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Improved EKF for SOC of the storage battery

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***Abstract* - Aiming at the electric automobile in the running state of the complicated working condition, an innovative battery SOC estimation method is presented. Based on a new type of on-line measurement in storage battery parameters, improved EKF algorithm is used to estimate the remaining battery capacity. By isolating single cells and acquainting parameters, the unit cell's SOC is estimated through the Kalman algorithm, and we can calculate assembled battery SOC by integrating unit cell's SOC. This algorithm overcomes the changes of electric vehicle battery parameters which are complicated and the traditional estimation algorithm has defects of low accuracy of SOC. The technology put forward in this paper overcomes the flaw. And the internal resistance of the battery can be estimated. The research has an important significance on SOH. Analysis of the test shows that, using this method for on-line estimation of battery SOC, the estimation accuracy is relatively high can reflect the real residual capacity of battery better**

Index Terms - State of charge; extended Kalman filter; storage battery; innovative topology.

I. INTRODUCTION

Nowadays, lead-acid battery is widely used as a power source to provide energy in electric vehicles (EV). So the battery's capacity and performance is very important for EV. So a battery management system (BMS) is essential to the endurance mileage of EV. In BMS, State of charge (SOC) is a very important issue [1]. SOC is defined as the quotient between the difference of the rated capacity and the net amount of charge discharge from a battery since the last full SOC on the one hand, and the rated capacity on the other hand. Owing to this definition, the full SOC is reached when the battery current drops below a predefined value at a constant charge voltage and constant temperature. It reflects the battery's storage energy. The SOC for a battery is calculated as follows:

$$SOC = SOC_0 - \int_0^T \frac{\eta I}{C_e} dt \tag{1}$$

where SOC_0 is the original SOC state of the storage battery, η the charge discharge efficiency, I the discharge current, C_e the rated capacity of the battery.

How to accurately estimate the SOC of the battery has been a hot area of research for several years. A series of vehicle driving tests have been taken about Lead-Acid Batteries [2]. Several techniques have been reported for measuring or estimating the SOC of battery cells [3]. The most common methods include current integration techniques, artificial neural networks and fuzzy-logic-based estimations, support vector-based estimators, Kalman filter-based estimators, and others [4]–[7]. Most of these methods have been widely used and achieve acceptable results in different applications. The most common technique for calculating SOC is the Ampere hour counting. In this method, the current must be measured periodically and accurately. The value of the current integral is thus a direct indicator for the SOC. However one drawback of current integration techniques is their reduced accuracy. Errors in the current detector are accumulated by the estimator. The longer the estimator is operated, the larger the cumulative errors become. For many SOC levels, this estimator carries an average ±15% error. For instance, the extended Kalman filters reduce the average error for SOC predictions to 5% over a wide range of operation. But the method can't reduce the error because of variable parameters such as the internal resistance of the battery of the battery mode, which are unpredictable.

The kalman filter was proposed in the early 1960s by R.E.Kalman, which is well-known that the Kalman filter is an optimal estimator and that it is the best linear estimator in the case of other statistics. The extended Kalman filter (EKF) can filter the high frequency measure noise and random disturbance, for that the method considers model-error and the statistical characteristics of measure noise [8]. In the past years, more and more accurate battery modes have been designed which are used to reduce the average error for SOC predictions [9]. It is an important research direction. But they all need complex math formula deduction. In this paper, an improved EKF based on a new measuring circuit of electrical parameter is proposed. The method avoids complex math formula deduction.

The remaining of the paper is organized as follows. The lead-acid battery model given by Massimo Ceraolo is shown in Section II. In Section III, the new measuring circuit is proposed. In Section IV, the improved EKF is used to do SOC estimation, and experimental results show the advantages of the proposed method. Finally, the conclusions are given in Section V.

II BATTERY MODELING

Good battery model should have the following characteristics : Matching the static and dynamic characteristics of battery; moreover having a low order model in order to reduce the operation time of the processor and realize easily in practice. So the simplified second order

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Massimo Ceraolo model is chosen. The chosen model is shown in Fig. 1.

