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Embedded State of Charge and State of Health Estimator Based on Kalman Filter for Electric Scooter Battery Management System

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***Abstract*—This article is about a state of charge (SOC) and the state of health (SOH) estimator designed for a battery management system (BMS). It was applied on a 48V lead-acid battery pack of an electrical scooter. A software Kalman based SOC sensor has been developed using a PIC microcontroller, by using a relatively simple battery model, combined with Kalman filter algorithm. The SOC has been estimated online (in real time) and displayed consequently on a low consumption LCD screen.**

***Index Terms*—State of charge (SOC), state of health (SOH), battery, battery management system (BMS), estimation, renewable energy, electrical vehicle.**

I. INTRODUCTION

The batteries are the best known electrical energy storage system for today. Hence, using batteries have become a part of everyday lives and consumer electronic devices. Furthermore, it is an expensive key element of any mobile electrical system (electric and hybrid vehicles, portable electronics) and standalone buildings. So, it is very important for the development of intermittent green energy production and new hybrid and electrical vehicles. However, using batteries in consumer electronic devices requires the association of a Battery Management System (BMS) with every battery pack, to avoid the overcharge and over discharge, to display the available power in the batteries pack, to balance the battery cells, to recharge the battery quickly, by an optimal way.

Over discharge the battery drops its voltage to a critical level which can be damaging for the battery and reduces their time life. However, overcharge a battery not only can decrease the battery time life, but it could be dangerous because of the production of hydrogen, then produce fire, in the case of Lead-acid batteries, and it may cause the explosion of the battery in Lithium-ion batteries case. However, the state of charge (SOC) estimation is the heart of modern BMS. It not only maintains an accurate estimation of the energy remaining in the battery pack, but also can serve as the host's battery data acquisition and management system, protection device, cell balancing system and helps for the state of health (SOH) estimation.

In a previous paper [1], we have validated a battery mathematical model using Extended Kalman Filter on a Lead-acid batteries pack of an electric scooter. A circuit of 15km has been done in the downtown of Amiens city in France. The aim of the experiment is to test the accuracy of our estimator in a realistic environment, in order to design an accurate embedded BMS for the scooter based on Kalman algorithm.

II. THE BATTERY MODEL

In the literature, there exist a variant battery models, less or more complicated. Comparison between two reduced order battery mathematical batteries models are presented in [5] and an electrochemical battery model in [6] and [7], those models remain complicated for the implementation in a microcontroller.

The equivalent electric circuit models are widely used in electrical engineering, because of their relative simplicity and accuracy. Figure 1 presents the Thevenin battery model equivalent circuit.

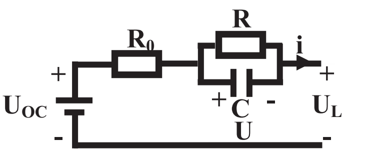

Fig. 1 Electric equivalent circuit battery model

This model is composed of four parts: The internal resistance (R_0), the equivalent capacitance (C), the equivalent resistance (R) and the open circuit voltage (U_{OC}). The equivalent capacitance (C) describes the electrochemical polarization and concentration capacitance and the internal resistance (R) describes the electrochemical polarization and concentration resistance.

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The mathematical equations of the model could be written as follows:

$$i = \frac{U}{R} + C\frac{dU}{dt} \tag{1}$$

$$\dot{U} = \frac{-1}{RC}U + \frac{1}{C}i \tag{2}$$

$$U_L = U_{OC} - U - R_0 i \tag{3}$$

As (i) is the charging/discharging current, (U) is the voltage inside the battery, it could not be measurable, and (U_L) is the battery loaded voltage. Figure1 illustrates the model's diagram in state space form.

