iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IV **Month of publication:** April 2025

DOI: https://doi.org/10.22214/ijraset.2025.69172

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

AI-Powered Battery Charging System Using Machine Learning Algorithms for EVs

Abisheak S[1], Muthuram G[2]
[1]PG Scholar, Department of Electrical and Electronics Engineering, Hindusthan College of Engineering and Technology, Coimbatore, Tamil Nadu
[2]Assistant Professor, Department of Electrical and Electronics Engineering, Hindusthan College of Engineering and Technology, Coimbatore, Tamil Nadu

Abstract: This paper presents an intelligent charging system powered by AI to boost performance and improve the State of Charge (SoC) and State of Health (SoH) of batteries in Electric Vehicles (EVs). Despite advancements in design and electrical specifications, the significance of effectively charging EV batteries is essential for ensuring safety, efficiency, and longevity. The prototype features a Raspberry Pi as its main controller, along with sensors that monitor key battery metrics including voltage, current, temperature, and pressure. The proposed system employs machine learning algorithms to forecast critical battery metrics such as SoC, SoH, and charging capacity based on the collected sensor data. These metrics are gathered in real-time, allowing the implementation of adaptive charging strategies that maintain consistent battery performance while adjusting to real-time variations in battery conditions to avoid issues like overheating, overcharging, and deterioration. This method not only prolongs battery life but also minimizes safety hazards. The proposed system is scalable, cost-efficient, and superior to traditional charging systems. Furthermore, it can be paired with renewable energy sources to further improve energy efficiency. This paper aims to promote the creation of an environmentally sustainable and smart battery charging system for electric vehicles.
Keywords: Raspberry Pi, Artificial Intelligence (AI), State of Health, State of Charge, EV, RandomForestRegressor AI Model, Machine Learning in BMS, Adaptive Charging, IOT based BMS

I. INTRODUCTION

In 2024, Electric Vehicles (EVs) accounted for 20% of all cars sold globally as per a report by International Energy Agency (IEA). Even though there have been advancements in battery technology, vehicle design, and the use of renewable resources, research on battery charging systems remains crucial due to its importance and increasing demand. A smarter charging system can enhance battery safety and longevity while improving overall EV efficiency.

Figure 1 illustrates the impact of charging and discharging cycles on the State of Charge (SoC) and State of Health (SoH) of batteries. Over time, frequent charging and discharging cycles negatively impact batteries, leading to poor SoC and SoH, increasing safety risks, and necessitating frequent battery replacements. An inefficient charging system worsens this issue, potentially causing overheating, overcharging, and degradation, which shortens the overall battery lifespan.

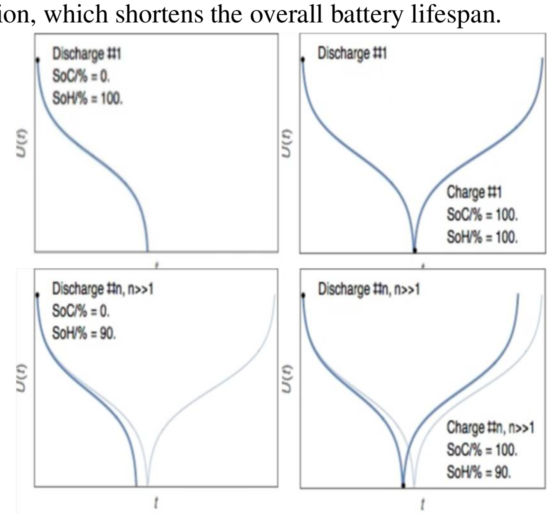


Figure 1. Impact of charge and discharge cycles on SoC and SoH

Standard charging systems rely on predefined algorithms to modify charging patterns. However, these systems are neither real-time nor adaptable to dynamic conditions, resulting in suboptimal performance and reduced battery lifespan. Utilizing Artificial Intelligence (AI)-based intelligent charging systems can help overcome these challenges. Real-time battery parameters can be processed using machine learning models, enabling the system to dynamically select the most suitable charging pattern.

The procedure includes gathering and assessing live battery information, including voltage, current, temperature, State of Charge (SoC), and State of Health (SoH). By identifying patterns and trends in battery behaviour, the system can make informed predictions about battery performance and potential degradation. To achieve this, machine learning algorithms are trained using historical and real-time battery data to accurately predict SoC and SoH. These predictions will serve as the foundation for an adaptive charging algorithm that dynamically adjusts voltage and current based on battery conditions. The AI-driven control system, implemented on a Raspberry Pi, will continuously monitor battery parameters through integrated sensors and modify the charging strategy in real time. By optimizing charging methods, it reduces risks like overcharging and overheating. It also focuses on enhancing energy efficiency, resulting in lower electricity consumption and cost savings. It also supports sustainable transportation through the integration of renewable energy sources. The AI-based adaptive charging approach presents an innovative step forward in battery management and sustainability.