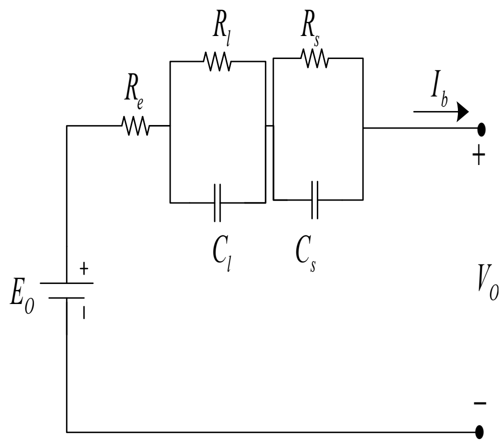

Fig.1 the simplified second order Massimo Ceraolo model

where E_0 is open circuit voltage(OCV) of the storage battery which changes with the SOC, V_0 the indicates the battery terminal voltage, R_e the ohmic internal resistance of the batteries which is non-measurable and changes with the SOC and the consumption of battery, R_s and R_l the polarized internal resistance of the battery, C_s and C_l the polarized capacity of the battery.

III THE PROPOSED MEASURING CIRCUIT

A BMS uses a charge estimation strategy (SOC) to estimate the endurance mileage of EV. A charge estimation strategy refers to a hardware topology employed to achieve the required cell voltage. Nowadays only the terminal voltage and current can be measured accurately during the charge-discharge cycles. The simplified second order Massimo Ceraolo model show that some parameters are non-measurable and changeable. Based on the above analysis, several resolution strategies are proposed. They are:

* reducing the non-measurable and changeable model parameters;

*making the non-measurable and changeable model parameters measurable.

We can see that the first solution is reasonable in practical application. So the paper proposes a new measuring circuit which is shown in Fig.2. From Figure 2, some switching devices and snubbed capacitors are put into the circuit. For isolating Battery1 from the battery pack, the switching devices S1and S8 are turned to right side to collect the terminal voltage of Battery1. In the mean time, the backup battery B5 take the place of Battery1. Similarly, other batteries' terminal voltage also can be measured. In term of the battery model, we can clearly see that ohmic internal resistance doesn't divide the voltage during measuring time.

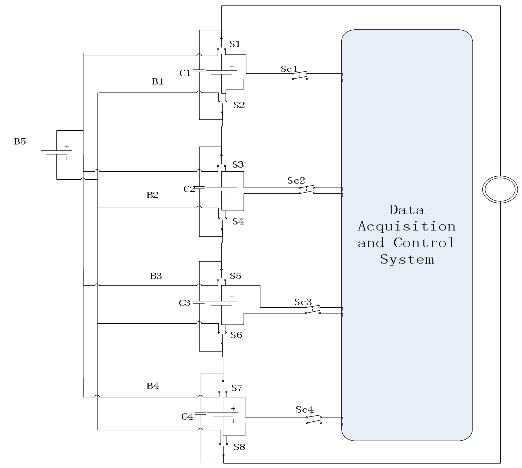

Fig.2 the proposed measuring circuit

IV. EXTENDED KALMAN FILTER

Kalman filter provides a recursive solution to optimal linear filtering, for both state observation and prediction problems. A nonlinear version of Kalman filter, extended Kalman filter (EKF) is applied to doing state estimation for nonlinear models.EKF uses the linearization process at each time step to approximate the nonlinear system. For most nonlinear applications, EKF has good performance. The computational flow diagram is shown in Fig.3.

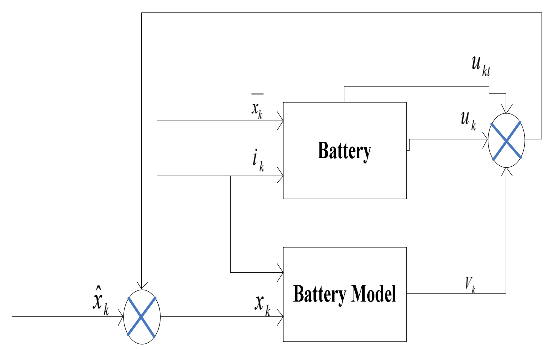

Fig.3 flow diagram of EKF

The discrete-time state-space equations for EKF are expressed as：

state equation：

$$\begin{bmatrix} SOC(k+1) \\ U_s(k+1) \\ U_l(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau_S}} & 0 \\ 0 & 0 & e^{-\frac{\Delta t}{\tau_l}} \end{bmatrix} \times \begin{bmatrix} SOC(k) \\ U_s(k) \\ U_l(k) \end{bmatrix} + \begin{bmatrix} -\frac{\eta \Delta t}{C} \\ R_S(1-e^{-\frac{\Delta t}{\tau_S}}) \\ R_l(1-e^{-\frac{\Delta t}{\tau_l}}) \end{bmatrix} \times i(k) + \omega(k) \tag{2}$$

output equation：

traditional output equation：

$$V_{ok} = OCV(SOC(k)) - i(k)R_e - U_S(k) - U_l(k) + \nu(k+1) \qquad (3)$$

At the measuring time, the battery which is being measured is isolated and the current i(k) ≈ 0A. In term of the battery model, we can clearly see that ohmic internal resistance doesn't divide the voltage during measuring time.