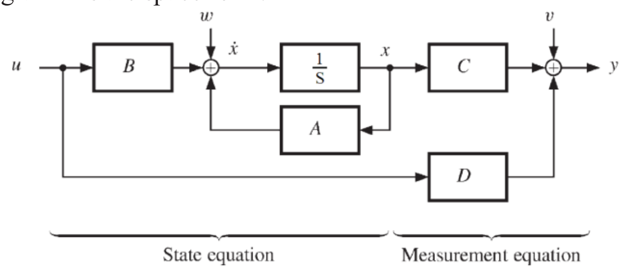

Fig. 2 diagram of the continuous time model in a state space form

Using a sampling method (Euler or zero-order holder) the discrete time model could be calculated and written on the state space form like equations (4) and (5). The state or process equation (4) describes the evolution of the system dynamics; It is used to determine the system's dynamics, stability, controllability and sensitivity against the disturbances. The matrices ($A_k \in R^{nxn}$), ($B_k \in R^{nxp}$), ($C_k \in R^{mxn}$) and ($D_k \in R^{mxp}$) represent the dynamics of the system, they could be constant or variable in the time. The systems vector at time (k) is ($x_k \in R^n$). The deterministic input of the system is ($u_k \in R^p$), is the current crossing our system (the battery). The variable ($w_k \in R^n$) is a stochastic process noise; it models unmeasured input which affects the state of the system. The equation (5) represents the output of the system; it is called the output equation, and used to compute the system's output ($y_k \in R^m$). The variable ($v_k \in R^m$), in the output equation, is the sensor noise; it models the measurement disturbances which affect the output of the system in a memory less way, without affecting the system state.

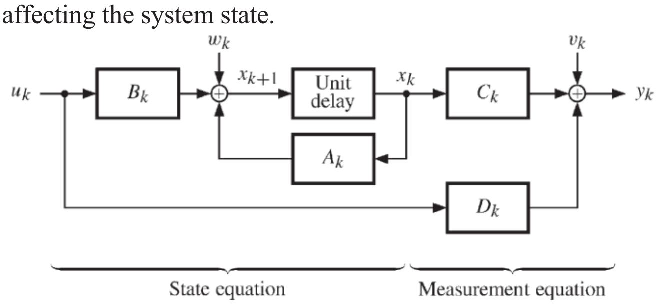

Fig. 3 diagram of the discrete time model in a state space form

$$x_{k+1} = A_k x_k + B_k u_k + w_k \tag{4}$$

$$y_k = C_k x_k + D_k u_k + v_k \tag{5}$$

The battery cell dynamics equations discretized upon a sampling period (by example one second); then, every measurement indexed by an integer value (k).

III. Kalman Filter Algorithm

The Kalman filter could be used to estimate the unmeasured system sate variables (x_k) which includes the model parameters. Then we will be able to estimate the battery's state of charge in real time. Firstly, the extended Kalman filter algorithm (EKF) has been programmed in Matlab to identify the model parameters (R and C) Fig. 4. [1] Then, in this work, Kalman filter will be implemented in a microcontroller in an embedded system circuit to estimate, online, the SOC of the battery of the electrical two wheels vehicle.

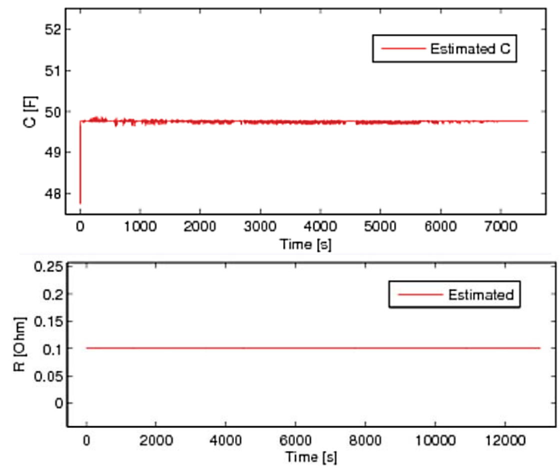

Fig. 4 Estimated internal resistance (R) and capacitance (C)

A. Discrete time Kalman filter algorithm

Before starting, the Kalman filter should be initialized:

- The Kalman filter initialization:

$$\hat{x}_0^+ = E(x_0) \tag{7}$$

$$P_0^+ = E[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T] \tag{8}$$

The Kalman filter equations. They are computed for each time step ($k = 1, 2, 3 \ldots$).

- A priori state estimate update:

$$\hat{x}_k^- = A_{k-1}\hat{x}_{k-1}^- + B_{k-1}u_{k-1} \tag{9}$$

- Error covariance time update:

$$P_k^- = A_{k-1}P_{k+1}^+ A_{k+1}^T + Q_{k-1} \tag{10}$$

- Kalman gain matrix:

$$K_k = P_k^- C_k^T (C_k P_k^- C_k^T + R_{k-1})^{-1} \tag{11}$$

$$K_k = P_k^+ C_k^T R_k^{-1} \tag{12}$$

- A posteriori sate estimate update:

$$\hat{x}_k^+ = \hat{x}_k^- + K_k[y_k - (C_k\hat{x}_k^- + D_k u_k)] \quad (13)$$

- Error covariance measurement update:

$$P_k^+ = (I - K_k C_k)P_k^- \quad (14)$$

The noises (w_k) and (v_k) assumed to be mutually uncorrelated white Gaussian random matrices. [8]

