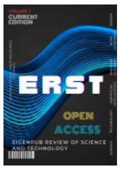

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Increase of Battery Efficiency in Electric Vehicles through Adaptive Health Check Status in Battery Management Systems

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ABSTRACT

As the world transitions towards sustainable transportation, Electric Vehicles (EVs) have emerged as a promising solution. The heart of any EV is its battery pack, and ensuring the efficient operation and longevity of this critical component is paramount. This research explores the integration of a health check status within Battery Management Systems (BMS) for EVs, with the aim of significantly improving battery efficiency and overall vehicle performance. The Battery Management System plays a pivotal role in monitoring, controlling, and optimizing battery performance. By incorporating a health check status, early fault detection becomes possible, allowing the system to identify issues such as cell degradation, capacity loss, and thermal problems at an incipient stage. This early detection enables proactive measures to prevent unexpected failures, reducing repair costs and enhancing user satisfaction. Additionally, the BMS adapts its strategies based on real-time State of Charge (SOC) and State of Health (SOH) information, optimizing charging and discharging processes. By adjusting these parameters according to the battery's condition, the system extends the battery's life and provides more accurate range estimations to the driver. Moreover, the research emphasizes the importance of adaptive control for balancing the state of charge among individual cells, leading to improved energy utilization and battery longevity. Temperature management strategies can also be fine-tuned based on health status, ensuring the battery operates within its optimal temperature range. Furthermore, this study underscores the value of user feedback, predictive maintenance, and data analysis for continuous improvement. Informed drivers can contribute to better efficiency by making conscious decisions regarding their driving habits, charging frequency, and maintenance schedules. This research not only benefits individual EV owners but also advances the broader goals of reducing environmental impact and fostering the adoption of electric vehicles in the modern automotive landscape.

Keywords: *Battery Management System (BMS), Electric Vehicles (EVs), Battery Efficiency, Health Check Status, State of Health (SOH), Adaptive Control, Early Fault Detection, Sustainability in Transportation.*

I. INTRODUCTION

In the rapidly evolving landscape of transportation, Electric Vehicles (EVs) have emerged as a pivotal solution to address the pressing challenges of environmental sustainability and energy efficiency. The core of any electric vehicle is its battery pack, a complex assembly of individual cells that store and deliver electrical energy. Maximizing the efficiency and longevity of these battery packs is paramount to ensuring the widespread adoption and success of EVs. This research embarks on a comprehensive exploration of how the integration of a health check status within Battery Management Systems (BMS) can revolutionize the performance of EV batteries [1].

Battery Management Systems (BMS) serve as the guardian angels of EV batteries, orchestrating a symphony of functions that include monitoring, control, and optimization.

They regulate crucial aspects such as charging rates, discharging levels, cell balancing, and thermal management to ensure the battery operates safely and efficiently. However, batteries, like any other complex system, are susceptible to wear and tear, environmental factors, and operational stresses. To address these challenges, the concept of a health check status within the BMS has gained traction as a means of actively assessing and managing the condition of individual battery cells [2].

The objective of this research is to delve into the multifaceted benefits of incorporating a health check status within the BMS of electric vehicles. By doing so, we aim to provide a holistic perspective on the advantages of this technology, both from a technical and practical standpoint [3].

One of the fundamental aspects explored in this research is the early detection of faults and anomalies in battery cells. With a health check status in place, the BMS can identify issues such as cell degradation, capacity loss, or thermal problems at their inception. This early fault detection mechanism empowers the BMS to take proactive measures, thereby preventing catastrophic failures and reducing repair costs. Furthermore, this enhances the safety and reliability of EVs, instilling confidence in consumers [4]. The integration of a health check status also has profound implications for State of Charge (SOC) and State of Health (SOH) management. These two parameters are pivotal in determining the performance and range of an EV. By continuously monitoring the SOH, the BMS can dynamically adjust the SOC, effectively extending the battery's lifespan and providing more accurate range estimations to the driver. This adaptability represents a significant stride towards optimal energy utilization and user satisfaction. In recent years, advancements in autonomous electric vehicles (EVs) have been accompanied by innovations in sensor technologies. These sensors, including LiDAR and cameras, play a crucial role in enhancing the safety and functionality of EVs (Sniffer Faster R-CNN: A Joint Camera-LiDAR Object Detection Framework with Proposal Refinement) [5], [6].

