Statistical Post-Processing in Ensemble Learning-based State of Health Estimation for Lithium-Ion Batteries

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***Abstract*-- Using ensemble learning (EL) for battery state of health estimation has become a research hotspot. Because the performance of a single estimator can get boosted, which is applicable in the field of the battery especially when the amount of aging data is insufficient. Traditional EL is to aggregate base models through averaging, which will introduce errors from poor base models. To fully use the estimation results from base models, a statical post-processing method is proposed in this paper. The EL algorithm is initially constructed by combining random sampling and training multiple extreme learning machines. Then the post-processing is performed by fitting the kernel probability distribution of all sub-outputs and determining the most likely estimate, i.e., the statistical mode. As for comparison, the performance of other aggregations using average, weighted average, and mode from a normal distribution are investigated. Finally, the effectiveness of the proposed method is verified by conducting aging experiments on an NMC battery. The root-mean-squared error is as low as 0.2%, which is an approximate 80% improvement in accuracy over the traditional average-based method. The proposed method tackles the unstable estimation in learning with a small dataset, which is suitable for practical applications.**

***Index Terms*—Lithium-ion batteries, post-processing, state of health, statistical analysis.**

I. INTRODUCTION

As electric vehicles and clean energy become more prevalent, lithium-ion batteries play a critical role in enabling the electrification and decarbonization of transportation [1]. However, the poor safety, short cruising range, long charging time, and high cost of lithium-ion batteries are still problems that need to be solved urgently. Health management is particularly important in avoiding thermal runaway, optimizing fast charging, and extending battery life. Consequently, it is essential to estimate accurately the state of health (SOH) that is calculated as the ratio between the current available capacity and the initial capacity. Generally, 20% or 30% capacity fade is adopted as the end-of-life criteria [2].

A significant amount of research has been conducted to estimate the state of health (SOH) of batteries in the prior art [3]. For example, one common and direct method is to measure the capacity or performance-related parameters from laboratory conditions. However, this approach is not practical in real-world scenarios, as stopping the battery from normal operation to carry out the performance test is not feasible [4]. Instead, various model-based filters are designed to estimate SOH based on a state-space model. However, building an accurate equivalent circuit model or electrochemical model which can capture the dynamic character of the battery system is essential [5].

Machine learning (ML) techniques have been successfully applied in fields such as image recognition, language translation, self-driving, etc. ML methods are widely used in battery SOH estimation due to their flexibility and the fact that it does not require a specific battery model [6], [7]. The representative algorithms include support vector machine, neural network, Gaussian process regression, and random forest [2]. In particular, the random forest algorithm is gaining popularity in recent years for its ability to handle large datasets and its robustness to outliers. However, using ML for SOH estimation comes with several challenges. One of the major challenges is that in consequence of the long battery aging process, complex degradation mode, and dependency on test conditions, it is difficult to obtain sufficient battery aging data for ML model training. In addition to insufficient data, estimation results are also subject to uncertainty due to the random initialization of ML model parameters and stochastic gradient descent algorithms. Hence, the development of reliable and robust ML algorithms based on small datasets for battery SOH estimation becomes the research focus.

Ensemble learning (EL) is an emerging approach that refers to aggregating the results of multiple base learners, which yields more accurate and robust results than a single base learner and boosts overall performance. This method has been shown to be very effective for a wide range of applications and can provide a good trade-off between data size and accuracy. Generally, the model aggregation can be achieved based on various methods, such as computing an average (AVG) of the base learner or through voting. However, because of random parameterization, each base learner may show a different performance. In this case, it may not be appropriate to assign equal weight to each base learner. Instead, it’s often necessary to assign different weights (WAVG) to each model [8] depending on their performance, or ignore the output outside one standard deviation of the mean [8]. However, AVG- and WAVG-based methods will still bring in the errors caused by poor models to some extent. Hence in this paper, to better utilize the output of multiple base learners, statistical post-processing is proposed to correct the SOH estimation.

