Toward Fast and Accurate SOH Prediction for Lithium-Ion Batteries

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***Abstract*—For timely maintenance and replacement in lithium-ion battery system, it is crucial to achieve fast and accurate State of Health (SOH) prediction. SOH is a dynamic status parameter of a battery indicated by its available capacity compared to the initial condition. SOH tends to decrease in the long-term because a battery is aged by its charging and discharging cycles due to the degradation of chemical composition. To ensure a battery has sufficiently good conditions, it is significant to predict the battery SOH precisely so that the depleted or weak battery can be replaced in time. However, the prediction of battery SOH is a difficult and complex task due to the following reasons (1) SOH degradation is a dynamic process because of the time-varying nature of both battery electrochemistry and working condition; (2) SOH prediction model usually involves numerous input attributes that lead to sheer complexity and computational cost for real-time battery management; (3) the balance of overhead-accuracy tradeoff is challenging to adapt to various application scenarios. In this paper, we propose a theoretical framework for fast and accurate SOH prediction based on the non-additive measure and overhead-accuracy balancing. Specifically, we characterize the interactions among battery attributes and their aggregated impacts on SOH prediction. By choosing the most significant subset of battery attributes, the computational complexity of SOH prediction can be substantially reduced while maintaining high accuracy. The tradeoff between accuracy and computational overhead can be balanced by adjusting the number of attributes and volume of training data. The experimental results validate the effectiveness and efficiency of the proposed framework.**

***Index Terms*—Attribute selection, lithium-ion batteries, modeling, non-additive measure theory, state of health.**

I. Introduction

LITHIUM-ION batteries have been widely used and become the major power source for portable electronic devices and electric vehicles due to their high energy and power densities compared to all other kinds of battery electrochemistries [1]. The usable capacity of a lithium-ion battery, which is often adopted to evaluate its State of Health (SOH), is inevitably degrading along the battery lifetime. As a long-term performance indicator, SOH is defined as the ratio of the current usable capacity of a battery compared to its nominal capacity as $SOH = \frac{C_{uc}}{C_{nc}} * 100\%$, where C_{uc} is the maximum usable capacity of an aged battery at present and C_{nc} is the nominal capacity of a battery. Typically, electric vehicle (EV) manufactures would recommend a battery to be replaced when its SOH degrades to 70%–80% of its nominal capacity. This capacity threshold is set as the end of life (EOL) of a battery, since the usable capacity is expected to decrease at a more rapid rate after exceeding EOL [2]. Except for battery replacement, SOH prediction also extends the battery lifespan by adopting aging-level-based charging strategy to vary the charge current according to a cell's health status [3]. Therefore, SOH prediction is crucial for the lithium-ion battery system to receive timely maintenance and/or replacement.

SOH prediction methods for lithium-ion batteries can be classified into two categories. In the first category, the equivalent circuit or electrochemical models are integrated with advanced filter techniques to predict SOH, such as Kalman filters [4], particle filters [5] and recursive least squares filters [6]. These methods are based on a series of state equations to approximate the electrochemical process of the battery. The second category is to apply machine learning techniques to predict battery SOH without knowing the exact battery model, which is usually extremely difficult to derive. Measurement data can be extracted from the differential voltage curve during charge process [7], voltage sequences and discharge rates during discharge process [8], or other related attributes [9]. One of the advantages of these methods is that they do not require any prior knowledge of battery electrochemical characteristics to predict battery SOH degradation.

However, the existing SOH prediction methods still face several challenges. Firstly, the performance of model-based methods heavily rely on the accuracy of state equations that approximate the complicated electrochemical process in lithium-ion batteries. Due to the time-varying nature of internal structure and external working conditions, the SOH degradation should be considered as a dynamic process. Methods based on exact battery models are limited to formulate SOH degradation with deterministic state equations, providing low prediction accuracy in the long term. Secondly, although machine learning (ML)-based methods are modeless since no prior knowledge is required to train the prediction model, they tend to involve numerous battery

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attributes that may lead to high demand for training data volume and computational power. The machine learning techniques, such as Neural Network [10], provides black-box models that can hardly be interpreted in the application domain, since the model parameters no longer correspond to the original battery attributes. As the physical meanings of model parameters are lost from the perspective of battery discipline, little information can be obtained except predicted SOH values to facilitate the study of SOH degradation insight. Thirdly, the balance of overhead-accuracy tradeoff is difficult for SOH prediction problem, since the required accuracy and affordable computational overhead vary among different scenarios. The computational overhead are determined by the volume of training data and complexity of prediction model, which are major restrictions of SOH prediction in real applications. For embedded devices with limited computational power, reducing the overhead while maintaining prediction accuracy is essential but challenging.

To address the aforementioned challenges, we propose a theoretical framework for SOH prediction based on non-additive measure and overhead-accuracy tradeoff balancing. Specifically, the proposed framework allows us to gain in-depth understanding on SOH degradation by systematically characterizing the interactions among battery attributes and quantifying their joint impacts on SOH prediction. In the proposed framework, the accuracy and overhead of SOH prediction are customizable upon the availability of training data and computation power. The main contributions of this paper are three-fold.

1) We propose a novel SOH prediction framework to combine the advantages of model-based and modeless methods by approximating the SOH degradation process with a system function based on non-additive measures. We quantitatively characterize the interactions among each subset of battery attributes with non-additive measures, which indicate their aggregated contributions to SOH prediction. The system function is iteratively updated to capture the dynamics within the degradation process based on supervised learning of observation data. On one hand, the proposed framework performs SOH prediction with deterministic function in closed-form expression, so that all model parameters can be interpreted with physical meanings in battery domain. On the other hand, the generation of system function require no prior knowledge to handle the complexity of battery internal structure and uncertainty of external working condition.

2) Based on the proposed theoretical framework, we develop a SOH prediction algorithm with considerations of accuracy and computational overhead. We select significant subset of battery attributes for the SOH prediction, instead of considering the whole set of battery attributes. By adjusting the number of involved attributes and volume of training data, we can balance the tradeoff between prediction accuracy and computational overhead to fulfill the requirements of different application scenarios.

3) The experimental results validate that compared to existing SOH prediction methods, the proposed framework substantially reduces the required training data volume and computational cost while maintaining the same desired prediction accuracy. The overhead reduction enables iterative changing of attribute selection and updating of system function, so that the prediction model remains adaptive to the time-varying SOH degradation process. Moreover, the proposed framework provides additional information on the significance of aggregated attributes to gain in-depth understanding on SOH degradation, which can hardly be derived from ML-based methods or common dimension reduction algorithms.

The remainder of the paper is organized as follows. In Section II, we review the related literatures. The concept of interaction measure and the proposed framework for SOH prediction are discussed in Section III. In Section IV, an experiment of lithium-ion battery charging and discharging is conducted and the results are presented to validate the proposed framework. Finally, a conclusion and work prospects are drawn in section V.

II. Related Works

In general, the battery system relies on SOH as a status indicator to forecast when a battery reaches its end of life. Various battery attributes, such as voltage, current and temperature, are extracted to formulate SOH prediction model. Open circuit voltage (OCV) method is a direct assessment method using equivalent circuit models to predict SOH in both online and offline states by defining SOH as a function of the OCV of the monitored battery. An online OCV method [11] considered OCV as an attribute of electrical model to predict the SOH of the battery. An offline OCV method is based on the mathematical model centered on the OCV value. Extensive tests need to be conducted on the monitored batteries to obtain the OCV-SOC curves under different ambient temperatures and their relationship with the battery SOH [12]. However, [13] also pointed out that measuring the battery OCV as an attribute to predict SOH is difficult in practical use due to the high processing power requirements and the hardware costs. Besides direct assessment, equivalent circuit models and electrochemical models are applied to approximate SOH degradation process with a series of state equations. Li *et al.* [14] proposed a Single Particle model to predict SOH based on Solid Electrolyte Interface layer formation integrated with electrolytic physics. Model-based methods are also integrated with advanced filter techniques to improve prediction accuracy, such as Kalman filter [15] and particle filter [16]. Park *et al.* [17] employed dual extended Kalman filter (DEKF) to predict SOH by using two pattern recognition of capacity and charging/discharging voltage to determine DEKF parameters. The representative patterns are identified with the application of Hamming neural network to improve prediction accuracy. Xue *et al.* [18] utilized unscented Kalman filter integrated with support vector regression for SOC and SOH prediction.

