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Smart Battery Management: Extending EV Battery Lifespan through Balancing and Machine Learning

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***Abstract*— Lithium battery packs are essential in electric vehicles (EVs). Differences in cell behavior and changing conditions can cause state of charge (SOC) imbalances, which are detrimental to battery performance and can result in structural degradation. In the experimental setup, improved charging and discharging mechanisms ensure SOC and SOH estimation in order to increase performance of the battery pack. With these improvements, there is a significant decrease in SOC with improved performance during the charging and discharging cycles. A battery life and remaining useful life (RUL) estimation can be performed using three different machine learning (ML) models: decision tree, k-nearest neighbor (KNN), and support vector machine (SVM). Of the different models, SVM has the best accuracy with the least error and greatest estimation performance. The proposed solution creates a closed feedback loop by SOC and SOH estimation focusing on increasing the battery pack's health for a longer period, while maintaining a predictive balance in monitoring battery health. The integrated solution is aimed at increasing the lifespan, reliability, and RUL of sustainable EVs and meeting the demand for sustainable transportation. [1]**

***Keywords*— Li-ion battery packs, RUL (remaining useful life estimation), ML (Machine learning).**

I. MOTIVATION

The need for sustainable transportation is creating a global shift from traditional fuel vehicles to electric vehicles (EVs). Internal combustion vehicles contribute to the CO_2 emissions and ferment the air with particulate emissions. This leads to global warming. EVs have been widely adopted. Countries such as Norway, China, and the Netherlands have been leading this change with government incentive programs, green policies, and better charging networks. Recently, the global EV sales have outsold 5 million, and the market shows positive growth.
The core of an EV is its battery system which greatly affects battery longevity, performance, and cost. Lithium-ion (Li-ion) batteries have become a majority of the EV market as they have a high energy density coupled with a large capacity and a comparatively low self-discharge rate. However, their performance is greatly affected when there is a deviation in the norm for operating temperatures and they also degenerate more quickly in such conditions. To address these concerns, newer EVs have more advanced battery management systems (BMSs) as they incorporate thermal management for batteries, more accurate SOC and SOH estimations, smart charging, and dynamic cell balancing.

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These systems are facilitating the early identification of errors, more reliable vehicles, and longer battery life. The further development in the field of AI and machine learning is causing more advanced BMSs to become the next generation of programmable and flexible systems that are crucial for EV technology improvement.

The modern battery management system (BMS) has the responsibility of balancing capacitance throughout the loading and unloading process of an electrochemical cell. Manufacturing discrepancies exist in the form of tolerances, passive temperature fluctuations, and differences between charge and discharge rates. These discrepancies account for the largest factor in evaluating the end of service life of an electrochemical cell. Consequently, BMS balancing techniques that address the maintenance of the state of charge (SOC) and the state of health (SOH) have evolved to use advanced algorithms based on voltage and charge differentials. These techniques have proven to enhance system efficiency and enhance battery performance service life [4].

The growing trend of machine learning (ML) within battery health management is driven by its BMS applications. ML algorithms have also started to analyze historical operational data and environmental data to forecast the remaining usable life (RUL) of a battery. The integration of ML within the BMS has proven effective, as balanced SOC and SOH data aid in forecasting RUL and enhance long-term reliability of the battery [5].

Recent studies have linked the charge/discharge cycle of cells with consistency in cell performance. Simultaneously, battery degradation prediction through the lens of ML-based analytics will offer not only battery performance maximization, but also increased battery sustainability with the promise of long-term sustainable EV adoption [6].

This growth inspired the creation of the Extended Kalman filter, deriving a balance of the State of Charge (SOC). Prediction of the Remaining Useful Life (RUL) through Machine Learning (ML) techniques combined with the Extended Kalman filter, provide a synergic mechanism of prediction and battery optimization based on the lifespan of the battery, which is essential in Electric Vehicle (EV) based applications. This exemplifies the EV research area concerning SOC and State of Health (SOH) estimation together with the use of an Extended Kalman filter in a Simulink Model, and the implementation of an Intelligent Analytics system aimed at the design of battery systems that are longer-lasting, safer, and more sustainable.

