Parameter Estimation of Valve Regulated Lead Acid Batteries Using Metaheuristic Evolutionary Algorithm

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***Abstract*— This paper investigates the use of a metaheuristic evolutionary algorithm. The algorithm, known as Bird Mating Optimizer (BMO), allows fault diagnosis and state-of-health estimation by comparing the battery parameters with the values for a brand new battery, in real time, which in turn allows the battery management system (BMS) to improve the energy management and eventually the lifetime of the battery. In this study, the equivalent-circuit model (ECM) parameters of a lead-acid battery are extracted from its voltage response using the BMO algorithm. The accuracy of the BMO method is then compared to traditional Least Square (LS) algorithm. The BMO extracted parameters showed close fit to the experimental data.**

Keywords- Battery Equivalent Circuit Model (ECM); Evolutionary Algorithms; Impedance Spectrum; Battery Modelling.

I. INTRODUCTION

Batteries are the core energy storage component in a range of consumer, industrial and power applications. Lead-acid batteries are a popular choice for most applications due to their low initial cost and availability. Over the course of its lifetime, batteries inevitably undergo certain degradation mechanisms, some of which could be accelerated when subjected to extreme operating conditions [1]. Some of the extensively studied ageing mechanisms affecting Valve-regulated lead-acid (VRLA) batteries include electrolyte stratification, hard sulfation and corrosion [2-4]. These mechanisms cause significant changes in battery chemical composition and result in development of faults which if remain undetected can lead to premature failure and irreversible damage. Hence, it is imperative that any fault occurring in the battery is immediately detected and accurately diagnosed for improved performance and service life.

Model-based fault diagnosis is widely used for several industrial applications involving batteries [5, 6]. An accurate fault diagnosis is heavily dependent on an accurate mathematical model that can effectively capture the system behavior and underlying characteristics. Depending on the type of application, a variety of batteries modeling tools have been implemented. The main approaches to battery modeling include chemical modeling [7], computational intelligence based modeling [8] and equivalent circuit modeling [9, 10]. For a variety of real-time applications, ECM is best suited for battery health and fault analysis due to its simple formulation and less computational power demand [11]. Faults developing inside the battery can cause significant variations in each of the ECM parameters. Hence parameter estimation and monitoring its variation serves as useful tool in determining these faults which could sometimes go undetected by the BMS [12].

II. MATHEMATICAL MODEL FOR BATTERY DYNAMICS

A simple model can be developed using the first-order Randle circuit shown in Fig. 1, commonly used to represent battery dynamics. The circuit parameters R_O models the ohmic resistance of the electrodes and electrolyte, R_1 models the charge transfer resistance which is the resistance encountered upon charge transfer from electrode to the electrolyte and C_1 models the double layer capacitance.

The Kirchhoff's Voltage law applied to the circuit yields

$$E_O - IR_O - V_C - V_t = 0 \tag{1}$$

E_O is the open circuit voltage and V_t is the battery terminal voltage at load current I. The Kirchhoff's Current law gives the capacitor voltage V_C

$$\dot{V}_C = \frac{1}{C_1}I - \frac{1}{R_1C_1}V_C \tag{2}$$

which is a first order differential equation with solution being

$$V_C(t) = V_C(0)e^{-\frac{t}{R_1C_1}} + IR_1(1 - e^{-\frac{t}{R_1C_1}}) \tag{3}$$

Combining this to the KVL equation gives the battery terminal voltage

$$V_t(t) = E_O - I(R_1 + R_0) + \left(IR_1 - V_C(0)\right)e^{-\frac{t}{R_1C_1}} \tag{4}$$

Where $V_C(0) = E_O - IR_O - V_{to}$ (5)

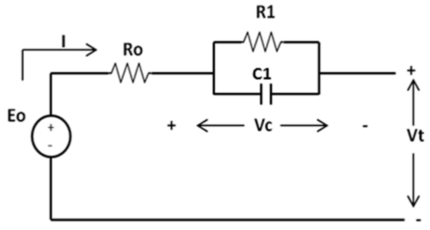


Fig. 1: Typical equivalent circuit model for Battery

During battery discharge, the influence of each parameter on the battery terminal voltage as described by the mathematical expression (4) is shown in Fig. 2.

