



IMPROVED HARRIS HAWK OPTIMIZED ATTENTIVE DEEP BELIEF NETWORK FOR RELIABLE LITHIUM-ION EV BATTERY SOC-SOH PREDICTION

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ABSTRACT

Lithium-ion batteries are an integral part of modern electrification systems, which provide power for Electric Vehicles (EVs), and many portable smart devices. Therefore, in order to maintain an accurate battery management system, accurate prediction of a lithium-ion battery's State of Charge (SoC) and its State of Health (SoH) is necessary. Since these batteries degrade slowly over time, it results in deterioration and decreased performance. This work describes a sophisticated data-driven Deep Learning (DL) model that accurately estimates the prediction of SoC and SoH. The model's creation begins with a thorough data preprocessing step, where all missing values, anomalies, and redundancies are addressed to maintain the integrity of the sensor data used to build the model. A complete exploratory analysis of the data aids in identifying the degradation-sensitive features of the data. A combination of two layers, a Deep Belief Network and an Attention Mechanism (DBN-AM), is used in the prediction stage to formulate a model that demonstrates non-linear dynamics of deterioration and significance assignment of the temporal dynamics to represent long-range temporal dependencies. The hyperparameters in this model are adjusted by means of Improved Harris Hawk Optimisation (IHHO) to enhance the proficiency and convergence stability of the prediction stage. This framework is a reliable and intelligent solution for predictive management of batteries for usage in real world applications and the results of simulation experiments carried out in python and achieves the lowest error. For SoC, MSE of 0.001, RMSE of 0.023 and MAE of 0.017, provides an accurate estimation of the battery charge and for SoH, MSE of 0.001, RMSE of 0.032 and MAE of 0.019 provides an accurate estimation of health of the battery.



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I. INTRODUCTION

The use of lithium-ion batteries has increased dramatically recently across a variety of industries, including transport, microelectronics, and stratosphere owed to their large temperature range, high energy density, low self-discharge rates and long cycle life [1]. Batteries such as lead-acid and nickel-metal hydride are less capable compared to lithium-ion batteries because of the greater amount of energy that contain in each unit volume, their ability to deliver more energy quickly, their significantly longer life cycle as measured by number of charge or discharge cycles, and much lower amount of self-discharge of the battery when it is in storage [2], [3]. Lithium-ion batteries continue to be the most popular and widely used batteries for customer low power products such as mobile, processors, and high-power applications such as electric vehicles, bicycles and so on based on its extensive market penetration. Although improvements have been made to the electrical characteristics of lithium-ion batteries such as energy density, the problem with lithium-ion batteries remains the non-uniformity of capacity and retention ratio. A properly designed Battery Management System (BMS) greatly increase the performance of a battery pack containing multiple cells in series. By using a BMS, excessive stress on the most weakened cell will be reduced. This will result in a more uniform capacity being experienced by all cells in a battery pack as well as a higher retention ratio over time [4-6]. Battery Prognostics and Health Management (PHM) encompasses the use of PHM methods for a battery and covers its health as well as the methods used to manage the battery's health [7].

Precise approximation of the SoC and SoH of a battery is required to manage the battery's remaining energy, capacity, and remaining life. Through consistent and accurate estimation and organisation of SoH, improved functioning security is provided for EVs and batteries which are appropriately replaced before causing damage. In addition, users have the ability to formulate battery maintenance strategies and plan for repair or replacement of batteries [8]. The evolution of battery technology and EV usage has made it increasingly critical to understand both the SoC and SoH of an EV's battery. For manufacturers and consumers, the SoC represents a key component of both driving range and charging behaviour [9]. In contrast to SoC, the SoH of an EV battery defines the long-term health of an EV battery, thus impacting its economic sustainability and longevity. Precise valuation of both SoC and SoH is necessary for manufacturers to maintain their competitiveness and reliability in the EV marketplace [10]. Similar to EVs, the evolution of SoC and SoH estimation procedures has gone from conventional methods that utilized only voltage measurements to data-driven methods that incorporate machine learning. Despite this significant advancement, the unique demands of electric mobility including rapid charge stress, thermal fluctuations, and dynamic driving conditions which continue to provide challenges for battery management systems and require specific solutions [11-13]. Additionally, SoC helps to maximize battery usage by eliminating the risk of depleting the battery too early or overcharging the battery. Both of these factors increase battery longevity. Real-time SoC information enables EV users to better plan their trips, thus maximizing the optimal use of energy while avoiding unexpected shutdowns due to battery failure [14]. Tracking SoC is critical to improve EVs' user experience and reliability. Additionally, knowing the SoH of the succession container is significant for tracking the battery degrades, ages, and performs. By monitoring SoH on a regular basis, operators are able to better understand the battery performs. Managing SoH effectively is key to enhancing the long-term viability of EVs and reducing their overall environmental impact.

While there is operational measurement of terminal voltage of each cell individually, the BMS compute and supply the SoC and SoH of each cell to determine the optimal loads should be applied to each cell based on best to maximize pack life [15], [16]. As such, having a BMS with precise SoC and SoH estimations enable to avoid overcharging each individual cell in the pack, therefore prolonging the overall life of the entire pack [17]. Although the conventional and machine-learning methods for estimating SoC and SoH have developed, many of these techniques rely on either a limited set of manipulated features as the single-estimate models of the actual batteries or static operational assumptions about the life of the batteries [18]. These two limitations cause the estimation accuracies to decrease under real-world conditions, such as when the batteries go through rapid churning cycles, changing thermal properties, differences from cell-to-cell in terms of how the cells were built and tested, and so forth. Additionally, very few of the present methods have the ability to model the complex, nonlinear behaviour of lithium-ion battery degradation, including permanent degradation and long-term temporal effects on battery usage, leading to poor estimating performance with less ability to generalize across different lithium-ion chemistries and performance styles [19]. To overcome these limitations, the proposed system uses an DL technique for attention mechanism. Through normalizing, eliminating redundant features, and cleaning the data for collection and pre-processing in the batteries, it improves the quality of the data [20]. The capacity degradation, time series trends, and interrelationships between important attributes of the batteries were examined in the exploratory analysis of the data collected. Then the model training is executed, the existing techniques are mentioned in the related works.

II. RELATED WORKS

By [21] have developed a Long Short-Term Memory (LSTM) framework allows for an precise combined estimation of the SoC and the SoH of Lithium-Ion battery packs used in EV to identify relationships over prolonged periods in response to variable driving conditions for EVs. In addition to these benefits, the framework provides better estimates than previous models. However, it requires extensive data for training, is computationally intensive, and is not easily understandable. Therefore, due to these factors, the LSTM framework is not able to be implemented in real-time applications such as battery management systems and will not generalize older models without retraining. By [22] have proposed the SoC and SoH for EVs battery management systems, utilizing ensemble methodologies, neural networks and the Tri layer neural network model, which is a simple method for representing the nonlinear relationship of the battery parameters, and being less demanding of computing resources, hence an obvious candidate for real-time application in EVs battery management systems. Nevertheless, its ability to model complex aging effects, exhibit long-term temporal correlation in its simulation of battery usage, and it lacks the ability to model the variability of the battery character in dynamic operating conditions. By [23] have established a Random Forest Regression and Artificial Neural Network (RFR-ANN) combination improves accuracy of modelling and monitoring the battery's SoC and SoH through the combination of the strengths of random forests in feature selection and robustness with the abilities of neural networks to model non-linearity. RFR-ANN models provide improved accuracy and better resistance to noise and data variances. But RFR-ANN enhance to computational complexity, require extensive tuning of multiple parts of the system, and limited in their ability to be implemented and interpreted using the management systems in real time.

