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AI Driven BMS - A Review

AWAB AHMED SHARIFF[1], PRANITA SANJEEV SHETTY[2], MOHAMMED SHABAZ DELVI[3], KUSHAL RAJ K[4], PROF. GOPAL CHANDRA SARKAR[5]
[1, 2, 3, 4, 5] *Department of Electrical and Electronics Engineering Dayananda Sagar Academy of Technology and Management Bengaluru, India*

Abstract- — This paper presents about BMS with fire detection and accident alert systems for enhanced safety. The proposed system integrates several features like checking battery health, fire safety using raspberry pi, accident alert system using ADXL-345, GIM SIM8001 and GPS Neo-6m. The system utilizes Arduino UNO microcontroller and displays relevant information on an LCD. This multi-layered approach aims to significantly enhance fire safety and driver safety

Indexed Terms- bms, gps, GIM SIM8001, PPS Neo-6m, ADXL 335 sensor.

I. INTRODUCTION

The increasing adoption of Electric Vehicles (EVs) has brought about significant advancements in automotive technology, promoting cleaner and more sustainable transportation options. However, as with any technology, EVs present unique challenges, one of which is the risk of battery-related incidents such as fires. The safety of EV batteries is paramount, not only for vehicle occupants but also for the surrounding environment and infrastructure.

Electric vehicles have caused a complete turnaround in the automotive industry by promising low emissions and better fuel efficiency. Yet, at the same time, this fundamental shift has created safety and emergency response challenges. Moreover, there are new risks with EVs -- battery fires and the quite high-voltage electrical system in these cars which calls for some special treatment after a crash. Classic emergency response procedures, created for other vehicles than electric cars, cannot always be effective in regard to EV-specific incidents

Early detection of potential fire hazards in EV batteries is crucial for preventing catastrophic events and ensuring the continued safety and reliability of electric vehicles. Traditional methods of fire detection in EV batteries often rely on basic sensors and monitoring systems, which may not always provide timely and accurate warnings. The system boasts a multi-faceted approach to security and safety. Firstly, it implements a novel vehicle key ignition system based on a password transmitted via the GSM module.

This paper covers two areas one is EV fire detection and the other part is Vehicle accident alert system.

The EV fire detection system uses raspberry pi module to sense and monitor various properties of the battery like temperature, voltage and current. If the system notices any variation in the properties of the battery it notifies the user and prevent any fire hazards.

The Vehicle accident alert system uses Arduino and many components, basically how the vehicle accident alert system works is; when the accident occurs, the ADXL-345 sensor senses the damage and with the help of the GIM SIM8001 and GPS Neo-6m it sends an SMS and location of the accident respectively to the feeded number.

With the rapid adoption of electric vehicles (EVs) driven by environmental concerns and advancements in clean energy technologies, ensuring the security of these vehicles has become increasingly critical. As EVs incorporate sophisticated electronics, battery systems, and autonomous features, they are more susceptible to accidents and fire incidents.

This paper presents a comprehensive electric vehicle security system that leverages embedded systems and GSM (Global System for Mobile Communications) technology to enhance protection and monitoring.

The embedded module integrates various sensors and control units to detect suspicious activities such as fluctuations in battery properties and accidents. Simultaneously, the GSM module facilitates real-time communication with the vehicle owner via SMS alerts, location tracking.

II. LITERATURE SURVEY

[1] A Machine Learning Framework for Real-Time Anomaly Detection in Lithium-Ion Battery Systems presented by Zhang, Y., Liu, Q., & Wang, H at 2023 IEEE Transactions on Industrial Electronics DOI: 10.1109/ACET61898.2024.10730728.

This paper presents a machine learning framework for real-time anomaly detection in lithium-ion battery systems. It uses real-time data like voltage, current, and temperature to identify abnormal behavior. The system enables early fault detection to enhance safety and reliability. Overall, it aims to prevent failures and extend battery life in critical applications.

