# Predictive Battery Health Management with Transfer Learning and Online Model Correction

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# Predictive Battery Health Management with Transfer Learning and Online Model Correction

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***Abstract*—Significant progress has been made in transportation electrification in recent years. As the main energy storage device, lithium-ion batteries are one of the key components that need to be properly managed. The remaining useful life, which represents battery health, has attracted increasing attention. Because accurate and robust predictions provide important information for predictive maintenance and cascade utilization. This paper proposes a novel method to predict remaining useful life based on the optimized health indicators and online model correction with transfer learning. Gaussian process regression is used to optimize the threshold for health indicators to determine the end of life, and a usefulness evaluation strategy is proposed to assess the health indicators. Then, a combination of transfer learning and gated recurrent neural network is designed to predict the remaining useful life based on the optimized health indicators directly, which can promote online applications. The prediction model initially trained based on a relevant battery is further fine-tuned according to the early degradation cycling data of the test battery to provide accurate predictions. Moreover, a self-correction strategy is proposed to retrain the regression models so that the models can gradually reach the optimal prediction performance during the operating cycles, which could not be achieved by traditional methods. The recommended input sequence lengths for potential applications are discussed. The method is verified by experiments of a batch of batteries under fast charging conditions, and the results show that, after fine-tuning, the proposed method predicts remaining useful life with an error of fewer than 5 cycles.**



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***Index Terms*—Batteries, remaining useful life, health management, transfer learning, predictive maintenance.**

## I. INTRODUCTION

ELECTRIFIED transportation is developing rapidly worldwide, which helps reduce greenhouse gas emissions and alleviate global warming. As the main energy storage device, lithium-ion batteries are one of the key components in electrified transportation systems. However, lithium-ion batteries will suffer from capacity and power degradation during operation and storage due to lithium inventory loss, active material loss, and impedance increase [1]. A major challenge is to develop advanced battery health management technologies to effectively manage lithium-ion batteries [2]. Accurate and reliable prediction of remaining useful life (RUL) provides important information for predictive maintenance and cascade utilization [3]. Advanced prediction methods are urgently needed. Generally, two types of methods are designed for RUL prediction, including model fitting and data-driven.

Methods based on model fitting can be further divided into semi-empirical methods and empirical methods [4]. Through offline testing of some key parameters, such as static capacity and electrochemical impedance spectrum, under different discharge depths, temperatures, and other conditions, the semi-empirical method maps the degradation to these parameters [5]. One obvious disadvantage is that this method requires a lot of experiments and labor costs. Different from the semi-empirical method, the empirical method fits models, such as linear, exponential, and polynomial models, by continuously updating the parameters through the measured/estimated parameters during cycling [6]. Most Bayesian filtering methods, including Kalman filter (KF), particle filter (PF), and their variants, can be used to update the parameters during cycling [7]. However, the accuracy of empirical models is highly dependent on the fitted model. Due to the complex nature of the aging mechanisms, one single model may not be enough to capture the complex degradation process.

Data-driven RUL prediction methods have been studied extensively and have many advantages, such as model-free, high accuracy, and strong robustness [8]. Unlike model-fitting methods that require specific model expressions, data-driven methods use machine learning or deep learning techniques to learn historical degradation[9]. Then, the future capacity values are predicted based on the trained model until the capacity reaches the end of life (EOL), which is usually defined as a 20% or 30% capacity loss of the nominal capacity [10]. And RUL is

TABLE I
THE SPECIFICATIONS OF THE TESTED BATTERIES

| Parameters | Value |
|---|---|
| Battery type | APR18650M1A |
| Capacity | 1.1 Ah |
| Environmental temperature | 30 ℃ |
| Voltage range | 2.0-3.6 V |
| Charge protocol: 4.8-5.2-5.2-4.16 C | Ce11#1-Cell#5 |
| Charge protocol: 3.6-6-5.6-4.755 C | Ce11#6-Cell#10 |
| Charge protocol: 4.4-5.6-5.2-4.252 C | Ce11#11-Cell#15 |
| Charge protocol: 6-5.6-4.4-3.834 C | Ce11#16-Cell#20 |
| Charge protocol: 5.2-5.2-4.8-4.16 C | Ce11#21-Cell#24 |

defined as the interval between EOL and the current cycle [11]. However, in most real applications, it is difficult to measure battery capacity directly due to incomplete discharge. Therefore, some health indicators (HIs) are extracted from the measured parameters to estimate capacity or state of health (SOH) [12, 13]. The SOH is defined as the ratio of current capacity to rated capacity in this paper. The HIs generally refer to the features extracted from the charging or discharging processes, which show regular variations with the aging status. Many researchers [14-16] have extracted various HIs and verified their effect by analyzing the correlation coefficients between capacities and using them for capacity/SOH estimation. Then, the estimated capacity or SOH is used for RUL prediction [17]. The two keys to RUL prediction are the HI selection for capacity estimation and the algorithm for regression model training [18]. Machine learning including support vector machine, Relevance vector machine, and Gaussian process regression (GPR) are usually used for model mapping [19, 20]. However, these machine learning methods are mostly affected by the phenomenon of capacity regeneration and cannot make long-term predictions. Recently, deep learning and extreme learning have become popular in the field of battery state estimation and health prediction due to their powerful ability to achieve accurate long-term degradation predictions [21, 22]. Recurrent neural networks (RNNs) are most commonly used because they can memorize the previous states [23]. However, the problems of vanishing gradient and gradient explosion will affect the prediction performance of traditional RNNs. Therefore, the gated RNNs (GRNN), including long short-term memory (LSTM) [24, 25] based and gated recurrent unit (GRU) [26] based, are proposed to solve the problem. These two methods determine what information is retained and what information is removed, so as to ensure the gradient changes normally.

Although data-driven methods have great prediction performance for RUL, there are still some shortcomings that limit their practical applications. For example, different HIs will affect the accuracy of capacity or SOH estimation and therefore the accuracy of RUL prediction. Besides, using estimated capacity/SOH to predict RUL has the problem of error accumulation. Moreover, batteries may experience different degradation patterns under different operating conditions, and how to make better use of available historical information is another challenge. Besides, it is also necessary to evaluate the input sequence of RNN to explore better input sequences with better accuracy and lower computational burden. In the actual applications for predictive maintenance, the estimation of capacity cannot be verified due to incomplete discharge. Therefore, it is of greater significance to directly use HIs for RUL prediction, which could be extracted during online usage. However, many HIs cannot be extracted effectively under fast charging conditions, and the different variation ranges of HIs will greatly affect the prediction performance. Therefore, it is necessary to evaluate the HIs when used for SOH estimation or RUL prediction.

