SOC Estimation Based Combined Model For Vehicle Batteries

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Keywords: combined model, SOC, Kalman filter, Vehicle Batteries

Abstract. Batteries play an essential role in electric vehicles, In order to achieve an optimum operation of systems with batteries it is necessary to estimate accurate of the state of charge (SOC). In this paper a combined model for SOC estimation in Vehicle Batteries, based on extended Kalman filter (EKF) is presented. The influence of the environmental temperature and charge-discharge rate are considered in the combined model, which makes it suitable for the acute change of current in driving. The effectiveness of the proposed method is verified using an Extensive experiment. This approach has strong capacity of resisting disturbance and will be implemented easily by hardware for an online SOC estimation.

Introduction

Vehicle batteries as the power source of electric vehicles is a key factor affecting the performance of electric vehicle, which could directly affect the driving distance, the ability of acceleration and the maximum climbable gradient[1]. State-of-charge (SOC) is used to described the remaining capacity of battery, couldn't direct measurement, is only calculated indirectly through battery voltage, charge-discharge current, internal resistance of the battery [2] etc. As the relationship between these parameters and SOC will changes with the process of the aging of battery, the accurate estimation of SOC has become a difficult problem in the electric vehicles.

The estimating method for SOC now most adapt such methods as OCV (open ciruit voltage detective), Ah Counting (Ampere hour Counting) and Fuzzy neural network method [3~7] etc. OCV method is based on the relationship between the SOC and the voltage when the battery is disconnected from any load and is fully relaxed, the battery must be relaxed for a few time to allow its open-circuit voltage to reach a steady-state status. Ah Counting needs the initial SOC, calculation of the internal consumptions of the battery, and accurate current sensors. The Fuzzy neural network method incurs large computation overload on the BMS, it can be a problem for online implementation.

In this paper, at first a state-space model of the SOC is proposed that is based on combined model, considering the factors of the environmental temperature and charge-discharge rate. Then, by using this model and the extended KF (EKF), is going through step by step to estimate the battery SOC. At last, Extensive experiments are conducted and a conclusion is given.

BATTERY MODEL

For the estimating the SOC of the vehicle battery, the first important thing is to select and build a suitable battery model. In this paper, we used the combined mode which consists of Sherpherd Model, Unnewehr Model and Nernst Model. The model can be viewed as a combination of the previous three models to obtain the most accurate performance [8, 9].

Sherpherd Model describes the electrochemical behavior of the battery directly in terms of voltage and current.

$$y_k = E_0 - Ri_k - K_i / x_k \tag{1}$$

Unnewehr universal Model simplifies the Shepherd Model and attempts to Model the variation in resistance with respect to SoC.

$$y_k = E_0 - Ri_k - K_i x_k \tag{2}$$

Nernst Model can be viewed as a modification to the Shepherd Model and uses exponential function with respect to SOC.

$$y_k = E_0 - Ri_k - K_2 \ln(x_k) + K_3 \ln(1 - x_k) \tag{3}$$

where x_k is the abbreviation for SOC at k time; E_0 is the OCV; R is the internal resistance; i_k is the load current at k time (while battery discharge, i_k is positive; while battery charge, i_k is negative) ; y_k is working voltage; K_1、K_2、K_3 are constants chosen to make the model fit the data well.

Considering the factors of the environmental temperature and charge-discharge rate, we introduce the u_k as the inputs, is influence factor of the environmental temperature and charge-discharge rate. Then the state-space of combined mode can be defined in the following.

The state equation is described as:

$$x_{k+1} = x_k - (\frac{\eta_i \Delta t}{\eta_T Q_n}) i_k + w_k \tag{4}$$

The observation equation is described as:

$$y_k = K_0 - Ri_k - K_1 / x_k - K_2 x_k + K_3 \ln(x_k) + K_4 \ln(1 - x_k) + v_k \tag{5}$$

Where K_0 is the OCV; η_i is the scale fator of charge-discharge rate at the rated temperature and discharge current is i_k ($\eta_i = 1$ at its rated charge-discharge rate); η_T is the scale factor of ambient temperature at the rated charge-discharge rate and temperature is T(η_T=1 at its rated temperature); Q_n is nominal capacity of the battery. w_k is state-noise; v_k is measurement-noise.

ESTIMATION ALGORITHM

The estimation algorithm, in this paper, is based on the EKF [10]. The performance of KF depends on several factors, e.g., the dependence on an accurate state-space model of the system that was proposed in the previous section.

