learning Models to Forecast Electric Vehicle Destination and Charging Event

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Executive Summary

California's regulations on greenhouse gas emissions have led to increased adoption of Battery Electric Vehicles (BEVs) in the state. However, range anxiety remains a challenge for BEV drivers. To address this issue, accurately predicting BEV charging behavior and informing drivers when they need to charge is crucial. This study aims to develop a prediction framework based on a Bidirectional Long Short-Term Memory Network (BLSTM) model to suggest when BEV drivers should charge their vehicles. The BLSTM model will be trained using a robust dataset of trips and charges from a subset of the eVMT dataset collected between 2015 and 2020. By providing essential information, the BLSTM model can adapt to changes in driving and charging patterns. This study aims to provide a more accurate and precise method of predicting charging events than conventional machine learning models. Our results show that implementing our model could reduce unnecessary charging by 15-22%.

Keywords: ZEV (zero emission vehicle), charging, infrastructure, intelligent, sustainability

1. Motivation and Background

Battery electric vehicles (BEVs) offer a range of benefits, including reducing carbon emissions, dependence on fossil fuels, and local air pollution. As the popularity of BEVs continues to grow, drivers face new challenges, such as limited battery range and the availability of charging infrastructure. These challenges can cause anxiety and stress for drivers, who may be uncertain about reaching their destination without running out of battery. Accurately predicting when drivers need to charge their vehicles based on their historical data and estimating when they can avoid unnecessary charging session has become increasingly important in addressing these challenges. Such predictions can help drivers feel more confident during their trips, increase trust in the technology, and potentially accelerate the adoption of BEVs [1], [2].

Auto manufacturers are actively developing algorithms for predicting charging behavior in electric vehicles to provide real-time information to drivers on when and where to charge their vehicles during their daily trips. The objective of this development is to mitigate range anxiety associated with BEVs. However, detecting any changes in trip and charging behavior is crucial to ensure the accuracy and precision of the prediction process. The prediction of charging behavior is a complex and multifaceted process as it involves human behavior, which is more challenging to forecast than other phenomena such as electricity prices and load demand. Therefore, the development of algorithms that can accurately predict charging behavior is essential to ensure the widespread adoption of BEVs and enhance the confidence of drivers in this technology.

In the context of addressing the challenges associated with BEVs, timeseries forecasting plays a crucial role in predicting the behavior of trip-related variables, including arrival time, destination, and charging behavior [3]. Various statistical and machine learning methods have been developed over the years for predicting charging behavior in BEVs, including linear regression, autoregressive integrated moving average (ARIMA), support vector regression (SVR), and artificial neural networks (ANN). Accurate prediction of charging behavior can lead to better utilization of charging infrastructure, reduced range anxiety, and improved battery health of BEVs [4]–[6].

Statistical methods are often limited by their predefined structure, which can lead to deficiencies in the resulting model. For example, Autoregressive Integrated Moving Average (ARIMA) is a popular statistical method for time series forecasting. ARIMA models capture patterns and dependencies in the data by combining autoregressive (AR), integrated (I), and moving average (MA) components. While ARIMA has been successful in forecasting behaviors of timeseries, it struggles to accurately capture sharp spikes [7]. To overcome this limitation, researchers have recently combined statistical methods with other techniques, such as the wavelet transform function. This function can decompose timeseries data into different frequency subseries and has been used in a hybrid approach with the autoregressive moving average (ARMA) model for short-term wind speed forecasting, resulting in improved forecasts for wind speed profiles with high fluctuations [8].

Artificial intelligence-based approaches, constructed using data engineering and machine learning techniques, are widely employed in various fields [9]. Conventional neural networks (C-NNs) with low hidden layers are a popular artificial intelligence method. To improve their performance, Rafiei et al. employed the Morlet wavelet function as the activation function of the hidden layers [10]. Support vector machines (SVMs) are another type of machine learning method that is commonly used in short-term forecasting, implemented using different kernel functions (e.g., linear, Gaussian) that map data into a new space [11]. Despite their advantages and disadvantages, these methods do not perform well when handling high-dimensional data.

Modern transportation systems often face big data problems, and to handle this large volume of data, deep learning approaches are the best solution [12]. In deep learning approaches, multiple processing layers are considered, which allows them to accurately extract the main features of the data with multiple levels of abstractions [13]. Deep learning, which utilizes neural networks with more hidden layers assembled through vigorous training procedures, has become a widely used technology in many research fields. Various studies have employed deep learning concepts in different forecasting fields, such as electricity price forecasting [14], load demand forecasting [15], wind speed forecasting [16], and more.

One particularly promising type of neural network is the long short-term memory (LSTM) network, which is a type of recurrent neural network (R-NN) capable of capturing long-term dependencies and complex patterns in time series data. LSTM has shown impressive results in a variety of timeseries forecasting tasks, including energy demand, stock prices, and weather data. Other studies have presented the LSTM for load demand and air quality forecasting [17], [18], respectively, showing the acceptable performance of deep LSTM in short-term forecasting tasks. Although some one-directional LSTM methods have been proposed, such as [18]–[20], they often produce errors in the results since they solely rely on memory in one direction. To overcome this issue, this article employs the bidirectional LSTM (BLSTM) method, which utilizes both past and future hidden layers data by means of two directional memories (feedforward and feedback loops). This approach enables the proposed forecasting method to efficiently extract all the hidden layers features, significantly enhancing the accuracy of the forecasting results. Table I provides a brief comparison between the benchmark forecasting methods.

