IJAREEIE

e-ISSN: 2278-8875
p-ISSN: 2320-3765

International Journal of Advanced Research

in Electrical, Electronics and Instrumentation Engineering

Volume 13, Issue 4, April 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.317

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE)

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.317|| A Monthly Peer Reviewed & Referred Journal |

||Volume 13, Issue 4, April 2024||

| DOI:10.15662/IJAREEIE.2024.1304054 |

Machine Learning Integration with Battery Management System

Siddhant Shekhar Daribe, Santosh Shahaji Kadam, Pranav Balaso Gavade, MR. Prashant S. Mali

Dept. of Electrical Engineering, Annasaheb Dange College of Engineering and Technology, Ashta, Madhya Pradesh, India

Dept. of Electrical Engineering, Annasaheb Dange College of Engineering and Technology, Ashta, Madhya Pradesh, India

Dept. of Electrical Engineering, Annasaheb Dange College of Engineering and Technology, Ashta, Madhya Pradesh, India

Assistant Professor, Dept. of Electrical Engineering, Annasaheb Dange College of Engineering and Technology, Ashta, Madhya Pradesh, India

ABSTRACT: Battery-powered gadgets operate more reliably and effectively when battery life is predicted. Although a number of technologies are able to monitor a battery's capacity, they are not able to ascertain the interval between a battery failure. The technique we provide here estimates the lifespan of a battery using Long Short Term-Memory (LSTM), an artificial Recurrent Neural Network (RNN) architecture in Machine Learning (ML). When calculating battery life, several factors are considered, including the charge-discharge cycle, battery temperature, load voltage, and individual cell voltage. The voltage and temperature of the battery cells are measured by a microcontroller and thermistor. The voltage and temperature of the battery cells are measured by a microcontroller and thermistor. The voltage readings retrieved by the microcontroller are sent to a web server, whereupon they are displayed by a web-based mobile application. Overcharge avoidance and balanced cell charging are ensured by routinely monitoring the battery state. The several circuit components, the model training technique, the Graphical User Interface (GUI), and the test results are all described in this study. Intelligent tables and other high-power applications requiring battery management systems (BMS) frequently employ lithium-ion battery packs. Hardware and software that are utilized for battery state estimation tasks connected to fault monitoring and control must be combined in order for the BMS to be deployed. This essay offers a thorough investigation at the most recent developments in machine learning strategies for BMS. It distinguishes between various techniques based on the performance, type, structure, and principle analysis.

I. INTRODUCTION

Battery-powered devices operate more smoothly and consistently when battery life is predicted. The creation of an intelligent battery management system is the primary objective. The suggested approach estimates battery life using a mixed machine learning (ML) technique. Multiple jobs including charge and discharge control, overcharge and over discharge prevention, charge state (SOC) computation and display, charge state (SOH), thermal management, etc. may be accomplished through both experimental and modulating activities. It's going to be done. The suggested technique increases accuracy without requiring more computing power by fusing machine learning models with electrical equivalent circuits. The digital twin of the battery may be used to update and modify machine learning-based models, which can then be flashed back to the BMS microcontroller.

II. MATHEMATICAL MODEL FLOW

Creating a mathematical model for a Battery Management System (BMS) using machine learning involves representing the behavior of a battery system using equations and relationships. The specific model you choose will depend on the level of detail required, the type of battery, and the accuracy needed. Here's a simplified example of a mathematical model for a lithium-ion battery BMS:

1. Battery Voltage Model:
 - A simple way to model the battery voltage (V) is to use Ohm's Law:

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.317|| A Monthly Peer Reviewed & Referred Journal |

||Volume 13, Issue 4, April 2024||

| DOI:10.15662/IJAREEIE.2024.1304054 |

V = E - I * R_int - I * R_ext
Where:
- The voltage of the battery is V.
- E is the battery's open-circuit voltage (OCV).
- I is the battery's current flowing through it.
- R int is the battery's internal resistance.
- The circuit's exterior resistance is denoted by R ext.

2. State of Charge (SoC) Model:
- The State of Charge represents how much energy is left in the battery. A simple linear model for SoC can be:
SoC(t) = SoC(0) - (I(t) / Q)
Where:
- SoC(t) is the State of Charge at time t.
- SoC(0) is the initial State of Charge.
- I(t) is the integrated current over time.
- Q is the battery capacity.

3. State of Health (SoH) Model:
- The State of Health represents the battery's aging or degradation over time. It can be modeled using various techniques, such as the capacity fade model, which may involve using empirical data to estimate SoH based on the number of charge/discharge cycles or other aging factors.

