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ARTIFICIAL INTELLIGENCE-DRIVEN SOC PREDICTION IN ELECTRIC VEHICLES USING DBN-AOA

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ABSTRACT

Automobiles powered by electricity are an effective solution for the transportation sector's disastrous pollutant emissions. The performance of electric vehicles (EVs) is a determining factor in their massive and widespread acceptance among automotive consumers, despite the reality that their number of active users continues to rise. The EV industry has shown significant interest in lithium-ion batteries (LIBs) due to their cost-effectiveness, extended longevity, nominal voltage, and power density. State-of-charge (SOC) prediction accuracy is essential for effective battery management in EVs. However, non-linearities and complex dynamics inherent to LIBs pose challenges for traditional methods. This proposed work presents a novel deep-learning (DL) model for SOC prediction in EVs utilizing a Deep Belief Network (DBN) coupled with an Aquila optimization algorithm (AOA). The data utilized for training the proposed network is sourced from the SiCWell Dataset. The data is preprocessed through the implementation of Z-score normalization. The DBN utilizes battery data to extract and classify complex features, whereas the AOA is employed to optimize the hyperparameters of the DBN to increase the accuracy of predictions. The DBN+AOA is trained utilizing a SiCWell battery dataset in which the battery experienced a dynamic process. The performance of the DBN+AOA model is evaluated using the Mean Squared Error (MAE), Root Mean Squared Error (RMSE), and Mean Squared Error (MSE) metric values. Accurate results for SOC prediction are generated by the proposed method, with RMSE, MAE and MSE falling below 0.14%, 0.013%, and 0.011%, respectively. The average values of RMSE, MAE, and MSE are 0.136, 0.0122 and 0.0101. Experiments confirmed that the proposed DBN+AOA model has the best performance among the other current models in comparison.
Keywords: *EV, State-of-Charge, DBN, AOA, SiCWell, Lithium-Ion Batteries, Deep Learning*.

1. INTRODUCTION

In recent times, there has been an increase in interest in EVs due to their notable capacity to decrease gasoline consumption and gas emissions. A new domain of scholarly investigation and industrial innovation has emerged as a result of the expanding market share of EVs and the rising demand to replace fossil fuels with electricity [1]. Although the initial EVs were constructed during the mid to late 19th century, they were unable to achieve commercial success until automobiles were propelled by internal combustion engines (ICE). As of now, approximately 25% of energy-related greenhouse gas emissions are attributed to the transportation sector's dependence on ICE. This matter instigated a call for the substitution of ICE vehicles with vehicles that utilize sophisticated technology, such as EVs [2]. The growth of EVs has many benefits, including, reducing dependency on hydrocarbon and gas discharges; advancing carbon neutrality and minimizing their emissions; and starting an environmentally sustainable transportation revolution and offering a promising solution to the challenge of climate change. Because globalization is highly dependent on electricity sources, the development of electric vehicles is regarded as one of the most effective solutions [3].

In recent years, a variety of energy storage systems have gained widespread acceptance for transportation purposes. These systems include lead acid, LIB, nickel-cadmium (NiCd), sodium nickel chloride (NaNiCl), sodium sulphur (NaS) batteries, vanadium redox flow battery (VRFB) and zinc-bromine flow battery (ZBFB). The Li-ion battery is distinguished by its exceptional dependability, energy density, longevity, low discharge rate, and high efficiency. Furthermore, the decreasing cost of LIBs is facilitating their increased adoption in the EV sector, thereby driving the expansion of the Li-ion battery market [4]. LIBs presently hold a dominant position not only in the portable electronics battery market but also in the rapidly expanding automotive and stationary energy storage industries. The rationale behind this is related to battery technology that came before LIBs (e.g., nickel-based or lead-acid batteries) and those that came after lithium, referred to as "post-lithium" technologies (e.g., sodium-ion batteries (SIBs)), have substantially reduced energy specificity and density than the most recent LIBs. LIBs are the most promising and developing technology for extending the driving range and energy density of EVs by a significant margin. The promotion of EVs and new energy automobiles by the government has served as an impetus for the exponential growth of battery components and automotive computer science, both of which are essential for intelligent mobility. China has declared that, by the global goal of carbon neutrality, the peak of emissions will be achieved prior to 2030. Fifty percent of newly produced automobiles in the United States will be free of emissions by the year 2030. By 2035, virtually all vehicles in Europe should be emission-free. For electric vehicle applications, the energy density of LIBs must approach 500 Wh kg−1 to be comparable to vehicles powered by fossil fuels [3].

In addition to batteries, effective battery management is critical for EV batteries to function reliably and safely. By implementing charging and discharging cycling, batteries can preserve their best performance and increase their operational lifespans. Therefore, every electric vehicle is equipped with a battery management system (BMS), which executes a range of tasks such as (i) determining the state of the battery, (ii) balancing battery cells and controlling pack charge and discharging, (iii) managing thermal conditions, (iv) providing fault prognosis and health diagnosis, and (v) facilitating correspondence. BMS is of the utmost importance in EVs to guarantee optimal capacity utilization, safety, and extended battery life. BMS capabilities have expanded from battery protection and safety to facilitate higher battery output and more secure battery systems over the past decade [5]. The overview of the BMS is shown in Fig. 1.

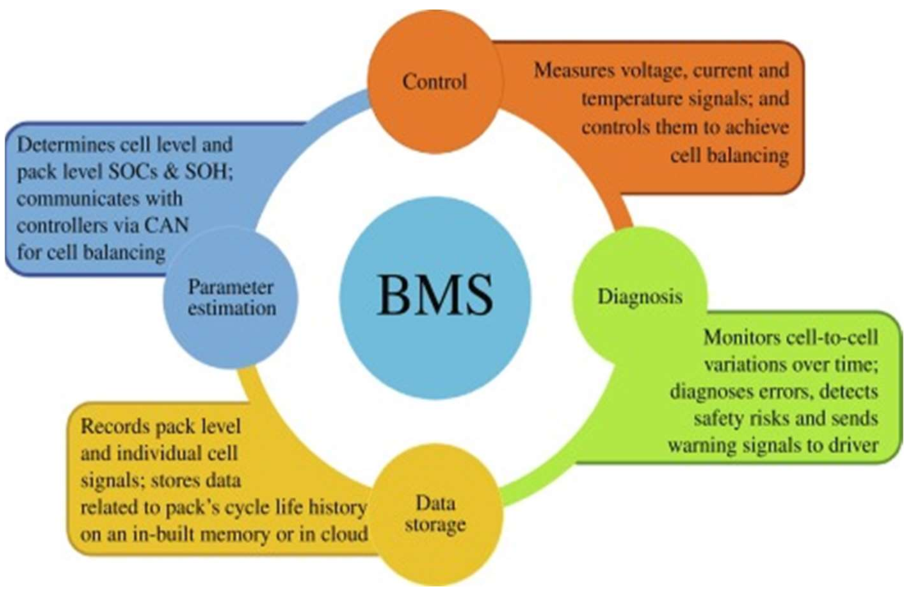

Figure 1. Overview of Battery Management System

1.1. Problem Statement

To ensure the safe operation of batteries in EVs, their state estimation is important. This involves determining the state of health (SOH) and SOC of batteries within an estimated range. SOH and SOC monitoring, which are highly correlated, are, in general, the most important factors and the foundation for enhancing dependability and guaranteeing safety [6]. This research investigates the SoC of a battery. The remaining functional percentage of a battery's capacity is referred to as its SoC. Therefore, a SoC of 100% signifies that the maximum capacity is available for utilization, whereas a SoC of 0% signifies that no further capacity is available for utilization. The SoC provides details related to the dependability, efficiency, and security of an electric vehicle, in addition to the usable capacity of the battery. Nevertheless, the SoC of a battery cannot be determined directly. To determine the SoC of a battery, several researchers have proposed their

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efforts for SoC estimation. There are five distinct categories of SoC estimation methods: utilize lookup table-based, data-model fusion techniques, model-based estimation, ampere-hour integrals and data-driven approaches [25].

