Optimizing Electric Vehicle Performance: Advanced Health Monitoring and Adaptive Strategies in Battery Management Systems

Sara Tarek Ahmed Ali
Department of Electric Engineering, Zagazig University, Zagazig, Egypt

Ahmed Tamer Ahmed Hossam
Department of Computer Engineering, Helwan University, Cairo, Egypt

Abstract

In the shift towards eco-friendly transportation, Electric Vehicles (EVs) have become a vital alternative. At the core of EVs lies the battery pack, whose efficient functioning and durability are crucial. This study delves into the integration of a health check feature in EV Battery Management Systems (BMS), aiming to enhance battery efficiency and vehicle performance significantly. The BMS is instrumental in supervising, managing, and optimizing battery function. Integrating a health check allows for the early identification of issues like cell wear, loss of capacity, and thermal anomalies, enabling the system to recognize and address problems early. This foresight aids in avoiding sudden failures, cutting down on repair expenses, and increasing user satisfaction. The BMS also tailors its approaches based on immediate State of Charge (SOC) and State of Health (SOH) data, refining charging and discharging methods. Adapting these factors to the battery's status helps prolong its life and offers drivers more precise driving range predictions. The study further highlights the need for adaptive control in equalizing charge among individual cells, which promotes better energy use and extends battery life. Temperature control strategies are also optimized according to health status, keeping the battery within its ideal operational temperature. The research also points out the significance of user involvement, predictive upkeep, and data analysis for ongoing enhancements. Educated drivers can enhance efficiency through mindful choices about driving patterns, charging intervals, and maintenance routines. This research is beneficial not just for individual EV users but also aids in minimizing environmental harm and encourages the broader adoption of electric vehicles in today's auto industry.

Introduction

With the increase in the carbon footprint of mankind, an increasing energy demand poses a difficult challenge to the world economies. The need for clean energy and optimized energy consumption have become paramount towards human success [1], [2]. Countries around the world are urging for clean energy production to tackle with this increasing energy demand [3]. Along with the increase in clean energy production, adoption of Electrical Vehicles (EVs) for commute has opened multiple avenues for smart transportation [4], [5]. The use of technology to help navigate vehicles on the road has proven to increase road safety and reduce traffic accidents [6]. The smart transportation also requires a reliable wireless network on the background [7], [8]. Several studies have discussed the reliability of wireless networks especially for vehicular network applications in the literature [9] [10]–[12]. Multiple ways to quantify the reliability have also been presented [13]

Although EVs and smart transportation promise a carbon-neutral future, effective battery pack management is also required for increasing the energy efficiency and environmental sustainability [14], [15]. The centerpiece of any electric vehicle (EV) is its battery pack, a sophisticated array of cells responsible for storing and supplying electrical power. The key to the success and widespread acceptance of EVs lies in optimizing these battery packs for maximum efficiency and lifespan. This study undertakes an in-depth examination of how incorporating a health check status in Battery Management Systems (BMS) can enhance the performance of EV batteries.

BMS acts as the protective overseer of EV batteries, conducting a range of tasks that include monitoring, controlling, and optimizing battery functions. They manage vital elements such as charge and discharge rates, cell balance, and thermal management, ensuring safe and effective battery operation. Given their complexity, batteries are prone to wear, environmental effects, and operational stress. Introducing a health check feature in the BMS is a proactive solution to actively monitor and maintain individual battery cells' health.

The research focuses on the comprehensive advantages of integrating a health check status in EV BMS, from both a technical and practical perspective. A key area of study is the early identification of battery cell faults and anomalies. The health check feature enables the BMS to spot issues like cell deterioration, capacity reduction, or thermal challenges early on. This proactive detection allows the BMS to take preventative actions, averting major failures and minimizing repair costs, thereby boosting EV safety and reliability, and bolstering consumer confidence.

