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Decentralized Deep Learning Approach for Lithium-Ion Batteries State of Health Forecasting Using Federated Learning

Kei Long Wong, Rita Tse, Su-Kit Tang, and Giovanni Pau

***Abstract*—The rapid advancement of deep learning techniques has expedited the progress of data-driven forecasting methods for lithium-ion battery health. The conventional deep learning techniques for battery health forecasting require the training and refining of the predictive model in a centralized manner. However, centralized approaches face challenges related to data privacy and scalability. Therefore, it is essential to explore a decentralized methodology for the forecasting of battery health in order to safeguard privacy, utilize onboard computing resources, and facilitate the rapid integration of new data. This article proposes the utilization of federated learning to train a lithium-ion battery health forecasting model in a decentralized manner. All the experiments carried out in this study have been specifically customized to align with real-world conditions. A client selection strategy designed specifically for battery health forecasting is presented, which is demonstrated to increase accuracy throughout the training process. The evaluation results show that the predictive model trained in a decentralized manner exhibits comparable overall performance to the centralized counterpart.**

***Index Terms*—Lithium-ion battery, battery degradation, state of health forecasting, federated learning, data-driven, deep learning.**

I. Introduction

Lithium-ion (Li-ion) batteries have revolutionized the world of portable electronics, transportation, and renewable energy storage systems, thanks to the characteristics of high energy density, low self-discharge rate, and long cycle life [1]. The lifespan of Li-ion batteries is finite and their performance degrades over time [2]. Repetitive charging and discharging cycles of Li-ion batteries (cyclic aging), as well as periods of inactivity or rest between cycles (calendar aging), lead to the degradation of their performance [3], [4]. Battery degradation prediction is necessary to ensure the dependable use of Li-ion batteries. Predicting accurately allows users to optimize battery performance and extend battery life, while designers and manufacturers can improve battery designs by investigating all the possible battery aging situations [5]. However, it is a complex task to forecast battery degradation, since a wide range of variables are involved, as well as the highly non-linear aging behavior of batteries [6].

With the rapid development of big data technology, the adoption of the data-driven approach for lithium-ion batteries' health degradation forecasting is accelerating. Data-driven approaches for Li-ion battery degradation forecasting utilize large amounts of historical battery operation data to develop predictive models [7]. The typical implementation of the data-driven method includes the statistical method, machine learning, deep learning [8], etc. Electric vehicle (EV), one of the most important applications of battery-powered technology nowadays, has a very complex degradation behavior due to the dynamic nature of its operation [9]. A significant amount of data-driven research has been conducted on battery health forecasting or estimation in the context of EVs field data [10], [11], [12].

The typical data-driven approach for battery health forecasting involves a data-centralized method where all operational data is stored on a remote computing unit for training the predictive models [13], [14]. Centralizing all operational data is beneficial for creating a comprehensive model that can capture the underlying attributes hidden within all the data. However, the centralized method can pose a barrier to model iteration as it could be time-consuming to collect new operational data. Furthermore, the centralized method raises privacy concerns [15] that users may be unwilling to upload their data. For example, it has been demonstrated that driving signals can be used to identify driving behavior [16].

The decentralized approach, such as federated learning [17], can address the concerns caused by the centralized approach. And thanks to the advancements in autonomous driving technology, it has become increasingly common for vehicles to have onboard graphic processing unit (GPU) embedded systems, as deep learning-based computer vision techniques are often employed [18]. With the implementation of GPU embedded systems, it is possible to allow EVs to train the battery health forecasting model locally. However, this decentralized approach is still rare in the existing research literature. Therefore, this study conducts a comprehensive

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investigation into the application of federated learning for the purpose of forecasting the health of Li-ion batteries.

In this study, we explore the utilization of federated learning for decentralized training of predictive models in the field of Li-ion battery state of health (SOH) forecasting. Particularly, the experiments conducted in this study are specifically designed to simulate real-world scenarios encountered in EVs operation. The main contributions of this study are as follows:

1) This study is the first work to explore the feasibility of applying federated learning for Li-ion battery health forecasting.
2) The experiments designed in this study are tailored to closely resemble real-world situations, particularly in the context of EV operations.
3) We propose a client selection strategy specifically designed for the domain of battery health forecasting, which is proven to enhance the overall accuracy throughout the training process.
4) The performance of the model trained through the decentralized approach exhibits comparable results to the model trained using the centralized approach.

The rest of this article is organized as follows. A comprehensive review of the battery SOH research is presented in Section II. Then, Section III explains the details of the decentralized setup for training the Li-ion battery health forecasting model. In Section IV, we evaluate the proposed method. Finally, Section V summarizes this work and presents the concluding remarks.

II. Battery State of Health

The objective of this work is to train a SOH forecasting model in a decentralized manner. Here, we set the distinction between SOH estimation and SOH forecasting. SOH estimation is the diagnostic of the present SOH value using operational data that is currently accessible. SOH forecasting, on the other hand, is the prognostic of future changes in SOH by considering the past degradation information combined with presumptive future usage conditions. By employing this forecasting scheme, users can assess how their batteries will behave and take necessary action in accordance with the prediction.

SOH forecasting is closely related to the use of the estimation technique, in which the historical degradation data is obtained from the SOH estimation module. Recent SOH estimation research can be broadly divided into two approaches: experimental methods and model-based methods. Experimental methods are commonly used to acquire insights into the degradation mechanism, whereas model-based methods are typically used in commercial applications [19]. Model-based methods include a variety of adaptive algorithms, such as the use of the Kalman filter [20], as well as data-driven techniques like artificial neural networks. Artificial neural networks have received a lot of attention in recent years due to their outstanding performance [21]. Furthermore, there has been a significant emphasis on the data-driven application of electrochemical impedance spectroscopy, which has shown higher accuracy and efficiency when compared to conventional approaches based on voltage and current measurements [22], [23].

In terms of SOH forecasting, the existing methods are generally categorized as model-based, data-driven, and hybrid methods that combine both [24]. This research places its emphasis on the utilization of the data-driven approach because of its capacity for minimizing computational expenses while achieving high accuracy [25]. As reviewed in [5], the data-driven methods employed in forecasting the health of Li-ion batteries can be classified into two distinct categories: those that incorporate future operational conditions and those that do not.

The assumption that future operations will be the same as those in the past is implied by forecasting SOH without taking into account future operations. This type of method usually obtains inputs from the battery's past operation. For instance, Semanjski and Gautama [26] proposed to use a linear function to fit the SOH decline by using real-world EVs operation data. Although the prediction method in their study is based on field testing data, the consideration of future operation is still absent. Furthermore, Gaussian process regression is applied to forecast SOH by using cycle number only [27]. The cycle number is only a representation of the past information so the future operation is ignored in their prediction.

It is essential to consider future operations when forecasting battery health to ensure that it can be applied to real-world situations. There exists considerable heterogeneity regarding the methods for defining future operations. For example, Wang and Xiang [28] investigated a sequence-to-sequence (seq2seq) approach with the future operation condition included as a sequence of model input. The features selected for the operation conditions are rest time, maximum charging and discharge current, ambient temperature, and state of charge (SOC) range. What is more, calendar aging is investigated in [29]. In their study, transfer learning is used; a base model is initially trained using a big, readily gathered dataset, and is then transferred to another small dataset. The future time period, current capacity, storage SOC, and temperature are used as the inputs of the long short-term memory (LSTM) model.

Another important aspect to consider when dealing with battery health forecasting problems is the output form. A common output form of battery health forecasting model is the future SOH at a specific moment. For instance, Wei *et al.* [30] proposed to use particle filter and support vector regression for remaining useful life (RUL) prediction. Severson *et al.* [31] proposed the use of an elastic net with only information extracted from the first 100 charge/discharge cycles to predict the cycle life of Li-ion batteries. von Bülow *et al.* [32] used neural network to forecast future SOH by using histogram-like features with various cycle windows considered. Greenbank and Howey [33] used Gaussian process regression with histogram-like features to model the change in battery capacity.

