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ESTIMATING THE CHARGING CONSUMPTION FOR EVs USING A NOVEL NEURAL NETWORK TECHNIQUE

G. Ezhilarasan[1]
Kalyan Acharjya
Ajay Kumar
Anup Kumar

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A B S T R A C T

In this study, we introduce the water wave optimized bidirectional long short-term memory (WWO-BLSTM) model for predicting the charging usage of electric vehicles (EVs).WWO can be utilized to optimize the charging schedules of EVs, enabling the flexible change of charging patterns. The estimation of EV charging use implements BLSTM, a model that analyzes sequential data in forward and backward directions. Initially, we collected a dataset that includes 10,595 unregulated charging operations from workplace charging. This dataset represents the diversity of EV charging .A comprehensive data cleansing procedure was performed. To ensure the suggested method is effective, we employ MATLAB software to conduct simulations. This model was able to obtain a recall of 96%, F1 score of 93%, accuracy of 88% and precision of 95%. We offer outstanding outcomes for the charging consumption of EVs using our innovative WWO-BLSTM methodology.

1. INTRODUCTION

The fast advancement of technology in recent years has resulted in a fundamental change in the automobile sector, characterized by an important growth in the acceptance of EVs (Muratori et al., (2021)). With increasing concerns about environmental sustainability, EVs have emerged as a possible option (Aijaz and Ahmad (2022)). They provide a cleaner and more energy-efficient alternative to conventional combustion engine vehicles (Cao et al., (2021)). EVs depend on electricity stored in high-capacity batteries, therefore eliminating the necessity for conventional fossil fuels (Wen et al., (2020)). The adoption of electric mobility has generated considerable interest attributed to its capacity to reduce greenhouse gas emissions and minimize reliance on finite energy resources (Salkuti et al., (2021)). Table 1 displays the standard power capacity and charging methods of an electric vehicle.

Table 1. Vehicle Power and Charging Capacity.

Charging Mode	**Normal Power Charging**		**High Power Charging**	
Power Rating (P)	≤ 7 kW	7 kW to 22 kW	22 kW to 50 kW	50 kW to 200 kW
Supply	DC and AC	DC and AC	Only DC	Only DC

[1] Corresponding author: G. Ezhilarasan
Email: g.ezhilarasan@jainuniversity.ac.in

Nevertheless, with the increasing popularity of EVs, it becomes crucial to comprehend and effectively control their charging use (Sharma et al., (2020)). The effectiveness of EVs depends on the presence of efficient charging infrastructure and the optimization of energy use (Aljaidi et al., (2020)). The energy requirements of various EV models, the amount of period required to charge and whether or not charging stations are compatible are all factors that must be carefully considered when assessing the effectiveness of electric vehicle charging (Patel (2023)). The complex interaction between technology and energy consumption requires a comprehensive investigation to enable the smooth incorporation of EVs into daily activities (Fakour et al., (2023)). EV charging usage estimation is a multi-step process that involves in-depth knowledge of all relevant aspects. Accurately forecasting the energy requirements is of utmost importance, encompassing factors such as the vehicle's battery capacity, charging voltage and current (Yang et al., (2021)). It entails utilizing mathematical models, real-world data and developments in smart charging technology to provide dependable estimation techniques that address the changing environment of electric mobility.