Isolated output equation

$$V_{okT} = OCV(SOC(k)) - U_S(k) \times e^{-\frac{T}{\tau_S}} - U_l(k) \times e^{-\frac{T}{\tau_l}} + \nu(k+1+\frac{T}{\Delta t}) \qquad (4)$$

When ignoring isolate-time

$$V_{okT} = OCV(SOC(k)) - U_S(k) - U_l(k) + \nu(k+1) \qquad (5)$$

State variable

$$X_k = \begin{bmatrix} SOC(k+1) & U_S(k+1) & U_l(k+1) \end{bmatrix}^T \qquad (6)$$

State-transition matrix and control matrix

$$A_k = \frac{\partial f}{\partial x} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau_S}} & 0 \\ 0 & 0 & e^{-\frac{\Delta t}{\tau_l}} \end{bmatrix}, \quad B_k = \begin{bmatrix} -\frac{\eta \Delta t}{C} \\ R_S(1-e^{-\frac{\Delta t}{\tau_S}}) \\ R_l(1-e^{-\frac{\Delta t}{\tau_l}}) \end{bmatrix} \qquad (7)$$

Measurement matrix

$$H_k = \frac{\partial g}{\partial x} = \begin{bmatrix} \frac{dOCV}{dS} & -1 & -1 \end{bmatrix} \qquad (8)$$

State equation of noise variance

$$Q = E[\omega_k \omega_k^T], k = 1 \sim N \qquad (9)$$

The matrix of measurement variance

$$R = E[v_k v_k^T], k = 1 \sim N \qquad (10)$$

The parameters of these are defined as follows:

Where the η --charge-discharge efficiency, $i(k)$ the current sampling data of the battery, k the sampling time, $SOC(k)$ the soc estimation value of battery in time k,. OCV is open-circuit voltage, which has a certain relationship with soc. So we can use $OCV(SOC(k))$ to show open-circuit voltage in time k; τ_S and τ_l show the time-constant respectively in part $\tau_S = R_S C_S$ ， $\tau_l = R_l C_l$ that is: $\tau_S = R_S C_S$ ， $\tau_l = R_l C_l$. $U_l(k)$ is the up voltage in r_S ； $U_l(k)$ is the up voltage in r_l ; t is the isolate-time;

$\omega(k)$, $\nu(k)$ the system error, which are irrelevant.

Through analyzing, we can know that voltage value V_{okT} in equation 4 didn't contain the ohmic internal resistance. In order to let battery model more precisely, we must refine internal resistance time and time again by comparing equation 3 with equation 4. Meanwhile, because SOC changes slowly, sampling period T is not so long. Through further analysis, we consider V_{ok} and V_{okT} are sampling at the same time, then equation 4 was simplified to equation 5. The discrete state-equation and output equation didn't contain ohmic internal resistance. We can see that the changing of the ohmic internal resistance had no effect on the OSC estimation. From equation 2 and equation 5, we can obtain the changing value of internal resistance:

$$R_e(k) = {(V_{okT} - V_{ok})}/{i(k)} \qquad (11)$$

V EXPERIMENTAL RESULT

The power battery we use in this experiment is lead-acid cell of "chaowei" series, whose capacity is 120ah, nominal voltage is 12v, parameters of battery model were set in table 1.Temperature change also had some influences on internal resistance.

Table 1
. IDENTIFICATION OF BATTERY PARAMETERS

Parameters	Value
Nominal voltage C_o / $(A.h)$	120
τ_S /s	44.6229
τ_l /s	435.1610
R_S /ω	0.0934
R_l /ω	0.1896
R_ω /ω（reference value）	0.0217

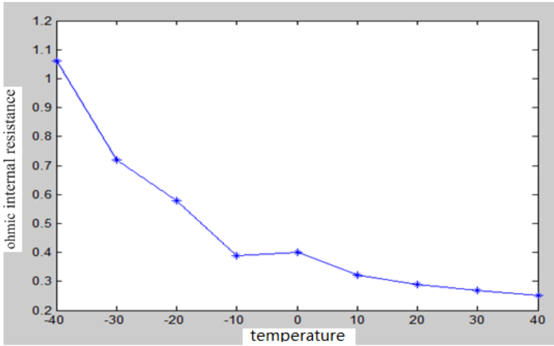

Fig 4. Relation Curve between Internal Resistance and Temperature

We can clearly see that when temperature rises, ohmic internal resistance descended. Temperature of EV is affected by environment temperature and battery glowing, so ohmic internal resistance identified by using traditional method was totally useless. In order to discuss temperature influence on soc estimation, we set various temperature in laboratory (when batteries were assembled in vehicle, their temperatures weren't to be controlled).