In turn [24] have suggested a CNN-BiLSTM method utilized for predicting SoC-SoH of batteries in EV using lithium-ion batteries. CNN-BiLSTM approach allows for spatial feature extraction via CNNs, while also allowing for long term temporal dependency capture through BiLSTMs, enabling more accurate predictions under complex dynamic conditions. Yet, it requires large sets of labelled training datasets, and a considerable amount of training time, which could present challenges for deployment within a real-time battery management system due to lack of interpretability and limited capability of deployment hardware. By [25] have introduced a SoH and SoC estimation using Recurrent Neural Networks (RNN) for Li-Ion batteries. RNN provide an effective way to estimate the SoC and SoH for a lithium-ion battery by utilizing and modelling the time of degradation under variable operating conditions. Nonetheless, it suffers from the vanishing gradient problems, high complexity in training, being very sensitive to noise, and inability to retain information over long-term. These problems can be improved by employing more advanced techniques such as DL. In order to solve the major disadvantages of current approaches such as high computational burden, low suitability for real-time applications, difficult to interpret, ineffective long-term degradation modelling capabilities, and low robustness under dynamic operation conditions, the proposed system utilizes Optimized Deep Belief Network integrated with Attention Mechanism to provide an accurate representation of nonlinearity in the battery degradation process and the long-term temporal dependencies that exist between the various degradation mechanisms. Furthermore, the integration of the two technologies ensures that the SoC-SoH estimation in battery management systems of EVs is performed in real-time and has sufficient robustness to withstand changes in dynamic operating conditions.

II.1 OBJECTIVES

The foremost purposes of this study include,

- ❖ To enhance model robustness and learning efficiency, preprocessing stages such as data cleaning, constant feature removal, and normalization is utilized.
- ❖ To comprehend battery parameter correlations, temporal patterns, and capacity degradation behaviour, exploratory data analysis is implemented.
- ❖ To efficiently learn temporal dependencies and salient features for precise battery SoC and SoH assessment, DBN-Att Network is executed in the suggested system
- ❖ To optimize the predictive model's weights and learning parameters for increasing prediction accuracy and convergence speed, IHHO is employed.

III. PROPOSED SYSTEM DESCRIPTION

The proposed system includes a smart battery-monitoring mechanism that provides accurate estimation of SoH and SoC. The diagram for the proposed block diagram is implemented in figure 1.

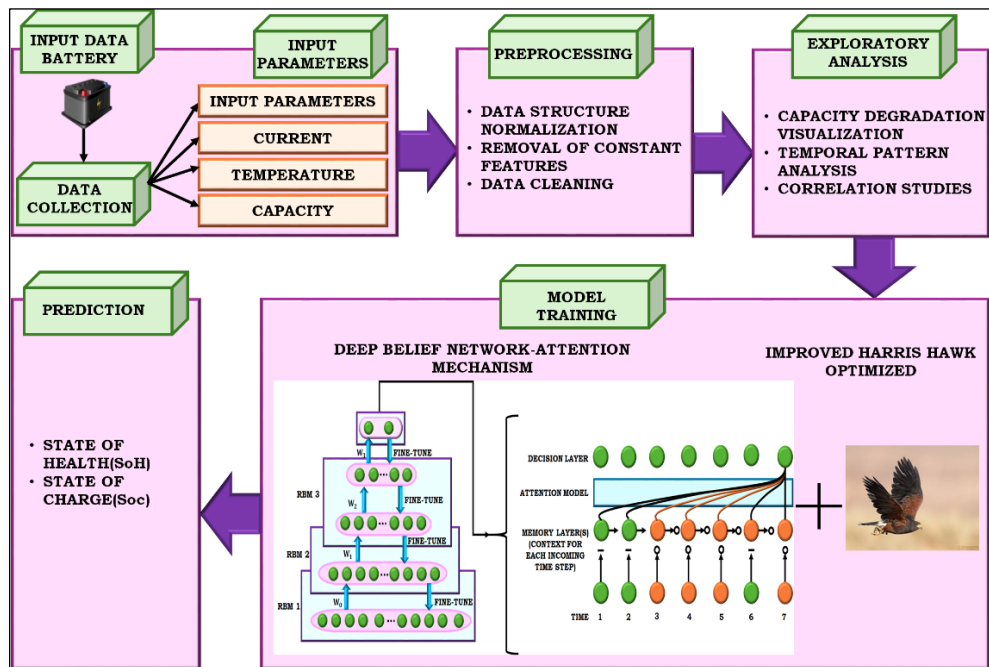


Figure 1: Proposed block diagram.

Source: Authors, (2026).

The operational data collected from the batteries contains voltage, current, temperature, and capacity. Once the raw data is cleaned and subjected to feature constant removal and normalization to ensure quality and uniformity throughout the data set, the cleaned data is analysed through exploratory analysis to identify the patterns of degradation behaviour and to recognize any significant correlation of characteristics. Once this is established, a DBN architecture augmented by an attention algorithm DBN-Attn is used to recognize complex nonlinear layers of patterns to accurately recognize the important characteristics of the data for the purpose of making reliable predictions. Additionally, Harris Hawk Optimization is used to apply an optimization function to the DBN-Attn Network to optimize the network and achieve a quicker convergence period along with a significant improvement of the DBN-Attn's overall predictability capability for accurately estimating both SoH and SoC.

IV. PROPOSED SYSTEM MODELLING

IV.1 PREPROCESSING

Precise and robust estimation of Lithium-Ion EV battery SoC and SoH depend on three methods such as data structure normalization, removal of constant features and data cleaning to preprocess data from data sets which are affected by noise and operating condition changes, which yield highly nonlinear results. To successfully capture battery degradation trends, a temporal structure around the data are based on their chronological sequence, using distinct charge or discharge cycles. Normalise data points are lie within the same range. This process ensures that all features within the predictive models, have larger features such as less-magnitude and provides improved numerical stability for the training phase. Furthermore, to improve data quality, features that remain constant provide no significant information regarding the battery state estimation. This reduces both the complexity of the model and possibility that obtain an overfit solution. To accurate sensor drift and outliers due to sudden load changes or measurement errors that exist in EV databases, a data cleaning process is applied. This includes the application of smoothing and filtering techniques to eliminate the noise from the data while preserving key electrochemical characteristics.

These above-listed preprocessing techniques provide a more accurate reflection of the condition of the battery. Consequently, it predicts accurate degradation rates for Lithium-Ion EV Batteries and enabling precise SoC and SoH estimation.

IV.2 EXPLORATORY ANALYSIS

Exploratory analysis provides valuable insight into different physical metrics impact battery performance. It offers valuable information regarding data quality, operational variance, room temperature aging and behaviours across multiple cells and different EV's and should ensure that the selected features derived from this analysis accurately represents battery performance.

IV.2.1 Capacity Degradation Visualization

The visualization of Lithium-Ion capacity degradation is crucial for accurate assessment of SoH estimates. Through the use of graphical representations of battery capacity degradation, for the life of the cell, long-term battery degradation is evaluated, wherein the loss of useful capacity is observed, based on the previous month's cycle count or month number. Visibility of batteries reduce in the establishment of accurate SoH classifications and assists with the evaluation of SoC-SoH modelling for EVs.