Table 1 benchmark forecasting methods comparison

Methods	Advantages	Disadvantages
Statistical Methods (ARMA, ARIMA)	Low computation time [15] Suitable for short term forecasting [7] Well performance in profiles with low fluctuation [22] No need for large training data [21]	Cannot follow the sharp spikes accurately [7], [8] Cannot analyze complex nonlinear patters [21] Model identification is difficult [21] Not suitable for long term prediction [23]
SVM	Without training difficulties like overfitting, and saturation [24] Well performance in classification task [25] Suitable for short term and long term forecasting [11], [21]	Low ability in feature extraction for large dimension data set [23] High computational burden for large data set [19] Lack of strong memory unit [21]
C-NN	Good performance for handling simple non-linear problems[9] Feature extraction ability [15] Implementing in classification task [27]	Without memory unit [26] Gradient vanishing problem[16] Overfitting problems during training [11], [21]
R-NN	Equipped with memory by recurrent weights [14] Modeling temporal dependencies ability [14], [23] Good performance for handling simple nonlinear problems [14] Feature extraction ability [1]	Low ability in feature extraction for large dimension data set[26] Gradient vanishing problem[28] Convergence and exploding gradients problems [17]
LSTM	Equipped with remarkable memory and operation gates [17], [20] Good performance in challenging and complex profiles [18] Do not have the gradient vanishing problem [29] High feature extraction ability [33]	Error accumulation problem [29], [30] Insufficient usage of temporal features [31], [32] Complex training procedure [31]

This paper proposes a stochastic model to aid BEV drivers in making decisions about when to charge their vehicles. By accurately predicting charging events and the next destination location, the model can help drivers avoid unnecessary charging stops and overcharging, which can damage the battery and reduce its lifespan. Unlike deterministic approaches that produce the same results for a particular set of inputs, the stochastic model accounts for certain levels of unpredictability or randomness in the data.

The model employs a BLSTM network that is trained using trip data such as GPS route, SOC, and time of day. The BLSTM model is integrated into the stochastic model, which predicts the likelihood of charging at the destination in three levels and next destination locations for individual BEV drivers based on their vehicle's historical data. This provides drivers with the necessary information to decide when to charge their vehicles. The proposed stochastic model represents a significant advancement in the field of BEV charging prediction and has the potential to increase the convenience and reliability of BEVs for drivers.

To illustrate the benefits of the proposed stochastic model, consider the scenario where a BEV with a SOC lower than the charging threshold stops at a location with public chargers. Deterministic approaches would recommend charging the vehicle at the public station, which can be costly. However, the next destination of the driver could be their home or workplace, where charging is cheaper and better for the battery lifespan. In this case, a stochastic model that utilizes historical data can assist the driver in making an optimal decision and avoiding unnecessary charging stops. This can help BEV drivers make informed decisions about when and where to charge their vehicles, leading to cost savings and improved battery lifespan.

Due to a lack of real-world BEV data, many researchers have used internal combustion engine data as a substitute [34] to study charging behavior, which could lead to less accurate results. Therefore, this study employs the real-world BEV trip and charging dataset to train the BLSTM model and better understand individual charging behaviors. By incorporating current destination and arrival time prediction, our proposed methodology significantly improves the accuracy of predicting charging events and next destination.

In addition to predicting charging events and assisting drivers in decision-making, the proposed stochastic model can detect and adapt to changes in travel and charging patterns. This dynamic nature of the model allows it to learn from new data as it becomes available. For example, if a BEV driver changes their typical travel pattern or charging behavior, the model can identify such changes and adjust its predictions accordingly. This adaptability ensures that the model remains effective and accurate over time, even as driving patterns and charging infrastructure evolve. This is particularly important given the rapid development of BEV technology and the growing popularity of electric vehicles. By continually adjusting its training procedure based on new data, the model can provide drivers with the most up-to-date and accurate predictions of when they need to charge their BEVs.

This study is structured as follows: Section 2 introduces the proposed method, which consists of various forecasting units. Section 3 outlines the data description employed in the study. Sections 4 and 5 present the forecasting results and examine the impact of the BLSTM. Finally, Section 6 concludes the article.

2. Proposed Methodology Framework

The objective of this research paper is to develop a predictive neural network-based model that can alleviate the range anxiety associated with BEVs and avoid unnecessary charging session by accurately forecasting charging events and next destinations of drivers during each trip. This will enable the estimation of whether drivers can relocate their charging sessions to their homes rather than public chargers based on their historical data. By doing so, drivers will have the necessary information to make informed decisions about when and where to charge their BEVs.

