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Charging Station Power System Data Prediction Model Based on Deep Learning

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Abstract. The increase growth and adoption of electric vehicles (EVs) are playing a crucial role in advanced transportation system, helping to minimizing the emissions of harmful greenhouse gases and enhancing environmental sustainability. The need for EVs to be charged immediately has gained significant attention due to the rise in EVs sales over the last years. As a result of this, need for electric car charging is important to reducing the impact of electric network and providing minimum charging fares. In order to calculate the demand for charging EVs, a novel Deep Learning (DL)-based Long-Short Term Memory (LSTM) recurrent neural network predictor model is attempted to be developed in this research study. The Modified Aquilla Optimizer Algorithm (MAOA) is used to optimizing the parameter of the new Deep LSTM (DLSTM) neural predictor models and Independent Component Analysis (ICA) is utilized to solve the input time series data while conserving its properties. In this research, a novel ICA—AOA—DLSTM neural predictor model was developed to addressed the challenges of vanishing and exploding gradient in basic recurrent neural learnings. The predictor model was tested on the EV charging dataset from Georgia Tech, Atlanta, USA, indicating its performance. During simulation, the predictor achieved a prediction accuracies of 96.24% with a mean absolute errors of 0.1083 and a RMSE errors of 3.0629 × 10^-5, outperforming previous techniques. Additionally, the mean absolute error was found to be 0.2083, with a mean square error of 3.25516 × 10^-10. These results highlight the effectiveness of the novel deep learning LSTM neural predictor for this dataset compared to existing techniques.

Key words. Charging Station, Power System, Data Prediction, Deep Learning Model, EV (Electric Vehicle).

1. Introduction

The auto industry has been concentrating on electric automobiles in recent years to combat the constant climatic condition found across the world and to reduce gas emissions as much as feasible. The jobs, economy, and power sectors have all benefited from the explosive rise of EV technology. Essentially, IC engines that use fuels are replaced with electric motors in EVs. These electric cars run on electricity generated from sources outside of the vehicle or include built-in solar panels or batteries for self-charging. There are many different types of electric vehicles (EVs): plug-in EV, airborneEVs, EVs, offroad electric vehicles, range extension of range EVs, and so forth. The most widely produced types of electric vehicles are plug-in hybrids and battery-powered EVs, or plug-in electric vehicles. Plug-in hybrid electric vehicles are those in which an on-board module or an external power source is used to charge the batteries. Pure electric cars (EVs) are powered by battery cars without an internal combustion engine that use the chemical energy stored in rechargeable batteries. Regarding the many benefits of electric vehicles: lower greenhouse gas emissions, air pollution health risks, less need for diesel or gasoline, reduced energy consumption while stationary, improved tank-wheel efficiency of EVs, reduced vibrations and production of noise, no need for gearboxes for conversion of torque, straightforward designing of mechanical equipment's , increased output power for the total range of speed, and so forth. According to this condition, the world's utility rate has been maximized by the quick delivery of millions of electric automobiles. In 2024, there were 7.9 million battery-powered vehicles in use worldwide, and about three million battery-electric vehicles were produced brand-new.

Currently, the charging of EVs is a serious concern because to the global increase in population and the millions of EVs on the road. EVs need to have a direct current (DC) supply to charge their batteries. Since the distribution of electric power is AC, a converters is necessary to provide the DC powers to the battery sources. The general rating of power and charging options for electric vehicles are shown in Table 1. EVs will receive conductive charging in both AC and DC modes.

When charging with AC power, an on-board chargers takes the power and transforms it into DC. DC charging eliminates the requirement for an on-board charger by converting power outside and supplying DC power straight to the battery source. Thus, for the electric car to work efficiently, it is imperative that the battery source be charged as needed. This helps both the company and the consumers by providing information on the amount of time and distance needed for charging an EV. When the battery runs out, customers will be able to find additional charging

stations nearby and plan their journey distance thanks to the EV charging demand prediction.
Since electric vehicles don't use fuels to run, they produce no gas emissions, which attests to their environmentally favorable characteristics. These cars are often powered by electricity, which makes them a renewable energy source as opposed to standard vehicles that use gaseous fuels. When Photovoltaic power is used at house and by businesses, the cost of energy is low compared to that of gasoline and diesel, and the cost of battery recharging is economical. Compared to conventional vehicles, electric vehicles require less maintenance because their auto parts experience less wear and tear. The cost of maintenance is less complicated than with combustion engines. First, they are more expensive than conventional vehicles, and there aren't as many charging stations as there are in a given area. Recharging takes longer than filling up with gas or diesel, which is finished in a matter of minutes. The electric vehicle's operating ranges are limited, and unlike conventional combustion vehicles, it is not appropriate for long-distance travel.

The primary goal of this work is to designing and developing a predictive model for predicting the charging demands for EVs, taking into account the necessary demand for EV charging. By doing so, it will be easier to maintain equilibrium between the amount of money spent and the time, distance, and time spent traveling and charging. Predicting the demand for EVs charging is necessary due to the growing need for electricity and the installation base of electric vehicles (EVs). This helps both the company and the consumers by providing information on the amount of time and distance needed for charging an EV.

2. Literature Review

Shanmuganathan, J., et al. [1] investigated a novel DL based LSTM recurrent neural network predictor models for predicting the demand of EV Charging. They tuned the model parameter utilizing the AOA and decomposing the input time series data using EMD.

Koohfar, S., et al. [2] investigated using the transformer model for forecasting EVs charging demand, compares it with conventional time series methods and other DL model. The Transformer model overcome RNN, LSTM, ARIMA, and SARIMA in both minimum-period and long-period EV charging prediction, signifies its effectiveness in addressing time series forecasting for EV load charging.

Van Kriekinge, G., et al. [3] presented an improved DNN for prediction of the day-ahead charging demand of EVs, adding new features such as indication of exact dates and weather Data of weather.

Chang, M., et al. [4] proposed a LSTM neural network-based prediction models to analyzing and prediction the compiled charging power demands from one or more fast-charging station. The model surpasses other DL approach in prediction of power demands of fast-charging power, addressing the challenge of by the different nature of instant-charging demand of power.

Boulakhbar, M., et al. [5] examined the performances of four DL model in forecasting of the charging demand for EVs after a charging session begins. The GRU regression models demonstrated the best performances, with an RMSE and MAPE of 2.80% and 0.76% in the testing stage, respectively, showing its potential for supporting in grid reliability and planning additional charging stations.

Wang, S., et al. [6] developed a LSTM neural network to predicting the minimum-term EV charging at the stations levels. They also found that the LSTM model's prediction accuracy was more regulated by the time span and interval than by input data structures and sample sizes.

Dabbaghjamanesh, M., et al. [7] proposed a Qlearning techniques to forecast PHEVs charging station load, improving upon traditional AI techniques such as RNNs and ANNs. The Q-learning techniques demonstrates the exact prediction under smart, uncoordinated, and coordinated charging situations, validating its effectiveness in managing EV load profile.

Yi, Z., et al. [8] proposed a Sequences to Sequences (Seq2Seq) deep learning approach for forecasting the monthly commercials EV charging demands, addressing the challenges of insufficient charging infrastructure. The model demonstrated superior performance in multi-step prediction comparing to several time periods and ML model, indicating its effectiveness in managing EV charging demand and supporting grid reliability.
Eddine, M.D., et al. [9] proposed a novel DL-based approach, Temporal Encoders-Decoders + LSTM (T-LSTM-Enc) integrated with Temporal LSTMs (T-LSTM-Ori-TimeFeatures), for predicting EVs charging energy demands.

Zamee, M.A., et al. [10] proposed a novel online forecasting model for electric vehicle (EV) charging demand, addressing data inadequacy issues in newly installed EV stations. The model, based on General Regression Neural Network (GRNN) and detailed feature engineering, outperformed traditional Artificial Neural Networks (ANN) and sophisticated models and demonstrating its effectiveness in forecasting EV charging demand with limited historical data.

Zhu, J., et al. [11] compared ANNs and LSTM model for forecasting EVs charging loads from the charging stations point of view. The LSTM model overcome traditional ANNs, demonstrating maximum accuracies in short-term EV load forecasting, which is important for maintaining stable and effective power system operations amidst the increasing usage of EVs.

Shen, X., et al. [12] investigated a GAN-based data generation methods to improve the accuracies of EVs load for prediction utilizing scarce dataset from very new operates EV charging station.

Zhou, H., et al. [13] investigated an LSTM-based ML algorithms for effective energy management in commercial buildings with EV charging pile and integrated solar panel, addressing challenges in conventional optimization-model-based systems.