1.2. SOC Prediction

Predicting the SOC is the key objective of this research. Importantly, the SOC of lithium batteries serves as an indicator of their energy. The range of EVs and the duration of battery life can be approximated with greater precision when the SOC is determined. However, indicative factors such as cell current, temperature and voltage can only be used to predict SOC, as it is not directly measurable. Additionally, ageing and operating conditions impact the precision of SOC forecasting [7]. SOC is typically expressed as a percentage and was described as the present available capability ratio of Qcurrent to the available capacity maximum Qnow, as illustrated in Equation (1).

$$SOC = \frac{Q_{current}}{Q_{now}} \times 100 \tag{1}$$

As the core and basis of EV design, the SOC should be continuously predicted throughout the life of the battery to ensure its accuracy as the battery ages continuously [7]. Furthermore, the SOC is critical for vehicle design, as it provides reference information regarding the range of the battery.

Presently, the research focus is presented on developing a Deep Learning (DL) model that can deliver precise predictions of SOC. DL methods efficiently automate the process of feature extraction with the least amount of domain expertise and computation required [8]. Difficult LIB state monitoring requires precise estimation of battery state; the DL method increases prediction precision and robustness. DL, which is also referred to as deep structured learning, is a category of machine learning that utilizes work-specific algorithms and multiple layers to extract a greater number of features. The process for constructing a DL-based EV battery SOC prediction model was represented in Fig 2.

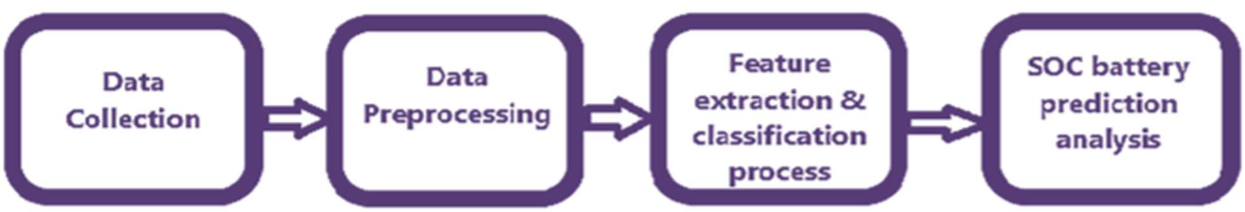

Figure 2. Basic Workflow Of The Soc Battery Prediction Model

The beginning phase consists of gathering real-time data from the EV datasets. To ensure the accuracy of deep learning model training, the original data obtained from the dataset must undergo preprocessing before the extraction and classification procedures. Following this, a classification model for the predictive model is constructed using an appropriate DL model, taking into consideration the model's complexity and accuracy. After undergoing training, the DL model can be employed to forecast the SOC of the battery by utilizing newly acquired data.

1.3. Research Objectives

The research objectives for this work on SOC prediction using the DBN+AOA model can be outlined as follows:

- To develop a new hybrid feature extraction and classification model for prediction of SOC.
- To enhance the pre-processing technique of a model by using the normalisation technique.
- To enhance the effectiveness of SOC prediction by implementing the DBN algorithm for feature extraction and classification.
- The effectiveness and efficiency of the DBN model are enhanced through the tuning of hyperparameters utilizing the AOA in this study.
- To assess the performance of the DBN+AOA model on SiCWell datasets.

- To assess its performance utilising the parameters MAE, RMSE and MSE metric values.
- To compare the performances of the DBN+AOA model with other reviewed approaches and to demonstrate the efficiency of the proposed model in enhancing SOC prediction.

This paper continues as, after an extended review of various prediction methods in the extant literature, that the SOC prediction method based on the Deep Belief Network with Aquila optimization algorithm (DBN+AOA) is the most appropriate strategy when compared to model-based and data-driven approaches. The SiCWell Dataset comprises data on lithium batteries used in battery EVs, specifically for modelling and diagnostics. The Z-score normalization is utilised for the processing of data collected from the Sicwell data set. Once the data collected from the datasets are pre-processed, the DBN model is applied for classification purposes. In addition, to tune the hyperparameters of DBN the Aquila optimization algorithm is used. In this paper, an enhanced SOC prediction model for LIBs is developed utilizing the DBN+AOA.

The research contribution addresses a critical challenge in EV technology by proposing a SOC prediction model for Lithium-ion batteries. By proposing a novel deep-learning model utilizing a Deep Belief Network (DBN) optimized with an Aquila algorithm (AOA), the research offers a promising solution to enhance battery management systems in EVs. The efficiency of the proposed model is evaluated by using the performance metrices MSE, RMSE and MAE. For further validation, proposed model is compared with existing models using the performance metrices namely MSE, RMSE and MAE. Based on the comparison with existing approaches, the SOC prediction model contributes sustainable transportation through EVs.

2. RELATED WORKS

This related works section analyze and discusses the current research methodologies published recently based on EV's battery SOC prediction and analysis. Using algorithms based on deep learning, reference [16] proposed a technique for estimating the real SOC of electric vehicle batteries by the driving cycle. The SOC of an EV battery was precisely estimated utilizing RDCs and deep learning techniques. RDC data for a real travel path were obtained directly by connecting an onboard diagnostics (OBD)-II adapter to their vehicle. The driving cycles containing the most similar patterns were identified by segmenting each cycles utilising Global Positioning System information of the traffic signals along the path and Dynamic Time Warping algorithm. Ultimately, it was confirmed that the Temporal Attention LSTM model predicts the SOC with the highest accuracy compared to the alternatives.

A CNN-LSTM combined algorithm for predicting the SOC of LIB was proposed in [17]. Various discharge profiles' data were utilized to train the network, including the DST, US06, and FUDS profiles. The experimental findings indicated that the SOC network exhibited superior tracking performance in comparison to the LSTM and CNN networks due to the nonlinear associations between SOC and measurable variables. The network rapidly converged to the true SOC when the initial SOCs were unknown and produced accurate and seamless results, with maximum MAE and RMSE remaining below 1% and 2%. Furthermore, the network under consideration effectively acquired knowledge of the impact of ambient temperature and could estimate the SOC of a battery across different temperatures with a maximum MAE of less than 1.5% and a maximum RMSE of less than 2%.

A hybrid deep learning approach was proposed in reference [18] as a means to ensure reliable and secure charging operations, thereby mitigating the risk of overcharging or discharging the battery. It was recommended to utilize Recursive Neural Networks (RNNs) to derive sufficient feature information regarding the battery. The research subsequently developed the bidirectional gated recurrent unit framework (GRU) to predict the state of the EVs. By receiving its input from the output of the RNNs, the model's performance was improved by GRU. Due to its considerably less complex architecture, the RNN-GRU exhibits a diminished processing capability. The results of the tests indicated that the method can monitor the mileage of an electric vehicle with precision. The algorithm provided a rapid convergence and a minimum error rate than the optimal method for estimating distances using conventional models.

In [19], AOS-ELM, adaptive online sequence extreme learning machines model was suggested as a potential method for forecasting the charge level of battery cells across varying ambient temperatures. In contrast to alternative

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methodologies, such as those based on extended Kalman filters (EKFs), the utilization of ELM-based learning resulted in reduced RMSE and quicker computation times. Comparing AOS-ELM to incremental-ELM, online sequential ELM (OS-ELM), bidirectional-ELM (B-ELM), and parallel-chaos search-based incremental ELM revealed that AOS-ELM generated a minimum RMSE and a reasonable training time. Furthermore, it was not necessary to identify the static capacity of the cells and the parameters of the battery through successive experiments to calculate the SOC of individual cells and the battery stack.

A novel DL approach, referred to as "GRU-RNN," was utilized in [20] to estimate the SOC of LIBs. This approach was founded on newly developed advanced deep learning techniques. An additional high-rate pulse discharge condition dataset and two publicly available data sets comprising vehicle drive cycles were utilized to evaluate the GRU-RNN's performance in estimating SOC under extreme conditions, mixed charge and discharge conditions, and complex and variable discharge conditions, respectively. The study also demonstrated that despite the limited quantity of data, the model maintains a high level of estimation accuracy. Furthermore, the comparison results between the RNN and the proposed method indicated that the proposed model outperforms the RNN in terms of accuracy and circumvents the issue of long-term dependencies. MAXIMUMS: 7.59%, 7.04%, and 2.22%; the MAEs of the experimental outcomes are 0.86%, 1.75%, and 1.05%. This statement was supported by the precision and durability of the suggested approach.