2.1 BLSTM Network

The R-NN is the improved form of C-NNs, which uses the temporal information of input data by adding the connections between output and hidden layers. In fact, R-NNs have a memory unit and can use previous output or hidden layer data to predict new data, leading to better time-series forecasting. However, they can struggle with the gradient vanishing problem during training, which can hinder learning. To address this, LSTM networks [28] were introduced as an elaborated version of R-NNs, which have gates that allow for better handling of long sequences of data. Figure 1 shows the architecture of LSTM networks. LSTMs are better than traditional R-NN at handling the problem of vanishing gradients, which can happen when working with long sequences of data. This problem occurs when the gradients in the backpropagation algorithm become too small to be useful, which can stop the network from learning. LSTMs have different gates that distinguish them from R-NNs and make them a more powerful memory unit. There are three main gates in each LSTM network: the input gate, which controls how much of the new input is added to the memory cell; the forget gate, which controls how much of the previous state is forgotten; and the output gate, which controls how much of the current state is sent to the next layer in the network.

The gates in the LSTM network are controlled by activation functions, which can either be sigmoid or hyperbolic tangent functions. The sigmoid function produces output values between 0 and 1, which are used to control the gates. On the other hand, the hyperbolic tangent function produces output values between -1 and 1, which are used to update the state of the memory cell. These gates allow the network to selectively retain or discard specific information from the previous time steps. The gates are designed to manage the flow of information into and out of the memory cell, which is the essential part of the LSTM architecture. The memory cell stores and processes the input data sequence, and its state is updated at each time step.

The proposed method utilizes deep learning techniques and consists of several stacked LSTM networks for the forecasting module. The input data for each network is taken from the output of the same network at the previous time step and the output of the previous network at the current time step. The input gate stores information from the current and previous time steps, while the forget gate discards unnecessary information from the memory cell, and the output gate retrieves useful information. Because of the stacked configuration, the features are propagated among the networks during the training process, allowing the deep LSTM networks to effectively learn complex and unpredictable phenomena. The equations that define the behavior of the LSTM network can be described as follows:

$$i_t = \sigma\left(W_{it}S_t^{(l-1)} + W_{ht}S_{(t-1)} + b_i\right) \tag{1}$$

$$f_t = \sigma\left(W_{i\varphi}S_t^{(l-1)} + W_{h\varphi}S_{(t-1)} + b_f\right) \tag{2}$$

$$c_t = f_t c_{t-1} + i_t \tanh\left(W_{i\gamma}S_t^{(l-1)} + W_{h\gamma}S_{(t-1)} + b_c\right) \tag{3}$$

$$O_t = \sigma\left(W_{io}S_t^{(l-1)} + W_{ho}S_{(t-1)} + b_o\right) \tag{4}$$

$$S_t = O_t \tanh(c_t) \tag{5}$$

Here, the model parameters are defined as W_{it}, $W_{i\varphi}$, $W_{i\gamma} \in \mathcal{R}^{r \times n_h}$ for input gates W_{ht}, $W_{h\varphi}$, $W_{h\gamma} \in \mathcal{R}^{n_h \times n_h}$ for hidden state and b_i, b_f , b_c, $b_o \in \mathcal{R}^{1 \times n_h}$ as bias variable. During the training process, these variables are adjusted using an optimization algorithm.

To address the issue of neglecting future features in LSTM networks, this study employs BLSTM networks which process data bidirectionally [29]. The BLSTM network consists of two main hidden layers, each composed of stacked identical LSTM networks - one for the forward direction and one for the backward direction. This allows the network to incorporate information from both past and future time steps, making it suitable for forecasting multistep ahead data. The BLSTM network can store all useful previous and future features with high precision, making it a powerful solution. BLSTM networks can transfer information in two directions: from the past to the future and from the future to the past. BLSTM is a suitable approach for predicting multi-step data, where the output is used as input in future steps [35]. Additionally, the BLSTM network is more precise in predicting phenomena with high stochastic and intermittent behavior since it does not follow the recursive process, which feeds back the previous information in an iterative manner. This process led to error accumulation, which has been demonstrated in [30] and [32].

For a given time step *t* in the BLSTM network, the mini-batch input data is represented as $X_t \in \mathcal{R}^{n \times r}$, and the forward and backward hidden states are assumed as $\vec{H}_t \in \mathcal{R}^{n \times n_h}$ and $\overleftarrow{H}_t \in \mathcal{R}^{n \times n_h}$, respectively. These two hidden states are then combined to form the hidden state $H_t \in \mathcal{R}^{n \times 2n_h}$, which consists of both forward and backward information.

The output data $O_{fn} \in \mathcal{R}^{n \times n_o}$ is then computed using the following equation:

$$\vec{H}_t = \tanh\left(X_t W_{xh}^{(f)} + \vec{H}_{(t-1)}\right) W_{hh}^{(f)} + b_h^{(f)} \tag{6}$$

$$\overleftarrow{H}_t = \tanh\left(X_t W_{xh}^{(b)} + \overleftarrow{H}_{(t-1)}\right) W_{hh}^{(b)} + b_h^{(b)} \tag{7}$$

$$O_{fn} = H_t W_o + b_o \tag{8}$$

Here, the model variable are defined as $W_{xh}^{(f)} \in \mathcal{R}^{r \times n_h}$, $W_{hh}^{(f)} \in \mathcal{R}^{n_h \times n_h}$, $b_h^{(f)} \in \mathcal{R}^{1 \times n_h}$ for forward processing and, $W_{xh}^{(b)} \in \mathcal{R}^{r \times n_h}$, $W_{hh}^{(b)} \in \mathcal{R}^{n_h \times n_h}$, $b_h^{(b)} \in \mathcal{R}^{1 \times n_h}$ for backward processing.