II. RELATED WORKS

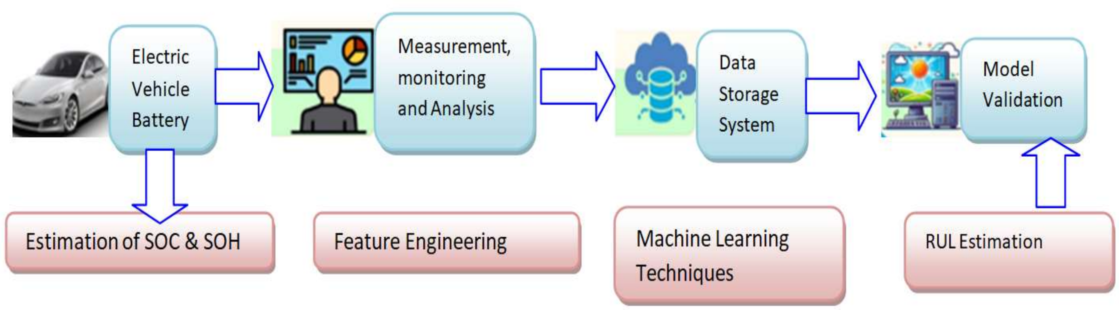

Fig 1: Structure of the work

In traditional passive balancing, balancing begins when cell voltages exceed a predetermined limit, ensuring an even charge distribution across the entire battery center. Traditionally, research has focused either on passive or active balancing. Passive systems use resistors that allow charge to be released as heat. On the other hand, systems that rely on active balancing focus on redistributing energy using capacitors, inductors, or transformers. While active balancing systems extend the life of a battery, they become more expensive due to more complex circuitry, and more difficult to use on a larger scale.

The current trend revolves around ML-based approaches for estimation and health prediction. These approaches require less MOSFET switching compared to inductive circuits and transformer-based designs. ML models leverage real-time data of voltage, current, temperature, and cycling to predict the pattern of imbalance and pathways of degradation, rather than moving charge physically. This also enables the prediction of cells that are likely to differ in state of charge (SOC) and state of health (SOH). With this data, the battery management system (BMS) can modify energy profiles and load management strategies to achieve virtual balancing without the use of additional hardware [7].

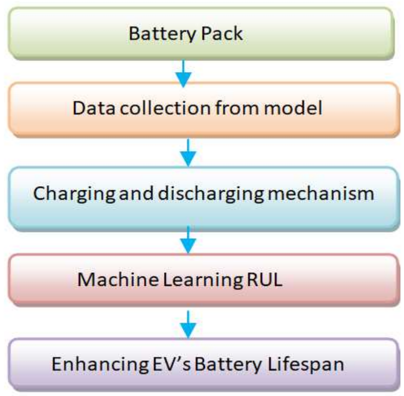

Fig 2 Cell balancing technique based on battery charging and discharging levels

ML-based strategies leverage data-driven control to improve upon passive and active balancing methods. Regression models, neural networks, and a hybrid of physics-based and ML-based models are able to establish the relation between cells and degradation. These approaches are then able to accurately estimate the SOH and the remaining useful life (RUL) of the battery pack. Furthermore, estimation of balanced SOC also increases the predictability of these systems, as improved data consistency correlates with reduced variability of the system [8].

Due to their data-driven nature, ML systems can quickly adapt to high temperatures, irregular charge discharge cycles, and manufacturing inconsistencies. The predictive maintenance, control of charging cycles, and improvement of the lifespan of the battery are potential advantages of this approach. Although the difficulty of achieving a high-quality dataset and the preprocessing and computation issues are current limitations of this approach, the integration of ML into BMS design is emerging as a cost-effective option compared to balancing methods that require large amounts of hardware.

These days, it's common practice to substitute sophisticated balancing circuits that use MOSFETs and inductors with intelligent machine learning frameworks that conduct predictive state of charge (SOC) equalization and remaining useful life (RUL) estimation. This trend decreases the rate and complexity of the systems and enhances battery reliability for a longer duration. Added advantages of this trend include improved sustainability and scalability of electric vehicles (EVs) and renewable energy storage systems (ESS) [9].