Another category of SOH prediction methods is based on machine learning techniques, which is modeless and becoming increasingly popular for its capability to generate prediction model without prior knowledge, given sufficient measurement data and attributes. Li *et al.* [19] formulated the battery charging process based on electrochemical model and applied particle swarm optimization to determine model parameters with measured impedance spectroscopy. Liu *et al.* [20] developed a data-driven

method by extracting a novel energy-based health indicator from discharge process to incorporate both voltage sequences and discharge rates as battery attributes. Song *et al.* [21] proposed an ensemble learning algorithm based on XGBoost model and achieved accuracy correction with Markov chain. Lei *et al.* [22] formulated a multi-objective optimization problem to improve the generating process of prediction model with non-dominated sorting genetic algorithm. The prediction model are established with support vector regression and the short-term battery attributes. Automotive prognostic methods are also proposed to provide black-box models for battery SOH prediction, such as Neural Network [23], [24], Support Vector Machine [25], regression analysis [26], [27], reinforcement learning [28], and extreme learning machine [29]. The ML-based methods take the advantage of no dependence on detailed information of battery characteristics and the robustness under different operating conditions.

However, for prediction methods based on equivalent circuit and electrochemical models, accurate approximation of SOH degradation process is difficult due to the complexity of battery system and uncertainty of working conditions. In real applications, such as EV battery management system, model-based methods need to monitor the battery health status constantly for safety purpose, requiring frequent update of the prediction model to adapt to battery aging process and environment dynamics. The formulation of state equations requires prior knowledge of application domain and vary among different scenarios, causing the lack of generality for prediction models. ML-based prediction methods address the drawbacks of model-based methods since they are modeless and data-driven, but also require large volume of training data and high computational overhead to provide reliable accuracy. For embedded devices with limited storage space and computational power, ML-based methods are expensive. Furthermore, the prediction models obtained by ML-based methods are considered as black-box, whose model parameters can hardly be interpreted from the respective of battery electrochemistry. As dimension reduction algorithms are usually applied in ML-based methods to avoid curse of dimensionality, the input attributes are composed to form new dimensions and no longer preserve their original physical meanings. The difficulty in interpreting the generated model hinders further study on battery SOH degradation process and the design of control strategy for battery management system. Therefore, a lightweight prediction framework is necessary to obtain the prediction model that formulates SOH degradation with interpretable equations, and reduce computational overhead while maintaining reliable accuracy. Table. I compares the features of recent works on SOH prediction and shows that our proposed framework addresses all the aforementioned challenges. In Table. I, N denotes the original input size considering the whole set of battery attributes, and n denotes the input size after attribute selection so that $n < N$.

TABLE I
COMPARISON OF THE LATEST SOH PREDICTION METHODS AND PROPOSED FRAMEWORK

Ref	Methodology	Complexity	Generality	Model	Accuracy
12	Open circuit voltage	O(N)	No	Model-based	5%
17	Dual extended Kalman filter	$O(N^2)$	No	Model-based	3%
18	Unscented particle filter	$O(N^2)$	No	Model-based	2.5%
20	Novel health indicator	$O(N^3)$	Yes	Modeless	3%
21	Ensemble learning	$O(N^2)$	Yes	Modeless	2%
22	Support vector regression	$O(N^3)$	Yes	Modeless	1.5%-2%
28	Reinforcement learning	$O(N^3)$	Yes	Modeless	1.5%
29	Extreme learning machine	$O(N^2)$	Yes	Modeless	2%
Proposed	Non-additive measure	$O(2^n)$	Yes	Model-based	<1%

III. THE PROPOSED FRAMEWORK FOR SOH PREDICTION

In this section, we introduce the preliminary concept of interaction measure and formulate the SOH prediction problem. Based on non-additive measure theory, we propose our framework that quantitatively studies the impact of each attribute subset. We illustrate the prediction procedure with reduced amount of data and different subsets of attributes to obtain tradeoff between accuracy and computational overhead.

A. Preliminary of Interaction Measure

In our proposed framework, the battery attributes are measured and applied as input data to learn SOH prediction model, so that their original physical meanings can be preserved for further analysis. However, to generate an accurate model is challenged by the complex interactions among battery attributes and their aggregated contribution on SOH. To preserve the physical meanings of model parameters, the relations between battery attributes and predicted SOH value should be formulated as a system function in closed-form expression. Traditionally, prediction models approximate the attribute-SOH relations by assigning model parameters to battery attributes individually as additive measures. However, the additive measures can cause model uncertainty in the context of SOH degradation, since the contribution of a certain attribute to SOH prediction may be affected by other attributes. For example, under higher ambient temperature, the charging voltage has greater positive correlation with SOH. Therefore, additive measure is no longer suitable for our problem due to the existence of model uncertainty and the lack of sufficient statistics during short-term observation intervals. To address this issue, we propose a quantitative and systematic characterization of all interactions among the battery attributes on SOH prediction. The interaction measure is defined based on non-additive measure.

To quantify the interactions among a set of attributes, a set function $\mu : P(X) \rightarrow R$ is defined, where input X is the set of all attributes $X = \{x_1, x_2, \ldots, x_N\}$, $P(X)$ is the power set of X, i.e. the set of all subsets of X, and R is the real domain. If the input is a null set, then $\mu(\phi) = 0$. Two traditional restrictions in non-additive measure theory are relaxed on the interaction measure: (1) the codomain of set function μ is R instead of R^+, so that the sign of μ indicates whether the correlation is positive or negative between the predicted SOH and the corresponding attributes in the input subset; (2) the monotonicity is unnecessary. For two attribute sets A and B, $A \subseteq B \subseteq X$ does not necessarily imply $\mu(A) < \mu(B)$. This property is to reflect the fact that attributes may have opposite impacts to the predicted value, so that the interaction among attributes may be decreased instead when more of them are involved. The defined set function μ can express the interaction among aggregated attributes on the predicted value in a more flexible and accurate manner. The properties of the proposed

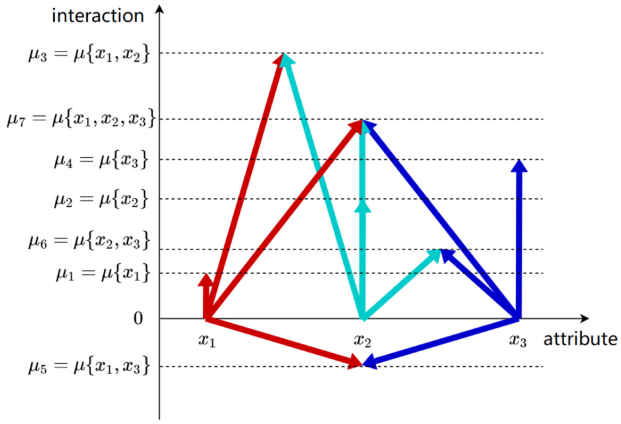

Fig. 1. Illustration of proposed interaction measures for SOH prediction with three attributes x_1, x_2, and x_3.

interaction measure are illustrated in Fig. 1. The figure shows that different subsets of model attributes may have various impacts to battery SOH. For instance, $\mu\{x_1, x_3\}$ is negative and indicates that increasing x_1 and x_3 together can negatively affect the predicted SOH. For the rest of interactions, their corresponding aggregated attributes have positive correlation with the predicted SOH. A larger $\mu(X)$ suggests that the predicted SOH is more sensitive to the change of the attributes in X. The nonadditivity of interaction measure is also be shown in the figure, such as $\mu\{x_2\} + \mu\{x_3\} \neq \mu\{x_2, x_3\}$. The nonadditivity property enables the prediction model to formulate the complicated interdependency among different attributes with various uncertainties in battery degradation. In addition, using a larger set of attributes does not necessarily provide larger interaction. We can observe that $\mu\{x_1, x_2\} > \mu\{x_1, x_2, x_3\}$, which implies that x_3 can be removed from the prediction model without affecting the accuracy. By applying interaction measures, we can quantitatively and systematically obtain the significance of various attributes in predicting battery degradation in a non-additive manner.

