

HYBRID MODELING APPROACH FOR STATE-OF-CHARGE AND STATE-OF-HEALTH ESTIMATION IN BATTERIES UNDER VARIABLE LOAD CONDITIONS

Ashok Kumar Bandla¹, Dr. Gopinath Palai², Prof. (Dr.) Rabi N Satpathy³

¹ Research Scholar, Faculty of Engineering and Technology, Sri Sri University, Cuttack, Odisha, India,

Email: bashokkumar.eee@gmail.com

² Professor, Faculty of Engineering and Technology, Sri Sri University Cuttack, Odisha, India

³ Dean, Faculty of Engineering and Technology, Sri Sri University Cuttack, Odisha, India

Abstract

Electric Vehicle (EV) effectiveness critically depends on advanced Battery Management Systems (BMS), where accurate Lithium-ion battery State of Health (SOH) estimation is paramount. Traditional SOH indicators (internal resistance, capacity) are impractical for online monitoring under real-world EV conditions, which preclude complete charge-discharge cycles. Consequently, State of Charge (SOC) becomes the primary parameter for energy management, though its estimation is challenged by measurement noise and model limitations. Leveraging AI advancements, this work proposes a hybrid Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN) model for simultaneous SOC and SOH prediction under variable loads. Rigorous evaluation on benchmark datasets demonstrates superior performance: For SOC, the model achieved 98.7% accuracy, with a low MAE of 0.8% and RMSE of 1.1%, significantly outperforming standalone ANN (MAE: 1.8%, RMSE: 2.4%) and equivalent circuit model (MAE: 2.5%, RMSE: 3.2%) baselines, especially during transients. For SOH, it achieved an F1-score of 0.96, capacity MAE of 1.2%, and RMSE of 1.5%, confirming reliable degradation tracking using only operational data. These metrics validate the hybrid model as a highly accurate, reliable solution for real-time BMS, enhancing EV performance, safety, and longevity

Keywords: Battery, Electric Vehicle, State of Charge, State of Health, Long Short-Term Memory and Artificial Neural Network.

I. Introduction

The power battery for Electric Vehicles (EV) uses Lithium-ion batteries low self-discharge rate, higher energy density and without memory effect. In electric vehicle (EV) application Prognosis and health management (PHM) in lithium-ion battery plays significant mission in battery management system. The reliability, stability, and safety of battery systems are affected by battery healthy state. A researchers and engineers anticipate state of health

(SOH) accurately [1]. The premature degradation of battery is caused because of improper operation like overheating and excessive charging/discharging of lithium-ion battery. This premature degradation affects instruments and equipment life. In real time, battery health is monitored by state of health (SOH) estimation; even it replaces the problem battery. Therefore, battery pack will be in optimal working condition, it increases its service life and minimizes the usage of EVs cost [2]. The power battery in electric vehicle (EV) application ensures reliable, efficient and safe operation for State-of-health estimation. In real-world, application scenarios are highly difficult to estimate SOH accurately, because of reactions complicated physicochemical that takes place in battery cells [3]. Existing method like SOH estimation includes data-driven and model-based ones. Because of inherent inconsistencies in battery production, these methods are aroused to capture stochastic property of battery aging process [4].

