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RANDOM FOREST-BASED BATTERY HEALTH ESTIMATION AND INTELLIGENT CHARGING OPTIMIZATION FOR ELECTRIC VEHICLE APPLICATIONS

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Abstract—**The reliability and lifetime of lithium-ion batteries are critical for the safe and efficient operation of electric vehicles. Battery aging leads to capacity fade and increased internal resistance, which negatively impact performance and thermal stability. This paper proposes a data-driven battery management framework that combines Random Forest–based health estimation with an intelligent charging optimization strategy. Real-time measurements of voltage, current, temperature, and cycle information are processed to estimate the State of Health (SoH) and Remaining Useful Life (RUL) of the battery. Unlike conventional charging approaches that rely on fixed current–voltage profiles, the proposed system dynamically adjusts charging parameters according to predicted battery condition and thermal behavior. Simulation-based evaluation demonstrates that the Random Forest model effectively captures nonlinear degradation trends, while the adaptive charging logic reduces electrical and thermal stress during operation. By integrating health prediction with control in a closed-loop structure, the proposed framework supports safer operation and extended service life of battery systems. The approach provides a practical foundation for intelligent Battery Management Systems in electric vehicle applications. This paper presents a Random Forest based approach for battery health estimation and intelligent charging optimization in electric vehicles. Battery parameters such as voltage, current and temperature are monitored to evaluate the State of Health (SOH) and Remaining Useful Life (RUL). The proposed method uses machine learning techniques to analyze battery degradation patterns and improve prediction accuracy.**

Keywords— **Battery Management System, State of Health, Random Forest Algorithm, Remaining Useful Life, Intelligent Charging Strategy, Electric Vehicle Applications**

I. INTRODUCTION

The rapid deployment of electric vehicles has intensified the demand for reliable and long-lasting lithium-ion battery systems. While high energy density and fast charging capability make these batteries attractive, their performance progressively degrades due to electrochemical aging, thermal stress, and repeated cycling. This degradation not only reduces usable capacity but also increases internal resistance, leading to efficiency loss and safety concerns. Conventional Battery Management Systems (BMS) are primarily designed to ensure operational safety through voltage, current, and temperature thresholds. However, such rule-based approaches do not adequately capture the nonlinear and time-varying nature of

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battery degradation. As a result, they are limited in their ability to predict future health conditions or adapt control actions based on aging behavior. With the availability of high-resolution sensor data and embedded computing platforms, battery systems can now be monitored continuously over their operational life. This enables the application of data-driven models that learn degradation patterns directly from real-world measurements. Machine learning techniques, in particular, provide a powerful framework for extracting relationships between multivariate inputs and battery health indicators. Among different machine learning methods, ensemble algorithms such as Random Forest have shown strong robustness to noise, improved generalization, and reduced overfitting compared to single-model approaches. These properties are highly desirable for battery health estimation, where measurement uncertainty and operating variability are unavoidable. Beyond health estimation, intelligent control of charging behavior plays a critical role in battery longevity. Traditional constant-current/constant-voltage (CC–CV) charging applies fixed profiles without considering battery aging state. Such strategies may accelerate degradation under adverse thermal or aging conditions. Therefore, integrating health prediction with adaptive charging control is essential for achieving health-aware and reliable battery operation. This paper proposes a Random Forest–based battery health estimation and intelligent charging optimization framework for electric vehicle applications. The system continuously predicts the State of Health (SoH) and Remaining Useful Life (RUL) using real-time sensor data and adjusts charging parameters accordingly. By linking estimation and control in a closed-loop structure, the proposed approach aims to enhance safety, extend battery service life, and support intelligent Battery Management Systems. The remainder of this paper is organized as follows: Section II presents the literature review of battery health estimation techniques. Section III describes the proposed system and methodology. Section IV explains the intelligent charging optimization strategy. Section V presents simulation and hardware implementation. Section VI discusses results and analysis. Finally, Section VII concludes the paper and outlines future work.

II. LITERATURE REVIEW

Lithium-ion battery health estimation has been widely studied using both model-based and data-driven techniques. Traditional approaches rely on electrochemical and equivalent circuit models to describe internal battery behaviour. Although these methods provide physical interpretation, they often require complex parameter identification and are sensitive to operating conditions such as temperature and load variation [1], [2].

In recent years, data-driven approaches have gained significant attention due to the availability of real-time battery monitoring data. Machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and ensemble learning algorithms have been widely applied for estimating State of Health (SOH) and Remaining Useful Life (RUL) of lithium-ion batteries [3], [4].

