METHOD FOR PREDICTING STATE OF HEALTH OF BATTERY AND RELATED APPARATUS

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] The present application is based on and claims the priority to the Chinese Patent Application No. 202310699711.1 filed on June 13, 2023, the disclosure of which is incorporated by reference herein in its entirety.

TECHNICAL FIELD

[0002] The present disclosure generally relates to the technical field of battery operation and maintenance, and more specifically, to a method for predicting a state of health of a battery and a related apparatus.

BACKGROUND

[0003] The law that a state of health (SOH) of a battery varies over time, i.e., an aging mode of the battery, may be used for evaluating a remaining lifespan of the battery, thus prediction of the state of health of the battery is one of core problems in the technical field of battery operation and maintenance.

SUMMARY

[0004] According to a first aspect of the present disclosure, there is provided a method for predicting a state of health of a battery, comprising: acquiring source domain battery data and target domain battery data, the source domain battery data comprising a voltage variation-over-time curve of each of a plurality of reference batteries in a full life cycle in respective one of a plurality of reference usage conditions, the target domain battery data comprising a voltage variation-over-time curve of a target battery in an early lifespan in an actual usage condition; identifying a characteristic voltage variation interval common to the plurality of reference batteries based on the voltage variation-over-time curves of the plurality of reference batteries, a voltage variation pattern of each reference battery in the characteristic voltage variation interval appearing periodically in the voltage variation-over-time curve of the reference battery; constructing a source domain sample set, comprising constructing one source domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of each reference battery, a sample input of the source domain sample comprising characteristic values and states of health of the reference battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval, the characteristic value being related to the state of health, and a sample output of the source domain sample comprising states of health of the reference battery in a second plurality of characteristic voltage variation intervals following the characteristic voltage variation interval; constructing a metric function based on the source domain sample set, the metric function being used for measuring similarity between the sample inputs; constructing one target domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of the target battery, a sample input of the target domain sample comprising characteristic values and states of health of the target battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval; and weighting the sample output of the source domain sample in the source domain sample set by taking similarity between the sample input of the target domain sample and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample as a predicted value of the state of health of the target battery.

[0005] According to a second aspect of the present disclosure, there is provided an apparatus for predicting a state of health of a battery, comprising: a battery data acquisition module configured to acquire source domain battery data and target domain battery data, the source domain battery data comprising a voltage variation-over-time curve of each of a plurality of reference batteries in a full life cycle in respective one of a plurality of reference usage conditions, the target domain battery data comprising a voltage variation-over-time curve of a target battery in an early lifespan in an actual usage condition; a characteristic interval identification module configured to identify a characteristic voltage variation interval common to the plurality of reference batteries based on the voltage variation-over-time curves of the plurality of reference batteries, a voltage variation pattern of each reference battery in the characteristic voltage variation interval appearing periodically in the voltage variation-over-time curve of the reference battery; a source domain sample construction module configured to construct a source domain sample set, comprising constructing one source domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of each reference battery, a sample input of the source domain sample comprising characteristic values and states of health of the reference battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval, the characteristic value being related to the state of health, and a sample output of the source domain sample comprising states of health of the reference battery in a second plurality of characteristic voltage variation intervals following the characteristic voltage variation interval; a metric function construction module configured to construct a metric function based on the source domain sample set, the metric function being used for measuring similarity between the sample inputs; a target domain sample construction module configured to construct one target domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of the target battery, a sample input of the target domain sample comprising characteristic values and states of health of the target battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval; and a state of health prediction module configured to weight the sample output of the source domain sample in the source domain sample set by taking similarity between the sample input of the target domain sample and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample as a predicted value of the state of health of the target battery.

[0006] According to a third aspect of the present disclosure, there is provided a computing device for predicting a state of health of a battery, comprising: one or more processors; and a memory storing computer-executable instructions which, when executed by the one or more processors, cause the one or more processors to perform the method for predicting a state of health of a battery according to any embodiment of the first aspect of the present disclosure.

[0007] According to a fourth aspect of the present disclosure, there is provided a non-transitory storage medium having thereon stored computer-executable instructions which, when executed by a computer, cause the computer to perform the method for predicting a state of health of a battery according to any embodiment of the first aspect of the present disclosure.

[0008] Other features of the present disclosure and advantages thereof will become more apparent from the following detailed description of exemplary embodiments thereof, which proceeds with reference to the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0009] The foregoing and other features and advantages of the present disclosure will become apparent from the following description of the embodiments of the present disclosure illustrated in conjunction with the accompanying drawings. The accompanying drawings are incorporated herein and form a part of the specification, to further serve to explain the principles of the present disclosure and enable those skilled in the art to make and use the present disclosure. In the drawings:

[0010] Fig. 1 schematically depicts battery SOH variation-over-time curves in different usage conditions;

[0011] Fig. 2 schematically depicts battery SOH variation-over-time curves in a full life cycle in a laboratory test scenario and battery SOH variation-over-time curves in an early lifespan in an actual prediction scenario;

[0012] Fig. 3 illustrates a flow diagram of a method for predicting a state of health of a battery according to some embodiments of the present disclosure;

[0013] Fig. 4 illustrates a flow diagram of a method for predicting a state of health of a battery according to some other embodiments of the present disclosure;

[0014] Fig. 5 schematically depicts battery voltage variation-over-time curves in different usage conditions;

[0015] Fig. 6 illustrates a schematic block diagram of an apparatus for predicting a state of health of a battery according to some embodiments of the present disclosure;

[0016] Fig. 7 illustrates a schematic block diagram of a computing device for predicting a state of health of a battery according to some embodiments of the present disclosure.

[0017] Note that in the embodiments described below, sometimes, same reference numerals are used in common between different drawings to represent same portions or portions having same functions, and their repetitive explanations are omitted. In some cases, similar items are indicated using similar reference numbers and letters, and thus, once an item is defined in a drawing, it need not be discussed further in subsequent drawings.