A. ECM Parameter Estimation Techniques

The most commonly used numerical optimization algorithm for battery ECM estimation is the Non-linear Least Square (NLLS) method and it's variants like the Complex Non-linear Least Square (CNLS) method [16, 17]. The core of these methods is a minimization function of the squared error between estimated and measured data. The response of the battery is measured at certain conditions (state of charge SOC and temperature) and is then fitted to the ECM using one of these methods. In this paper, we investigate a more recently developed evolutionary algorithm called the Bird Mating Optimizer (BMO) and its application for battery modeling.

BMO is a heuristic technique that is based on different birds breeding strategies observed in the nature. For certain applications, the algorithm exhibited superior results compared to other similar metaheuristic algorithms [18, 19]. BMO has managed to establish a reasonable balance between the exploration and exploitation during the search space, which led to avoid unanticipated premature convergence to reach the global solution successfully. BMO evaluates all battery parameters simultaneously to avoid the impact of SOC and temperature variation on the parameters. In this paper the battery ECM parameters for a lead acid battery type are extracted from its voltage response measurements to an input current profile using the BMO algorithm. The error and goodness of fit of the simulated model are also evaluated.

B. Optimization fitness function

The target in this algorithm is to minimize the fitness function for number of generations (i.e. iterations) with respect to the parameters defined ranges. The fitness function is the value of homogeneous form of (4) as follows in (6):

$$F(V_t, t, \chi) = V_t(t) - \left[E_O - I(R_1 + R_0) + \left(IR_1 - V_C(0)\right)e^{-\frac{t}{R_1C_1}}\right] \quad (6)$$

Then the RMSE is:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(F(V_t, t, \chi)\right)^2} \quad (7)$$

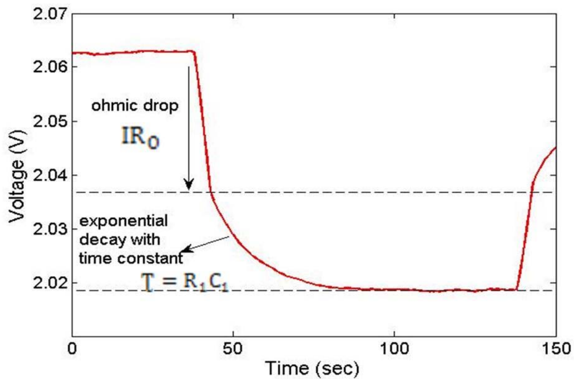


Fig. 2: Battery voltage response dynamics during discharge, showing initial ohmic drop and subsequent exponential decay

Where F is the value of the fitness function as the homogeneous form of (4), χ is a vector of the three-parameters of the battery ECM $\chi = [R_O, R_1, C_1]$.

C. Simplified bird mating optimizer

The first step of the algorithm is initialization of a society with random birds having genes encoded as three parameters. Next, the birds of the society are ranked according to the fitness value from minimum to maximum. Then, these birds are classified into three different types according to predefined rank ranges, and the breeding process is performed accordingly. Finally the birds of generation (i) are compared with the new generation (i+1) by means of their fitness. The brood with higher fitness (i.e. lower RMSE) is added to the society and the adjacent bird from the previous generation is discarded, otherwise, the bird with better fitness will stay in the society. The algorithm will repeat in iterations until the stopping criterion is met.