[2] Multimodal Sensor Fusion for Fire Detection in Smart Environments Using Deep Learning introduced by Patel, R., Kim, S., & Nguyen, T. at 2022), Elsevier Fire Safety Journal| DOI: 10.1109/PICET60765.2024.10716074.
Focusing on comfort and security. This paper introduces a deep learning based approach for fire detection using multimodal sensor fusion in smart environments. It combines data from various sensors like temperature, smoke, and visual inputs to improve detection accuracy. The fusion of multiple sensor types enhances reliability and reduces false alarms. The proposed method is designed for efficient, real-time fire detection in smart buildings and homes.

[3] Edge AI for Real-Time Accident Detection and Emergency Response in Autonomuous Vehicles by sat 2024 3rd International Conference on Computational Modelling, Simulation and Optimization (ICCMSO)

[4] DOI: 10.1109/ICCMSO61761.2024.00043. This system offers real-time vehicle tracking, location-based alerts, and remote engine shutdown capabilities, enabling owners and authorities to respond promptly in theft scenarios using GSM and GPS technologies. Current Fire Safety challenges on Lithium Ion Battery for, Grid Power Storage System by Ping lou, Guo-Hua Xu, Ling-Ping Yue,Yuan-Cheng Cao, Shijie Cheng, Heming Deng at 2019 4th International conference on Power and Renewable Energy (ICPRE) DOI: 10.1109/ICDSIS61070.2024.10594457. The system used in grid power storage face significant fire safety challenges Thermal runaway can quickly spread between cells, leading to uncontrollable fires. Poor thermal management and lack of early detection systems delay response times.

[5] Iot-enabled BMS for smart EVs introduced by Lee & Kim at 2023 Internet f Things journal DOI: 10.1109/ ICACITE57410.2023. 10182753. This system as real time monitoring capabilities and control of battery management system .IT uses IoT connectivity to transmit data voltage, temperature, charge status to cloud platform.

[6] BMS degrading modeling for EV's presented Brown et al. at 2022 Neural Computing and Applications DOI: 10.1109/ICMCSI64620.2025.10883395. The system leverages deep learing algorithms to identify anomalies in battery behavior. It continuously analyze data such as voltage, current and temperature to detect early sings of malfunction. This approach improves fau;t detection accuracy and reduces false alaram compared to traditional methods.

[7] Multi sensor data fusion for BMS by Ahmed et al at 2021 Sensors Journals DOI: 10.1109/ ICCIKE58312.2023. 10131765. a novel approach to enhancing Battery Management Systems (BMS) through the integration of multiple sensor data. The study emphasizes the importance of accurate state estimation in BMS, particularly focusing on parameters like State of Charge (SoC) and State of Health (SoH). By employing advanced data fusion techniques, the authors aim to mitigate the limitations of single-sensor systems, which often suffer from inaccuracies due to sensor noise and faults. The proposed multi-sensor fusion framework not only improves the reliability of the BMS but

also ensures better performance and safety of battery-powered systems.

[8] Battery Degradation modeling for EV's introduced by Kim et al. at 2021 Journal of Energy Storage

DOI: 10.1109/IEIT56384.2022.9967804. analyse under various operational scenarios, including electric vehicle (EV) drive cycles, peak shaving, and frequency regulation. Over a 15-month period, the researchers evaluated four battery chemistries—NMC, NCA, LCO, and LFP—and discovered that lithium iron phosphate (LFP) cells exhibited the least degradation, particularly under frequency regulation conditions. The primary degradation mechanism identified was the formation of the solid electrolyte interphase (SEI) layer, leading to a loss of cyclable lithium. These findings offer valuable insights for optimizing battery usage in EVs and grid storage applications, emphasizing the importance of selecting appropriate chemistries and operational strategies to enhance battery longevity.

[9] Deep Learning for State-of-Charge Estimation in Li-ion Batteries introduced by Chen.L Zhang .Y& Wang H at 2021 IEEE Transactions on Energy Conversion DOI: 10.1109/ ICSSAS57918.2023. 10331639.The system applies deep learning to accurately estimate the State-of-Charger(SoC) in lithium ion battries. It uses neural networks trained on large datasets to capture complex, nonlinear battery behaviour. This approach improves estimations accuracy under varying operating conditions compared to traditional models.