This paper, for the first time, proposes a novel framework for battery RUL prediction under fast charging conditions based on optimized HIs and online model self-correction. The main contributions are summarized in the following four areas. 1) GRNNs are adopted for RUL prediction based on HIs, and transfer learning (TL) is proposed to improve the prediction accuracy by transferring the most useful information of source data. 2) A self-correction strategy is designed to perform threshold correction and RUL regression model adjustment during the operating cycles, thereby solving the model adaptation problem. 3) HIs are extracted from part of the data collected during fast charging, and the firstly proposed usefulness evaluation strategy proves that the extracted HIs used as an alternative to the estimated capacity is effective for battery RUL prediction. 4) An adaptive optimization method for probabilistic threshold search based on GPR is proposed.

The remainder of this paper is organized as follows, the experimental data and the HI extraction method are introduced in Section II. Then, the methods for usefulness evaluation and RUL prediction are proposed in Section III. Next, the results and discussion are presented in Section IV, and the main conclusion is summarized in Section V.

## II. DATA ACQUISITION AND HI EXTRACTION

Generally, cycling tests are conducted to accelerate the battery aging process to collect experimental data for the verification of SOH estimations and RUL predictions. The most commonly used charging protocol is the constant voltage and constant current (CC-CV) method. However, it is less used in actual xEVs. Recently, Massachusetts Institute of Technology (MIT) and Stanford University [27] provided experimental aging data under optimized fast-charging protocols using LiFePO4 (LFP) batteries. Batteries are charged to a SOC of 80% through four fast-charging stages and then charged to full SOC through the CC-CV stage. The fast-charging stages include multiple constant currents (CC1-CC4). In the first three stages, each stage uses the preset charging rate to complete 20% SOC charging. In the last stage, the charging rate is determined by ensuring that all protocols can charge the battery from 0% to 80% SOC in the same total time (10 minutes). All batteries are discharged at 4 C constant current until 2.0 V. In this study, 24 battery cells with the longest cycle life from the last batch (cycled to failure) are chosen, and their specifications are listed in Table I.

HI extraction is critical for RUL prediction. In our previous work, it has been verified that the change points between fast charging stages have a great correlation with capacity degradation [28, 29]. At such a large charging rate, HIs from the incremental capacity curve and differential voltage curve

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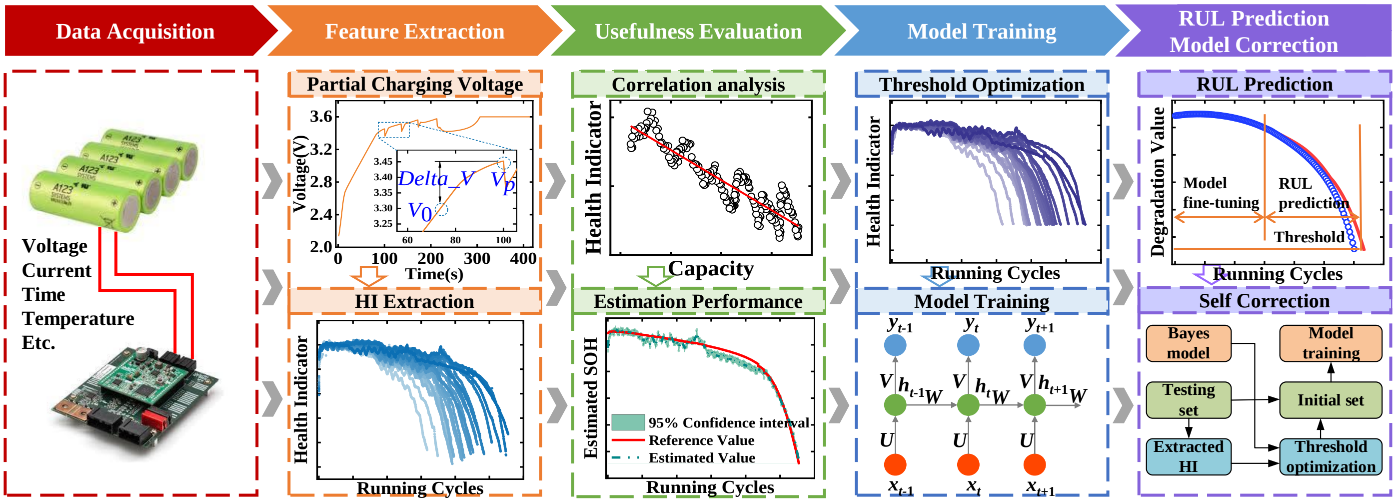


Fig. 1. Flowchart of the RUL prediction based on deep learning

cannot be extracted effectively. In this paper, in order to verify the RUL prediction without capacity data, the peak voltage ($V_p$) at the change point between the first two charging stages is used. Instead of using HI to estimate capacity/SOH and then using the estimated value for RUL prediction, this paper directly uses the optimized HI for RUL prediction to achieve online self-correction.

## III. Methodology

Data-driven RUL prediction usually includes data acquisition, data preprocessing, model training, and prediction [30]. In this paper, an improved method is proposed, which includes a self-correction function and a usefulness evaluation strategy, as shown in Fig. 1. Specifically, the HI will go through a usefulness evaluation process before being used for model training and prediction. The thresholds are optimized by GPR and then TL+GRNNs are used for regression training. After obtaining new measurement values, the models are corrected through a self-correction process. The details will be presented in the following subsections.

### A. Usefulness evaluation and threshold optimization

Although the most commonly used HIs in the literature have strong correlations with capacity, the degradation pattern of each battery is different, and the mapping between HIs and capacity may change under different degradation patterns, which may lead to poor capacity/SOH estimation. Battery capacity can be used for RUL prediction due to the fixed failure threshold (usually defined as 80% SOH). However, HIs usually have different values when the capacity reaches 80%, which will also lead to poor SOH estimation results and large prediction errors if the estimated SOH is used for RUL prediction. In addition, the capacity cannot be measured in actual applications. Therefore, it is very important to use extracted HIs instead of capacity for RUL prediction in actual predictive maintenance applications. In real applications, it usually uses one battery for model training and others for verification. So, the generality of HIs should be evaluated by the SOH/capacity estimation using one battery training for other battery estimation.