The prediction of a specific moment (single-point prediction) is not adequate to meet all the potential use cases. Instead, a comprehensive forecast of future degradation is more advantageous. One approach to achieve this is to anticipate the trajectory of the degradation curve (a sequence of SOH value) until their end-of-life (EOL). Unlike a single-point prediction, the degradation trajectory provides a broader perspective on future degradation. Although single-point prediction can be applied repeatedly to provide a series of future forecasts, leveraging trajectory prediction offers several benefits, including lower computational resources and avoiding cumulative errors. For example, Li *et al.* [13] proposed to use a deep LSTM-based seq2seq model for forecasting the Li-ion battery capacity degradation trajectory based on the past capacity degradation. Li *et al.* [34] expanded upon their earlier work by employing the technique of multi-task learning to forecast both capacity degradation and power fading. Xu *et al.* [35] proposed a hybrid method to extract features based on data and physics attributes for predicting battery capacity degradation trajectory using LSTM encoder-decoder.

Considering the aforementioned aspects, in this work, we train a predictive model for forecasting the trajectory of the future degradation curve. Moreover, to ensure the feasibility of our approach in real-world scenarios, we incorporate future operations as one of the inputs in the predictive model. As the main focus of this study is the forecasting of SOH in the future. We consider the present and previous battery capacity as a known variable, which is obtained from the SOH estimation module in the battery management system. The proposed method is designed to be compatible with any SOH estimation methods.

III. Methodology

A. Federated Learning

Federated learning is a machine learning paradigm that facilitates collaborative model training among multiple clients without data centralization. Google first introduced this technique as a means of training machine learning models with decentralized data [36]. Federated learning involves decentralizing the model training process to the clients. With this technique, knowledge can be gathered from several data sources without the necessity for data exchange [37].

There are generally two primary types of federated learning architectures based on the system requirements, namely vertical federated learning, and horizontal federated learning [38]. Vertical federated learning involves the distribution of features, with each client sharing the same set of samples but with different sets of features. It is appropriate for situations in which various business units produce data for instance at various locations. In contrast, horizontal federated learning distributes different sets of samples among multiple clients with a shared set of features. This technique is particularly useful in scenarios where data instances are generated across independent clients.

The federated learning training process incorporates a client selection mechanism that proceeds during each training round. Client selection aims to identify a subset of clients to perform local model updates based on their local data. This mechanism holds considerable significance in accelerating the model's convergence towards the desired accuracy level [39]. Random selection is one of the methods commonly used for client selection, with the primary objective of ensuring an impartial representation of the client population. It involves randomly sampling a subset of clients for each round of training. Other selection methods can be applied depending on the requirements and considerations of the system, such as adaptive client selection strategy [40], resource conditions aware strategy [41], etc.

Taking into account the above factors, we adopt the horizontal federated learning approach in our work, in which each client retains ownership of their respective data. In addition, we propose a client selection strategy that is intended to work with battery health forecasting tasks.

B. Decentralized Platform

In this article, we examine a decentralized data-driven approach for forecasting the health degradation of Li-ion batteries based on federated learning. Fig. 1 illustrates the overview of the decentralized platform training process. The designed experiment involves the collaboration of multiple EVs for the purpose of training a predictive model. The entire platform includes two phases: training and production. This work focuses on the training phase, wherein we apply federated learning techniques to train the predictive model for production usage. The utilization of the trained model during the production phase follows the same principles as traditional deep learning methods.

During the training phase, the predictive model undergoes decentralized training within each EV. The process involves the server distributing the global model to a selected set of EVs, referred to as clients. This work proposes specific strategies to select clients in each training round, which are explained in detail in Section III-F. In each training round, every selected EV collects its own local battery aging data and employs this data to train a local model based on the global model received from the server. The training of the local models is designed to perform in the EV's onboard GPU. Subsequently, the server receives the updated local models from all EVs and performs aggregation. This decentralized training process obviates the necessity for the server to gather battery operation data. All the data generated within the EV side can be kept local and the computation power in EVs is utilized to process its local data.

The decentralized training setup is premised upon the assumption that the local data within each EV is unbalanced, so as to emulate real-world scenarios. That is, the aging situation of EV batteries vary due to different factors such as driver behavior [42], [43], the operational environment [44], etc. Hence, in each training round, data availability and the batteries' health status differ within each EV.

In the production phase, the trained predictive model is delivered to the clients. The predictive model generates a degradation curve for batteries by utilizing input features derived from both past degradation records and future operational data. The incorporation of future operations as the model input ensures that the forecasted future degradation is adaptable to specific future operational conditions.

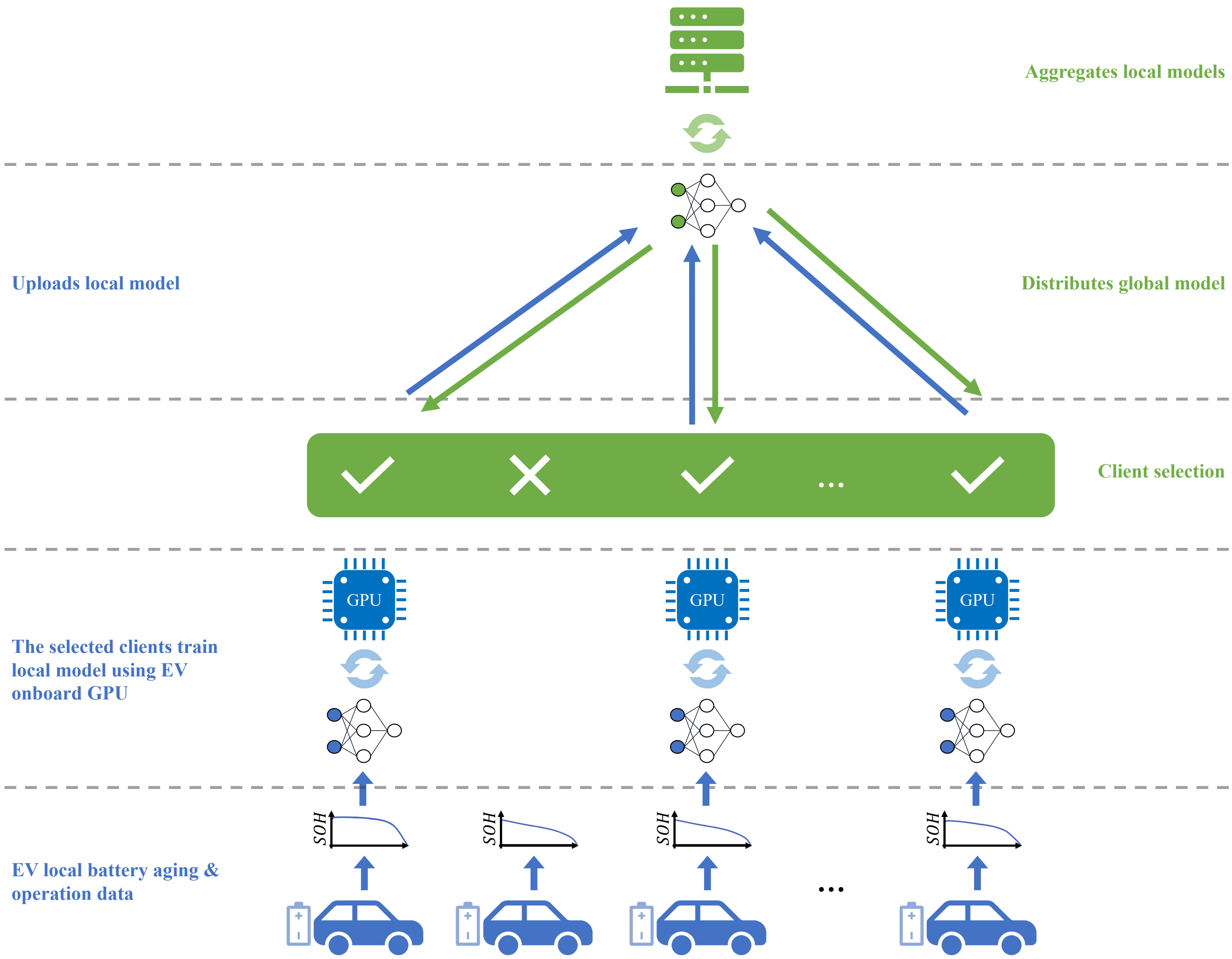

Fig. 1. Decentralized platform training overview. The blue annotation represents the action executed on the client side, while the green annotation represents the action executed on the server side.

