Smart Battery Management System for Portable Devices to Enhance Battery Life Based on Machine Learning

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Abstract— In order to enhance battery performance, this study introduces a unique smart battery management system (BMS) for portable devices that makes use of machine learning. The system makes use of a trained machine learning model to predict patterns in energy use and a data collection setup to get accurate sensor readings. By keeping an eye on user activity, battery health, and dynamically altering power allocations, the BMS attempt to prolong battery life. Temperature control prevents overheating, and an adaptive charging method prevents overcharging. With the help of customization and insights from the user interface, a complete solution to prolong the life of portable device batteries and enhance user satisfaction has been developed.

Index Terms— SOC, ANN, ML, BATTERY MANAGEMENT SYSTEM.

I. INTRODUCTION

The growing popularity of portable electronics is driving new trends in the creation of battery packs, which are energy storage devices. A significant trend for many portable gadgets is miniaturisation. A decrease in accessible energy is the consequence of portable device size reductions, which also imply battery size reductions. One of the key parts of electric vehicles (EVs) or portable gadgets that ensures the safe, dependable, efficient, and long-lasting operation of a Li-ion battery while navigating the electric grid and difficult driving conditions is an effective battery management system (BMS). State of available power (SOP), state of charge (SOC), state of life (SOL), and state of health (SOH) are just a few of the battery states that an effective BMS may offer information on. This essay seeks to offer a suitable perspective on an intelligent battery management system regulates battery utilisation, charging and discharging procedures, and communication between batteries and other system components that use Artificial Neural Network (ANN) algorithms.

Lithium-ion batteries packaged in cylindrical shapes are among the most popular types. They are found in a variety of portable gadgets, including power banks, laptops, and flashlights. These batteries, which are cylindrical in shape and usually available in conventional sizes like 18650 or 21700, are utilized in this project.

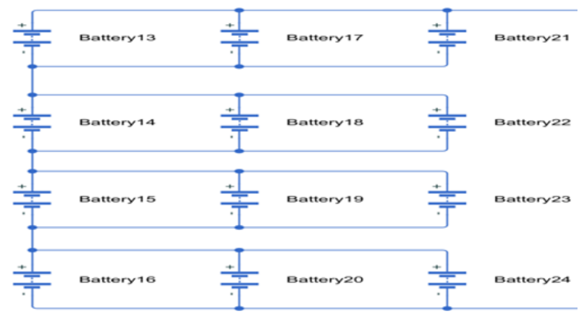
Cylindrical lithium-ion cells are one of the most common forms of packaging. They are used in devices such as flashlights, laptops, power banks, and many other portable electronics. These cells are used in this project as cylindrical shape and typically come in standardized sizes, such as 18650 or 21700

In conclusion, estimating state of charge (SOC), tracking state of health (SOH), balancing cells, communication, data recording, thermal management, overvoltage and undervoltage protection, and overcurrent protection are the main duties of a smart battery management system

II. LITHIUM BATTERY PACK CONFIGURATIONS

A. Lithium 18650 - 3S4P Configuration:

Three groups of four 18650 batteries linked in parallel (4P) and series (3S). Applications requiring a balance between voltage and capacity frequently adopt this arrangement



B. Lithium 18650 - 4S3P Configuration:

Each of three 18650 batteries. Every set is linked together in series (4S), and these sets are then linked together in parallel (3P). This arrangement is frequently utilised in situations when a greater voltage is necessary, but it's still crucial to strike a balance between voltage and capacity

III. SENSORS

A. Current Sensors ACS712

Based on a precise, low-offset linear Hall circuit with a copper conduction channel close to the die's surface, the 20A Range Current Sensor Module ACS712 is constructed. This copper conduction line generates a magnetic field when applied current flows over it; the Hall IC converts this magnetic field to a proportional voltage.

B. Voltage Detector Sensor

Using a potential divider, the straightforward yet incredibly helpful Voltage Detection Sensor Module reduces any input voltage by a factor of five. This enables us to monitor voltages greater than the microcontroller can perceive by using its analogue input pin. For instance, you can monitor voltages up to 25V using an analogue input range of 0V to 5V. Additionally, this module has convenient screw terminals that allow for safe and speedy wire connections.

