RESEARCH ARTICLE

Safety-Oriented Multi-Parameter Monitoring and Response Time Assessment of Battery Energy Storage Systems

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Abstract

The rapid integration of battery energy storage systems (BESS) into modern power grids necessitates robust safety architectures to prevent catastrophic failures such as thermal runaway. Current diagnostic frameworks are often reliant on isolated, single-parameter thresholds and lack direct linkage to hardware-level execution. This work proposes a comprehensive, multi-parameter early warning and hierarchical protection methodology that bridges the gap between software-based fault detection and practical electromechanical response. The proposed algorithm calculates a dynamic, weighted safety score in real-time by structurally integrating internal battery management system (BMS) metrics, such as cell temperature and voltage deviation, with enclosure-level environmental indicators, particularly early gas emissions. To ensure ultra-low latency, the architecture utilizes discrete analog signal conditioning to bypass computational delays found in complex software models. The assessed score drives a hierarchical state machine branching to a preventive pre-alarm phase initiating HVAC support and load reduction, and a critical protection phase executing closed-loop electromechanical isolation. Transient state simulations performed via LTspice verify the deterministic performance of the system. These simulations demonstrate the system's ability to identify leading anomalies, secure critical response time, and guarantee absolute hardware isolation before critical thermal safety limits are exceeded.

Keywords: battery safety, early warning, multi-parameter fusion, thermal runaway.

1 Introduction

The global energy transition has led to the rapid growth of battery energy storage systems (BESS) across various sectors, particularly for renewable energy integration, grid support, peak load mitigation, and comprehensive energy management. As these systems become more widely used, ensuring their safe, stable, and reliable operation has become a major concern. Beyond meeting basic performance criteria, modern BESS applications must proactively address operational anomalies that could compromise safety, reduce system efficiency, and disrupt service

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continuity [1–4]. In grid-scale deployments, an unmitigated BESS failure does not remain an isolated event; cascading thermal or electrical faults can propagate to connected power network infrastructure, triggering protection relay operations, unplanned load shedding, and broader grid instability. Consequently, robust safety architectures for stationary BESS are not merely device-level concerns but are integral to the reliable protection and stable operation of modern electric power networks and systems.

Addressing these grid-level safety implications requires solving a fundamental technical challenge in large-scale BESS applications: the early and accurate identification of anomalous operating conditions. Currently, anomaly detection is fragmented; monitoring relies on isolated parameters or independent warning mechanisms rather than a clear and unified diagnostic framework. The link between anomaly recognition, decision-making logic, and physical protective actions is not clearly defined in practical applications. Therefore, a collective, system-wide review is needed, rather than addressing thermal or electrical hazards in isolation. This underscores the urgent need for a comprehensive methodology to ensure rapid detection and decisive response in BESS applications [4–8]. To address this issue, this study aims to propose a structured, multiparameter early warning methodology for BESS. This framework is designed to facilitate the early detection of hazardous situations and to tightly couple anomaly recognition to relevant phased warning and protection actions.

To achieve this general objective, the present study focuses on the following specific goals:

1. To classify the primary anomalous operating conditions in BESS environments that are most critical for security, continuous monitoring, and early failure detection.
2. To select a representative, dual-layer BMS and BESS-level monitoring parameter set for a robust, multi-parameter security assessment.
3. To design a hierarchical alert logic that evaluates prioritized parameters and effectively separates early pre-alarm conditions from critical protection states.
4. To establish a direct, closed-loop relationship between identified anomalies and subsequent hardware-level alerts and protective actions within the system.
5. To verify the proposed methodology using mathematical modeling and transient LTspice-based simulation.

The remainder of this paper is structured as follows: The next section reviews the current literature on BESS implementations, security vulnerabilities, and existing early warning strategies. This contextualizes the proposed study within the broader academic environment.

2 Literature Review

Ensuring the safe and sustainable operation of battery energy storage systems (BESS) requires the simultaneous monitoring of macroscopic variables at the grid level and microscopic parameters at the cell level. A review of the current literature reveals that safety paradigms for these systems are shaped by two engineering disciplines: electrical engineering, which focuses on system robustness and grid integration, and electronic engineering, which emphasizes signal reception, hardware filtering, and local decision-making.

This section analyzes recent trends, technological constraints, and research gaps in BESS safety monitoring from these perspectives. Subsequent subsections provide a methodological synthesis of the current literature, detailing the physical interaction between different monitoring parameters and their roles in the safety hierarchy. This comprehensive review establishes the scientific basis for the proposed multi-layered methodology (Section 3) and clearly defines the industry gaps it aims to address.

2.1 Literature Review from the Electrical Engineering Perspective

Recent investigations underscore the growing importance of battery energy storage systems (BESS) in modern power networks, particularly in regard to renewable energy integration, grid stabilization, peak shaving, and comprehensive energy management [1–3, 9, 10]. From an electrical engineering standpoint, the current literature emphasizes how BESS enhances grid resilience, delivers ancillary services, improves reliability, and facilitates the integration of volatile renewable sources [1, 2, 9]. These analyses demonstrate that BESS should be recognized as dynamic grid components with substantial operational and safety responsibilities, not merely as passive storage units [2, 3].

As BESS are extensively deployed, ensuring safety and operational reliability has become a paramount challenge [4, 5]. A substantial body of research investigates anomalous operational states, including thermal escalation, excessive current, voltage imbalances, thermal runaway, volatile gas venting, and cascading fire propagation [4–7, 11, 12]. These studies emphasize that hazardous conditions cannot be evaluated solely at the cell level because localized failures often spread through the module, rack, and enclosure, endangering the entire installation [4, 5, 11]. Therefore, there is an urgent need for structured safety evaluations, robust anomaly detection, and synchronized protection strategies in stationary BESS facilities.

Another critical focus of the literature is the proactive identification of early warning signs and the reduction of battery-related failures. Numerous studies examine failure diagnosis, thermal runaway estimation, and risk mitigation methods [8, 13–20]. These studies argue that anomalous battery signatures should be identified in advance and that the paradigm should shift from retrospective, post-failure analysis to proactive, alert-centric architectures. However, most of these studies either offer generalized safety overviews or focus on isolated diagnostic techniques. They fail to explicitly integrate anomaly detection with a practical, multi-stage response framework. This underscores the critical need for a more integrated architecture that translates monitored physical conditions into actionable alerts and hardware protection commands.

Another limitation in contemporary research is the tendency to address the problem in a one-dimensional way. While a subset of the literature focuses on grid utilities and energy distribution, another subset focuses solely on hazard analysis, failure identification, or isolated alert models. Translating these diverse areas into a practical, early warning methodology for grid-scale BESS applications has not been sufficiently explored. Therefore, the current literature strongly encourages the formulation of a multiparameter diagnostic framework that can identify anomalous conditions and translate them directly into sequential, ready-to-implement warning and protection protocols.

2.2 Literature Review from the Electronics Engineering Perspective

From an electronic engineering perspective, current research primarily examines how anomalous battery behaviors are detected, processed, and translated into actionable control commands via specialized hardware and logic architectures [21–26]. This scope extends beyond parameter measurement to include holistic design of signal acquisition pipelines, dynamic threshold assessments, microcontroller-based monitoring, and decision frameworks. Numerous studies have demonstrated that impending battery failures can be diagnosed in advance by monitoring subtle deviations in voltage, current, temperature, and impedance. These measurements can be used as measurable precursors to critical emergencies [21–26].

A parallel and equally vital area in the electronics literature concerns environmental and gas-focused monitoring. Detection of volatile emissions, particulate smoke, and associated electrochemical shifts is crucial because these physical manifestations often precede visible combustion or catastrophic structural collapse [27–30]. Consequently, scientists advocate combining internal battery status data with external atmospheric monitoring channels to create robust early warning mechanisms [27–30]. Furthermore, the implemented detection logic relies heavily on established thresholds, signal filtering, and multi-stage decision trees. While many frameworks detect anomalies using static temperature limits, gas concentration maxima, or voltage deviation limits, practical applications face challenges. In industrial monitoring environments, raw sensor data is often affected by switching ripple, electromagnetic noise, and transient spikes. This makes unconditional threshold comparisons susceptible to false positives and premature triggering [21, 22, 25, 26, 31].

Contemporary research highlights the importance of incorporating rigorous filtering stages, logical validation routines, and multidimensional cross-validation mechanisms into system design to reduce sensing errors [24, 26, 30, 31]. In physical applications, these validated warning signals directly interface with electromechanical hardware responses, including audible alarms, active HVAC ventilation, isolation relays, and high-voltage contactors. Simultaneously, academic consensus is shifting toward multi-factor diagnostic architectures. By synthesizing electrical, thermal, environmental, and impedance-based characteristics, these advanced methodologies significantly increase diagnostic confidence compared to univariate monitoring. The critical contribution of these studies is to demonstrate that diverse sensor flows can be effectively combined within a centralized, microcontroller-driven topology to execute highly reliable, phased protection protocols.

