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ENHANCED BATTERY LIFE AND EFFICIENCY USING DEEP LEARNING BASED THERMAL PREDICTION IN ELECTRIC VEHICLE

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ABSTRACT:

The rise in demand for Electric Vehicles (EVs) is driven by the global shift toward sustainable transportation. However, managing battery life and efficiency remains a critical challenge, particularly concerning thermal management. Efficient thermal control is essential for optimizing the performance and longevity of EV batteries, as temperature fluctuations can negatively impact their health and overall performance. This study introduces an innovative deep learning-based framework aimed at improving battery performance through accurate thermal forecasting. By utilizing advanced neural networks, we analyse a wide range of data, including historical temperature trends, charge and discharge cycles, and environmental factors such as external temperature, humidity, and driving conditions. Using this data, the model creates predictive algorithms that forecast thermal behaviour in real time. A key advantage of this approach is its ability to identify potential thermal changes early. By doing so, it enables proactive adjustments to the vehicle's operational parameters, including charging rates and cooling systems, to ensure the battery remains within optimal thermal ranges. This helps minimize energy loss, and improve overall efficiency. The results show significant improvements in both energy efficiency and battery lifespan, regardless of varying driving and environmental conditions. Furthermore, the ability to anticipate thermal changes ensures consistent battery performance even in unpredictable conditions. This research contributes to the development of intelligent thermal management systems in EVs, paving the way for smarter, more sustainable electric transportation. By using deep learning based thermal forecasting, this study enhances EV battery performance and longevity, improving sustainability, efficiency, and the overall user experience.

KEY WORDS: Electric Vehicles, Battery Thermal Management, Deep Learning, Thermal Forecasting, Battery Efficiency, Energy Optimization, EV Performance, Neural Networks, Sustainable Mobility, Heat Management.

INTRODUCTION:

The global transition to electric vehicles (EVs) is propelled by the urgent need to mitigate greenhouse gas emissions, reduce dependence on fossil fuels, and encourage environmentally sustainable transportation alternatives. As the adoption of EVs increases, optimizing battery performance and efficiency becomes crucial to enhancing vehicle functionality and user satisfaction. One of the most important aspects of battery performance is thermal management, which significantly impacts energy consumption, driving range, and overall battery life. Poor thermal control can lead to overheating, accelerated wear, and diminished battery performance.

Thermal regulation is particularly complex due to dynamic driving conditions, fluctuating external temperatures, and varying power demands. Excessive heat can result in higher energy consumption due to the need for enhanced cooling, while low temperatures can reduce the battery's efficiency and driving range. To address these challenges, an effective thermal management system is required to keep the battery within an optimal temperature range, thus improving both its operational efficiency and longevity.

Recent advancements in machine learning, particularly deep learning, have shown great potential in various predictive modelling applications. Deep learning techniques are adept at handling complex and high-dimensional datasets, uncovering patterns that might be missed by traditional approaches. By applying these techniques to thermal forecasting, it is possible to predict temperature changes under different conditions, allowing for more precise control over the battery's thermal state. This research introduces a new methodology using deep learning to forecast the thermal behaviour of EV batteries. By leveraging sensor data, including temperature, voltage, and current, we aim to predict battery temperature profiles in real-time, enabling more effective thermal management.

The goal is to improve battery efficiency, extend its lifespan, and enhance overall EV performance. To achieve this, it is essential to create systems capable of intelligently managing the thermal state of the battery under various driving conditions. Proper thermal management is key to preventing overheating, which can both damage the battery and cause increased energy consumption due to excessive cooling needs. Conversely, low temperatures can restrict battery discharge efficiency, reducing the vehicle's driving range. Therefore, a flexible and adaptive thermal management system is necessary to optimize both energy usage and battery lifespan.

The challenge of accurately predicting battery temperature profiles arises from several factors, including driving behaviour, weather conditions, battery load, and charge/discharge cycles. These variables create fluctuating temperatures that require continuous monitoring and adjustment. Traditional thermal management methods are typically reactive, addressing temperature issues only when they become critical. In contrast, deep learning models provide the ability to forecast temperature changes in real-time, enabling proactive regulation of the cooling and heating systems to avoid overheating or excessive cooling.

Models like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are particularly effective for this task, as they can analyse time-series data and recognize patterns over time. By incorporating a variety of sensor data—such as temperature, voltage, current, and environmental factors—these models can generate highly accurate predictions of the battery's future thermal state. Moreover, as more data becomes available, these models can continuously adapt, improving their accuracy and performance.

