AUTOMATIC BATTERY HEALTH MONITORINGUSING MACHINE LEARNING FOR E-VEHICLES

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Abstract- Batteries, which are made of a combination of electrochemical cells, provide the necessary electrical current for powering electrical equipment. Batteries continuously transform chemical energy into electrical energy,and for them to operate at their peak efficiency, appropriate maintenance must be given. In addition to the use of batteries, it is also believed that health management systems with expertisein various battery conditioning features, such as temperature, current, and voltage regulation, charging and discharging management mechanisms, and other mechanisms, will help to reduce risks to people's health, safety, and property. These systems regulate battery performance using merit-based standards. In thispaper, we provide a data-driven perpetual literacy system for neural networks to cover the foreseen parameters. We use a machine learning technique to extract crucial features from the discharge curves in order to estimate these values. Extensive simulations have been performed in order to evaluate the performance of the suggested technique at different currents and temperatures.

1. INTRODUCTION

The battery management system monitors individual cells in the battery pack. It then calculates how much current can safely go in (charge) and come out (discharge) without damaging the battery. The current limits prevent thesource (usually a battery charger) and the load (such as an inverter) from overdrawing or overcharging the battery. This protects the battery pack from cell voltages getting too high or low, which helps increase the battery's longevity.

The BMS also monitors the remaining charge in the battery. It continually tracks the amount of energy entering and exiting the battery pack and monitors cell voltages. It uses this data to know when the battery is drained and shut the battery down. This is why lithium-ion batteries don't show signs of dying like a lead-acid, but just shut off.The Battery Management System on an electric vehicle monitors each cell in the battery pack closely. It ensures that the battery pack is safe to use and protects the car if the cells are not working correctly.In addition, it estimates the range that the vehicle can travel and helps improve the battery pack's overall lifecycle. Therefore, a Battery Management System is a critical part of an electric vehicle, and a good battery management system can improve the life of an electric vehicle by several years. To address this inherent shortcoming of Lithium ion batteries, a battery management system is required to secure the entire system and keep track of the most efficient way to consume energy. These battery management systems must ensure that battery functions, such as SOH and SOC. A battery is used as a secondary power source in automobiles. An electric vehicle battery is a secondary (rechargeable) battery. It useschemical energy stored in rechargeable battery packs for power and therefore does not require any combustion engine for propulsion. An electricvehicle battery or traction battery powers the propulsion of battery electric vehicles. Forinstance, the SOH and SOC in electrical cars are analogous to an odometer and a gasoline-powered car's fuel gauge, respectively. SOH and SOC are critical metrics because, if calculated properly, they can stop overcharging, reduce overheating, and increasebattery life.

2. RELATED WORK

Limited number of studies have demonstrated the potential of automatic battery health tracking using various ideologies.

An adaptive Gaussian mixture model (AGMM) was created by Yu, Jianbo, et al. for addressing of various changes of battery health over the courseof the battery's existence. A Bayesian-inference method is used to detect novel health states that are online modelled by removing and adding components in AGMM.

According to Banaei et al., a novel technique for calculating a Lithium-Ion battery's State Of Health using impulse response has been developed. The proposed approach forecasts the terminal voltage of a battery using the terminal current measurement and exhibits the impulse response of a healthy battery.

A system to diagnose a battery cell fault using a Deep Neural Network was developedby Lee, et al. The discharge voltage data that was obtained by operating the lithium battery cell at a high temperature was used by the DNN state in this method.

Yu et al. developed a battery health prognostics system based on Bayesian-inference probabilistic (BIP) indicator and a state-space model (SSM) that integrates logistic regression (LR) and particle filtering (PF). Considering the lack of documented fault patterns, this system use generative topographic mapping to mimic the distribution of multisensor data from a healthy battery.