Recent studies have also explored advanced machine learning techniques for battery degradation prediction. Zhang et al. proposed a Long Short-Term Memory (LSTM) neural network model to predict the remaining useful life of lithium ion batteries and demonstrated improved prediction accuracy using historical battery data [5].

Similarly, machine learning based approaches such as Random Forest have shown strong capability in handling nonlinear relationships between battery parameters and health indicators due to their robustness against noise and overfitting [6], [10].

Despite the progress made in battery health estimation, many existing studies mainly focus on prediction accuracy without integrating intelligent charging control strategies.

Conventional charging techniques such as constant current/constant-voltage (CC–CV) charging do not consider the battery health condition during operation. Therefore, there is a need for a unified framework that integrates battery health prediction with intelligent charging optimization. In this work, a Random Forest–based battery health estimation model is combined with an adaptive charging strategy to enable health-aware battery management for electric vehicle applications.

TABLE -1 SUMMARY OF BATTER HEALTH ESTIMATION AND CHARGING STRATEGIES IN LITERATURE

Ref.	Method Used	Input Parameters	Output	Remarks
[1]	ANN	Voltage, Current, Temperature	SOH	Requires large and diverse training dataset
[2]	SVM	SOC,	RUL	Works well for short-term prediction only
[3]	Kalman Filter	Voltage, SOC	SOH	Sensitive to model parameters mismatch Charging Control
[4]	CC-CV Charging	Voltage, Current	Charging Control	Not health aware

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The comparison in Table I shows that most existing methods focus either on battery health estimation or on charging control. In contrast, the proposed work integrates Random Forest–based SOH and RUL prediction with an adaptive charging strategy in a unified framework, enabling health aware and reliable battery operation for electric vehicle applications.