This approach not only enhances temperature regulation but also optimizes energy efficiency, minimizing energy losses related to unnecessary heating or cooling. In turn, this contributes to longer battery life, reduced operational costs, and improved overall sustainability of the vehicle. Therefore, the integration of deep learning and thermal forecasting has the potential to revolutionize electric vehicle technology, offering significant benefits in terms of performance, energy optimization, and sustainability.

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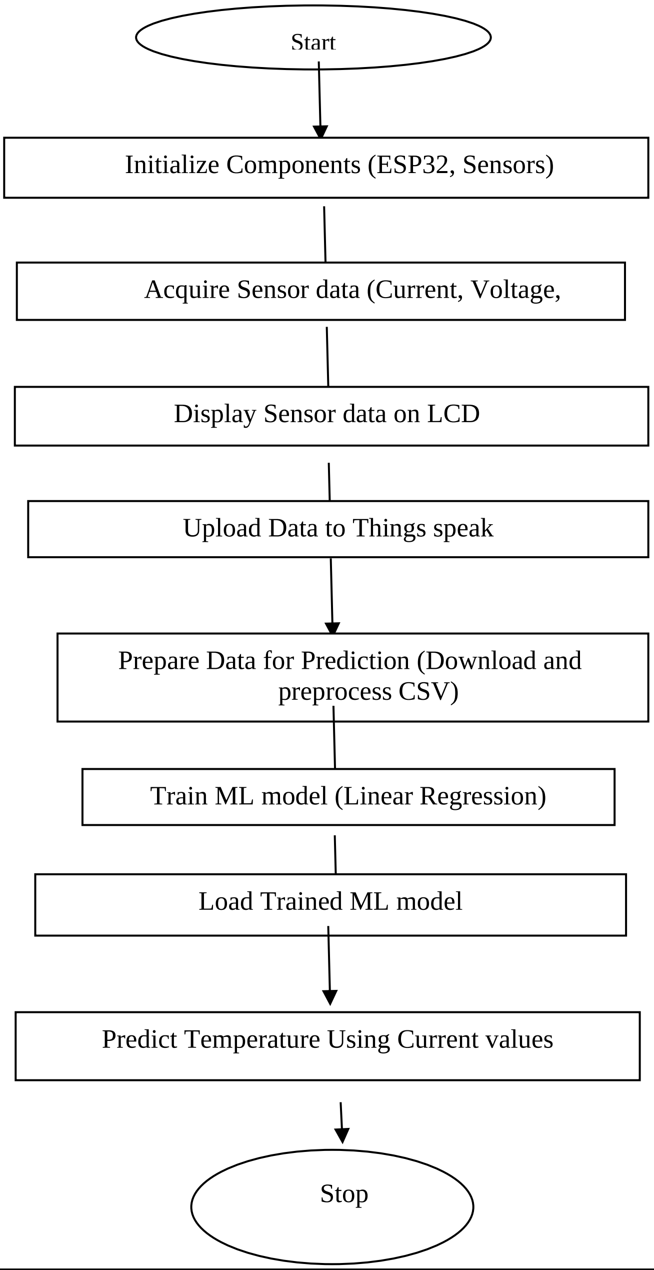
IMPLEMENTATION PROCESS



EXPERIMENTAL PROCEDURE

The procedure for implementing the Electric Vehicle Battery Management System (BMS) with linear regression for predictive maintenance and optimization begins with hardware setup, where the ESP32 microcontroller is used as the core controller to collect real-time data from sensors measuring current, voltage, and temperature. This data is processed by interfacing sensors like current sensors, voltage sensors, and the DS18B20 temperature sensor, with outputs displayed on an LCD screen. The system controls the cooling fan and alerts the user via a buzzer when the temperature exceeds a set threshold. Additionally, push buttons and slide switches are used to adjust charging modes and manage the DC motor load for efficient system operation. The collected data is uploaded to the Things Speak server, where it is stored for further analysis.

Before applying linear regression, several preprocessing steps are performed on the data. These steps include normalization, removing outliers, and dividing the data into training and testing sets. The linear regression models are trained to forecast battery temperature based on current load and voltage, which are influenced by both current and temperature. After training, the model's performance is assessed using metrics such as Mean Absolute Error (MAE) and R-squared. Once deployed, the model is used to predict real-time battery temperature and voltage, allowing the system to activate cooling mechanisms and adjust charging parameters automatically.

