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Parameter estimation of a lead-acid battery model using genetic algorithm

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Abstract. A classification of the battery models is presented. The battery model used and its charging and discharging equations are shown. These equations are expanded to find the value of the time constant of this model, which is fixed at a given value. A genetic algorithm is applied to these expanded equations to estimate the value of the time constant. Some battery charging and discharging cycles are used for estimation and validation of the proposed system. The value of the time constant found in this paper is different from that previously established in the literature. The results are based on simulations to analyze the feasibility of the proposed method.

Keywords: Lead-Acid Battery. Battery Model. Estimation Technique. Genetic Algorithm.

1 Introduction

The lead-acid battery technology of 1859 is still widely used nowadays in different areas. Even with a number of new battery technologies, this battery technology is still preferred in many circumstances, because when compared to other types with equal power, they have the lowest cost. Several researches have been carried out with lead-acid batteries as can be seen in the works of Sayeed et al. (2019), Li et al. (2019), Nizam & Wicaksono (2018) and Al-Jabarti, Al-Mutairi & Al-Harbi (2018).

Society has become increasingly dependent on energy consumption (ROSEMBACK, 2004). This dependence can be identified in the production of goods and services, in the automation of industrial processes, in modern telecommunications systems, in the storage and processing of data necessary for any organization, in the production and transformation of different forms of energy and in the economy in a way general (CHAGAS, 2007).

Nowadays, it can be observed that more failures in electricity supply are not tolerated, for example, critical systems of companies, hospitals and banks. The failure of some equipment can cause serious losses, with economic, material and even human losses (CHAGAS, 2007). Therefore, in order to meet the need to support power supply systems, battery banks are used. This equipment is used when there is a need to supply power during faults in the main power supply system.

According to Ketzer, Oliveira & Jacobina (2013), systems with battery banks operate with multiple charging and discharging cycles. The problem of using battery banks is in the need of periodically evaluating your SOC (State of Charge) to check if they will take over during power failures.

Schneider (2011) highlights the need to use techniques to determine batteries characteristics. Thus, battery models are designed to identify their actual operating characteristics, and can be used to predict their behavior over many cycles. These models are useful tools for the design of battery-powered systems, because they allow the analysis of their behavior under different design specifications, as presented by Sousa (2008). Battery modeling is important both for analysis and for the design of energy storage systems, since the uncertainty associated with its lifetime affects the cost of the energy generated by that system, since the battery replacement could be performed (BINDNER; CRONIN; LUNDSAGER, 2005).

Thus, this paper aims to determine the value of the time constant of the filtered electric current of the model studied, from the estimation using a genetic algorithm. In the model presented, the time constant is fixed to any lead-acid battery. Thus, it is not possible to predetermine the value of the time constant for a battery type, since they undergo different degradation processes (storage, temperatures, aging and initial tests).

The next section presents the classification of battery models. Section 2 presents the battery model used in the work. The genetic algorithm is studied in section 4. In the following section, the results are presented and discussed. Finally, section 6 concludes the paper.

2 Model Classification

The purpose of using a battery model is to represent its characteristics and to have a prediction of its operation in several charging and discharging cycles (SOUSA, 2008). There are many types of lead acid battery models and they can represent the same charge cycle, for example, with different levels of complexity. Different models have been proposed to represent a lead-acid battery. These models can be classified as electrochemical, analytical and analog, as discussed by Freitas, Ketzer & Lima (2016), Freitas, Lima & Morais (2016) and Freitas et al. (2015).

Electrochemical models simulate the physical and chemical properties of the battery. These models analyze the thermal, mechanical and electrical properties of materials (LIAW; BETHUNE; YANG, 2002).

The analytical models used interpolation of the manufacturer's test data to perform model analysis. They have reduced complexity when compared to the model mentioned above (SCHIFFER et al., 2007; SHEPHERD, 1963; TREMBLAY; DESSAINT, 2009; TREMBLAY; DESSAINT; DEKKICHE, 2007).

Analog models are based on electrical circuits. They have in their structure voltage sources, resistors, capacitors and inductors. These models are presented by Durr et al. (2006), Ceraolo (2000), Kaiser (2003) and Jackey (2007).

The analytical model proposed by Tremblay & Dessaint (2009) in this paper. This chosen model can be used for both charge and discharge of the battery. It can also accurately represent the voltage when the current changes and considers the open circuit voltage to be a function of the SOC. Some terms of the model equations of Tremblay, Dessaint & Dekkiche (2007) were added and modified to better represent a lead-acid battery. The characteristic parameters of the charge and discharge equations can be obtained from the battery discharge curve.