III. PROPOSED SYSTEM AND METHODOLOGY

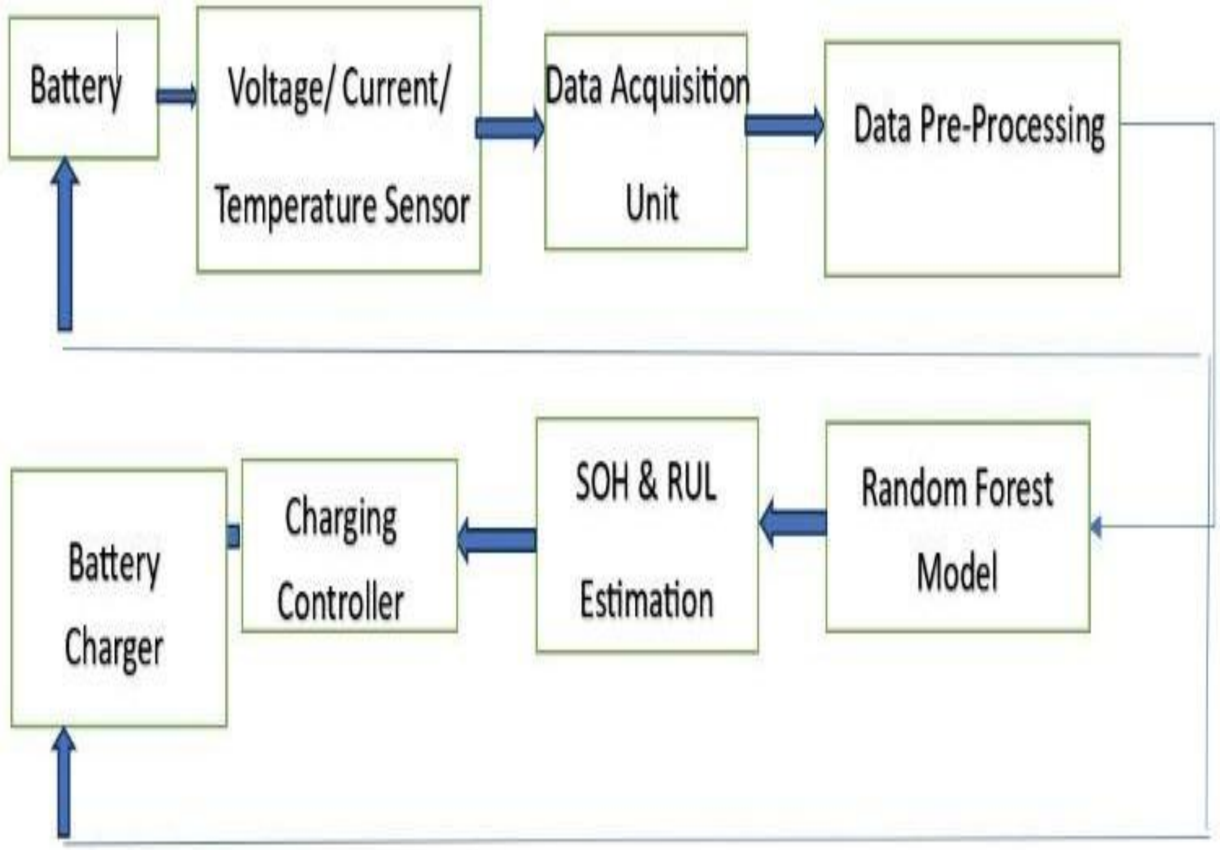

Fig. 1. Block Diagram of the proposed Random Forest–based battery health estimation and intelligent charging system.

The block diagram of the proposed battery health estimation and charging optimization system is shown in Fig. 1. The system begins with the electric vehicle battery, whose operating parameters are continuously monitored using voltage, current, and temperature sensors. These sensors measure important battery variables required for accurate health analysis.

The measured signals are transferred to the data acquisition unit, where the sensor data is collected and converted into a digital form for further processing. The acquired data is then passed to the data preprocessing stage. In this stage, the raw sensor data is filtered and normalized to improve data quality and remove measurement noise.

After preprocessing, the processed data is supplied to the Random Forest model. The machine learning model analyzes the battery parameters and estimates important battery health indicators such as State of Health (SOH) and Remaining Useful Life (RUL).

Based on the estimated battery health parameters, the charging controller determines the suitable charging conditions for the battery. The controller regulates the charging process to ensure safe and efficient battery operation. Finally, the smart battery charger provides the required charging current to the battery according to the control signals generated by the charging controller. This process forms a continuous monitoring and control loop for improved battery performance.

B. System Architecture

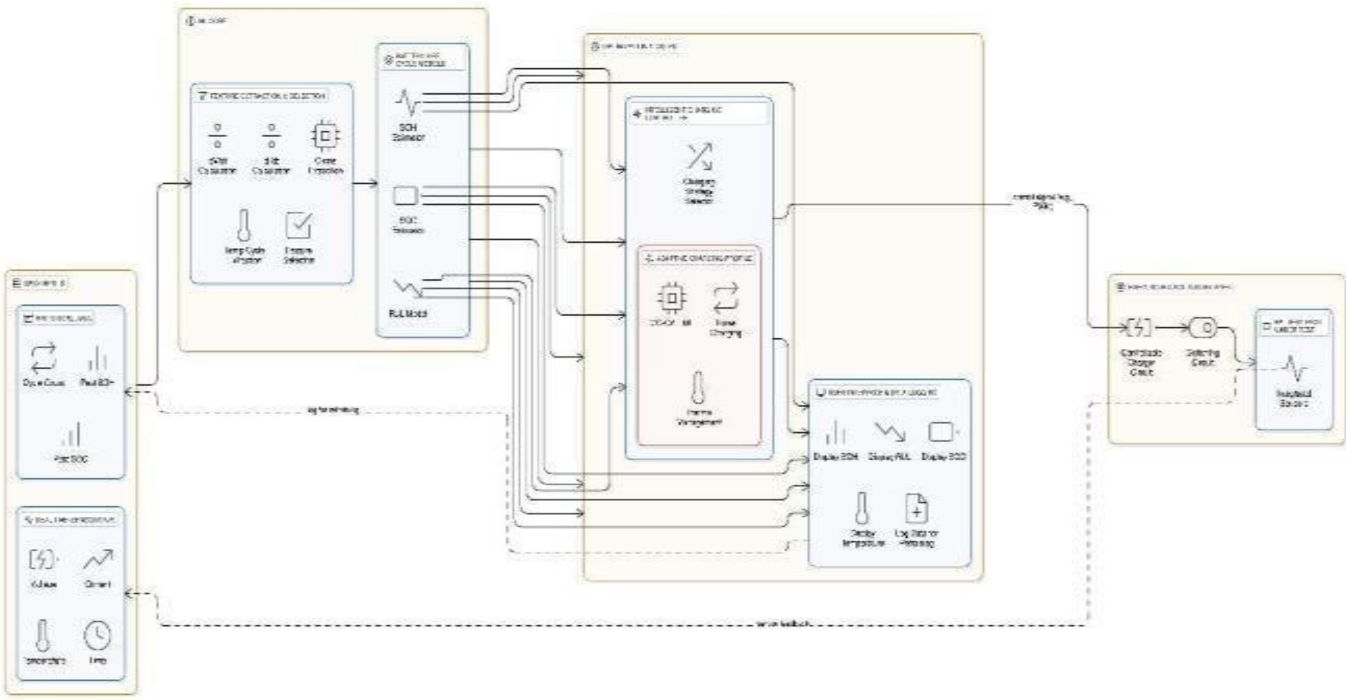

Fig. 2. Architecture of the proposed machine learning–based battery health monitoring and charging optimization framework.