Predictive maintenance is achieved by optimizing temperature management and charging efficiency, ensuring the battery operates within safe limits. The ESP32 continuously monitors these parameters, compares them to model predictions, and makes real-time decisions regarding the cooling fan, charging modes, and motor load. Remote monitoring via Things Speak allows users to track battery health and adjust settings, while the system's performance is continually evaluated using CSV file. This comprehensive approach enhances battery life, efficiency, and safety in electric vehicles.

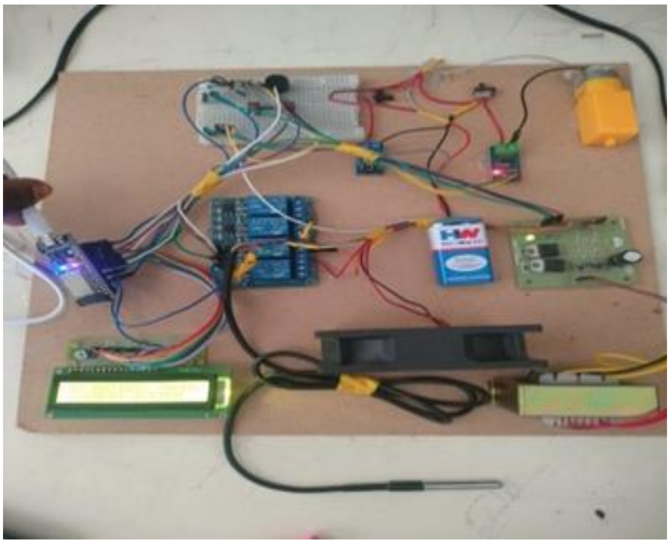


Fig.1. Working model of experiment

ADVANTAGES OF PROPOSED SYSTEM

Real-Time Energy Monitoring

The proposed system provides real-time updates on voltage, current, and energy consumption of connected loads. With sensors integrated into the system, users can monitor the performance of appliances and identify energy usage patterns instantly. This capability helps in avoiding overloading and enhances the overall efficiency of the energy system.

Interactive User Experience

The system's interface, combined with a display module and GSM messaging alerts, ensures users are always informed about system status. The user-friendly design allows individuals to easily interact with the system, receive critical alerts, and take immediate action without requiring technical expertise.

Efficient Energy Management

By leveraging the power of automated controls and sensors, the system ensures energy is used effectively. Appliances are monitored for power usage, and any unusual increase (like power theft) triggers automatic shutdowns and alerts, preventing unnecessary energy wastage and enhancing operational efficiency.

Immediate Theft Alerts

With the integration of current sensors and GSM modules, the system detects unauthorized energy consumption or power theft in real time. The system promptly alerts users via text messages, enabling swift actions to prevent or resolve such issues, thereby ensuring energy security and reducing costs.

Centralized Data Analysis

The proposed system collects and uploads all performance data, such as voltage, current, and load variations, to a centralized database or server. This data can be analysed to derive insights into energy usage trends, identify potential issues, and optimize energy distribution. This feature is particularly useful for predicting maintenance needs and improving system reliability.

EXPERIMENTAL RESULTS

The Electric Vehicle Battery Management System (BMS) discussed integrates several advanced features and technologies, including real-time monitoring, thermal management, and charging optimization. The implementation of linear regression for predictive maintenance and optimization in this system follows a structured approach. Below is a step-by-step breakdown of how each component of the system is implemented, with a focus on how linear regression models contribute to the overall performance and safety of the battery.

1.Hardware Implementation

1.1 ESP32 Controller

The central component of the system is the ESP32 microcontroller, which handles:

- Collecting real-time data from sensors.
- Controlling the cooling fan, buzzer, and charging modes.
- Uploading data to Things Speak for remote monitoring.

Implementation Steps:

1. **Sensor Interface:**
- Current Sensors (e.g., Hall effect sensors) are connected to measure the load current.
- Voltage Sensors track the battery voltage.
- A Dallas temperature sensor (e.g., DS18B20) It is utilized to track the temperature of the battery.
- The sensors communicate with the ESP32 via analog/digital inputs.

2. **Display:**
- An LCD display is used to show real-time data (current, voltage, and temperature).

3. **Cooling and Alert System:**

Table.1 – CSV file format

S.NO	FIELD-1 CURRECT (AMPS)	FIELD-2 TEMP (CELSIUS)	FIELD-3 VOLTAGE (VOLTS)
1	1	25.598	11.21
2	2	30.909	11.32
3	4	21.547	12.46
4	6	32.649	11.20
5	4	27.633	12.78

- When the temperature exceeds a predefined threshold, the cooling fan is activated.
- A buzzer provides an alert for the user.

