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Research papers

Feature-based lithium-ion battery state of health estimation with artificial neural networks

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ABSTRACT

Precise online lithium-ion battery state of health estimation is critical for the correct operation and management of battery-based energy storage systems such as microgrids and electric vehicles. However, in such applications it is necessary to maintain standard operation and therefore difficult to experimentally determine. Advancements in machine learning techniques and capabilities allow for precise and efficient data-driven predictions. In this paper we propose a simple, yet effective state of health estimation model based on the extraction of features observed from patterns in the voltage, current and temperature profiles during the charging process, which then through artificial neural networks allow for per cycle estimations. We then apply this model to two groups of batteries from the NASA Ames PCoE Battery data set. Results show that the proposed model is capable of estimating the state of health of batteries discharged under varied conditions with resulting coefficients of determination between 0.896 and 0.992 while also employing significantly less input data than other works.

1. Introduction

In today's world lithium-ion (Li-ion) batteries play a fundamental role in decarbonizing our world economy [1] by providing the necessary energy storage for a wide range of applications and devices: from microgrids and renewable energies [2], to electric vehicles (EVs) [3] and consumer electronics. The reasons why Li-ion technology is considered the main form of energy storage is due to its favorable characteristics: high energy density, high efficiency, and long-life cycles [4]. Because their long lives are a critical characteristic, it is essential to know, model and prevent battery degradation.

Li-ion batteries degrade due to irreversible changes in cell chemistry such as positive electrode oxidation and negative electrode reduction as a result of repeated charge and discharge cycles, overcharging and overheating [5]. Studies show that the discharging process tends to be more damaging than its respective charging cycle [6]. Battery degradation is most commonly quantified by the state of heath (SoH) parameter. SoH represents a measurement of a battery's current condition with respect to their nominal or design conditions. By knowing a battery's SoH, we can look to improve overall battery performance and even prolong battery life [7]. Therefore, SoH estimation is crucial for optimal battery performance in a wide variety of applications that require long battery lives, such as electric vehicles [8].

There are many studies on SoH estimation and prediction. In [9] the authors present a complete review of different battery SoH estimation methods that can be split into three different categories: experimental and model-based methods, which represent the more traditional approaches, and the more modern data-driven methods.

Experimental methods normally represent offline and laboratory conducted experiments to accurately determine battery degradation in accordance with different measurements, such as internal resistance [10,11], impedance [12,13] and capacity levels [14,15]. The main disadvantages of experimental methods are the time-consuming nature of the necessary measurements as well as their inability to be conducted in real-time when estimating SoH.

Model-based methods employ different indicators to construct models that can accurately describe battery SoH behavior. Commonly employed techniques include Kalman filters, observers, and equivalent circuit models (ECM). In [16] the authors demonstrate that the dual extended Kalman filter commonly used in state of charge (SoC) and SoH estimation is hampered over the battery lifetime. In [17] the authors propose a multi-time-scale observer for dual SoC and SoH estimation. Meanwhile in [18] the authors integrate the effects of decreasing SoH into an ECM to accurately determine Thevenin parameters. Model-based SoH estimation has proven to achieve high accuracy

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and precision, yet often incurs high computational cost and may be dependent on a large number of parameters and variables.

Data-driven SoH estimation methods, more specifically machine learning techniques, look to combine the advantages of both the aforementioned traditional methods. They are inherently dependent on these traditional methods as they require data, obtained via measurements or models, to accurately train the estimation models and are therefore reliant on the quality of this data. Despite this, they have proven to provide high estimation accuracy as well as simple implementation. There is a wide range of machine learning techniques being used for SoH estimation. In [9] the authors highlight support vector machines (SVM) [19–21], fuzzy logic [22] and artificial neural networks (ANN). Others such as the regression tree and random forest models are implemented in [23] with varying degrees of accuracy.

The main focus of this paper is the application of artificial neural networks for battery state of health estimation. There is a wide variety of ANN applied in the literature. In [24] the authors propose a dynamic long short-term memory (D-LSTM) neural network to predict Li-ion battery remaining useful life (RUL), the sister parameter of SoH that considers the number of cycles remaining before crossing a certain SoH threshold, with errors as low as two cycles. Similarly, the authors of [25] implement a variety of neural networks to predict SoH and RUL while varying the starting point of different predictions. Lastly in [26] the authors implement an ANN-based capacity estimation model that considers only the charging profiles, while also comparing the performance of different ANN configurations such as simple feed-forward neural networks (FNN) and LSTM. This last approach in considering only the charging parameters serves as the basis for our proposed model.