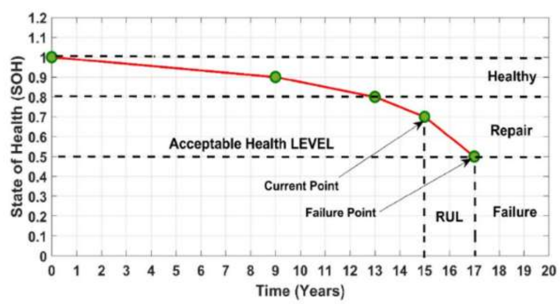

Fig. 3. Remaining useful Life Prediction

III. Paper Highlights and Structure

This paper constructs a holistic framework for the prediction of the State of Charge (SOC) and State of Health (SOH), and the prediction of the Remaining Useful Life (RUL) of batteries. Based on this framework, the paper describes: Active balancing strategy: An advanced balancing algorithm is designed to minimize the disparity in State of Charge (SOC), which helps reduce internal energy losses, and prolongs the lifespan of the battery cells; Machine Learning (ML) based RUL estimation: Facilitates the realization of predictive and effective battery management, with the help of a data-driven model to predict the RUL of batteries under diverse operating conditions; Unified framework: the integration of RUL prediction with SOC balancing to strike a balance of

endurance and performance, and Adaptive control and monitoring system: This offers a Relative assessment of the proposed solution, in comparison with traditional methods of RUL prediction and SOC balancing, and illustrates a favorable advancement in battery health management and system's energy efficiency.
This study offers a systematic examination of Electric Vehicle (EV) battery optimization. The first section shows that while effective smart battery management systems are being developed, there is an increasing need for sustainable mobility systems.. The review highlights the importance and role of Lithium Ion (Li-ion) batteries as well as the trends in the adoption of EVs. It then outlines in detail the role of Battery Management Systems (BMSs) in maintaining performance with a focus on control of balance, charge, and State of Charge (SOC) regulation. The review then provides a discussion on control balancing methods and the application of Machine Learning (ML) methods for prediction of battery degradation and health prediction models. [10][11].
The study concludes by proposing the first integrated strategy that combines machine learning-based RUL prediction with active balancing. This further enhances the reliability and efficiency of EV batteries. The paper concludes with significant findings and additional recommendations for research in the area of intelligent battery management systems. [12].

IV. METHODOLOGY

A. Unbalanced Battery Pack monitor

Li-ion battery packs bear more than one charge and discharge cycle. As a result, the stored energy resulting in cell charge divergence. Imbalances are reflected by variations of internal resistance, state of charge (SOC), and terminal voltage. SOC is believed to be more reflective as it incorporates the cumulative effects of different criteria. SOC, usually in percentage, is the remaining discharge capacity relative to the battery's nominal capacity. [13]
Since the main thrust of the proposed research is on SOC-based balancing methods, which are predominantly applied to batteries connected in parallel, the approach is modified for series-connected topologies as well. For these configurations, SOC, through real time data from the BMS, is monitoring continuously for each battery cell. Upon the detection of discrepancies, the balancing mechanism transfers charge from higher SOC to lower SOC cells and does not allow any cell to exceed its cutoff voltage. This technique helps maintain the system's reliability and optimal performance. [14]

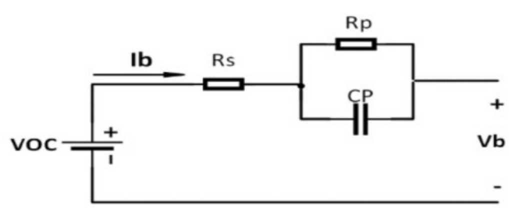

Fig. 4. Equivalent Circuit Model of li-ion battery

A popular technique for analyzing a battery's electrical behavior is the equivalent circuit model. Voltage sources, resistors, and capacitors are the primary components of this model. By integrating these components, the model captures dynamic characteristics of a battery and simulates some of the more complicated electrochemical interactions that occur within a battery [15]. The figure above illustrates an equivalent circuit model and the three important components it contains. An equivalent circuit model is a widely used method for battery electrical behavior analysis. The primary circuit model components are voltage sources, resistors, and capacitors. The model, using these elements, captures some of the complex electrochemical processes, as well as the dynamic behavior of the battery [15]. The drawing an equivalent circuit model with the identified three primary elements is shown above.