To derive SOC estimation for LIBs in EVs, a Robust Adaptive Online Long Short-Term Memory (RoLSTM) model was introduced in [21]. Optimization involved the implementation of the Robust and Adaptive online gradient learning method (RoAdam). Each network parameter can be learned by the method's self-learning algorithm. The proposed algorithm was applicable for estimating SOC at different ambient temperatures. Moreover, the overall model's quantity of LSTM units was diminished. Experimental outcomes demonstrated that RoLSTM outperformed neural network modelling and the Kalman filter method when it comes to estimating the SOC of Li-Ion batteries using real-world databases. Maximum estimation error and RMSE have reduced substantially for both battery varieties under investigation.

In [22], the battery SOC estimation was performed using a CNN-GRU-LSTM approach that combined a GRU-LSTM and an RNN with explainable artificial intelligence (EAI). By training the model with a dataset of LG 18650HG2 LIBs, a dynamic process was simulated on the batteries. Additionally, during the training process, the method was provided with data that was captured at temperatures of 10°C, 25°C, -50.0°C, and 0°C. In contrast to other existing networks, the proposed method generated more consistent, precise, and dependable estimations of the SOC by encapsulating the temporal relationships within the network weights. For operating temperature varied from -10°C to 25°C, in which the hybrid model produced an MAE of 0.41% to 1.13%.

Dual cascaded filtering stages, namely a fading Kalman filtering (FKF) and a recursive least square (RLS) filtering, were utilized to develop and experimentally validate an SoC estimation technique for the LiFePO4 battery [23]. The computational expense of the suggested methodology was effectively reduced through the integration of cascaded linear filter stages and the simplified circuit models. Through the implementation of fading factor optimization, the FKF demonstrated a SoC estimations error of merely 2% in UDDS experiments and 3% in actual vehicle driving cycles trials. In contrast, a conventional Kalman filter introduced estimation errors of over 9% and 14%, respectively. The proposed method offered the simplified and practicability required for real-time implementation while precisely estimating SoC through its simplified model.

To enhance the precision and promptness of fault identification, [24] introduced an innovative extreme learning machine optimized by a genetic algorithm-based method (GA-ELM). This machine was capable of estimating the present system status. Additionally, the modified feature parameters were unprecedentedly incorporated as state input parameters of the ELM algorithm. By assessing the degree of volatility in the voltage data, the voltage defects were classified into four distinct levels. In conclusion, by comparing multiple approaches and validating measured data, the efficacy and accuracy of the proposed method were further demonstrated. Predicting battery faults using the voltage signal, the method exhibited considerable performance.

A methodology for forecasting SoC and output voltage was presented in [25]. It employed a

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hybrid architecture consisting of long short-term memory (LSTM) and vector autoregressive moving average (VARMA). The aforementioned method successfully captured both the characteristics (linear & nonlinear) of the battery voltage and the SoC of the battery. For data at 25 and 0 degrees Celsius, the model produced RMSEs of 0.161 and 0.193, respectively. One cycle in advance of the forecast produced the smallest error. The number of cycles that needed to be predicted led to an escalation in the error. The experimental findings indicated that alterations in the pace of the electric motorcycle result in a corresponding change in the SoC of its battery.

A model for representing battery data based on RNNs was constructed to obtain the proper vector representation. Following this, [26] introduced a model based on multi-channel extended CNNs that was supplied with the thoroughly trained battery vector. A comprehensive simulation was performed using real-world datasets, and the approach was evaluated in comparison to several methods. By utilizing a dependable vector representation and extracting adequate features, the suggested approach has the potential to enhance the performance of SOC prediction. The prediction performance of the proposed method was 4.3% and 11.3% better than that of RNN and the Ah counting method, respectively.

In reference [27], a bidirectional encoder-decoder long short-term memory and stacked bidirectional LSTM architecture were combined. By simultaneously training the encoder and decoder elements, the implementation of an encoder-decoder architecture aided in the reduction of training time. In contrast to the stacked bidirectional LSTM architecture and the isolated encoder-decoder architecture, the experimental findings indicated that the proposed work outperformed both. The implemented algorithm demonstrated its practicality by yielding an MAE of merely 0.62% when estimating the SOC at different temperatures. At 25°C, the HWFET condition exhibited the smallest Mean Absolute Error of 0.62%, confirming the proposed architecture's excellent functionality.

The HWFET condition exhibited the smallest MAE of 0.62% at 25°C, confirming that the proposed architecture implemented in [28] was functional. Following the weighing of distinct inputs based on their contribution to the output by the spatial attention module, the pre-processed data was transmitted to the upgraded CLSTM network. The average RMSE of the suggested work in the SOC prediction experiment for the LIBs in EVs was reduced by 32%, 67%, 178% and 35%, respectively, when compared with MLP and other LSTM-based models. The outcomes of the experiments demonstrate that the proposed model was effective.

The battery system-on-a-chip was predicted using six machine learning algorithms [29]: ensemble bagging and ensemble boosting algorithms, artificial neural network (ANN), Gaussian process regression (GPR), linear regression (LR) and support vector machine (SVM). The performance of the proposed ANN and GPR approach was exceptional, surpassing that of alternative methods, with an MAE of 85%. The MAE of the GPR-linear approach was 10% lower, indicating superior performance compared to the SVM-ANN. All six algorithms were subsequently evaluated in terms of performance indices. The optimal techniques were determined to be ANN and GPR, with respective MSE and RMSE values of (0.0004, 0.00170) and (0.023, 0.04118).

The literature review highlights the environmental issues associated with conventional combustion engine vehicles and presents Electric Vehicles (EVs), which are powered by Lithium-Ion Batteries (LIBs), as a possible solution to reduce greenhouse gas emissions and air pollution. It highlights the essential role of accurate SOC prediction in improving battery management systems for electric vehicles (EVs). This, in turn, boosts consumer confidence and adoption by maximizing battery utilization and extending battery lifespan. Furthermore, it acknowledges the intricate nature of LIBs and the need for sophisticated approaches, such as deep learning algorithms and hybrid models as proposed in this research, to address issues in SOC prediction and promote progress in battery management systems. Finally, it highlights the advantages of accurate SOC prediction in terms of operational efficiency, such as optimizing energy usage, increasing the distance a vehicle can travel, and reducing operational expenses. This ultimately supports the overall sustainability and viability of EVs.

2.1. Research Gap Analysis

The research gap in the presented reviews lies in the need for further exploration and comparison of DL-based methodologies for predicting the battery SOC, particularly in EVs. These methodologies leverage advanced

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techniques such as RNNs, CNNs, and LSTM networks to achieve accurate SOC estimations under diverse conditions. For instance, the utilization of TA-LSTM models in one study enabled precise SOC predictions by segmenting driving cycles and incorporating GPS data. Another approach, a CNN-LSTM network, showcased superior tracking performance for lithium iron phosphate batteries compared to traditional LSTM and CNN networks, even when initial SOC values were unknown. Additionally, hybrid deep learning architectures, such as RNN combined with bidirectional GRU, demonstrated enhanced model performance while maintaining computational efficiency. Furthermore, while some studies focus on specific aspects such as SOC estimation accuracy or computational efficiency, there is a need for holistic assessments considering factors like real-time applicability, robustness under varying conditions, and potential integration into practical battery management systems. The proposed study aims to fill these gaps by providing a systematic and standardized comparative analysis, assessing the performance of multiple algorithms comprehensively, and emphasizing interpretability, ultimately contributing to the development of robust EV battery prediction models. The literature review provides a comprehensive overview of existing research and sets the groundwork for the proposed DBN-AOA approach to improving IoT-IDS capabilities.

The problem statement defines a critical challenge in EV technology, considering the accuracy of SOC estimation in LIBs for safe and efficient battery management. Based on analyzed existing works the complexity of SOC estimation due to the indirect nature of battery measurements and the nonlinearities inherent in LIBs, the research aims to address this challenge by proposing a novel deep-learning model utilizing a Deep Belief Network (DBN) optimized with an Aquila algorithm (AOA). By leveraging recent advancements in deep learning techniques and optimization algorithms, the research seeks to develop a robust and adaptable SOC prediction model that outperforms existing methodologies. This problem statement highlights the importance of the research contribution in enhancing battery management systems for EVs and connecting it with the most recent advancements in the area.

