Predictive prognostic for Li-Ion batteries in electric vehicles

Inès Jorge, Ahmed Samet, Tedjani Mesbahi, and Romuald Boné

ICube, CNRS (UMR 7357)
INSA Strasbourg – University of Strasbourg
ines.jorge@insa-strasbourg.fr

Abstract. The development of clean vehicles and more specifically electric and hybrid vehicles relies on the performances of Lithium Ion batteries. More efficient than all the other battery chemistry in terms of energy density and output power, these batteries bring hybrid and electric vehicle in line with thermal vehicles. However, they still suffer from a limited driving range and lifespan, and their performances can be affected by numerous factors, one of the most important one being the driving profile imposed by a user.
Prognostics and health management strategies make use of operating data in order to better understand the ageing mechanisms of Lithium Ion batteries and to forecast their future degradation trend. In this article, we introduce our method to predict the Remaining Useful Life of Lithium Ion batteries based on the dataset published by the Massachusetts Institute of Technology, through the use of low computational cost machine learning algorithms. Our artificial neural networks take both historical data and time series representing the driving profile of a battery as input, and predict with accuracy the Remaining Useful Life of a battery. Compared to previous approaches in the literature, we obtain reliable and accurate predictions of the Remaining Useful Life of any battery at any moment in its life from the observation of only charge and discharge cycle. The importance of driving data in prognostics and health management strategies of Lithium Ion batteries is shown throughout this article.

Keywords: Lithium Ion batteries, Prognostics and Health Management, Machine Learning, Artificial Neural Networks, Feature extraction, Remaining Useful Life

1 Introduction

In the case of hybrid vehicles (HEV), and even more so in the case of all-electric power-trains, the on-board energy storage system remains the weak link: very expensive, limited in driving range, slow to recharge, main cause of over-costs... The challenge for any car manufacturer wishing to develop a HEV or an Electric Vehicle (EV) is therefore not only to optimise the electric power-train, both in terms of cost and range, but also to bring the battery into line with the life of the vehicle. Battery lifetime is therefore a crucial element for the development of EVs under acceptable cost conditions. Indeed, the battery is the key component and the most expensive one in a HEV or EV. In this context, the failure of battery could lead to serious inconvenience, performance deterioration, accelerated ageing and costly maintenance.
Therefore, the prognostics and health management (PHM) of on-board energy storage systems, which aims to monitor their health and to predict their degradation trend, appears to be a crucial element in the development of new battery powered vehicles.

PHM strategies make it possible to forecast the evolution of the storage capacity of a battery and to predict its Remaining Useful Life (RUL), which correspond to the number of charge and discharge cycles it can withstand before reaching its end of life. That allows to perform maintenance service in advance if necessary, using the past and current information about battery usage and capacity degradation trend.
The aim of this article is to present a method based on machine learning for the predictive prognostics of Li-Ion batteries in EV applications. The challenge is to use ageing data of Li-Ion batteries in order to extract knowledge on the state of health (SOH) of the batteries. In this paper, we focus specifically on the dataset published in [1] as it is the largest available and contains extremely valuable data that apply very well to machine learning techniques. The key contributions are (*i*) the development of low computational models based on Artificial Neural Networks (ANN), (*ii*) an online forecasting of the RUL of batteries, (*iii*) the use of driving data in the predictive model.

The remainder of this article is structured as follows : section 2 is a brief introduction to related work in the fields of predictive prognostics of Li-Ion batteries, section 3 provides a detailed presentation of the dataset on which we based our work, section 4 focuses on the developed architecture for RUL prediction based on ANN and feature extraction, section 5 presents all experimental results with a comparison with other approaches found in the literature and section 6 offers a brief conclusion with a presentation of future works.

2 Background

Concerning Li-Ion batteries, prognostics and health management strategies (PHM) aim at determining how and when a failure will occur and to give a long term image of the state of health (SOH) of the battery [2]. This can be done either by observing previous data acquired through various sensors or by simulating the behaviour of a battery in its environment thanks to physical models.

