Predicting Residual Energy In Batteries Using Machine Learning

Mr.R.Jeevanandh[1], V. Dhananjeyan[2], T. Dhanush kumar[3], S.Palanisamy[4], M. Srinesik[5]
[1]Assistant professor, Dept of Electrical and Electronics Engineering
[2, 3, 4, 5]Dept of Electrical and Electronics Engineering
[1, 2, 3, 4, 5]Paavaicollege of Engineering,Namakkal,Tamil Nadu,India.

Abstract- *The increasing reliance on battery-powered systems in renewable energy and electric vehicle applications necessitates accurate estimation of battery residual energy for efficient power management. This project presents a smart battery monitoring and prediction system using machine learning, particularly linear regression, to forecast the remaining energy of a lithium iron battery pack. The battery system consists of six lithium iron batteries (3.7V, 2900mAh each), grouped into three parallel-connected pairs, which are further arranged in series to create a higher capacity battery bank. A Battery Management System (BMS) is integrated to ensure safety and manage the charging and discharging operations effectively. The core of this system lies in precise voltage sensing and prediction. Three voltage measurement sensors monitor the battery voltage in real time and feed the data to a PIC microcontroller. These voltage levels are displayed on an LCD for user reference. When the sensed voltage of the battery system drops below 5V, a relay is triggered, and the system activates a boost converter to step up the voltage to a suitable level for the load. This voltage regulation mechanism ensures uninterrupted power supply to the load while maintaining battery safety and prolonging its lifespan. To enhance the intelligence of the system, a machine learning algorithm—linear regression—is employed to predict the residual energy of the batteries based on historical voltage data and discharge rates. By analyzing the pattern of voltage decline over time, the system can estimate future battery levels and provide advance alerts, aiding in decision-making for charging cycles. This predictive functionality helps in avoiding unexpected power losses and supports proactive energy management, especially in critical applications.*

Keywords- Battery Monitoring, Machine Learning, Predictive Maintenance, Energy Management, Battery Management System (BMS)

I. INTRODUCTION

In modern energy systems, efficient battery management is crucial for enhancing performance, safety, and the longevity of battery-powered applications. Lithium Iron Phosphate ($LiFePO_4$) batteries are widely used due to their high energy density, long cycle life, and thermal stability. In this project, six $LiFePO_4$ batteries are arranged such that each pair is connected in parallel to form three sets, which are then connected in series. This configuration offers both high capacity and voltage suitable for mid-power loads. The Battery Management System (BMS) plays a central role in monitoring the individual battery voltages through dedicated voltage sensors and ensures that the system operates within safe voltage thresholds.

To improve real-time monitoring, the voltages from all three battery sets are measured using sensors and displayed on an LCD screen. Each battery provides 3.7V at 2900mAh, and the system is designed to trigger a relay once the total voltage drops below a predefined threshold of 5V. This action activates a boost converter that steps up the voltage to maintain a stable supply to the connected load. This control logic ensures continuous operation even under low voltage conditions, thereby enhancing energy utilization and system reliability.

Beyond conventional hardware-based battery monitoring, this project incorporates a machine learning algorithm—specifically linear regression—to predict residual energy more accurately. Linear regression is used to model the relationship between measured voltage levels and estimated remaining energy. By training the algorithm with voltage data and corresponding discharge profiles, the system can estimate how much usable energy remains, helping to avoid unexpected power loss and allowing for more informed energy management decisions.

Integrating machine learning into battery energy prediction opens new possibilities for smart power systems, especially in electric vehicles, IoT devices, and renewable energy applications. This intelligent battery monitoring approach enables predictive maintenance, longer battery life, and improved efficiency by anticipating when batteries need recharging or replacing. The combination of real-time voltage sensing, controlled switching through relays, energy boosting, and predictive analytics through linear regression forms a robust solution for next-generation energy management systems

II. LITERATURE SURVEY

Existing systems

A. A Novel Approach for Predicting Remaining Useful Life andCapacity Fade in Lithium-Ion Batteries Using Hybrid Machine Learning - Sadiqa Jafari; Yung Cheol Byun; 2020.