Miri et al., (2021) accomplished by simulating the electric vehicle (EV) characteristics of a commercially available model, the BMW i3, utilizing the MATLAB/Simulink software package. Vehicle powertrain systems and longitudinal vehicle dynamics are part of the electric vehicle model. With an error range of 2% to 6% between experimental findings and simulations for EPA and NEDC tests, the vehicle model was evaluated against published energy consumption values and showed a reasonable level of accuracy. Savari et al., (2020) presented an improved EV charging system that makes use of the benefits of IoT technology. Using the integration of numerous sensors and broadcasting instruments, the present establishments were provided with an interactive perspective of the external environment in real-time through the IoT paradigm. Kavianipour et al., (2023) assessed potential reductions in emissions of CO_2, HC, CO and NO_x that would result from the earlier study's proposed infrastructure for light-duty vehicles along with the anticipated rate of electrification (Amin et al., 2020). The suggested framework for estimating emissions was compared to a more conventional approach that relies on the miles traveled (VMT). Tian et al., (2020) proposed an approach that combined an adaptive “cubature Kalman filter (ACKF) with a long short-term memory (LSTM)” network. In applying the ACKF to smooth the LSTM network's outputs and achieve accurate and steady SOC estimating, the LSTM network were utilized for learning the nonlinear connection among the SOC and data, such as current, voltage and temperatures. How et al., (2020) introduced forth a Li-ion battery SOC computation system that made use of an improved "deep neural network (DNN)" method designed for EV uses. They discovered that a DNN can reliably predict the SOC of driving cycles that weren't part of the training set, provided that the amount of concealed layers is sufficient. Almaghrebi et al., (2020) examined to predict the amount of power required to charge "Plug-in Electric Vehicle (PEV)" customers once the electrical charging session starts. We validated the method by analyzing data acquired from public charging stations in Nebraska, USA, over a period of seven years. Based on the data, it appears that the XGBoost regression technique outperforms other methods when it comes to estimating recharging requirements. Amin et al., (2020) determined the most efficient method for charging EVs based on dynamic power pricing regulations such as “real-time pricing (RTP), critical peak pricing (CPP) and time-of-use (ToU)”. The optimal scheduling of electric car charging involves the identification of objectives and the application of optimization techniques reached a desired outcome. Zhang et al., (2023) presented a systematic approach for managing the charging and discharging process of EVs. The approach incorporated a dynamic updating mechanism for recharging pricing and carbon income, while considering the travel patterns of EVs and the users' capacity to adapt. Basso et al., (2019) presented the “Two-stage Electric Vehicle Routing Problem (2sEVRP)”, which integrated enhanced energy consumption estimation by incorporating intricate topography and velocity patterns. Initially, a technique for determining energy cost coefficients for the road network were described. In addition, a comprehensive two-step methodology was outlined, which first identifies the optimal routes among pairs of locations and determines the most favorable routes while considering battery and time-window limitations. Lan et al., (2021) presented a method for managing energy in renewable microgrids using machine learning. The method takes into account a reconfigurable structure that relies on remote tie changing and sectionalizing. “Hybrid electric vehicle (HEV)” charging demand estimation and modeling was the focus of the proposed approach, which takes sophisticated support vector machine through account. Fachrizal et al., (2021) introduced a comprehensive analysis of integrating “photovoltaic (PV) and electric vehicle (EV) systems into a residential low voltage (LV)” distribution grid. It included an evaluation of the grid's hosting capacity under four different “energy management system (EMS)” scenarios. The integrated PV–EV hosting capacity was illustrated through an innovative graphical method, allowing for the simultaneous analysis of PV and EV hosting capacity. The findings indicated that EV smart charging can enhance the ability to accommodate EVs, while providing a minor improvement for PV.

Unpredictable elements, various user behaviors and fluctuating infrastructure conditions contribute to being difficult to estimate EV charging demand. The difficulties are further complicated by the fact that there are no established methods and very little data on people's habits. The intricate interplay between weather, traffic and charging infrastructure further adds to the difficulty of making accurate predictions. Improving reliability requires a reassessment of data collection methods, user behavior modeling approaches and efforts to standardize. It remains difficult to strike a balance among these considerations. The objective of this study was to introduce a novel approach for evaluating the energy usage of EVs known as the Water Wave Optimized Bidirectional Long Short Term Memory (WWO-BLSTM) method.

1.1 Key contributions

The following are the main conclusions to be derived from the electric vehicle charging consumption.

- To evaluate the dataset on the diversity of EV charging, the dataset comprises 10,595 unregulated charging procedures obtained via workplace charging.
- A thorough data cleansing technique was applied.
- Furthermore, a novel approach known as WWO-BLSTM is employed to measure the charging consumption of EVs. We assess the experimental data's accuracy, precision, recall and f1-score.

A four-part framework has been employed in this essay to ensure clarity. The methods employed in the study are detailed in section 2. The investigation's results are summarized in section 3. As a conclusion, section 4 provides a summary of the main results and their implications.

2. METHODS

Figure 1 depicts the sequential advancement of the stages. We gathered EV charging diversity dataset for this investigation and a comprehensive data cleansing procedure was performed. The electric vehicle charging prediction was conducted utilizing the Water Wave Optimized Bidirectional Long Short-Term Memory (WWO-BLSTM) model. The discovered findings are presented and evaluated.