To reflect the capacity degradation, HIs should have the following characteristics when used for RUL prediction. 1) the value change during cycling (degradation process) should be smooth; 2) the variation of the HIs during cycling (from fresh to failure) should be large; 3) a great correlation with the capacity; 4) the suitability of replacing capacity, which can be evaluated by the capacity/SOH estimation performance based on the HIs; and 5) similar failure thresholds for HIs and EOL. In this paper, we propose these five criteria as the usefulness evaluation for HIs. One important step is to determine the threshold for different batteries using the same HI. Bayesian optimization has great advantages in automating design choices and has been used in many prediction problems [31]. GPR is a popular method that uses the Bayesian framework for regression tasks, which provides prediction results with uncertainties. In this paper, the GPR is used to optimize the threshold for test batteries. The detailed calculation process of the GPR method can be found in our previous studies [28, 32]. For the threshold optimization here, the historical values of $V_p$ are selected as the inputs, and the output is the delta voltage ($\Delta$) that $V_p$ minuses. All the data of source batteries are used to develop the GPR regression model. Then, the trained model is used for the test battery, and extracted HI is used for delta voltage optimization. The GPR model could be further updated when more HIs are extracted. In this way, HIs are reduced to 80% when capacity is reduced by 20%, and the delta voltage ($\Delta$) is calculated by,

$$\Delta = 5 * V_{p,initial} - 4 * V_{p,\mathrm{end}}, \tag{1}$$

where, $V_{p,initial}$ *and* $V_{p,end}$ are the initial value and last value of the HI. In this way, each HI ($V_{p,normal}$) is normalized by,

$$V_{p,normal} = (V_{p,initial} - \Delta) / (V_p - \Delta). \tag{2}$$

Due to the simple acquisition process, the threshold can be modified repeatedly, so that the model has a good self-correcting ability, thereby improving the accuracy during operating cycles in actual applications.

### B. Gated recurrent neural network

Once the HI satisfied the above usefulness evaluation criteria, it can be used as an alternative to capacity for RUL predictions. Due to the nonlinear mapping capability and strong prediction

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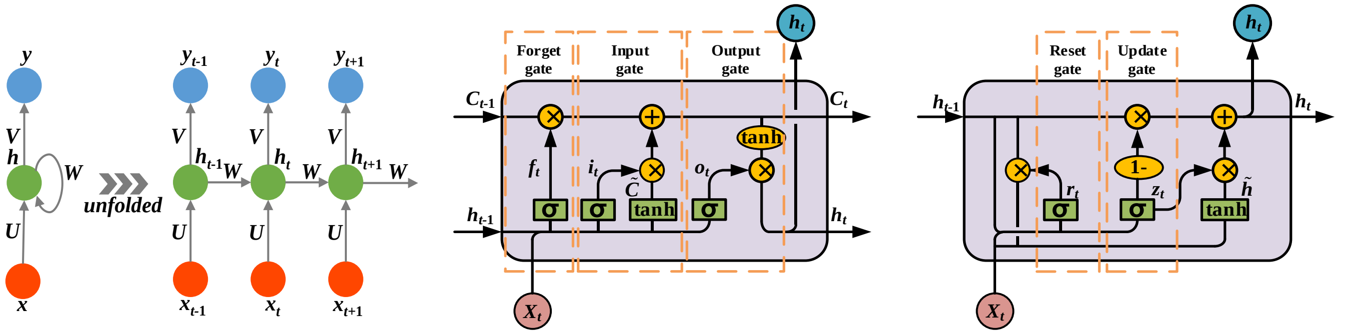


(a) Typical structure of RNN (b) Internal information transfer process of LSTM cell (c) Internal information transfer process of GRU cell

Fig. 2. Structure and information transfer process for GRNN.

performance based on historical information, RNNs have great advantages for battery RUL prediction. One typical structure of RNN is shown in Fig. 2(a), where the output of the previous step is combined with the input of the current step to form the inputs. For an input sequence $\boldsymbol{x}=[x_1, x_2, ..., x_N]$, at time step $t$, the hidden state $h_t$ and output $y_t$ are calculated as follows [33]:

$$h(t)=f(Ux(t)+Wh(t-1)+b_h), \tag{3}$$

$$y(t)=f(Vh(t)+b_y), \tag{4}$$

where the $W$, $U$, and $V$ are the weights, $b_h$ and $b_y$ are the biases. $f$ is the activation function, such as the sigmoid and tanh functions. For RUL prediction, the input matrix contains several previous values of HI, and the output is defined as the predicted value, expressed as:

$$\boldsymbol{x}_t=[HI_{t-m}, HI_{t-m+1}, ..., HI_{t-1}, HI_t], \tag{5}$$

$$\boldsymbol{y}_t=HI_{t+1}. \tag{6}$$

In this way, a network structure with $m$ - dimension input and 1 - dimension output is established.

A problem of typical RNN is that when the weight is greater than 1, it will produce infinity in the iterations, and using weights less than 1 will produce an infinitesimal value. That is known as the gradient explosion and gradient vanishment problem. Gated RNNs have been proposed to solve the problem by integrating multiple gates to control the information transfer. LSTM (Fig. 2(b)) and GRU (Fig. 2(c)) are the two popular types.

In LSTM, the forget gate, input gate, and output gate decide what information can pass. Specifically, the forget gate uses a sigmoid layer to determine the information to be discarded; the input gate determines the information to be stored in the cell state using a sigmoid function and a tanh function; finally, the output information is determined by the output gate using another sigmoid function. The algorithms are shown below [23]:

forget gate: $$f(t)=\sigma(W_{fx}x(t)+W_{fh}h(t-1)+b_f), \tag{7}$$

input gate: $$i(t)=\sigma(W_{ix}x(t)+W_{ih}h(t-1)+b_i), \tag{8}$$

$$\tilde{C}(t)=\tanh(W_{cx}x(t)+W_{ch}h(t-1)+b_c), \tag{9}$$

update: $$C(t)=f(t)\odot C(t-1)+i(t)\odot\tilde{C}(t), \tag{10}$$

output gate: $$o(t)=\sigma(W_{ox}x(t)+W_{oh}h(t-1)+b_o), \tag{11}$$

$$h(t)=o(t)\odot\tanh(C(t)), \tag{12}$$

where the $W$ and $b$ are the weights and biases, $\sigma$ and tanh are the sigmoid and tanh function.

