EV BMS WITH CHANGE MONITOR AND FIRE PROTECTION WITH ZONE SPEED CONTROL

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ABSTRACT

Battery storage forms the most important part of any electric vehicle (EV) as it stores the necessary energy for the operation of EV.So, in order to extract the maximum o/p of a battery & to ensure its safe operations it is necessary that a efficient battery management system exist is the same .It monitors the Parameters, determine SOC and provide necessary services to ensure safe operation of battery. Hence BMS forms a integral part of any EV and safe guards both the user and the battery by ensuring that the cell operates within its safe operating parameters. The proposed system only monitor the battery and charge it safely but also protect it to avoid accidents from occurring. The proposed model has following functions current, voltage measurement, state of charge (SOC) calculation, protection, battery status detection, liquid crystal display (LCD) etc. Electric vehicles (EVs) are automobiles powered by one or more electric motors, which draw energy from rechargeable batteries instead of relying solely on internal combustion engines (ICEs) that consume fossil fuels. A Battery Management System (BMS) is a critical component in electric vehicles (EVs) and other battery-powered systems. It monitors and controls the operation of the battery pack, ensuring its optimal performance, safety, and longevity. State of Charge (SoC) refers to the measure of the remaining energy in a battery, expressed as a percentage of its total capacity. It indicates how much charge is available in the battery at a given time, allowing users to estimate the remaining range or usage time before recharging is required.

INTRODUCTION

An electric vehicle EVs is a type of vehicle that uses one or more electric motors for propulsion. Instead of using an internal combustion engine (ICE) that burns fuel, an EV use a battery pack to store electrical energy to power an electric motor, which turns the wheels. Compared to conventional ICE vehicles, EVs provide a number of benefits, such as decreased emissions, quieter operation, and a lessened reliance on fossil fuels. Since electricity is frequently less expensive than gasoline and electric motors are more efficient than ICEs, they also typically have reduced operational expenses. The popularity of EVs is fast rising as the globe moves towards a cleaner, more sustainable future. Governments all around the world are granting incentives to stimulate the use of EVs, and numerous automakers are already selling a variety of EV models. In addition to its benefits, common EV problems include internal cell shorts that may result in thermal runaway. An EV typically catches fire because of excessive heating. The electric vehicle's battery warms up, and when that heat interacts with petrol that has leaked, the battery simply catches fire. A battery management system (BMS) is an electrical device that controls and keeps track of the operation of rechargeable batteries, such as those found in renewable energy sources and electric cars. By regulating the charging and discharging process, keeping track of the battery's state of charge and overall health, and guarding the battery from harm brought on by overcharging or overheating, the BMS aids in ensuring the safe and effective operation of the battery. The BMS normally consists of a number of parts, such as sensors for measuring the temperature, voltage, and current of the battery as well as control circuits for controlling how the battery is charged and discharged in response to various conditions. Software algorithms that forecast the battery's remaining capacity and project its remaining life may also be present in the BMS. One of the key functions of a BMS is to prevent the battery from being overcharged or over-discharged, which can cause permanent damage to the battery and reduce its lifespan. The BMS accomplishes this by controlling the charging and discharging process and shutting down the battery if any abnormal conditions are detected. Another important function of a BMS is to ensure that the battery is operating within a safe temperature range. If the battery gets too hot, the BMS may reduce the charging rate or shut down the battery to prevent damage. If the battery gets too cold, the BMS may increase the charging rate to help warm up the battery. Overall, a BMS is an essential part of any rechargeable battery system since it ensures the battery's safe and effective operation and increases its longevity. EV batteries that are frequently utilised are 2-cell lithium-ion (Li-ion) batteries. A 2-cell Li-ion battery should have a voltage of roughly 6.0V when it is fully depleted, and a maximum charge voltage of roughly 8.4V The balancing charger will keep track of each cell's voltage during the charging procedure and modify the charge rate as necessary to guarantee that all of the cells receive an equal charge. The balancing charger will automatically cease charging when the battery is fully charged. It is crucial to remember that overcharging a Li-ion battery might cause it to malfunction, which could cause a fire or explosion. As a result, it's crucial to pay close attention to the charging process and prevent leaving the battery alone while it's being charged. In our project, we keep an eye on battery voltage, temperature, and detect the presence of fire. If the battery temperature rises beyond a certain threshold, the power to the lithium-ion battery is automatically shut off using a relay.

