The State Of Charge estimating methods for rechargeable Lead-acid batteries

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***Abstract*— State of Charge (SOC) is a key element for battery energy assessment, performing the stored energy. An accurate estimation of the SOC is fundamental for the safe and reliable operation of photovoltaic systems. To this end, the scientific literature covers a broad range of methodologies with extensive accuracy and complexity. However, the accuracy of the SOC is highly dependent on the methodology adopted. This paper investigates four methods of estimating the SOC for lead-acid battery manufacturers. For this purpose, four methods were selected and then used in practice, including the Modified Coulomb Counting (MCC) method, the Neural Network (NN), and two other machine learning based techniques, namely the Support Vector Machines (SVM) and the Nearest Neighbours Algorithm (KNN), respectively. An experimental test is considered through a detailed analysis based on a statistical evaluation covering the real cycle of charge and discharge modes. It means that the NN algorithm has given more accuracy. The algorithm showed high prediction accuracy, the majority of predictions had a relative error close to zero, reaching a maximum error value of about 0.1%. Simulation results were performed in Matlab software. All of these results confirm the accuracy and efficiency of the chosen methodology.**

Keywords—SOC estimation, lead acid battery, intelligent algorithm, off grid system.

I. INTRODUCTION

Lead-acid batteries have always been the most popular battery type, accounting for 75% of all energy sold in the rechargeable battery industry [1] They can be used in a variety of situations. The majority are used in automobiles as a power source for starting, lighting, and ignition. Another application for its accessibility is backup and emergency power provision; it is also employed as a propulsion battery for electric scooters and other compact battery-powered vehicles. Lead-acid batteries are commonly used for solar energy storage. [2] A storage system in photovoltaic systems (PV) is commonly made up of many battery cells connected in series or parallel to protect and ensure the operation at night. These batteries normally require a separate management system to keep track of their status and ensure that they do not operate outside of their safe operating range [3]. Until now, the battery management system (BMS) has done many calculations and computed a lot of variables relevant to the battery state. The battery SOC [4], which represents the actual capacity, is an important parameter.

Unfortunately, having an exact computation of the SOC is extremely difficult, if not impossible, to measure and trace. A range of models and strategies for forecasting SOC from observable properties like temperature, voltage, and current will be examined in order to address this. However, depending on the battery technology and application, the predicted level of technical accuracy may vary significantly [5].

There is no consensus on the best storage options because solar energy extraction is an extremely new topic of study.

Fortunately, there is consensus on which technologies are typically suitable for a novel battery application in the wide and long-lived field of energy storage [6]. A suitable approach can be deduced and the understanding of its application can be expanded by judiciously testing these tried-and-true methods on new cases. A thorough understanding of the case is needed before an experimental methodology can be established. The following is a summary of the paper's goal: Investigate the existing SOC estimate literature and choose the best one for our needs. Get diverse SOC estimation findings from multiple selected methodologies in the context of solar energy storage, perform an error analysis, and compare different state of charge estimation methods.

All simulation results were performed using the Matlab software.

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This paper is organized as follows: Section 2 discusses the materials and methods used in this study, including a brief description of the SOC algorithms. Section 3 discusses the results of the battery SOC estimation, followed by a detailed analysis in Section 4 that validates the best-suited SOC technique, and finally a conclusion in Section 5.

II.METHODOLOGY

This section aims to pose the SOC estimation problem for Lead-acid batteries. A rundown of four chosen models is given and used later in practice for that purpose. We attempt to explain the theory behind each model for varying degrees of complexity while also elucidating the model's approach to the problematic. Many SOC estimation models have been conceived, each having its own advantages and disadvantages. In our case, we had to select a set of models that would be compatible with the measurements carried out in the experimental set up and the lead-acid battery technology used. In other words, we had to choose models that would use measures related to the solar radiation, the battery temperature, voltage, and current of the battery, the load, and the source (PV). The models settled for were the Coulomb-counting method, the Modified Coulomb-counting method, Neural Networks, and Machine Learning algorithms (Support Vector Machines and K-Nearest Neighbors).