3. PROPOSED METHODOLOGY OF THE DBN-AOA MODEL

This research proposes a model to improve battery SOC prediction in EVs by combining DBN for feature extraction and classification. By incorporating these techniques, the model aims to resolve the challenges of battery prediction in EV environments and enhance detection accuracy. This research developed a novel DBN-AOA algorithm for predicting the SOC performance of LIBs in EVs. The model that has been presented consists of several stages: accumulation of datasets, pre-processing, feature extraction and classification. In the preprocessing stage, the normalisation technique is incorporated by using Z-score normalisation to improve the model performance. DBN is used for feature extraction from the processed data and classification to reduce the complexity of the model. After classification, for tuning hyperparameters obtained in the DBN, and AOA algorithm is used algorithm for the effective output. The effectiveness of this DBN-AOA model is assessed across a range of temperatures using the Sicwell dataset and is subsequently compared to pre-existing models.

The DBN-AOA algorithm's overall procedure is depicted in Fig 3. It consists of the following stages: data collection, pre-processing, feature extraction and classification, parameter tuning, training, testing and performance measures. The following sections explain and discuss the implementation of these stages.

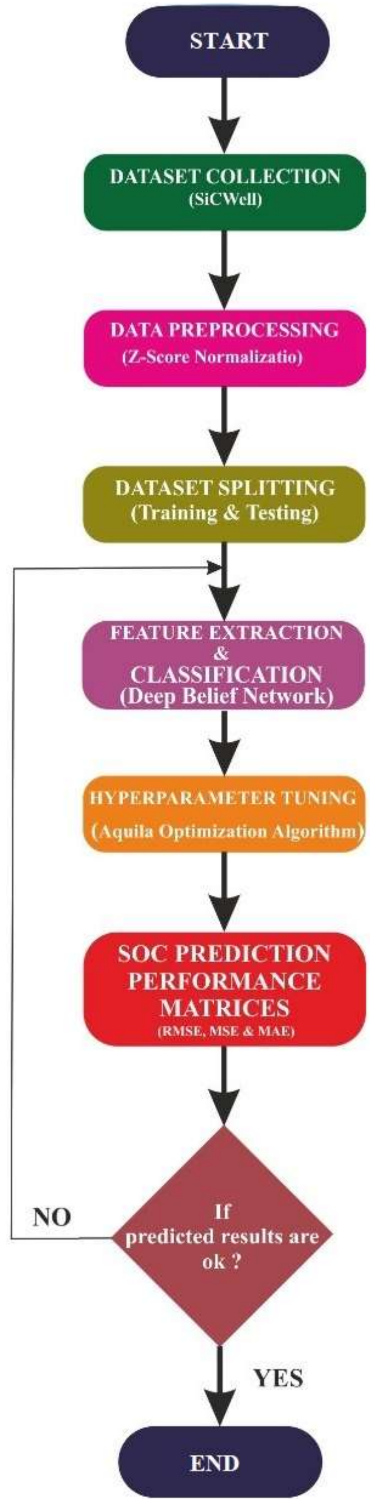

Figure 3. Workflow Of The Proposed Model

As shown in the workflow of the proposed research model, the research initially operates by collecting the dataset related to the EV's LiB features. The collected SicWell dataset is first preprocessed by employing a data preprocessing technique called Z-score normalization to standardize the input data fed to the proposed model. After preprocessing, the preprocessed data

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is divided into two sets, one to train the model and another to evaluate the model. Using the training set of data, the feature extraction and classification operations are performed utilizing the proposed DBN classifier. To further increase the prediction accuracy and overall performance, the DBN classifier's hyperparameters are fine-tuned and optimized using the AOA technique. For evaluation, the test set was evaluated using the trained model and the performances are measured based on metrics like RMSE, MAE, and MSE. The obtained results are then compared with the current models discussed in the literature for proper validation.

3.1. SicWell Dataset

By applying the SiCWell dataset, this work employs a novel method to determine the SOC of EV batteries. Due to the utilization of wide-bandgap semiconductors (e.g., silicon carbide), significant attention has been developed to the switching frequency components of the ripple current in the SiCWell, which permit higher switching frequencies and consequently cause frequency components to shift. The current spectrum exhibits main harmonics at specific frequencies, which are determined by the switching (fs) and fundamental (fg) frequencies: fs ± 3 fg; fs ± 6 fg; 2 fs; 4 fs; 2 fs ± 6 fg; 3 fg. The amplitudes are extremely operation point dependent [31]. The SiCWell Dataset consists of information about LIBs utilized in battery EVs, with a specific focus on diagnostics and modelling. The battery's cycling data possesses favourable characteristics for the development and verification of state-of-charge diagnosis techniques within an authentic setting. The dataset's realistic ripple testing comprises the current profiles of numerous battery cells during two driving cycles. Thus, a standard is established for an extensive array of battery diagnosis techniques. By using the following link, the dataset can be downloaded. https://ieee-dataport.org/open-access/sicwell-dataset.

3.2. Data Preprocessing

Preprocessing is an essential procedure that transforms the input information into a format that is more suitable for importing into the developed algorithm. The unprocessed data collected from the dataset is deemed unfit for additional analysis. As a result of the potential presence of absent, duplicate, or irrelevant feature data. Subsequently, the dataset undergoes preprocessing procedures to attain clarity. Encoding of labels, elimination of special characters, and removal of duplicate data cases containing null values are included in these processes [18]. The Z-score normalization method is employed to analyze the information obtained from the Sicwell dataset. To attain zero normalization, an approach known as Z-score normalization is necessary to compute the standard deviation (SD) of each attribute within the set of training and mean. These values are then separated by several variables that are also present in the training set. The mean and SD of each attribute are calculated [30]. The general formula defines the operation to be executed as the transformation.

$$C = \frac{(C-\mu)}{\sigma} \tag{2}$$

where the average of C is μ and its SD is σ [30]. The z-score method is employed to normalize every feature in the dataset before commencing the training procedure. It is essential, following the computation of a set of training data, to preserve the mean and standard deviation for each feature to be able to utilize them as weights in the architecture of the system.

3.3. Deep Belief Network for Feature Extraction and Classification

Deep Belief Network (DBN) has been effectively implemented in collaborative filtering, feature learning, and classification [30]; it was originally developed by Hinton. Following the preprocessing of the dataset's collected data, the DBN model is proposed to facilitate classification. In the context of battery SOC prediction for EVs, DBNs are utilized for feature extraction and classification to enhance the accuracy and robustness of SOC estimation models. DBNs are composed of multiple layers of hidden units, where each layer learns increasingly abstract representations of the input data. In battery SOC prediction, the input data typically consists of various parameters such as voltage, current, temperature, and possibly additional sensor readings. The DBN learns to extract meaningful features from this input data through unsupervised learning algorithms such as Restricted Boltzmann Machines (RBMs). RBMs are used to pre-train each layer of the DBN by capturing statistical dependencies within the input data. As a result, the hidden units in each layer learn to represent high-level features that are relevant for SOC prediction, such as charge/discharge patterns, voltage fluctuations, and temperature effects. Through this process, the DBN effectively extracts a compact and informative representation of the input data, which can improve the model's ability to capture complex relationships between input features and SOC. Once the DBN has learned to extract meaningful features from the input data, it can be used for classification tasks such as predicting the SOC of the battery. The output layer of the DBN is typically a softmax layer, which produces probability distributions over the possible classes (e.g., different SOC levels). During the classification phase, the learned features from the DBN are fed into the network, and the model's parameters are fine-tuned using supervised learning techniques such as backpropagation. The DBN learns to map the extracted features to the corresponding SOC values based on the training data, adjusting its parameters to minimize the prediction error. As a result, the trained DBN can accurately classify new instances of input data and SOC prediction of the battery with high precision.