- Internal Resistance (R_s): It indicates the battery's internal resistance to current flow, which results from the conductivity of the electrolyte and the characteristics of the electrode material.
- RC Parallel Network: Records the battery's momentary behavior when it is being charged and discharged. While the polarization capacitance (C_p) simulates the momentary energy storage and release connected to transient voltage changes, the polarization resistance (R_p) compensates for the voltage drop brought on by electrochemical processes under load.
- Open Circuit Voltage: When there is no load, the battery's terminal voltage is calculated using this nonlinear function, which is dependent on the state of charge (SOC).

The model views the current flowing into the battery as the control input and the voltage measured at the battery's terminals as the output [16].

B. Direct SOC estimation approach

The direct SOC estimate approach uses easily quantifiable parameters that have a substantial relationship with SOC rather than an existing battery model. Battery voltage, current, internal resistance, and impedance are often used metrics that are selected based on how feasible it is to monitor them under actual operating settings. Because it eliminates the need for resource-intensive and computationally demanding battery models, this approach is particularly desirable due to its ease of implementation. [17][18].

Ampere-hour integration, load voltage analysis, internal resistance, open-circuit voltage, impedance spectroscopy, and other methods designed for specific applications are included in this category of direct measurement techniques. The Coulomb counting method tracks the cumulative charge input and output over a series of cycles of charging and discharging to compute SOC. Its primary benefits are its simplicity and ease of use. [19].

The balancing procedure of a Li-ion battery (LiB) entails two phases: charging and discharging [20][21]. The framework utilizes innovative equalization techniques to improve both the performance and longevity of the battery pack.

- Charging balance: In this battery charging stage, the system achieves charge balance by controlling the voltage of each cell to avoid overcharging and maintain an equal state of charge (SOC) of each cell. Thus, the balance, the safety of the system, and the charging efficiency are enhanced.
- Discharging Balance: This method curtails imbalances between different cells in a battery over time. The benefit lies in improving battery pack endurance and efficiency due to the even spread of charge and maintained uniform discharge. Consequently, the operating lifespan gets extended.