LITERATURE SURVEY

- Battery Energy Storage System (BESS) and Battery Management System (BMS) for Grid-Scale Applications Due to a discrepancy between the quantity of energy consumers use and the amount of energy generated by generation sources, the current electric grid is an inefficient system that wastes a considerable amount of the electricity it generates. In order to assure adequate power quality, power plants often produce more energy than is required. Many of these inefficiencies can be eliminated by making use of the energy storage that already exists inside the grid. To accurately monitor and regulate the storage system while using battery energy storage systems (BESS) for grid storage, comprehensive modelling is needed. The storage system is controlled by a battery management system (BMS), and a BMS that makes use of sophisticated physics-based models will enable considerably more reliable operation of the storage system.
- A Battery Modular Multilevel Management System (BMS) For Electric Vehicles And Stationary Energy Storage Systems. Although the reliance of energy systems on battery storage systems is constantly growing, there are still a number of issues that need to be resolved. Current battery systems are rigid; only cells with the same electrical characteristics may be coupled; and cell flaws significantly shorten the lifespan of the entire battery or even

trigger a system blackout. Additionally, the system's weakest cell restricts the system's maximum useful capacity and maximum charging current. Current Battery Management Systems (BMS) are able to enhance the maximum useful charging current as well as the useable battery capacity to some extent. A very adaptable, fault-tolerant, and economical battery system can be developed with the help of the Battery Modular Multilevel Management System (BM3) described in this work. With the current setup

- A Battery Modular Multilevel Management System (BMS) For Electric Vehicles And Stationary Energy Storage Systems The dependency of energy systems on battery storage systems is constantly increasing, but there are still several unsolved problems. Current battery systems are inflexible, only cells with the same electrical parameters can be combined, and cell defects cause a high reduction of the overall battery lifetime or even a system black out. In addition, the maximum usable capacity and the maximum charging current are limited by the weakest cell in the system. Current Battery Management Systems (BMS) can www.ijcrt.org © 2023 IJCRT | Volume 11, Issue 5 May 2023 | ISSN: 2320-2882 IJCRT2305773 International Journal of Creative Research Thoughts (IJCRT) www.ijcrt.org g355 increase the usable battery capacity to some extend and are able to enlarge the maximum usable charging current. With the Battery Modular Multilevel Management System (BM3) presented in this paper, a very flexible, fault tolerant, and cost-efficient battery system can be implemented. With the system it is possible to establish either serial or parallel connections between neighboring cells or to bypass a cell.
- Battery Management System Via Bus Network For Multi Battery Electric Vehicle This paper proposes multi-battery design of battery management control using bus communication method based on loop shaping. The experiment of proposed method shows that the capacity dynamics of battery has been improved. The multiple of

battery control system is implemented in electric vehicle's model, and we modify the origin control system using bus communication method auto tuning based on loop shaping. The result of modified control system using bus method based on loop shaping is shown in the implementation design response of battery management that the cost and reliability are improved. Moreover, this method could maintain the error steady state to be zero. of five years. The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

D. Chao, C. Shen, and K. S. Low, "Real-time state-of-charge estimation for electric vehicle batteries using a coupled electrochemical-thermal model," Journal of Power Sources, vol. 329, pp. 261-268, Jan. 2017.