In [27], the authors perform a comprehensive review of SoC methods for Li-ion batteries using Neural Networks; this review is centered around the characteristics of the ANN employed in different approaches, the authors analyze more than 100 references; one of the conclusions drawn by the authors is that, generalizing the results obtained for one type of battery to other types of battery can be achieved through certain specific methods. Also, in [28] the authors review a large number of papers centered in SoH modeling; although their focus is centered on maritime applications, many of their conclusions and studies can be generalized for other uses; the authors stress the fact that data availability and quality is key for any machine learning application.

In this paper we propose a simple battery state of health estimation model with ANN based on the extraction of features observed in the battery charging parameters. As with all machine learning-based approaches, the utilized data performs an important role in both idea and model conception as well as testing and results analysis. In this case we employ the NASA Ames PCoE Battery data set [29]. Note that the authors in [23–26] employ the same data set, which therefore allows for potential results comparisons. We highlight our main contributions as follows:

- Larger and more varied data set for training, validating, and testing model performance as we incorporate a larger number of batteries from the complete data set, which are also discharged under different conditions.
- Exploitation of clear and observable patterns in the charging profiles with the use of feature extraction which therefore decreases the amount of input data required.
- The use of smaller and simpler ANN as a result of the need for less model input data.

This paper is structured into the following sections: Section 2 describes the problem and the available data set, Section 3 explains the necessary data analysis and preprocessing, Section 4 presents the proposed state of health estimation model based on ANN, Section 5 details and discusses the estimation results, and Section 6 presents the final conclusions.

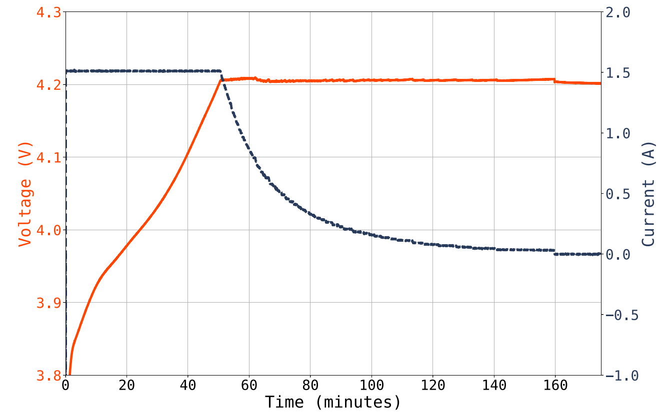

Fig. 1. CC–CV charging protocol.

2. Problem statement

State of health represents a commonly employed measurement of battery degradation but lacks a universally accepted definition. Some definitions are based on different battery parameters such as internal resistance, voltage, and self-discharge [30]. The most widely utilized definition is based on battery capacity and in this paper we define it as:

$$SoH(\%) = \frac{C_i}{C_o} \times 100 \tag{1}$$

where C_0 is the initial capacity of the cell and C_i is the measured capacity at cycle i. It is widely accepted that battery end of life (EoL) is reached once the SoH drops to 70%, at which point performance and reliability is considered to be insufficient [31].

The main idea behind machine learning-based SoH estimation methods is that through easily available real-time data we can observe changes in measured parameters such as voltage and current, and then accurately infer battery degradation. Specifically, we propose the use of artificial neural networks to determine battery SoH on a per cycle basis, which therefore means we need per cycle parameters to train the network.

As we are proposing the use of a supervised machine learning technique, the selected battery data set must contain the required state of health or capacity measurements to train the estimation models. Therefore, we employ the data set provided by the NASA PCoE [29]. This repository contains data from 34 lithium-ion 18650 cells with a nominal capacity of 2.0 Ah cycled under varying discharging and ambient temperature conditions. Each cycle consists of a charge and discharge process while also including impedance measurements obtained with an electrochemical impedance spectroscopy (EIS). The fixed charging process consists of a constant current–constant voltage (CC–CV) protocol in which the battery is charged at a fixed current of 1.5 A until the cell voltage reaches 4.2 V, at which point it maintains constant voltage until the cell current drops below 20 mA (Fig. 1).

