State of Health Estimation of Lithium Batteries for Automotive Applications with Artificial Neural Networks

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***Abstract*—This paper presents an algorithm based on Artificial Neural Networks (ANNs) for the estimation of the State of Health (SOH) in Lithium batteries. The method exploits a feed-forward pattern recognition classifier trained with datasets collected at different temperatures and at a predefined current mean value of the discharging profile. During the real implementation, the algorithm scans the time history of the battery load and analyses it on buffers of 60 seconds. Whenever the same conditions of the training dataset are encountered during the scanning (i.e. the same temperature and current mean value), the designed algorithm is enabled and provides an estimation of the SOH. The classifier acquires as input a set of predictors extracted from the direct measurement of characteristic parameters of the battery, namely voltage, temperature, capacity, energy and estimated State of Charge (SOC). The networks are trained and validated by means of a battery model based on look-up tables and previously characterized in a laboratory environment.**

Keywords—Artificial Neural Networks, State of Health, Lithium batteries, Electric Vehicles, Pattern recognition, Classifier

I. INTRODUCTION

In automotive industry, the monitoring of the battery conditions is crucial to ensure reliability in predicting the energy and power availability for electric and hybrid powertrains, while ensuring safety and optimizing the charging/discharging cycles. During the battery lifetime, the nominal capacity and power experience a fading due to phenomena associated with processes like electrolyte decomposition or growth of a Solid Electrolyte Interface (SEI) on the anode surface [1]. Moreover, other factors are involved in the degradation process, such as the phase change of the electrode material, dissolution of active substances and thermal stresses [2]. These effects can lead to criticalities due to a possible battery failure and psychological effects such as the driver range anxiety. The major battery parameters to be considered for a real-time battery monitoring are the State of Charge (SOC) and State of Health (SOH). Unfortunately, these states cannot be directly measured, thus the adoption of indirect estimation methods is compulsory. A wide literature dedicated to the SOC estimation is available, with methods exploiting mainly model-based [3] or artificial intelligence-based approaches [4][5]. On the other hand, the literature dedicated to the estimation of the SOH is less exhaustive.

The capacity and power of the cell depends on several factors, such as the average discharge current, overall discharge time, operating temperature, storage time (related to self-discharge phenomena), and aging processes in general [6]. Some methods are based on the real-time evaluation of the internal impedance of the battery. The Electrochemical Impedance Spectroscopy (EIS) is used for the purpose in [7], by measuring offline the internal resistance of the battery. Although this approach is characterized by a low computational effort, only a small subset of all the possible influential factors for the SOH degradation are considered for the estimation and this results in a lack of accuracy [8][9]. Moreover, the real-time application of the internal resistance measurement is demonstrated to be very difficult [10]. Alternative approaches are based on the analytical representation of the battery model [11] or on a classification algorithm based on the Multiple Kernel Support Vector Machine (SVM) [12]. However, the variation in the signal was not explicitly considered for all the possible variations in the temperature range, both in [11] and [12] and this may cause low estimation accuracy. The application of a Dual Extended Kalman Filter (DEKF) is investigated in [13]. However, this method requires an accurate modelling phase and the need for quadratic programming can result into a computationally demanding algorithm. In [14], a dual filtering technique is investigated. This method consists on the interaction between a standard Kalman Filter (KF) and an Unscented KF to predict the internal battery states of the model, in combination with a Support Vector Machine (SVM). To overcome some of the well-known issues associated with model-based approaches, artificial intelligence solutions have been recently investigated. In this context, the adoption of the Artificial Neural Networks (ANNs) is presented in [2],[15] and [16]. Another ANN-based algorithm is integrated with a DEKF in [10]. Although accurate, in these works the phenomenon is studied only with repeated discharging and charging cycles, which is a far from real driving condition, where the supplied load continuously depends on the driver's needs.