[0018] For convenience of understanding, positions, sizes, ranges, and the like of structures shown in the drawings and the like sometimes do not represent actual positions, sizes, ranges, and the like. Therefore, the present disclosure is not limited to the positions, sizes, ranges, and the like disclosed in the drawings and the like.

DETAILED DESCRIPTION

[0019] Various exemplary embodiments of the present disclosure will be described in detail below with reference to the accompanying drawings. It should be noted that: relative arrangements of components and steps, numerical expressions and numerical values set forth in these embodiments do not limit the scope of the present disclosure unless specifically stated otherwise.

[0020] The following description of at least one exemplary embodiment is merely illustrative in nature and is in no way used as any limitation on this disclosure and its application or use. That is, a structure and method herein are shown in an exemplary way to illustrate different embodiments of the structure and method in the present disclosure. Those skilled in the art will understand, however, that they are merely illustrative of exemplary ways in which this disclosure may be implemented, rather than exhaustive ways. Furthermore, the accompanying drawings are not necessarily drawn to scale, some features may be enlarged to show details of specific components.

[0021] In addition, techniques, methods, and devices known to one of ordinary skill in the related art might not be discussed in detail but are intended to be part of the description where appropriate.

[0022] In all examples shown and discussed herein, any specific value should be construed as exemplary merely and not as limiting. Thus, other examples of the exemplary embodiments may have different values.

[0023] An aging mode of a battery is closely related to a usage condition (i.e. a usage mode of the battery, including a charging mode, a discharging mode, or a work loading mode, etc.) of the battery, and even a same battery will experience different aging modes in different usage conditions, as shown in Fig. 1, for example. Therefore, a battery state of health prediction model trained from battery data in a given usage condition (e.g., a laboratory full charge-discharge test condition) might be difficult to be applicable to predicting a state of health variation-over-time law of a battery in a new usage condition. In addition, when a state of health of a battery needs to be predicted actually, there is often at most only a small amount of early lifespan data of the battery, unlike a case where full life cycle data of a battery can be obtained when the battery is tested in a laboratory, as shown in Fig. 2, for example. Therefore, in an actual prediction scenario, scarcity of battery data samples might make it difficult to accurately predict the state of health of the battery.

[0024] The present disclosure provides a method for predicting a state of health of a battery, which can accurately predict long-term variations over time of the state of health of the battery in future across various usage conditions using a small amount of early lifespan data of the battery in the target domain, by searching for a battery in a source domain that has a similar battery early aging mode to that of the battery in the target domain, thereby obtaining a full life cycle aging mode of the battery, and can predict a calendar lifespan of the battery, which is more intuitive and convenient compared with prediction of a cycle lifespan.

[0025] Fig. 3 illustrates a method 100 for predicting a state of health of a battery according to some embodiments of the present disclosure. The method 100 comprises: at step S102, acquiring source domain battery data and target domain battery data. The source domain battery data includes a voltage variation-over-time curve of each of a plurality of reference batteries in a full life cycle in respective one of a plurality of reference usage conditions. The target domain battery data includes a voltage variation-over-time curve of a target battery in an early lifespan in an actual usage condition. The curve, herein, is not limited to data in a form of a chart, and may be data in another form such as text, for example, it may be textualized as an array, matrix, set, or the like, as long as it is data that can be presented as a curve. The reference battery and the target battery both may, for example, be a rechargeable battery such as a lithium battery. The plurality of reference usage conditions may include various known usage conditions, for example, a usage condition in which one full discharge and charge is performed at regular intervals like a backup battery of a data center, a usage condition in which one non-full charge is performed every few days according to driving habits of a vehicle owner like a power battery of a new energy electric vehicle, and the like. The actual usage condition of the target battery does not necessarily need to be one of the aforementioned various known usage conditions, but may be a new usage condition. The target battery may have been used for a period of time, so that battery data in its early lifespan (such as voltage variations over time, SOH variations over time, etc.) is known.

[0026] The method 100 comprises: at step S104, identifying a characteristic voltage variation interval common to the plurality of reference batteries based on the voltage variation-over-time curves of the plurality of reference batteries, a voltage variation pattern of each reference battery within the characteristic voltage variation interval appearing periodically in the voltage variation-over-time curve of the reference battery. For example, referring to Fig. 5, a reference battery in usage condition 1 is subjected to one full charge-discharge at regular intervals, while a reference battery in usage condition 2 is subjected to one non-full charge-discharge at regular intervals. It may be noted that although voltage variation-over-time curves in the usage conditions 1 and 2 seem quite different, they each vary from a voltage v_1 to v_2 at regular intervals, so that they have a common characteristic voltage variation interval [v_1,v_2] which appears periodically. Although durations and/or appearance periods of the characteristic voltage variation interval [v_1, v_2] are not necessarily the same in the usage conditions 1 and 2, since the characteristic voltage variation interval [v_1,v_2] appears periodically in various usage conditions, an aging law of the battery with time can be directly determined by determining an aging law of the battery with the number of appearances of the characteristic voltage variation interval [v_1,v_2]. In some embodiments, the voltage variation pattern of each reference battery within the characteristic voltage variation interval may be monotonic. The "monotonic" voltage variation pattern, herein, may refer to the voltage continuously increasing over time, or the voltage continuously decreasing over time. When the voltage increases over time, it can be considered that the voltage variation pattern is in a charge stage. When the voltage decreases over time, it can be considered that the voltage variation pattern is in a discharge stage. In some embodiments, the voltage variation pattern of each reference battery within the characteristic voltage variation interval may be in the charge stage. In some embodiments, the voltage variation pattern of each reference battery within the characteristic voltage variation interval may be in the discharge stage. In some examples, the characteristic voltage variation interval common to the plurality of reference batteries may be identified by: letting B be a set of the plurality of reference batteries, b be a reference battery in B, and $V_b(t)$ be a voltage variation-over-time curve of the reference battery b, then the characteristic voltage variation interval $[v_1, v_2]$ is: $v_1, v_2 = \arg\max_{v1,v2} |v_1 - v_2|$, so that for any $b \in B$ and a non-negative integer n, there are time t_1, time t_2, and a period T, which satisfy: $t_1 < t_2$, and $V_b(t_1 + nT) = v_1$, $V_b(t_2 + nT) = v_2$, and for times $t_1', t_2' \in [t_1 + nT, t_2 + nT]$, $t_1' < t_2'$, then $V_b(t_1') < V_b(t_2')$. In this way, the characteristic voltage variation interval may be selected so that the voltage variation pattern of each reference battery within the characteristic voltage variation interval is monotonic and in the charge stage, which may be preferred in some cases, as the monotonic voltage variation pattern facilitates finding a periodic law existing in the voltage variation-over-time curve of the battery, and the charge stage tends to be more stable and controllable compared to the discharge stage. Assuming that T^b is a period that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the reference battery b and N^b is the number of times that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the reference battery b, then as described above, for different reference batteries b, T^b and N^b may be different.