B. Problem Formulation

Without loss of generality, let $S = \{x_1, x_2, \ldots, x_N\}$ be a set of battery attributes of measured in charging and discharging cycles. Let $f : S \to R$ be the SOH function, which is a nonlinear function of $\{x_1, x_2, \ldots, x_N\}$ and R is the real domain of the predicted SOH in the future cycle. A general SOH prediction problem can be formulated as

$$\min \sum_{i=1}^{Q} (f(x_{i1}, x_{i2}, \ldots, x_{iN}) - y_i)^2 \quad (1)$$

$$\text{subject to: } h_m \geq 0, \text{ where } m \in \{1, 2, \ldots, M\}.$$

Here, x_{ij} is the observed value of attribute j in cycle i, y_i is the real SOH value in cycle i, Q is the number of observed cycles, and $h_1, \ldots, h_M$ are M constraints posed by physical limitations, application's power requirements, and attribute boundsc.

To derive an accurate system function f and minimize total prediction error, we need to evaluate the contribution made by

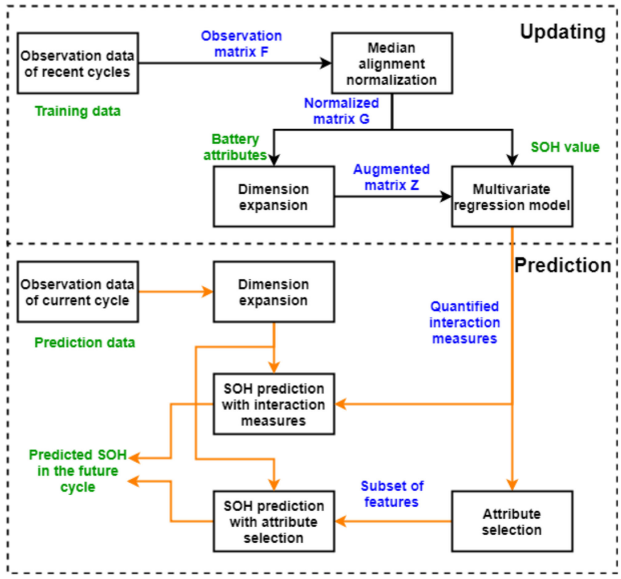

Fig. 2. Summary of the proposed framework.

attributes $\{x_1, x_2, \ldots, x_N\}$ and their interactions on the predicted SOH. However, battery degradation is a dynamic complex process due to the existence of uncertainty and nonlinearity [30]. As a result, the prediction model has to be updated periodically to generate the time-varying system function under dynamic environment. In addition, since SOH prediction is based on a nonlinear function of attributes, it is difficult to derive a closed-form expression for the prediction model. Furthermore, due to the uncertainty and randomness existing in battery degradation process, it is challenging to characterize the interactions among attributes that may significantly affect the predicted SOH values. To gain in-depth understanding of SOH degradation, it is highly desirable to quantitatively measure the contribution of each subset of attributes in $\{x_1, x_2, \ldots, x_N\}$. Motivated by these challenges, we propose a SOH prediction framework based on the properties of interaction measures.

C. SOH Prediction With Reduced Amount of Data Sets

In this subsection, we present the proposed framework that enables fast convergence in learning the SOH prediction model, so that it can be operated with reduced amount of observation data collected from only recent charge/discharge cycles. The process of SOH prediction is shown in Fig. 2, which includes the preprocessing for incommensurable data set, nonlinear multivariate regression for quantification of interaction measures, and prediction of future cycles based on partial observation. We organize the observed battery attributes and SOH values as matrix X and vector Y

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ x_{q1} & x_{q2} & \cdots & x_{qN} \\ \vdots & \vdots & \vdots & \vdots \\ x_{Q1} & x_{Q2} & \cdots & x_{QN} \end{bmatrix}, Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_q \\ \vdots \\ y_N \end{bmatrix} \quad (2)$$

Algorithm 1: Median Alignment Normalization of Operation Data.

Input: observation matrix $X = \{x_{ij}\}$, N, Q
Output: normalized observation matrix $G = \{g_{ij}\}$
1: **for** $j = 1 : N$ **do**
2: $X_j = \{x_{1j}, x_{2j}, \ldots, x_{Qj}\}$
3: $M[j] = median(X_j)$
4: **for** $i = 1 : Q$ **do**
5: $g_{ij} = x_{ij} * M[1]/M[j]$
6: **return** $G = \{g_{ij}\}$

where each row of X represents an observation of battery attributes in a charge/discharge cycle. The fineness of different attributes in X usually have large difference, resulting in the interaction measures to have bias towards attributes with larger scales. To guarantee all attributes share the same scale level, we need to pre-process the incommensurable observation dataset with median alignment normalization as implemented in Algorithm 1. After pre-processing, the observation matrix X is transformed into normalized matrix G.

After normalization, all attributes in operation dataset share identical median and similar scale levels. To formulate the prediction model, Choquet integral is applied to achieve interaction measures and significance analysis for battery attributes. The Choquet integral is a generalization of the Lebesgue integral, defined over a set of non-additive measures

$$z = (C)\int_S x d\mu = \sum_{s \in P(S)} \mu_s f(s), \tag{3}$$

where z is the objective value, $S = \{x_1, x_2, \ldots, x_N\}$ is a set the attributes, s is a subset of S, μ is the proposed interaction measure on subset s, and $f(s)$ is the tuple of evaluated values on s determined by all of the involved attributes $\{x | x \in s\}$. In this case, Choquet integral provides nonadditivity to the prediction model and quantitatively measures the interactions among attributes towards the objective value.

To derive the interaction measures among all attributes from operation data, a multivariate regression model is generated after median alignment normalization, so that normalized matrix G is applied as training dataset

$$Y = e + (C)\int_S g d\mu + N(0, \delta^2), \tag{4}$$

where Y is the real SOH, e is the regression constant that represents the bias of model when no attributes is used for prediction, $(C)\int_S$ is the Choquet integral over the attribute full set S, g is the normalized input attribute values, μ is the non-additive measure that describes the interactions among attributes, $N(0, \delta^2)$ is the normally distributed random perturbation with expectation 0 and variance δ^2, and δ^2 is the regression residue error. Suppose the operation data of battery charging/discharging process contains N attributes and Q cycles, the size of interaction measures should be 2^N equaling to the number of subsets in $\{x_1, x_2, \ldots, x_N\}$. To denote the interaction measures for different subsets, a positive integer $k < 2^N$ is used as index, which can be expressed in binary form $k = k_N k_{N-1} \ldots k_n \ldots k_1$ and each k_n represents the binary value in the n^{th} bit. Denote X_k as the subset of attributes in $X = \{x_1, x_2, \ldots, x_N\}$ such that $X_k = \cup_{n \in \{n | k_n = 1\}} \{x_n\}$. The interaction measure of X_k is denoted as $\mu_k = \mu(X_k)$. For example, as $k = 5 = 0 \ldots 0101_2$, $k_1 = k_3 = 1, k_2 = k_4 = \cdots = k_N = 0$, we can use μ_5 to denote the interaction for subset $\{x_1, x_3\}$.