Despite these theoretical advances, a significant gap remains in the literature. The vast majority of research focuses on fundamental sensing principles, sensing accuracy, or isolated software performance. Generally, they are far from offering a comprehensive, hardware-oriented methodology that seamlessly integrates raw signal acquisition, analog conditioning, threshold evaluation, and precise electromechanical activation within a single deployable system. Consequently, there is a clear need for an integrated diagnostics framework that successfully integrates localized electronic engineering practices with the overall safety and operational requirements of grid-scale BESS environments.

2.3 Overall Research Gap

A closer examination of the reviewed electrical engineering literature reveals several recurring themes that directly influenced the development of the proposed framework. Jaradat and Khatib [1] emphasized the strategic deployment of BESS and the importance of safety-oriented operational policies. Sakib et al. [2] highlighted the role of BESS integration within renewable energy zones and stressed the need for reliable monitoring under grid disturbances. Nazaralizadeh et al. [3] identified battery health metrics and energy management indicators as essential components of long-term system reliability.

Safety-oriented investigations by He et al. [4], Lian et al. [5], and Yao et al. [6] demonstrated that thermal risk management, fault diagnosis, and preventive protection mechanisms are fundamental requirements for large-scale energy storage systems. Similarly, Liu et al. [7] and Kong et al. [8] emphasized the importance of thermal runaway early-warning indicators, while Pan [11] and Zhi et al. [12] focused on risk mitigation and thermal runaway prevention strategies. These findings collectively indicate that effective BESS protection requires continuous monitoring of multiple interacting electrical and thermal parameters rather than reliance on a single threshold variable.

From the electronics engineering perspective, the reviewed studies primarily focus on signal acquisition, sensor fusion, fault identification, and hardware-level implementation. Xiong et al. [21] investigated multidimensional sensing approaches for next-generation battery systems, while Abdolrasol et al. [22] reviewed advanced data-driven fault diagnosis architectures. Hu et al. [23] demonstrated the effectiveness of electrochemical parameters for early-warning applications, and Zhang et al. [24] presented multidimensional fault-feature extraction techniques.

Additional contributions by Duan et al. [25] and Zhao et al. [26] highlighted the benefits of combining multiple electrical indicators for fault diagnosis. Gas-based and multimodal warning approaches were investigated by Song et al. [27], Tao et al. [28], Pu et al. [29], and Liu et al. [30], demonstrating the value of integrating gas, acoustic, and environmental measurements. Finally, Yan et al. [31] proposed a hierarchical warning strategy based on multi-parameter fusion, providing a foundational reference for the layered decision-making structure developed in the proposed methodology.

A comprehensive review of the current literature reveals a clear distinction between the fields of electrical and electronic engineering, despite their inherent interconnectedness. The reviewed electrical engineering studies collectively address BESS deployment, safety management, fault diagnosis, thermal runaway prevention, risk assessment, and operational reliability. In contrast, the reviewed electronics engineering studies focus on multidimensional sensing, signal conditioning, fault-feature extraction, sensor fusion, embedded controller implementation, and hardware-assisted warning mechanisms. However, a significant discontinuity persists as these dual perspectives are rarely synthesized into a unified, structured methodology that combines high-level BESS safety prerequisites with low-level electronic execution logic [4, 5, 8, 18–20, 31].

Consequently, there is a persistent demand for a multi-parameter diagnostic framework that can seamlessly integrate continuous monitoring, threshold-based interpretation, hardware signal conditioning, and controller-based linkage logic. Such a framework should provide incremental alert and protection outputs simultaneously at both BMS and BESS levels [24, 27, 29–31]. The proposed methodology is detailed in the following section, creating a holistic, practical architecture for anomaly monitoring, weighted decision-making, and precise protective responses specific to BESS security applications.

As summarized in Table 1, contemporary academic work has focused predominantly on identifying early warning signals, implementing hazard assessments, and developing localized monitoring methodologies to improve battery safety standards [4, 7, 8, 11, 18, 27, 30, 31]. However, it is clear that most of these contributions are largely limited to univariate detection principles. A precise, closed-loop relationship between the recognition of abnormal conditions and the implementation of hierarchical, structured protective countermeasures is lacking [8, 18, 20, 23, 31].

As shown in Table 1, a comparative analysis of recent literature on BESS safety monitoring has clearly demonstrated that anomalous conditions cannot be effectively mitigated by isolated, single-parameter thresholds. The interaction matrix reveals the hierarchical roles of various monitoring parameters and their cascading effects on overall system stability.

The fundamental causal relationships governing battery degradation and failure become discernible within this complex parameter interaction. Long-term performance metrics such as dynamic internal resistance (Ri) and Coulomb efficiency function as critical conditioning variables. While these events do not inherently trigger catastrophic events, their degradation directly increases ohmic heating (I^2R). This structural degradation has been shown to accelerate the rate of temperature change (dT/dt) and dynamically narrow the functional safety margins of the system. Simultaneously, electrical indicators, particularly cell voltage deviation, serve as high-priority early warnings. These sensors can identify local operational stress and cell-level imbalances long before critical thermal hotspots physically manifest.

Limiting level indicators such as volatile organic compounds (VOCs) and acoustic emissions provide the earliest physical evidence of irreversible cell ventilation. Integration of these parameters allows the control system to achieve a significant response time, thus preventing complete thermal runaway. Recent studies increasingly support integrating these multidimensional monitoring signals into unified multi-parameter safety frameworks. Although many contemporary studies use artificial intelligence (AI) and machine learning to prioritize and rank these parameters, the computational complexity inherent in AI models often leads to unacceptable processing latency in real-time industrial hardware.

The reviewed studies indicate that a structured methodology combining weighted parameter prioritization with deterministic hardware execution could significantly improve practical BESS safety performance. It underscores the necessity of a system that directly links sequential anomaly detection to physical electromechanical isolation without computational delay. In line with these defined requirements, Section 3 presents the proposed multilayer methodology designed to process these interrelated signals through a low-latency, hierarchical execution framework.

3 Methodology

The proposed methodology establishes a hierarchical, multidimensional safety framework for Battery Energy Storage Systems (BESS), unlike traditional single-threshold alert algorithms. The methodology aims to transition from a simple reactive alarm to a proactive diagnostic tool, integrating hardware-level signal conditioning with a weighted parameter sequencing system. This approach is inspired by feature importance analysis found in recent AI safety studies. However, it is designed for low-latency, deterministic execution on the Microcontroller Unit (MCU).

3.1 System Architecture and Discrete Signal Acquisition

To ensure industrial reliability and minimize sensing latency, the proposed architecture avoids standard, pre-packaged digital sensor modules, which often lead to communication delays. Instead, a discrete analog front-end (AFE) and a custom signal conditioning approach are implemented.

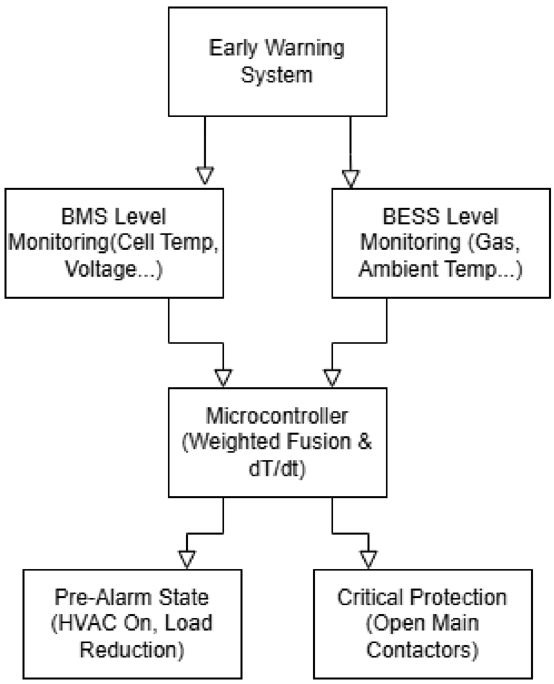

Figure 1. Conceptual architecture of the proposed multi-layered early warning system, illustrating the integration of BMS and BESS level monitoring with microcontroller-based fusion logic.

Table 1. Summary of monitored parameters and system priorities.

