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Article

Modelling, parameters identification and experimental validation of a lead acid battery bank using genetic algorithms

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Abstract: Accurate and efficient battery modeling is essential to maximize the performance of isolated energy systems and to extend battery lifetime. This paper proposes a battery model that represents the charging and discharging process of a lead-acid battery bank. This model is validated over real measures taken from a battery bank installed in a research center placed at "El Chocó", Colombia. In order to fit the model, three optimization algorithms (Particle Swarm Optimization, Cuckoo Search, and Particle Swarm Optimization+Perturbation) are implemented and compared, being the last one a new proposal. This research shows that the model with the proposed algorithm is able to estimate and manage the real battery characteristics as SOC and charging/discharging voltage. The comparison between simulations and real measures shows that the model is able to absorb reading problems, signal delays, and scaling errors. The approach we present can be implemented in other types of batteries especially those used in stand-alone systems.

Keywords: Modelling; lead-acid battery; parameter identification; genetic algorithms; experimental validation.

1. Introduction

The energy storage system most often used is battery technology [1]–[5]. Batteries are used as power source for electric vehicles (EV), communication systems, electrical and electronic devices, renewable energy systems (RES), etc. In RES such as stand-alone photovoltaic and wind power, the battery type commonly used is lead acid battery due to their maturity and low cost [6]. These batteries are composed of two-volt elements that connect in series and provide voltages of 12V, 24V, 48V, etc. However, lead acid batteries have a high impact on the lifetime costs of stand-alone power-supply systems [6]. Some studies [7,8] reveal that batteries may account for up to 40% of the overall system cost over its lifetime.

Accurate and efficient battery modeling is essential to maximize the performance of a system and its battery lifetime. However, due to its non-linear nature [9] the battery charging and discharging process is complex to be accurate modeled. Moreover, many aging phenomena take place inside the battery during its life cycle such as corrosion, gassing effect, self-discharging, diffusion process, etc. [10]. Different models have been developed and implemented to capture the battery performance for various purposes [11]–[15]. Nevertheless, in order to effectively use a specific mathematical model to a real system, highly accurate modeling and low computational time

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are required [16]; therefore a parameters number must be tuned in order to accurately represent the system working. Because system working depends on a high number of variable factors such as environmental variables, life cycle, or type of facility, among others, some method has to be applied to tune the model parameters.

Different methods have been proposed in the literature to identify the battery parameters [17]–[20]. However, genetic algorithms (GA) have shown great performance. GA is a technique for stochastic search, learning, and optimization [21]. GAs work on a set of potential solutions called population. This population is composed of a series of solution known as individuals. The individuals are formed by a series of positions that represent the variables called chromosomes. GA has wide applications in bioinformatics, engineering, physics, computational science, mathematics, and other related fields [22]–[26]

Regarding the optimization of hybrid energy system with battery PSO is considered as one of the most used GA due to its good performance, flexibility, and simplicity [27]. Previous studies show that this algorithm is used in the electrochemical model parameter identification of a li-ion battery for automotive applications [28]–[32]. While the application of GA for the parameter identification of lead acid batteries as those used in RES research is scarce, e.g., Guasch et al. [33] used the battery model proposed by [34] and they added two extra parameters: level of energy and state of health. These new parameters are able to predict the degradation of the battery capacity and the increase of self-discharge current in the long time. In order to fit the model, they applied a Levenberg–Marquardt algorithm to achieve a mean voltage error around 1%. Besides to the 21 parameters identified in [34], Blaifi et al. [35]–[37] propose an improvement of 4 parameters for the estimation approximately of the gassing and the saturation levels. The simulation results shows that mean error with parameters given by [34] was 1.49%. While the mean error with parameters identification by GA was 0.45%. However, one disadvantage of the model is the high calculation time due to the large number of samples required for a good identification.

Another very attractive GA that can be used in the parameters identification is Cuckoo Search (CS) [38, 39]. In this genetic algorithm, the random walk is generated via Lévy flights as search strategy. CS is considered as a modern meta-heuristic algorithm able to solve complex optimization problems with high accuracy [40]–[42].

Taking into account the above-mentioned, this paper explores the use of GA to fit a mathematical model of batteries in order to represent the real working of a research center. This research has chosen the model developed by [34] because of its ability to cope with a widest range of lead acid batteries. Additionally, three GA (PSO, PSO+Perturbation, and CS) are implemented and compared to identify the parameters of a lead acid OPzS type battery bank. Where, we present PSO+Perturbation GA as a new proposal for the parameters identification. Moreover, four new parameters are added to the Copetti model. These parameters allow a better adjustment of the curves of charging/discharging voltage of the acid lead battery. Equivalent circuit models and GAs are simulated on LabView. The simulation results are validated with experimental data obtained from a research center "Centro de Investigación en Energías Renovables del Departamento del Chocó (Colombia) – CIERCHOCÓ.

This paper is organized as follows. In Section 2, a system description of the research center is presented. In Section 3 presents the battery model, the parameters proposed by Copetti and the addition of four new parameters to the model. Section 4 describes the GAs and their implementation. The results obtained are presented in Section 5. Finally, the conclusions are presented in Section 6.