Since lithium-ion batteries (LIBs) are essential to many different sectors, accurate estimates of their Remaining Useful Life (RUL) are necessary to maximize Battery Management Systems (BMS). In this study, we introduce an innovative approach that combines machine learning techniques to create a hybrid model, enhancing the precision and reliability of battery analysis. Our proposed model leverages the power of k-Nearest Neighbours (KNN), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) algorithms to capture complex relationships and patterns in battery data effectively. Our major objective is to precisely estimate the residual energy and RUL of LIBs, allowing for the efficient evaluation of battery health and deterioration over time. We meticulously curate a comprehensive dataset comprising essential battery parameters, including capacity, voltage, cycle, and temperature

B.Residual Energy Prediction Scheme for Wireless Sensor Devices –SungroYoon, Chongkwon Kim; 2019

Because sensor nodes have very limited resources, energy efficiency is thought to be one of the most essential parts of wireless sensor networks. Many schemes including routing and MAC protocols have been proposed which attempt to make the operation of sensor networks more energyefficient.While most of these schemes assume that precise amount of residual energy is already known, it is never easy to find out remaining life of sensor nodes in reality. We investigate the problem and propose a scheme to predict the remaining energy of sensor nodes.

C. Accurately Predicting Residual Energy Levels in MANETS -Thomas Kunz; 2019

To support energy-efficient routing, accurate state information about energy level should be available. But due to bandwidth constraints, communication costs, high loss rate and the dynamic topology of MANETs, collecting and maintaining up-to-date state information is a non-trivial task. In this work, we use Optimized Link State Routing (OLSR) as the underlying routing protocol and focus on residual energy level as QoS metric, which has been used for routing decisions in many energy-efficient routing protocol proposals. Our experiments show that nodes have at best imprecise state information, especially under high traffic rates. We propose and evaluate two additional techniques to reduce inaccuracies and compare them against the basic OLSR protocol.

D. Implementation of Machine Learning in Battery Management System of Electric Vehicles - Sandeep Kumar Sunori, Shilpa Jain, Pradeep Juneja, Amit Mittal; 2024

This research is based on ML (Machine Learning) based predictive modelling for assessing the SOC (State of Charge) of a BMS (Battery Management System). For the reliable and efficient use of a battery -based system, mainly in EVs, the accurate estimation of SOC is paramount. In this work, a secondary dataset including 93 samples of 4 key parameters namely Voltage, Current, Temperature, and SOC has been used to train the ML models for SOC estimation. The ML techniques which are implemented here in MATLAB are Linear Regression, and Support Vector Machine (SVM), for SOC prediction. While 80 % of this dataset has been used for training and 20 % for testing. The Linear regression model provides a basic linear approach for SOC estimation. Whereas, the SVM has the ability of handling non-linear connection between input parameters and the output. The performance is compared on the basis of the test data inputs. Various graphical representations are also shown for illustrating the performance of developed models. The findings contribute significantly towards advancements in intelligent BMSs.

III. PROPOSEDSYSTEM

Predicting and managing the remaining energy in lithium-ion batteries through a smart system that integrates machine learning algorithms. In this setup, six lithium iron phosphate ($LiFePO_4$) batteries are used.The batteries are grouped into three sets, where each set consists of two batteries connected in parallel These sets are then connected in series, which allows the system to achieve a higher voltage level while maintaining efficient energy storage and management.

The batteries are monitored by a Battery Management System (BMS), which ensures safe and efficient operation by tracking each battery's voltage and ensuring they are within their optimal operating rangeThe voltage level of each battery is continuously monitored using three voltage sensors that send real-time data to the system. These sensors measure the voltage levels of each battery, typically 3.7V when fully charged, and the data is displayed on an LCD screen for the user to observe.

The system works in such a way that when the voltage level of any of the batteries falls below a threshold of 5V, the system activates a relay.This relay is responsible for triggering the boost converter, which steps up the voltage to a level suitable for powering the load.This ensures that the system continues to provide power even as the individual battery voltage decreases, thus preventing the batteries from being discharged below a critical level that could potentially damage them.

Machine learning, specifically linear regression, is employed in this system to predict the remaining energy in the batteries. Linear regression works by establishing a relationship between the battery's voltage and the residual energy, allowing the system to predict how much energy is left based on the current voltage levels.