The remainder of this paper is structured as follows. Section II introduces the theory of the proposed post-processing method for SOH estimation. Section III presents the cyclic aging tests for one of the most common lithium-ion chemistries: Nickel Manganese Cobalt (NMC). Additionally, SOH estimation results using different aggregation methods are compared. Finally, Section V concludes the paper.

II. Methodology

Fig. 1 gives an illustration of the proposed EL-based method. It consists of three parts: sub-dataset generation by bagging (i.e., by random sampling with replacement from the original training data), base model training, and statistical post-processing. Bagging can avoid the correlation of different subsets, thus increasing the diversity of small datasets. While extreme learning machine (ELM) is chosen as the base model for its good performance such as the simplest network structure and lowest computation complexity. It can further demonstrate the effectiveness of the proposed post-processing method. Then in the statistical post-processing, the probability distribution function (PDF) from all sub-outputs is fitted, where the statistical mode is considered as the final output. For comparison, the AVG and WAVG are calculated, as well as the mode from the normal distribution (MODE_normal) and mode from the kernel smoothing distribution (MODE_kernel). Battery voltage data during aging is measured through various laboratory tests. Considering the real application where batteries are typically operated in a partial (between 10% and 90% SOC or even a narrower SOC range) rather than a full SOC range, a partial voltage was chosen as the input for the ML model. Through model training on known data, the relationship between input and output can be established. Finally, the established model is then validated on the unseen dataset. The whole framework for battery SOH estimation has been implemented in MATLAB code. The model training was performed on a PC with an Intel core i7 processor and Nvidia MX450, with 48GB RAM.

In the WAVG method, the predicted value of a new observation, $\mathbf{x}_{new}$, is expressed as (1), where the weight is determined by the estimation accuracy of the base learner.

$$\hat{Y}_{new} = \frac{1}{B}\sum_{b=1}^{B} w_b \cdot \hat{f}_b(\mathbf{x}_{new}) \tag{1}$$

$$w_b = \frac{1}{\left(S\hat{O}H_b - SOH\right)^{0.4}} \tag{2}$$

where B is the number of bootstrap samples, $\hat{f}_b(\cdot)$ is the bth single ELM, $S\hat{O}H_b$ is the output from bth single ELM, and w_b is the assigned weight. A larger power in (2) means a small weight assigned to the base model with a larger training error, which is equivalent to removing the base model with a large error. To avoid overfitting, a small power, i.e., 0.4, is chosen. In the MODE method, the PDF of the output distribution is calculated as

$$g(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-x^2/(2\sigma^2)} \tag{3}$$

where σ is the scale parameter. $\sigma = 1$ and $\sigma \neq 1$ represent variables that follow the symmetrical and asymmetrical distribution. The final estimated SOH is

$$\hat{Y}_{new} = \text{mode}\left[\text{PDF}(\hat{f}_b(\mathbf{x}_{new}), b = 1,\ 2,\ \ldots, B)\right] \tag{4}$$

Fig. 2(a) and Fig. 3(a) show the estimation results of the NMC battery from 60 and 600 single ELMs respectively, along with the corresponding probability density distribution in Fig. 2(b) and Fig. 3(b). The statistical mode of the kernel smoothing distribution, i.e., the peak value in the PDF, represents the most probable case. As shown in Fig. 2(b) and Fig. 3(b), the mode is closer to the real SOH than the AVG. Compared with simply averaging the output, the post-processed estimation model yields higher accuracy. This suggests that the post-processed model is more reliable for determining the SOH of NMC battery. Additionally, it can be observed that as the number of bagging increases from 60 to 600, the difference between the mode value of kernel distribution and the mode value of the normal distribution decreases, indicating a convergence of the two values. In another word, the mean value may not always provide a complete picture of the data distribution. Therefore, it is important to consider mode in conjunction with the mean to gain a more comprehensive understanding of the data. Overall, the mode value can correct the estimate, particularly when the EL model contains fewer base learners.