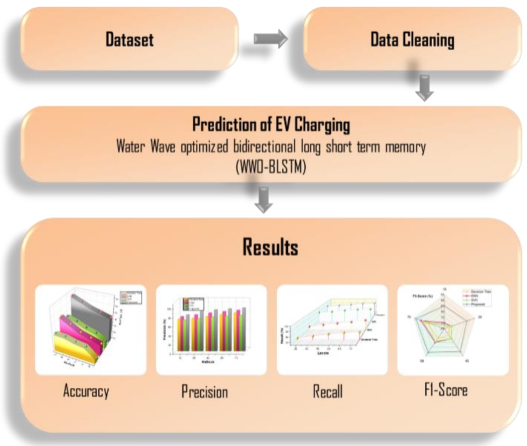

Figure 1. The flow of Charging Consumption for EVs

2.1 Dataset

The dataset includes 10.595 uncontrolled charging processes collected from workplace charging.

All of the procedures are based on data collected from 1001 EVs between 2016 and 2018. Accessing 338 charging outlets spread over 8 cities. The electric vehicle fleet is diverse, with 18 different models representing a wide range of specifications in terms of maximum charging rate, battery capacity and three-phase charging specifications. Though PHEVs use one charging phase, BEVs use three. Charging methods typically take 7 hours and 17 minutes that add 7.01 kWh to the total energy charged (Frendo et al., (2020)).

2.2 Data cleaning

To guarantee the accuracy and dependability of the dataset, a number of significant procedures were carried out during the data cleaning process for the project. Depending on the type and degree of the missing data, the first steps required addressing it by either eliminating rows with partial information or imputing missing values using statistical measures. By closely examining and using the proper statistical procedures, outliers were found and dealt with. To enable uniform analysis, inconsistent or incorrect inputs were fixed and data formats were standardized. In order to avoid redundancy, duplicate records were found and removed. In order to maintain consistency, time stamps and formatting problems were fixed and pertinent variables were chosen for analysis while redundant or unnecessary ones were eliminated. The cleaned dataset provides a strong basis for relevant and reliable estimation of electric vehicle charging consumption, improving the dependability of further analysis and modeling endeavors.

2.3 Water wave optimization

EVs can have their charging schedules optimized with the help of Water Wave Optimization (WWO), which allows for the dynamic adjustment of charging use. In order to minimize energy expenditures and satisfy customer preferences, WWO refines the charging approach, drawing inspiration from the movement of ocean waves. Efficient and cost-effective charging options for EVs can be estimated with the use of WWO by taking grid constraints, customer requirements and power pricing into account.

Metaheuristic algorithm WWO solves global optimization issues by drawing inspiration from water wave theory. Every solution in WWO's solution space is like a "wave" with its own unique height (h) and wavelength (λ), like a seabed area. Seabed depth is used to assess the footness of each wave, with a shorter distance to still water level representing a higher footness. The WWO algorithm's population is defined by waves, with g_{max} and λ set to 0.5 for each wave. At each iteration, WWO defines three

operations breaking, propagation and refraction to achieve the global optimum.
For each wave(W), the propagation operation adds a new wave (X') to the original wave according to Equation 1, which is based on displacement at each dimension(c).

$$W' = W + rand(-1,1) \times \lambda \times K_c \tag{1}$$

Here, "K_c is the length for the cth dimension of the search space and rand is the random function" that generates random numbers in a specified range. If the new wave's ftness$(e(W'))$ is greater than the old wave's ftness $(e(W))$, then the old wave is replaced by the new wave (W') and the height is reset to g_{max}. Else, the wave height is dropped by one.

Deep water waves are characterized by their long wavelength and low amplitude. Shallow water waves are characterized by low wave heights and short wavelengths. Transitioning from a region of greater water depth to a region of lesser water depth results in a reduction in the wavelength of the wave. The value of each wave's wavelength (λ) is determined by applying Equation 2.

$$\lambda = \lambda \times \alpha^{\frac{-(e(W)-emin+\varepsilon)}{(fmax-fmin+\varepsilon)}} \tag{2}$$

A small constant ε is employed to avoid division-by-zero, $e(W)$is the fitness of wave w, α is the parameter for wavelength reduction and "$fmax$ and $fmin$ are the maximum and minimum fitness values in the current population", respectively. As a result, waves with greater height can travel farther and with shorter wavelengths.