4. **Push Buttons:**
- These buttons enable slow or fast charging modes, with each mode connected to separate relays for flexible charging control.

5. **Slide Switch:**
- Used to turn the battery supply and the DC motor load on and off for system efficiency.

1.2 Things Speak Server

The data from the sensors is uploaded to the Things Speak server for remote monitoring. The data can be downloaded in CSV format, making it easier to perform further analysis and apply machine learning models.

Implementation Steps:

- ESP32 sends the current, voltage, and temperature data to Things Speak using the Wi-Fi module.
- Each value is timestamped and stored in a channel for easy analysis and visualization.

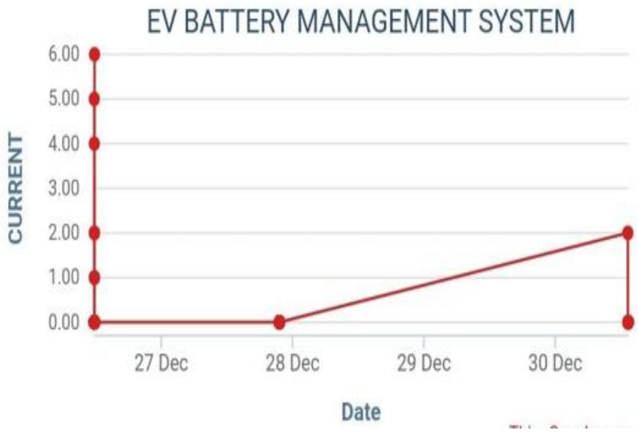
2. Data Collection for Machine Learning

2.1 Data Logging

As the system collects real-time data from sensors, it logs the following parameters:

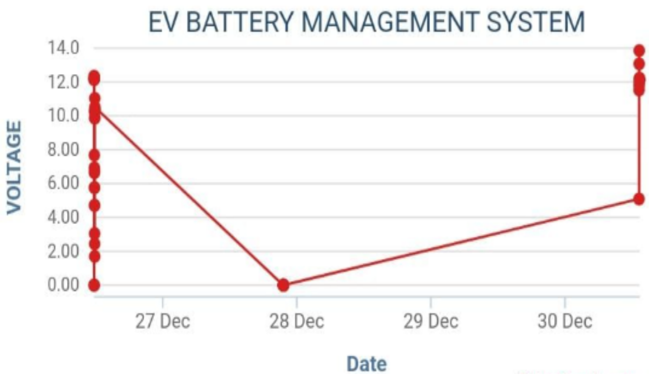
- **Load Current**: Measured by the current sensor.

Fig.2.Current vs Dataset



- **Battery Voltage**: Measured by the voltage sensor.

Fig.3. Voltage vs Datasets



- **Battery Temperature**: Measured by the Dallas temperature sensor.

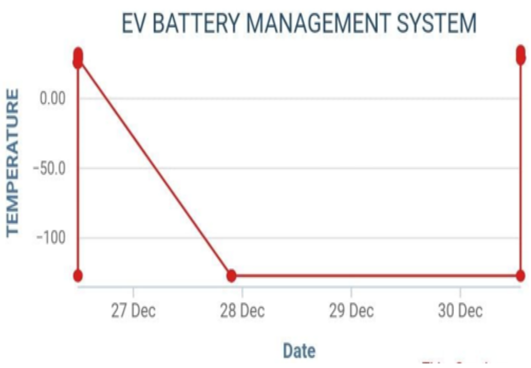


Fig.4. Temperature vs Datasets

This data is crucial for building a reliable dataset for machine learning. The data is uploaded to Things Speak in real-time and can be downloaded for offline analysis.

2.2 Preprocessing Data for Linear Regression

Before applying linear regression, the data undergoes the following preprocessing steps:

1. **Normalization**: Ensure that data values are scaled (e.g., by normalizing between 0 and 1) to help the model converge faster and improve performance.
2. **Outlier Removal**: Any extreme values (e.g., sudden spikes in temperature) are removed to prevent misleading predictions.
3. Data Division: Divide the dataset into training and testing sets, typically using an 80% for training and 20% for testing ratio.

3. Linear Regression Model Implementation

3.1 Training the Linear Regression Model

Using the pre-processed data, we can apply linear regression to predict various battery parameters like temperature and voltage under different current loads.