IV.2.2 Temporal Pattern Analysis

Temporal pattern analysis pertains to monitoring the parameters of batteries change over time while being operated dynamically in EVs with features like acceleration, regenerative braking, and different ambient temperatures. Time series analyses communicate a model to identify non-linear dependencies between a battery's SoC and SoH. This approach helps to increase the ability to predict accurately the short-term dynamics associated with instantaneous changes in performance while taking into account the effects of long-term degradation of the battery.

IV.2.3 Correlation Studies

Correlation Studies identify the relationships between SoC, SoH, temperature, current, voltage and associated degradation indicators. Knowing the strength of these correlations provides insight into the features that have the greatest effect on the accuracy of SoC and SoH estimations. Consequently, this methodology establishes the better suite parameters for selecting features and designing models to minimize redundancy and maximize the reliability and interpretability of SoC and SoH predictions within lithium-ion battery management systems for EVs.

IV.3 MODEL TRAINING - DEEP BELIEF NETWORK-ATTENTION MECHANISM

In order to accurately predict both the SoC and SoH of Lithium-Ion EV batteries, a DBN is used to capture multi-level features from operational data captured through high-dimensional inputs. Essentially, a DBN is a series of layered generative networks that consist of stacked Restricted Boltzmann Machines (RBM). An RBM consists of two layers like visible (v) layers which allow for the collection of battery data and hidden (h) layers which contain the extracted latent features, creating a stochastically functioning RBM. The relationship between the visible vector and hidden vector is expressed in terms of the joint probability of both vectors,

$$p(v, h) = \frac{e^{-E(v, h)}}{\sum_{v, h} e^{-E(v, h)}} \quad (1)$$

The energy function for an RBM with binary outputs is expressed mathematically as follows.

$$E(v, h) = -\sum_{i=1}^m a_i v_i - \sum_{j=1}^n b_j h_j - \sum_{i=1}^m \sum_{j=1}^n h_i W_{ij} v_j \quad (2)$$

The term W_{ij} , stands for the weight matrix of the connections amongst visible and hidden units, and the terms a_i, b_j represent the bias terms. When trained, using the Contrastive Divergence (CD) algorithm, are the parameter estimates updated the following expression.

$$\Delta W_{ij} = \varepsilon (\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{reconstruction}) \quad (3)$$

$$\Delta a_i = \varepsilon (\langle v_i \rangle_{data} - \langle v_i \rangle_{reconstruction}) \quad (4)$$

$$\Delta b_j = \varepsilon (\langle h_j \rangle_{data} - \langle h_j \rangle_{reconstruction}) \quad (5)$$

The initial step in training a prediction model to denote a SoC and SoH for lithium-ion battery EVs consists of carrying out unsupervised pre-training. The second step is to perform supervised fine-tuning in order to refine all model parameters to reduce prediction error with respect to both SoC and SoH. However, not every extracted feature is as beneficial towards making an accurate SoC or SoH prediction decision. Therefore, in this case, an attention mechanism (AM) is utilized to identify key pieces of battery related data by concentrating on only those hidden representations that provide insight into battery performance. Once the key hidden features, represented as h_t , are identified and assigned an attention score a_t , are computed as,

$$s_t = \tanh(W_h h_t + b_h) \quad (6)$$

These scores are then normalized by way of the softmax equation, as shown below and the diagram of the DBN-AM Network is demonstrated in figure 2.

$$a_t = \frac{\exp(s_t)}{\sum_t \exp(s_t)} \quad (7)$$

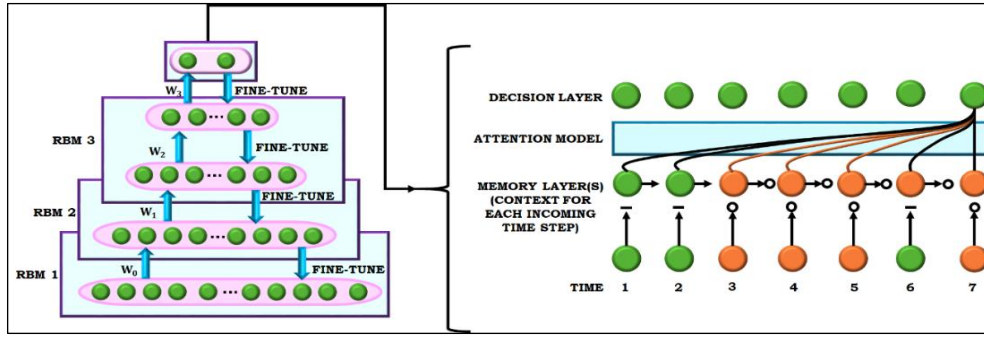


Figure 2: Diagram of DBN-AM.
Source: Authors, (2026).

The final attention-weighted feature vector is represented as,

$$s = \sum_t a_t h_t \quad (8)$$

Thus, the DBN-AM provides the ability for a model to focus on important behaviours of EV lithium-ion batteries, such as a sudden voltage dip and thermal event, while filtering out uninformative noise, thereby resulting in a higher quality and more reliable prediction of lithium-ion EV battery SoC and SoH.

IV.4 IMPROVED HARRIS HAWK OPTIMIZATION

The enhancement process used an improved HHO methodology was designed to find an optimal way to tune hyperparameters. The Optimization methodology is composed of four phases of actual hunting. In the initialization phase of HHO, the fitness value of all the hawks' positions was determined by randomly generating candidate values for the hawk positions and computing each hawk's fitness. The parameter values of the hawks were constrained by defining lower (*lb*) and upper (*ub*) bounds for the parameters. The hawks start their exploration either randomly or by considering the positions of the other hawks in the search space and making adjustments to their current position based on this information. The rule for updating the current position is as follows, and the flowchart for the proposed optimization is shown in figure 3.

$$X(t+1) = X_{rand}(t) - r_{d1}|X_{rand}(t) - 2r_{d2}X(t)| \quad (9)$$

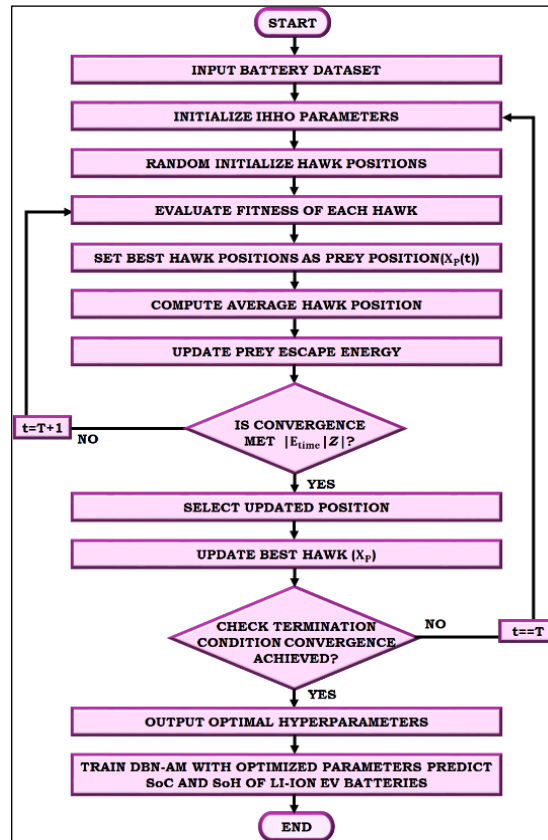


Figure 3: Flowchart for IHHO.
Source: Authors, (2026).

