

The experimental comparison of state of charge estimation methods in electrical vehicle batteries

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Abstract - One of the most difficult problems in battery pack management aboard an electrical vehicle is the estimation of the state of charge (SOC). However, the state of charge gives information about how much longer the battery can be used and when the charging process will be cut off.

This paper presents the experimental comparison study of different state of charge estimation methods (discharge voltage method, coulomb counting method and artificial neural networks method) in electric vehicles batteries. For state of charge (SOC) estimation we require voltage, current and temperature, all these data are nonlinear function of SOC and are depends on charge and discharge operation. Also, experimental results are carried out in order to validate this study.

Keywords - State of Charge, Discharge Voltage, Artificial Neural Networks, Coulomb Counting.

I. INTRODUCTION

Battery SOC, according to its definition, represents the ratio of available battery capacity compared with the current battery rated capacity [1]. The available battery capacity can influence and even determine how long a battery can be fully charged, and consequently how far a vehicle can drive. Thus, it is imperative to estimate the battery SOC precisely. An accurate SOC can present the battery available capacity status, prevent a battery pack from overcharge or over-discharge, and can effectively protect the battery, there by potentially prolonging the battery life [2-8].

Mathematical, electrical, and electrochemical methods are used to determine the SOC of the battery; mathematical and electrochemical methods include complex equations, which is why it is hard to calculate them. These equations must be redesigned for other types of batteries. The electrical method is easy to calculate and the user can develop a battery model by looking at a datasheet of the battery or measuring the battery parameters. Successful battery models can be achieved using data sets generated by electrical methods. SOC can be estimated by direct measurement of parameters like open circuit voltage, terminal voltage (discharge voltage), impedance, impedance spectroscopy [9–12], adaptive systems like coulomb counting, modified coulomb counting, back propagation neural network, radial basis neural network, neural network, support vector machine, fuzzy neural network, Kalman filter [13–18], extended Kalman filter

[19], hybrid systems like coulomb counting and extended Kalman filter combination, coulomb counting and Kalman filter combination, per-unit system and extended Kalman filter combination [20], and wavelet neural network based [21]. Most of these methods are widely used and give acceptable results in various applications [22].

In this study, a comparison of different methods, which are the discharge voltage method, coulomb counting method and artificial neural networks method are proposed to estimate the SOC of a Lead-acid battery.

The aim of this work is to estimate the SOC of a Lead-acid battery using: discharge voltage method, coulomb counting method and artificial neural networks method through experimental measurements of the battery voltage, current and ambient temperature. Thus, in order to demonstrate the effectiveness and the robustness of these methods.

II. DISCHARGE VOLTAGE METHOD

The discharge test is a SOC estimation method which involves a battery spending a part of its charge under controlled conditions in order to compare measurements to a known scenario. According to [23], this method is the most reliable one.

Interrupting the normal functioning of the circuit, the method imposes the battery to a constant current of 0.1C. During the time that the battery is delivering 0.1C to the load, the voltage to its terminals is measured and compared to a previously known characteristic curve (voltage vs SOC). The voltage versus SOC curve is attained through battery discharge with very low current. In this way, not only less energy is spent during the SOC estimation period, but also more accurate results are obtained because a very low current discharge is more accurate on the calculation of the total capacity of the battery.

III. ARTIFICIAL NEURAL NETWORKS METHOD

Artificial neural networks (ANN) are becoming increasingly important in the field of analysis and control [24]. This technique is used to overcome the complexity of the process studied and to find solutions to overcome the limitations inherent in traditional techniques [25], [26]. Indeed, it is extremely difficult to integrate all the

dependencies and uncertainties concerning the determination of the state of charge and the state of health of the battery [27]. However, ANNs present a particularly interesting alternative for understanding and predicting their behavior [28]. ANNs can identify and learn correlated patterns between input data sets corresponding target values. After training, ANNs imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data are imprecise and noisy. Thus it is ideally suited for state of charge estimation of battery. [29]. The weights of an ANN are calculated in 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 back-propagation, or back-propagation of errors, which is a supervised learning method that is commonly used in the training phase to calculate the weights of a neural network. Back-propagation uses a steepest descent technique based on the computation of the gradient of the loss function with respect to the network parameters, [29].

To evaluate the performance of ANN in estimating the SOC, a nonlinear input-output (NIO) feed-forward network architecture is used in this paper, and the Levenberg-Marquardt back-propagation algorithm is used in training.