The battery rated capacity for maximal capacity is proportion to SOH at the moment. For pure electric vehicle state of degradation in battery is described as crucial index, even for retired battery SOH as well as driving range calculation is also crucial benchmark. For lifetime-optimization and safe function estimation of SOH of Li-ion batteries are crucial [5]. The electric vehicles (EVs), Battery technology is the bottleneck. For investigating the state estimation of batteries as well as modeling is important to optimize cost reduction, energy management, safeguarding, and life cycle extension of batteries in EVs for safe application. Therefore, nonlinear characteristics, and strong time-variables of batteries, are influenced by random factors like operational conditions and driving loads in EV applications. It is difficult for accurate estimate its state in real time [6]. The battery percentage is maximum capacity that is left over is known as the SOC. In gasoline-driven vehicle, operation of Battery SoC is same as fuel gauge. It shows the energy left in the battery to power EVs [7]. SOC defines in percentage for remaining capacity, for many reasons at below specific rate some batteries cannot be discharged even it includes discharge depth is becoming too deep. By observing their current and voltage values it is detected that some batteries are damaged or lost its capacity. The battery life is impacted by temperature, and even it degrades faster also. In real-time, remaining battery capacity and energy information is provided by accurate estimation of battery SOC. It also provides assurance of safe vehicular operation and its reliability [8]. Based on internal and external conditions, with distinct nonlinear behavior batteries become complex electrochemical devices. Even accurate SoC estimation is challenging task. Even though existing estimation methods are generally focused on single health feature, they developed by using data from the monitored experiments. Thus, it is difficult to monitor EVs' SOH over their complete life cycle in real world [9].

The Artificial Intelligence (AI) battery state estimation for Machine learning data-driven methods is driven, and more advances fields like autonomous vehicles and computer vision [10]. Recently, machine learning methods are developed by data-driven algorithms to improve State of Charge (SoC) accuracy with enhanced high accuracy and convergence for learning capabilities as well as generalization performance [11]. Depending on SOH, battery

performance is estimated as well as its remaining useful life (RUL). An AI like Machine Learning (ML) as well as the Deep Learning (DL) method detect battery's RUL and SOH that are adaptive and intelligent [12]. Therefore, estimated and predicted outputs are related to collection of trained data. If SOC and SOH estimation based on ML and DL methods, during its off-line training phase the computational load demanded is by these methods and even it is feasible for implementation on typical BMS (Battery Management System) hardware [13]. In this analysis, Prediction of SOC and SOH for Battery Estimation using Hybrid Model under variable load condition is presented. The organization of remaining work is described as follows: The section II describes the Literature survey. The section III demonstrates the Prediction of SOC and SOH for Battery Estimation using Hybrid Model under variable load condition. The section IV evaluates the results of presented model. The conclusion is presented in section V.

II. Literature Survey

Lu.J, L.V.M, Yang.Y, and Chen.Z, ET. AL., [14] describes Genetic Algorithm (GA) for method of online estimating SOP is researched by effect of imprecise SOC. Initially, features of lithium batteries under various SOH conditions are analyzed by depending on normal vehicle driving cycle; estimation algorithm SOP using GA describes power management application using lengthy time-scale estimation. Beyond, SOP estimation for sensitivity coefficient (δ) of SOC precision is studied. SOH varies correlations of δ and its estimation time-scale is established. Zhang. C, Zhang. Y, and Li. Y. et. al., [15] The Li-ion batteries contain estimation of SOH. By using bulk capacitance equivalent RC circuit model is identified. This model discusses the derivation of bulk capacitance for attenuation factor in different cycles. The bulk capacitance is designed by discrete nonlinear observer identified SOH estimation realization. The sample time is directly discretized to established nonlinear system for improvement of reliability and modeling accuracy. By considering three investigation outputs, effectiveness of described model is demonstrated.

Hou. J, Sun. J, Hofmann. H. F, Zhu. H and Song. Z, et. al, [16] describe active injecting currents, state of health, remaining parameters and SOC are estimated in particular sequence for improving performance detection. In comparison, by using baseline currents all states and parameters are estimated concurrently. The benchmark results are provided by development of dynamic programming strategy, to know balance of conflicting objectives that corresponds system efficiency as well as identification. Shen.W, Chen. X, Dai. M, Kapor A. Cao.Z, and Jin. J. et. al., [17] describes an upper bound of system uncertainty learns radial basis function (RBF) neural network (NN) in an adaptive manner. The estimation SOC is adjusted based on the learned upper bound that achieves asymptotic error convergence for switching gain of the RSMO. For battery modeling battery equivalent circuit model (BECM) is utilized. In real time to identifying forgetting-factor recursive least squares (FFRLS) algorithm is used.