Monitored Parameter	Hardware / Acquisition Method (Discrete Design Focus)	Parameter Interplay (How they affect each other)	Detection Stage/ Action Priority	Ref.
Internal Resistance (Ri) & Impedance	Dynamic current pulse measurement and discrete analog filtering circuits.	Increased Ri directly amplifies I^2R ohmic heating. Higher resistance accelerates thermal stress (dT/dt), deteriorating overall efficiency.	Long-term Monitoring: Precursor to electrical faults and thermal instability.	[26]
Coulombic Efficiency (CE) Capacity Fade	Continuous Coulomb counting processed by the MCU, integrated with OCV estimation.	Drops in CE signify parasitic side reactions. This consumes active lithium, increasing Ri and causing premature voltage drops under load.	Long-term Monitoring: Crucial for State of Health (SoH) and energy dispatching.	[6]
State of Charge (SoC) Depth of Discharge (DoD)	Software-level estimation combining current integration and voltage correction.	Operating at extreme SoC limits (*>95% or <10%*) accelerates efficiency drop. Thermal runaway triggered at a high SoC is significantly more violent, leading to faster gas release.	Operational Constraint: Defines the dynamic boundaries for safe operation.	[3]
Cell Voltage Deviation (dV/dt) & Imbalance	Discrete operational amplifiers structured as a differential AFE for precise per-cell scaling.	Voltage imbalance forces weaker cells into overcharge or deep discharge states during pack operation, acting as a primary catalyst for localized thermal hotspots.	Early Warning: Triggers BMS balancing; persistent deviation triggers load reduction.	[24]
Load Current Peak Stress	High-precision shunt resistors with discrete low-pass filter stages.	High C-rates exacerbate voltage deviations across unbalanced cells and exponentially increase internal heat generation.	Conditioning Variable: Defines dynamic safety limits.	[20]
Insulation Resistance (Ground Fault)	Active high-voltage injection network with discrete voltage dividers.	Humidity or coolant leaks degrade insulation. Combined with internal cell stress, a ground fault creates an immediate short-circuit risk.	Critical Protection: Direct trigger for system isolation (opening contactors).	[4]
Temperature Change Rate (dT/dt)	NTC thermistor networks implemented with discrete Wheatstone bridges.	A sharp rise in dT/dt indicates the onset of self-heating internal exothermic reactions, preceding physical cell venting.	Critical Warning: Primary threshold for protective actions.	[8]
VOC & Flammable Gas Emissions (H_2, CO, CO_2)	NDIR or MOX gas sensing elements interfaced via custom signal conditioning.	Gas venting is the direct physical consequence of uncontrolled dT/dt. It almost always occurs just before catastrophic thermal runaway.	Pre-alarm / Critical: The most distinct physical evidence of irreversible cell failure.	[27]
Smoke Particulate Matter	Optical or ionization sensors within the enclosure.	Occurs after Volatile Organic Compound (VOC) venting. Confirms active combustion or severe thermal propagation. At this stage, dT/dt is already extreme and isolation has failed.	Late-stage Critical: Direct trigger for fire suppression systems.	[29]
Ambient Temperature Humidity	Enclosure-level discrete environmental sensors.	High ambient temperatures lower HVAC efficiency, accelerating cell dT/dt, while high humidity causes PCB leakage.	Preventive: Triggers enclosure HVAC before cell temperatures rise.	[5]
Contactor / Relay State Contact Resistance	Auxiliary contacts read by MCU General Purpose Input/Output (GPIO) with discrete hardware debouncing.	High contact resistance generates localized heat outside the cells but within the cabinet. Also verifies if protective isolation commands were successfully executed.	Hardware Verification: Closes the loop between logic and physical response.	[31]
Internal Pressure Cell Swelling Force	Strain gauges or thin-film pressure sensors on cell surfaces.	As temperature and gas generation increase internally, pressure rises before the safety valve bursts (venting). Correlates strongly with sudden Ri fluctuations.	Early/Mid Warning: Detects physical anomaly before gas escapes the cell.	[23]
Acoustic Emission	Piezoelectric elements with discrete amplification stages.	Mechanical strain and acoustic pops (gas bubble formation) happen before the safety valve breaks, preceding both VOC release and massive dT/dt.	Emerging Detection: Very early warning, highly sensitive to noise.	[30]
Dynamic SoC Grid Frequency Deviation	System-level telemetry integrating grid inverter data with the BMS communication bus.	Rapid charge/discharge cycles driven by grid frequency regulation demand high current bursts. This directly accelerates thermal loading (I^2R) and requires strict dynamic SoC boundary management.	Operational Constraint: Defines and adjusts dynamic charging boundaries based on external grid load interactions.	[32]
Active Cell Balancing Voltage Dynamics	Active BMS topology utilizing bidirectional DC-DC converters for continuous individual cell monitoring.	Continuous active balancing prevents localized voltage overshoots during cycling, mitigating uneven thermal stress and extending cell lifecycle before hotspots form.	Preventive: Regulates operational limits and balances cells before voltage deviations reach critical thresholds.	[33]

As shown in Figure 1, the proposed dual-channel data acquisition strategy is illustrated. Separating internal battery measurements (BMS level) from external anomaly indicators (BESS level) allows the microcontroller to independently weight and process these parallel data streams. This architectural combination has two functions. The first is to isolate the relevant signaling regions. The second is to allow for the verification of an anomaly in a region before the implementation of protective measures.

The proposed detection scheme collects raw data in two main domains:

- The internal state (BMS level) is resolved by operating high-sensitivity shunt resistors in conjunction with discrete low-pass filter stages. This stage suppresses switching noise variations, thus enabling accurate measurement of dynamic internal resistance (Ri) and precise load tracking. Differential amplifiers enable precise detection of local cell imbalances by measuring dV/dt, the rate of cell voltage deviation.

- The containment state (BESS level) is achieved as follows: In discrete Wheatstone bridge configurations, NTC thermistor networks continuously monitor temperature change rate (dT/dt). Additionally, NDIR/MOX gas sensing elements are integrated via dedicated analog circuits to detect volatile organic compounds (VOCs) and combustible gas emissions without processing delays.

These signals are processed directly at the hardware level, allowing the MCU to receive clean, deterministic inputs, thus significantly reducing the incidence of false alarms caused by cell-level noise.

3.2 Parameter Priority Ranking and Interplay Logic

A key innovation of this methodology is the systematic prioritization of the monitored parameters. The algorithm does not treat all sensor inputs equally; instead, it uses a feature-ordering approach. Parameters are structurally weighted according to their physical interactions and their temporal significance to catastrophic failures.

1. The following indicators should be given the highest priority: the rate of cell temperature change (dT/dt) and VOC/gas emissions.

   A sharp increase in dT/dt indicates the onset of spontaneous exothermic reactions. Gas emission is the direct physical consequence of this thermal escalation. These parameters carry the highest mathematical weights and therefore serve as the highest-priority indicators within the weighted decision process.

2. Secondary Indicators (High Priority): This study will examine cell voltage deviation and insulation resistance.

   Severe voltage imbalances cause certain cells to enter overcharge or deep discharge states. This localized electrical stress is the primary catalyst for the formation of thermal hotspots, which in turn triggers the primary conditioning indicators.

3. The following are the intermediate priority Conditioning Indicators: The parameters of interest are internal resistance, denoted by Ri, and Coulomb efficiency.

   As resistance (Ri) increases due to the aging process, ohmic heating (I^2R) increases. While high resistance alone does not cause an immediate failure, it acts as a thermal stress amplifier. It has been observed that this event accelerates thermal degradation, thus dynamically reducing the safety margin for the entire system.

3.3 Mathematical Modeling of Weighted Fusion

To implement the prioritization discussed earlier, traditional Boolean logic is replaced with a weighted combination model. It is important to note that each conditional signal I_i is normalized and assigned a static weight w_i derived from the prioritization. The comprehensive early warning score (S_{pre}) is calculated in real-time as follows:

$$S_{\text{pre}} = \sum_{i=1}^{n} (w_i \cdot I_i) = (w_G \cdot I_G) + (w_T \cdot I_T) + (w_V \cdot I_V) + (w_R \cdot \tag{1}$$

where w_G and w_T represent the highest weights for gas and dT/dt (Primary Indicators), w_V represents the weight for voltage deviation (Secondary Indicator), w_R represents the weight for internal resistance/efficiency drop (Conditioning Indicator).

As shown in Equation (1), the specific values for the static weights (w_G, w_T, w_V, w_R) were determined heuristically, guided by the physical interaction hierarchy and temporal criticality established in recent multi-parameter fusion studies [31–36]. Primary indicators, such as gas emissions and dT/dt, are assigned dominant weights to ensure an immediate system transition to the pre-alarm state, while conditioning variables act as supplementary multipliers [31]. To ensure the robustness of these assigned values, a preliminary sensitivity analysis was conducted during the system design phase. This analysis confirmed that minor variations $(\pm 10\%)$ in the weighting factors do not fundamentally alter the deterministic activation of the critical protection states, aligning with established fusion methodologies [36].

This mathematical combination allows the microcontroller to detect an impending failure if multiple secondary and conditioning indicators appear simultaneously, even before the primary critical threshold is exceeded.

