Development of a Test Method to Evaluate Lithium-Ion Batteries for Second Life in Renewable Energy Applications

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Abstract— Lithium-ion batteries can still be used in many applications after removal from their first use in electric vehicles, e.g. as a storage media in photovoltaic systems and for grid support. Therefore, there is a great need to develop reliable methodologies and tools to characterize the expected performance of lithium-ion batteries after their first life in electric vehicles to enable the economical and sustainable re-use of the large amount of lithium-ion batteries, which will be available in the near future. In this paper, we will develop a robust, fast, and non-destructive measurement procedure using artificial intelligence to estimate their state of health.

Keywords— Lithium-ion batteries, Second life of batteries, Battery modelling, Artificial neural networks, State of charge, State of health, Electrical vehicle, Energy storage systems

I. INTRODUCTION

Due to the increase in the use of electric vehicles (EVs) in the past few years and the expected shift of the automotive market in the near future towards EVs. It is certain that the market will have large amounts of lithium-ion batteries (LIBs) that are no longer fit for use in EVs, but may represent a viable solution to the problem of high cost of batteries in energy storage systems (ESS). The re-use of LIBs in various applications and putting them into service as a second life requires a reliable measurement and testing system in order to achieve the optimal efficiency of the re-use.

In addition to cell temperature and voltage, the two most important parameters for Li-ion batteries are [1]:

- State of charge (SoC)
  The state of charge is the percentage of charge available in the battery, 100% indicating full capacity and 0% indicating that no more charge is left in the battery. The SoC parameter is very important to monitor the battery capacity level.

- State of health (SoH)
  State of health indicates the amount of charge the battery can store. When a battery is new, the SoH should be close to the manufactured specification, i.e. SoH=100% but as the battery ages the SoH will start to drop. For example, a 100 Ah battery that is only able to produce 50 Ah is deemed to have 50% SoH, and it can still be charged to a SoC=100% tacking into account that the amount of charge that the battery can store being reduced.

It is assumed that EV battery packs have reached the end of life when the SoH falls below 70% to 80%, at this level of SoH become the battery pack no longer fit for EVs due to the reduction in the power level, which means the battery, be either recycled or repurposed for other applications [1].

As the need for stationary energy storage systems (SESS) increases, the rapid proliferation of electric vehicles creates a fleet of millions of lithium-ion batteries that after a few years of operation are deemed unsuitable for the rigorous transportation operating cycle/environment. Because EV owners are expected to replace their battery system as soon as they have lost 20% of their capacity, these used batteries offer a tremendous opportunity to be used in new applications where the duty cycle and amperage are less burdensome than EVs. They may provide an inexpensive source of LIBs for new applications as SESS, extend the life of a battery and defer the eventual costs of recycling [2].

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II. METHOD SUMMARY

This paper presents an advanced procedure for estimating the battery states (SoC and SoH) based on the artificial neural network (ANN) technology. This procedure is fast, reliable, non-destructive and accurate as described in next sections. As shown in Fig. 1, the procedure is divided into four blocks. In the first stage, the electrical parameters are derived by applying the hybrid pulse power characterization (HPPC) and temperature (T) is measured. These parameters and T provide a good assessment of the effective capacity and SoC of the battery and this will be the task of the second stage of the improved procedure. At this stage, measured electric parameters are entered with T to a neural network to evaluate SoC. The parameters of the equivalent circuit model (ECM) will be derived in third stage as described in our previous research (Developing an advanced equivalent circuit model for LIBs for battery monitoring purpose) [3]. Finally, in the fourth stage, SoH is estimated through the second neural network, which has all of parameters of the internal model and SoC as inputs.

Fig. 1. Block diagram of improved test method

All stages will be explained in detail in the following sections.

III. BATTERY MODELLING

A. Background:

The modelling of LIBs is very important for state monitoring. Modelling methods are classified generally into three categories: white-box, black-box, and grey-box modelling [4].

White-box models require a thorough knowledge of the internal cells’ characteristics and the interactions within them. In this type of modelling, all reactions in the cell are considered during all operational work situations (charging, discharging and standby) and under all conditions depending on the required accuracy. However, obtaining a robust and accurate model with improved system-wide performance in this way remains critical, therefore this method cannot be recommended for upgrading the model from single-scale cells to larger modules or to a LIBP, unless many simplifications are taken in consideration [4][5].

