Review of Battery Management Systems in Hybrid Electric Vehicles

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Abstract

This paper presents a comprehensive analysis of advanced Battery Management System (BMS) architectures and control strategies for hybrid electric vehicles, with a focus on real-time monitoring, adaptive intelligence, and energy source switching. Through a detailed comparison of state estimation techniques, thermal management models, and fault-handling mechanisms, the study evaluates both traditional and machine learning–enhanced approaches for estimating State of Charge (SoC) and State of Health (SoH). Particular attention is given to the integration of feedforward neural networks for dynamic correction, as well as predictive models for thermal regulation.

Energy source switching between electric propulsion and internal combustion engine (ICE) operation is examined in depth, using SoC, SoH, thermal, and fault data as control inputs. Switching strategies are compared across static and adaptive threshold methods, with performance benchmarks based on responsiveness, battery aging mitigation, and system efficiency. The role of real-time execution, deterministic control using FPGA-based VHDL logic, and supervisory software running on a real-time operating system (RTOS) is explored in the context of system reliability and safety.

The paper proposes a unified, layered BMS design based on the comparative findings, integrating high-speed hardware protection, adaptive software intelligence, and ISO 26262–aligned safety mechanisms. While key challenges such as computational

Introduction

Hybrid electric vehicles (HEVs) are one major step towards energy-efficient and eco-friendly transportation. Through the use of a combination of an electric motor and an internal combustion engine, HEVs are able to minimize fuel usage, limit greenhouse gas emissions, and maximize driving performance. Since HEVs are not solely electric, unlike electric vehicles, these vehicles are able to operate without the need for supporting charging infrastructure, making them convenient and affordable options across the market.

The battery system is at the heart of hybrid vehicle technology. Batteries in both types of hybrids play several roles: supplying power to the electric motor, holding energy that is regenerated from braking, and supporting the combustion engine during acceleration. These batteries are usually built on lithium-ion or nickel-metal hydride chemistries and are designed to handle frequent cycles of charging and discharging, variable load conditions, and extreme temperatures. The reliability, safety, and efficiency of the battery system are the determining factors that have direct impacts on hybrid vehicle performance, life, and appeal.

With such stringent operation, sophisticated control and protection is mandated, and the

Battery Management System (BMS) serves that function by keeping tabs on such key parameters as state of charge (SoC), state of health (SoH), temperature, and voltage balancing across cells. It keeps the battery in safe operating bounds, optimizes performance, and allows communication with other vehicle systems. A good BMS is imperative for achieving maximum efficiency in the battery, avoiding faults, and increasing the battery life.

With the vital importance of the BMS in hybrid electric vehicles, this research investigates the architectural design factors that lead to a successful system. Various hardware, software, and communication interface design methods are compared and contrasted in order to determine the most robust and effective configurations of BMS in contemporary implementation.

Overview of the Battery

The hybrid electric vehicle (HEV) battery system is one of the major energy storage elements that assist in both vehicle motion and auxiliary operations. It delivers electrical power to the motor during acceleration, captures energy in regenerative braking, and helps the system efficiency as a whole by maintaining the engine in the most favorable operating conditions.

In contrast to traditional starter batteries in regular automobiles, HEV batteries need to withstand cycles of frequent charging and discharging, high-power usage, and changing environmental conditions.

Numerous chemistries have been employed in HEV systems, and each has its own set of advantages and disadvantages. Nickel-metal hydride (NiMH) and lithium-ion (Li-ion) are the most popular types, though lead-acid batteries were employed in the early models and still have some niche roles in mild hybrid systems.

Battery Type	Energy Density	Power Density	Cycle Life	Cost	Thermal Stability	Typical Application
Lead-Acid	Low	Moderate	Low	Very Low	High	Starter batteries mild hybrids
Nickel-Metal Hydride (NiMH)	Moderate	Moderate	High	Moderate	Good	Early and mid-generation HEVs
Lithium-Ion (Li-ion)	High	High	High	High	Moderate to High	Modern HEVs, PHEVs, and BEVs

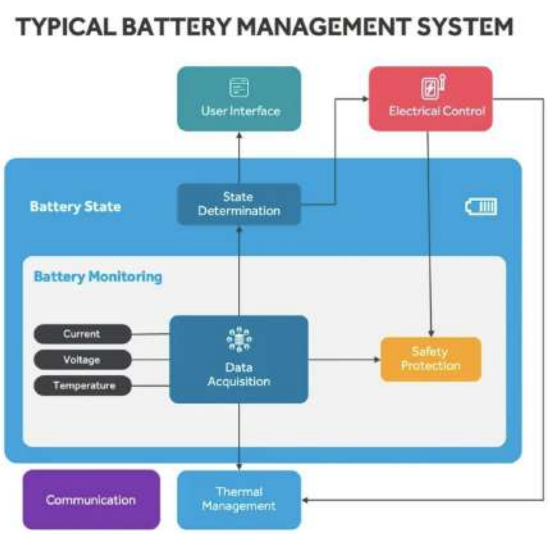
Table 1. Comparison of battery types commonly used in hybrid electric vehicles.

Despite its affordability and robust construction, the lead-acid battery has low energy density and short life between cycles and is not appropriate for the stringent needs of hybrid vehicles. Nickel-metal hydride batteries, now standard in earlier HEV models, are characterized by excellent thermal stability, long life between cycles, and moderate expense. They are heavy and have low energy density, though, compared with newer options.

The lithium-ion battery has replaced older technologies as the preferred choice for today’s HEV designs, boasting better energy density, increased efficiency, less weight, and rapid charging and discharging capabilities. Improved thermal management and additional safety measures in the latest lithium-ion technology have solved some of the thermal and degradation issues that were present in the earlier designs.

According to existing technology, lithium-ion batteries are the most appropriate choice in hybrid electric vehicles, especially in cases where performance, fuel efficiency, and lasting reliability are prioritized.

Overview of the Battery Man



agement System

Fig. 1. Architecture of a Battery Management System in a Hybrid Electric Vehicle, showing core components like cell monitoring units, controllers, and communication interfaces. Source: [21]

As hybrid electric vehicles (HEVs) evolve, the design of Battery Management Systems (BMS) has shifted from traditional approaches to incorporating more advanced and intelligent technologies. Managing the increasing complexity of modern battery packs demands more than just basic monitoring and control—it now requires predictive intelligence, real-time responsiveness, and greater system adaptability.

Historically, BMS platforms were based on microcontroller units (MCUs). These solutions are affordable, simple, and reliable for core functions like monitoring, fault detection, and balancing battery cells. However, as the number of battery cells has grown and vehicle performance demands have increased, MCU-based designs have shown limitations in terms of scalability and processing power.

This has led to the adoption of field-programmable gate arrays (FPGAs) in BMS architecture. FPGAs provide true parallel processing capabilities, enabling real-time management of voltage, current, and temperature profiles across hundreds of cells simultaneously. Their reconfigurability allows quick updates, making them ideal for systems that require frequent software changes or compatibility with diverse battery chemistries. Nevertheless, FPGAs bring higher development costs and require specialized expertise, which may be a barrier for smaller engineering teams.