Sate of charge (SOC) accurate estimation is one of the most important functions in a battery management system for battery packs used in electrical vehicles. This paper focuses on battery SOC estimation and its issues and challenges by exploring different existing estimation methodologies. The key technologies of lithium-ion battery state estimation methodologies of the electrical vehicles categorized under five groups, such as the conventional method, adaptive filter algorithm, learning algorithm, nonlinear observer, and the hybrid method, are explored in an in-depth analysis. Lithium-ion battery characteristic, battery model, estimation algorithm, and cell unbalancing are the most important factors that affect the accuracy and robustness of SOC estimation. Finally, this paper concludes with the challenges of SOC estimation and suggests other directions for possible research efforts.The Nissan Altra EV was introduced as the first production lithium-ion battery electric vehicle in 1997 [1]. The goals for EVs are to operate at a temperature from −30 to +52 °C with a driving range of 300 miles per single charge and a use life of 15 years, according to the U.S. Advanced Battery Consortium (USABC) [2]. Implementation of rechargeable batteries for electrical vehicles (EVs) has become very popular because they can displace the consumption of fossil fuels and reduce the emissions of greenhouse gas [3]. Lithium-ion batteries are widely adopted due to their high energy and power density, high efficiency, high open-circuit cell voltage, broad temperature operating, and long lifespan [4].

In 1980, John Goodenough [5] created the first lithium-ion batteries, which use lithium cobalt oxide and lithium manganese dioxide as cathodes. Commercial lithium-ion batteries such as lithium cobalt oxide (LCO), lithium iron phosphate (LFP), lithium manganese oxide (LMO), lithium nickel manganese cobalt oxide (NMC), lithium nickel cobalt aluminum oxide (NCA), and lithium titanate oxide (LTO) have been widely accepted by electric vehicles in recent years [6]. According to USABC, today's lithium-ion batteries cannot meet the standards of EVs. At present, lots of scholars, scientists, and engineers are focusing on new battery research such as Li-O_2 batteries , lithium–sulfur batteries lithium metal batteries all-solid-state lithium batteries [17], al-ion batteries [18], fuel cells supercapacitorsand so on. Electric vehicles require a high power and high capacity for lithium-ion battery systems, thus demanding a battery management system to ensure a reliable and safe operation [25]. Additionally, a battery model is very important in states estimation of the model-based battery management system in EVs [26]. Haran [27] introduced a single particle model in order to develop a lumped structure. A physics-based model can predict microscopic behavior and performance, but requires a large computational power to solve the differential equations [28]. Equivalent circuit models (ECMs) have also been proposed to control-oriented purposes to estimate the electrical response and the amount of heat generation, which are frequently used to model cells due to their simplicity, the fact that their parameters are easy to obtain, and their real-time adaptability Various ECMs are now extensively used in EV studies, such as the Rint [30], Thevenin [31], The Partnership for a New Generation of Vehicles, (PNGV) [31], General nonlinear model (GNL) [32], and Resistance-Capacitance (RC)model [31]. In recent years, many new battery models have been put forward or improved, such as the fractional order PNGV model [33], invariant imbedding method [34], improved equivalent-circuit model [35], reduced order equivalent circuit battery models [36], fractional order impedance model fuzzy model [40], kinetic battery model (KIBaM) [41], electrochemical/electrical-thermal coupled model [42], battery degradation model [42], and so on. The limitations of current battery technology include underutilization, capacity fade, thermal runaway, and stress-induced material damage [28].

In such a large number of models, the first step is to accurately identify the parameters of the model for battery state estimation. Two methods for battery model identification are electrochemical impedance spectroscopy (EIS) and pulse tests [43]. Because these methods rely on specific equipment for testing and processing large amounts of data, they are not suitable for online applications of electric vehicles. Therefore, some researchers have proposed recursive least squares (RLS) methods or adaptive filtering (AF) methods for on-line identification of battery model parameters [44]. Practice has proved that these methods are easier to implement in on-line applications. Besides, these methods can help to compensate for parameter values for battery variations and aging.