2. Experimental system in CIERCHOCÓ

The real battery energy storage system (BESS) is composed of 48 TECHNO SUN 2V-OPzS-TCH2765 electrochemical accumulators divided into two branches of 24 cells connected in series. According to the manufacturer's characteristics, a single cell provides: nominal capacity 2770 Ah (C120). Additionally, the building integrates a photovoltaic (BIPV) system (see Figure 1). It is composed of 80 polycrystalline silicon modules (Amerisolar ASP-6P30; 250 W each one), a 20 kW

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(STP 20000TL-30; SMA) DC/AC inverter, a multicluster box (220V, 60Hz), and 6 sunny island ac/dc chargers inverters. Moreover, a data acquisition system stores data every 15 minutes.

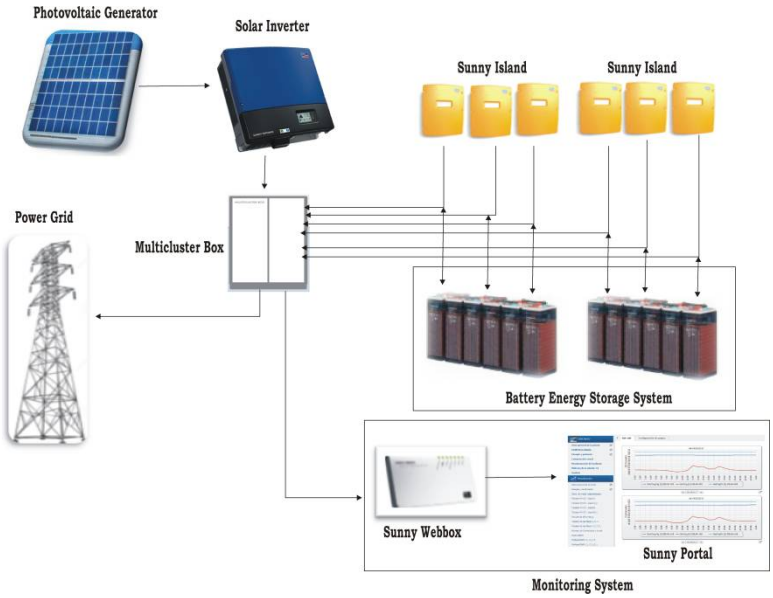

Figure 1. Block diagram of the BIPV system

3. Battery model test

The Copetti's model describes four operation modes for the battery system: a charging zone, a discharging zone, an overcharging zone and an intermediate zone representing a soft transition between charging/discharging modes [43]. Moreover, this model is based on a simple resistor model (see Figure 2) that is composed of an open circuit voltage source (Voc) based on the batteries state of charge (SOC), and a resistor R dependent on current (Ibat), temperature (T) and SOC [34], [44], [45].

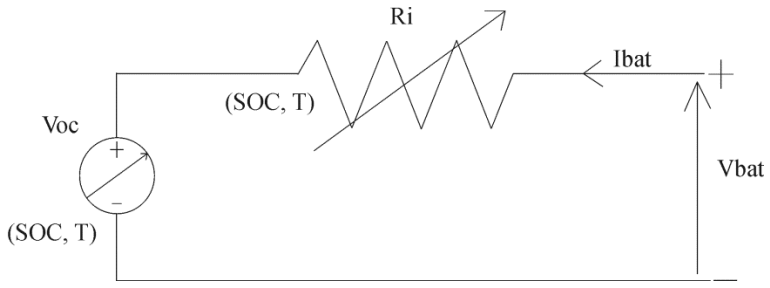

Figure 2. Equivalent circuit battery model.

According to Figure 2, Vbat is given by equation (1):

$$V_{bat} = V_{oc} \pm I_{bat} R_i \quad (1)$$

where, I_{bat} is the current circulating through battery. $I_{bat}<0$ during charge and $I_{bat}>0$ during discharge.

The discharge voltage is simulated through equation (2), while the charge voltage is simulated with equation (3). Where, n_s are the electrochemical accumulator's number, and ΔT is the temperature variation.

$$V_{dc}(t) = n_s[V_{bodc} - K_{bodc}(1 - SOC(t))] - n_s \frac{|I_{bat}(t)|}{C_{10} * k_{c10dc}} \left(\frac{P_{1dc}}{1+|I_{bat}(t)|^{P_{2dc}}} + \frac{P_{3dc}}{SOC(t)^{P_{4dc}}} + P_{5dc} \right) * \left(1 - \alpha_{rdc} \Delta T(t)\right) \quad (2)$$

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$$V_c(t) = n_s(V_{boc} + K_{boc}SOC(t)) + n_s\frac{I_{bat}(t)}{C_{120} * k_{c120c}}\left(\frac{P_{1c}}{1 + I_{bat}(t)^{P_{2c}}} + \frac{P_{3c}}{(1 - SOC(t))^{P_{4c}}} + P_{5c}\right) * \left(1 - \alpha_{rc}\Delta T(t)\right) \quad (3)$$

$$\Delta T = T - T_{ref} \quad (4)$$

The reference temperature (T_{ref}) is 25 ^{0}C. The terms P_{1dc}, P_{2dc}, P_{3dc}, P_{4dc}, and P_{5dc} are losses associated with the internal resistance as a function of the duty point [33], while the terms P_{1c}, P_{2c}, P_{3c}, P_{4c}, and P_{5c} are charge parameters. The terms V_{bodc} is the remaining voltage when the battery is discharged, K_{bodc} and K_{boc} relates the open circuit voltage of the battery with its SOC in the discharge and charge cycles respectively. K_{c120c} is a gain associated with battery capacity. α_{rdc} and α_{rc} provides the relationship with temperature [33].

