To Charge or To Sell? EV Pack Useful Life Estimation via LSTMs and Autoencoders

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Abstract

Electric Vehicles (EVs) are spreading fast as they promise to provide better performances and comfort, but above all, to help facing climate change. Despite their success, their cost is still a challenge. One of the most expensive components of EVs is lithium-ion batteries, which became the standard for energy storage in a wide range of applications. Precisely estimating the Remaining Useful Life (RUL) of battery packs can open to their reuse and thus help to reduce the cost of EVs and improve sustainability. A correct RUL estimation can be used to quantify the residual market value of the battery pack. The customer can then decide to sell the battery when it still has a value, i.e., before it exceeds its end of life of the target application and can still be reused in a second domain without compromising safety and reliability. In this paper, we propose to use a Deep Learning approach based on LSTMs and Autoencoders to estimate the RUL of Li-ion batteries. Compared to what has been proposed so far in the literature, we employ measures to ensure the applicability of the method also in the real deployed application. Such measures include (1) avoid using non-measurable variables as input, (2) employ appropriate datasets with wide variability and different conditions, (3) do not use cycles to define the RUL.

1 Introduction and Background

Electric Vehicles (EVs) are becoming central to the automotive industry as they can address current automotive limits. Their constant growth is due to their improved performance and efficiency but especially for their suitability in addressing environmental challenges, i.e., urban pollution and global warming [1] [2]. Internal combustion based vehicles contribute to global carbon emission by 14% of the total [3] thus they are facing restrictions in leading markets that targets to reduce their environmental footprint [2] [4]. Internal combustion based vehicles are also a prominent source of artificial fine particulate matter (PM$_{2.5}$) [5] [6]. Air pollution is one of our greatest social issues since it has a severe impact on health and society [7], possibly causing different diseases and even premature death [8] [9]. EVs are a milestone in addressing such humanity challenges as they can potentially remove individual transportation from the environment impact equation.

A core component of EVs is the battery. Lithium-ion (Li-ion) batteries became the standard for energy storage in EVs [10] [11]. They have several advantages compared to traditional batteries such as lead-acid or nickel-metal hydride: high energy and power density, low self-discharge, environmental adaptability, long lifetime, and high reliability [12] [13]. Those advantages lead to the wide use of Li-ion batteries not only in EVs but also in several safety-critical areas such as space applications [14], aircraft, and backup energy systems. The safety and reliability of Li-ion batteries is a critical concern for such applications [15]. As Li-ion batteries are employed in safety-critical areas, their defects can cause fatal...
system failures. For example, various Boeing 787 caught fire because of a Li-ion battery malfunction in 2013 [16], and NASA lost a spacecraft because of the lack of power supply due to a false battery over-charging indication in 2006 [17]. Such high-impact failures have recently appeared also in the EV domain, with well-known manufacturers recalling hundreds of thousands of EVs due to fire risk [18, 19]. Another far greater challenge for li-ion batteries is their cost. While EVs are promising on various fronts, their expensiveness is still a major drawback [20] and the battery is one of the most expensive components of EVs [21].

The design of an appropriate Battery Management System (BMS) is crucial to reduce costs and increase vehicle efficiency and security [22, 23]. One of the major tasks of the BMS is to evaluate the current health conditions of the battery as they degrade over time. This degradation is an irreversible process related to the repetitive charging and discharging operations and electrochemical reactions inside the battery [24]. Predominant indicators are battery capacity and internal resistance, which inform us about the battery residual energy and power capabilities respectively [24], indicated by the State of Health (SOH). The SOH and the Remaining Useful Life (RUL) are the most crucial parameters of battery health that must be estimated by the BMS [12]. The SOH quantifies the deterioration level compared to a brand new battery. While it has not been formally defined by industry [26], it is typically expressed through a percentage of capacity loss or power loss (increase of battery resistance) [27, 28]. We will consider the capacity loss (SOHc), which is defined by

\[
SOH = \frac{C_t}{C_0} \cdot 100(\%)
\]

where \(C_t\) is the current capacity and \(C_0\) is the nominal capacity. The BMS adjust therefore its functioning according to the estimated SOH to ensure the vehicle performance and safety, until the health indicators reach the target limits, after which the battery should be replaced. The battery manufacturers usually set the capacity threshold under which the battery is no more suitable for EVs application to 80% of the nominal capacity [29], measured under a standardized test. Such threshold is called end-of-life (EOL). Despite this, the battery might be replaced before the threshold if the internal resistance goes above a normal level [25]. The threshold is recommended to be 80% also by the Center for Advanced Life Cycle Engineering (CALCE) in the University of Maryland [30] and 70% by the NASA’s Prognostics Center of Excellence (PCoE) [31]. In the context of replacement and secondary use planning, it is useful to predict how the SOH will evolve through time and when the battery will reach its EOL. This is defined by the RUL which is typically described as the number of cycles remaining until EOL [32, 33, 34].