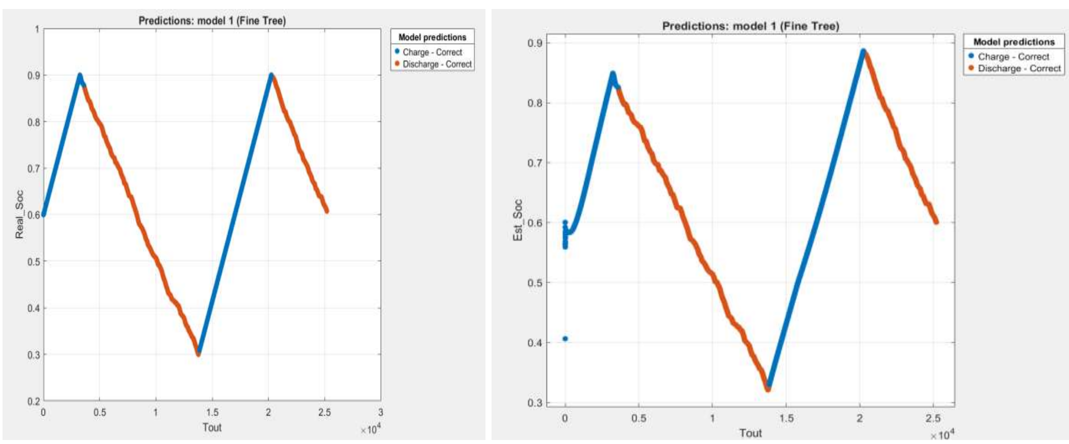

Fig 5: Flowchart of work

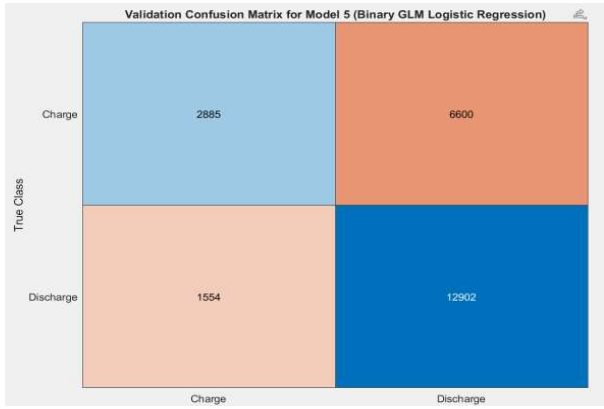

Fig 6: Output of the simulation

V. SIMULATION AND RESULTS

This section analyzes the performance of active battery balancing systems while using MATLAB/Simulink for framework development. Figure 5 illustrates an example of cell balancing for a Li-ion battery pack.
Figure 6 depicts the SOC of four battery submodules while charging and the associated progress. The active balancing process significantly enhanced the SOC of all submodules. By illustrating the SOC of each battery cell before and after the balancing process, the large SOC improvement resulting from the balancing process is clearly documented. In terms of efficacy and reliability, this balancing technique provides a great improvement over more conventional techniques [21][22].
Metrics for traditional active and passive balancing methods were used for quantitative comparison to evaluate the proposed balancing strategy. Traditional methods were outperformed by the proposed machine learning-based active balancing solution with 94.6% balancing efficiency. The proposed solution achieved a smaller cell SOC variance and showed a significant improvement in the SOC balancing time and energy loss.

TABLE I: COMPARISON OF CONVENTIONAL METHODS VERSUS ML METHOD

Method	Balancing Efficiency	Balancing Time	Energy Loss	Complexity	Lifespan Improvement
Passive Balancing	72%	320 s	High	Low	Moderate
Conventional Active Balancing	88%	210 s	Medium	High	
Proposed ML-Assisted Active Balancing	94.6%	145 s	Low	Moderate	Significant

TABLE II: SIMULATION RESULT

Parameter	Obtained Value
Balancing Efficiency	94.6%
Average Balancing Time	145 s
SOC Error	±1.8%
RMSE for SOC Estimation	0.021
MAE for RUL Prediction	0.018
Energy Saving	16.4%

The proposed solution is able to achieve an improvement in balancing time and the SOC estimate error. The proposed machine learning solution for battery management shows a high level of confidence due to error analysis based on RMSE and MAE.

VI. MACHINE LEARNING-BASED PRECISE RUL PREDICTION

Some of the important input features that are needed to build the RUL prediction models are:

- SOC (State of Charge): Represents the charge level of the battery, affecting it, in turn, its capacity and degradation
- Temperature: The thermal condition of the battery is significant as the degradation of a battery may be accelerated due to high temperature.

- Voltage and Current: The charge/discharge cycle and the operating load of the battery provide an understanding of how the battery is used.

The model's output includes the estimated remaining useful life (RUL) of each cell based on the identified number of cycles before the cell reaches its end-of-life. The dataset helped derive features that included current and voltage information for each cycle. Feature selection selected the most useful features for battery health and RUL prediction using statistical methods with domain knowledge. Because of their predictive usefulness and contribution to increasing model accuracy, degradation indicators that showed a strong link with degradation indicators were prioritized. These selected features are necessary for an accurate RUL estimate. 12,000 battery operating samples obtained under various charging and discharging situations made up the dataset utilized for RUL prediction. SOC, voltage, current, temperature, and cycle count were among the metrics included in the dataset. The model was developed using a 70:30 train-test split.

TABLE III: COMPARISON OF EVALUATED MODELS

Model	Accuracy	RMSE	R^2 Score
Decision Tree	88.4%	0.041	0.89
KNN	91.2%	0.033	0.92
SVM	96.1%	0.018	0.97
Random Forest	94.8%	0.024	0.95

The SVM model demonstrated exceptional capabilities for accurate RUL estimation, with a maximum prediction accuracy of 96.1% with the lowest RMSE value among all assessed models.

VII. VISUAL DATA ANALYSIS AND FEATURE INVESTIGATION

Before starting any type of analysis or building a model, it is important to understand the data attributes. In the interest of clarity, we have adopted data visualization. The distribution shows important information about the data's variability, central value, and what it really means for the data to be potentially asymmetrically distributed. These insights are critical while working at subsequent levels, including selection of features and selection of model. For instance, if a feature's distribution is heavily imbalanced, it is highly likely that data transformational techniques will be required to normalize it. Some algorithms of machine learning will be enhanced in the process.