We use the refraction operator when the wave height drops to zero. We use the mean (M) and standard deviation (SD) to characterize a Gaussian function, which we use to compute the next wave (W').

$$W' = Gaussian(\mu, \sigma) \tag{3}$$

Equations 4, 5 and their respective computations define μ as the mean and σ as the standard deviation, which are used in Equation 3.

$$\mu = \frac{Wbestc+Wc}{2} \tag{4}$$

$$\sigma = \frac{Wbestc-Wc}{2} \tag{5}$$

The current wave (W) and the best wave (W_{bestc}) are used to calculate the mean (μ). The difference between the best wave (W_{bestc}) and the present wave (W) is the standard deviation (σ). In addition, we use Equation 6 to fix the wavelength and return the wave height to$fmax$.

$$\lambda' = \frac{e(W)}{e(W')} \tag{6}$$

In Equation 6, λ' represents the next wave's wavelength, $e(W')$ signifies the new wave's ftness, $e(W)$ denotes the old wave's fitness and λ denotes the prior wavelength. Whenever the breaking operator in WWO reaches a better site than the current best solution (W_{bestc}), it breaks the wave (W). Equation 7 is used to calculate the single wave (W').

$$W' = W + Gaussian(0,1) \times \beta \times Kc \tag{7}$$

The function Gaussian $(0, 1)$ produces a random integer between 0 and 1, where β is the breaking coefficient. If wave $W'$is superior to wave W, then wave W' will supersede wave W. In Algorithm 1, the WWO pseudocode is mentioned.

Algorithm 1: Water wave optimization (WWO)

Initialize:

Set the number of waves (n)

Set the number of iterations (max_iter)

Set the population size (pop_size)

Initialize the position of each wave randomly in the search space

Main Loop:

for iteration = 1 to max_iter do

for each wave in waves do

Evaluate the fitness of the current position of the wave

if fitness of current position is better than the best fitness so far then

Update the best position and fitness

Apply the update rule to move the wave

Update the position using the wave equation

Apply the boundary constraints to ensure that the new position is within the search space

Apply the exploration-exploitation balance strategy to determine the movement direction

end for

end for

2.4 Bidirectional long short term memory (BLSTM)

EV charging consumption estimation makes use of BLSTM, which processes sequential data in both ways. In addition, a consequence, the model is able to accurately represent the charging time series' dependencies and patterns. Improved prediction accuracy and more robust assessment of EV charging use are both achieved by BLSTM, by including previous charging data from past and future time steps into account.

Sequence categorization applications including sentiment evaluation and identifiable entity recognition use neural networks, with BLSTM classifiers that are among the most common. It improves upon the basic LSTM model by considering the present and future states of all input tokens. An ordered set of features is sent into the BLSTM classifier, with each vector standing in for a time step in the sequence. Some examples of input types utilized in natural language processing problems include word integration and character-level features. In order to create the BLSTM layer, two LSTM layers one bidirectional and one forward-forward are combined.

The input sequence is represented by the symbol $x = \{x1, x2, \ldots, xT\}$, in which xt stands for the input feature vector at time $step\ t$. A mathematical representation of a forward long short-term memory circuit is shown in Figure 2. Considering ahead $g_e = \{g_{e_1}, g_{e_2}, \ldots, g_{e_w}\}$ is the hidden state sequence that is calculated by the LSTM layer. In the procedure of right-to-left processing of the input sequence, $g_{\{e,w\}}$ represents the hidden state at time step t. The following is the formula for the forward input gate $j_{\{e,w\}}$:

$$j_{\{e,w\}} = \sigma\left(X_{\{jw\}w_s} + X_{\{jg\}g_{\{e,s-1\}}} + a_j\right) \quad (8)$$

Here is the derivation of the forward forget gate ($e_{\{e,w\}}$):

$$e_{\{e,w\}} = \sigma\left(X_{\{ew\}w_s} + X_{\{eg\}g_{\{e,s-1\}}} + a_e\right) \quad (9)$$

To derive the forward output gate ($p_{\{e,w\}}$), one follows these steps:

$$p_{\{e,w\}} = \sigma\left(X_{\{pw\}w_s} + X_{\{pg\}g_{\{e,s-1\}}} + a_o\right) \quad (10)$$

Here is the process for deriving the forward candidate gate ($h_{\{e,w\}}$}):

$$h_{\{e,w\}} = tanh\left(X_{\{hw\}w_s} + X_{\{hg\}g_{\{e,s-1\}}} + a_h\right) \quad (11)$$