A robust SOH estimation by the BMS is fundamental to ensure battery reliability as well as prevent failures and hazards [22, 35], but also to determines the acceleration performance and the driving range of the EV [30, 37] – necessary for a pleasant driving experience –, and finally to quantify the residual market value of the batteries [38]. Whereas, the correct estimation of the RUL opens to the reuse of the batteries as removing the battery before it exceeds its end of life of the target application allows to reuse it in a second domain without compromising safety and reliability [39]. Batteries can therefore be employed in secondary applications with lower power requirements. This can have a great impact in terms of both sustainability and market value [40]. To summarize, improving the estimation of SOH and RUL contributes to the spreading of EVs in two ways: (1) by ensuring security and reliability, (2) by reducing costs and waste through batteries re-use.

The estimation of the SOH is a challenging task. The capacity of a cell can not be directly measured, so, indirect measurements are used instead by using related variables. It can be precisely computed in laboratory conditions but it is significantly different from the working conditions of real applications [25]. This unfortunately does not apply to the real-world EVs that have to employ online estimation algorithms [22]. Battery aging involves many variables such as charge/discharge current, voltage, and operating temperature. EV batteries working conditions are also highly dynamic as they change...
with the environment and the user’s driving style \[36\]. As a result, it is difficult to design accurate physical models due to complex degradation mechanisms and operations. Furthermore, it requires much knowledge about the phenomena involved and experimental data acquired in controlled situations which could be not available or quite expensive to be collected \[39\]. The SOH estimation techniques can be classified into two macro-categories: experimental methods and model-based estimation methods \[22, 25\]. Experimental methods analyze the aging behavior through numerous laboratory tests. As mentioned above, this is typically not achievable on-board due to the required equipment and the dynamic driving context. Model-based methods can be further divided into adaptive algorithms and data-driven methods. Adaptive algorithms use mathematic models and numerical filters (e.g. Equivalent Circuit Model and Kalman filters) while data-driven methods use black box models which find the mapping between input and the target. Figure 1 summarizes the main categories of SOH estimation methods. In the following section, we will focus on machine learning based SOH estimation and RUL prediction techniques and their advantages. For a detailed review of the other methods for SOH estimation please refer to \[25\]. For RUL prediction please refer to \[41\].
2 Related Works

The recent success of machine learning in several domains as well as the availability of data and computing power has motivated the development of novel methods for battery state estimation. Data-driven methods for battery state estimation are becoming more and more popular [28]. In particular, the attention to the use of Deep Learning (DL) for batteries’ status estimation increased over time. Data-driven methods provide several advantages [22]. They allow us to get better results in complex real applications, as the complete knowledge about degradation mechanisms is still lacking. They do not require expert knowledge about the degradation phenomena as they only rely on enough operational data from which key features are extracted. They are also suitable for the execution on hardware with limited capabilities compared to adaptive algorithms that are more computing demanding [37, 42].

While the training phase is demanding as well, the execution is efficient and can run on BMS hardware, with inference models in the order of a few hundred Megabytes [43]. Last but not least, data-driven methods open to the prediction of the SOH (i.e., the RUL) while other techniques are typically limited to the estimation of the current SOH. The drawbacks are not missing, but they are compensated by the benefits. The main ones are limited interpretability and inaccessibility to physical parameters (e.g. internal resistance) [44]. Before proceeding, it is worth noting that we may have a conflict of terms: while, in the context of deep learning, “prediction” typically indicates the result of a neural network, in the context of signal processing it means predicting the future value of a time series. In this paper, we will use the term estimation to indicate indeed the estimation of the current SOH, while we will use the term prediction to indicate the expected RUL as it can be conceived as the prediction of the future SOH.

In the last two years, numerous works using DL for SOH and RUL estimation have been proposed in the literature. In the following, the common approaches (and issues) of the various papers are first presented to avoid repetitions, and then the single articles are analyzed.