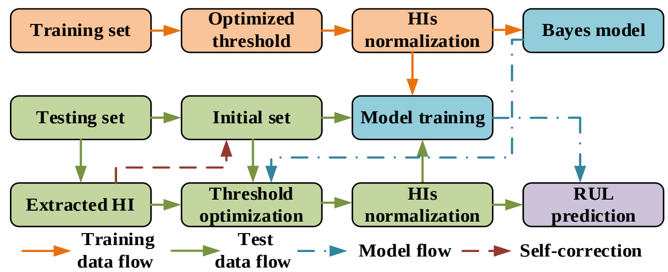


Fig. 3. Structure of the proposed method for RUL prediction

GRU can be seen as a variant of LSTM, which integrates the forget gate and input gate of LSTM into an update gate, and combines another reset gate to control information flow. Specifically, the update gate determines how much information should pass, while the reset gate determines how much previous information should be discarded. The mathematical expressions of the GRU are shown below [23]:

reset gate: $$r(t)=\sigma(W_{rx}x(t)+W_{rh}h(t-1)+b_r), \tag{13}$$

update gate: $$z(t)=\sigma(W_{zx}x(t)+W_{zh}h(t-1)+b_z), \tag{14}$$

state update: $$\tilde{h}(t)=\tanh(r(t)\odot W_{hx}x(t)+W_{hh}h(t-1)+b_h), \tag{15}$$

$$h(t)=(1-z(t))\odot h(t-1)+z(t)\odot\tilde{h}(t). \tag{16}$$

The network in this paper is similar to that in Ref. [30], which is constructed by an input layer, a (gated) RNN layer, and two fully-connected layers. During TL, the last two layers are set as justable while others are frozen.

## C. Transfer learning and RUL prediction

Generally, different batteries undergo different degradation patterns under different operating conditions. However, traditional machine learning techniques assume that training data and test data have identical statistical distribution [30]. If we use all available historical data of all batteries for model training, the computational burden will greatly increase. And some quite different training data may also negatively affect the prediction performance of the regression model. Therefore, it is very important to transfer the most relevant information from the source domain to the target domain, which not only improves accuracy but also reduces the computational burden. In this paper, the relevant information means the trained model (based on the batteries in the source domain) which has the most similar degradation curve with the test battery (in the target domain). TL provides an effective solution to this task, which does not require the test battery to have the same statistical distribution as the source batteries. Three main concerns are "What", "How", and "When" to

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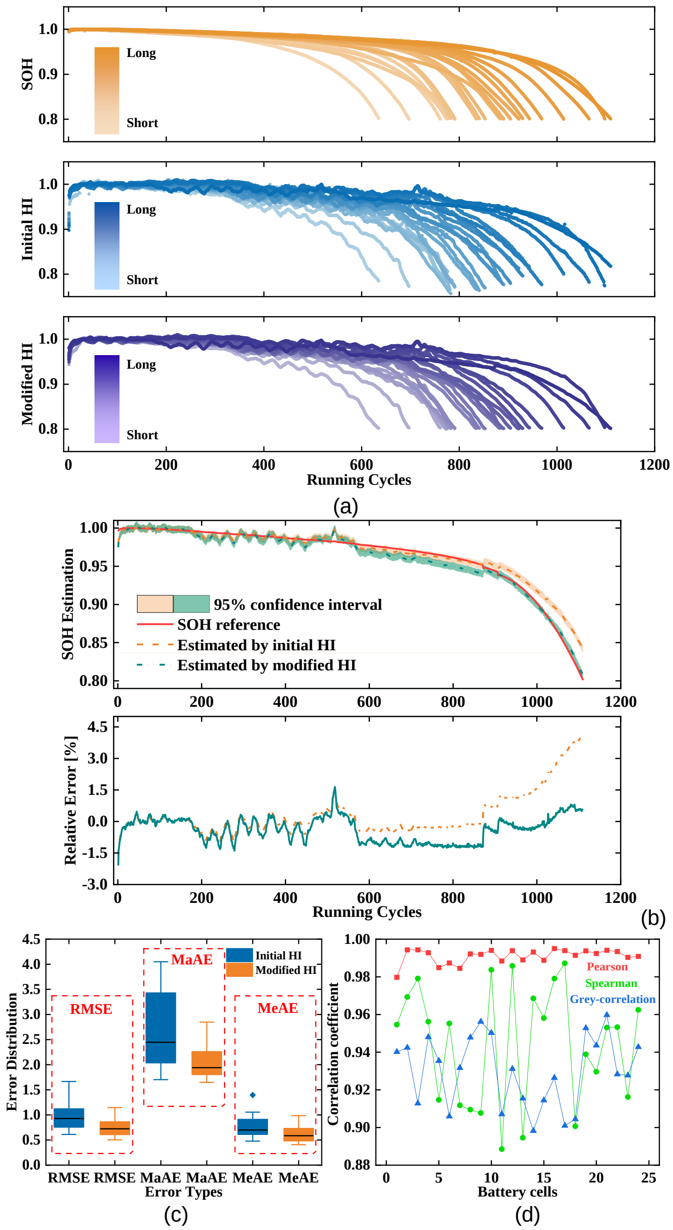



Fig. 4. Usefulness evaluation results: a) HI degradation paths compared to SOH variation; b) SOH estimation performance comparison; c) SOH estimation error distribution of 24 batteries based on the two different HI; d) Correlation analysis results between the modified HIs and capacities.

transfer the information from the source data to the target domain [34]. In this paper, a TL method is proposed to transfer the model information, which is trained based on the battery with a similar degradation pattern, to the test battery. The degradation patterns of the test battery and the source battery are compared by using Euclidean distance, which is expressed below:

$$r_{ij} = \sqrt{(x_{ij} - u_i)^2 + (y_{ij} - v_i)^2}\,, \tag{17}$$

where $r_{ij}$ is the distance between $j^{\text{th}}$ battery and the test battery at $i^{\text{th}}$ sample, while $u_i$ and $v_i$ are the coordinate values of the test battery. The root mean square error (RMSE) of $r_{ij}$ is calculated to show the similarity between $j^{\text{th}}$ battery and the test battery.

$$rmse_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m} r_{ij}}\,. \tag{18}$$

where $m$ represents the number of the HIs for the test battery. The battery with minimum *rmse* is selected for the initial model training. Then, the information of the initial model will be transferred to the test battery and fine-tuned using the HIs of early cycles to satisfy the prediction requirement.