On the contrary, black-box technologies provide practical simplification, which is why they are so widely adopted. These models are done using some techniques like support vector regression, artificial neural networks, and fuzzy logic. However, the model's ability to predict the state of the battery remains limited when any of the operational parameters are drifting outside the model's training field, because there is insufficient knowledge of the battery characteristics and the reasons for this drift [5][6].

The grey-box models were presented as a compromise between black and white-box models. The equivalent circuit model is one example of a grey-box technique [6].

Table 1 presents briefly a comparison of the three types of models [7][8].

| Feature               | White Box | Grey Box | Black Box |
|-----------------------|-----------|----------|-----------|
| Deterministic equations | Prior knowledge | Data driven |
| Base/Needs            | Physical knowledge | Unknown parameters estimated from empirical data or literature | Inputs-Outputs representation |
| Complexity            | Very high | Medium | Medium |
| Accuracy              | High      | Medium | Low-Medium |
| Applications          | Battery design | Battery management/monitoring | Offline analysis |

B. Second-order equivalent circuit model:

As shown in Table 1, the most suitable type for the purposes of our paper is the grey box model, and the RC-equivalent circuit model is the most important form of this model. Where this type has an acceptable accuracy and do not need a deep physical knowledge or internal electrochemical analysis. This is one of the main advantages of this model, that it shifts work from a complex and dynamic electrochemical field to a relatively simple electric field.

In this paper, a second-order equivalent circuit model of battery cells is considered as describe in our previous paper and shown in Fig. 2 [3].
This model consists of three components: an open circuit voltage (Uoc), a series charge/discharge resistance (Rc/Rd), two parallel RC networks connected in series (R1-C1 and R2-C2), and two Ideal diodes (do not have a threshold voltage). The internal resistance would be zero when any forward voltage is applied across their terminals, and don’t have a breakdown voltage) to connect the appropriate resistance depending on the operational condition of the battery (charging/discharging) \([9][10][11][12]\).

**C. Model parameters identification:**

According to the Kirchhoff’s laws, we can describe the relationships among capacitors, voltage, battery voltage (Ub), and battery current (Ib) mathematically as follows \([9][10]\):

\[
\begin{align*}
U_1 &= \frac{I_b}{C_1} - \frac{U_1}{R_1C_1} \\
U_2 &= \frac{I_b}{C_2} - \frac{U_2}{R_2C_2} \\
U_b &= U_{oc} - U_1 - U_2 - I_bR_{c,d}
\end{align*}
\]

For calculation we need to apply a charging and discharging pulses. Fig. 3 shows a brief illustration of the HPPC test profile, applying period of charge/discharge pulses is 10 sec and relaxation period is 40 sec.

**D. Experimental results:**

Measurements were performed on a used cylindrical LIB: ICR14430-500 mAh; 3.7 V; SoH=97% using:

- PC-oscilloscope HANTEK/VOLT CRAFT-DSO2250-100 MHz/2CH/250 MSa/s for measuring voltage and current.
- ELV-ALC8500-2Expert for charging/discharging cycles.

Experimental measurements were made at different SoCs (10%, 30%, 50%, 70%, and 90%) and ambient temperatures (5°C, 20°C, 30°C, and 35°C). The model-parameters were conducted with the help of exponential function fitting (EFF). The variations of the final identified parameters versus temperature are fitted by using the cubic polynomials in Matlab under discharge and charge conditions. Table 2 illustrate the experimental results.

![Fig. 2. Second-order equivalent circuit model](image)

![Fig. 3. Illustration of the HPPC test profile for parameters calculation](image)

\[ R_c, R_d, \text{ and } U_{\infty} \text{ under charging and discharging are determined as follows } [10][11][12]: \]

\[
R_d = \frac{U_A - U_B}{|I_b|} \quad (4)
\]

\[
R_c = \frac{U_B - U_E}{|I_b|} \quad (5)
\]

The battery voltage during the relaxation period \(U_d(t)\) while charging/discharging can be fitted to the exponential function form expressed as \([10][11][12]\):

\[
U_d(t) = U_{oc} - R_1I_b e^{-\frac{t}{\tau_1}} - R_2I_b e^{-\frac{t}{\tau_2}} - I_bR_{c,d}
\]

\[
P_0 - P_1e^{-k_1t} - P_2e^{-k_2t} \quad (6)
\]

After determining \(P_0, P_1, P_2, k_1, \text{ and } k_2\) experimentally, other model parameters could be determined in additional to \((4), (5)\) as follows \([10][11][12]\):

\[
\begin{align*}
R_1 &= \frac{P_1}{I_b} \\
R_2 &= \frac{P_2}{I_b} \\
C_1 &= \frac{1}{R_1k_1} \\
C_2 &= \frac{1}{R_2k_2}
\end{align*}
\]