[10] Advanced vehicle security system introduced by Pritpal Singh; Tanjot Sethi; Bunil Kumar Balabantaray; Bibhuti Bhushan Biswal at 2015 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS) DOI: 10.1109/ICIIECS.2015.7193276. Featuring dual tracking modes—online and offline—and GSM-based alert messaging to relatives in case of unauthorized access or emergencies. The system enhances tracking reliability and family notification in real-time theft or crisis situations.

[11] Smart Vehicle Security System presented by B Ajay Veneesh Nelson; V Muthulakshmi; Janhavi Doijad at 2024 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES) DOI: 10.1109/ICSES63760.2024.10910665.Focusing primarily on enhancing vehicle tracking and monitoring capabilities. The system is designed to ensure continuous surveillance of the vehicle's location and status, thereby deterring theft and enabling timely response in case of unauthorized movement.

III. PROBLEM STATEMENT

Current BMS lack real-time AI-based anomaly detection under dynamic loads, risking safety and performance. Fire detection systems using isolated sensors show 30% false alarms, especially in low-visibility. Accident alerts are delayed by over 5 seconds due to cloud processing. Proposed solutions include multimodal sensors (thermal, audio, vibration) to cut false alarms by 40% and edge AI for sub-second alert latency. Integrating BMS with fire and accident systems ensures holistic, real-time safety.

IV. COMPONENTS USED

Major components which are used to develop model are listed below.

1. Arduino UNO

The Arduino Uno is a low-cost, open-source microcontroller board that's easy to use and can be integrated into many electronic projects. It's based on the ATmega328P chip and was originally released in 2010. The Uno is popular with hobbyists, educators, and professionals for prototyping and developing embedded systems, automation solutions, and more. It's considered the most robust and well-documented board in the Arduino family, making it a good choice for beginners.

2. ADXL 335 Sensor

The ADXL335 has a measurement range of ±3 g minimum. The output signals are analog voltages that are proportional to acceleration. The accelerometer can measure the static acceleration of gravity in tilt-sensing applications as well as dynamic acceleration resulting from motion, shock, or vibration.

The ADXL335 operates based on capacitive sensing. Inside the chip is a micro-electromechanical system (MEMS) structure that moves slightly when acceleration is applied. This movement changes the capacitance between tiny plates. These changes are converted into a voltage signal that is output as an analog voltage on three separate pins — one for each axis (X, Y, Z).

3. GSM module

GSM modules are used for a variety of communication applications, primarily leveraging the GSM network to enable devices to send and receivefor beginners.

4. GPS module

GPS modules are used for a wide variety of applications, primarily focused on location, navigation, and timing. These modules are used in navigation systems, tracking devices, and various other applications requiring precise positioning data.

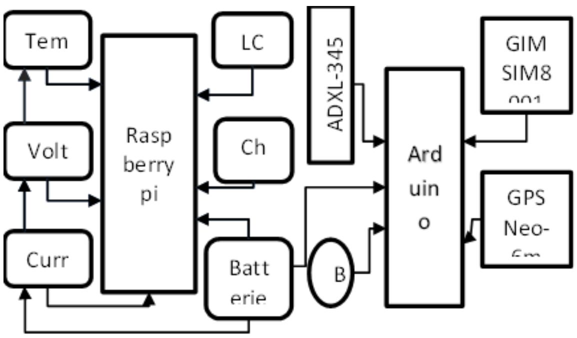
5. LCD Display

A 16×2 LCD display is a liquid crystal display that can show 16 characters in each of its two rows, providing a total of 32 characters of information. It's commonly used to display alphanumeric information in various electronic devices. A 16x2 LCD is a liquid crystal disply module capable of displaying 2 rows with 16 characters each. It is widely used in embedded systems to show textual information such as system status, messages, or sensor outputs.