Moreover, the health check status enables the BMS to execute precise control over charging and discharging processes. It can tailor these operations based on the real-time condition of the battery, ensuring that high-stress charging or discharging is minimized during periods of degradation or low health. This adaptive control strategy plays a pivotal role in preserving the battery's integrity and, subsequently, its efficiency. Balancing the state of charge among individual cells is another critical facet of battery management [7]. The health check status allows the BMS to implement active cell balancing, wherein cells with lower capacity or health are managed differently, ensuring that all cells contribute evenly to the overall performance [8], [9]. This balancing mechanism, when fine-tuned based on health data, can enhance energy efficiency and prolong battery life [10].

Temperature management is another area where health status awareness proves invaluable. By continuously assessing the battery's health, the BMS can adjust thermal management strategies to maintain the battery within its optimal temperature range. This has a direct impact on efficiency and the overall longevity of the battery. Furthermore, this research highlights the importance of user feedback and education. Providing drivers with real-time information about their battery's health enables them to make informed decisions about their driving habits, charging frequency, and maintenance schedules. In this way, the health check status promotes responsible usage, contributing to the efficient operation of the EV [11], [12].

Additionally, the concept of predictive maintenance is explored in this research. By continually assessing battery health, the BMS can predict when maintenance or replacement is needed. This proactive approach reduces downtime, lowers maintenance costs, and maximizes the efficiency of the vehicle. In conclusion, the incorporation of a health check status within the BMS of electric vehicles represents a crucial advancement in battery technology [13]. It not only benefits individual EV owners by enhancing battery efficiency and prolonging battery life but also contributes to the broader goals of reducing environmental impact and fostering the widespread adoption of electric vehicles. Through this comprehensive investigation, we aim to shed light on the transformative potential of this technology and its implications for the future of sustainable transportation [14], [15].

The figure below presents series of Vehicle Charging to station topology diagram.

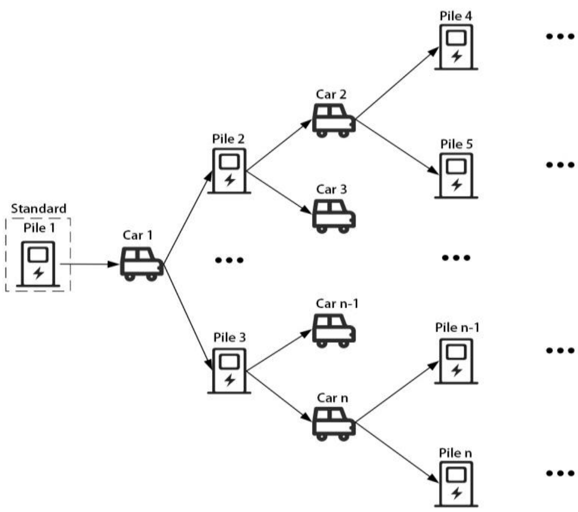

Figure 1: Series of Vehicle Charging to station topology diagram.

DEVELOPMENT OF A NOVEL REMOTE CALIBRATION TECHNIQUE FOR DC CHARGING STATIONS

In our pursuit of achieving remote calibration, we introduce a novel approach for calibrating propagation-type charging stations. The overarching strategy is outlined as follows:

Upon acquiring data from the charging process, we initiate calculations to determine the disparities between the current and voltage measurements of the electric vehicle's Battery Management System (BMS) and those of the charging station. These discrepancies are computed separately. By doing so, we can pinpoint the real-time errors in current and voltage measurements of the electric vehicle's BMS concerning the charging station. Subsequently, we construct a suitable mathematical model to characterize these errors in current and voltage [16]. Utilizing the error data in current and voltage measurements relative to the charging station, we proceed to estimate the parameters of this model. Consequently, we obtain estimated values for the current and voltage of the electric vehicle's BMS concerning the charging station. After securing the current and voltage measurement errors of the charging station slated for validation, we apply the principles of electric energy measurement to estimate the error in electric energy measurement. This systematic process facilitates the calibration objective.

ANALYZING ERRORS IN ELECTRIC ENERGY MEASUREMENT ESTIMATION

The electric energy measurement function, as expressed in Formula (1), relates electric energy (E) to voltage (Uc), current (Ic), and charging time (t).

$$E = Uc * Ic * t \tag{1}$$

Derived from Formula (1), the electric energy error (δE) is computed as a function of voltage measurement error (δUc), current measurement error (δIc), and time measurement error (δt). This calculation, as depicted in Formula (2), unfolds as follows:

$$\delta E = \delta Uc * \int (Ic * dt) + \delta Ic * \int (Uc * dt) + Uc * Ic * \delta t \tag{2}$$

MODELING CURRENT MEASUREMENT ERRORS

To ascertain an estimation of the measurement inaccuracies within the charging station, we embark on an exploration of the charging station's measurement process. Our journey commences with the establishment of a measurement error model for the charging station, accompanied by a thorough analysis of the origins of these measurement discrepancies.