II. LITERATURE REVIEW

1) As the global EV market grows, the need for efficient, safe, and sustainable battery charging solutions becomes increasingly important. The development of Electric Vehicle (EV) technology is deeply connected with the progress in battery charging methods. Conventional charging methods for electric vehicle batteries typically employ constant-current/constant-voltage (CC/CV) charging techniques. These systems operate under preset parameters and do not adapt to the battery's real-time state. In a research conducted by S. S. G. Acharige, M. E. Haque, M. T. Arif, N. Hosseinzadeh, K. N. Hasan, and A. M. T. Oo, the writers examine these conventional approaches, noting that while they are reliable, their static nature limits them. Fixed charging protocols can lead to inefficient energy use and problems like overcharging and overheating, which speed up battery degradation (S. S. G. Acharige, M. E. Haque, M. T. Arif, N. Hosseinzadeh, K. N. Hasan and A. M. T. Oo, "Review of Electric Vehicle Charging Technologies, Standards, Architectures, and Converter Configurations," in IEEE Access, vol. 11, pp. 41218-41255, 2023)
2) The paper "Battery Management Systems for Electric Vehicles using Lithium Ion Batteries" also provides a detailed look at conventional charging techniques. It emphasizes that even though the CC/CV method offers safety and consistency during charging, it doesn't address the complex behavior of lithium-ion batteries under different environmental and operational conditions. As a result, battery performance can decline faster, leading to safety concerns and the need for early battery replacements. These issues highlight the need for more adaptive and responsive charging methods (V. Vaideeswaran, S. Bhuvanesh and M. Devasena, "Battery Management Systems for Electric Vehicles using Lithium Ion Batteries," 2019 Innovations in Power and Advanced Computing Technologies (i-PACT), Vellore, India, 2019).
3) Due to the limitations of traditional charging methods, researchers have started incorporating sensor-based monitoring into battery management systems. These systems gather real-time information such as voltage, current, temperature, and cell impedance to offer a clearer understanding of the battery's condition. A recent study by M. Cherukuri and M. Kanthi, they described a comprehensive BMS design that uses multiple sensors to monitor battery conditions, allowing for better decision-making during charging. Real-time monitoring helps reduce the risks of overcharging and overheating by providing immediate feedback on battery conditions (M. Cherukuri and M. Kanthi, "Battery Management System Design for Electric Vehicle," 2019 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), Manipal, India, 2019).
4) Further, the paper "Charging System for Electric Vehicles" discusses advanced sensor technologies and data collection systems that improve the accuracy of battery state estimates. It highlights the importance of using high-precision sensors to detect subtle changes in battery behavior that conventional systems might miss. While sensor-based monitoring represents a significant improvement over fixed algorithms, the literature shows that these systems often rely on predetermined thresholds. Thus, they still lack the flexibility needed to optimize charging in all situations, especially during rapid changes in battery conditions (D. Pant, N. Singh and P. Gupta, "Charging System for Electric Vehicles," 2022 IEEE Delhi Section Conference (DELCON), New Delhi, India, 2022).

5) Recent advancements in artificial intelligence have brought a revolutionary approach to addressing the shortcomings of both traditional and sensor-based systems. AI techniques, especially machine learning algorithms, have proven to be highly effective in predicting and managing battery parameters in real time. In a study by Vinodkumar and N. Singh Singha, they explore the use of AI for monitoring battery health. This indicates that machine learning models have the capability to learn from both historical and current data to effectively estimate key metrics like the State of Charge (SoC) and the State of Health (SoH). (Vinodkumar and N. Singh Singha, "Battery Management System Health Monitoring Using Artificial Intelligence," 2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET), Ghaziabad, India, 2023).
6) Supporting this perspective, "A Comprehensive Overview of AI-Based Methods for SoC Estimation in Li-Ion Batteries" provides a thorough review of various AI methodologies applied to battery state estimation. This study explores various machine learning methods, such as linear regression, neural networks, and assessing their effectiveness concerning prediction accuracy as well as computational efficiency. The findings indicate that incorporating AI into charging systems not only improves the accuracy of SoC and SoH predictions but also allows for the dynamic adjustment of charging protocols. This adaptability is essential in preventing issues that cause battery degradation, such as overcharging or thermal runaway (I. Baccouche and N. E. Ben Amara, "A comprehensive overview of AI based methods for SoC estimation of Li-ion Batteries in EV," 2024 10th International Conference on Control, Decision and Information Technologies (CoDIT), Vallette, Malta, 2024).

III. EXISTING SYSTEMS

The development of Electric Vehicle (EV) charging systems has come a long way, but many current charging methods still depend on fixed algorithms that may not efficiently adapt to the battery's real-time conditions. Standard charging approaches, such as constant current (CC) and constant voltage (CV) charging, have been popular in EVs due to their straightforwardness and ease of implementation. Figure 2 shows the CC-CV model with maximum voltage 26V [1]. It functions in two stages: initially, the Constant Current (CC) stage, during which a consistent current is delivered, permitting the battery voltage to increase steadily. After the battery attains its maximum voltage limit, the charger transitions to the Constant Voltage (CV) stage, where it sustains a constant voltage while the charging current slowly diminishes until it hits a cutoff point, guaranteeing the battery is charged safely and completely. However, these methods fail to dynamically adjust to battery conditions, resulting in inefficiencies, potential overcharging, and faster battery degradation.