From the authors' analysis of the state of the art about the online SOH estimation, most of the above-mentioned research works have resulted in appreciable outcomes, although they are based on some implicit rigid assumptions. As a matter of fact, a repetitive trend can be identified in the literature when using preset discharging and charging cycles. Moreover,

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another huge limitation of many research works could be associated with poor preliminary considerations on the influential factors of SOH or computationally demanding algorithms.

This paper presents an approach exploiting a pattern recognition ANN classifier for the SOH estimation. The training datasets are collected by means of a look-up table-based model tuned in a laboratory environment. During the learning phase, specific condition of temperature and a predefined current mean value of the discharging profile are adopted to produce the training dataset. In the real implementation, the algorithm continuously analyses the battery load time history and, as soon as this has the same conditions of the training in terms of temperature and current load, the classifier produces an estimation of the SOH. The algorithm acquires as input a set of predictors extracted from the direct measurement of characteristic parameters of the battery, namely voltage, temperature, capacity, energy and estimated State of Charge (SOC). The method has been validated using dynamic discharging current profiles obtained from real load current conditions extracted from the literature. The accuracy of the algorithm is conducted by analyzing the Confusion Matrix of the classifier, which produces promising results.

II. METHODOLOGY

The proposed classification method is based on the layout represented in Figure 1. The battery pack is composed of thirteen Lithium cells connected in a *13s1p* configuration (1 parallel branch with 13 cells in series), with a nominal voltage equal to 54 V and nominal capacity of 10 Ah. The method exploits a feedforward pattern recognition classifier realized by means of ANNs.

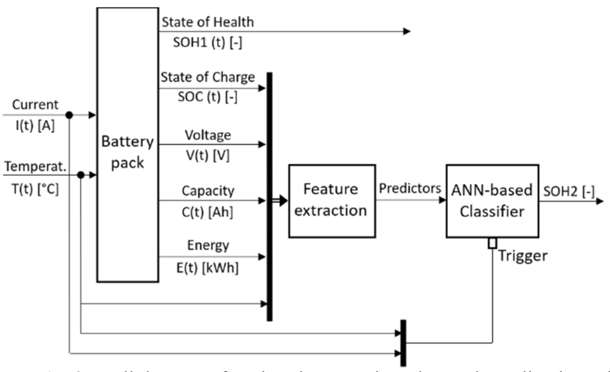

Figure 1. Overall layout of estimation. During the real application, the classifier is enabled when the detected current and temperature are coherent with the training dataset. $SOH1$: time history of the target State of Health for the training and validation phases. $SOH2$: estimated class of State of Health.

During the training phase, a look-up table-based model of the battery pack is exploited to obtain the behaviour of the SOH as function of the battery aging. The model was previously tuned by means of laboratory characterization tests conducted in different conditions in terms of temperature and charging/discharging current profile.

The objective of the method is to train the classifier in a specific load condition and then, during the real implementation, detect real-time the same training condition to perform the estimation. To this end, the classifier was trained with datasets collected from the battery model when a mean value of the current load equal to 12A is required to the battery on a time window of 60 seconds and the operating temperature is equal to 20, 25, 30, 35, 40, 45, 50, 55 and 60°C. The classifier is trained by means of predictors extracted from the model results considering the operating conditions reported in Table 1. During the real implementation of the method, the predictors are extracted from the real measurements and the SOH estimation routine is enabled whenever the battery load conditions fall within the ranges adopted for the training (Table 1). The real-time detection is conducted on buffers with a duration of 60 seconds (t_b).

Table 1. Overall experimental conditions considered for the training dataset related to the battery model.

Variables	Unit	Value
Mean charging/discharging current	$[A]$	12
Temperature	$[°C]$	$[20 \div 60]$
SOH	$[-]$	$[100\% \div 75\%]$

A. Training dataset preparation and system characterization

The data collection phase for the training is performed to cover the operating conditions of the battery listed in Table 1. The considered SOH range goes from 100% to 75% since batteries are commonly supposed to reach the end of life when the SOH is lower than 80% in automotive industry [11].

