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State of charge estimation of lead acid battery using a kalman filter

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***Abstract*—For saving energy, lead acid battery plays an important role in photovoltaic system. Battery state of charge estimation is a key function of battery management system due to the requirement of ensuring optimum operation and safety. Therefore, for achieving a fiable operation, it is necessary to develop an accurate model for the estimation of the state of charge (SOC) of battery. In this paper, a RC equivalent circuit model has been presented. A state representation of battery has been developed. A kalman filter has been proposed to determine the SOC. The model of battery and the recursive algorithm have been implemented on Matlab-Simulink and Simpower softwares. Recovered simulation results have been compared by an experimental works applied to a lead acid battery 12V,7Ah. Obtained results show an acceptable correspondence with the experimental test. The kalman filter approach can be an useful tool for researchers to imitate the real behaviour of the battery and to ensure the accurate estimation of SOC.**

***Index Terms*—Lead acid battery, RC model, parameter identification, Kalman Filter, Estimation of state of charge (SOC).**

I. Introduction

Nowadays, the use of the photovoltaic system, as an electric source of energy, has become widespread. But, the major drawbacks of this renewable source is its intermittence.

For that, battery application in energy saving has emerged. However, technological battery development is unable to guarantee all the requirements being needed by the application.

Therefore, to safeguard the good performance of the battery pack and to extend its life, it is necessary to make a good control, protection, and management for batteries. In fact, a battery management system must fulfil many tasks such as thermal management, battery state estimation, cell balancing, and parametric battery estimation.

From all of them, the state of charge estimation is a fundamental parameter for any application using battery.

A good estimation is one of the most challenging that ensures a precise knowledge of consumption, an effective functioning of this device, prevents it from over discharging and over charging, and guarantee the safety of the battery so the security for all the system.

The state of charge is defined as the ratio of the actual battery capacity to the rated capacity. However, because of its complicated nonlinear electrochemical process and time variable system, the SOC can not be directly measured. It should be deduced with an indirect ways.

In order to estimate accurately the remaining capacity of the battery, several methods have been proposed such as Coulomb Counting, Open Circuit Voltage, Fuzzy Logic, and Kalman Filter [1], [2], [3], [4], [5], [6], [7], [8], [9].

The Coulomb Counting estimation is usually used thanks to its simplicity. But, this technique have some limitations because of the accumulated measurement errors due to noise and the necessity of knowledge of initial value [10].

The Open Circuit Voltage method is also frequently trained. Unfortunately, it is difficult to measure the OCV in real time.

The Fuzzy Logic is a numerical method that can estimate the SOC, but it is limited because the estimated values are very sensitive to disturbances. [11].

The kalman filter is an efficient recursive technique that can be used to accurately estimate the state of charge.

In the literature, many work have been done concerning the use of KF and EKF.

In [12], a kalman filter with the open circuit voltage have been applied to estimate the SOC of lithium battery for Aircraft energy manegement

In [2], An adaptive extented kalman filter algorithm and an on line open circuit voltage approach have been built to evaluate the state of charge for lithium battery with a maximum error less than 2%.

[3], [4], [5] show how can a battery parameter and a state of charge can be determined from an algorithm based on kalman filter.

An extented kalman filter for extraction of SOC and a system of Fick's diffusion equation have been described to modulate the battery and to estimate the SOC in [1].

This paper shows how can the open circuit voltage be determined from the parameter of the RC equivalent circuit model using a kalman filter in order to estimate the state of charge of a lead acid battery. For it, this work is structured as follows. Section II describes the proposed equivalent model of battery, its state representation and reveals the method of identification of internal parameter. Section III develops the recursive algorithm of kalman filter. Experimental work has been established in section IV. And finally, section V summarizes results and the main conclusion.

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II. Lead acid battery model

Developing an equivalent circuit for the battery is necessary to describe its real electrical behaviour.

Various electric circuit have been proposed for the lead acid battery. But, in order to obtain an accurate results, a convenient and good battery model is crucial in the implementation of kalman filter .

A. Electrical model

The RC electrical equivalent circuit used is shown in Fig1. The model consists of an R_t terminal resistance which is in series with two parallel branches: The first branch is composed by a capacitor C_1 that describes the storage capacity of the battery. The second includes a capacitor C_2 which reflects the effects of diffusion in the battery. Each capacity is in series with a resistance respectively R_1, and R_2 [12],[13],[14].