Initialization

In order to obtain the curve between the OCV and the SOC, the measure experiment of constant discharge in different discharge rate must be taken. By the OCV-SOC curves, it is easy to get the initial state of the SOC by the initial state of the OCV [11]. Then the initial vale of status as:

$$x_{0|0} = E[x_0] = SOC_0 \tag{6}$$

Also when the sampling time of battery data acquisition process is T=1s, the initial covariance value of mean square error as:

$$P_0 = E[(x_0 - x_{0|0})(x_0 - x_{0|0})^T] \tag{7}$$

Linearization of the Proposed Model

The KF that is estimating the states of a linear time-varying model, which approximates the nonlinear model, is called the EKF. Since battery is a nonlinear system. So the combined model of state observation must be linearized. The Taylor series expansion and the higher truncation are used as the linearization method for the state equation and the observation equation of the model. Based on this method, the dynamic characteristic matching coefficient for the state equation can be solved as:

$$A_k = 1 \tag{8}$$

$$B_k = -\frac{\eta_i \Delta t}{\eta_T Q_n} \tag{9}$$

Also the dynamic characteristic matching coefficient for the state equation can be solved as:

$$H_k = \frac{\partial g(x_k, u_k)}{\partial x_k} | x_k = x_{k|k} = \frac{K_1}{{x_{k|k}}^2} - K_2 + \frac{K_3}{x_{k|k}} - \frac{K_4}{1 - x_{k|k}} \tag{10}$$

$$D_k = -R \tag{11}$$

Moreover, the system input is defined as:

$$u_k = i_k \tag{12}$$

By combining Eq. 4 and Eq. 5 with Eq. 8 and Eq. 9 and Eq. 11 and Eq. 12, we get the linearized Eq. 13 and Eq. 14 describing the nonlinear system.

$$x_{k+1} = A_k x_k + B_k u_k + w_k \tag{13}$$

$$y_k = H_k x_k + D_k u_k + v_k \tag{14}$$

Kalman Filter Algorithm

The algorithm consists mainly of two stages: "time update" and "measurement update". Steps are described as follows, from step1 to step3 is the time update and setp4 to step5 is the measurement update.

Step1: new state estimation

The new state variables, from t=k to k+1, can be expressed as follows:

$$x_{k+1|k} = f(x_{k|k}, u_{k|k}) = x_{k|k} - (\frac{\eta_i \Delta t}{\eta_T Q_n}) i_k \tag{15}$$

Step2: error covariance estimation

The new error covariance variables at t=k to k+1, can be expressed as follows:

$$P_{x,k+1|k} = A_{k+1} P_k A_{k+1} + Q_k \tag{16}$$

If the system is stable then is contractive. This will reduce the uncertainty of the state estimation over the time. The process noise term Q_k always increases the uncertainty because w_k cannot be measured.

Step3: new observation estimation

The new error observation variables, from t=k to k+1, can be expressed as follows:

$$y_{k+1|k} = K_0 - Ri_{k+1} - K_1 / x_{k+1|k} - K_2 x_{k+1|k} + K_3 \ln(x_{k+1|k}) + K_4 \ln(1 - x_{k+1|k}) \tag{17}$$

Step4: Kalman gain Calculation

Kalman gain is used for expressing the gain of residual,which is defined to minimization error covariance.

$$K = P_{x,k+1|k} H_{k+1}^T (H_{k+1}^T P_{x,k+1|k} H_{k+1}^T + R_{k+1})^{-1} \tag{18}$$

If the current state estimation $x_{k+1|k}$ is very uncertain, then P_k tends to be "large" which leads to a large Kalman gain, which means a large update for the state estimation. If the current sate estimation is certain, the Kalman gain tends to be small which means a small update to the state estimation. Also if the measurement noise is large through a high R value, this will lead to a small Kalman gain and the update is small.

Step5: state optimal estimation

$$x_{k+1} = x_{k+1|k} + K(y_{k+1} - y_{k+1|k}) \tag{19}$$

If the K is larger, then the weight of the observed variables will be smaller and the weight of the observation variables will be lager.

Step6: error covariance optimal estimation

$$P_{x,k+1} = P_{x,k+1|k} - KP_{y,k+1} K^T \tag{20}$$

The error covariance is also corrected through Eq. 20. In this formula the Kalman gain is also used and the state uncertainty is decreased due to the new information provided by the measurement.

Iteration

Go on the recursive EKF algorithm until the setting.

EXPERIMENTAL AND COMPUTATIONAL RESULTS

Experimental Environment

Extensive experiments are conducted to demonstrate the promising performance of the proposed algorithm. We use the UBM4024 from the Zhejiang Delaware Power Systems Corp, Composed of 7 pieces of single battery with nominal voltage of 3.7 V and nominal capacity of 10.3Ah. The UBM4024 has a rated voltage of 24V (operating range from 21V to 29.4V) and a rated capacity of

40Ah. Furthermore, the Jartual JT6313A DC electronic load has been applied for battery discharge. The picture of the UBM4024 and JT6313A is shown in Fig.1.

