Transfer-Learning-Based State-of-Health Estimation for Lithium-Ion Battery With Cycle Synchronization

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Abstract—Accurately estimating a battery’s state of health (SOH) helps prevent battery-powered applications from failing unexpectedly. With the superiority of reducing the data requirement of model training for new batteries, transfer learning (TL) emerges as a promising machine learning approach that applies knowledge learned from a source battery, which has a large amount of data. However, the determination of whether the source battery model is reasonable and which part of information can be transferred for SOH estimation are rarely discussed, despite these being critical components of a successful TL. To address these challenges, this article proposes an interpretable TL-based SOH estimation method by exploiting the temporal dynamic to assist TL, which consists of three parts. First, with the help of dynamic time warping, the temporal data from the discharge time series are synchronized, yielding the warping path of the cycle-synchronized time series responsible for capacity degradation over cycles. Second, the canonical variates retrieved from the spatial path of the cycle-synchronized time series are used for distribution similarity analysis between the source and target batteries. Third, when the distribution similarity is within the predefined threshold, a comprehensive target SOH estimation model is constructed by transferring the common temporal dynamics from the source SOH estimation model and compensating the errors with a residual model from the target battery. Through a widely used open-source benchmark dataset, the estimation error of the proposed method evaluated by the root mean squared error is as low as 0.0034 resulting in a 77% accuracy improvement compared with existing methods.

Index Terms—Canonical variate analysis (CVA), cycle synchronization, gated recurrent unit (GRU) network, lithium-ion battery (LiB) state-of-health (SOH) estimation, transfer learning (TL).

I. INTRODUCTION

RECYCLABLE lithium-ion battery (LiB), as the primary energy storage component used in electronics products like mobile phones, computers, and electric cars [1], serves a vitally critical role in reducing the global carbon footprint and combating the climate crisis [2]. It has the characteristics of high energy density, and outstanding high-temperature performance [3]. The state of health (SOH) of LiB, commonly indicated by its capacity, degrades during charging and discharging [4], [5], reflected by the capacity loss or the resistance increment. For device performance management and maintenance, the ability to accurately estimate the LiB’s SOH is critical.

Data-driven machine learning approaches have been widely applied to estimate the SOH during battery degradation. It has the benefit of avoiding the examination of the internal battery mechanics like the model-based technique [6], [7]. It utilizes the information extracted from recorded or real-time measurement [8] and estimates the regression connection by mapping nonlinear functions [9]. Support vector machine (SVM) [10], Gaussian process regression (GPR) [11], and recurrent neural network (RNN) [12] are most popular algorithms employed for the regression models in the literature. Specifically, RNN models represented by the long short-term memory (LSTM) [13] and the gated recurrent unit (GRU) [14] are popular in SOH and RUL prediction as they are good at processing long sequence data [15]. For instance, Jayasinghe et al. [16] combined temporal convolution layers and LSTM layers to predict the RUL by learning the prominent characteristics and complicated temporal variations in sensor values. Zhang et al. [17] employed LSTM with Monte Carlo simulation to generate a probabilistic RUL prediction by detaining the underlying long-term dependencies during the degradation. Cui et al. [18] proposed a dynamic spatial-temporal attention-based GRU model, and its results outperformed SVM and GPR in SOH estimation of LiB.

To make the data-driven methods work, massive data need to be collected to train the model, which is time consuming and expensive [19]. Furthermore, due to the divergent electrochemistry reactions throughout different deterioration stages, the data collected in the past on a single battery have different data distribution from the estimation period. Thus, the model built by the historical information might not be applicable to estimate the online SOH status. There is a necessity for using less data yet acquiring the same information to make the estimation
work [20]. Transfer learning (TL) has recently come up as an emerging machine learning method to fulfill this. It utilizes the model built by the existing source battery, in which abundant data are available to cover a comprehensive system process and transfer the generic features to the new prediction task on the target battery [21]. Applying TL to battery SOH estimation saves the cost of collecting data on the target battery, shortens the time to retrain the model from scratch, and improves the accuracy at the same time. Shu et al. [22] integrated TL with a fine-tuning strategy to predict SOH by using the charging duration at a predefined voltage range as the health feature and proposed an improved LSTM network. Tan et al. [23] developed a feature expression scoring rule and implemented TL to fine-tune or rebuild the last two fully connected layers based on the feature expression scoring for SOH prediction. Che et al. [24] combined TL and gated RNN, including LSTM and GRU, to train the model with the most relevant battery and fine-tune it using early cycling data of the target battery. Kim et al. [25] proposed a VarLSTM-TL to facilitate accurate SOH forecasting and RUL prediction for different LIB types to predict RUL values at a single point in time and forecast capacity-degradation patterns with credible intervals. Ma et al. [26] introduced a TL-based method by combining a convolutional neural network (CNN) with an improved domain adaptation method that is used to construct an SOH estimation model.