To formalize the dynamic threshold evaluation and avoid oscillatory behavior (chattering) between the operational states due to sensor noise, a discrete hysteresis band (ΔH) is mathematically integrated into the state-machine logic. The transition from Normal Operation to the Pre-Alarm state is strictly governed by $S_{\text{pre}} \geq Th_{\text{pre}}$. However, to prevent premature resetting due to transient fluctuations, the system only reverts to Normal Operation if the safety score satisfies the reset condition:

$$S_{\text{pre}} < Th_{\text{pre}} - \Delta H_{\text{pre}} \tag{2}$$

where ΔH_{pre} is the hysteresis margin used to prevent state oscillation. Similarly, the digital signal validation layer executed by the MCU incorporates a first-order recursive exponential moving average (EMA) filter to smooth out high-frequency switching ripple without inducing unacceptable processing latency ($t_{\text{processing}}$), defined mathematically as:

$$Y[n] = \alpha \cdot X[n] + (1 - \alpha) \cdot Y[n-1] \tag{3}$$

where $X[n]$ is the raw validated ADC input, $Y[n]$ is the filtered output, and alpha (α) represents the smoothing factor ($0 < \alpha < 1$), which is dynamically tuned based on the parameter's priority ranking.

This digital filtering approach guarantees that transient anomalies, such as electromagnetic switching noise, do not prematurely trigger the hardware protection sequence. Consequently, the microcontroller maintains highly deterministic operational stability without compromising the ultra-low latency required for critical fault isolation.

3.4 Hierarchical Response and Hardware Verification

The assessed score (S_{pre}) is continuously compared against two different thresholds, thus creating a two-tier evaluation: a preventive pre-alert status and a definitive critical protection status.

To provide a comprehensive overview of the system's operational logic, the hierarchical state machine illustrated in Figure 2 evaluates the validated parameters through four primary discrete branches:

- **Sensor / BMS Fault State**: The algorithm continuously executes boundary validation checks ($V_{\text{min}} < V_{\text{signal}} < V_{\text{max}}$) on all raw incoming ADC streams. If any signal violates these predefined operational constraints or if the active fault flags from the BMS CAN bus are raised, the system branches immediately to a dedicated fault state to prevent erroneous protection triggers.
- **Normal Operation State**: Under nominal conditions where all indicators remain below the safety margins, the MCU focuses strictly on data acquisition, dynamic internal resistance (R) tracking, and continuous calculation of the moving averages.
- **Pre-Alarm State**: When the multi-parameter safety score satisfies the conditional threshold

$$Th_{\text{pre}} \leq S_{\text{pre}} < Th_{\text{crit}}, \tag{4}$$

the state machine transitions to the pre-alarm state. This branch dynamically initiates full-capacity HVAC cooling and issues a load reduction command to mitigate internal ohmic heat generation without shutting down the system.
- **Critical Protection State**: If the score escalates to $S_{\text{pre}} \geq Th_{\text{crit}}$ or if critical absolute limits (such as critical temperature T_{crit} or smoke detection) are breached, the execution completely bypasses the preventive loops. The MCU drives the GPIO pins to instantly open the main electromechanical contactors and isolates the affected battery racks.

The operational backbone of the multi-parameter safety monitoring framework is governed by the hierarchical state-machine architecture detailed within Section 3.4. Rather than executing isolated, static threshold checks that are highly susceptible to environmental noise and transient spikes, the embedded controller continuously assesses the dynamically calculated comprehensive safety score (S_{pre}). This multi-layered logic effectively bridges the gap between software-based risk evaluation and the physical electromechanical layout, establishing a continuous verification routine that monitors both internal battery metrics and enclosure-level atmospheric conditions in real-time.

As systematically mapped out in the algorithmic execution flow of Figure 2, the system logic dynamically branches into prioritized paths based on anomaly severity. Immediate signal validation

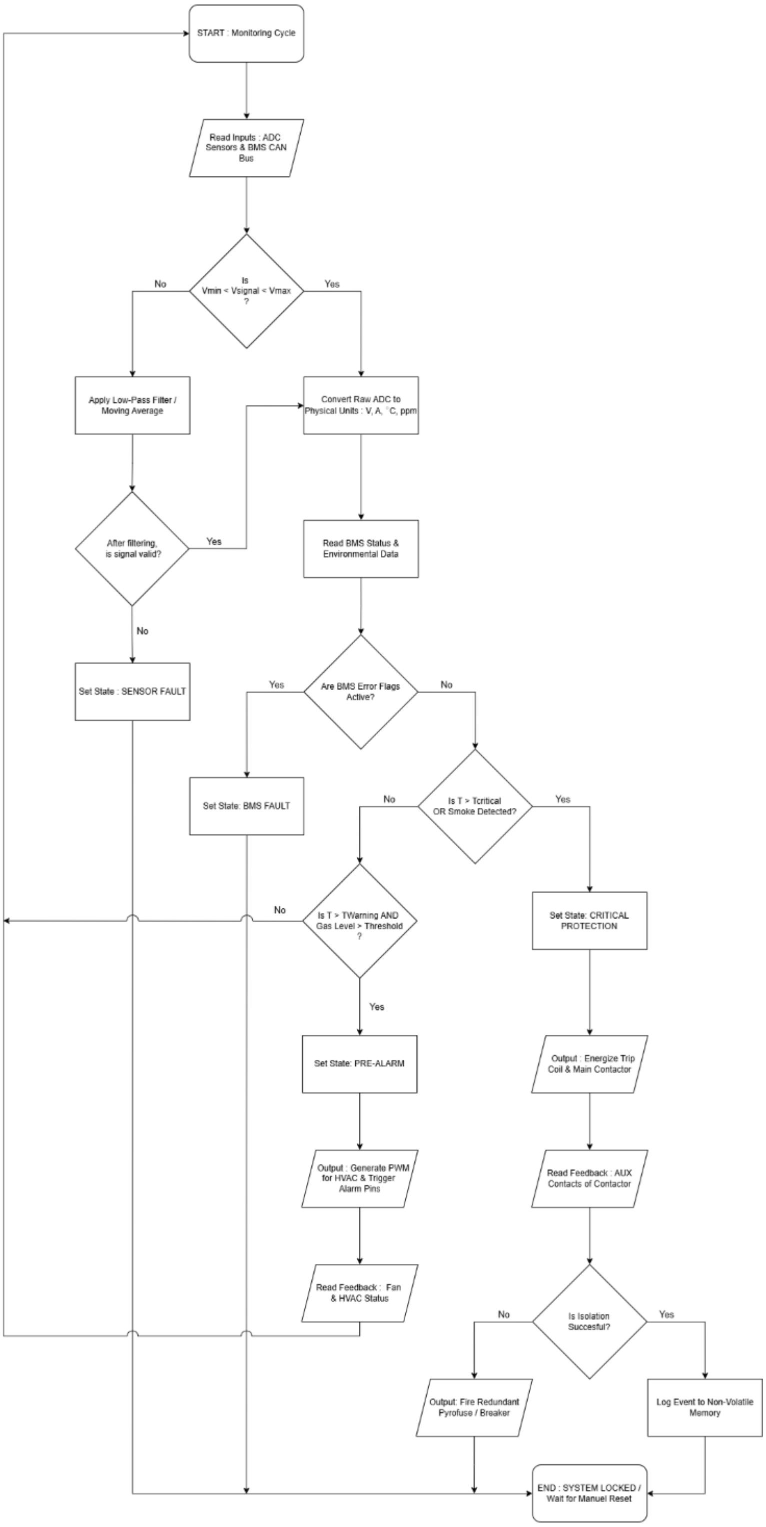

Figure 2. Hierarchical execution flow of the proposed safety monitoring system.

and boundary checks isolate localized sensor faults, ensuring that only verified physical inputs drive the subsequent state machine. This approach allows early preventive countermeasures, such as localized HVAC activation and targeted load reduction, to operate independently from the critical electromechanical isolation sequences.

Notably, the proposed state-based architecture provides a structured mechanism for handling fault progression in a deterministic manner, ensuring that each operational condition is evaluated according to predefined safety criteria rather than ad hoc decision rules. In addition, the separation of monitoring, preventive response, and critical protection functions allows the controller to maintain operational flexibility while preserving rapid intervention capability during abnormal events. Likewise, the hierarchical arrangement of states minimizes unnecessary computational burden by enabling direct transitions to higher-priority protection layers whenever severe indicators are detected. As a result, the framework can effectively coordinate multiple monitoring channels, combine their weighted contributions, and execute appropriate mitigation actions without introducing excessive processing latency. Yielding a predictable and transparent decision process, this implementation philosophy is particularly suitable for industrial Battery Energy Storage Systems, where response consistency, hardware compatibility, and operational safety are considered fundamental design requirements.

As shown in Figure 2, the primary algorithm begins by continuously receiving raw analog and digital data from the BMS CAN bus. To ensure robustness against interference and sensor anomalies, these inputs undergo rigorous hardware validation. This validation includes boundary checks and low-pass filtering. Following verification of signal integrity and conversion to physical units, the microcontroller performs data evaluation against active fault flags and a calculated comprehensive score (S_{pre}). Depending on the severity of the anomaly, the logic dynamically branches to the aforementioned states: initiating sequential preventive measures or triggering immediate electromechanical isolation with closed-loop validation.