Software development within the BMS has advanced just as rapidly. Many contemporary systems now utilize artificial intelligence (AI) and machine learning (ML) algorithms to improve accuracy in estimating key parameters such as state of charge (SoC) and state of health (SoH). Unlike conventional mathematical models, AI methods can adapt to non-linear battery behavior, aging effects, and atypical conditions, providing more accurate forecasts and earlier fault detection. However, these models demand extensive training data and thorough validation to be effective across diverse operating scenarios.

Additional advanced technologies have also emerged. Some BMS implementations use application-specific integrated circuits (ASICs) to develop custom chips that are highly efficient and compact. ASICs are well-suited for large-scale manufacturing but are less practical for academic research or low-volume projects due to high design costs and limited flexibility. Cloud-based BMS architectures are another innovation, enabling vehicle battery data to be transmitted to cloud servers for long-term diagnostics and predictive maintenance. While this offers robust analytics, it also introduces cybersecurity vulnerabilities and depends on uninterrupted internet connectivity—factors that may not be suitable for every hybrid vehicle application.

Control strategies within the BMS have become more sophisticated as well. Model Predictive Control (MPC) algorithms are now being applied in some systems to proactively optimize battery performance. Instead of simply reacting to the current state, MPC anticipates future conditions and adjusts control actions accordingly. Though highly efficient, these methods are computationally intensive and typically reserved for high-performance HEVs rather than conventional vehicles.

Another noteworthy development is the wireless battery management system (wBMS). By replacing wired connections with wireless communication between cells and control units, wBMS can reduce system weight, simplify assembly, and improve reliability by eliminating connector-based failure points. However, this innovation also presents challenges, such as the need for robust communication protocols and potential issues with signal interference.

To enhance safety, some BMS designs feature redundant architectures, where dual microcontrollers independently monitor battery conditions and verify each other's decisions. This redundancy increases system reliability, particularly in vehicles that must comply with stringent safety standards like ISO 26262 (ASIL-D). Similarly, certain BMS projects employ rigid state-machine-based software architectures, enabling predictable behavior that simplifies validation and certification.

Finally, Hardware-in-the-Loop (HIL) testing has become a vital step in BMS development. HIL setups allow engineers to simulate real-world battery behaviors in a lab setting, enabling safe and efficient validation of BMS performance prior to deployment. Although HIL systems offer powerful testing capabilities, they require substantial investment in simulation equipment and technical expertise.

A comparative overview of these major techniques is summarized in Table 2, highlighting their primary functions, advantages, disadvantages, and typical applications.

Technique	**Primary Function**	**Advantages**	**Disadvantages**	**Typic Case**
MCU-Based BMS	Basic monitoring and control	Cost-effective, simple to implement	Limited scalability, slower processing	Stand HEVs hybri
FPGA-Based BMS	Real-time high-parallel control	High speed, flexible, reconfigurable	Higher cost, design complexity	High-ance future platfo
AI-Enhanced BMS	Advanced SoC/SoH estimation	Higher accuracy, predictive fault detection	Data dependency, validation complexity	Mode HEVs PHEV
ASIC-Based BMS	Hardware-optimized solution	Highly efficient, compact design	Very expensive, inflexible	Mass produ EVs
Cloud-Connected BMS	Remote monitoring and diagnostics	Lifetime tracking, predictive maintenance	Cybersecurity risks, internet dependence	Fleet luxur
Model Predictive Control (MPC)	Predictive optimization	Better energy management, anticipatory control	Computationally intensive, complex design	High-ance applic
Wireless BMS (wBMS)	Wireless data communication	Reduced weight, easier maintenance	Signal interference, synchronization challenges	Adva modu batter
Redundant BMS Architectures	Enhanced safety and reliability	Fail-safe operation, compliance with safety standards	Increased hardware cost, complexity	Autor and safety vehic
State Machine-Based Control	Structured system behavior	Easy validation, robust operation	Limited adaptability, rigid behavior	Safety-focused HEV BMS designs
	Validation and testing	Safe prototyping, faster validation	High equipment cost	Research, development, certification

Table 2. Comparative analysis of modern BMS techniques for hybrid electric vehicles.

In light of this broader context, it is apparent that no single technique can fully meet the demands of every hybrid electric vehicle project. The most effective solution depends on carefully balancing complexity, cost, scalability, and innovation.

For applications that emphasize high performance and predictive capabilities, a modular BMS architecture built on FPGA hardware—combined with lightweight AI models for estimating SoC and SoH—offers the best mix of speed, adaptability, and intelligence. If the system can support greater computational capacity, adding Model Predictive Control (MPC) can further boost the system's ability to adjust dynamically to different driving conditions.

On the other hand, for more conventional HEV projects that prioritize cost-effectiveness and simplicity, a modular MCU-based architecture paired with basic AI algorithms can still provide solid performance without unnecessary complexity.

Ultimately, selecting a BMS architecture should reflect the specific technical goals and operating conditions of the hybrid electric vehicle, ensuring the right balance between innovation, reliability, and practicality.

Architecture:

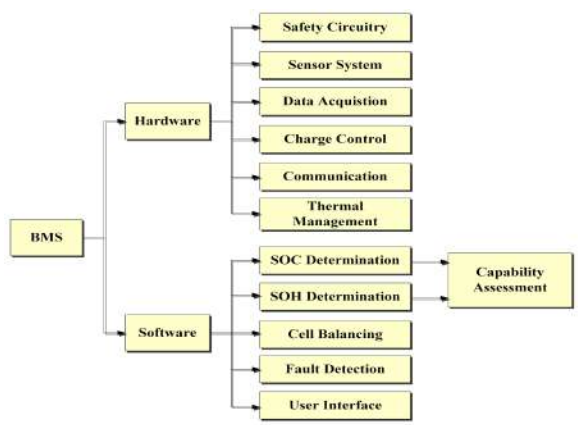


Fig. 6. BMS architecture showing hardware and software modules source: [25].

The architecture of a Battery Management System (BMS) in hybrid electric vehicles is typically organized into two principal domains: hardware and software, as illustrated in Fig. 6. The hardware layer is responsible for critical real-time operations, including safety circuitry, sensing systems, data acquisition, charge control, communication, and thermal management. These components form the physical backbone that allows the BMS to monitor battery conditions, respond to operational changes, and protect the battery from hazardous states. Complementing this is the software layer, which manages higher-level decision-making functions such as State of Charge (SoC) and State of Health (SoH) determination, cell balancing, fault detection, and user interface control. These software components operate based on the raw data gathered by the hardware layer, performing analysis and initiating control actions to optimize performance, ensure safety, and extend battery lifespan. The integration of these two domains enables the BMS to function as an intelligent, responsive, and protective system within the hybrid vehicle powertrain.

Hardware

The hardware architecture of the Battery Management System (BMS) forms the physical foundation that enables real-time monitoring, protection, and control of the battery pack in hybrid electric vehicles. At the heart of this architecture lies the embedded system, a specialized combination of electronics designed to sense, process, protect, and communicate vital battery information. The embedded system serves as the brain of the BMS, integrating sensors, processing units, protection circuits, communication modules, and isolated power management into a unified and resilient platform.