In a great majority of papers, PHM of Li-Ion batteries consists in determining their RUL, which is the number of charge and discharge cycles it can go through before reaching the End of Life (EoL) criteria. A battery is considered out of use for an electric vehicle when it has reached a SOH of 80%. The SOH of a battery represents the storage capacity at a given time compared to its initial storage capacity :

$$SOH = \frac{Q_{actual}}{Q_{nominal}} \quad and \quad SOH\% = \frac{Q_{actual}}{Q_{nominal}} * 100 \tag{1}$$

Most approaches deal with the prediction of the RUL in terms of cycles. This can be done either by designing a complete physical model and simulating the behaviour of a battery, or by focusing on real data taken as input of machine learning models. This latter type of models makes it possible to forecast the temporal evolution of the battery SOH using a sliding window approach, or to predict the RUL directly from the observation of ageing features.

2.1 Model based approaches

Model-based techniques were the first ones to be developed, before massive data acquisition and challenges linked to big data appeared. A model-based approach for the PHM of a system relies on the establishment of a simulation model according to physical rules and functioning equations. The aim is to understand and reproduce the behaviour of a system in order to obtain simulated data that could be exploited, in particular with

the introduction of disturbances. It implies a complete understanding of the system and gives a global representation of the different answers to solicitations. Downey **et al.** in [3] have modeled the degradation phenomena of active materiel loss in Li-Ion batteries in order to estimate the battery capacity. The battery was represented by an electrochemical model that takes into account heat generation equations in [4]. Zhang *et al.* [5] elaborated a comprehensive lead-acid battery model made of seven sub-models each modeling a physical phenomena. The model estimates internal resistance, terminal voltage, internal temperature, SOC and battery capacity using the load current and ambient temperature.

2.2 Data driven approaches

Data driven approaches for PHM have emerged with the development of industry 4.0 and massive data acquisition strategies. Real operating data is collected and given as input to a black box model, that uses past data to forecast the evolution of a system. Operating data most of the time consists in physical features observed according to time through different sensors linked to a battery or a battery cell during ageing tests (observation of current, voltage, internal resistance, temperature...). This results in very large sequences of data as the cycle life of a Li-Ion battery can reach more than 2000 cycles. All data driven strategies require a data prepossessing step in order to make operating data compatible with data driven models. However, there can be a great variety of approaches when building a data driven predictive model, mainly due to the development of machine learning algorithms that apply very well to large amounts of data and PHM problematic. This quick state of the art of data driven approaches separates the different models found in the literature into two categories : window-based models and early cycle models.

Window approach As explained earlier, operating data of Li-Ion batteries can result in very larges sequences of data due to their very high lifespan. A common approach for simplifying the problem is to use a window approach. There are two types of data sequences in Li-Ion battery ageing data. The first one are historical data sequences, which are represented as a function of the number of cycles. For example, SOH is computed at each cycle, just as internal resistance or charging time. For each of these data sequences, there is one value for each cycle, and a sequence window is therefore composed of several consecutive cycles. The second type of data sequence are temporal data, which are represented as a function of time. Here, operating data is directly acquired though sensors, and for each cycle, the temporal evolution of several features such as current, voltage or temperature can be observed. Temporal data represent the real use of the battery. A window of time sequences can then either be a sample of time series from one cycle, or a succession of time series that corresponds to several consecutive cycles. Most approaches deal only with the observation of window of historical data, and especially the SOH. The evolution of SOH contained in one window makes it possible to forecast the future degradation trend and therefore to predict the RUL according to the predicted SOH fade. This method has proved very effective and can be applied to a great variety of ML techniques [6–10]. However, the main drawback is that the accuracy of the prediction depends on the size of the window. The larger the amount of historical data, the better the accuracy. Moreover, very few approaches take advantage of time series.