III. Experimental System Setup

The tested battery is an EnerSys Cyclon lead-acid cell with a rated capacity of 2.5Ah shown in Fig. 3. The battery is discharged using three input current pulses of 0.1, 0.5 and 1 A magnitude of fixed width (10-second duration) and the corresponding terminal voltage response was measured. The voltage response to an input current pulse of 0.5A is shown in Fig. 4. EZSTAT-Pro battery test device from Nuvant Systems Inc. was used for testing. The measured voltage response is then fit using LS and BMO algorithm to estimate the ECM parameters. Both the alogrithms were constrained to run for 100 iterations. The parameters to be estimated were initialised before the start of the algorithm, and boundary conditions were not specified for any of them. The accuracy of the two algorithms is evaluated in the next section. The BMO MATLAB code was developed at the UAE University Renewable Energy Lab.

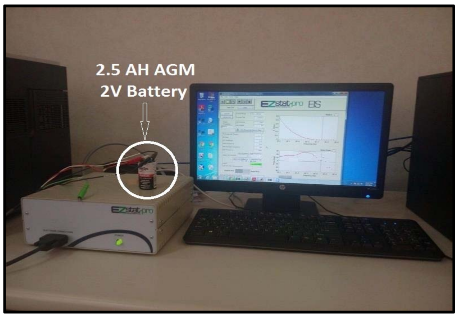
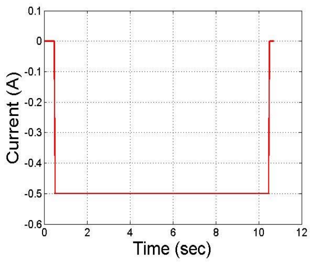


Fig. 3: Experimental test bench showing the testing device and lead acid battery

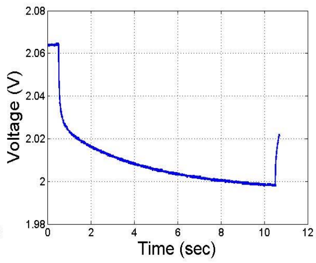
IV. Results and Discussion

The modeled voltage responses are shown in Fig. 5. The parameters extracted using BMO are listed in Table I and corresponding RMSE values are plotted in Fig. 6(b). The LS algorithm converged at iterations below 100; however the estimated parameters were unrealistic and produced worse fit compared to BMO. In order for LS method to converge accurately, along with parameter initialization, the setting of boundary constraints for each parameter was necessary. In the case of BMO, at the end of 100 iterations, the estimated parameters are highly accurate and fall within the expected range defined in Table II. Also, BMO algorithm has a clear advantage over LS as it did not require pre-specified parameter boundary constraints. The deviation of modeled response from the measured data using both algorithms is shown in Fig. 6(a).

It should be noted that each of these parameters could greatly vary depending on SOC and temperature. In this work, the testing was carried out at constant SOC and temperature. To account for the variations in operating conditions and SOC, complex modeling would be required.

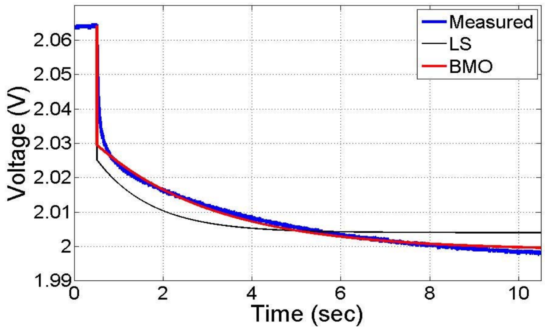


(a)

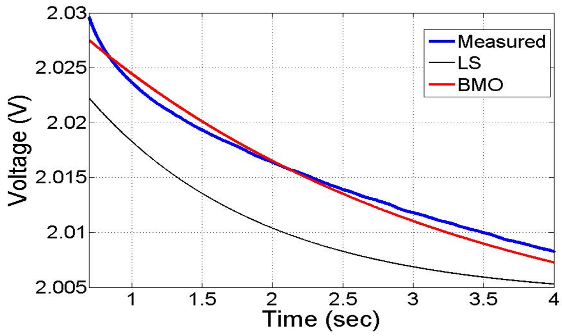


(b)