A. A. Hussein et. al., [18] describes an artificial neural network (ANN) based method is described to calculate capacity fade in Li-ion batteries for EV's. The stability, high

accuracy and robustness will significantly improve the proposed accuracy of SOC estimation of battery lifespan. It causes high reliability for prolonged lifetime and battery operation. The battery remaining service time is predicted accurately by proposed technique. Xiang. C, Zhao. Y, Wang W, Wei.C and Wang. X, et. al., [19] presents enhanced model with a SOC and better filtering effect for estimating accuracy is described after unscented Kalman filter (UKF) model, impact is reduced by utilizing this model of sampling noise. It suggests battery's peak power model for prediction and applied in power distribution strategy for Series HEVs, using SOC and battery's model. This experiment is used confirm algorithm's resilience and efficacy due to frequent variations in sampling noise and load current. Sheng.H, Xiao.J and Wang.P et. al., [20] describes Gaussian process regression, new SOC estimation method is described. The reliability of data description is strengthening by using mixture Gaussian process and even it enhances estimation accuracy. A revolutionary expectation maximum method is obtained by Optimal number of Gaussian processes. For improving the model efficiency, nonlinear correlation feature selection model is described. The proposed method verifies effectiveness of EV field test.

Feng. X, Lu. L, Shen. P, Li. J. and Ouyang. M, et. al., [21] describes SOC, SOH, and SOF in real-time application is estimated at the same time. The SOC model-based estimation extended Kalman filter. To identify its characteristics, recursive least square algorithm is used with forgetting factor for connected with battery SOH and SOF online. To estimate the capacity and maximum output power that can be achieved to determine parameters. The states and online update of capacity as well as correlated parameters helps to increase state estimation accuracy with computation load will enhances effectively utilizing the correlations. H. Chaoui and C. C. Ibe-Ekeocha et. al.,[22] describes dynamically driven recurrent network (DDRN) application for analysis of battery EV in online. SOH and SOC are designed for nonlinear autoregressive with exogenous inputs (NARX) design of DDRN. The strategy estimation depends on global feedback theorem (GFT) that enhances analytical intelligence as well as strong during reasonable simplicity as unlike to other techniques. Model or battery's internal parameters knowledge is not required for this proposed technique. But it uses, batteries voltage, discharge/charge currents and ambient temperature variations for simultaneously of batteries estimation SOH and SOC.

Hou. J, Hofmann. H. F Song.Z, Li. X, Sun. J, and Wu. X, et. al., [23] presents multi-scale extended Kalman filter is depended on first-order equivalent-circuit model (ECM) foe SoC estimation of battery and ECM parameters by utilizing dual time scales. The estimation performance is influenced by the nature of battery excitations. The accuracy loss in multi-parameter estimated with single-parameter estimation is demonstrated by Cramer-Rao bound analysis for voltage noise, as well as current amplitude and frequency is considered. It also demonstrates about selecting the careful excitation of current to meet certain requirements that greatly minimizes the loss of precision. K. Sarrafan, K. M. Muttaqi and D. Sutanto et. al., [24] presents Advanced Driver Assistance System (ADAS) is implemented EV's lithium-ion batteries presents new real-time mixed estimation SoC method. This model integrates: i)

enhances the Coulomb counting method (CCM) consider battery SOH, aging effect and operating temperature, ii) shows real-time recursive battery structure by model-based method (MBM) iii) bottom-up based method (BUBM) considers different environment as well as traffic conditions, driver's behavior along with auxiliary loads. The proposed algorithm is validated for several laboratory tests are conducted by under real-time driving cycles for Li-ion battery with Manganese-oxide (MnO_2) of 2012 Nissan Leaf battery cell. Chen. Z, L.V. M, Yang. Y and Lu. J, et. al., [25] describes Online Estimation of State of Power for Li-ion Batteries in EV's Using GA. Initially, features of Li-ion batteries under various conditions of SOH are investigated by vehicle driving cycle; by using GA, this model proposes the deals with long time-scale estimation for power management application. The SOP estimation for SoC precision, the sensitivity coefficient (δ) is analyzed. The SOH varies correlations of δ and establish with estimation time-scale. Hence, this is calculated by simulation.