The SOC is understood as the fraction or percentage of the capacity is still available in the battery and is estimated by equation (5). SOC_o corresponds to the battery initial SOC and C_{bat} is battery capacity in Ah.

$$SOC\ (t) = SOC_o - \int_0^t \frac{I_{bat}(t)}{C_{bat}}dt \quad (5)$$

where, $0 \leq SOC\ (t) \leq 1$. Equation (5) discrete implementation is:

$$SOC\ (t+1) = k_{soc} * \left[k_I * \Delta(t)\left(\frac{I(t+1) - I(t)}{2} + I(t)\right) * \frac{1 * k_{c\_bat}}{C_{bat}}\right] \quad (6)$$

where k_{soc} is an overall gain of SOC; k_I is related to coulomb efficiency; Δt is the sampling period; and k_{c_bat} is an associated parameter to battery aging. New parameters (k_{c120}, k_{soc}, k_I, k_{c_bat}) have an initial value of 1 to maintain the original model performance.

Table 1, compares the parameters identified by [34] with the values published by [33] and [35]–[37] showing a high dispersion between the different authors.

Table 1. Nominal values of the identified parameters by some authors.

Parameters	Guasch [33]	Copetti [34]	Blaifi [35], [36]	Blaifi [37]
V_{bodc} (V)	2.147	2.085	2.148	2.1612
K_{bodc} (V)	0.284	0.12	0.127	0.219
P_{1dc} (VAh)	4.083	4	0.406	9.5044
P_{2dc}	-6.634	1.3	3.041	4.9361
P_{3dc} (Vh)	0.27	0.27	1.218	0.9311
P_{4dc}	1.5	1.5	0.7812	0.037
P_{5dc} (Vh)	0.02	0.02	0.484	1.8837
α_{rdc} (^{o}C^{-1})	0.007	0.007	0.0197	0.0167
V_{boc} (V)	1.98	2	1.781	1.9016
K_{boc} (V)	0.149	0.16	0.5313	0.16
P_{1c} (VAh)	5.923	6	7.234	6.0809
P_{2c}	0.024	0.86	0.667	1.6701
P_{3c} (Vh)	0.48	0.48	0.078	0.3375
P_{4c}	1.2	1.2	0.492	0.9853
P_{5c} (Vh)	0.036	0.036	0.7421	1.7838
α_{rc} (^{o}C^{-1})	0.025	0.025	0.43	0.01

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The model is able to choose the discharging equation when the input signal has a positive sign (+A); otherwise, the model chooses the charging equations if the current sign is negative (-A). Current and temperature are taken as input signals.

Figure 3 shows a comparison between the experimental system performance and the battery model using parameter sets from Table 1. Furthermore, Table 2 presents the mean errors obtained by simulation with parameters reported in [33]–[37]. In the Table 2 it is observed that with the parameters reported by [34] it obtains the lowest mean error.

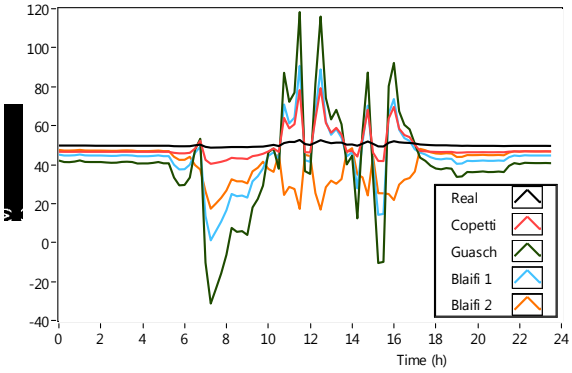

Figure 3. Model test using the parameters published in Table 1.

Table 2. Mean error using the parameters reported in the literature.

Mean error (%)	Charge voltage	Discharge voltage
[33]	40.06	37.91
[34]	16.93	7.79
[35], [36]	20.98	22.16
[37]	42.10	14.00

In the simulation of battery voltage, it is observed that this model represents the battery dynamics but with different scales and time delays. Therefore, the battery model must be used to fit the real battery dynamics.

4. Parameter identification

Due to the nonlinearity and complexity of the battery model, this proposal uses GA to find one possible optimal solution that belongs to a Pareto's front. Parameter identification was carried out in the same conditions with different GA in order to compare the algorithms. The general identification process for all GA is shown in **Error! Reference source not found.**, it starts with the estimation of initial coefficients values that are grouped in a parameter set (*PS*), in the second step, the initial PS is used to creates a random population of size *j*. In the third step, each single *PS* is evaluated into the model using inputs signals taken of real system. In the fourth step, the simulated outputs are compared with real outputs to estimate the *PS error*. Next, if the stop condition is fulfilled the process ends, otherwise, the GA creates a new population using specific criteria and back to the fourth step for a second iteration. The stop condition could be a defined iterations number or get an error lowest that a defined umbral.

