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Intelligent electrical systems in modern automobiles: a review of advanced sensors, vehicle control, and predictive diagnostics

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ABSTRACT

Modern automobiles increasingly depend on interconnected electrical and electronic systems to achieve higher levels of safety, efficiency, reliability, and driving intelligence. This transformation is driven by the integration of advanced sensors, electronic control units (ECUs), intelligent control algorithms, and data-driven diagnostic technologies. However, growing system complexity introduces challenges related to sensor reliability, computational constraints, fault propagation, and the timely identification of component degradation. This review examines the development of intelligent automotive electrical systems, emphasizing sensor technologies, artificial intelligence (AI), vehicle control, ECU architectures, and predictive maintenance. It discusses how multi-sensor data acquisition and fusion support vehicle perception and condition monitoring, while machine learning and model-based methods improve fault detection, diagnosis, and prognosis. The review also evaluates intelligent control approaches, including model predictive control (MPC) and adaptive strategies, and considers their integration into distributed and centralized ECU platforms. A comparative synthesis identifies persistent limitations involving data availability, model interpretability, real-time implementation, functional safety, and cybersecurity. Finally, an integrated framework and future research directions are proposed to support dependable, intelligent, and maintainable automotive electrical systems.

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1. INTRODUCTION

The rapid development of automotive technology has transformed conventional vehicles into complex electrical and electronic systems. Modern automobiles integrate numerous sensors, electronic control units (ECUs), communication networks, actuators, and embedded software to coordinate powertrain operation, braking, steering, thermal management, driver assistance, and vehicle safety. These components generate substantial operational data that can be used to improve vehicle performance and identify abnormal operating conditions. Consequently, intelligent electrical systems have become essential to the development of safer, more efficient, and more reliable automobiles [1]–[4].

Traditional automotive control and maintenance approaches, however, face limitations when dealing with increasingly interconnected vehicle subsystems. Conventional diagnostic procedures often depend on predefined fault codes, threshold-based monitoring, periodic inspection, and technician experience, which may not identify gradual degradation before a component fails. Meanwhile, increasing sensor density and software complexity create additional challenges involving data consistency, computational demand, communication reliability, and fault isolation. These limitations indicate the need for more integrated approaches that combine advanced sensing, intelligent control, and predictive diagnostics [5]–[8].

Recent research has addressed individual aspects of this transformation, including automotive sensor fusion, machine-learning-based predictive maintenance, intelligent vehicle control, and ECU architecture. Sensor technologies support environmental perception and internal condition monitoring, while AI methods extract useful information from operational data to identify abnormal patterns. In parallel, model predictive

control (MPC) and adaptive control techniques improve the coordination of vehicle dynamics and automated driving functions [9]–[13]. Nevertheless, these research areas are frequently investigated separately, leaving a gap in understanding how sensing, control, ECU processing, and predictive maintenance can operate as an integrated automotive electrical system.

This review addresses that gap by examining the relationships between advanced sensors, intelligent control, AI-based diagnostics, and automotive ECU architectures. It evaluates the technical contributions and limitations of existing approaches published no later than 2021. The review also discusses how diagnostic information can be incorporated into vehicle control and maintenance decisions rather than being treated as an independent monitoring function. Its main contribution is an integrated perspective connecting vehicle data acquisition, intelligent decision-making, fault prediction, and reliable ECU implementation.

2. ADVANCED SENSORS AND AUTOMOTIVE DATA ACQUISITION

Advanced sensors provide the fundamental information required by intelligent automotive electrical systems. Conventional vehicle sensors measure parameters such as engine temperature, pressure, rotational speed, acceleration, wheel speed, throttle position, and battery voltage. Modern vehicles additionally employ cameras, radar, LiDAR, ultrasonic sensors, global navigation satellite systems, and inertial measurement units to monitor surrounding environments and vehicle motion. The development of micro-electromechanical systems has contributed to smaller, more economical, and increasingly capable automotive sensors [2], [3], [9].

Sensor fusion improves the reliability and completeness of information obtained from individual sensing devices. Cameras provide visual information, radar supports distance and relative-velocity estimation, and LiDAR generates spatial representations of surrounding objects. Meanwhile, inertial and vehicle-dynamics sensors provide information about acceleration, angular velocity, and motion stability. Combining these different data sources can compensate for individual sensor limitations and improve environmental perception, although calibration errors, measurement uncertainty, and adverse operating conditions remain important challenges [2], [3].

Automotive sensors also support internal vehicle health monitoring. Temperature, vibration, current, voltage, pressure, and rotational-speed measurements can indicate changes in the operating condition of electrical and mechanical components. Continuous acquisition of these measurements creates opportunities to identify abnormal behavior before it develops into a critical failure. Vehicular sensor networks and data analytics therefore provide an important foundation for vehicle health and usage management [14], [15].

