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Deep Learning-Based Ensemble Method for Li-ion Battery State-of-Charge Estimation

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ABSTRACT

Lithium-ion batteries (LIB) are vital components of modern electric vehicles and load management in smart grids due to their relatively high energy density, power density, and efficiency. It is important that onboard battery management systems in battery electric vehicles have accurate battery state of charge (SOC) information to gauge the remaining vehicle range and minimize battery degradation through power management. However, owing to highly dynamic vehicle driving habits and the nonlinear nature of SOC relative to other battery parameters such as current, voltage, and temperature, SOC is unable to be measured directly and is difficult to be accurately estimated in real-time. This article proposes a novel Li-ion battery SOC estimation method through a Deep Feedforward Neural Network Multimode Ensemble (DNN-ME). K-means clustering is used to separate the training data into differentiable data subsets, which are then each fed into N deep feedforward neural network (DNN) base learners. The final ensemble output through weighted averaging is less susceptible to error from weight initialization variation than single models, ensuring greater prediction accuracy.

Keywords: Ensemble learning, state-of-charge, deep feedforward neural network

NONMENCLATURE

Abbreviations	
SOC	State of Charge
DNN	Deep feedforward neural network
DNN-ME	Deep feedforward neural network multimode ensemble
SVR	Support vector regression

1. INTRODUCTION

Lithium-ion batteries (LIB) are vital components of modern electric vehicles and load management in smart grids due to their relatively high energy density, power density, and efficiency. Battery state-of-charge (SOC), defined as the ratio of the remaining charge of a battery to its nominal capacity, is an important indicator in electric vehicle battery management systems for gauging the remaining vehicle range and minimizing battery degradation in power management. However, owing to highly dynamic vehicle driving habits and the nonlinear nature of SOC relative to other battery parameters such as current, voltage, and temperature, battery SOC is difficult to accurately estimate during the online operation of electric vehicles [1].

Existing methods for online SOC estimation include model-driven and data-driven techniques. Traditional model-driven SOC estimation techniques such as Coulomb counting [2] and open-circuit voltage (OCV) [3] are accurate but have been shown to be impractical for real-time applications. Model-driven algorithms such as Extended Kalman Filters, particle filters, least-square filters, and adaptive Luenberger observers require a thorough understanding of physical processes in the battery system and may need manual parametrization for different battery types. Data-driven SOC estimation is based on machine learning techniques that train on large quantities of battery data and are computationally less expensive due to being composed of a series of matrix multiplications, as opposed to potentially having to solve differential equations in model-driven methods. Overall, these techniques outperform model-driven methods, however, generalization capability will be low if data-driven models are only trained on a single type of driving condition [4]. Furthermore, training on a variety of

driving conditions each with different SOC relationships will decrease overall model accuracy.

Ensemble learning addresses these shortcomings by combining multiple weak learners to achieve a more accurate prediction than any single model usually by averaging the predictions of each base model. The final ensemble output will be less susceptible to error from weight initialization variation than single models, which decreases variation in prediction accuracy.

However, these methods do not account for variations in driving conditions in real-time applications. [5] proposes an ensemble model that first clusters the training data, where a support vector regression (SVR) base model is built on each data subset. The prediction of each base model for a given time step is then weighted dynamically by the distance of the test data to the center of its training data subset.

This paper follows the method in [5] by proposing a novel Li-ion battery SOC estimation method through a Deep Feedforward Neural Network Multimode Ensemble (DNN-ME), where deep feedforward neural networks (DNN) are used in place of SVRs in the ensemble to increase prediction accuracy. The proposed ensemble model is expected to outperform a single DNN model and achieve good SOC estimation accuracy.

2. METHOD

2.1 Deep Feedforward Neural Networks

Although in principle traditional feedforward neural networks with two layers of transformations can learn any nonlinear relationship, DNNs with deeper architectures have allowed for considerable improvements in prediction accuracy. Despite drawbacks in longer training times, DNNs still allow for fast online computational speeds due to being composed of a series of matrix multiplications.