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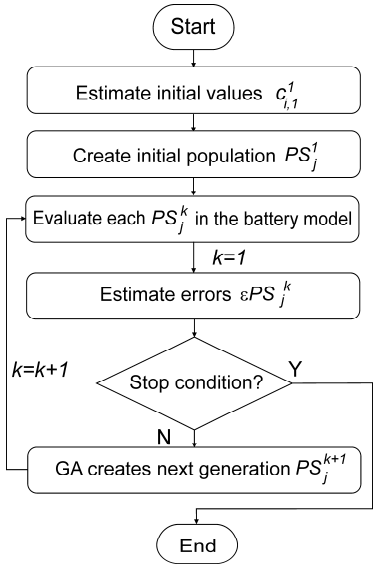

Figure 4. Global identification process algorithm

The model describes both charging and discharging processes whit different equations. The input current signal may change from positive sign (discharge) to negative sign (charge) several times in the same simulation, then the identification a *PS* that represents the real BESS with accuracy, requires the identification of one *PS* for each working mode. Therefore, a particular *PS* in the battery model consists of:

$$PS = \begin{vmatrix} I(A) < 0; & PS = \{V_{boc},\ K_{boc}, P_{1c},\ P_{2c}, P_{3c},\ P_{4c}, P_{5c}, \alpha_{rc},\ k_{c120c}, k_{socc}, k_{Ic}, k_{c\_batc}\} \\ I(A) \geq 0; & PS = \{V_{bodc}, K_{bodc},\ P_{1dc},\ P_{2dc},\ P_{3dc},\ P_{4dc}, ?P_{dc}, \alpha_{rdc}, k_{c120dc}, k_{socdc}, k_{Idc}, k_{c\_batdc}\} \end{vmatrix}$$

A general *PS* is defined as:

$$PS_j^k = \{c_{1,j}^k, c_{2,j}^k, c_{3,j}^k, \ldots c_{i,j}^k\}$$

where $c^k{}_{i,j}$ represents any parameter of the *PS*; e.g, $c_{1,2}^8$ is the value of first parameter (V_{bo}) in second parameter set of the 8th population PS28. This parameter involve both *Vboc* and *Vbodc*.

In the first step, the initial values coefficients were taken from literature (Table 1). In the second step, the initial population ($k=1$) of size j is an array of *PS* that is creates following the bellow rules:

$$PS_j^1 = \begin{vmatrix} j = 1; & c_{i,1}{}^1 = c_{i,1}{}^1 \\ j \geq 1; & c_{i,j}{}^1 = (c_{i,j}{}^1 \cdot z \cdot v_d) + c_{i,j}{}^1 \end{vmatrix}$$

$j=1$ ensure that the first population keeps the initial coefficients. For $j \geq 1$, the coefficients values change in a random way, where z represents a is random number ($z \in [-1, 1]$) and v_d is a value which generates a possible dispersion of the parameters $c_{i,j}{}^1$ in the initial population such that $c_{i,j}{}^1 \in [-v_d * c_{i,j}{}^1, v_d * c_{i,j}{}^1]$.

In third step, each $PS_j{}^1$ is evaluated in battery model, and for the next step, different error $\varepsilon PS_j{}^1$ is calculated for charging/discharging operation mode for both system signals, battery Voltage and battery SOC, in first place, the battery voltage error $\varepsilon_V PS_j{}^1$ is calculated as:

$$\varepsilon_V PS_j^k = (\varepsilon Vc + \varepsilon Vdc)/2 \quad (7)$$

where, εVc and εVdc are the battery voltage error (charging/discharging). The mean errors are calculates as:

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$$\varepsilon Vc = \frac{1}{jc}\left(\sum_{i=1}^{jc}\frac{|Vc_m - Vc_s|}{V_{cm}}\right) \quad \text{and} \quad \varepsilon Vdc = \frac{1}{jdc}\left(\sum_{i=1}^{jdc}\frac{|Vdc_m - Vdc_s|}{Vdc_m}\right) \tag{8}$$

where V_m and V_s are the measured and simulated battery voltage respectively, and j is number of samples. In similar way, the battery SOC error $\varepsilon_{SOC}PS_j^1$is calculated as:

$$\varepsilon_{SOC}PS_j^k = (\varepsilon SOCc + \varepsilon SOCdc)/2 \tag{9}$$

where, $\varepsilon SOCc$ and $\varepsilon SOCdc$ are the battery voltage error (charging/discharging). The mean errors are calculates as:

$$\varepsilon SOCc = \frac{1}{jc}\left(\sum_{i=1}^{jc}\frac{|SOCc_m - SOCc_s|}{SOC_{cm}}\right) \quad \text{and} \quad \varepsilon Vdc = \frac{1}{jdc}\left(\sum_{i=1}^{jdc}\frac{|SOCdc_m - SOCdc_s|}{SOCdc_m}\right) \tag{10}$$

where SOC_m and SOC_s are the measured and simulated battery SOC respectively, and j is number of samples.