C. Federated Learning Training Procedure

This section provides a description of the training procedure employed in the federated learning setup throughout the training process. Algorithm 1 describes the overall training procedure with the corresponding section annotated. Here we provide a general overview of the training procedure, details of each step are elaborated in the corresponding sections. We implement the experiments using the PyTorch framework [45] and perform all training on the DGX station with V100 GPUs. The source code is available online[1].

Within this framework, a global model is maintained by the server and undergoes iterative training through multiple rounds T. The dataset is resegmented as per demand at the beginning of each training round (as described in Section III-E). A subset of clients C_s is then selected using a desired client selection strategy (as described in Section III-F), followed by individual local training on each client's local data. This local training consists of multiple local epochs E for updating the global model received from the server. Once all the clients have completed their local training, the server collects the updated weights w_t^c from each client and aggregates them to update the global model w_{t+1}. In this study, we take the average of all the updated weights from the clients as the aggregation method for updating the global model.

[1]Code for the federated learning experiments is at https://github.com/KeiLongW/decentralized-battery-health-forecast

D. Battery Operation Features

In the context of battery health forecasting using deep learning, feature extraction plays a critical role in capturing relevant information from raw battery operation data. By extracting features from the data instead of utilizing it in its raw form, several benefits can be achieved, including dimensionality reduction, information compression, and the identification of relevant features that are informative for the forecasting task. Moreover, as the extracted features are representations of future battery operations, it is crucial to preserve their interpretability to ensure usability by users without specialized knowledge in the electrochemical domain. Hence, the feature extraction process in this context primarily

Algorithm 1 Federated learning training procedure. T is the number of global ground, D is the complete dataset, C represents all the clients, K is the number of selected clients, E is the number of local epochs, η is the local learning rate, N is the number of clients, and w is the model weights.

```
w ←initialize global model
for each global round t = 1, . . . , T do
    D_t ←resegment from D                          ▷ Section III-E
    C_s ← select K clients from C                   ▷ Section III-F
    for each selected clients c ∈ C_s do
        w_t^c ← copy w_t
        B_t^c ← split D_t^c into batches
        for each local epoch e = 1, . . . , E do
            for each batch b_t^c ∈ B_t^c do         ▷ Section III-G
                w_t^c ← update by b_t^c with step size η
            end for
        end for
        Send w_t^c to server
    end for
    w_{t+1} ← Σ_{c∈C_s} (1/N) w_t^c                 ▷ Aggregation
end for
```

TABLE I
DURATION FEATURE CONDITIONS

	Condition
Charge cycle	$I_t > 0$
Discharge cycle	$I_t < 0$
Idling	$I_t = 0$
Temperature intervals	$T_t > S_T, T_t \leq S_T + 1$
Charge current intervals	$I_t > S_I, I_t \leq S_I + 1$

I_t is the current value at time t,
T_t is the temperature value at time t,
$S_T \in [min(T), min(T) + 1, .., max(T) - 1]$,
$S_I \in [min(I), min(I) + 1, .., max(I) - 1]$,
min is the minimum value,
max is the maximum value.

revolves around the utilization of current and temperature variables, as they possess a higher degree of interpretability for regular users.

The features can be classified into two categories: duration and maximum value. The duration features quantify the duration of a charge/discharge cycle when it satisfies a specific condition. A similar approach can be found in [32], however, we acknowledge that multiple-dimensional features may pose challenges in terms of interpretation for regular users. Hence, to prioritize simplicity, we employ one-dimensional features, each with a single condition. The calculation of the duration feature F_D can be expressed as follows:

$$F_D = \int_{t_0}^{t_1} f(t)dt$$
$$f(t) = \begin{cases} 1 & \text{if condition at time } t \text{ is met} \\ 0 & \text{else} \end{cases} \tag{1}$$

We propose to use five conditions to extract duration features, presented in Table I. The temperature intervals and charge current intervals are designed to extract multiple features by traversing through all the specified intervals. Fig. 2 illustrates the examples of the five duration features. The figure shows a complete charge and discharge cycle with the current and temperature variables. As shown in the sub-figures, the blue highlighted areas represent the durations that satisfy the specified condition. It is worth mentioning that certain blue highlighted areas look like vertical lines are observed, which is because of the relatively short duration occurring in the time period. What is more, besides the duration features, we also consider the maximum value of charge current and discharge current. Therefore, in total, we propose to extract features by utilizing seven methods. These methods encompass various criteria for capturing relevant information from the battery operation data.

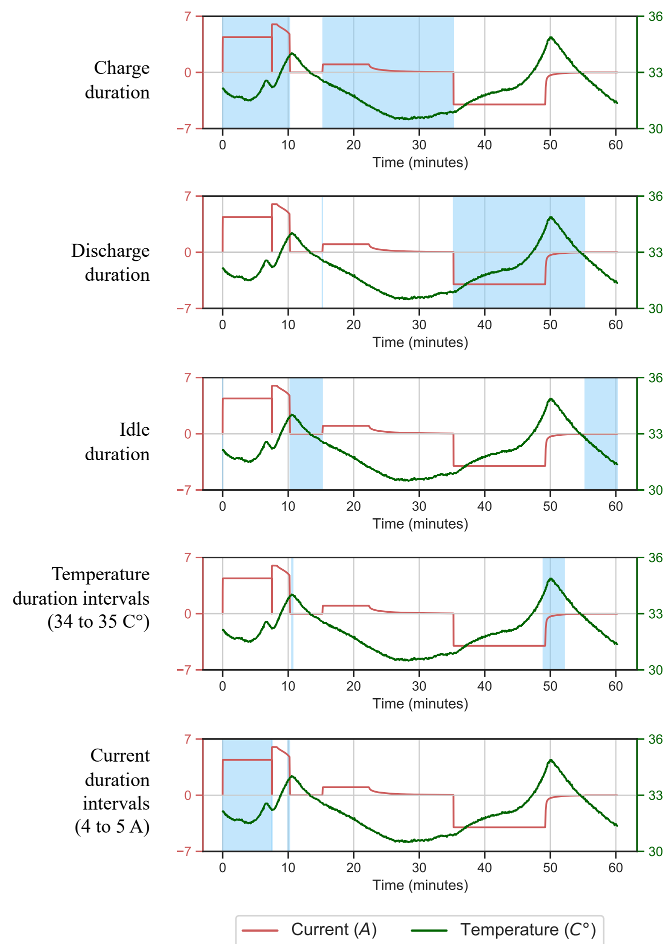

Fig. 2. Examples of duration features. The areas highlighted in blue indicate the duration that meets the condition.