Capacity Of Resisting Disturbance

Since the SOC will be affected much by the factors of the environmental temperature and charge-discharge rate. An experiment is designed to verify the affection of charge-discharge rate, the pulse is used to simulation the seriously fluctuates of discharge, Fig.2 shows the current curve of the pulse discharge. Fig.3 shows SOC estimation results for the combined model using EKF in comparison to Ah counting results. The estimation error has steadily expanded over time in our EKF algorithm.

Fig.1: The experimental environment

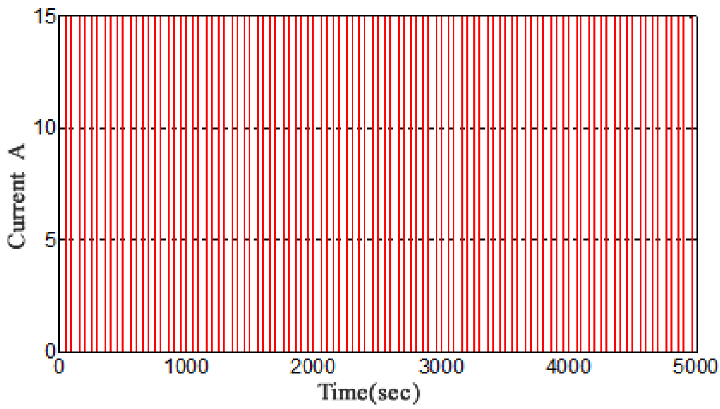

Fig.2: Current curve of the pulse discharge

Convergence At Difference SOC Initial Values

An accurate SOC estimation depends on two aspects. The first is the initial SOC value, and the second is the calculation method. In order to investigate how the SOC estimation is affected by the initial value for SOC. A range of the SOC Initial Values are set to run our EKF algorithm, Fig.4 shows very well that SOC estimation starts with wrong values and converges very quick towards the real SOC value.

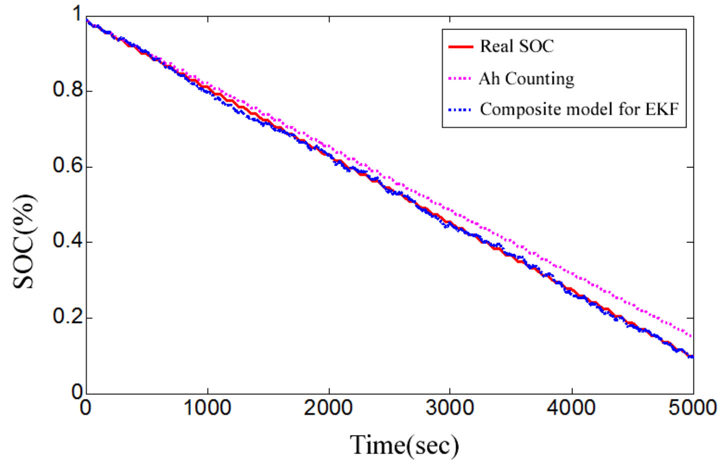

Fig.3: SOC estimation values using Ah Counting and Combined model for EKF

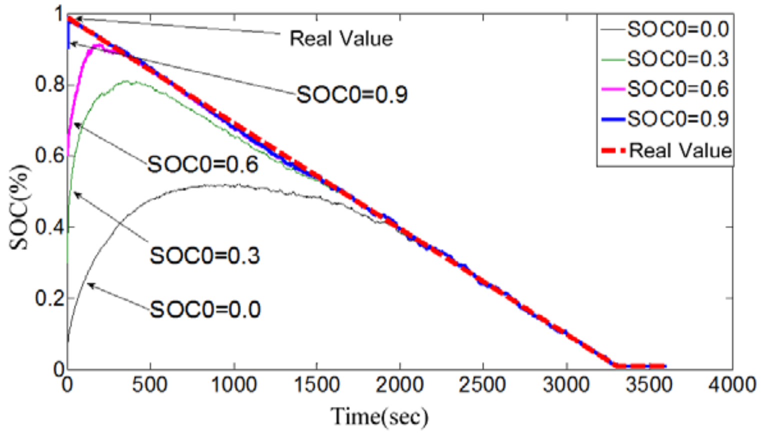

Fig.4: Convergence at difference SOC Initial Values

CONCLUSION

This paper presents the application of an extended kalman filter on Vehicle Batteries to obtain the optimum estimation of SOC. For this purpose combined model and Kalman filter methods are applied. Through the experiments, our approach has strong capacity of resisting disturbance since the combined model has been considered the factors of the environmental temperature and charge-discharge rate. Further, the effect of incorrect initial values on the SOC estimation has been demonstrated. In a continuation of this research the effect of aging will be taken into account. Finally the algorithm will be implemented easily by hardware for an online SOC estimation.

Acknowledgements

The research work was supported by Public Projects in Zhejiang province under Grant No. 2012C21062.

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