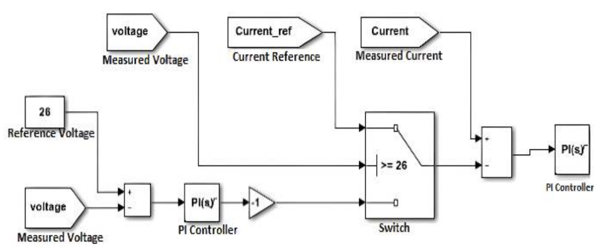


Figure 2. A CC-CV model with maximum 26V

To overcome the shortcomings of conventional charging methods, smart charging systems have been created. These systems utilize microcontrollers and IoT-based technologies to enable managed charging. Smart chargers can modify the power supply based on real-time grid demand and battery condition, thereby enhancing charging efficiency. Some cutting-edge smart charging stations incorporate bidirectional charging, which supports Vehicle-to-Grid (V2G) functions that allow energy to be returned to the grid [2]. In load leveling, Electric Vehicles (EVs) are charged when demand is low, helping to increase the grid load to a designated level. On the other hand, during peak load shaving, EVs release stored energy back into the grid when demand surpasses the target, thus decreasing the load. Recent advancements in artificial intelligence (AI) have introduced predictive analytics and deep learning techniques into battery management systems (BMS). AI-driven BMS solutions can analyze historical battery data and real-time sensor inputs to dynamically adjust charging parameters. Figure 3 depicts the process of data driven methods. Battery data from the past is analyzed using machine learning techniques such as neural networks, linear regression, and support vector machines to improve the lifespan and performance of batteries by predicting state of charge (SoC) and state of health (SoH) [3]. This method faces obstacles including data quality, computational efficiency, and model interpretability, highlighting the necessity for real-time battery monitoring and predictive maintenance in EV applications.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

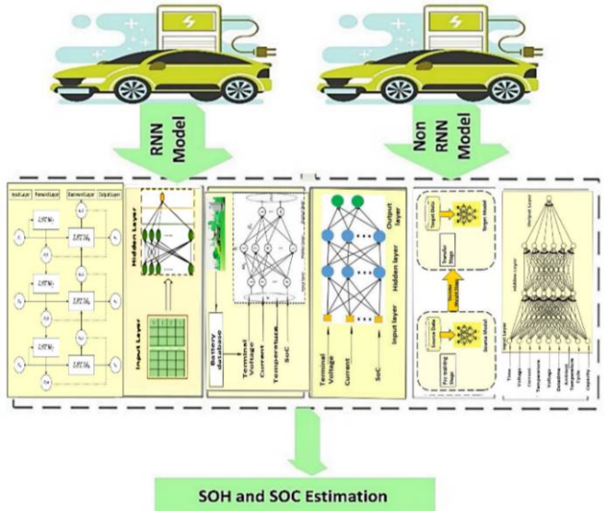


Figure 3. Process of data-driven methods.

Recognizing the inherently cyber-physical characteristics of smart charging networks, these systems are vulnerable to a range of cyber-physical attacks. Recent studies have highlighted the potential threats associated with the smart WinSmartEV™ infrastructure and validated their evaluation methodology [4]. The researchers emphasize the necessity for creating strong security protocols and standardized practices to bolster the resilience of smart charging systems against emerging cyber-physical risks. The infrastructure facilitates remote monitoring and management of EV charging through a smart communication network known as WINSmartGrid™, enabling multiple vehicles to connect to one circuit. Furthermore, the high costs and pressing need for addressing cybersecurity vulnerabilities in smart charging networks pose significant risks, as hacking threats can interrupt power supply or jeopardize user data privacy.

Taking into account the limitations of current EV charging technologies, there is a growing need for an AI-driven smart charging system that includes real-time battery monitoring, adaptable charging strategies, and predictive analytics. This system would utilize sophisticated machine learning algorithms to assess battery performance and continuously adjust charging parameters to enhance both efficiency and battery lifespan, while also addressing cybersecurity and cost-effectiveness issues. This initiative suggests an AI-enabled intelligent charging solution that connects traditional smart charging with advanced predictive analytics. Through the utilization of AI and networks of IoT-connected sensors, this system enhances the State of Charge (SoC) and State of Health (SoH), resulting in a longer lifespan for batteries while lowering the chances of overcharging and thermal runaway. Implementing such a system would not only enhance EV battery performance but also decrease long-term ownership expenses for EV users.

IV. PROPOSED SYSTEM

To address the limitations of conventional and existing Electric Vehicle (EV) charging systems, the suggested solution integrates a sophisticated, AI-driven charging framework. This system is designed to adaptively adjust charging parameters in real-time by combining advanced data-driven model which is the RandomForestRegressor model with Internet of Things (IoT) connectivity producing a robust battery management system. The main goal is to improve the State-of-Charge (SoC) and State-of-Health (SoH) of electric vehicle batteries, which will extend battery life, boost safety, and optimize overall charging effectiveness.

A. *Data Collection and Preprocessing*

Real-time information from sensors, including voltage, current, and temperature, is gathered and analyzed to eliminate noise and anomalies.

1) Microcontroller: A Raspberry Pi acts as the main processing unit, connecting with battery sensors.
2) Sensors: High-accuracy sensors (INA219 for measuring current/voltage, FS-L-0055 for pressure (battery swelling) and DS18B20 for temperature) are utilized for ongoing monitoring.
3) Communication Protocol: The system interacts with IoT devices utilizing the MQTT protocol. The communication module is set up on the Raspberry Pi, which employs its integrated WiFi adapter and the Python library paho-mqtt to operate as an MQTT client.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

B. Feature Extraction and Model Training

The real-time data from the battery is collected and input into the RandomForestRegressor model alongside historical data related to the battery's performance metrics (SoC and SoH). After deployment, the model analyzes incoming data to deliver real-time assessments of battery health. These predictions guide the adaptive charging algorithm to adjust charging parameters, thus enhancing the charging prcedure according to the battery's current condition.