As shown in Figure 3, the execution flow for the Pre-Alarm Condition (Preventive) is configured as a continuous, closed-loop preventive mechanism. When the threshold condition

$$Th_{\text{pre}} \leq S_{\text{pre}} < Th_{\text{crit}}$$

is met, the Microcontroller Unit switches the system to preventive mode. Instead of performing an immediate hard shutdown, the logic triggers a series of countermeasures. Initially, the enclosure's HVAC systems are activated at their maximum capacities to prevent ambient and intracellular thermal buildup. Simultaneously, a directive is transmitted to the primary energy management system requesting an immediate reduction in battery load. This aims to reduce internal ohmic heating (I^2R). Following the implementation of these actions, the system enters a cooling and stabilization phase and repeatedly returns to the monitoring loop to determine if the anomaly has stabilized.

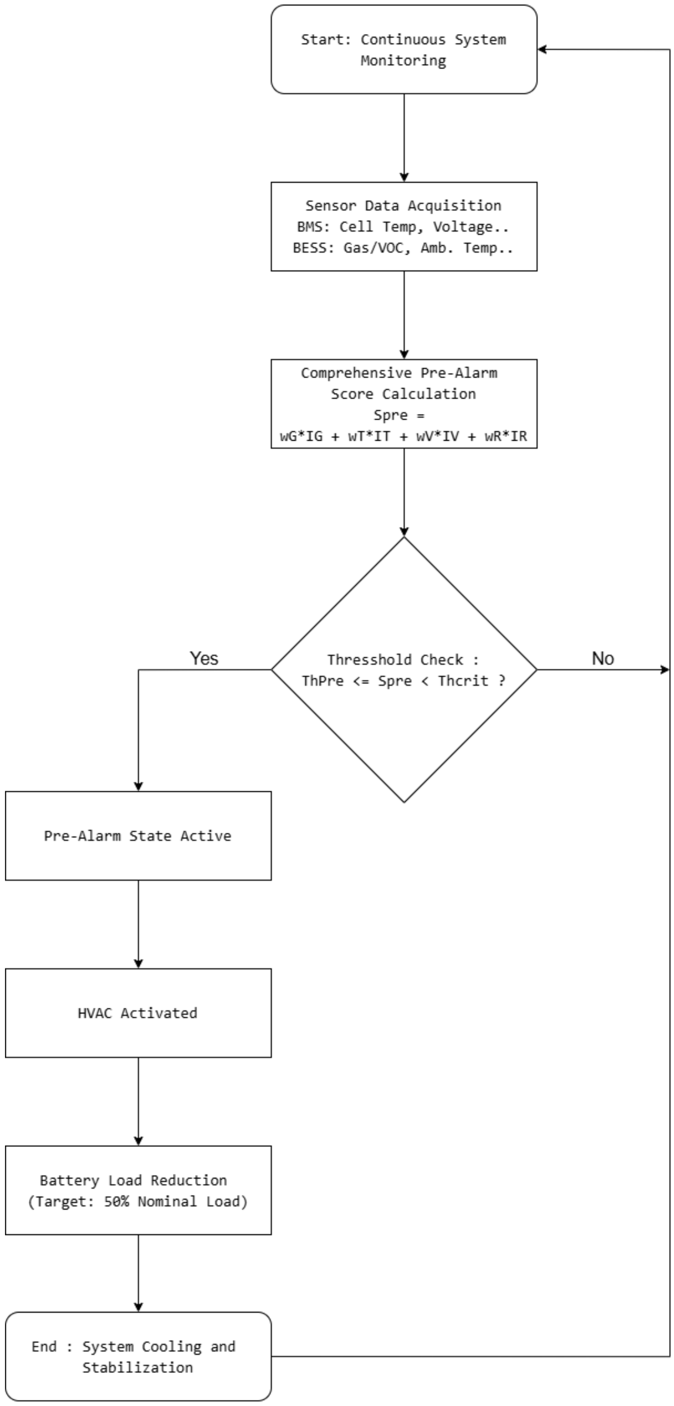

Figure 3. Algorithmic execution flow of the Pre-Alarm state, demonstrating continuous monitoring and sequential preventive actions.

Conversely, if the anomaly increases and the score exceeds the critical limit $S_{pre} \geq Th_{crit}$, or if a primary physical indicator is detected, the system bypasses the preventive loop and enters Critical Protection State (see Figure 4). In this protection mode, the microcontroller unit (MCU) electrically isolates the affected battery

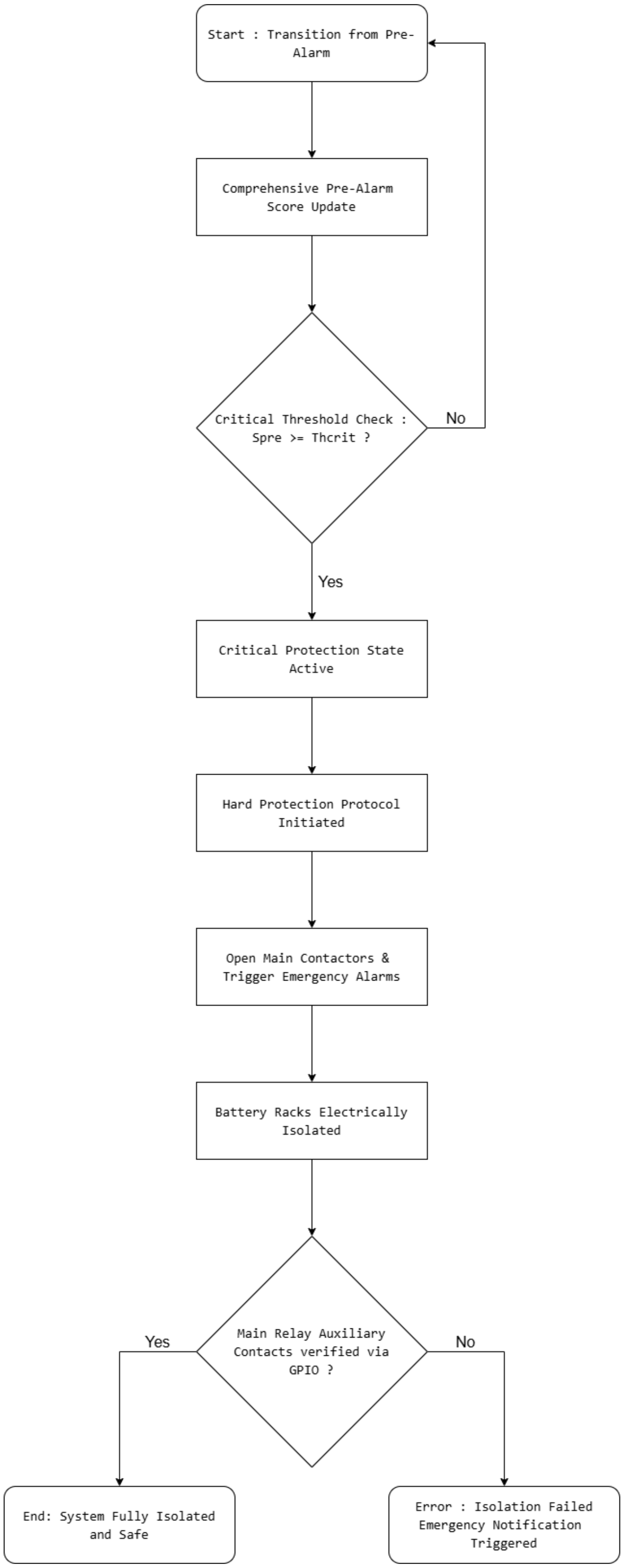

Figure 4. Algorithmic execution flow of the Critical Protection state, highlighting hardware isolation and closed-loop contactor verification.

racks by sending direct hardware commands to open the main contactors. To ensure absolute system integrity, the method closes the control loop by actively monitoring the auxiliary contacts of the main relays via GPIO pins. This critical hardware verification step confirms that the commanded physical isolation has been successfully performed. If a mechanical failure is detected, secondary, redundant protocols are initiated. After the verification process, the system is securely locked and secured, effectively closing the gap between software decision-making and hardware protection.