3. ARTIFICIAL INTELLIGENCE AND INTELLIGENT VEHICLE CONTROL

AI enables automotive systems to interpret complex operational data and support decisions that are difficult to achieve using fixed thresholds or conventional control rules. Supervised learning methods, including artificial neural networks, support vector machines, and decision-tree algorithms, can classify operating conditions using previously labelled data. Unsupervised learning methods, including clustering and anomaly detection, can identify unusual patterns when labelled fault data are limited. Deep learning further supports automatic feature extraction from complex sensor signals, although its performance depends on data quality, training coverage, and computational resources [5], [6], [16].

Intelligent vehicle control uses sensor information and computational models to coordinate vehicle behavior under changing operating conditions. MPC is particularly relevant because it evaluates predicted system behavior while considering operating constraints and multiple control objectives. Applications include vehicle trajectory tracking, stability control, energy management, and advanced driver-assistance functions. Reviews of MPC in autonomous ground vehicles and advanced driver-assistance systems demonstrate its potential, while also identifying computational complexity and model accuracy as important implementation considerations [10], [11].

AI-guided control extends conventional model-based strategies by learning patterns from vehicle operation and adapting control decisions to changing conditions. Data-driven methods can support decision-making in mixed traffic environments, where autonomous vehicles interact with human-driven vehicles and unpredictable road conditions. However, purely data-driven control may produce decisions that are difficult to interpret or validate in safety-critical situations. A practical automotive architecture should therefore combine physical models, control constraints, sensor feedback, and AI-based adaptation rather than relying exclusively on a single learning algorithm [12], [13].

4. ECU ARCHITECTURE AND INTELLIGENT SYSTEM INTEGRATION

ECUs form the computational foundation of modern automotive electrical systems. Individual ECUs traditionally manage specific functions, including engine operation, transmission, braking, steering, body

electronics, and battery management. These controllers exchange information through in-vehicle communication networks, enabling coordinated operation across vehicle subsystems. Increasing automation and connectivity, however, have raised demands for higher processing capability, communication bandwidth, software flexibility, and system-level coordination [17]–[19].

The evolution of automotive electrical and electronic architectures reflects the need to manage these increasing demands. Distributed architectures offer functional separation but can create challenges related to wiring complexity, duplicated computing resources, and communication overhead. Centralized and hierarchical architectures seek to consolidate processing and improve coordination between vehicle domains. Such architectural changes also require careful consideration of functional safety, cybersecurity, software development, and the integration of diagnostic functions [17], [18].

An integrated ECU design process is particularly important because safety, cybersecurity, and system functionality influence one another. A sensor fault, for example, may produce an incorrect measurement that affects a control decision, while manipulated communication data may create similar consequences. Therefore, sensor plausibility checks, fault-tolerant operation, secure communication, and diagnostic monitoring should be considered during ECU development rather than added only after system integration. Research on ECU design frameworks emphasizes the importance of coordinating these engineering activities throughout the development process [19].

5. PREDICTIVE MAINTENANCE AND INTELLIGENT FAULT DIAGNOSIS

Predictive maintenance aims to identify degradation and estimate potential failures before they interrupt vehicle operation. Unlike corrective maintenance, which responds after a fault occurs, predictive maintenance uses historical and real-time operating data to estimate component condition and support maintenance planning. Automotive applications include engine health monitoring, fuel and ignition systems, cooling systems, electrical drives, batteries, and vehicle subsystems. Machine learning has become particularly relevant because modern vehicles generate operational data that can be analyzed to identify patterns associated with component degradation [1], [14], [20].

Intelligent fault diagnosis generally involves three connected functions: fault detection, fault classification, and fault prognosis. Fault detection determines whether the observed behavior differs from normal operation, while fault classification identifies the likely failure type or affected subsystem. Prognosis estimates degradation trends and, where sufficient information is available, the remaining useful life of a component. These functions can be implemented using model-based, signal-based, data-driven, or hybrid approaches, each of which offers different advantages depending on the available data and the physical characteristics of the monitored system [6], [7], [21].

Data-driven diagnostic systems can process sensor measurements to identify patterns that are difficult to detect through conventional threshold-based monitoring. Neural networks and other machine-learning models have been investigated for vehicle fault prediction, while fuzzy logic can help represent uncertain operating conditions. A study of onboard vehicle fault diagnosis demonstrated the use of neural-network and fuzzy-logic techniques to classify vehicle conditions using operational data. Nevertheless, the deployment of these methods requires attention to data representativeness, model complexity, computational limitations, and the consequences of incorrect diagnostic decisions [20], [22].

The integration of predictive diagnostics with ECU functions can improve the usefulness of vehicle monitoring. Instead of generating fault alerts only after a predefined threshold has been exceeded, an intelligent ECU can evaluate trends, compare measurements with expected behavior, and communicate warnings about possible degradation. Such information can support adaptive control, protective operating modes, and maintenance scheduling. However, reliable implementation requires diagnostic outputs to be validated against physical system behavior and to remain consistent with automotive functional-safety requirements [7], [19], [21].