1) Machine Learning Framework: Python-based library (Scikit) is utilized to create and train the RandomForestRegressor AI model to predict SoC and SoH [5].
2) Control Algorithms: Customized algorithm executes the adaptive charging strategy referring to a predefined charging profile and decides the charging strategy based on the predicted SoC and SoH [6].
3) Simulation: In the prototype phase, a Python environment utilizing libraries like NumPy, Pandas, Matplotlib, and scikit-learn integrated with MQTT protocol on Flask-based dashboard is used to simulate charging scenarios and validate the system's performance prior to actual deployment [7].

Figure 4 presents the flowchart of the suggested system. It begins by gathering real-time sensor data (voltage, current, temperature, pressure) from the battery and then processes the raw information by cleaning and normalizing it. Using the RandomForestRegressor AI model, the battery's State of Charge (SoC) and State of Health (SoH) are predicted. The control algorithm determines the appropriate charging mode (such as fast charge, pulse charging, or constant voltage) based on these predictions and other variables, modifies the charging current and voltage in real time, and transmits updates via IoT.

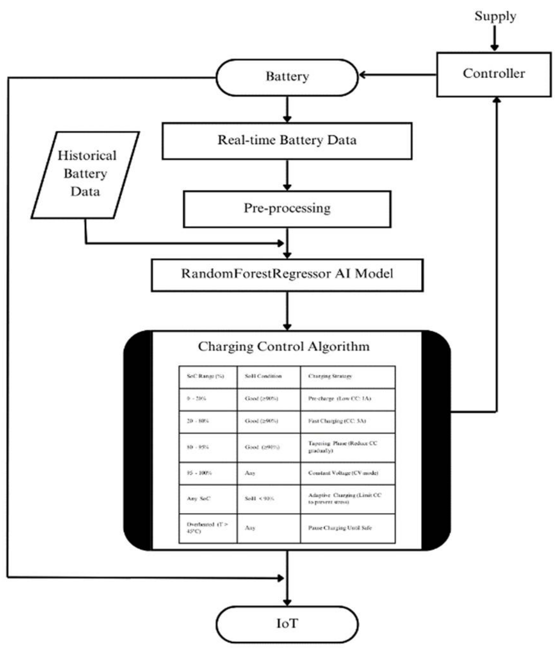


Figure 4. Flowchart of the Proposed System

C. Raspberry Pin Configuration [8]

1) To measure voltage and current, a INA219 sensor module is utilized. The INA219 communicates through the I²C protocol and is connected to the I²C pins on the Raspberry Pi, namely SDA on GPIO2 and SCL on GPIO3. The sensor receives power from the 3.3V or 5V supply, depending on the specifications of the module, along with a ground connection.
2) For temperature measurements, a DS18B20 sensor is used, which employs the 1-Wire protocol. This sensor is generally connected to GPIO4, with a 4.7 kΩ pull-up resistor placed between the data line and the 3.3V power rail to maintain proper signal levels.
3) Furthermore, the FS-L-0055 flex sensor is implemented to monitor pressure changes that may indicate battery swelling, a common indicator of battery decline. The FS-L-0055 typically outputs an analog signal, connecting to one of the analog input channels of an ADC such as the MCP3008. The MCP3008 interfaces with the Raspberry Pi via the SPI interface, connecting to the MOSI, MISO, SCLK, and CE0 pins to enable accurate analog readings from the FS-L-0055 sensor. Figure 5 illustrates the prototype picture of the system.

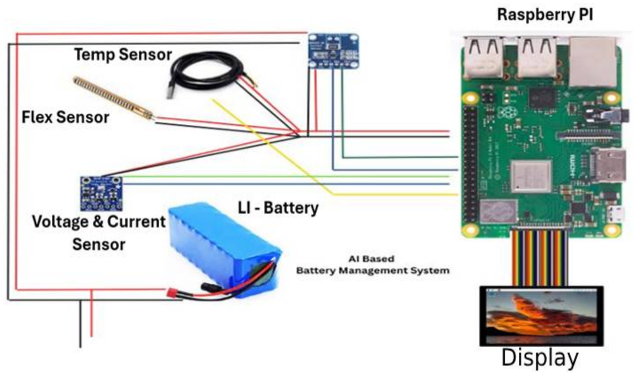


Figure 5. Prototype Picture

D. Software Setup

4) It runs on a Raspberry Pi operating with Raspberry Pi OS, utilizing Python as its main programming language. Sensor data is gathered from the INA219, DS18B20, and FS-L-0055 (through the MCP3008 ADC) using libraries such as RPi.GPIO and SMBus.

5) The information is quickly analyzed by a RandomForestRegressor machine learning model created with the scikit-learn framework to evaluate the State-of-Charge (SoC) and State-of-Health (SoH) of batteries [9].

6) The control algorithms modify charging parameters dynamically, alternating between constant-current and constant-voltage phases according to these predictions. Furthermore, the software framework incorporates data logging and IoT connectivity (through MQTT protocols) to facilitate remote oversight and management [10].

7) A web interface—developed with Flask offers operators real-time visual representations of battery performance and system diagnostics, guaranteeing that the entire charging procedure is optimized for both safety and efficiency.

