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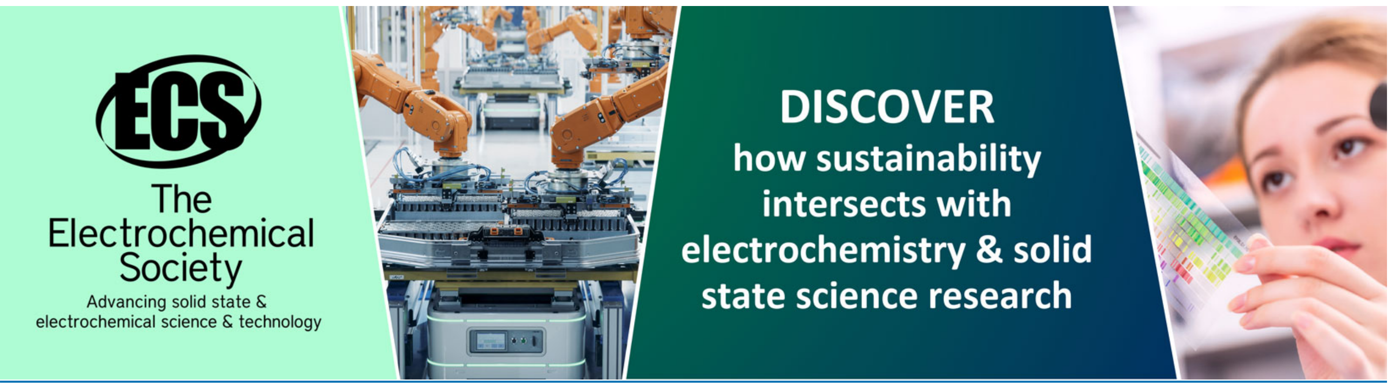

Estimation of state-of-charge of Li-ion batteries in EV using the genetic particle filter

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Abstract: Estimating the state of charge (SOC) of electric vehicle (EV) batteries accurately and timely is of great significance to the safe trip of pure EV. Based on the nonlinear properties of the battery, and the standard particle filter (PF) has certain adaptability for this feature, so it can be used to accurately estimate the SOC of the batteries. However, the standard PF has particle degeneracy phenomenon, which will make the accuracy of prediction lower. Therefore, in this paper, the genetic algorithm is applied to the standard PF, and the estimation of SOC is optimized, which makes the improved filter algorithm more accurate. Based on the measured data of Beijing pure electric sanitation vehicle, an experiment is defined to verify the algorithm. The experimental results show that the genetic particle filter (GPF) can increase the diversity of particles and has better prediction accuracy and timeliness than the PF.

1 Introduction

Pure EV is the future development direction of automobile. However, power batteries are the only source of pure EV energy, in order to make better use of power battery and prolong its life, it is necessary to accurately estimate the most important parameter SOC in EV battery management system. SOC is the ratio of the current battery remaining power to the rated capacity of the battery, which can't be measured directly. It can be estimated merely by parameters of the batteries, such as voltage, resistance, current and temperature.

At present, estimating methods of SOC are discharge test, open-circuit voltage, the Amper-Hour integral, neural network, Calman filtering etc. In these methods, the discharge test is not suitable for application [10]; Amper-Hour integral requires high current accuracy [5]; open-circuit voltage can only be used in a stable state of the voltage, the actual measurement is not convenient [6, 8]; neural network uses a large number of reference data for training, the error in the application is affected by the training data and methods [2]; Calman filtering exploits the mean and variance to characterize the state probability distribution, however, which can't guarantee the estimated accuracy for nonlinear and non Gauss distributed state models [3, 4].

Traditional PF can deal with nonlinear problems well, which is applicable to the nonlinear stochastic system represented by various state space models and effectively improves the effect of optimal estimation [7]. But, PF has particle degradation phenomena and affects the prediction precision. Therefore, this paper attempts to apply the principle of genetic algorithm to the PF. Using the unique optimization ability of genetic algorithm to optimize the resampling process, and then improve the utilization of particles to ensure that the algorithm has a higher accuracy.

This paper is organized as follows. Section 2 proposes the battery model. Section 3 shows the description of GPF. Section 4 carries out experiments and compares the results. Finally, Section 5 gives some conclusions.

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2 Battery Modeling

State space model is the basic of GPF. The State space model consists of the state equation and observation equation.