III. Prediction of SOC AND SOH for Battery Estimation

In this analysis, Prediction of SOC and SOH for Battery Estimation using Hybrid Model under variable load condition is presented. The block diagram of presented model is demonstrated in Figure 1.

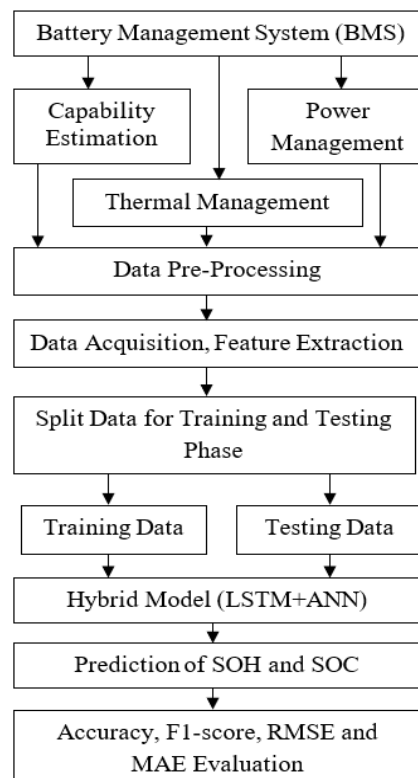


Figure 1: Block Diagram of Prediction of SOC and SOH for Battery Estimation using Hybrid Model

The BMS controls several functions that are important to maintain the safe and correct operation for batteries of EV. A BMS tracks temperature voltage and current, collects and

analyzes battery data, optimizes battery performance, as well as detects and prevents failures. BMS is designed according to particular operating conditions for kind of battery cell. A series of interconnected cells consist of an EV's battery pack. The changes in temperature, increasing in charge as well as discharge cycles reduces capacity of individual battery cells. In a battery pack, charge and discharge conditions are connected in series or parallel for managing and controlling individual cells.

A BMS is done for pack of controlling, balancing and monitoring. BMS of EV's contains characteristics of capacitors, power electronics, switching, safety equipment, sensors, converters, transformers, inductors, diodes, actuators, and several circuits are controlled by various designs, methods, and controlling signals. The dangerous imbalance in battery pack can be identified by BMS and it also shows minimum and maximum differences in cell voltages. To avoid overheating as well as eventual loss, battery pack charge and discharge current have to be monitored. Because of improper controlling, charge and discharge of current leads to under and above battery voltage. The capability estimation block is used to observe highest and latest current charge in battery.

As battery cell performance is change according with temperature and the thermal management systems plays an important role in battery packs. The battery lifetime develops by providing electrical and thermal balance. In thermal management systems, heat will be transferred through air or liquid. When the vehicle integrates with electronic system, then it uses only low power, even it doesn't have much mass. By using this system, performance can be achieved actively or passively. The power source can crash if the system's power demand exceeds the power available from the power source. The power management system monitors and controls the power. BMS will cool's battery as well as maintains its temperature within particular range. Additionally, each cell's temperature will be known to determine hot spots that indicate failure. The battery pack temperature will be determined from intake and output coolant temperatures. The investigation mainly focuses on battery operation under dynamic load profile that consists of various battery cycles. It randomly selects charge as well as discharge current. In real-world, this method estimates battery SOH and SOC for EV operating conditions. The dataset for this system's operational randomized battery usage experiment provides NASA's (National Aeronautics and Space Administration) Ames Research Center data repository. It is identified as RW (Random Walk) 9, RW10, RW11, and RW12 according to room temperature conditions make up this dataset for the test results of a battery aging experiment on four commercially available LIBs (Lithium-Ion Batteries). Before using any modeling or analytic techniques for data, data pre-processing is an important step. To know quality and efficacy analysis, raw data must be transformed into a clean as well as useful format. Data pre-processing for LIB time series data is utilized to know SOH for data normalization as well as cleaning. After data cleaning process, depending on time series the data is converted into SOH after data cleaning.