4. Temperature Model:
- Battery performance is highly dependent on temperature. A simple thermal model can be used to estimate the battery's temperature based on heat generation during charging and discharging:
T(t) = T(0) + (I(t)^2 * R_int) / (m * C)
Where:
- T(t) is the battery temperature at time t.
- T(0) is the initial temperature.
- m is the mass of the battery.
- C is the specific heat capacity.

5. Machine Learning Integration:
- In addition to these basic models, machine learning models can be integrated to capture more complex and dynamic relationships. For example, you can use regression or neural networks to predict voltage, SoC, and SoH based on a combination of features like current, voltage, temperature, and cycle history.

2.1 Block Diagram-

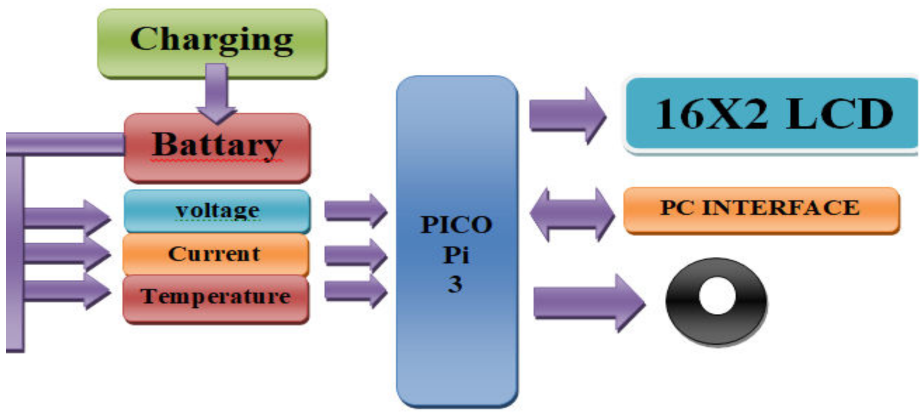


Fig.1Block diagram of BMS By machine learning

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.317|| A Monthly Peer Reviewed & Referred Journal |

||Volume 13, Issue 4, April 2024||

| DOI:10.15662/IJAREEIE.2024.1304054 |

The suggested BMS employing machine learning system's functional block diagram. In this case, the controller measures the battery's voltage condition using the Measure Voltage, Current, and Temperature blocks. To predict the lifespan of the battery cells, a machine learning system examines the data that has been recorded in memory. The LCD shows this result as well as the temperature and cell voltage. The BMS circuit itself provides various charging safeguards and balance charging of the battery cells. A BMS is a battery management system. It keeps track of the battery's continuous charging and draining and guarantees that each battery cell receives the same amount of charge throughout the process. Hardware makes up BMS. A BMS has circuits for protection, balance, and measurement. Each cell in the battery pack as well as the battery as a whole are measured for voltage and current in the voltage and current measurement portion. Every battery cell in the pack has its temperature measured by the temperature control section. In order to prevent the battery cells from being overcharged or undercharged, a balancing circuit ensures that they are charged and discharged equally. The battery is shielded from various threats by the protective circuit.