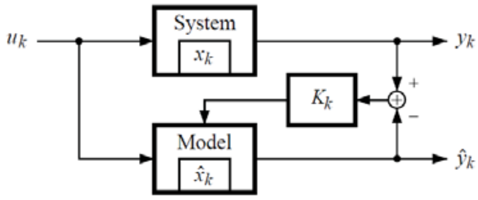

Fig. 5 Kalman algorithm state update diagram

B. *Kalman filter algorithm functioning*

Previous to the beginning of the algorithm of Kalman filter, and before any computing is done; the initialization step should be realized firstly. So, the initial values of the state and the error covariance should be set up as shown in equations (7) and (8). The Kalman filter repeated to be very robust against poor initialization, even with fare initial values; it will converge to the true values as it runs.

Firstly, two different estimates of the state and covariance matrices are computed each sampling interval. The first prior state estimate $\hat{x}_k^-$ is based on the previous estimation of $\hat{x}_{k-1}^+$ which has been computed previously in the precedent iteration, before any measurements information on the system's output.

Secondly, after measuring the output of the system (y_k), the state $\hat{x}_k^+$ is estimated to update (tune up) the first estimation $\hat{x}_k^-$. Hence, the updated estimated state $\hat{x}_k^+$ and covariance P_k^+ incorporate a knowledge on the output of the system, so they are more accurate than x_k^- and P_k^-, and they will be used to display the estimated SOC.

The two major steps of Kalman filter are: prediction (time update), then, correction (measurement update). In the prediction step, Kalman filter predicts the values of the present state $\hat{x}_k^-$, the system's output $\hat{y}_k$ and the covariance error P_k^-, and then it corrects the predicted values using the measurements of the real system output. The expected state value is computed at the next measurement point, by entering the system's input into the system model, assuming that the expected process noise is zero, equations (9) and (10).

Then, the state correction step will update the state value using the real measured system output compared it with the estimated output, equation (13). The output estimation error (term in the square brackets) represents the difference between the measured loaded battery voltage and the estimated value of the battery voltage. The measurement noise, the incorrect state x_k^- estimation and the inaccuracy of the battery model could lead this subtraction to be different to zero. This new information on the measurement called the innovation process. It will be multiplied by the Kalman gain matrix (K) calculated by equation (11) and (12). Fig. 5.

Finally, the step of the covariance correction is computed using equation (14).

Comparing the level of the measured signal (y_k) and the level of the measurement noise (v_k), the Signal to noise ratio (SNR or S/N) could be an indicator for the Kalman Gain (K_k) value. If SNR is high the (K_k) gain matrix will be high, and if SNR is low the gain is low. This influences the convergence of the Kalman filter. The convergence will be faster with a higher SNR.

IV. State of Charge and Sate of Health Estimation

The state of charge (SOC) is the amount of the energy left in the battery compared to the energy of the fully charged battery. In the hybrid and electric vehicles, it replaces the "Gas Gauge" or the "Fuel Gauge". The SOC reference range value is between 0% of SOC for the completely discharged battery, and 100% of SOC for the fully charged battery. [9]

It could be mathematically expressed as follows:

$$SOC = SOC(0) - \int_0^t \frac{n \times i(\tau)}{C_n} . d\tau \quad (15)$$

As:

SOC(0): initial SOC of the battery

C_n: the nominal capacity of the battery, in (Ah)

i(τ): instantaneous current, in (A) (assumed to be positive for discharge and negative for charge)

n: coulomb efficiency (no unit) it could be taken one for discharging and less than or close to one when charging. It depends on the battery characteristics (technology); it is variable against the temperature, the charging/discharging current, the SOC and SOH of the battery. In our case, it assumed to be constant.