For the purpose of estimating the SOC, the input time series $x(t)$ consists of the battery terminal voltage, current and the ambient temperature where the output or target is the SOC. The output equation of this network is given in (1).

$$Y(t) = f(x(t-1) \dots x(t-d)) \quad ([30]) \quad (1)$$

In (1) $f(\cdot)$ represents the unknown function, $x(t)$ indicates the input time series that consists of the battery terminal voltage, current and ambient temperature, $y(t)$ is the output time series which is the actual SOC, and d is a delay parameter ($d = 1, 2, 3, \dots$). The number of neurons in the hidden layer was set at 10. The number of these neurons was varied in order to find the effect of the selected values on the network performance.

IV. COULOMB COUNTING METHOD

The Coulomb Counting method, also called the method of current integration, is a coulomb counting method, which calculates the number of ampere hours in and out the battery, [31]. The accuracy of this method depends mainly on the resolution of the current sensor. This counting should reflect the coulombic efficiency depending on the charge or discharge rate. However, these methods only allow the determination of the relative changes of state of charge and do not allow taking into account the self-discharge.

The determination of the state of charge therefore requires knowledge of the initial state of charge [32-34]. The state of charge of the battery estimation based on this method is as following [35]:

$$SOC = SOC_0 - \frac{1}{C_N} \int_{t_0}^t \eta \cdot I(\tau) d\tau \quad (2)$$

Where:

SOC_0 : the initial state of charge.

C_N : the battery capacity in the standard condition (Ah).

η : the Coulombic efficiency.

$I(\tau)$: the current versus time (negative during charge and positive during discharge).

If the initial value of the state of charge SOC_0 is specified, the coulomb counting method becomes very precise and particularly easy to determine the SOC [36]. But if the SOC_0 is not known, this method is less accurate. In addition, the coulombic efficiency depends on operating conditions (SOC, temperature, current, etc.) [37], [38] that is difficult to obtain. As the current sensor may introduce an offset that increases the imprecision of this estimate. All these factors cause the increase in the error of SOC with the time especially in the reserve batteries (Back-up) and in packs for hybrid electric vehicle (HEV). However, the method of coulomb counting is widely used in practice because of its simplicity. [35].

V. EXPERIMENTAL METHOD

A. Battery specification

The Battery used in this work was AGM Lead acid battery (6FM100E-X) with nominal voltage of 12V and capacity of 100Ah. This battery type is chosen because it is available in our laboratory. While charged with standby usage, recommended voltage for individual cell is 2.28 V (6 cells in series). In addition, for cycle usage that requires fast charge, maximum voltage is 2.45 V.

B. Measurement System Setup



Fig 1. Test bench

1. Supply table
2. Lead acid battery
3. Stabilized power supply
4. Multimeter
5. Current sensor
6. Variable resistor as load

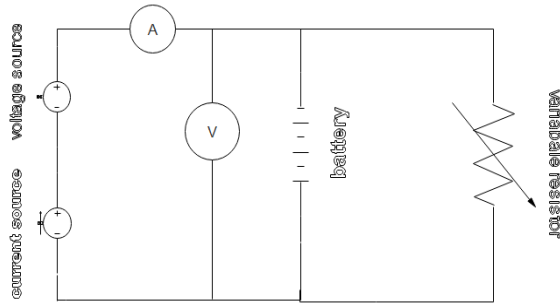


Fig. 2. Electrical circuit showing setup system

C. The test of the Charge process.

The battery is charged by a stabilized power supply. Before connecting the battery the value of the voltage is regulated to 14 V, and the value of the current is limited to 5.5 A. Then, the battery is connected to the stabilized power supply. The voltage, current and ambient temperature are measured respectively (by using a Multimeter, a hall sensor and portable device) every 10 min, until the battery is filled. At this point, the value of the voltage and the current respectively are equal to $V_{end} = 13.92$ V, $I_{min} = 0.89$ A. Also, the value of the current given by the manufacturer is equal to 0.85 A, in these value the battery is disconnected from the stabilized power supply. This test was carried out for 05 days, it is equal to $T_{ch} = 1518$ min or $T_{ch} = 25.3$ h.

D. The test of the Discharge process.

The variable resistor is connected with the battery (before, starting the discharge process, the value of this resistor is regulated in the value of the current of 10 A. the value of this resistor is not varied all the discharge process) then, the voltage, current and ambient temperature are measured every 5 min during the discharge process. After 10 h and 17 minutes, the value of the cut off voltage is achieved to 10.8 V. In this value, the variable resistor is disconnected.