A. Experiments

In this experiment, two 250 Ah/12 VDC sealed gel lead-acid batteries were connected in series to obtain a 24 VDC lead-acid battery. A 750 Wp PV array supplies this battery, connected through a battery charge controller TS 45 to protect the device from overcharging and a BG 60 A charge controller, which prevents depth discharge. The controllers keep the SOC in a 30%–90% range. The PV array supplies the charging current while the load comprises 20 DC lamps of 220 W. The charging process begins when the battery is considered fully discharged, i.e., (SOC = 30%) and the load is disconnected. whereas the discharge can only begin when the battery is considered fully charged (SOC above 85%) and the PV array is disconnected. Lead-acid batteries take a longer time to charge; the time step used is five minutes. Fig. 1 shows the test bench for the measurement and Fig. 2 is the associated test bench diagram for the PV system. SOC models

B. SOC models

1) *Coulomb Counting method*

The Coulomb counting method measures the charging or discharging current of a battery and integrates it over time to estimate the SOC [7] as given by equation (1):

$$SOC(t) = SOC(t_0) - \int_{t_0}^{t} \frac{\eta . I(t) . \Delta t}{Q_n} \quad (1)$$

I(t) denotes charging or discharging current, which is negative during charge and positive during discharge. η is the battery efficiency, assumed equal to 1. Δt is the sampling interval time, and Q_n is the nominal battery capacity. The coulomb-counting method presents many disadvantages. The main one is its reliance on the battery nominal capacity (Q_n), which, contrary to its nature in the equation, is not constant and is affected by temperature and current direction. Despite that, it will serve as a standard reference that we attempt to approximate using the following models. Using the Coulomb counting estimation of the SOC as a reference is a common practice in SOC estimation. This is due to its simplicity of implementation and the accuracy it offers without needing any data related to the chemistry of the battery. However, its use is often limited to serving as a reference to tune other estimation models in the testing phase (on PC) rather than being practically used in battery management systems [8].

2) *Modified coulomb counting method*

As previously explained, the Coulomb counting is dependent on a constant value of the battery efficiency. As temperature, charge/discharge current, and voltage. Meanwhile, the desired output will be the SOC as a function of the coulomb couting method (a parameter that varies in theory) is quite inconvenient [9], [10]. To make the model more practical, as given by Eq. (2) and Eq. (3), the battery efficiency is assumed to be 100% for discharge and 98% for charging instead of having one constant value for all scenarios. For what follows, this variant of the Coulomb Counting will be referred to as the Modified Coulomb Counting (MCC).

$$SOC_{t+1} = SOC_t - \sum \frac{\eta \, \Delta t}{C_n} I_{dis} \quad (2)$$

$$SOC_{t+1} = SOC_t + \sum \frac{0.98 \, \Delta t}{C_n} I_{ch} \quad (3)$$

I_{dis} and I_{ch} depicts the discharge and charge current respectively.

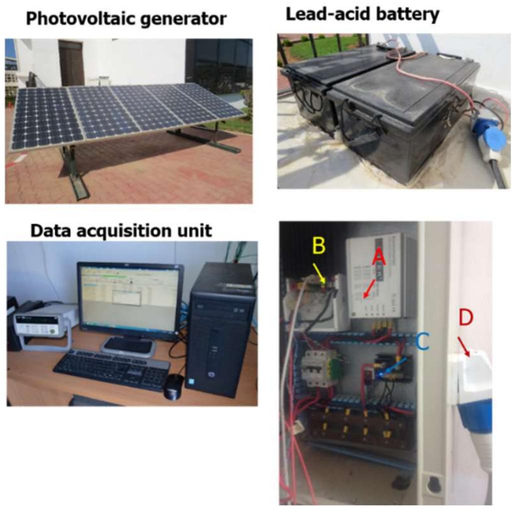

Fig 1. Experimental test bench; (A) DC-DC converter, (B) Charge regulator, (C) BG Guard. (D) PV input.