Early cycle prediction Some approaches mention other RUL prediction techniques based on features calculated from early cycles data. Severson *et al.* have computed several

features from cycle 1 to cycle 100 and applied a linear regression as a supervised learning technique to predict the cycle life of a given cell. This method also removes the problem of dealing with temporal or sequential values but requires to use only brand-new batteries, after cycling them 100 times.

3 Battery ageing data

Throughout the literature, several datasets are often cited and used for data driven approaches concerning PHM of Li-Ion batteries. The NASA Prognostics Center of Excellence (PCoE) published a massively used dataset for SOH prediction [11]. It consists in 34 batteries tested under different charge and discharge conditions until the EoL criteria is reached. More batteries were tested in this dataset without reaching end of life though, which limits the applications.

The NASA PCoE also published a dataset that consists in testing 4 batteries with random charge and discharge currents during 1500 cycles [12]. After 1500 cycles, characterisation cycles are performed in order to evaluate the evolution of the batteries' SOH.

An other dataset published by the Sandia National laboratories aims at studying the effect of Depth of Discharge (DoD), load current and temperature on battery degradation. 86 cells of three different chemistries (LFP, NMC and NCA) are tested in this study.

Some papers also mention custom battery ageing datasets [13]. The main drawback when testing batteries for health prognostics is that EoL criteria need to be reached. Considering the performances of Li-Ion batteries, this may take a long time and require a lot of resources for testing a representative number of cells. To overcome the resource and time problem, a paper also shows the use of training data generated with a physic-based model of Li-Ion battery [14].

Even though all this data is of great interest, we decided to base our approach on a new dataset described in [1] (with supplementary information in [15]). This dataset gathers more information than all earlier mentioned datasets, to our knowledge, as it offers complete operating data of 124 cells tested from beginning to EoL.

3.1 MIT dataset

In [1], the department of chemical engineering of the Massachusetts Institute of Technology, in collaboration with Toyota engineering and with the Department of Materials Science and engineering of Stanford university, have built the largest available dataset regarding Li-Ion battery ageing. This dataset is a highly valuable source of information as very few public data can provide that much resource. The cells that were used for testing are LFP/graphite cells from A123 manufacturer, model APR18650M1A. These cells have a 3.3V nominal voltage and a 1.1Ah nominal capacity. They can provide discharge currents up to 30A.

The cells were tested in a 30°C chamber and cycled with an battery tester from Arbin manufacturer. The batteries are always discharged at a constant current of 4.4A. The most important factor in the tests is the charging policy. Batteries are charged following a multi-steps constant-current/constant-voltage (CC-CV) policy which makes it possible to reduce the charging time. By applying a fast charging policy, batteries are tested under conditions that are close to the real use of batteries in an EV. Indeed, one of the main challenges that EV are facing is the charging time, which should be as short as possible without damaging the cells.

As explained in section 2.2, there are two different kind of data sequences in this dataset : historical data sequences and times series.

Figures 1, 2 and 3 are representations of time series for one given cycle (the charging pattern, evolution of external temperature during one cycle, discharge voltage...) and figures 4, 5 and 6 show the global evolution of a given historical data sequence over the full life cycle of a battery.

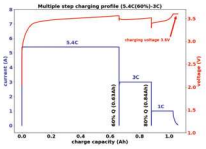

Fig. 1. Charging pattern

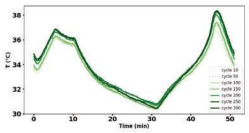

Fig. 2. Cell T°

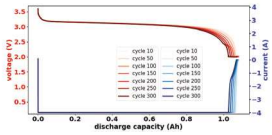

Fig. 3. Discharge V and I

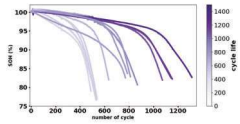

Fig. 4. Capacity fade

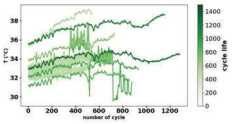

Fig. 5. Average cell T°

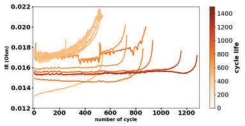

Fig. 6. Internal resistance

The available dataset offers a considerable amount of ageing data from the first cycle of each cell to the EoL. Every cycle gives information about ageing signs and SOH that should be taken into account. Both historical data and time series contain information about the RUL and SOH of the battery at a given time, but they need to be pre-processed and combined in order to highlight the factors that most represent the degradation trend of a battery.