**TABLE II. EXPERIMENTAL RESULTS**

| Parameter | SoC \(\%\) | Temperature | Temperature | Temperature | Temperature |
|-----------|-------------|-------------|-------------|-------------|-------------|
|            | \(5°C\)    | \(20°C\)    | \(30°C\)    | \(35°C\)    |
| \(R_c\) m\(\Omega\) | 10 | 132.72 | 114.48 | 108.41 | 106.38 |
|            | 30 | 126.64 | 112.46 | 107.39 | 106.38 |
|            | 50 | 119.55 | 110.43 | 103.34 | 101.31 |
|            | 70 | 114.48 | 90.17  | 82.06  | 70.92  |
|            | 90 | 110.43 | 87.13  | 79.02  | 67.88  |
| \(R_d\) m\(\Omega\) | 10 | 150.96 | 120.56 | 111.44 | 108.41 |
|            | 30 | 135.76 | 121.58 | 111.44 | 99.29  |
|            | 50 | 131.71 | 119.55 | 109.42 | 91.18  |
|            | 70 | 127.65 | 92.20  | 87.13  | 81.05  |
|            | 90 | 123.60 | 89.16  | 84.09  | 80.04  |
| \(R_{oc}\) m\(\Omega\) | 10 | 13.17  | 11.14  | 10.13  | 9.12   |
|            | 30 | 16.21  | 14.18  | 13.17  | 11.14  |
E. Model validation:

The verification is done by comparing the experimental and simulation battery voltage under HPPC test profile at \( T = 25^\circ C \), and SoC=70%.

As shown in Fig.4, observed voltage error of simulated values comparing to measured voltage was less than 0.019 V as mean absolute error (less than 0.61% as percentage error of simulated values).

Through this model, as a result, we are able to determine with acceptable accuracy the relationship between the temperature and change of the internal parameters, which makes this model a good basis for the systems of measuring and analyzing the state and aging of lithium-ion batteries based on artificial intelligence techniques.

| \( R_{st} \) m\( \Omega \) | \( C_{st} \) F | \( V_{measured} \) | \( V_{estimated} \) |
|---|---|---|---|
| 10 | 3697.9 | 3902.0 | 3495.3 |
| 30 | 4255.2 | 4401.4 | 4067.6 |
| 50 | 4863.0 | 5169.8 | 4595.1 |
| 70 | 4761.7 | 5057.8 | 4595.1 |
| 90 | 5369.6 | 5491.7 | 4863.0 |

A: Background:

State of charge is a very important indicator for assessing the status of the available energy capacity of batteries in ESS used in various applications. Especially when it comes to online battery monitoring and measurement.

However, the matter may differ when it is required to assess the state of the batteries offline, here SoC will only be very important with indirect estimation of battery aging state.

Therefore, the SoC estimate of LIBs has been extensively studied due to their fast charge, long life cycle, and high energy density properties. However, an accurate SoC assessment remains a challenge due to their varying characteristics under different working environments [13].

The state of charge is indicated digitally as the percentage of charge available in the battery. Where 100% indicating full capacity and 0% indicating that no more charge is left in the battery [1]. SoC refers normally to the available battery capacity that can be withdrawn from the battery and its estimation is very important to prevent its over-discharge or over-charge as well as to operate the battery in such a manner that aging effects are reduced [14].

A several different methods have been proposed to estimate SoC with varying degrees of accuracy and complexity for each of them.

Table 3 describes the most common methods with their main drawbacks [15][16].

### TABLE III. OVERVIEW ON THE SOC ESTIMATION METHODS [15][16]

| Method | Description | Advantages | Drawbacks |
|---|---|---|---|
| Coloumb | Discrete | Simple and intuitive approach. | It requires to know the initial SoC value. |
| Counting | integral of the input current. | | |
Low-cost sensors It is affected by error for current measurement. It does not consider any physical property of the cell. It requires accurate current measurements. It is not able to cope with partial charge/discharge cycles. It requires to know the actual capacity C.<n>

Combination with other techniques is possible

Computationally efficient.

Matching of the terminal voltage with the OCV-SoC lookup table.

It takes into account physical properties of the cell. Internal resistance and charge redistribution phenomena weak the correlation between voltage and SoC. Flat SoC-OCV curves make the SoC prediction more sensible to measurement noises and errors.