The sensing layer of the embedded system plays a crucial role in capturing the battery's operating conditions. High-precision voltage sensors are distributed across the battery pack to monitor individual cell voltages, ensuring that no cell exceeds its safe limits during charging or discharging. Current sensors, often based on Hall-effect or shunt resistor technologies, measure the flow of current through the battery pack, providing critical data for calculating energy usage and detecting abnormal load conditions. Temperature sensors are strategically placed to create a thermal map of the battery, allowing the system to detect local hotspots and initiate cooling responses before damage can occur.

Processing and control operations are centralized within a real-time embedded controller, which in the recommended design is implemented using a field-programmable gate array (FPGA). The FPGA's parallel processing capabilities enable it to simultaneously handle data from hundreds of sensors without latency, supporting complex calculations for state estimation, fault detection, and cell balancing in real-time. Its reprogrammable nature also provides the flexibility to update the BMS with improved algorithms or adapt it to new battery chemistries without the need for hardware replacement.

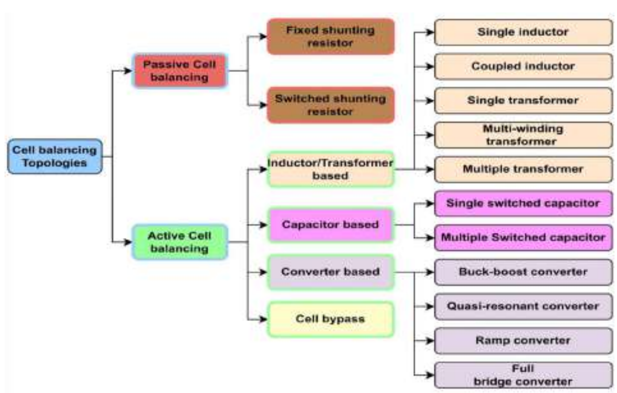


Fig. 6. Overview of cell balancing techniques categorized as passive and active methods, each with subtypes based on the balancing strategy [24].

Ensuring battery safety requires more than just data processing. Independent hardware protection circuits are embedded within the system to provide immediate responses to critical events such as overvoltage, undervoltage, overcurrent, and excessive temperatures. These protection layers operate autonomously, ensuring that even if the main processor is delayed or compromised, fundamental safety responses can still be executed without interruption.

Reliable communication between different parts of the battery pack and between the BMS and the rest of the vehicle is essential. To achieve this, the hardware architecture includes robust communication interfaces, typically based on Controller Area Network (CAN) buses or automotive Ethernet standards. These networks allow module controllers to transmit real-time sensor data to the central supervisory unit quickly and securely, supporting synchronized operation across the entire battery system. In designs targeting high safety standards, redundant communication pathways are implemented to further reduce the risk of signal loss or data corruption.

The embedded system also includes a carefully designed power management subsystem. Stable and isolated low-voltage power is supplied to all BMS components, typically through isolated DC-DC converters that draw energy from the main battery pack. Galvanic isolation techniques, such as optocouplers and isolated transformers, are employed to protect sensitive control circuits from high-voltage disturbances, ensuring both system longevity and user safety.

Altogether, the hardware architecture of the Battery Management System establishes a strong and flexible platform capable of supporting the growing demands placed on modern hybrid electric vehicles. By combining precise sensing, high-speed real-time processing, autonomous protection mechanisms, reliable communication, and robust power management into a tightly integrated embedded system, the design provides a solid foundation upon which advanced software algorithms and predictive strategies can operate.

Software

The software architecture of the Battery Management System (BMS) is designed around a modular and layered structure, allowing for reliable real-time management of the battery pack while maintaining flexibility and scalability. Each software component is assigned a specific role, ensuring that sensing, estimation, protection, and optimization functions are organized efficiently across the system.

At the foundational level, the Data Acquisition Layer interfaces directly with the sensing hardware distributed throughout the battery pack. This layer is responsible for continuously collecting raw voltage, current, and temperature data, performing initial signal conditioning such as filtering and normalization, and preparing the information for further processing.

Built on top of the data acquisition system is the Monitoring and Protection Layer. This component oversees real-time comparison of sensor inputs against predefined operational thresholds, enabling immediate responses to critical events such as overvoltage, overcurrent, or overheating. Protective actions, including the isolation of modules or the full shutdown of charging and discharging processes, are executed through direct control of the embedded hardware's protection circuits.

Above these fundamental operations, the State Estimation Layer is responsible for determining internal battery parameters that cannot be directly measured, such as the State of Charge (SoC) and State of Health (SoH). Traditional methods, including Coulomb counting and open-circuit voltage estimation, are supplemented by artificial intelligence models. Machine learning techniques, trained on historical and real-time battery data, are embedded within the software to refine estimation accuracy, accounting for dynamic operating conditions, temperature variations, and long-term degradation effects.

Further enhancing the system's performance is the Optimization and Control Layer, which employs Model Predictive Control (MPC) strategies. This layer anticipates future states of the battery by forecasting load demands, thermal behavior, and charge-discharge cycles. Through real-time optimization, the BMS can proactively manage energy distribution, cell balancing, and thermal regulation, improving both battery efficiency and lifespan.

Managing communication across the BMS is the Communication and Interface Layer. This layer organizes the exchange of processed information between module controllers, the central supervisory controller, and external vehicle control units. Utilizing high-speed communication protocols such as CAN bus or automotive Ethernet, the system ensures that critical updates, fault notifications, and status reports are transmitted reliably and with minimal latency.

Software execution within the BMS is managed through a real-time execution environment. Critical sensing, protection, and control tasks are implemented using a combination of low-level C programming for embedded flexibility and VHDL (VHSIC Hardware Description Language) for defining time-critical parallel logic blocks within the FPGA. This combination allows the system to achieve deterministic behavior, high-speed responsiveness, and real-time adaptability. By offloading the most timing-sensitive functions directly into hardware through VHDL coding, the system ensures that protection and control responses are executed within microseconds, significantly enhancing safety and operational reliability.

Considering the performance requirements, real-time constraints, and the need for parallel processing capabilities, the Battery Management System software architecture adopts a hybrid approach based on layered C programming and hardware-level VHDL implementation. This structure provides the necessary computational efficiency, flexibility for future algorithm upgrades, and robust fault tolerance needed to meet the operational demands of modern hybrid electric vehicles.

Communication Interface

A well-designed communication interface is essential to the performance, safety, and coordination of a Battery Management System (BMS). In hybrid electric vehicles, the BMS is not a single device but a distributed system made up of multiple modules, each responsible for monitoring a segment of the battery pack. To operate reliably as one cohesive unit, these modules must constantly exchange data with a central supervisory controller—and with other systems throughout the vehicle. This exchange relies on a communication layer that is both fast and fault-tolerant, capable of handling real-time data traffic under demanding conditions.