3.2 Exploitation of driving data

As detailed in section 2.2, most approaches are based on the exploitation of SOH historical curves only to forecast the future SOH degradation trend [7, 16, 13]. We see two major drawbacks in designing a SOH forecasting model based on previous SOH data only. First, as all available data consists of experimental data built from laboratory cell tests, the degradation trend is quite steady. Indeed, in the MIT dataset, cells are discharged at a constant current rate, identically throughout their whole cycle life. Similarly, the charging protocol does not vary from beginning to end of life. This results in SOH degradation patterns that are very similar from one battery to another, as can be seen in fig 4. Therefore, forecasting future SOH degradation trend from past SOH data is simplified and can be implemented with most machine learning algorithms.

Secondly, studying the global trend of SOH can give a good idea of the long term degradation but could not make it possible to catch local variations due to a specific use of the battery. Current (I), voltage (V) and temperature (T°) time series reflect the real use of the battery : I and V curves represent the driver solicitations (acceleration, speed, breaks...) and T°brings information about the environment in which the battery is used (cold or warm weather, night or day etc . . .). Therefore, we believe that using

driving data as input to our PHM model is crucial in understanding all possible causes of deterioration.

3.3 Training dataset

The RUL of a battery decreases at each cycle. Our target is to predict the RUL of a battery at any given cycle, focusing on only one cycle. That means that in this paper, a window based approach is used, where the window size is of one cycle. RUL can be calculated for each cycle following equation 2 :

$$RUL = k_i - n \tag{2}$$

where k_i is the cycle life of cell number i and n is the observed current cycle of the cell.

Our approach mixes the use of historical data and temporal series. These two types of data can't be used directly together as historical data have one scalar value per cycle and time series have one vector of varying length per cycle. Therefore, before using time series in our model, a feature extraction technique is used to condense the information contained in each vector into one scalar value. For example, several features are computed from each time series such as the root mean square value, area under the curve or average value. Computed features from time series can then be exploited as input to any given model in the same way as historical data. The training dataset as used in our approach is represented in figure 7.

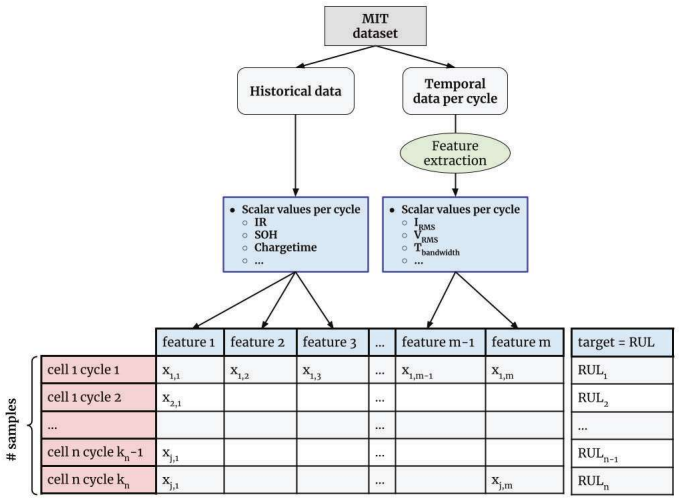

Fig. 7. Training dataset composed of historical data and time series features

In order to compare the performances of different combinations of features, two models were developed : one using only historical data, and another one using a selection of historical data and time series features.

