Novel Neural Network Optimizer Integrating Feature Engineering for Communicating Accurate SOC to the Battery Management System

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Abstract

Researchers have developed various machine learning models for estimating the battery state of charge, and they have employed different optimization techniques due to the uncertainty of the most appropriate option. This study investigates and develops a state-of-the-art optimization technique, which is the most important parameter of a neural network model. Accurate communication of the state of charge is essential for a battery management system to function appropriately. Therefore, a gradient descent algorithm that is modified and optimized exclusively for training a state-of-charge estimation machine learning model is developed in this study.

Ⅰ. Introduction

Among all the roles of the BMS, state-of-charge (SOC) estimation is the primary and most crucial. State-of-charge is an indicator of the remaining available battery capacity. However, accurate SOC communication poses a significant challenge because it cannot be measured directly, unlike normal battery variables like voltage, current, resistance, and temperature. This is because lithium-ion batteries have highly time-varying and dynamic characteristics. Currently, the most common methods to estimate and communicate the SOC of a battery are conventional, model-based, and data-driven methods[1].

The data-driven method does not require the simulation of a battery model or any information about the internal parameters of the battery. A machine learning (ML) model or algorithm is used in this technique, and the technique directly investigates the nonlinear relationship between the SOC and measured battery features such as voltage, current, and temperature[2]. This study develops the foundation for a neural network (NN) model for optimal SOC communication by investigating the most important parameter, the optimizer/optimization technique. The optimization technique is essential for achieving the best values for the weights and biases, which are the parameters responsible for deriving the SOC values from NN models under various circumstances.

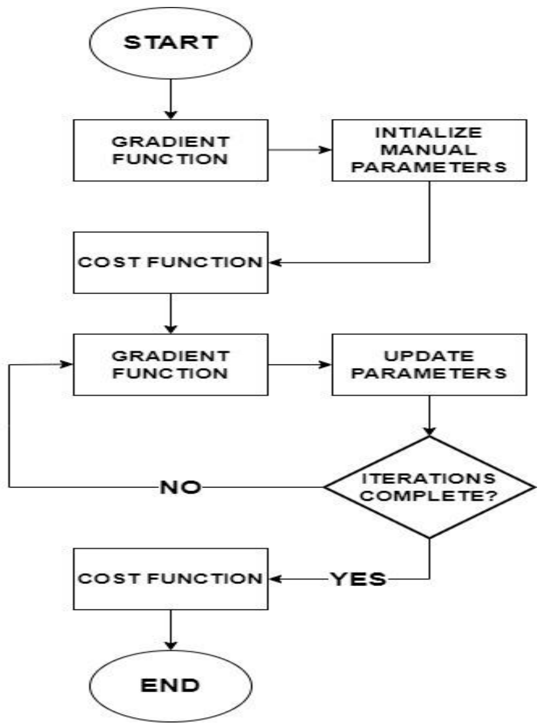
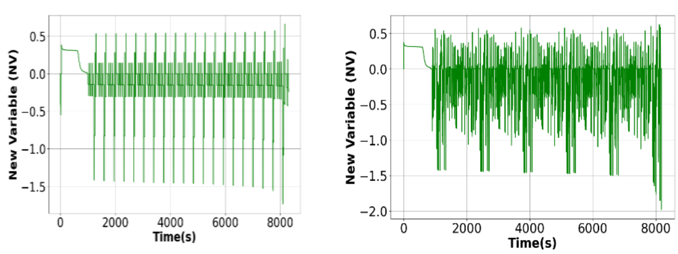


Fig. 1 Flowchart of the optimization process.

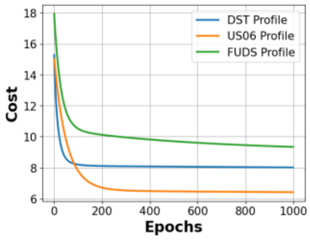


(a) DST profile (b) FUDS profile

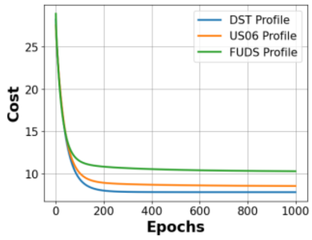
Fig. 2 New Variable from feature engineering.