Table 2 provides a description of the variables, parameters, and sets that have been used in the equations. BLSTMs are effective in processing time-series data with complex non-linear relationships and temporal dependencies, particularly second-by-second trip logs found in BEV trip dataset [36]. Additionally, BLSTMs can extract critical features and can be used for classification tasks. This study aims to develop a BLSTM model that can predict trip arrival time and classify EV trips into various destination categories, such as home and work. The model will also calculate the probability of charging at each destination and probability of next destination, while considering other travel parameters. Unlike previous studies, this model will be configured using empirical data from 5 BEVs over the course of one year in the eVMT project dataset [37].

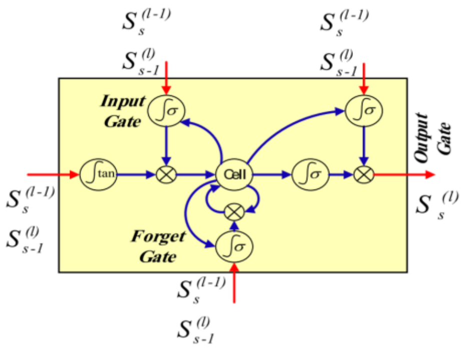


Figure 1- LSTM cell

Table 2- Nomenclature

Category			*Definition*	
Variables	i_t	Data vector of input gate at time t.	W_{it}	Weight vector for input of current state input gate
	$i_{h,t}$	Desired output in iteration *s* for class *c*	$W_{i\varphi}$	Weight vector for input of current state forget gate
	b_c	Bias vector for cell block.	$W_{i\gamma}$	Weight vector for input of current state cell block.
	b_f	Bias vector for forget gate.	W_{io}	Weight vector for input of current state output gate.
	$b_h^{(f)}$	Bias vector for forward hidden layer.	$\vec{H}_t$	Hidden vector for forward layer at time t.
	$b_h^{(b)}$	Bias vector for backward hidden layer.	$\overleftarrow{H}_t$	Hidden vector for backward layer at time t.
	b_i	Bias vector for input gate.	O_{fn}	Output vector of the final layer
	b_o	Bias vector for output gate.	$W_{xh}^{(f)}$	Weight vector of forward layer input data.
	c_t	Data vector of cell block at time *t*.	$W_{hh}^{(f)}$	Weight vector of forward layer output data.
	O_{fn}	Total Sum of error in iteration *s*	$W_{xh}^{(b)}$	Weight vector of backward layer input data.
	O_t	Total sum of error	$W_{hh}^{(b)}$	Weight vector of backward layer output data.
	W_{ht}	Output of neuron *j* in layer *l* in iteration *s*	W_o	Weight vector of the output layer.
	$W_{h\gamma}$	Weight vector for neuron *j* in layer *l* in iteration *s*	X_t	Input data vector at time *t*.
	$O_{h,t}$	Activation function for neuron j in layer *l* in iteration *s*		
	S_t	Activation function input for neuron j in layer *l* in iteration *s*		
	$W_{h\phi}$	Output of neuron *j* in layer *l* in iteration *s* for class *c*		
	W_{ho}	Weight vector between sample *i* of the input layer and neuron j in hidden layer *l* in iteration *s*		
Parameters	n	Total number of input data.		
	n_h	Total number of hidden units.		
	r	Dimension of each input data sequence		
	n_0	Total number of outputs.		
index	i	Index of sample vector of each cluster.		
	t	Index of hidden layer sample		
	l	Index of hidden layer.		

2.2 Overall Structure of the Proposed Methodology

This study is divided into three stages, as shown in Figure 2. First, the model's training, validation, and testing datasets are generated using the eVMT project's dataset. In the second stage, the BLSTM model is defined and configured using the training and validation data from the previous stage. Finally, a series of experiments are conducted on the defined models using the testing dataset from stage one to evaluate the BLSTM model.

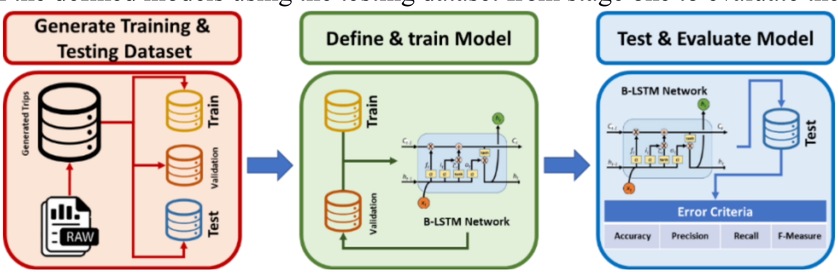


Figure 2 BLSTM Framework

The study is structured into four stages for predicting drivers' next destination and charging behavior. First, the initial BLSTM model forecasts the trip's arrival time using historical data. Second, the predicted arrival time is combined with input variables from the previous model and fed into the second model, which predicts the trip's destination. Third, using the predicted arrival time and destination, the third BLSTM model predicts the charging behavior at the end of the trip. Finally, all the predicted data is combined with initial data to predict the next trip destination location of drivers. Accurate next destination prediction is critical, as it empowers drivers to decide whether to charge their cars at current location or wait until the next stop to charge their car at a lower cost. The study results indicate that the model can converge on results within 3-5 minutes of starting the trip. Figure 3 illustrates the prediction framework used in this study.