2.1 *State equation*

The state equation is determined by the *SOC* definition in the paper. In general, the expression of *SOC* uses Amper-Hour integral method, the specific calculation formula:

$$SOC(t) = SOC_0 - \int_0^t \frac{n_i i(\tau)}{C_n} d(\tau) \tag{1}$$

Where, *SOC(t)* is the value of *SOC* at time t, SOC_0 is the initial value of *SOC*, $i(t)$ is the instantaneous current at time t ($i(t) > 0$ for discharge, $i(t) < 0$ for charge). C_n is the rated capacity, n_i is the Columbic efficiency ($n_i = 1$ for discharge and $n_i \leq 1$ for charge). The state equation is derived as Eq.(2):

$$x_k = x_{k-1} - \left(\frac{n_i V_t}{C_n}\right) i_{k-i} \tag{2}$$

Where, x_k is the value of *SOC* at time k, i_{k-1} is the instantaneous current at time $k-1, Dt$ is the sampling interval.

2.2 *Observation equation*

The paper selects the simplified electrochemical model [4] applying to Li-ion battery as the observation equation which is an analytical model and easy to estimate voltage or *SOC*.

$$y_k = k_0 - Ri_k - \frac{k_1}{x_k} + k_2 x_k + k_3 \ln x_k + k_4 \ln\left(1 - x_k\right) \tag{3}$$

Where, y_k is the battery terminal voltage at time k, R is the battery resistance and $k0, k1, k2, k3, k4$ are a set of parameters to fit.

Above all, the structure of battery model consisting of Eq. (2) and Eq. (3) is overall described in Eq. (4).

$$\begin{cases} x_k = x_{k-1} - \left(\frac{n_i V_t}{C_n}\right) i_{k-1} + w_k \\ y_k = k_0 - Ri_k - \frac{k_1}{x_k} + k_2 x_k + k_3 \ln x_k + k_4 \ln\left(1 - x_k\right) + v_k \end{cases} \tag{4}$$

The model has the advantages of simple operation, small computation, easy to be realized in the micro controller, and easy to identify the parameters of the model. As long as N battery data obtained, it can be obtained by the least squares identification model parameters.

3 Genetic Particle Filter

3.1 *The rationale for genetic particle filter*

Compared with PF and genetic algorithm, their similarities are as follows: firstly, both algorithms have an initialized group, and each individual in the population represents a feasible solution of the system; secondly, each individual changes according to certain criteria and copy the individual with high fitness. Therefore, this paper attempts to apply the adaptive genetic algorithm to the PF, and use the genetic algorithm to optimize the traditional resampling process, so as to achieve the purpose of inhibiting particle degradation and increasing particle diversity. In this algorithm, we consider the particle swarm as a group, each particle is regarded as a chromosome, the importance of the weight of the particles as a personal fitness value.

The unique search ability of the genetic algorithm greatly improves the utilization of the particles, so that the number of particles required to approximate the true posterior probability density function is greatly decreased, which not only reduces the computational complexity of the algorithm, but also improves the algorithm real-time.

3.2 *The steps of genetic particle filter*

Step1: Initialization

Step2: Particle Sample

Sample from the initial probability density function and yield a set of particles containing N particles with an initial weight of $1/N$ [1] for each particle.

Step3: Predicting

Use the Eq. (2) to predict the value of $x_k^i\{i = 1,2, \dots N\}$.

Step4: Weight update

Using Eq. (5), the weight (w_k^i) is computed. The normalization of weight w_k^i is calculated according to Eq. (6).

$$w_k^i = \frac{1}{\sqrt{2ps}} e^{-\frac{(y_k - y_k^i)^2}{2s^2}} \tag{5}$$

$$w_k^i = \frac{w_k^i}{\sum_{i=1}^{N} w_k^i} \tag{6}$$

Step5: Resampling

According to the Eq. (7) to determine whether the particles need to genetic resampling. If yes, go to Step6. If not, go to Step10.

$$N_{eff} = 1/\sum_{i=1}^{N} (x_k^i)^2 < N_{threshold} \tag{7}$$

Step6: Crossover and mutation

The weight (w_k^i) is taken as the fitness of the individual. $f_k^i = w_k^i\{i = 1,2, \dots, N\}$

According to adaptive genetic algorithm [9], the corresponding crossover probability (p_c) and mutation probability (p_m) are calculated by Eq. (8) and Eq. (9).