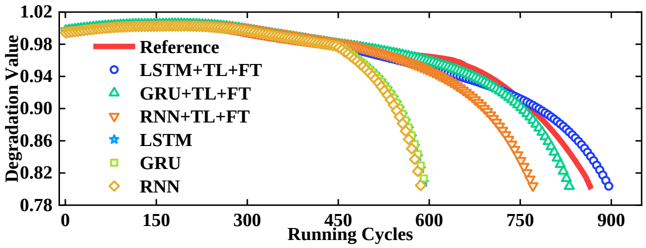
The flowchart of the proposed hybrid method for battery RUL prediction is shown in Fig. 3. Firstly, the training dataset of initial HIs is extracted from the partial voltage curves during fast charging. Then the extracted HIs are normalized by specific delta voltages according to equations (1) and (2). All modified HIs are input for the GPR model and RUL model training, but which HIs to use is determined by considering both training data and testing data. After obtaining the testing data, we first form an initial data set for fine-tuning the RUL initial model and threshold optimization through the GPR model. Then the initial dataset is combined with the GPR model to optimize the delta voltage for HI normalization. Also, the relevance between the initial testing dataset and each training dataset is searched, and the one that is most relevant to the testing dataset is selected for RUL initial model training. Meanwhile, the normalized HIs for the test battery are used in the model training process for the fine-tuning of the RUL prediction model. Moreover, a self-correction strategy is designed to optimize the model, and improve the prediction accuracy during the operating cycles. When a newly extracted HI is obtained, the GPR model can use more HIs from the training set for model training, and more HIs can be used for fine-tuning the RUL model. This is a significant advantage of the proposed method because the models can be modified during operation, which cannot be achieved when using capacity/SOH for RUL prediction.

## IV. Results and Discussion

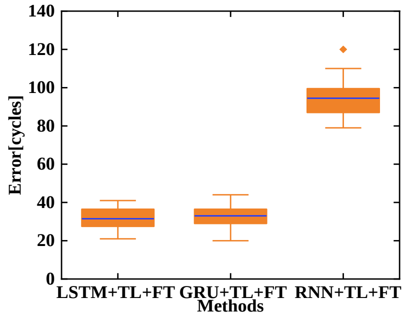
In this section, the usefulness evaluation results are firstly presented to demonstrate the suitability of replacing capacity with HIs and the significance of HI threshold optimization. Then, the RUL prediction results based on different deep learnings and input sequence lengths are given and discussed.

### *A. Usefulness Evaluation*

The usefulness of HI determines the effectiveness of the prediction model and significantly affects the RUL prediction performance. Therefore, it is necessary to evaluate the HIs before using them for RUL prediction. The usefulness of HIs is evaluated according to the evaluation strategy in this section. The usefulness evaluation results are shown in Fig .4. The extracted $V_p$ has a small variation range, and the initial HI in Fig. 4(a) is the value of $V_p$ minus a fixed delta (3.2 V), and the modified HI is the $V_p$ minus an optimized delta. It can be seen that the HI has a smooth downtrend except for a slight fluctuation in the medium range. This is important because if the noise of HI is large, it is difficult to obtain an accurate prediction. The initial HIs have various ranges, while the ranges will be almost similar through the delta voltage optimization by GPR. It can be explained in Fig .4(b) why it is necessary for HIs to have a similar variation range. The SOH estimation based on GPR is used to evaluate the usefulness of HI. Cell# 14 with a smaller initial $V_p$ range is tested using a model trained on




(a) RUL prediction evaluation for Cell#1.




(b) Statistical results of the RUL predicted error for all the batteries.

Fig. 5. Evaluation of the TL-FT-GRNN performance in RUL prediction.

TABLE II
NUMERICAL RESULTS OF TL-FT-GRNN PERFORMANCE

| Results | Ref | LSTM TL+FT | GRU TL+FT | RNN TL+FT | LSTM | GRU | RNN |
|---|---|---|---|---|---|---|---|
| RUL [cycles] | 443 | 475 | 409 | 350 | 171 | 172 | 165 |
| Error [cycles] | - | 32 | -34 | -93 | -272 | -271 | -278 |
| Time[s] | - | 32.46 | 34.67 | 26.32 | 22.59 | 23.24 | 17.54 |

another cell with a different initial $V_p$ range. It clearly demonstrates that the initial HI cannot estimate the SOH accurately due to the different HI variation ranges, while the modified HI provides a more satisfactory SOH estimation. The SOH estimation errors of all batteries based on these two HIs are demonstrated in Fig. 4(c), where the modified HI has smaller estimation errors than that of the initial HI. Specifically, the RMSE of the results of the initial HI is mostly greater than 1%, while almost all results of the modified HIs are less than 1%. The maximum absolute errors (MaAE) are mostly greater than 2.5% when using the initial HI, and some are even greater than 4%. In contrast, the MaAEs are mostly less than 2% when using the modified HI. The same is true for the mean absolute errors (MeAEs). This result shows that even if the estimated capacity is used for RUL prediction, it is necessary to obtain HIs with similar variation ranges. Three types of correlation analysis methods, including Pearson correlation coefficient (PCC), Spearman correlation coefficient (SCC), and Grey-relation analysis (GRA) are adopted for correlation analysis between the modified HI and capacity, and the results for each battery are shown in Fig. 4(d). The PCC is greater than 0.98 for all batteries, and most of them are greater than 0.99, which means that HIs have a great linear correlation with capacity. SCC and GRA are mostly greater than 0.9 and some are greater than 0.95, indicating that the variation trend of HI is close to the battery capacity and has a good temporal correlation. From the above usefulness evaluation, the normalized HI can replace the battery capacity for RUL prediction.