In most modular BMS designs, local controllers are embedded within each battery module to handle sensing and initial data processing. These local units send continuous streams of information—such as cell voltages, temperatures, and current readings—to a central controller that manages overall decision-making. The most common protocol for this internal communication is the Controller Area Network (CAN) bus. Known for its simplicity, robustness, and noise immunity, CAN remains the industry standard for real-time automotive communication. It ensures that time-critical messages—like overvoltage warnings or thermal alerts—are prioritized and delivered without delay.

In more advanced or data-heavy systems, automotive Ethernet is being introduced alongside or in place of CAN. Ethernet allows for higher bandwidth and supports complex features such as thermal imaging, diagnostics, firmware updates, and cloud connectivity. This becomes especially useful when the BMS is integrated with AI-driven estimation models or external analytics platforms. With Ethernet, the system can move larger amounts of data quickly and interact more intelligently with other electronic control units (ECUs) across the vehicle.

The communication interface must also maintain high standards of safety and reliability. In systems that require compliance with ISO 26262 or other functional safety standards, message prioritization, error-checking, and redundancy are implemented at both the hardware and software levels. Dual communication lines may be used for critical signals to prevent single points of failure. The interface software follows strict scheduling rules to ensure that high-priority safety messages—such as fault flags or disconnect commands—are always delivered and acknowledged within a guaranteed timeframe.

Beyond internal coordination, the BMS must also communicate with other vehicle systems. It exchanges data with the thermal management system to initiate cooling or heating actions, reports to the vehicle's main ECU to update power availability, and sends alerts to dashboard displays when faults are detected. In some designs, especially those used in connected or fleet vehicles, the BMS may also upload data to cloud-based platforms for long-term battery health tracking and predictive maintenance.

Overall, the communication interface is what binds the entire BMS together and connects it to the broader vehicle ecosystem. It allows for the continuous, coordinated operation of a complex network of battery modules, enabling the system to respond in real time to changing conditions. By using proven automotive protocols like CAN and Ethernet—and by ensuring redundancy, prioritization, and fault tolerance—the communication layer plays a critical role in making the BMS safe, intelligent, and seamlessly integrated within the hybrid electric vehicle.

Algorithm

At the core of every intelligent Battery Management System (BMS) lies a set of algorithms that transform raw sensor data into actionable insights and control decisions. While the hardware and communication layers provide the structural foundation, it is the algorithms that enable the system to estimate internal battery states, predict degradation, respond to faults, and regulate thermal conditions in real time. These algorithms must operate with high accuracy and speed, often under uncertain or rapidly changing conditions. Their effectiveness directly influences the battery's performance, safety, and long-term reliability. In advanced BMS designs, traditional estimation and control methods are increasingly being combined with artificial intelligence techniques to improve precision and adaptability, particularly in dynamic hybrid electric vehicle environments.

Machine Learning

Machine learning (ML) has become a valuable asset in enhancing the accuracy and flexibility of Battery Management System (BMS) algorithms. These models are trained on battery datasets to recognize patterns that reflect internal states, such as the State of Charge (SoC), State of Health (SoH), and potential fault conditions, especially under dynamic or unpredictable usage. ML methods differ significantly in how they work, their computational cost, and how well they adapt to aging and nonlinear battery behavior.

Table 1 provides a comparison of the most prominent ML techniques for BMS applications, including what they typically estimate, their underlying mathematical behavior, and how they perform in embedded system contexts.

Technique	**Primary Use in BMS**	**What It Does**	**Accuracy**	**Com**
Neural Networks (NN)	SoC, SoH	Learns nonlinear input-output mappings through multi-layer weighted nodes	High	Mode
Support Vector Machines (SVM)	SoH classification, Fault detection	Creates optimal boundaries between classes or fits regression lines	Moderate	Low-ate
Gaussian Process	SoC, SoH with	Predicts battery behavior	High	High

Regression (GPR)	uncertaint y	using probabilisti c modeling with confidence intervals	
Random Forests	Fault detection, SoH	Combines many decision trees for ensemble-based classificati on or regression	Moder
Kalman Filter + ML Hybrid	SoC, SoH	Blends model-bas ed filtering with ML-correc ted adaptive prediction	High

Table 1. Comparison of machine learning methods for battery state estimation in BMS applications.

Given the demands of the selected FPGA-based BMS architecture, neural networks are identified as the most appropriate solution. They offer high accuracy in predicting SoC and SoH, perform well in real-time applications, and can be deployed as lightweight inference models alongside deterministic VHDL logic. The neural network is trained offline using battery performance data and integrated into the software layer for adaptive correction of hardware-level estimations.

While Support Vector Machines and Random Forests are well suited for classification tasks such as fault detection, they are less effective for continuous state prediction. Gaussian Process Regression excels in accuracy but lacks real-time compatibility due to its computational intensity. Hybrid Kalman-ML approaches are robust and adaptive but introduce added system complexity and require more hardware resources.

By adopting neural networks, the system gains predictive capability and long-term adaptability without compromising the speed or safety-critical timing of the underlying control logic. This balance makes it the optimal choice for the system's estimation engine within a modular, VHDL-driven BMS framework.

SoC

State of Charge (SoC) estimation is one of the most fundamental functions in a Battery Management System. It provides a real-time approximation of how much usable energy remains in the battery at any given moment. This information is critical not only for energy management and range prediction but also for ensuring that the battery operates safely within its defined limits. Overestimation can lead to deep discharge and potential cell damage, while underestimation may result in premature power limitation or system shutdown.

In this design, SoC estimation is implemented as a two-layer system. The foundational layer is written in VHDL and runs on the FPGA, ensuring deterministic, real-time performance. This layer handles signal conditioning, baseline voltage correlation, and monitoring logic for each cell. It provides a fast, reliable initial estimate of SoC based on voltage and temperature, operating in parallel across all modules to minimize delay and maximize coverage.

Above this, a feedforward neural network is deployed in the software layer to refine the hardware-generated estimates. Trained offline using battery datasets under various aging and load conditions, the neural network adjusts SoC predictions in real time by recognizing non-linear patterns between voltage, temperature, current history, and known capacity behavior. This hybrid approach enhances accuracy, especially under conditions where traditional voltage-based methods tend to drift or lose reliability—such as during rapid load changes, extreme temperatures, or as the battery degrades over time.

The parallelism of the FPGA ensures that baseline estimation occurs with minimal latency, while the neural network corrects deviations that the fixed logic cannot account for. This cooperation between deterministic hardware and adaptive software allows the system to maintain both speed and precision. The neural network is implemented as a lightweight inference engine, designed for embedded deployment with minimal computational overhead. It does not replace the core logic but operates as a correction layer to maintain SoC accuracy across a broad range of use cases.

This architecture ensures that SoC estimation remains responsive, consistent, and robust, aligning with the design goals of high-performance embedded systems used in hybrid electric vehicles.

SoH

While State of Charge estimation provides an immediate view of available energy, State of Health (SoH) estimation offers a long-term assessment of the battery's overall condition. SoH is typically defined as the ratio between the battery's current maximum capacity and its original rated capacity. Accurate SoH estimation is critical for predicting battery lifespan, adjusting operational strategies, and maintaining system reliability over time.