E. Battery Aging Dataset and Data Allocation

A publicly available Li-ion battery aging dataset called MIT-Stanford [31] is used in this research. It was published by researchers at both MIT and Stanford University using 124 commercial Li-ion batteries manufactured by A123 Systems (APR18650M1A). The nominal capacity of all the battery cells is 1.1Ah and their nominal voltage is 3.3V. In their experiments, the battery cells were subjected to a designated two-step fast-charging policy during the charging process,

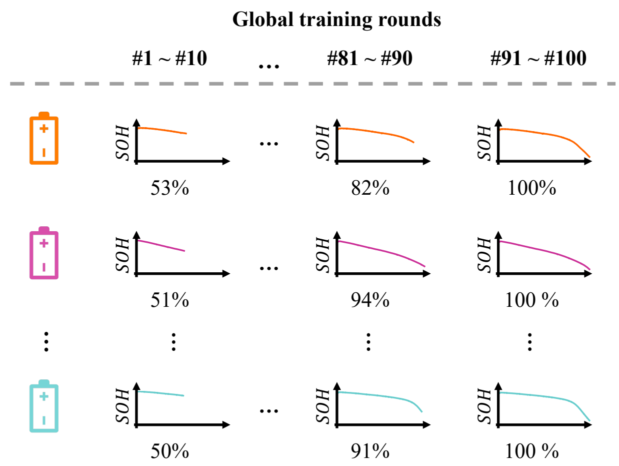

Fig. 3. Illustration of the progressive segmentation of degradation curve. Each battery cell (client) has unique battery degradation curve data with variable lengths that are used during several global training rounds.

followed by discharge using a constant current approach. Each battery cell undergoes cycling until a predefined stop cycling SOH value (EOL) is reached. Therefore, the degradation curve from the initial state to the EOL of all the battery cells is presented in the dataset. It is important to note that each battery cell is used under different use profiles. That is, although all the battery cell data are from the same dataset, each cell's use condition was unique.

The dataset contains three batches of data, and each batch includes a different experiment configuration with a variety of charge policies, stop cycling SOH, rest time, etc. In this research, a subset of six battery cells from each batch is randomly selected for use as validation and testing data, resulting in a total of 36 cells allocated for validation and testing purposes. The remaining battery cells (83 in total) are used as training data. To simulate the decentralized training setup, each battery cell is assigned as an independent client.

In this work, we introduce a specific data allocation approach to simulate real-world conditions where EV batteries age gradually with daily usage. The aim of this approach is to capture the dynamic nature of battery degradation and to better align the training process with the actual aging process observed in EV batteries during normal operation. Fig. 3 illustrates the concept of segmenting the degradation curve for all battery cells. Instead of providing the complete degradation curve of all clients in each training round, we progressively allocate portions of the degradation curve throughout the successive training rounds. The degradation curve of all the batteries is incrementally segmented into proportions ranging from 50% to 100%. More precisely, the degradation curve is resegmented at intervals of 10 training rounds, with each segment representing a 5% step (e.g., 50%, 55%, 60%, and so on). The length of each segmentation is randomly determined within a 5% range. Random segmentation allows for variability in the segmentation process.

F. Client Selection

For each training round, a subset of clients is selected to perform local training. Examining the utilization of the decentralized approach in real-world scenarios is a crucial component of our work. As previously stated, it is anticipated that battery operation data across the various clients will exhibit differences. That is, each EV is considered to have undergone different operational conditions over time. Therefore, during the training process, the data accessible within each client (EV) differ with regard to battery health status, degradation curve, and operational patterns.

We do not adopt the conventional approach wherein all clients are granted access to the complete local training data in each round of the training process. The battery degradation data is expected to be progressively accumulated during the training process. As a result, it is essential to establish a designated client selection strategy that is appropriate for the purpose of battery health forecasting. This work investigates six client selection strategies that leverage statistical attributes to enhance the accuracy of the model. The main objective of client selection is to reduce validation loss during the training process. The details and reasoning of all the methods are described in the following.

1) Full Selection: This method entails selecting all clients for each training round, with the aim of evaluating the effectiveness of an appropriate client selection approach. By considering all clients in all the training rounds, the objective is to assess the efficiency and performance of the model without any client exclusion or prioritization.

2) Random: The random approach is widely employed in federated learning, wherein client selection for each training round is conducted in a random manner. It does not incorporate any explicit exclusion or prioritization criteria during the selection process.

3) Degradation Curve Standard Deviation: In this method, clients exhibiting a higher standard deviation of SOH values are given priority in the selection process. The standard deviation of the SOH values recorded in the accumulated degradation curve is utilized as one of the criteria for client selection. By employing the standard deviation of SOH, we gain insights into the sparsity of SOH fluctuations throughout the degradation process. It is expected that training with a more sparsely distributed degradation curve can enhance the overall performance of future degradation forecasting due to the provision of more dynamic data.

4) The Latest Health Status: This selection strategy relies on the most recent battery health status of each client. Specifically, it involves comparing the SOH value of the latest cycle within the degradation curve for all clients. Batteries with a lower SOH value indicate inferior performance compared to others. This lower SOH value can be attributed to factors such as a higher number of cycling events or more intense operation conditions experienced by these batteries. Prioritizing batteries with lower SOH values is anticipated to enhance the predictive model's capability to effectively handle extreme aging scenarios. Consequently, this method preferentially selects clients characterized by the lowest battery SOH value.

5) Number of Cycling: This method assigns higher priority to clients with a greater number of charge and discharge cycles, as they are expected to contribute valuable insight into the degradation patterns. The number of cycling refers to the count of charge and discharge cycles experienced by the battery, serving as an indicator of its usage duration. It is important to note that a higher number of cycling does not necessarily lead to a lower battery SOH, as the degradation process also depends on the specific usage patterns it has been subjected to. A prolonged usage duration can offer a larger pool of degradation information during the model training process.

6) Battery Operation Status Duration: The utilization of batteries constitutes an important factor in the process of battery aging. Therefore, this selection strategy relies on the statistical analysis of their duration under specific operational conditions. In this strategy, we select the clients by using (i) total charging duration, (ii) total discharging duration, and (iii) total idling duration. The durations are all calculated by equation 1. In the case of charging and discharging, we give priority to clients with a longer cumulative duration of charging and discharging time. On the other hand, for the idling status, clients with minimal idling time are prioritized.

G. Model Structure

The task of forecasting Li-ion battery health degradation is formulated as a seq2seq problem in the study. This approach enables the prediction of multiple future degradation states by leveraging historical degradation data of the battery. Specifically, we use the encoder-decoder structure to model the seq2seq task. The encoder-decoder structure is widely adopted in the field of forecasting battery health degradation [13], [28], [34], [35].

In this work, the predictive model incorporates information from past health degradation and features extracted from the batteries' operation. The encoder component takes in the time series of past SOH changes, as well as the features extracted from the historical operation. The encoder's role is to compress and encode the information from the past into a compact state vector. After that, the state vector is combined with a time series of features extracted from the projected future operation. These features serve as a representation of the potential operational characteristics that may occur in the future. The decoder then utilizes the state vector and the future features to generate a time series of forecasted future SOH values. This process involves decoding and reconstructing the future SOH based on the encoded information and the anticipated future operation. Fig. 4 illustrates the overall idea of the model structure.

The underlying model of the encoder-decoder structure in this work is based on LSTM. An LSTM cell comprises several essential components, including a forget gate, input gate, output gate, cell state, and hidden state. These components enable the LSTM cell to effectively capture and retain long-term dependencies in the input sequence. The calculation steps

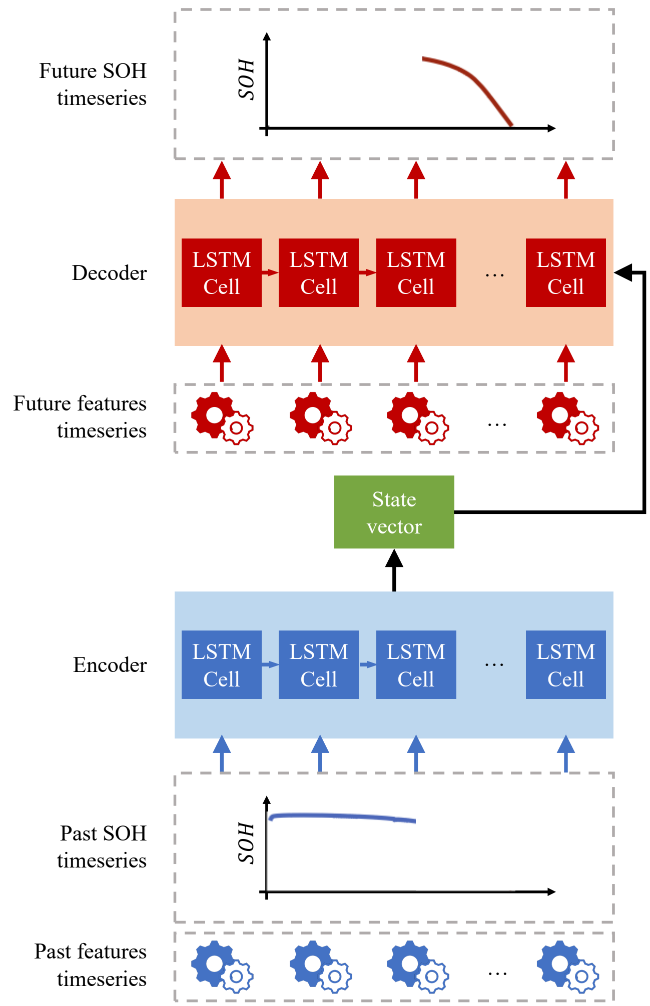

Fig. 4. Model structure of the predictive model with LSTM based encoder-decoder structural.