To calculate the Choquet integral in Eq. (4), the dimensionality of normalized observation matrix G needs to be expanded to fit the size of interaction measure μ defined over the power set of X. Given N attributes and Q cycles, the $Q - by - N$ normalized matrix G is transformed into a $Q - by - 2^N$ augmented matrix Z. For each row in the matrix:

$$z_{i0} = 1, z_{ik} = \max\left\{ \min_{j \in \{j | k_j = 1\}} \{g_{ij}\} - \max_{j \in \{j | k_j = 0\}} \{g_{ij}\}, 0 \right\} \tag{5}$$

where $i = 1, 2, \ldots, Q,\ j = 1, 2, \ldots, N,\ k = 1, 2, \ldots 2^N - 1$, and k_n is the n^{th} bit in the binary form of k. The nonlinear multivariate regression model in Eq. (4) can be expressed in matrix form

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_Q \end{bmatrix} = \begin{bmatrix} 1 & z_{11} & \cdots & z_{1(2^N-1)} \\ 1 & z_{21} & \cdots & z_{2(2^N-1)} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & z_{Q1} & \cdots & z_{Q(2^N-1)} \end{bmatrix} * \begin{bmatrix} e \\ \mu_1 \\ \mu_2 \\ \vdots \\ \mu_{2^N-1} \end{bmatrix} + N(0, \delta^2). \tag{6}$$

The interaction measures $\{e, \mu_1, \mu_2, \ldots, \mu_{2^N-1}\}$ cover all possible attribute combinations, including the null set represented by regression constant e indicating the bias when no attribute is applied. We formulate the relation between augmented matrix Z and vector μ in Eq. (6) as a linear relation for simplicity of supervised learning. As Z and μ expand the dimension of training dataset from N to 2^N, the linear relationship is sufficient to approximate the system function between battery attribute and SOH values accurately. Given the operation data, the solution for μ_k can be determined by using the least square method to minimize residue error δ^2

$$\mu = (Z^T Z)^{-1} Z^T y. \tag{7}$$

The regression residue error δ^2 can be calculated by

$$\delta^2 = \frac{1}{Q} \sum_{i=1}^{Q} \left(y_i - e - \sum_{k=1}^{2^N-1} z_{ik} \mu_k \right)^2. \tag{8}$$

The quantified interaction measures $\{e, \mu_1, \mu_2, \ldots, \mu_{2^N-1}\}$ are also needed to predict SOH for future cycles. As the interaction are measured based on normalized operation data with aligned attribute scales, they are necessary to be denormalized to fit the original scales of attributes before prediction. The denormalization of interaction measures is implemented in Algorithm 2.

After denormalization, the prediction model can be generated based on the obtained interaction measures and the attribute values of current cycle. However, due to the dynamic environment of battery degradation process, the prediction model has to be updated repeatedly with the operation data collected recently. The observation is conducted in short term for SOH prediction

Algorithm 2: Denormalization of Interaction Measures.

Input: observation matrix $X = \{x_{ij}\}$, derived interaction measures $\{\mu_1, \mu_2, \ldots, \mu_{2^N-1}\}$, N

Output: denormalized interaction measures $\{\omega_1, \omega_2, \ldots, \omega_{2^N-1}\}$

1: **for** $j = 1 : N$ **do**
2: $X_j = \{x_{1j}, x_{2j}, \ldots, x_{Qj}\}$
3: $M[j] = median(X_j)$
4: **for** $s = 1 : (2^N - 1)$ **do**
5: **for** $j = 1 : N$ **do**
6: $s_j \leftarrow n^{th}$ lowest bit of binary form of s
7: $k_j = s_j * M[1]/M[j]$
8: **for** $i = 1 : (2^N - 1)$ **do**

$$min_{j\in\{j|s_j=1\}}\{k_j\} - max_{j\in\{j|s_j=0\}}\{k_j\} :$$

9: $t_i = \{if\, i\, is \geq 0$

$$0 : otherwise$$

10: $\omega_s = \sum_{i=1}^{2^N-1}(t_i * \mu_i)$
11: **return** $\{\omega_1, \omega_2, \ldots, \omega_{2^N-1}\}$

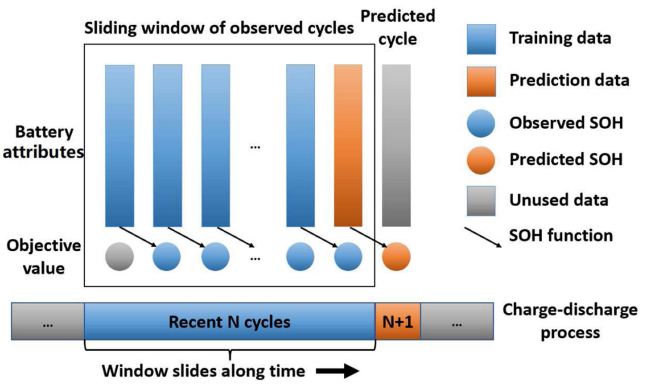

Fig. 3. Prediction procedure with sliding window of N recent observation cycles: the attributes of first $N-1$ cycles are used as training data to model the relationship between attributes in current cycle and SOH in next cycle; the attributes of last/current cycle are used as prediction data to forecast the SOH in the future; the rest of cycles beyond the sliding window are irrelevant to SOH prediction in this cycle.

by using a sliding window that determines which cycles are used as training data. As shown in Fig. 3, the sliding window involves N most recent observation cycles including the current cycle. The attributes of previous $N-1$ cycles are used to form the aforementioned observation matrix in regression model, and the SOH of their next cycles are treated as objective values. The denormalized interaction measures $\{e, \omega_1, \omega_2, \ldots, \omega_{2^N-1}\}$ can be derived from previous $N-1$ observations to quantify the impacts of different attribute subsets on objective value of next cycle. Given the current attributes, the attribute vector can be expanded into higher dimension in the same way as the augmented observation matrix Z using Eq. (5). Then SOH of next cycle $N+1$ can be predicted

$$\hat{y} = \sum_{k=1}^{2^N-1} z_k \omega_k + e \tag{9}$$

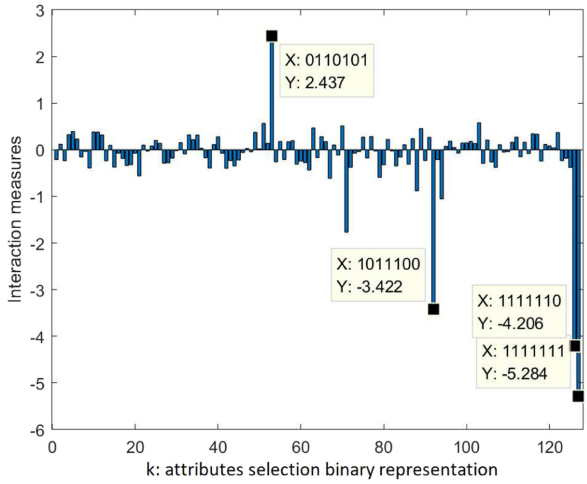

Fig. 4. Interaction measures of attribute subsets: let index $k = 0\ldots127$ represents the elements in attribute subsets, transform k into binary value so that $k = \{0,1\}^7$. The i^{th} attribute is in the subset if $k_i = 1, i = 1\ldots7$.

where $\hat{y}$ is the predicted SOH in future cycle, z_k is the augmented vector calculated with Eq. (5) based on current attributes, ω_k is the derived interaction measure, e is the derived regression constant. By applying sliding window, the proposed framework only relies on the observation of recent cycles to generate prediction model. As the window slides, the model keeps being updated based on the changes of operation data, so that the deduced SOH function is time-varying and adaptive to the dynamic operating environment. By utilizing interaction measures, the proposed framework can guarantee the prediction accuracy even if the monitored battery operates for only a limited number of cycles.