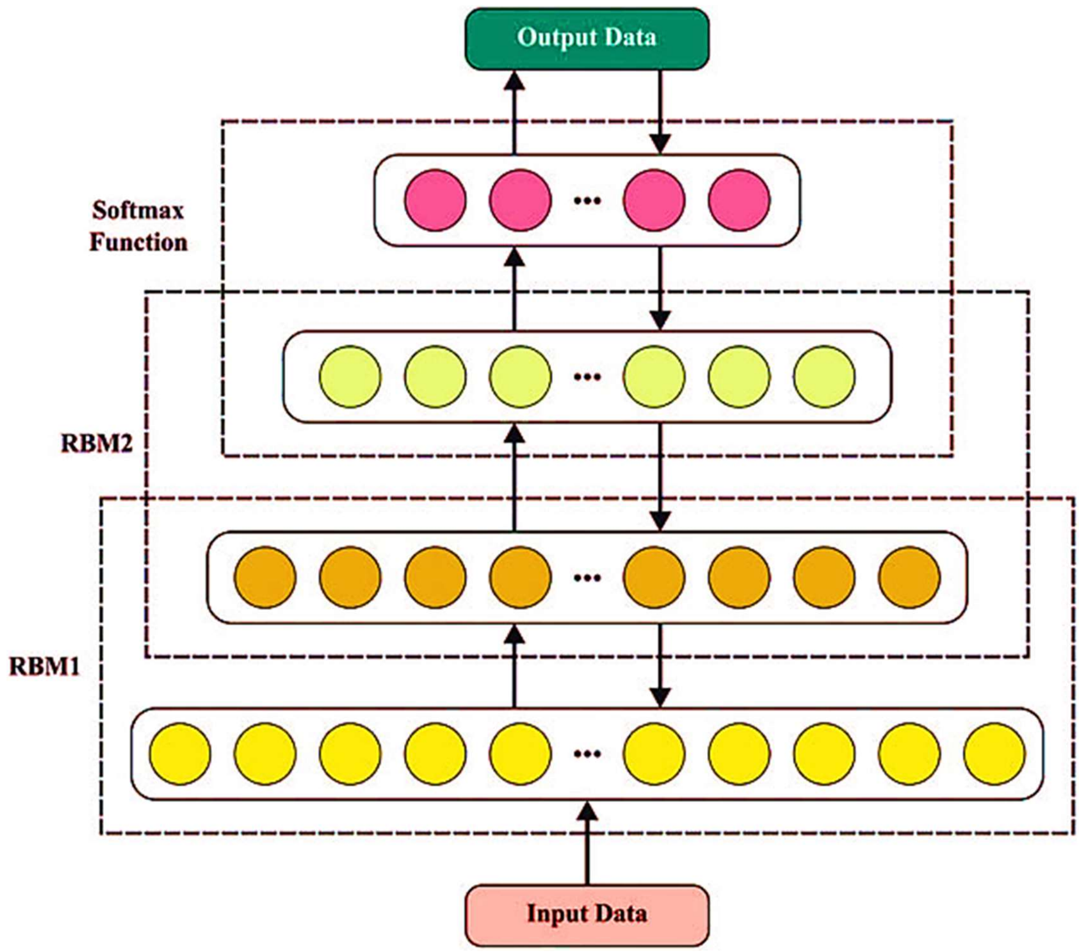

Figure 4. Structure Of DBN Model

The DBN is composed of numerous neural network layers, which can be categorized as either visible or concealed [22]. In contrast to the visible layer, which is employed to receive inputs, the concealed layer is utilized to extract features. The DBN is regarded as a DNN model composed of unsupervised RBM networks with multiple layers and single-layer BPNN. Beginning with the initial layer, the vector relative to the initial unit is initialized via mapping by layer as a consequence of layer-wise training. By utilizing the mapping process, the visible layer 'v' of DBN ascends to the hidden unit 'h,' which is subsequently followed by the hidden unit. The 'h' unit will be the 'v' units of the subsequent network until the training of the multi-layer DBN. This information would be obtained through additional means such as mapping. The weight of each layer is increased throughout the training procedure by the correlation between the ‘h’ & ‘v’ layers. The reconstructed error is propagated from the DBN initial layer to the subsequent layers. Fig 4 shows the structure of the DBN.

In the same way, the reconstructed error is transferred from the secondary to the succeeding layers of the DBN, until it reaches the concluding layer at the end. It is trained in layers. For optimal performance, it simply assures that the weights of every layer are mapped nonlinearly to the eigenvector of the current layer. During training, it is unable to ensuring that the eigenvectors of every network layer are mapped nonlinearly to the optimal value. Therefore, the DBN output dataset is utilized as input to the BPNN to train the BPNN on the trained dataset. Additionally, the pre-training model obtains the learning rate of ε and θ= (W, b, c) as module parameters subsequently. The σ_i error gradients for every visible layer element in v_i can then be calculated as follows:

$$\sigma_i = Q_i(1 - Q_i)(e_i - Q_i) \tag{3}$$

The visible layer of the output unit is denoted by Q_i in Equation (3), which represents the desired output as e_i . The following expression is used to compute the σ_j error gradients for each h_i hidden layer element.

$$\sigma_j = Q_i(1 - Q_i) \sum_i \theta_{ij} \, \sigma_i h_i \tag{4}$$

The predictive module for the durability of concrete structures is established by the error gradient value. The coefficient of expected value is represented by C, while the *t* is represented as g_t.

The module for predicting the durability of concrete structures is installed by the previously mentioned error gradient value. The term *t* is indicated as g_t and the Coefficient of expected value is represented by the term C.

$$E_t = \sigma_j + (1 - \lambda) g_t \tag{5}$$

For model training, the module for predicting concrete durability structures receives the training and testing datasets; the output layer is represented by the term P.

$$P_p = E_t CH \tag{6}$$

The term C denotes the DBN memory model state, while H represents the output of the model, as shown in Equation (6).

3.4. Aquila optimization algorithm for DBN hyperparameter tuning

The enhancement of classification performance through the optimization of model hyperparameters. Until the loss function of DBN reaches its minimum, it is necessary to make minor adjustments to the parameters under supervision. The effectiveness of the DBN model are enhanced through the tuning of hyperparameters utilizing the AOA in this study. Regularly, DBN employs a top-down approach throughout the fine-tuning procedure. The aquila optimization algorithm draws inspiration from the hunting behavior of the Aquila raptor as a metaheuristic optimization algorithm. It aims to efficiently search through the hyperparameter space of DL models to find the optimal set of hyperparameters that maximize the performance of the model on a given dataset. Here's how the AOA can be used for hyperparameter tuning: The optimization process begins by initializing a population of potential solutions, each representing a set of hyperparameters for the machine learning model. The hyperparameters can include parameters such as learning rate, regularization strength, number of layers, number of neurons per layer, etc. By employing the AOA for hyperparameter tuning, researchers can efficiently search the hyperparameter to find configurations that optimize the performance of SOC prediction models, leading to more accurate and reliable predictions for electric vehicle battery management.

AOA is an innovative, modern swarm intelligence algorithm. Aquila employs four distinct hunting strategies. In response to different categories of prey, the kind may adapt its hunting approach accordingly and subsequently utilize its swift speed, strong feet, and claws to attack the prey. Utilize the following procedures to define the summary of the mathematical expression:

Step 1: Extended exploration (Z_1): Increased altitude by employing a vertical squat Here, the Aquila rises to a greater altitude than the ground and conducts a broad survey of the area in issue.

After locating the prey area, the AOA descends in a vertical trajectory. This behavior can be represented mathematically in the following way:

$$Z_1(t+1) = Z_{best}(t) \times \left(1 - \frac{t}{T}\right) + (Z_M(t) - Z_{best}(t) \times p_1) \quad (7)$$

$$Z_M(t) = \frac{1}{N}\sum_{i=1}^{N} Z_i(t) \quad (8)$$

$Z_{best}(t)$ denotes the location that was obtained optimally, while Z(t) signifies the mean location of every Aquila in the current iteration. The variables t and T represent the current iteration and the maximum number of iterations, respectively. N and p_1 denote the population size and an arbitrary integer between 0 and 1, respectively.

Step 2: Narrowed exploration (Z_2): glide attack reduction and contour flight This is a widely utilized foraging strategy for Aquila. It attacks the prey using brief gliding, then falls within the specified region and encircles the prey in flight. The position has been updated as follows:

$$Z_2(t+1) = Z_{best}(t) \times LP(D) + (Z_P(t) + (y - x) \times p_2) \quad (9)$$

In Equation (9), $Z_P(t)$ signifies a region of Aquila that is arbitrary, D represents the size of dimension, and p_2 indicates a random integer that ranges between 0 and 1. $LP(D)$ represents the Levy flight function, which is defined as follows:

$$LP(D) = s \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}} \quad (10)$$

$$\sigma = \left(\frac{p(1+\beta) \times \sin\frac{\pi\beta}{2}}{p\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right) \quad (11)$$

The expression denotes constant values s and β, which correspond to 0.01 and 1.5, respectively. Arbitrary numbers u and v are defined as such and fall within the range [0, 1].