The predictors used as input to the classifier are the variation of the SOC, voltage, capacity, energy and the mean temperature recorded on the considered buffer of time length t_b. The output of the estimator is the indication of the SOH class among five discretized intervals ranging from 75% to 100% with a 5% step.

Table 2. Training dataset characterization: input and output of the ANN-based algorithm. The input predictors are computed on a buffer with a time length $\boldsymbol{t_b}$ equal to 60 seconds.

Input Predictors				Output SOH classes	
#	Variable	Feature	Unit	Class	Range [%]
1	SOC variation	ΔSOC	$[-]$	1	$100 \div 95$
2	Voltage drop	ΔV	$[V]$	2	$95 \div 90$
3	Requested Capacity	ΔC	$[Ah]$	3	$90 \div 85$
4	Requested Energy	ΔE	$[Wh]$	4	$85 \div 80$
5	Mean Temperature	T_m	$[°C]$	5	$80 \div 75$

The SOC (input 1) is obtained from an estimation algorithm previously installed on the vehicle Battery Management System (BMS) and based on a look-up table model. Input features 2 and 5 in Table 2 have a straightforward definition. The requested capacity (input 3 in Table 2) is obtained by means of the Coulomb counting method by integrating the discharging current over time [6],[17] as

$$\Delta C \quad = \int_{t_o}^{t_o+t_b} I(t)\, dt \qquad (1)$$

where $I(t)$ is the load current.

In order to consider large voltage variations at different values of the battery capacity, the requested energy ΔE (input feature 4 in Table 2) is taken into account and is computed as

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$$\Delta E = \int_{t_0}^{t_0+t_b} V(t)I(t)\,dt \qquad (2)$$

B. System characterization

The training dataset is obtained by means of a system characterization phase allowing to reproduce the aging of the battery in different operating conditions. Specifically, the dataset is obtained considering the temperature range and current load indicated in Table **1**. Figure **2** reports the SOH behaviour as a function of the battery voltage and capacity at a temperature of 30°C.

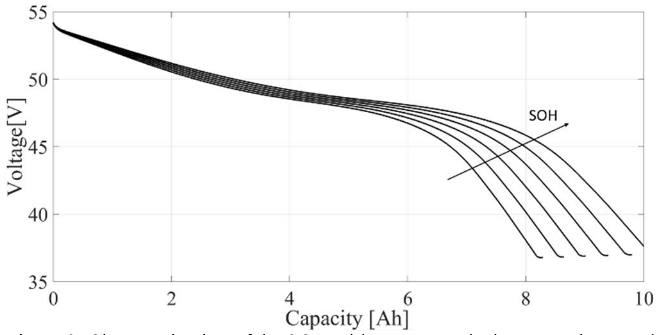

Figure 2. Characterization of the SOH with respect to the battery voltage and capacity, at an operating temperature of 30 °C.

A further representation of the SOH behaviour as a function of voltage, capacity and SOC at a temperature of 30°C is illustrated in Figure **3**.

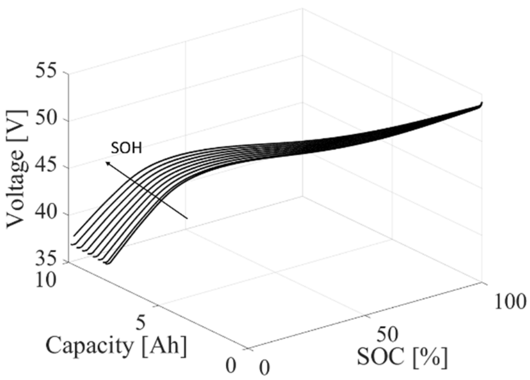

Figure 3. Characterization of SOH as function of voltage, capacity and SOC, at an operating temperature of 30 °C.