[0027] Next, the method 100 comprises: at step S106, constructing a source domain sample set. One source domain sample may be constructed for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of each reference battery, a sample input of the source domain sample comprising characteristic values and states of health of the reference battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval, and a sample output of the source domain sample comprising states of health of the reference battery in a second plurality of characteristic voltage variation intervals following the characteristic voltage variation interval. The characteristic value related to the state of health may be extracted from the characteristic voltage variation interval by using any suitable method now known or later developed. The characteristic value may be any suitable variable capable of indicating state-of-health variation, for example, it may be, but not limited to, an electricity quantity variation value per unit voltage variation range, and the like. The state of health of the battery may be characterized by any suitable method now known or later developed, for example, it may be, but not limited to, a ratio of battery capacity to rated capacity, a ratio of battery internal resistance to rated internal resistance, and the like.

[0028] In some embodiments, let B be a set of the plurality of reference batteries, b be a reference battery in B, and a characteristic voltage variation interval i of the reference battery b have a characteristic value x_i^b and a state y_i^b of health, then the constructing a source domain sample set $\mathcal{D}$ comprises: constructing one source domain sample for each characteristic voltage variation interval appearing in a voltage variation-over-time curve of each reference battery b, a sample input of the source domain sample comprising characteristic values and states of health of the reference battery in r characteristic voltage variation intervals preceding the characteristic voltage variation interval, and a sample output of the source domain sample comprising states of health of the reference battery in $(R \times s)$ characteristic voltage variation intervals following the characteristic voltage variation interval, so that a source domain sample for a kth characteristic voltage variation interval of the reference battery b comprises:

a sample input $\mathcal{X} = \{x_{k-1}^b, y_{k-1}^b, x_{k-2}^b, y_{k-2}^b, \dots, x_{k-r}^b, y_{k-r}^b\}$, and

a sample output $\mathcal{Y} = \{y_{k+s}^b, y_{k+2s}^b, \dots, y_{k+R\times s}^b\}$, wherein r, R, s, and k are positive integers.

[0029] In some examples, it is possible to determine r based on the number of times that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the target battery, and determine $(R \times s)$ based on a preset time domain scaling ratio of the sample output to the sample input. For example, for a lithium battery with a complete cycle lifespan of 1000-3000 cycles, it may be set that r=100, R=100, and s=10, so that long-term state-of-health variations of 1000 characteristic voltage variation intervals in future may be predicted by using characteristic values and states of health of 100 characteristic voltage variation intervals in succession of an early lifespan.

[0030] In some embodiments, the constructing a source domain sample set $\mathcal{D}$ may further comprise: performing time domain scaling on the source domain samples at different period scaling ratios, respectively, to obtain source domain samples enhanced at the different period scaling ratios, wherein a source domain sample enhanced at a period scaling ratio l for a kth characteristic voltage variation interval of the reference battery b comprises:

a sample input $\mathcal{X} = \{x_{k-l}^b, y_{k-l}^b, x_{k-2l}^b, y_{k-2l}^b, \dots, x_{k-r\times l}^b, y_{k-r\times l}^b\}$, and

a sample output $\mathcal{Y} = \{y_{k+s\times l}^b, y_{k+2s\times l}^b, \dots, y_{k+R\times s\times l}^b\}$, where l is a positive integer. For example, for a lithium battery with a complete cycle lifespan of 1000-3000 cycles, it may be set l=1, 2, 3. In some examples, the period scaling ratio l may be determined based on a ratio of a period that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the target battery to a period that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the reference battery. In some examples, the period scaling ratio l may be determined based on a ratio of an aging rate of the target battery to an aging rate of the reference battery. By setting the value of l reasonably, the method can be applicable to causing the knowledge of the source domain battery data to be migrated to a target battery with a different aging rate.

[0031] Continually referring to Fig. 3, the method 100 further comprises: at step S108, constructing a metric function based on the source domain sample set, the metric function being used for measuring similarity between the sample inputs. In some embodiments, the metric function f_θ may be constructed based on the source domain sample set $\mathcal{D}$, so that

$$P(\mathcal{Y} \mid \mathcal{X}, \mathcal{D}) = \mathop{\mathbb{E}}_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}} f_\theta(\mathcal{X}, \mathcal{X}_i) \cdot P(\mathcal{Y}_i \mid \mathcal{X}_i),$$

where $f_\theta(\mathcal{X}, \mathcal{X}_i)$ represents similarity between sample inputs $\mathcal{X}, \mathcal{X}_i$, $P(\mathcal{Y}_i \mid \mathcal{X}_i)$ represents a probability that the sample input is $\mathcal{Y}_i$ when the sample input is $\mathcal{X}_i$, and $P(\mathcal{Y} \mid \mathcal{X}, \mathcal{D})$ represents a probability that the sample input is $\mathcal{Y}$ when the sample input is $\mathcal{X}$, and $\mathbb{E}$ is used for calculating an expectation. In some embodiments, a parameter θ of the metric function f_θ may be further solved by creating a training dataset based on the source domain sample set $\mathcal{D}$ to train a neural network model, whose loss function L_θ may be constructed as, for example,