The main difference between discharging conditions are the varying currents and cut-off voltages. The repository can be split into different groups following these criteria. In this paper we propose the use of different groups of batteries to obtain a more varied data set and thus a more robust estimation model. Specifically, we employ eight different batteries from two different groups, referred to in this paper as group 1, discharged at 2 A, and group 2, discharged at 4 A. Both groups are discharged with constant current (CC) at their respective currents. In Table 1 we include the different operating conditions for each battery as well as the number of available cycles. Note that although group 1 provides significantly more cycles, and therefore data, group 2 is subjected to a more aggressive discharge process at higher current and temperature.

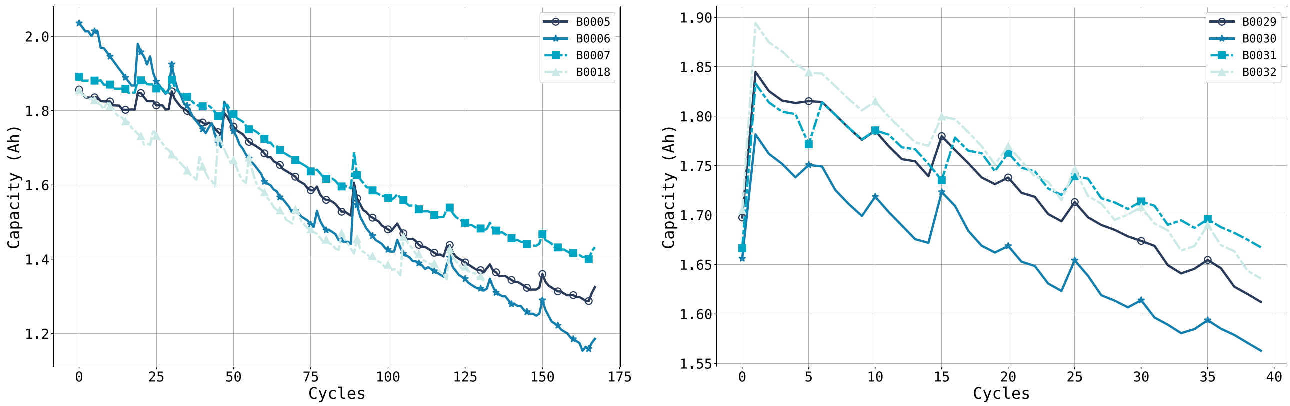

Fig. 2. Battery capacities — group 1 (left) & group 2 (right).

Table 1
Varying conditions of included batteries.

Group	Battery No.	Temperature (°C)	Available cycles	Discharge	
				Current (A)	Cut-off voltage (V)
1	B0005	24	168	2	2.7
	B0006	24	168	2	2.5
	B0007	24	168	2	2.2
	B0018	24	132	2	2.5
2	B0029	43	40	4	2.0
	B0030	43	40	4	2.2
	B0031	43	40	4	2.5
	B0032	43	40	4	2.7

For each cycle included in the data there is a measurement of battery capacity obtained during the discharge process, which is presented in Fig. 2. This data represents the degradation per cycle for each cell in the data set.

3. Data analysis and preprocessing

The battery capacity degradation curves included in Fig. 2 represent the desired outputs for our proposed estimation model. While we wish to accurately reflect the present data, we first prepare the data by removing significant outliers, notably the initial values of group 2.

In Fig. 3 we represent the voltage, current and temperature (V-I-T) curves of various cycles for one of the batteries included in the data set (battery No. B0005). Note that while the pattern in these curves remains constant there is a clear evolution of these curves as the battery degrades. This change reflects the battery aging process and is therefore useful for estimating the cell's SoH as these are measurements easily available during battery operation. The authors in [26] demonstrate better performance considering all three parameters versus just the voltage, with improvements between 25%–58% depending on the estimation model configuration.

The main advantage in considering only the charging process is that as all batteries employ the same charging protocol we can easily identify, extract, and deploy features present in the data for all cells. Note that the effects of the different discharging conditions are implicitly considered as these reflect on the evolution of the battery parameters during charging. Therefore, we propose the use of features to determine the battery degradation. This represents a simpler and more precise method than sampling which inevitably leads to redundant data as all the curves are similar in form.

We initially consider six features present in the V-I-T curves but finally settle for three features that identify significant points of interest in the data and enable us to easily observe the variation between cycles. In Table 2 we include the proposed features and in Fig. 4 the extracted features are visually presented.