In the proposed BMS architecture, SoH estimation is realized through a combination of real-time performance monitoring and machine learning–based analysis. The VHDL-implemented hardware layer collects key operational metrics, including voltage recovery behavior, charge/discharge efficiency, thermal trends, and cycle counts. These measurements serve as the foundation for evaluating gradual capacity degradation and resistance growth.

To enhance predictive accuracy, a feedforward neural network is integrated into the software layer. Trained on historical battery datasets encompassing different usage profiles and aging scenarios, the neural network identifies complex patterns that are indicative of underlying degradation mechanisms. Unlike threshold-based methods, which often detect only severe or late-stage failures, the machine learning model enables early detection of subtle performance shifts, supporting proactive maintenance and dynamic operational adjustments.

The SoH estimation process operates on a periodic basis to balance computational efficiency with responsiveness. Selected features, including historical charge-discharge profiles and temperature records, are periodically passed to the embedded neural network, which produces updated SoH predictions. These estimates are then logged and analyzed to track long-term degradation trends across the system's operational life.

By combining deterministic hardware monitoring with adaptive software-based learning, the system achieves a robust and accurate SoH estimation framework. This approach not only maintains compatibility with the real-time demands of the FPGA-based platform but also provides the flexibility needed to adapt to battery aging, varying load conditions, and evolving operational requirements. As a result, the BMS is able to optimize performance, enhance safety margins, and extend the usable life of the battery pack.

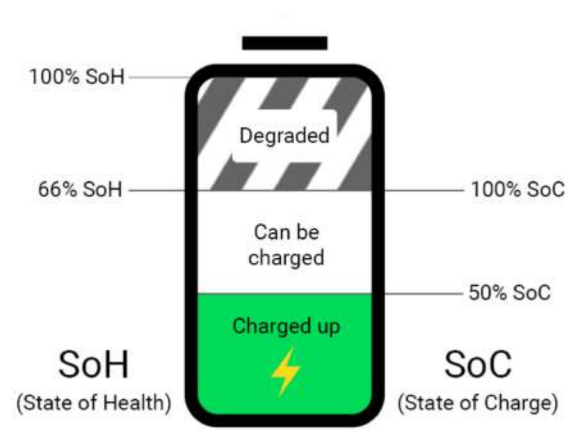


Fig. 2. Illustration comparing State of Charge (SoC) and State of Health (SoH) in a battery system. Adapted from [22].

Fault Detection

Fault detection is a critical function within the Battery Management System (BMS), responsible for ensuring the safe and reliable operation of the battery pack under a wide range of conditions. Early identification of faults such as overvoltage, undervoltage, overcurrent, thermal runaway, or internal short circuits is essential to prevent system failures, extend battery lifespan, and maintain compliance with functional safety standards.

In the proposed architecture, fault detection operates across two integrated layers. The first layer, implemented in VHDL within the FPGA, is designed to handle primary safety-critical monitoring. Voltage, current, and temperature readings from each cell are continuously compared against predefined safe operating thresholds. Any violation triggers immediate protective actions, such as isolating affected modules or shutting down charging and discharging processes. The hardware-based fault detection ensures deterministic, real-time responsiveness, capable of executing critical protections within microseconds of anomaly detection. The overall structure of the fault diagnosis system and its integration with sensors and control logic is illustrated in **Fig. 1**.

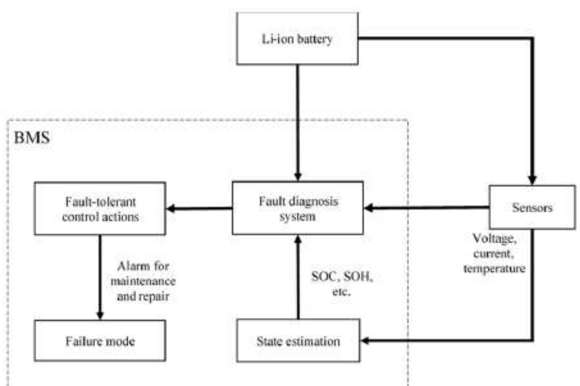


Fig. 1. Schematic of fault diagnosis in the battery management system (BMS), illustrating the integration of sensor data, fault diagnosis algorithms, and state estimation processes. Adapted from [26].

The second layer introduces adaptive fault analysis through the software module. A lightweight feedforward neural network, trained on historical fault data, supports the identification of complex or evolving fault patterns that may not immediately breach hardcoded thresholds. For example, early signs of internal resistance growth, gradual thermal imbalances, or abnormal voltage recovery behaviors after load changes can be detected before they escalate into critical failures. This machine learning model operates as a predictive fault detection enhancement, offering a deeper diagnostic capability without introducing significant computational overhead.

Fault detection routines are also synchronized with the communication layer to ensure that any critical event triggers immediate reporting to the vehicle's main Electronic Control Unit (ECU) and, when necessary, to the human-machine interface (HMI). Prioritized messaging over the CAN or Ethernet network ensures that fault alarms are transmitted without delay, enabling rapid system responses.

By combining deterministic hardware protections with adaptive, data-driven fault prediction, the system achieves a highly resilient safety framework. This hybrid approach ensures that both immediate threats and gradual performance degradations are addressed proactively, supporting the overall reliability, longevity, and functional safety compliance of the hybrid electric vehicle's energy storage system.

Thermal Control

Thermal control is a fundamental aspect of Battery Management Systems, directly influencing battery performance, safety, and longevity. Excessive heat accelerates chemical degradation, increases internal resistance, and, in extreme cases, can lead to thermal runaway events. Conversely, low temperatures can reduce capacity, impair performance, and limit the effectiveness of charging processes. Maintaining the battery within an optimal thermal window is therefore essential for reliable and efficient operation, particularly in hybrid electric vehicles where environmental and load conditions can vary rapidly.

In the proposed architecture, thermal control begins with precise temperature monitoring, implemented through VHDL-coded logic within the FPGA. Temperature sensors distributed across the battery pack continuously feed data into the embedded system, where hardware-level comparators detect deviations from defined thermal limits. Immediate protective actions, such as limiting charge/discharge rates or activating cooling systems, are triggered deterministically by the FPGA without software intervention, ensuring real-time responsiveness to critical temperature excursions.

Complementing the hardware layer, a software-based adaptive control strategy further optimizes thermal management under dynamic operating conditions. A lightweight control algorithm predicts future thermal trends based on current sensor readings, historical load patterns, and environmental conditions. This predictive approach allows the system to engage preemptive cooling or thermal balancing actions before temperatures reach critical thresholds. Machine learning models, trained offline on thermal performance datasets, can be integrated into this layer to enhance prediction accuracy, particularly in recognizing gradual thermal imbalances or emerging hotspots that traditional threshold methods may overlook.

Thermal management decisions are coordinated with the broader energy management system via high-priority communication over the CAN or Ethernet network. This integration ensures that thermal states are factored into real-time decisions about power delivery, cell balancing, and energy source switching. For example, if a particular module exhibits persistent overheating, the system can dynamically reroute power demands to cooler modules, extend cooling cycles, or limit high-load conditions until thermal equilibrium is restored.