4 Proposed architecture

As the dataset is quite recent, only little work has been based on it. In this paper, the architecture described consists in extracting features from temporal series and use them along with historical data to predict the RUL of a battery. Our predictive model is based on a well known machine learning regression tool : Artificial Neural Networks (ANN). Our goal here is not to investigate new predicting approaches but to prove that the available data combined with low computational models can lead to very efficient prediction performances. We only used ANN in this work because they can adapt to a great variety of data types and size. Moreover, we based our approach on a prediction of RUL as a scalar value. No sequential prediction of SOH or ageing features is made.

Two different ANN were built according to the number of features they take as input. The first one takes as input features extracted from time series and SOH, and will be referred to as TSF ANN (Time Series Features ANN). The second one takes as input only historical features and will be referred to as HF ANN (Historical Features ANN).

As explained is the previous section, this article also studies the impact of input features on the prediction performances. In the dataset described in section 3.3, each cycle is considered as one training sample, and the target is the RUL of the battery. As each cycle of each cell is considered, the dataset results in more than 99000 samples and a varying number of features according to the model. As there is a great amount of available data, the structure of the ANN can extend to several layers, each with a great number of neurons. Dropout was added after each layer in order to avoid over fitting during training. In order to find the best combination of hyper parameters (number of layers, number of units per layers, activation function, dropout rate...), several configurations where tested following a Bayesian optimisation procedure. In all cases, the output layer of our model only contains one unit and no activation function as a regression is made on the RUL, directly in terms of number of cycles.

5 Experiments

The following section describes how each model was tested on the different feature selections and compares the performances of our different models between them and in comparison with other RUL prediction approaches on the same dataset as us.

5.1 Training process

The first step of the training process is to perform the optimisation of the hyper parameters as explained earlier. After having completed the setup of hyper-parameters for different models, optimised models are completely re-trained. The dataset described in section 3.3 is randomly separated into three distinct ensembles : a training, a validation and a test set. In order to obtain reliable results, the process is repeated several times. The error measure is computed as the mean of all obtained measures during successive training.

5.2 Error metrics

During training, the back propagation process for weight optimisation is carried out with the Adam optimiser. The loss is calculated with Mean Square Error and performance is judged with the Mean Absolute Error metrics. We used mini-batch gradient descent in

order to obtain an efficient and relatively short training time combined with an accurate convergence towards the minimum loss.

In order to compare the performances of our models between them and with other approaches in the literature, several scoring measures are used. In a vast majority of works, the evaluation of models is based on the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). We also add the Normalised Mean Square Error (NMSE) in order to compare the performances of our models with future works, and the Standard Deviation of the MAE (σ_{MAE}) in order to evaluate the reliability of the model. These quality measures are expressed as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{pred,i} - y_i)^2} \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_{pred,i} - y_i| \tag{4}$$

$$\sigma_{MAE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_i - MAE)^2} \tag{5}$$

$$NMSE = \frac{\sum_{i=1}^{N}(y_{pred,i} - y_i)^2}{N * V} \tag{6}$$

In all these formulas, $y_{pred,i}$ is the RUL predicted by the model, y_i is the real RUL and N is the number of samples on which error is calculated.

In the equation of standard deviation, a is the absolute error of sample i.

V is the variance of y. For example, the use of the mean of y as the predicted values would give an NMSE of 1.

5.3 Prediction performances

In this section the predicting results of our ANNs will be compared between them. Our two models are built to predict one single value of RUL. A 2D dataset is fed to the networks and a 1D output is given, which corresponds to the predicted RUL in terms of cycle. The output can take any possible positive value. Figures 8 and 9 represent the predicting performances of the different networks. The predicted RUL is plotted as a function of the real RUL.

Table 1 details the predicting performances of the two developed models. The best prediction performances are obtained with the TSF ANN, which proves that the information contained in time series is highly valuable when designing a PHM strategy for Li-Ion batteries. Not only is the MAE lower with the TSF ANN (11.44 cycle compared to 15.08 with the HF ANN), but the predictions are more reliable. Indeed, the standard deviation of absolute error is lower with the TSF ANN, which means that there are less aberrant predictions and that more prediction errors are closer to the MAE. Histograms of the absolute error are represented in figures 10 and 11 show that a greater number of prediction with the TSF ANN have an error between 0 and the MAE.