Although approaches discussed previously have yielded good results in battery SOH prediction, gaps are observed ranging from feature extraction, model interpretability, and how to achieve TL, which are specified as follows:

1) Current research uses several ways to prepare the data to meet the standard input requirement of RNN, like selecting health indicators [27], manual truncation [28], zero-padding [29], etc. Rough processing of battery data likely results in information loss and negatively influences the transferring performance owing to the failure to pick a portion of the data.

2) The transfer performance may be poor if the similarity between the source and target batteries is far away. By implicitly assuming the target battery is related to the source battery, the “when to transfer” is not explicitly articulated.

3) The current TL applications update the last one or two layers of the network by using a small set of data from the target battery. It leaves most of the work for end-to-end models to perform feature extraction from the source battery. In this way, the interpretability is unclear, as the “what to transfer” information fades once the weights are updated through retraining.

To address the challenges mentioned previously, this article presents a novel TL-based SOH estimation model. First, to acquire the unified data structure, a cycle synchronization method using dynamic time warping (DTW) is proposed in this article to transform the time index to be on the vertical axis and synchronize the uneven length of the discharge cycles. Next, to determine “when to transfer,” the hidden temporal mechanism during the battery discharging process is exploited by canonical variate analysis (CVA) [30]. Statistics control limits measure the degradation distribution similarity between target and source batteries to determine the transfer capability of the source battery. Finally, to clearly identify “what to transfer,” the source SOH estimation model is constructed by using canonical variates (CVs) from the source battery, and the target SOH estimation model is constructed by transferring the common CVs from the source SOH estimation model and improved by the target battery residual model trained by the target battery-specific residual variate (RV). The contributions of this work are summarized as the following:

1) Cycle synchronization is meant to deal with LiB’s variable-length cycle data, overcoming data loss or distortion caused by improper data processing.

2) Battery degradation distribution similarity analysis provides a benchmark to evaluate the source battery’s ability to transfer.

3) A hybrid target SOH estimation model is proposed by transferring the common features from the source SOH estimation model and dynamically adjusting them with a small dataset of target domain-specific features to achieve a superior estimation outcome.

The remaining parts of this article are organized as follows. Section II illustrates battery degradation behavior and how machine learning can be applied to estimate battery SOH. Section III proposes TL-based SOH estimation with cycle synchronization in detail, and Section IV discusses the experiment results. Finally, Section V concludes this article.

II. PRELIMINARY

This first section describes the LiBs’ degradation behavior. Next, high-level comparisons of traditional machine learning and TL on battery SOH estimation are provided for a better understanding.

A. Battery Degradation Behavior

The SOH of the battery is commonly defined as the ratio of its maximum available capacity to its nominal capacity [31]. A fresh battery is considered to be at full capacity, which means 100% SOH. Along with the charging and discharging process, the battery deterioration follows an inconsistently repeating but comparable aging pattern [32]. Fig. 1(a) illustrates an example of the battery degradation pattern from the dataset provided by the Massachusetts Institute of Technology (MIT) and Stanford.
to transfer them. To decide “when to transfer,” in battery’s SOH estimation, it is critical to consider whether the source and target battery data distributions are highly related. It can be done by statistical approaches to extract the temporal correlation as the degradation is significantly tied to time.

### III. TL-BASED SOH ESTIMATION WITH CYCLE SYNCHRONIZATION

The proposed target SOH estimation process flow is presented in Fig. 3. The entire procedure begins with cycle synchronization to convert discharge voltage cycles to the same length. Subsequently, source and target batteries’ data distribution similarities are assessed. Finally, a TL-based target SOH estimation model is created by integrating the estimation from the source SOH estimation model by common features and the one from the target battery residual model by target battery unique features.

#### A. Cycle Synchronization With DTW

During the discharging process, the discharge cycle time reduces due to battery degradation. The discharge cycle’s inconsistency is incompatible with CVA processing and RNN input. It is crucial to extract time-domain features for a continuous dynamical process [36] and synchronize the cycles with their temporal information retained. In order to achieve these purposes, we develop cycle synchronization techniques using DTW [37] to convert varying length voltage-based discharge time series into time-index-based time series.