Using the deep learning (DL) approach, Noman Khan et al. offer a battery management system (BMS) based on MCCPs, where the patterns in these CPs vary as the battery matures over time and is subjected to more cycles. In order to offer ameaningful comparison study of our strategy, we therefore thoroughly investigate both machine learning (ML) and DL-based methodologies. To find the best method for estimating battery capacity and state of health (SOH), the adaptive boosting (AB) and support vector regression (SVR) are frequently compared with long short-term memory (LSTM), multi-layer perceptron (MLP), bi- directional LSTM (BiLSTM), and convolutionalneural network (CNN).

Hu and colleagues are interested in battery State-of-Health (SOH) indication and prognosis using machine learning. Short voltage sequence sample entropy is utilized as a reliable indicator of capacity loss. The underlying correlation between the capacity loss and sample entropy is capturedusing sophisticated sparse Bayesian predictive modeling (SBPM) methodology.

In this study, Xing, et al. reviewed the most recent techniques for life prediction and condition assessment based on battery health monitoring.Prognostics-based fusion technique is suggested that blends data-driven technology with physics-of-failure (PoF) by contrasting their distinctproperties.

A multistep-ahead prediction model was created by Li, Hong, and colleagues based on the mean entropy and relevance vector machine (RVM) and used to anticipate the battery's state of health (SOH) and remaining life. The RVM model incorporates a wavelet denoising method to determine trend information and to lessen uncertainty. The ideal embedding dimension is then chosen for accurate time series reconstruction using the mean entropy based technique.

To address this problem, Tang et al. addressed battery management system (BMS) as application health monitoring technique. First, the investigation of the estimation dispersion of a single indicator(SI) and the extraction of three health indicators from actual EV operating conditions serve toillustrate the need for multiple indicators (MIs).

A battery management system that can manage, monitor, and log data to an online database was proposed by M. Senthilkumar et al. to be integrated with the monitoring framework. The battery's voltage, current, temperature, power, and state of charge are all monitored by this system. These parameters are then transmitted and saved in a database through the internet, which an android app subsequently uses to display to the user.

A vibration-based health monitoring system was suggested by Chetan et al. Regular vibration data for car batteries has proven useful in identifying the need for maintenance or replacement. A series of vibration sensors, a setup centered around a battery, and a microcontroller for data acquisition from the sensors are utilized to gather this data.

A diagnostic design for lithium-ion batteries was created by Miftahullatif et al. actively detecting the voltage transient response during the rest period afterdischarge, when each battery cell reaches equilibrium. We discovered that the battery cells' SOH is represented by this brief response. We can predict the SOH variation inside the battery storage system by measuring the voltage variation because the cell balancing controller is not active during this restperiod after discharge (BSS).

3. PROPOSED SYSTEM

A battery health monitoring system consists of a temperature sensor, a current transformer, an LCD display, a buzzer, and a GSM module. The temperature, current, and voltage levels are continuously monitored after the system is turned onin the car. With a connected liquidcrystal display, this gives accurate readings of the fundamental parameters in real time. The system is made up of three main components: gathering data from all sensors, sending that data to a microcontroller for processing, and then sending user feedback. To monitor input current and voltage, we use voltage sensors and current sensors.. Also receiving this data is the microcontroller. After gathering all of this information, GSM technology will notify the user whenever a predetermined parameter—such asinput voltage, current, or battery percentage—changes. With the aid of the GSM module, the user will get SMS on his or her phone. We utilized the Arduino IDE and embedded C to code the system's components. Before enabling the battery charging circuit, make sure all of the components and the inputvoltage and current are within the specified limits. The user will also be informed when the battery drops below 10%.The rise and fall in the values are additionally shown through a buzzer-based notification system. This technology will analyze thebattery's precise condition and notify the user. To make sure that users are adequately informed of the batteries' state, another component of the system has a GSM Module. The controller notifies the user of the battery status together with the outcome shown on the LCD Display.

