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An enhanced dynamic model of battery using genetic algorithm suitable for photovoltaic applications

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HIGHLIGHTS

- We proposed a developed dynamic battery model suitable for photovoltaic systems.
- We used genetic algorithm optimization method to find parameters that gives minimized error.
- The validation was carried out with real measurements from stand-alone photovoltaic string.

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ABSTRACT

Modeling of batteries in photovoltaic systems has been a major issue related to the random dynamic regime imposed by the changes of solar irradiation and ambient temperature added to the complexity of battery electrochemical and electrical behaviors. However, various approaches have been proposed to model the battery behavior by predicting from detailed electrochemical, electrical or analytical models to high-level stochastic models. In this paper, an improvement of dynamic electrical battery model is proposed by automatic parameter extraction using genetic algorithm in order to give usefulness and future implementation for practical application. It is highlighted that the enhancement of 21 values of the parameters of CEIMAT model presents a good agreement with real measurements for different modes like charge or discharge and various conditions.

1. Introduction

In Photovoltaic Systems (PVS), particularly in stand-alone systems, the Battery remains one of the most important components for energy storage. In addition to its complexity due to the electrochemical behavior, the Battery in PVS is subject to dynamic regime resulting from continuous change in irradiation and temperature. Therefore, the battery is considered as a major problem in PVS and it has been interested in by several researches in order to achieve a deep comprehension of its interaction.

To obtain a best prediction, which gives a good agreement with real Battery behavior, it is necessary to establish accurate battery model. Several models have been proposed in the literature based on the electrical approach [1–12] and other different approaches like electrochemical, analytical and stochastic models [13–16]. The electrical approach allows us to have a profound comprehension for behavior analysis.

Based on Thevenin battery model, Salameh et al. [1] developed a mathematical model by addition of nonlinear components. Another appropriate model for PVS has been proposed by Copetti et al. [2,17]. This model presents a good dynamic performance, but its main disadvantage is that a large number of its parameters are considered as constants, which make this model not accurate with any type of batteries. In the same approach, Ceraolo [3] introduced a development of Thevenin model by addition of linear component of *n* order. The validation of this model with static current for different batteries presented a good agreement with the real measurement [4]. Later on, an important contribution was proposed by Guasch and Silvestre [5]. It was an improvement of Copetti model by automatic extraction of 11 parameters using Levenberg–Marquardt algorithm. Moreover, D. Guasch introduced also the factor of the battery's state of health in this model. This factor is able to predict the degradation of the battery capacity and the increase of self-discharge current in the long time.

Also from the electrical approach, Illanes et al. [6], introduced in the simulation of stand-alone PVS a modification of CIEMAT model

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by addition of linear components in the Battery equivalent circuit without enhancement of model parameters. Based on equivalent circuit, Waag and Sauer [7] gives an online prediction of Battery state of charge and capacity from the open circuit Voltage after relaxation time. The validation of this model has been given in static mode. In another prediction of the energy stored in the Battery for electric vehicle applications, Liu et al. [8] propose a predictive–adaptive model from the electrical equivalent circuit. Real validation of this prediction gives a good agreement with the measurements. Fares et al. [9], a dynamic model based on equivalent circuit taking open circuit Battery Voltage that varies as function battery state of charge, and constant Battery internal resistance.

In another enhancement of the Thevenin model, Juang et al. [10] replaced the linear components of the model by non-linear Butler–Volmer equations with addition of Kalman filter for identification of model's parameters.

Although several approaches of battery modeling have been proposed in literature as some of them mentioned previously, it still remains insufficient to response to the requirements posed in the PVS, precisely, in stand-alone systems suggested for the simulation or the control charge. In addition, these models have not been validated in dynamic working. In this paper we proposed a development of CIEMAT Model [2] by the amelioration of 21 parameters that have been given as constants in the former models to make it more accurate, followed by a real dynamic validation with measurements of current and temperature.