D. SOH Prediction With Subsets of Battery Attributes

In the previous subsection, we illustrate that the proposed framework is capable of handling the challenge of insufficiency of training data with the assistance of interaction measures. However, there are other two challenges remain in the SOH prediction problem for battery system. The frequent update of prediction model requires the algorithm to be computationally efficient. Meanwhile, numerous number of model attributes can be involved in the prediction model to cause overfitting and high computational cost. The proposed framework tends to tackle these challenges through proper attribute selection, so that tradeoff can be achieved between prediction accuracy and computational overhead. Once the interaction measures $\{e, \mu_1, \mu_2, \ldots, \mu_{2^N-1}\}$ are obtained, the framework is able to identify which subsets of attributes have higher significance to determine the predicted SOH.

Fig. 4 shows an example of quantified interaction measures among 7 model attributes. The absolute values of interaction measures indicate the aggregated contribution of corresponding attribute subsets on SOH prediction. It can be observed that the full set of attributes has the largest contribution, which implies that the accuracy becomes the highest if all attributes are applied to train the prediction model. The subset with second largest contribution excludes the last attribute, which implies that the accuracy slightly decreases if the last attribute is ignored. If more

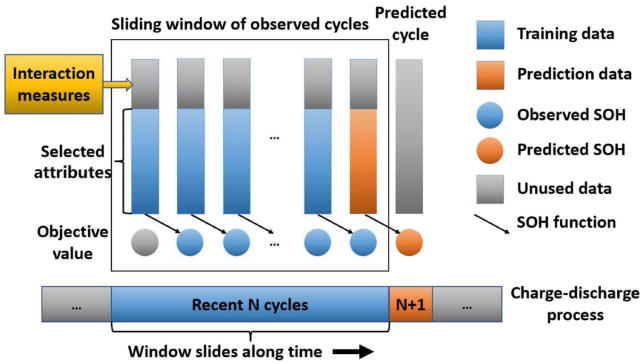

Fig. 5. Prediction procedure integrated with attribute selection based on interaction measure: part of the model attributes are discarded to reduce computational cost while maintaining sufficient accuracy. The amount of training data is determined by the size of sliding window. The model dimension is determined by the selection of attribute subset.

Fig. 6. Equipments for battery SOH degradation experiment.

computational cost needs to be reduced, the subset with third largest contribution can be selected, which contains the first, third, fourth and fifth attribute. This example demonstrate how attribute selection can be performed based on the quantification of interaction measures. By adjusting model dimensionality, overhead-accuracy tradeoff can be balanced according to the requirements of applications. Fig. 5 illustrates the process to generate the prediction model integrated with attribute selection. Therefore, by applying the proposed framework, SOH prediction can be performed based on both limited operation data and small number of attributes while achieving sufficient accuracy and low computational cost.

IV. Experimental Results

In this section, we evaluate the proposed framework for SOH prediction on a lithium-ion battery to evaluate the effectiveness of the framework and illustrate the tradeoff between accuracy and computational overhead. The following subsections include experiment environment, prediction results and result analysis.

A. Experiment Environment

To collect operation data of battery degradation process, a lithium-ion battery is fully charged and discharged with 1 C rate repeatedly as shown in Fig. 6. The monitored battery has nominal capacity of 27Ah and median voltage of 3.2 V. The battery SOH degradation experiment is conducted under the temperature of both 25 °C and 55 °C, where 2668 and 940 cycles are observed respectively. For each cycle, there are seven operating attributes of the monitored battery collected. The raw data of observed attributes and SOH values are presented in Table. II. In this experiment, training data is added with random noise in normal distribution $\hat{x} \sim N(x, 0.01x)$, where x is the original attribute values and $\hat{x}$ is applied training data carrying the uncertainty in data measurement. SOH prediction is repeated for multiple iterations with data affected by white noise, so that the mean and variance of the normalized prediction error can be computed to validate the robustness of the proposed framework against measurement uncertainty. In each iteration, we firstly generate prediction model with all the attributes to derive interaction measures of their subsets based on the limited observation cycles within a sliding window. As the window slides over time, the SOH of future cycles are predicted and compared to the real values. Different sizes of sliding window are adopted to show how the amount of operation data can affect the prediction accuracy and computational time. Secondly, we reduce model dimensionality by selecting subsets of attributes based on their interaction measures and repeat the prediction procedure. Different window sizes and number of attributes are adopted to illustrate how the overhead-accuracy tradeoff can be balanced by selecting proper training data volume and attributes. Therefore, the experimental results are presented in the following subsection with three variations: (1) sizes of sliding window to collect operation data; (2) number of attributes in selected subsets; (3) temperatures of operating environment. The proposed framework is implemented and run on a computer with Intel Core i7-6600 U processor at 2.6 GHz using 16 GB of RAM, running Win10 Pro version.

TABLE II
Raw Data of Observed in Charging/Discharging Cycles

Sequence number	1	2	3	...
Charging capacity(Ah)	26.739	26.829	26.882	...
Constant current ratio(%)	98.45	98.12	98.77	...
Charging efficiency(%)	99.998	99.992	99.964	...
Charging energy(Wh)	90.458	90.65	90.773	...
Discharging energy(Wh)	85.024	85.287	85.281	...
Median voltage(V)	3.211	3.213	3.212	...
SOH (%)	100	99.9	99.9	...

B. Prediction Results

1) Different Window Sizes: As shown in Table II, 7 attributes are collected from the monitored battery. The prediction model is generated with the operation data of recent cycles within the sliding window, for which the sizes of 10, 20, and 30 cycles are adopted, respectively. The comparison between predicted SOH and real SOH under 25 °C and 55 °C are presented in Fig. 7 with magnified details of the plots. Under both environment temperatures, the prediction errors of most cycles are below 1%, which validates the effectiveness of our proposed framework with reduced number of training data. The influence of various window sizes on the prediction results is further discussed in the next subsection.

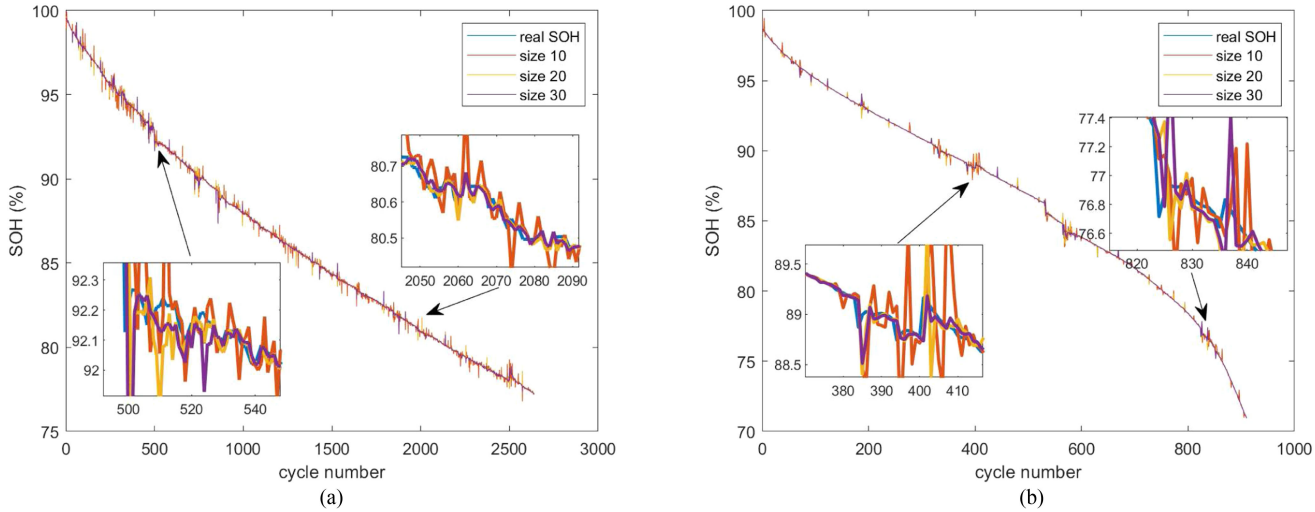

Fig. 7. Real and predicted SOH using different sizes of sliding window: (a) under 25 °C environment: the details are magnified around 500th and 2100th cycles and the prediction errors are within 1%; (b) under 55 °C environment: the details are magnified around 400th and 850th cycles and the prediction errors are also within 1%.