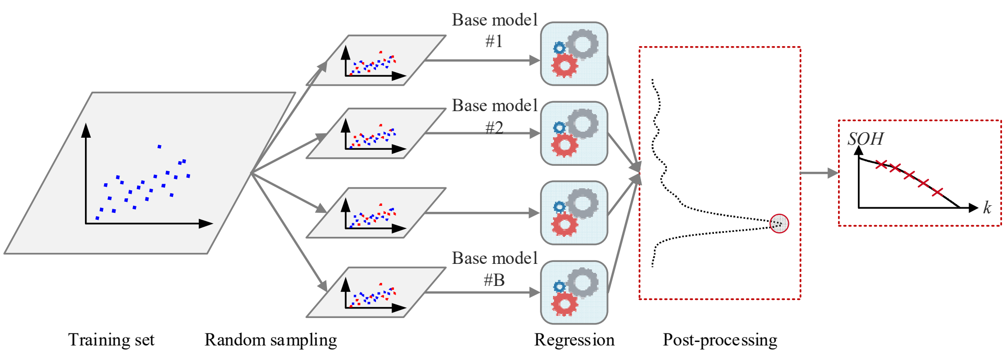

Fig. 1. Schematic diagram of the proposed EL method with statistical post-processing.

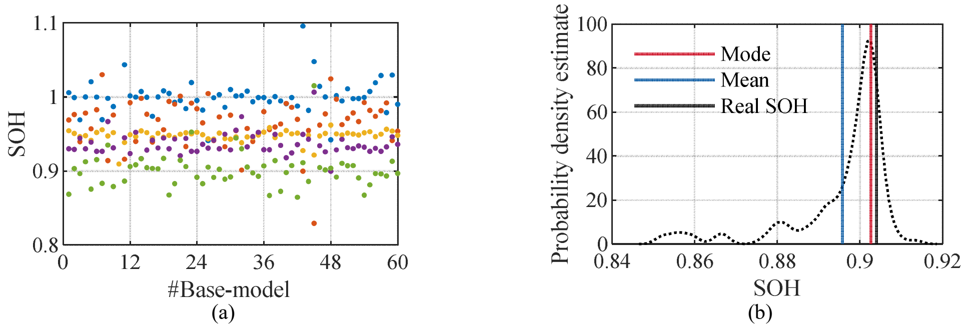

Fig. 2. Statistical plot of estimated SOH from each base model (in the case of a small value of *B*, e.g., *B*=60). (a) SOH estimates (dot points with different colors represent different SOH). (b) PDF of the output results under a specific SOH value.

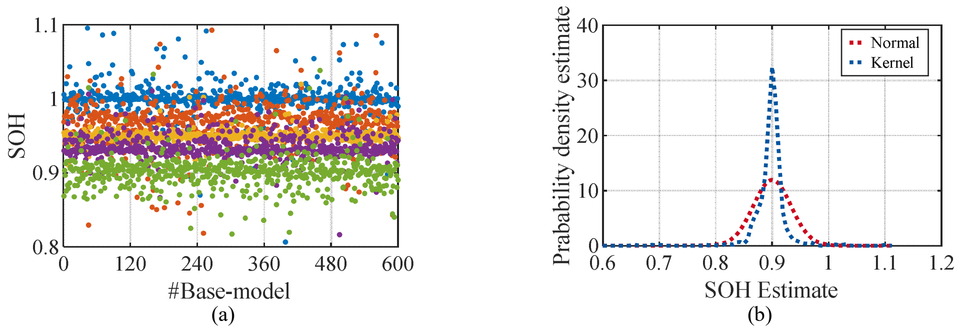

Fig. 3. Statistical plot of estimated SOH values from each base model (in the case of a large value of *B*, e.g., *B*=600). (a) SOH estimates. (b) PDF of the output results under a specific SOH value.