The gate that represents the forward cell state ($d_{\{e,s\}}$) is obtained in the following way:

$$d_{\{e,s\}} = e_{\{e,s\}} * d_{\{e,s-1\}} + j_{\{e,s\}} * h_{\{e,s\}} \quad (12)$$

The following is the process for deriving the forward hidden state gate ($g_{\{e,s\}}$):

$$g_{\{e,s\}} = p_{\{e,s\}} * tanh\ tanh\left(d_{\{e,s\}}\right) \quad (13)$$

Within this framework, concepts including the sigmoid activation function (SAF), Tanh activation function (TAF), element-wise addition, X and a, as well as the learnable biases and weights of the LSTM, are brought up. A concealed condition is discovered by the backwards LSTM layer by analyzing the input series from left to right. Sequence $g_a = \{g_{a_1}, g_{a_2}, \ldots, g_{a_S}\}$, where g_a ,s represents the hidden state at time step s. The following procedures can be followed to create the backward input gate ($j_{\{a,s\}}$}):

$$j_{\{a,s\}} = \sigma\left(X_{\{jw\}w_s} + X_{\{jg\}g_{\{a,s+1\}}} + a_j\right) \quad (14)$$

The following is the derivation of the backward forget gate ($e_{\{a,s\}}$):

$$e_{\{a,s\}} = \sigma\left(X_{\{ew\}w_s} + X_{\{eg\}g_{\{a,s+1\}}} + a_e\right) \quad (15)$$

To develop the backward output gate ($p_{\{a,s\}}$), one follows these steps:

$$p_{\{a,s\}} = \sigma\left(X_{\{pw\}w_s} + X_{\{pg\}g_{\{a,s+1\}}} + a_p\right) \quad (16)$$

The following is the derivation of the backward candidate gate ($h_{\{a,s\}}$):

$$h_{\{a,s\}} = tanh\left(X_{\{hw\}w_s} + X_{\{hg\}g_{\{a,s+1\}}} + a_h\right) \quad (17)$$

To derive the backward cell state gate ($d_{\{a,s\}}$), one takes these steps:

$$d_{\{a,s\}} = e_{\{a,s\}} * d_{\{c,s-1\}} + j_{\{a,s\}} * h_{\{a,s\}} \quad (18)$$

The following is the derivation of the backward hidden state gate ($g_{\{a,s\}}$):

$$g_{\{a,s\}} = p_{\{a,s\}} * tanh\ tanh\left(d_{\{a,s\}}\right) \quad (19)$$

A merged hidden state sequence, denoted as $g_a = \{g_{a_1}, g_{a_2}, \ldots, g_{a_S}\}$, is created by combining the forward and backward-LSTM layers' concealed states. Here $g_a = \{g_{\ 1}, g_{\ 2}, \ldots, g_{\ S}\}$.

Therefore, the BLSTM can take into account the state of each input character both in present and in the future. To generate a probability distribution that encompasses the potential output categories, the output layer takes as input the concatenation undetectable state sequences h. It is possible to use a basic fully linked layer as the output layer after applying a SoftMax activation function. Algorithm 2 makes note of the BLSTM pseudocode.

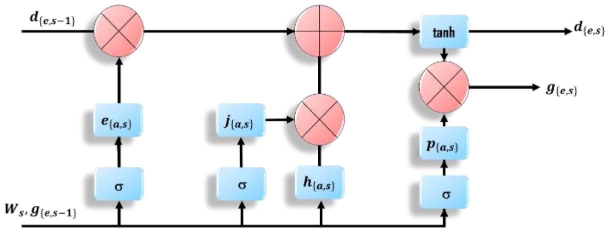

Figure 2. BLSTM.