The spiral shape in the search space is denoted by y and χ, which are computed as follows:

$$\begin{cases} x = p \times \sin(\theta) \\ y = p \times \cos(\theta) \\ p = p_3 + 0.00565 \times D_1 \\ \theta = -\omega \times D_1 + \frac{3 \times \pi}{2} \end{cases} \quad (12)$$

In Equation (12), p_3 signifies the quantity of search cycles that fall within the range of 1 to 20, If D_1 consists of integer values ranging from one to the dimension of D, then ω equals 0.005.

Third Step: Expanded exploitation (Z_3): attack with a slower descent and lower trajectory After a consensus has been reached on the location of the prey, the Aquila descends vertically to launch its initial attack. The designated area is utilized by AOA to approach and attack the prey. The subsequent equation serves as a mathematical representation of this behavior:

$$Z_3(t+1) = \left(Z_{best}(t) \times Z_M(t)\right) \times \alpha - p_4 + \left((uB - LB) \times p_5 + LB\right) \times \delta \quad (13)$$

In Equation (13), $Z_{best}(t)$ represents the location that was effectively attained, and $Z_M(t)$ indicates the present position average value. α and δ represents the tuning exploitation parameter set as 0.1, uB and LB denote the limits (upper and lower), and p_4 and p_5 refer to values present randomly in the intervals of 0 and 1.

Step 4: Narrow exploitation (Z_4): Prey capture and movement

In this scenario, the Aquila pursues the prey along its escape trajectory before charging it from the ground. The equation for the behavior is given as:

$$\begin{cases} Z_4(t+1) = QF \times Z_{best}(t) - (G_1 \times Z(t) \times p_6) - G_2 \times LF(D) + p_7 \times G_1 \\ QP(t) = t^{\frac{2 \times rand - 1}{(1-T)^2}} \\ G_1 = 2 \times p_8 - 1 \\ G_2 = 2 \times \left(1 - \frac{t}{T}\right) \end{cases} \quad (14)$$

Equation (14) defines the current location as Z(t), while the quality function value QF(t) represents the equilibrium of the searching approach. G1 indicates the movement parameters of aquila while pursuing preys, a random integer that falls between the interval [-1, -1]. G2 denotes the slope flight that decreases sequentially from 2 to 0 while following prey. p_6, p_7, and p_8 were numbers randomly that lies between [0, 1]. To improve the efficacy of classifiers, the AOA system calculates a fitness function (FF). A positive integer is designated to represent candidate outcomes that exhibit superior performance [32]. The following section includes the pseudocode for the DBN-AOA model.

Pseudocode For DBN-AOA Algorithm

Initialize the parameters of DBN and AOA
Load EV battery data
load('battery_data.mat');
Preprocess data
X = normalizeData(battery_data.X);
y = battery_data.y;
Split data using MATLAB's crossvalind function
cv = cvpartition(size(X,1), 'Holdout', 0.2); % 20% for validation
X_train = X(training(cv);
y_train = y(training(cv);
X_val = X(test(cv);
y_val = y(test(cv);
Define hyperparameter search space
learning_rates = [0.01, 0.001, 0.0001];
hidden_neurons = {[10, 5], [15, 10], [20, 15]};
best_params = [];
best_performance = inf;
Hyperparameter tuning
for lr = learning_rates
  for neurons = hidden_neurons
    Train the model
    Evaluate the model
    Update best parameters and performance
  end
end
Final training with best hyperparameters
Evaluate final model on test data.

4. EXPERIMENTAL ANALYSIS

4.1. Experimental Setup

The experiments are performed in a system with 12 GB operating memory. The system is equipped with a CPU, Intel i5 CPU @3.2 GHz. The performance evaluation of this research was carried out using the SiCWell Dataset. The DBN+AOA classification algorithm and the analysis of data are both performed with the help of the MATLAB module.

4.2. Performance Metrics

Measuring performance is critical to achieving success in the data-driven society of today. The efficiency of the research model is determined by evaluating the outcomes by the classification parameters. Three parameters—RMSE, MSE, and MAE—were essentially employed to assess the proposed model's ability to predict SoC values. Consequently, the performance metrics are evaluated using the subsequent metrics: The MAE measures the average absolute differences among the actual and predicted values computed across the dataset. MAE measures accuracy for the model's performance on the same scale, as the final objective remains unchanged. A model is considered more accurate as the MAE approaches zero.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}) \quad (15)$$

The MSE quantifies the variation among the predicted and actual values by taking the square root of the average variance throughout the whole dataset.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2 \quad (16)$$

RMSE is the error value obtained by taking the square roots of the MSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2} \quad (17)$$

4.3. Performance Evaluation

This section presents the evaluation of the proposed predictive model's comparative analysis. The data from the SicWell dataset are given as input to the predictive model. The data from the dataset are divided into training and test sets. According to these sets, the performance evaluation is performed with all the models. The performances of the DBN+AOA method in battery SoC prediction are measured based on various parameters like MSE, MAE and RMSE.

Table 1. Proposed Model's Performances Of SOC Estimation Under Varying Temperatures

Temperature (◦C)	RMSE	MAE	MSE
10	0.13	0.015	0.012
20	0.18	0.012	0.008
30	0.08	0.010	0.005
40	0.20	0.008	0.010
50	0.12	0.016	0.0155
AVERAGE	0.136	0.0122	0.0101

As shown in Table 1, the proposed DBN+AOA model produces excellent SOC estimation results across a range of temperatures. All RMSEs are within 0.2%, MAEs are within 0.17%, and MSEs are within 0.15%, according to the results. RMSE, MAE, and MAE have respective averages of 0.136, 0.0122, and 0.0101. Consequently, the suggested network can capture the impact of ambient temperature and delivering accurate SOC estimations despite varying temperatures.

Figure 5 shows the graphical plot of the proposed model RMSE parameter for SOC prediction under varying temperatures like 10, 20, 30, 40, and 50 degrees respectively. The RMSE values vary from a maximum of 0.20 to a minimum of 0.08. The average RMSE value obtained is 0.136 with a difference of 0.12. The graphical plot of MAE values under varying temperatures is shown in Figure 6. The MAE values vary from a maximum of 0.016 to a minimum of 0.008. the average value of 0.0122 is obtained by the DBN+AOA model.