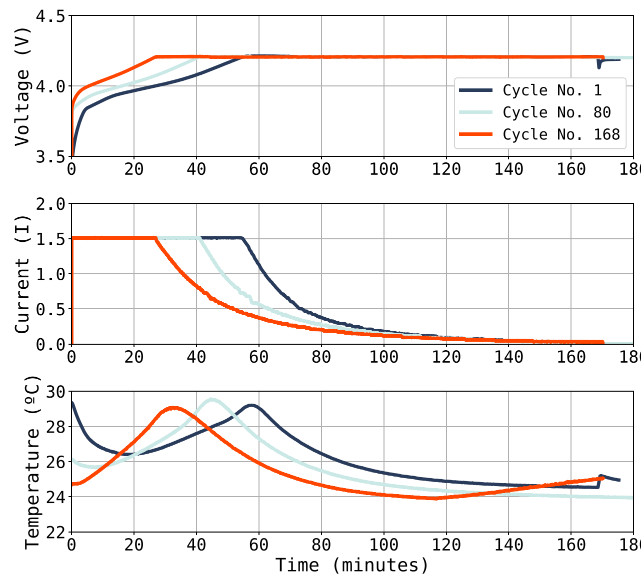

Fig. 3. Evolution of cell voltage, current and temperature curves during charging process (battery No. B0005).

Table 2
Feature description.

No.	Curve	Type	Feature description
1	V	Voltage	Initial inflection point
2	V / I	Time	Rise time to 4.2 V / Destabilization time from 1.5 A
3	T	Time	Time to peak value

From the voltage curve we include an initial inflection point whose value was observed to vary significantly over cycles. Note that the second feature selected is present both in the voltage as well as the current curves as this represents the time in which the CC–CV charging protocol switches from constant current to constant voltage. These represent the only significant differences in the V-I charging curves between cycles.

On the other hand, the temperature curves initially show more promise for feature selection as there are various points of interest. However, points such as the initial and peak temperatures proved to not display significant evolution. Finally, we include the time at which the peak temperature value is obtained.

In Fig. 5 we include the evolution of the proposed features for one of the selected cells. We apply a light interval correction fixed at ±3%

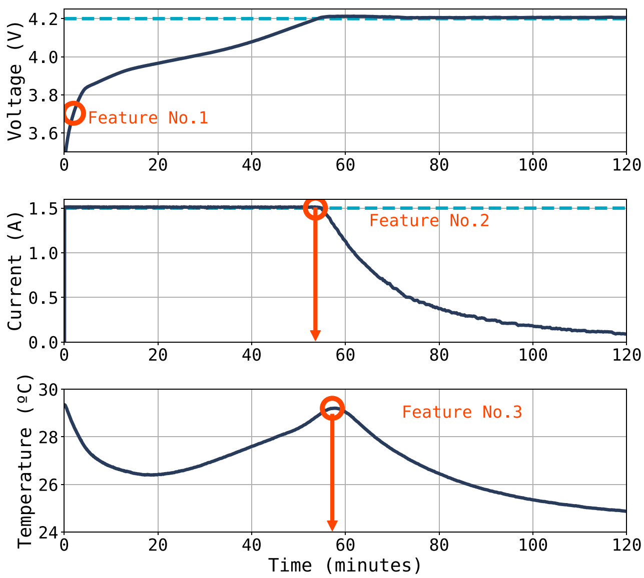

Fig. 4. Extraction of proposed features (battery No. B0005, cycle No. 1).

to eliminate significant outliers while also maintaining the small variability in the features as this is also present in the capacity degradation curves that we wish to accurately estimate. Finally, we normalize these values between 0–1 to improve estimation model performance.

4. SoH model

4.1. Feedforward neural networks

Feedforward neural networks are a simple and widely used form of machine learning that have no feedback connections in a multi-layer structure of interconnected artificial neurons with activation functions. Their main advantage is their ability to handle and process non-linear data in such a way that they can easily be combined into more advanced models [32].

The selection of an appropriate network structure and parameters is part of the design process for FNN. In this paper we identify potential configurations via an experimental process of varying different parameters and noting the corresponding results. We observe that there is not an objectively perfect configuration and therefore a criterion based on simplicity and precision is proposed. The main parameters varied are as follows:

- Number of layers and neurons. We vary the number of hidden layers between one and three as well as the number of neurons per layer between one and nine. Results show little influence in the parameters, with slightly better results observed for one or two hidden layers and three to six neurons.
- Activation functions. Varying the activation functions of both the hidden and output layers varied the results more significantly. While functions such as Tanh and Swish presented unreliable performance, others such as ReLU (Rectified Linear Unit), Linear and Sigmoid presented good performance.