It studies the electrical behaviour of the battery. It requires to know the reference initial parameters of the battery which can only be parameterized accurately for new batteries in the laboratory. The accuracy of the estimation depends largely on climate variables.

SoC estimated from the relationship between measured battery signals (voltage, current, and temperature), and SoC employing a battery model.

Combination with other techniques is possible

Usefull for on-line monitoring because of on-line measurement of model input signals

Combination with other techniques is possible

SoC estimated with a black-box function approximation tool

Usefull for on-line monitoring.

High accuracy after good training and fine tuning.

Combination with other techniques is possible

It uses nonlinear KFs for estimating SoC as a state variable of the system.

Self correction method. It can provide information about the system.

Can be computationally demanding.

It requires an accurate model of electrochemical cells

Estimation accuracy

B. A theoretical introduction to artificial neural networks:

Artificial neural networks are machine learning technique, it is a powerful processing tool enclosing the ability of learning from experience. From a general point of view ANNs are a data-driven black box technique aiming at learning and modeling the input-output relationship of a given process from the knowledge of a set of input-output measurements only \([17][18]\).

Similar to other machine learning algorithms, neural networks are also natural inspired techniques. In particular, ANNs aim to emulate the functionality and learning ability of the animal brain. They are therefore organized as a network of atomic computing units called artificial neurons. Each of these units processes its inputs very simply and forwards the resulting output to the other neurons \([15]\).

Several different structures of ANNs have been developed but the feed-forward neural networks are the basic architecture of ANNs and the most suitable example is the Multi-Layer Perceptron (MLP) shown in Fig. 5 \([15]\).

Feed-forward MLPs usually consist of a succession of layers in which the output of each neuron is connected to the immediate following layer only. Therefore, the inputs \(x_1\) are processed and propagated in only one direction moving layer by layer to the output neuron \(y\). Equation (8) describes the relation between output and inputs \([15]\).

\[
y = \varphi(x_1w_1 + \ldots + x_nw_n + b)
\]

where \(w_i\) is the related weight, \(b\) is a bias term, and \(\varphi\) is a nonlinear or linear transformation called activation function.
function, the most common activation functions are shown in Fig. 6.

Choosing the appropriate activation function depends on the characteristics of the input values and their relationship to the outputs [15][19].

From the above we can conclude that feed-forward neural networks are pure combinatorial and memoryless processing tools because the current output depends only on the current input. In particular, MLPs are characterized by fully connected layers, meaning that each neuron receives as input the output of all the neurons composing the previous layer and it propagates its output to all the neurons of the following layer. The MLP architecture is organized in three groups: the input layer, one or more hidden layers, and the output layer. In particular, the input layer is not composed of real neurons, but it aims only at feeding the first hidden layer with the overall inputs of the network [15].

The weights $w_i$ are determined during the training phase of the neural network. Thus, training ANNs is the most critical phase that determines how those ANNs are accurate [20].

The weights are calculated during the training phase by minimizing the loss function (usually a quadratic function of the output error), one common technique that is widely used in training ANNs is the backpropagation, which is a supervised learning method that is commonly used in the training phase in order to calculate the weights. Backpropagation uses a steepest-descent technique based on the computation of the gradient of the loss function with respect to the network parameters [20].

After the input and target for training data is created, next step is to divide the data up into training, validation and test subsets. In the case of 100 samples for training, (70%) of data are used for the training and 21 samples (15%) of each data for validation and testing. Table 4 shows the numbers of samples for training, validation and test data [19].

### TABLE IV. THE NUMBER OF SAMPLES FOR TRAINING, VALIDATION AND TEST SET [19]

| Data Types | Number of Samples |
|------------|------------------|
| Training   | 100              |
| Validation | 21               |
| Testing    | 21               |

Neural networks are sensitive to the number of the hidden layers and their neurons. Too few neurons in the hidden layer prevent it from correctly matching inputs to outputs. On the other hand, too many may impede generalization and increasing training time. Therefore the number of hidden layers and their neurons is selected through experimentation to find the optimum number of neurons for a predefined minimum of mean square error in each training process [19].

### C. SoC-Estimation using neural networks:

These methods are often referred to as the black box functional approximation tools. Which is seen as a disadvantage of these methods as the relationship between voltage, temperature, current and SoC is hidden.