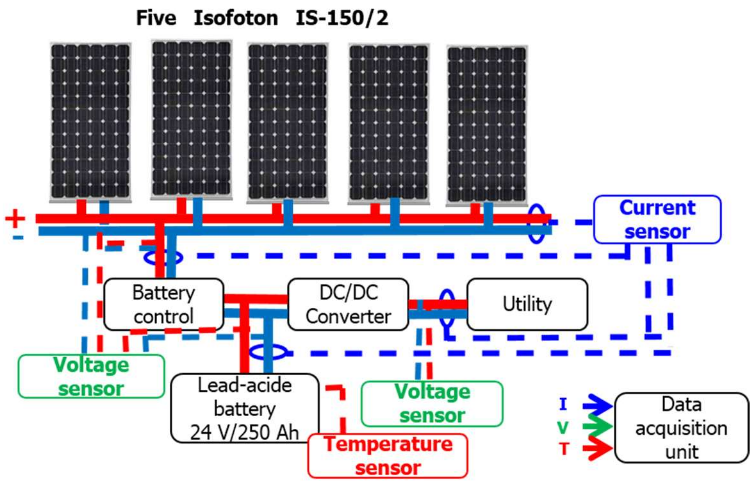

Fig 2. Test bench diagram.

3) *Artificial Neural-Networks*
Artificial neural networks are computational models composed of artificial neurons (called perceptrons) connected by weights that can be updated according to performance parameters assessing the accuracy of the current prediction [5], [11]. The primary neural network has three main layers, the first being the input layer. The middle one is called the hidden layer, and the last layer produces the outputs. The input vector consists of recorded or measured variables called features. These are passed to the hidden layers where they are multiplied by weights and added to the bias. At the end of the network, the linear combination passes through an activation function, which produces an output or prediction.

4) *Support Vector Machines*
This algorithm attempts to find the prediction function f (x) that has at most a deviation of ε from the actual values yi but must also be as flat as possible. This paper considers the machine (SVM) regression method principle described in [12]. Where X is the training data and Y is the target output, this algorithm attempts to find the prediction function f (x) that has at most a small deviation from the actual values, yi, but must also be as flat as possible.

5) The K- Nearest Neighbors Regressor
The K-*Nearest Neighbors Regressor* (KNN) in regression is very similar to its classification. If X is the training data and y is the target output [13], the KNN classifier will compute the distances between the current test point and X (where the expected output is predicted) and for every training point Xi, the k-label points with the closest distance to X will be chosen. Among the labels of the selected k points, the most frequent one will be selected as the final prediction. This process is called the "voting process," and it involves finding the mode among the training points.

III. RESULTS AND DISCUSSIONS

In this study, the charging period of the battery spans over four days. We notice that during the first seven hours of charging, the voltage increases gradually with irradiation. This is called the boosting phase. Note also that the battery temperature increases with the charging current. After four days, the latter hits its minimum value of zero, after which the battery maintains a relatively constant voltage, signaling the beginning of the floating phase. The battery charging profile corresponding to the lead-acid battery was conducted in two phases: boost and Floating. The battery charge controller integrated into the storage unit case study displays the battery charging profile. As shown in Fig. 3,

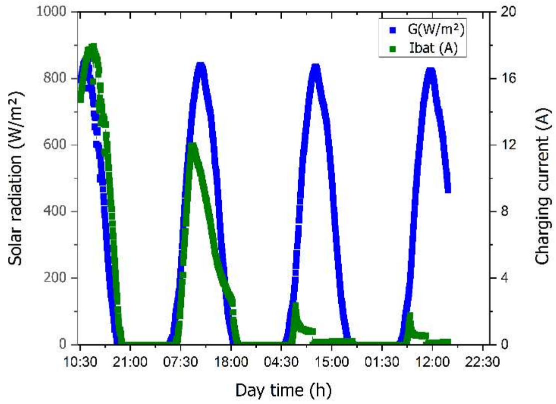

Fig. 3. Charging profile

Fig. 4 shows the evolution of the four battery SOC models considering both charge and discharge modes of the lead-acid battery. It is observed that most of the models have close convergences to the reference. A statistical analysis of the results is performed to ensure that the correct technique for estimating battery SOC against the reference is used. In this way, quantitative analysis guided by statistical metrics is applied to the results provided by the previously discussed algorithms. In a first step, the study is based on the cumulative frequency distribution as a function of the relative percentage error (RE (%)) described by equation (4). Furthermore, the performance of the SOC is verified under the analysis of numerical data as a function of residuals.

$$RE(\%) = \left(\frac{SOC_{ref} - SOC_{sim}}{SOC_{ref}}\right) \times 100 \tag{4}$$

Where; SOC_{ref} depicts the referenced battery SOC, and SOC_{sim} is the battery simulated SOC.