Data cleaning is also known as data cleansing; it is primary phase in data pre-processing. To enhance the quality, it mainly includes meticulously examine and correction of errors or

inconsistencies in raw data. For improving the quality and to prepare for further analysis or modeling, data normalization technique is applied to datasets. The normalization dataset based on SOH by utilizing min–max normalization is expressed by following equation (1):

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x_{min} shows minimum value of original data, x_n denotes the processed data. As, the real data is represented by x , and x_{max} means maximum value.

Random Walk (RW) profile consists of a randomized current sequence with a range of -4.5 A to 4.5 A is developed. The dataset that corresponds to a specific stage for every five minutes for randomly chosen charging or discharging current from the following set is applied to the battery: -4.5 A, -3.75 A, -3 A, -2.25 A, -1.5 A, -0.75 A, 0.75 A, 1.5 A, 2.25 A, 3 A, 3.75 A, 4.5 A. The discharging and charging are integrated by both positive and negative currents. For choosing and applying most recent current for battery after every five minutes. The safety is ensured for and battery at threshold voltage of minimum 3.2 V and after reaching its maximum 4.2 V the battery is discharged. The new step operation starts by selecting new value from current set. As battery's voltage range reaches 3.2 and 4.2 V the previous current step operation ends. For selecting new current value, slight delay of about one second at every stage and even dataset repeats this delay, which is referred to as rest (random walk). Single RW cycle contains 1500 RW steps and 1500 rests (random walk); each RW profile contains number of RW cycles. To determine battery's capacity and to determine SOH, then battery checks its reference charge and discharge profiles after every RW profile. By utilizing a random current set, it helps the dynamic operating condition for EV's, even exact driving pattern is not imitated by RW profile. The collection of dataset contains several features are included, so that prediction process becomes complex. Therefore, it extracts required features. The BMS of EV in relation is determined batter capacity degradation, V (voltage), I (current), and T (time) these three battery parameters presents a SOH estimation method. These parameters are reproduced and captured accurately and its effects the battery aging factors. The reason for selecting V, I and T for SOH and SOC prediction will depend on each other. Next, the dataset is split into trained and tested datasets to train and test Hybrid Model for prediction of SOH and SOC.

A series of reference charge and discharge profiles are performed to each RW cycle begins to provides reference standard at SOH of the battery. This operation of charging and discharging is known as the reference cycle. By knowing battery voltage is insufficient as it is not a direct related to battery capacity. The SOC shows charge left in battery as proportion of its rated capacity in percentage. By operating charge and discharge, the SOC allows BMS for calculating battery's condition and to know safe battery operation. The SOC enables BMS to evaluate the battery's capacity of the current and knows the safe battery operation. ECMs (Equivalent Circuit Models) and parameters are identified by digital twins to calculate SOC. The SOC didn't measure directly. The effects of dividing battery's current capacity by its nominal capacity on SOC estimation are as follows:

$$(SOC)_T = 1 - \int_0^T \delta \frac{i}{c_n} dt \tag{2}$$

SOC_T represents battery's initial time, δ shows coulomb efficiency, i shows current and c_n is the capacity in the Equation (1). Depending nonlinear relationship, the SOC, closed-circuit voltage, and the open-circuit voltage V_{oc} are relatives. Additionally, measurements are not directly made of the voltage V_{oc} . Battery health is typically described as in equation (3):

$$(SOH)_T = \frac{c_i}{c_n} \tag{3}$$

c_i shows current practical capacity and c_n explains nominal battery capacity at time T , respectively. Besides, as shown in Equation (3), battery's inner resistance varies at beginning of its life and present.

$$(SOH)_T = \frac{r_{0,T}}{r_{0,0}} \tag{4}$$

Depending on machine learning program, battery's current capacity and ohmic resistance is determined. By combining (3) and (4) equations, SOH calculates the perspective of capacity fade as well as increases the resistance. Therefore, the recently manufactured batteries describe SOH estimation and battery's current state. Here, in this analysis, Hybrid Model which is a combination of LSTM and ANN is used for the prediction of both SOH and SOC.