V. TEST RESULTS

The intended system seeks to improve the process of charging Electric Vehicle (EV) batteries by adapting charging parameters in real-time. It comprises four primary phases:

Phase 1. Collection and Preprocessing of Sensor Data

The system's foundation is built on the ongoing collection of sensor data from the EV battery, which encompasses voltage and current measurements from the INA219 module, temperature information from the DS18B20 sensor, and pressure readings from the FS-L-0055 flux sensor, to observe battery performance in real-time. The data is subsequently refined to eliminate noise, standardized, and important features are developed. The charging cycle data is collected for a period of time, with measurements taken every few seconds automatically. The Table 1 presents the first 10 rows of the generated data.

Table 1: Sensor Data

Time (min)	Voltage (V)	Current (A)	Temperature (°C)	Pressure (kPa)
0.00	3.05	10.10	25.27	100.26
0.17	3.03	9.88	25.60	100.40
0.33	3.06	9.91	25.90	100.53
0.50	3.08	9.83	26.20	100.68
0.67	3.10	9.68	26.45	100.75
0.83	3.12	9.65	26.67	100.82
1.00	3.14	9.59	26.80	100.78
1.17	3.16	9.54	26.92	100.70
1.33	3.18	9.50	27.00	100.68
1.50	3.20	9.47	27.10	100.65

For visualization purposes, we can execute scripts to generate a pandas DataFrame using python that contains the recorded values for Time, Voltage, Current, Temperature, and Pressure. Afterward, it produces four subplot graphs, each representing one of the sensor parameters plotted against Time, which is shown in Figure 6. Furthermore, a single graph consolidates all sensor readings together, facilitating the observation of trends as a whole is shown in Figure 7.

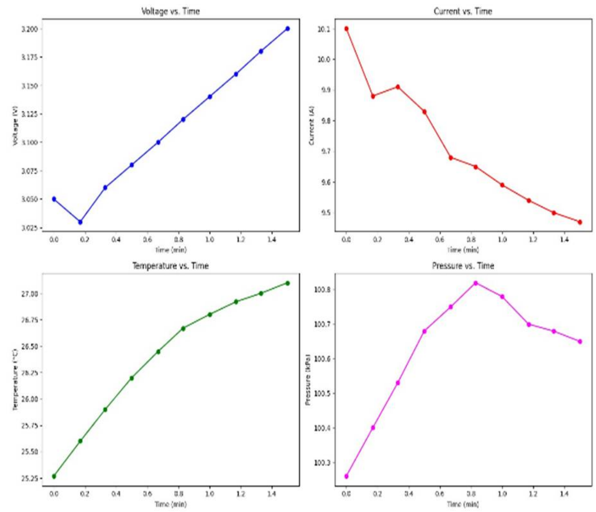


Figure 6. Each sensor data vs Time

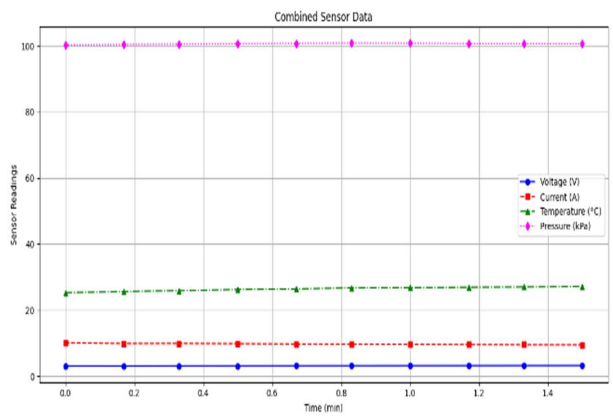


Figure 7. Consolidated sensor data

Phase 2. Prediction of Battery Condition through Machine Learning

Once the sensor data has been gathered, the following step is to forecast the State of Charge (SoC) and State of Health (SoH) using data-driven techniques. The implemented Python code utilizes the recorded sensor data to compute synthetic targets for SoC and SoH, constructs a machine learning model with scikit-learn to predict these values, and subsequently displays a table and graphs comparing the true versus predicted values.

The State of Charge (SoC) is estimated by the formula below mathematically

$$\text{SoC} = 100 - ((\text{Voltage} - 3.0) / 1.2) \times 100. \tag{1}$$

The formula is based on the assumption of a linear correlation between the voltage of a lithium-ion battery and its charge level, which spans from 3.0 V (nearly depleted) to 4.2 V (fully charged). It functions by calculating the voltage offset (Voltage - 3.0), normalizing this value through division by 1.2, converting the resulting fraction into a percentage, and then inverting that percentage.

The State of Health (SoH) is estimated by the formula below mathematically

$$\text{SoH} = 100 - (10 - \text{Current}) \times 10. \tag{2}$$

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

This equation connects the charging current to the condition of the battery. It assesses the difference between the current and a standard value (10 A) using the expression 10 - Current, where a reduced current may suggest deterioration in battery performance. By multiplying this difference by 10, the effect is adjusted to a percentage scale.

Model Building:

i. The dataset is divided into training and testing portions to avoid overfitting, and two separate pipelines are created (one for State of Charge and another for State of Health) utilizing StandardScaler and RandomForestRegressor.
ii. Random forests capture non-linear relationships and improve prediction accuracy. Real-time data and historical records enhance the model's ability to predict SoC and SoH accurately.
iii. Sensor data from EV batteries is normalized and processed, and the continuous influx of real-time data ensures the model stays up-to-date and accurate, enhancing battery safety and lifespan.