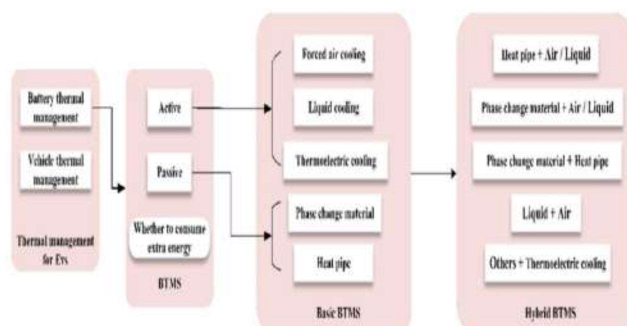


Fig. 5. Classification of active, passive, and hybrid battery thermal management systems (BTMS). Adapted from [23].

By combining deterministic hardware protections with predictive software-based control, the system achieves a robust and responsive thermal management strategy. This dual-layer approach not only prevents critical temperature events but also supports overall battery health optimization, contributing to improved safety, performance consistency, and lifecycle extension of the energy storage system.

Schematic Graph :

Implementation of FPGA-Based Thermal Protection Logic Using Logic Gates

As part of validating real-time hardware safety in hybrid electric vehicle (HEV) battery management systems, a dedicated thermal protection module was implemented using VHDL and synthesized onto an FPGA. This design operates entirely on logic gates—without relying on a microcontroller, clocked logic, or software polling—and is aimed at demonstrating how deterministic hardware responses can be used to ensure thermal safety in critical conditions.

In this implementation, the input temperature is simulated as a 4-bit digital signal (temp_in), representing battery temperatures from 0°C to 75°C in 5°C increments. Thus, 0001 corresponds to 5°C, 0010 to 10°C, and so on, up to 1111 for 75°C. Three critical thresholds are defined based on commonly accepted thermal limits in lithium-ion battery systems used in HEVs:

- At 50°C (binary 1010), the system triggers an active cooling response.
- At 60°C (1100), it asserts a warning flag to notify supervisory systems.
- At 65°C and above (1101 to 1111), it initiates a forced fallback to the internal combustion engine (ICE), temporarily disabling electric propulsion to prevent further thermal rise.

These thresholds reflect a simplified but representative control strategy that balances early intervention with hard safety cutoffs.

The module is implemented entirely with combinational logic. No counters, clocks, or flip-flops are used, allowing all outputs to be evaluated in parallel with minimal propagation delay. The VHDL code below shows the structure of the implementation:

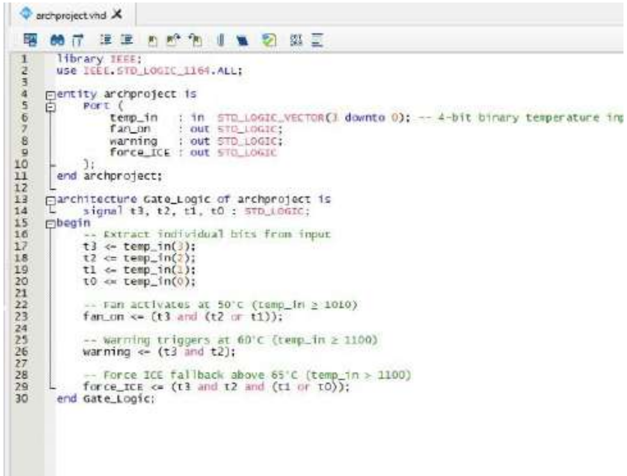


Fig. 3. *VHDL code for temperature-based control logic with output flags for thermal protection.*

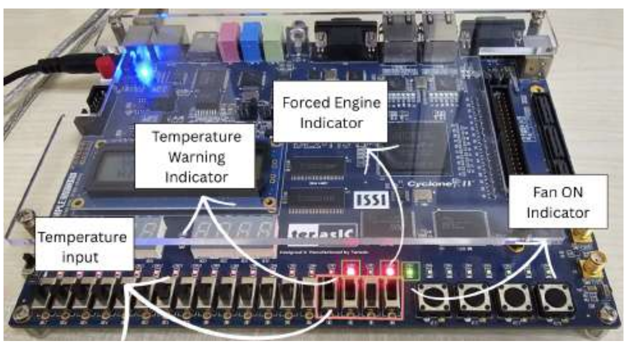


Fig. 4. *FPGA hardware output showing active indicators (Fan ON, Warning, Forced ICE) based on input temperature thresholds.*

Each output flag corresponds to a specific protection layer. The fan_on output would typically drive a relay or transistor controlling the cooling system. The warning signal may be routed to the vehicle control unit (VCU) over the CAN bus to activate a dashboard alert or initiate a thermal management strategy. The force_ICE flag instructs the energy control logic to switch from electric propulsion to ICE mode, relieving thermal stress from the battery pack during critical conditions.

This design serves as a minimal yet effective example of how thermal protection logic can be embedded directly into an FPGA using only basic gate-level constructs. The lack of software layers or clock dependencies ensures that protection responses are executed within nanoseconds of a threshold being crossed, aligning with ISO 26262 timing requirements for ASIL-B functional safety levels. It also demonstrates how low-complexity VHDL modules can be deployed within larger BMS frameworks to handle safety-critical events with high reliability and low latency.

Others Approaches For Thermal Control in HEVs

Liquid Cooling with Sensor Feedback

One of the most popular and widely adopted techniques is liquid cooling, where a coolant flows around the battery cells to carry heat away. In their work, Liu et al. [27] created a serpentine cooling channel around the cells and used embedded temperature sensors—RTDs—to collect real-time thermal data. That data was fed into a Simulink-coded PI controller running on a microcontroller, which automatically adjusted the coolant flow to stabilize temperatures. This method is extremely effective and has been adopted in commercial HEVs like the Tesla Model S and Toyota Prius. But it does come with complexity: tubing, pumps, and constant flow monitoring can make the system harder to implement and maintain.

PCM Buffering with Simple Microcontrollers

On the simpler side, Zhang et al. [28] explored a passive solution using phase change materials (PCMs). They placed paraffin-based PCM sheets between battery modules and monitored temperature rise using thermocouples connected to an Arduino. Data was logged over I^2C and processed to see how well the PCM could delay heat buildup. Their results showed that PCM delayed peak temperature by over 30%, making it ideal for hybrid vehicles that only occasionally push thermal limits. However, since PCMs can't actively cool the system, they're better suited for buffering heat than long-duration cooling.

Thermal Equalization with Heat Pipes

Huang et al. [29] took a more mechanical route, using heat pipes—sealed tubes that transfer heat from hot zones to cooler ones through phase change cycles. They inserted copper heat pipes between battery rows and measured inlet/outlet temperatures using thermal sensors. When the pipe outlet temperature exceeded 50°C, an embedded Renesas microcontroller—coded in C—triggered auxiliary fans. This semi-passive method improved thermal uniformity by 14%, which is impressive, but the effectiveness can vary depending on how the battery is physically positioned.