Xin, F., et al. [23] studied the prediction of EV charging load using a hybrid approach combining clustering and deep learning techniques. Spectral clustering was placed to identify distinct patterns in the various dataset, providing the construction of cluster-specific CNN-LSTM models for exact load predictions. Outputs shows the good prediction accuracy compared to other methods, signifying the method's efficiency in improving grid load dispatch and management of EV charging infrastructure.

Qu, H., et al. [24] investigated the challenges in accurately predicting EV charging demand in urban areas, emphasizing the limitations of existing data-driven deep learning methods in understanding complex factors such as charging prices. They highlighted the potential misinterpretation of pricing signals during peak times, which can lead to erroneous demand predictions.

Jayaraman, R. et al. [25] investigated the challenge of accurately predicting the state of charge (SOC) in lithium-ion batteries used in electric vehicles (EVs), highlighting the critical role of SOC in suggesting the vehicle reliability and safety. They proposed a novel approach combining deep learning and dimensionality reduction techniques to enhance SOC prediction accuracy. The research study outcome shows that it utilized current, voltage, and temperature data from a publicly available dataset, applying normalization to standardize the data.

Xiong, X., et al. [26] investigated methods for accurately estimating the State of Health (SOH) of lithium-ion batteries in Electric Vehicles (EVs), addressing challenges posed by random charging-discharging behaviour and incomplete data. They proposed an efficient data preprocessing algorithm for handling data slicing, cleaning, alignment, and recombination to improve SOH estimation accuracy.

Kumari, P. et al. [27] investigated the development of estimation models for State of Charge (SoC), State of Health (SoH), and State of Temperature (SoT) in lithium-ion batteries, emphasizing the critical role of Battery Management Systems (BMS) in ensuring optimal performance and safety of electric vehicle batteries. They proposed an improved EP-based R110-BLSTM approach, combining Emperor Penguin based Residual Network-110 with Bidirectional Long-Short Term Memory (BLSTM). This hybrid model was designed to accurately estimate SoC, SoH, and SoT while offering fast estimation speed and strong generalization capabilities.

Table 1. Summary of Literature Review

Sl.No	Author and Citation	Techniques	Advantages	Disadvantages
1.	Shanmuganathan, J., et al. [1]	DL-based LSTM RNN	Achieved high prediction accuracy, improved forecasting compared to previous techniques	Requires tuning of parameters using AOA, decomposing input data using EMD, computationally intensive
2	Koohfar, S., et al. [2]	Transformer Model	Outperformed RNN, LSTM, ARIMA, SARIMA in shortterm and longterm EV charging predictions	Limited interpretability of Transformer model, requires large amounts of data for training
3	Van Kriekinge, G., et al. [3]	Deep Neural Network	Reduced MAE and root-mean-square errors (RMSE), effective in forecasting day-aheadcharging demand of EVs	Prone to overfitting, may require significant computational resources
4	Chang, M., et al. [4]	LSTM Neural Network	Outperformed other deep learning approaches in prediction of fast-charging power , addressed challenges of fluctuating nature of demand	Vulnerable to vanishing gradient problem, sensitive to hyperparameter tuning
5	Boulakhbar, M., et al. [5]	ANN, RNN, LSTM, GRU	GRU regression model demonstrated best performance, potential for assisting in grid reliability and planning additional charging stations	Limited generalization to unseen data, complex architecture may lead to longer training times
6	Wang, S., et al. [6]	LSTM Neural Network	Outperformed ARIMA and MLP models, influenced by time span and interval for prediction accuracy	Susceptible to noise in data, requires careful preprocessing

Sl.No	Author and Citation	Techniques	Advantages	Disadvantages
7	Dabbaghjamanesh, M., et al. [7]	Q-learning Technique	Accurate forecasting under smart, uncoordinated, and coordinated charging scenarios, validating its effectiveness in managing EV load profiles	Limited scalability to large datasets, complex implementation
8	Yi, Z., et al. [8]	Seq2Seq Deep Learning Approach	Superior performance in multi-step prediction, effective in managing EV charging demand and supporting grid reliability	High computational cost, potential for overfitting due to complex architecture
9	Eddine, M.D., et al. [9]	Temporal LSTM Models	Promising performance in managing EV charging stations' energy consumption and grid utilization	Limited interpretability of LSTM models, potential for overfitting
10	Zamee, M.A., et al. [10]	GRNN, Detailed Feature Engineering	Outperformed traditional ANN and sophisticated models like RNN, LSTM, Bi-LSTM, GRU, and DNN, effective in forecasting EV charging demand	May require expert domain knowledge for feature engineering, sensitive to noise in input data
11	Zhu, J., et al. [11]	LSTM neural network	Outperformed traditional artificial neural networks, higher accuracy in short-term EV load forecasting	Vulnerable to vanishing gradient problem, training time increases with dataset size
12	Shen, X., et al. [12]	GAN-based Data Generation, LSTM with Mogrifier	Improved accuracy of EV load prediction using scarce datasets, enhanced LSTM performance	GAN training can be unstable, Mogrifier mechanism adds complexity to model
13	Zhou, H., et al. [13]	LSTM Neural Network	Effective energy management in commercial building with EV charging pile and solar panel, addressing challenges in conventional systems	Limited flexibility in handling dynamic environments, potential for over-fitting

3. Problem Statement

The research study aims to address the pressing need for accurate and efficient prediction of EV charging demand. With the rapid expansion of EVs, there is a critical requirement for effective management of charging infrastructure to alleviate strain on electric networks and ensure affordable charging rates [14]. Existing prediction techniques often encounter challenges such as diminishing and exploding gradient in basic recurrent learning. Consequently, there is a clear necessity for innovative approaches, like the proposed DLSTM neural predictor, to enhance the accuracy and reliability of EV charging demand forecasts.

4. Proposed Methodology

Charging prediction of the Automobile is the crucial parameter for the any automobile in case of the Electric vehicles, In this proposed data's are collected from the datasets of the charging stations of the Nevada region and these datasets contains the cumulative data's of how the charging demands may vary at different climatic conditions etc., Because while considering the Datasets all these parameters are very crucial and important, because the learner and end-user want to ensure that how the charging rate may varying. Data are taken during the rainy period, sunny periods so that datasets are taken from the inclusive of all data for accurate predictions. Deep learning concept was introduced which is LSTM RNNs, A RNNs is a type of ANNs commonly used in prediction and forecasting and some other deep-learning based prediction methods. RNNs will recognize data's sequential characteristics and identify the usage of patterns to forecast the next likely scenarios. Consideration of this particular neural network is due to its best ability to predict the charging scenarios with so much exactness and with precise manner.

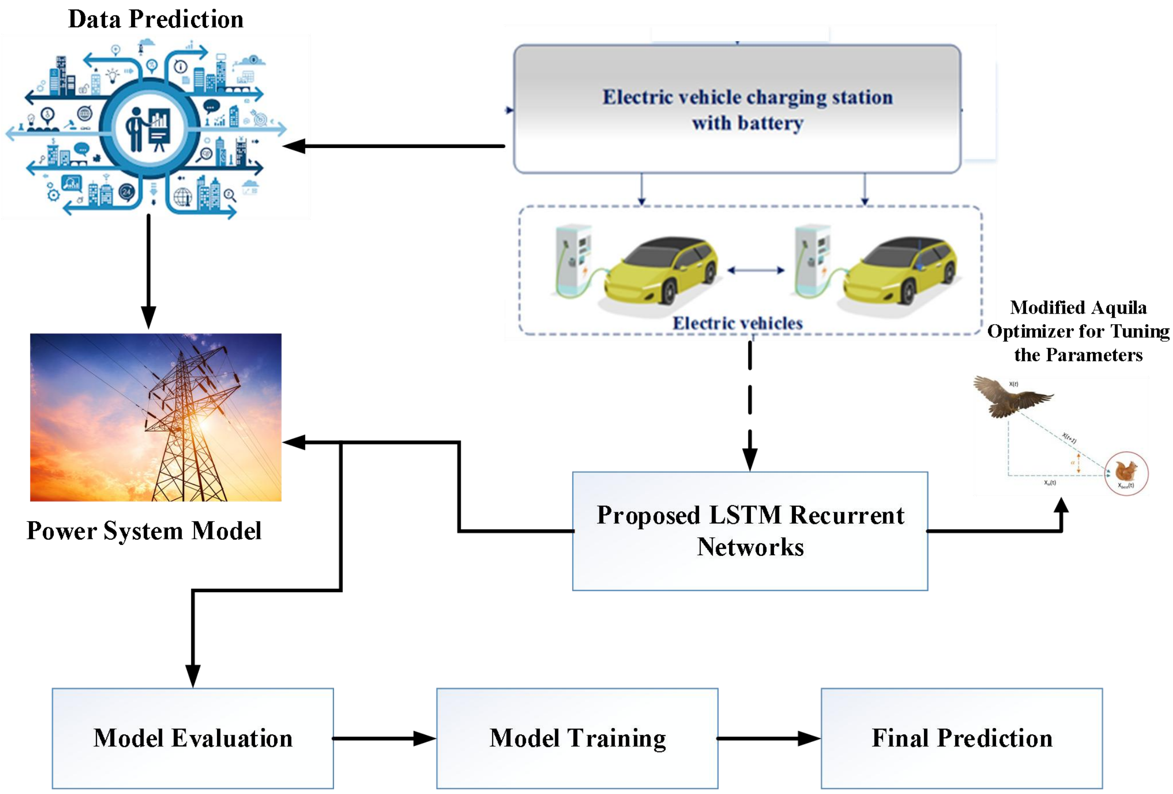

Figure 1. Proposed Architecture for Charging station Power System Data Prediction