6. COMPARATIVE ANALYSIS OF INTELLIGENT AUTOMOTIVE TECHNOLOGIES

Table 1 summarizes the main technologies reviewed in this paper, their principal functions, potential benefits, and implementation challenges. The comparison indicates that sensors, AI algorithms, intelligent control, ECU architectures, and predictive maintenance should be treated as complementary elements. Sensor systems provide the data, AI methods interpret patterns, control algorithms translate information into operational decisions, and ECU platforms coordinate execution. Predictive diagnostics connects these functions by identifying degradation and supporting timely intervention.

Table 1. Comparison of intelligent technologies in modern automotive electrical systems

Technology	Main function	Potential benefits	Key challenges
Advanced sensors	Measure vehicle and environmental conditions	Improved monitoring and perception	Noise, calibration, sensor degradation
Sensor fusion	Combine heterogeneous sensor information	Greater data reliability and coverage	Synchronization and computational demand
AI and machine learning	Recognize patterns and anomalies	Improved classification and prediction	Data quality, explainability, generalization
Intelligent vehicle control	Coordinate vehicle dynamics and automated functions	Better stability, safety, and adaptability	Real-time computation and model accuracy
ECU architecture	Process data and coordinate subsystems	Integrated operation and system flexibility	Complexity, safety, and cybersecurity
Predictive maintenance	Estimate degradation and potential failures	Reduced unexpected failures and maintenance planning	Limited failure data and uncertain predictions

The comparison in Table 1 highlights that no individual technology can independently deliver a fully intelligent automotive electrical system. Advanced sensors may provide extensive measurements, but their value depends on reliable calibration, communication, and interpretation. AI models can identify complex patterns, but their predictions must be sufficiently accurate and explainable for safety-related applications. Similarly, intelligent control and ECU integration must ensure that decisions are executed within real-time constraints and validated operating limits.

7. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

Despite significant progress, data availability remains a major obstacle to the widespread implementation of predictive automotive diagnostics. Many machine-learning approaches require labelled fault data, but real vehicle failures may be rare, expensive to reproduce, and difficult to classify consistently. Differences in vehicle models, operating environments, component age, and driving behavior can also reduce the generalization capability of trained models. Future research should therefore prioritize representative datasets, cross-vehicle validation, data-sharing mechanisms, and methods that can learn effectively from limited or imbalanced data [1], [5], [14].

Another challenge concerns the integration of intelligent algorithms into resource-constrained automotive ECUs. High-performance deep-learning models may require processing power, memory, and energy that are not available in conventional embedded controllers. Model compression, efficient feature extraction, edge computing, and hardware-aware algorithm design may help address these limitations. Furthermore, diagnostic models should be evaluated not only by classification accuracy but also by response time, robustness, computational cost, and reliability under abnormal operating conditions [6], [16], [19].

Functional safety, cybersecurity, and explainability must also be addressed as interconnected design requirements. Incorrect sensor information, software faults, or malicious manipulation of in-vehicle communication can affect both control performance and diagnostic reliability. Research on automotive communication and intrusion detection highlights the importance of protecting vehicle networks while maintaining dependable information exchange. Future intelligent automotive systems should combine secure communication, fault-tolerant sensing, interpretable AI, and systematic verification to support safe operation throughout the vehicle lifecycle [17], [19], [23], [24].

A promising research direction is the development of integrated vehicle health management architectures. Such architectures would combine sensor fusion, ECU-level data processing, AI-based anomaly detection, predictive models, and control-system feedback within a coordinated framework. The framework should distinguish between immediate safety-critical faults and gradual degradation that can be managed through planned maintenance. It should also provide traceable diagnostic information to technicians and vehicle operators, enabling maintenance decisions to be supported by both measured evidence and validated predictions.

8. CONCLUSION

Intelligent electrical systems are becoming central to modern automobiles because they connect sensing, computation, control, and vehicle health management. Advanced sensors and sensor fusion provide information about vehicle dynamics, surrounding environments, and component conditions, while AI methods improve the interpretation of complex operational data. Intelligent control techniques, including MPC, support coordinated vehicle operation under changing conditions, and evolving ECU architectures provide the computational infrastructure required for these functions. Together, these technologies create opportunities to improve vehicle safety, performance, reliability, and maintainability. Predictive maintenance

and intelligent fault diagnosis represent important steps beyond conventional threshold-based monitoring and periodic inspection. Their effectiveness, however, depends on representative data, reliable sensors, interpretable algorithms, real-time implementation, and secure ECU integration. The reviewed literature indicates that future progress requires a unified approach that connects data acquisition, intelligent decision-making, fault prognosis, and vehicle control. Developing such integrated architectures will be essential for dependable automotive systems capable of detecting degradation, responding to abnormal conditions, and supporting safer vehicle operation throughout their service life.

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