VI. RESULTS AND DISCUSSION

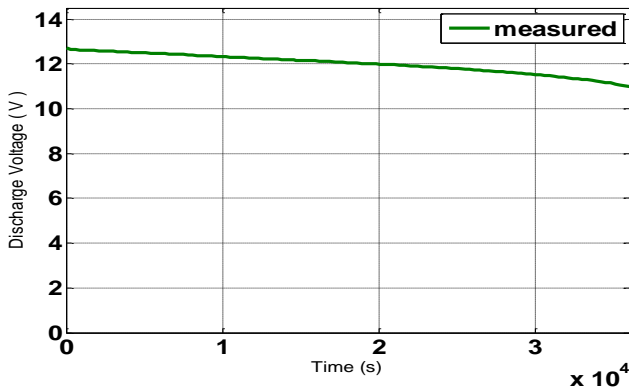


Fig. 3. The discharge voltage vs. time.

Figure.3 shows that the measured voltage of the battery during the discharging process, this voltage decreases to the

value of 10.8 V after a period of 10h and 17 min, this value which is called the cut-off voltage. The value of 10.8 V does not correspond to the full discharge of the battery (SOC = 0%) but is suitable to minimum SOC value which is equal to nearly 20%. [39], [5].

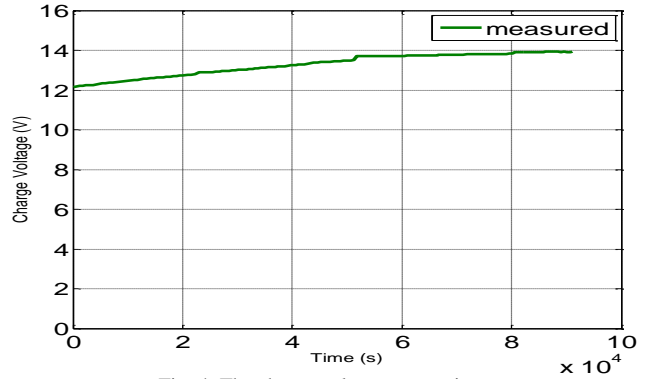


Fig. 4. The charge voltage versus time

The Figure.4 shows that the measured voltage during the charging process, this voltage increases to 14 V after a period of 25 h and 18 min. Note that the initial value of the charging voltage of the battery is equal to 12.6 V, this is explained by the initial state of charge or the amount of charge remaining in the battery, ($SOC_0 = 20\%$). [40]. In fact, there are two intervals: the first is [0-13] h corresponding for the charging mode with a constant current (CC) [41]. The second interval is [13-25] h corresponds to the charging mode by a constant voltage (CV). [28]. In fact, the charge phase depends on several factors (charging mode, SOC_0 , ambient temperature, charging current, charging voltage). To avoid overcharging the battery, cut off the supply voltage of the charger when the end of charge current is equal to 0.85 A.

In order to estimate the SOC at a given moment, only the voltage and the V-SOC curve are needed. The voltage is acquired via Multimeter and the curve V-SOC is calculated as an initial condition for SOC estimation program. The resulting input curve is characterized in figure.5 through various fitting methods. That phenomenon can be observed with higher detail in figure.6 which represents a zoomed frame of figure.5.

A function which can approximate the sampled data with little error should be achieved. Some methods were tested with a Matlab fit function concluding that the region between 100% and around 20% of the SOC could easily be approximated by every tested methods, only the zone where almost all charge has already been consumed, from 20% to 0% of SOC represents a great threat to a small error function approximation.

The method that showed the best performance was polynomial 7, representing a polynomial of degree 7, the equation to this method is presented in equation 3.

$$SOC = p1.V^7 + p2.V^6 + p3.V^5 + p4.V^4 + p5.V^3 + p6.V^2 + p7.V + p8 \quad (3)$$

Where: $p1, p2, \dots, p8$, the coefficients are given.

As expected, throughout the time, the SOC was estimated, represented in figure.7. Although the estimation shown in figure.6 has a meaningful trend, the error inherent to the stated estimation exists and is mainly due to error in the approximation procedure. As expected, throughout the region between 100% and 20% of the battery's charge, the decay was without major slope changes.