As a matter of fact, the SOH variation is highly non-linear and influenced by the operating temperature. The battery model accounts for the thermal effects considering the influence of the temperature.

The battery behaviour characterization is conducted providing a constant load current profiles (12 A) at different temperature values (20, 25, 30, 35, 40, 45, 50, 55 and 60°C). For each condition the battery is aged from 100% to less than 80% of SOH with the needed number of complete discharging cycles, which is obviously different for each aging condition, as different is the amount of time taken for a complete discharge. In Figure **4**, the obtained characterization is illustrated at varying the temperature. The SOH decreases with the increasing number of cycles and decreases when increasing the temperature.

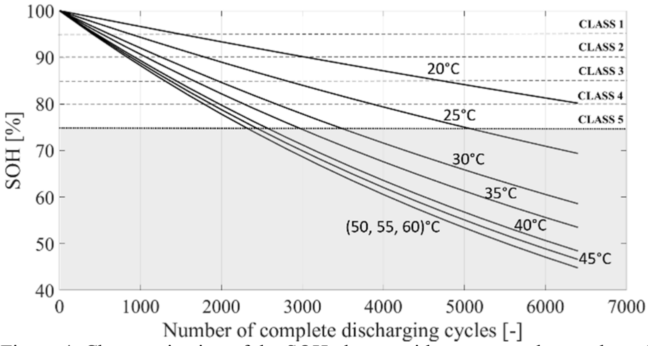

Figure 4. Characterization of the SOH classes with respect to the number of complete discharging cycles, at different operating temperatures. The grey region indicates the discarded data, under 75% of SOH.

Figure 5 reports the behavior of the discharging time as function of the number of cycles when the temperature ranges from 20°C to 60°C.

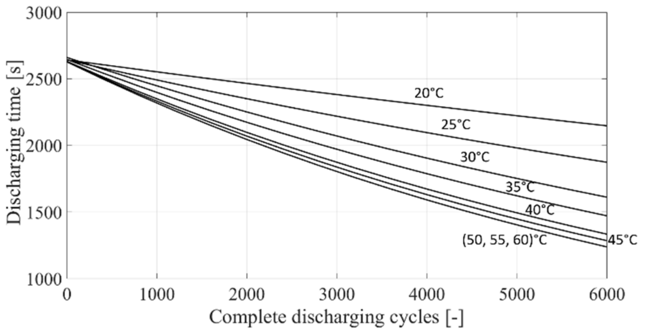

Figure 5. Discharge time vs. number of cycles, considering the effect of different operating temperatures.

C. Design and training of the classifier

The architecture of the classifier is shown in Figure 6.

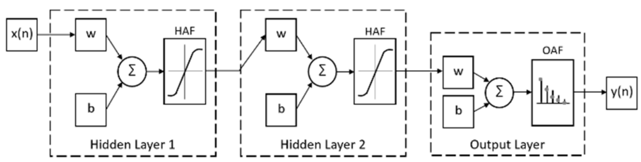

Figure 6. Pattern recognition feed-forward ANN architecture for the SOH classification.

The training phase of the neural classifier is performed by means of the Scaled Conjugate Gradient (SCG) back-propagation training function [16]. This approach gives good performance over a wide range of pattern recognition problems with large sets of parameters guaranteeing low performance degradation while reducing the training error. Additionally, this function features a relatively low computational cost and memory requirements [18] and its ability to provide well-separated classes in data mining and classification problems has been proven in many research works [19][20].

The network consists of the input layer, two hidden layers with ten neurons each, and the output layer. The number and size of the hidden layers is defined heuristically, by means of a trial and error procedure.

During the training process, a matrix of weight (w), a vector of bias (b) and an activation function (AF) are defined for each layer. The Hidden Activation Function (HAF) is a

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hyperbolic tangent sigmoid, and the Output Activation Function (OAF) is a normalized exponential function. The back-propagation SCG algorithm aims to minimize the cost function related to the output error computed with respect to the expected outputs. The cross-entropy cost function is used to evaluate the performance of the training process. Once the training stage is completed, the cross-entropy value is equal to $1.06 \cdot 10^{-3}$ after 2759 training epochs, as shown in Figure 7.