The state variables number increases the uncertainty of the estimation; so, in order to estimate the SOC, a two states model derived from the presented model in equations (2) and (3) is more suitable for the SOC estimation and the implementation in the PIC microcontroller.

$$x_{k+1} = \begin{bmatrix} SOC_{k+1} \\ U_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 - \frac{T_s}{RC} \end{bmatrix} \begin{bmatrix} SOC_k \\ U_k \end{bmatrix} + \begin{bmatrix} -\frac{T_s}{C_n} \\ \frac{T_s}{C} \end{bmatrix} i_k \quad (16)$$

$$U_{L,k} = a_k \times SOC_k + b_k - U_k - R_0 i_k \quad (17)$$

$$U_{OC} = a \times SOC + b \quad (18)$$

The (U_{OC}) in the output equation (3) has been replaced by the linear relation between it and the SOC, equation (17). Hence, two constant parameters need to be identified (a_k) and (b_k).

Using the polynomial interpolation in Matlab, the constants (a_k) and (b_k) has been identified. Fig. 6

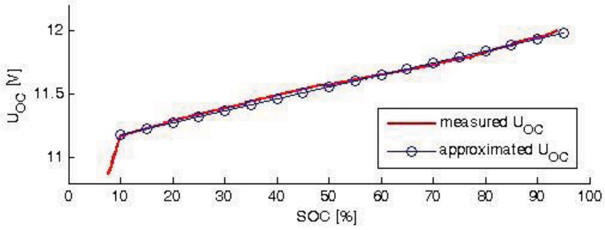

Fig. 6 The relation between U_{OC} and SOC

Hence, following the shape of the curve illustrated in (Fig. 6) the constants (a_k) and (b_k) found to be as shown in Table. I.

TABLE I. SOC CONSTANTS

a_k	=	0.0225
b_k	=	10.75

The Kalman filter is robust and accurate. We can use it to estimate the SOC. The last one could be easily estimated by the coulomb counting method [10], [11], but it will fail if the estimation error increases and/or when the measurements are noisy.

V. PRACTICAL TEST AND RESULTS

A discharge test has been effectuated by doing a cycle on the electrical scooter in Amiens city downtown (more than 15 km). The scooter has an 800 W, 48 V brushless motor. The discharging current is shown in Fig. 9. A voltage and current sensor (Xantrex LinkPro battery monitor) has been used to record the values of the voltage, the current and the temperature every second, by using a datas acquisition (Xantrex) card, which communicates by the RS232 serial bus with a host computer. The following diagram illustrates the test architecture.

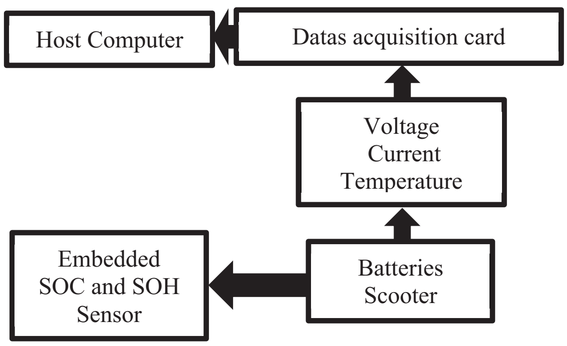

Fig. 8 The test architecture diagram

The embedded SOC and SOH sensor is based on an 8 bits PIC microcontroller (PIC 18F45K22). It has been chosen because of its extreme low power consumption (100 nA in sleep mode and 500 nA in watchdog timer mode) and several peripheral I/O. The Kalman algorithm has been implemented in the microcontroller to estimate the SOC and SOH. The voltage measurement has been realized by using resistances in form of a tension divider bridge; it divides the battery voltage (48 V) to be adaptable for the analogue input of the microcontroller. Then, the received value will be affected to a variable and converted to 48 V range value. Using a very small shunt resistor, the voltage across the shunts resistance terminals has been measured; as the resistance value is known, it is easy to convert the measured voltage across the shunt to a current using the Ohm law. This method, allows us to measure a large current amounts. A one wire temperature sensor has been used for the security purpose, to protect the system in the case where the batteries overheat. During the test, the temperature of the batteries dose not reached a dangerous value, it was usually stable.

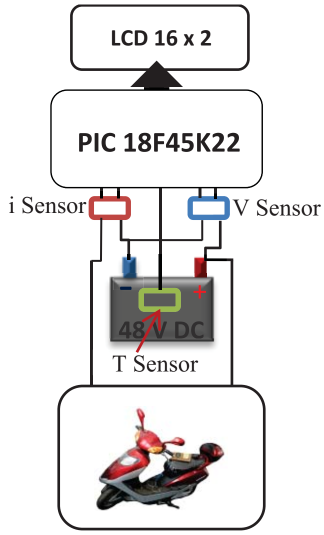

Fig. 7 the SOC and SOH sensor overview

The following figure illustrate the SOC estimation, the current and voltage measurement. We can note that Kalman filter allows us to have a good estimation of the SOC. The voltage drops down when the current consumption is important, the SOC evaluate upon the time in function of the current and voltage amounts.