of an LSTM cell at time step t can be outlined as follows:

$$\begin{aligned}
f_t &= \sigma(W_x^f x_t + W_h^f h_{t-1} + b^f) \\
i_t &= \sigma(W_x^i x_t + W_h^i h_{t-1} + b^i) \\
\tilde{c}_t &= tanh(W_x^c x_t + W_h^c h_{t-1} + b^c) \\
c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
o_t &= \sigma(W_x^o x_t + W_h^o h_{t-1} + b^o) \\
h_t &= o_t \odot tanh(c_t)
\end{aligned} \tag{2}$$

where f represents the forget gate, i represents the input gate, o represents the output gate, c represents the cell state, h represents the hidden state, σ denotes the sigmoid function, $\odot$ represents the element-wise multiplication (Hadamard product), W denotes the weight matrix, x represents the input vector, and b represents the bias. These steps encompass determining which information from the previous step should be forgotten, deciding whether new information should be stored in the cell state, combining the current cell state with the previous cell state, and determining which part of the cell state should be propagated to the hidden state using the output gate with the sigmoid function. The adoption of LSTM

TABLE II
EXPERIMENT CONFIGURATION

Configuration	Value
Global training rounds	100
Client selection ratio	0.5
Local epochs	30
Optimizer	Adam [46]
Learning rate	0.001 ($\beta 1 = 0.9$, and $\beta 2 = 0.999$)
Local batch size	256
Model structure	4 layers of bidirectional LSTM
Hidden state of LSTM	64 features

offers advantages over traditional recurrent neural networks by mitigating issues related to gradient exploding and vanishing.

IV. Result and Discussion

A. Experiment Setup

The experiments conducted in this study primarily focused on investigating two key aspects within the domain of Li-ion batteries health forecasting. Firstly, we evaluate the performance impacts of diverse client selection strategies within the context of a decentralized training process. Secondly, we examine the performance characteristics of our decentralized approach in contrast to the centralized approach. In our experiments, we employ specific hyperparameters to govern the training process. The detailed configuration is shown in Table II. Based on the experiment configuration, we conduct our experiment on training the predictive models in a decentralized manner. Here, we list every step of the experiment to illustrate how the decentralized training is set up.

1) Preprocessing the battery aging dataset with all features extracted.
2) Allocating each battery cell data into segmentations that fit the desired degradation curve in each global training round.
3) Initializing the global model based on the hyperparameters listed in Table II, pick a client selection strategy on a sequence.
4) Starting the training process with the initialized global model.
5) Iteratively train the global model following the predefined global training rounds.
6) In each global training round, locate a group of clients based on the selected client selection strategy.
7) Under each selected client, the global model is assigned as the local model and trained independently using the client's segmented data.
8) Collecting all the trained weights from the local models and aggregating them to update the global model.
9) Repeating steps 6 to 8 until finishing the global training rounds.
10) Saving the trained global model for evaluation purposes.
11) Repeating steps 3 to 9 until it goes through all the client selection strategies.
12) Using the testing dataset to evaluate the performance of all the trained models.

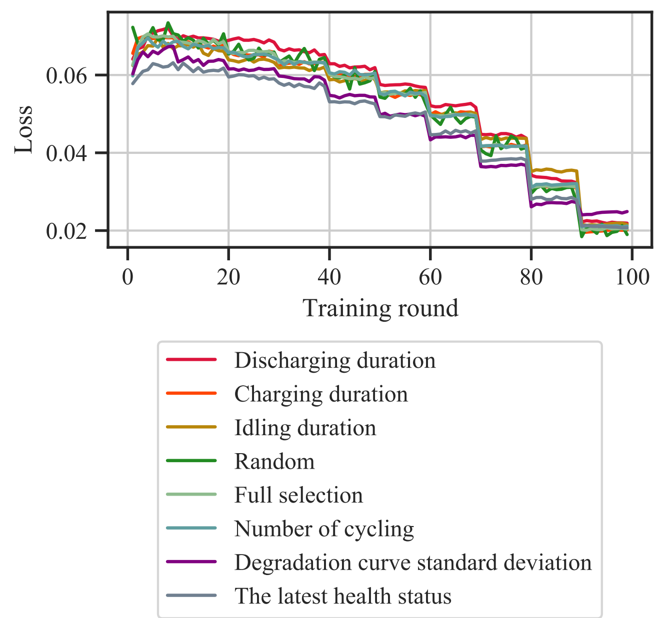

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Fig. 5. Validation loss during the training process of different client selection strategies.

The aforementioned steps demonstrate the decentralized training process. We also use the traditional approach to train a LSTM model using the same hyperparameters but without the decentralization for comparison. Specifically, all training data is gathered in one place and used to train the LSTM model. In our experiment setup, the model is trained over the course of 50 epochs.

B. Evaluation Metric

The predictive model generates a sequence of SOH values that indicate the anticipated battery degradation in the future. Therefore, the evaluation primarily centers around the accuracy of the forecasted SOH values within the degradation curve ahead. The performance of the SOH forecasting task is quantitatively evaluated by the root mean square error (RMSE), which is given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{3}$$

where y is the ture SOH value and $\hat{y}$ is forecasted SOH value.

C. Validation Loss during Training

Various client selection strategies have a notable impact on the enhancement of the predictive model throughout the training process. In this context, we assess the overall performance of the predictive model during training by comparing it across different client selection strategies. The validation loss across all training rounds is illustrated in Fig. 5. The loss curves from all the client selection strategies reveal that the validation losses gradually decrease as the number of training rounds increases. The reduction in validation losses can be

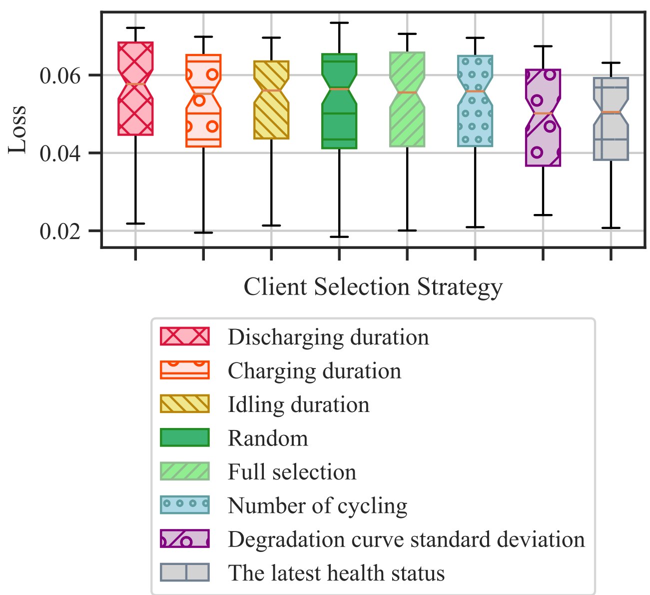

Fig. 6. Validation loss distribution of different client selection strategies.

attributed to two primary factors. Firstly, it is a result of the predictive model gradually converging during the training process, leading to improved accuracy in forecasting battery aging. Secondly, our data allocation strategy ensures that an increasing amount of battery aging data become available as the training progresses, which further enhances the model's performance. Together, these factors contribute to the observed gradual decrease in validation loss over time.