DTW is renowned for determining the best alignment of two series by expanding and contracting localized portions to obtain the smallest possible distance between them [38]. Given a reference discharge voltage series \( v_s = [v_1^s, v_2^s, \ldots, v_m^s] \) from a source battery as illustrated in Fig. 4(a), a warping path \( W \) based on minimum-distance between \( v_s \) and the target discharge voltage series \( v_i = [v_1^i, v_2^i, \ldots, v_n^i] \) is built by DTW, where the reference series has \( m \) samples and target series has \( n \) samples. By using each sample in the time series, warping path \( W \) starts from \( w_1 = (0, 0) \) and ends with \( w_{m+n} = (m, n) \). Multiple steps in the reference series can be matched to a step on the target series, and vice versa. The warping path \( W \) is denoted as

\[
W = [w_1, w_2, \ldots, w_m, w_n]
\]

where \( G \) is the length of the warping path, and \( \max(m, n) \leq G \leq m + n \).

The \( g \)-th point of the warping path where the \( j \)-th step of the target series is mapped to the \( i \)-th step in reference series is

\[
w_g = (g_x^i, g_y^j)
\]

where \( g_x^i \) is the time index on the source series and \( g_y^j \) is the time index on the target series.

The mapping information transforms point \( v_i(g_x^i, v_x^j) \), the voltage coordinate at the point \( j \) on the target discharge voltage cycle, to \( x_s(g_y^i, v_y^j) \) on the synchronized cycle. By putting the \( g_x^i \) on the x-axis and the \( g_y^j \) on the y-axis, a new series is produced. The reference series is transformed into a diagonal line as \( v_s(g_x^i, v_x^j) \) is converted into \( x_s(g_y^i, v_y^j) \) putting both \( g_x^i \) on the x- and y-axes, as illustrated in Fig. 4(b). For those many time
steps on the target series that are mapped to a single time step on the reference series, the mean of them $g_{jt}$ is used. The cycle synchronized voltage time-index-based time series is created as $x_t = [g_{1t}, g_{2t}, \ldots, g_{jt}, \ldots, g_{nt}]$. Finally, all the $K$ discharge voltage cycles in the source battery are converted to $X_s = [X_{s,1}, X_{s,2}, \ldots, X_{s,K}]$ and all the $L$ discharge voltage cycles in the target battery are converted to $X_t = [x_{t,1}, x_{t,2}, \ldots, x_{t,L}]$.

**B. Degradation Distribution Similarity Analysis by CVA**

1) Feature Engineering by CVA: CVA is a dissimilarity measurement approach that aims to maximize the correlation of two different sets of variables in terms of their within-groups variation [39]. It is performed by selecting CVs, which are the linear combinations of one variable set that are better correlated with the linear combinations of another variable set [40], [41]. CVA uses the complete degradation source battery voltage synchronized cycles to generate the transformation matrices and the threshold. The transformation matrices aid in generating the CVs from the source battery to feed into the estimation model, as well as converting the target battery’s high-dimensional data into an indicator, which is then compared with the threshold [42] to determine how similar the source and target batteries’ discharge data distributions are.

In order to consider the time correlation within a cycle, at each sample $i$ in $x_{s,k}$, the $k$th cycle of source battery $X_s$, will be expanded by considering the past $p$ and future $f$ samples to generate the past and future vectors as $x_{p,k}(i)$ and $x_{f,k}(i)$, given as follows:

$$x_{p,k}(i) = \begin{bmatrix} x_{s,k}(i-1) \\ x_{s,k}(i-2) \\ \vdots \\ x_{s,k}(i-p) \end{bmatrix}$$

$$x_{f,k}(i) = \begin{bmatrix} x_{s,k}(i) \\ x_{s,k}(i+1) \\ \vdots \\ x_{s,k}(i+f-1) \end{bmatrix}$$ (1)

where $p$ and $f$ are past and future lags, which is normally chosen to encapsulate the data autocorrelation [43].

The past and future vectors from each point in the cycle are put together to form the past and future Hankel matrix, namely $X_{p,k}$ and $X_{f,k}$, given as follows:

$$X_{p,k} = [x_{p,k}(m-f), \ldots, x_{p,k}(p+1), x_{p,k}(p)]$$

$$X_{f,k} = [x_{f,k}(m-f+1), \ldots, x_{f,k}(p+2), x_{f,k}(p+1)]$$ (2)

where $m$ is the total samples in the cycle.

Finally, the complete past and future matrices $X_p$ and $X_f$ are created by putting $X_{p,k}$ and $X_{f,k}$ from all the cycles, respectively

$$X_p = [X_{p,1}, X_{p,2}, \ldots, X_{p,K}]$$

$$X_f = [X_{f,1}, X_{f,2}, \ldots, X_{f,K}]$$ (3)

where $K$ is the total cycles of the source battery.
The same symbol $X_p$ and $X_f$ are still used for normalized matrices, respectively. With the normalized $X_p$ and $X_f$, the covariance and cross-covariance matrices of the past and future observations can be found as the following,

$$
\Sigma_{pp} = \frac{1}{H - 1}X_pX_p^T
$$

$$
\Sigma_{ff} = \frac{1}{H - 1}X_fX_f^T
$$

$$
\Sigma_{fp} = \frac{1}{H - 1}X_fX_p^T
$$

(4)

where $H = K(m - f + 1)$.