III. CIRCUIT DIAGRAM

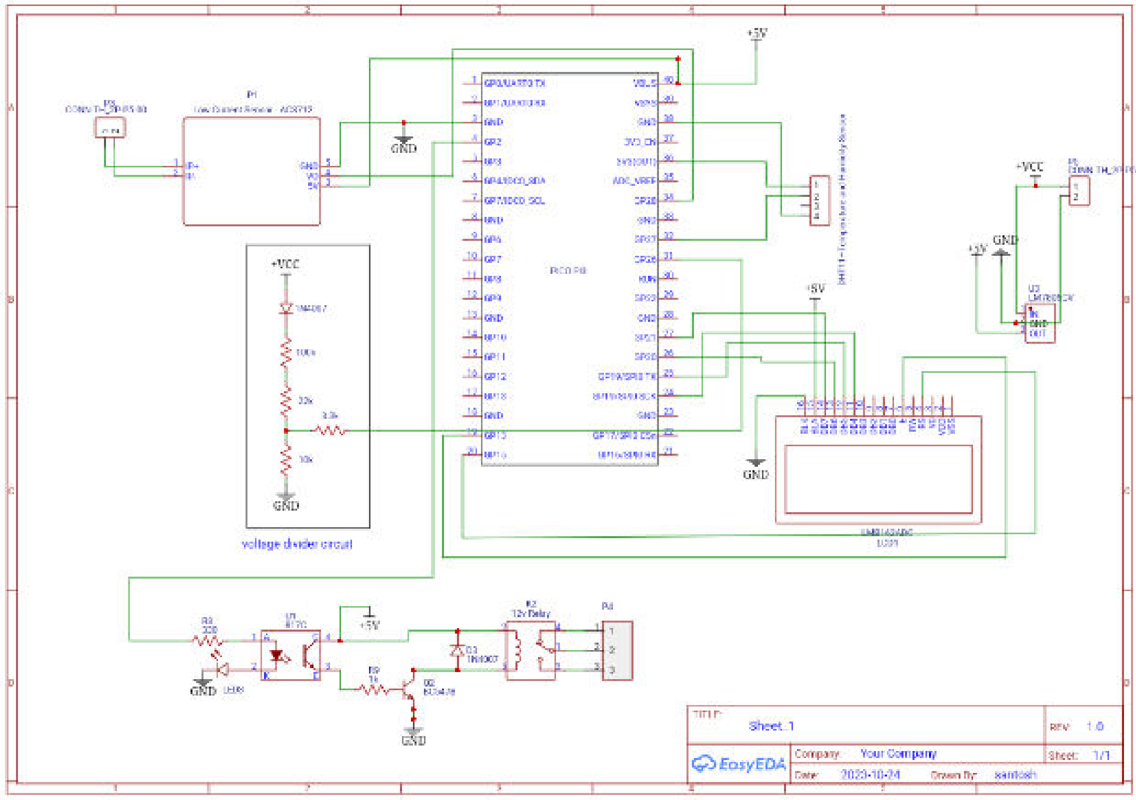


Fig.2 Circuit Diagram

3.1 Mathematical Analysis

Voltage divider Circuit Calculations:

Where ,

Diode circuit= 300Ω

R1 circuit = 100k Ω and 22k Ω

R1 circuit = 10k Ω and 3.3k Ω

$$\boldsymbol{ADC\ voltage} = \frac{\boldsymbol{R1}}{\boldsymbol{R1+R2}} * \boldsymbol{V(battery\ voltage)}$$

1. For 30V battery voltage level

$$= \frac{1000}{300+100000+22000+10000} * 30$$

= 2.26V

2. For 12V battery voltage level

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.317|| A Monthly Peer Reviewed & Referred Journal |

||Volume 13, Issue 4, April 2024||

| DOI:10.15662/IJAREEIE.2024.1304054 |

$$= \frac{1000}{300 + 100000 + 22000 + 10000} * 12$$

= 0.90V

3. For 30V battery voltage level

$$= \frac{1000}{300 + 100000 + 22000 + 10000} * 10$$

= 0.75V

And so on for different voltage level of battery

IV. CONCLUSION

A Battery Management System (BMS) using machine learning represents an advanced and data-driven approach to monitor, control, and optimize the performance of batteries. In theory, the application of machine learning to BMS offers several key advantages, and it has the potential to revolutionize the management of battery systems in various domains, including electric vehicles, renewable energy storage, and portable electronics. In conclusion, the integration of machine learning techniques into Battery Management Systems (BMS) represents a significant advancement in the field of energy storage and management. The literature review reveals that machine learning-based BMS has the potential to revolutionize how we monitor, control, and optimize battery performance. It offers several key benefits, including improved accuracy in state-of-charge (SoC) and state-of-health (SoH) estimation, enhanced fault detection and prognosis, adaptive control, and more efficient energy management. These advancements are crucial in various applications, such as electric vehicles, renewable energy systems, and consumer electronics.

V. FUTURE SCOPE

The future scope for Battery Management Systems (BMS) using machine learning is promising, with ongoing research and development offering numerous opportunities for advancements in battery technology and energy management.

REFERENCES

1. K. M. Abraham, Z. Jiang, ”A polymer Eelctrolyte-Based Rechargeable Lithium/Oxygen Battery”, Journal of the Electrochemical Society, Vol. 143, 1996

2. Matthew Barth, Jie Dy, Jay Farell, Shuo Pang, ”Battery state-of-charge estimation”, Proceedings of the American Control Conference, Vol. 2, June 2001