The model analyzes live battery data to estimate the State of Charge (SoC) and State of Health (SoH). To assess its precision, performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) are employed. MAE assesses the average size of errors, RMSE emphasizes more significant errors, and R^2 reflects how effectively the model corresponds to the data. A set of actual and estimated values is created, and Figure 8 shows the two graphs that are created to visualize and compare these values for SoC and SoH, providing clear insights into the model's predictive performance.

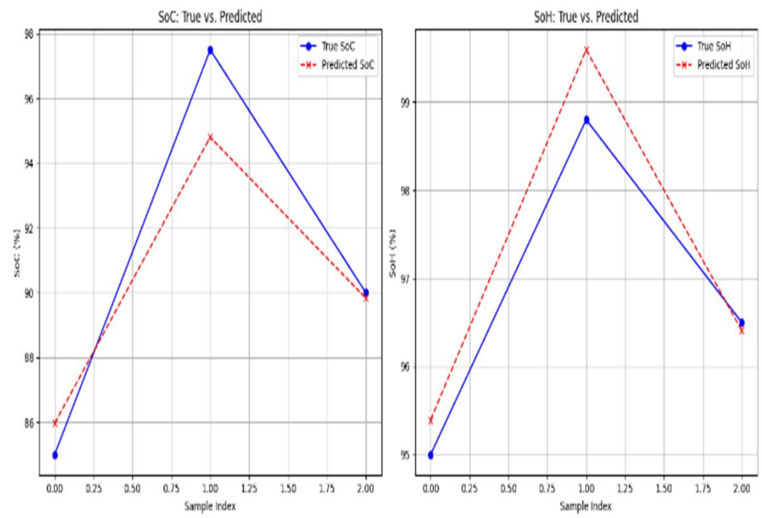


Figure 8. Predicted SoC and SoH vs True Values

SoC Model Performance:

- MAE: 1.2777777777777999
- RMSE: 1.6585357218766248
- R2 Score: 0.8957614035087695

SoH Model Performance:

- MAE: 0.42600000000002086
- RMSE: 0.5137320962006108
- R2 Score: 0.891934212920835

By integrating historical performance data of batteries across various conditions, the model acquires better understanding of the patterns and trends associated with different states of charge and health, resulting in enhancements in its overall performance

Phase 3. Execution of a Dynamic Charging Control Mechanism

The core of the suggested system lies in its adaptive charging control mechanism. This algorithm, which relies on AI, adjusts the charging profiles in real time based on the predicted State of Charge (SoC) and State of Health (SoH), along with extra factors like battery temperature. The control system will categorize the charging status of the battery into various profiles as shown in Table 2:

Table 2: Charging Profiles

SoC Range (%)	SoH Condition	Charging Strategy
0 - 20%	Good (≥90%)	Pre-charge (Low CC: 1A)
20 - 80%	Good (≥90%)	Fast Charging (CC: 5A)
80 - 95%	Good (≥90%)	Tapering Phase (Reduce CC gradually)
95 - 100%	Any	Constant Voltage (CV mode)
Any SoC	SoH < 90%	Adaptive Charging (Limit CC to prevent stress)
Overheated (T > 45°C)	Any	Pause Charging Until Safe

The python code implemented makes use of the recorded sensor data and employs the multi_stage_charging_control function to identify a charging mode and charging current for each data entry. The final DataFrame, df_control, includes all sensor readings alongside the associated charging mode decisions. A dictionary named mode_mapping assigns a numeric value to each charging mode (as a string), Table 3 shows the recorded values against the allocated charging pattern. This allows us to create a line graph that represents the charging mode over time. The resulting graph as shown in Figure 9, illustrates the charging mode (on the y-axis, with labels) in relation to time (on the x-axis), highlighting the variations in the charging pattern throughout the entire charging cycle.

Table 3: Allocated charging pattern for different SoC and SoH

SoC (%)	SoH (%)	Temperature (°C)	Charging pattern
95.83	101.0	25.27	Constant Voltage
97.50	98.8	25.60	Constant Voltage
95.00	99.1	25.90	Constant Voltage
93.33	98.3	26.20	Pulse Charging (Low)
91.67	96.8	26.45	Pulse Charging (High)
90.00	96.5	26.67	Pulse Charging (Low)
88.33	95.9	26.80	Pulse Charging (High)
86.67	95.4	26.92	Pulse Charging (Low)
85.00	95.0	27.00	Pulse Charging (High)
83.33	94.7	27.10	Pulse Charging (Low)

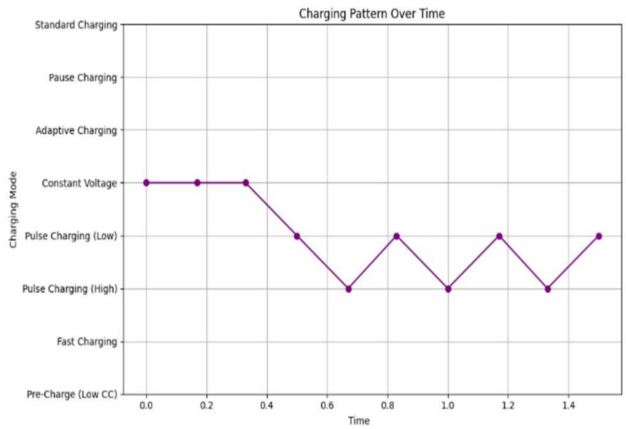


Figure 9. Charging pattern overtime

Phase 4. IoT Integration for Continuous Monitoring.