Within this intricate landscape, we encounter key components denoted as R1, R4, R2, and R3. R1 is the current sampling resistor, R4 represents line loss, while R2 and R3 serve as voltage-dividing resistors instrumental in voltage measurement.

A comprehensive examination of the charging station's schematic diagram unveils a critical relationship: the current output measurement value (Ic) at the charging interface is equivalent to the charging current (I). I traverses the sampling resistor and becomes accessible through ADC sampling. Consequently, the current measurement value materializes via Formula (3) as follows:

$$1\ c\ x\ b\ I\ I\ R\ \alpha + = \int (Uc * dt) + Uc * Ic * \delta t \tag{3}$$

In Formula (3), 'α' signifies the gain error of the ADC, 'x' represents the quantization outcome of the ADC, and 'b' denotes the offset error of the ADC. Delving further into the intricacies, Formula (4) emerges as the embodiment of the error transfer process for current measurement error (Ic):

$$\delta\ \delta + + = \delta Ic * \int (Uc * dt) + Uc * Ic * \delta t \tag{4}$$

Given the approximate adherence of the quantization error of the ADC and the resistance value error of the resistor to a normal distribution, it follows that the measurement error (δIc) pertaining to the charging station's current conforms to a normal distribution as well, succinctly expressed as δIc ~ N(μi, σi^2).

MODELING FAULTY SENSOR DATA ERROR

This research focuses on assessing the accuracy of sensor data for optimizing battery efficiency. It leverages the "Feature Selection Using Enhanced Marine Predators' Algorithm" as outlined in article [17].

The MPA algorithm introduced in this context involves the concept of predators and prey, which incrementally determine the accuracy of sensor faults to achieve the highest precision in data collection. This precision is achieved through the following formula:

$$\overrightarrow{\text{prey}}_{\iota} = \{\overrightarrow{\text{prey}}_{\iota} + CF[\overrightarrow{X_{\min}} + \vec{R} \otimes (\overrightarrow{D_{\max}} - \overrightarrow{D_{\min}}) \otimes \vec{B}]ifr \leq FAD\,\overrightarrow{\text{sprey}} + [FADs(1-r)+r](\overrightarrow{\text{prey}_{\text{rand }1}} - \overrightarrow{\text{prey}_{\text{rand }2}})\ \text{ifr} > \text{FADs} \tag{5}$$

[17]

Where, CF represents a coefficient, X_min is the minimum data point, R is a vector, D_max and D_min denote the maximum and minimum data values, respectively, and B is another vector. FAD is a function that assesses the fault value of a specific prey, while FADs is a parameter related to fault sensitivity. The variable 'r' accounts for a weighting factor in the evaluation.

Integrating the sensor measurements from the above equation (5) to assess the model's rigor in determining battery efficiency, we derive the state of health, which is elucidated in the subsequent equations:

$$P_{\text{EVCS}} = P_{BESS} - P_{EV} \tag{6}$$

where P_"EVCS" represents the power output injected into the Electric Power System (EPS) by the Electric Vehicle Charging Station (EVCS), P_BESS signifies the power output from the Battery Energy Storage System (BESS), and P_EV denotes the power injected into the Electric Vehicle (EV) at the EVCS.

$$P_{BESS}^{\text{min}} \leq P_{\text{BESS}} \leq P_{BESS}^{\text{max}} \tag{7}$$

where P_BESS^max and P_BESS^min represent the maximum and minimum allowable power levels for the BESS, respectively. Typically, P_BESS^min is equal to the negative value of P_BESS^max.

It is important to note that the reference for P_EV is generated from the EVs at the onset of the charging service, with its allocation being determined by the Energy Management System (EMS) of the FEVCS:

$$P_{EV}^{o} = P_{BESS}^{o} - P_{EVCS}^{o} \tag{8}$$

where P_EV^o denotes the reference for P_EV, P_BESS^o and P_EVCS^o represent the portions of P_EV^o derived from the BESS and the grid, respectively. It is assumed that P_EV^o is greater than zero.