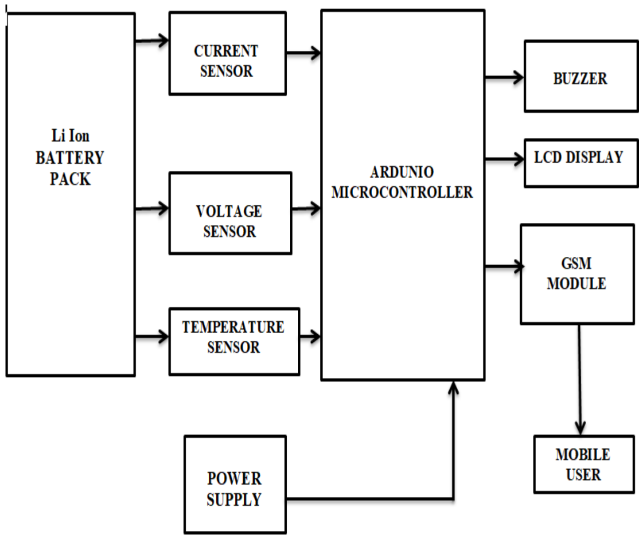

Fig. Proposed Block Diagram

WORKING

It primarily consists of three key components: gathering information from all sensors, sending that information, and processing it with amicrocontrollerbefore delivering user feedback. Weuse a voltage sensor and a current sensor to measureinput current and voltage. These sensors will keep an eye on the voltage and current going into the UPS battery and transmit the information to themicrocontroller. After gathering all of this information, GSM technology will notify the user whenever any of the preset parameters change. Withthe aid of the GSM module,the individual will receive SMS on his or her phone. The user will be able to learn the battery's present status with the help of this. The code is set up so thatthe motor will rotate to show the change in value in the event of a sudden rise in temperature or the temperature levels exceeding the threshold value, let's say 40 degrees Celsius. When it comes to training a model, the backpropagation method] is utilized rather frequently. This method first estimates the partial derivative of the error based on the values of the weight and bias, and then adjusts the weight and bias in accordance with those estimations. This helps to keep expenses to a minimum. The total number of epochs equals the number of times the entire training set was completed in its entirety. This is the benchmark that will be used to establish when a training programme should come to an end.

4. COMPONENTS

DHT11 Sensor

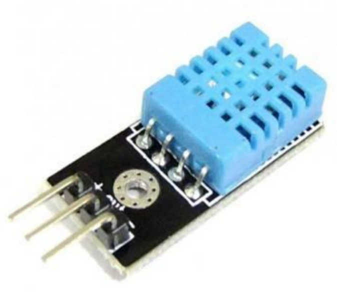

Fig.DHT11 Sensor

It has an advanced 8-bit microcontroller. Its innovation ensures high dependability and outstanding long haul stability. This sensor is primarily responsible for measuring the temperature of the batteries inreal time. It has excellent quality, rapid response, impedance resistance, and high performance.

Liquid Crystal Display

Fig. Liquid Crystal Display

LCDs are used to display the outputs and desired results obtained from sensors through the use of controllers. LCD displays are widely utilized in telecommunications and entertainment gadgets. The LCD Display is primarily used in our project to display real-time values of current, temperature, and voltage, as well as to indicate the state of charge.

Piezoelectric Buzzer

Fig. Piezoelectric Buzzer

The Piezoelectric Buzzer is used to provide feedback in the form of a sound or alarm. They are electrically powered sounds that operate on DCvoltage. The core of this buzzer is made up of a piezoelectric element. Due to this element the core of the buzzer constantly expands and shrinks when Dc Voltage passes through it. This continuous action produces vibrations which are responsible forthe production of the sound. The use of Piezo electric buzzer in this project is to indicate and alertthe user about the changes in voltage, current and temperature.