Ⅱ. Method

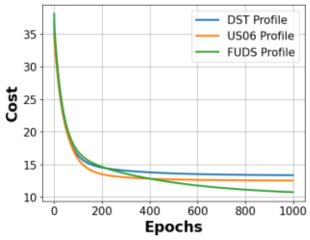
A Python function was built to develop the optimization technique. This function used eight input arguments: a dataset (which included all battery variables), target SOC values, initial gradient descent



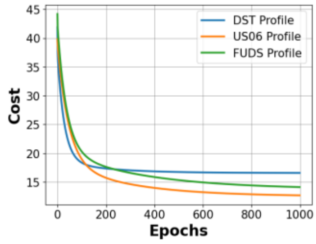
(a) −10°C profiles



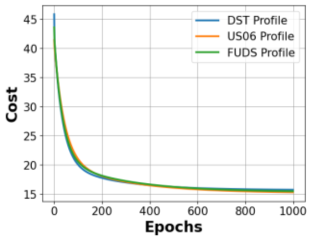
(b) 0°C profiles



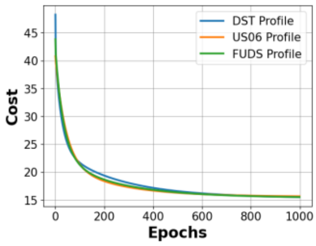
(c) 10°C profiles



(d) 20°C profiles



(e) 30°C profiles



(f) 40°C profiles

Fig. 3 Convergence curves of the driving profiles at each temperature.

(weights and bias) parameters, function, cost function, learning rate or alpha, and desired number of iterations. The output of this algorithm was a set of updated weights and bias parameters after all iterations.

The working process of this developed optimizer is displayed in Fig. 1. The first set of weights and biases implemented were manually inputted; then, using these parameters, the gradient function computed the next set of weights and biases that gets the predicted SOC value closest to the real SOC value. The cost of implementing these parameters was calculated using the cost function, and the results were recorded in an array. These two processes were repeated for the desired number of iterations, and depending on the value selected for alpha, the cost either decreased or increased after each iteration leading to an accurate SOC value that will be communicated to the BMS.

A battery dataset from the Battery Research Group of the Center for Advanced Life Cycle Engineering (CALCE) was employed for the SNNA [3]. Feature engineering was used to create a new battery variable, called New Variable (NV), for the developed optimizer from the available battery features in the dataset as shown in Fig. 2. Following the feature engineering technique, the input dataset has been transformed from three to four features as expressed in Eq. (1). This dataset simulated three driving cycles: the dynamic stress test (DST), US06 highway driving schedule, and federal urban driving schedule (FUDS), at six temperatures ranging from −10°C to 40°C. This makes a total of 18 datasets for the SNNA.

$$X = \left[I_m \quad V_m \quad T_m \quad NV_m \right] \tag{1}$$

Ⅲ. Results

The cost curves provided the opportunity to determine the appropriateness of the learning rate after each optimization iteration and allow the value of the cost function to be assessed. It was observed from the 18 implementations, as shown in Fig. 3, that the costs declined, which proved the effectiveness of the developed optimizer.

For the three profiles, the −10°C dataset exhibited the lowest initial and final costs at the end of each iteration. As the temperature increased, the initial and final costs also increased. The convergence behaviors of the three drive profiles were highly distinct at low temperatures; however, as the temperature increased, they developed similarities. Additionally, the convergence characteristics of the driving profiles nearly matched at temperatures higher than the room temperature.

Ⅳ. Conclusion

This study developed a novel optimization algorithm that incorporates a machine-learning technique called feature engineering. This optimizer was tweaked and tuned specifically for use in SOC estimation machine learning models so as to communicate accurate SOC to the BMS. The convergence results obtained from implementing this algorithm proved the validity of the developed optimizer for training any machine learning model and to communicate accurate SOC to the BMS.

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REFERENCES

[1] M. Adaikkappan and N. Sathiyamoorthy, “Modeling, state of charge estimation, and charging of lithium-ion battery in electric vehicle: A review,” 2021.

[2] C. L. Batteries and M. Fowler, “Comparative Study of Equivalent Circuit Models Performance,” MDPI Batter., 2021.

[3] “Battery Data | Center for Advanced Life Cycle Engineering.” https://calce.umd.edu/battery-data#Citations.