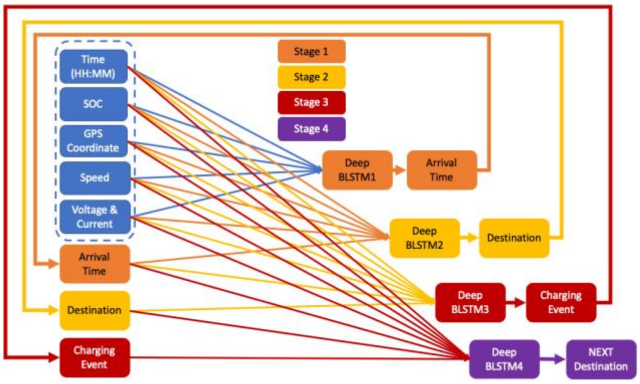


Figure 3- Prediction model framework

3. Case Study Definition

3.1 Data Overview

The models used in this research were configured using a subset of the eVMT project's dataset, which is a California-wide study spanning five years (2015-2020). The eVMT project aimed to gain insight into the driving and charging behaviors of Plug-in Electric Vehicles [37]. In this study, a subset of data from the Nissan Leaf, Chevy Bolt, and Tesla was utilized to train and test the BLSTM model.

Table 3: BEV dataset [37]

EV Type		Number of Vehicles	Number of Trips	Total Miles Traveled	Number of Charging
Battery	Nissan Leaf-24	3	4201	27,638	854
Electric	Chevrolet Bolt 66	1	1582	10,486	325
Vehicles	Tesla Model S-60_80	2	1610	29,753	450

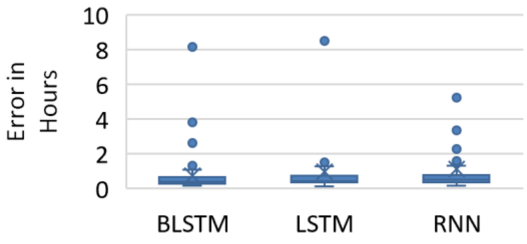
4. NUMERICAL RESULTS

4.1 Forecasting Results

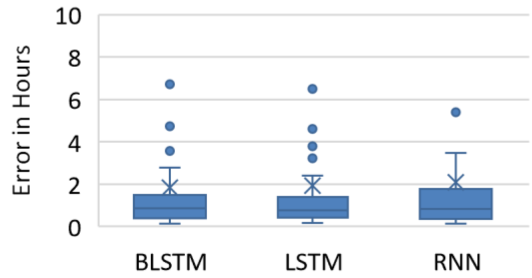
The BLSTM networks used in this study were trained on earmarked datasets. We determined that 50 hidden layers were optimal for the BLSTM network by performing a grid search, where we experimented with various numbers of hidden layers and evaluated the performance of the model on the task at hand. It should be noted that the BLSTM network is more sensitive to the learning rate values than the LSTM network to prevent saturation during the training process. Therefore, the initial learning rates for the BLSTM network were set to 0.01 and 0.005, respectively [38]. To prevent overfitting and improve the stability of the proposed method, an L2 regularization term with a coefficient of 0.001 was implemented to prevent rapid and sharp changes in the weights during training [38]. Furthermore, a dropout layer with a probability of 0.5 was implemented to prevent co-adaptation of neurons, and a mini-batch gradient descent method was applied to reduce the variance of the updating parameters and achieve more stable convergence [38]. These measures are essential for deep learning-based networks. The maximum number of epochs for the training phase was determined through experimentation to be 30, based on the model's performance on the validation set. Additionally, we set the validation step to 10 to ensure the robustness of the proposed method. These values were selected by performing a grid search. Finally, a comprehensive comparison was made among various approaches for three different Nissan Leaf. Due to the time-consuming nature of the training process, this study focused on comparing three different neural network models using data from three Nissan Leaf vehicles. The primary objective was to identify the most effective model, which could then be generalized to the Tesla and Bolt vehicles. By selecting the best-performing model for the Nissan Leaf, we can ensure that our predictions for the other two vehicles are also reliable and accurate.

I. Arrival Time

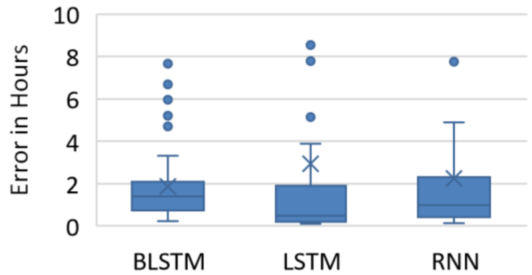
Our study utilized a deep learning algorithm to predict the arrival time of three Nissan Leaf, which is an important factor in determining the charging behavior and accurately forecasting the next destination. We evaluated the performance of three neural network models, R-NN, LSTM, and BLSTM, using mean squared error (MSE) for the prediction results. The three models were trained and tested on Nissan LEAFs dataset to ensure a fair comparison. As shown in Figure 4, the BLSTM model outperformed the other models in predicting arrival time with the lowest MSE where the Y axis represents the error in hours. This finding suggests that the BLSTM network can be an effective method for accurately forecasting BEV arrival time and detecting anomalies in driver behavior. The ability to detect changes in driver behavior is valuable for adjusting the algorithm and retraining it based on new driving habits.