As we know that optimization is the needed steps in any prediction operations, because it finds a best outcome to the problem, LSTM Recurrent neural networks is optimized using the modified Aquila optimizer algorithm. The LSTM module's hyper-parameter adjustment in this study can be accomplished through the application of the MAO method. The AO is primarily dependent on the Aquila's ability to capture prey [15]. The population-based method known as AO quickly demonstrates its efficacy in the realm of complex and nonlinear optimization. And ICA was considered for the assigning the input parameters for the best training session and finally all these are validated and trained and best model was obtained.

A. Independent Component Analysis (ICA)

The raw time series data's from the integrated plant at Georgia Tech, Atlanta, GA, USA, will undergo Independent Component Analysis (ICA) to be divided into various sub-series. These sub-series will then be individually predicted before being reconstruction to determine the overall forecasted demand value [16]. The electric vehicle charging data's are initially represented as a single series, which will be decomposed and processed as described. Additionally, ICA can be used to further decompose the data into statistically independent components, enhancing the prediction process. The objective function formulation is carried out by,

$$RS = Min\left[RS_1, RS_2\right] \tag{1}$$

Here, RS_1 indicates the first defines active power losses minimization and RS_2 indicates the second represent the minimization power of tie-line.

$$RS_1 = \sum_{j=1}^{i_j}\sum_{l=1}^{i_l} A^j_{Loss,l} \times BA \tag{2}$$

$$A_{Loss} = \sum_{m=1}^{G_H} x_{mn}\left(x_m^2\left(Uhb_{mn,l}\right)^2 + d_n^2 - 2d_m d_n Uhb_{mn,l}\cos\alpha_{mn}\right) \tag{3}$$

Here, MG active power loss at period j for current state l can be denoted as $A^j_{Loss,l}$, period instant counts as i_j, state counts as i_l, merged probability of PV irradiations, WT speed and load demands as BA, total number of line can be denoted as G_H, conductance's of the lines in-between buses m and bus n can be denoted as x_{mn}, $Uhb_{mn,l}$ can be represented as the instant Tap Changing (OLTC) tap position of the lines between buses m and bus n.

$$RS_2 = \sum_{j=1}^{i_j}\sum_{l=1}^{i_l} A^j_{Tie-line,l} \times BA \tag{4}$$

Here, tie-lines power between MG and utilities as $A^j_{Tie-line,l}$.

ICA plays an important role in preprocessing the input time series data for the DLSTM neural predictor model which focuses at prediction of EV charging demand. By encompassing the raw data into statistically component, ICA preserves the original structure and temporal dependency is very crucial for exact and correct prediction. This selection of this method is justified by ICA's ability to solve non-Gaussian and non-linear relationships in the data, which are very common in EV charging pattern for demands. PCA or wavelet-based methods, ICA provides the extraction of meaningful feature while minimizing noise, thus improving the robustness and definable of the DLSTM model. This preprocessing section contributes to achieving the fine prediction accuracies compared to normal technique, shows the vital importance of data preprocessing in advancing predictive analytics for EVs infrastructure management.

1 Constraints

The equation (5) to (19) signify about the constraint of the recommended systems and are formulated in (5(;

$$i_m A^j_{DU,m,l} + A^j_{AE,m,l} - A^j_{a,m,l} \pm A^j_{AH,m,l} - d^j_{m,l}\sum_{n=1}^{i_k} d^j_{n,l}\left[x_{mn}\cos\alpha^j_{mn,l} + Y_{mn}\sin\alpha^j_{mn,l}\right] = 0 \quad (5)$$

Here, Y_{mn} can be denotes as line susceptances between bus, $d^j_{m,l}$ can be denotes as the magnitude of voltage magnitude at m^{th} node, $\alpha^j_{mn,l}$ can be denoted as the differences of voltages angles at bus, $A^j_{a,m,l}$ denotes the peak load demands, $A^j_{AH,m,l}$ can be denoted as the parking lot powers, wind turbines generated power at buses m can be denoted as $A^j_{DU,m,l}$, PV generation power at buses m can be denoted as $A^j_{AE,m,l}$, total numbers of node can be denoted as i_k, permissible numbers of WT at bus i can be denoted as i_m

$$M^j_{DU,m,l} + M^j_{mid,AE,m,l} + M^j_{mid,DU,m,l} - M^j_{a,m,l} - d^j_{m,l}\sum_{j=1}^{i_k} d^j_{n,l} Uh A\left[x_{mn}\sin\alpha^j_{mn,l} + Y_{mn}\cos\alpha^j_{mn,l}\right] = 0, \quad (6)$$

Here, power load demand can benoted as $M^j_{a,m,l}$, power load demand of PV at m^{th} nodes can be denotes as $M^j_{mid,AE,m,l}$, reactivepower of WT at m^{th} nodes can be denotes as $M^j_{mid,DU,m,l}$, set of the system bus can benoted as ϕ_k.

$$d^{\min} \le d^j_{m,l} \le d^{\max}, \quad \forall m \in \phi_k, l, j \quad (7)$$

Here,low and high voltage extent of the systems can be termed as $d^{\min}$ and $d^{\max}$.

$$A^{\min,j}_{AH,m,l} \le A^j_{AH,m,l} \le A^{\max,j}_{AH,m,l}, \quad \forall m \in \phi_k, l, j \quad (8)$$

$$i^{\min}_m \le i_m \le i^{\max}_m, \quad \forall m\ \phi_k \quad (9)$$

$$B^{\min}_{AE,i} \le B_{AE,i} \le B^{\max}_{AE,i}, \quad \forall m \in \phi_k \quad (10)$$

$$B^{\min}_{DU,m} \le B_{DU,m} \le B^{\min}_{DU,m}, \quad \forall m \in \phi_k \quad (11)$$

Here, capacities of PV and WT can be indicated as $B_{DU,m}$ and $B_{DU,m}$.

$$\sum_{m=1}^{G_{AE}} A_{AE,m} \le T^{\max}_{AE} \quad (12)$$

$$\sum_{m=1}^{G_{DU}} A_{AE,m} \le T^{\max}_{DU} \quad 13)$$

Here, high total magnitude of source can be denoted as $T^{\max}_{AE}$ and $T^{\max}_{DU}$.

$$\sum_{m=1}^{G_{AE}} A_{AE,m} \le T^{\max}_{AE} \quad (12)$$

$$\sum_{m=1}^{G_{DU}} A_{AE,m} \le T^{\max}_{DU} \quad (13)$$

Here, high total magnitude of source can be denoted as $T^{\max}_{AE}$ and $T^{\max}_{DU}$.

$$M^{\min,j}_{mid,AE,m,l} \le M^j_{mid,AE,m,l} \le M^{\max,j}_{mid,AE,m,l}, \quad \forall m \in \phi_k, l, j \ (14)$$

$$M^{\min,j}_{mid,DU,m,l} \le M^j_{mid,DU,m,l} \le M^{\max,j}_{mid,DU,m,l}, \quad \forall m \in \phi_k, l, j \ (15)$$

$$\begin{cases} M^{\max,j}_{mid,AE,m,l} = \sqrt{N^2_{mid,AE,m,l} - \left(A^j_{AE,m,l}\right)^2} \\ M^{\min,j}_{mid,AE,m,l} = -\sqrt{N^2_{mid,AE,m,l} - \left(A^j_{AE,m,l}\right)^2} \end{cases} \quad (16)$$

$$\begin{cases} M^{\max,j}_{mid,DU,m,l} = \sqrt{N^2_{mid,DU,m,l} - \left(A^j_{DU,m,l}\right)^2} \\ M^{\min,j}_{mid,DU,m,l} = -\sqrt{N^2_{mid,DU,m,l} - \left(A^j_{DU,m,l}\right)^2} \end{cases} \quad (17)$$

$$Uhb^{\min} \le Uhb^j_{mn} \le Uhb^{\max}, \quad \forall (m,n) \in \phi_q \quad (18)$$

Here, total number of systems branches can be indicated as ϕ_q.

$$SOC_{i,a,l} \ge SOC_{i,\min,l} \quad (19)$$

Here, SOC of i^{th} batteries at time of parking can be denoted as $SOC_{i,a,l}$, calculated SOC with low values can be noted as $SOC_{i,\min,l}$.