The variables measured by the BMS are usually voltage (V), current (I), and temperature (T). Such variables are sampled at high rates during the various subsequent charge and discharge cycles, resulting in very long time series. The variables most used as input are in fact voltage, current, and temperature, as they are able to capture the battery aging factors [37], but sometimes also the sampling time and the State of Charge (SOC; i.e. the charge level) are used. In the case of the RUL, the SOH itself has also been used as input. It is recalled, however, that care must be taken when non-measured variables (i.e. SOC, SOH) are employed, as errors could accumulate and robust estimation of the input variable might not always be available — first issue affecting applicability. The variables can originate from the charging cycles, the discharging cycles, or both. The resulting time series are often presented to the network through a moving window, i.e., the NN makes the estimation based on the set of features at time \( t \) plus their last \( N \) values. A popular approach is to use a Recurrent Neural Network (RNN) — in one of its various forms — to find the relation between the SOH or RUL and the time series. The Long Short-Term Memory (LSTM) [45] networks are peculiar RNNs able to handle long-term sequences that have become the baseline of recurrent networks. LSTMs and their variants are therefore widely used also in the battery context. Some experiments try instead to use Convolutional Neural Networks (CNNs) to process time series, or to use a simple feed-forward NN (FFNN) preceded by some kind of pre-processing. The literature offers several battery datasets to conduct such experiments. One of the most used datasets is the NASA “Battery Data Set” [31]. It has been the first battery dataset publicly available, thus it has had a significant impact in the field [40]. The dataset consist of 34 Li-ion 18650 cells cycled at various ambient temperature, however, it includes only Constant Current (CC) cycled batteries. Even though the dataset contains 34 batteries, the most common approach is to use a specific subset of three or four batteries. In 2014, NASA released another dataset (“Randomized Battery Usage Data Set”) [47] containing also batteries cycled with a random current. A review of battery datasets is available in [46]. The second issues to be addressed to ensure the suitability of the SOH and RUL
methods to real scenarios is the quality of the dataset used during testing. The vast majority of the works uses simplified databases with batteries cycled under CC discharge, a condition not applicable to EVs operation. Another applicability obstacle in the case of RUL is in the definition of RUL itself. As already mentioned, the RUL is defined as the remaining cycles before EOL. In the EVs context, we have partial charge and discharge cycles (e.g., discharge to 40%, charge to 80%, discharge to 30%, and so on) as the vehicle can be recharged starting from different SOC and can be unplugged before full charge. An equivalent full cycle (0% to 100%) has little practical meaning, so, the definition of RUL has to be rethought. A valid candidate to represent the RUL in the EVs setting is the remaining ampere hour (Ah) that the battery can deliver before reaching EOL. The measures to prevent applicability pitfalls are then (1) avoid using non-measurable variables as input, (2) employ appropriate datasets with wide variability and different conditions, (3) do not use cycles to define the RUL.

The estimation of the SOH has recently become quite robust as it has been applied to realistic datasets. SOH estimation is well established on simplified dataset [22, 28, 48]; here we report the recent advances on complex datasets. In [27] a hybrid network composed of a Gated Recurrent Unit (GRU; a well-known variation of LSTM) and a CNN is used for SOH estimation. The inputs are the raw data of V, I, T of the charging curve, converted to a fixed size history of 256. The input goes toward the two parallel streams (GRU and CNN) that are concatenated in the last layer. A maximum estimation error of 4.3% on the Randomized NASA dataset is reported. Authors of [37] proposed a SOH estimation method based on Independently RNN (IndRNN) and tested on the Randomized NASA dataset. Here, a discharge cycle is represented by 18 features including average V, I, and T, as well as the capacity, the time elapsed, and the time periods of each current load. While it achieves superior results, it is not clear if it will work in real applications as it takes as input also the capacity. In the experiments, the capacity in input is calculated, while the proper way to conduct the experiment should have used the capacity estimated by the network itself in the previous time step. In [39] a CNN takes as input the V, I, and capacity of the charging cycle discretized in 25 segments. The output is the capacity computed on the corresponding discharge cycle. Both capacities are computed with the coulomb counting. Applicability is at least doubtful in this case too. In [39] a private database of real-world data collected from 700 vehicles (full-electric or hybrid) is used to train an FFNN for SOH estimation. The parameters employed are the accumulated mileage of vehicles, the C-rates distribution, the SOC range (the SOC is divided into five ranges and the SOC range indicates such range), and cell temperatures. The number of variables is reduced to a lower dimensionality using the principal components analysis (PCA). The results are impressive, with a maximum error of 4.5% and RMSE of 1.1%, which becomes 2.2% and 0.45% if considering only full-electric vehicles.