The model proposed in this paper takes into account all phenomena of Battery behavior according to the current and temperature variation, and presents a good performance to represent dynamic and complex battery operation for PVS. Thereby, an improvement of this model in real condition is suggested using the automatic parameter extraction. In order to obtain adequate parameters that give the best matching between measured and simulated output battery voltage, it is required to introduce a novel method that meets the complexity of this model. For this reason, we propose a minimization of the cost function, which represents a mean error value between the evolution of measured and simulated battery voltage using a genetic algorithm strategy. This algorithm is an inspiration of biological genetic process to find approximate solutions for mathematical problem. It is a stochastic search technique based on iteration. As in the natural concept, the chromosome is the information holder, which represents the genes that the child can take from his parents, wherever the genes represent the variables of the mathematical function. This algorithm generates a population in random manner of chromosomes. Each chromosome is a vector of the optimization problem solution. The chromosomes are different from each other through their genes. Then, chromosomes are randomly selected from the current population, and are used as parents. These parents are then reproduced to generate the new children in crossover and mutation process [18–26]. The Genetic algorithm can be a suitable approach for battery parameter extraction because of the complexity of this model and the large number of its parameters. The proposed improvement of the battery model gives a more accurate behavior prediction, which is suitable for any type of Lead–acid battery and for several dynamics applications. In addition, the model proposed is helpful for the implementation in embedded systems for a real application. Moreover, this algorithm written can be implemented for online parameters extraction.

2. Lead acid battery modeling

The equivalent electrical circuit of a lead acid battery is illustrated in Fig. 1 [2,5,17]. The battery is represented by an open-circuit voltage V_{oc}, which models the electromotive force resulting from electrochemical activities of the solution and an internal resistance R_b that represent all losses during charge/discharge process.

The voltage at the output terminals can be expressed by the following expression:

$$V_{bat} = V_{oc} \pm I \cdot R_b \tag{1}$$

where I is the charge/discharge current. This current is positive during charge process and negative during discharge process.

It is well known that terminal voltage of battery varies according to the working zone (charge/discharge), the state of charge SOC and strongly according to the temperature T. On the other hand, internal resistance has a complex behavior and its value depends on some operating points of the battery [2,5,17,27]. Thus, Copetti et al. have introduced an empirical relationship as given in Eq. (2), which express internal resistance as a nonlinear function of charge/discharge current I, state of charge SOC, and operating temperature T [2,17].

$$R_b = \left(\frac{P_1}{1+I(t)^{P_2}} + \frac{P_3}{(1-\mathrm{SOC}(t))^{P_4}} + P_5\right)\left(1-\alpha_T(T-T_{ref})\right) \tag{2}$$

In where P_1 to P_5 and α_T are empirical parameters to be identified.

2.1. Battery state of charge

The state of charge is an indicator of the remaining charge in terms of percentage relative to the battery capacity [2,13,28,29]. It's obtained by the addition of incoming and outgoing amperes from and to the battery relative to its instantaneous capacity. Time evolution of both state of charge and actual capacity are expressed by Eqs. (3) and (4) [5]:

$$\mathrm{SOC}(t) = \mathrm{SOC}_0 + \frac{1}{C(t)}\int_0^t \eta_c(t)I(t)\partial t \tag{3}$$

$$C(t) = \frac{C_{nominal}\cdot C_{tcoef}}{1+A_{cap}\left(\frac{|I(t)|}{I_{nominal}}\right)^{B_{cap}}}\left(1+\alpha_c\Delta T+\beta_c\Delta T^2\right) \tag{4}$$

$$I_{nominal} = \frac{C_{nominal}}{n} \tag{5}$$

$C(t)$ is the instantaneous capacity, η_c is the Coulomb efficiency and $I(t)$ is the instantaneous charge/discharge current of the battery. C_{tcoef}, A_{cap}, B_{cap}, α_c and β_c are the empirical parameters to be identified. $C_{nominal}$ and $I_{nominal}$ are nominal capacity and nominal current respectively taken for 10 h [30].

2.2. Operating zones

Battery voltage terminals exhibit different behavior depending on its operating mode (charge or discharge mode). In charge mode, there are three operating zones: charge zone, overcharge zone and saturation zone. While in discharge mode of operation, the output voltage transit through transition zone, overdischarge zone and exhaustion zone respectively [2,5,17,28,29]. Time evolution of

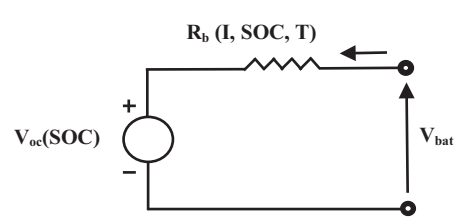

Fig. 1. Equivalent circuit for the battery.