The state of the battery cell includes State of Charge (SOC) [45], State of Health (SOH) [46], State of Energy (SOE) and State of Power (SOPIn order to estimate these states of batteries, the researchers need to put forward a new mathematical model or an algorithmic model besides the battery model mentioned above. The well-known techniques include the Kalman filter (KF) [51], extended Kalman filter (EKF) [52], unscented Kalman filter (UKF) [45], fading Kalman filter algorithm(FKF) [53], strong tracking cubature extended Kalman filter (STCEKF)], multirate strong tracking extended Kalman filter (MRSTEKF) [55], lazy extended Kalman filter (LEKF) , particle filter (PF) [57], sliding mode observer (SMO) H-infinity Luenberger observer , etc. The filter algorithms based on the equivalent circuit model with fixed model parameters are often used to estimate the battery state. However, the parameters of the equivalent circuit model are often affected by temperature, C-rate, SOC, and battery aging. Therefore, some joint-estimation methods have been proposed to handle these problems. These methods are usually made up of two parts. The first part is used to identify the parameters of the model with recursive least squares (RLS) on-line. The second part is used to estimate the battery state parameters with filter algorithms. Recently, because of the improvement of embedded hardware performance, some researchers have wanted to estimate battery state only using data, instead of using battery models. The Artificial Intelligence (AI) based learning approach including artificial neural network (ANN) modelling as well as the support vector machine (SVM) was proposed , and could be very accurate depending on the training data.

In order to make a perfect EV, scientists, academics, researchers, and engineers have performed much research to improve the accuracy of lithium-ion battery SOC estimation for EVs. In this paper, the SOC estimation approaches and shortcomings of the EV battery system are reviewed. This paper focuses on battery SOC estimation and its issues and challenges by exploring different existing estimation methodologies. At the beginning of the article, the lithium-ion battery characteristics of the EVs are reviewed. Following this, the common key technologies of battery state estimation are explored in an in-depth analysis. Besides, the various SOC issues and challenges are also discussed. At the end of this article, the development direction of SOC is summarized. This review paper will be very helpful for scientists, academics, researchers, engineers, and automobile engineers and manufacturers for using the appropriate estimation method, which is especially important for the development of implementing a new battery management system or upgrading the battery management system in EVs in the future.

W. Cheng, X. Luo, and B. Yang, "Online fault diagnosis for lithium-ion batteries in electric vehicles using neural network ensemble," IEEE Transactions on Industrial Informatics, vol. 14, no. 4, pp. 1735-1744, Apr. 2018.

Power batteries are the core of electric vehicles, but minor faults can easily cause accidents; therefore, fault diagnosis of the batteries is very important. In order to improve the practicality of battery fault diagnosis methods, a fault diagnosis method for lithium-ion batteries in electric vehicles based on multi-method fusion of big data is proposed. Firstly, the anomalies are removed and early fault analysis is performed by t-distribution random neighborhood embedding (t-Sne) and wavelet transform denoising. Then, different features of the vehicle that have a large influence on the battery fault are identified by factor analysis, and the faulty features are extracted by a two-way long and short-term memory network method with convolutional neural network. Finally a self-learning Bayesian network is used to diagnose the battery fault. The results show that the method can improve the accuracy of fault diagnosis by about 12% when verified with data from different vehicles, and after comparing with other methods, the method not only has higher fault diagnosis accuracy, but also reduces the response time of fault diagnosis, and shows superiority compared to graded faults, which is more in line with the practical application of engineering.In the context of the global energy transformation and the proposal of “dual carbon”, lithium-ion batteries play a crucial role in the development of vehicle mileage and global energy storage technology. Lithium-ion batteries are widely used in intelligent devices and electric vehicles due to their high specific energy density, strong endurance and long life [1]. However, globally, electric vehicle accidents caused by battery faults is threatening people’s lives and property. During the operation of electric vehicles, small failures in the battery are not easily detected, and continued operation increases the risk of generating more heat, which may trigger thermal runaway [2]. It is difficult to change the model and structure of the lithium-ion battery in a short time to improve safety; therefore, using real vehicle data to give a timely warning of lithium-ion battery failure is necessary.

