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Weak Cell Analysis and Verification for EV System with Dynamic Load

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Abstract: Lithium-ion batteries (LIBs) are essential parts of electric vehicle (EV) systems, however internal resistance fluctuations, cell degeneration, and heat issues affect their dependability. Early detection of weak cells under dynamic load conditions is crucial to ensuring safety and extending battery life. This paper proposes a two-stage approach to identify weak cells during time-varying load operation. Thermal validation is used to locate the damaged cell within the battery string after voltage variation and threshold-based analysis are used to identify abnormal cell behaviour. Strip voltage response under dynamic loading isempirically validated and mathematically analysed. The proposed WAVES framework enhances BMS performance by providing a scalable and computationally efficient solution for real-time problem diagnosis in EV without requiring complex hardware or a significant amount of training data.

Key words: Battery Management System (BMS), Electric Vehicles (EVs), Internal Resistance (IR), Li ion battery pack (LIB), Neither Charging nor Discharging (NCND), Open Circuit Voltage (OCV), Passive Cell Balancing, Solid Electrolyte Interface (SEI), State of Charge (SoC)

I. INTRODUCTION

The high energy density, extended lifespan, and high efficiency of lithium-ion batteries (LIBs) make them popular in contemporary energy storage applications [1]. Reliability and safety are crucial issues due to their extensive use in consumer devices, electric cars, and grid storage [2]. However, problems such internal short circuits, thermal runaway, and capacity deterioration have a big impact on operational stability [3]. Therefore, improving safety, performance, and lifetime requires early detection of such defects [4].

Although they are useful for broad supervision, conventional monitoring techniques based on voltage, current, and temperature data are unable to precisely locate weak cells or identify early-stage problems [5]. Data-driven approaches, especially machine learning, have been extensively investigated for fault detection and State of Health estimate in order to overcome these constraints [6]. In order to detect weak cells more accurately, identify degradation patterns, and classify abnormal circumstances, machine learning models can examine historical data [7]. Neural networks, Random Forest, Support Vector Machines, and optimization techniques like Particle Swarm Optimization and Genetic Algorithm have demonstrated encouraging outcomes [8]-[9]. Nevertheless, these methods necessitate extensive labelled datasets and a variety of fault scenarios, which are hard to come by in real-world battery systems.

The challenge of identifying localized weak cells is further complicated in series-parallel battery configurations, where labelling individual cell faults is not feasible. Although Battery Management Systems provide voltage and current monitoring along with cell balancing, they are limited by sparse temperature sensing and the inability to distinguish individual cells within parallel groups [10]. Advanced sensing techniques such as infrared thermography are constrained by cost and accessibility.

Because weak cells have lower voltage and higher internal resistance, they put more strain on healthy cells by drawing extra charge, which can cause overheating and hastened degradation. Thermal runaway could occur if this is not addressed [11]-[12]. In order to provide precise and localized fault detection with little reliance on sensors and fewer computing limitations, an effective solution is needed so proposed WAVES under NCND condition [13].

The rest of this document is structured as follows: Section II examines current developments and the body of extant literature; The problem formulation and mathematical analysis are presented in Section III; the suggested approach is described in Section IV;

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II. LITERATURE REVIEW

Lithium-ion battery (LIB) defect detection in electric vehicles (EVs) has made significant strides recently, but there are still a number of issues. Precise fault isolation is made possible by model-based techniques, such as switched designs that use comparable cell modelling. These techniques are effective, but they are not suitable for real-time applications due to their high implementation complexity and substantial processing overhead [14].

Techniques based on data and machine learning have been widely used to improve the accuracy of fault detection. These methods enable automated diagnostics and take fault investigation from detection to quantification [15]. However, their scalability and real-time application are limited by their reliance on huge training datasets and high processing requirements, especially in dynamic and uncertain operational settings.

Aging features are successfully incorporated into the diagnostic process by methods intended to handle both new and old battery cells [16]. Although it is restricted to errors linked to voltage, the weighted Euclidean distance approach [17] successfully detects voltage discrepancies. Although it has problems with scalability and flexibility, the diagnostic technique in [18] improves practical applicability. High accuracy is attained using machine learning approaches [19], but they demand substantial computer power and vast datasets. Automated fault analysis in charging stations is made possible by the method in [20]. However it has trouble with dynamic and unexpected fault patterns. Although segmented regression [21] is straightforward and efficient, it performs badly in a variety of operating environments. Although it requires more validation, a transferable diagnostic approach [22] enhances flexibility between cells. While [23] offers a thorough analysis but lacks innovative techniques, [24] facilitates practical diagnosis using driving data in real circumstances, and [25] detects tiny problems with higher granularity, increasing complexity.