In order to get away from the disadvantages of adopting this method on the black-box principle, we have in our research relied on the electrochemical dynamic response of ECM-parameters which affected directly by SoC as inputs to the neural network. Several attempts have been developed to estimate SoC using measuring of internal resistance, and the results have been mixed. Additives affect strongly Internal Resistance and make its behaviour very complex, making ohmic test unreliable for SoC estimation [21]. The electrochemical dynamic response gives a clearer perception of the change in the characteristics of the battery with the change in its state of charge. To illustrate the idea, two short brief load pulses are applied, the response time on attack and recovery is measured. As seen in Fig. 7, a battery with SoC=100% resists the attack and recovers quickly whereas the impact of a battery with SoC=70% is larger and the recovery is slower [21].

![Fig. 7. Electrochemical dynamic response [21]](image-url)
The same is also the case when charging pulses are applied, since due to the variation in the acceptability of the charge when the state of charge is different, this also causes variations in the shape and amount of voltage drop and time constants in recovery and relaxation period.

The non-linear variation of the internal resistance of the battery versus SoC leads to nonlinearity in the relationship between the SoC and the time constant and the voltage drop in the electrochemical dynamic response curve. This is a main reason that makes artificial neural networks a suitable solution to this issue, as the neural networks are distinguished by their ability to deal with these complex dynamic variations.

According to Fig. 7, which illustrates the concept of our method, the voltage drops due to ohmic resistance by applying the charge and discharge pulses, as well as the time constants in the recovery and relaxation period after these pulses, will be considered with temperature as inputs of the neural network.

Since the ECM is employed to characterize the physical processes occurring in the battery, the ohmic resistance $R_{c,d}$ is related to the electrolyte and connection resistance, the RC network ($R_{1,2}$/$C_{1,2}$) represents the effect of the activation polarization (charge-transfer and double-layer). In general, the majority of the concentration polarization processes have larger time constants ($\tau_{2c,d}$) compared to time constants of the activation polarization processes ($\tau_{1c,d}$) [22][23].

The detailed architecture of the ECM with the second-order RC network is shown in Fig. 8, it shows all SoC relevant parameters ($\Delta U_{c,d}$, $\tau_{1c,d}$, $\tau_{2c,d}$) connected to the corresponding RC network ($R_{1,2}$/$C_{1,2}$) [22][23].

With this, we have completed the final visualization of the inputs of the neural network: $T$, $|I_b|$, $\Delta U_c$, $\Delta U_d$, $\tau_{1c}$, $\tau_{1d}$, $\tau_{2c}$, $\tau_{2d}$

The developed feed-forward MLP neural network in this paper for SoC estimation with back-propagation training, shown in Fig. 9, consists of input layer with eight inputs, one hidden layer with 35 neurons (obtained experimentally), and output layer with one output (SoC).

The linear activation function is used in the output layer, and the sigmoid activation function in the hidden layer.

In the next section, we will present the experimental results and the results of the neural network training.
process, and we will discuss the final results of estimating SoC.

D. Neural network training and SoC-estimation results:

From the HPPC test of charging and discharging pulses applied in section of battery modelling, shown in Fig. 3 (period of charge/discharge pulses is 10 sec and relaxation period is 40 sec), we obtained \( t_{1c} = t_{1d} = t_{2c} = t_{2d} \) from (6) by applying exponential fitting function. 

\( I_b \) is 0.5C=250mA during charge pulse and 0.5C=250mA during discharge pulse.

\[ \Delta U_c, \Delta U_d \] are obtained as:

\[ \Delta U_c = R_c \times I_b \]  \hspace{1cm} (9)

\[ \Delta U_d = R_d \times I_b \]  \hspace{1cm} (10)

Table 5 illustrate the experimental results for training ANN.

| Parameter | Illustration of Experimental results |
|-----------|-------------------------------------|
| \( \tau_c \) (sec) | | |
| | | | | |
| 10 | 228.54 | 179.63 | 152.27 | 133.44 |
| 30 | 237.11 | 182.45 | 158.12 | 136.72 |
| 50 | 256.20 | 200.82 | 184.76 | 149.09 |
| 70 | 241.21 | 198.72 | 161.66 | 138.88 |
| 90 | 228.49 | 169.26 | 147.81 | 124.71 |

| \( \tau_d \) (sec) | | | | |
| | | | | |
| 10 | 199.44 | 137.75 | 152.12 | 105.31 |
| 30 | 274.98 | 200.67 | 168.13 | 155.71 |
| 50 | 276.63 | 198.62 | 165.77 | 145.50 |
| 70 | 254.97 | 186.81 | 152.43 | 139.60 |
| 90 | 290.69 | 196.15 | 167.52 | 122.76 |