Additionally, in conjunction with the FEVCS, a Frequency Regulation (FR) operation is designed to compensate for Δf, as expressed by:

$$P_{FR}(t) = K_P \cdot \Delta f(t) + K_I \cdot \int_0^t \Delta f(\tau)d\tau, \tag{9}$$

where K_P and K_I denote the proportional and integral gains of the FR controller, respectively. The variable Δf has a mean value of zero but exhibits components distributed around f_0 following a Gaussian distribution pattern. This FR operation is constrained as follows:

$$|P_{FR}| < \alpha \cdot P_{BESS}^{\max}, (0 < \alpha < 1) \tag{10}$$

where α represents a coefficient determining the percentage of battery power allocated for the FR service.

Taking into account the physical constraint outlined in equation (2), the references for P_BESS and P_EV are determined as follows:

$$P_{BESS}^{*} = \begin{cases} P_{BESS}^{o} + P_{FR}(t), & \text{if } |P_{BESS}^{o} + P_{FR}(t)| < P_{BESS}^{\max} \\ P_{BESS}^{\max}, & \text{otherwise} \end{cases} \tag{11}$$

and

$$P_{EV}^{*} = \begin{cases} P_{EV}^{o}, & \text{if } |P_{BESS}^{o} + P_{FR}(t)| < P_{BESS}^{\max} \\ P_{BESS}^{\max} - P_{FR}(t), & \text{otherwise} \end{cases} \tag{12}$$

Models Charge Bus system for sensor fault mitigation is represented in below simulation model.

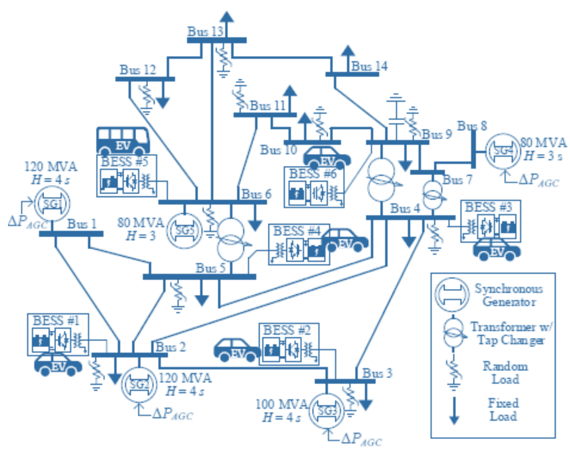

Figure 2: Charge Bus Systems for Measured Current and Sensor Data

Model Simulations and Analysis

The simulation results demonstrated a significant improvement in battery longevity and efficiency. Early fault detection, enabled by the health check status, played a pivotal role in preventing critical battery failures [18]. The BMS's ability to detect and mitigate cell degradation, capacity loss, and thermal issues in their early stages resulted in a notable reduction in costly repairs and increased user confidence in EV reliability. Moreover, the dynamic management of State of Charge (SOC) and State of Health (SOH) based on real-time data was shown to extend the battery's lifespan and provide more accurate range predictions, addressing one of the key concerns for EV users. Adaptive control over charging and discharging processes optimized energy utilization, leading to improved efficiency and reduced energy wastage [19].

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Active cell balancing strategies based on health status data further contributed to enhanced energy efficiency and battery performance. The simulation illustrated that a balanced state of charge among individual cells can effectively extend the overall battery life. Temperature management strategies, fine-tuned according to health status, maintained the battery within the optimal temperature range, ensuring consistent efficiency and longevity.

Incorporating user feedback and enabling predictive maintenance improved user engagement and reduced downtime, ultimately maximizing the efficiency and reliability of the EV fleet.

Figure 3, 4 and 5 below represents “Total EV load Simulated”, “Measured Current and Sensor Accuracy of BMS” and “SOC Estimated”