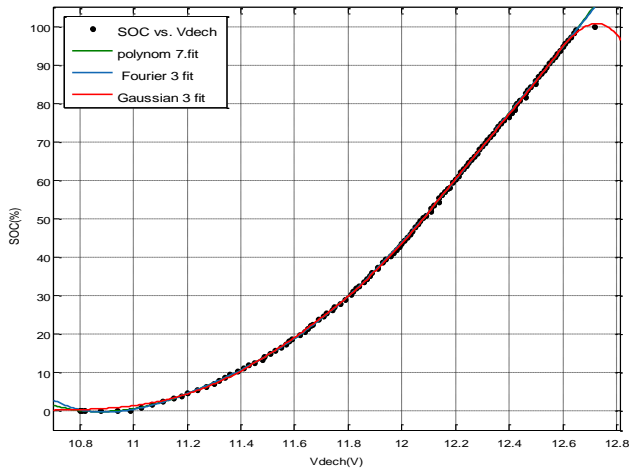


Fig. 5. V-SOC curves obtained through various fitting methods

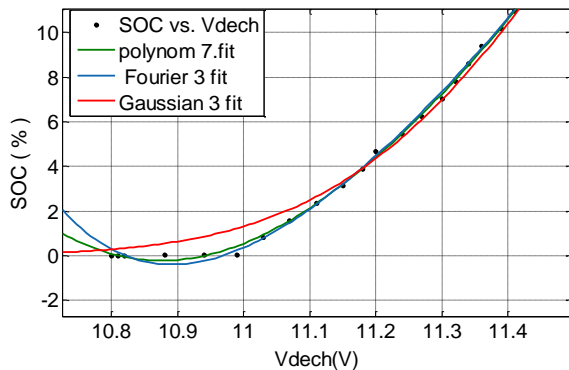


Fig.6. V-SOC curves in detail

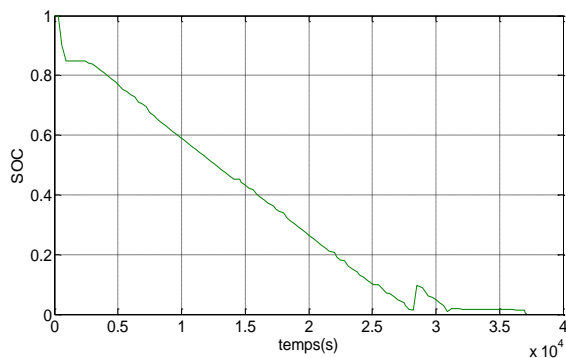


Fig.7. Discharge SOC versus time.

According to figure.8, note that the battery is initially full ($SOC_0 = 100\%$) and after 10 hours the state of charge of the battery decreases to the minimum value ($SOC = 20\%$). This value corresponds to the actual value of the Lead-acid battery ($SOC_{min} = 20\%$) [42], [37], [43]. Furthermore, this value must not be exceeded in the aim to prevent the damage of the battery. The curve of the SOC estimated by the estimator of coulomb counting shows that the discharge of the battery is under a constant discharge current ($I_{disch} = 10A$). Although, this technique follows the state of charge of the battery throughout the discharge time (10h). SOC_{exp} and SOC_{th} are fitted which show that this technique is very precise and robust.

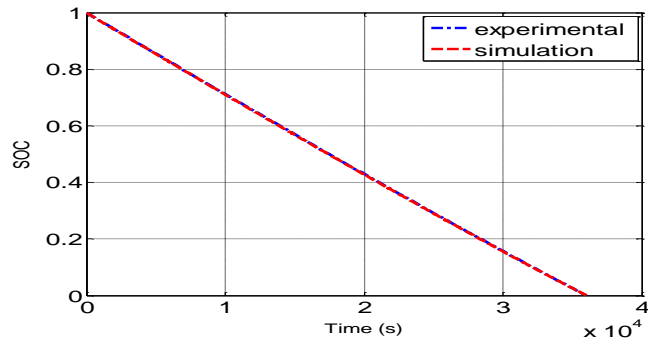


Fig.8. The state of charge (SOC) of the battery versus time

The figure.9, shows that the SOC curve (experimental and simulation) is slightly different; this difference is caused by the inaccuracy of the battery model in the charging process. In addition, the generic model of the battery is more accurate by using the experimental data than by using the manufacturer data. [44]. Also, in this figure we are noted that the coulomb counting method is followed although the SOC during the charging process, that is mean this method does not depend of the model and the battery technology.

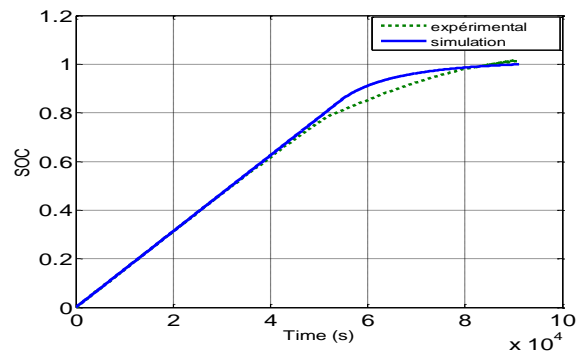


Fig.9. The battery state of charge (simulation and experimental) versus time.