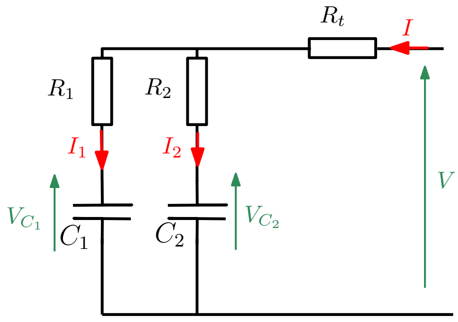

Fig. 1. Electric Equivalent Circuit of the lead acid battery

The battery voltage V(t) is expressed according to the following equations:

$$V(t) = V_{c2} + R_2 I_2 + R_t I \tag{1}$$

$$V(t) = V_{c1} + R_1 I_1 + R_t I \tag{2}$$

Equations 1 and 2 lead to:

$$R_1 I_1 = V_{c2} - V_{c1} + R_2 I_2 \tag{3}$$

Since

$$I_2 = I - I_1 \tag{4}$$

And

$$I_1 = \dot{V}_{c1} C_1 \tag{5}$$

Equation (3)becomes as follows:

$$\dot{V}_{c1} = \frac{R_2 I}{C_1(R_1+R_2)} + \frac{V_{c2}}{C_1(R_1+R_2)} - \frac{V_{c1}}{C_1(R_1+R_2)} \tag{6}$$

Similarly:

$$\dot{V}_{c2} = \frac{R_1 I}{C_2(R_1+R_2)} - \frac{V_{c2}}{C_2(R_1+R_2)} + \frac{V_{c1}}{C_2(R_1+R_2)} \tag{7}$$

The terminal voltage of the battery can be expressed as

$$V = \left[R_T + \frac{R_1 R_2}{(R_1+R_2)}\right] I + \left[\frac{R_2}{(R_1+R_2)} \quad \frac{R_1}{(R_1+R_2)}\right] \begin{bmatrix} V_{c1} \\ V_{c2} \end{bmatrix} \tag{8}$$

The derivative of terminal voltage of the battery can be expressed as

$$\begin{aligned} \dot{V} \;=\; & \left[\frac{-R_2}{C_1} + \frac{R_1}{C_2}\right] \frac{1}{(R_1+R_2)^2} V_{C1} \\ & + \left[\frac{R_2}{C_1} - \frac{R_1}{C_2}\right] \frac{1}{(R_1+R_2)^2} V_{c2} \\ & + \left[\frac{R_1^2}{C_2} + \frac{R_2^2}{C_1}\right] \frac{1}{(R_1+R_2)^2} I \end{aligned} \tag{9}$$

B. Identification of model parameter

During lead acid battery modeling process, identification of model parameters is a necessary step to improve modeling quality. The unknown parameters have been determined from an experimental test.

For the battery resistances R_1 and R_2, there are assumed equivalent and equal to 80% of the internal resistance of the battery R_i.

$$R_1 = R_2 = 0.8 R_i \tag{10}$$

The terminal resistance R_t can be calculated as follow:

$$R_t = R_i - \frac{R_1 R_2}{(R_1+R_2)} \tag{11}$$

The capacity C_1 is calculated from the energy E_c stored within the battery.

E_c is expressed as follow:

$$E_c = \frac{1}{2} C_1 (V^2_{(100\% soc)} - V^2_{(20\% soc)}) \tag{12}$$

$$E_c = 3600 * C_n * V_{(20\% soc)} \tag{13}$$

From equations (10) and (11), C_1 can be deduced:

$$C_1 = \frac{E_c}{1/2(V^2_{(100\% soc)} - V^2_{(20\% soc)})} \tag{14}$$

C_n is the nominal capacity of the battery. In general, C_n is considered equal to C_{20}. C_{20} is the ability of the battery to unload during 20 hours.

Whereas for capacity C_2, it is determined from the following equation:

$$C_2 = \frac{\tau}{(R_1+R_2)} \tag{15}$$

- τ (s): constant time

τ is obtained by discharging the battery with an high current for a small period.

$$\tau = -\Delta t * log(1 - \frac{V_4 - V_3}{V_1 - V_3}) \tag{16}$$

Fig 2 shows the voltage of the battery for a rapid discharge.