Singualar value decomposition is performed accordingly to find the CVs

$$
\Sigma_{pp}^{-1/2}\Sigma_{fp}^{-1/2} = U\Sigma V^T
$$

(5)

where $\Sigma = \text{diag}[\alpha_1, \alpha_2, \ldots, \alpha_s]$ is a diagonal matrix of nonnegative singular values with the order of $1 > \alpha_1 > \alpha_2 > \ldots, > \alpha_s$, $U$ is right-singular and $V$ is left-singular matrix.

The first $C$ largest $\alpha$ has exhibited the most correlated CV, indicating a high temporal dynamic correlation. To indicate the space to be retained, the first $C$ columns of $V$ are chosen accordingly as $V_c$. The remainder of the $\alpha$, which has lower values and is linked to low correlation, is grouped as RVs under residual space. The source transform matrix $J_{s,c}$ and $J_{s,r}$ to convert the past matrix to CVs and RVs are calculated as follows:

$$
J_{s,c} = V_c^T\Sigma_{pp}^{-1/2}
$$

$$
J_{s,r} = (I - V_cV_c^T)\Sigma_{pp}^{-1/2}.
$$

(6)

By source transform matrix $J_{s,c}$ and $J_{s,r}$, the source battery CV $Z_{s,c}$ and RV $Z_{s,r}$ are obtained as

$$
Z_{s,c} = J_{s,c}X_p = V_c^T\Sigma_{pp}^{-1/2}X_p
$$

$$
Z_{s,r} = J_{s,r}X_p = (I - V_cV_c^T)\Sigma_{pp}^{-1/2}X_p.
$$

(7)

Source battery $Z_{s,c}$ span the retained space while $Z_{s,r}$ span the residue space. To quantify the variance of $Z_{s,c}$ and $Z_{s,r}$, the statistical indicators Hotelling’s $T^2$ statistic and $Q$ statistic are introduced

$$
T^2_c(k) = \sum_{i=1}^{C}z^2_{s,c,i}(k)
$$

$$
Q_c(k) = \sum_{i=1}^{p}z^2_{s,r,i}(k)
$$

(8)

where $z_{s,c,i}(k)$ and $z_{s,r,i}(k)$ are the $k$th row and $i$th column of $Z_{s,c}$ and $Z_{s,r}$, respectively.

The control limits CL$T^2_c$ and CL$Q_c$ of $T^2$ and $Q$ are derived based on a significant level $\beta$ to cover a certain percentage of data. In this article, the probability distribution is estimated using kernel density estimations, and its control limits are calculated accordingly [44].

2) Similarity Evaluation: Due to internal electrochemical reactions during charging and discharging, LiB deterioration varies vastly. The information from the source battery may not be suitable to be applied to the target battery if their degradations are dissimilar. The degradation distribution variability in the source retained space and residual space within each cycle is reflected by $T^2_c$, which represents the total variation in the retained space, and $Q_c$, which represents the sum of the squared variation errors in the residual space. Therefore, the control limits CL$T^2_c$ and CL$Q_c$ generated from $T^2_c$ and $Q_c$ are employed as significant level indicators.

As such, an evaluation method based on canonical CL$T^2_c$ and residual CL$Q_c$ is presented to benchmark the similarity between the target and source batteries and choose the appropriate estimation model accordingly. The steps are as follows:

Step 1: Following the methods in Section III-A, the target battery’s limited discharge cycle data is converted to a time-index series under the same reference cycle as the source battery.

Step 2: Using the same time lags $p$ and $f$, the past matrix $X_{t,p}$ is generated through (1)–(3). To convert the target battery’s discharge voltage data to the same baseline as the source battery’s, the CVs $Z_{t,c}$ and RVs $Z_{t,r}$ are obtained by projecting $X_{t,p}$ onto the source transform matrix $J_{s,c}$ and residual matrix $J_{s,r}$ as follows:

$$
Z_{t,c} = J_{s,c}X_{t,p}
$$

$$
Z_{t,r} = J_{s,r}X_{t,p}.
$$

(9)

Step 3: Using the same number of singular values $C$ derived from the source battery, the statistical indicators $T^2_t$ and $Q_t$ are calculated as (10). Simultaneously, their control limit CL$T^2_t$ and CL$Q_t$ are developed under the same significant level $\beta$ as the source battery.