The average location of the hawks is indicated by the equation $X_m(t)$.

$$X_m(t) = \frac{1}{N_{sum}} \sum_{i=1}^{N_{sum}} X_i(t) \quad (10)$$

The intent of the prey escape energy E_{time} is evolving through the transition phase to provide a means for the hawks to shift amongst exploration and exploitation.

$$E_{time} = 2E_{init} \left(1 - \frac{t}{T}\right) \quad (11)$$

Where, E_{init} is the initial prey escape energy, t is the current iteration and T is the maximum number of iterations. The hawks explore the environment if $|E_{time}| \geq 1$, the hawks begin the exploitation phase. During the exploitation phase, the hawks implement adaptive strategies for soft and hard besiege tactics as well as progressive rapid dives based on the probability of escaping (g) and the amount of energy required for escape $|E_{time}|$. The flowchart for the proposed optimization is shown in figure 3.

$$Y = X_p(t) - E_{time} |BX_p(t) - X(t)|, Z = Y + S \cdot LF(dim) \quad (12)$$

$$Y = X_p(t) - E_{time} |BX_p(t) - X_m(t)|, Z = Y + S \cdot LF(dim) \quad (13)$$

In this, $LF(dim)$ denotes the Levy flight function and S is an arbitrary $1 \times dim$ path. The updated positions are selected based on improved fitness criteria of SoC-SoH prediction error,

$$X(t+1) = \begin{cases} Y, F(Y) < F(X(t)) \\ Z, F(Z) < F(X(t)) \end{cases} \quad (14)$$

By modifying the DBN-AM parameters through the new HHO, the DBN-AM is able to learn hierarchical features from the battery data while utilizing the attention mechanism to concentrate on key signals. The DBN-AM-HHO exhibited great predictability for unreliable and predictable SoC and SoH for Lithium-Ion EV batteries that present differing conditions.

V. RESULT AND DISCUSSION

The NASA battery dataset is provided for an evaluation of the novel improved HHO-DBN-AM for predicting SoC and SoH of batteries. The NASA battery dataset consists of 29,180 samples in 7 columns containing key parameters related to a given battery. They include measured values for voltage, current, temperature, cycle count and Battery Identification (ID). SoC and SoH are the dependent variables used to determine the battery's charge. Through providing actual cycle and degradation state data, the NASA battery dataset provide an accurate technique for prediction.

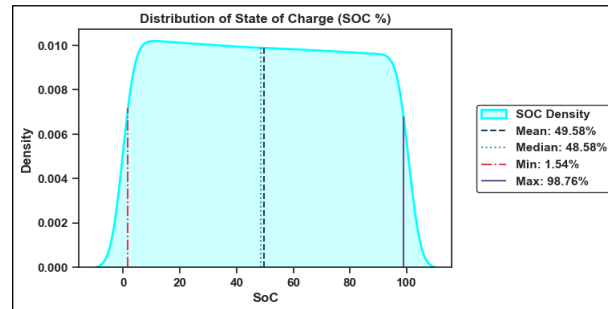


Figure 4: SoC distribution.

Source: Authors, (2026).

Figure 4 illustrates the SoC distribution and demonstrates a wide and consistent distribution of SoC values that are grouped together at the mid-level, with some values falling below the mid-level of SoC and approaching full charge. This indicates that there are likely to be many different conditions under which this battery operates.

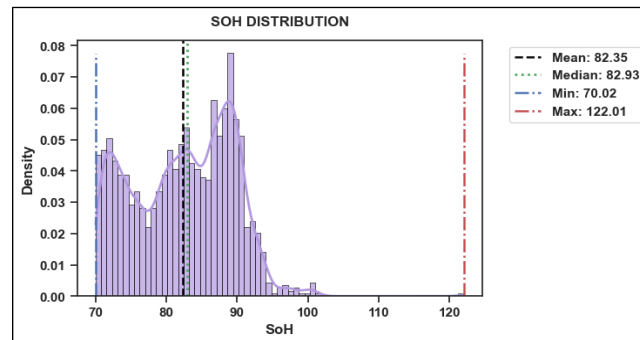


Figure 5: SoH distribution.

Source: Authors, (2026).

Figure 5 demonstrates the distribution of SoH and shows that the majority of the samples, with most samples being at the mid to lower end, meaning that most batteries are in good condition. The mean and median are similar, indicating consistency in the health of the batteries.

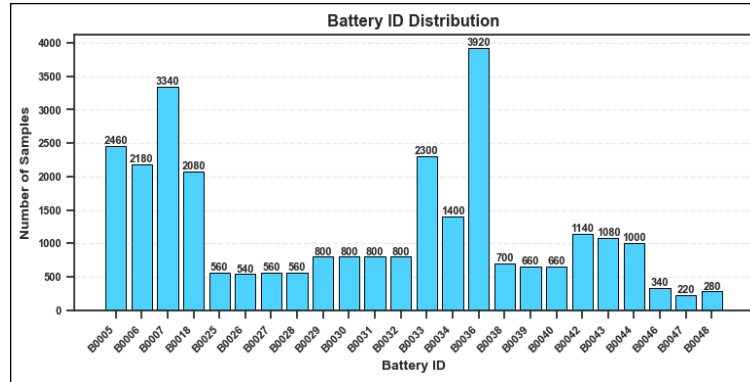


Figure 6: Battery ID distribution.

Source: Authors, (2026).

Figure 6 establishes the distribution of battery IDs is highly irregular, with some battery IDs having an extremely high number of samples and others having low to moderate numbers of samples, representing an unbalanced distribution of datasets.

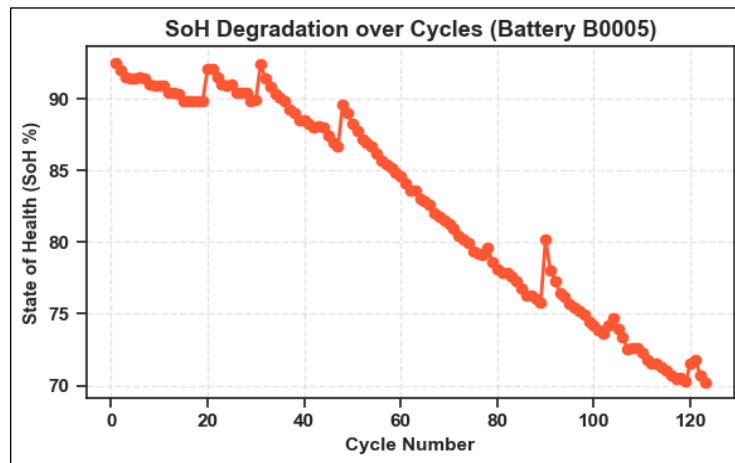


Figure 7: SoH degradation over cycles.

Source: Authors, (2026).

Figure 7 indicates the SoH degradation over cycles. In this diagram, the number of charging cycles increases the SoH continues to decline and illustrates that the SoH experiences fluctuations.

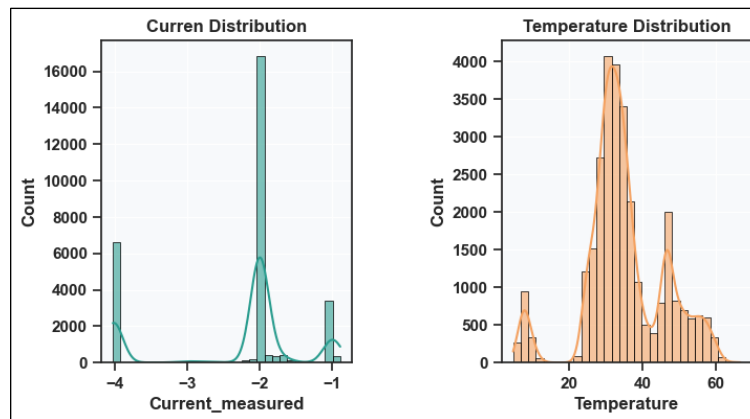


Figure 8: Current and temperature distribution.