$$L_\theta(\mathcal{X},\mathcal{Y},\mathcal{D}^{batch}) = MSE\left(\frac{\sum_{\mathcal{X}_i,\mathcal{Y}_i\in\mathcal{D}^{batch}} f_\theta(\mathcal{X},\mathcal{X}_i)\cdot\mathcal{Y}_i}{\sum_{\mathcal{X}_i,\mathcal{Y}_i\in\mathcal{D}^{batch}} f_\theta(\mathcal{X},\mathcal{X}_i)},\mathcal{Y}\right),$$

where $\mathcal{D}^{batch}$ is batch data randomly sampled in the source domain sample set $\mathcal{D}$, MSE is used for calculating a mean square error, and where the parameter θ of the metric function f_θ is determined as a parameter θ minimizing the loss function L_θ. For example, the parameter θ of the metric function f_θ can, by minimizing the loss function L_θ, be determined as $\hat{\theta} = \arg\max_\theta \mathbb{E}_{\mathcal{X},\mathcal{Y}\in\mathcal{D}}[L_\theta(\mathcal{X},\mathcal{Y},\mathcal{D})]$. Although such a metric function f_θ is trained using data of the source domain sample set, it may be used for measuring similarity between sample inputs across domains (e.g., between the source domain and the target domain). The identifying the characteristic voltage variation interval in step S104 may ensure comparability between across-domain sample inputs. The constructing of the source domain sample in various ways in step S106 improves diversity of the source domain sample input, so that a generalization capability of the metric function is enhanced.

[0032] Still referring to Fig. 3, the method 100 further comprises: at step S110, constructing a target domain sample. Similar to constructing the source domain sample, one target domain sample may be constructed for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of the target battery, a sample input of the target domain sample comprising characteristic values and states of health of the target battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval. In some embodiments, let c be a target battery (T^c is a period that a characteristic voltage variation interval appears in a voltage variation-over-time curve of the target battery c, N^c is a number of times that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the target battery c), and a characteristic voltage variation interval j of the target battery c have a characteristic value x_j^c and a state y_j^c of health, then the constructing a target domain sample may comprise: constructing one target domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of the target battery c, a sample input of the target domain sample comprising characteristic values and states of health of the target battery in r characteristic voltage variation intervals preceding the characteristic voltage variation interval, so that a target domain sample for a gth characteristic voltage variation interval of the target battery c comprises a sample input $\mathcal{X}_c = \{x_{g-1}^c, y_{g-1}^c, x_{g-2}^c, y_{g-2}^c, \ldots, x_{g-r}^c, y_{g-r}^c\}$, where g is a positive integer.

[0033] The method 100 further comprises: at step S112, weighting the sample output of the source domain sample in the source domain sample set by taking similarity between the sample input of the target domain sample and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample as a predicted value of the state of health of the target battery. In some examples, a future state of health of the target battery may be determined as $\mathcal{Y}_c = \frac{\sum_{\mathcal{X}_i,\mathcal{Y}_i\in\mathcal{D}} f_\theta(\mathcal{X}_c,\mathcal{X}_i)\cdot\mathcal{Y}_i}{\sum_{\mathcal{X}_i,\mathcal{Y}_i\in\mathcal{D}} f_\theta(\mathcal{X}_c,\mathcal{X}_i)} = \{y^b_{k+s}, y^b_{k+2s}, \dots, y^b_{k+R\times s}\}$, where $y^b_{k+s}, y^b_{k+2s}, \dots, y^b_{k+R\times s}$ are predicted values of states of health of the target battery in $(k+s)$ th, $(k+2s)$ th, $\cdots$, and $(k+R\times s)$ th appearances of the characteristic voltage variation interval, respectively. In some embodiments, the method 100 further comprises: at step S120, performing interpolation on the predicted value of the state of health of the target battery (for example, $y^b_{k+s}, y^b_{k+2s}, \dots, y^b_{k+R\times s}$), thereby predicting a state of health variation-over-time curve of the target battery in a full life cycle in the actual usage condition.

[0034] Fig. 4 illustrates a method 100' for predicting a state of health of a battery according to some other embodiments. The method 100' differs from the method 100 in that the step S112 is replaced with step S114, step S116, and step S118. Specifically, the method 100' comprises: at step S114, performing time domain scaling on the target domain sample at different period scaling ratios, respectively, to obtain target domain samples enhanced at the different period scaling ratios; at step S116, determining, based on the metric function, degrees of matching between the target domain samples enhanced at the different period scaling ratios and the source domain samples in the source domain sample set, and determining a target domain sample with a highest degree of matching as a target domain sample enhanced at an optimal period scaling ratio; and at step S118, weighting the sample output of the source domain sample in the source domain sample set by taking similarity between a sample input of the target domain sample enhanced at the optimal period scaling ratio and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample enhanced at the optimal period scaling ratio as a predicted value of the state of health of the target battery.

[0035] Specifically, in some embodiments, a target domain sample enhanced at a period scaling ratio q for the gth characteristic voltage variation interval of the target battery c comprises a sample input $\mathcal{X}_c^q = \{x_{g-q}^c, y_{g-q}^c, x_{g-2q}^c, y_{g-2q}^c, \ldots, x_{g-r\times q}^c, y_{g-r\times q}^c\}$, where q is a positive integer. The period scaling ratio q may be set independent of the period scaling ratio l. In some embodiments, it is possible to set only the period scaling ratio q without setting the period scaling ratio l. In some embodiments, it is possible to set only the period scaling ratio l without setting the period scaling ratio

q. In some embodiments, both of the period scaling ratios q and l may be set. By the cooperative setting of the period scaling ratio q and the period scaling ratio l, the method can advantageously cause the knowledge of the source domain battery data to be migrated to the target domain in the case where the aging rate of the reference battery is a non-integral multiple of the aging rate of the target battery.