The goal is to minimize both εPS_j^k. The optimization process ends when a stop condition is met. If the stop condition is not fulfilled, the GA creates a new population PS^{k+1}.This new population is evaluated again. Therefore, at each step k, the system runs the model j times. Each time the systems uses a row of PS^k. Simulation results are compared with real data so there is a simulation error for each PS. This error is used to generate the next population to be tested or to decide if it is small enough to finish the process. The stop condition is usually defined as a threshold for the minimum εPS_j^k or as a maximum number of iterations.

Each GA uses a particular policy to create the new population from the previous evaluated one. The goal is to converge to the optimal solution in a minimum number of steps. In order to perform this operation, GAs includes random components to search for the global best solution which include values of dispersion to spread or to focus the offspring near a possible solution. The model parameters identification were set with an initial dispersions values between [-5, 5] from the initial value.

4.1. GAs description

The PSO algorithm is a GA that emulates the behavior of a swarm in the action of the crop [28]. The swarm moves around a particle that finds a possible good place (solution) and explores this location; if another particle finds a better solution, the swarm moves to this new place. The advantages of PSO include the gradual reduction of the movement distance at each step (ω) to focus the research on a small area and the capacity to keep the better solution found at each step in the swarm memory (P_{Best}) and the best solution of overall process (G_{best}). The algorithm uses two coefficients in order to modulate the influence of P_{best} and G_{best} in the new swarm step (iteration).

On the other hand, one of the most recent published GA is CS [38]–[40], that emulates the behavior of cuckoo birds related to their aggressive strategy of reproduction that colonize and parasite the nests of another bird. The cuckoo chooses a nest with eggs, leaves its own egg; if the egg is accepted and hatches, the brood will be fed by foster's birds. In CS, the probability that the egg be found out and rejected is configurable as $Pa \in [0, 1]$. The CS movement strategy follows the Lévy flights; each step has a random distance and an angular movement conditioned by configurable values: α ($\alpha > 0$), and λ ($\lambda \in [1, 3]$).

4.2. New proposal

One important feature of PSO is its ability to gradually focus the search around the local minimum. However, when the algorithm falls around a local minimum it is difficult to get a better solution. This paper proposes the introduction of periodic perturbations inside the population in order to force PSO reactivation. The perturbation will consist of a new population PS_j^l based on the best global solution.

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$$PS_j^l = \left\{ c_{1,j}^l, c_{2,j}^l, c_{3,j}^l, \ldots c_{i,j}^l \right\}$$

$$c_{i,j}^l = (c_i^{GBest} \cdot z \cdot n) + c_i^{GBest} \quad (11)$$

where c_i^{GBest} is coefficient belonging to G_{Best} until iteration l-1, and n is perturbation value. Because the use of perturbations this proposal is named PSO+P. The perturbation is introduced into iteration around the stabilization of PSO, and then is necessary run first the PSO.

4.3. Algorithms configuration criteria

Different criteria currently exist for the algorithms configuration. This paper works with the more common configuration [28], [41], [46], [47] as it is shown in Table 3. Population size (j), iterations number (k) and initial dispersion (v_d) take equal values in all the algorithms.

Table 3. Genetic algorithms configuration.

Criteria	PSO	PSO+P	CS
Population size (j)	1000	1000	1000
Iterations (k)	100	100	100
Weight initial (ω_1)	0.9	0.9	-
Weight final (ω_2)	0.1	0.1	-
c_1	1	1	-
c_2	1	1	-
v_d	5	5	5
Iteration to perturb	-	10	-
Pa	-	-	0.5
α	-	-	1
λ	-	-	2

5. Results and discussion

5.1. Optimization results

The model duality allows the use of different errors for both battery operation modes (charging/discharging). Therefore, we can study separately each behavior. Figure 5 shows both. In the charge mode, the CS does not find an optimal value of error and its last change takes place near 80th iteration. PSO and PSO+P achieve similar error values. Despite PSO presents a fast search, it presents an early jam around a non-optimal solution. On the other hand, the perturbation feature of PSO+P lets it make a wide search and obtaining better results than previous GAs.

Related to discharge mode, the GAs performance shown similar performances as in charge mode. CS presents a more dynamic behaviour that obtains stabilization in iteration 36th, but with non-adequate optimization value. The fastest algorithm is PSO, which reaches an acceptable value less than 1.0% around the 10th iteration. PSO+P show a slightly slower behavior, but it obtains better results from the 43rd iteration onwards.