We split the available data into training, validation, and test sets. For training we employ 4 of the available batteries (B0005, B0006, B0029, B0030), 2 for validation (B0007, B0031) and finally 2 for testing (B0018, B0032). Note that although we split the data by batteries to designate the different sets, the respective training and validation data is shuffled and combined to eliminate any bias from individual batteries and potential correlations in consecutive cycles. This allows

Table 3
Expert ANN configurations.

Network	No. hidden layers (HL)	No. neurons per HL	Activation functions	Epochs
No. 1	1	3	Sigmoid Linear	500
No. 2	1	3	ReLU ReLU	500
No. 3	2	6/3	ReLU - ReLU Linear	750

the estimation model to base its predictions solely on the available cycle data.

To evaluate the training process, we designate a specific metric. In this study we vary this parameter and find that the best results are obtained for the mean square error (MSE) metric, defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

where y_i and $\hat{y}_i$ represent the actual state of health and the estimated value, respectively, for cycle i out of a total of n cycles. MSE focuses on larger errors as they are more pronounced due to the square operation. We also calculate other widely used metrics such as root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE(%)) [33,34].

For the selection of different configurations, we focus mainly on the MSE and MAPE(%) results for the validation process while also considering the average coefficient of determination (R^2) for both the whole set as well as the test set. Unlike metrics, which are measurements of error with an objective to minimize these, the coefficient of determination represents a measurement of the quality of estimation models in regression problems. Therefore, the objective is to reach the maximum value of R^2 which is 1. It can be defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \frac{1}{n}\sum_{i=1}^{n} y_i)} \tag{3}$$

In [35] the authors state that the coefficient of determination represents a more reliable and informative measurement than other widely used metrics such as MSE and MAPE(%) as it does not present the same interpretability issues.

4.2. Neural network consensus-based model

In this paper we propose an estimation model based on combining multiple FNN into a multi-network consensus model. Multiple network models [36] opt for a combination of simpler neural networks versus a more complete neural network to handle complex tasks. In this case the use of a multiple network model can potentially solve erroneous estimations in single problematic cycles.

In Table 3 we present three different network configurations for our consensus model. These networks are selected for their varied configurations as well as their good results during the network design process. Note the different number of hidden layers and activation functions.

The proposed framework is presented in Fig. 6. First, we preprocess the available battery data to prepare for feature extraction and normalization. Then we split the available data into three sets: with the training data we train the three networks that form our consensus model and employ more data to validate the model. Finally, we employ the test data to obtain state of health estimations and evaluate model performance. Implementation of the framework is done in Python with the TensorFlow and Keras libraries.

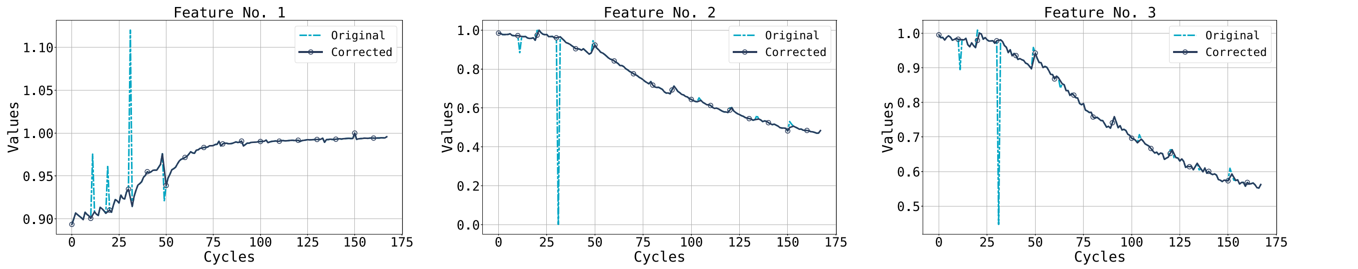

Fig. 5. Proposed features (battery No. B0005).