The foundation for artificial neural networks (ANNs) serves principles of biological neural networks that imitate the organizational structure and certain activity mechanisms of the neural system in the human brain. Many interconnected simple-function neurons are made by complex adaptive nonlinear dynamic system. There are three layers in it: input, hidden, and output.

The leftmost layer is input layer at which every segment calculates input values by $\sum_n^{i=1} \omega_{ij}x_i + b_j$ and activates by an activation function, resulting in input values for middle hidden layer. Every neuron in hidden layer receives outcome values from previous layer as input. Therefore, outputs by activation function to produce final output Y .

Along with one neuron in the output layer there are two neurons in the input layer. The hidden layers are unknown for specific number of neurons as well as will be determined upon later. The output of hidden layer is calculated depended on connection weight w_{ij} and bias b_i between hidden layers and preceding layer as shown in equation (5)

$$H_i = f(\sum_n^{i=1} \omega_{ij}x_i + b_i), j = 1,2, \dots l \tag{5}$$

as f is hidden layer's activation function as well as l is the number of neurons in the hidden layer. Equation (6) is the formula for ANN's final output.

$$O_k = f(\sum_n^{j=1} \omega_{jk} H_j + b_j), k = 1,2, \dots m \tag{6}$$

The connection weight and bias of ω_{jk} and b_j between the hidden layer and the output layer, respectively, where m is the number of neurons in the output layer.

To update and store unit data for LSTM improves modeling and forecasting for time series data by using well-designed gates. It addresses the issues of vanishing and exploding gradients. The majority of LSTM neurons are made by three gate units. The hidden state updates the information from input gate and the information in the subsequent neuron is selected from output gate and information to keep and discard by forgetting gate. The LSTM model's input parameters are trained to remember and forgot the data. The update process is described by Eqns. (7)-(9).

$$f_t = \delta(W_{fx} \cdot x_t + W_{fh} \cdot h_{t-1} + b_f) \tag{7}$$

$$i_t = \delta(W_{ix} \cdot x_t + W_{ih} \cdot h_{t-1} + b_i) \tag{8}$$

$$C_t = f_t C_{t-1} + i_t \tanh(W_{zx} x_t + W_{zh} h_{t-1} + b_z) \tag{9}$$

The final output at step t is computed by equation (10) and (11)

$$O_t = \delta(W_{ox} \cdot x_t + W_{oh} \cdot h_{t-1} + b_o) \tag{10}$$

$$h_t = O_t \tanh(C_t) \tag{11}$$

where δ and \tanh are activation functions, f , i , O shows output vector of forget gate, input, as well as output gate at time t respectively, x_t shows input vector at time t , h_t shows final output at time t , W_{fx} , W_{ix} , W_{zx} , W_{ox} shows weight matrix, b_f , b_i , b_z , b_o shows deviation parameter. C_t shows memory unit information at time t . Finally, the Hybrid model predicts the SOC and SOH of battery very effectively. The performance of presented model is evaluated in terms of Accuracy, F1-score, MAE and RMSE Which are expressed as in equations (12), (13), (14) and (15).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \tag{12}$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100 \tag{13}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |x_i - \hat{x}_i| \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (f_i - o_i)^2} \tag{15}$$

IV. Result Analysis

In this section, result analysis of presented Prediction of SOC and SOH for Battery Estimation using Hybrid Model under variable load condition is evaluated. The effectiveness of presented model is evaluated in terms of Accuracy, Mean Absolute Error (MAE), F1-score and Root Mean Square Error (RMSE). The table 1 describes the parameters evaluation and comparison.