Fig.5 provides the cumulative frequency via the relative error percentage RE (%) during both charge and discharge modes, respectively, for lead-acid batteries.
Fig.5 (a) and Table 1 present the cumulative frequencies achieved for RE within a range of 0 to ± 8%; during the charging mode. It is worth noting that more than 92% of the SOC simulated by KNN have a RE of less than 0%, whereas the battery SOC simulated by SVM achieved all data with a RE of less than 2%.96% of the data is recorded, and more than 96% for the KNN method for the same error. In addition, the NN and MCC methods recorded
All of the data with relative error of 4% or less. Fig 5 (b) and Table 2 shows the cumulative frequency distribution function of the RE in percentage during the discharge mode. During this cycle, the SOC simulated by the NN method obtained more data than the other methods (recording 89% of all data with zero RE), followed by the SVM, KNN, and MCC methods, respectively, for the same error. Meanwhile, the NN method recorded all the data with a RE of ±6%. However, the MCC. The KNN methods achieved all the data with ±3% RE, the SVM method with ±11% error, and the KNN method with ±8% error, respectively. To enhance a practical selection for the lead-acid battery model operating in the PV system. Another analysis is provided in a further step. A detailed study aimed at statistical metrics is carried out to determine which of the above techniques is the most optimal. A comparative study between the four methods was performed using the Mean Bias Error (MBE) and Root Mean Square Error (RMSE)[14][15], which present the functional accuracy measures given by equations (5) and (6) over charging and discharge modes.

$$MBE = \frac{1}{N}\sum_{1}^{N}(SOC_{ref} - SOC_{sim}) \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N}(SOC_{ref} - SOC_{sim})^{2}} \tag{6}$$

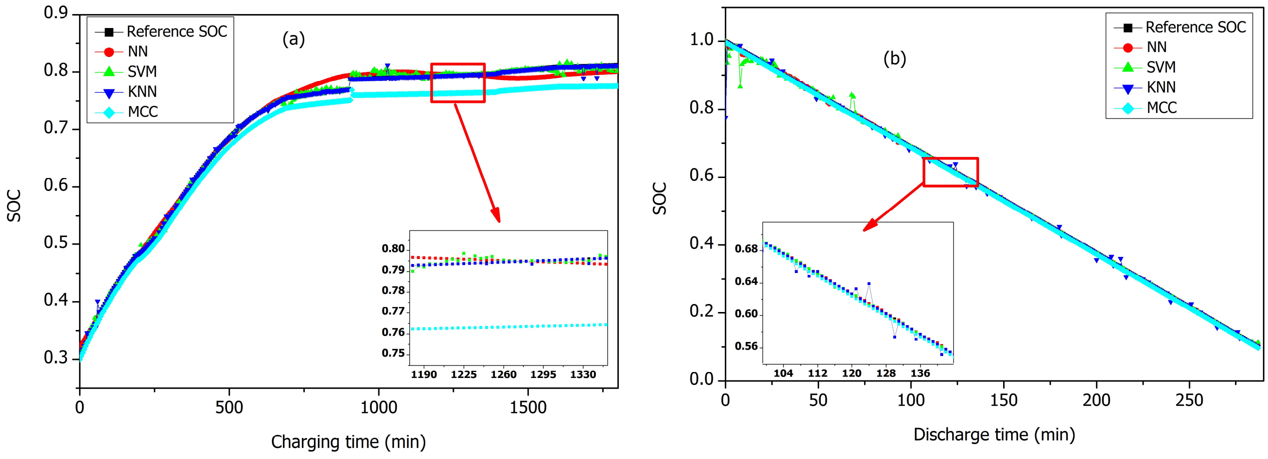

Fig. 4. Simulation of SOC models: (a) charge mode, (b) discharge mode.