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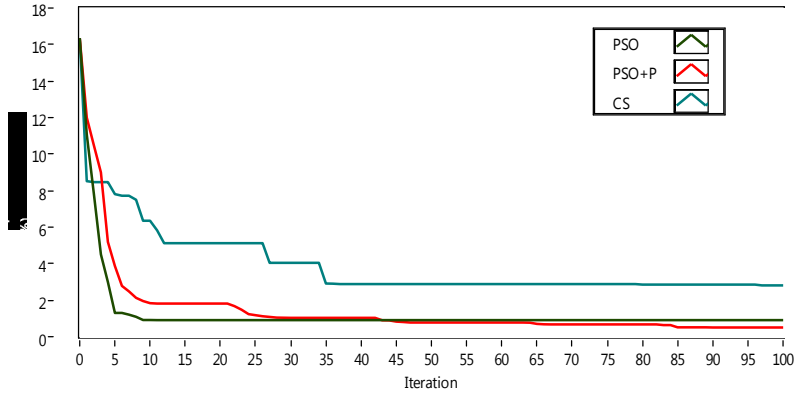
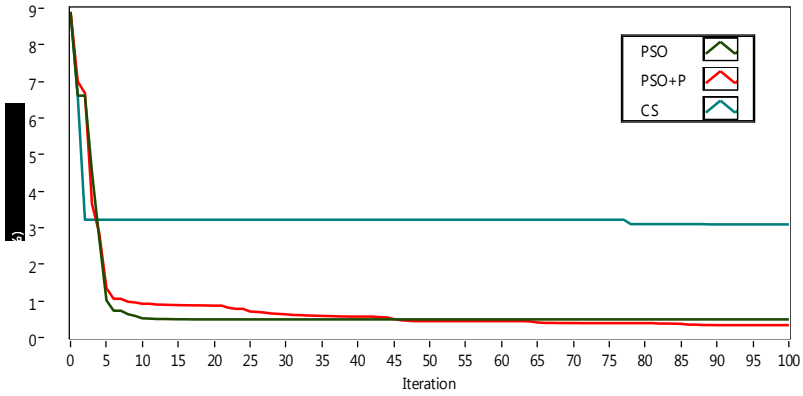


(a)



(b)

Figure 5. Optimization algorithms. (a) shows the algorithm performance in charge mode for a mean battery voltage, and (b) shows the discharge mode algorithm performance.

Results discard CS as a suitable method to fit the battery behavior. Therefore, only PSO and PSO+P need a closer look in order to select the best algorithm. A fast analysis over the curves shows that PSO is the faster algorithm but it falls in local minima so it loses search ability, thus confirming its known limitations. PSO+P obtain the best results but it requires more iterations to achieve it. A quantitative comparison is shown in Table 4. Criteria used to evaluate each algorithm are precision, velocity and computational cost. First, precision value is measured as the lowest error value reached by a GA. Second, the optimization speed is measured with the iteration when the algorithm makes its last improving. At last, computational cost is measured as the average time used by the computer to make single optimization iteration. Scores are calculated in each operation mode (charging/discharging) through the ratio between the obtained value by the algorithm and the lowest value achieved by algorithm. Therefore, a value of 1.00 represents the best result and a value of 2,000 stands for a 100% deviation from the best result. The algorithms ran under a PC with Intel core i5-3200, 31.GHz, 8 GB RAM and operating system W7-64 bits.

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Table 4. Algorithms Comparison using the minimal mean error reached. d*= discharge mode; c*= Charge mode.

Criteria/Algorithm		PSO		PSO+P		Cuckoo	
		d*	c*	d*	c*	d*	c*
Precision (error)	Value	0.50	0.91	0.34	0.51	3.09	2.81
	Score	1.48	1.78	1.00	1.00	9.23	5.53
Velocity (iteration)	Value	17.00	11.00	91.00	90.00	89.00	97.00
	Score	1.00	1.00	5.35	8.18	5.24	8.82
Computational cost (ms/iteration)	Value	0.41	0.41	0.42	0.42	0.71	0.71
	Score	1.00	1.00	1.03	1.03	1.72	1.72

5.2. Model performance and validation

Data in Table 4 describes PSO as the best algorithm regarding velocity and computational cost. However, PSO+P show the most accurate fit. Therefore, the model is fit from PSO+P results. These parameters are shown in Table 5.

Table 5. Parameters from PSO+P identification in daily data files.

Discharge		Charge	
V_{bodc} (V)	2.3003	V_{boc} (V)	2.2823
K_{bodc} (V)	0.1898	K_{boc} (V)	1.0227
P_{1dc} (VAh)	20.4751	P_{1c} (VAh)	2.4048
P_{2dc}	0.9282	P_{2c}	1.1928
P_{3dc} (Vh)	0.1481	P_{3c} (Vh)	0.0061
P_{4dc}	2.3350	P_{4c}	0.0285
P_{5dc} (Vh)	0.0362	P_{5c} (Vh)	0.0054
α_{rdc} ($^oC^{-1}$)	0.0365	α_{rc} ($^oC^{-1}$)	0.1008
k_{Idc}*	2.2087	k_{Ic}*	0.3254
k_{c_batdc}*	2.5517	k_{c_batc}*	0.3603
k_{socdc}*	2.5509	k_{socc}*	16.7918
k_{c120dc}*	0.0470	k_{c120c}*	0.3097

Figure 6 shows the results of the identification process with PSO+P. The simulated plot follows with high accuracy the real plot in battery voltage. The battery model with new extracted parameters presents a good matching with the reals measurement obtained from the research center.