C. Temperature Sensors

The W1209 thermostat module has keys, an LED display, a temperature sensor, and a relay. A DC 12V power supply is needed for it. It's a high-quality, reasonably priced thermostat controller. Thermostats are electronic devices that monitor and maintain the temperature of a system at or close to a predetermined level.

The module can automatically handle different electrical devices according to their temperature thanks to the NTC temperature sensor. Because of their negative temperature coefficient, NTC thermistors are thought to have a decreasing resistance as temperature increases.

IV. BATTERY MANAGEMENT SYSTEM

The Drill Motor Lipo Cell Module, Model number 3 Series 40A 18650 Lithium Battery Protection Board 11.11V 12.6V with Balance, features an integrated 10 low load resistance MOS tube and an AUTO Recovery function.

It provides a balanced current of 100mA with a continuous discharge of 40A for LED lights, low-power inverters, electric drills, and sprayers. (If the cooling environment needs improvement, please reduce the amount of current used for load).The range of the nominal voltage of 3.6V to 3.7V lithium batteries, which include polymer lithium batteries like the 18650 and 26650, and a charging voltage that can vary from 16.8V to 18.1V. With a constant charging current of (maximum limit): 20A, the board functions flawlessly. With balancing, the balanced version is appropriate for starting current below 80A and power below 135W for the drill.

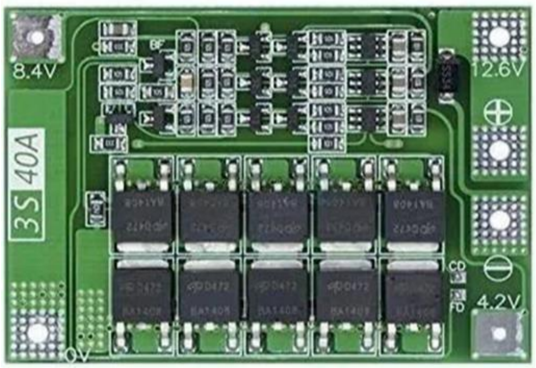


Fig. 1. 3s4P Battery Management System for 12 V output

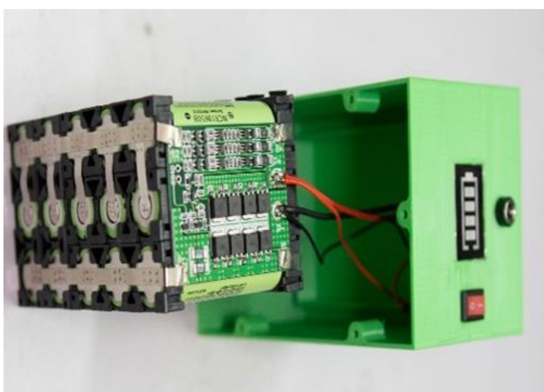


Fig. 2. Lithium 3s4P configuration Battery Pack for 11.1 V output

V. SYSTEM ARCHITECTURE

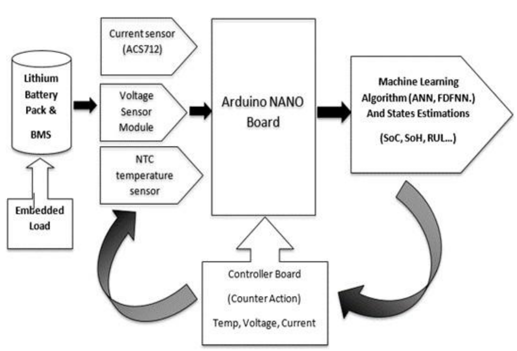


Fig. 3. The proposed methodology for Smart Battery Management System

A variety of quality indicators, including State of Charge (SoC), State of Health (SoH), State of Energy (SoE), Remaining Useful Life (RUL), and End of Life (EoL), are used to assess the health of Li-ion batteries.