This study also explores the significant effects of health check integration on State of Charge (SOC) and State of Health (SOH) management. These crucial factors influence an EV's performance and driving range. Constant SOH monitoring lets the BMS dynamically adjust SOC, thus prolonging the battery's life and offering more precise range predictions. This adaptability marks a major advance in energy use and user satisfaction.

Moreover, the health check status enables the BMS to precisely control charging and discharging processes, adapting these based on the battery's current condition. This reduces stress on the battery during times of degradation or poor health, preserving its integrity and efficiency. The research also examines the importance of active cell balancing. The BMS can manage cells differently based on their capacity or health, ensuring uniform contribution to overall performance. This approach boosts energy efficiency and extends battery life.

Temperature management is another crucial area where health monitoring is beneficial. By continuously assessing the battery's health, the BMS can tailor thermal management strategies to keep the battery within its ideal temperature range, enhancing efficiency and longevity.

The study also highlights the role of user feedback and education. Informing drivers about their battery's health status encourages responsible driving, charging, and maintenance habits, leading to more efficient EV operation. The concept of predictive maintenance is also investigated, where continuous health assessments can foresee maintenance or replacement needs, reducing downtime and costs while maximizing vehicle efficiency.

The integration of a health check status in EV BMS is a significant development in battery technology. It offers individual benefits like improved battery efficiency and extended lifespan, and contributes to broader objectives like environmental impact reduction and promoting EV adoption. This thorough investigation aims to illuminate the transformative potential of this technology for sustainable transportation's future.

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

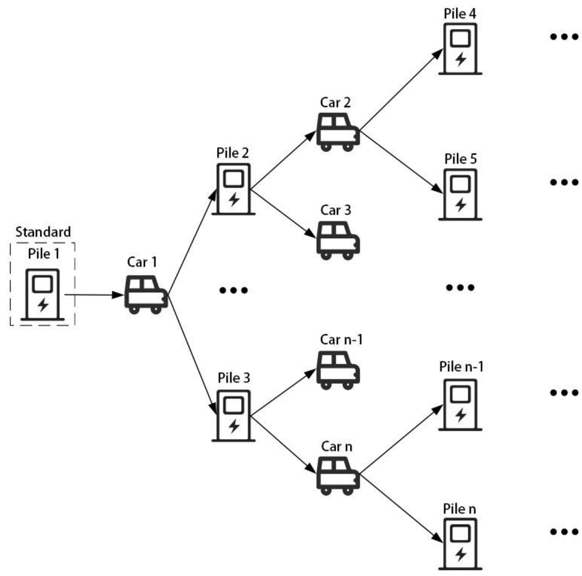

Figure 1: Series of Vehicle Charging to station topology diagram.

Development of a novel remote calibration technique for dc charging stations

In an effort to achieve remote calibration, this research introduces a new method for calibrating direct current (DC) charging stations for electric vehicles (EVs). The procedure is as follows:

The process begins by collecting data during the charging session. This data is used to calculate the differences in current and voltage readings between the EV's Battery Management System (BMS) and the charging station. These discrepancies are analyzed separately. This approach allows for the precise identification of real-time errors in the EV's BMS current and voltage measurements in relation to the charging station. Next, a mathematical model is developed to accurately represent these errors in current and voltage [16], [17].

Using the error data in current and voltage measurements compared to the charging station, the parameters of this model are then estimated. This leads to the determination of estimated values for the current and voltage of the EV's BMS as they relate to the charging station. Once the errors in current and voltage measurements at the charging station designated for validation are established, the principles of electric energy measurement are applied to calculate the error in electric energy measurement [18], [19]. This methodical approach effectively facilitates the calibration of the charging station.

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 accurately estimate measurement inaccuracies in a charging station, this study delves into the station's measurement process. The first step involves developing a measurement error model for the charging station, followed by an in-depth investigation into the sources of these measurement errors.

The research navigates through a complex network of components, specifically identifying R1, R4, R2, and R3. Here, R1 acts as the current sampling resistor, R4 symbolizes line loss, and R2 and R3 function as voltage-dividing resistors crucial for voltage measurement.