[0036] In some embodiments, the determining, based on the metric function f_θ, degrees of matching between the target domain samples enhanced at the different period scaling ratios and the source domain samples in the source domain sample set $\mathcal{D}$ may comprise: quantifying the degree of matching as $Affinity(q) = \sum_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}} f_\theta\left(\mathcal{X}_c^q, \mathcal{X}_i\right)$. The optimal period scaling ratio may be determined as $\hat{q} = \arg\max_q Affinity(q)$. A sample input of the target domain sample enhanced at the optimal period scaling ratio may be represented as $\hat{\mathcal{X}} = \mathcal{X}_c^{\hat{q}}$. In some embodiments, a future state of health of the target battery may be determined as:

$$\hat{\mathcal{Y}} = \frac{\sum_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}} f_\theta(\hat{\mathcal{X}}, \mathcal{X}_i) \cdot \mathcal{Y}_i}{\sum_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}} f_\theta(\hat{\mathcal{X}}, \mathcal{X}_i)} = \left\{y^b_{k+s\times\hat{q}}, y^b_{k+2s\times\hat{q}}, \cdots, y^b_{k+R\times s\times\hat{q}}\right\}.$$

where $y^b_{k+s\times\hat{q}}, y^b_{k+2s\times\hat{q}}, \cdots, y^b_{k+R\times s\times\hat{q}}$ are predicted values of states of health of the target battery in $(k + s \times \hat{q})$th, $(k + 2s \times \hat{q})$th,$\cdots$, and $(k + R \times s \times \hat{q})$th appearances of the characteristic voltage variation interval, respectively. Further, the method 100' may further comprise: at step S120, performing interpolation on the predicted value of the state of health of the target battery (e.g., $y^b_{k+s\times\hat{q}}, y^b_{k+2s\times\hat{q}}, \ldots, y^b_{k+R\times s\times\hat{q}}$), thereby predicting the state of health variation-over-time curve of the target battery in the full life cycle in the actual usage condition. According to the interpolated state of health variation-over-time curve of the target battery in the full life cycle in the actual usage condition, a remaining calendar lifespan of the target battery can be conveniently evaluated, for example, a time when its state of health drops to a certain value (e.g., 80% of a rated value) can be known. Such a calendar lifespan provides a lifespan in a more intuitive time notion than the cycle lifespan.

[0037] Referring to Fig. 6, the present disclosure further provides an apparatus 200 for predicting a state of health of a battery. The apparatus 200 comprises a battery data acquisition module 202, a characteristic interval identification module 204, a source domain sample construction module 206, a metric function construction module 208, a target domain sample construction module 210, and a state of health prediction module 212. The battery data acquisition module 202 is configured to acquire source domain battery data and target domain battery data, the source domain battery data comprising a voltage variation-over-time curve of each of a plurality of reference batteries in a full life cycle in respective one of a plurality of reference usage conditions, and the target domain battery data comprising a voltage variation-over-time curve of a target battery in an early lifespan in an actual usage condition. The characteristic interval identification module 204 is configured to identify a characteristic voltage variation interval common to the plurality of reference batteries based on the voltage variation-over-time curves of the plurality of reference batteries, a voltage variation pattern of each reference battery in the characteristic voltage variation interval appearing periodically in the voltage variation-over-time curve of the reference battery. The source domain sample construction module 206 is configured to construct a source domain sample set, comprising constructing one source domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of each reference battery, a sample input of the source domain sample comprising characteristic values and states of health of the reference battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval, the characteristic value being related to the state of health, and a sample output of the source domain sample comprising states of health of the reference battery in a second plurality of characteristic voltage variation intervals following the characteristic voltage variation interval. The metric function construction module 208 is configured to construct a metric function based on the source domain sample set, the metric function being used for measuring similarity between the sample inputs. The target domain sample construction module 210 is configured to construct one target domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of the target battery, a sample input of the target domain sample comprising characteristic values and states of health of the target battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval. The state of health prediction module 212 is configured to weight the sample output of the source domain sample in the source domain sample set by taking similarity between the sample input of the target domain sample and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample as a predicted value of the state of health of the target battery.

[0038] In some embodiments, the target domain sample construction module 210 may be further configured to perform time domain scaling on the target domain sample at different period scaling ratios, respectively, to obtain target domain samples enhanced at the different period scaling ratios, and the state of health prediction module 212 may be further configured to: determine degrees of matching between the target domain samples enhanced at the different period scaling ratios and the source domain samples in the source domain sample set based on the metric function, and determine a target domain sample with a highest degree of matching as a target domain sample enhanced at an optimal period scaling ratio; and weight the sample output of the source domain sample in the source domain sample set by taking similarity between the sample input of the target domain sample enhanced at the optimal period scaling ratio and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample enhanced at the optimal period scaling ratio as a predicted value of the state of health of the target battery.

[0039] Embodiments of the apparatus 200 are substantially similar to the embodiments of the method described above, thus the description thereof will not be repeated here, and reference may be made to the description of the method embodiment described above for relevant parts.

[0040] The present disclosure further provides a computing device for predicting a state of health of a battery, which may comprise one or more processors and a memory storing computer-executable instructions which, when executed by the one or more processors, cause the one or more processors to perform the method for predicting a state of health of a battery according to any of the foregoing embodiments of the present disclosure. As shown in Fig. 7, the computing device 300 may comprise (one or more) processor(s) 302 and a memory 304 storing computer-executable instructions which, when executed by the (one or more) processor(s) 302, cause the (one or more) processor(s) 302 to perform the method for predicting a state of health of a battery according to any of the foregoing embodiments of the present disclosure. The (one or more) processor(s) 302 may be, for example, a central processing unit (CPU) of the computing device 300. The (one or more) processor(s) 302 may be any type of general purpose processor, or may be a processor specifically designed for predicting a state of health of a battery, such as an application specific integrated circuit ("ASIC"). The memory 304 may include a variety of computer-readable media accessible by the (one or more)processor(s) 302. In various embodiments, the memory 304 described herein may include volatile and nonvolatile media, removable and non-removable media. For example, the memory 304 may include any combination of the following: a random access memory ("RAM"), a dynamic RAM ("DRAM"), a static RAM ("SRAM"), a read-only memory ("ROM"), a flash memory, a cache memory, and/or any other type of non-transitory computer-readable medium. The memory 304 may store the instructions which, when executed by the processor 302, cause the processor 302 to perform the method for predicting a state of health of a battery according to any of the forgoing embodiments of the present disclosure.