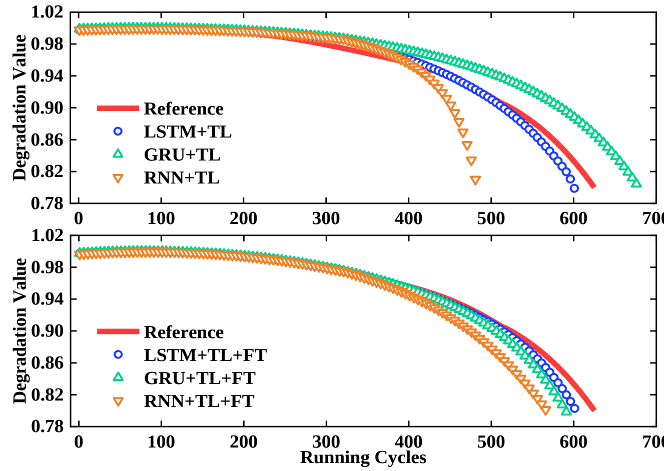



Fig. 6. RUL prediction evaluation based on self-correction strategy.

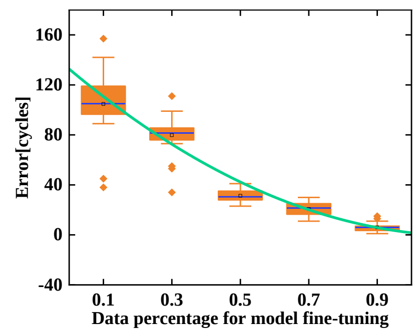



Fig. 7. Evaluation of self-correction convergent effect during life cycle.

TABLE III
NUMERICAL RESULTS OF THE SELF-CORRECTION PERFORMANCE

| Results | Ref | LSTM +TL | GRU +TL | RNN +TL | LSTM+ TL+FT | GRU+ TL+FT | RNN+ TL+FT |
|---|---|---|---|---|---|---|---|
| RUL | 318 | 288 | 372 | 196 | 294 | 286 | 260 |
| Error | - | -30 | 54 | -122 | -24 | -32 | -58 |

### *B. RUL Prediction*

Predictive maintenance requires accurate and reliable RUL predictions. Capacity cannot be measured directly in actual use. Therefore, a proper method for predicting battery RUL in early cycles through indirect HIs is of great significance and practical application value. In this section, the RUL prediction results based on the TL+GRNNs and the normalized HIs are presented and discussed. First, different RUL predictions based on various methods are evaluated. Then, the self-correction strategy is demonstrated during the operating cycles. Finally, the choice of input sequence length is discussed. It is worth noting the input sequence length is set to ten for the first and second subsections. Besides, it can be seen that there are some slight fluctuations in the middle of the HI curves, which may affect the extrapolation during RUL prediction. A Savitzky-Golay filter [35] is adopted to smooth these fluctuations without affecting the overall degradation trends.

1) *Prediction results based on TL-FT-GRNN*

In order to illustrate the performance based on the proposed TL-GRNN with a self-correcting fine-tuning strategy, the RUL prediction results are shown in Fig. 5, where the results of the other several methods are also provided for comparison. Specifically, RNN, LSTM-RNN, GRU-RNN, as well as their combinations with TL+FT (fine-tuning) are demonstrated

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TABLE IV
NUMERICAL RESULTS FOR THE INPUT SEQUENCE EVALUATION

| Results | Ref | 2 | 5 | 10 | 20 | 50 |
|---|---|---|---|---|---|---|
| RUL | 106 | 82 | 96 | 110 | 101 | 109 |
| Error | - | -24 | -10 | 4 | -5 | 3 |
| Time | | 37.33 | 39.59 | 40.22 | 42.04 | 46.05 |

using Cell#1, as shown in Fig. 5(a). And the results are listed in Table II, where the time is calculated by the mean value of all batteries and the training steps are set to 5000. All the results are obtained by TensorFlow 1.15 on a computer with an i7-9700k CPU and a 16GB RAM. The negative sign means the predicted RUL is less than the actual value. It is worth noting that the results without TL+FT are obtained by the models trained based on the first half of the testing data, and the results with TL+FT use the same data for model fine-tuning.

The improvements for the RUL prediction using TL together with fine-tuning are obvious. It shows that when the previous model parameters are not obtained, all the three methods can only perform well in the training data set, but the predicted values will quickly decrease to the threshold when RUL is predicted by extrapolation. The predicted errors are all above 250 cycles, which means they cannot provide an effective prediction. On the contrary, when TL is used to transfer the former information trained based on a relevant battery, and the fine-tuning strategy is used for model correction, all the predicted results become better. Specifically, the GRNN (LSTM or GRU) based methods can obtain accurate RUL predictions with all errors less than 35 cycles. However, the RNN based method still has a larger error (93 cycles), which means that GRNNs have better performance for long term RUL prediction. However, the computational burden of GRNNs is larger than RNN, and a TL plus fine-tuning strategy would cause more computational time (about 10 seconds). Fig. 5(b) shows the statistical results of the RUL predicted errors obtained based on all batteries. It suggests that the LSTM and GRU have similar prediction performance and both have satisfactory prediction results while RNN may not be able to get an accurate RUL. It may be difficult to be implemented for onboard applications in xEVs. However, with the big data cloud technology, the proposed method can be implemented for the onboard usage and guide for predictive maintenance.

### 1) *Self-correction strategy*

One significant advantage of the proposed method is that the HI can be obtained during the operation, therefore, the regression model can be fine-tuned to fit the test battery. As mentioned earlier, a self-correction module is integrated into our method for model adjusting. Here, the advantage of fine-tuning during operation is demonstrated. First, the results with fine-tuning and without fine-tuning based on RNN and GRNNs are evaluated. The prediction results of Cell#10 are shown in Fig. 6, and the numerical results are listed in Table III. Because the number of the running cycles of Cell#10 is the smallest, so the performance can be clearly shown. It can be seen from the figure that when there is no fine-tuning, the trajectory of the degradation is more likely to deviate from the real value. On the contrary, when the fine-tuning function is added, the model can be corrected to follow the trajectory of the test battery. It is clearly illustrated that around 300 cycles, the predicted values are closer to the real value. Therefore, the model after fine-tuning has a better prediction of the real degradation. By comparing with the results in Fig. 5 (a), when the pre-information is obtained, the predicted results are also better even without the fine-tuning strategy. This is because the knowledge of the degradation process can be obtained by the initial model training based on a relevant battery, while that cannot be achieved without TL. Thanks to the fine-tuning strategy, the RUL predicted accuracy is further improved due to the adaption to the characteristic of the test battery. The predicted errors are reduced to 24 cycles for LSTM+TL+FT and 32 cycles for GRU+TL+FT, while the error for RNN is still larger. The results suggest that even the degradation pattern is different from the training source, the method can achieve satisfactory results based on the TL and self-correction strategy.