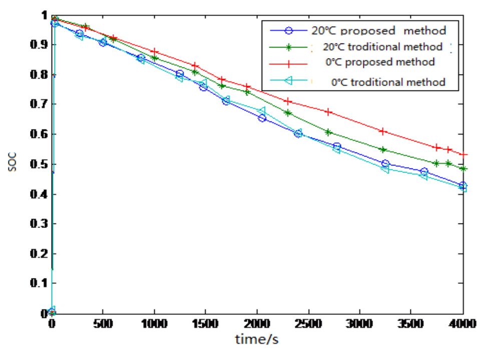

Fig.5 SOC Estimation Under Various Temperatures

When using the proposed method under various temperatures, we can see from figure 5 that the SOC estimation result is relatively stable. While the traditional method was not the same, its results were changing with battery internal resistance, and when temperature was low, it would lead to higher result in internal resistance and then the results of SOC estimation also would be turn to larger side. Because the temperature wasn't to be controlled when in real road conditions, traditional method would probably lead to more errors.

The car used in this experiment was an independent research by Institute for EV& System Control, as shown in Figure 6.

Fig.6 Test car

Adding the proposed new topology to dynamic battery packs, we build experimental circuit as shown in Figure 7.

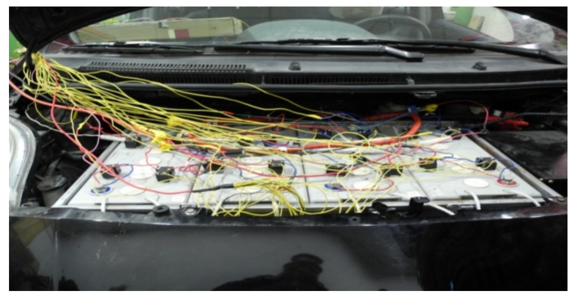

Fig.7 Experimental Circuit

Before starting to do this experiment, we should charge battery and let SOC value become 100%. The relationship between SOC and OCV of these battery series were measured by experiment. We used our own researched data acquisition card to collect data, and processed it in MATLAB, then got the internal resistance variation curve as shown in Figure 6. It can be seen from the linear fitting curve that internal resistance didn't change significantly in the early but turn to be a rising trend. With the decrease of battery SOC, internal resistance increased sharply. At this time traditional second-order RC model can't reflect the true state of battery. With temperature changing, internal resistance would change too.

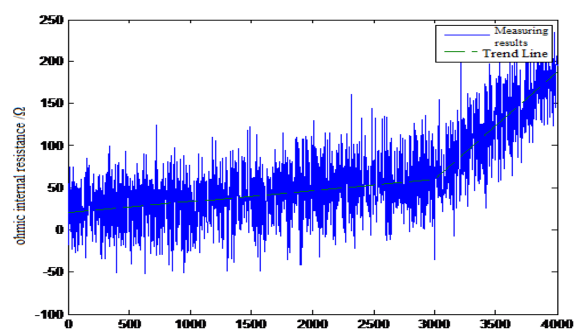

Fig.8 Vibration Curve of Internal Resistance

As shown in Figure 9, we can see that at the beginning of the battery discharge, the traditional Kalman Filtering method can better reflect the SOC of the battery. But with further discharge of battery, precision will decline gradually, the value of SOC estimation was lager. In the later period of battery discharge, the predictive value even rose. The SOC estimation used this proposed method was consistent with expectations.

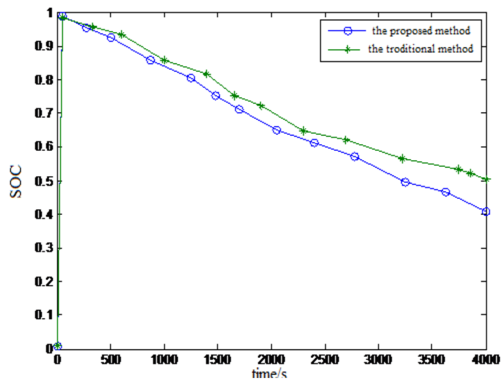

Fig. 9 the SOC curve in two method

Method and Traditional Kalman Method after De-Noising

As shown in Figure 10, we can easily see that SOC estimation of this method was smaller than that of Ampere-Hour Method, especially at the end of discharge, was very obvious. The reason for this phenomenon is that Ampere-Hour Method may accumulate error, and don't consider the internal loss and self-discharge, all these have led to larger results. The experimental results were fully in line with expectations. SOC curve obtained by the proposed approach was relatively smooth, corresponded to the actual SOC changes, and had a high precision.