$$
T^2_t(k) = \sum_{i=1}^{C}z^2_{t,c,i}(k)
$$

$$
Q_t(k) = \sum_{i=1}^{p}z^2_{t,r,i}(k).
$$

(10)

Step 4: Being converted on the same basis as the source battery, the control limit of the target battery data can be used to compare the corresponding cycles to determine the similarity with the source battery. For the first 100 discharge voltage cycles, control limits CL$T^2_c$ and CL$Q_c$ are separated as Scenario 1 (S1) and Scenario 2 (S2). S1 examines if the control limit CL$T^2_c$ is within the 15% error zone of the source battery control limits CL$T^2_c$ for 90% of the cycles, while S2 compares CL$Q_c$ with CL$Q_c$, under the same guideline. When both S1 and S2 are met, the target battery’s degradation pattern is considered to be similar to that of the source battery.

C. Target SOH Estimation by TL

Two critical factors in TL, “what to transfer” and “how to transfer,” are discussed in this section in order to achieve an outstanding estimate result.

1) Source SOH Estimation Model: The source SOH estimation model $F_{s}(\cdot)$ is developed using source battery $Z_{s,c}$ from (7) as input.
The measured value of the capacity $Y$.

Fig. 5. Illustration of the development of the target battery SOH estimation model.

The estimation model contains one input layer, multilayers of the GRU network, and an output layer to estimate the battery capacity. The model is trained by minimizing the loss function between the estimation and the actual value

$$\min \sum (Y_s(k) - \hat{Y}_s(k))^2$$

(11)

subject to

$$\hat{Y}_s(k) = F_s(z_{s,c}(k))$$

(12)

where $z_{s,c}(k)$ is the $k$th row of $Z_{s,c}$. $\hat{Y}_s(k)$ is the estimated capacity, and $Y_s(k)$ is the measured capacity.

The source SOH estimation model is trained by the complete life cycle data; it delivers comprehensive degradation information to the target battery to serve as the base model for target battery SOH estimation. However, due to the specific degradation path unique to each target battery, the model performance on each target battery requires further adjustment.

2) Target SOH Estimation Model: By feeding a small amount of CVs $Z_{t,c}$ from the target battery into the source SOH estimation model (12), the output $Y_{t,c(k)}$ estimates the capacity affected by the system CVs. To further improve the estimation accuracy, a target battery-residual variance model $F_t(\cdot)$ is trained by feeding the RVs $Z_{t,r}$ as input and minimizing the gap between the measured value of the capacity $Y_t(k)$ and the estimated capacity generated from $F_s(z_{t,c,c}(k))$

$$\min \sum (Y_t(k) - \hat{Y}_t(k))^2$$

(13)

subject to

$$\hat{Y}_t(k) = F_s(z_{t,c,c}(k)) + F_t(z_{t,r,c}(k))$$

(14)

where $z_{t,c,c}(k)$ is the $k$th row of $Z_{t,c}$, $z_{t,r,c}(k)$ is the $k$th row of $Z_{t,r,c}$. $Y_t(k)$ is the $k$th cycle of measured capacity $Y_t$, and $\hat{Y}_t(k)$ is the estimated capacity of $Y_t(k)$.

The proposed method, which is a lightweight LSTM network, has a training time complexity of per time step $O(W)$ [45], where $W$ is the total number of weights in the network, and the model development is shown in Fig. 5.

3) Online Target SOH Estimation: Once the residual model $F_t(\cdot)$ is trained by limited target battery data, the target SOH estimation model is ready to use. When a new discharge cycle occurs, the voltage data will be used to create $Z_{t,c,new}$ and $Z_{t,r,new}$ by performing Steps 1 and 2 in Section III-B. For a new cycle, the estimated capacity is achieved as follows:

$$\hat{Y}_{t,new} = F_s(z_{t,c,new}) + F_t(z_{t,r,new})$$

(15)

Remark: It is possible that a certain target battery may differ from any source batteries. In such an extreme situation, we recommend increasing the number of source batteries as many as possible. Besides, it is worth pointing out that the selected common features from the source battery will contribute to the estimation accuracy improvement, even though the target battery is different from the source battery.