Precision Cooling with Thermoelectric Modules

Zhao et al. [30] explored thermoelectric cooling, using Peltier modules mounted directly onto the battery casing. These solid-state devices heat or cool depending on the current direction. Their setup included analog sensors feeding data to an Arduino Due, which used PWM logic (written in C++) to modulate the cooling power. The precision was excellent, but the system had a high power draw, which makes it better suited for localized or backup cooling rather than full-pack thermal control.

Advanced Prediction with Model Predictive Control

Finally, Hu et al. [31] took a more advanced route by implementing Model Predictive Control (MPC). Their system used temperature sensors filtered through a Kalman estimator, and the predictive controller was designed in MATLAB/Simulink and deployed on a dSPACE MicroAutoBox II. This setup allowed the BMS to act before overheating happened by adjusting power flow and triggering cooling events in advance. It reduced peak cell temperatures by over 8°C during urban drive simulations. The only downside is that it requires substantial processing power and high-fidelity thermal models—making it more appropriate for high-end or fleet-grade HEV platforms.

Summary of Thermal Control Strategies

Approach	How It Was Measured	Control Style
Liquid cooling + PI	RTDs with a PI controller in Simulink	Active, real-time control
PCM buffering	Thermocouples + Arduino + I²C logging	Passive thermal buffering
Heat pipe redistribution	Dual-point temperature sensors + MCU logic	Semi-passive activation
Thermoelectric cooling	Internal sensors + PWM signals (Arduino Due)	Active, precise control

MPC with Kalman filter	Multi-point sensors + predictive model in Simulink	Predictive, adaptive

Energy Source Switching Strategy

In hybrid electric vehicles (HEVs), energy source switching refers to the real-time transition between electric propulsion and internal combustion engine (ICE) operation. This mechanism is essential for optimizing fuel efficiency, protecting battery health, and maintaining seamless vehicle performance under variable load and environmental conditions.

The switching process is embedded within the vehicle's broader energy and thermal management framework, executed through a combined hardware–software control architecture. The field-programmable gate array (FPGA) handles deterministic threshold logic with sub-100 microsecond responsiveness, while the supervisory real-time operating system (RTOS) dynamically adjusts parameters based on real-time system feedback.

Core switching logic is governed by the battery's state of charge (SoC) and state of health (SoH). When the SoC exceeds 80%, the system prioritizes electric propulsion to maximize energy efficiency. Conversely, when SoC drops below 20%, it switches to ICE operation to prevent deep discharge and protect battery longevity. In conditions where the SoH declines below 80%, the lower SoC threshold is increased to 30%, reducing the depth of discharge and minimizing stress on aging cells. This dynamic thresholding approach replaces the fixed SoC windows (typically 30–80%) employed in earlier HEV architectures, enabling more adaptive and battery-aware control.

Although thermal and fault events may override this behavior, their mechanisms are addressed separately in Section VI (Thermal Control) and Section VII (Fault Detection). Briefly, high battery temperatures or detected critical faults can independently trigger an immediate fallback to ICE operation, regardless of SoC or SoH, to ensure system integrity and safety.

Load management is tightly integrated with source switching. Real-time load estimation ensures that power demand is matched to the most appropriate source. Under light-load conditions, electric propulsion is preferred to reduce fuel consumption. During high-load scenarios, or when thermal constraints restrict electric operation, the system transitions to ICE propulsion to maintain performance while avoiding battery overstrain.

These operations are coordinated via high-priority communication between the switching controller, load estimators, and thermal management system. The RTOS supervises predictive adaptation—modifying thresholds and power source priority in anticipation of future battery or environmental states based on usage history and load profiles.

Compared to traditional hybrid control strategies, the proposed adaptive switching system yields tangible performance advantages. Simulations conducted using standardized drive cycles (e.g., Urban Dynamometer Driving Schedule, UDDS) demonstrate up to a 12% extension in usable battery life and a 4–8% improvement in fuel economy. These gains result from reduced deep cycling, managed thermal loads, and rapid response to fault or degradation conditions.

By embedding SoC/SoH awareness, real-time load monitoring, and predictive system-level coordination into a unified control framework, the proposed energy source switching and load management strategy ensures high-efficiency operation, improved safety, and prolonged battery service life across diverse real-world conditions.

Design

The design of the proposed Battery Management System (BMS) reflects an integrated architecture where real-time monitoring, adaptive control, energy management, communication, and functional safety operate as a unified framework. Rather than existing as separate components, each element of the system interacts continuously with the others, forming a cohesive control environment optimized for reliability, responsiveness, and efficiency.

Real-Time Monitoring and Protection Foundation

At the core of the BMS is a real-time monitoring and protection layer, constructed around a modular sensing architecture and a field-programmable gate array (FPGA) for deterministic execution. Distributed across the battery pack, each module continuously measures cell voltage, temperature, and current, sending this data to a centralized Battery Control Unit (BCU). Inside the BCU, VHDL-coded logic within the FPGA instantly compares sensor inputs against critical thresholds.

When deviations such as overvoltage, undervoltage, overcurrent, or thermal limits are detected, the FPGA initiates immediate protective actions, such as module isolation or controlled shutdown, within microseconds. This real-time foundation guarantees that the battery system remains protected from hazardous conditions without relying on software layers that might introduce delay or uncertainty.

The modular structure of the hardware not only facilitates scalability across different vehicle platforms but also ensures that local faults can be contained without compromising the integrity of the overall energy storage system. This structure sets the stage for a layered, intelligent control strategy where protection is immediate, and optimization is continuous.

Adaptive Intelligence for Battery Management

Building on the hardware foundation, the system introduces adaptive intelligence through a lightweight software supervisory layer running on a real-time operating system (RTOS). While the FPGA safeguards the system instantaneously, the RTOS-managed software environment performs higher-level tasks such as State of Charge (SoC) estimation, State of Health (SoH) tracking, and predictive thermal control.

Here, a feedforward neural network plays a crucial role. Trained offline on extensive battery aging datasets, the network operates within the embedded environment to refine SoC and SoH estimations beyond what static voltage-current models can provide. It captures nonlinear dependencies and evolving degradation patterns, allowing the system to adapt dynamically as the battery ages or operating conditions change.

Thermal management follows a similar dual-layer approach. The FPGA reacts instantly to dangerous temperature rises, while the RTOS software uses predictive models to adjust operational parameters before reaching critical thermal states. For instance, if historical load profiles and current operating trends indicate an approaching thermal limit, the software can preemptively adjust energy routing, cooling strategies, or even signal the energy source switching mechanism.

The close collaboration between hardware-deterministic responses and software-adaptive corrections forms the foundation for an intelligent BMS capable of maintaining performance and safety without sacrificing efficiency or flexibility

Communication and System Coherence

None of the monitoring, control, or switching mechanisms can function effectively without continuous, robust communication between system elements. The BMS employs a fault-tolerant communication architecture using either Controller Area Network (CAN) or automotive Ethernet protocols, depending on the system's performance and scalability requirements.