Regulator

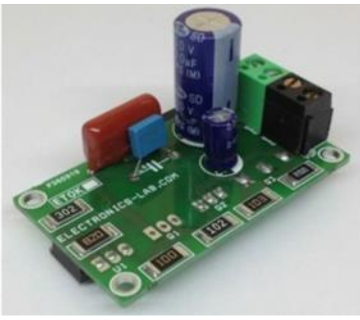

Fig: Regulator

A capacitor regulator's operating voltage and capacitance are both crucial characteristics. The operating voltage must be at least as high as the power supply's outputvoltage when there is no load. When current is pulled from the circuit, the capacitance controls how much ripple is visible on the Dc output.

GSM Module

Fig. GSM module

A GSM modem is adevice that makes use of GSM mobile phone technology to offer wireless data connectivity to a network. GPRS/GSM technology allows a mobile sim card to connect with the module. In the 900 and 1800MHz frequency bands, it allows users to receive and send SMS messages as well as make mobile phone calls. Programmers may create customized apps using the keypad and display interface. It also has two modes: data mode and command mode. Every nation employs a unique set of protocols and frequencies, including GPRS/GSM. Using command mode, developers may change the default settings.

5.RESULTS AND DISCUSSION

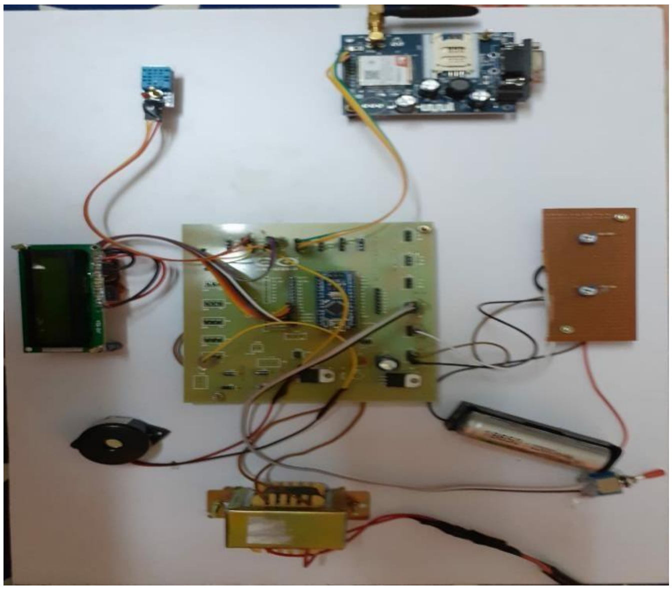

Fig. Hardware part consisting of sensors to monitor healthparameters of the battery and display in the Liquid Crystal display

Sensors are used in the hardware to monitor thehealth of the batteries. These sensors include the DHT 11 Temperature Sensor and regulators to measure the battery's current and voltage. These sensors are used for live monitoring, and the readings are displayed on an LCD display. Hereonce the vehicle is started the temperature, current, voltage and the state of charge parameter readings are shown in the Liquid Crystal display.

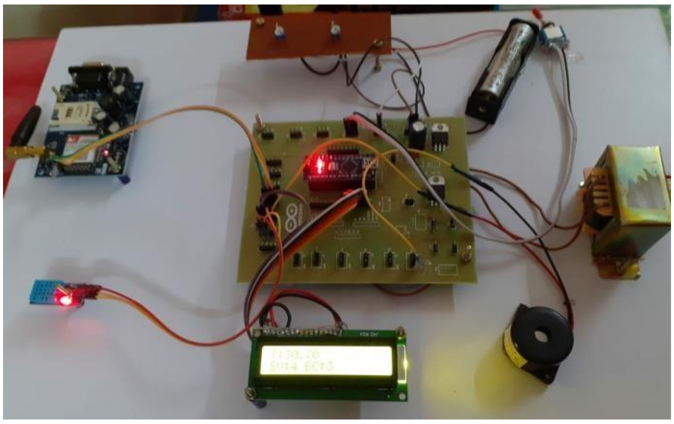

Fig. Hardware Part

Any deviation in the readings will result in an alert message being sent to the user's phone. If the temperature rises, a message labeled "Temp High" will be sent to the user's mobile device. This will be