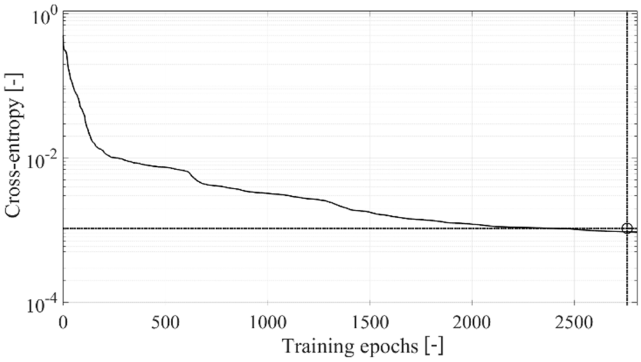

Figure 7. Training performance for the adopted Scaled Conjugate Gradient (SCG) training function.

SOH output class [-] \ SOH target class [-]	100-95	95-90	90-85	85-80	80-75	
100-95	90038 27.3%	103 0.0%	20 0.0%	0 0.0%	0 0.0%	99.9% 0.1%
95-90	65 0.0%	57899 17.5%	74 0.0%	0 0.0%	0 0.0%	99.8% 0.2%
90-85	10 0.0%	89 0.0%	60271 18.3%	71 0.0%	1 0.0%	99.7% 0.3%
85-80	0 0.0%	1 0.0%	51 0.0%	56961 17.3%	31 0.0%	99.9% 0.1%
80-75	0 0.0%	0 0.0%	0 0.0%	39 0.0%	64258 19.5%	99.9% 0.1%
	99.9% 0.1%	99.7% 0.3%	99.8% 0.2%	99.8% 0.2%	100.0% 0.0%	99.8% 0.2%

Figure 8. Overall Confusion Matrix obtained for the ANN trained with the SCG algorithm considering the training dataset.

A first evaluation of the classification accuracy is conducted by means of the Confusion Matrix computed at the end of the learning procedure on the training dataset and illustrated in Figure 8. The training dataset consists of 329982 discrete instances extracted from the same number of buffers of length t_b. The 60s buffers of data are shifted in time of 5s each, to guarantee a sufficient overlapping. In the Confusion Matrix, the values on the diagonal shows the number of correctly classified instances, while the off-diagonal cells represent the number of misclassifications.

III. Results

The validation is conducted by means of datasets reproducing operating conditions similar to the ones adopted in the training datasets. Two different discharging current profiles were taken from the experimental dataset recorded by the Center for Advanced Life Cycle Engineering (CALCE) at University of Maryland [21] and represented in Figure 9 and Figure 10. The current mean value is equal to 12 A and the temperature ranges from 20°C to 60°C, as defined for the training dataset. Although with the same current mean value, the adopted current profiles have a different dynamic behavior.

The current profiles have been replicated over time to completely discharge the battery and build the validation datasets recording all the possible operating conditions.

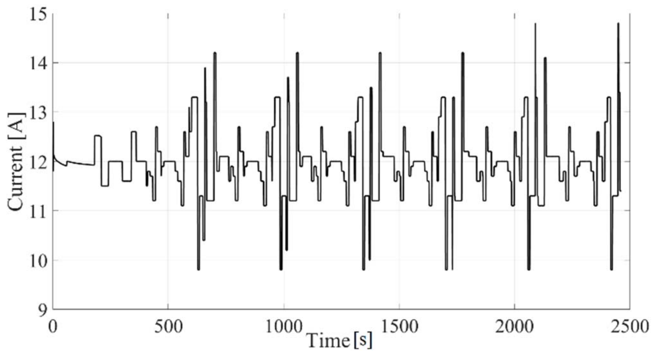

Figure 9. Validation current profile 1.