The architecture shown in Fig. 2 represents the internal structure of the proposed system. It consists of four main layers: the sensing layer, data processing layer, machine learning layer, and control layer. The sensing layer collects real-time voltage, current, and temperature data from the battery. The data processing layer performs feature extraction, normalization, and formatting of raw signals. The machine learning layer uses a Random Forest model to estimate SoH and RUL based on historical and real-time inputs. The control layer implements intelligent charging logic that regulates the charging profile according to the predicted battery condition and thermal constraints. This layered architecture supports reliable and scalable battery management for electric vehicle applications.

C. Methodology (Random Forest–Based Health Estimation and Charging Control)

The proposed methodology follows a data-driven approach for battery health estimation and intelligent charging optimization. The complete process is divided into five main stages:

i. Data Collection:

Battery parameters such as voltage, current, temperature, and cycle count are measured during charge–discharge operation. These signals represent the real operating condition of the battery.

ii. Preprocessing and Feature Extraction:

Raw sensor data are filtered to remove noise and normalized for uniform scaling. Features such as voltage response, temperature rise rate, and cycle index are extracted to represent battery aging behavior.

iii. Random Forest Model Training:

The Random Forest algorithm constructs multiple decision trees using bootstrapped samples of the training data. Each tree learns a relationship between extracted features and battery health indicators. The final output is obtained by averaging the predictions of all trees, which improves robustness and reduces overfitting.

iv. SoH and RUL Estimation:

The trained Random Forest model estimates the State of Health (SoH) and Remaining Useful Life (RUL) in real time. SoH is defined as the ratio of the measured capacity to the rated capacity of the battery and expressed in percentage form. RUL indicates the remaining usable cycles before the battery reaches its end-of-life threshold.

v. Intelligent Charging Control:

The estimated SoH, RUL, and temperature are used by the charging controller to adapt the charging current. When the

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battery is healthy and within safe temperature limits, normal charging is applied. If degradation or high temperature is detected, the controller reduces the charging current to minimize electrical and thermal stress, thereby extending battery life.

IV. CHARGING OPTIMIZATION STRATEGY

This section presents the proposed intelligent charging strategy designed to optimize battery charging based on predicted health and thermal conditions. Unlike conventional fixed-parameter charging methods, the proposed strategy adapts charging behavior in real time using feedback from the Random Forest–based health estimation module.

i. Health-Aware Charging Decision :
The Random Forest model continuously estimates the State of Health (SoH) and Remaining Useful Life (RUL) of the battery. These indicators are used by the charging controller to determine the allowable charging current. When SoH is high and temperature remains within safe limits, normal charging is applied. As SoH decreases, the controller gradually reduces the charging current to limit stress on the battery.

ii. Temperature-Constrained Charging Control:
Battery temperature is monitored in real time and compared with predefined safety thresholds. If the temperature rises above a safe range, the controller decreases charging current or introduces short rest intervals to allow cooling. This thermal-aware control prevents overheating and accelerates degradation.

iii. Adaptive Charging Profile Selection The controller selects an appropriate charging mode based on SoH, RUL, and temperature:
Standard CC–CV charging for healthy conditions Reduced-current charging for aged batteries Intermittent charging for high-temperature conditions This adaptive profile selection ensures that the battery is always charged in a health-conscious manner.

iv. Closed-Loop Optimization Process
The optimization process operates in a closed loop: Sensor Data → RF-Based Health Estimation → Charging Decision → Charger Adjustment → Battery