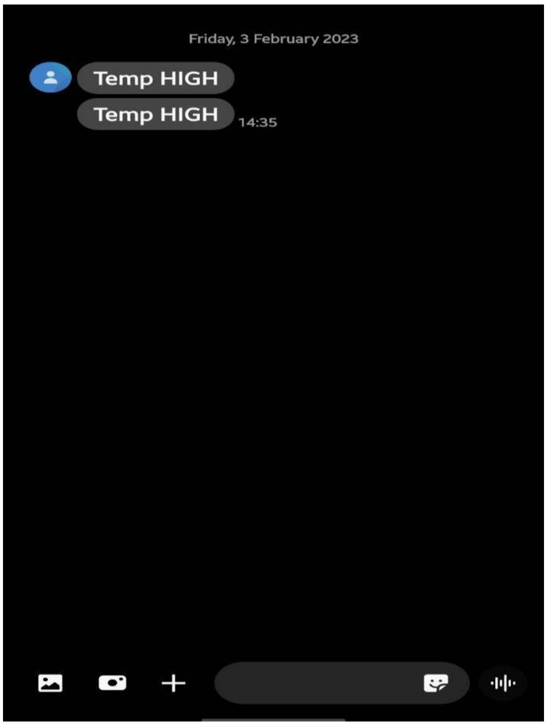

Fig. Message sent when High Temperature is measured

The changes in the battery are also shown on the LCd Display screen. In case of voltage fluctuation the display will show a message as "Low Voltage". If the battery becomes overcharged, the system displays a "Overload" message..

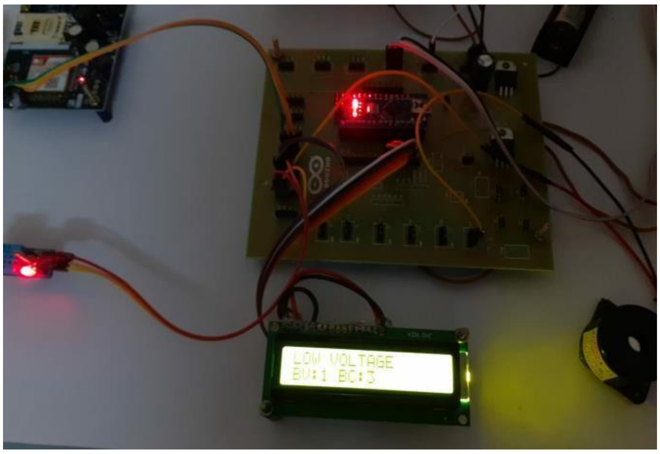

Fig. Message is displayed when change in battery parameters are measured is measured

Readings were obtained using the designed system and compared to sensor readings. The error percentage is calculated, and the system is trained again to reduce errors.