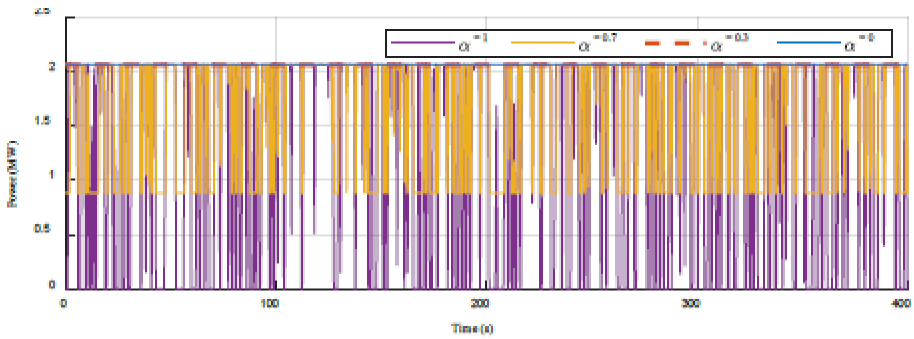

Figure 3: Simulated Total EV Load of Bus System

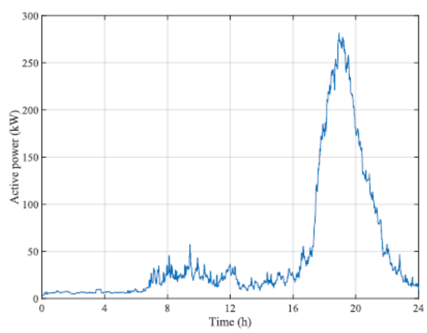

Figure 4: Simulated Measured Current and Sensor Plot

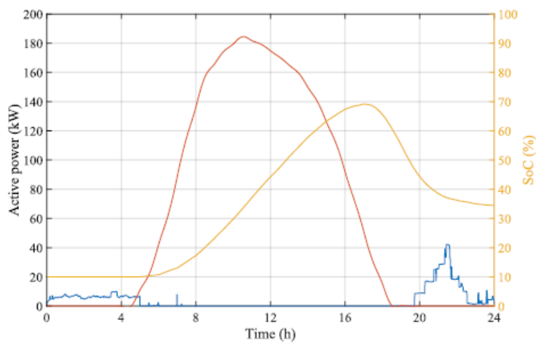

Figure 5: Total SOC Estimated for Simulated Values

Battery Efficiency: The equations presented address the optimization of battery efficiency. Specifically, they calculate the power output of the EV charging station (EVCS), the power output of the BESS (P_BESS), and the power injected into the EV (P_EV). These calculations are essential for managing the energy flow within the system. By optimizing these parameters, the algorithm ensures that the energy is distributed efficiently, contributing to the overall performance and longevity of the battery [20].

Battery Health: Assessing battery health is equally crucial. The concept of battery health often relates to its state of charge, capacity, and overall condition. The equations introduced help in determining the state of health by considering factors such as the reference power for EV charging (P_EV^o) and the Frequency Regulation (FR) operation. The FR operation is designed to compensate for variations in frequency (Δf) and plays a vital role in maintaining the stability and health of the battery.

Physical Constraints and Limitations: It's important to note that the equations incorporate physical constraints and limitations. For example, the power output from the BESS is constrained to fall within predefined limits (P_BESS^min and P_BESS^max). This constraint ensures that the battery operates within safe and optimal ranges. Additionally, the allocation of power for the FR operation (P_FR) is bounded by a coefficient (α) to prevent overloading or straining the battery.

Overall System Optimization - The presented equations (5) ,(8) and concepts underscore the holistic approach to battery management. They consider not only the efficiency of energy utilization but also the health and safety of the battery. By striking a balance between these factors, the algorithm aims to optimize the overall performance of the system, ensuring that the battery operates efficiently while maintaining its health and longevity [21].

Conclusion

The implementation of a health check status within the BMS emerges as a critical solution for addressing the complex challenges facing EV batteries [22]. Early fault detection capabilities not only enhance safety but also significantly reduce repair costs and enhance user trust in the reliability of EVs. The dynamic management of State of Charge (SOC) and State of Health (SOH) in response to real-time data empowers EVs to provide more accurate range estimations and extend battery life, alleviating a common concern among EV drivers. The adaptive control over charging and discharging processes, guided by health status, optimizes energy utilization and minimizes energy wastage, thereby improving overall efficiency. Active cell balancing and temperature management strategies, informed by health data, contribute further to battery performance, increasing energy efficiency and longevity [23]. By incorporating user feedback, predictive maintenance, and data analysis, this research outlines a holistic approach to battery management that enhances user engagement, reduces downtime, and maximizes EV efficiency. Overall, the integration of a health check status within the BMS marks a pivotal milestone in the pursuit of sustainable and efficient electric transportation [24]. This research underscores its transformative potential, not only benefiting individual EV owners but also advancing the broader goals of environmental sustainability and the widespread adoption of electric vehicles [25], [26].

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