An extensive review of the charging station's schematic diagram reveals a pivotal relationship: the measured current output value (Ic) at the charging interface is the same as the actual charging current (I). This current flows through the sampling resistor and is then captured through ADC (Analog-to-Digital Converter) sampling. As a result, the value of the current measurement is determined using Formula (3). This formula plays a key role in quantifying the current measurement, allowing for a more accurate understanding of the station's performance and the identification of any discrepancies in its measurements:

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

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):

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

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".

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:

$$\overrightarrow{\mathrm{prey}_{\iota}} = \{ \overrightarrow{\mathrm{prey}_{\iota}} + CF[\overrightarrow{X_{\mathrm{min}}} + \vec{R} \otimes (\overrightarrow{D_{\mathrm{max}}} - \overrightarrow{D_{\mathrm{min}}}) \otimes \vec{B}] ifr \\ \leq FAD\ \overrightarrow{\mathrm{sprey}} + [FADs(1-r) + r](\overrightarrow{\mathrm{prey}_{\mathrm{rand}\ 1}} - \overrightarrow{\mathrm{prey}_{\mathrm{rand}\ 2}})\ \mathrm{ifr} > \mathrm{FADs}$$
(5) [9]

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:

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

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.

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

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:

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

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:

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

and

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

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

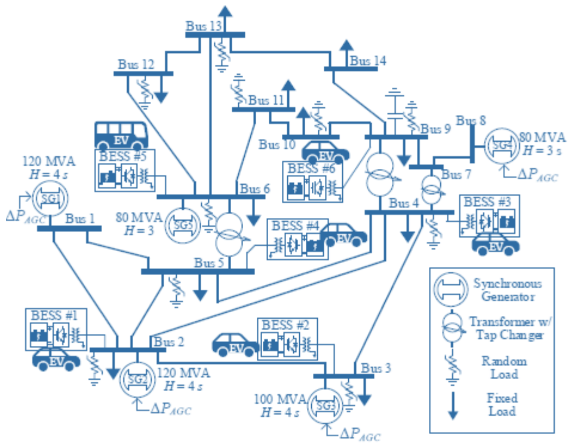

Figure 2: Charge Bus Systems for Measured Current and Sensor Data

Model Simulations and Analysis

The simulation results showed a marked improvement in battery life and efficiency, highlighting the critical role of early fault detection through the health check status in preventing major battery failures. The Battery Management System's (BMS) capability to identify and address cell degradation, capacity loss, and thermal issues early on led to a significant decrease in expensive repairs and bolstered user trust in the reliability of electric vehicles (EVs).

A key finding was the dynamic management of State of Charge (SOC) and State of Health (SOH) using real-time data, which was proven to prolong battery life and offer more precise driving range estimates, addressing a major concern for EV users. The ability to adaptively control charging and discharging processes optimized energy use, enhancing efficiency and minimizing energy waste.

The simulations also underscored the benefits of active cell balancing strategies informed by health status data, which further improved energy efficiency and battery performance. It was shown that maintaining a balanced state of charge among individual cells can significantly extend the overall battery lifespan. Additionally, temperature management strategies, adjusted based on the battery's health status, kept the battery within its ideal temperature range, promoting consistent efficiency and longevity.

Incorporating user feedback and enabling predictive maintenance were also key factors in improving user engagement and reducing vehicle downtime, ultimately maximizing the efficiency and reliability of the EV fleet. This holistic approach to battery management not only enhances the individual vehicle's performance but also contributes to the broader objectives of sustainable and reliable electric transportation.