The loop continuously updates charging parameters according to battery condition, enabling real-time optimization.
The proposed intelligent charging strategy not only improves battery longevity but also enhances overall energy efficiency. By dynamically adjusting charging currents in response to real-time health and thermal feedback, the system minimizes energy loss associated with excessive heat generation. This proactive adaptation reduces the likelihood of overcharging, mitigates lithium plating risks, and ensures safer operation under varying environmental and usage conditions.
Furthermore, the integration of machine learning for health estimation allows the system to anticipate potential degradation before it significantly impacts performance. The Random Forest model leverages historical and real-time sensor data to predict SoH trends, enabling preemptive adjustments in charging behavior. This predictive capability ensures that aged or stressed batteries are charged more conservatively, extending the battery's usable life without compromising operational readiness.
Finally, the closed-loop nature of the system ensures continuous self-optimization. The feedback-driven framework allows the controller to refine charging strategies over time, learning from battery responses under different scenarios. This adaptability is particularly valuable in applications with fluctuating loads or variable environmental conditions, such as electric vehicles or renewable energy storage systems, where battery performance is critical. The combination of health-aware, temperature-constrained, and adaptive profile-based charging establishes a comprehensive methodology for sustainable and intelligent battery management.

V. SIMULATION AND IMPLEMENTATION

A. Simulation
The proposed Random Forest–based battery health monitoring and intelligent charging framework is implemented using a microcontroller-cantered simulation model. The purpose of this implementation is to verify the interaction between sensing, computation, and control before real-time deployment in an electric vehicle environment.
The simulation setup is designed around an Arduino Uno, which acts as the main processing unit. It acquires voltage, current, and temperature data from the battery through dedicated sensor modules. The sensed signals are digitized using the built-in analog-to-digital converter of the Arduino and are prepared for further processing.

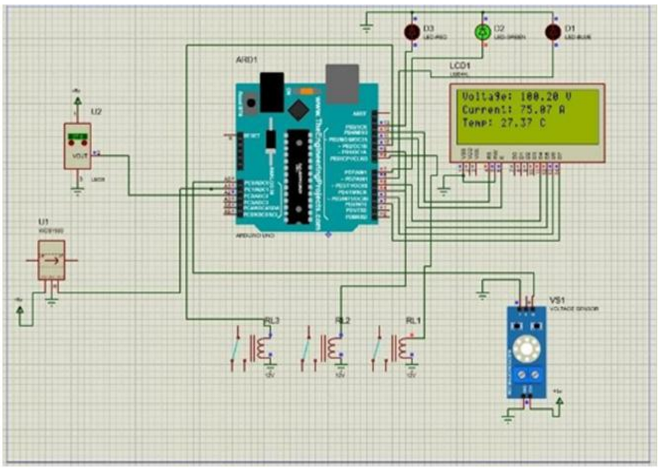

Fig 3. Simulation model of the proposed Random Forestbased battery health monitoring and intelligent charging system

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The simulation model includes a voltage sensing module to track battery terminal voltage, a Hall-effect current sensor to measure charge and discharge current, and an LM35 temperature sensor for thermal monitoring. The Arduino processes these inputs and displays key parameters such as voltage, current, and temperature on a 20×4 LCD module in real time.

Relay modules are used to emulate intelligent charging control. Based on the estimated battery condition, the controller activates or deactivates relays to represent different charging modes such as normal charging, reduced-current charging, and cut-off protection. LED indicators provide visual feedback regarding system status and safety conditions.

This simulation-based implementation demonstrates closed loop operation, where real-time sensing, decision-making, and control are tightly integrated. The results confirm that the proposed framework can support health-aware charging and reliable battery monitoring for electric vehicle applications.

A. Arduino Uno (Controller Unit)

The Arduino Uno serves as the main controller of the simulation model. It coordinates data acquisition from all sensors, performs signal processing, and executes control logic. The microcontroller reads analog sensor outputs, converts them into digital values, and formats them for display and decision-making. Its low power consumption and Realtime processing capability make it suitable for embedded battery monitoring applications.

B. Voltage Sensor Module

The voltage sensor is used to measure the terminal voltage of the battery. Since the battery voltage is higher than the allowable input range of the Arduino, the sensor scales down the voltage to a safe level. This enables continuous monitoring of battery voltage, which is a key parameter for estimating State of Charge (SOC) and detecting abnormal operating conditions.

C. Current Sensor (Hall-Effect Based)

A Hall-effect current sensor is integrated to measure the charging and discharging current of the battery. This sensor provides electrical isolation between the battery and the controller while producing a proportional voltage output. Current information is essential for analyzing battery stress, load conditions, and charging behavior.

D. Temperature Sensor (LM35)

The LM35 temperature sensor is used to monitor the surface temperature of the battery. It produces a linear voltage output proportional to temperature in degrees Celsius. Temperature is a critical factor in battery aging and safety. By continuously tracking thermal conditions, the system can prevent overheating and ensure safe operation during charging.