DNNs are composed of three parts: the input layer, hidden layers, and the output layer. Battery indicators such as voltage, current, and ambient temperature are fed into the input layer where they are transformed through L hidden layers, each with a given number of neurons. The output layer holds a single neuron in SOC estimation, which holds the predicted SOC value for a time step.

Training datasets for DNNs in SOC estimation can be generalized as $D = \{(\psi(1),\ SOC\ (1))), (\psi(2),\ SOC\ (2)), \dots, (\psi(t),\ SOC\ (t))\}$ where t is the given time step in the battery cycle, $SOC(t)$ is the true SOC value at t derived through Coulomb counting, and $\psi(t)$ is the input vector consisting of $V(t)$, $I(t)$, $T(t)$, $V_{avg}(t)$ and $I_{avg}(t)$ representing the normalized voltage, current, temperature, average voltage, and average current at t respectively. $V_{avg}(t)$ and $I_{avg}(t)$ are included to encode time dependencies in the network model.

The output or activation of each neuron in the hidden layers can be defined as

$$h_k^l(t) = \eta\left(\sum_k w_{j,k}^l h_k^{l-1}(t) + b_k^l\right)$$

for neuron k in layer l, where $w_{j,k}^l$ is the weight applied to the activation value of neuron k in the previous layer. A bias b_k^l is added to the sum of all weighted activation before an activation function η is applied.

When training the DNN, a forward pass is when all the data pairs in the dataset D have been passed through the DNN, after which a backward pass updates the weights and biases in the network to decrease the overall loss. An epoch is composed of a forward and backward pass, where the model has seen and trained on all the training pairs in the dataset. It should be clarified, however, that only a forward pass is used when validating or testing the model on unseen data.

2.2 Data Clustering

K-means clustering is used to first cluster the battery data into N differentiable data subsets such that each subset can represent a different driving condition for which a DNN can be specialized. As each DNN base learner is trained on a different data subset, N is also the number of base learners in the ensemble. Thus, the data subsets can be represented by $D_n(n = 1, 2, \dots, N)$ with subset D_n having a cluster center C_n.

2.3 Training of Base Learners

Each DNN base learner in the proposed DNN-ME has three hidden layers, each with 4 neurons. The specific activation function chosen for each base learner is the Leaky ReLU function, which addresses the dying ReLU problem in regular ReLU by adding a small positive slope for negative values instead of returning zero. It is defined below:

$$\eta(x) = \begin{cases} -0.05x, & x \le 0 \\ x, & x > 0 \end{cases}$$

The positive slope for $x \leq 0$ was optimized to be 0.05 after experimentation.

The mean squared error (MSE) loss function is chosen to calculate the overall loss in each DNN, which is used by the *Adam* backpropagation optimizer to update all the weights and biases in each DNN. When training the proposed DNN-ME model, each DNN base learner is trained for 50 epochs using a 0.0001 learning rate, although the number of epochs could be increased to achieve better accuracy.

2.4 Integration of Ensemble

The SOC prediction outputs of each DNN base model are combined through a weighted averaging method, which outputs the final ensemble prediction. The weight applied to each base DNN is inversely proportional to the Euclidean distance from the cluster center C_n of the DNN's training data subset D_n to the test data *p*, which weighs the importance of each base learner trained on the similarity of its training data subset to the input vector data at time step *t*. Thus, the final ensemble output can be described as:

$$H(p) = \sum_{n=1}^{N} w_n h_n(p) \Big/ \sum_{n=1}^{N} w_n$$

$$w_n = \frac{1}{\|C_n - p\|^{\alpha}}$$

where $H(p)$ is the ensemble SOC prediction, w_n is the weight applied to base model n, $h_n(p)$ is the SOC prediction for base model n, and α is a weight parameter that is set to 12 based on the optimization process in [5].

3. EXPERIMENTATION

An experimental method is used to evaluate the performance of the DNN-ME. First, battery drive cycle data with various ambient temperatures is augmented with Gaussian noise. Then, the number of base models in the DNN-ME is optimized through an iterative approach. The best performing ensemble model is then compared with a single DNN to evaluate estimation performance.