Source: Authors, (2026).

Figure 8 shows the consistent operating levels for current are found at specific charge and discharge levels and the temperature were grouped with very few samples which are included at low or high ends of temperature.

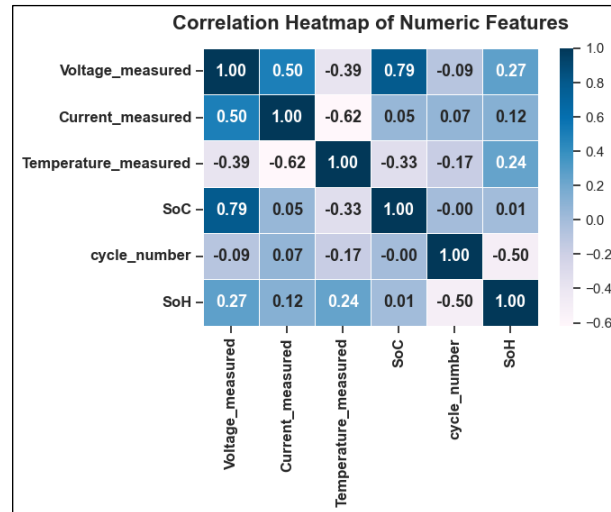


Figure 9: Correlation heatmap of numeric features.
Source: Authors, (2026).

According to the Heatmap in figure 9, the SoC has a strong correlation with most battery voltage readings and SoH has a reverse, moderate correlation to the increasing cycle number, it depicts weak to moderate correlations between the other features, suggesting limited dependency between these features.

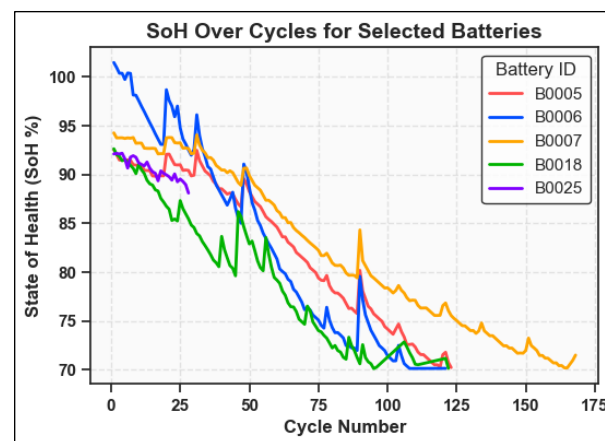


Figure 10: SoH over cycles for selected batteries.
Source: Authors, (2026).

The figure 10 consistently depicts a continuous decrease in SoH due to additional charging cycles for each of the four cells selected for the study with varying corresponding rates of degradation, this suggests that the batteries degrade is inconsistent and different from one another.

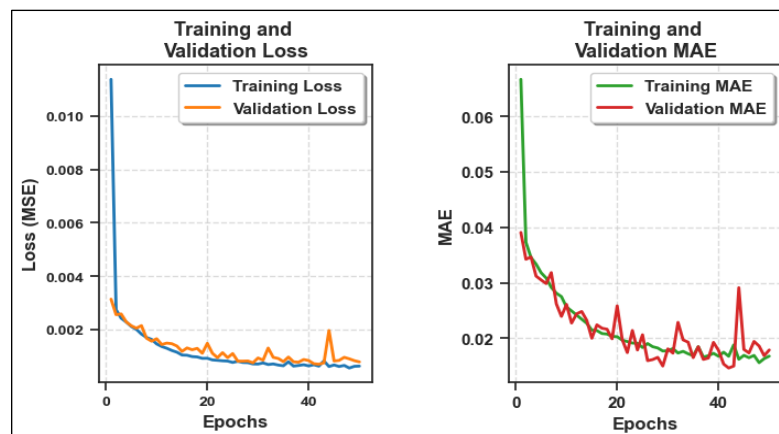


Figure 11: Comparison of training vs validation loss and MAE.
Source: Authors, (2026).

In Figure 11, each cell decreased steadily and progressed through the training epochs, and the training and validation curves are very meticulously affiliated, indicating very upright convergence and low levels of overfitting for each model.

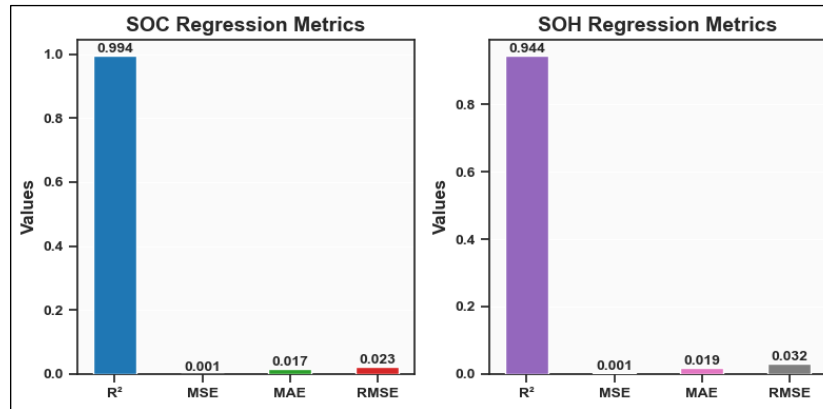


Figure 12: SoC and SoH regression metrics.
Source: Authors, (2026).

In figure 12, the SoC regression model performed the best, with a very high R^2 value (0.994) and relatively few errors compared to the SoH model, thus rates of accuracy for predicted SoC are higher than rates for predicted SoH.

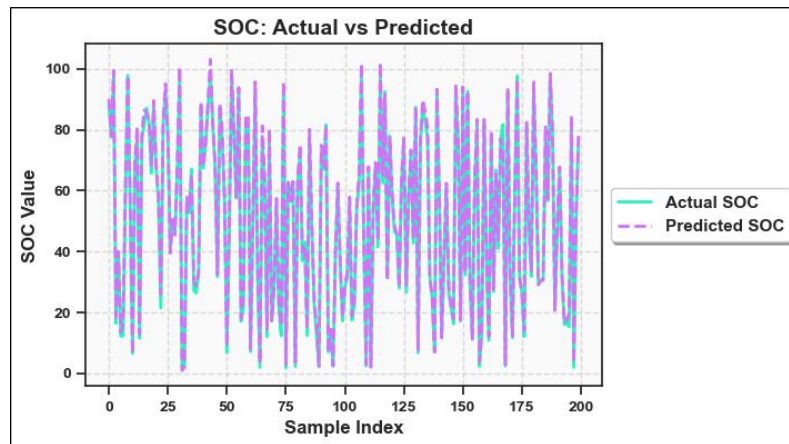


Figure 13: Actual vs predicted of SoC.
Source: Authors, (2026).

Figure 13 demonstrate that predicted SoC is very similar to the SoC value for all samples in the dataset, and therefore, the model provides a very accurate prediction of SoC, and demonstrates that the model has the ability to accurately capture changes in SoC throughout its training.