3.5 Theoretical Response Time and Latency Modeling

To evaluate the safety performance of the proposed framework, the total system response time t_{total} needs to be modeled both mathematically and conceptually at the methodology layer. The time interval between the occurrence of an anomaly at the physical cell level (e.g., the onset of volatile gas release or a sudden thermal increase) and the implementation of protective measures is defined as a multi-stage delay accumulation.

$$t_{\text{total}} = t_{\text{acquisition}} + t_{\text{processing}} + t_{\text{actuation}} \tag{5}$$

where $t_{\text{acquisition}}$ represents the hardware front-end signal conversion and propagation delay. By utilizing a discrete Analog Front-End (AFE) circuit instead of digital communication buses for primary indicators, this term is constrained purely to analog component propagation and hardware RC filter stabilization times, reducing it to a sub-millisecond scale ($< 1\,\text{ms}$), $t_{\text{processing}}$ defines the algorithmic execution latency within the MCU. This encompasses the execution time of digital low-pass filtering algorithms, the real-time calculation of the weighted fusion score (S_{pre}), and the rule-based conditional evaluations within the hierarchical state machine, $t_{\text{actuation}}$ constitutes the electromechanical response delay dictated by the physical transit time of isolation contactors or HVAC relays once the MCU drives the corresponding GPIO pins.

The system integrates a structural modeling approach into the methodological framework, enabling critical protection paths to skip unnecessary firmware routines when a high-priority indicator is triggered. This establishes a deterministic upper bound for the total response time, which is verified in the following section through transient circuit simulations.

To quantify these theoretical delay stages, the discrete arithmetic operations within a standard 32-bit industrial microcontroller ($t_{\text{processing}}$) introduce a negligible latency of approximately $10\,\text{to}\,50\,\mu s$ [31]. The primary system delay is governed by the electromechanical clearance time of standard high-voltage DC contactors ($t_{\text{actuation}}$), which typically ranges from $20\,\text{ms}$ to $50\,\text{ms}$ in BESS applications [4, 31]. Consequently, factoring in the sub-millisecond $t_{\text{acquisition}}$, the total estimated system response time (t_{total}) is conservatively bounded within $25\,\text{ms}$ to $55\,\text{ms}$. This represents a highly deterministic and ultra-low latency response, functioning well within the necessary temporal safety margins to prevent thermal runaway propagation.

4 Mathematical Verification and Simulation Analysis

To rigorously evaluate the practical implementation of the proposed multi-parameter alert logic, a mathematical model was created, and then a transient simulation framework was developed using LTspice. This section is devoted to the verification of the hierarchical state machine (Pre-Alarm and Critical Protection) under dynamic operational anomalies.

4.1 Mathematical Formulation of the Dynamic Thresholds

In the initial stages, failures may not immediately exceed a critical temperature threshold. However, by their nature, they create an anomalous thermal rise trend. The rate of thermal change is mathematically defined as follows:

$$\frac{dT_{\text{cell}}}{dt} \approx \frac{T_{\text{cell}}(t) - T_{\text{cell}}(t - \Delta t)}{\Delta t} \tag{6}$$

Unlike traditional binary security logic, identified anomaly indicators are translated into a comprehensive score (S_{pre}) introduced in Section 3. Transitions in system state are strictly governed by defined operational limits.

The preventative pre-alarm state is definitively activated when the score falls within the warning threshold:

$$Th_{\text{pre}} \leq S_{\text{pre}}(t) < Th_{\text{crit}} \tag{7}$$

On the other hand, the critical protection protocol that initiates emergency electromechanical isolation is mathematically determined either by a critical point violation or an absolute physical limit:

$$S_{\text{pre}}(t) \geq Th_{\text{crit}} \quad \text{or} \quad T_{\text{cell}}(t) \geq T_{\text{crit}} \tag{8}$$

4.2 LTspice Simulation Framework and Circuit Modeling

To observe the temporal response and delay of the proposed algorithm, a transient simulation environment was created using LTspice. Within the confines of this simulation framework, the physical BESS parameters were modeled as continuous voltage-type signals to rigorously monitor the progression of anomalous conditions and the subsequent logic-based system responses. The primary input sources and fixed reference levels governing the simulation thresholds are shown in Figure 5.

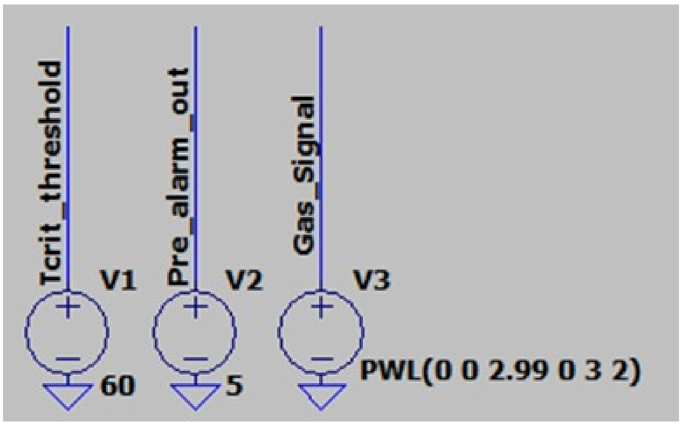

Figure 5. LTspice input and reference sources used in the simulation, including the critical threshold reference, the pre-alarm output level, and the gas-related input signal.

The critical threshold reference, denoted as V_1, is explicitly set to $60\,°\text{C}$. This value was not chosen arbitrarily; the acceptable safe operating temperature range for conventional lithium-ion batteries has been consistently reported in the literature to be approximately $60\,°\text{C}$ [34]. Consequently, this value functions as a highly representative physical and mathematical upper limit reference point to initiate the critical protection phase. The pre-alarm output level, denoted by V_2, is defined as 5, simulating the standard 5V logical high alert signal generated by the microcontroller hardware. In addition, the early environmental anomaly indicator showing gas emissions is modeled using a piecewise linear (PWL) source, V_3. Implementing the programmed parameter PWL (0 0 2.99 0 3 2) causes the gas signal to transition from an initial inactive state to an active state precisely at $t = 3$ seconds. This modeling approach serves as a highly effective early detection parameter, accurately reflecting the physical phenomenon where initial cell venting events often occur before a complete catastrophic thermal runaway [35].

After the operational limits and early environmental triggers have been accurately defined, the next critical phase of the simulation involves evaluating the response of the control logic to the increasing thermal anomaly.

In addition to static thresholds, the dynamic thermal behavior and the corresponding conditional logic were modeled using arbitrary behavioral voltage sources, as shown in Figure 6.

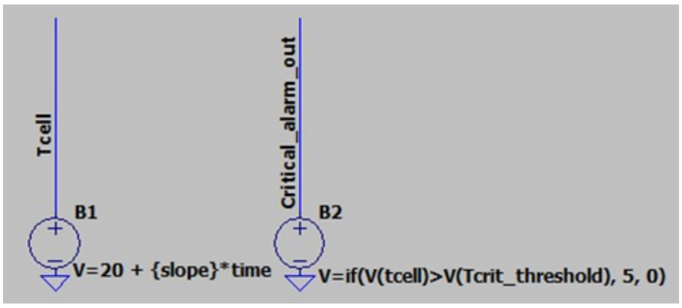

Figure 6. LTspice representation of the dynamically increasing temperature-related input signal and the behavioral critical-alarm logic.

The temperature-related input signal, T_{cell}, was implemented using the behavioral source $B1$. The source is defined by the linear expression $V = 20 + \text{slope} \times \text{time}$, which generates a gradually increasing ramp signal starting from a nominal room temperature of $20\,^{\circ}\text{C}$. This effectively simulates a continuous internal thermal runaway event over time. The transition from the monitoring state to a decisive protective action is managed by source $B2$, which represents the critical alarm output. The basic principle of this source is based on the behavioral condition

$$V = \big(\text{if}\, V(T_{\text{cell}}) > V(T_{\text{crit\_threshold}}),\, 5,\, 0\big). \quad (9)$$

Through this continuous logical evaluation, it has been shown that the critical alarm output is maintained at 0 volts while the simulated cell temperature remains within safe limits. Furthermore, it has been shown that this system instantly generates a logical high signal of 5 volts the moment the thermal trajectory exceeds the defined critical limit, thus enabling the system to be instantly isolated.

In addition to the signal-level simulation structure, a conceptual implementation environment at room-level was also considered to reflect the practical electronic aspect of the proposed system. From an electronic engineering perspective, this environment is crucial because it demonstrates that the proposed warning algorithm is not limited to theoretical signal processing; instead, it is designed to work seamlessly with a physical control panel, environmental monitoring nodes, display interfaces, active ventilation units, battery cabinets and fire suppression related components [4, 5, 21, 27, 31].

Furthermore, ensuring robust operational safety and accurate fault diagnosis in high-capacity storage environments largely depends on the integration of multi-source feature assessment and combined model fusion [36]. Direct integration of these multi-parameter diagnostic principles with the spatial deployment of enclosure-level hardware such as active exhaust paths and localized sensor nodes closes the gap between theoretical software-level decision delay and physical implementation. Consequently, real-time behavioral warnings validated during transient simulations can be precisely mapped to electromechanical isolation loops, guaranteeing reliable mitigation before irreversible thermal degradation occurs.