By analyzing historical data and voltage readings, the system can forecast when the battery might be fully discharged, enabling better decision-making for load management and ensuring that energy is distributed efficiently. This machine learning model helps predict the battery life accurately and provides insights into when the batteries need recharging or replacement.

The combination of hardware components and machine learning ensures that this system can maintain optimal performance while protecting the batteries. By leveraging the power of predictive analytics, it not only provides real-time voltage information but also anticipates future battery behavior, allowing for smarter energy management.

Hardware Requirements

The hardware requirements for this project include a lithium iron battery pack, a Battery Management System (BMS) to ensure safety and manage charging/discharging operations, voltage measurement sensors to monitor battery voltage in real-time, a PIC microcontroller to process data and control the system, a relay to trigger the boost converter when voltage drops below a certain level, an LCD display to display voltage levels and system status, and a boost converter to step up voltage to a suitable level for the load. These components work together to create a smart battery monitoring and prediction system.

MODULE LIST

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BMS
Voltage Regulator
PIC Controller
Relay
LCD Display
Boost Converter

POWER SUPPLY

The power supply provides regulated DC voltage to all
components. It converts AC mains power to low-voltage DC using a transformer, rectifier, and voltage regulator. This ensures a stable power source for microcontroller operation.

BLOCK DIAGRAM:

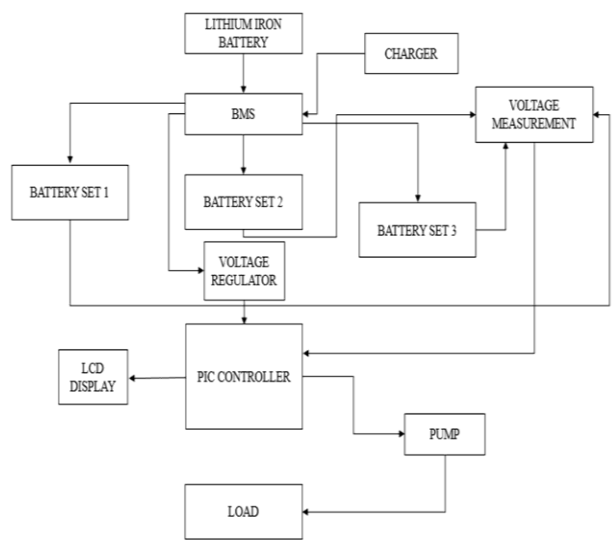

Fig.1.Proposed Block Diagram

BATTERY

Lithium-ion (Li-ion) batteries are a type of rechargeable battery that has become widely popular for various applications due to their high energy density, long cycle life, and relatively lightweight design. These batteries use lithium ions as the charge carriers, moving back and forth between the positive and negative electrodes during the charging and discharging cycles.

The chemical reactions within the battery allow for efficient storage and release of electrical energy, making lithium-ion batteries a preferred choice in consumer electronics, electric vehicles, and renewable energy storage systems.

The basic components of a lithium-ion battery include a positive electrode (cathode), a negative electrode (anode), an electrolyte, and a separator. The cathode typically consists of lithium cobalt oxide ($LiCoO_2$), lithium manganese oxide ($LiMn_2O_4$), or other lithium-based compounds, while the anode commonly uses graphite. The electrolyte is a lithium salt dissolved in a solvent, and the separator prevents direct contact between the cathode and anode to prevent short circuits.

Fig.2. Battery

BMS

A **Battery management system**does not have a fixed or unique set of criteria that must be adopted. The technology design scope and implemented features generally correlate with:

The costs, complexity, and size of the battery pack Application of the battery and any safety, lifespan, and warranty concerns

Certification requirements from various government regulations where costs and penalties are paramount if inadequate functional safety measures are in place

There are many **BMS** design features, with battery pack **protection management** and **capacity management** being two essential features. We'll discuss how these two features work here. Battery pack protection management has two key arenas: electrical protection, which implies not allowing the battery to be damaged via usage outside its SOA, and thermal protection, which involves passive and/or active temperature control to maintain or bring the pack into its SOA.