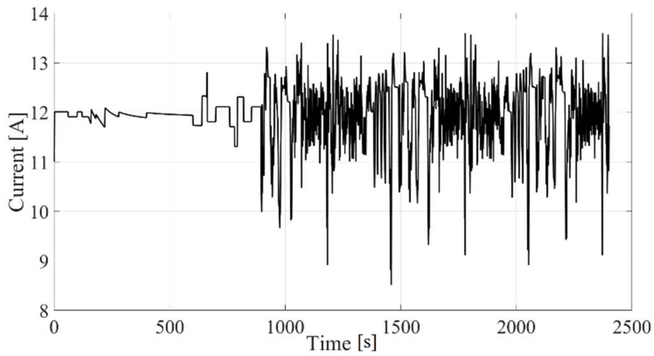

Figure 10. Validation current profile 2.

In Figure 11, the Confusion Matrix relative to the validation dataset obtained considering the profile 1 is represented. The overall classification accuracy is 99.4% in this case.

SOH output class [-] \ SOH target class [-]	100-95	95-90	90-85	85-80	80-75	
100-95	23962 24.4%	137 0.1%	3 0.0%	0 0.0%	0 0.0%	99.4% 0.6%
95-90	69 0.1%	16235 16.5%	92 0.1%	0 0.0%	0 0.0%	99.0% 1.0%
90-85	29 0.0%	61 0.1%	17896 18.2%	80 0.1%	0 0.0%	99.1% 0.9%
85-80	0 0.0%	8 0.0%	54 0.1%	17923 18.2%	47 0.0%	99.4% 0.6%
80-75	0 0.0%	0 0.0%	0 0.0%	42 0.0%	21607 22.0%	99.8% 0.2%
	99.6% 0.4%	98.7% 1.3%	99.2% 0.8%	99.3% 0.7%	99.8% 0.2%	99.4% 0.6%

Figure 11. Confusion matrix for the validation dataset obtained considering the validation current profile 1 (Figure 9).

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Figure 12 represents the Confusion Matrix relative to the validation dataset obtained considering the profile 2 shown in Figure 10. The overall classification accuracy is 98.7% in this case.

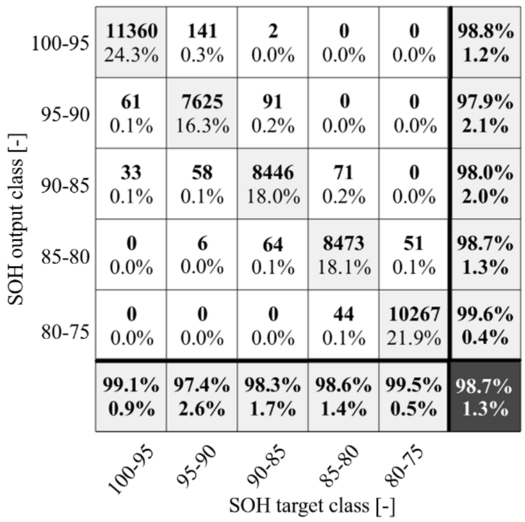

Figure 12. Confusion matrix for the validation dataset obtained considering the validation current profile 2 (Figure 10).

IV. CONCLUSIONS

This paper presented an algorithm based on pattern recognition feed-forward ANNs for the State of Health estimation of Lithium batteries in Automotive applications. The proposed method exploits a classifier trained with a specific load conditions in a temperature range going from 20°C to 60°C. The training has been conducted by means of datasets extracted from a previously design battery model. During the deployment on the real application, the algorithm is enabled when conditions similar to the ones adopted for the learning phase are detected. The technique has been validated on different load current profiles and its accuracy has been evaluated by means of Confusion Matrices. The promising results encourage the deployment and test on a real electric or hybrid vehicle.

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