As shown in Figure 7, the proposed warning algorithm functions as an electronically focused room-level structure where the controller receives inputs not only from internal channels related to the BMS but also from environmental monitoring points at the enclosure level. In this context, the physical control panel, the positioning of ambient sensors, ventilation paths and suppression arrangements support the practical interpretation of the algorithm as a hardware-integrated protection system rather than just a software-level decision model [4, 5, 27, 31].

4.3 Simulation Results and Interpretation

To verify the real-time execution capability and temporal accuracy of the proposed hierarchical protection logic, the system's response to a dynamic thermal runaway scenario was evaluated. This section analyzes the transition dynamics between normal operation, the preventive pre-alarm state, and the critical protection phase. The resulting transient waveforms, which illustrate the correlation between the rising cell temperature, early gas emission triggers, and the dynamically calculated safety score, are presented and discussed below.

Specifically, the simulated scenario focuses on the precise timing of system interventions under accelerating failure conditions. By simultaneously injecting a sudden gas anomaly and a linear

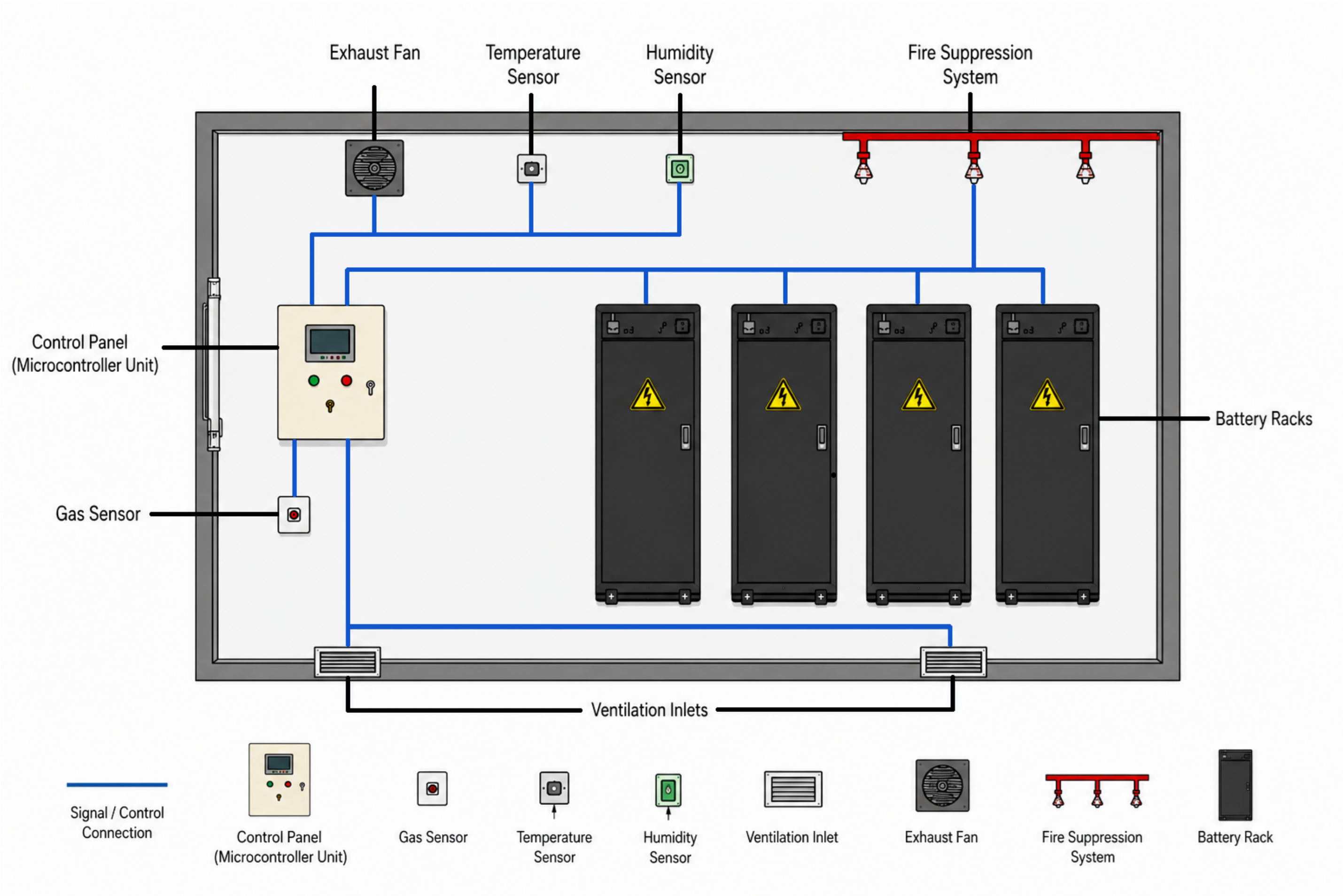

Figure 7. Conceptual room-level implementation layout.

thermal increase, the simulation aims to demonstrate the algorithm's ability to trigger early preventive countermeasures, tightly coupled to the weighted fusion score, long before absolute thermal limits are reached.

As shown in Figure 8, the transient effectively verifies the hierarchical execution capability of the proposed architecture. In the simulated scenario, the gas-related signal, an early containment level indicator, is activated at approximately the third second. The weighted fusion logic facilitates the rapid increase of the comprehensive score (S_{pre}), triggering the 5V Pre-Alarm output well before the critical thermal limit is reached. For clarity and visualization purposes, only the dominant gas-related and temperature-related indicators were represented in the transient simulation, while the remaining weighted parameters were incorporated conceptually within the safety-score calculation.

Simultaneously, the temperature-related signal continues its linear increase. When the simulated cell temperature exceeds the critical reference threshold at approximately the sixth second, the microcontroller logic dynamically skips the preventive loop and activates the Critical Alarm output. This sequential behavior – initiating a preventive pre-alarm at $t = 3\,\text{s}$ and definitive critical protection at $t = 6\,\text{s}$ – clearly demonstrates that the proposed algorithm can accurately identify an evolving anomalous condition and ensure critical response time before the system reaches a catastrophic end state.

While the transient LTspice simulations effectively verify the deterministic execution of the proposed hierarchical logic, it is important to acknowledge the practical limitations of this validation. The current simulation environment utilizes simplified, predefined signal models that do not fully capture the complexities of real-world BESS installations. In practical, large-scale applications, the proposed methodology would face physical challenges such as dynamic sensor noise, electromagnetic interference (EMI) from high-power inverters, and complex spatial temperature gradients across extensive battery racks. Furthermore, although the discrete analog front-end

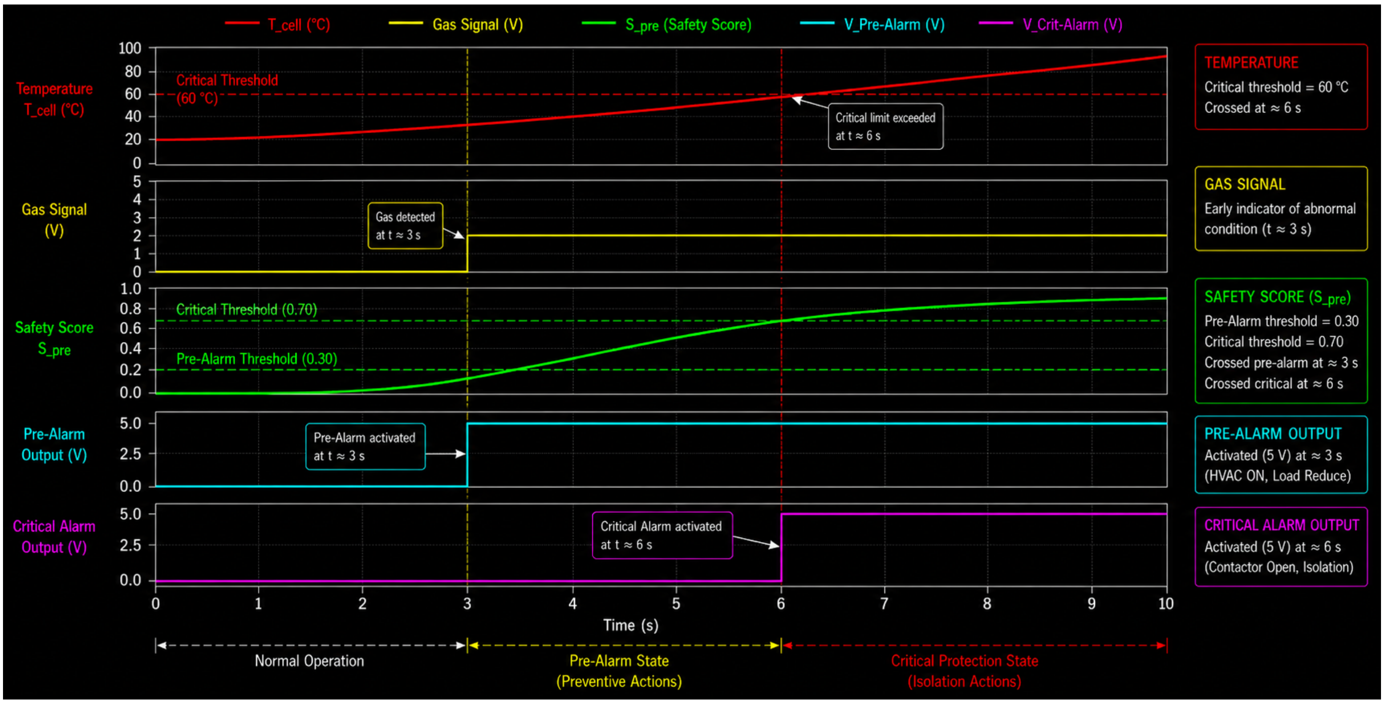

Figure 8. LTspice transient simulation results.

mitigates processing latency, physical propagation delays between localized sensor nodes and the central control panel must be accounted for in actual deployments. Therefore, translating this conceptual framework into an industrial setting requires acknowledging these environmental variables, which may influence the precise timing and threshold behaviors observed in idealized simulations.