Monitoring battery pack current and cell or module voltages is the road to electrical protection. The electrical SOA of any battery cell is bound by current and voltage. Figure 1 illustrates a typical lithium-ion cell SOA, and a well-designed BMS will protect the pack by preventing operation outside the manufacturer's cell ratings. In many cases, further derating may be applied to reside within the SOA safe zone in the interest of promoting further battery lifespan.

Fig.3. BMS

VOLTAGE REGULATOR

7805 Voltage regulator also finds usage in building circuits for inductance meters, phone chargers, portable CD player, infrared remote-control extension, and UPS power supply circuits. Also, we designed a Stopwatch Circuit using IC7805.The 7805-voltage regulator is a widely used integrated circuit (IC) that belongs to the 78xx series of linear voltage regulators. Specifically, the 7805 is a positive voltage regulator designed to provide a stable and regulated output voltage of +5 volts. This IC is commonly employed in electronic circuits to ensure a constant voltage supply, making it a popular choice for powering various components within a circuit.

Fig.4. Voltage Regulator

PIC CONTROLLER

The PIC16F877 is a powerful and widely used 8-bit microcontroller from Microchip Technology. It belongs to the PIC16 series and is known for its versatility, compact size, and low power consumption.

It is especially suitable for educational, industrial, and embedded system applications due to its rich peripheral set and ease of programming. This microcontroller can handle various control and interface tasks in real-time systems.

One of its standout features is the presence of both EEPROM and Flash memory, allowing for data storage and programmability. The microcontroller supports both low- and high-speed operations, which makes it flexible for time-critical applications. Its architecture is based on the Harvard model, which allows separate paths for data and instruction memory, enabling faster execution.

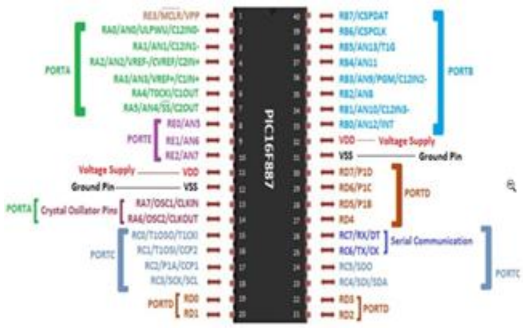

Fig.5. Pic Controller

In terms of development support, the PIC16F877 is compatible with a wide range of programming tools and simulators, including MPLAB IDE and PICkit programmers. It features In-Circuit Serial Programming (ICSP), which enables programming the microcontroller without removing it from the circuit, saving time and effort during testing and deployment.

The device supports a variety of applications, including motor control, remote sensing, home automation, and data acquisition. Its reliability and low cost make it a go-to choice for both beginners and professionals working on microcontroller-based projects.

RELAY

A relay is an electromagnetic switch that can turn on or off a substantially greater electric current using a very tiny electric current. An electromagnet is at the core of a relay (a coil of wire that becomes a temporary magnet when electricity flows through it). Consider a relay to be an electric lever: turn it on with a little current, and it turns on (or "levers") another device with a much larger current. A relay, on the other hand, utilizes an electrical signal to drive an electromagnet, which in turn connects or disconnects another circuit, rather than a manual process. Several types of relays exist, such as electromechanical and solid state. Electromechanical relays are commonly employed. Let us first examine the internal components of this relay before learning how it works. Despite the presence of several types of relays, their operation is the same. Every electromechanical relay is made up of an electromagnet. Contact that can be moved mechanically spring and switching points an electromagnet is made by winding a copper coil around a metal core. The coil's two ends are attached to the relay's two pins as illustrated. These two serve as DC power supply pins.

Fig.6. Relay

LCD

A liquid-crystal display (LCD) is a flat-panel display or other electronic visual display that makes advantage of liquid crystals' light-modulating characteristics. Liquid crystals do not directly emit light. The command register holds the LCD's command instructions. A command is an order issued to an LCD to do a specific action such as initializing it, clearing its screen, setting the cursor location, managing the display, and so on. The data register saves the information that will be presented on the LCD. Computer monitors, TVs, instrument panels, aircraft cockpit displays, and signs are all examples of electronic displays. They are widespread in consumer gadgets such as DVD players, gaming devices, clocks, watches, calculators, and telephones, and have virtually completely replaced cathode ray tube (CRT) displays.