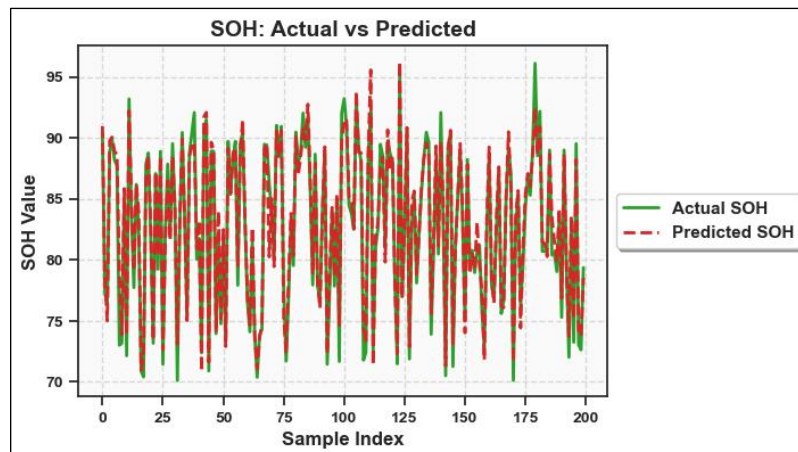


Figure 14: Comparison of training vs validation loss and MAE.
Source: Authors, (2026).

Figure 14 shows a close tracking of predicted SoH by the actual values across all samples, although there are small deviations from the predicted trend. The model performed admirably in its ability to predict the SoH values.

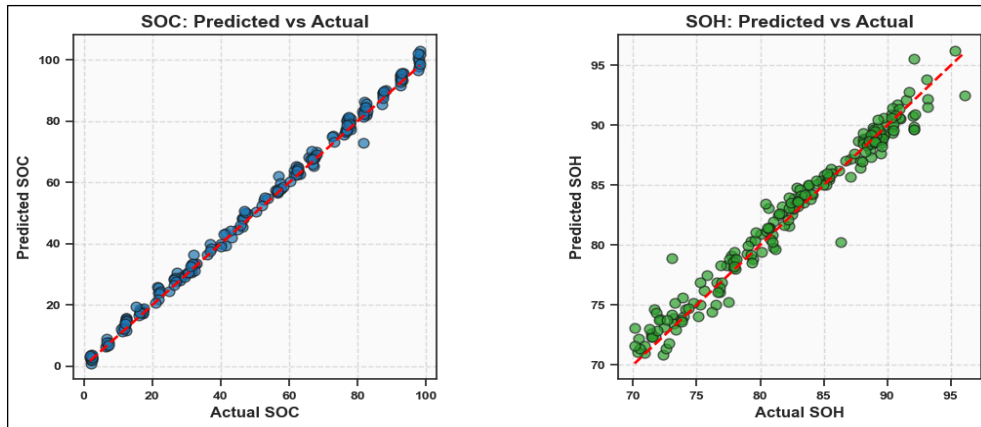


Figure 15: Comparison of predicted vs actual of SoC and SoH.
Source: Authors, (2026).

In figure 15, the predicted SoC and SoH values from the final model trained are highly aligned to the actual SoH and SoC values, and therefore demonstrate a strong linear relationship between predicted and actual values, indicating a very accurate and efficient model with minimal errors.

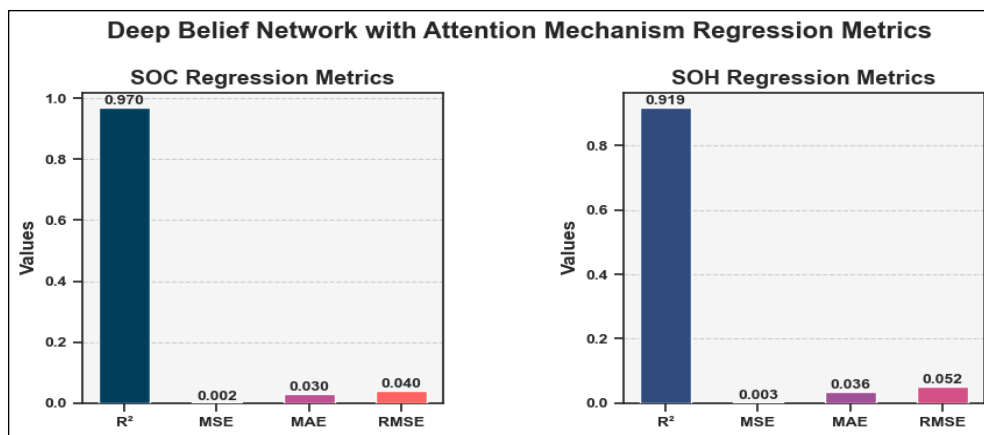


Figure 16: Comparison of SoC and SoH regression metrics of DBN-AM.
Source: Authors, (2026).

Figure 16 depicts a strong performance metrics for the regression models indicate that SoC is estimated accurately by R^2 of 0.97 with an absolute MSE value (error) lower than one, while SoH produces an R^2 of 0.919 and SoC has low absolute error on average.

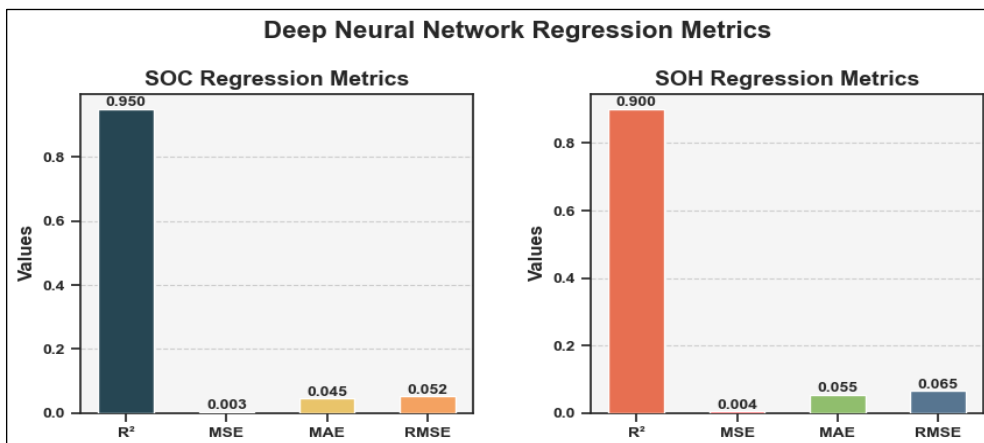


Figure 17: Comparison of SoC and SoH regression metrics of DNN.
Source: Authors, (2026).

The results achieved by the DNN regression in figure 17 show that both SoC and SoH produce high R^2 of 0.95 and 0.90 respectively. The MSE values of SoC is 0.003 and SoH is 0.004, the MAE values of SoC and SoH are 0.045 and 0.055 and the RMSE value for SoC and SoH are 0.052 and 0.065.

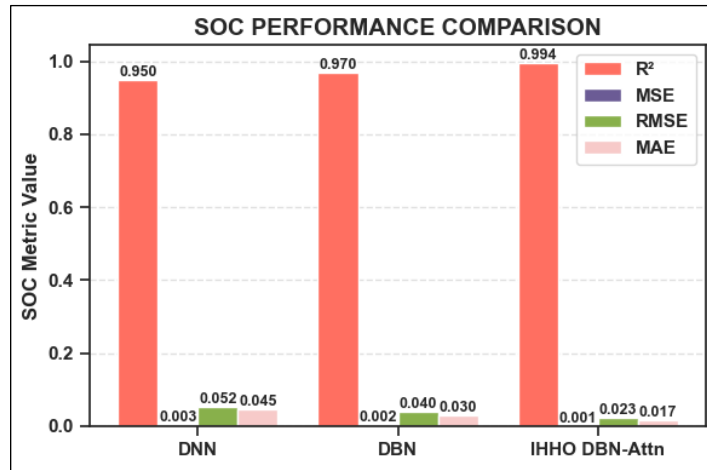


Figure 18: Comparison of SoC performance.