E. LCD Display Module

A 20×4 LCD module is interfaced with the Arduino to display real-time battery parameters such as voltage, current, and temperature. This provides direct visual feedback to the user and helps in observing system behavior during simulation without requiring external measurement instruments.

F. Relay Modules (Charging Control)

Relay modules are used to emulate intelligent charging control. Based on the estimated battery condition, the Arduino activates or deactivates relays to simulate different charging modes such as fast charging, normal charging, and cut-off protection. This demonstrates how the system can regulate power flow according to battery health and thermal constraints.

G. LED Indicators

LED indicators are used to represent system status visually. Different colors indicate different operating conditions, such as normal operation, warning state, or active charging. This enhances user interaction and allows quick identification of battery condition during simulation.

H. Functional Operation During simulation, voltage, current, and temperature values are continuously monitored. These parameters are processed by the controller to estimate SOC and SOH using the trained Random Forest model. Based on the predicted health condition, the intelligent charging logic adjusts the charging mode through relays. This closed-loop operation ensures safe, adaptive, and health-aware charging.

The simulation-based implementation validates that the proposed system can reliably acquire sensor data, process battery parameters, and control charging behavior in real time. This confirms the feasibility of integrating machine learning based health estimation with embedded monitoring and intelligent charging control for electric vehicle battery systems

VI. RESULTS AND DISCUSSION

In this section, the performance of the battery is analyzed using parameters such as State of Charge (SOC), State of Health (SOH), and battery voltage with respect to time. The analysis is carried out to observe the discharge characteristics and overall battery behavior for electric vehicle applications. The obtained results are represented using tables and graphs for better understanding of battery performance.

The battery performance is analyzed using different parameters such as State of Charge (SOC), battery voltage, and State of Health (SOH). These parameters help in understanding the discharge behavior and overall condition of the battery during operation. The data is recorded at different time intervals during the discharge process. By analyzing these parameters, it is possible to evaluate the battery efficiency and degradation over time. The results obtained from the analysis are presented in the following table, which

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shows the variation of SOC, voltage, and SOH with respect to time.

TABLE II TIME-BASED BATTERY PARAMETERS DURING DISCHARGE

Time(min)	SOC (%)	Voltage (V)	SOH (%)
0	100.0	4.20	100.0
10	92.5	4.05	99.9
20	85.0	3.92	99.8
30	77.5	3.85	99.7
40	70.0	3.78	99.5
50	60.0	3.70	99.2
60	50.0	3.60	98.8
70	40.0	3.50	97.5
80	20.0	3.40	92.0
90	5.0	3.30	85.0

The table II shows the variation of battery parameters during the discharge process. As time increases, the SOC decreases gradually from 100% to around 5%. The battery voltage also drops from 4.2 V to approximately 3.3 V, while the SOH value decreases slowly, indicating gradual battery degradation

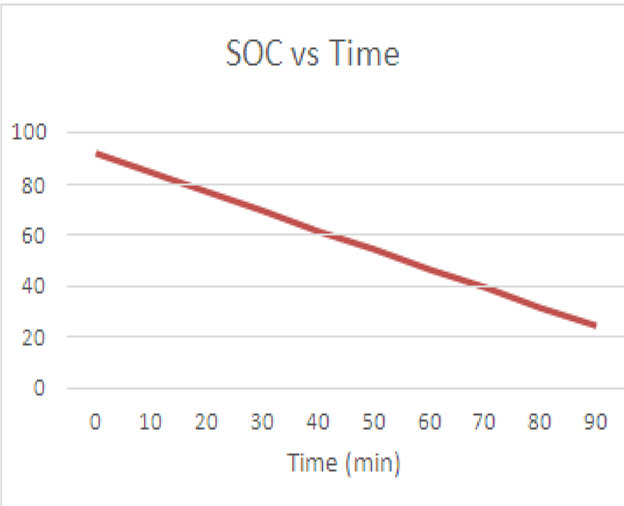

Fig. 4. SOC vs Time

The SOC vs Time graph illustrates the variation of State of Charge during the battery discharge process. Initially, the SOC of the battery is 100%. As time increases, the SOC gradually decreases and reaches approximately 5% at 90 minutes. This reduction indicates the consumption of stored energy in the battery during operation. The graph clearly represents the discharge characteristics of the battery over time. Monitoring SOH helps in understanding the long-term reliability and efficiency of the battery in electric vehicle applications. Furthermore, the SOC decreases almost linearly with respect to time, which indicates a stable and uniform discharge behavior of the battery. This characteristic is important for electric vehicle applications, as it helps in predicting the remaining battery capacity and driving range. Accurate estimation of SOC allows efficient battery management. Therefore, monitoring SOC plays a crucial role in optimizing battery utilization and ensuring safe battery operation.