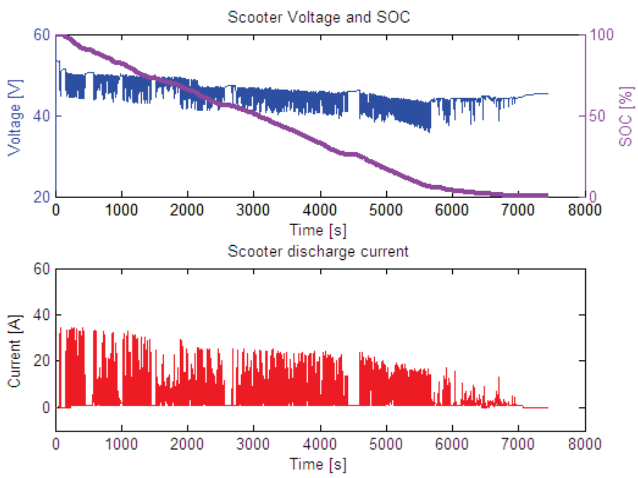

Fig. 9 The scooter's Current (red) Voltage (blue) and SOC (violet)

The next diagram explains the SOC/SOH estimation algorithm running online inside the microcontroller.

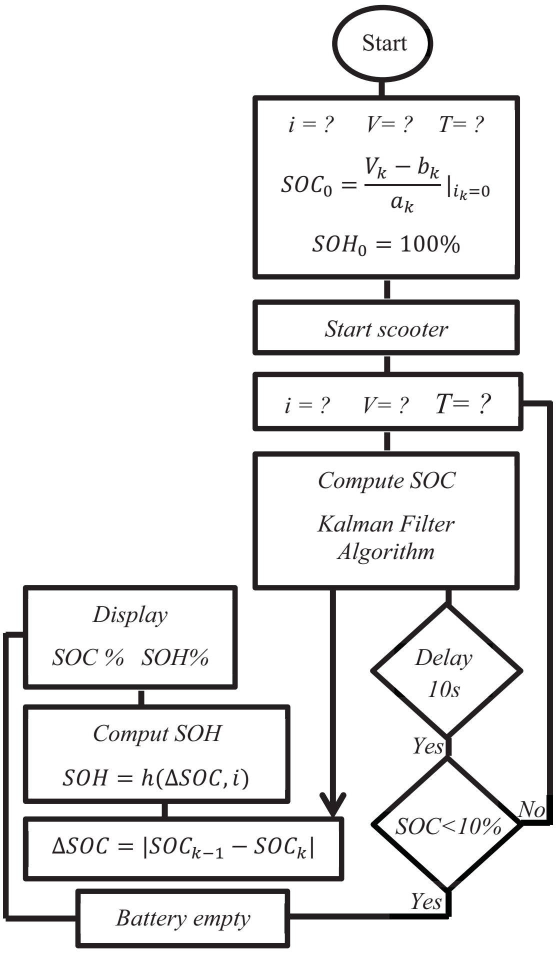

Fig. 10 The Embedded SOC and SOH estimator algorithm

The equation (19) estimate the rest number of cycles (1 cycle = 10 s) stayed for the battery to be discharged, it is used to estimate the SOH.

$$Z = \frac{SOC_0}{\Delta SOC} \tag{19}$$

The SOH estimation is based on the current measurement and the SOC estimation. If SOC are estimated correctly, and the current measurement was correct; we will obtain a good SOH estimation. In this test the SOH was constant; it takes a long time and number of charge/discharge cycle to evaluate.

VI. CONCLUSION

Using Kalman filter algorithm, the SOC could be accurately estimated online in a harsh application such as an electrical vehicle, which requires a consumption current up to 36 A; while coulomb counting method could fail, because of the measurement error incrementing (no correction step in coulomb counting method) and its sensibility against the measurement noise. A SOC/SOH estimation embedded algorithm has been implemented in a PIC microcontroller. The SOH and SOH has been estimated and displayed on a LCD screen. Satisfying SOC estimation results has been obtained for this type of application.

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