Source: Authors, (2026).

In figure 18, the IHHO DBN-Attention has a better performance than both DNN and DBN for SoC. Specifically, the IHHO DBN-Attention model has an R^2 score of 0.994 and the lowest of the MSE, RMSE, and MAE metrics of any of the models.

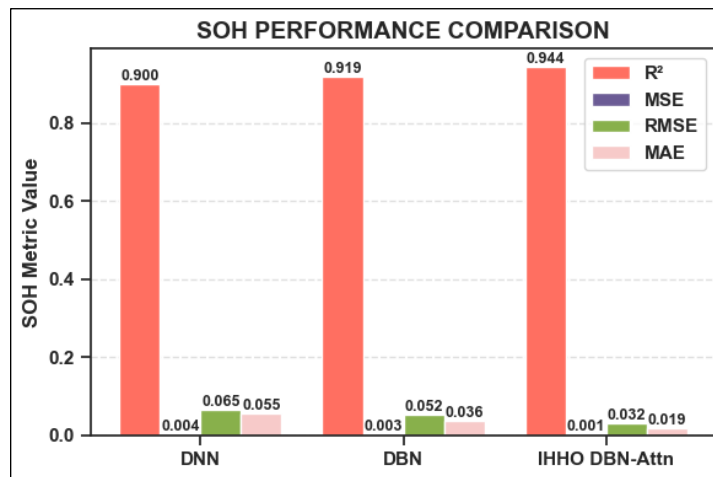
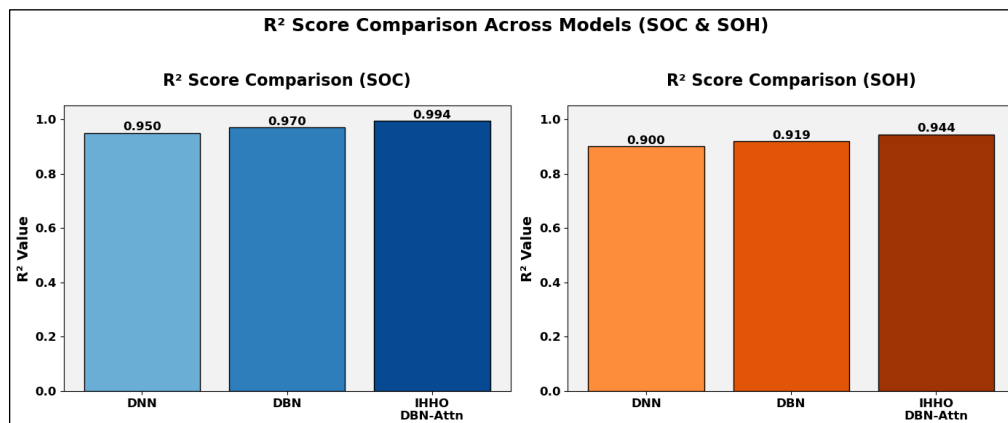


Figure 19: Comparison of SoH performance.

Source: Authors, (2026).

In figure 19, the IHHO DBN-Attention model was able to provide more accurate SoH predictions than DNN and DBN, with a higher R^2 of 0.944 and lower error metrics than both of the models.

Figure 20: R^2 comparison of SoC and SoH performance.

Source: Authors, (2026).

The comparison of R^2 values in figure 20 clearly shows that the faults of the DBN methods are lesser than that of DNN models, and that the IHHO DBN-Attention achieved the highest R^2 values for both SoC and SoH of 0.944.

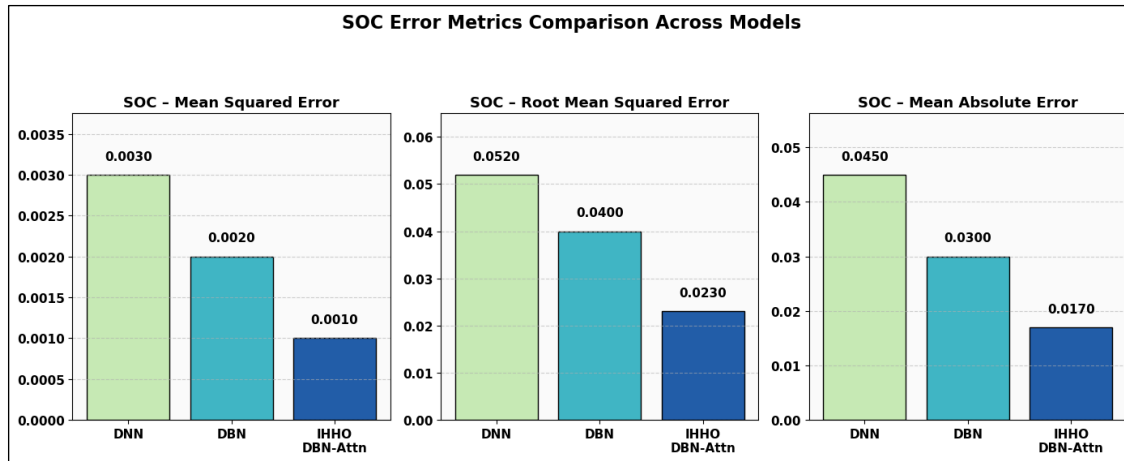


Figure 21: SoC error metrics comparison across models.
Source: Authors, (2026).

Figure 21 shows the comparison of SoC error metrics across models. The overall error metrics for SoC are lower using DBN than DNN, with the best error metrics of MSE, RMSE, and MAE from the IHHO DBN-Attention model.

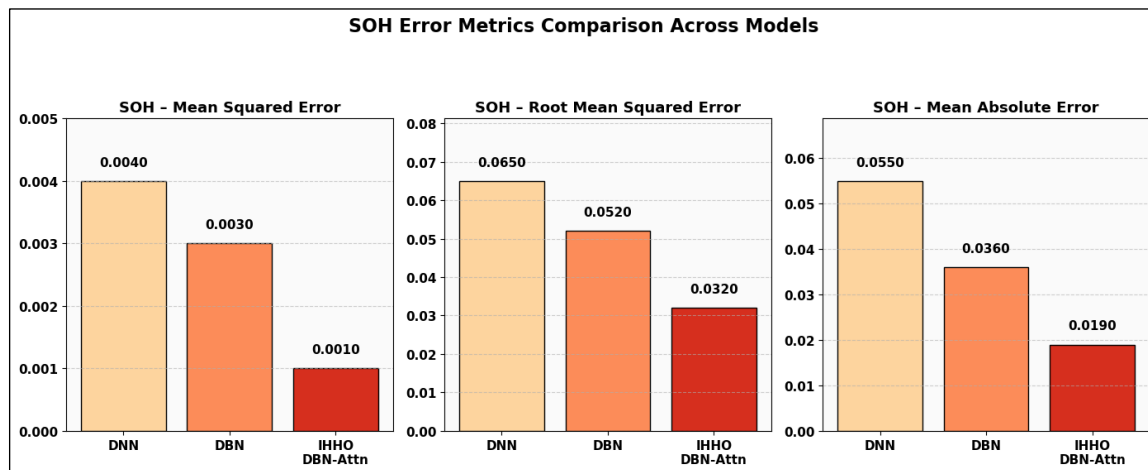


Figure 22: SoH error metrics comparison across models.
Source: Authors, (2026).