The battery has nonlinear characteristics and a complex internal structure. When a fault occurs, the internal parameters referred to are limited, such as current, voltage, state of charge (SOC), temperature, etc., which makes battery fault diagnosis more difficult [3]. The current methods for power battery fault diagnosis are mainly divided into knowledge-based, model-based and data-driven methods Knowledge based diagnosis needs experience and a rule base for qualitative diagnosis, which are difficult to establish. This makes it difficult to apply this type of diagnosis to most fault situations. Model based fault diagnosis is performed by comparing the parameters obtained from the established accurate model with the set threshold.

For example, Xiong et al. [8] used the residual generated by the difference in SOC to compare with the set threshold value in order to judge the fault diagnosis of the battery pack sensor. Pan et al. used an observer to diagnose the fault of the battery input current sensor based on the battery thermoelectric coupling dynamic model that was established, and used the residual evaluation function of the norm for evaluation. Schmid et al. [11] found the sensor group with the best fault isolation characteristics through structural analysis of the thermoelectric model of the battery, and carried out fault diagnosis by calculating the minimum structural super stator (MSO). Wang et al. [12] obtained a transition probability correction function based on the *n*-th variance of the model probability, and improved the accuracy of battery fault diagnosis by introducing the jump threshold of the model to achieve rapid model conversion. Deyetal.performed battery thermal fault diagnosis by identifying the temperature difference between two batteries through the established partial differential equation model. Model-based fault diagnosis needs to establish different fault models for different faults, and it is not easy to apply to engineering practice due to its cumbersome calculation and poor robustness. However, fault diagnosis based on laboratory fault data can be flexibly applied to different fault types; for example, Yang et al. [14], Zhao et al. [15] used the failure life data to establish a long-term and short-term memory neural network model and set a threshold for fault diagnosis. Zhao et al. [16] used data driven models and multi-scale system statistics to predict battery failure through health status. Xue et al. [17] used K-means clustering algorithm and 3-screening strategy to detect abnormal battery cells. However, the method based on laboratory data does not fully consider the actual complex conditions and lacks integration with engineering applications. In order to improve the accuracy of battery fault diagnosis in real vehicle environment, this paper proposes a fault diagnosis method based on real vehicle data driven multi method fusion. First, the data of China National Monitoring and Management Center for New Energy Vehicles is preliminarily analyzed by means of statistics, the t-distribution random neighborhood embedding (t-Sne) is used for early fault diagnosis, and wavelet transform is used to process the data, so that the points with large deviation will not affect the results of feature extraction. Then, the factor analysis method is used to analyze the fault influence of battery features, The bidirectional short- and long-term memory network method of convolutional neural network is used to extract the features with great influence on the fault. Finally, self-learning Bayesian network is used to diagnose the fault. Compared with traditional methods, this method accurately extracts the features, reduces the diagnosis time, and improves the robustness.

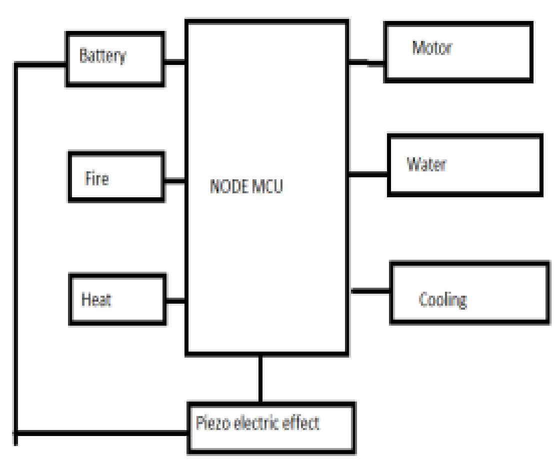
The fault diagnosis method based on the big data of real vehicles avoids the tedious calculation process of battery model modeling and has a broad application prospect when applied to electric vehicles. The proposed method enables the battery to reach an accuracy of about 92% in graded fault diagnosis, which is more reliable, accurate and fast compared with other methods. It opens up a new direction for solving the fault diagnosis problem of nonlinear coupled objects.