- State of Charge (SOC):

The definition of SOC, or the ratio of a battery's current available charge to its rated capacity, is shown by the following equation:

$$SOC = (Q(t))/Qn \times 100 \quad (1)$$

Where Q(t) is the battery's available capacity at time t, and Qn is the nominal capacity, or the maximum charge that may be retained in the battery. It is especially challenging to accurately measure the current available charge of a battery since it depends on complex chemical interactions with nonlinear properties. SOC is therefore always based on an estimate.

- State of Health (SOH):

A method of measuring how badly a battery deteriorates over time with repeated discharges and recharges. It is the battery's maximum charge to rated capacity ratio. The formula in Eq. (2) is used to calculate a battery's SOH following the nth recharge cycle:

$$SOC = (Qmax(n))/(Qmax(0)) \quad (2)$$

Where Qmax(n) is the maximum charge that may be achieved after the nth recharge cycle and Qmax(0) is the battery's nominal maximum attainable charge.

- State of Energy (SOE):

The ratio of the residual energy to the nominal total energy of the battery as expressed in Eq. (3):

$$SOC(t0) = \frac{\int_0^{t0} P(t)dt}{E_N} \quad (3)$$

Where SOE(t0) is the State of Energy at time t0, P(t) is the effective power at time t and ***EN*** is the nominal total energy.

Remaining Useful Life (RUL):

An estimate of the number of battery cycles left before end of life. Usually, it is employed to lessen disastrous errors. Typically, the connection in Eq. (4) is used to estimate RUL:

$$\text{RUL} = n_{end}{}^{-n} \qquad (4)$$

Where N_end represents the last cycle before battery failure and n is the current cycle number.

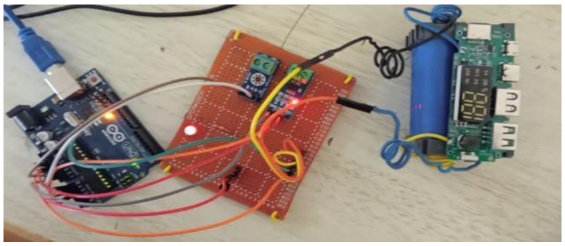


Fig. 4. Prototype of the design Battery Management System to enhance battery life based on Machine Learning,

VI. ANN-BASED ESTIMATION OF BATTERY STATES AND PARAMETERS:

A. Performance evaluation metrics

Before we go into the review, it is important to clarify a few concepts related to the assessment metrics used in the research to determine the accuracy of machine learning models. A few of these metrics include the mean absolute deviation (MAD), mean square error (MSE), root mean square error (RMSE), mean absolute error (MAPE), and coefficient of determination (R2).

B. SOC estimation

A gated recurrent neural network (GRNN) was used to assess the state of charge (SOC) of a Li-ion battery. Datasets from the Dynamic Stress Test (DST) profiles and the Federal Unified Driving Schedule (FUDS) were used to train and assess the model. Three factors were supplied into the model: voltage, current, and temperature. At room temperature, the GRNN produced an initial SOC estimate error of 4% before quickly converging to 2%. As a consequence, the MAE was 0.77% and the RMSE was 1.05%.

C. Exploratory Analysis

Exploratory analysis is an approach to data set analysis that focuses on highlighting salient aspects via the use of statistical graphics and other data visualisation tools. It is used to understand the structure, patterns, and relationships inside data before making formal inferences or building models. The act of investigating patterns, correlations, and trends in data by utilising plots like as scatter plots, box plots, histograms, and so on to create visual representations of the data is known as data visualisation. Link analysis: Investigate the relationships between variables using correlation analysis, cross-tabulations, or scatter plots.

```
df = pd.read_csv('battery_data.csv')
df.head()
```

	SOC	Current	Voltage	month	Temp	Charged
0	1.000000	3.059	4.133	0	0	0
1	0.999873	3.043	4.132	0	0	0
2	0.999682	3.046	4.131	0	0	0
3	0.999428	3.041	4.130	0	0	0
4	0.999174	3.044	4.129	0	0	0