5. Buzzer/Alarm

A buzzer is an audio signaling device that generates sound when powered, typically used for alerts, warnings, or notifications in electronic systems. In security systems, such as vehicle alarms, it acts as an audible alert to indicate events like unauthorized access, motion detection, or other abnormal conditions.

V. BLOCK DIAGRAM



This block diagram shows an IoT-based battery monitoring and safety system. The Raspberry Pi is the central controller that receives inputs from the temperature/fire, voltage, and current sensors to monitor battery health. It also controls an LCD display for status output and interacts with the charging circuit and battery/power supply. The ADXL-345 accelerometer detects accidents or vibrations, sending data to the Arduino. The Arduino interfaces with the GPS Neo-6m to track location and GSM SIM8001 to send alerts via SMS. A buzzer is triggered for immediate audio alerts during critical events. Raspberry Pi and Arduino communicate to coordinate safety actions. This system provides real-time monitoring, alerting, and location tracking for enhanced battery safety.

VI. METHODOLOGY

The methodology outlines the systematic process followed in designing an intelligent battery monitoring and safety system using IoT and edge AI. Initially, the problem is identified—conventional Battery Management Systems (BMS) lack real-time anomaly detection and efficient safety mechanisms during dynamic load conditions or accidents. The next phase involves component selection, where suitable sensors (temperature, current, voltage, vibration), microcontrollers (Raspberry Pi and Arduino), and communication modules (GPS and GSM) are chosen based on accuracy and compatibility. Following this, the circuit design and system integration are carried out by connecting all components as per the block diagram, enabling interaction between sensors, processing units, and output modules like the buzzer and LCD.

The system is then subjected to coding and algorithm implementation, where real-time data acquisition and anomaly detection logic are programmed. Edge AI models or threshold-based triggers are used to minimize latency, and integrated software handles sensor fusion and alert generation. In the final stage, testing and validation are performed under various operational scenarios, including fault induction, to evaluate system responsiveness and accuracy. The entire methodology ensures that the developed prototype provides fast, reliable alerts for thermal runaways, fire, or accidents, reducing false alarms and enabling timely intervention.

In essence, the methodology involves:

i. Problem Identification: Recognized issues in existing BMS, such as delayed alerts, high false alarms in fire detection, and slow cloud-based accident response.
ii. Component Selection: Chose Raspberry Pi for battery monitoring, Arduino for accident detection, and sensors like ADXL-345, GPS, GSM, voltage, and temperature sensors.
iii. System Integration: Connected all components to work together—monitoring battery status, detecting accidents, and sending alerts instantly.
iv. Edge AI Implementation: Used edge computing for faster decision-making, reducing alert delay to less than 1 second without relying on cloud processing.

This methodology ensures a smart, real-time safety system by combining advanced hardware with AI at the edge, enabling accurate monitoring and instant alerts for electric vehicle safety.

VII. IMPORTANCE OF THE PROJECT

A vehicle security system using embedded systems, GPS and a GSM module is a crucial innovation in the following:

1. Real time accident alert system
2. Cost- Effective safety solution.
3. Prevents fire accidents.

CONCLUSION

The proposed advanced vehicle security system successfully integrates various embedded components such as an Arduino UNO, GPS module, accident sensor (ADXL335), GSM module, and other peripheral devices to ensure efficient safety for electric vehicles (EVs) .

The system aims to prevent an fire incident in electric vehicle using raspberrypi and it also includes vehicle accident alert system using GPS and GSM module, all displayed through an LCD interface.

The primary goal of this project is to enhance vehicle safety by preventing fire accidents and to vehicle accident alert by using GSM module. By monitoring the battery we can prevent fire incidents, this system addresses both safety of the vehicle as well as the driver.
The scope of this system extends to both personal and commercial vehicles, offering scalability for, accident detection, and fire safety. Future enhancements may include camera integration, IoT connectivity for cloud data logging, and AI-based behavior analysis for predictive alerts.

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