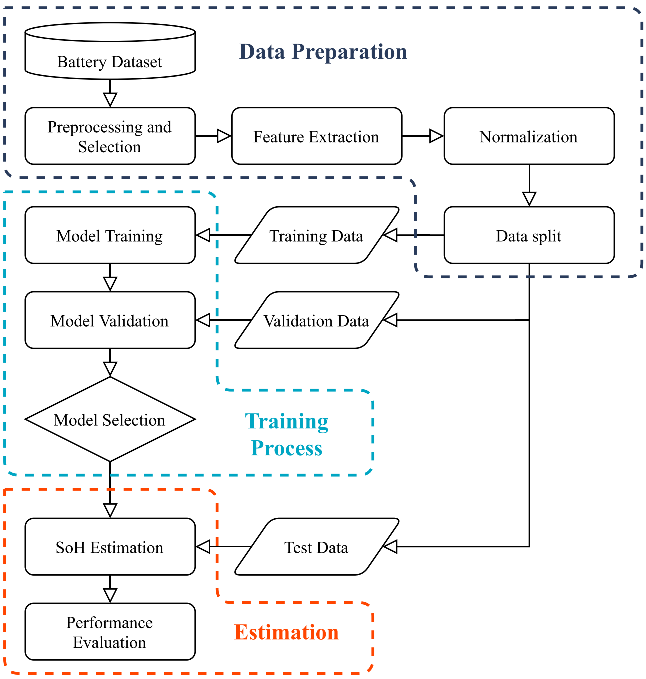

Fig. 6. Model framework.

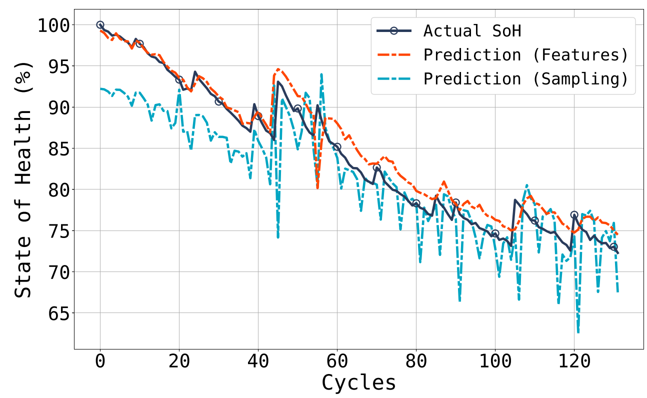

Fig. 7. Estimation — test battery B0018 (group 1).

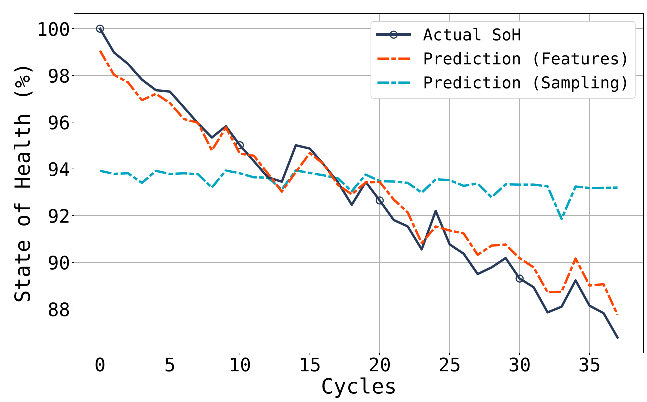

Fig. 8. Estimation — test battery B0032 (group 2).

5. Results and discussion

We compare the performance of our proposed model with a sample-based approach as presented in [26], in which the authors uniformly sample the V-I-T charging curves with 10 data points per curve. They then compare the performance of different artificial neural networks such as FNN and LSTM. In this case we consider both decreasing and increasing the number of data points sampled per curve to 5 and 15, respectively. However, just 5 data points prove to be insufficient while the performance difference between 10 and 15 points is negligible. The implementation process is the same as our proposed model, considering the different network size due to the change in data. After varying different network parameters and configurations we opt for a FNN with 2 hidden layers with 30 and 15 neurons respectively, as well as Sigmoid and Tanh activation functions.

We perform SoH estimation for both groups with the same trained models by combining the data. In Table 4 we present the results for both the proposed feature-based model and our implementation of the sampling model presented in [26]. The MSE and MAPE(%) metrics are calculated from the test set results. We can clearly see that the feature-based model provides lower estimation errors and higher coefficients of determination, while the sample-based model results are heavily worsened by the estimation errors for batteries from group 2. This is reflected in the estimations for the test batteries B0018 (group 1) and B0032 (group 2) in Figs. 7 and 8, respectively.

In Fig. 7 the sampling method is capable of identifying the general trend of the battery's degradation; however, the estimation presents high levels of oscillation. On the other hand, the feature-based method provides a significantly improved estimation that both follows the general trend and identifies small jumps in the SoH values.