To further assess the performance of various client selection strategies, we analyze the distribution of validation loss for each strategy. Fig. 6 presents the graphical representation of these error distributions by using the box plot, allowing for a comprehensive comparison among the different client selection strategies. The figure demonstrates that employing the latest health status and the degradation curve standard deviation as the client selection criterion yields the lowest average validation loss throughout the training process. This suggests that the overall training performance can be enhanced by prioritizing batteries with the worst health status. Prioritizing the use of older batteries can help improve the accuracy of health forecasting. Particularly during the initial stage when all batteries are still in their early lifespan. On the other hand, the random, full selection, the number of cycling, charging duration, discharging duration, and idling duration strategies exhibit similar validation performance, which is relatively less favorable compared to the aforementioned top-performing strategies.

D. Model Performance in Testing

Subsequently, following the completion of the training process, we evaluate the predictive model's performance by examining the error derived from the testing dataset. In order to assess the feasibility of employing the decentralized approach for forecasting Li-ion batteries health, we adopt identical setups (battery operation features and model structure) to train an additional predictive model using a centralized approach. In the centralized training, we follow the conventional approach, wherein all the training data is utilized in each training epoch, without any segmentation. It is anticipated that the results obtained from the centralized training approach will exhibit the best performance, as it trains with the entire training dataset in a centralized manner. It is worth noting that the objective of comparing the results of decentralized and centralized training is not to surpass the performance of the centralized approach, but rather to examine how closely the decentralized approach can approximate the performance of the centralized one.

TABLE III
TESTING INPUT CYCLES IN DIFFERENT SCENARIOS

	Input cycles
Early	$S = \{c_1, c_2, ..., c_i\}, i = 0.3l$
Middle	$S = \{c_1, c_2, ..., c_i\}, i = 0.5l$
Late	$S = \{c_1, c_2, ..., c_i\}, i = 0.7l$
All	$S = \{c_1, c_2, ..., c_i\}, i \in \{100, 101, 102, ..., l-100\}$

S is the set of input cycles,
c is a charge/discharge cycle,
l is the length of cycle life.

To provide an objective evaluation of the predictive models, the performance evaluation involves a quantitative measurement of the forecasting loss using the testing dataset. It should be noted that the testing dataset consists of three batches of batteries, with each batch comprising data from six battery cells. What is more, within each test batch, three distinct scenarios are considered, which involve varying lengths of the past time series used as the input of the predictive model. Table III represents the details of extracting the input cycles in different scenarios. These scenarios, namely 'early', 'middle', and 'late', are determined based on the ratio of their input length to their total cycle life, with ratios of 30%, 50%, and 70%, respectively. Furthermore, an 'all' scenario is included to assess the predictive model's performance across all input lengths within a specific test batch. That is, an iterative approach is employed to examine the entire range of potential lengths for both the past degradation curve and the target forecasting curve, starting from a minimum length of 100 cycles.

Table IV shows a comparison of the testing performance, specifically the RMSE, between the centralized training approach and various decentralized approaches with different client selection strategies. Based on the presented table, it is apparent that the testing performance of the results obtained through decentralized training closely aligns with the performance achieved through centralized training. In this study, rather than assessing the performance by averaging results from all scenarios, we aim to evaluate the performance in every individual scenario. We emphasize the importance of consistently good performance across all scenarios, it is crucial for the model to deliver accurate forecasts in each case. In particular, we establish the RMSE of 2% as the threshold for determining the performance of different client selection strategies. Among all the client selection strategies, it is shown that both the full selection strategy and the latest health status

TABLE IV
COMPARASION OF TESTING LOSS

Scenario		RMSE (%)		
		Batch I	Batch II	Batch III
Centralized training	Early	0.91%	1.60%	1.14%
	Middle	0.90%	1.41%	1.11%
	Late	1.04%	1.12%	1.08%
	All	0.93%	1.45%	1.09%
Discharging duration	Early	1.57%	2.22%	1.44%
	Middle	1.50%	2.39%	1.42%
	Late	1.28%	2.42%	1.26%
	All	1.38%	2.28%	1.32%
Charging duration	Early	1.30%	2.27%	1.45%
	Middle	1.37%	2.35%	1.45%
	Late	1.17%	2.40%	1.22%
	All	1.20%	2.30%	1.30%
Idling duration	Early	1.15%	2.35%	1.58%
	Middle	1.15%	2.37%	1.72%
	Late	1.00%	2.47%	1.61%
	All	1.10%	2.37%	1.50%
Random	Early	1.28%	2.00%	1.59%
	Middle	1.28%	2.02%	1.54%
	Late	1.14%	1.98%	1.32%
	All	1.20%	1.98%	1.36%
Full selection	Early	1.23%	1.96%	1.68%
	Middle	1.23%	1.99%	1.66%
	Late	1.12%	1.95%	1.57%
	All	1.17%	1.95%	1.49%
Number of cycling	Early	1.69%	2.30%	1.33%
	Middle	1.55%	2.34%	1.36%
	Late	1.28%	2.42%	1.12%
	All	1.46%	2.32%	1.22%
Degradation curve standard deviation	Early	1.26%	1.84%	2.13%
	Middle	1.28%	1.77%	2.14%
	Late	1.51%	1.55%	2.07%
	All	1.28%	1.74%	2.00%
The latest health status	Early	1.39%	1.88%	1.66%
	Middle	1.47%	1.86%	1.71%
	Late	1.54%	1.66%	1.55%
	All	1.31%	1.78%	1.55%

strategy consistently demonstrate relatively good overall performance across all testing scenarios, as their performance in these scenarios does not exceed 2% RMSE loss. The efficacy of the full selection strategy can be primarily attributed to its utilization of all clients for local training. Nevertheless, it is rare in practice to have all clients engage in the local training phase. Therefore, the most effective client strategy is observed to be one that leverages the latest health status strategy.

Here, we analyze the battery health forecasting results obtained from models trained using both centralized and decentralized training approaches. Among the decentralized training approaches, the one utilizing the client strategy based on the latest health status achieves the highest overall performance. Hence, we consider this approach as the representative of the decentralized training approach. Fig. 7 depicts the forecasting results obtained under the three battery batches and the three aforementioned distinct input scenarios. Each sub-figure within Fig. 7 shows the following elements: the past SOH curve, which serves as the input for the models; the actual future SOH curve, representing the true output; the forecasted future SOH curve obtained from the centralized training model; the forecasted future SOH curve derived from the decentralized training model; and the error between the actual SOH and the forecasted ones.

The figures demonstrate that the forecasting results obtained from both the centralized and decentralized training models closely align with the actual degradation curve. This observation holds true for both the three batches and the three input scenarios. Furthermore, the performance comparison between the centralized training model and the decentralized training model reveals a similarity, as no significant drop in performance is observed in the decentralized training approach. In certain instances, such as the initial forecasting of batch III batteries, the decentralized training approach showcases even superior performance compared to the centralized training approach. Furthermore, it is notable that the error from the decentralized training model tends to increase toward the end of the forecasting horizon. This phenomenon is consistently exhibited in all the figures. One possible explanation for this phenomenon is attributed to our data allocation scheme, which leads to the progressive availability of training data. Due to this allocation scheme, the degradation data near the EOL of the battery contributes less to the overall decentralized training process. Therefore, this reduced representation of nearing EOL degradation data may contribute to the observed increase in error towards the end of the decentralized training model's output.

E. Robustness in the Presence of Missing Information

In addition, to further assess the robustness of the predictive models, we extend our investigation to include scenarios where the initial information is partially missing. Specifically, we examine the performance of the models when a certain portion of the initial degradation data is deliberately removed. In our experiments, we consider the removal of the first 10%, 20%, and 30% of the degradation curve data, while the subsequent 40% of the available data is utilized as the input for the past degradation curve.