TABLE III
NOTATIONS OF MODEL ATTRIBUTES IN THE EXPERIMENT

attribute	Notation
Cycle number	α
Charging capacity (Ah)	β
Ratio of constant current (%)	γ
Charge/discharge efficiency (%)	δ
Charging energy (Wh)	ϵ
Discharging energy (Wh)	ζ
Median voltage (V)	ν

TABLE IV
TOP 5 MOST SIGNIFICANT ATTRIBUTE SUBSETS AND THEIR INTERACTION MEASURES

Temperature 25°C			Temperature 55°C		
Set	Features	Measure	Set	Feature	Measure
1	$(\beta, \gamma, \delta, \epsilon, \zeta)$	4.627	1	$(\alpha, \beta, \gamma, \delta, \epsilon, \zeta)$	4.687
2	$(\alpha, \beta, \gamma, \delta, \epsilon, \zeta)$	4.627	2	$(\beta, \gamma, \delta, \epsilon, \zeta)$	4.686
3	$(\gamma, \delta, \epsilon, \zeta)$	4.546	3	$(\gamma, \delta, \epsilon, \zeta)$	4.304
4	$(\alpha, \beta, \gamma, \delta, \epsilon, \zeta, \nu)$	4.533	4	$(\beta, \gamma, \delta, \epsilon, \zeta, \nu)$	4.282
5	$(\alpha, \gamma, \delta, \epsilon, \zeta)$	0.946	5	$(\gamma, \delta, \epsilon)$	0.910

2) Different Attributes Subsets: To further reduce the computational cost while maintaining sufficient accuracy, attribute selection is performed before generating the prediction model in the experiment. All the observed attributes are denoted as shown in Table III. Our proposed framework quantitatively measures the interactions among these attributes on SOH based on the whole operation dataset. The top 5 subsets with the most contributions on SOH prediction are presented in Table IV for both environment temperatures. Under both temperatures, we apply the top 3 subsets to generate the prediction model with the number of attributes 4, 5, and 6 respectively. The size of 20 cycles for sliding window is applied as the experiment parameter according to the prediction results obtained in the previous subsection. The predicted SOH of different numbers of attributes are compared with the real values and presented in Fig. 8. We can observe that even if the model dimension is reduced from seven to four, our proposed framework can still provide accurate SOH prediction as long as proper attribute set can be selected based on quantified interaction measures.

C. Tradeoff Balancing and Comparison

To further discuss the impacts of different sliding window sizes and numbers of attributes on SOH prediction performance, we apply three metrics to evaluate our proposed framework. The first metric is the mean value of prediction errors to evaluate the general accuracy

$$mean = \sum_{i \in O} \frac{|SOH_i^{pred} - SOH_i^{real}|}{SOH_i^{real}} \tag{10}$$

where O is the set of all observed cycles, SOH_i^{pred} is the predicted SOH of cycle i, and SOH_i^{real} is the real SOH of cycle i. The second metric is the variance of prediction errors to evaluate the constancy of prediction results

$$variance = \frac{1}{|O|} \sum_{i \in O} \left(\frac{|SOH_i^{pred} - SOH_i^{real}|}{SOH_i^{real}} - mean \right)^2 \tag{11}$$

The third metric is the computational time to complete SOH prediction for all observed cycles. The comparison of three metrics under different sliding window sizes and attribute numbers are presented in Fig. 9 and Fig. 10, respectively.

From the experimental results we can observe several outcomes. Firstly, for both temperature conditions, increasing the size of sliding window provides better accuracy, lower variance of prediction error and higher computational time. In this experiment, an appropriate choice for window size can be 20 cycles, which guarantees the framework performance to be accurate and constant while achieving sufficient efficiency. However, the optimal value of sliding window size may vary among different application scenarios. The window size optimization are affected by several factors. For example, if the data measurement for battery operating condition has low frequency, the window size need to be decreased to avoid involving old observation data that

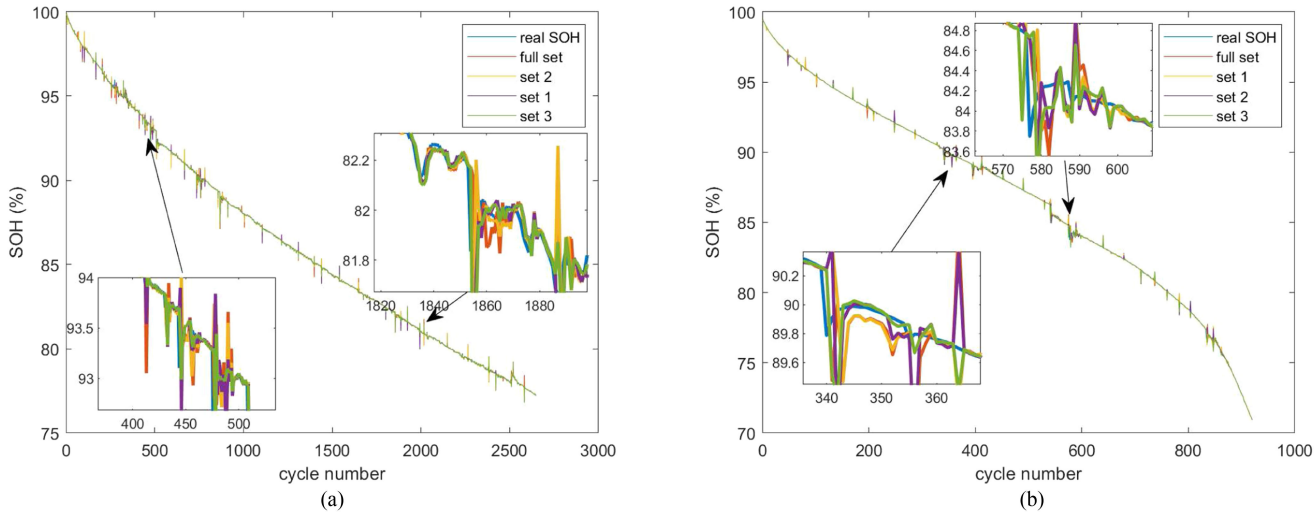

Fig. 8. Real and predicted SOH using different numbers of attributes: (a) under 25 °C environment: the detail is magnified around 450th and 1850th cycles; (b) under 55 °C environment: the detail is magnified around 350th and 600th cycles.

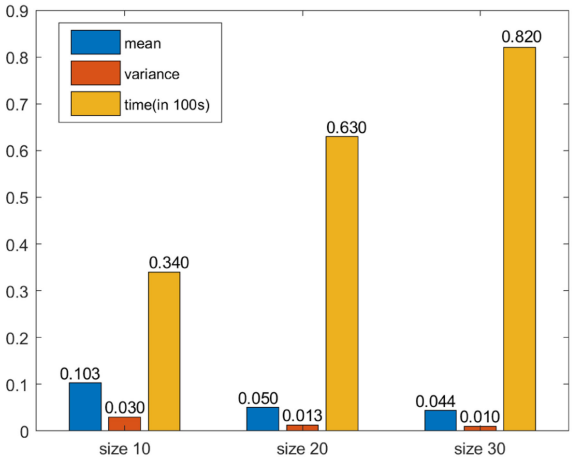

Fig. 9. Prediction error mean, variance and computational time under 25 °C environment: the metric values are grouped into sliding window sizes of 10, 20, and 30 cycles. For convenience, the computational time uses 100-second as unit to have a similar scale to the error mean and variance.