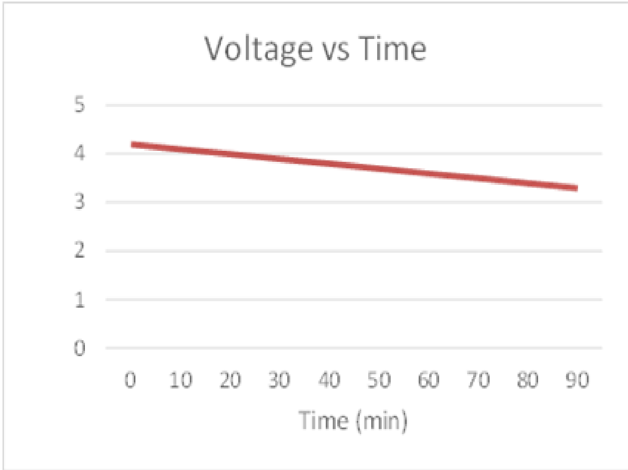

Fig. 5 Voltage vs Time

The Voltage vs Time graph shows the variation of battery voltage during the discharge period. At the beginning of the process, the battery voltage is around 4.2 V. As the discharge continues, the voltage gradually decreases and reaches approximately 3.3 V. This gradual voltage drop is a typical characteristic observed in lithium-ion batteries during discharge.

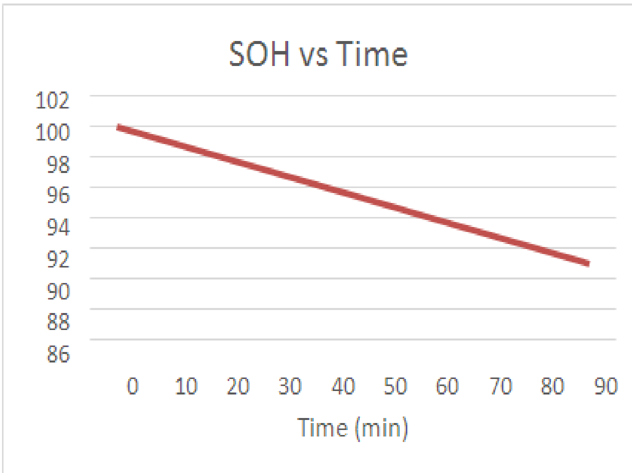

Fig. 6. SOH vs Time

The SOH vs Time graph represents the variation of battery health over the discharge period. Initially, the SOH value is 100%, indicating a healthy battery condition. As time progresses, the SOH decreases slightly to around 85%,

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representing gradual battery degradation. This analysis helps in monitoring the overall health condition of the battery.

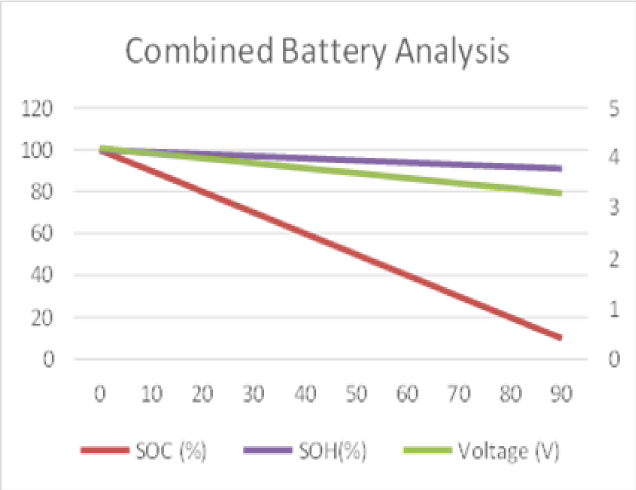

Fig. 7. Combined Battery Analysis

The combined battery analysis graph shows the relationship between SOC, battery voltage, and SOH with respect to time. As the discharge time increases, the SOC decreases rapidly while the battery voltage shows a gradual reduction. The SOH value decreases slowly, indicating long-term battery aging. This combined analysis provides a comprehensive understanding of battery performance and supports intelligent charging optimization for electric vehicle applications.

