**Machine Learning Integration With Battery management system**

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**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).

**CHAPTER 1**

**1.1 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.

**1.2 Objectives :**

1. To monitor state of charge (SOC) and state of health (SOH) :
2. Optimal charging and discharging strategies and Temperature control and management:
3. Temperature control and management
4. Fault detection and diagnosis

**CHAPTER 2**

**2.1 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:

 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.

The integration of machine learning allows for adaptive modeling and predictive capabilities, making your BMS more robust and efficient.

**CHAPTER 3**

**3.1 Circuit diagram :**

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**3.2 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

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

1. For 30V battery voltage level

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

 = 2.26V

1. For 12V battery voltage level

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

 = 0.90V

1. For 30V battery voltage level

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

 = 0.75V

 And so on for different voltage level of battery

**State of Charge (SoC) Calculation:**

SoC represents the current energy level of the battery as a percentage of its maximum capacity. Machine learning can be used to estimate SoC using a regression or classification approach.

Regression Approach:

Collect historical data that includes battery voltage, current, and temperature, as well as the corresponding true SoC values.

Use machine learning algorithms like linear regression, support vector regression, or neural networks to build a model that predicts SoC based on the input features.

Train the model on your dataset and evaluate its performance using metrics like Mean Absolute Error (MAE) or Root Mean Square Error (RMSE).

Classification Approach (for discrete SoC levels):

Divide the SoC range into discrete levels (e.g., 0-10%, 10-20%, etc.).

Train a classification model using machine learning algorithms like decision trees, random forests, or deep learning to classify the battery into one of these discrete SoC levels.

**State of Health (SoH) Calculation:**

SoH represents the overall health or capacity of the battery, often measured as a percentage of its original capacity. Machine learning can be used to estimate SoH based on various features and historical data.

Collect data over time that includes battery charge and discharge cycles, temperature, voltage, and current measurements, along with corresponding true SoH values. The SoH values can be determined through periodic battery capacity tests or reference measurements.

Use machine learning techniques like regression, time-series analysis, or recurrent neural networks (RNNs) to build a model that predicts SoH based on the collected data.

Train the model on your dataset and evaluate its performance. Common evaluation metrics for SoH prediction include Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), or correlation coefficients.

It's important to consider different degradation mechanisms, such as capacity fade and impedance growth, which may affect the battery's SoH.

**3.3 Experimental Analysis**

1. **Data Collection:**

Collect real-world data from the battery system you intend to manage. This data should include measurements such as voltage, current, temperature, state of charge (SoC), state of health (SoH), and any other relevant parameters. Ensure that the data is collected over a range of operating conditions and scenarios.

1. **Data Preprocessing:**

Clean and preprocess the collected data. This may involve tasks like handling missing values, outlier detection, and scaling the data to ensure it's suitable for machine learning algorithms.

1. **Feature Engineering:**

Extract relevant features from the data that will be used as inputs to the machine learning models. These features may include time-series data, statistical metrics, and other relevant information.

1. **Model Training:**

Select machine learning algorithms that are suitable for your BMS application, such as regression, neural networks, or decision trees. Split your data into training and testing sets to train and evaluate the models. Use appropriate metrics like mean squared error, R-squared, or others to assess model performance.

1. **Model Validation and Tuning:**

Fine-tune the machine learning models by adjusting hyperparameters and performing cross-validation to prevent overfitting. Validate the models on a separate validation dataset to ensure their generalization capabilities.

1. **Real-time Integration:**

Integrate the trained machine learning models into the BMS for real-time battery monitoring and management. Ensure that the BMS can make decisions based on the predictions, such as adjusting charging or discharging rates.

1. **Control and Decision Making:**

Implement control algorithms that use the machine learning predictions to make real-time decisions, optimizing battery performance and safety. Evaluate how well the BMS manages the battery in various scenarios.

1. **Safety Testing:**

Conduct safety testing to ensure that the BMS can respond to faults and emergency situations appropriately. Simulate and experiment with scenarios like overcharging, over-discharging, and thermal management.

1. **Performance Evaluation:**

Continuously monitor and evaluate the BMS's performance in real-world conditions. Assess its ability to predict and control battery behavior, ensuring that it meets safety and efficiency requirements.

1. **Feedback Loop and Adaptation:**

Implement a feedback loop that allows the BMS to adapt to changing conditions and recalibrate the machine learning models as needed. This ensures that the BMS maintains its accuracy and reliability over

**CHAPTER 4**

**4.1 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.

Machine learning enables the BMS to predict and estimate critical parameters like State of Charge (SoC), State of Health (SoH), and temperature with a high degree of precision. Traditional BMS methods often rely on simplified models that may not capture the full complexity of battery behavior.

By leveraging machine learning algorithms, a BMS can optimize battery charge and discharge strategies, extending battery life and improving overall performance. The models adapt to changing conditions, such as temperature, load, and usage patterns, leading to increased efficiency.

Machine learning provides robust anomaly detection capabilities, identifying unusual behavior in the battery system. This is crucial for early fault detection, preventive maintenance, and ensuring the safety and reliability of the battery. A BMS with machine learning has the capacity to continuously learn and improve. As it receives new data, it can update its models and adapt to changing conditions, providing accurate and up-to-date information.

In conclusion, a Battery Management System empowered by machine learning holds great promise for optimizing battery performance, extending their lifespan, and enhancing safety. The theory behind a machine learning-based BMS suggests that it can adapt to a wide range of battery technologies, make precise predictions, automate maintenance, and contribute to the efficient utilization of energy resources in a variety of applications. While challenges exist, the potential benefits are substantial, making machine learning an exciting area of research and development for battery management.

**4.2 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. Here's a detailed theoretical overview of the future scope for BMS with machine learning:

**1.Integration with Smart Grids:**

Machine learning-driven BMS can play a critical role in the integration of batteries with smart grids. By predicting energy demand, optimizing energy storage and distribution, and managing grid stability, BMS can contribute to a more resilient and efficient energy infrastructure.

**2.Enhanced Energy Storage Solutions:**

The development of more efficient, longer-lasting, and safer batteries will rely heavily on advanced BMS. Machine learning can enable real-time optimization and predictive maintenance, facilitating the integration of energy storage into various sectors, including renewable energy, electric vehicles, and IoT devices.

**3.Advanced Battery Diagnostics:**

Future BMS can provide more comprehensive diagnostics for batteries. By leveraging machine learning, these systems can detect and diagnose a broader range of battery health issues, from internal faults to thermal management, enabling timely maintenance and reducing downtime.

**4.Self-Learning and Self-Healing Batteries:**

BMS with machine learning has the potential to enable self-learning and self-healing battery systems. These systems can continuously adapt to changing conditions, self-optimize their performance, and even predict failures before they occur.

**5.Quantum Leap in Electric Vehicles (EVs):**

As the EV market grows, BMS with machine learning can contribute to faster charging, longer-range, and safer EVs. It can also address concerns related to battery degradation and reduce the total cost of ownership.

**6.Customized BMS for Different Battery Types:**

BMS can be tailored to different battery chemistries and applications. Future BMS will provide customized solutions for lithium-ion, solid-state, flow batteries, and other emerging battery technologies, adapting to their specific requirements.

In summary, the future scope for Battery Management Systems using machine learning is a dynamic and evolving field. It offers opportunities to enhance energy efficiency, reduce environmental impact, improve battery performance, and contribute to a more sustainable and reliable energy landscape. Advancements in machine learning, battery technology, and the integration of BMS with various sectors will drive this field forward in the coming years.

**4.3 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