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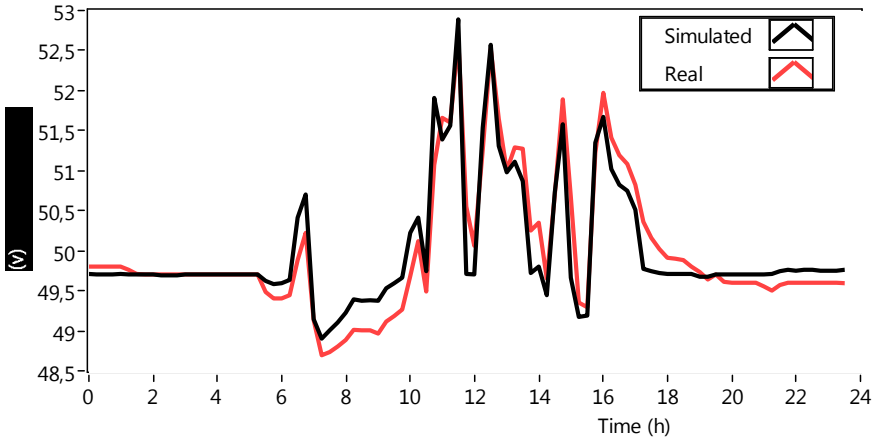
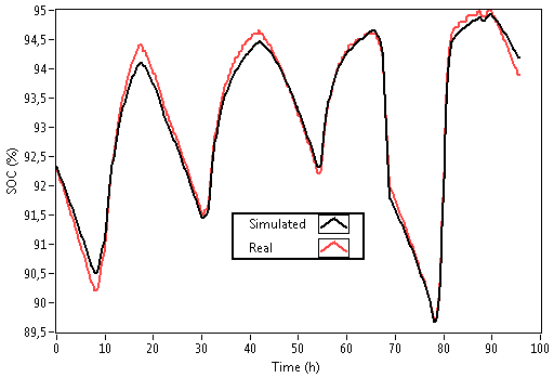


Figure 6. Simulation using identified parameters by PSO+P algorithm with one day data files.

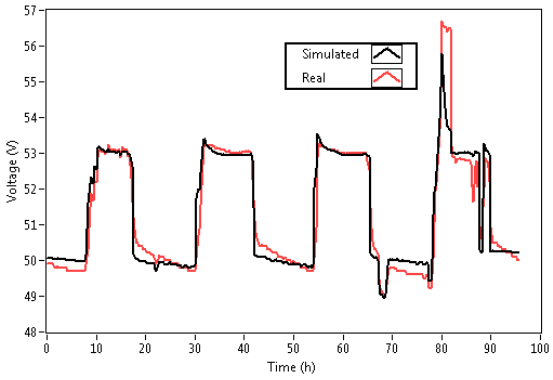
The simulation using the identification of parameters with PSO+P significantly improved the mean errors presented in Table 2. The mean errors achieved with this method were 0.29% and 0.44% for the battery voltage signal (discharging/charging, respectively) for an average between the two signals of 0.365%.

5.3. Experimental validation

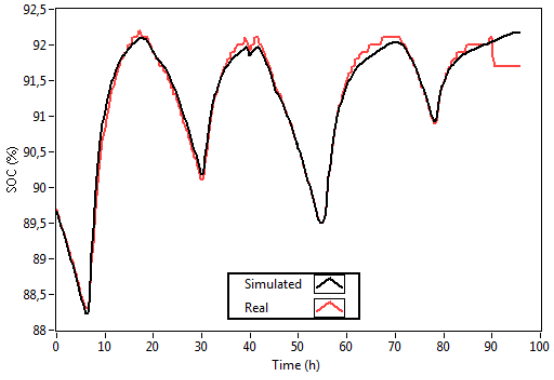
Model validation is carried out with data from three months divided into 4-day packages to be compared with the results presented in [35]–[37]. In order to validate the developed model under real conditions, this paper uses the parameters shown in Table 5. Figure 7 shows the results of the experimental validation of several data packages for different months; left side shows the simulation of SOC and right side presents the Voltage signal.



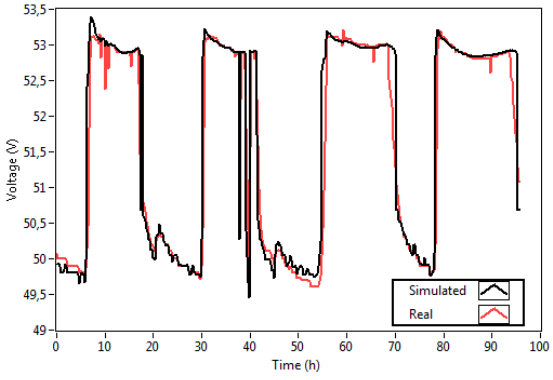
1(a)



1(b)



2(a)



2(b)

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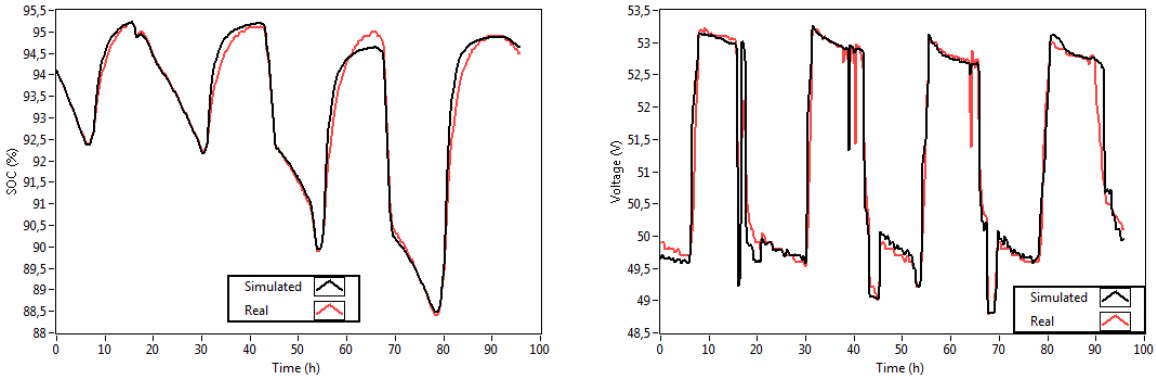