Algorithm 2: BLSTM

$Initialize\ weights\ and\ biases\ for\ forward\ and\ backward\ LSTMs$
$Initialize\ hidden\ states\ and\ cell\ states\ for\ both\ directions$
$Input\ sequence\ X$
$Split\ X\ into\ forward\ and\ backward\ sequences: X\_forward, X\_backward$
$Initialize\ empty\ arrays\ for\ forward\ and\ backward\ hidden\ states: h\_forward, h\_backward$
$Initialize\ empty\ arrays\ for\ forward\ and\ backward\ cell\ states: c\_forward, c\_backward$
$For\ t\ in\ range(length(X\_forward))$
$Forward\ LSTM\ step$
$h\_forward[t], c\_forward[t] \ = LSTM\_forward(X\_forward[t], h\_forward[t-1], c\_forward[t-1])$
$Backward\ LSTM\ step:$
$h\_backward[t], c\_backward[t] \ = LSTM\_backward(X\_backward[t], h\_backward[t+1], c\_backward[t+1])$
$Concatenate\ forward\ and\ backward\ hidden\ states: h\_concat\ =\ concatenate(h\_forward, h\_backward)$
$Output\ sequence\ Y$
$Initialize\ weights\ and\ biases\ for\ the\ output\ layer$
$Initialize\ empty\ array\ for\ the\ final\ output: Y\_output$
$For\ t\ in\ range(length(h\_concat))$
$Y\_output[t]\ =\ Output\_layer(h\_concat[t])$
$Loss\ calculation\ and\ backpropagation$
$Update\ weights\ and\ biases\ using\ optimization\ algorithm\ (e.g., gradient\ descent)$
$Repeat\ steps\ 4-19\ for\ each\ training\ iteration$

2.5 Water wave Optimized bidirectional long short-term memory (WWO-BLSTM)

The WWO-BLSTM algorithm is utilized to predict the charging usage of EVs by exploiting its ability to capture forward and backward temporal relationships in sequential data. This hybrid model combines the bidirectional nature of LSTM with the optimization capabilities of the WWO algorithm to improve the accuracy of predicting EV charging consumption trends. The WWO-BLSTM model acquires knowledge and adjusts to the intricate temporal patterns of EV charging behavior, considering variables such as charging station accessibility, user inclinations and external impacts. Through the examination of past charging data, the model can generate accurate forecasts, assisting in the optimization of charging infrastructure planning and energy management techniques. This facilitates a more sustainable and effective integration of EVs into the power grid. In Algorithm 3, the WWO-BLSTM pseudocode is mentioned.

Algorithm 3: Water wave Optimized bidirectional long short-term memory (WWO-BLSTM)

```
function WWO_BLSTM(input_data)
initialize_parameters()
for epoch in range(num_epochs)
for i in range(num_batches)
batch_data = get_next_batch(input_data, batch_size)
forward_pass_result = forward_pass(batch_data)
loss = calculate_loss(forward_pass_result, batch_data)
backward_pass(loss)
evaluate_model()
test_model()
functionforward_pass(batch_data)
forward_lstm_output = forward_lstm_layer(batch_data)
backward_lstm_output =
backward_lstm_layer(batch_data)
final_output = concatenate(forward_lstm_output,
backward_lstm_output)
returnfinal_output
functionbackward_pass(loss)
compute_gradients(loss)
update_parameters()
functionforward_lstm_layer(input_data)
functionbackward_lstm_layer(input_data)
functioninitialize_parameters()
functioncalculate_loss(predictions, targets)
functioncompute_gradients(loss)
functionupdate_parameters()
functionevaluate_model()
functiontest_model()
input_data = load_data()
   WWO_BLSTM(input_data)
```

3. RESULTS

3.1 Experimental setup

The suggested approach running in the MATLAB R2021 environment, the simulation makes use of an 8 GB physical memory system and an Intel dual core i5 CPU.

3.2 Metrics for evaluating effectiveness

This section examines the metrics of precision, F1-score accuracy and recall. A comparison is being performed concerning the classification performance of the "Decision tree, K-Nearest Neighbors (KNN) and Support Vector Classifier (SVC) models" (Harippriya et al., (2022)).

In estimating charging consumption for EVs, accuracy evaluates the overall correctness, precision evaluates the dependability of the predicted consumption values, recall evaluates the model's capacity to identify real high consumption instances and the F1-score offers a balanced metric that requires precision and recall into consideration. Collectively, these parameters examine the predictive ability of models, assuring precise and comprehensive evaluations of estimates for EV charging use.