B. Load Demand Probabilistic Modelling

In microgrids where the power demand is uncertain, a common approach is to use a Probability Density Function (PDF) to model the load at each bus. The formulation for modeling the load demand as a normal PDF is represented by the following equation.

$$g^j_G(s) = \left(\frac{1}{\beta_l\sqrt{2\pi}}\right)\exp\left[-\left(\frac{s-\varepsilon_s}{2\beta_s^2}\right)\right] \quad (20)$$

Here, demand for normal load PDF can be denoted as $g_G^j(s)$, load demand mean can be signifies as ε_s, load demand standard deviations can be denoted as β_s.

$$prob_{s,m}^{j} = \int_{s_1}^{s_2} g_G^j(s).dl \quad (21)$$

Here, load demand limit in the intervals m can be denoted as s_1 and s_2.

C. Modelling of Charging Station Integrated with Batteries

The State of Charge (SOC) of a battery varies based on the power used for charging and discharging at charging stations. This relationship can be represented by an equation for each time instant.

$$NRB_{i,l}^{j} = NRB_{i,l}^{j-1} + \eta_{ur,i} A_{ur,i,l}^{j} \Delta t\delta - \frac{\Delta j \gamma A_{au,i,l}^{j}}{\eta_{au,i}} \quad (23)$$

Here, i^{th} EV charging stations at period can be denoted as $A_{ur,i,l}^{j}$, i^{th} EV period at the charging rates at charging stations power at period can be denoted as $A_{au,i,l}^{j}$, state as l, EV battery charging and discharge efficiencies of i^{th} can be denoted as $\eta_{ur,i}$ and $\eta_{au,i}$.

$$P_{ch,n,s}^{t} = \frac{\left(c_{b,n} - SOC_{n,s}^{t} \times c_{b,n}\right) \times P_{PL,s}^{t}}{T_{rem,n} \times \sum_{j=1}^{m} \frac{1}{T_{rem,n}} \left(c_{b,j} - SOC_{j,s}^{t} \times c_{b,j}\right)} \quad (24)$$

$$A_{au,i,l}^{j} = \frac{U_{rem,i}\left(SOC_{i,l}^{j} \times u_{k,i}\right) \times A_{AH,i,l}^{j}}{\sum_{n=1}^{t} T_{rem,i}\left(SOC_{n,l}^{j} \times u_{k,i}\right)} \quad (25)$$

$$U_{rem,i} = U_{a,i} - U_{hq,i} \quad (26)$$

Here, $u_{k,i}$ can be denotes as the EV charging stations capacities, $SOC_{i,l}^{j}$ can be denotes as the EV current SOC, $U_{hq,i}$ can be termed as the EV arriving period, EV parting period can be denoted as $U_{a,i}$. The EV daily arrival time is described by the equation below, which may be written as follows:

$$g_i^j\left(U_{hq}\right) = \exp\left[\frac{-\left(U_{hq} - \varepsilon_{U_{hq}}^{j}\right)^2}{2\left(\beta_{U_{hq}}^{j}\right)^2}\right] \Big/ \left(\beta_{U_{hq}}^{j}\sqrt{2\pi}\right) \quad (27)$$

Here, daily arrival time mean can be indicated as $\varepsilon_{U_{hq}}^{j}$, daily arrival time standard deviation can be specified as $\beta_{U_{hq}}^{j}$.

D. Proposed Modified Aquila Optimizer (mAO) Algorithm

In this part, the Modified Aquila Optimizer (mAO) scheduling's for source generations optimizations in MG combined with EVCS is di. AO (Aquila Optimizer) simulate the natural predating techniques of Aquila birds . At the stage of exploitations, the CLS techniques improve the abilities to search. At the exploration stages, the OBL and RS methods improve the abilities to search.

1 Fitness Function

The fitness functions is derived by minimize the tie-line power as well as active power losses in the systems using the equation (1).

2 Notation Definition

The notation definitions for the equations given in the Pseudo codes are shown in the following: agent positions can be denoted as X ,different AO motions can be denoted as G_1, chasing prey slope can be termed as G_2, is a constants, i^{th} generation mean position can be denoted as $X_M(t)$, found Aquila best positions in iterations can be denoted as X_{best}, random generations can be denoted as $rand$, exploitations parameter can be termed as α and β, high and minimum boundary can be indicates as UB and LB, values produced by CLS in iterations i as Cs, shrinkings factors can be denoted as μ, maximum and minimum boundary can be denoted as $ub \text{ and } lb$, random number in the values of [0, 1] can be denoted as $rand$, x is denoted as a vector with number of values.

Table 2. Pseudo Code of mAO Technique

Pseudo Code for mAO Techniques
AO Population initialization X Calculate the of $\overline{X}$ & select finest N from $X U \overline{X}$ AO parameters initializations while $(t < T)$ do Objective function values computations Best agents X_{best} selections

for $(i = 1,2,\cdots,N)$ do
Current solution mean Updations
$y, x, G_1, G_2, Levy(D)$ computations
if $\left(t \le \left(\frac{2}{3}\right)T\right)$ then
if $rand \le 0.5$ then
Current position updating using $X_1(t+1) = X_{best}(t) \times \left(1 - \frac{t}{T}\right) + \left(X_M(t) - X_{best}(t) * rand\right)$
else
Update current position using $X_2(t+1) = X_{best}(t) \times Levy(D) + X_R(t) + (y - x) * rand$
Compute opposite position using $\overline{x_j} = ub_j + lb_j - x_j$
if Fitness $rand \le 0.5$ then
else
Update current position using $X_4(t+1) = QF \times X_{best}(t) - (G_1 \times X(t) \times rand) - G_2 \times Levy(D) + rand \times G_1$
Compute opposite position using $\overline{x_j} = ub_j + lb_j - x_j$
end if
end if
end if
end for
Apply RS strategy using $X(t+1) = lb + rand.(ub - lb)$ and $X(t+1) = rand.(ub + lb) - X(t)$
end while
Return best solution

E. LSTM Recurrent Neural Networks

The LSTM neural network is a type of recurrent neural network that incorporates an additional memory components. Within the LSTM architecture, there are distinct components for long-term memory and short-term data handling. This design allow the models to assign weight in a manner that enables it to incorporate new information, forget unnecessary data, and generate outputs based on previously stored information from data samples. LSTM models are particularly well-suited for tasks requiring the retention of input data over extended periods and for performing operations on that memory effectively. This network employs a memory configuration in the form of gated cell, which determine whether to retain or discard data within the networks [18].