However, their restricted scalability and decreased efficacy in highly dynamic contexts frequently limit their performance. Voltage-based methods, such as curve analysis and distance-based methods, offer accurate detection of internal flaws and voltage irregularities. However, these approaches are usually restricted to particular fault types and fail to account for the multi-parameter interactions found in actual battery systems.

To deal with changing battery behaviour and concept drift, statistical and adaptive methods, such as unsupervised learning techniques, have been developed. Although these techniques offer flexibility, they also increase computing complexity and make it more difficult to discern between noise and real fault events [26]. Similar to this, methods for identifying small irregularities and recreating malfunctioning sensor signals improve data dependability and diagnostic granularity but rely significantly on sensor accuracy and system setup [27]. Large training datasets are also needed. The technique in [28] is limited to voltage-related defects but uses partial voltage curves to detect internal short circuits with good accuracy. Although the method in [29] can identify problems with parallel battery packs, such as sensor and internal resistance problems, it is not scalable for bigger systems.

The practical relevance of defect detection techniques has increased as a result of efforts to close the gap between laboratory diagnostics and practical applications. Scalability, data variability, and environmental adaption issues still exist, nevertheless. Although cloud-based diagnostic systems provide better scalability and centralized analysis, latency and data security issues are raised [30].

Internal problems such micro short circuits can be found with high precision using sophisticated diagnostic methods based on electrode parameters, relaxation voltage, and incremental capacity analysis [31]. Despite their accuracy, these techniques are frequently restricted to particular fault circumstances and necessitate precise parameter estimation. Additionally, early thermal runaway detection methods improve safety but are difficult to integrate with current battery management systems (BMS). In general, real-time monitoring of critical parameters like voltage, current, and temperature is emphasized by contemporary BMS frameworks. However, because of the interconnectedness of cells and the nonlinear nature of fault propagation, weak cell identification continues to be a major difficulty. Conventional threshold-based techniques are frequently insufficient since they may produce false alarms and are unable to identify minor flaws.

- A systematic two-stage diagnostic methodology is suggested that uses strip voltage for the first electrical examination and thermal imaging for validation under dynamic load circumstances. At a time multiple weak cells are identified.
- MATLAB / Simulink are used to validate the suggested method, showing consistent patterns of voltage and heat behaviour.
- According to experimental findings, aged cells with higher internal resistance show higher surface temperatures and sharper voltage drops, making it possible to identify weak cells.
- Practical implementation in battery management systems is made possible by the method's avoidance

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of invasive measurements and expensive impedance-based diagnostic equipment.

III. METHODOLOGY

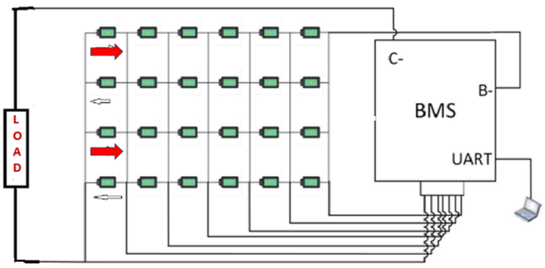

Fig 1: Block diagram of the BMS

For real-time weak cell detection in lithium-ion battery packs utilized in electric car applications, a dynamic load-based framework is suggested. Fig 1 explains the suggested method uses a controlled dynamic load to replicate actual operating conditions, in contrast to conventional approaches that function under Neither Charging Nor Discharging (NCND) conditions, when fault detection is limited due to minimal voltage change. This makes capacity mismatches and variations in internal resistance between cells more visible.

Each parallel strip is observed by the architecture as a functional unit. Weak cells show more voltage drops and more heat production under dynamic loading because of higher internal resistance and lower charge retention. The system incorporates temperature sensors, voltage sensors, and a dynamic load module to continuously monitor thermal and electrical activity. Significant voltage reductions are correlated with aberrant temperature increases to identify weak cells, increasing detection accuracy and dependability.

The contact resistances value is calculated as 0.00964mΩ, hence R=0.00964mΩ. However, the value of R can also be obtained from the manufacturer. Similarly, the values of V_H and V_F can also be user defined. The LIB configuration details will be provided by the manufacturer, thus M and N are also user defined [13].

Table 1: Nickel Strip Specifications

Dimension (mm)	Cell Spacing (mm)	Width (mm)	Dimension of square hole (mm)
0.15x27x19.5	19.75	27	12.5x12.5

The expected strip voltage in a lithium-ion battery strip with a weak cell is estimated using a straightforward yet efficient linear model. The method begins by identifying the total strip resistance R and the voltage of a healthy cell (V_H) and a weak cell (V_F), where V_F is less than V_H. These characteristics are then arranged into an input matrix X, where a single weak cell is positioned at different locations within a four-cell strip to indicate distinct fault states.