$$p_c = \begin{cases} \dfrac{p_1(f_{\max} - f_c)}{f_{\max} - f_{avg}} & f_c \geq f_{avg} \\ p_3 & f_c < f_{avg} \end{cases} \tag{8}$$

$$p_m = \begin{cases} \dfrac{p_2(f_{\max} - f_m)}{f_{\max} - f_{avg}} & f_m \geq f_{avg} \\ p_4 & f_m < f_{avg} \end{cases} \tag{9}$$

Where f_{max} is the maximum fitness value of the individual, f_c is the larger fitness value in the two intersecting individuals, f_m is the fitness value of the variant individual, and f_{avg} is the average of the individual fitness in the population.

Using Eq. (10) and Eq. (11) to perform the crossover and mutation operations.

$$\begin{cases} (x_k^i)' = \beta x_k^i + (1-\beta)x_k^j \\ (x_k^j)' = \beta x_k^j + (1-\beta)x_k^i \end{cases} \tag{10}$$

$$(x_k^i)' = \begin{cases} x_k^i + \left(1 - r^{\left(1-\frac{g}{G}\right)^t}\right)(N_k - x_k^i) & p \geq 0.5 \\ x_k^i - \left(1 - r^{\left(1-\frac{g}{G}\right)^t}\right)(x_k^i - M_k) & p < 0.5 \end{cases} \tag{11}$$

Where β is a random number evenly distributed over intervals 0 to 1, x_k^i, x_k^j are the two particles to be crossed, and $(x_k^i)', (x_k^j)'$ are the new particles that are produced after crossing.

Step7: Determine whether the evolution of algebra has reached. If yes, go to Step8, or back to Step6.

Step8: Particle optimization

The roulette method is used to optimize the particle to obtain a new set $\{(x_k^i, w_k^j), i=1,...,N\}$ of particles.

Step9: State estimation

The estimated state is given as

$$x_k = \sum_{i=1}^{N} w_k^i x_k^i \tag{12}$$

Step10: Determine whether the algorithm is over. If it is out of the algorithm, otherwise, back to Step3.

4 Experimental Results Of Soc Estimation

In this experiment, the discharge data of two different periods of the same sanitation electric vehicle was collected from 8:13 am to 10:21 am on May 19, 2014 and from 14:23 pm to 16:30 pm on May 20, 2014.The particles are encoded using real numbers, and the parameters required for the experiment are shown in Table 1. The formula of the weight of the particle is used as the fitness function. The parameters of the battery model are identified by the recursive least squares method of forgetting factor. The input and output data of the model are the measured data of the pure electric sanitation vehicle. The battery model parameters are shown in Table 2.

Table 1: Crossover and mutation probability calculation formula parameter values. *N* represents the population size.

N	p_1	p_2	p_3	p_4
300	0.75	0.9	0.2	0.45

Table 2: The final estimated parameter values.

k_0	k_1	k_2	k_3	k_4	P
453.771	-37.284	97.003	133.428	-1.139	5

The process noise and measurement noise are subject to the normal distribution of Q = 0.005 and P = 5, respectively. The variance of the measured noise is R = 5.

According to the specific steps of the GPF and PF, through the Matlab software to achieve the estimation process of the SOC, after repeated debugging and running, the final prediction results and error curves are as follows:

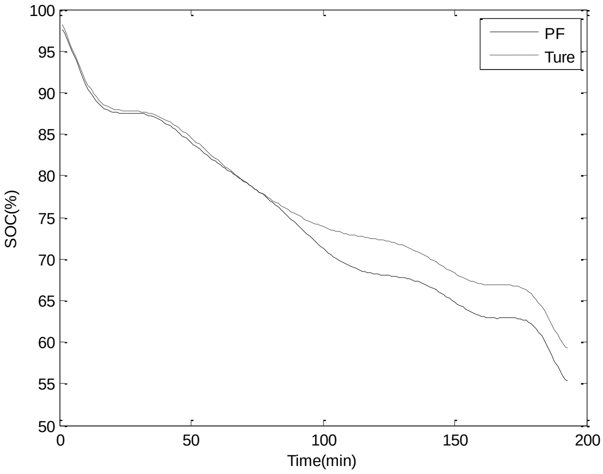

Figure 1.1: The results of SOC estimation based on PF (May 19th)