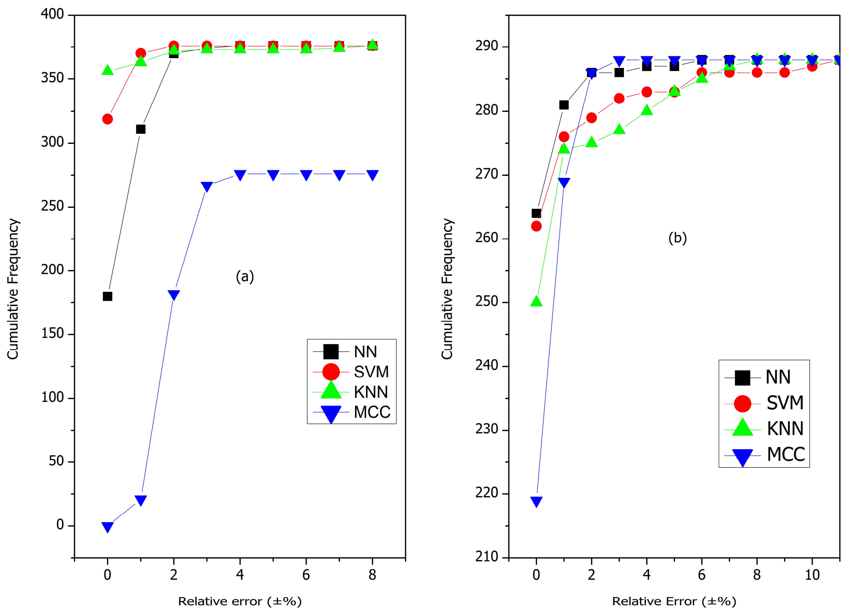

TABLE I Comparative results of cumulative frequency distribution Vs. The relative error for charge mode.

RE (± %)	0	1	2	3	4	5	6	7	8
NN	60	80.86	96.2	97.24	100	100	100	100	100
SVM	82.94	96.20	100	100	100	100	100	100	100
KNN	92.56	94.38	96.72	96.98	97.24	100	100	100	100
MCC	0	5.46	47.32	69.42	100	100	100	100	100

TABLE II Comparative results of cumulative frequency distribution Vs. The relative error for discharge mode.

RE (± %)	0	1	2	3	4	5	6	7	8	9	10	11
NN	89.76	95.54	97.34	97.24	97.58	97.58	100	100	100	100	100	100
SVM	89.09	93.84	94.86	95.88	96.22	96.22	97.24	97.24	97.24	97.24	97.58	100
KNN	85	93.16	93.5	94.18	95.2	96.22	96.9	97.58	100	100	100	100
MCC	74.46	91.46	97.24	100	100	100	100	100	100	100	100	100

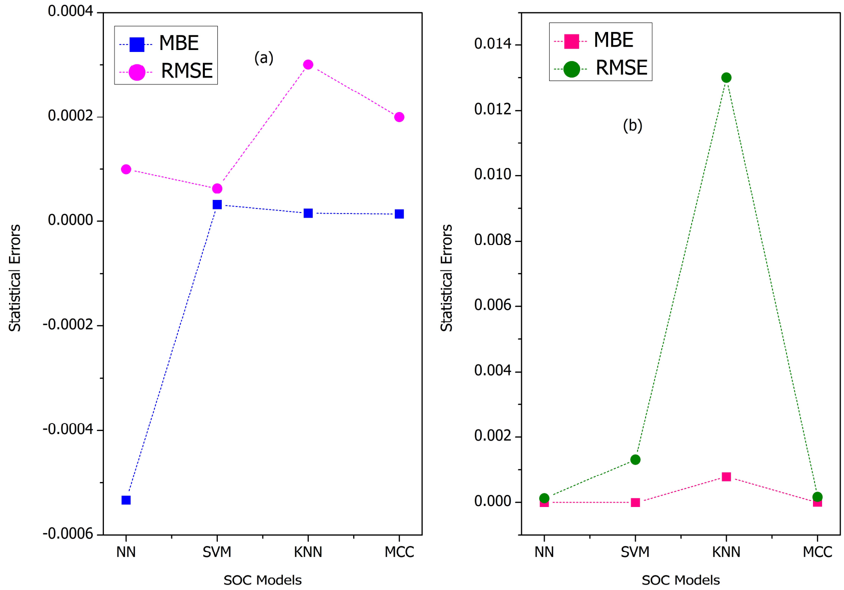

Fig. 6. Statistical errors of lead-acid battery: (a) charge mode, (b) discharge mode.