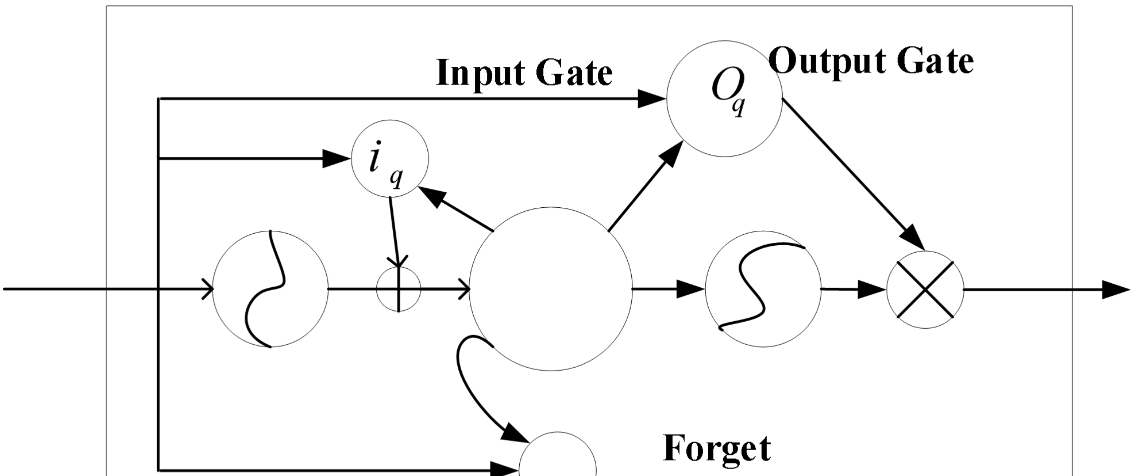

Figure 2. Gated Structure of LSTM Recurrent Neural Networks

The LSTM neural network utilizes back-propagation with gradient descent learning to address issues like diminishing and limitation of gradient. Figure 2 provides a visual representation of the Gated Structure LSTM neural network architectures. Within the LSTM framework, the memory modules is expanded, with units forming the RNN models [19]. The recurrent LSTM is essential in this context for several reasons:

- Addressing the saturations of the training models to ensure convergence.
- Ensuring balanced and biases during training.
- Selecting appropriate activation functions for evaluating network output.
- Preventing premature termination of the training process.
- Improving the gradient for more efficient training.
- Expanding memory cells and organizing data classification for enhanced training and testing.
- Preventing instability in the designed recurrent neural network model.

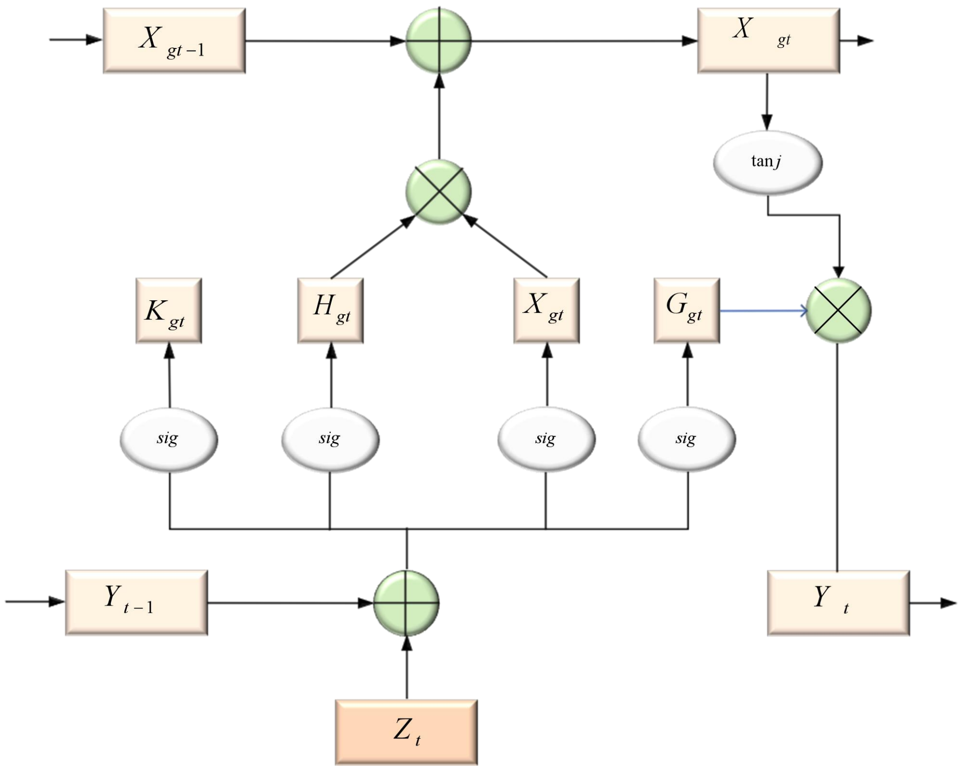

Figure 3. Architecture of LSTM Neural Network Predictor

The algorithmic steps of the training of the LSTM networks are as given below.

Step 1: The networks establishes the initial weight and learning parameter. Through its sigmoidal functions, the networks decides which data to retain from gated cell and which to discard during a specific timeframe. The current input ‘ Z_t and the previous state $Y_{(t-1),}$ compute the function and is defined by,

$$K_{gt} = \alpha(M_{gt}[Y_{(t-1)}, Z_t] + L_{ogt}) \quad (28)$$

In Equation (1), K_{gt} denotes the forget gates, ‘ α ’ is the learning rates metrics, M_{gt} denotes the weight of the models and L_{ogt} denotes the biasing of the neural models.

Step 2: During this stage, memory units are integrated into the existing state along with activation functions, namely tangential and sigmoidal, which facilitate the addition of memory units. The decision on whether to pass data (0 or 1) is determined by the sigmoidal functions and is determined by following equations

$$H_{gt} = \alpha(M_{it} * [Y_{(t-1)}, Z_t] + M_{it}) \quad (29)$$

$$Y_{gt} = \tan j(S_{ct} * [Y_{(t-1)}, Z_t] + Moct) \quad (30)$$

Where, H_{gt} denotes the input gates and M_{it} assign the weight to the datas through the sigmoidal functions.

Step 3: During this phase, the determination of the memory cells states from which the outputs is to be extracted takes place [21]. The sigmoidal layer is engaged to activate and identify both the outputs and the specific segment of the memories cell responsible for its computation.

$$G_{gt} = \alpha * (M_{ot} * [Y_{(t-1)}, Z_t] + M_{oct}$$

$$Y_t = G_{gt} * (\tan j(X_{gt})) \quad (31)$$

In the Equation (31), G_{gt} represent the output gates and this gates present the outputs from the memory cell and Y_t denotes the current states from which the outputs is collected.

F. Proposed ICA – MAOA – Deep LSTM Recurrent Neural Predictor

Proposed ICA – MAOA – Deep LSTM Recurrent Neural Predictor investigates into the development of the innovative DLSTM neural networks, integrates the ICA and Modified Aquila Optimizer (MoA) for time-period EVs data decompositions of data and neural parameter optimizations, respectively [22]. The DLSTM model proposed employs deep and dense layer stacking to construct a robust deep learning framework, aimed at creating a pivotal predictor model [20].

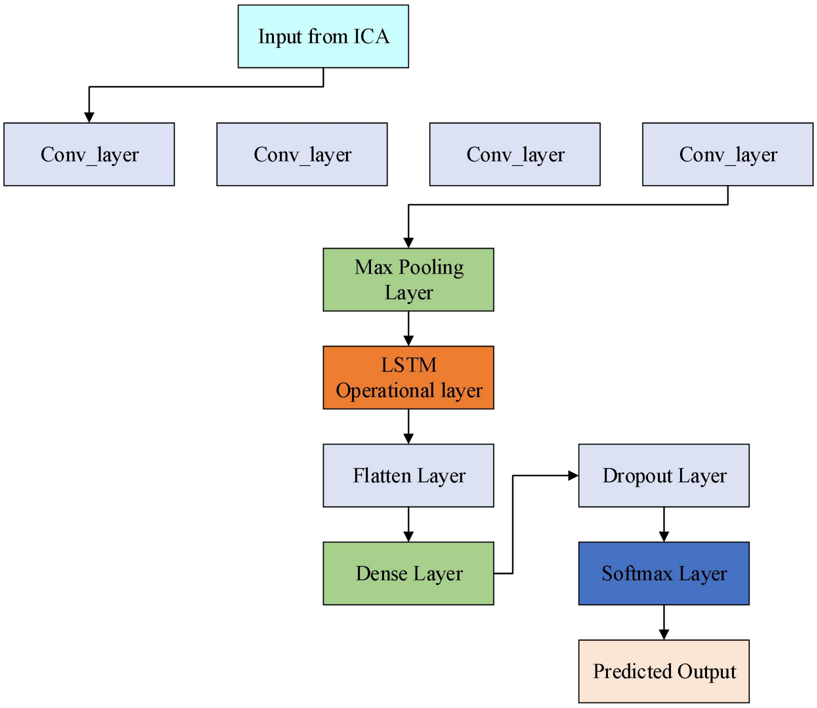

Figure 4. Proposed Architecture of DLSTM Neural Predictor Model

This research investigates to forecast EVs demand of charging, where the charging period is important. To ensure steady output from convolutional layer, padding zero to the input data's is much needed. The DLSTM models comprise of convolutional layer, a pooling layers, a dense layers, an LSTM layers, a dropout layer, and a soft-max layer for output representation.