Fig. 4: (a) Input discharge current pulse of 0.5A for 10 seconds (b) corresponding measured voltage response to the profile in (a)

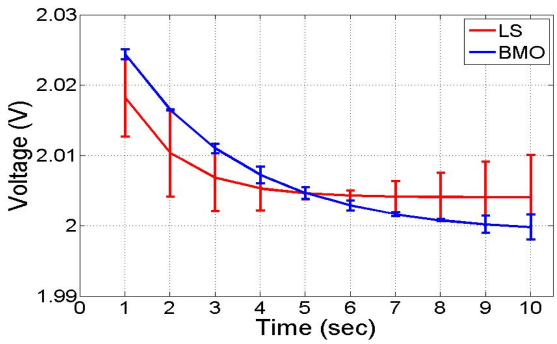


(a)

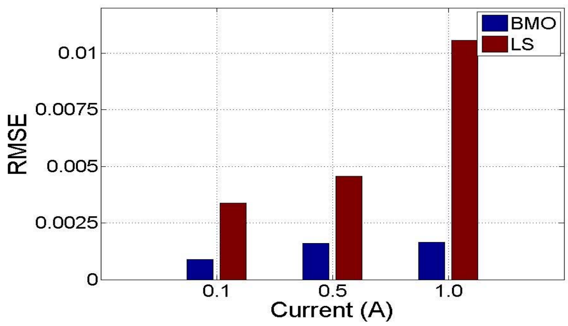


(b)

Fig. 5: (a) Comparison of the the modeled voltage response to the measured data for 0.5A current pulse, (b) zoomed-in view of (a)



(a)



(b)

Fig. 6: (a) Error comparison of both algorithms from the experimental data after every second during the 0.5A discharge curve, (b) Comparison of accuracy between BMO and LS for the three discharge current pulses.

TABLE I: ESTIMATED PAPAMETERS USING BMO ALGORITHM

Current Pulse	*ECM PARAMETERS*		
	$R_0(m\Omega)$	$R_1(m\Omega)$	$C_1\,(F)$
0.1A	*9.92*	*218.60*	*15.41*
0.5A	*10.75*	*119.79*	*23.38*
1 A	*9.99*	*79.97*	*22.96*

Table II shows the maximum and minimum ranges for the ECM parameters, which were defined by studying the impedance spectrum characteristics of the cell shown in Fig. 7. Analytically, the value of R_0 can be approximated as the real part of the impedance at the point on the impedance spectrum with zero imaginary part. The diameter of the semicircle gives the value of R_1 [13, 14, 15].

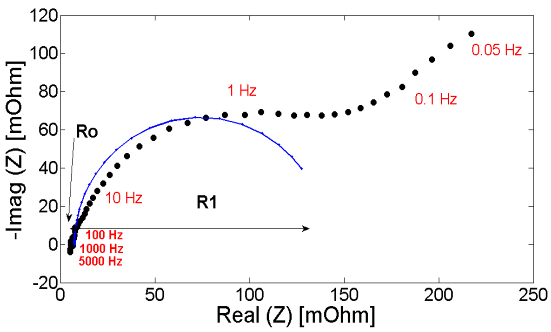


Fig. 7: Measured AC Impedance Spectrum for test battery

TABLE II: BATTERY PARAMETER RANGES

ECM Parameters	*Value from spectrum*	*Range*
$R_0(m\Omega)$	*7.5*	$\|7.5 \pm 20\|$
$R_1(m\Omega)$	*133.2*	$\|133.2 \pm 100\|$

V. CONCLUSION

This paper presented and evaluated the application of the BMO algorithm for estimating the ECM parameters for a lead acid battery. Parameter monitoring must be considered as an essential task of the BMS, as the variation in parameters is likely an indication of a fault developing in the battery. Accurate estimation of battery parameters is vital to assess battery state-of health and avoid premature failure. The BMO algorithm showed superior results for modeling battery dynamics compared to the commonly used LS algorithm.

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