In the matrix X, each row denotes a specific failure condition: Depending on where the weak cell is located, the first four columns in each row represent the voltages of individual cells, with values of either V_H or V_F.

The known strip resistance R which takes into account the voltage drop brought on by resistive effects, is always found in the fifth column. By resolving the linear equation, the model ascertains the relationship mathematically:

$$X \cdot A = Y \text{..........(1)}$$

where:

- X is a (N+1)×(N+1) matrix consisting of voltage arrangements and resistance,
- Y is a (N+1)×1 output vector representing expected strip voltages.
- A is the unknown coefficient vector estimated using MATLAB's backslash operator (A=X\Y), which computes the least-squares solution to the linear system.

$$Avg = V_F + (N - 1)V_H /N,\ d = V_H - avg/N\text{...(2)}$$

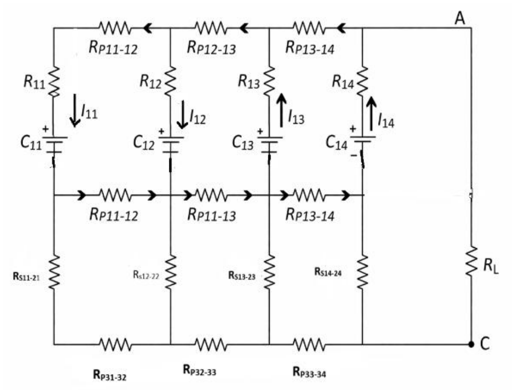

Fig 2: cells C11,C12 are weak

When C_{11}, C_{12} are weak:

Where $R_{12\text{–}11,13\text{-}11}$ refers to the resistance path for the current contributed by cell C_{13}, R_{11}, R_{12} and R_{13} represent the IR of the cell C_{11} and C_{12} respectively.

$$R_{13\text{-}12,13\text{-}11}=R_{13}+R_{P12\text{-}13}+R_{12}+R_{P11\text{-}12}+R_{11}\text{.....(3)}$$

Where $R_{14\text{–}12,14\text{-}11}$ refers to the resistance path for the current contributed by cell C_{14}, R_{11}, R_{12} and R_{14} represent the IR of the cell C_{11},C_{12} and C_{14} respectively. The cell C_{14} is the

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farthest from C_{11}, C_{12} and feeds charge through path resistance.

$R_{14-12,14-11}=R_{14}+R_{P13-14}+R_{P12-13}+R_{P11-12}$
$+R_{11}$..........(4)

$R_{13-12,13-11}<R_{14-12,14-11}$......(5)

$I_{13-12,13-11}>I_{14-12,14-11}$........(6)

For weak cell C_{11}:

$$V_{AC,11} = V_H - \Delta V_{IR,11} - I_L \cdot R_L \ldots\ldots (7)$$

For weak cell C_{12}:

$$V_{AC,12} = V_H - \Delta V_{IR,12} - I_L \cdot R_L \ldots\ldots (8)$$

Now both weak cells contribute to voltage drop:

$$V_{AC} = V_H - \left(\Delta V_{IR,11} + \Delta V_{IR,12}\right) - I_L R_L \ldots (9)$$

$V_{MN}= \sum_{j=1}^{N} A_j \,.V_j + B.R$....(10)

Where;

M=no of cells connected in series

N=no of cells connected in parallel

A_j, B=unknown coefficients

X.A=Y..........(11)

Avg = V_F + (N − 1)V_H /N.........(12)

d = V_H − avg/ N......................(13)

d=decremental setup

IV. RESULTS AND DISCUSSION

The enhanced simulation model of the EV battery system used to more precisely identify weak cells is shown in Fig 2 by the Simulation Diagram . By including voltage threshold analysis and temperature monitoring for several cells under dynamic load conditions, this model expands on the base scenario.

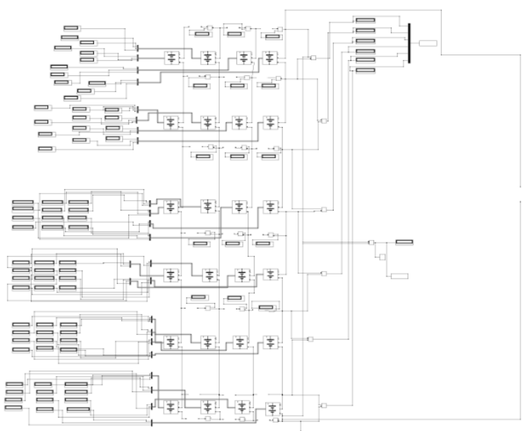

Fig 3: Simulation diagram

1. Battery Pack Model: A battery pack made up of several lithium-ion cells connected in series is used to start the simulation. During operation, each cell generates voltage and temperature values. The extension model allows for the purposeful weakening of two or more cells in order to examine system behaviour.