[0041] The present disclosure further provides a non-transitory storage medium having thereon stored computer-executable instructions which, when executed by a computer, cause the computer to perform the method for predicting a state of health of a battery according to any of the foregoing embodiments of the present disclosure.

[0042] The present disclosure further provides a computer program product, which may comprise instructions which, when executed by a processor, may implement the method for predicting a state of health of a battery according to any of the foregoing embodiments of the present disclosure. The instructions may be any set of instructions to be executed directly by one or more processors, such as machine code, or any set of instructions to be executed indirectly, such as scripts. The instructions may be stored in an object code format for direct processing by the one or more processors, or in any other computer language, including scripts or collections of independent source code modules that are interpreted as needed or compiled in advance.

[0043] The words "left", "right", "front", "back", "top", "bottom", "upper", "lower", "high", "low", and the like in the description and claims, if any, are used for descriptive purposes and not necessarily for describing permanent relative positions. It should be understood that the words so used are interchangeable under appropriate circumstances so that the embodiments of the present disclosure described herein can, for example, operate in other orientations than those illustrated herein or otherwise described. For example, when a device in the drawings is inverted, a feature originally described to be "above" another feature may be described to be "below" the another feature at this time. The device may further be otherwise oriented (rotated 90 degrees or in another orientation), and at this time, a relative spatial relation may be interpreted accordingly.

[0044] In the description and claims, when an element is described to be located "above", "attached" to, "connected" to, "coupled" to, or "in contact" with another element, the element may be directly located above, directly attached to, directly connected to, directly coupled to, or in direct contact with the another element, or there may be one or more intermediate elements. In contrast, when an element is described to be "directly located above", "directly attached to", "directly connected to", "directly coupled to", or "in direct contact with" another element, there will be no intermediate element. In the description and claims, one feature being arranged to be "adjacent" to another feature may refer to the one feature having a portion that overlaps with or is located above or below the adjacent feature.

[0045] As used herein, the word "exemplary" means "serving as an example, instance, or illustration", rather than as a "model" that is to be reproduced exactly. Any implementation exemplarily described herein is not necessarily to be construed as preferred or advantageous over another implementation. Moreover, this disclosure is not limited by any expressed or implied theory presented in the TECHNICAL FIELD, BACKGROUND, SUMMARY, or DETAILED DESCRIPTION.

[0046] As used herein, the word "substantially" means encompassing any minor variation caused by an imperfection of design or manufacturing, a tolerance of a device or component, an environmental influence and/or another factor. The word "substantially" further allows for a difference from a perfect or ideal situation that is caused by parasitic effect, noise, and another practical consideration that might exist in a practical implementation.

[0047] In addition, for reference purposes only, similar terms such as "first" and "second" may also be used herein, and thus are not intended to be limiting. For example, unless clearly indicated in the context, the words "first", "second" and other such numerical words that are related to structures or elements do not imply a sequence or order.

[0048] It should be further understood that the word "comprise/include", when used herein, indicates the presence of stated features, entireties, steps, operations, units, and/or components, but do not exclude the presence or addition of one or more other features, entireties, steps, operations, units, components, and/or combinations thereof.

[0049] In the present disclosure, the term "provide" is used broadly to encompass all ways of obtaining an object, and thus "provide an object" includes, but is not limited to, "purchase", "prepare/manufacture", "arrange/set”, "install/assemble", and/or "order" the object, and the like.

[0050] As used herein, the term "and/or" includes any and all combinations of one or more of associated listed items. The terms used herein are for the purpose of describing specific embodiments only and are not intended to limit the present disclosure. As used herein, singular forms "a", "an", and "the" are also intended to include plural forms, unless clearly indicated in the context otherwise.

[0051] Those skilled in the art should appreciate that boundaries between the above operations are merely illustrative. Multiple operations may be combined into a single operation, the single operation may be distributed in additional operations, and the operations may be performed at times that are at least partially overlapped. Moreover, alternative embodiments may include multiple instances of specific operations, and the order of the operations may be altered in various other embodiments. However, other modifications, variations, and alternatives are also possible. The aspects and elements of all the embodiments disclosed above may be combined in any way and/or in combination with aspects or elements of other embodiments to provide multiple additional embodiments. Therefore, the description and drawings should be regarded illustrative rather than restrictive.

[0052] Although some specific embodiments of the present disclosure have been described in detail by examples, it should be understood by those skilled in the art that the above examples are for illustration only and are not intended to limit the scope of the present disclosure. The embodiments disclosed herein may be combined arbitrarily without departing from the spirit and scope of the present disclosure. Those skilled in the art should also appreciate that various modifications may be made to the embodiments without departing from the scope and spirit of the present disclosure. The scope of the present disclosure is defined by the attached claims.

WHAT IS CLAIMED IS:

1. A method for predicting a state of health of a battery, comprising:

acquiring source domain battery data and target domain battery data, the source domain battery data comprising a voltage variation-over-time curve of each of a plurality of reference batteries in a full life cycle in respective one of a plurality of reference usage conditions, the target domain battery data comprising a voltage variation-over-time curve of a target battery in an early lifespan in an actual usage condition;

identifying a characteristic voltage variation interval common to the plurality of reference batteries based on the voltage variation-over-time curves of the plurality of reference batteries, a voltage variation pattern of each reference battery in the characteristic voltage variation interval appearing periodically in the voltage variation-over-time curve of the reference battery;

constructing a source domain sample set, comprising constructing one source domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of each reference battery, a sample input of the source domain sample comprising characteristic values and states of health of the reference battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval, the characteristic value being related to the state of health, and a sample output of the source domain sample comprising states of health of the reference battery in a second plurality of characteristic voltage variation intervals following the characteristic voltage variation interval;

constructing a metric function based on the source domain sample set, the metric function being used for measuring similarity between the sample inputs;

constructing one target domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of the target battery, a sample input of the target domain sample comprising characteristic values and states of health of the target battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval; and

weighting the sample output of the source domain sample in the source domain sample set by taking similarity between the sample input of the target domain sample and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample as a predicted value of the state of health of the target battery.