In order to demonstrate the significance of the proposed self-correction function, the results using different amounts of data for fine-tuning are carried out and evaluated. The statistical results of all batteries are shown in Fig. 6, where the fitted curve is a quadratic fitting of the mean. The results are obtained by LSTM+TL+FT. It shows the RUL prediction errors become smaller with the cycle number, where more data can be obtained for model correction. Because the early cycling data of all batteries are similar, and there is not enough data available for model correction, the errors are also large. Some small values are due to similar degradation for some batteries. However, as more data is obtained, more information can be captured and used to adjust the regression model, and the threshold determined by the GPR model can also be more accurate. The decline rate of HIs is low during cycles before 70%, where the battery RUL value is greater than 0.95. Since then, the decline rate accelerates, especially in the last 10 percent of the life cycle, which contains about half of the degradation range. The proposed prediction strategy shows the advantages in this stage, which provides more accurate RUL prediction near the end-of-life. When 90% of data is obtained for model fine-tuning, the predicted errors are mostly less than 5 cycles. It provides an accurate prediction for the end of life, which can guide predictive maintenance and cascade utilization.

### 2) *Input sequence discussion*

The input of the regression model at each timestep is several previous values. The length of the input sequence would not only determine the training cost but also affect prediction accuracy. Therefore, it is important to investigate the length of the input sequence in order to strike a balance between accuracy and computational burden. The results based on Cell#15, which has a long life span, are listed in Table IV, where the last 0.1 life cycles (80-90.1% SOH range) are used for evaluation. It is important to predict RUL accurately within this range to ensure that the overuse of the battery is avoided. The results suggest that an input sequence with 10 units has a good prediction accuracy and proper computational burden. When the input sequence is short, it may be difficult to capture the characteristics, and when the input sequence is long, it will result in a large data dimension. 10 units for the input sequence achieve a good tradeoff and are suggested for potential usages.

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## V. Conclusion

Accurate RUL prediction plays an important role in battery predictive health management and cascade utilization. The absence of accurate capacity values in actual applications is one of the key bottlenecks that limit the application of most existing methods. In this paper, a novel method for battery RUL prediction using HIs directly, which is based on threshold optimization and TL-GRNNs with a self-correction strategy. The HI is extracted directly from the partial voltage curves during fast charging, which can be obtained in the actual applications. In order to replace the capacities for RUL predictions, the GPR is adopted to optimize the EOL threshold. And a usefulness evaluation strategy is established to assess the suitability of HIs for RUL prediction. The TL combined with GRNNs is used to improve the prediction accuracy, which uses the most relevant battery to train the pre-model and fine-tune the model using early cycling data of the test battery. The prediction performances are evaluated under different deep learning algorithms and different input sequences. In addition, a self-correction strategy is designed to improve the model accuracy during cycling thanks to the available HIs in actual applications, which further demonstrates the advantages of the proposed method. Experimental results show that the proposed method can provide more accurate RUL prediction than the conventional method, and the TL + online fine-tuning strategy ensures the model adaption for different batteries. The predicted error is expected to be less than 5 cycles after sufficient correction. The method shows great superiorities in real applications because HIs could be obtained and the model could be fine-tuned online as well. This paper shows that replacing capacity with HIs has great potential for real applications with the support of the strong computing power of big data platforms. Future work will focus on the application using real data from xEVs combined with cloud technology.

## References


[1] X. Hu, L. Xu, X. Lin, and M. Pecht, "Battery Lifetime Prognostics," *Joule,* vol. 4, no. 2, pp. 310-346, 2020.

[2] X. Hu, F. Feng, K. Liu, L. Zhang, J. Xie, and B. Liu, "State estimation for advanced battery management: Key challenges and future trends," *Renewable and Sustainable Energy Reviews,* vol. 114, 2019.

[3] K. A. Severson *et al.*, "Data-driven prediction of battery cycle life before capacity degradation," *Nature Energy,* vol. 4, no. 5, pp. 383-391, 2019.

[4] M. S. H. Lipu *et al.*, "A review of state of health and remaining useful life estimation methods for lithium-ion battery in electric vehicles: Challenges and recommendations," *Journal of Cleaner Production,* vol. 205, pp. 115-133, 2018.

[5] E. Sarasketa-Zabala, I. Gandiaga, E. Martinez-Laserna, L. M. Rodriguez-Martinez, and I. Villarreal, "Cycle ageing analysis of a LiFePO4/graphite cell with dynamic model validations: Towards realistic lifetime predictions," *Journal of Power Sources,* vol. 275, pp. 573-587, 2015.

[6] J. Wei, G. Dong, and Z. Chen, "Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-Ion Batteries Using Particle Filter and Support Vector Regression," *IEEE Transactions on Industrial Electronics,* vol. 65, no. 7, pp. 5634-5643, 2018.

[7] P. L. T. Duong and N. Raghavan, "Heuristic Kalman optimized particle filter for remaining useful life prediction of lithium-ion battery," *Microelectronics Reliability,* vol. 81, pp. 232-243, 2018.

[8] Y. Li *et al.*, "Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review," *Renewable and Sustainable Energy Reviews,* vol. 113, 2019.

[9] G. Dong, F. Yang, Z. Wei, J. Wei, and K.-L. Tsui, "Data-Driven Battery Health Prognosis Using Adaptive Brownian Motion Model," *IEEE Transactions on Industrial Informatics,* vol. 16, no. 7, pp. 4736-4746, 2020.

[10] K. Liu, Y. Li, X. Hu, M. Lucu, and W. D. Widanage, "Gaussian Process Regression With Automatic Relevance Determination Kernel for Calendar Aging Prediction of Lithium-Ion Batteries," *IEEE Transactions on Industrial Informatics,* vol. 16, no. 6, pp. 3767-3777, 2020.