Accuracy in charging consumption for EVs pertains to the exactness of estimating the quantity of electrical energy needed for recharging the vehicle's battery, assuring minimal difference between anticipated and real energy usage.

$$Accuracy = \left(1 - \frac{|Actual\ consumption|}{Predicted\ consumption}\right) \times 100\% \quad (20)$$

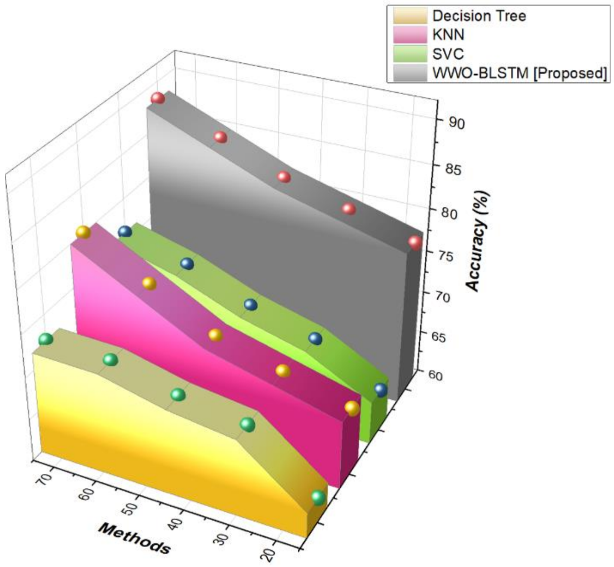

Figure 3. Results of accuracy

Table 2. Values of accuracy

Methods	Accuracy (%)			
	Decision Tree	KNN	SVC	WWO-BLSTM [Proposed]
15	63	68	65	78
30	69	70	69	80
45	70	72	71	82
60	71.8	76	74	85
75	72	80	76	88

Equation 20 quantifies the accuracy of a method in determining its current position based on available information. Table 2 and Figure 3 display the assessment of both the proposed and existing approaches. Considering existing methods of Decision tree (72%), KNN (80%) and SVC (76%), if our proposed methodology achieves a WWO-BLSTM accuracy of 88%, it is evident that it outperforms the current strategy for estimating the charging consumption of EVs.

Precision, in the framework of Charging Consumption for electric vehicle pertains to the precise measurement and regulation of the quantity of electric energy consumed during the process of recharging, guaranteeing effective and dependable power transmission to the electric vehicle.

$$Precision = \frac{Actual\ charged\ energy}{Requested\ charged\ energy} \times 100\% \quad (21)$$

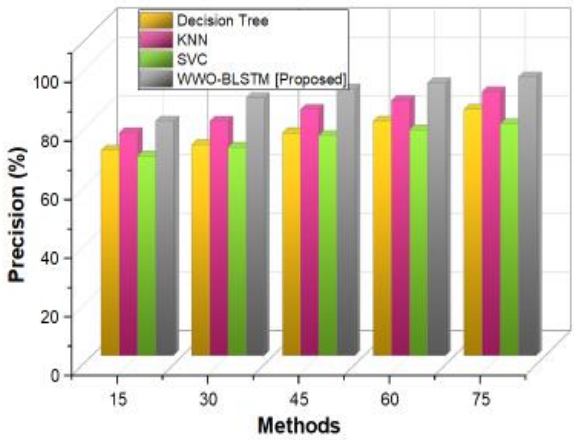

Figure 4. Results of precision

Table 3 Values of precision

Methods	Precision (%)			
	Decision Tree	KNN	SVC	WWO-BLSTM [Proposed]
15	70	76	68	80
30	72	80	71	88
45	76	84	75	91
60	80	87	77	93
75	84	90	79	95

The calculation has been executed using the designated Equation 21. Figure 4 and Table 3 provide a comparison of the precision between the existing approach and the suggested method. The proposed approach WWO-BLSTM established a precision of 95%, which is higher than the popular methods scoring decision tree (84%), KNN (90%) and SVC (79%). Hence, the suggested methodology exhibits an important reduction in the charging consumption of EVs.

For recall, consider the sum of every positive sample and divide it by the number of positive samples that were accurately designated as positives. The accuracy with which the model can identify positive samples is quantified by the recall metric. As recollection improves, the number of positive samples found increases proportionately.

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives} \quad (22)$$

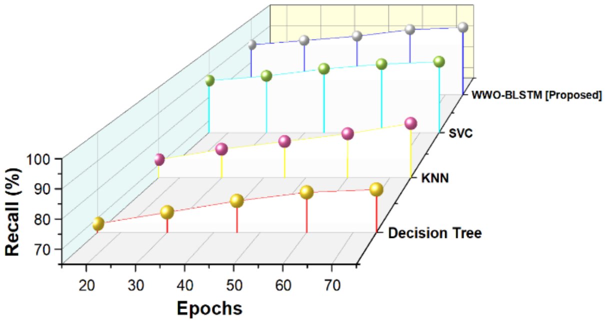

Figure 5. Results of recall

Table 4. Values of recall

Methods	Recall (%)			
	Decision Tree	KNN	SVC	WWO-BLSTM [Proposed]
15	68	72	87	88
30	72	76	89	90
45	76	79	92	92
60	79	82	94	95
75	80	86	95	96

Figure 5 and Table 4 provide a comparison between the recall Equation 22 of the suggested method along with the standard approach. Among the existing methods, including decision tree, KNN as well as SVC, which achieved reliability scores of 80%, 86% and 95% respectively, the proposed approach, WWO-BLSTM, achieved a score of 96%. This outcome immediately enhances the considerably greater effectiveness of the technique we have proposed.