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

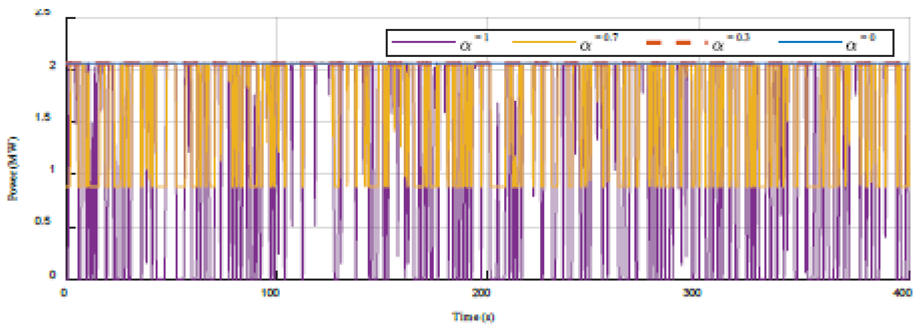

Figure 3: Simulated Total EV Load of Bus System

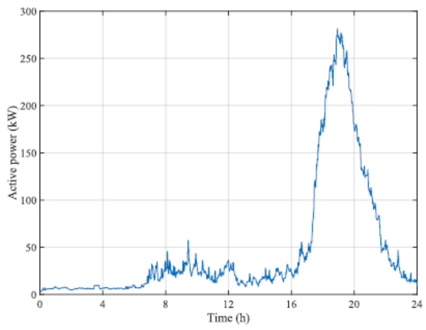

Figure 4: Simulated Measured Current and Sensor Plot

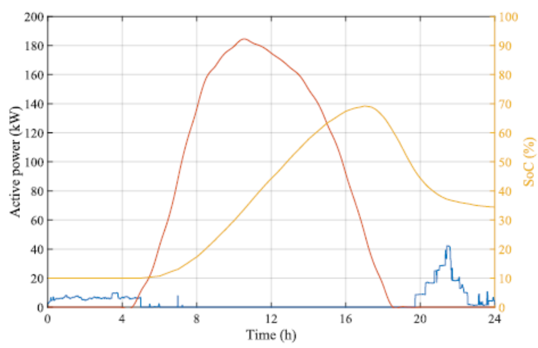

Figure 5: Total SOC Estimated for Simulated Values

Battery 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 [20], [21].

Conclusion

The inclusion of a health check status in the Battery Management System (BMS) is identified as a crucial innovation for tackling the intricate challenges of Electric Vehicle (EV) batteries. The capability for early fault detection not only boosts safety but also considerably cuts down on repair expenses, bolstering confidence in the dependability of EVs. The real-time dynamic management of State of Charge (SOC) and State of Health (SOH) enables EVs to deliver more precise range forecasts and prolong battery lifespan, mitigating a key concern for EV operators. This adaptive approach to charging and discharging, steered by the battery's health status, optimizes energy use and diminishes waste, thereby enhancing overall efficiency.

Moreover, strategies for active cell balancing and temperature regulation, driven by health data, further amplify battery efficiency and durability. The integration of user feedback, along with predictive maintenance and data analysis, presents a comprehensive battery management strategy that increases user involvement, reduces operational interruptions, and maximizes the efficiency of EVs. The adoption of a health check feature within the BMS represents a significant advancement in the quest for sustainable and efficient electric mobility. This study highlights its transformative impact, offering benefits not just to individual EV owners but also contributing to the broader objectives of environmental sustainability and encouraging the widespread use of electric vehicles.