2. The method according to claim 1, further comprising:

performing time domain scaling on the target domain sample at different period scaling ratios, respectively, to obtain target domain samples enhanced at the different period scaling ratios;

determining, based on the metric function, degrees of matching between the target domain samples enhanced at the different period scaling ratios and the source domain samples in the source domain sample set, and determining a target domain sample with a highest degree of matching as a target domain sample enhanced at an optimal period scaling ratio; and

weighting the sample output of the source domain sample in the source domain sample set by taking similarity between a sample input of the target domain sample enhanced at the optimal period scaling ratio and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample enhanced at the optimal period scaling ratio as a predicted value of the state of health of the target battery.

3. The method according to claim 1 or 2, wherein the voltage variation pattern of each reference battery within the characteristic voltage variation interval is monotonic and in a charge stage.

4. The method according to claim 3, wherein the characteristic voltage variation interval common to the plurality of reference batteries is identified by:

letting *B* be a set of the plurality of reference batteries, *b* be a reference battery in *B*, and $V_b(t)$ be a voltage variation-over-time curve of the reference battery *b*, then a characteristic voltage variation interval $[v_1, v_2]$ is:

$$v_1, v_2 = \arg\max_{v1,v2} |v_1 - v_2|,$$

so that for any $b \in B$ and a non-negative integer *n*, there are time t_1, time t_2, and a period T, which satisfy:

$t_1 < t_2$, and

$V_b(t_1 + nT) = v_1$, $V_b(t_2 + nT) = v_2$, and

for times $t_1', t_2' \in [t_1 + nT, t_2 + nT]$, $t_1' < t_2'$, then $V_b(t_1') < V_b(t_2')$.

5. The method according to claim 1 or 2, wherein the characteristic value is an electricity quantity variation value per unit voltage variation range.

6. The method according to claim 2, wherein,

let *B* be a set of the plurality of reference batteries, *b* be a reference battery in *B*, and a characteristic voltage variation interval *i* of the reference battery *b* have a characteristic value x_i^b and a state y_i^b of health, then the constructing a source domain sample set $\mathcal{D}$ comprises:

constructing one source domain sample for each characteristic voltage variation interval appearing in a voltage variation-over-time curve of each reference battery b, a sample input of the source domain sample comprising characteristic values and states of health of the reference battery in r characteristic voltage variation intervals preceding the characteristic voltage variation interval, and a sample output of the source domain sample comprising states of health of the reference battery in $(R \times s)$ characteristic voltage variation intervals following the characteristic voltage variation interval, so that a source domain sample for a kth characteristic voltage variation interval of the reference battery b comprises:

a sample input $\mathcal{X} = \{x_{k-1}^b, y_{k-1}^b, x_{k-2}^b, y_{k-2}^b, \ldots, x_{k-r}^b, y_{k-r}^b\}$, and

a sample output $\mathcal{Y} = \{y_{k+s}^b, y_{k+2s}^b, \ldots, y_{k+R\times s}^b\}$, wherein r, R, s, and k are positive integers.

7. The method according to claim 6, wherein r is determined based on the number of times that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the target battery, and $(R \times s)$ is determined based on a preset time domain scaling ratio of the sample output to the sample input.

8. The method according to claim 6, wherein the constructing a source domain sample set $\mathcal{D}$ further comprise: performing time domain scaling on the source domain samples at different period scaling ratios, respectively, to obtain source domain samples enhanced at the different period scaling ratios, wherein a source domain sample enhanced at a period scaling ratio l for a kth characteristic voltage variation interval of the reference battery b comprises:

a sample input $\mathcal{X} = \{x_{k-l}^b, y_{k-l}^b, x_{k-2l}^b, y_{k-2l}^b, \dots, x_{k-r\times l}^b, y_{k-r\times l}^b\}$, and

a sample output $\mathcal{Y} = \{y_{k+s\times l}^b, y_{k+2s\times l}^b, \dots, y_{k+R\times s\times l}^b\}$, where l is a positive integer.

9. The method according to claim 8, wherein,

the period scaling ratio l is determined based on a ratio of a period that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the target battery to a period that the characteristic voltage variation interval appears in the voltage variation-over-time curve of the reference battery; or

the period scaling ratio l is determined based on a ratio of an aging rate of the target battery to an aging rate of the reference battery.

10. The method according to claim 8, wherein the metric function f_θ is constructed based on the source domain sample set $\mathcal{D}$, so that

$$P(\mathcal{Y} \mid \mathcal{X}, \mathcal{D}) = \mathop{\mathbb{E}}_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}} f_\theta(\mathcal{X}, \mathcal{X}_i) \cdot P(\mathcal{Y}_i \mid \mathcal{X}_i),$$

where $f_\theta(\mathcal{X}, \mathcal{X}_\mathrm{i})$ represents similarity between sample inputs $\mathcal{X}, \mathcal{X}_\mathrm{i}$, $P(\mathcal{Y}_i \mid \mathcal{X}_i)$ represents a probability that the sample input is $\mathcal{Y}_\mathrm{i}$ when the sample input is $\mathcal{X}_\mathrm{i}$, and $P(\mathcal{Y} \mid \mathcal{X}, \mathcal{D})$ represents a probability that the sample input is $\mathcal{Y}$ when the sample input is $\mathcal{X}$, and $\mathbb{E}$ is used for calculating an expectation.

11. The method according to claim 10, wherein a parameter θ of the metric function f_θ is solved by creating a training dataset based on the source domain sample set $\mathcal{D}$ to train a neural network model, whose loss function L_θ is constructed as

$$L_\theta(\mathcal{X}, \mathcal{Y}, \mathcal{D}^{batch}) = MSE\left(\frac{\sum_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}^{batch}} f_\theta(\mathcal{X}, \mathcal{X}_i) \cdot \mathcal{Y}_i}{\sum_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}^{batch}} f_\theta(\mathcal{X}, \mathcal{X}_i)}, \mathcal{Y}\right),$$

where $\mathcal{D}^{batch}$ is batch data randomly sampled in the source domain sample set $\mathcal{D}$, MSE is used for calculating a mean square error,

and where the parameter θ of the metric function f_θ is, by minimizing the loss function L_θ, determined as

$$\hat{\theta} = arg \max_{\theta} \mathop{\mathbb{E}}_{\mathcal{X}, \mathcal{Y} \in \mathcal{D}} [L_\theta(\mathcal{X}, \mathcal{Y}, \mathcal{D})].$$

12. The method according to claim 10, wherein let c be a target battery and a characteristic voltage variation interval j of the

target battery c have a characteristic value x_j^c and a state y_j^c of health, then the constructing a target domain sample comprises:

constructing one target domain sample for each characteristic voltage variation interval appearing in a voltage variation-over-time curve of the target battery c, a sample input of the target domain sample comprising characteristic values and states of health of the target battery in r characteristic voltage variation intervals preceding the characteristic voltage variation interval, so that a target domain sample for a gth characteristic voltage variation interval of the target battery c comprises

a sample input $\mathcal{X}_c = \{x_{g-1}^c, y_{g-1}^c, x_{g-2}^c, y_{g-2}^c, \dots, x_{g-r}^c, y_{g-r}^c\}$,

and wherein a target domain sample enhanced at a period scaling ratio q for the gth characteristic voltage variation interval of the target battery c comprises

a sample input $\mathcal{X}_c^q = \{x_{g-q}^c, y_{g-q}^c, x_{g-2q}^c, y_{g-2q}^c, \dots, x_{g-r\times q}^c, y_{g-r\times q}^c\}$, where g and q are positive integers.

13. The method according to claim 12, wherein the period scaling ratio q is set independent of the period scaling ratio l.

14. The method according to claim 12, wherein the determining, based on the metric function f_θ, degrees of matching between the target domain samples enhanced at the different period scaling

ratios and the source domain samples in the source domain sample set $\mathcal{D}$ comprises:

quantifying the degree of matching as $Affinity(q) = \sum_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}} f_\theta\left(\mathcal{X}_c^q, \mathcal{X}_i\right)$,

and wherein the optimal period scaling ratio is determined as $\hat{q} = arg \max_q Affinity(q)$, and a sample input of the target domain sample enhanced at the optimal period scaling ratio is $\hat{\mathcal{X}} = \mathcal{X}_c^{\hat{q}}$.

15. The method according to claim 14, wherein a future state of health of the target battery is determined as $\hat{\mathcal{Y}} = \frac{\sum_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}} f_\theta(\hat{\mathcal{X}}, \mathcal{X}_i) \cdot \mathcal{Y}_i}{\sum_{\mathcal{X}_i, \mathcal{Y}_i \in \mathcal{D}} f_\theta(\hat{\mathcal{X}}, \mathcal{X}_i)} = \left\{y_{k+s\times\hat{q}}^b, y_{k+2s\times\hat{q}}^b, \dots, y_{k+R\times s\times\hat{q}}^b\right\}$, where $y_{k+s\times\hat{q}}^b, y_{k+2s\times\hat{q}}^b, \dots, y_{k+R\times s\times\hat{q}}^b$ are predicted values of states of health of the target battery in $(k + s \times \hat{q})$th, $(k + 2s \times \hat{q})$ th, ⋯ , and $(k + R \times s \times \hat{q})$ th appearances of the characteristic voltage variation interval, respectively.

16. The method according to claim 1, further comprising:

performing interpolation on the predicted value of the state of health of the target battery, thereby predicting a state of health variation-over-time curve of the target battery in a full life cycle in the actual usage condition.

17. An apparatus for predicting a state of health of a battery, comprising:

a battery data acquisition module configured to:

acquire source domain battery data and target domain battery data, the source domain battery data comprising a voltage variation-over-time curve of each of a plurality of reference batteries in a full life cycle in respective one of a plurality of reference usage conditions, the target domain battery data comprising a voltage variation-over-time curve of a target battery in an early lifespan in an actual usage condition;

a characteristic interval identification module configured to:

identify a characteristic voltage variation interval common to the plurality of reference batteries based on the voltage variation-over-time curves of the plurality of reference batteries, a voltage variation pattern of each reference battery in the characteristic voltage variation interval appearing periodically in the voltage variation-over-time curve of the reference battery;

a source domain sample construction module configured to:

construct a source domain sample set, comprising constructing one source domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of each reference battery, a sample input of the source domain sample comprising characteristic values and states of health of the reference battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval, the characteristic value being related to the state of health, and a sample output of the source domain sample comprising states of health of the reference battery in a second plurality of characteristic voltage variation intervals following the characteristic voltage variation interval;

a metric function construction module configured to:

construct a metric function based on the source domain sample set, the metric function being used for measuring similarity between the sample inputs;

a target domain sample construction module configured to:

construct one target domain sample for each characteristic voltage variation interval appearing in the voltage variation-over-time curve of the target battery, a sample input of the target domain sample comprising characteristic values and states of health of the target battery in a first plurality of characteristic voltage variation intervals preceding the characteristic voltage variation interval; and

a state of health prediction module configured to:

weight the sample output of the source domain sample in the source domain sample set by taking similarity between the sample input of the target domain sample and the sample input of the source domain sample in the source domain sample set that is determined based on the metric function, as a weight, thereby synthesizing a sample output of the target domain sample as a predicted value of the state of health of the target battery.

18. A computing device for predicting a state of health of a battery, comprising:

one or more processors; and

a memory storing computer-executable instructions which, when executed by the one or more processors, cause the one or more processors to perform the method for predicting a state of health of a battery according to any of claims 1 to 16.

19. A non-transitory storage medium having thereon stored computer-executable instructions which, when executed by a computer, cause the computer to perform the method for predicting a state of health of a battery according to any of claims 1 to 16.

20. A computer program product comprising instructions which, when executed by a processor, implement the method for predicting a state of health of a battery according to any of claims 1 to 16.