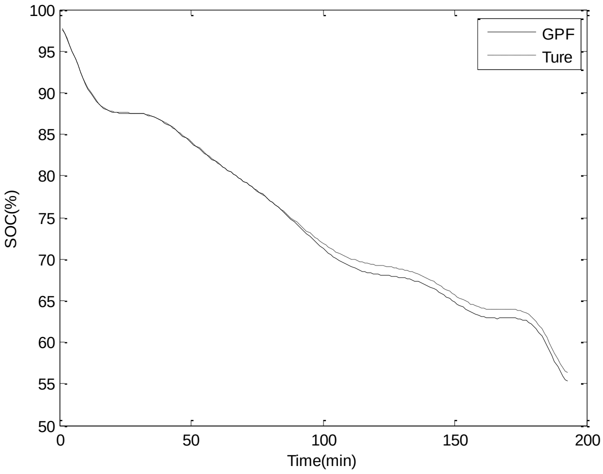

Figure 1.2: The results of SOC estimation based on GPF (May 19th)

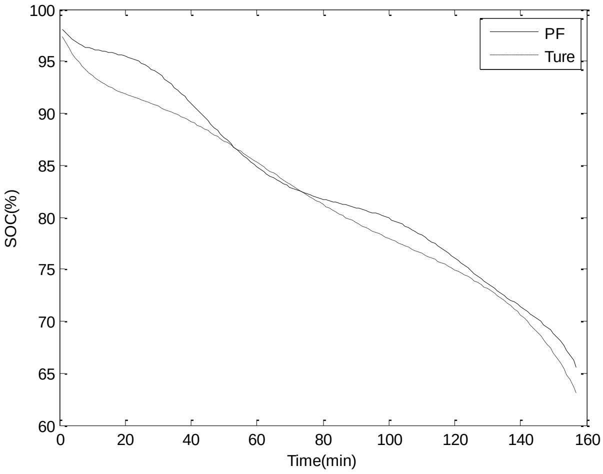

Figure 2.1: The results of SOC estimation based on PF (May 20th)

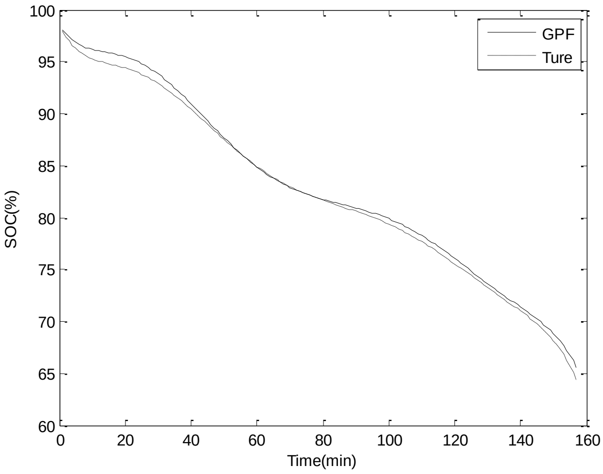

Figure 2.2: The results of SOC estimation based on GPF (May 20th)

Based on the above experimental data, this paper uses the root-mean-square error (RMSE) and root-mean-square-relative error (RMSRE) to further evaluate the estimation results. The mathematical expressions are as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2} \tag{13}$$

$$RMSRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\frac{y_i - y_i}{y_i})^2} \tag{14}$$

In the above equation, y_i is the true value and y_i is the predicted value.

Table 3 and table 4 show the results of the comparison.

Table 3: Particle filter performance evaluation

Index / Date	RMSE	
	PF	GPF
May 19th	0.0272	0.0095

May 20th	0.0127	0.0077

Table 4: Particle filter performance evaluation

Index / Date	RMSRE	
	PF	GPF
May 19th	0.0409	0.0137
May 20th	0.0220	0.0110

The experimental results show that the SOC estimation curve of the GPF is closer to the real curve than the PF. A further comparison shows that the RMSE and RMSRE of the GPF are reduced by about 40% relative to the standard PF. Therefore, the GPF is more effective than the PF in the estimation of the SOC of the electric vehicle batteries.

5 Conclusion

In this paper, a new PF optimization method, the genetic particle filter, is proposed to predict the SOC of the batteries, which effectively suppresses the degradation of particles in the standard PF. The statistical results of the battery discharge experiment based on the data of the actual operation of EV show that the genetic particle filter can effectively increase the diversity of the particles and own higher accuracy of the prediction than the standard PF, and has better SOC estimated characteristics.

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