2. Dynamic Load Block: This involves applying a dynamic load to the battery pack. Dynamic load refers to a demand that varies over time, much like actual EV circumstances like braking, acceleration, and hill climbing. This makes it easier to see how each battery cell responds to actual driving circumstances.

3. Voltage Measurement Unit: This device continually measures the voltage of every cell in the battery string. The analysis block receives these voltages.

4.Voltage Threshold Analysis: A predetermined threshold value is compared to each cell voltage. Abnormal or weak cell behaviour is indicated when a cell voltage falls below the threshold. The extension model allows the system to simultaneously identify several weak cells.

5.Temperature Monitoring: Temperature of the cell is tracked once anomalous voltage behaviour is identified. Due to greater internal resistance, weak or malfunctioning cells typically exhibit higher temperatures. This stage aids in identifying the precise cell and verifying the error.

6.Output of fault detection: Temperature variation and voltage deviation results are the outputs of the system. These outputs are used to determine which battery pack cells are weak

7.Visualization of Results: The findings of the simulation reveal:
Cells falling below the threshold on the voltage graph.
A temperature graph that displays elevated temperatures for weak cells.

According to the testing findings, the strip with the lowest voltage is the weakest part since lower voltage indicates greater internal resistance and degradation. According to the obtained data, the C_{63}–C_{64} strip records the greatest temperature among the cells while exhibiting relatively lower voltage values. C_{63} and C_{64} are the weakest cells in the pack, as evidenced by the association between voltage drop and temperature rise, which implies higher internal losses.

Voltage deviation and temperature variation helps us to detect the weak cell location.This two stage dectection makes the model more reliable for battery Management Systems(BMS) in EVs.

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BASE CASE RESULTS

Table 2: Voltage Threshold Analysis

	V_{ab}	V_{bc}	V_{cd}	V_{de}	V_{ef}	V_{fg}	V_{Total}
All healthy	4.042	4.042	4.042	4.042	4.042	4.042	24.255
C21	4.041	4.055	4.041	4.041	4.042	4.042	24.265
C22	4.12	4.39	4.125	4.063	4.047	4.043	24.796
C23	4.074	4.531	4.076	4.043	4.040	4.041	24.809
C24	4.067	3.981	4.069	4.048	4.044	4.043	24.214

Table 3: Cell Temperature

	C21	C22	C23	C24
1	19.8	19.8	19.8	19.83

PROPOSED RESULTS

Table 4: Voltage Threshold Analysis

	V_{ab}	V_{bc}	V_{cd}	V_{de}	V_{ef}	V_{fg}	V_{Total}
All healthy	4.042	4.042	4.042	4.042	4.042	4.042	24.255
C11, C12	3.147	3.400	3.44	3.44	3.42	3.28	20.15
C13, C14	2.92	3.46	3.45	3.45	3.43	3.29	20.02
C21, C22	3.25	3.19	3.41	3.44	3.43	3.29	20.03
C23, C24	3.31	3.11	3.48	3.45	3.43	3.28	20.09
C31, C32	3.28	3.40	3.27	3.41	3.42	3.28	20.09
C33, C34	3.28	3.46	3.03	3.48	3.43	3.29	20.01
C41, C42	3.28	3.42	3.41	3.27	3.39	3.28	20.08
C43, C44	3.28	3.43	3.47	3.13	3.45	3.29	20.08
C51, C52	3.28	3.42	3.44	3.41	3.21	3.26	20.09
C53, C54	3.28	3.42	3.44	3.41	3.21	3.26	20.09
C61, C62	3.29	3.43	3.44	3.44	3.38	3.02	20.01
C63, C64	3.30	3.43	3.45	3.46	3.50	2.61	19.77

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Table 5: Cell Temperature

	C61	C62	C63	C64
1	20.05	20.05	20.11	20.15

CONCLUSION

An effective technique for detecting weak cells utilizing strip voltage analysis and thermal validation is presented in this research. With the least amount of sensors and calculation, the WAVES method with dynamic load precisely locates the defective cell and determines the weakest strip. The findings verify that weak cells exhibit greater temperatures and lower voltages as a result of higher internal resistance. The technique's practical application is enhanced by its capacity to detect numerous weak cells at once and its extension to dynamic load circumstances. All things considered, it offers a dependable and affordable way to diagnose battery problems in EV systems.

FUTURE SCOPE:

Increase accuracy by incorporating SoC, SoH, and IR. For more practicality, use electrical or model-based techniques to lessen the dependence on thermal imaging. Incorporate safety features like automatic weak cell isolation and thermal runaway prevention.

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