| \( \Delta U_c \) (mV) | | | | |
| | | | | |
| 10 | 33.18 | 28.62 | 27.10 | 26.59 |
| 30 | 31.66 | 28.11 | 26.85 | 26.59 |
| 50 | 29.89 | 27.61 | 25.83 | 25.33 |
| 70 | 28.62 | 22.54 | 20.52 | 17.73 |
| 90 | 27.61 | 21.78 | 19.76 | 16.97 |

| \( \Delta U_d \) (mV) | | | | |
| | | | | |
| 10 | 37.74 | 30.14 | 27.86 | 27.10 |
| 30 | 33.94 | 30.39 | 27.86 | 24.82 |
| 50 | 32.93 | 29.89 | 27.35 | 22.80 |
| 70 | 31.91 | 23.05 | 21.78 | 20.26 |
| 90 | 30.90 | 22.29 | 21.02 | 20.01 |

As a result of training the SoC-ANN, table 6 presents the results and error and performance of the ANN.

| Number of Layers | 2 |
| Number of Neurons in Hidden Layer | 35 |
| Length of Input Vector | 8 |
| Number of Training Vectors | 20 |
| The rate of Training Vectors | 3 |
| The rate of Test Vectors | 3 |
| Length of Output Vector | 1 (SoC) |
| Error MSE (e^2) | -18 |
| Number of epochs | 273 |

As shown in Table 6, the training process stopped after 273 epochs successfully after reaching the expected performance at an internal training error of rank e^2 as MSE.

The performance of the neural network was verified by inserting two vectors at which the network was not trained.

The estimation of SoC, as shown in Table 7, was with acceptable accuracy performed, as the maximum prediction error was 1.89%.

| Actual SoC | 60 | 95 |
| Estimated SoC% (ANN Output) | 59.1 | 96.8 |

| Estimation Error | 1.52% | 1.89% |

V. SOH ESTIMATION

A. Background:

The battery state of health and capacity decrease after a battery is repeatedly charged and discharged, because of the output power of battery is affected as a function to number of cycles, which results in performance degradation [24][25].

For second life batteries operation, accurate prediction of the efficient performance and SoH of batteries is very critical, because of the wrong selecting leads to ineffective performance and storage system failure, here SoH estimation is very important as the batteries performance should be identified to ensure the capability of serving in any condition. And since LIBs can still be used in many applications after removal from their first use in electric vehicles, e.g. as a storage media in photovoltaic systems and for grid support. Therefore, there is a great need to develop a reliable methodologies to characterize the expected performance of LIBs after their first life in Evs [24].

Figure 10 shows a summary of the life cycle of lithium-ion batteries. In early life in EVs the batteries are consumed up to a state of health in the range of 70-80%, at which the use of batteries in EVs becomes practically ineffective. In theory, the batteries could then be
transported for service in second life in many applications such as stationary storage systems. But that depends on the state of health of the batteries, as they must be at least 40% in order for their investment in the second life to be feasible from a practical and economic point of view. Otherwise, the batteries must be recycled [25][26].

Fig. 10. The life cycle of lithium-ion batteries used in EVs

Several methods in the previous researches are discussed and implemented different techniques for the SoH estimation with varying degrees of accuracy and complexity for each of them.

Table 8 describes the most common methods with their main drawbacks [15][16].

| TABLE VIII. OVERVIEW ON THE SOH ESTIMATION METHODS [15][16] |
|----------------------------------|-----------------|----------------------------------|
| **SoH Estimation Methods**      | **Advantages**  | **Drawbacks**                    |
| Direct measurement of Cn by     | Simple and      | Offline procedure.               |
| performing a controlled charge/ | intuitive        |                                  |
| discharge test.                 | approach.       |                                  |
| Internal resistance measurement | Takes into      | Offline procedure.               |
| by applying a short current      | account physical |                                  |
| pulse to the cell.               | properties of the |                                  |
| Electrochemical Impedance        | A simple theory  |                                  |
| Spectroscopy (EIS)               | of approach.    |                                  |
| SoH estimated with a black-box   | Takes into       |                                  |
| function approximation tool.     | account physical |                                  |
| Machine Learning                | It is necessary  |                                  |
|                                 | to disassemble   |                                  |
|                                 | the ESS.         |                                  |
|                                 |                 |                                  |

B. SoH-Estimation using neural networks:

In contrast to the SoC, there is no defined and clarified relationship between SoH and electrical operating parameters, such as I_s and U_n. Therefore, new parameters for characterizing and defining SoH must be looked for.