a- Mean Squared Error - 1001-LEAF



b- Mean Squared Error - 1003-LEAF

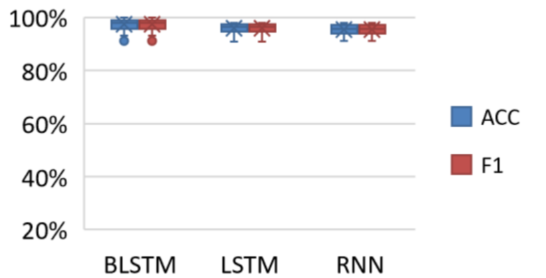


c- Mean Squared Error - 1004-LEAF

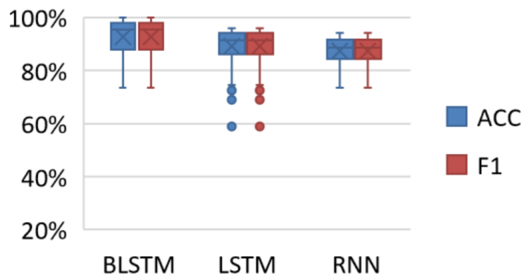
Figure 4- Arrival time prediction- Mean Squared Error.

II. Destination

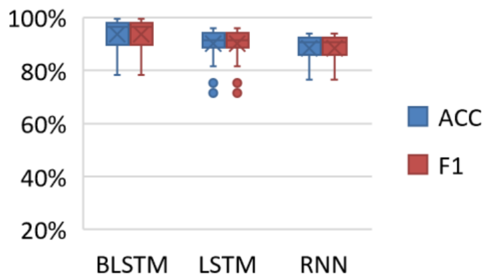
In the second stage of our study, we aimed to predict the destination of each trip using a new deep learning network at the start of the trip. To improve the accuracy of our prediction, we utilized the output of the previous network along with the initial inputs, as the arrival time and destination are interrelated. Accurately predicting the destination is crucial for accurately predicting charging behavior and notifying drivers about when to charge their car. Therefore, improving the accuracy of destination prediction can significantly increase the likelihood of accurately predicting charging behavior. As shown in Figure 5, the BLSTM model outperformed the other models in predicting the destination with higher accuracy (ACC) and F1 score (F1).



a- Destination Prediction - 1001-LEAF



b- Destination Prediction - 1003-LEAF



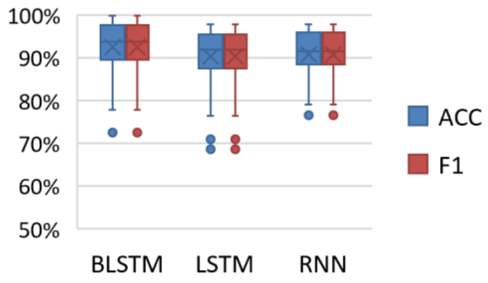
c- Destination Prediction - 1004-LEAF

Figure 5- Destination Prediction Error Criteria

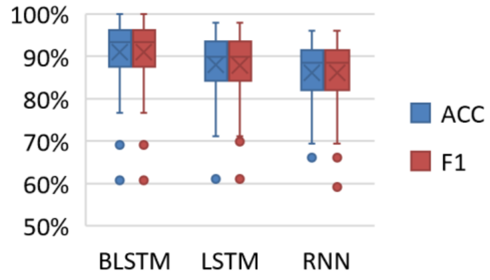
III. Charging Behavior

As illustrated in Figure 3, the third step of our algorithm utilizes the outputs of the previous two steps to predict the driver's charging behavior. In Figures 6a, 6b, and 6c, we compare the prediction accuracy (ACC) and F1 score (F1) for neural network-based model on three Nissan LEAF vehicles to identify the best stochastic model and configuration for predicting complex charging behaviors. We observed that for vehicle

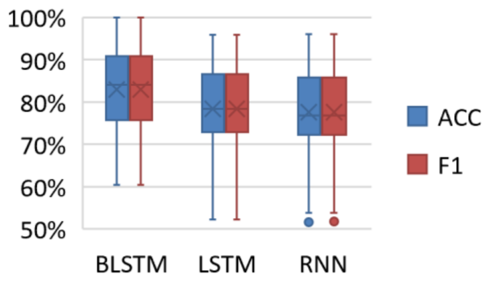
1001, the accuracy and F1 score did not vary significantly different among different neural network models, as it does not exhibit complex charging behavior. However, for vehicles 1003 and 1004, which have more complex charging behaviors, the BLSTM model outperformed a better ability to extract features and predict charging behavior with higher accuracy.