III. Experimental Results

A. Experimental aging test

To verify the effectiveness of the proposed SOH estimation method, an NMC battery was subjected to accelerated aging tests at 35°C using the standardized Worldwide harmonized Light vehicles Test Cycle (WLTC) driving cycle for class B vehicles. Initially, the NMC battery was cycled weekly at 25°C and after then its capacity was measured. After 14 weeks of cycling, it was found that the battery capacity fades slowly, so the capacity test was changed to every 3 weeks. At the end of the test, the cells reached a capacity fade of 13%. The primary parameters of the tested battery are summarized in Table I, including information such as its capacity and voltage. The obtained voltage and the corresponding SOH curve during the capacity test can be seen in Fig. 4.

TABLE I
THE DATASHEET OF THE TESTED NMC BATTERY

Item	Values
Nominal capacity	3.4 Ah
Nominal voltage	3.6 V
Maximum voltage	4.2 V
Cut-off voltage	2.65 V
Maximum continuous charge current	2 A
Maximum continuous discharge current	8 A

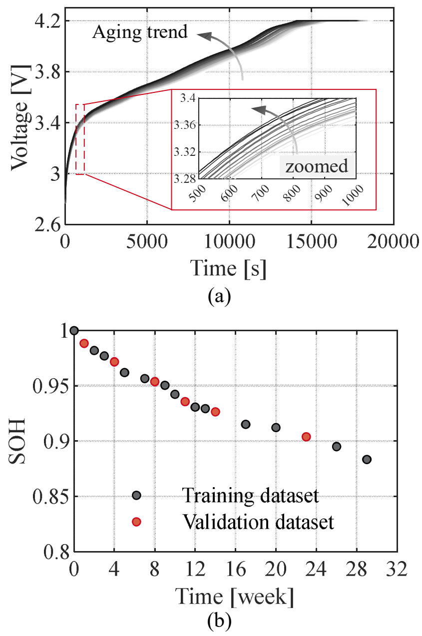

Fig. 4. Dataset obtained from cyclic aging. (a) Voltage responses under CC-CV charging. (b) SOH curves.

B. SOH estimation result

The root-mean-squared error (RMSE), mean absolute percentage error (MAPE), and maximum absolute percentage error (maxAPE) are the metrics used to evaluate the effectiveness of the proposed method. The aging datasets of the tested batteries are divided into a training group (65% of the dataset, i.e., the black points in Fig. 4(b)) and a validation group (35% of the dataset, i.e., the red points in Fig. 4(b)).

Fig. 5 to Fig. 8 show the SOH estimation results when 60 and 600 random ELMs are trained and aggregated, respectively. It can be seen that accurate estimation can be achieved by the EL-based method, even when a simple AVG method is used. But through post-processing, the estimation performance can be further enhanced. To this end, the WAVG method is preferred, as it has been shown to result in approximately 40% improvement in estimation accuracy compared to the AVG method (see Fig. 5(b) and Fig. 8(b)). In contrast, MODE_normal makes no obvious performance difference due to the improper assumption that the probability follows a normal distribution. It is worth noting that the MODE_kernel method is highly effective. With kernel smoothing, the estimation errors are reduced by around 80% across three considered error metrics.

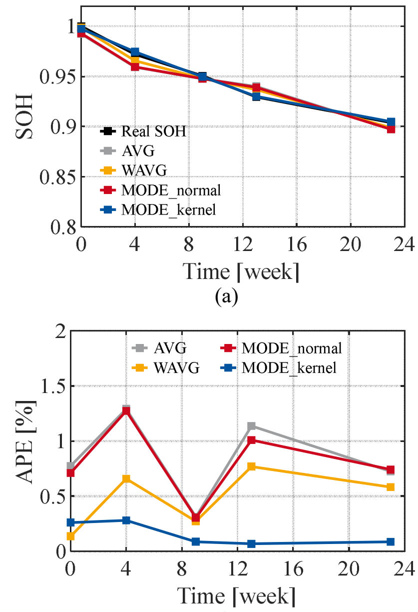

Fig. 5. SOH estimation results with different post-processing methods (in the case of a small value of B, e.g., B=60) for NMC battery. (a) SOH estimation results. (b) SOH estimation errors.