[11] C.-P. Lin, J. Cabrera, F. Yang, M.-H. Ling, K.-L. Tsui, and S.-J. Bae, "Battery state of health modeling and remaining useful life prediction through time series model," *Applied Energy,* vol. 275, 2020.

[12] X. Shu, G. Li, J. Shen, Z. Lei, Z. Chen, and Y. Liu, "A uniform estimation framework for state of health of lithium-ion batteries considering feature extraction and parameters optimization," *Energy,* vol. 204, 2020.

[13] X. Li, C. Yuan, X. Li, and Z. Wang, "State of health estimation for Li-Ion battery using incremental capacity analysis and Gaussian process regression," *Energy,* vol. 190, 2020.

[14] X. Feng *et al.*, "Online State-of-Health Estimation for Li-Ion Battery Using Partial Charging Segment Based on Support Vector Machine," *IEEE Transactions on Vehicular Technology,* vol. 68, no. 9, pp. 8583-8592, 2019.

[15] B. Gou, Y. Xu, and X. Feng, "State-of-Health Estimation and Remaining-Useful-Life Prediction for Lithium-Ion Battery Using a Hybrid Data-Driven Method," *IEEE Transactions on Vehicular Technology,* vol. 69, no. 10, pp. 10854-10867, 2020.

[16] Z. Deng, X. Hu, X. Lin, L. Xu, Y. Che, and L. Hu, "General Discharge Voltage Information Enabled Health Evaluation for Lithium-Ion Batteries," *IEEE/ASME Transactions on Mechatronics,* pp. 1-1, 2020.

[17] X. Li, C. Yuan, and Z. Wang, "Multi-time-scale framework for prognostic health condition of lithium battery using modified Gaussian process regression and nonlinear regression," *Journal of Power Sources,* vol. 467, 2020.

[18] X. Hu, Y. Che, X. Lin, and S. Onori, "Battery health prediction using fusion-based feature selection and machine learning," *IEEE Transactions on Transportation Electrification,* pp. 1-1, 2020.

[19] Y. Wang, Y. Ni, S. Lu, J. Wang, and X. Zhang, "Remaining Useful Life Prediction of Lithium-Ion Batteries Using Support Vector Regression Optimized by Artificial Bee Colony," *IEEE Transactions on Vehicular Technology,* vol. 68, no. 10, pp. 9543-9553, 2019.

[20] A. A. Chehade and A. A. Hussein, "A Collaborative Gaussian Process Regression Model for Transfer Learning of Capacity Trends Between Li-Ion Battery Cells," *IEEE Transactions on Vehicular Technology,* vol. 69, no. 9, pp. 9542-9552, 2020.

[21] P. Li *et al.*, "State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network," *Journal of Power Sources,* vol. 459, 2020.

[22] X. Shu, G. Li, Y. Zhang, J. Shen, Z. Chen, and Y. Liu, "Online diagnosis of state of health for lithium-ion batteries based on short-term charging profiles," *Journal of Power Sources,* vol. 471, 2020.

[23] Y. Yu, X. Si, C. Hu, and J. Zhang, "A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures," *Neural Comput,* vol. 31, no. 7, pp. 1235-1270, Jul 2019.

[24] K. Liu, Y. Shang, Q. Ouyang, and W. D. Widanage, "A Data-driven Approach with Uncertainty Quantification for Predicting Future Capacities and Remaining Useful Life of Lithium-ion Battery," *IEEE Transactions on Industrial Electronics,* pp. 1-1, 2020.

[25] Y. Zhang, R. Xiong, H. He, and M. G. Pecht, "Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries," *IEEE Transactions on Vehicular Technology,* vol. 67, no. 7, pp. 5695-5705, 2018.

[26] J. Chen, H. Jing, Y. Chang, and Q. Liu, "Gated recurrent unit based recurrent neural network for remaining useful life prediction of nonlinear deterioration process," *Reliability Engineering & System Safety,* vol. 185, pp. 372-382, 2019.

[27] P. M. Attia *et al.*, "Closed-loop optimization of fast-charging protocols for batteries with machine learning," *Nature,* vol. 578, no. 7795, pp. 397-402, Feb 2020.

[28] X. Hu, Y. Che, X. Lin, and Z. Deng, "Health Prognosis for Electric Vehicle Battery Packs: A Data-Driven Approach," *IEEE/ASME Transactions on Mechatronics,* pp. 1-1, 2020.

[29] Y. Che, A. Foley, M. El-Gindy, X. Lin, X. Hu, and M. Pecht, "Joint Estimation of Inconsistency and State of Health for Series Battery Packs," *Automotive Innovation,* 2021.

[30] Y. Tan and G. Zhao, "Transfer Learning With Long Short-Term Memory Network for State-of-Health Prediction of Lithium-Ion Batteries," *IEEE*

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*Transactions on Industrial Electronics,* vol. 67, no. 10, pp. 8723-8731, 2020.

[31] B. Shahriari, K. Swersky, Z. Wang, R. P. Adams, and N. de Freitas, "Taking the Human Out of the Loop: A Review of Bayesian Optimization," *Proceedings of the IEEE,* vol. 104, no. 1, pp. 148-175, 2016.

[32] Z. Deng, X. Hu, X. Lin, Y. Che, L. Xu, and W. Guo, "Data-driven state of charge estimation for lithium-ion battery packs based on Gaussian process regression," *Energy,* vol. 205, 2020.

[33] X. Li, L. Zhang, Z. Wang, and P. Dong, "Remaining useful life prediction for lithium-ion batteries based on a hybrid model combining the long short-term memory and Elman neural networks," *Journal of Energy Storage,* vol. 21, pp. 510-518, 2019.

[34] Sinno Jialin Pan and Q. Yang, "A Survey on Transfer Learning," *IEEE Transactions on Knowledge and Data Engineering,* vol. 22, no. 10, pp. 1345 - 1359, 2010.

[35] S. R. Krishnan and C. S. Seelamantula, "On the Selection of Optimum Savitzky-Golay Filters," *IEEE Transactions on Signal Processing,* vol. 61, no. 2, pp. 380-391, 2013.

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