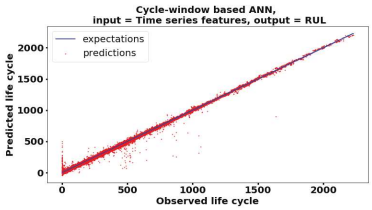

Fig. 8. TSF ANN predicting performances

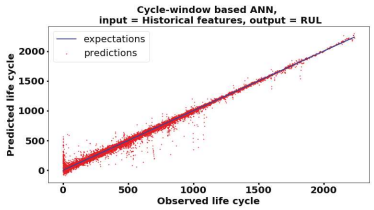

Fig. 9. HF ANN predicting performances

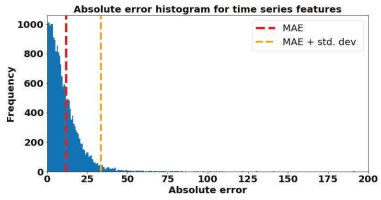

Fig. 10. TSF ANN absolute error histogram

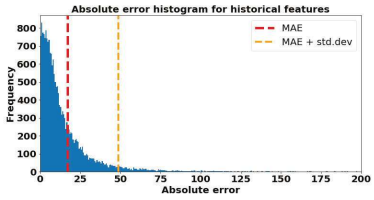

Fig. 11. HF ANN absolute error histogram

Table 1. Performance of the cycle-window based ANN according to the type of features

	MAE	σ_{MAE}	RMSE	NMSE
Historical features	15.08	31.45	34.88	$8.4*10^{-3}$
Time series features	**11.44**	**26.78**	**29.16**	$\mathbf{5.9*}10^{-3}$

5.4 Comparison with other approaches

Although many papers in the literature mention their performances in the prediction of RUL, we can only compare our results with others that were obtained using the same dataset. For now, very few papers have based their approach on this dataset. The original paper [1] proposed a feature-based approach using a linear combination of the selected features. The only other approach we have found using this dataset was proposed by a research group in an online application designed to predict the RUL and current cycle of any battery [10]. They have based their approach on a CNN.

Table 2. Comparison of different approaches in the literature

	RMSE	MAE
Historical Cycle based ANN	34.88	15.08
TSF Cycle based ANN	**29.16**	**11.44**
LR from [15]	173	N/A
CNN from [10]	N/A	115

Table 2 compares the results obtained by all existing approaches with our best performing model. Although not all the same scoring measures were used in the two comparative works, the available scores show that our approach outperforms the prediction performances of the linear model developed by [1] and CNN developed by [10]. These

results illustrate the fact that accurate prediction through machine learning needs a great number of training samples and a good feature extraction strategy. Designing a window based approach at the scale of one cycle, and extracting features from driving curves is more efficient than building features from early cycles or from a temporal window over several consecutive cycles for a use in ANN.

6 Conclusions

This paper is a description of our work on an innovative dataset published by the MIT, dealing with the ageing of Li-Ion batteries. Building a performing data-driven model relies essentially on the quality of data. With this work, we have proved that the dataset that had triggered our attention contains highly valuable information, with features representing the ageing phenomenon both in the historical domain and time series domain (driving data). We propose a low computational cost technique with well-known machine learning models such as artificial neural networks combined with features extraction techniques based on the exploitation of driving curves.
Our results show that a basic approach can outperform more complex models such as CNN. With our one cycle window based approach, we take advantage of all the information contained in the dataset. The prediction of RUL can be made at any cycle when testing a battery, and can above all be applied to cells whose current cycle is not known. For future work, we plan to dig further in the same direction. The use of driving data appears to be crucial, and we believe that employing Recurrent Neural Networks that are particularly adapted to the study of temporal series and forecasting problems could improve the performances of our models.