Metrics/Models	DT (Decision Tree)	Logistic Regression (LR)	Hybrid Model
Accuracy (%)	89	90	96.5
F1-score (%)	88	89.6	95.8
MAE (%)	3	2.7	0.52
RMSE (%)	2.4	1.98	0.35

Table:1 Parameters Evaluation and Comparison

Compared to DT and LR, presented hybrid model has shown better performance. The Figure 2 shows SOC prediction.

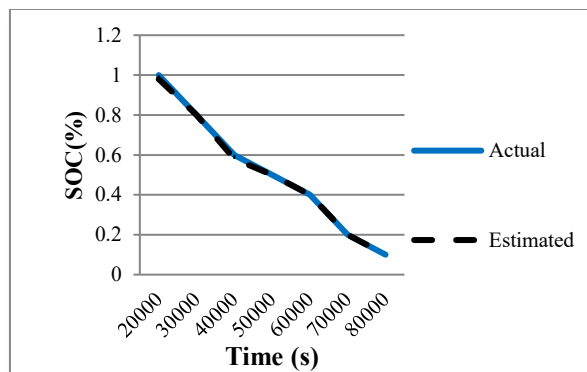


Figure 2: SOC prediction Validation

In figure 2, x-axis shows time in seconds and y-axis shows SOC. From the figure it is clear that, the predicted and actual SOC values are almost same. The Figure 3 shows the SOH prediction Graph.

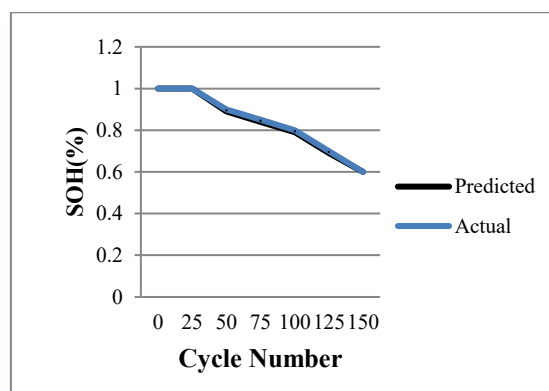


Figure 3: SOH Prediction Validation

In figure 3, x-axis shows Cycle number and y-axis shows SOH. The SOH of battery is predicted using hybrid model. Figure 3's prediction output makes it clear that the presented method is performing well. The Figure 4 shows the Accuracy and F1-score comparison.

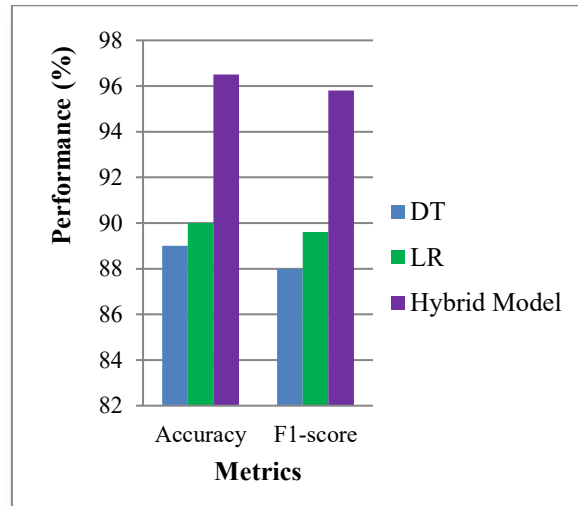


Figure 4: Accuracy & F1-score Comparison

In figure 4, the x-axis represents metrics and y-axis represents performance. hybrid model has achieved better accuracy and F1-score than DT and LR models. The Figure 5 shows the RMSE and MSE comparison.