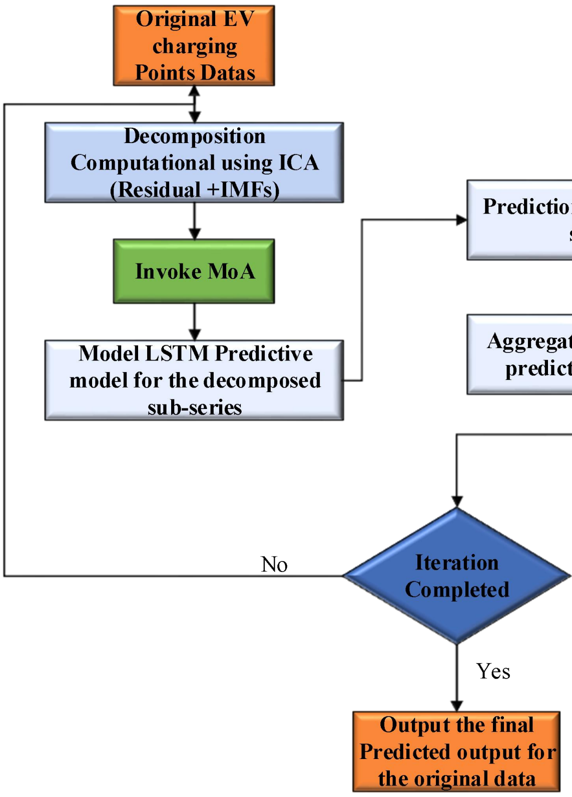

Figure 5. Proposed Architecture of DLSTM Neural Predictor model

During the reconstruction process, the auto-encoder and decoder-equipped deep learning layers adjust to decrease the error criterion and produce improved prediction metrics. The new DLSTM's loss function is provided by,

$$g(loss\_function) = \frac{1}{N}\sum_{j=1}^{N} X_{data}, G_{decoder}(G_{encode}(X_{data})) \quad (32)$$

During the process of deep learning, the existence of non-linearity is determined using,

$$G_{encode}(X) = g\,f\_encode\,(K_0 + Kx) \quad (33)$$

$$G_{decode}(X) = g\,f\_decode\,(K_0 + K_X^T) \quad (34)$$

In Equation (34), $g\,f\_encode$ and $g\,f\_decode$ specifies the encoder and decoder activation function of the deep learnings predictor models, 'K_0' represents the bias element and the weight matrices are 'Kx' and 'K_X^T'. The error is evaluated during deep training process of deep training using. The final predicted output from the DLSTM neural model is,

$$M_{predicted\_DL_{out}} = G_{encode\_}N + 1(En_{vectorn}) \quad (35)$$

In Equation (35), $G_{encode\_}N+1$ represent the training value at the LSTM layer and the new weight based on the gradient are determined to be,

$$W_{new\_de} = W_{old\_de} + \beta \, \mathrm{X} \, \frac{\lambda Error_{DLSTM}}{\lambda W_{new\_de}} \quad (36)$$

Figure 5 depicts the overall process flows of the recommended ICA – AOA – DLSTM neural predictor model. The approaches of AOA tuned to obtaining the optimization weights and biasing components to be demonstrated as starting value during the deep learnings of training phases of LSTM.

$$MSE_{prediction} = \frac{1}{Iter_{\max}} \sum_{i=1}^{Iter\max} (Y_{DL\_predicted} Y_{Original\_data})^2 \quad (37)$$

The evaluated steps are repeated for the proposed DLSTM predictor model until the error value comes to the most possible minimal values.

5. Results and Discussions

The novel EMD–AOA–DLSTM predictor models was evaluated for its effective in predicting EVs charging energies demands at the Georgia Tech charging station in Kentucky, USA. The simulations were conducted in MATLAB R2021a on an Intel dual-cores i5 processor with 8GB of physical memories. It resulting in extracted residual and other intrinsic mode functions (IMFs). These sub-series were then used as input for the deep long short-term memory (LSTM) neural network model. Table 4 depicts the parametric values utilized during the training process of the proposed EMD–AOA–DLSTM neural predictor. Dataset is taken from (https://www.kaggle.com/code/meisenbach/electric-vehicle-charging-eda)

Table 3. Input Data Parameters

Energy (kWh)	**GHG Savings (kg)**	**Gasoline Savings (gallons)**	**Cost Incurred USD**
1.569	0.659	0.197	0.36
21.311	8.951	2.675	4.9
17.40999	7.312	2.185	0
5.666	2.38	0.711	1.3
6.605	2.774	0.829	1.52
18.955	7.961	2.379	4.36
7.988	3.355	1.003	1.84
45.916	19.285	5.762	0
3	1.26	0.376	0.69
6.64	2.789	0.833	1.53
3.401	1.428	0.427	0.78
2.600952	1.092	0.326	0

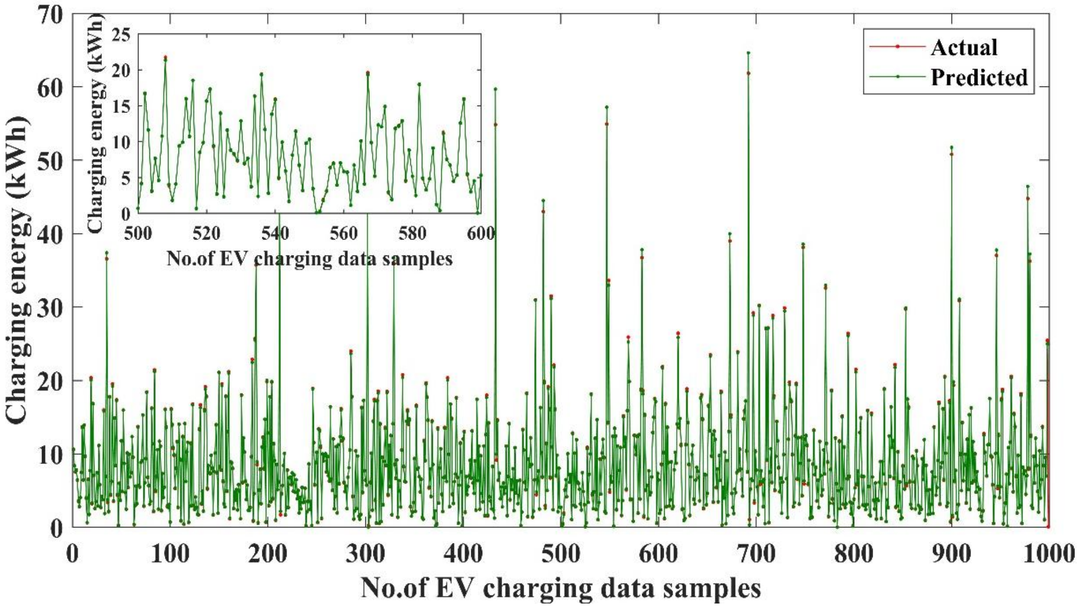

Figure 6. Comparison of Testing Phase – Actual Vs Predicted

Figure 6 demonstrates the comparison between the predicted and actual charging energy level at the EV charging station. The plot denotes a close relation between the predicted and actual values, indicating the recommended EMD–AOA–DLSTM predictor models effectively capture the charging patterns of energy demand. This alignment is very important for maintaining efficient management of the EV charging stations, as it allows operator to predict and respond to fluctuation in energy demands accurately.

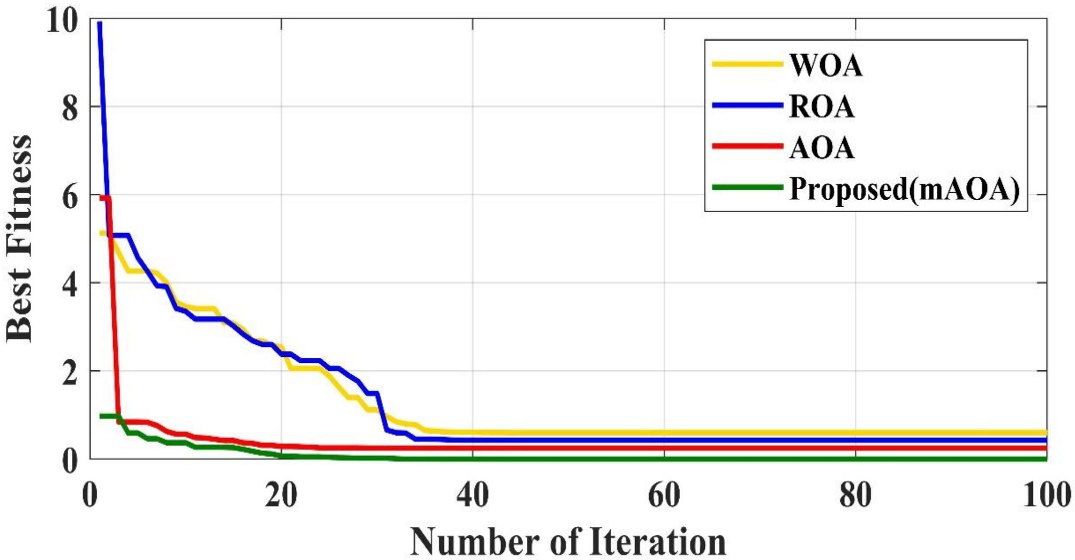

Figure 7. Convergence Plots for the Proposed Predictor Models during DL Training

Figure 7 indicates the convergence curves obtained during the DL processes of the recommended predictor model. The convergence curve was reached at the 251st epochs during the period training, with a MSE of 5.2516 × 10−10. For testing and validations, the measured MSE value were 6.36333 × 10−10 and 7.5317 × 10−10, respectively. This denotes a maximum level of accuracy in the model's prediction, with less errors.