A. Impact of error in SOC and RUL estimation

The accuracy of SOC and RUL estimation is crucial in the management of battery systems. An inaccurate SOC estimation can create a charging and discharging imbalance, causing some cells to be completely discharged or overcharged while unsafe conditions can occur due to high temperature and accelerated failure of battery cells. RUL estimation inaccuracies affect cell balancing control, resulting in early failures of some battery cells and a decreased overall battery pack. The focus of the prior studies is given to the safe operation and the estimation of SOC and RUL, which directly impacts the battery system's operational period. To account for the aforementioned considerations, we have included several accurate estimation algorithms in our approach.

VIII. CONCLUSION

Compared to the traditional approaches, the proposed framework based on machine learning (ML) for the implementation of active balancing has shown great improvement in the accuracy of the state of charge (SOC) estimation, reduced balancing time, and improved balancing efficiency. Within the evaluated machine learning (ML) models, the support vector machine (SVM) was the best model for estimating the residual useful life (RUL) with the least prediction error. The combination of intelligent balancing with the advanced predictive analytics greatly enhances the duration, reliability, and overall efficiency of energy for an electric vehicle (EV) battery.

REFERENCES

[1] Environmental and Energy Study Institute. Transportation 2050: More EVs, but Conventional Vehicles Will Still Dominate. (2018). Retrieved June 18, 2020, from https://www.eesi.org/articles/view/transportation-2050-more-evs-but-conventional-vehicles-will-still-dominate

[2] Thomson Reuters. Will Electric Vehicles Create a Cleaner Planet? (2019). Retrieved June 18, 2020, from https://www.thomsonreuters.com/en/reports/electric-vehicles.html