TABLE I
Parameters used of the battery model

Parameter	$V_{100\% soc}$	$V_{20\% soc}$	C_{20}	R_i	Δt
Value	12.64V	10.86V	7Ah	0.022Ω	1.5s

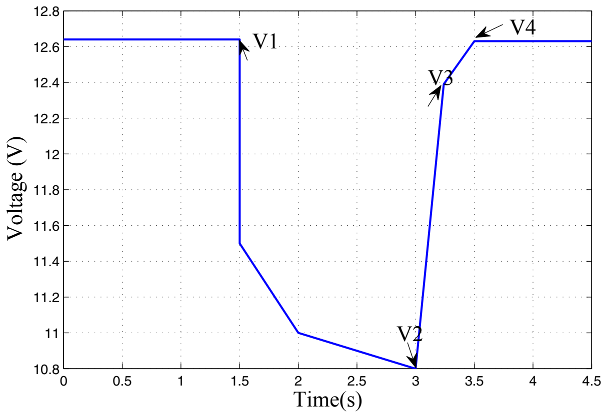

Fig. 2. battery discharge curve

The identified parameters of the lead acid battery are summarized in Table I.

TABLE II
IDENTIFIED PARAMETERS OF THE BATTERY MODEL

Parameter	C_1	C_2	R_1	R_2	R_t
Value	17820F	137.1705F	0.0176Ω	0.0176Ω	0.0132Ω

C. State space model

The state space model can be represented as follow:

$$\dot{X}(t) = AX(t) + BI(t) \tag{17}$$

$$V(t) = CX(t) + DI(t) \tag{18}$$

$$X(t) = \begin{bmatrix} V_{c1} \\ V_{c2} \\ V \end{bmatrix} \tag{19}$$

$$\begin{bmatrix} \dot{V}_{c1} \\ \dot{V}_{c2} \\ \dot{V} \end{bmatrix} = \begin{bmatrix} \frac{-1}{C_1(R_1+R_2)} & \frac{1}{C_1(R_1+R_2)} & 0 \\ \frac{1}{C_2(R_1+R_2)} & \frac{-1}{C_2(R_1+R_2)} & 0 \\ A_1 & 0 & A_3 \end{bmatrix} \begin{bmatrix} V_{c1} \\ V_{c2} \\ V \end{bmatrix} + \begin{bmatrix} \frac{R_2}{C_1(R_1+R_2)} \\ \frac{R_1}{C_2(R_1+R_2)} \\ B_3 \end{bmatrix} I \tag{20}$$

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$$A_1 = \frac{-R_2}{C_1(R_1+R_2)^2} + \frac{R_1}{C_2(R_1+R_2)^2} - \frac{R_2^2}{C_1R_1(R_1+R_2)^2} + \frac{R_2}{C_2(R_1+R_2)^2} \tag{21}$$

$$A_3 = \frac{R_2}{C_1R_1(R_1+R_2)} - \frac{1}{C_2(R_1+R_2)} \tag{22}$$

$$B_3 = \frac{R_1^2}{C_2(R_1+R_2)^2} - \frac{R_2R_t}{C_1(R_1+R_2)} + \frac{R_t}{C_2(R_1+R_2)} + \frac{R_2R_1}{C_1(R_1+R_2)^2} \tag{23}$$

III. ESTIMATION OF STATE OF CHARGE OF BATTERY BY KALMAN FILTER

To evaluate the SOC estimation for lead acid battery management system, this section well describes the kalman filter (KF).

This technique guarantees an accurate value of SOC by observing the terminal voltage and current of battery and by minimizing the error between the output of the model and the device. The method of estimation by KF is based on dynamics model using a discrete representation taking into account the input noise and also the measurement noise.

$$x_k = A_d x_{k-1} + B_d u_{k-1} + \omega_{k-1} \tag{24}$$

$$y_k = C_d x_k + D_d u_k + \nu_{k-1} \tag{25}$$

- A_d: State transition matrix [n,n]
- B_d: Control input matrix [n,1]
- C_d: Transformation matrix [1,n]
- D_d: Feedforward matrix [1,1]
- y_k: The output (Voltage battery)
- u_k: the input (discharge current)
- ω_k: Stochastic process noise
- ν_k: Stochastic measurement noise

$$A_d = Id + A * h \tag{26}$$

$$B_d = B * h \tag{27}$$

$$C_d = C \tag{28}$$

$$D_d = D \tag{29}$$

- A, B, C, D: Battery model matrix
- Id: Identity matrix
- h: Sampling period

The ω_k and ν_k are assumed to be uncorrelated white Gaussian random processes with zero mean and covariance matrices.

$$p_\omega \sim N(0, Q) \tag{30}$$

$$p_\nu \sim N(0, R) \tag{31}$$

The architecture of KF is presented in fig 3.