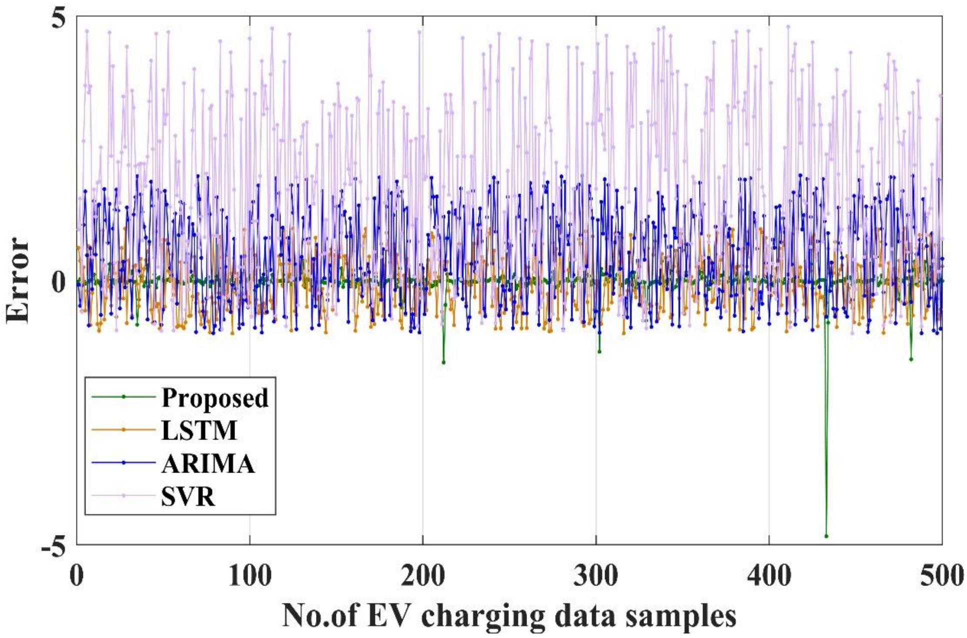

Figure 8. Testing Error Analysis

Figure 8 indicates the testing error analysis of three various models used for predicting charging station power system data ' s: the recommended LSTM models, ARIMA, and SVR. The x-axis represent the number of EV charging data sample utilized to train the models, while the y-axis denotes the error rates. Testing error analysis is important for measuring a ML model's performances of hidden data, providing valuable insight into its generalizability. Predicting charging station power system data ' s, this experiment help to assess that a model can predict future power demand based on historical datas.

Table 4. Parameters of Testing Phase

Actual	Predicted (proposed)	LSTM	ARIMA	SVR
10.618	10.666	11.238	10.536	11.586
8.413	8.386	8.789	7.935	9.962
7.55	7.625	6.977	7.454	6.958
7.794	7.845	8.046	8.845	10.431
6.448	6.505	5.881	8.134	10.135
3.559	3.607	3.366	4.036	8.272
2.825	2.835	3.474	1.977	6.381
4.061	4.058	3.218	4.672	7.737
7.492	7.469	7.26	7.33	7.939

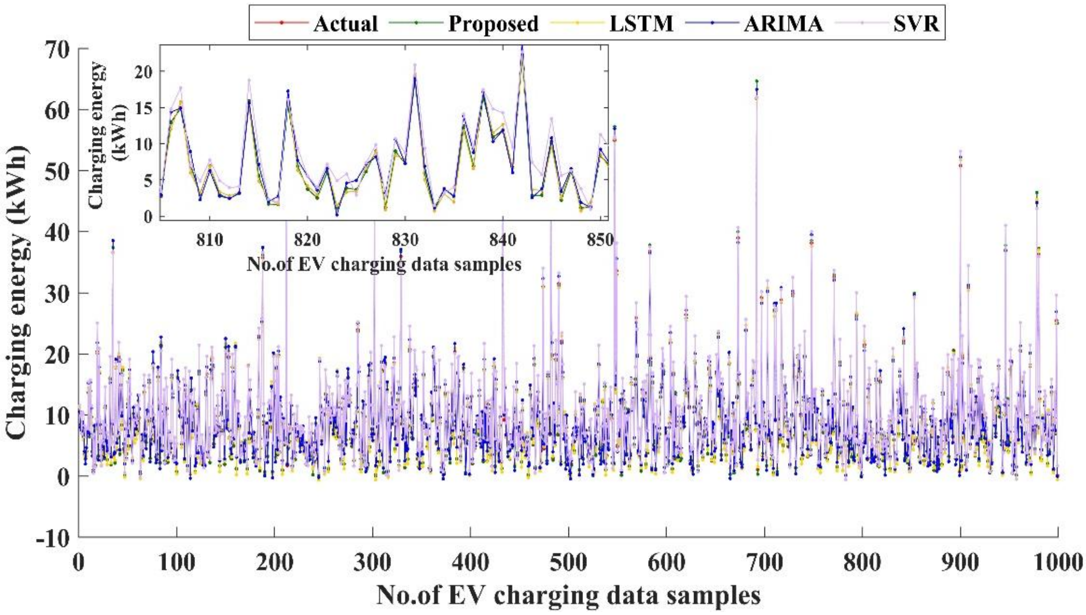

Figure 9. Testing Phase - Actual Vs other comparison parameters

Figure 9 depicts the testing error analysis of four various models for forecasting charging energy in a charging station power system Actual model, proposed models, LSTM-ARIMA models, and SVR models. The graph indicates that the proposed model performs better than the other three models in terms of MSE, with a lower MSE indicating a good fit.

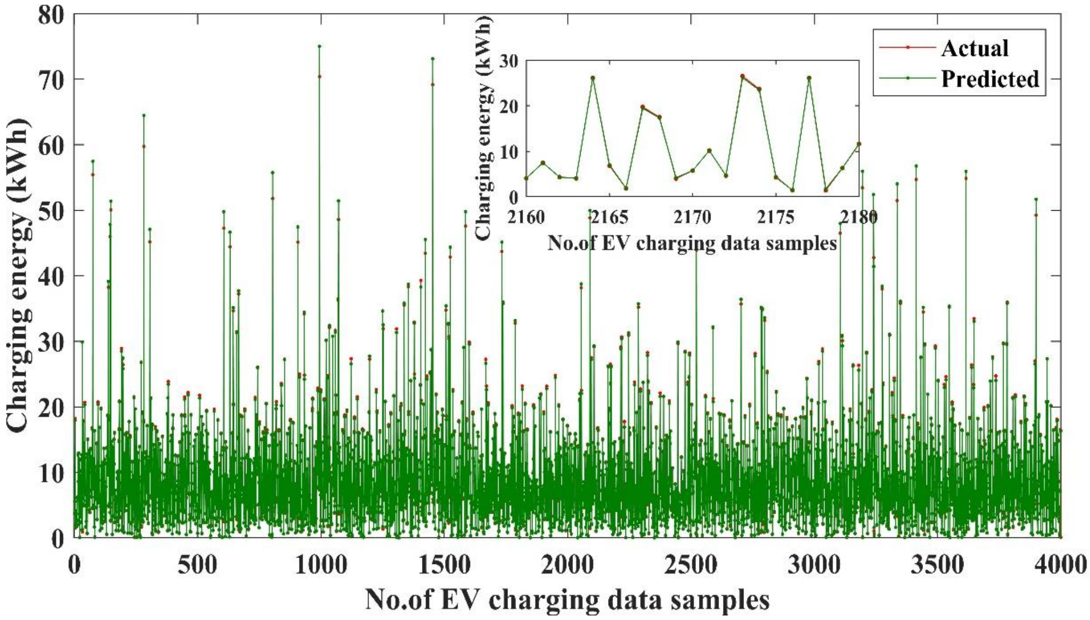

Figure 10. Comparison of Training Phase – Actual Vs Predicted

Figure 10 depicts the performance of a deep learning-based charging station power system data prediction model. The graph shows a comparison between the actual charging energy (in kWh) and the predicted charging energy based on the number of EV charging data samples. The training phase involves feeding the models with data to learn and improving its prediction accuracies. The close relation between the predicted value and the actual value suggests that the model is performing well in predicting future power consumptions based on charging station usage patterns.