A characteristics of this model is the use of filtered current i_F. Results presented by Tremblay & Dessaint (2009) show that the voltage presents a dynamic behavior after applying a current step. In this dynamics, the response time for this model is 30 s. This time is widespread for all battery types this model can represent.

3 Battery Model

The model of Tremblay, Dessaint & Dekkiche (2007) can represent the dynamics of variation of load and discharge current, as shown in Figure 1.

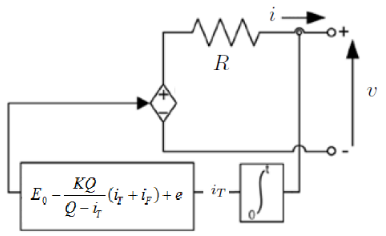

Figure 1: Battery model with a voltage source controlled in series with an internal resistance.

This model is a proposition to improve some undesirable effects that happened in the models of Tremblay, Dessaint & Dekkiche (2007) and Shepherd (1963), for example, with the battery completely discharged and without current circulation, the voltage became close to 0 V. A new term was added in the equation proposed by Tremblay, Dessaint & Dekkiche (2007), representing the bias voltage, to better represent the behavior of the open circuit voltage. Equation 1, given by

$$v = E_0 - Ri - K\frac{Q}{i_T - 0.1Q}(i_T + i_F) + e \qquad (1)$$

is used during discharging. At the time of charging, Equation 2 is used.

$$v = E_0 - Ri - K\frac{Q}{i_T - 0.1Q} i_F - K\frac{Q}{Q - i_T} i_T + e. \quad (2)$$

In Equations 1 and 2, variables represented by v, i, i_F, i_T and e are time dependent. The parameters used are: $v(t)$ is the battery voltage, E_0 is the internal voltage of the battery, R is the internal resistance, $i(t)$ is the charge or discharge current, K is the polarization constant, Q is the rated capacity of the battery, i_T is the current load consumed, i_F is the filtered current and $e(t)$ is the exponential voltage term. The Tremblay & Dessaint (2009) model is designed to be used in up to four battery types, including lead-acid batteries. The term exponential in this model varies for each of the batteries. In the case of lead acid batteries, the exponential term of voltage $e(t)$ is represented by

$$\frac{de(t)}{dt} = B \mid i(t) \mid (e(t) + Au(t)), e(0) = 0. \quad (3)$$

where $\frac{1}{B}$ is the time constant of the exponential zone, A is the amplitude of the exponential zone and

$$u(t) = \begin{cases} 1 & i_F(t) < 0 \\ 0 & i_F(t) \geq 0. \end{cases} \quad (4)$$

The filtered current for the lead-acid battery is given by the differential equation

$$\frac{di_F(t)}{dt} = \frac{1}{\tau}(i(t) - i_F(t)), i_F(0) = 0. \quad (5)$$

where τ is the time constant of the current filter.

Another relevant factor was the change of the charging and discharging equations for the four battery types. This is due to the fact that the behavior of each one is different in the exponential zone and in the final decay of the discharge curve. For example, the exponential component in a lead-acid battery is small, favoring the change of the exponential term (TREMBLAY; DESSAINT, 2009). Tremblay & Dessaint (2009) validated the dynamic behavior of this model for four types of battery in an electric car simulation system.

4 Genetic Algorithm

The method used in this paper to estimate the parameters is optimization with genetic algorithm (GA) (MITCHELL, 1998; GOLDBERG, 1989). A GA was used because they are very efficient in searching for optimal solutions because they do not impose many limitations found in traditional search methods. The following steps summarize the operation of the algorithm.

- The algorithm starts with the creation of a random individuals in a population;
- At each step, the algorithm uses individuals of the current generation to create the new population with the new individuals. The algorithm performs the following steps to create the new population:
  - punctuates each member of the current population by calculating its fitness value;
  - selects members, called parents, based on the best skills;
  - some individuals of the present population are chosen as elite and pass to the next population;
  - parents produce children. Children are produced in two ways: by making random changes (mutation) or by combining parents' vectors (crossover),
  - the current population is replaced by the new one (which has children produced);
- The algorithm ends when some stop criterion is reached.