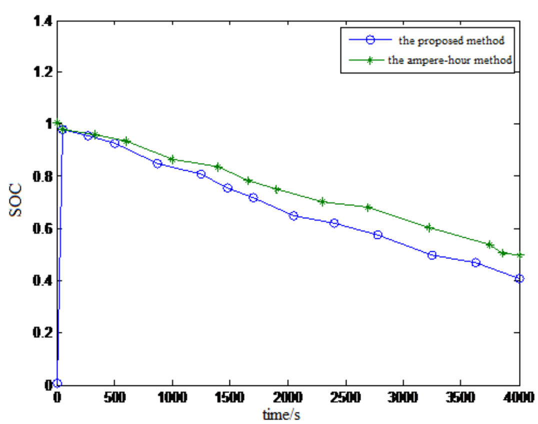

Fig 10. Comparison Curve between

the Proposed Method and Ampere-Hour Method

By using the data above, the comparison results among the improved Extended Kalman Filter (EKF) algorithm, the traditional estimating algorithm and the Ampere-Hour algorithm were shown in Figure 9. Through experiment verification, the proposed algorithm used to estimate SOC is accurate, not sensitive to parameter variations, and has good real-time performance and good robustness.

The result shows that SOC estimation precision is greatly improved, after using the improved Extended Kalman Filtering algorithm in the new measuring system. Meanwhile, it can also estimate internal resistance as shown in Figure 8, and lay a foundation for studying in SOC estimation for batteries.

VI CONCLUSION

This paper puts forward a new kind of topology for measuring the power battery parameters, and it uses Extended Kalman Filtering algorithm to establish a new SOC prediction mathematical model of vehicle power battery. In this solution, because variation regularity of battery model internal resistance is not strong and cannot be directly measured, then we proposes two methods to solve them, and the result is very good. In the mean time, through building the experimental platform and experimental analysis, we confirm the feasibility and reliability of this method. This solution has a simple algorithm and is not sensitive to battery parameters, and good robustness. It's suitable for SOC prediction of vehicle power battery, at the same time, this solution has a certain enlightening significance for processing parameters which can't be directly measured.

REFERENCES

[1] S. Piller, M. Perrin, and A. Jossen, "Methods for state-of-charge determination and their applications," *J. Power Sources*, vol. 96, pp. 113–120,2001.

[2] M. J. Kellaway, P. Jennings, D. Stone, E. Crowe, and A. Cooper, "Early results from a systems approach to improving the performance and life-time of lead acid batteries," *J. Power Sources*, vol. 116, pp. 110–117,2003.

[3] A. H. Anbuky and P. E. Pascoe, "VRLA battery state-of-charge estimation in telecommunication power systems," *IEEE Trans. Ind. Electron*,vol. 47, no. 3, pp. 565–573, June 2000.

[4] C. Chan, L. E. Lo, and S. Weixiang, "The available capacity computation model based on artificial neural network for lead-acid batteries in electric vehicles," *J. Power Sources*, vol. 87, pp. 201–204, 2000.

[5] T. Hansen and C. J. Wang, "Support vector based battery state of charge estimator," *J. Power Sources*, vol. 141, pp. 351–358, 2005.

[6] G. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs—II: Modeling and identification," *J. Power Sources*, vol. 134, pp. 262–276, 2004.

[7] H. Dai, X. Wei, and Z. Sun, "Online cell SOC estimation of Li-ion battery packs using a dual time-scale Kalman filtering for EV applications," *Appl. Energy*, vol. 95, pp. 227–237, 2012.

[8] Amir Vasebi, Maral Partovibakhsh, S. Mohammad Taghi Bathaee, "A novel combined battery model for state-of-charge estimation in lead-acid batteries based on extended Kalman filter for hybrid electric vehicle applications," *J. Power Sources*, Vol.174, no. 1, pp. 30-40, November 2007.

[9] G.L.Plette, "Extended kalman filtering for battery management system of LiPB-based HEV battery packs-Part 2. Modeling and identification" *J. Power Source*, Vol. 134. no.2, pp. 262-276, August 2004