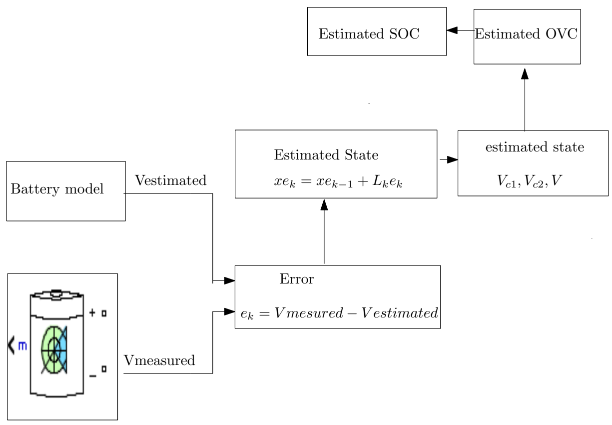

Fig. 3. Implementation of the KF algorithm

Firstly the kF is initialized:

$$x_{\hat{k-1}} = E(x_0); \tag{32}$$

$$p_{k-1} = E[(x_0 - \hat{x_0})(x_0 - \hat{x_0})^T] \tag{33}$$

The state and error covariance update :

$$\hat{x_k^-} = Ax_{\hat{k-1}} + BU_{\hat{k-1}} \tag{34}$$

$$p_k^- = Ap_{\hat{k-1}}A^T + Q \tag{35}$$

The kalman gain:

$$L_k = \frac{p_k^- C^T}{(Cp_k^- C^T + R)} \tag{36}$$

The measurement update:

$$\tilde{y_k} = y_k - (C\hat{x_k^-} + Du_k) \tag{37}$$

The state estimate update

$$\hat{x_k} = \hat{x_k^-} + L_k\tilde{y_k} \tag{38}$$

The output estimated:

$$\hat{y_k} = C\hat{x_k} + DU_k \tag{39}$$

Error covariance measurement update:

$$p_k = (Id - L_k)p_k^- \tag{40}$$

The model of battery and the kalamn filter algorithm have been implemented on Matlab Simulink software.

The covariance matrix:

$$p_0 = \begin{bmatrix} 100 & 0 & 0 \\ 0 & 100 & 0 \\ 0 & 0 & 100 \end{bmatrix} \tag{41}$$

The input covariance matrix:

$$Q = \begin{bmatrix} 10^{-5} & 0 & 0 \\ 0 & 10^{-5} & 0 \\ 0 & 0 & 10^{-5} \end{bmatrix} \tag{42}$$

The measurement covariance matrix:

$$R = 0.005 \tag{43}$$

After estimating the capacitors voltage V_{c1} and V_{c2}, the open circuit voltage VOC can be deduced.

VOC is expressed as follow:

$$V\hat{O}C = \begin{bmatrix} \frac{R_2}{R_1+R_2} & \frac{R_1}{R_1+R_2} \end{bmatrix} \begin{bmatrix} \hat{V_{c1}} \\ \hat{V_{c2}} \end{bmatrix} \tag{44}$$

In addition, The VOC is expressed by [12],[15], [16]:

$$V\hat{O}C = V_e + SOC(V_f - V_e) \tag{45}$$

Consequently, the SOC can be estimated where

- V_f: the fully charged voltage (2.2V)
- V_e: the limit of discharge voltage(1.7V)

IV. Experiemental work

An experimental test has been established, in order to validate the theoretical results. [17].

Fig 4 shows the test bench of discharging and charging 12V/7Ah lead acid battery under real conditions.

The components used are:

- Battery : 12V/7Ah Lead acid battery.
- The current sensor: permits the measurement of the battery current.
- The voltage sensor: allows the measurement of the voltage of terminal battery.
- Variable resistance: lets to change the resistance of the connected load.
- ARDUINO Boards: permits the acquisition of voltage and current data.
- Voltage source 12V: used for loading the battery.