In figure 22, SoH metrics decrease from the DNN model to the DBN model, the IHHO DBN-Attention model produces the lowest metrics for RMSE, MAE, and MSE, demonstrating higher accuracy and greater robustness than the DBN or DNN models.

Table 1: Comparison of SoC error metrics across models.

METRICS	DNN	DBN	IHHO DBN-Attn
MSE	0.003	0.002	0.001
RMSE	0.052	0.04	0.023
MAE	0.045	0.03	0.017

Source: Authors, (2026).

Table 1 shows SoC error metrics for the three models compared to the IHHO DBN-Attn, which has the lowest metric values of MSE is 0.001, RMSE is 0.023, and MAE is 0.017, with the IHHO DBN-Attn model outperforming the other two models in accuracy.

Table 2: Comparison of SoH error metrics across models.

METRICS	DNN	DBN	IHHO DBN-Attn
MSE	0.004	0.003	0.001
RMSE	0.065	0.052	0.032
MAE	0.055	0.036	0.019

Source: Authors, (2026).

In table 2, the IHHO DBN-Attn model has the lowest SoH estimation errors when related to the DBN and DNN methods such as MSE of 0.001, RMSE of 0.032 and MAE of 0.019, which shows the model's superior accuracy and reliability.

Table 3: Comparison of R^2 values.

SI.NO	MODELS	R^2
1	CNN-BiLSTM [24]	0.959
2	RFR-ANN [23]	0.960
3	PROPOSED	0.994

Source: Authors, (2026).

In table 3, comparing the R^2 values for the different models identifies the proposed model as the most accurate with an R^2 of 0.994, compared to CNN-BiLSTM of 0.959 and RFR-ANN of 0.960. This means the proposed model has a significantly better fit and predictive ability than either of the other two models.

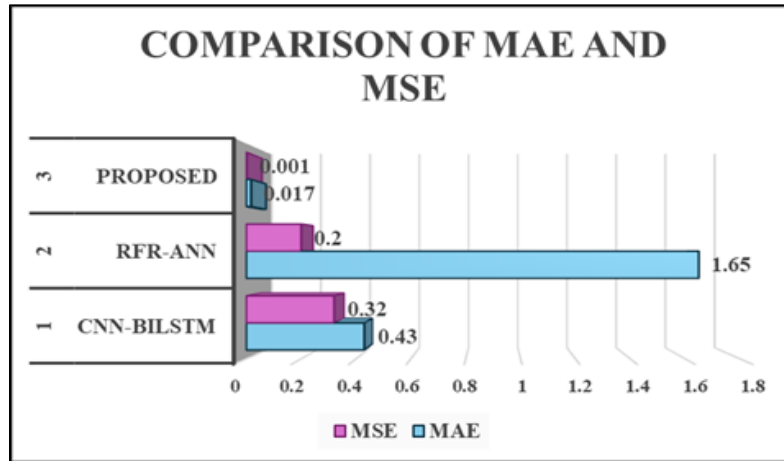


Figure 23: Comparison of MAE and MSE of various methods.

Source: Authors, (2026).

The bar chart in figure 23 presents the comparison of MAE and MSE between three models such as CNN-BiLSTM, RFR-ANN and proposed Model. The suggested method has the smallest MAE and MSE of 0.017 and 0.001, reflecting its greater accuracy in predictions.

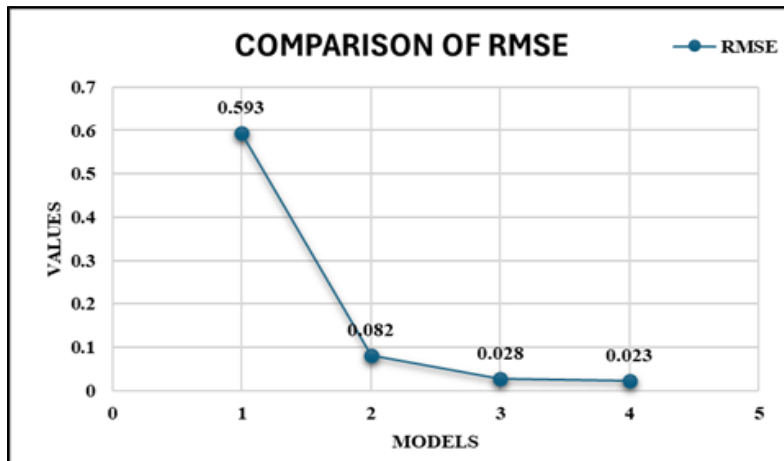


Figure 24: Comparison of RMSE.

Source: Authors, (2026).

In figure 24, The RMSE comparison indicates the total error decreased substantially across all of the models. RMSE decreased from 0.593 for model one to 0.082 for model two and to 0.028 for model three, ultimately culminating at the lowest RMSE of 0.023 for the final model. Therefore, there is a continuous improvement in prediction accuracy over time consequently, the proposed method generated the maximum level of accurateness in its prediction performance.

VI. CONCLUSION

The proposed IHHO-DBN-AM is an excellent method for accurately predicting the SoC and SoH for lithium-ion batteries in EVs. The first step is collecting all the necessary parameters for the battery from various sources. Next, all the collected data are pre-processed through normalization, feature cleansing, and removing redundant data so that the highest quality input into the DBN-AM model is utilized. The exploratory analysis conducted during the data processing phase helps in identifying battery degradation trends and correlations among the various parameter sets, thus improving the model development process. The primary benefit of the IHHO-DBN-AM framework allows for the tuning of the hyperparameters of the DBN-AM Model during the training of the model through the utilization of the IHHO algorithm.

By tuning the model hyperparameters through optimization, DBN-AM models learn to identify deep hierarchical patterns in the input data and efficiently use their attention mechanisms to recognize important signals from the battery, resulting in increased accuracy in predicting SoC and SoH values. The improved DBN-AM model enables the accurate and reliable prediction of SoC and SoH values, which will improve battery management practices and ultimately lead to extended battery operating lifetimes and safer operations in EVs. Furthermore, the proposed framework achieves the high accuracy and low error values associated with the IHHO DBN-Attention model for both SoC and SoH predictions. For SoC, MSE of 0.001, RMSE of 0.023 and MAE of 0.017 which provides an accurate estimation of the battery charge and for SoH, MSE of 0.001, RMSE of 0.032 and MAE of 0.019 provides an accurate estimation of health of the battery. Therefore, these results validate the ability of the IHHO-DBN-AM to accurately model the behaviour of lithium-ion EV batteries.

VII. AUTHOR'S CONTRIBUTION

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Investigation: Anaparthi Lakshmi Ravi Teja and Dondapati Ravi Kishore.

Discussion of results: Anaparthi Lakshmi Ravi Teja, Dondapati Ravi Kishore, B Kavya Santhoshi, and Vendoti Suresh.

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Writing – Review and Editing: Anaparthi Lakshmi Ravi Teja and Dondapati Ravi Kishore.

Resources: Dondapati Ravi Kishore.

Supervision: Dondapati Ravi Kishore, B Kavya Santhoshi, and Vendoti Suresh.

Approval of the final text: Anaparthi Lakshmi Ravi Teja, Dondapati Ravi Kishore, B Kavya Santhoshi, and Vendoti Suresh.

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