a- Charging Prediction - 1001-LEAF



b- Charging Prediction - 1003-LEAF

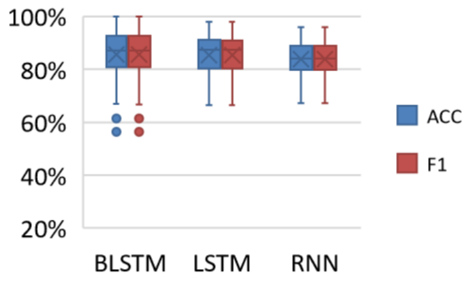


c- Charging Prediction - 1004-LEAF

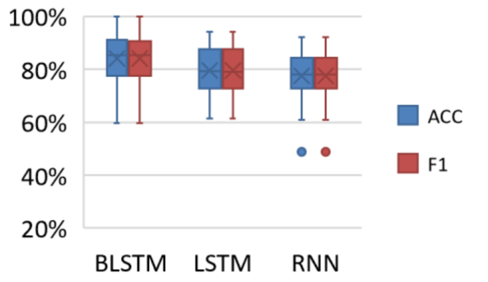
Figure 6- Charging Prediction Error Criteria

IV. Next Destination Prediction

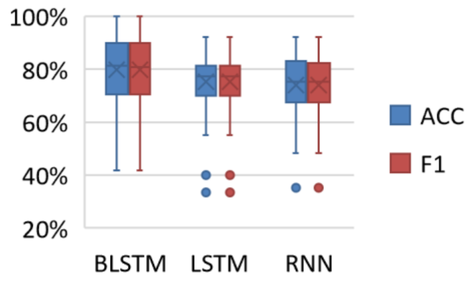
In the final step of our algorithm, we use the outputs of the previous three steps to predict the driver's next destination. The model utilizes all input information, including the outputs of the previous three steps, to make this prediction. Figure 7 compares the performance of three different neural network-based algorithms in predicting the next destination. We observed that for vehicle 1001, the accuracy (ACC) and F1 score (F1) did not significantly differ among the different neural network models, as it does not exhibit a complex driving pattern involving visits to different locations. However, for vehicles 1003 and 1004, which have more complex driving patterns, the BLSTM model outperformed other models by showing a better ability to extract features and predict the next destination with higher accuracy.



a- Destination Prediction - 1001-LEAF



b- Destination Prediction - 1003-LEAF



c- Destination Prediction - 1004-LEAF

Figure 7- Destination Prediction Error Criteria

5. Discussion

The primary aim of this study is to develop an effective tool that can help BEV drivers to avoid unnecessary charging at public stations and instead charge their vehicles at home, where the cost of energy per unit is usually lower. Also, lower power rate is better for battery health because it reduces the stress on the battery's internal chemistry and prolongs its lifespan. When a battery is charged at a high rate, it generates more heat and can cause degradation of the battery's internal components, leading to a reduction in capacity and performance over time. In contrast, charging at a lower rate allows for a slower and more controlled transfer of energy, reducing the risk of damage and maintaining the battery's health and longevity. Therefore, BEV owners should aim to charge their vehicles at a lower rate to maximize the lifespan of their batteries.

As depicted in Figure 8, our analysis found that, on average, drivers in our case study initiated their charging session with a SOC above 40% in other and workplace charging stations. However, Figure 9 illustrates that most of these drivers usually head home after charging, where the cost of electricity is relatively cheaper than at public charging stations.

To achieve our research goal, we adopted a stochastic machine learning-based model to predict drivers' behavior based on their historical data. While on a trip, the model guides drivers on whether they need to charge their vehicle at their current destination or move their charging session to their next destination, thereby helping them avoid unnecessary charging that can damage the battery's lifespan and prove costly in the long run. To accomplish this, the model predicts the charging behavior and destination of the next trip to estimate whether drivers can reach their destination with a state of charge above 20%, which is the minimum rate to avoid any damage to the battery health [39].