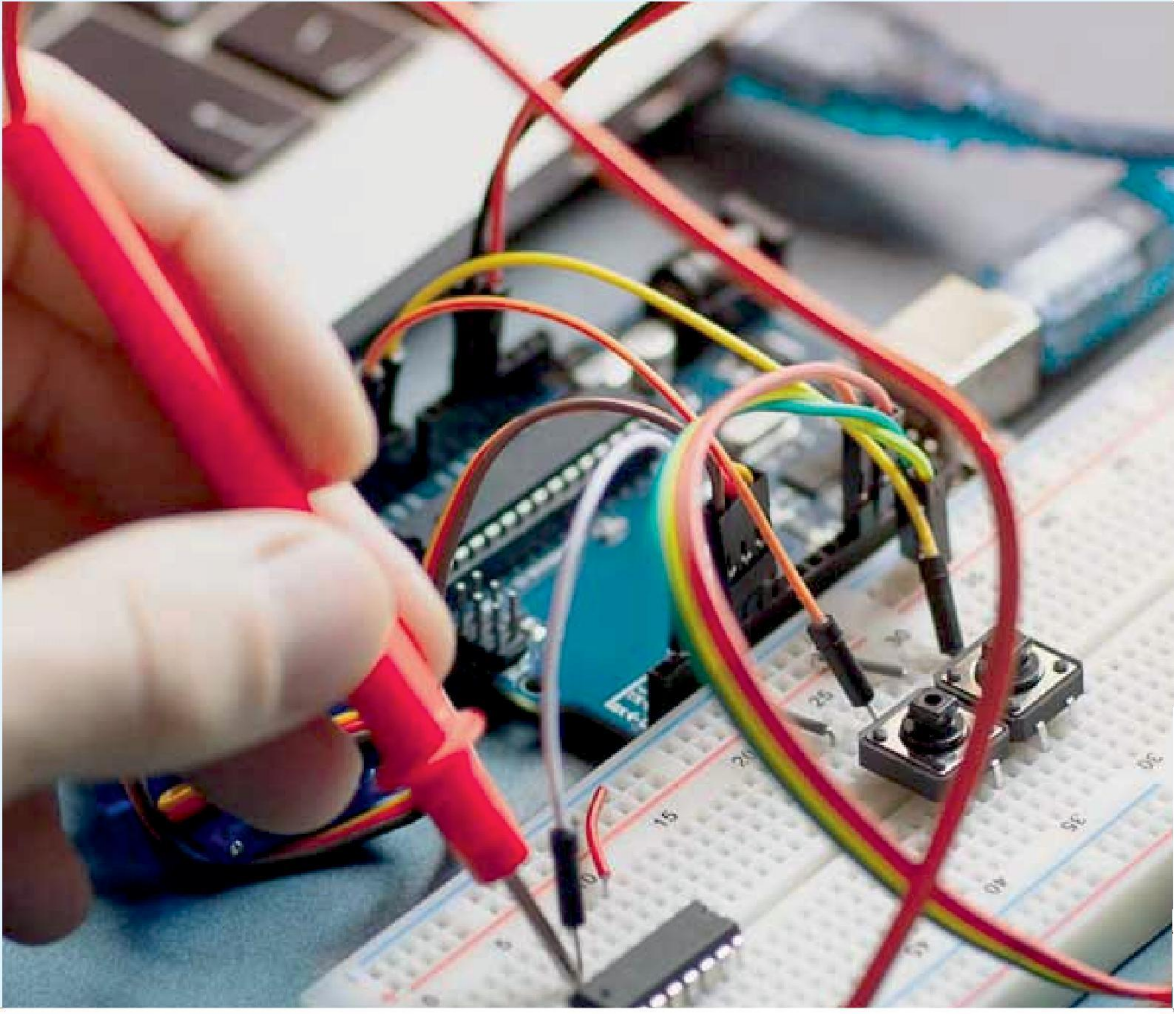
3. Massimo Ceraolo, “New Dynamical Models of Lead-Acid Baatteries”, IEEE Transactions On Power Systems, Vol. 15, NO. 4, November 2000

4. D. Sutanto, H.L. Chan, “ A New Battery Model for use with Battery Energy Storage Systems and Electric Vehicles Power Systems”, Power Engineering Society Winter Meeting, January 2000

5. John Chiasson, Baskar Variamohan, “Estimating the State of Charge of a Battery”, Transactions on Control Systems Technology, Vol. 13, NO. 3, May 2005

6. D.Jaya Deepti, V. Ramanarayanan, “State of Charge of Lead Acid Battery”, Proceedings of India International Conference on Power Electronics, 2006

7. Francisco M. González-Longatt, “Circuit Based Battery Models: A Review”, 2DO Congreso Iberoamericano De Estudiantes De IngenierÍa Eléctrica, 2006



International Journal of Advanced Research

in Electrical, Electronics and Instrumentation Engineering