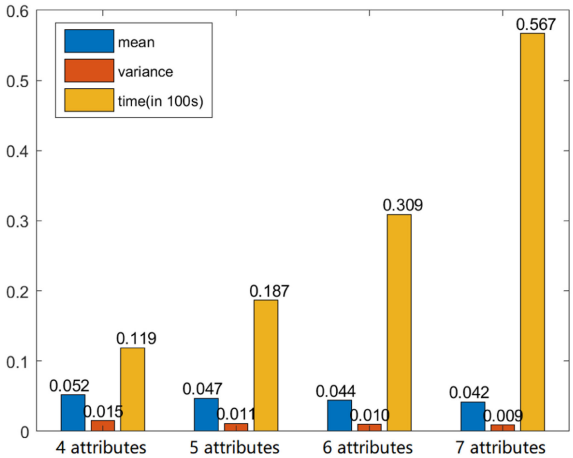

Fig. 10. Prediction error mean, variance and computational time under 25 °C environment: the metric values are grouped into model dimensions of 4, 5, 6, and 7 attributes.

may affect prediction accuracy. In some cases, such as embedded devices with limited computational power, users may apply a smaller window to reduce the modeling overhead. Depending on the resource constraints and application requirements, our proposed framework allows users to achieve overhead-accuracy tradeoff under different scenarios by adjusting sliding window size. The comparison of window sizes validate that the proposed framework achieves fast convergence in modeling, so that SOH prediction can rely on data collected from only recent charge/discharge cycles. The SOH prediction model can therefore be updated frequently to keep track of the time-varying battery electrochemistry and working condition. Secondly, the experimental results verify that by adjusting the attribute number, we can remove less significant attributes from the prediction model and still maintain its accuracy and constancy. Attribute selection can be performed by identifying the impacts of different subsets of battery attributes on SOH, so that on one hand the dimensionality of the prediction model can be substantially reduced to avoid overfitting and save computational cost. On the other hand, decreasing the number of attributes does not have obvious impact on prediction error mean and variance. By removing insignificant battery attributes from the prediction model, SOH prediction can reduce its computational cost substantially while maintaining accuracy and constancy.

Although the existing dimension reduction methods can also reduce model complexity, such as Principle Component Analysis and Factor Analysis, the attribute selection in our proposed framework has unique advantages. Firstly, it does not require additional computation to apply specific algorithms, since the attribute selection is based on the interaction measures that are already obtained. Secondly, instead of creating new aggregated dimensions, applying original battery attributes can preserve their physical meanings, so that the formulated prediction model is more understandable to achieve deeper insight on the behavior of SOH degradation. In the case under 25 °C temperature, we can have the following observations about attribute selection: (1) Given the same experiment conditions, the attribute combination

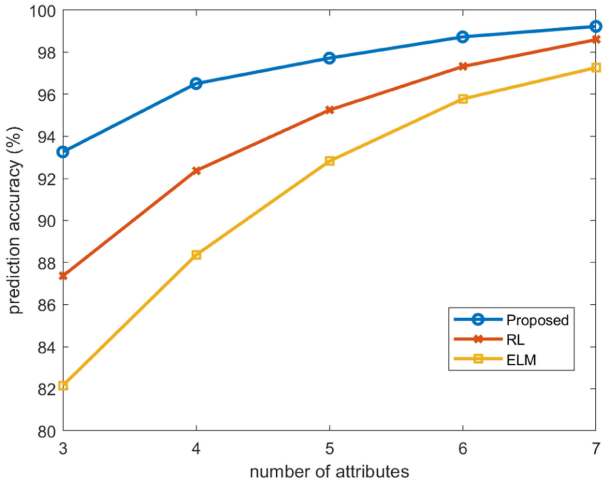

Fig. 11. Prediction accuracy by applying different numbers of attributes: the proposed framework select attributes based on interaction measures; RL and ELM select attributes randomly and iterate selection for multiple times to compute the average accuracy.

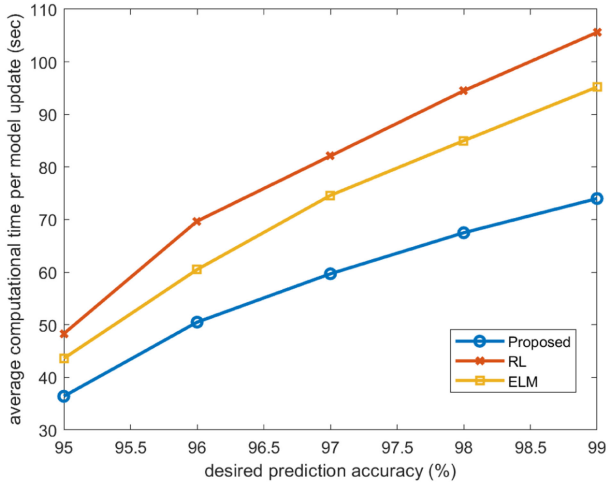

Fig. 12. Average computational time per model update versus desired prediction accuracy: the proposed framework maintains the lowest modeling overhead compared with RL and ELM.

of charging capacity, ratio of constant current, charge/discharge efficiency, charging energy, and discharging energy has the most contribution on SOH prediction for the monitored battery. Changing values of these attributes is expected to result in the largest impact on predicted SOH; (2) Applying full set of attributes does not necessarily provide most accurate formulation of SOH function. Involving the other attributes into prediction, such as cycle index and median voltage, can instead attenuate the aggregated impact of attribute set on SOH; (3) The reason of less interaction among full set of attributes is that some attributes have opposite influences on the objective value. For example, the increment of cycle index indicates that the battery has been operated for longer time, for which its SOH tends to decrease. While some other attributes have positive correlation with the objective value, the attributes in the subset have less interaction after including cycle index. Through changing the window size and attribute number, the proposed framework allows the amount of training data and model dimension to be adjusted flexibly. It is crucial for the configurations of prediction framework to be changeable and adaptive, since the electrochemical characteristics of monitored battery vary from case to case, and the conditions of operating environment can be quite mutable.

To further illustrate the advantages of our proposed framework, we compare its performance with two existing SOH prediction methods based on reinforcement learning (RL) [28] and extreme learning machine (ELM) [29] in two aspects. Note that in the experiment, two benchmark methods update the prediction model with the same training data included in the sliding window as in the proposed framework. For the first aspect, all three methods are required to apply the same number of attributes for modeling to compare their prediction accuracy. The proposed framework selects attributes based on interaction measures, while two benchmark methods select attributes randomly, for which the random selections are repeated for multiple times to obtain their average accuracy. Fig. 11 validates that the proposed framework maintains reliable prediction accuracy compared to benchmark methods while reducing the model complexity through proper attribute selection. In comparison, decreasing the number of applied attributes in RL and ELM cause serious drops in accuracy. For the second aspect, all three methods are required to achieve the same accuracy by adjusting training data volume in term of window size and model complexity in term of number of attributes. The prediction model keeps being updated as new observation data are collected over operating time and included into the sliding window. The average computational time per model update are compared among the three methods to achieve different desired prediction accuracy. The result shown in Fig. 12 validates that compared with RL and ELM, the proposed framework reduces computational overhead substantially while maintaining favorable prediction accuracy. As the proposed framework can easily adjust the model dimension through attribute selection, the tradeoff can be balanced between prediction accuracy and computational overhead under different scenarios. Therefore, the proposed framework can adapt to various applications to provide accurate and consistent prediction, while fulfilling the requirements for quick response in real-time battery health monitoring, especially for embedded devices with limited computational power.

V. Conclusion

In this paper, we have proposed a theoretical framework for fast and accurate SOH prediction and in-depth understanding of battery SOH degradation process. Specifically, we have exploited non-additive measure theory to quantitatively characterizes the interactions among battery attributes and their aggregated impacts on predicted SOH. Based on the proposed framework, we have developed a SOH prediction algorithm with consideration of both accuracy and speed by 1) adjusting the amount of observed charge/discharge data and 2) selecting different subsets of battery attributes to learn the SOH prediction model. The experimental results validate that the proposed framework is capable of customizing its configuration upon the availability of training data and computation power. This unique advantage enables our proposed framework to adapt to various battery electrochemical characteristics, working conditions and application requirements. For the future work, we

will involve more relevant battery attributes, such as internal resistance, into training data to decrease model uncertainty and improve prediction accuracy of the proposed framework. New prediction algorithms will be developed and integrated with function approximation technique to handle the modeling of SOH degradation in higher dimensions.