Fig.6 displays a simulation of the statistical metrics of a lead-acid battery. The SOC simulated by the NN method displays very low values of MBE and RMSE during both charge and discharge cycles compared with the remaining models, achieving -5.33.10-6 of MBE and 0.0001 of RMSE.

The previously obtained results suggest that the battery SOC simulated by NN followed by the MCC methods is more adequate for the lead-acid battery.

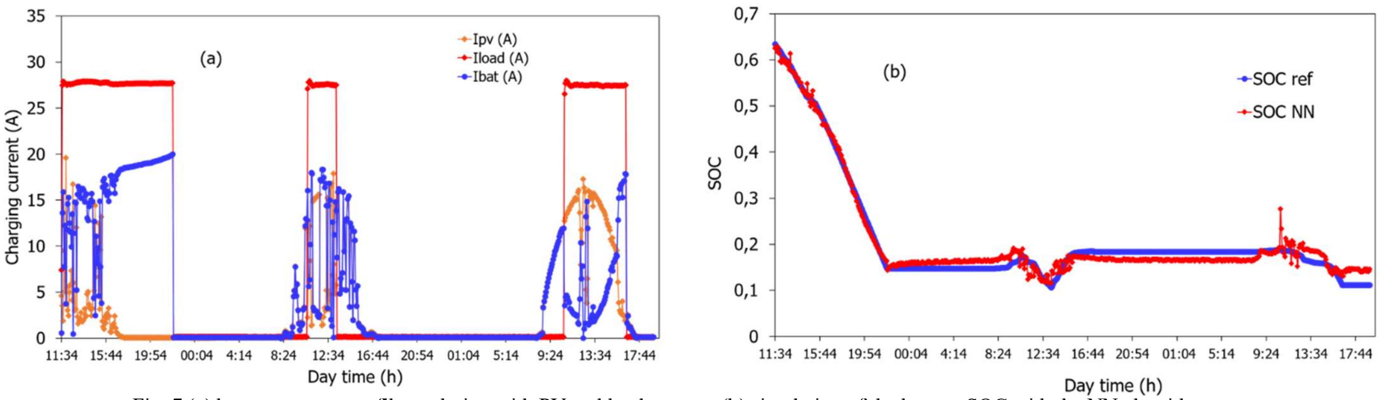

Fig. 7 (a) battery current profile evolution with PV and load current; (b) simulation of the battery SOC with the NN algorithm.

6

IV.VALIDATION

This section's objective consists of validating the updated SOC model simulated by the NN algorithm in a real-operating standalone PV system. The system consists of a PV array with a nominal power of 750 Wp, a lead-acid battery, and a DC load. The model validation involved two operating days with a linear consumption profile, which means the consumption I_{load} remains constant when the irradiance varies; the model was tested along with two working days with a charged battery. Fig. 7 (a) displays two typical periods of operation for the PV system under study, during which the PV current produced from the daily solar irradiance I_{pv}, the charging current I_{bat}, and the load consumption I_{load} are reported. Fig. 7 (b) shows the battery SOC evolution of the NN algorithm against the reference. A good similarity between the simulated SOC with the NN algorithme and the reference is observed during both charge and discharge modes.

V.CONCLUSION

In this paper, we have displayed the collected data, analyzed the different SOC estimation methods quantitatively and qualitatively, selected the optimal one, and validated it in a real standalone PV cycle. A lead-acid battery has gone through this process. A detailed analysis was performed on the different results produced by the models. First, we represented the estimations in the form of regular graphs, which showed convergent behavior towards the reference from most algorithms. This warranted the need for a more sophisticated way to distinguish between their performances. We resorted to statistical metrics like the cumulative frequencies of the relative errors along with the mean bias.

The Mean Square Error (MBE) and the Root Mean Square Error (RMSE) are two types of errors. We have concluded that the neural network model is best for the lead-acid battery, achieving at least 60% of data with zero error during charge mode and 89% during discharge mode, with a maximum error of 0.1%.

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