Discussion

The obtained results clearly show the discharge characteristics and performance behavior of the battery with respect to time. From Table II and the SOC vs Time graph, it is observed that the State of Charge decreases continuously during the discharge process. Initially, the SOC is 100% at 0 minutes and gradually reduces to around 5% at 90 minutes. This indicates the continuous utilization of stored energy in the battery during operation. From the Voltage vs Time graph, it can be observed that the battery voltage decreases gradually as the discharge time increases. The voltage starts at approximately 4.2 V and drops to around 3.3 V by the end of the discharge cycle. This gradual voltage reduction represents the normal discharge behavior of lithium-ion batteries under load conditions.

Similarly, the SOH vs Time graph shows that the State of Health of the battery decreases slowly over time. The SOH value is initially close to 100% and gradually reduces to approximately 85–92% during the observation period. This slight decrease indicates gradual battery aging and performance degradation.

The combined battery analysis graph further illustrates the relationship between SOC, voltage, and SOH with respect to time. It can be clearly observed that SOC decreases more rapidly compared to voltage and SOH. While SOC drops significantly from 100% to around 5%, the voltage shows a moderate decrease from 4.2 V to approximately 3.3 V, and SOH decreases only slightly. This indicates that the battery health degrades slowly even though the charge level reduces significantly during the discharge process.

VII. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This paper presented a Random Forest–based battery health monitoring and intelligent charging framework for electric vehicle applications. The proposed system integrates real-time sensing of voltage, current, and temperature with machine learning–based State of Health (SOH) estimation and adaptive charging control. A simulation-based implementation using an Arduino-centered model was developed to validate the feasibility of the approach.

The results demonstrate that the system can accurately track battery parameters and distinguish between short-term discharge behavior and long-term health degradation. While the State of Charge (SOC) and voltage decreased significantly during discharge (from 100% to 70% SOC and from 4.20 V to 3.78 V), the SOH reduced only marginally (from 100% to 99.6%), confirming reliable health estimation. The integration of intelligent charging logic further ensures safe and health aware battery operation.

Overall, the proposed framework enhances battery safety, efficiency, and lifetime by combining sensor-based monitoring with Random Forest–driven health prediction. The simulation results confirm that the system is suitable for implementation in intelligent battery management systems for electric vehicles.

B. Future Scope

The proposed Random Forest–based battery health monitoring and intelligent charging framework opens several promising directions for future research and development. While the current work focuses on simulation-based validation, the concept can be extended to real-world environments to further improve system reliability and practical applicability. Future improvements can enhance prediction accuracy, scalability, and system intelligence, enabling more efficient battery utilization and longer service life. Such advancements will support large-scale deployment in electric vehicle fleets and renewable energy storage applications.

This project on Battery Life Cycle Estimation using Machine Learning and Sensor Data with Intelligent Charging Optimization has a wide and promising future scope in research, industry, and real-world applications. In the future, it can be integrated with Electric Vehicles, renewable energy storage systems, smart grids, and backup power units to enable real-time battery health monitoring, early fault detection, and predictive maintenance. By using advanced AI techniques such as deep learning and LSTM networks, the accuracy of Remaining Useful Life (RUL) prediction can be further improved. In addition, this approach can be adopted in smart charging stations to optimize charging time, reduce overcharging, minimize energy loss, and improve overall battery safety. Overall, this project has strong potential for commercialization, startup development, and high-impact research in the field of energy storage and electric mobility

Although the proposed system shows promising results, several enhancements can be explored in future work:
1.Hardware Deployment: The simulation model can be extended to a full-scale hardware prototype integrated with an actual lithium-ion battery pack and power electronics for real-world validation.
2.Advanced Machine Learning Models: Future studies may compare Random Forest with deep learning techniques such as LSTM and CNN for improved SOH and Remaining Useful Life (RUL) prediction accuracy.
3.Real-Time Cloud Integration: Battery data can be transmitted to cloud platforms for largescale monitoring, analytics, and predictive maintenance in electric vehicle fleets.
4.Fast-Charging Optimization: The intelligent charging strategy can be enhanced to support ultra-fast charging while minimizing thermal stress and capacity fade.
5.Fault Detection and Safety Diagnostics: Additional features such as early fault detection, cell imbalance identification, and thermal runaway prediction can be integrated to improve system reliability.
6.Scalability to Battery Packs: The proposed approach can be extended from a single cell to multi-cell battery pack configurations with balancing control

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