In Fig. 8 the feature-based method again follows the actual SoH curve closely, identifying all significant variations. However, the sampling method proves to be inadequate for this representative battery from the second group. This is due to a series of differences between the groups that simply sampling the data does not distinguish. The reason that the second group of estimations is more heavily punished than for the first group is due to the lower number of available cycles with which to train the models.

In Fig. 9 we present the resulting coefficients of determination for every battery using the feature-based model. Here we wish to note two observations. Firstly, note that there is no significant difference in the results obtained between batteries from group 1 and group 2, meaning that the proposed feature-based model is capable of generalizing for

Table 4
SoH estimation results.

Model	MSE	MAPE (%)	R^2 (average)	R^2 (Test)	R^2 (Group 1 average)	R^2 (Group 2 average)
Feature	1.9e−4	1.39	0.948	0.946	0.973	0.923
Sampling	0.003	3.565	0.473	0.400	0.858	0.088

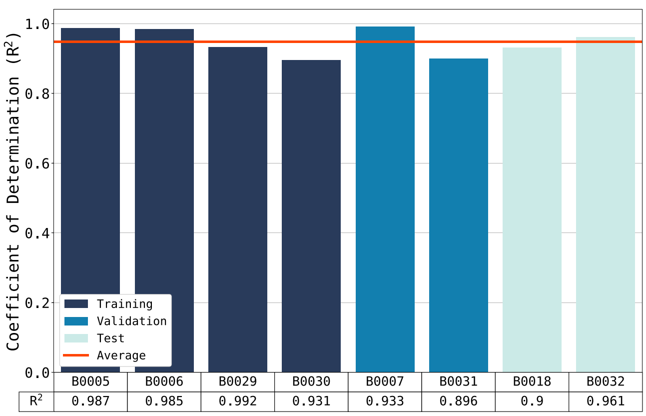

Fig. 9. Estimation results per battery (feature model).

different discharging conditions unlike the sampling method. Secondly, note that the results from the training, validation and test sets are comparable and so in this case the model has avoided overfitting, which is again a sign of good generalization. This is notable despite the difference in available data: 636 charge–discharge cycles for group 1 versus 160 cycles for group 2.

The use of different metrics and scales in individual publications makes direct comparison between these difficult. However, one metric that is not subject to this problem is MAPE(%), which is considered in this work as well as in [26], where the authors obtain MAPE(%) results between 1.0321% and 2.8961% depending on the type of ANN used. Our best result of 1.39% falls within the range of results from [26]. We consider this to be an excellent result as it is worth noting that firstly we are employing a much simpler and smaller ANN configuration, owing to our previous feature extraction, and secondly, we are considering a wider variety of data as we include two groups of batteries from [29] discharged under different conditions and not just one single group as is custom.

6. Conclusion

This paper presents an effective artificial neural network state of health estimation model based on lithium-ion battery data available from [29]. In the data preprocessing stage, we identified features observed from varying patterns in the voltage, current and temperature profiles during the charging process, which then through artificial neural networks allow for per cycle estimations. This approach then allowed us to enlarge the number of batteries, and therefore data, with which to train our estimation model to eight batteries from two different sets of discharging conditions as well as allowing us to employ significantly simpler artificial neural network configurations such as feedforward neural networks with only one or two layers. We then compared the performance of our proposed feature-based model with a similar artificial neural network configuration based on sampling the same available data. Our approach proved to be both more accurate for each individual group of batteries as well as being capable of accurately performing state of health estimation for both groups simultaneously with a mean absolute percentage error of 1.39% and a coefficient of determination of 0.946 for the test set. In future work, the proposed feature-based extraction method could be employed on a larger and more varied data set as well as allowing for further study into the use of different supervised learning techniques.

In the work presented here we detail a method that allows us to estimate the state of health of a battery, provided that we have access to data regarding charge/discharge measurements of the same type of battery, we do not claim that our methods are immediately valid for any other possible chemical composition of the battery. We have presented results that allow us to conclude that our method is correct, within these limitations.

CRediT authorship contribution statement

Lewis Driscoll: Methodology, Software, Validation, Investigation, Writing – original draft, Visualization. **Sebastián de la Torre:** Conceptualization, Methodology, Investigation, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Jose Antonio Gomez-Ruiz:** Conceptualization, Methodology, Investigation, Writing – review & Editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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