Model for Temperature Prediction: The first model predicts battery temperature (T) based on the current load (I):

T=m × I +b T = m \times I + b T=m × I +b

Where:

- **T** = Battery temperature (dependent variable).
- **I** = Load current (independent variable).
- **m** = Slope (how temperature changes with current).
- **b** = Intercept (the initial temperature).

Fig.5. Outcomes of experiment

```
Model Accuracy: 0.96

Predicted Temperatures:
Current: 4.0 A -> Predicted Temperature: 33.71 °C
Current: 5.0 A -> Predicted Temperature: 35.87 °C
Current: 6.0 A -> Predicted Temperature: 38.03 °C

Predicted values saved to 'predicted_temperatures.csv'
```

- **Model for Voltage Prediction**: A second model can predict battery voltage (V) based on current (I) and temperature (T):

V=m1×I+m2×T+bV = m_1 \times I + m_2 \times T + b V=m1×I+m2×T +b

Where:

- **V** = Battery voltage (dependent variable).
- **I** = Charging current.
- **T** = Temperature.
- **m_1, m_2** = Coefficients for current and temperature.
- **b** = Intercept.

3.2 Model Evaluation

Once the model is trained, it is assessed using the testing dataset. The performance is evaluated with the following metrics:

- **Mean Absolute Error (MAE):** This metric calculates the average difference between the predicted and actual values.
- **Mean Squared Error (MSE):** This metric measures the average of the squared differences between predicted and actual values.
- **R-squared:** This metric indicates the degree to which the model explains the variance in the data.

3.3 Real-Time Prediction

Once trained, the linear regression model is used for real-time prediction. For instance:

- **Temperature Prediction**: Given the current load, the system predicts the temperature and triggers the cooling fan if necessary.
- **Voltage Prediction**: The system predicts the battery voltage, adjusting charging parameters to avoid overcharging.

Predicted Temperature: [[21.88876]]

4. Optimization and Predictive Maintenance

4.1 Temperature Management

Using the trained linear regression model, the system can predict battery temperature variations under different current loads. If the temperature is predicted to exceed a safe threshold, the system triggers cooling mechanisms (fan activation) and alerts the user via the buzzer.

4.2 Charging Optimization

Linear regression models can predict charging efficiency by relating current, voltage, and temperature.
The system optimizes charging parameters to improve battery performance while maintaining safety.

5. Real-Time System Control and Feedback

5.1 Dynamic Control

The ESP32 continuously monitors the real-time values (current, voltage, and temperature) and:

- Compares them with the predictions from the linear regression models.
- Makes real-time decisions, such as:
  - Activating or deactivating the cooling fan.
  - Switching between slow or fast charging modes.
  - Turning the DC motor load on or off based on battery parameters.

5.2 Remote Monitoring

The data collected and processed by the ESP32 can be accessed remotely via Thing Speak, allowing users to monitor the battery status and adjust settings remotely. This is particularly useful for fleet management or EV owners who want to track the health of their battery and take proactive actions.

Fig.6. Outcome of experiment is shown in display

6. Evaluation and Performance Monitoring

6.1 Model Accuracy

The linear regression model is assessed for its effectiveness in predicting battery performance under different conditions. Metrics like MAPE (Mean Absolute Percentage Error) and RMSE (Root Mean Squared Error) are used to measure the accuracy of the model.

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Conclusions

In this study, we examined the application of deep learning techniques for thermal prediction to enhance the efficiency and lifespan of electric vehicle (EV) batteries. By utilizing advanced deep learning models for thermal management, we demonstrated how precise temperature forecasts can optimize lithium-ion battery performance, leading to improved thermal regulation and extended battery life. Our results show that accurate thermal predictions help maintain optimal operating temperatures, reduce the risk of overheating and thermal runaway, and ultimately improve the safety and efficiency of EV batteries. Furthermore, incorporating thermal prediction models into battery management systems ensures that EV batteries function under ideal conditions, maximizing their lifespan and energy efficiency.

Although deep learning models offer significant advantages in predicting battery behaviour and managing thermal performance, the study also emphasizes the importance of continuous model optimization, especially when dealing with real-world variations like temperature changes and charging cycles. Future research could explore the influence of environmental factors and hybrid modelling approaches to enhance prediction accuracy. Overall, the application of deep learning for thermal prediction holds great potential in boosting the performance, safety, and sustainability of electric vehicle batteries, making it a key factor in the development of more efficient and reliable EV technologies.

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