To further verify the proposed framework against diverse fault domains, a secondary simulation scenario was conducted focusing on electrical anomalies, specifically cell voltage deviation and insulation degradation. As illustrated in Figure 9, a localized cell imbalance is introduced using an arbitrary behavioral source, characterized by a progressive increase in voltage deviation (dV/dt). Simultaneously, a continuous degradation in insulation resistance (R_{ins}) is modeled. As these secondary and conditioning indicators escalate, their weighted combination drives the comprehensive safety score (S_{pre}). At $t \approx 5\,\text{s}$, the score crosses the defined pre-alarm threshold ($S_{\text{pre}} \geq Th_{\text{pre}}$ where $Th_{\text{pre}} = 0.40$), successfully activating the 5V preventive output. Subsequently, as the simulated insulation degradation becomes more severe, the score rapidly exceeds the critical threshold ($S_{\text{pre}} \geq Th_{\text{crit}}$ where $Th_{\text{crit}} = 0.70$) at $t \approx 7\,\text{s}$. This initiates the immediate isolation command, demonstrating the system's multidimensional responsiveness to complex electrical failure trajectories.

This secondary scenario demonstrates that the proposed framework is not limited to thermal indicators alone. Progressive voltage imbalance and insulation degradation are recognized as precursor electrical anomalies that frequently precede severe thermal events in large-scale BESS installations. The simulation confirms that the weighted fusion mechanism can aggregate multiple low-level indicators and initiate preventive actions before the emergence of primary thermal signatures. This behavior highlights the capability of the proposed methodology to address diverse fault trajectories while maintaining deterministic response characteristics.

5 Conclusion

This study presented a hardware-oriented multi-parameter early warning and protection methodology for Battery Energy Storage Systems (BESS). Unlike conventional single-threshold protection approaches, the proposed framework combines internal BMS parameters and enclosure-level environmental indicators within a weighted hierarchical decision structure.

The proposed methodology prioritizes critical physical indicators such as rapid temperature increase (dT/dt) and volatile gas emissions, enabling earlier anomaly recognition before catastrophic thermal runaway conditions fully develop. By integrating discrete analog signal conditioning with deterministic

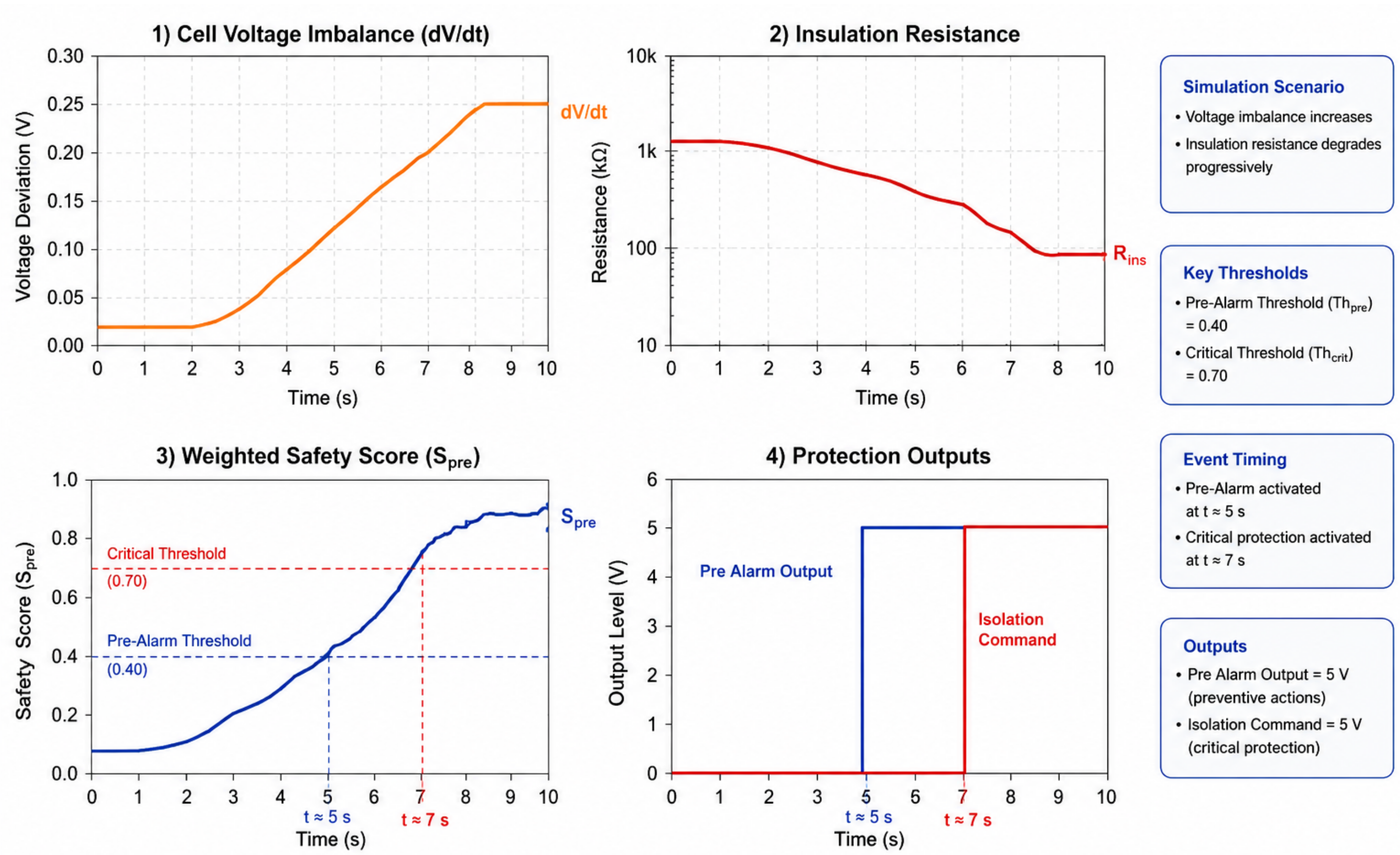

Figure 9. Transient simulation results of the secondary fault scenario, illustrating the system's hierarchical response to progressive cell voltage imbalance and continuous insulation resistance degradation.

microcontroller-based logic, the framework minimizes computational latency and improves real-time operational reliability.

Transient LTspice simulations verified the sequential execution capability of the proposed architecture. Simulation results demonstrated that the system successfully initiated preventive pre-alarm actions before the thermal threshold was exceeded and subsequently executed closed-loop electromechanical isolation once critical conditions were reached.

In the primary simulation scenario, the Pre-Alarm state was activated at approximately $t = 3\,\text{s}$, while the Critical Protection state was triggered at approximately $t = 6\,\text{s}$. Furthermore, the theoretical response time analysis estimated a deterministic response interval of approximately $25 - 55\,\text{ms}$.

The proposed approach contributes to bridging the gap between theoretical battery diagnostic algorithms and practical industrial hardware implementation. In addition, the framework establishes a direct relationship between multi-parameter anomaly detection, hierarchical decision-making, and verified hardware-level protection.

Future work will focus on real-time Hardware-in-the-Loop (HIL) implementation and experimental validation using physical sensor networks. These subsequent investigations will explicitly address the challenges associated with real-world deployments, including potential sources of uncertainty such as dynamic sensor drift over the battery lifecycle, electromagnetic interference (EMI) from high-power switching components, and complex spatial temperature gradients across large-scale enclosures. Accounting for these physical variables will be crucial for refining the adaptive weighting strategies and ensuring the absolute robustness of the proposed framework under varying operational conditions.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Darius Andriukaitis served as an Associate Editor of the *ICCK Transactions on Electric Power Networks and Systems* at the time of manuscript submission. To ensure the integrity of the peer-review process, Darius Andriukaitis was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. The remaining authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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