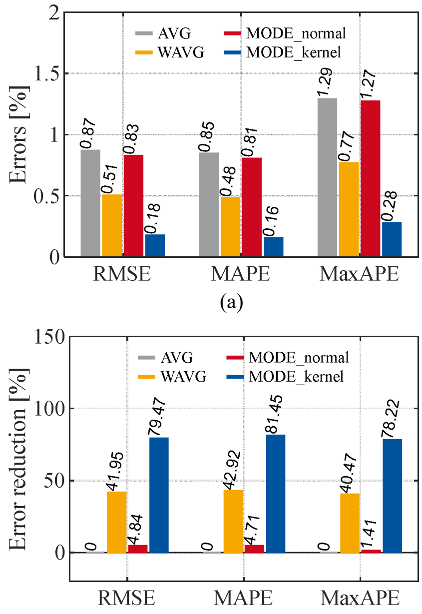

Fig. 6. Comparison in SOH estimation error using different post-processing methods (in the case of a small value of B, e.g., B=60). (a) Estimation error. (b) Error reduction compared to AVG method.

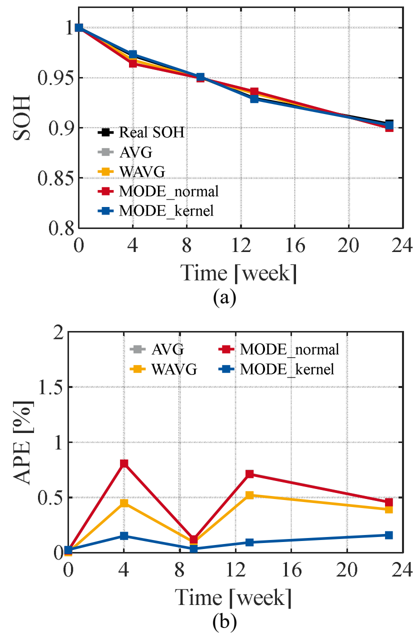

Fig. 7: SOH estimation results with different post-processing methods (in the case of a large value of B, e.g., B=600) for NMC battery. (a) SOH estimation results. (b) SOH estimation error.

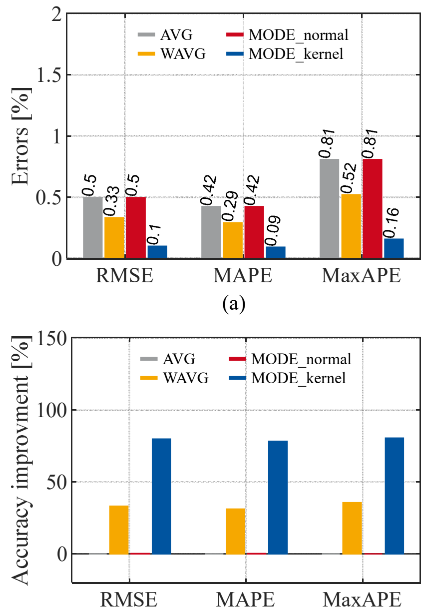

Fig. 8. Comparison of SOH estimation error between different post-processing methods (in the case of a large value of B, e.g., B=600). (a) SOH estimation error. (b) Accuracy improvement compared to simple average ensemble

To eliminate the influence caused by the number of subsets B on the comparison results, the EL algorithm with different numbers of ELM ranging from 10 to 1500 is trained. As demonstrated in Fig. 9 and Fig. 10, regardless of the value of B, the WAVG and MODE_kernel methods help improve the estimation accuracy to varying degrees while MODE_normal method has the same effect as the AVG method. Obviously, the sub-outputs do not simply follow the normal distribution. Instead, they manifest as an asymmetrical distribution that is the superposition of multiple normal distributions. Therefore, the statistical mode from the kernel distribution is closer to the real SOH