### IV. EXPERIMENT RESULT AND DISCUSSION

The LiFePO4 cells from the dataset [30], manufactured by A123 Systems (APR18650M1A), were put in a forced convection temperature chamber set to 30°C. They are under 10-min fast-charging protocols with one of 224 six step. The charging protocols have the format “CC1-CC2-CC3-CC4.” They were discharged constantly at 4 C until the voltage dropped from 3.3 to 2 V. This article uses 39 battery cells in Batch 9 under eight charge protocols, and their specifications are summarized in Table I. The battery cells with the highest starting capacity and the most extended discharge cycle from the raw data from four different fast-charging protocols are used as source batteries.
The root mean squared error (RMSE) is minimized to train the model. Furthermore, both RMSE and mean absolute error (MAE) are employed to measure estimate accuracy, as illustrated in the following calculation:

\[
\text{MAE} = \frac{1}{K} \sum_{k=1}^{K} |Y(k) - \hat{Y}(k)| \quad (16)
\]

\[
\text{RMSE} = \sqrt{\frac{1}{K} \sum_{k=1}^{K} (Y(k) - \hat{Y}(k))^2} \quad (17)
\]

where \(Y(k)\) is the measured capacity, \(\hat{Y}(k)\) is the estimated capacity, and \(K\) is the total number of all the discharge cycles.

### A. Cycle Synchronization With DTW

Following the procedure in Section III-A, the original time series are synchronized. The source battery’s first discharge cycle is chosen as the reference cycle, during which the battery is deemed to be at full capacity. Taking source battery CH25 namely CH01, CH21, CH25, and CH37. Due to the batteries being drained at a consistent current at a set temperature, only voltage data are used to estimate capacity.

The root mean squared error (RMSE) is minimized to train the model. Furthermore, both RMSE and mean absolute error (MAE) are employed to measure estimate accuracy, as illustrated in the following calculation:

\[
\text{MAE} = \frac{1}{K} \sum_{k=1}^{K} |Y(k) - \hat{Y}(k)| \quad (16)
\]

\[
\text{RMSE} = \sqrt{\frac{1}{K} \sum_{k=1}^{K} (Y(k) - \hat{Y}(k))^2} \quad (17)
\]
for illustration, the voltage-based discharge cycles are shown in Fig. 1(b). Cycle 1 has 264 samples. As shown in Fig. 6(a), the other discharge cycles with different time steps are translated to the time-index-based time series with the same steps of 264. The target battery’s first 100 discharge cycles are used to benchmark its similarity with the source battery. DTW converted these target batteries’ voltage-based time series to time-index-based time series based on the first discharge cycle of the source battery. The results of the first 100 discharge cycles of target battery CH28 are given in Fig. 6(b), which are transformed into 264 steps as source battery CH25.

B. Degradation Distribution Similarity Analysis by CVA

1) Feature Extraction by CVA: Following (1)–(7), CVs and RVs are extracted by CVA from the time-index-based time series. The autocorrelation function of the lag to have a certain impact is 25 with a 95% confidence level. By adding a robust margin, time lags \( p \) and \( f \) are chosen as 32. To determine the number \( C \) of retained CVs, the singular values are accumulated and the curve is plotted as Fig. 8. To find the transition of the curve, the early 15 points and last 5 points are fit using linear regression, and the connected point of the two lines are located [46]. The connected point will be the location to determine the number \( C \) of retained CVs. The four source batteries CH01, CH21, CH25, and CH37 have 20, 19, 20, and 20 retained CVs, respectively.

At the same time, control limit \( \text{CL}_{T_2} \) and \( \text{CL}_{Q_1} \) based on 95% significant level are obtained for the source battery each cycle. The transform matrix \( J_{s,c} \) and \( J_{s,r} \) are reserved for later target battery CVs and RVs generation.

2) Performance Evaluation: The performance of the source SOH estimation model is evaluated here to decide whether the TL is triggered or not by comparing \( T^2 \) and \( Q \) with their respective control limits \( \text{CL}_{T_2} \) and \( \text{CL}_{Q_1} \). Following that, the \( Z_{t,c} \) and \( Z_{t,r} \) are extracted and \( \text{CL}_{T_2} \) and \( \text{CL}_{Q_1} \) are obtained for each cycle based on (9) and (10). For the first 100 cycles, the \( \text{CL}_{T_2} \) with \( \text{CL}_{Q_1} \) under S1 and \( \text{CL}_{Q_1} \) under S2 are compared. If both S1 and S2 are met, it is considered the degradation distribution of the target battery to be similar to the source battery.

Fig. 7 depicts the comparison results for two target batteries that are comparable to the source battery and two target batteries that are not similar, with the others omitted for brevity. For source battery CH01, under S1, that \( \text{CL}_{T_2} \) of target battery CH33 has less than 90 cycles within 15% error zone, whereas under S2, that \( \text{CL}_{Q_1} \) of target battery CH32 has less than 90 cycles within 15%, both of their data distribution are considered not similar as CH01, despite under the other scenario, they are within. The same rule applies to CH15 for source battery CH21. For target battery CH19 to source battery CH21, target battery CH06, CH47 to source battery CH25, target battery CH02, CH03 to source battery CH37, they are classified under not similar as they fail in both S1 and S2. It is not effective to use the source SOH estimation model on those target batteries. On the other hand, for target battery CH22, CH29 to source battery CH01, target battery CH26, CH45 to source battery CH21, target battery CH28, CH41 to source battery CH25, target battery CH15, CH27 to source battery CH37, they are meeting both S1 and S2. The source SOH estimation model can serve as a good base model to transfer the knowledge learned by complete degradation cycles. The details are shown in Table II.
TABLE II
SOURCE SOH ESTIMATION PERFORMANCE EVALUATION