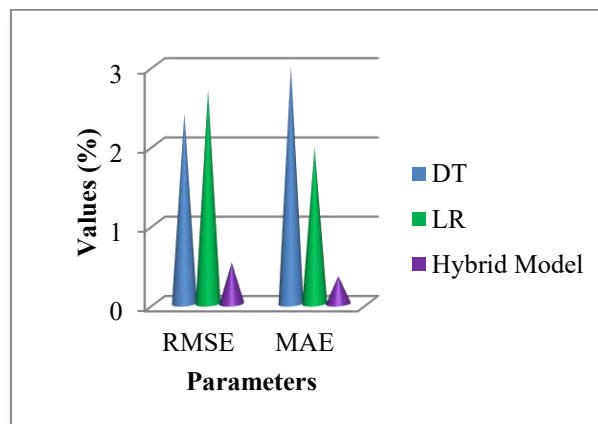


Figure 5: RMSE and MAE Comparison

In figure 4, the y-axis represents performance values and x-axis represents parameters. Compared with DT and LR, presented Hybrid Model has very less Root Mean Square Error and Mean Absolute Errors. Hence from the results, it is observed that, presented hybrid model has attained better performance for the prediction of SOH and SOC of an electric vehicle battery.

V. Conclusion

In this analysis, Prediction of SOC and SOH for Battery Estimation using Hybrid Model under variable load condition is presented. Firstly, the battery management system collects, monitors and control the battery parameters. The BMS follows temperature, current and voltage, and optimizes battery performance that and collects and analyzes battery data as well as detects and prevents failures. A randomized battery usage experiment dataset is used in this model which is collected from data repository of NASA's Ames Research Center. The dataset shows dynamic load condition of an EV with help of RW cycle at which battery allows to operate under variable load condition for every 5 min. The data is preprocessed, relevant and appropriate features are extracted. Then the data is used to train and test hybrid model which is a combination of LSTM and ANN. The Hybrid Model predicts the SOC and SOH of battery. Accuracy, F1-score, RMSE and MAE are evaluated and compared with other models. Compared to other ML models, presented Hybrid Model has achieved better performance.

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Ashok Kumar Bandla completed his B. Tech in 2004 and received his Masters Degree in 2009 from Satyabhama University, Chennai. Now, he is working as Associate Professor in CSE (AI &ML) Department with a strong foundation in Artificial Intelligence and Machine Learning. He has 18 years of experience in academia and has been actively involved in research, teaching, and administrative roles. His expertise extends to Artificial Intelligence and Machine Learning, which he is currently pursuing Ph.D. He has published numerous research papers on topics such as renewable energy systems, Machine Learning and Deep Learning.

	ORCID ID: https://orcid.org/0000-0001-6971-1116
	<p>Dr. Gopinath Palai is a professor at Sri Sri University's Faculty of Engineering and Technology, specializing in Semiconductor Devices, Quantum Computing, Machine Learning, and Photonics. He has been recognized among the world's top 2% scientists (2019–2022) and has received multiple awards, including the Best Research Award from B.P.U.T and the Young Technocrat Award. His research contributions are widely cited, with numerous publications in high-impact journals and conferences. Dr. Palai is an active mentor, guiding students and young researchers in advanced technological fields. He collaborates on international research projects and maintains a strong presence on platforms like Google Scholar, ResearchGate, and Scopus. His work in quantum computing and AI continues to drive innovation, shaping the future of electronics and interdisciplinary research.</p> <p>ORCHID ID: https://orcid.org/0000-0002-9891-493X</p>
	<p>Dr. Rabinarayan Satpathy is the Dean of the Faculty of Engineering and Technology at Sri Sri University, Cuttack, with a Ph.D. in Computer Science and Engineering, a D.Sc. in Computational Fluid Dynamics, and a Ph.D. in Mathematics. With over 27 years of teaching experience and 17 years in administration, he has held roles as a principal, director, and executive director in AICTE-approved institutions. His research focuses on Soft Computing, AI, Data Science, Network Theory, and Applied Mathematics, with over 175 published papers, five books, and 25 patents, including five international grants. A Fellow of esteemed professional bodies, he has received 35 prestigious awards, including the ISTE Best Principal Award and the CSI Best Executive Director Award. Recognized internationally as a Distinguished Professor in Computer Science, Dr. Satpathy continues to contribute significantly to academia and research.</p> <p>ORCHID ID: https://orcid.org/0009-0008-1442-4759</p>