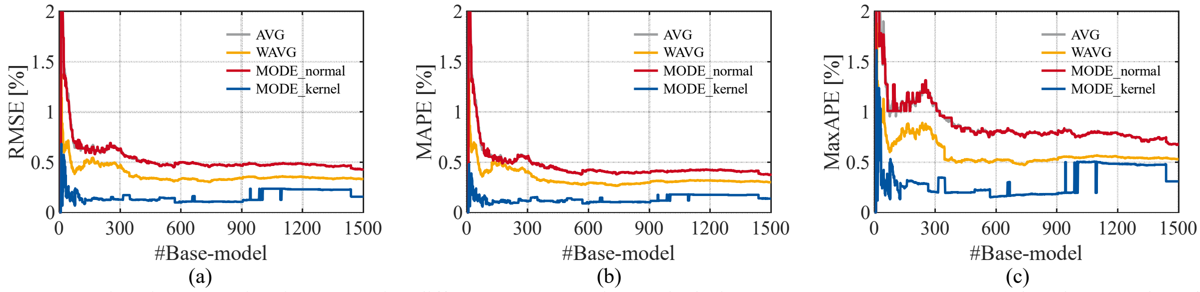

Fig. 9. Comparison in SOH estimation error using different post-processing methods, i.e., AVG, WAVG, MODE_normal, and MODE_kernel when *B* is changing from 10 to 1500. (a) RMSE. (b) MAPE. (c) MaxAPE.

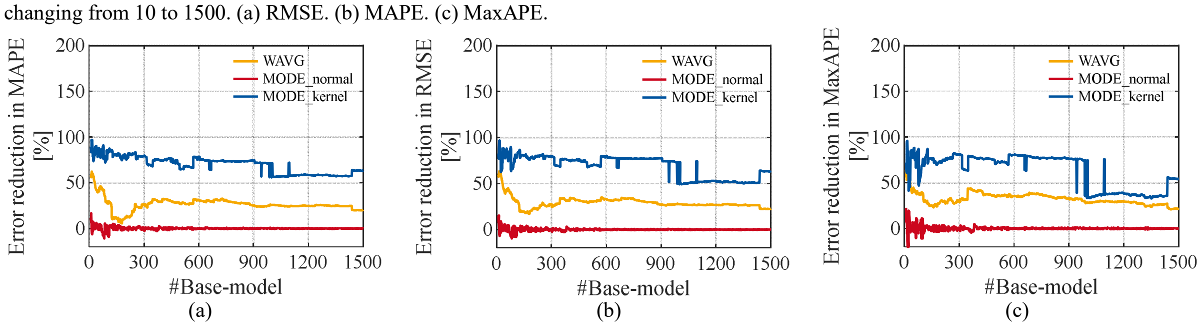

Fig. 10. Reduction of SOH estimation error using different post-processing methods compared to AVG method when *B* is changing from 10 to 1500. Error reduction in (a) RMSE, (b) MAPE, and (c) MaxAPE.

value. Overall, estimation errors (e.g., RMSE and MAPE) are around 0.5% for AVG and MODE_normal methods. Through post-processing by WAVG and MODE_kernel, the estimation error is reduced to 0.4% and 0.2%, respectively. The results highlight the importance of using appropriate post-processing methods to improve the accuracy of the estimations, especially when dealing with EL with fewer sub-outputs and when sub-outputs do not follow a normal distribution.

IV. Conclusions

In this paper, an EL-based SOH estimation method with statistical post-processing is proposed. The method utilizes bagging-based random sampling to generate multiple sub-datasets, which helps to augment the original small dataset. ELM is selected as the base mode due to its simple network structure and less computation. For the final estimate, the probability density distribution of all sub-outputs is analyzed, and the mode value is selected. To verify the effectiveness of the proposed SOH estimation method, the cyclic aging data from an NMC battery is introduced. The estimation results show that the proposed method is effective in correcting SOH estimation from base models, and its estimation error is as low as 0.2%. Moreover, the proposed statistical mode-based method outperforms the average- and weighted average-based aggregation regardless of the number of base learners.

Acknowledgment

This work was funded by the "SMART BATTERY" project, granted by Villum Foundation in 2021 (project number 222860).

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