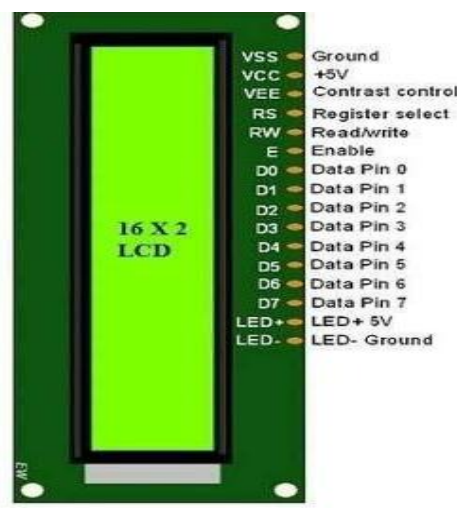

Fig.7. Pin diagramofLED

BOOST CONVERTER

A boost converter is basically a step-up chopper or step-up dc-to-dc converter by which we can obtain an output voltage greater than the input voltage. In other words, boost converters are regulator circuits that generate a voltage at the output side whose magnitude will be greater than or equal to the input applied voltage.In many domestic and industrial applications, there is a requirement for conversion of DC voltage source to different levels. Thus there is a need for a dc-to-dc converter that converts a fixed-voltage dc source into a variable-voltage dc source. A DC chopper is a static device by which we can obtain variable dc voltage from a source of constant dc voltage. It is similar to a function of an AC transformer used to step up or step down the dc voltage source. Besides saving in power, the dc chopper offers various advantages like high efficiency, fast response, compact in size, easy and smooth control, low maintenance & low cost.

Fig.8. Boost Converter

RESULT

The developed system successfully integrates real-time voltage monitoring of a lithium iron phosphate battery pack with machine learning-based prediction of residual energy using linear regression. Voltage sensors continuously track the battery status, and when the voltage drops below 5V, a relay activates a boost converter to maintain stable power output to the load. The linear regression model analyzes historical voltage and discharge data to accurately predict the remaining battery capacity, enabling proactive energy management and early warnings for recharging. This approach enhances battery safety, optimizes energy utilization, and reduces the risk of unexpected power failures, demonstrating promising applications in renewable energy systems, electric vehicles, and portable electronics.

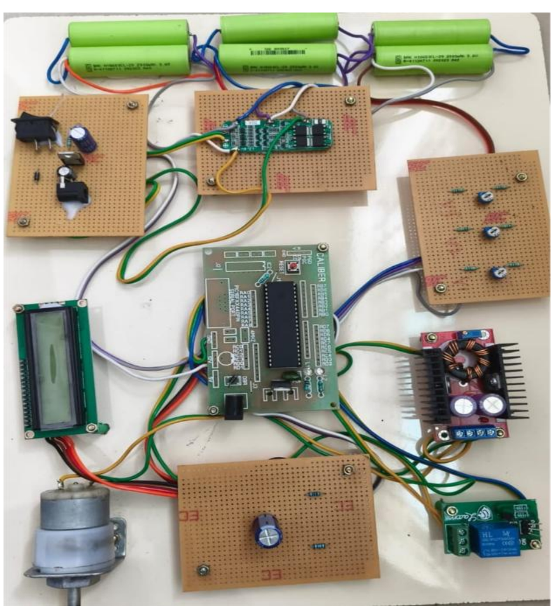

Fig.9 Prototype Model

V. CONCLUSION

In this project titled "Predicting Residual Energy in Batteries Using Machine Learning," a battery pack composed of six 3.7V, 2900mAh lithium iron cells (arranged in a 2P3S configuration) is monitored in real-time using voltage sensors and a PIC controller. The system measures the voltage of each parallel battery pair through three separate voltage measurement points and displays the readings on an LCD. When the system detects that the combined voltage drops below 5V, a relay is triggered to activate a boost converter, ensuring stable power delivery to the load.

By integrating linear regression as the machine learning technique, the system analyzes historical voltage data to predict the residual energy and anticipate when a critical voltage drop might occur, thereby optimizing energy usage and protecting battery health. This predictive capability enhances the reliability of power systems, especially in energy-sensitive or off-grid application.

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