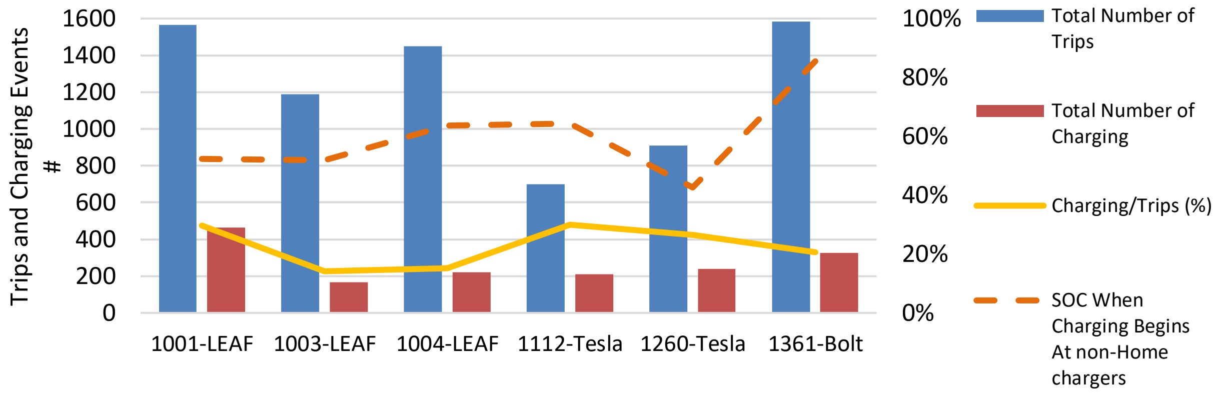


Figure 8: Vehicle Trips and Charging Events

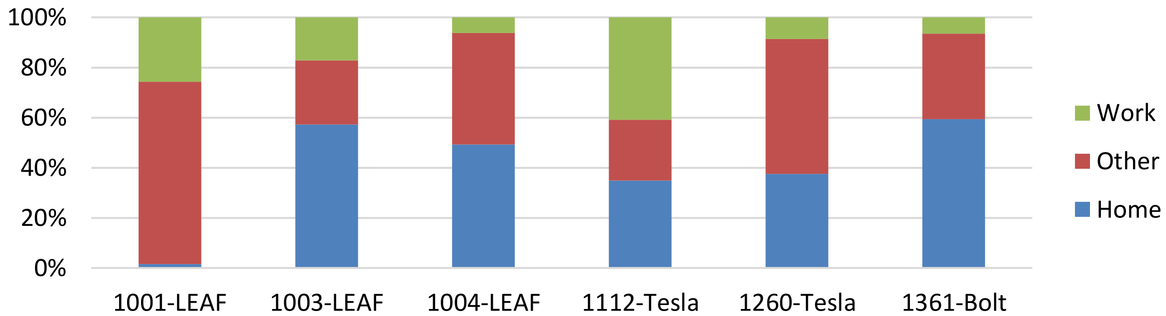


Figure 9: Next Destination After Charging

The results of our study demonstrate that the BLSTM prediction model can be an effective tool for reducing unnecessary charging by accurately predicting the next destination and current charging behavior of BEV drivers. Although there is always a risk of incorrect predictions due to errors during training, the low number of incorrect predictions compared to the correct ones indicates that our model can assist drivers in making informed decisions and avoid unnecessary charging. Our model can help mitigate these issues by suggesting when drivers can move their charging session to their home, where the cost of electricity is generally lower than at public charging stations.

As shown in Figure 10, the potential value of the BLSTM charging and destination framework is significant. For 5 out of 6 vehicles in our case study, our model identified that 15% to 22% of their charging session was unnecessary and could be avoided by moving the charging session to their home. This indicates that the model has the potential to significantly reduce the cost of charging for BEV drivers and prolong the battery life of their vehicles. The presented BLSTM charging, and destination prediction framework provides a reliable solution for addressing the issue of unnecessary charging and can be beneficial for both BEV drivers and the environment. However, Figure 10 reveals that the BLSTM model employed in this study did not have a significant impact on the charging behavior of vehicle number 1001. This can be attributed to the fact that the driver predominantly charges the vehicle at home. As a result, the prediction tool was unable to assist the driver by suggesting that they move their charging sessions from public or workplace chargers to their home charger.

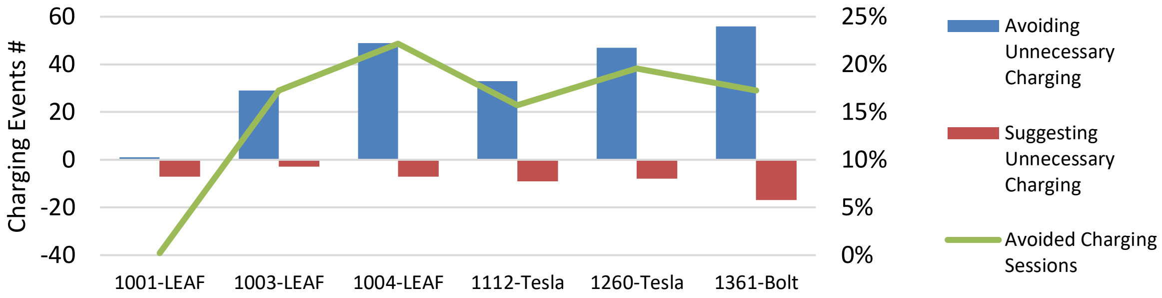


Figure 10: BLSTM Model Suggestion

6. Conclusion

In recent years, artificial intelligence has had a significant impact on many aspects of human life by providing useful information to assist with daily routines. Concurrently, many countries have developed policies to promote the use of BEVs as part of their efforts to reduce greenhouse gas emissions. However, the adoption of BEVs presents a new challenge such as range anxiety. This study aimed to develop a machine learning-based model to assist BEV drivers in making informed decisions about charging their vehicles and avoiding unnecessary charging sessions.

Our study evaluated the effectiveness of R-NN, LSTM, and BLSTM neural network-based models in predicting the charging behavior of BEVs. Our results show that the BLSTM models outperformed the other models by accurately predicting complex charging behaviors in a shorter time with a smaller sample size. Our prediction framework, which predicts charging behavior and the next destination of the drivers' trip, estimates the amount of SOC required for the next trip if the driver does not charge at the current location and moves the charging session to the next location if it is home.

The results of our study show that implementing this framework can reduce public charging sessions by 15-22%, resulting in cost savings for BEV owners and potentially extending battery lifespan due to lower power transfer rates from the grid to the vehicle. While our current model can predict the next destination, future work should consider estimating charging needs for the entire day rather than just the next trip.

In conclusion, our study highlights the importance of developing accurate and efficient charging behavior prediction systems to make BEVs more practical and appealing to consumers. By addressing the challenges of predicting difficult charging behaviors and exploring new prediction methods, we can advance the field of BEV charging prediction and help accelerate the transition to a more sustainable transportation system.

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