References

[1] B. Balasingam, M. Ahmed, and K. Pattipati, “Battery Management Systems—Challenges and Some Solutions,” *Energies*, vol. 13, no. 11, p. 2825, Jun. 2020.
[2] S. G. Li, S. M. Sharkh, F. C. Walsh, and C. N. Zhang, “Energy and Battery Management of a Plug-In Series Hybrid Electric Vehicle Using Fuzzy Logic,” *IEEE Trans. Veh. Technol.*, vol. 60, no. 8, pp. 3571–3585, Oct. 2011.
[3] H. Kaja and D. T. Barki, “Solar PV technology value chain in respect of new silicon feedstock materials: A context of India and its ambitious National Solar Mission,” in *2011 Annual IEEE India Conference*, 2011, pp. 1–4.
[4] S. Li and P. Zhao, “Big data driven vehicle battery management method: A novel cyber-physical system perspective,” *Journal of Energy Storage*, vol. 33, p. 102064, Jan. 2021.
[5] M. Brandl *et al.*, “Batteries and battery management systems for electric vehicles,” in *2012 Design, Automation & Test in Europe Conference & Exhibition (DATE)*, 2012, pp. 971–976.
[6] H. Kaja, J. M. Stoehr, and C. Beard, “V2X-assisted emergency vehicle transit in VANETs,” *SIMULATION*, p. 00375497231209774, 2023.
[7] M. S. Ramkumar *et al.*, “Review on Li-Ion Battery with Battery Management System in Electrical Vehicle,” *Advances in Materials Science and Engineering*, vol. 2022, May 2022.
[8] W. Liu, T. Placke, and K. T. Chau, “Overview of batteries and battery management for electric vehicles,” *Energy Reports*, vol. 8, pp. 4058–4084, Nov. 2022.
[9] H. Kaja, *Survivable and Reliable Design of Cellular and Vehicular Networks for Safety Applications*. University of Missouri-Kansas City, 2021.
[10] G. L. Plett, “Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 1. Background,” *J. Power Sources*, vol. 134, no. 2, pp. 252–261, Aug. 2004.
[11] H. Kaja and C. Beard, “A Multi-Layered Reliability Approach in Vehicular Ad-Hoc Networks,” *International Journal of Interdisciplinary Telecommunications and Networking (IJITN)*, vol. 12, no. 4, pp. 132–140, 2020.
[12] M. S. Hossain Lipu *et al.*, “Intelligent algorithms and control strategies for battery management system in electric vehicles: Progress, challenges and future outlook,” *J. Clean. Prod.*, vol. 292, p. 126044, Apr. 2021.
[13] H. Kaja, R. A. Paropkari, C. Beard, and A. Van De Liefvoort, “Survivability and Disaster Recovery Modeling of Cellular Networks Using Matrix Exponential

Distributions," *IEEE Trans. Netw. Serv. Manage.*, vol. 18, no. 3, pp. 2812–2824, Sep. 2021.

[14] T. A. D. K. Duraisamy, "Active cell balancing for electric vehicle battery management system," *Int. J. Power Energy Syst.*, vol. 11, no. 2, pp. 571–579, Jun. 2020.

[15] R. Xiong, *Battery Management Algorithm for Electric Vehicles*. Springer Nature Singapore, 2020.

[16] C. Sen and N. C. Kar, "Battery pack modeling for the analysis of battery management system of a hybrid electric vehicle," in *2009 IEEE Vehicle Power and Propulsion Conference*, 2009, pp. 207–212.

[17] M. Lelie *et al.*, "Battery Management System Hardware Concepts: An Overview," *NATO Adv. Sci. Inst. Ser. E Appl. Sci.*, vol. 8, no. 4, p. 534, Mar. 2018.

[18] L. Lu, X. Han, J. Li, J. Hua, and M. Ouyang, "A review on the key issues for lithium-ion battery management in electric vehicles," *J. Power Sources*, vol. 226, pp. 272–288, Mar. 2013.

[19] K. W. E. Cheng, B. P. Divakar, H. Wu, K. Ding, and H. F. Ho, "Battery-Management System (BMS) and SOC Development for Electrical Vehicles," *IEEE Trans. Veh. Technol.*, vol. 60, no. 1, pp. 76–88, Jan. 2011.

[20] K. Liu, K. Li, Q. Peng, and C. Zhang, "A brief review on key technologies in the battery management system of electric vehicles," *Front. Mech. Eng. Chin.*, vol. 14, no. 1, pp. 47–64, Mar. 2019.

[21] A. Szumanowski and Y. Chang, "Battery Management System Based on Battery Nonlinear Dynamics Modeling," *IEEE Trans. Veh. Technol.*, vol. 57, no. 3, pp. 1425–1432, May 2008.