The F1 score is a metric that quantifies the harmonic mean of precision and recall. The F1 score combines precision and recall to provide a comprehensive measure of model performance.

$$F1 - score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \quad (23)$$

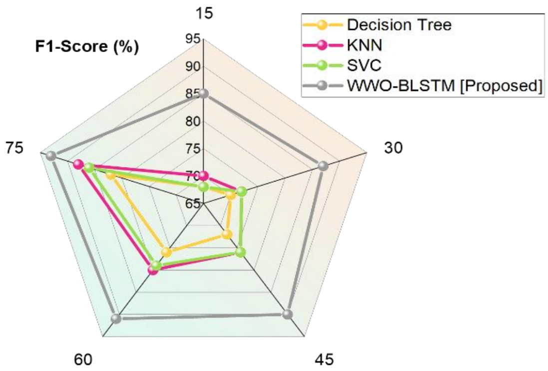

Figure 6 Results of F1-score

Table 5. Values of F1-score

Methods	F1-Score (%)			
	Decision Tree	KNN	SVC	WWO-BLSTM [Proposed]
15	68	70	68	85
30	70	72	72	87
45	72	76	76	90
60	76	80	79	91
75	82	88	86	93

The suggested method is compared to the usual approach's F1-score in Figure 6, Table 5 and Equation 23. By comparison, the proposed WWO-BLSTM technique achieved a score of 93%, whereas the established methods of decision tree, KNN, and SVC had scores of 82%, 88%, and 86% respectively. The result is closely linked to the enhanced effectiveness of our suggested method.

4. CONCLUSION

In summary, the amount of energy used to charge EVs is an important factor that needs to be considered as we continue to move toward more environmentally friendly modes of transportation. We conclude by presenting the Water Wave Optimized Bidirectional Long Short-Term Memory (WWO-BLSTM) model as a novel method for forecasting the amount of time that EVs will require to charge. When WWO is used, EV charging schedules can be optimized, allowing for flexible modifications to charging patterns. To calculate the estimated length of time needed to charge an electric vehicle, we employ the BLSTM model, which can process sequential input in both directions. We have included all possible EV charging scenarios in our dataset. which consists of 10.595 unregulated workplace charging procedures. We have a thorough data cleaning process to guarantee the accuracy of our findings. Using MATLAB software, simulations were run to verify the efficacy of our suggested strategy. Our WWO-BLSTM methodology yielded successful results, as evidenced by the model's 88% accuracy, 95% precision, 96% recall and 93% F1 score. These results highlight our approach's ability to provide precise estimates for EV charging consumption. One approach that shows promise for improving EV charging schedules and promoting the effective as well as sustainable use of EVs is the combination of bidirectional LSTM coupled with water wave optimization. To achieve broad acceptance of fair and efficient electric vehicle charging solutions, there can be obstacles in standardization, infrastructure development and dealing with the intermittent nature of renewable energy sources. Smart grid integration, dynamic pricing models and improved energy management systems are the possibilities for the future of electric vehicle charging use.

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G. Ezhilarasan
JAIN (Deemed-to-be University), Ramanagara District, Karnataka, India
g.ezhilarasan@jainuniversity.ac.in
ORCID 0000-0002-5335-2347

Kalyan Acharjya
Maharishi University of Information Technology, Uttar Pradesh, India
kalyan.acharjya@gmail.com
ORCID 0000-0001-7802-7332

Ajay Kumar
Noida Institute of Engineering & Technology, Greater Noida, Uttar Pradesh, India
ajaykumar@niet.co.in
ORCID 0000-0002-6977-8844

Anup Kumar
Arka Jain University, Jamshedpur, Jharkhand, India
dr.anup@arkajainuniversity.ac.in
ORCID 0000-0003-3205-9341