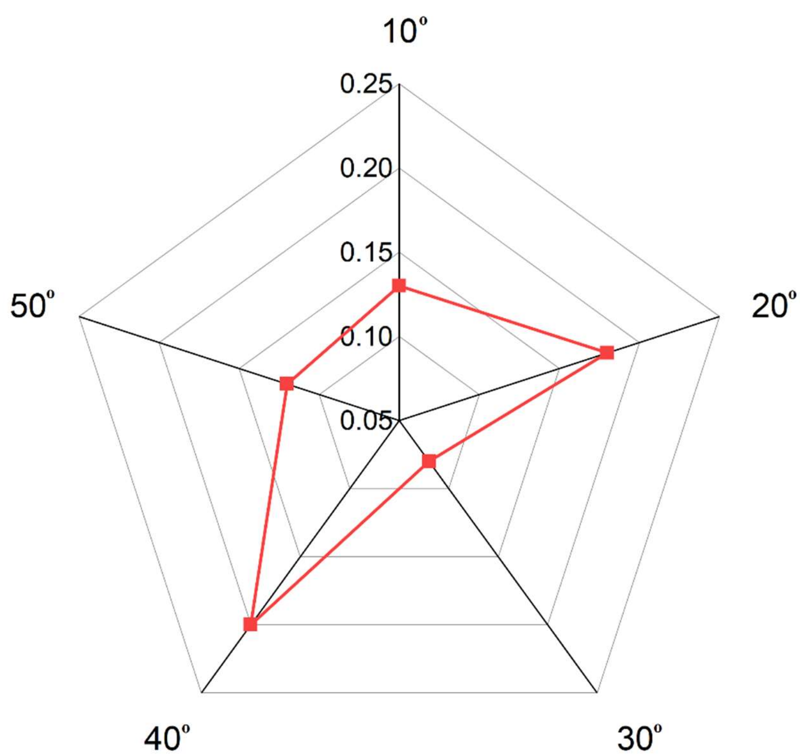

Figure 5. Graphical Plot Of RMSE Under Varying Temperatures

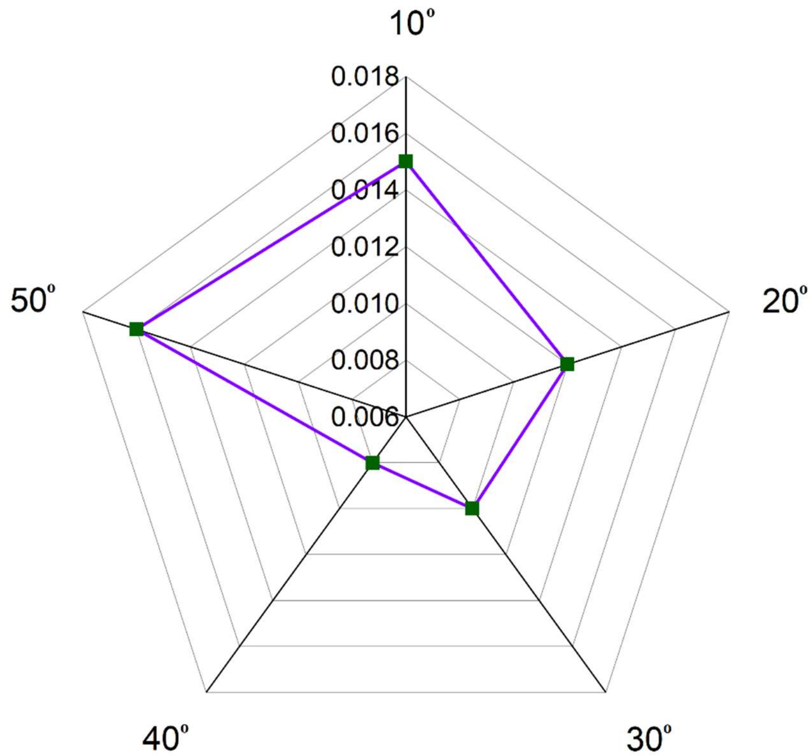

Figure 6. Graphical Plot Of MAE Under Varying Temperatures

Figure 7 illustrates the MSE values of the proposed model under different temperature conditions. MSE vary from a maximum of 0.0155 to a minimum of 0.005 with a difference of 0.15.

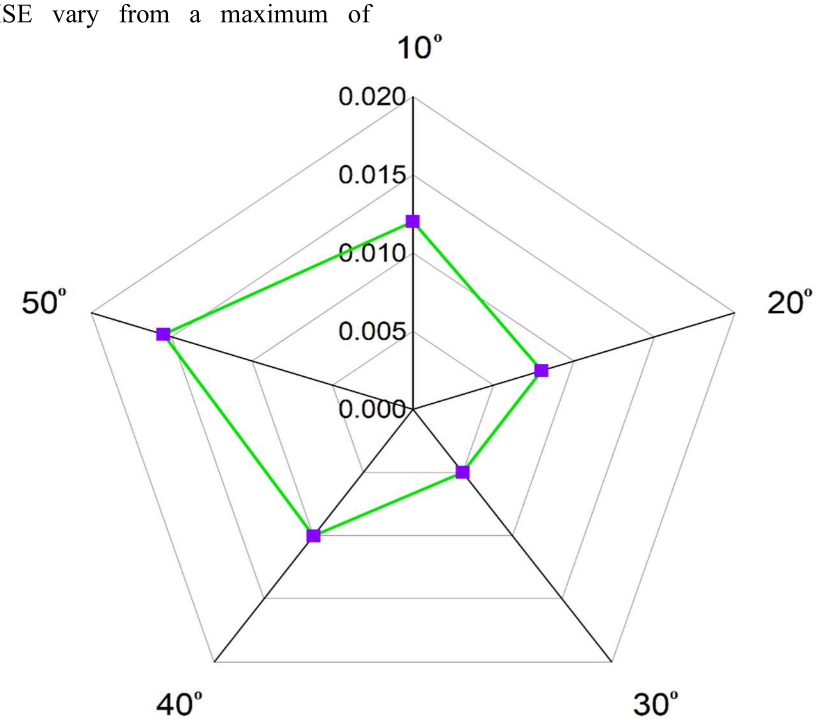

Figure 7. Graphical Plot Of MSE Under Varying Temperatures

Table 2 compares the proposed model's testing performance with existing models included in the review. The performance analysis was compared with models like XGBoost, NARX-Net & ARIMA, MLP + LSTM, RF + LSTM and CNN + LSTM.

Table 2. Comparison of Performance Analysis

S.NO	MODEL	RMSE	MAE	MSE
1	XGBoost [35]	0.1515	0.1426	-
2	NARX-Net & ARIMA [36]	0.1707	0.0291	0.1383
3	MLP + LSTM [37]	1.527	1.161	0.023
4	RF + LSTM [38]	0.453	0.343	0.206
5	CNN + LSTM [17]	1.31	0.92	-
6	PROPOSED MODEL DBN+AOA	0.136	0.0122	0.0101

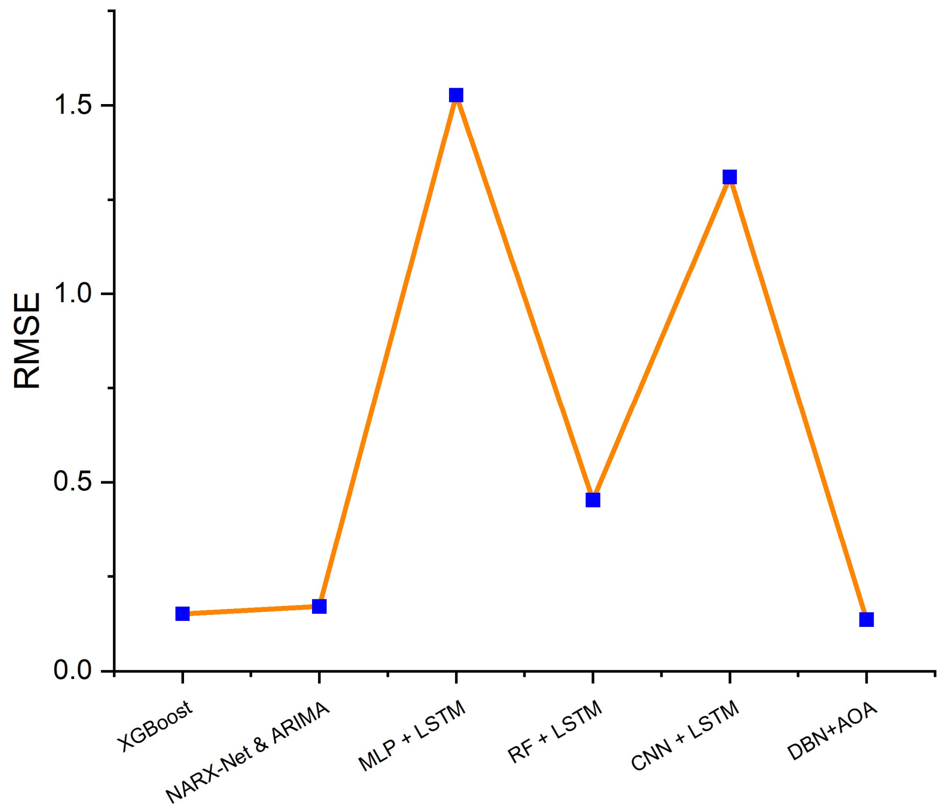

Figure 8. Graphical Plot Of RMSE Comparison

Figure 8 shows the graphical plot for the comparison of RMSE values with various models. Based on the test performance comparison made with the existing models, the proposed model has a lower error rate than the other models. The research model has an RMSE of 0.136, which is 1.291 to 0.015 lower than the other models. Figure 9 shows the graphical plot for the comparison of values. The MAE value of the research model was 0.012, which is 1.14 to 0.016 lower than the compared models. Figure 10 shows the graphical plot for the comparison of MSE values with existing models excluding XGBoost and CNN + LSTM models. The MSE score of the research model was 0.0101, which is 0.19 to 0.012 reduced than the NARX-Net & ARIMA, MLP + LSTM and RF + LSTM models. As a result, according to this comparison, the DBN+AOA model has obtained better results than the compared models in this research.