| Source battery | Target battery | Evaluation |
|----------------|----------------|------------|
| Channel        | Total cycles  | Initial capacity | Number (C) of retained CVs | Channel | Total cycles  | Initial capacity | $\delta^1_*$ | $\delta^2_*$ | Similarity |
| CH01           | 958           | 1.061          | 20                           | CH22    | 834           | 1.065           | Yes          | Yes          | Yes        |
|                |               |                |                               | CH29    | 805           | 1.044           | Yes          | Yes          | Yes        |
|                |               |                |                               | CH32    | 1074          | 1.045           | Yes          | No           | No         |
|                |               |                |                               | CH33    | 501           | 1.032           | No           | Yes          | No         |
| CH21           | 885           | 1.057          | 19                           | CH26    | 917           | 1.039           | Yes          | Yes          | Yes        |
|                |               |                |                               | CH45    | 1166          | 1.056           | Yes          | Yes          | Yes        |
|                |               |                |                               | CH5     | 1006          | 1.036           | Yes          | No           | No         |
|                |               |                |                               | CH19    | 497           | 1.057           | No           | No           | No         |
| CH25           | 984           | 1.055          | 20                           | CH28    | 1075          | 1.049           | Yes          | Yes          | Yes        |
|                |               |                |                               | CH41    | 990           | 1.049           | Yes          | Yes          | Yes        |
|                |               |                |                               | CH6     | 903           | 1.055           | No           | No           | No         |
|                |               |                |                               | CH7     | 762           | 1.048           | No           | No           | No         |
| CH37           | 957           | 1.065          | 20                           | 20CH13  | 1006          | 1.036           | Yes          | Yes          | Yes        |
|                |               |                |                               | CH27    | 995           | 1.050           | Yes          | Yes          | Yes        |
|                |               |                |                               | CH32    | 844           | 1.054           | No           | No           | No         |
|                |               |                |                               | CH33    | 823           | 1.054           | No           | No           | No         |

*$\delta^1_*$: 90% of $C_{L_{2-2}}$ within $C_{L_{2-2}}$ error zone
*$\delta^2_*$: 90% of $C_{L_{2-2}}$ within $C_{L_{2-3}}$ error zone

TABLE III
TARGET BATTERY SOH ESTIMATION RESULTS

| Source battery | Target battery | SELF-GRU (Proposed-w/o TL) | DCVA-GRU (Proposed-w/o TL) | DCVA-GRU-TL (Proposed-w/ TL) | Accuracy improvement by TL (DCVA-GRU-TL VS DCVA-GRU) |
|----------------|----------------|-----------------------------|----------------------------|----------------------------|-----------------------------------------------------|
| Channel        | Similarity     | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE (%) | RMSE (%) |
| CH01           | Yes            | 0.0520 | 0.0909 | 0.0661 | 0.0777 | 0.0026 | 0.0034 | 68% | 55%     |
| CH29           | Yes            | 0.0546 | 0.0811 | 0.0197 | 0.0201 | 0.0037 | 0.0047 | 81% | 77%     |
| CH32           | No             | 0.0527 | 0.0868 | 0.0188 | 0.0192 | 0.0079 | 0.0147 | 58% | 23%     |
| CH33           | No             | 0.0541 | 0.0941 | 0.0140 | 0.0164 | 0.0081 | 0.0149 | 42% | 9%      |
| CH21           | Yes            | 0.0557 | 0.0905 | 0.0037 | 0.0046 | 0.0033 | 0.0040 | 11% | 12%     |
| CH45           | Yes            | 0.0500 | 0.0754 | 0.0114 | 0.0150 | 0.0053 | 0.0067 | 53% | 56%     |
| CH15           | No             | 0.0522 | 0.0882 | 0.0151 | 0.0162 | 0.0087 | 0.0110 | 43% | 32%     |
| CH19           | No             | 0.0639 | 0.1078 | 0.0344 | 0.0390 | 0.0181 | 0.0234 | 47% | 40%     |
| CH25           | Yes            | 0.0515 | 0.0858 | 0.0186 | 0.0188 | 0.0034 | 0.0044 | 82% | 77%     |
| CH41           | Yes            | 0.0588 | 0.0949 | 0.0150 | 0.0159 | 0.0031 | 0.0039 | 79% | 76%     |
| CH6            | No             | 0.0485 | 0.0864 | 0.0160 | 0.0180 | 0.0133 | 0.0154 | 17% | 15%     |
| CH7            | No             | 0.0371 | 0.0604 | 0.0122 | 0.0149 | 0.0109 | 0.0146 | 10% | 7%      |
| CH37           | Yes            | 0.0521 | 0.0882 | 0.0180 | 0.0182 | 0.0070 | 0.0079 | 61% | 57%     |
| CH32           | Yes            | 0.0555 | 0.0917 | 0.0130 | 0.0133 | 0.0034 | 0.0043 | 74% | 67%     |
| CH3            | No             | 0.0521 | 0.0906 | 0.0166 | 0.0202 | 0.0106 | 0.0166 | 36% | 18%     |
| CH03           | No             | 0.0516 | 0.0906 | 0.0272 | 0.0303 | 0.0177 | 0.0231 | 35% | 24%     |