3(a) 3(b)

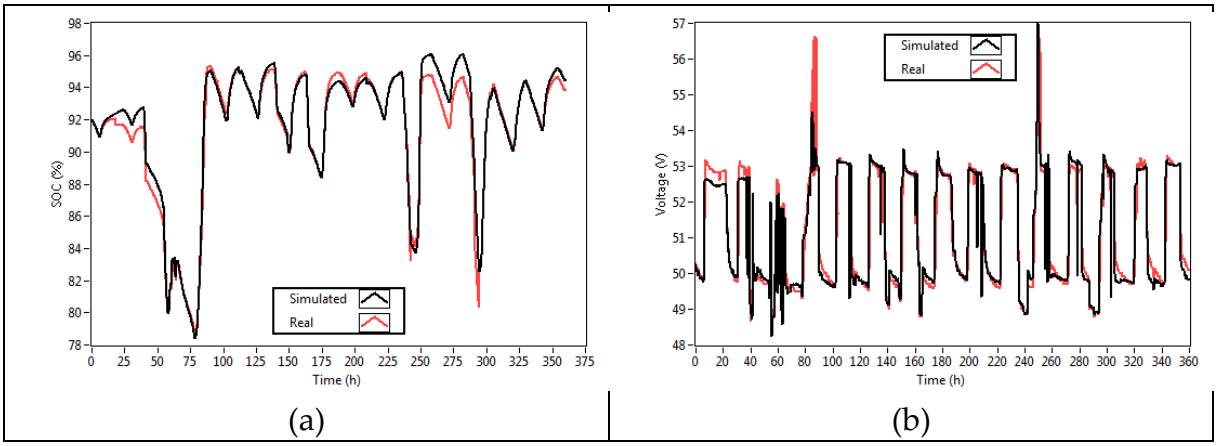
Figure 7. Battery voltage measurements (red plot) and simulation (black plot) results obtained by PSO+P algorithm identified parameters. 1-3(a) represents the Battery SOC signal; 1-3(b) represent the Battery Voltage Signals.

Validations 1 to 3 show that the model is able to follow the dynamics of the battery, despite in some cases it presents possible mistakes reading in the signal which may be due to of the measurement equipment. Those errors are shown as vertical falls and peaks without physic explanation due the reading period of 15 minutes. The mean error of each simulation regard to measured voltage is shown in Table 6.

Table 6. Mean error simulated vs measured voltage for 4-day package.

Signal	**SOC**			**Voltage**		
Simulation	(a)	(b)	(c)	(a)	(b)	(c)
Charge Mode Error (%)	0.0606	0.0827	0.1787	0.2163	0.2504	0.2446
Discharge Mode error (%)	0.1223	0.1335	0.1383	0.3824	0.3347	0.5242
Mean	0.0956	0.1076	0.1602	0.3075	0.2904	0.3582

When the battery model is validated for a 15-day package with the parameters shown in Table 5 the SOC mean error was 0.46% and voltage mean error 0.45% (see Figure 8). Again the model presents a good matching with the measured signal. However, on day 4th and 11th overcharging events occurred, and the model only was able to represent the second event.



(a) (b)

Figure 8 Battery voltage measurements and simulation results obtained by PSO+P algorithm for 15 days. (a) represents the Battery SOC signal; (b) represents the Battery Voltage Signals.

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6. Conclusions

The battery model proposed by Copetti has a good performance to represent battery dynamics. However, when tested with real measurements, this model presents problems of scaling and delay in the signal, so this paper have propose the inclusion of four new parameters to improve its modelling capabilities. Despite, the Battery voltage equation includes the SOC equation, and the battery voltage simulation result shows the SOC results in an implicit way, get the SOC simulation results separately lets the model more useful for condition monitoring and the BBES management.

The model has been fit to represent the real behavior of a BESS placed at "El Chocó". Colombia. Despite, improvements should be made to the model. The complexity of the model implies the use of GA to perform the optimization, so this paper has tested three GA in order to find the best approach. Besides some well-known algorithms like CS and PSO, a new proposed algorithm (Particle Swarm Optimization+Perturbation) have been used to identify and extract the parameters of the lead acid OPzS type battery. The inclusion of the disturbance makes PSO+P more accurate than PSO.

The present proposal has the ability to find *PS* to fit the model no matter the start point from however, to continue the present work is necessary to make a sensibility analysis of the parameters to define the influence of each parameter in the simulation results, and establish its adequate boundaries

The battery model with the new extracted parameters presents a good matching with the reals measurement obtained from the research center. The main advantage of the developed model is its low computational cost and its ability to absorb reading problems, and scaling errors when the simulation is valid with real measurements. The model and its fitting approach presented in this paper may be applied to other types of batteries especially those used in stand-alone systems.

The battery model will be used to make a better battery energy management system from research center placed at "El Chocó". Colombia.

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