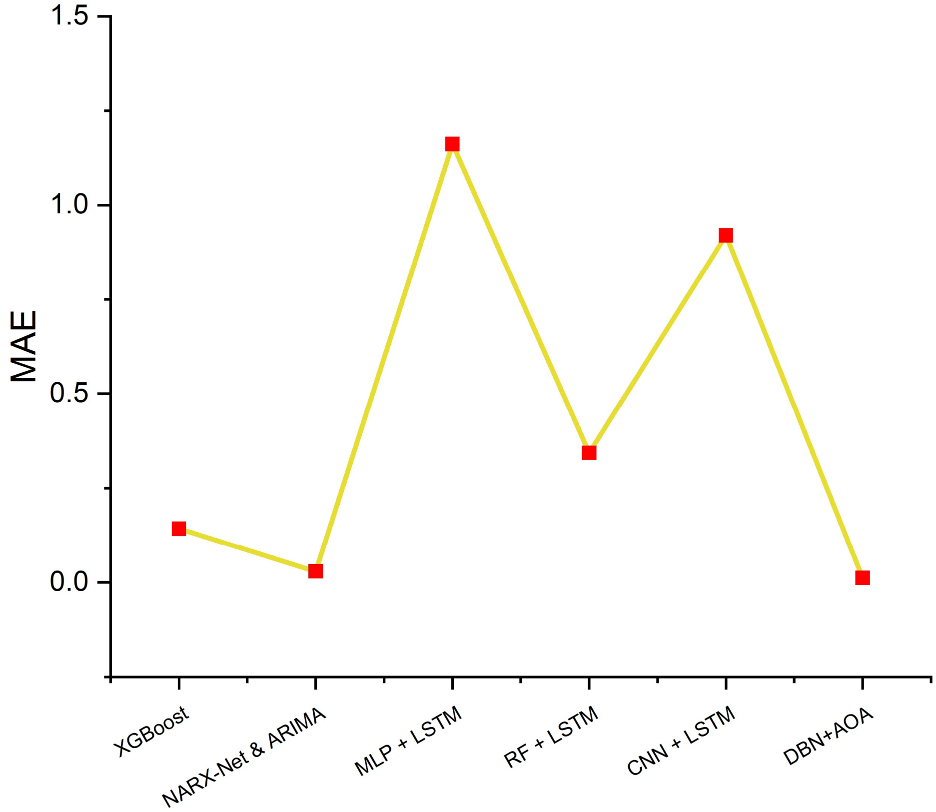

Figure.9. Graphical Plot Of MAE Comparison

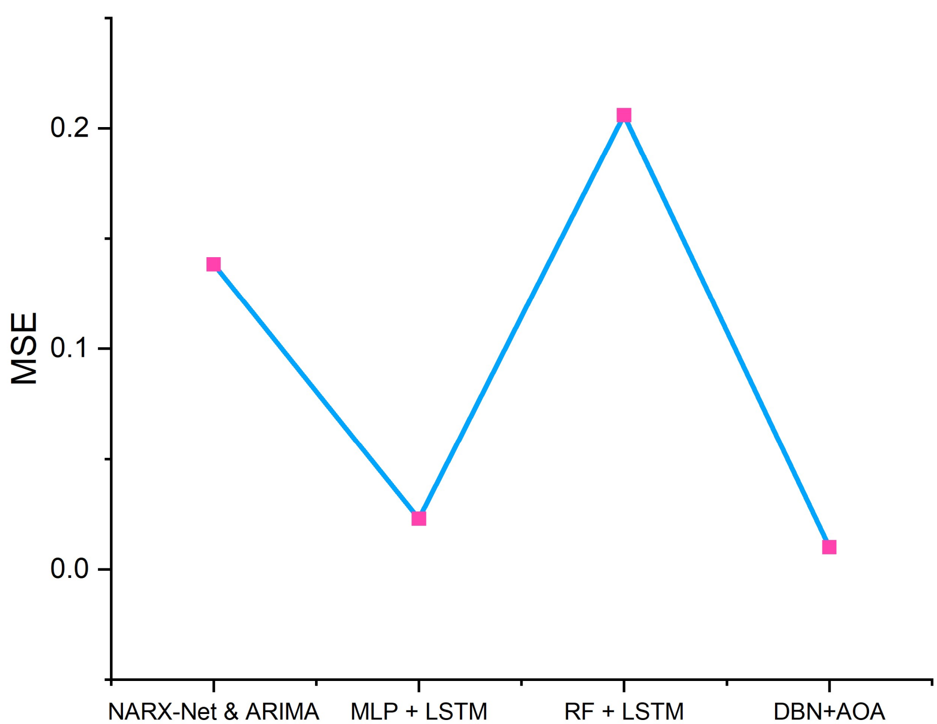

Figure.10. Graphical Plot Of MSE Comparison

The model demonstrates superior performance in estimating SOC parameters with low error metrics. The model's effectiveness is demonstrated across various temperature conditions, showcasing its robustness in handling different environmental factors that influence battery behavior. The model's performance is compared with various other models commonly used for SOC prediction, demonstrating its superiority over alternative approaches such as XGBoost, NARX-Net & ARIMA, MLP + LSTM, RF + LSTM, and CNN + LSTM.

The research topic concluded by assessing the effectiveness of the suggested model based on specified criteria outlined in the study. The research probably consisted of accuracy metrics such as RMSE, MAE, and MSE, which were employed to objectively evaluate the model's predicted accuracy. In addition, a temperature sensitivity analysis was performed to assess the model's robustness under different environment circumstances. A comparative analysis may have been conducted to determine the superiority or effectiveness of the suggested model, in comparison to existing SOC estimate models. This conclusion confirms that the proposed model effectively addresses the challenges of estimating SOC in EVs powered by LIBs.

The scientific contribution of the proposed DBN+AOA model is in its higher performance for SOC estimation in EVs powered by LIBs, compared to other methods described in existing research. The existing models, including XGBoost, NARX-Net, ARIMA, MLP + LSTM, RF + LSTM, and CNN + LSTM, have different levels of accuracy in predicting SOC. However, the suggested DBN+AOA model outperforms them greatly in all metrics, such as RMSE, MAE, and MSE. The remarkable reduction in RMSE and MAE values achieved by the proposed model, indicating its enhanced precision and reliability in SOC estimation. The DBN+AOA model is more effective and superior compared to previous research in solving the issues of SOC prediction in EVs. This model significantly contributes to the improvement of battery management systems in the context of sustainable transportation.

5. CONCLUSION

In this paper, a combined DBN+AOA model for the SOC estimation of LIBs was proposed. The research model has a series of workflows including data pre-processing, feature extraction, classification and hyperparameter tuning. Data collected from the SiCWell dataset are preprocessed by Z-score normalization. DBN was used for classification and feature extraction. The hyperparameters were tuned by using an Aquila optimization algorithm. The proposed model's performance was assessed by the SOC parameters such as RMSE, MAE, MSE. The DBN+AOA model produced the best results with RMSE under 0.14%, MAE under 0.013% and MSE less than 0.011% respectively. The average values of RMSE, MAE, MAE are 0.136, 0.0122 and 0.0101 respectively. The proposed results are compared with the various models like XGBoost, NARX-Net & ARIMA, MLP + LSTM, RF + LSTM and CNN + LSTM. The comparative analysis shows that the proposed DBN+AOA model was the best method for SOC prediction under different temperatures, with minimum error values of RMSE, MAE, and MAE. To conclude, the SOC estimation method for LIBs that was suggested, which is founded upon the DBN+AOA, has undergone extensive validation and produced excellent results. The DBN+AOA model has some limitations as the performance of the model heavily relies on the availability and quality of the training data. Ensuring access to comprehensive and representative datasets may pose challenges in real-world applications. While the model demonstrates promising results across various temperature conditions, its generalizability to other environmental factors or battery chemistries may require further investigation and validation. In future, implementing the proposed model into real-time battery management systems may require addressing latency and resource constraints to ensure practical applicability in dynamic operational environments.

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