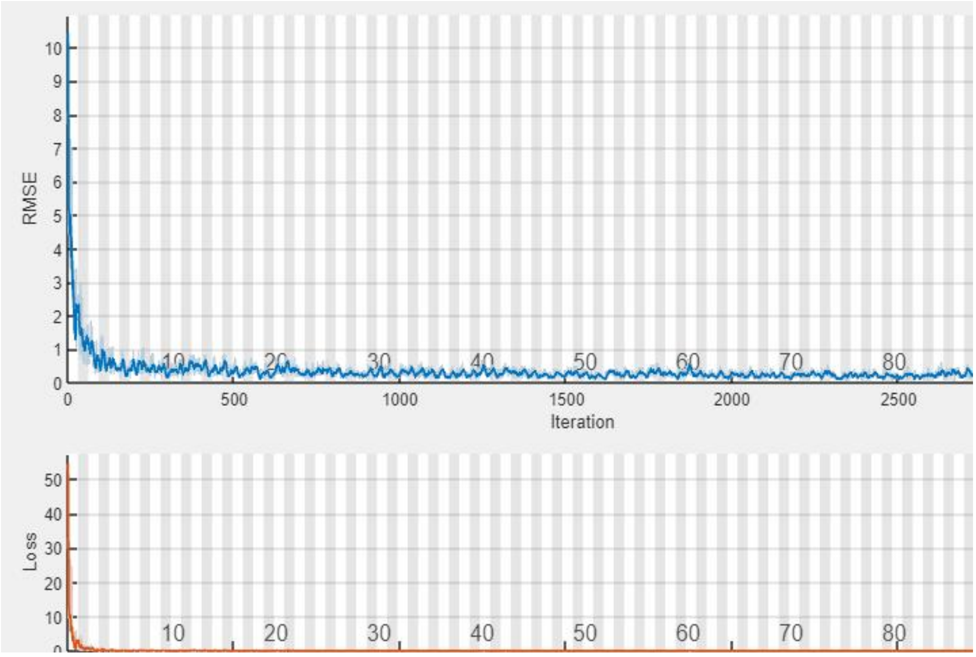

Figure 11. Loss v/s RMSE

Figure 11 indicates the training progress of a DL models for forecasting charging station power system data. The graph shows the losses and RMSE value change as the model is trained on more data. Decrease in these values over iteration, indicates the model is improving in its ability to predicting charging stations power system data exactly.

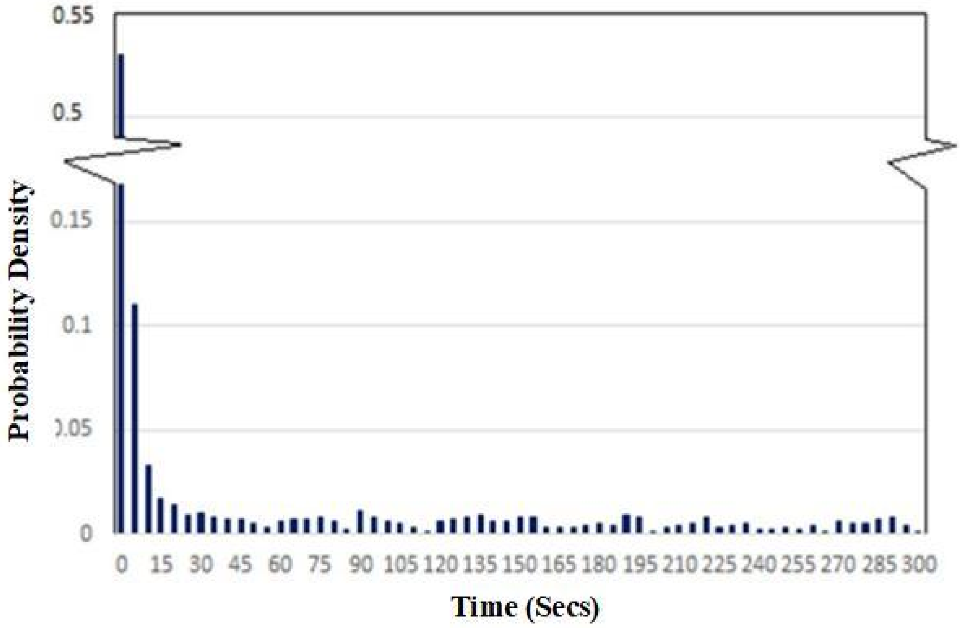

Figure 12. Distribution of Time between the end Time of the Last Journey of the Day and the Start Time of an Overnight Charging Event

Figure 12 illustrates the distribution of times between the end time of the last journey of the day and the start time of an overnight charging event. Approximately 70% of the time a vehicle is plugged-in immediately at the end of the last journey of the day but approximately 30% of the time there is a relatively evenly distributed delay in plugging-in between 15 minutes and 5 hours. This was accounted for in the model by simulating a value from this distribution and adding it to the end time of the last journey of the day to simulate the starting time of a charging event.

Table 5. Comparison with Various Optimization Algorithms

Optimization Algorithm	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
MAOA (Proposed)	0.1083	3.0629 × 10-5
Genetic Algorithm (GA)	0.1456	4.2712 × 10-5
Particle Swarm Optimization (PSO)	0.1321	3.8921 × 10-5
Simulated Annealing (SA)	0.1589	5.0012 × 10-5
Ant Colony Optimization (ACO)	0.1623	5.4398 × 10-5
Differential Evolution (DE)	0.1378	4.0123 × 10-5

The increase of EVs makes a vital impact on the rapid development of charging infrastructure, influencing the charging adoption rate and societal benefits. Extensive and wide networks of EV charging stations are trying to pacify the range anxiety, inhibits the widespread adoptions as seen in cities like Oslo and Luxembourg. Rural areas would be benefitting much from strategically placed charging stations along the tourist route, boosting local economy and minimizing the dependence on fuels alleviate, given by initiatives in regions of Scandinavia and Canada. Combining these infrastructures with smart grid technologies enhances the energy usage, improving the stability of grid, and supports integration of renewable energy. Societal gains include improved air quality and minimized emissions, which is very important for public health and urban liabilities. Advancements in battery technology and policy framework are given to further acceleration of the transitions towards a fully electric transportation future, EV infrastructure's important roles in sustainable development.

6. Conclusion

In this study, a novel predictor model, ICA–mAOA–DLSTM, was developed to forecast EV charging demand using EV datasets. The model combines ICA to decompose signals into sub-series without data loss, and MAOA for better exploration and exploitation, LSTM recurrent model for retaining past information, and DL to improve architecture depth and intensive trainings for more exact prediction. Simulation using the proposed model on EV datasets demonstrated its superiority over existing prediction models, achieving training and testing efficiencies of 97.72 and 96.03, respectively, which outperformed other techniques. The prediction accuracy of 98.24% with minimal mean squared error (MSE) in the order of 10^-10 further validates its effectiveness. The EMD–AOA based DLSTM predictor offers superior accuracy and minimal error in forecasting EV charging demand.

7. Future Scope and Challenges

A. Recommendations for Future Research

Future research of the EV Charging prediction must focus on combining the external factors such as weather (Rainfall, wind, Sun Intensity) conditions and charging station utilization rates into the accurate prediction models to improve the accuracy and robustness. Exploring the various method for very long-term performances for monitoring to maintenance needs for based on utilization pattern for and environmental factors could enhance the operational efficiencies. Improvements in data collection technique, such as real-time IoT sensor integrations and data fusion systems, will also be very important for capturing extensive datasets.

B. Challenges in Implementing the Proposed Model

DL-based prediction model for charging station power systems faces several challenges. Qualities of Data and reliability to overcome the impact of missing data is very important for maintains the accuracy prediction. Scalabilities of the multiple charging stations and different infrastructure environment needed careful considerations to give the consistent performance. Improving the model output to give the insights and navigating regulatory and standard compliances associated to privacy of data and interoperability are additional challenges that must be addressed for successful real-world deployment.

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