References

1. Severson, K.A., Attia, P.M., Jin, N., Perkins, N., Jiang, B., Yang, Z., Chen, M.H., Aykol, M., Herring, P.K., Fraggedakis, D., Bazant, M.Z., Harris, S.J., Chueh, W.C., Braatz, R.D.: Data-driven prediction of battery cycle life before capacity degradation. Nature Energy **4**(5) (2019) 383–391
2. Wang, J., Wen, G., Yang, S., Liu, Y.: Remaining Useful Life Estimation in Prognostics Using Deep Bidirectional LSTM Neural Network. Proceedings - 2018 Prognostics and System Health Management Conference, PHM-Chongqing 2018 (2019) 1037–1042
3. Downey, A., Lui, Y.H., Hu, C., Laflamme, S., Hu, S.: Physics-based prognostics of lithium-ion battery using non-linear least squares with dynamic bounds. Reliability Engineering and System Safety **182**(October 2018) (2019) 1–12
4. Kozlowski, J.D., Byington, C.S., Garga, A.K., Watson, M.J., Hay, T.A.: Model-based predictive diagnostics for electrochemical energy sources. IEEE Aerospace Conference Proceedings **6** (2001) 63149–63164
5. Zhang, Y., Xiong, R., He, H., Liu, Z.: A LSTM-RNN method for the lithuim-ion battery remaining useful life prediction. 2017 Prognostics and System Health Management Conference, PHM-Harbin 2017 - Proceedings (20150098) (2017)
6. Chen, C., Pecht, M.: Prognostics of lithium-ion batteries using model-based and data-driven methods. Proceedings of IEEE 2012 Prognostics and System Health Management Conference, PHM-2012 (2012) 1–6
7. Li, X., Zhang, L., Wang, Z., Dong, P.: Remaining useful life prediction for lithium-ion batteries based on a hybrid model combining the long short-term memory and Elman neural networks. Journal of Energy Storage **21**(December 2018) (2019) 510–518
8. Zhang, L., Mu, Z., Sun, C.: Remaining Useful Life Prediction for Lithium-Ion Batteries Based on Exponential Model and Particle Filter. IEEE Access **6** (mar 2018) 17729–17740

9. Zheng, S., Ristovski, K., Farahat, A., Gupta, C.: Long Short-Term Memory Network for Remaining Useful Life estimation. In: 2017 IEEE International Conference on Prognostics and Health Management, ICPHM 2017, Institute of Electrical and Electronics Engineers Inc. (jul 2017) 88–95
10. H. Knobloch, A. Frenk, W.C.: Predicting Battery Lifetime with CNNs (2019)
11. Saha, B., Goebel, K., Christophersen, J.: Comparison of prognostic algorithms for estimating remaining useful life of batteries. Transactions of the Institute of Measurement and Control **31**(3-4) (2009) 293–308
12. Bole, B., Kulkarni, C.S., Daigle, M.: Adaptation of an electrochemistry-based Li-ion battery model to account for deterioration observed under randomized use. PHM 2014 - Proceedings of the Annual Conference of the Prognostics and Health Management Society 2014 (2014) 502–510
13. Zhang, Y., Xiong, R., He, H., Pecht, M.G.: Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries. IEEE Transactions on Vehicular Technology **67**(7) (2018)
14. Veeraraghavan, A., Adithya, V., Bhave, A., Akella, S.: Battery aging estimation with deep learning. 2017 IEEE Transportation Electrification Conference, ITEC-India 2017 **2018-Janua** (2018) 1–4
15. Severson, K.A., Attia, P.M., Jin, N., Yang, Z., Perkins, N., Chen, M.H., Aykol, M., Herring, P., Fraggedakis, D., Bazant, M.Z., Harris, S.J., Chueh, W.C., Braatz, R.D.: (Supplementary information)Data-driven prediction of battery cycle life before capacity degradation
16. Qu, J., Liu, F., Ma, Y., Fan, J.: A Neural-Network-Based Method for RUL Prediction and SOH Monitoring of Lithium-Ion Battery. IEEE Access **7** (2019) 87178–87191