Several properties of battery change with aging, such as Loss of Lithium Inventory (LLI), processes that make the lithium unusable for cycling. Loss of Active Materials (LAM), reduced amount of material enabling the lithium transfer, and structural damage to the components of the battery. The aging of the battery might depend on how it is used, referred to as cycle aging, or it may degrade without being used, referred to as calendar aging [27]. That means, the chemical structure of the battery will be affected primarily by the effect of aging, and this naturally leads to thinking about the internal impedance of the battery to try to find parameters to monitor SoH [28].

In this paper we will use the battery internal resistance, represented by the parameters of ECM which derived in section 3, taking into consideration the effect of SoC to monitor SoH, temperature will not be tacked into account because it was considered while estimating SoC and ECM parameters and both of them will be an input to estimate SoH.

SoH can be estimated by simple statistic methods, such as direct capacity test, but this type of methods will cost much time to obtain SoH as experimental result. As previously mentioned, ANNs considered an effective solution for handling with the behaviour of non-linear systems, cross-interaction between system variables and existing patterns in the data used to train the network [28][29].

In this paper we will use a feed-forward MLP neural network for SoH estimation.

The researcher Raghavendra Arunachala in [30] presented experimental study of LIBs aging with in details results of cycle aging of 8 Ah cell inclusive all parameters of second order ECM in case of discharge and from cycle zero until the cycle 1600. In this paper, the ANN will be trained using these results and we will refer to SoH as a cycle number not as a percentage rate as in the original reference. By the cycle 1600, the cell reaches to about SoH=70% as percentage rate.
Table 9 presents the experimental aging results as obtained in the previous study [30]. The inputs of the neural network will be then: R0, R1, R2, C1, C2, and SoC. The architecture of this network is shown in Fig. 11.

The back-propagation will be used as training method, the network consists of input layer with six inputs, one hidden layer with 30 neurons (obtained experimentally), and output layer with one output (SoH).

The linear activation function is used in the output layer, and the sigmoid activation function for the hidden layer.

As shown in Table 10, the training process stopped after 198 epochs successfully after reaching the expected performance at an internal training error of rank e^-24 as MSE.

The performance of the neural network was verified by inserting five vectors at which the network was not trained.

The estimation of SoH, as shown in Table 11, was with acceptable accuracy performed, as the maximum prediction error was 2.8%.

| SoC% | Cycle# | R0 (mΩ) | R1 (mΩ) | C1 F | R2 (mΩ) | C2 F |
|------|--------|---------|---------|------|---------|------|
| 0    | 0      | 6.599   | 1.922   | 2379 | 3.45    | 2319 |
| 500  | 7.96   | 2.273   | 2041    | 3.606 | 2227    |
| 800  | 9.328  | 3.054   | 1660    | 3.745 | 2071    |
| 1200 | 14.389 | 3.239   | 1568    | 3.775 | 2035    |
| 1600 | 20.051 | 4.074   | 4002    | 4.073 | 2248    |

| 10   | 0      | 7.086   | 1.726   | 4468 | 3.377   | 1889 |
| 500  | 8.556  | 2.243   | 3156    | 3.41  | 1781    |
| 800  | 9.736  | 3.099   | 1987    | 3.556 | 1677    |
| 1200 | 14.711 | 3.355   | 1721    | 3.614 | 1698    |
| 1600 | 20.131 | 4.288   | 4179    | 3.867 | 1906    |

| 20   | 0      | 7.131   | 1.647   | 5371 | 3.369   | 1860 |
| 500  | 8.697  | 2.385   | 2980    | 3.322 | 1707    |
| 800  | 9.834  | 3.141   | 2029    | 3.423 | 1609    |
| 1200 | 14.856 | 3.485   | 1679    | 3.476 | 1608    |
| 1600 | 20.187 | 4.413   | 4159    | 3.668 | 1846    |

| 30   | 0      | 7.041   | 1.729   | 4170 | 3.332   | 2082 |
| 500  | 8.711  | 2.567   | 2412    | 2.984 | 1937    |
| 800  | 9.78   | 3.298   | 1710    | 3.022 | 1846    |
| 1200 | 14.748 | 3.433   | 1534    | 3.089 | 1919    |
| 1600 | 20.294 | 4.326   | 3836    | 3.444 | 2002    |