To enable remote monitoring and control, the proposed solution integrates IoT technology by utilizing the MQTT protocol along with a lightweight web dashboard built on Flask. Both MQTT and Flask are open-source, this system presents a cost-efficient and scalable option for practical implementation. Eclipse Mosquitto (MQTT Broker) is protected through TLS/SSL encryption, client authentication, and access control lists, whereas Flask is implementing HTTPS, effective authentication and authorization, along with secure libraries and extensions.

i. The MQTT publisher delivers instantaneous updates concerning the State-of-Charge (SoC), State-of-Health (SoH), charging profile, and additional information like temperature to an MQTT broker..
ii. The Flask-based dashboard operates as the subscriber, obtaining this information from the MQTT broker to ensure it receives the most current updates.
iii. When the data is received, the dashboard refreshes its user interface in real-time, showcasing the existing status of the battery parameters.

By running the MQTT publisher alongside the Flask-app codes in the console with Python, the dashboard output is viewed on the local server. This configuration enables real-time observation and visualization of battery parameters. The dashboard automatically refreshes to show the most recent data on State-of-Charge (SoC), State-of-Health (SoH), and the chosen charging profile. This interactive platform ensures effective monitoring and prompt action when necessary. Figure 10 shows an illustration of the test output results presented in a dashboard format on a local web browser.

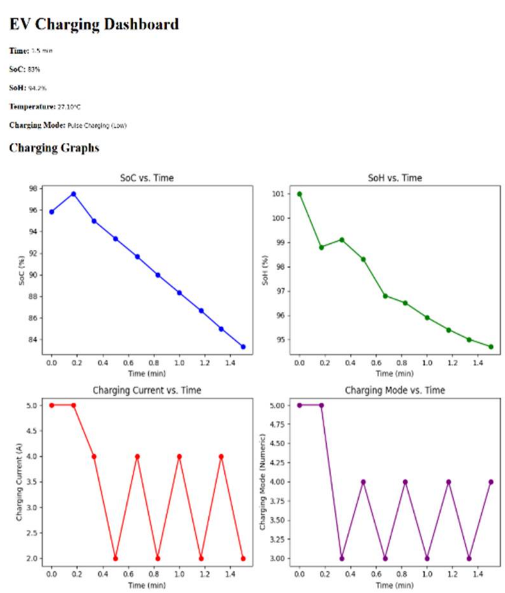


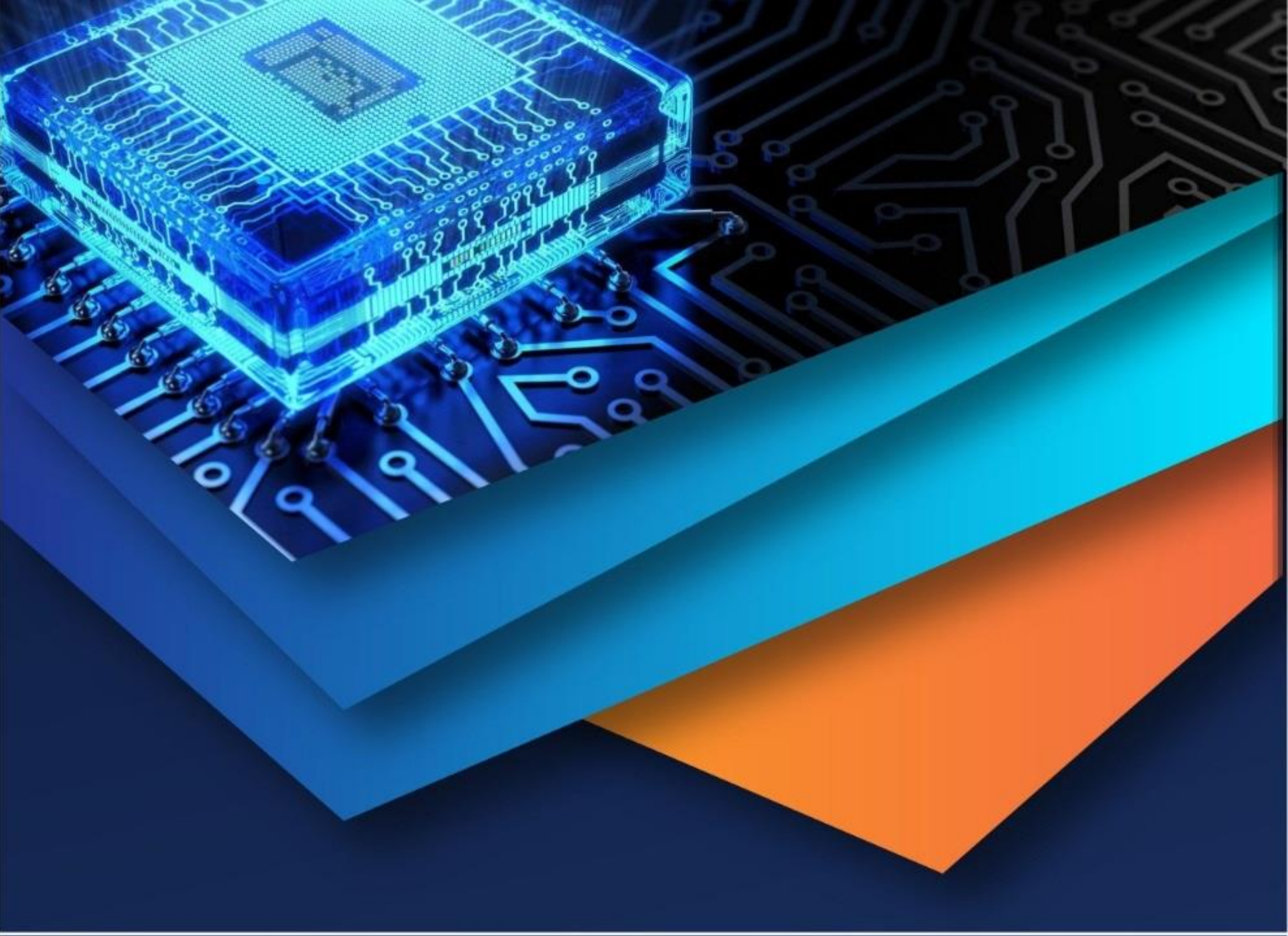
Figure 10. Results in EV Charging Dashboard