Table V presents the comparison of performance metrics obtained under varying ratios of removed past information. Similarly, the model trained by the decentralized training approach showcases performance that is comparable to the model trained by the centralized approach. Furthermore, it is observed that the utilization of the latest health status client selection strategy during the training process demonstrates commendable overall performance, characterized by an absence of testing loss exceeding 2%.

Examples of the forecasting result with the presence of missing information in the past degradation are depicted in Fig. 8. The model trained by utilizing the latest health status client selection strategy is used as the representation of a decentralized training approach. The figures illustrate that the models exhibit robustness even in the absence of an initial degradation curve. Also, a notable similarity in performance can be observed between the results obtained from both the centralized and decentralized approaches. Additionally, the decentralized approach exhibits a comparable behavior to the

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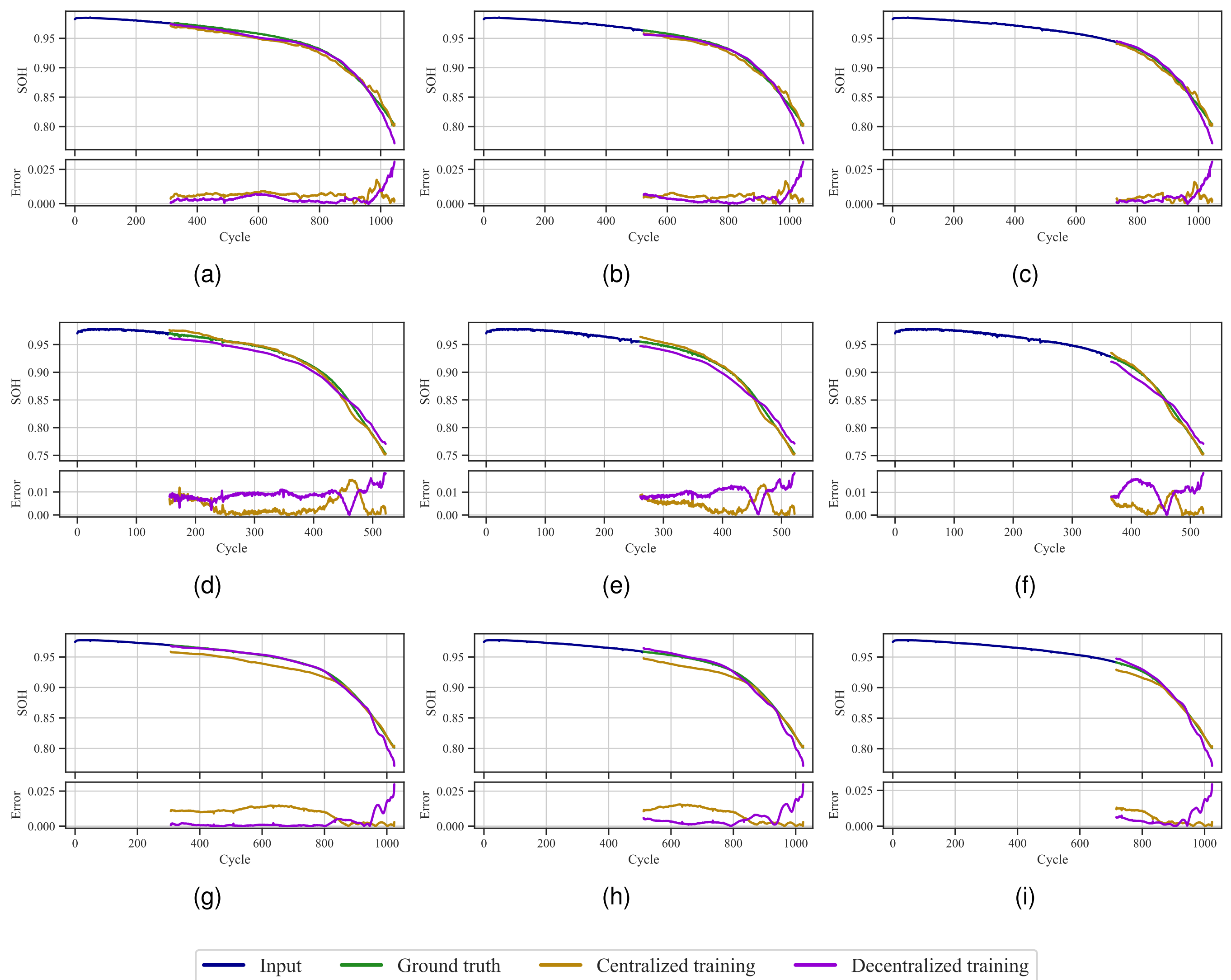

Fig. 7. Testing results of different input lengths. (a)-(c) are batch I with input scenarios 'early', 'middle', and 'late', respectively. (d)-(f) are batch II with input scenarios 'early', 'middle', and 'late', respectively. (g)-(i) are batch III with input scenarios 'early', 'middle', and 'late', respectively.

observed in standard tests, as evidenced by the increase in error towards the end of the output.

F. Testing on Driving Condition Data

Testing the trained models with real-world battery operations is crucial to examine the practicality of the models created using our proposed methodology. To this end, we extend our testing by employing battery datasets that include instances where batteries have been discharged following driving conditions. Two public datasets are utilized for this testing purpose, namely 'Samsung INR21700 30T 3Ah Li-ion Battery Data' [47], and 'LG 18650HG2 Li-ion Battery Data' [48]. For simplicity purposes, we name them 'Samsung' and 'LG' datasets respectively. Both of the aforementioned datasets are structured to discharge the batteries under predefined driving conditions, such as UDDS, HWFET, LA92, US06, and cycles that randomly mix them. All the discharge tests are repeated across various ambient temperatures. In this study, we specifically utilize cycles conducted under positive ambient temperatures. Following each discharge cycle, the batteries are charged at a 1C rate. To facilitate these datasets for the battery health forecasting task, we calculate the integrated current in the charge cycle as the reference battery health. Given that each dataset contains only one battery cell data, they are not employed for the training process. Instead, they serve as the testing dataset for the models trained by our proposed decentralized approach using the MIT-Stanford dataset, allowing for comparing the results with the baseline centralized approach.

Table VI shows the testing loss from the model trained using centralized and decentralized approaches. Same as the previous experiments in Section IV-D, the model trained with the client strategy based on the latest health status is used to represent the decentralized approach. Also, we test with different input scenarios, 'early', 'middle', 'late', and 'all'. As seen from the results, the overall testing loss derived from the driving condition data is marginally higher than