In this work, parameters are estimated for both charging and discharging cycles. In this section the parameters obtained with the iterative nonlinear optimization method INLOM, presented by Freitas et al. (2015), will be used to estimate the value of the time constant. Four parameters were estimated for charging and four for discharging, in order to minimize

$$T_N = \frac{1}{N}\sum_{t_1}^{t_2}[v(t) - \hat{v}(t, \theta_N)]^2 \quad (6)$$

$$\hat{\theta}_N = argmin T_N \quad (7)$$

$$\hat{\theta}_N = [\hat{E}_0^d, \hat{K}_d, \hat{A}_d, \hat{B}_d, \hat{E}_0^c, \hat{K}_c, \hat{A}_c, \hat{B}_c] \quad (8)$$

$$\hat{\theta}_N(i)^l < \hat{\theta}_N(i) < \hat{\theta}_N(i)^u, i = 1, 2, 3, ..., 8 \quad (9)$$

where T_N is the objective function, $\hat{v}(t, \theta_N)$ is an estimate of the measured voltage at the terminals of the battery calculated from an estimate based on the genetic algorithm and $\hat{\theta}_N(i)^l$ and $\hat{\theta}_N(i)^u$ are, respectively, the lower and upper limits of $\hat{\theta}_N(i)$. These limits are based on the work of Bindner, Cronin & Lundsager (2005). The parameters obtained with the INLOM are shown in Table 1.

Table 1: Values estimated by method INLOM.

Parameter	INLOM
E_0^d	12.14
K_d	0.0115
A_d	3.1125
B_d	1.0701
E_0^c	12.9830
K_c	0.0212
A_c	5.29
B_c	5.0154

The indices/exponents c and d represent, respectively, charge and discharge of the battery. All units of each of the estimated parameters are shown in Table 1 and can be seen in Freitas et al. (2015).

5 Results and discussion

In the simulations, a maximum of 3000 generations in the genetic algorithm was used. Equations 1 and 2, expanded in the exponential term and in the filtered filter term with the data on Table 1 (TREMBLAY; DESSAINT, 2009), are given by:

$$v_{est}^d = E_0^d - 0.00333i - K_d\frac{Q}{Q-i_T}(i_F + \frac{\Delta t(i-i_F)}{\hat{\tau}} + i_T) + \frac{e + A_d B_d u \mid i \mid \Delta t}{1 + B_d \mid i \mid \Delta t} \tag{10}$$

when the battery is being discharged and

$$v_{est}^c = E_0^c - 0.00333i - K_c\frac{Q}{i_T + 0.1Q}(\frac{\Delta t(i-i_F)}{\hat{\tau}} + i_T + i_F) - \frac{K_c Q i_T}{Q - i_T} + \frac{e + A_c B_c u \mid i \mid \Delta t}{1 + B_c \mid i \mid \Delta t} \tag{11}$$

when the battery is being charged.

For the estimation and validation of the voltage, two intervals were defined, as shown in Figure 2. The interval for the estimation of the parameters goes from the initial point of the graph to the point indicated by X (end of the first discharge). After that, a complete charge in the battery is realized, between the points X and Y, of Figure 2. The validation interval used is from point Y until the end of the simulation (at 65000 s).

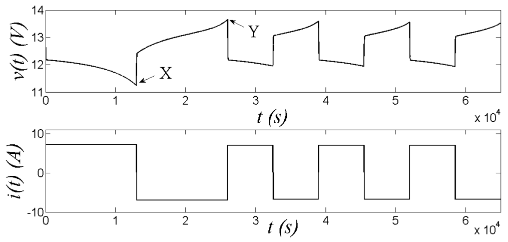

Figure 2: Voltage (top) of the simulation model for a charging and discharging cycles. The current is represented in the inner figure. Charge and discharge are simulated by controlled voltage and current sources.

With the current profile shown in Figure 2, the voltage of the battery model and the estimated voltage of the battery are shown in Figure 3.

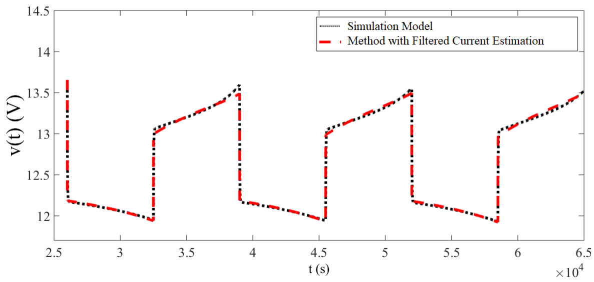

Figure 3: Comparison between lead-acid battery model voltage and estimated battery voltage.

The genetic algorithm was applied in the voltage graph of Figure 3. After the estimation, a value of 44.69 s was found for the time constant of this battery, with a mean square error of 0.002265 V^2 between the estimated voltage and the voltage of the battery model.

6 Conclusion

In this work, a genetic algorithm was used to estimate the value of the time constant of the current filter, present in both the discharge and the load curve. The equations and initial values of the parameters to be estimated were presented. A value of the time constant of 44.69 s different from the fixed value of 30 s indicated in the model of Tremblay & Dessaint (2009) was obtained. A fixed value of this time constant does not represent a class of batteries, such as lead-acid batteries, since batteries of the same lot undergo unequal degradation processes. Thus, the value must be calculated and/or estimated to better represent the parameter and the battery.

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