Sensor readings, real-time status updates, fault events, and energy switching commands are transmitted across prioritized communication channels, ensuring that critical information is delivered with minimal latency. Redundant pathways and error-checking protocols enhance reliability, allowing the system to detect and recover from communication faults in real time.

Through this synchronized communication framework, all subsystems—including the FPGA monitoring core, RTOS supervisory software, energy management algorithms, and vehicle Electronic Control Unit (ECU)—operate with shared, up-to-date information. This coherence ensures seamless transitions, accurate fault handling, and consistent battery and vehicle performance across all operational scenarios.

Functional Safety Integration and System Robustness

Throughout the design, compliance with functional safety standards such as ISO 26262 remains a guiding principle. The system architecture is built to ensure that critical safety mechanisms are deterministic, redundant, and verifiable. Real-time threshold detection and immediate fault response through FPGA logic form the hard safety barrier. The adaptive software layer, although providing intelligent flexibility, is always monitored against safe operating limits established by the hardware.

Achieving ISO 26262 compliance requires not only robust fault detection and handling but also systematic validation of hardware and software interactions, communication integrity, and fault recovery processes. The integration of deterministic hardware protection, real-time task scheduling under the RTOS, and prioritized communication pathways reflects an intentional design philosophy aimed at meeting these rigorous standards.

The interplay between instant protection, predictive adaptation, dynamic energy management, and synchronized communication creates a BMS that is not simply a collection of safety features but a fully integrated, intelligent control system. This design ensures that the hybrid electric vehicle operates with optimized efficiency and battery health, even under challenging environmental, mechanical, and aging conditions.

Challenges and Future Trends

While the proposed Battery Management System (BMS) design provides a robust, real-time, and adaptive platform for hybrid electric vehicle energy management, several implementation challenges and forward-looking opportunities remain. As the automotive industry continues its transition toward increasingly intelligent and electrified architectures, addressing these challenges will be essential to ensuring system scalability, maintainability, and regulatory compliance.

One of the most significant practical challenges lies in balancing computational complexity with real-time execution constraints. Although the use of an FPGA for monitoring and protection enables microsecond-level responsiveness, integrating machine learning algorithms within the software layer introduces processing overhead. Even lightweight neural networks, once deployed for inference on embedded platforms, require careful optimization to avoid overloading the system or introducing timing unpredictability. This tension is particularly acute when combining multiple tasks under a real-time operating system (RTOS), where scheduling must guarantee deterministic execution under tight memory and processing budgets.

Thermal modeling is another area where further refinement is needed. While predictive thermal algorithms improve battery protection and switching logic, their accuracy depends heavily on the availability of high-fidelity input data and well-calibrated models. Environmental noise, sensor latency, and cell-level thermal variation make it difficult to develop universally reliable models without adding additional sensing hardware—raising both system cost and integration complexity.

Achieving full compliance with ISO 26262 remains a resource-intensive endeavor. While the design philosophy aligns closely with the standard's goals—through fault detection redundancy, deterministic switching, and modular fault isolation—formal certification requires exhaustive testing, documentation, failure mode analysis, and traceability throughout the hardware and software development process. For academic or early-stage industrial designs, these requirements can pose logistical and financial barriers that extend development timelines.

From a communication standpoint, ensuring cybersecurity within the BMS network is emerging as a critical concern. As hybrid vehicles increasingly adopt over-the-air updates, cloud-based diagnostics, and remote performance tuning, the security of real-time BMS data becomes essential. Protecting the communication links between modules, control units, and the central ECU—especially in Ethernet-based architectures—will require advanced encryption, intrusion detection mechanisms, and compliance with emerging automotive cybersecurity standards such as ISO/SAE 21434.

Looking ahead, several trends point to promising directions for next-generation BMS development. One major advancement will be the integration of self-adaptive machine learning models—capable of online learning and retraining based on real-time battery performance data. Rather than relying solely on static models trained offline, future BMS implementations may support edge-based learning architectures that continuously refine estimation accuracy based on usage history and evolving degradation patterns.

Another trend is the move toward cloud-connected BMS frameworks, where performance data is aggregated across fleets and fed into centralized platforms for analytics, predictive maintenance, and software updates. Such systems will enable not only vehicle-level optimization but also system-wide learning across thousands of battery profiles, allowing automakers to proactively identify design flaws, usage anomalies, or emerging safety risks across their fleets.

Finally, the integration of model-predictive control (MPC) for dynamic load balancing, solid-state battery chemistries, and multi-source energy coordination (e.g., solar-assisted hybrids or regenerative braking optimization) will push BMS requirements even further. These developments will demand more advanced control algorithms, increased computational resources, and tighter integration between BMS, powertrain, and vehicle operating systems.

As BMS platforms evolve, their role will extend beyond passive protection and into the realm of intelligent, predictive, and distributed energy management. The design presented in this work provides a strong architectural foundation—layered, real-time, and modular—that can be scaled, adapted, and extended as automotive power systems become more autonomous, connected, and software-defined.

Conclusion

This work presents a comprehensive design and analysis of an advanced Battery Management System (BMS) tailored for hybrid electric vehicles, with a focus on integrating real-time control, adaptive intelligence, and functional safety into a cohesive architectural framework. By combining high-speed, deterministic fault detection using FPGA-based VHDL logic with a supervisory software layer running on a real-time operating system (RTOS), the proposed system achieves both immediate responsiveness and long-term adaptability.

Key battery parameters such as State of Charge (SoC), State of Health (SoH), and thermal behavior are continuously monitored and refined using machine learning models, enabling the BMS to respond not only to critical thresholds but also to subtle changes in battery condition over time. This dual-layer approach ensures accurate state estimation, proactive thermal control, and dynamic adjustment of operating limits in response to battery aging and environmental stress.

The system's energy source switching strategy, which governs transitions between electric propulsion and internal combustion engine (ICE) operation, is deeply integrated into this framework. Informed by real-time SoC, SoH, thermal, and fault data, switching decisions are executed in under 100 microseconds through hardware logic, while software intelligence adjusts thresholds dynamically to optimize efficiency and extend battery life. Fault detection, thermal management, and load balancing are all coordinated across deterministic and adaptive layers to maintain system safety and performance under diverse driving conditions.

Communication between system components and the vehicle's ECU is handled through prioritized CAN or Ethernet networks, ensuring seamless integration, real-time coordination, and functional redundancy. The system architecture supports compliance with ISO 26262 functional safety standards, making it suitable for deployment in safety-critical automotive environments.

While several challenges remain—including real-time resource management, model calibration, ISO certification complexity, and cybersecurity—the modular and scalable nature of the design provides a strong foundation for future development. The architecture is well positioned to support emerging advancements such as online machine learning, cloud-integrated diagnostics, and intelligent fleet-level energy optimization.

In conclusion, the proposed BMS design demonstrates how layered architecture, real-time execution, and embedded intelligence can be combined to build a next-generation battery management platform. It not only addresses the operational demands of current hybrid vehicles but also anticipates the needs of future electric and autonomous mobility systems.

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