EXISTING SYSTEM

Ensures that individual cells in the battery pack are charged and discharged evenly, preventing overcharging or deep discharging of any particular cell.Provides accurate information about the current charge level of the battery.Monitors the temperature of each cell to prevent overheating.Measures and maintains individual cell voltages within safe limits.Detects and protects against excessive current flow, preventing damage to the battery.Manages the rate of charge to optimize battery life and prevent overheating.Provides information to the user about the current charging status. Ensures efficient charging to minimize energy losses.Integrated sensors to detect abnormal temperature increases or the presence of smoke.In the event of a potential fire hazard, the system should be capable of initiating an emergency shutdown to isolate the battery pack.Some advanced systems may include fire suppression mechanisms to contain and extinguish a fire.Allows for remote monitoring of the battery status, charge level, and potential issues. Records historical data for analysis and troubleshooting.Utilizes standard communication protocols for integration with other vehicle systems.Ensures that the new BMS seamlessly integrates with the existing electric vehicle system.Allows for firmware updates to accommodate changes or improvements in the system.Ensures that the system complies with relevant safety standards and regulations for electric vehicles.

IMPLEMENTATION

BLOCK DIAGRAM



Designing an Electric Vehicle Battery Management System (BMS) with charge monitoring and fire protection is a complex task that involves several key components and functionalities. Monitor the voltage of each individual cell in the battery pack to ensure balanced charging and discharging. Measure the temperature of each cell to prevent overheating and ensure optimal operating conditions. Track the current flowing in and out of the battery pack to manage charging and discharging rates. Implement algorithms to estimate the SOC of the battery, providing accurate information about the remaining charge. Balance the charge levels of individual cells to maintain uniformity and prolong the overall battery life. Implement protection mechanisms to prevent overcharging and under voltage conditions, which can lead to reduced battery life or safety hazards. Integrate a thermal management system to regulate battery temperature, preventing overheating and ensuring optimal performance. Implement a charge control mechanism to manage the charging rate based on the battery's state and temperature. Detect when the battery is fully charged and implement actions to stop charging or switch to a lower charging rate. Monitor and optimize the efficiency of the charging process to enhance overall system performance. Implement measures to detect and prevent thermal runaway, a condition where a localized increase in temperature can trigger a self-sustaining reaction. Integrate a fire suppression system that can activate in case of a fire hazard, using methods such as chemical suppression or isolation of the affected area. Implement algorithms to detect faults in the battery system and isolate the faulty components to prevent cascading failures. Design a mechanism for emergency shutdown in the event of a critical fault or fire, ensuring the safety of the vehicle and its occupants. Use robust communication protocols to facilitate data exchange between the BMS, charge monitoring system, and fire protection system. Provide a user interface for monitoring the battery status, charging progress, and any potential issues. Ensure that the system complies with relevant safety standards and regulations for electric vehicles. Conduct thorough testing and validation to verify the effectiveness and safety of the proposed system.

CONCLUSION

In conclusion, an essential part of electric vehicles that guarantees the security, dependability, and longevity of the battery pack is the EV BMS with charge monitor and fire prevention. By supplying crucial safety features like temperature control, fault detection, cell balancing, and fire prevention, the system lowers the possibility of battery fires and enhances the overall efficiency of electric vehicles.In order to improve the features and capabilities of EV BMS with charge monitor and fire prevention, more research and development is still possible. A few potential future work areas include eenhancing the precision and dependability of battery monitoring systems to deliver more accurate and timely data regarding the charge, health, and function of the battery pack.

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