3.1 Drive Cycles

Training data was obtained from [6], where a 3A LG 18650HG2 lithium-ion battery cell was tested under various drive cycles and temperature conditions in a controlled thermal chamber. In order to test generalization capability on new driving conditions, the ensemble model is trained and validated using different battery drive cycles. The models are trained using the high acceleration US06 drive cycle and tested with the Urban Dynamometer Driving Schedule or UDDS and the LA-92 drive cycles. All drive cycles are repeated for ambient temperatures 10C, 25C, and 40C.

Before use, the input data are standardized and moving averages of the previous values of *V* and *I* in the previous 400 time steps are taken to produce V_{avg} and I_{avg}. When $t \leq 400$,

$$V_{avg} = \sum_{t=1}^{400} V(t) \,/\, t$$

$$I_{avg} = \sum_{t=1}^{400} I(t) \,/\, t$$

3.2 Data Augmentation

To obtain adequate training data and make the models robust for battery sensor error in real world applications, Gaussian noise with μ = 0 and σ = 0.03 is introduced to the US06 training dataset. Every V, I, and T value in the US06 dataset is thus augmented and V_{avg} and I_{avg} are recalculated. The training dataset is augmented twice such that the final dataset is three times the size of the original.

3.3 Optimization

The number of DNN base learners N must be optimized to find the best ensemble configuration. The DNN ensemble is trained on the US06 training dataset and validated using the UDDS dataset. This is repeated iteratively from $N = 1$ to $N = 10$, and the mean absolute error (MAE) for each ensemble is noted. As can be seen in Figure 1, the MAE drops to its lowest of 4.6% at $N = 5$, before increasing. This increase in error is attributed to the decreasing amount of training data available for each base learner as the number of dataset partitions increases. The best performing DNN-ME with 5 base learners is selected for final comparison.

Table 1 SOC Estimation Results

Driving Conditions	Mean Absolute Error	
	DNN-ME	Single DNN
UDDS	0.0460	0.0510
LA92	0.0367	0.0422

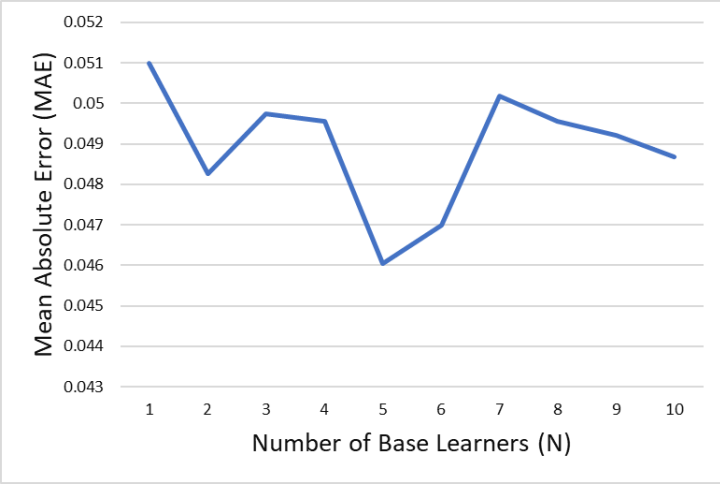

Fig. 1 DNN-ME Loss for Different Numbers of Base Learners

3.4 SOC Estimation Performance

The MAEs of the DNN-ME and a single DNN model is compared when trained on the same US06 dataset and tested using the UDDS and LA-92 datasets. All other hyperparameters are kept the same. The results in Table 1 show that the DNN-ME model achieves lower estimation error than a single DNN model for both drive cycles.

4. CONCLUSION

A novel ensemble model using DNNs as base learners was proposed for Li-ion battery SOC estimation, using a clustering method to dynamically adapt the weights of its base learner predictions according to different driving conditions in real-time. Findings indicate the proposed method has superior estimation accuracy compared to a single DNN model when tested on unseen driving conditions. Further investigation is needed to optimize ensemble hyperparameters and to compare the DNN-ME to other ensemble algorithms such as bagging and boosting, as well as other single machine learning models such as SVRs, extreme learning machines, and recurrent neural networks. Future scholarship should consider the additional computational costs of ensemble methods and whether that impacts their real-world application.

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