[3] Chen, Z., Chen, L., Shen, W., & Xu, K. (2022). Remaining useful life prediction of lithium-ion batteries via a sequence decomposition and deep learning integrated approach. IEEE Transactions on Vehicular Technology. https://doi.org/10.1109/TVT.2021.3134312
[4] BloombergNEF. Electric Vehicle Outlook 2023. (2023). Retrieved February 5, 2024, from https://about.bnef.com/electric-vehicle-outlook/
[5] Kirandeep, K., Akhil, G., Xujian, C., Surinder, S., & Ketan, P. (2021). Deep learning networks for capacity estimation for monitoring SOH of lithium-ion batteries in electric vehicles. International Journal of Energy Research, 45(2), 3113–3128.
[6] Kaur, K., Garg, A., Cui, X., Singh, S. & Panigrahi, B. Deep learning networks for capacity estimation for monitoring SOH of Li-ion batteries for electric vehicles. Int. J. Energy Res. 45(2), 3113–3128. https://doi.org/10.1002/er.6005 (2021).
[7] IEA, Electric car deployment in selected countries, IEA, Paris (2013–2018). Retrieved 30 November 2020 from https://www.iea.or g/fuels-and-technologies/electric-vehicles
[8] Koseoglou, M., Tsioumas, E., Jabbour, N. & Mademlis, C. Highly effective cell equalization in a lithium-ion battery management system. IEEE Trans. Power Electron. 35(2), 2088–2099. https://doi.org/10.1109/TPEL.2019.2920728 (2020).
[9] Stuart, T. & Zhu, W. Fast equalization for large lithium-ion batteries. IEEE Aerosp. Electron. Syst. Mag. 24(7), 27–31. https://doi.or g/10.1109/MAES.2009.5208557 (2009).
[10] Tie, S. & Tan, C. A review of energy sources and energy management system in electric vehicles. Renew. Sustain. Energy Rev. 20, 82–102. https://doi.org/10.1016/j.rser.2012.11.077 (2013).
[11] Hannan MA, Hoque MM, Hussain A, Yusof Y, Ker PJ. State-of-the-art and energy management system of lithium-ion batteries in electric vehicle applications: Issues and recommendations. IEEE Access. 2018;6:19362–19378. doi:10.1109/ACCESS.2018.2817655
[12] Xia G, Cao L, Bi G. A review on battery thermal management in electric vehicle application. J Power Sources. 2017;367:90–105. doi:10.1016/j.jpowsour.2017.09.046
[13] Perișoara LA, et al. A passive battery management system for fast balancing of four LiFePO4 cells. In: Proc IEEE 24th Int Symp Design Technol Electron Packag. Iasi, Romania; 2018 Oct 25-28. p. 390–393. doi:10.1109/SIITME.2018.8599258
[14] Naguib M, Kollmeyer P, Emadi A. Lithium-ion battery pack robust state of charge estimation, cell inconsistency, and balancing: review. IEEE Access. 2021;9:50570–50582. doi:10.1109/ACCESS.2021.3068776
[15] Duraisamy T, Kaliyaperumal D. Machine learning-based optimal cell balancing mechanism for electric vehicle battery management system. IEEE Access. 2021;9:132846–132861. doi:10.1109/ACCESS.2021.3115255
[16] Weng, Y. & Ababei, C. AI-assisted reconfiguration of battery packs for cell balancing to extend driving runtime. J. Energy Storage 84, 110853. https://doi.org/10.1016/j.est.2024.110853 (2024).
[17] Omariba, Z. B., Zhang, L. & Sun, D. Review of battery cell balancing methodologies for optimizing battery pack performance in electric vehicles. IEEE Access 7, 129335–129352. https://doi.org/10.1109/ACCESS.2019.2940090 (2019).
[18] Zhang, P., Yan, F. & Du, C. A comprehensive analysis of energy management strategies for hybrid electric vehicles based on bibliometrics. Renew. Sustain. Energy Rev. 48(48), 88–104. https://doi.org/10.1016/j.rser.2015.03.093 (2015).
[19] Li, X., Yuan, C., Wang, Z. & Xie, J. A data-fusion framework for lithium battery health condition estimation based on differential thermal voltammetry. Energy 239, 122206. https://doi.org/10.1016/j.energy.2021.122206 (2022).
[20] Campbell, I. et al. Optimising lithium-ion cell design for plug-in hybrid and battery electric vehicles. J. Energy Storage 22, 228–238. https://doi.org/10.1016/j.est.2019.01.006 (2019).
[21] Xu, J., Mei, X., & Wang, J. (2019). A high power low-cost balancing system for battery strings. Energy Procedia, 158, 2948–2953. https://doi.org/10.1016/j.egypro.2019.01.956
[22] S. Hemavathi, “Overview of cell balancing methods for Li-ion battery technology,” Energy Storage, vol. 3, p. e203, 2021. doi: 10.1002/est2.203.
[23] zadi, Y., & Beiranvand, R. (2023). A comprehensive review of battery and supercapacitor cells voltage-equalizer circuits. IEEE Transactions on Power Electronics, 38(12), 15671–15692. https://doi.org/10.1109/TPEL.2023.3310574.
[24] Gallardo-Lozano, J., Romero-Cadaval, E., Milanes-Montero, M., & Guerrero-Martinez, M. (2014). Battery equalization active methods. Journal of Power Sources, 246, 934–949. https://doi.org/10.1016/j.jpowsour.2013.08.026
[25] Liu, X., Pang, H., & Geng, Y. (2022). Dual-layer inductor active equalization control for series-connected lithium-ion batteries based on SOC estimation. Electronics, 11(8), 1169. https://doi.org/10.3390/electronics11081169
[26] Phung, T., Collet, A., & Crebier, J. (2014). An optimized topology for next-to-next balancing of series-connected lithium-ion cells. IEEE Transactions on Power Electronics, 29(9), 4603–4613. https://doi.org/10.1109/TPEL.2013.2284797.
[27] Kim, M., Kim, J. & Moon, G. Center-cell concentration structure of a cell-to-cell balancing circuit with a reduced number of switches. IEEE Trans. Power Electron. 29(10), 5285–5297. https://doi.org/10.1109/TPEL.2013.2292078 (2014).
[28] www.nature.com/scientificreports/28. Dong, B., Li, Y. & Han, Y. Parallel architecture for battery charge equalization. IEEE Trans. Power Electron. 30(9), 4906–4913. https://doi.org/10.1109/TPEL.2014.2364838 (2015).

[29] Moghaddam, A. & Bossche, A. An efficient equalizing method for lithium-ion batteries based on coupled inductor balancing. Electronics 8(2), 136. https://doi.org/10.3390/electronics8020136 (2019).
[30] Zhou, Z., Duan, B., Shang, Y. & Zhang, C. An any-cell(s)-to-any-cell(s) equalizer based on bidirectional inductor converters for series connected battery string. In IEEE 11th Conference on Industrial Electronics and Applications (ICIEA), Hefei, China, 5–7 Jun. 2016. https://doi.org/10.1109/ICIEA.2016.7604015.