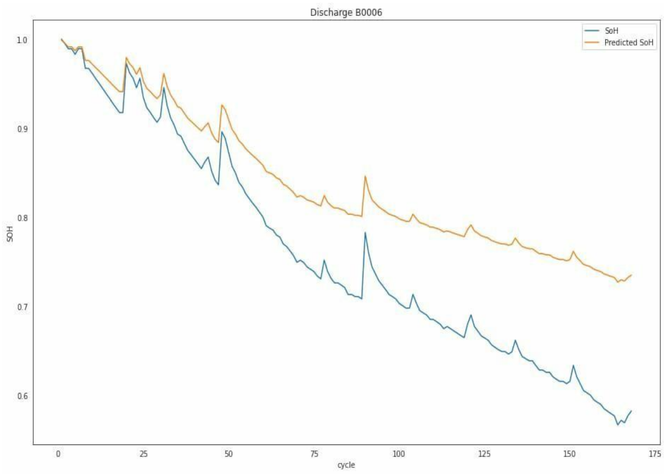

Fig. Battery capacity with SOH

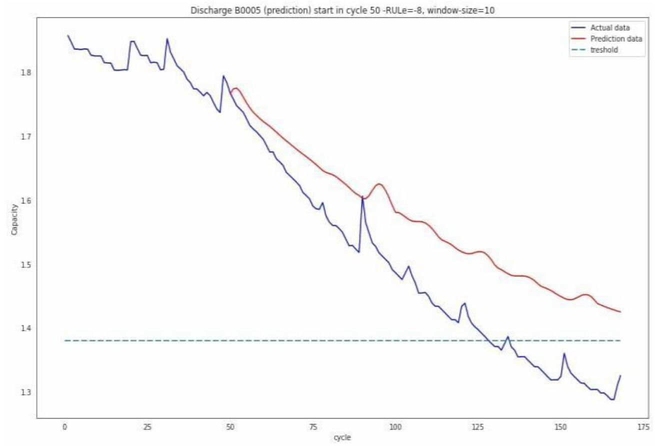

Fig. Graphical representation of actual, predictionvs threshold data

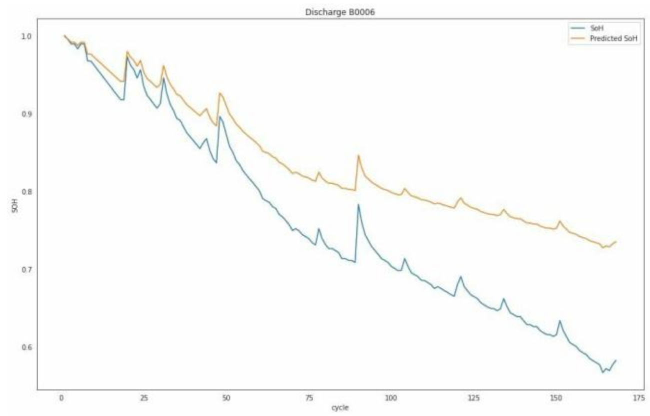

Fig. Graphical representation of SOH vs predictedSOH

The dataset is prepared in such a way that it can be used by Tensorflow in the training phase, for this, two structures are created corresponding to the input and output expected to be obtained. For the input data, the relevant characteristics of the dataset are filtered, Instant of time. For the output data, the SoH of the battery is calculated and in both input and output cases, the values are normalized to a range of values between [0-1].For the estimation of SoH, it can be seen that the data pattern is learned by the model correctly, as predicted by the theory, since the shape of the curves is almost identical. The SoH shown has the same behavioras expected in theory, which is corroborated with the root mean square error value of the graph in illustration 8, whose value of 9% is very similar to that found previously. This reaffirms the precision when making the prediction.For the estimation of SoH, it can be seen that the data pattern is learned by the model correctly, as predicted by the theory, since the shape of the curves is almost identical. The SoH shown has the same behavior as expected in theory, which is corroborated with the root mean square error value of the graph, whose value of 9% is very similar to that found previously. This reaffirms the precision when making the prediction. By RUL estimation, in the same way that was done for the estimation of SoH, the training and testing dataset is prepared, in this particular case the battery capacity data is used using the first data of the first 50 cycles to predict the capacity in the following cycles in such a way as to be able to know when the threshold of the battery is reached and estimate the remaining cycles to reach the End of Life of the battery.

6.CONCLUSION

To achieve almost minimal equipment downtimeand optimum productivity, battery health degradation detection and monitoring are essential. The difficulty lies in developing an efficient monitoring system that can reliably show how battery health degrades over the course of its lifespan. This study suggests a continuous learning system for tracking the health of batteries (SOH).The goal of this critical analysis is to provide a strategy for the advancement of these technologies. When one considers the possibility of an informationand energy internet for the purpose of transferring data and power, the significance of this issue becomes further clearer. Among its most significant problems are limitations on storage space, charging speed, safety, and the ability to produce accurate real-time forecasts of LIB states using a realistic dataset. The ultimate objective is to create a live, data-driven electrothermal model that can be used for state prediction, health monitoring, and charge regulation in real time. This will be accomplishedover the course of several years.

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