REFERENCES

[1] N. Lin, S. Ci, D. Wu, and H. Guo, "An optimization framework for dynamically reconfigurable battery systems," *IEEE Trans. Energy Convers.*, vol. 33, no. 4, pp. 1669–1676, Dec. 2018.

[2] S. Shen, S. Ci, K. Zhang, and X. Liang, "Lifecycle prediction of second use electric vehicle batteries based on arima model," in *IEEE Globecom Workshops*, 2019, pp. 1–6.

[3] C. Lee, Z. Wu, S. Hsu, and J. Jiang, "Cycle life study of li-ion batteries with an aging-level-based charging method," *IEEE Trans. Energy Convers.*, vol. 35, no. 3, pp. 1475–1484, Sep. 2020.

[4] W. Yan, B. Zhang, G. Zhao, S. Tang, G. Niu, and X. Wang, "A battery management system with a lebesgue-sampling-based extended Kalman filter," *IEEE Trans. Ind. Electron.*, vol. 66, no. 4, pp. 3227–3236, Apr. 2019.

[5] Y. Ma, Y. Chen, X. Zhou, and H. Chen, "Remaining useful life prediction of lithium-ion battery based on gauss-hermite particle filter," *IEEE Trans. Control Syst. Technol.*, vol. 27, no. 4, pp. 1788–1795, Jul. 2019.

[6] H. Li *et al.*, "SOH-aware charging of supercapacitors with energy efficiency maximization," *IEEE Trans. Energy Convers.*, vol. 33, no. 4, pp. 1766–1775, Dec. 2018.

[7] X. Li *et al.*, "A capacity model based on charging process for state of health estimation of lithium ion batteries," *Appl. Energy*, vol. 177, pp. 537–543, 2016.

[8] W. Liu and Y. Xu, "A data-driven method for online health estimation of li-ion batteries with a novel energy-based health indicator," *IEEE Trans. Energy Convers.*, vol. 35, no. 3, pp. 1715–1718, Sep. 2020.

[9] H. Dai, G. Zhao, M. Lin, J. Wu, and G. Zheng, "A novel estimation method for the state of health of lithium-ion battery using prior knowledge-based neural network and Markov chain," *IEEE Trans. Ind. Electron.*, vol. 66, no. 10, pp. 7706–7716, Oct. 2019.

[10] H. Chaoui and C. C. Ibe-Ekeocha, "State of charge and state of health estimation for lithium batteries using recurrent neural networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 8773–8783, Oct. 2017.

[11] Y. Cui *et al.*, "State of health diagnosis model for lithium ion batteries based on real-time impedance and open circuit voltage parameters identification method," *Energy*, vol. 144, pp. 647–656, 2018.

[12] X. Bian, L. Liu, J. Yan, Z. Zou, and R. Zhao, "An open circuit voltage-based model for state-of-health estimation of lithium-ion batteries: Model development and validation," *J. Power Sources*, vol. 448, p. 227401, 2020.

[13] Z. Guo, X. Qiu, G. Hou, B. Y. Liaw, and C. Zhang, "State of health estimation for lithium ion batteries based on charging curves," *J. Power Sources*, vol. 249, pp. 457–462, 2014.

[14] J. Li, K. Adewuyi, N. Lotfi, R. G. Landers, and J. Park, "A single particle model with chemical/mechanical degradation physics for lithium ion battery state of health (SOH) estimation," *Appl. Energy*, vol. 212, pp. 1178–1190, 2018.

[15] L. Fang, J. Li, and B. Peng, "Online estimation and error analysis of both SOC and SOH of lithium-ion battery based on dekf method," *Energy Procedia*, vol. 158, pp. 3008–3013, 2019.

[16] D. Liu, X. Yin, Y. Song, W. Liu, and Y. Peng, "An on-line state of health estimation of lithium-ion battery using unscented particle filter," *IEEE Access*, vol. 6, pp. 40990–41001, 2018.

[17] J. Park, M. Lee, G. Kim, S. Park, and J. Kim, "Integrated approach based on dual extended Kalman filter and multivariate autoregressive model for predicting battery capacity using health indicator and SOC/SOH," *Energies*, vol. 13, no. 9, p. 2138, 2020.

[18] Z. Xue, Y. Zhang, C. Cheng, and G. Ma, "Remaining useful life prediction of lithium-ion batteries with adaptive unscented kalman filter and optimized support vector regression," *Neurocomputing*, vol. 376, pp. 95–102, 2020.

[19] S. E. Li, B. Wang, H. Peng, and X. Hu, "An electrochemistry-based impedance model for lithium-ion batteries," *J. Power Sources*, vol. 258, pp. 9–18, 2014.

[20] W. Liu and Y. Xu, "A data-driven method for online health estimation of li-ion batteries with a novel energy-based health indicator," *IEEE Trans. Energy Convers.*, vol. 35, no. 3, pp. 1715–1718, Sep. 2020.

[21] S. Song, C. Fei, and H. Xia, "Lithium-ion battery SOH estimation based on XGBoost algorithm with accuracy correction," *Energies*, vol. 13, no. 4, p. 812, 2020.

[22] C. Lei, J. Meng, D.-I. Stroe, J. Peng, G. Luo, and R. Teodorescu, "Multi-objective optimization of data-driven model for lithium-ion battery SOH estimation with short-term feature," *IEEE Trans. Power Electron.*, vol. 35, no. 11, pp. 11855–11864, Nov. 2020.

[23] H. Chaoui, C. C. Ibe-Ekeocha, and H. Gualous, "Aging prediction and state of charge estimation of a lifepo4 battery using input time-delayed neural networks," *Electric Power Syst. Res.*, vol. 146, pp. 189–197, 2017.

[24] Z. Chen, Q. Xue, Y. Liu, J. Shen, and R. Xiao, "State of health estimation for lithium-ion batteries based on elman neural network," *DEStech Trans. Environ., Energy Earth Sci.*, no. *iceee*, 2019.

[25] Z. Chen, M. Sun, X. Shu, R. Xiao, and J. Shen, "Online state of health estimation for lithium-ion batteries based on support vector machine," *Appl. Sci.*, vol. 8, no. 6, p. 925, 2018.

[26] J. Jia, J. Liang, Y. Shi, J. Wen, X. Pang, and J. Zeng, "SOH and RUL prediction of lithium-ion batteries based on gaussian process regression with indirect health indicators," *Energies*, vol. 13, no. 2, p. 375, 2020.

[27] D. Yang, X. Zhang, R. Pan, Y. Wang, and Z. Chen, "A novel gaussian process regression model for state-of-health estimation of lithium-ion battery using charging curve," *J. Power Sources*, vol. 384, pp. 387–395, 2018.

[28] X. Hu, T. Liu, X. Qi, and M. Barth, "Reinforcement learning for hybrid and plug-in hybrid electric vehicle energy management: Recent advances and prospects," *IEEE Ind. Electron. Mag.*, vol. 13, no. 3, pp. 16–25, Sep. 2019.

[29] H. Pan, Z. Lü, H. Wang, H. Wei, and L. Chen, "Novel battery state-of-health online estimation method using multiple health indicators and an extreme learning machine," *Energy*, vol. 160, pp. 466–477, 2018.

[30] D. Wu, S. Ci, H. Luo, and H.-F. Guo, "A theoretical framework for interaction measure and sensitivity analysis in cross-layer design," *ACM Trans. Model. Comput. Simul.*, vol. 21, no. 1, pp. 1–26, 2010.

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