| 40   | 0      | 6.565   | 1.923   | 1908 | 3.83    | 1923 |
| 500  | 8.409  | 2.861   | 1423    | 3.527 | 1919    |
| 800  | 9.576  | 3.439   | 1317    | 3.52  | 1872    |
| 1200 | 14.831 | 3.828   | 1254    | 3.553 | 1827    |
| 1600 | 20.095 | 4.676   | 3471    | 3.852 | 1895    |

| 50   | 0      | 6.596   | 2.003   | 1967 | 4.059   | 1920 |
| 500  | 8.477  | 3.106   | 1413    | 3.661 | 1959    |
| 800  | 9.754  | 3.926   | 1274    | 3.613 | 1851    |
| 1200 | 14.955 | 4.289   | 1228    | 3.614 | 1814    |
| 1600 | 19.829 | 5.424   | 2986    | 3.954 | 1911    |

| 60   | 0      | 6.672   | 2.113   | 2006 | 4.393   | 1864 |
| 500  | 8.526  | 3.386   | 1410    | 3.927 | 1885    |
| 800  | 9.905  | 4.338   | 1285    | 3.848 | 1752    |

As a result of training the SoH-ANN, Table 10 presents the results and error and performance of the ANN.

TABLE X. TRAINING OF SOH ANN RESULTS

| Number of Layers | 2 |
| Length of Input Vector | 30 |
| Number of Training Vectors | 50 |
| The rate of Validation Vectors | 7 |
| The rate of Test Vectors | 7 |
| Length of Output Vector (SoH) | 1 |
| Error MSE (e^2) | -24 |
| Number of epochs | 198 |
The integration of second life EV and J., in generalizing this methodology have concluded:

From the results of the research, the following can be obtained for this type and capacity. However, several methods which used ANNs in SoC estimation have depended on the online measurement of current and voltage as inputs of ANN, so they referred to as the black box functional approximation tools, because the relationship between voltage, current and SoC is hidden. In the method presented in this paper this disadvantage was overcome relied on the electrochemical dynamic response parameters (voltage drops and time constants) which affected directly by SoC as inputs to the neural network.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion:

This paper presents a robust, fast, and non-destructive measurement procedure to estimate the state of charge and state of health of Li-ion batteries using one of artificial intelligent tools, artificial neural networks, to overcome the obstacles of very long testing time in traditional methods and to obtain a good level of accuracy suitable for this kind of applications. From the results of the research, the following can be concluded:

- Several methods which used ANNs in SoC estimation have depended on the online measurement of current and voltage as inputs of ANN, so they referred to as the black box functional approximation tools, because the relationship between voltage, current and SoC is hidden. In the method presented in this paper this disadvantage was overcome relied on the electrochemical dynamic response parameters (voltage drops and time constants) which affected directly by SoC as inputs to the neural network.
- The same applies also to the state of health, the battery internal resistance represented by the parameters of ECM are used as neural network inputs for SoH estimation because of the chemical structure of the battery will be affected primarily by the effect of aging.
- Because temperature has a high degree of influence on the behavior and performance of battery systems, it was taken into account during the derivation of the ECM parameters, as well as during the estimation of the SoC, which in its entirety were taken into account to estimate the SoH.
- The developed idea and methodology have been applied experimentally on a specific type and specific capacity of batteries. As we have seen through the results in the previous paragraphs a very good results have been obtained for this type and capacity. However, the challenge remains in generalizing this model and developing the structure of the neural networks used in terms of adding new inputs to reach a flexible methodology capable to deal with different types of batteries and with different nominal capacities within a specified range. Of course, this requires additional inputs to the neural networks to indicate the type used, as well as the suitability of the network in terms of activation functions, the number of hidden layers and possibly the type of networks used.

B. Future work:

- The training data used in the SoH neural network was only taken for the discharging status. Additionally, experiments and measurements have yet to be done for the charge status to obtain a larger number of training data in order to obtain better accuracy as well as developing the neural network for possible error correction by comparing the SoHs values resulting from the charging and discharging status.
- A lot of experiments and measurements must be made, as well as researching ways to develop neural network structures in order to try to generalize the system to include a wide range of types of battery cells with different capacities. Also, it may be necessary to add the HPPC-pulse amplitude control feature to fit the nominal capacity of the tested battery cell automatically.
- Developing the HPPC test of the SoC neural network by adding other consecutive pulses at specific intervals and varying amplitudes in order to obtain consecutive SoCs values with a time delay and a specific charge difference in order to provide the neural network with the self-calibration feature.

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