Fig. 5. The training data set of Current, Voltage and Temperature over Few months

D. Data Cleaning

Finding and fixing missing data, handling anomalies, and ensuring data consistency are all examples of data cleaning. The process of calculating summary statistics, such as mean, median, mode, and standard deviation, that describe the shape, central tendency, and dispersion of the data is called descriptive data. using techniques like principal component analysis (PCA) or t-distributed stochastic neighbour embedding (t-SNE) to reduce the dimensionality of the data while preserving its key properties.

```
print(df.shape)
df = df.drop_duplicates()
print(df.shape)

(249205, 6)
(249205, 6)
```

Fig. 6. The resultant data after cleaning process

E. Features engineering

The Feature selection is the process of choosing a subset of features from the original features that satisfy predefined criteria and minimise the feature space as much as feasible. Feature selection is an important step in the feature production process. Some words just don't appear frequently in problems with text classification. Positively, it seems that there is just one training document where the term "groovy" is used. Is keeping this term as a feature really necessary? It's a dangerous endeavour since it's challenging to distinguish between noise and true correlation between a single training example and the positive class.

	SOC	Current	Voltage	month	Temp	Charged	Vmean
249200	0.523254	30.0000	2.8074	10	1	1	2.888221
249201	0.523149	29.9977	2.8054	10	1	1	2.886684
249202	0.523037	30.0000	2.8037	10	1	1	2.885141
249203	0.522942	29.9973	2.8021	10	1	1	2.883595
249204	0.522847	29.9995	2.8003	10	1	1	2.882046

Fig. 7. KPIs data selection from the data for insights

F. Algorithm and Model Selection

In machine learning, model selection is the process of deciding which algorithm and model architecture is suitable for a certain job or dataset. It involves contrasting and assessing several models to find the one that best fits the data and produces the best results. A number of factors are taken into account while choosing a model, including data processing skills, generalizability to new cases, and model complexity. To evaluate and compare models, methods like grid search and cross-validation are used with metrics like accuracy and mean squared error.

```
lasso <class 'sklearn.pipeline.Pipeline'>
ridge <class 'sklearn.pipeline.Pipeline'>
enet <class 'sklearn.pipeline.Pipeline'>
rf <class 'sklearn.pipeline.Pipeline'>
gb <class 'sklearn.pipeline.Pipeline'>
mlp <class 'sklearn.pipeline.Pipeline'>
```

Fig. 8. Different Algorithms and Models Available on ScikitLearn

G. Insights and Analysis

Battery health monitoring, use trends, predictive maintenance, ambient circumstances, user experience optimisation, and interaction with energy systems are just a few of the many issues covered by SoC insights and analysis. By effectively using SoC data, analysts can enhance battery performance, increase lifespan, and optimise energy use across a wide range of applications and sectors.

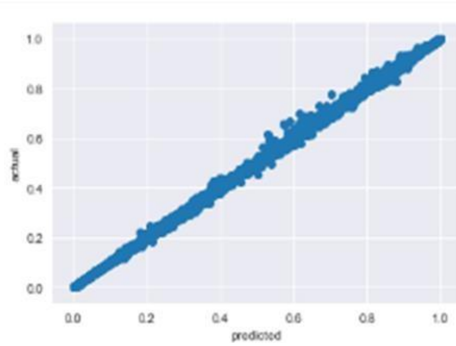


Fig. 9. Insights and Analysis Regression Line for Actual and Predicted SoC

CONCLUSION

This paper reviews machine learning techniques for estimating, monitoring, and controlling battery management systems, such as remaining usable life, health, and state of charge, with an emphasis on their advantages and disadvantages. Due to the abundance of portable battery-powered devices available on the market, machine learning solutions must be able to use many battery kinds, independent of the manufacturer and specifications. The suggested method comprises a battery-charging plan that is optimised and uses BMS to forecast how long the battery will last between charges and discharges without compromising performance. The battery may be protected against imbalanced charging and discharging of the battery cells, overvoltage, over discharge, excessive temperature, and overcharging by the specifically built BMS circuit.

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