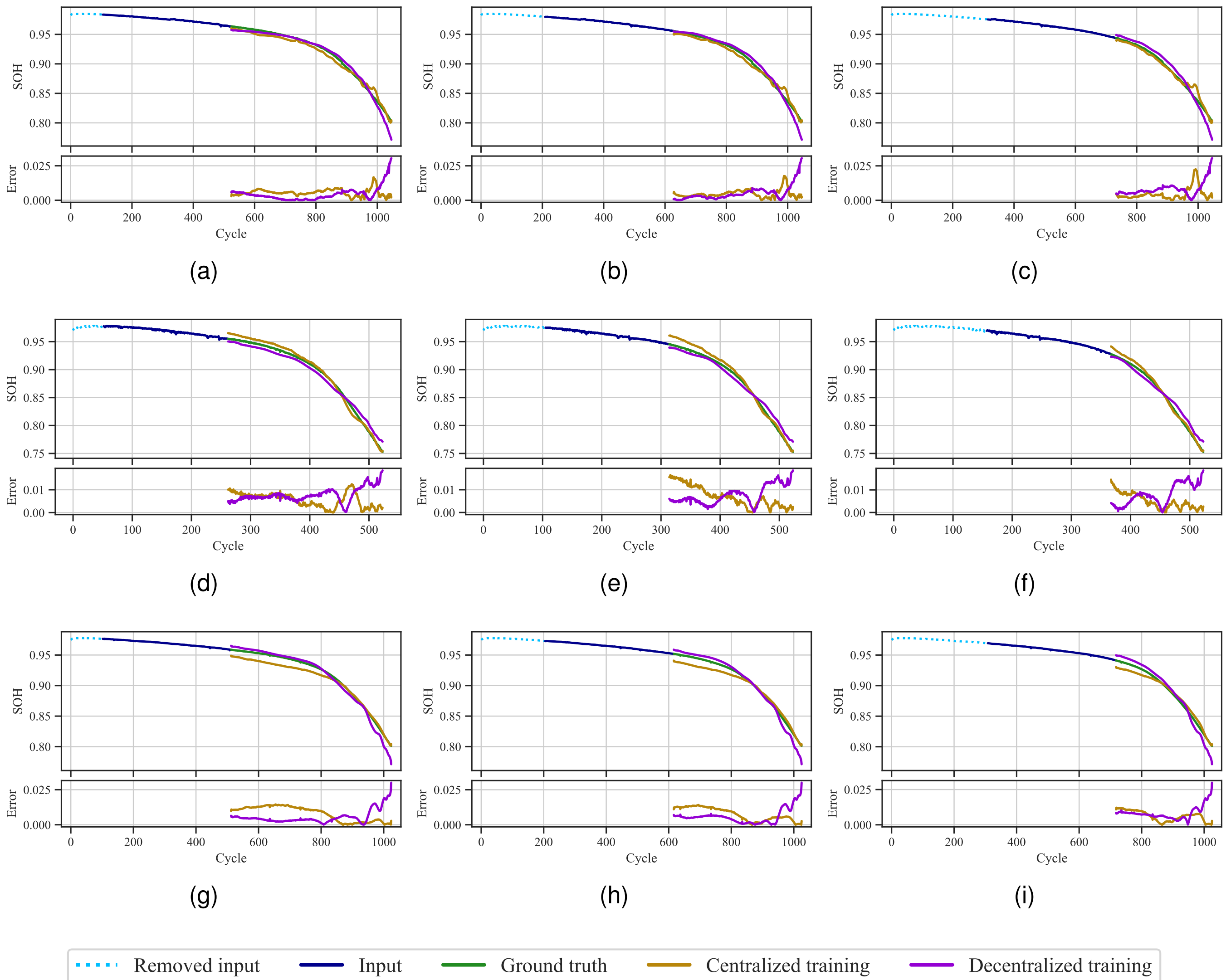

Fig. 8. Testing results with initial degradation curve removed. (a)-(c) are batch I with 10%, 20%, and 30% initial degradation curve removed, respectively. (d)-(f) are batch II with 10%, 20%, and 30% initial degradation curve removed, respectively. (g)-(i) are batch III with 10%, 20%, and 30% initial degradation curve removed, respectively.

in the tests with the MIT-Stanford dataset in Section IV-D. This discrepancy in testing loss could be a result of the fact that the batteries' specifications and usage patterns within the 'Samsung' and 'LG' datasets differ from those utilized during the training phase. Nevertheless, this difference in battery specification is considered advantageous, as it aligns with our objective of testing the trained model across various data sources. Also, compared to the 'LG' dataset, the error from the 'Samsung' dataset shows an overall increase, primarily because of a more noticeable degree of fluctuation in the battery degradation trend.

Interestingly, it is observed that the decentralized approach outperforms the centralized approach. This outcome further underscores the practicality of the model trained by our proposed methodology. Training the forecasting model in a decentralized manner proves beneficial in improving the generalization ability. The baseline centralized approach introduces bias into its forecasting by relying on the battery specifications and usage patterns of the training dataset. This tendency is primarily due to the visibility of the entire training dataset during the training process. On the other hand, the model trained using the decentralized approach exhibits a reduced bias towards the training batteries. Despite resulting in higher loss when testing with identical battery specifications and usage patterns (as indicated in Section IV-D), the model trained with the decentralized approach performs better against different battery specifications and usage patterns. The decentralized approach maintains a balance between the accuracy and generalization of the forecasting task.

G. Discussion and Future Work

Based on the above results, this study demonstrates the viability of employing federated learning as a decentralized method for training a battery health forecasting model. The

TABLE V
COMPARASION OF TESTING LOSS WITH INITIAL DEGRADATION CURVE REMOVED

	Removed ratio	RMSE (%)		
		Batch I	Batch II	Batch III
Centralized training	10%	0.92%	1.55%	1.11%
	20%	0.99%	1.23%	1.11%
	30%	1.14%	0.93%	1.11%
Discharging duration	10%	1.42%	2.35%	1.47%
	20%	1.27%	2.35%	1.45%
	30%	1.15%	2.36%	1.37%
Charging duration	10%	1.23%	2.33%	1.55%
	20%	1.15%	2.36%	1.52%
	30%	1.03%	2.45%	1.40%
Idling duration	10%	1.04%	2.40%	1.78%
	20%	1.02%	2.47%	1.89%
	30%	1.04%	2.64%	1.88%
Random	10%	1.15%	2.02%	1.65%
	20%	1.06%	2.03%	1.63%
	30%	1.03%	2.06%	1.55%
Full selection	10%	1.08%	2.00%	1.79%
	20%	1.03%	2.04%	1.85%
	30%	1.09%	2.11%	1.86%
Number of cycling	10%	1.47%	2.32%	1.38%
	20%	1.28%	2.41%	1.39%
	30%	1.11%	2.48%	1.29%
Degradation curve standard deviation	10%	1.22%	1.80%	2.23%
	20%	1.30%	1.72%	2.33%
	30%	1.51%	1.63%	2.27%
The latest health status	10%	1.40%	1.82%	1.75%
	20%	1.33%	1.73%	1.74%
	30%	1.38%	1.58%	1.68%

TABLE VI
TESTING LOSS WITH DRIVING CONDITION DATA

Scenario	RMSE (%)			
	'Samsung' data [47]		'LG' data [48]	
	Centralized	Decentralized	Centralized	Decentralized
Early	4.25%	3.34%	2.73%	1.73%
Middle	5.03%	2.53%	2.41%	2.04%
Late	5.26%	2.91%	3.79%	1.12%
All	4.87%	3.16%	2.56%	2.07%

predictive models generated through this approach exhibit comparable performance to those produced using the centralized training method across different testing scenarios. Furthermore, the client selection strategy contributes to enhancing the overall training performance, thereby enabling it to closely approximate the performance achieved through centralized training.

The predictive model in this study is implemented utilizing the LSTM-based seq2seq method, a widely employed deep learning approach for battery health forecasting. While this technique has shown effectiveness in addressing the battery health prediction problem, it is important to acknowledge the potential for further exploration of alternative methods in future research endeavors.

This research relies on laboratory-tested battery operation data as its foundation. The designated data allocation method guarantees the authenticity of training scenarios by progressively accumulating battery operation data. In future studies, it is essential to assess the decentralized training setup using field-testing data. Utilizing field-testing battery operation data ensures diverse testing cases and instills confidence in the models' suitability for production usage. Also, exploring the experiment of decentralized training with various battery models or even different EV models holds potential value.

V. CONCLUSIONS

Accurately forecasting Li-ion battery degradation is of utmost importance for promoting the widespread adoption of EVs. While deep learning approaches are widely employed in this forecasting task, the centralized training setup remains predominant in the research field. In order to address privacy concerns, leverage onboard computing resources, and accelerate the integration of new data, there is a compelling need to decentralize the model training process.

In this study, we propose the application of federated learning to train a health predictive model in a decentralized manner. The decentralized platform we introduce is specifically designed for Li-ion battery health forecasting. We consider real-world scenarios related to EVs operation in the domain of battery health forecasting. We utilize simplified and intuitive battery operation features to represent both past and potential future battery operations. An LSTM-based seq2seq predictive model is adopted to perform one-time forecasting of the entire degradation curve. To simulate progressively accumulated training data in real-world situations, we employ a specialized data allocation approach. Additionally, the client selection strategies we propose enhance the validation performance throughout the decentralized training process.

The experimental results demonstrate that the performance of the decentralized training model closely aligns with the centralized training model. This study provides valuable contributions towards enabling a decentralized setup for accurately forecasting Li-ion battery health degradation.

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