VI. CONCLUSION

The suggested system improves Electric Vehicle (EV) charging by combining real-time sensor data, machine learning-driven battery state evaluation, an adaptive multi-stage charging control strategy, and IoT-enabled remote oversight. By collecting key variables such as voltage, current, temperature, and pressure, a robust data foundation is established. Using scikit-learn, the system effectively forecasts the battery's State of Charge (SoC) and State of Health (SoH). Additionally, its adaptive charging control, which utilizes a pulse charging method, continuously modifies the charging profile in real-time to guarantee optimal efficiency, safety, and a longer battery life. By integrating MQTT and a Flask-based dashboard, the system provides an economical solution for real-time remote monitoring and control. This intelligent charging system represents a major leap forward in EV battery management, delivering a scalable, efficient, and secure solution, with opportunities for future enhancements such as advanced predictive analytics and integration with renewable energy sources.

REFERENCES

[1] D. Pant, N. Singh and P. Gupta, "Charging System for Electric Vehicles," 2022 IEEE Delhi Section Conference (DELCON), New Delhi, India, 2022.
[2] M. S. Hashim, J. Y. Yong, V. K. Ramachandaramurthy, K. M. Tan and M. Tariq, "Coordinated Vehicle-to-Grid Scheduling to Minimize Grid Load Variance," 2019 International Conference on Electrical, Electronics and Computer Engineering (UPCON), Aligarh, India, 2019.
[3] A. Haraz, K. Abualsaud and A. Massoud, "State-of-Health and State-of-Charge Estimation in Electric Vehicles Batteries: A Survey on Machine Learning Approaches," in IEEE Access, vol. 12, pp. 158110-158139, 2024.
[4] D. Reeh, F. Cruz Tapia, Y. -W. Chung, B. Khaki, C. Chu and R. Gadh, "Vulnerability Analysis and Risk Assessment of EV Charging System under Cyber-Physical Threats," 2019 IEEE Transportation Electrification Conference and Expo (ITEC), Detroit, MI, USA, 2019.
[5] A. Haraz, K. Abualsaud and A. M. Massoud, "Ensemble Learning for Precise State-of-Charge Estimation in Electric Vehicles Lithium-Ion Batteries Considering Uncertainty," in IEEE Access.
[6] Lan-Ron Dung and Jieh-Hwang Yen, "ILP-based algorithm for Lithium-ion battery charging profile," 2010 IEEE International Symposium on Industrial Electronics, Bari, Italy, 2010
[7] Dhairya Parikh, Raspberry Pi and MQTT Essentials: A complete guide to helping you build innovative full-scale prototype projects using Raspberry Pi and MQTT protocol , Packt Publishing, 2022.
[8] Monk, Simon. Raspberry pi cookbook. " O'Reilly Media, Inc.", 2022.
[9] A. K. P, P. K. S, M. K. A, S. B. S, P. B. D and D. K. R, "Recurrent Neural Network based Data-Driven SOC Estimation in Lithium-Ion Battery," 2023 International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), Ballar, India, 2023.
[10] M. El-Hajj and D. Vorotilov, "Testing the Security and Performance of MQTT Protocol on Raspberry Pi for IoT Applications," 2024 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob), Bali, Indonesia, 2024.
[11] Hanlei Sun, Jianrui Sun, Kun Zhao, Licheng Wang, and Kai Wang. Data-driven ica-bi-lstm-combined lithium battery soh estimation. Mathematical Problems in Engineering, 2022:1–8, 2022.
[12] B. Wukkadada, K. Wankhede, R. Nambiar, and A. Nair, “Comparison with http and mqtt in internet of things (iot),” in 2018 International Conference on Inventive Research in Computing Applications (ICIRCA). IEEE, 2018, pp. 249–253.
[13] D. B. C. Lima, R. M. B. da Silva Lima, D. de Farias Medeiros, R. I. S. Pereira, C. P. de Souza, and O. Baiocchi, “A performance evaluation of raspberry pi zero w based gateway running mqtt broker for iot,” in 2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), 2019, pp. 0076–0081.
[14] M. El-Hajj and D. Vorotilov, "Testing the Security and Performance of MQTT Protocol on Raspberry Pi for IoT Applications," 2024 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob), Bali, Indonesia, 2024.
[15] P. Vogel, T. Klooster, V. Andrikopoulos and M. Lungu, "A Low-Effort Analytics Platform for Visualizing Evolving Flask-Based Python Web Services," 2017 IEEE Working Conference on Software Visualization (VISSOFT), Shanghai, China, 2017,



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY