

- 1 -

RECHARGEABLE BATTERY PARAMETER DETERMINATION AND OPTIMISATION

Field of the Invention

This invention relates to computer-implemented methods of determining a predicted operational lifetime for charge storage devices such as batteries. This invention further relates to
5 determination of appropriate materials for use in charge storage devices and appropriate charging protocols and profiles to maximise the operational lifetime.

Background of the Invention

Over the last several decades, global energy demands have
10 increasingly been met by generation of electricity from renewable sources (such as from solar panels and wind farms). In tandem with this energy production, it has been necessary to develop high capacity mass energy storage devices which are capable of storing charge which has been produced from these
15 renewable sources and which are configured to be able to deliver the required charge to a downstream user as and when it is required.

Additionally, an increasing part of the worldwide vehicle fleet has been electrified. An inherent consequence of this
20 electrification is appropriate energy storage devices also need to be provided within electric vehicles (EVs) for the purpose of their operation. As for mass energy storage devices, energy storage devices within EVs are configured to be able to deliver the charge to the EV to power it during journeys. An additional
25 consideration in particular for EVs is to be able to provide storage sufficient to power the EV for long journeys. Further, such devices typically are configured to enable efficient recharging, such that a total recharge time is minimised subject to constraints of the energy storage device to shorten the
30 downtime of the EV between journeys.

- 2 -

In both of the above use scenarios, a limiting factor which is to be considered is the total operational lifetime of the energy storage devices. Energy storage devices have a finite lifetime for which they are able to store charge effectively, with the total capacity of the devices typically reducing over this lifetime. Beyond this lifetime, the devices are no longer fit for purpose and will require replacement. It is therefore advantageous to develop energy storage devices which are able to maximise this lifetime.

10 The lifetime of an energy storage device may be affected by several factors. These include (but are not limited to) the energy storage material used in the devices, as well as the charging protocols / profiles which are used when recharging the device from a totally or partially discharged state to full
15 (particularly in the use case of an EV).

 Whilst the above factors which affect the lifetime of an energy storage device are known, it is typically difficult to ascertain the magnitude of the effect on the lifetime of the device without performing extensive testing on the device. When
20 testing the lifetime of an energy storage device which uses a particular energy storage material or which uses a particular protocol when recharging, laboratory tests involving battery charging and discharging cycling methods are typically used. An inherent disadvantage of using such methods is that a large
25 number of time consuming cycles (often demanding several hours per cycle, typically around 4 to 6 hours per cycle) are required in order to provide accurate results, which could require hundreds or thousands of cycles in order to obtain reasonably accurate results. Cycling data can also be used to train data-
30 driven machine learning models in order to obtain estimates of lifetimes. However, such models are often poor when predicting examples which have not been seen during training (e.g. unexpectedly high or low discharge rates, unseen electrochemical

- 3 -

configurations). As such, these methods are not generalisable and can only accurately be applied to the specific material and protocols upon which testing has been performed.

Additionally, it can sometimes be necessary to test the energy storage device to destruction (end-of-life cycling) to ascertain the operational lifetime (e.g. to test the device for the duration of its operational lifetime). This is clearly disadvantageous as the process is time inefficient, and the energy storage device itself cannot then be subsequently used. Further, there is no guarantee that the results of the testing will be positive i.e., the testing may indicate that the material or protocol being used results in a lifetime for the energy storage device which is below a required (or desirable) threshold. As such, in present approaches, a large amount of resource can be expended without resulting in determination of a suitable energy storage material or charging protocol.

It is also noted that similar testing regimes are presently required in order to determine other parameters of energy storage devices, such as the reduction in capacity of the device over time as a result of repeated charge cycling (i.e. capacity fade / capacity fade off).

A technical challenge therefore exists in developing new approaches which can provide accurate predictions of lifetimes and other parameters for energy storage devices in a generalisable manner, and in a manner which minimises the size of dataset required to arrive at the predictions.

It is an object of the present invention to overcome one or more of the problems described above.

Summary of the Invention

According to an aspect of the invention, a computer-implemented method is provided for determining a characteristic of a rechargeable battery, the rechargeable battery being associated with an adjustable battery parameter. The computer

- 4 -

implemented method comprises determining a physics-based prediction of a correlation between the characteristic and a quantity of interest of the rechargeable battery, where the physics-based prediction is based upon the adjustable battery parameter, and wherein the quantity of interest comprises a function of one or more cycling features, and the one or more cycling features comprise variables which are measurable during a charge-discharge cycle of the rechargeable battery. The computer implemented method further comprises receiving cycling data comprising measured values of the one or more cycling features during one or more charge-discharge cycles of the rechargeable battery. The computer implemented method further comprises coupling the physics-based prediction of the correlation to a trained data-driven model, wherein the data-driven model has been trained using a machine learning algorithm and is configured to determine a correction to the physics-based prediction of the correlation as a function of the quantity of interest, and determining the characteristic based on the physics-based prediction of the correlation, the correction to the physics-based prediction of the correlation and the received cycling data.

With the computer-implemented method according to the invention, accurate assessment of rechargeable battery characteristics such as operational lifetime and capacity fade / capacity fade off can be more quickly be arrived at when compared to conventional approaches. In particular, a generalised approach across different adjustable battery parameters such as battery chemistries and charging profiles and protocols is established without requiring specific training of data-driven models for each parameter. The benefit of this is to enable rapid screening of new battery characteristics to determine their suitability for use.

- 5 -

The computer implemented method may comprise determining whether the rechargeable battery associated with the adjustable battery parameter is suitable for use by comparing the characteristic with a user determined minimum threshold value, wherein the rechargeable battery is determined as being suitable for use when the characteristic is equal to or greater than the minimum threshold value. In so doing, the method may also determine whether the determined characteristic is in accordance with a user specified requirement to determine suitability for use.

The computer implemented method may comprise training the data-driven model.

Where the computer implemented method comprises training the data-driven model, the training may comprise determining a physics-based prediction of a correlation between the characteristic and the quantity of interest for a plurality of rechargeable batteries, wherein each rechargeable battery of the plurality of rechargeable batteries comprises a different value of the adjustable battery parameter and the physics-based prediction is based upon the adjustable battery parameter, receiving cycling data comprising measured values of the one or more cycling features during one or more charge-discharge cycles of each rechargeable battery of the plurality of rechargeable batteries, determining a physics-based prediction of the characteristic of each rechargeable battery of the plurality of rechargeable batteries based on the respective received cycling data and the respective physics-based prediction of the correlation, determining a characteristic residual for each rechargeable battery of the plurality of rechargeable batteries, wherein each characteristic residual comprises the difference between the physics-based prediction of the characteristic for the respective rechargeable battery and a measured value of that characteristic, and providing each

- 6 -

characteristic residual and the received cycling data as training data to the data-driven model. The training of the data-driven model in this manner is different to conventional approaches, in which typically the data-driven model will be
5 trained by with raw characteristic data. This typically requires a large amount of data to ensure accuracy and is susceptible to error when making predictions which lie outside the scope of the trained data. The approach taken by this embodiment trains the data-driven model using differences between predictions made by
10 the physics-based model and the actual characteristic value and results in a data driven model which provides accurate corrections and is able to be trained using far less data than conventional approaches.

The computer implemented model may comprise determining the
15 physics-based prediction of a correlation between the characteristic and the quantity of interest of the rechargeable battery by determining a correlation between the characteristic and comparative values of the quantity of interest between two charge-discharge cycles of the battery. In particular, the
20 correlation may be determined between the characteristic and a discharge energy loss between two cycles of charge-discharge of the rechargeable battery, or between the characteristic and a ratio of charges as a function of voltages between two cycles of charge-discharge of the rechargeable battery. Further, the
25 two charge-discharge cycles may be the first charge-discharge cycle and the thirtieth charge-discharge cycle.

The machine learning algorithm may be a gradient boosted decision tree.

The characteristic may be an operational lifetime of the
30 battery, or may be a parameterisation of a capacity fade off curve of the battery.

The adjustable battery parameter may be an energy storage material of the rechargeable battery, or may be a charging

- 7 -

protocol used to charge the rechargeable battery between two charge levels.

According to another aspect of the invention, a machine-readable non-transitory medium is provided, having stored thereon machine-executable instructions for determining a
5 characteristic of a rechargeable battery, the rechargeable battery being associated with an adjustable battery parameter, wherein the instructions are adapted to instruct a processor to perform such a computer-implemented method.

10 According to a further aspect of the invention, a system for determining a characteristic of a rechargeable battery is provided, the rechargeable battery being associated with an adjustable battery parameter, wherein the system comprises a data store comprising instructions, and a processor configured
15 to carry out the instructions in the data store. The processor is configured to carry out the instructions to determine a physics-based prediction of a correlation between the characteristic and a quantity of interest of the rechargeable battery, where the physics-based prediction is based upon the
20 adjustable battery parameter, and wherein the quantity of interest comprises a function of one or more cycling features, and the one or more cycling features comprise variables which are measurable during a charge-discharge cycle of the rechargeable battery, to receive cycling data comprising
25 measured values of the one or more cycling features during one or more charge-discharge cycles of the rechargeable battery, to couple the physics-based prediction of the correlation to a trained data-driven model, wherein the data-driven model has been trained using a machine learning algorithm and is
30 configured to determine a correction to the physics-based prediction of the correlation as a function of the quantity of interest, and to determine the characteristic based on the physics-based prediction of the correlation, the correction to

- 8 -

the physics-based prediction of the correlation and the received cycling data.

Brief Description of the Drawings

In order that the disclosure may be more readily
5 understood, reference will now be made, by way of example, to the accompanying drawings in which:

Figure 1 is a flow diagram illustrating the flow of data in the hybrid model architecture;

Figure 2 is a set of three graphs illustrating behavioural
10 trends of a data-driven approach, a physically-based approach, and the hybrid model architecture of the present embodiments;

Figure 3 is a set of two scatter plots illustrating relationships between physical parameters and rechargeable battery lifetimes;

15 Figure 4 is a flow diagram of present embodiments illustrating a method of operation of the hybrid model architecture of Figure 1;

Figure 5 is a flow diagram of present embodiments illustrating a method of training of the hybrid model
20 architecture of Figure 1;

Figure 6 is a flow diagram of present embodiments illustrating a further method of operation of the hybrid model architecture of Figure 1; and

Figure 7 is a schematic and system view of present
25 embodiments illustrating a hardware configuration of the hybrid model architecture of Figure 1.

These drawings depict one or more implementations in accordance with the present teachings , by way of example only, not by way of limitation. In the figures, like reference numerals
30 refer to the same or similar elements.

Detailed Description of the Drawings

The present invention is directed toward computer-implemented methods for predicting characteristics such as

- 9 -

operational lifetimes and capacity fade / capacity fade off
curves of rechargeable electrical energy storage devices (i.e.
rechargeable batteries). In particular, the present invention
is directed toward the use of a hybrid model based architecture
5 which combines elements of physics-based models and data-driven
models in order to determine accurate operational lifetime and
capacity fade / capacity fade off predictions for rechargeable
electrical energy storage devices. Throughout this description,
the terms "battery" and "rechargeable battery" will be used for
10 simplicity when referring to the rechargeable electrical energy
storage devices.

A key consideration in the development of rechargeable
batteries for mass storage of energy or for use in EVs is the
operational lifetime of the battery (i.e., the expected total
15 use time of the battery in a regular use case). The operational
lifetime is typically expressed as a total number of cycles
(i.e., the number of times a battery is charged to a required
level and then subsequently discharged to a particular level)
which the battery undergoes before it is no longer fit for use.
20 Typically, the point at which a battery is classified as no
longer fit for use is when the "full" capacity of the battery
has degraded to a particular user determined percentage of its
maximum (or nominal) capacity. By way of illustrative example,
a battery may be classified as no longer fit for use when its
25 "full" capacity is 80% of its nominal capacity (although this
percentage may be varied in dependence upon user preference).
The operational lifetime may be impacted by several factors,
included but not limited to, the materials used in the battery
and the protocols and profiles used when recharging a battery
30 from a lower charge level to a higher charge level (e.g., 0%
capacity to 100% capacity, 20% capacity to 80% capacity etc).
The use of the proposed hybrid model architecture enables a
rapid screening process for determination of appropriate

- 10 -

materials for use in a rechargeable battery as well as rapid determination of appropriate charging protocols and profiles which may be used to charge the battery (to be referred to collectively as "adjustable battery parameters").

5 Another consideration in the development of rechargeable batteries for mass storage of energy or for use in EVs is the capacity fade / capacity fade off of the batteries over repeated cycles. As known rechargeable batteries are cycled, their maximum capacity typically will degrade, ultimately resulting
10 in degradation to such an extent that the rechargeable battery is no longer fit of purpose. This is typically referred to as capacity fade / capacity fade off. Whilst overall operational lifetime is of interest to a user, it may also be useful to ascertain the rate at which the maximum capacity of a
15 rechargeable battery degrades over time, known as a capacity fade / capacity fade off curve. The present embodiments may also be used to determine accurate predictions for the capacity fade / capacity fade off curve of a rechargeable battery.

20 *Use of Hybrid Model Architecture in Predicting Operational Lifetime*

 An approach for providing accurate predictions for operational lifetimes of rechargeable batteries is now
25 discussed. It is to be appreciated that the operational lifetime of the battery is one of a plurality of battery characteristics which may be measured by use of the present embodiments. A further example, relating to capacity fade / capacity fade off curves is described in greater detail below.

30 Figure 1 is a high-level flow diagram which illustrates the hybrid model architecture 10 approach adopted in present embodiments for predicting battery lifetimes.

- 11 -

The hybrid model architecture 10 of the present embodiments is an ensemble consisting of a generalisable base learner 15 coupled with additional learners 20. The generalisable base learner 15, in particular a physics-based model, provides
5 initial predictions 22 for a battery lifetime, denoted in Figure 1 as $\hat{y}_{life}$. A physics-based model uses relationships and phenomena known from physical theory, electrochemical theory, and principles relevant to the battery being tested to establish the initial prediction. Such physics-based models may be generated
10 without any input data in some embodiments. In some embodiments, the physics-based models may be semi-empirical.

The physics-based model will typically be configured to determine an initial prediction 22 for the operational lifetime of the battery based on one or more physical variables (cycling
15 features) of the battery, denoted in Figure 1 as x_{feat} , of the battery. Cycling features are measurable physical quantities or variables which illustrate (typically in combination) a relationship with the operational lifetime of the battery during a charge-discharge cycle of the battery which will typically
20 vary in dependence upon how many times the battery has been charged and discharged (i.e., the cycle number). By way of example, such cycling features may include the charge, voltage, and current being supplied by the battery during discharge over a cycle. These cycling features may be integrated over the total
25 discharge time where relevant. It is to be appreciated that whilst the above cycling features relate to quantities related to the discharge portion of a charge-discharge cycle, in some embodiments, cycling features may relate to quantities related to the charging portion of a charge-discharge cycle. In present
30 embodiments, the one or more physical variables are functionally combined to create quantities of interest which are related / correlated to the operational lifetime. In particular, the difference in the quantities of interest between cycles will

- 12 -

typically demonstrate a correlative connection to the operational lifetime. Non-limiting examples of such quantities of interest are the ratio of charges as a function of voltages between different cycles, and the loss in total energy discharged between cycles (discharge energy loss). As above, whilst these quantities of interest relate to the discharge portion of a charge-discharge cycle, in some embodiments, quantities of interest may relate to the charging portion of a charge-discharge cycle. The model generated by the generalisable base learner 15 will typically be based on known electrochemical theory and principles relevant to the battery being tested, and utilises identified correlations between the difference in the quantities of interest between cycles and the lifetime of the battery in order to make a prediction 22 of the operational lifetime of the battery (typically expressed as a number of cycles). The correlation identified in the model will typically show dependence upon additional quantities beyond x_{feat} and the quantities of interest alone, and these additional quantities are denoted as α, β , in Figure 1. Accordingly, the lifetime prediction 22 will be made in the form of a function of the one or more physical variables, denoted in Figure 1 as $f_{phys}(x_{feat}; \alpha, \beta)$. In some embodiments, the physics-based model may be programmed by a user based on these known electrochemical principles. In other embodiments, the physics-based model may be automatically generated based on existing known models.

The electrochemical models may also vary in dependence upon specific (and adjustable) battery parameters. These parameters may include the specific chemistry of the material used in the rechargeable battery, as well as a particular charging protocol used when charging the battery between a partially discharged state to a full or less discharged state. The adjustable battery parameters in some embodiments may comprise varying states of the battery being tested (e.g. temperature of the battery,

- 13 -

liquid or solid electrolytes etc). In some embodiments, for each adjustable parameter, a new physical model may be generated (either through programming by a user, or automatically generated in accordance with embodiments described above).

5 However, in some embodiments, it is not necessary to generate a new physical model in each instance and a single model may be used. These embodiments are discussed in greater detail below.

Following the generation of the physics-based model, cycling data 30 is provided to the physics-based model in order
10 to obtain a prediction 22 of the lifetime for the battery. The cycling data 30 contains measured experimental data for the cycling features x_{feat} for a plurality of charge-discharge cycles of the battery. The cycling data 30 will typically include experimental data which indicates the state of the one or more
15 cycling features as the battery being tested is being discharged from a starting state to an ending state. The start state will typically be defined as where the battery is fully charged (i.e. at "full" capacity). The end state will typically be defined as when the voltage being delivered by the battery has reached a
20 threshold level (i.e. the cut off voltage). In some cases, the end state may instead be defined as a threshold state of charge.

The cycles for which the cycling data 30 is provided will typically be taken early in the lifetime of the battery e.g. cycles 1 to 100, 1 to 50, 1 to 30, 1 to 10 etc. It is to be
25 appreciated that the examples provided regarding the cycles that the cycling data 30 provides information regarding are for illustrative purposes only and that the cycles that information is provided for may occur earlier or later in the lifetime of the battery. Furthermore, the cycling data 30 may contain
30 information regarding more or fewer cycles than is provided in the examples above. Use of cycling data 30 from early in the life cycle of the battery being tested is advantageous since it enables predictions to be made regarding the operational

- 14 -

lifetime of the battery without requiring the battery to be tested for a long period. Furthermore, the battery itself may still be usable following the testing stage.

As discussed above, the prediction of the battery lifetime
5 will be made based on a determined correlation between the battery lifetime and a quantity of interest. As such, upon receiving the cycling data 30, the physics-based model will be configured to generate a value for the quantity of interest and use the established correlation between the quantity of interest
10 and the battery lifetime to generate a prediction 22 for the battery lifetime. In present embodiments, the quantity of interest will be the difference in a particular value of a particular combination of cycling features x_{feat} between cycles (i.e. the ratio of charges as a function of voltages between two
15 cycles, and the discharge energy loss between two cycles). It is to be noted that when discerning the difference in a particular value of a particular combination of cycling features x_{feat} between cycles, the cycles which are used to ascertain the difference do not need to be consecutive. Typically the greater
20 the difference between the two cycles, the more appreciable a difference will be noted in the quantity of interest. This in turn can lead to a more accurate prediction of the lifetime. The corresponding increase in the accuracy however mandates that additional cycles of the battery are performed. In the present
25 embodiments, in order to achieve a sufficiently accurate result typically far fewer number of cycles of the battery need to be performed when compared with existing methods which utilise cycling data 30. For example, in some embodiments, the differences between cycles 1 and 100, 1 and 50, 1 and 30 or 1
30 and 10 may be used. In further embodiments described below, the differences between cycles 5 and 60 are used. These examples are provided by way of illustration only and the results from any

- 15 -

two cycles may be used where the functionality described herein is enabled.

The prediction 22 obtained from the physics-based model alone described above will typically not be sufficiently accurate when predicting operational battery lifetimes. This can occur as a result of a lack of expertise on the part of model developers, or as a result of the scope of the model not including all modelling aspects which need to be accounted for when developing the model. The result of a purely physics-based model approach is that a qualitative trend will typically be formed, however this trend will not be accurate across the range of predicted lifetimes when compared to corresponding experimental lifetimes.

In order to address this, the hybrid model architecture 10 of the present embodiments introduces additional learners 20 in the form of one or more data-driven models. The additional learners 20 are provided in order to provide a corrective term 26 to the predictions 22 which are generated by the base learner 15. The additional learners 20 which are provided reconstruct the remainder of the mapping between cycling features (i.e., the one or more physical variables discussed above) and the quantities of interest, and lifetime outputs.

In order to train the additional learners 20 in the required manner, the hybrid model architecture 10 is configured to determine lifetime residuals 32 between the predicted lifetimes 22 made by the base learner 15 as a result of the cycling data 30 ($\hat{y}_{life}$) and the actual lifetimes of the battery for which a prediction is being made, denoted as y_{life} in Figure 1. The lifetime residuals 32 are denoted by $y_{life} - \hat{y}_{life}$ in Figure 1, and are the difference between the predictions 22 made in the physics-based model using the provided cycling data 30 and the actual lifetime of the battery being tested. In some embodiments, the actual lifetime of the battery may already be known (as a result of

- 16 -

prior testing or as provided by a battery manufacturer). In some embodiments, the actual lifetime of the battery is determined through laboratory testing, where the battery is cycled until it is no longer determined to be fit for use in accordance with definitions described above.

Once established, the lifetime residuals 32 for the battery are then provided to the additional learners 20, and these are provided alongside the same cycling data 30 provided to the base learner 15 which enabled the prediction $\hat{y}_{life}$ 22 to be made.

The lifetime residuals 32 are provided to the additional learners 20 as training data. Typically, the additional learners 20 will be provided in a machine learning system. In present embodiments, the machine learning system being used will be in the form of a tree based model. In some instances, the model will utilise a gradient-boosted decision tree. Machine learning features for these gradient-boosted decision trees could include not only the inputs (i.e., the cycling features) for the physics-based model but also other more complex dependencies, which remain unaccounted for in the physical modelling. One example of a suitable gradient-boosted decision tree which may be adapted for this purpose is CatBoost. Other examples of tree based models which may be used are Random Forest, LightGBM, and XGBoost. It is to be appreciated that the above examples are provided for illustrative purposes only, and that any machine learning model may be used which enables the functionality described herein.

The training data provided to the additional learners 20 enables a corrective function ($f_{ds}(\{x_{feat}\})$) to be determined through machine learning, which provides a predictive correction 26 to the prediction 22 provided by the physics-based model, denoted as $\hat{y}_{resid}$ in Figure 1. In particular, the provided lifetime residuals 32 are associated with the relevant values of x_{feat} and the related difference in quantity of interest values between

- 17 -

two cycles provided by the cycling data 30. This enables an accurate correction to be determined for the original physics-based model prediction 22.

The above process of creating a physics-based prediction
5 22 based on cycling data 30 and cycling features x_{feat} and determining a lifetime residual 32 based on the actual lifetime of the battery may be repeated a plurality of times for different battery chemistries (or charging protocols) to create a larger set of training data for the additional learners 20. The machine
10 learning aspect of the additional learners 20 may then use this larger set of training data to ascertain accurate corrections to be made for a variety of values of cycling features x_{feat} and subsequently extrapolate a trend of lifetime prediction corrections 26 to be made for all potential values of cycling
15 features x_{feat} (even where explicit experimental data has not been provided for a particular set of values). This establishes a system wherein the additional learners 20 are able to accurately predict a lifetime correction to a physics-based model prediction 22 for a set of cycling data 30 which has not
20 previously been encountered. Thus the hybrid model architecture 10 approach of present embodiments offers a greater degree of generalisability which is commonly not achievable in known approaches (see Generalisability of Hybrid Model Approach section below)

25 In standard data-driven approaches, the training data which is provided to the additional learners 20 are typically the raw lifetimes of the battery, in conjunction with the cycling data 30, as opposed to the lifetime residuals 32 approach taken in present embodiments. Whilst this approach can be used, it
30 typically results in predictions which may bear artifacts from machine learning algorithms, such as "step-like" behaviour. Furthermore, data-driven models are more susceptible to error in situations which they have not been trained on, for example,

- 18 -

varying material chemistries used in different battery cell types. This behaviour can be mitigated against; however this requires large data samples to achieve, typically hundreds or thousands of cycles. Even then, such data-driven models are
5 still susceptible to inaccuracies when encountering scenarios for which data has not been provided (e.g., different battery chemistries or charging protocols).

Returning to the example of Figure 1, following the training of the additional learners 20 in accordance with
10 embodiments described above, the additional learners 20 are configured to be coupled to the physics-based model provided by the generalisable base learner 15, whereby the corrections predicted by the additional learners 20 are used to modify the predictions 22 provided by the physics-based model for a
15 particular set of cycling features x_{feat} . This results in an overall predictive function through use of the hybrid model architecture 10, denoted in Figure 1 as $\hat{y}_{life+cor}$, which yields a corrected predicted operational lifetime when provided with cycling data 30 indicating a particular value for a quantity of
20 interest in accordance with embodiments described above. It is to be noted that when the physics-based model and the data-driven models are connected in this manner, the cycling data 30 and the lifetime residuals 32 used to train the data-driven model aspect are removed. As such, the predictive function
25 generated by the hybrid model architecture 10 is not based on the lifetime residuals 32 which are provided.

In a non-limiting example of the hybrid model architecture 10, the architecture 10 may consist of a semiempirical power law coupled to gradient-boosted decision trees. The semiempirical
30 power law correlates physical variables, such as initial energy loss, to battery lifetime. Physics-based models, including semiempirical correlations, are attractive as such models can be founded upon first principles. Further, physics-based models

- 19 -

tend to offer predictable trends. Such properties can make rapid materials screening for battery manufacturing more robust. Similarly such properties also enable rapid and efficient determination of whether a suggested charging protocol or
5 profile is suitable for purpose.

Referring now to Figure 2, there are shown three graphs 202, 204, 206 illustrating predictive performance for battery lifetimes when using a purely data-driven approach (using a tree-based algorithm) 202, a purely physics-based model approach
10 204 and the hybrid model architecture 10 approach of present embodiments 206. In each case, predictions are made for the same set of a plurality of batteries. The data-driven approach 202 uses raw lifetime data combined with cycling data 30 in accordance with standard approaches as detailed above. Each
15 graph 202, 204, 206 illustrates a predicted lifetime made by the model in comparison to an associated measure lifetime for a particular battery chemistry. For ease of reference, a line illustrating the correct prediction to be found is also provided.

20 As can be seen, the tree-based data-driven approach 202 results in predictions which, whilst accurate with respect to experimental lifetime at discrete points, demonstrates step-like behaviour and no discernible trend is established. Referring to the illustrated physics-based approach 204, it can be seen that
25 the predicted behaviour illustrates trend-like behaviour, with a dashed line indicated a fitted trend to the predicted behaviour. However, the predicted trend lies significantly away from the accurate trend to be established (i.e. the solid line). Referring to the hybrid model architecture 10 approach which has
30 been implemented in accordance with embodiments described above 206, what can be seen is trend like behaviour which is in much closer accordance with the correct trend (i.e. where the predicted lifetime is the same as the experimentally measured

- 20 -

lifetime across all possible lifetimes). In addition, the step-like behaviour associated with the data-driven approach has been reduced.

5 *Generalisability of Hybrid Model Approach*

In embodiments described above, the systems and methods described include a training step in which the data-driven aspect of the hybrid model architecture 10 is provided with lifetime residuals 32 in order to provide corrections to the physics-based model predictions 22. Whilst this step is initially required when initially training the hybrid model architecture 10, and may sometimes be required when determining lifetimes for a new adjustable battery parameter (e.g. battery chemistry of the energy storage material or charging protocol) which have significantly different physics-based models, it is to be noted that this step may not always be required when predicting lifetime for a particular adjustable battery parameter. In particular, the hybrid model architecture 10 approach taken in the present embodiments demonstrates a level of generalisability between varying adjustable battery parameters.

Referring now to Figure 3, there are shown two scatter plots 302, 304 illustrating correlations between two quantities of interest (comprising a function of physical parameters x_{feat}) and battery lifetimes, wherein the differences in the quantities of interest are taken between values obtained at cycle 5 and cycle 60 for 4 types of battery cell. The two parameters shown are a ratio of charges as a function of voltages between the two cycles on the left 302, and the discharge energy loss between the two cycles on the right 304. The 4 types of battery cell are a Lithium Iron Phosphate (LFP) cell and three Nickel Manganese Cobalt (NMC) cells with varying battery chemistries with each

- 21 -

of the NMC cells being grouped by general battery chemistry traits. Further, each data point on the scatter plot within each group represents a cell within the general group with a slightly altered battery chemistry (i.e., illustrating slightly varying underlying physical and chemical characteristics).

In both graphs 302, 304, it is demonstrated that despite the differing battery chemistries between the 4 types of battery cell groups and within each general group, there is a discernible shared correlation between the quantity of interest measured and the lifetime of the cell. This is highlighted by the solid line in the right hand graph 304. This indicates that when using these particular quantities of interest when using the hybrid model architecture 10, that the models used may be generalised across different battery chemistries. In such cases, it can be sufficient to simply import an existing trained data-driven model to be coupled to the generalisable base learner to yield an accurate prediction of a lifetime for a particular adjustable battery parameter without needing to first train a new data-driven model based on cycling data 30 and lifetime residuals 32. In such cases where an existing trained data-driven model exists, the high level architecture of Figure 1 is modified such that the provision of lifetime training residuals 32 is removed (since these are not needed for the purpose of training the data-driven model). In such embodiments, a new physics-based model may still first need to be created in order to account for slightly different underlying electrochemical and physical factors for the new adjustable battery parameter.

This generalisable approach affords additional advantages when predicting lifetimes for rechargeable batteries, since no training needs to be provided when providing corrections to a physics-based model. This enables a faster prediction to be made which can be of particular use when testing new adjustable battery parameters. It is to be appreciated that whilst the

- 22 -

scatter plots of Figure 3 illustrate data points indicating varying battery chemistries, an analogous level of generalisability can be applied when considering varying charging protocols, where a correlation is noted between a quantity of interest and the operational lifetime of the battery even where the charging protocol is varied.

Methodology

Referring now to Figure 4, there is shown a flow chart illustrating a method 400 which may be implemented in accordance with present embodiments. In particular, the illustrated method 400 relates to prediction of an operational lifetime of a rechargeable battery where a data-driven model trained using lifetime residual data 32 has already been established.

The method 400 proceeds by creating, at Step 402, a physics-based model for the battery. This is conducted at the generalisable base learner 15. The physics-based model will be based on known electrochemical theory and will typically predict a correlation between a difference between quantity of interest comprising a function of cycling features of the battery, x_{feat} between two cycles of the battery to the lifetime of the battery. Additional parameters α, β (which are not directly subsequently measured) will typically also be included as part of this model. This is in accordance with embodiments described above.

Following this, the method proceeds by receiving, at Step 404, cycling data 30 relating to the battery for which the prediction is to be made. The cycling data 30 includes data relating to a number of charge-discharge cycles of the battery in accordance with embodiments described herein and typically includes values for relevant cycling features x_{feat} . The provided cycling data 30 provides experimental measurements of the cycling features 30 used to predict the operational lifetime of

- 23 -

the battery by the physics-based model (i.e. for the physical parameter being tested at a particular cycle). In some embodiments, the testing process by which the cycling data 30 is obtained may be included as part of the method.

5 Following this, the physics-based model (initial prediction 22) and the data-driven model (corrective prediction 26) are then coupled at Step 406. As noted above, this method 400 is in respect of embodiments in which a trained data-driven model has already been created. A flow diagram from the process by which
10 a data-driven model may be trained is provided with reference to Figure 5. Returning to the present method 400, once coupled, the initial prediction and the corrective prediction functions are then combined to provide a corrected prediction. Following this combination, the received cycling data 30 is provided, at
15 Step 408 to the coupled models. This provides the relevant values upon which a lifetime prediction may be established. Once the data is provided, the operational lifetime of the battery is predicted, at Step 410, based on the corrected prediction function and the cycling data 30. The method 400 then ends.

20 The methodology outlined above enables for an operational lifetime to be predicted based on early life data. The operational lifetime will typically be in the region of 1000+ cycles of the battery, and the present methodology enables an accurate prediction of the operational lifetime based on a
25 number of cycles worth of data which is several orders of magnitude lower than the predicted lifetime.

Turning now to Figure 5, there is shown a method 500 for training a data-driven model which may be used in the method 400 of Figure 4, and in accordance with embodiments described above.
30 This method 500 establishes differences between predictions made by a physics-based model for the operational lifetime of a battery and the established lifetime of that battery, and uses this difference (i.e. the lifetime residual 32) as training data

- 24 -

to be provided to the data-driven model. This process is repeated for a plurality of batteries to establish a robustly trained data-driven model for use with methods described above.

The method 500 proceeds by creating, at Step 502, a physics-based model for a first battery. This is conducted at the generalisable base learner 15. The physics-based model will be based on known electrochemical theory and will typically predict a correlation between a difference between quantity of interest comprising a function of cycling features of the battery, x_{feat} between two cycles of the battery to the lifetime of the battery. Additional parameters α, β (which are not directly subsequently measured) will typically also be included as part of this model. This is in accordance with embodiments described above.

Following this, the method proceeds by receiving, at Step 504, cycling data 30 relating to the battery for which the prediction is to be made. The cycling data 30 includes data relating to a number of charge-discharge cycles of the battery in accordance with embodiments described herein and typically includes values for relevant cycling features x_{feat} . The provided cycling data 30 provides experimental measurements of the cycling features 30 used to predict the operational lifetime of the battery by the physics-based model (i.e. for the physical parameter being tested at a particular cycle). In some embodiments, the testing process by which the cycling data 30 is obtained may be included as part of the method.

Once the cycling data 30 is provided, the method 500 proceeds to predict, at Step 506, the operational lifetime of the battery based on the values of the cycling features and the prediction made by the physics-based model. This differs from the method 400 in that the prediction is made on the basis of the physics-based model alone. As such, the prediction will typically be expected to be inaccurate. As a result, the method 500 proceeds by creating, at Step 508, a lifetime residual 32

- 25 -

for the battery. The lifetime residual 32 is created by calculating the difference between the predicted lifetime and an otherwise established lifetime for the battery. This established lifetime may be known from a manufacturer, or may
5 be experimentally calculated by testing the lifetime of the battery in a laboratory (in accordance with embodiments described above).

Once the lifetime residual 32 has been created, it is provided, at Step 510, to the data-driven model alongside the
10 cycling data 30 which was used to establish the prediction made by the physics-based model. This creates a training point for the data-driven model. Following this provision, the method 500 proceeds to Step 512, where it is determined if any further training data is to be provided, i.e. whether lifetime residuals
15 32 and cycling data 30 for another battery need to be provided to the data-driven model. This will typically be determined by a user requirement as to how accurate the data-driven model needs to be to establish a sufficiently accurate predictive model, with more data offering greater accuracy. If it is
20 determined that more training data is to be provided, the method 500 returns to Step 502 and the process is repeated for a different battery (or indeed a different charging protocol in some embodiments). If it is determined however that the data-driven model is sufficiently trained, the method 500 then ends.

25

Cycling Data

As noted above, cycling data 30 is obtained in order to train the data-driven models to provide corrections to the
30 physics-based model predictions of battery characteristics by training the data-driven models based on residuals 32 between experimental data and predicted data. A benefit of this approach over standard use of data-driven models which make predictions

- 26 -

through training on the experimental data directly is that typically far fewer cycling data 30 is required to arrive at an accurate prediction. In particular, the accuracy of predictions obtained through use of the hybrid model architecture 10 can be
5 achieved using fewer training data points (e.g., fewer variations in materials chemistries, fewer variations in charging protocols etc). It is to be appreciated that the hybrid model architecture 10 is not limited to using 30 cycles worth of data when the data-driven model is trained. More or less data
10 can be used resulting in more or less accurate corrections being implemented by the data-driven model, and this can be adjusted based on the requirements of the user. By way of example, the training data provided to the data-driven model can include anywhere between 10 and 100 cycles worth of data.

15

Use of Hybrid Model Architecture in Predicting Capacity Fade / Capacity Fade Off Curves

The above embodiments have been described in the context
20 of using the hybrid model architecture 10 to predict an operational lifetime of a battery. However it is to be appreciated that the hybrid model architecture 10 approach may be used to predict other characteristics of the battery. In particular, the hybrid model architecture 10 may be used to
25 predict a capacity fade / capacity fade off curve for the battery.

As rechargeable batteries are cycled, their maximum capacity typically will degrade, ultimately resulting in degradation to such an extent that the rechargeable battery is
30 no longer fit of purpose. This is typically referred to as capacity fade / capacity fade off. Whilst overall operational lifetime is of interest to a user, it may also be useful to ascertain the rate at which the maximum capacity of a

- 27 -

rechargeable battery degrades over time and repeated charge and discharge cycles, known as a capacity fade / capacity fade off curve.

5 An element which is involved in predicting a capacity fade / capacity fade off curve for a particular battery is the operational lifetime of the battery. As such, when predicting the capacity fade / capacity fade off curve, a prediction of the operation lifetime of the battery can be performed in accordance with embodiments described above.

10 In addition, in order to model the curve itself, it is typically necessary to parameterise elements of the curve. Accordingly, the embodiments described herein may be used in order to make accurate predictions of relevant curve parameters in order to provide an overall prediction of a parameterisation
15 of the capacity fade / capacity fade off curve.

In a similar manner as described above with respect to predicting the operational lifetime of the battery, certain physical parameters of the battery (i.e. x_{feat}) or combination of these physical parameters show a correlation to these curve
20 parameters. As a result, the hybrid model architecture 10 described above for predicting a battery lifetime may also be utilised in an analogous manner for predicting the curve parameters of the capacity fade / capacity fade off curves. As such, a physics-based model may initially be used to predict the
25 curve parameters in terms of a quantity of interest comprising a combination of cycling features of the battery. Cycling data 30 may then be provided to determine the difference between the measured curve parameter and the predicted curve parameter in order to provide a set of parameter residuals in an analogous
30 manner to the method used above with respect to predictions of battery lifetimes. These curve parameter residuals are then used to train a data-driven model to determine an appropriate correction function to the physics-based model prediction. This

- 28 -

may then be repeated for a plurality of adjustable battery characteristics (e.g., battery chemistries, charging protocols) to establish additional training points for the data-driven model.

5 Since curves are typically parameterised by a plurality of parameters, this methodology may be repeated a plurality of times in order to provide predictions for each parameter.

 Once a prediction has been made for the battery lifetime and each of the curve parameters, these are combined in order
10 to obtain an overall prediction for the capacity fade curve.

Methodology

 Referring now to Figure 6, there is shown a method 600 of
15 operation of the present embodiments when the hybrid model architecture 10 is used to predict a capacity fade / capacity fade off curve for a battery in accordance with embodiments described above. The method 600 is relevant where a data-driven model trained using lifetime and curve parameter residual data
20 has already been established.

 The method 600 is similar to the method 400 in Figure 4, but is modified to consider the additional predictions to be made in respect of the curve parameters.

 The method 600 proceeds by creating, at Step 602, a physics-
25 based model for the battery. This is conducted at the generalisable base learner 15. The physics-based model will be based on known electrochemical theory and will typically predict a correlation between a difference between a quantity of interest comprising a function of cycling features of the
30 battery, x_{feat} between two cycles of the battery to the lifetime of the battery. Additional parameters α, β (which are not directly subsequently measured) will typically also be included as part of this model. This is in accordance with embodiments described

- 29 -

above. In addition, the physics-based model at this time will also be configured to create a physics-based model encompassing one or more curve parameters associated with the capacity fade / capacity fade off curve in accordance with embodiments
5 described above. These predictions will again be based on a difference between a quantity of interest comprising a function of cycling features of the battery, x_{feat} between two cycles of the battery to the lifetime of the battery. Typically, this quantity of interest may be different to the one used for
10 predicting the battery lifetime and may vary between different curve parameters.

Following this, the method proceeds by receiving, at Step 604, cycling data 30 relating to the battery for which the prediction is to be made. The cycling data 30 includes data
15 relating to a number of charge-discharge cycles of the battery in accordance with embodiments described herein and typically includes values for relevant cycling features x_{feat} . The provided cycling data 30 provides experimental measurements of the cycling features 30 used to predict the operational lifetime of
20 the battery by the physics-based model (i.e. for the physical parameter being tested at a particular cycle). In some embodiments, the testing process by which the cycling data 30 is obtained may be included as part of the method. As above, the cycling data 30 will also provide experimental data for which a
25 prediction of the curve parameters can also be made.

Following this, the physics-based model (initial prediction) and the data-driven model (corrective prediction) are then coupled at Step 606. As noted above, this method 600 is in respect of embodiments in which a trained data-driven
30 model has already been created. Once coupled, the initial prediction and the corrective prediction functions are able to be combined to provide a corrected prediction. This combination will use the corrected prediction for the operational lifetime

- 30 -

and each curve parameter for which a prediction has been made (and corrected) to generate a corrected prediction for the capacity fade / capacity fade off curve. Following this combination, the received cycling data 30 is provided, at Step 5 608 to the coupled models. This provides the relevant values upon which the predicted capacity fade / capacity fade off curve may be established. Once the data is provided, the capacity fade / capacity fade off curve of the battery is predicted, at Step 610, based on the corrected prediction function and the cycling 10 data 30. The method 600 then ends.

As for method 400, in some embodiments there is a level of generalisability between adjustable battery parameter (e.g. battery chemistry, charging protocols). As a result, in these 15 embodiments it may not be necessary to generate a new data-driven model for providing corrections to a created physics-based model.

It is to be appreciated that in some cases, an existing trained data-driven model will not have been created. Therefore it may be necessary to first train such a model. This is achieved 20 in an analogous manner to the method 500 of Figure 5. In particular, a physics-based model creates initial predictions for the operational lifetime and relevant curve parameters based on received cycling data 30. These predictions are then compared to experimentally determined lifetimes and curve parameters to 25 create lifetime and curve parameter residuals. These are then used in conjunction with the cycling data 30 as training data for the data-driven model. This will then be repeated for a plurality of battery chemistries and/or cycling protocols to obtain a plurality of training data points, with the amount of 30 data points required being determined by the required level of accuracy of the predictions. Typically, more training points leads to a more accurate prediction in the hybrid model architecture 10.

- 31 -

Selection

The above embodiments describe systems and methods in which characteristics for a rechargeable battery may be predicted. In
5 further embodiments, these predictions may be used to assess suitability of a particular adjustable battery parameter (e.g., energy storage material or charging protocol).

In particular, in some embodiments there may be a user defined criterion indicating that in order for an energy storage
10 material or charging protocol to be suitable for purpose, the battery must reach a minimum operational lifetime threshold (typically expressed as a number of cycles). In such embodiments, the prediction of the operational lifetime made by the hybrid model architecture 10 may be compared to the minimum
15 operational lifetime threshold to determine whether the threshold has been met. In cases where the threshold is met, the adjustable battery parameter may be accepted and indicated as being acceptable for use. In cases where the threshold is not met, the adjustable battery parameter may be rejected and no
20 longer considered.

In such embodiments, a computer system may be arranged to perform this comparison. In particular, a memory may be provided in which the minimum operational lifetime threshold is stored. The computer system may be configured to receive the prediction
25 generated by the hybrid model architecture 10 and a processor of the computer system may be configured to compare the results with the minimum operational lifetime threshold and to determine whether the threshold has been met.

The above example has been provided with reference to an
30 arrangement in which it is the operational lifetime of the battery that is predicted. However, it is to be appreciated that these embodiments may be appropriately adapted in order to assess adjustable battery parameters when the hybrid model

- 32 -

architecture is configured to predict other battery characteristics (e.g. capacity fade / capacity fade off curves).

Hardware Architecture

5

Referring now to Figure 7, there is shown a high level illustration of an example hardware system 700 configured to enable the functionality described above.

10 The system 700 comprises a central system 702, as well as the generalisable base learner 15 and additional learner 20 in accordance with embodiments described above. Each of the three elements is configured to be able to communicate via a wireless communication network 703. In some embodiments, communication between the elements may be achieved through wired means. Whilst
15 only one generalisable base learner 15 and additional learner 20 is shown, it is to be appreciated that this is for illustrative purposes only and that further such learners may be included where required.

Each of the central system 702, the generalisable base
20 learner 15 and additional learners 20 may be provided with processors, receivers, transmitters and data stores/memories to enable the functionality described herein.

The central system 702 may be provided in order to provide instructions to each of the generalisable base learner(s) 15 and
25 additional learner(s) 20 to enact the functionality described above. In particular, the central system 702 may be configured to instruct each of the learners to create predictions and corrections based on the cycling data 30. In some embodiments, the cycling data 30 is received by the central system 702 and
30 disseminated to the learners where appropriate. In some embodiments, the central system may also be configured to receive initial predictions 22 from the generalisable base learner 15 in addition to the cycling data 30 in order to

- 33 -

determine the various residuals described herein. The residuals may then subsequently be provided to the additional learner 20 in the form of training data. The central system 702 may also be configured to receive the corrective functions generated by the additional learner 20 and combine these with the prediction 22 generated by the generalisable base learner 15 in order to create the final prediction generated by the hybrid model architecture 10.

The data stores and processors of the generalisable base learner 15 and the additional learner 20 may be configured to enable physics-based models and data-driven models respectively to be created in accordance with a set of instructions which have been previously provided. Further, the generalisable base learner 15 may also be configured to receive inputs from a user which indicate the physics-based model to be used when creating an initial prediction 22. Additionally or alternatively, the generalisable base learner 15 may also be configured to generate a physics-based model based on instructions provided to it and stored in the data store 718.

In embodiments in which the system 700 is configured to make a selection in accordance with embodiments described above, the central system 702 may be configured to store acceptable threshold values in its data store 710 and, upon determining a prediction for a battery characteristic as described herein, the processor 704 may be configured to compare the prediction with the threshold value to determine whether the adjustable battery parameter is acceptable. The central system 702 may then be configured to generate an indication of the acceptance (or otherwise).

It is to be appreciated that in the examples described, three separate and communicable systems are shown for illustrative purposes only. In some embodiments, each of these systems may be distinct and configured to communicate with one

- 34 -

another in order to enable the functionality described herein.
In such cases, each element of the system 700 may be located
remotely from one another or in the same location. In some
embodiments, each element of the system 700 may be included as
5 part of a single centralised system. In such cases, the features
of each element (i.e. the processors, receivers, transmitters
and data stores) may accordingly be shared.

Having described several exemplary embodiments of the
present embodiments and the implementation of different
10 functions of the device in detail, it is to be appreciated that
the skilled addressee will readily be able to adapt the basic
configuration of the system to carry out described functionality
without requiring detailed explanation of how this would be
achieved. Therefore, in the present specification, several
15 functions of the system have been described in different places
without an explanation of the required detailed implementation
as this not necessary given the abilities of the skilled
addressee to implement functionality into the system.

Furthermore, it will be understood that features,
20 advantages, and functionality of the different embodiments
described herein may be combined where context allows.

SP3050

- 35 -

C L A I M S

1. A computer implemented method (400) of determining a characteristic of a rechargeable battery, the rechargeable battery being associated with an adjustable battery parameter, the computer-implemented method (400) comprising:

5 determining (402) a physics-based prediction (22) of a correlation between the characteristic and a quantity of interest of the rechargeable battery, where the physics-based prediction (22) is based upon the adjustable battery parameter, and wherein the quantity of interest comprises a function of one
10 or more cycling features, and the one or more cycling features comprise variables which are measurable during a charge-discharge cycle of the rechargeable battery;

receiving (404) cycling data (30) comprising measured values of the one or more cycling features during one or more charge-
15 discharge cycles of the rechargeable battery;

coupling (406) the physics-based prediction (22) of the correlation to a trained data-driven model, wherein the data-driven model has been trained using a machine learning algorithm and is configured to determine a correction to the physics-based
20 prediction of the correlation (26) as a function of the quantity of interest; and

determining (410) the characteristic based on the physics-based prediction (22) of the correlation, the correction to the physics-based prediction of the correlation (26) and the
25 received cycling data (30).

2. The computer implemented method (400) of Claim 1, further comprising determining whether the rechargeable battery associated with the adjustable battery parameter is suitable for use by comparing the characteristic with a user determined
30 minimum threshold value, wherein the rechargeable battery is

- 36 -

determined as being suitable for use when the characteristic is equal to or greater than the minimum threshold value.

3. The computer implemented method (400) of any previous claim, further comprising training the data-driven model.

5 4. The computer implemented method (400) of Claim 3, wherein training the data-driven model comprises:

10 determining (502) a physics-based prediction of a correlation between the characteristic and the quantity of interest for a plurality of rechargeable batteries, wherein each rechargeable battery of the plurality of rechargeable batteries comprises a different value of the adjustable battery parameter and the physics-based prediction is based upon the adjustable battery parameter;

15 receiving (504) cycling data (30) comprising measured values of the one or more cycling features during one or more charge-discharge cycles of each rechargeable battery of the plurality of rechargeable batteries;

20 determining (506) a physics-based prediction of the characteristic of each rechargeable battery of the plurality of rechargeable batteries based on the respective received cycling data (30) and the respective physics-based prediction of the correlation;

25 determining (508) a characteristic residual for each rechargeable battery of the plurality of rechargeable batteries, wherein each characteristic residual comprises the difference between the physics-based prediction of the characteristic for the respective rechargeable battery and a measured value of that characteristic; and

30 providing (510) each characteristic residual and the received cycling data (30) as training data to the data-driven model.

5. The computer implemented method (400) of any previous claim, wherein determining (402) the physics-based prediction (22) of a correlation between the characteristic and the

- 37 -

quantity of interest of the rechargeable battery comprises determining a correlation between the characteristic and comparative values of the quantity of interest between two charge-discharge cycles of the battery,

5 6. The computer implemented method (400) of Claim 5, wherein the correlation is determined between the characteristic and a discharge energy loss between two cycles of charge-discharge of the rechargeable battery.

10 7. The computer implemented method (400) of Claim 5, wherein the correlation is determined between the characteristic and a ratio of charges as a function of voltages between two cycles of charge-discharge of the rechargeable battery.

15 8. The computer implemented method (400) of any of Claims 5 to 7, where the two charge-discharge cycles are the first charge-discharge cycle and the thirtieth charge-discharge cycle.

9. The computer implemented method (400) of any previous claim, wherein the machine learning algorithm is a gradient boosted decision tree.

20 10. The computer implemented method (400) of any previous claim, wherein the characteristic comprises an operational lifetime of the battery.

11. The computer implemented method (400) of any of Claims 1 to 9, wherein the characteristic comprises a parameterisation of a capacity fade off curve of the battery.

25 12. The computer implemented method (400) of any previous claim, wherein the adjustable battery parameter comprises an energy storage material of the rechargeable battery.

30 13. The computer implemented method (400) of any of Claims 1 to 11, wherein the adjustable battery parameter comprises a charging protocol used to charge the rechargeable battery between two charge levels.

14. A machine-readable non-transitory medium having stored thereon machine-executable instructions for determining

- 38 -

a characteristic of a rechargeable battery, the rechargeable battery being associated with an adjustable battery parameter, wherein the instructions are adapted to instruct a processor to perform the computer-implemented method (400) of any of Claims 1 to 13.

15. A system (700) for determining a characteristic of a rechargeable battery, the rechargeable battery being associated with an adjustable battery parameter, wherein the system comprises:

10 a data store (710) comprising instructions; and
a processor (704) configured to carry out the instructions in the data store (710) to:

determine (402) a physics-based prediction (22) of a correlation between the characteristic and a quantity of interest of the rechargeable battery, where the physics-based prediction (22) is based upon the adjustable battery parameter, and wherein the quantity of interest comprises a function of one or more cycling features, and the one or more cycling features comprise variables which are measurable during a charge-discharge cycle of the rechargeable battery;

20 receive (404) cycling data (30) comprising measured values of the one or more cycling features during one or more charge-discharge cycles of the rechargeable battery;

couple (406) the physics-based prediction (22) of the correlation to a trained data-driven model, wherein the data-driven model has been trained using a machine learning algorithm and is configured to determine a correction to the physics-based prediction of the correlation (26) as a function of the quantity of interest; and

25
30 determine (410) the characteristic based on the physics-based prediction (22) of the correlation, the correction to the physics-based prediction of the correlation (26) and the received cycling data (30).