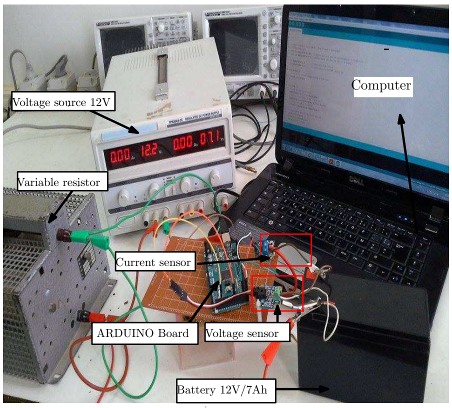

Fig. 4. Experimental test

V. Results

To follow the dynamic characteristics of the battery, a discharge constant current (-1.19A) is applied.

Fig 4 shows the dynamics behaviour of the battery.

Fig 5 presents the evolution of the SOC.

Fig 6 shows the curve of the open circuit voltage.

Firstly, the model has been implemented on simulink matlab without taking into consideration the Kalman filter.

Therefore, as a consequence the discharge characteristic of the battery is linear. Whereas, with the addition of the KF algorithm, the estimated voltage will imitate the real behaviour of the device. The KF track the battery terminal voltage very well.

A good concordance between the measured voltage and estimated values can be deduced from fig 4.

The analysis of these figure 5 and 6 lead to the following comments:

The SOC can be easily estimated from the open circuit voltage. Both the coulomb counting and kalman filter allows an accurate estimation of the SOC. But with the first method, the initial value must be knoun which is not the case for the second.

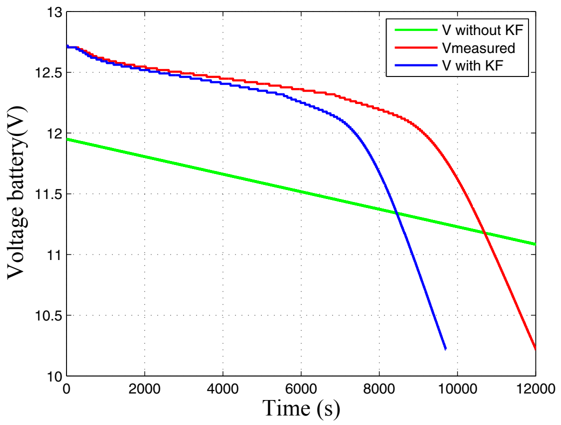

Fig. 5. Behaviour of battery model

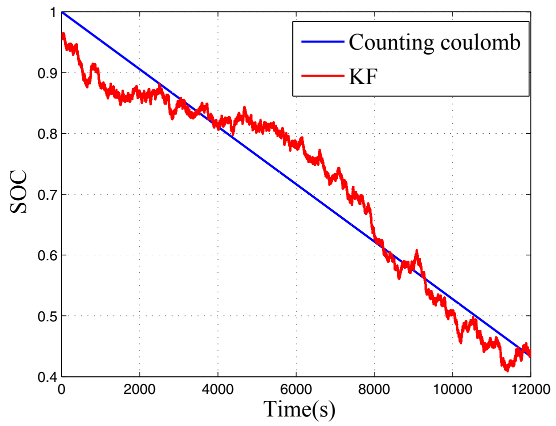

Fig. 6. State of charge estimated

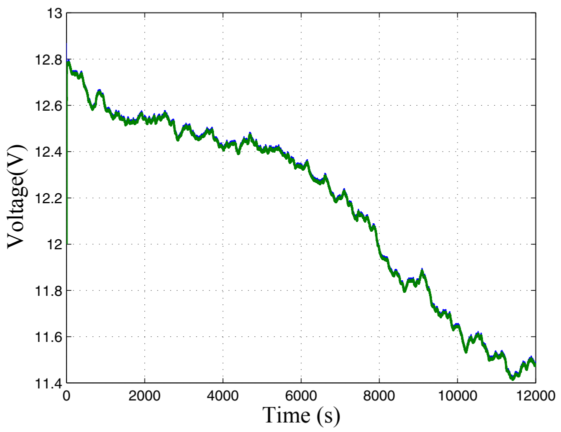

Fig. 7. Open circuit voltage estimated

VI. Conclusion

In this paper, an RC equivalent circuit model of battery lead acid has been developed. The studied model has been built on Matlab-Simulink. An experimental test has been applied on a battery lead acid 12V/7Ah to obtain the discharge characteristic under real condition. Identification of the internal components has been trained. In order to estimate the state of charge of the battery, a Kalman filter is presented. An acceptable correspondence has been developed between the measured and estimated battery voltage. The KF can be an useful tool for imitating the real behaviour of the battery and for obtaining an accurate estimation for the soc.

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