Moving to the RUL estimation, it has not yet reached the robustness and applicability of SOH estimation. The experiments offered by the literature are limited to oversimplified datasets that present only CC cycled batteries. While adequate performances are typically achieved, there are still some critical issues regarding data quality and applicability. In [49], a Temporal Convolutional Network (TCN) produces RUL estimations. The input is the history of the SOH, processed through a moving window. Tests are performed on three CC batteries from the NASA dataset and two CC batteries from the CALCE dataset. As it uses the history of SOH, a robust SOH estimation is necessary to ensure its applicability. As the experiments rely on ground truth SOH, it is not clear if the proposed method will have the same performance using estimated SOH levels that are thus affected by some level of error. Also, a long warm-up is required, as the first output is produced after a minimum t of 30 cycles. Both [50] and [51] propose the use of an LSTM network that takes as input the history of the SOH. In the first case, the output is the RUL, in the second case, it is the k-step ahead SOH – that can be reduced to the RUL. The datasets used are a single Panasonic CC battery and four CC batteries from the NASA set respectively. Both works present the same issues of the TCN-based one (here the warm-up is even longer). The most promising article is [52] that presents a variant of LSTM, namely AST-LSTM. Two AST-LSTM are trained, one for estimating the SOH and one for the RUL. The input
of the first model includes V, I, T, and the sampling time of the discharge cycles. The second model uses instead the history of SOH estimated from the previous one. As the SOH in input is estimated, the RUL approach is suitable also for real scenarios. Experiments are conducted on 12 batteries from the NASA dataset. The approach still needs to be tested on better datasets, and the warm-up is too long. In [13], the IC discharge curve is computed from the V, I, and sampling time. The features extracted from the curve are given in input to a small NN that estimates the SOH and RUL. This method is however applicable only to CC discharging, besides, it has a high computation complexity and low performance. In [53] an autoencoder is used to perform the dimensionality reduction starting from the V, I, T, and sampling time of both charge and discharge cycles, plus the capacity estimated during discharge. Besides the applicability doubts, the accuracy is so low that the approach is substantially inapplicable. The properties of the above-mentioned works are summarized in table [1]
| Method                  | Input                                      | Output                       | Dataset                                      | Performances                                      | Issues                                                                 |
|------------------------|--------------------------------------------|------------------------------|----------------------------------------------|---------------------------------------------------|----------------------------------------------------------------------|
| TCN [49]               | History of SOH                             | RUL                          | NASA (3 CC batteries - #5, #6, #18) CALCE (2 CC batteries - #CS_34, #CS_35) | RMSE up to 0.048                                   | - It requires a robust SOH estimation - It is not clear whether it will work if the SOH is affected by errors - Insufficient dataset variability - Long warm-up (minimum starting cycle for NASA is 30 and the starting cycle for CALCE is 360) |
| LSTM network [50]      | History of SOH                             | RUL                          | Panasonic 18650 (1 CC battery)               | -                                                | - It requires a robust SOH estimation - It is not clear whether it will work if the SOH is affected by errors - Insufficient dataset variability - Long warm-up (start after 50% of battery life) |
| LSTM network [51]      | History of SOH                             | K-step ahead SOH             | NASA (4 CC batteries - #5, #6, #7, #18)     | MAE 1.92 (on battery #5)                          | - It requires a robust SOH estimation - It is not clear whether it will work if the SOH is affected by errors - Insufficient dataset variability - Long warm-up (start at cycle 60) |
| Variant of LSTM.       | V, I, T, sampling time (discharge)         | SOH and RUL                  | NASA (12 batteries)                          | SOH: RMSE up to 0.059 RUL: RMSE up to 0.026 (on battery #5) | - Insufficient dataset variability - Long warm-up (start at cycle 50) |
| Feature extraction with | V, I, T, sampling time (discharge)         | SOH and RUL                  | NASA (4 CC batteries - #5, #6, #7, #18)     | SOH: MRER up to 1.25% RUL: RMSE up to 5.41       | - Applicable only to CC discharging - Computational complexity - Insufficient dataset variability - Low performances |
| autoencoder followed by | V, I, T, sampling time (charge + discharge), capacity i.e. SOH (discharge) | RUL                          | NASA (3 CC batteries - #5, #6, #7)          | RMSE up to 13.2% (on battery #7)                 | - It requires a robust SOH estimation - It is not clear whether it will work if the SOH is affected by errors - Insufficient dataset variability - Insufficient performances |

Table 1: Summary of current DL-based RUL estimation approaches
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