The Figure.10 shows that the SOC estimated by the NIO network in the discharging process. Not that the SOC estimated is slightly fitted to the SOC measured all the process of discharge (10 H and 17 min). Then, the SOC

estimated by NIO is decreased of the value of 100% until the value of 20%, these value is corresponds of the last values of measured voltage (10.8V), current and ambient temperature.

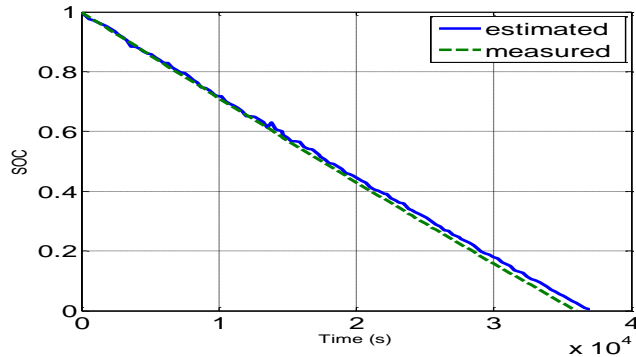


Fig .10. SOC in discharging process vs. time

According to the figure.11 show that the SOC estimated by the NIO network in the charging process. Not that the SOC estimated is fitted to the SOC measured, all the process of charge (25 H and 18 min). Thus see that the first value of SOC estimated by NIO is equal to 20% it corresponds to the first values of measured voltage (12.60V), current and ambient temperature. However, the calculated weight functions for the NIO model is optimal in the sense that they gave the best possible performance, the weight functions must be able to adapt to changes in the ambient conditions or battery parameters [30]. Then, the SOC estimated in the charge process is more accuracy than in the discharge process because; the size of examples datasets (measured battery voltage, current and ambient temperature) in the charge process is more than in the discharge process.

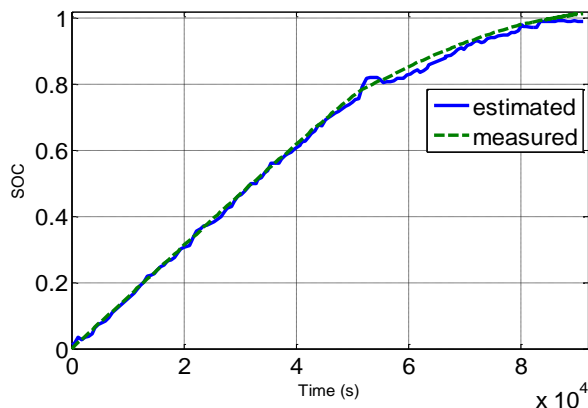


Fig.11. SOC in charging process vs. time.

VII. CONCLUSION

The discharge voltage method is very accurate for SOC estimation especially in the zone of SOC between (90% and 10%).Furthermore it is applied in the all batteries technology.

The need to open the main circuit and perform both a time and energy consuming task to estimate the SOC appears as evident drawbacks of this method.

The estimator of the state of charge of the battery by coulomb counting method is very accurate and is widely used in practice especially in embedded applications type hybrid / electric vehicles; or renewable energy applications in the case of photovoltaic systems for example.

The disadvantage of this technique is an inaccuracy and difficulty to finding the initial SOC. Also, it requires high-precision measuring instruments (voltage, current, and temperature sensor), i.e. it has to calibrate these devices every time otherwise, gives less accurate results.

The estimator of the state of charge of the battery by the neural network method is very precise in the two modes of charge and discharge and does not require the model of the battery. Then, the electrical measurements of the voltage, current and ambient temperature for the learning of this technique are needed. The learning basis in the discharge and the charge process is different. Indeed, the learning basis in the charge process is larger than in the discharge process, for this reason it gives a more precise estimation of SOC, because the increase in the number of iterations (Ne) increases the accuracy of the network.

The disadvantage of this technique is that each time it is necessary to train this ANN to obtain a more accuracy. Then, the calculation time is important if the size of the training set is very large. So, in order to implement the ANN SOC estimators, advanced hardware (sensors, memory, microprocessor, etc.) must be used, which will consequently lead to a relatively high implementation cost. Practically, ANN estimators can be used in applications where the current is very dynamic such as in electric vehicles.

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