C. Target SOH Estimation by TL

1) Source SOH Estimation Model: The source SOH estimation model is trained by the entire life cycle and transfers the extracted common features to the target battery, explicitly stating “what to transfer.” The GRU-based estimation model DCVA-GRU is constructed by a GRU layer of 300 neurons and another GRU layer of 500 neurons. Before the output layer, the two GRU layers are fully linked to a normal layer with 100 neurons. Adam is chosen as the optimizer here. Ninety epochs are conducted to discover the best weights and biases.

2) Target SOH Estimation Model: The proposed TL target battery SOH estimation method DCVA-GRU-TL is investigated here for those target batteries with a similar degradation distribution as the source battery. The source battery SOH estimation model trained under CVs can be transferred to the target battery and compensated by the target battery residual model through its unique RVs using the target battery’s first 100 discharge voltage cycles only.

“How to transfer” is finalized by combining both the source battery SOH estimation model and the target battery residual estimation model to perform target battery SOH estimation. The residual model is built by a GRU layer of 300 neurons followed by a dropout layer of 20%, then another GRU layer of 500 neurons followed by a 20% dropout. Before the output layer, a normal layer with 100 neurons is inserted. Thirty epochs are run. The same optimizer Adam is used.

Compared with the source battery SOH estimation model DCVA-GRU as described in Fig. 2(b), for those with similar
degradation distribution, DCVA-GRU-TL has achieved excellent estimation results to achieve RMSE going below 0.01 as shown in Table III. While for those target batteries that are not similar to the source battery, RMSE cannot go below 0.01 even after target battery residual model compensation. Using source battery CH25 for illustration, similar target battery CH28 MAE and RMSE improved by 82% and 77%, hitting 0.0034 and 0.0044, while CH41 MAE and RMSE improved by 79% and 76%, going as low as 0.0031 and 0.0039. For CH06, which is not similar, although 15% RMSE improvements are recorded, RMSE is still 0.0154. The same finding is for CH47, where RMSE only improves by 2% to 0.0146. Both RMSEs are significantly higher than 0.01. The model described in Fig. 2(a) was also put to the test. With only the first 100 discharge voltage cycles, it fails to predict the SOH with such a small training dataset that MAE is larger than 0.05 and RMSE is greater than 0.08. For further visualization, the detailed prediction trends of all methods are illustrated in Fig. 9. Compensated by the target battery’s unique feature, the proposed method DCVA-GRU-TL yields the best estimation result of RMSE below 0.01 for the battery having a similar degradation distribution as the source battery.

V. CONCLUSION

This research utilizes temporal dynamic correlation during discharging and presents an innovative TL-based SOH estimation approach. DTW translates the target battery discharge voltage-based time series into a time-index-based time series based on the source battery’s discharge voltage cycle at full capacity. It synchronizes discharge data while also extracting temporal information. CVA underlines the temporal correlation within the cycles and separates them into common and domain-specific features. The source SOH estimation model is built by the common feature and its ability to estimate the target battery SOH is assessed by statistic indicators. It serves as a benchmark for the target batteries to choose the best source SOH estimation model for a better estimation result. Based on the outcome of the assessment, target battery is able to select the best source SOH estimation model from source battery pool to optimize the estimation accuracy. Then, using common feature CVs, TL functioned as a bridge to transfer the knowledge obtained by the source SOH estimate model, which was trained by data from the complete degradation process. Estimation is further enhanced and precise when it is combined with the target residual SOH estimation model, built by the target battery’s unique feature. The proposed methods are validated by a public dataset and show effectiveness for SOH estimation by using as little as the first 100 discharge cycles regardless of charging policy.

Considering the importance of temperature on the battery performance aging, future work is recommended to design a generic source SOH model that involves the influence of varying ambient temperatures.

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