Estimation of health status of lithium-ion battery based on PF-SA

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Abstract: The aging of lithium-ion batteries is a gradual process, which can usually be expressed by the state of health (SOH). Effective estimation of its SOH is helpful to reduce the probability of fire, fire and other dangerous accidents. In this paper, particle filter (PF) is used to predict the health of the battery, and then the simulated annealing algorithm (SA) is used to optimize the PF to realize the prediction of battery SOH.

1. INTRODUCTION
With the gradual promotion of energy storage policies, the application of energy storage batteries has become more and more widespread, but the popularity of new energy vehicles, aerospace and other equipment will also become more and more obvious with the aging of lithium-ion batteries[1,2]. Many parameters of lithium-ion batteries have non-linear characteristics, which bring certain challenges to their state evaluation and modeling, and therefore become one of the core work contents that need to be studied in the battery management system[3,4]. At present, there have been certain achievements in the research and modeling analysis of battery health status. Related research includes battery degradation mechanism analysis, battery life prediction, battery health status estimation, etc. Among them, the battery state of health estimation can more intuitively show the aging degree of the battery than in other related studies[5].

The current general lithium-ion battery performance evaluation methods include battery degradation model based on capacity degradation, Kalman filter state estimation method, BP neural network model, etc.[6]. These methods have their own advantages and disadvantages, but it is difficult to completely solve the above problems. Based on this, this paper combines particle filter and simulated annealing algorithm, and uses simulation software to simulate and verify the particle filter prediction method based on simulated annealing algorithm. The results prove the effectiveness of the method.

2. PARTICLE FILTER
The particle filter[7-9] algorithm is based on the idea of probability, randomly sampling the training samples and then re-sampling the importance, so as to deal with the prediction problem of the future time period. This method first performs a large number of samples based on the previous state of the state to be predicted at a certain moment and the probability distribution that the state obeys, and the resulting sampling points are called particles. The state transition equation and measurement equation
of the particle filter are shown in equations (1) and (2):
\[ x_k = f_k(x_{k-1}, u_{k-1}) \]
\[ y_k = h_k(x_k, n_k) \]

Among them, \( x_k \) is the system state at time \( k \), \( y_k \) is the measured data at time \( k \), \( f \) and \( h \) are state transition functions and measurement functions, \( U_{k-1} \) and \( n_k \) are the process noise at time \( k-1 \) and the measured noise at time \( k \), respectively.

In the process of state transition change, applying the corresponding control amount to obtain the predicted particle after each particle change, and then calculate the probability of obtaining the observed value of a certain predicted particle in the real state. The probability is used as the weight of each predicted particle in the state transition equation. The greater the probability, the closer the predicted particle is to the true predicted value.

Finally, in order to solve the phenomenon of particle scarcity, re-sampling is used to remove the predicted particles with lower weights, and the remaining predicted particles after removal are calculated through the state transition equation to obtain the true state of the prediction at a certain moment. The implementation flow chart of particle filtering is shown in Figure 1:

Particle filtering does not require complicated internal modeling, only a large amount of test data is needed to obtain the results, and the obtained results can directly reflect the performance degradation of the battery, and are favored by many scholars and researchers. However, due to the problem of random setting in its parameters, the results obtained have certain errors, which need to be further optimized.
3. SIMULATED ANNEALING

The simulated annealing [10-12] theory seeks the global optimal solution of the algorithm by simulating the crystal cooling process, which is used for particle filter parameter correction and improves the prediction accuracy. Its method is simple and the calculation is convenient.

In the simulated annealing algorithm, if the energy is reduced, the current solution will move to a low energy location; if the energy is increased, the current solution will not directly give up moving at the high energy of the network, but will be generated in the interval \([0,1]\) random number. If the current probability of accepting the transition is higher than the random number, you can move to a high-energy place, and vice versa. As shown in Figure 2, taking the global optimal solution of the objective function in a two-dimensional state space as an example, Assuming that the initial optimal solution set is at point A, as the temperature decreases and energy is released, point A will jump to point B. At this time, some energy needs to be added to the solid, corresponding to the increase in the objective function value, and point B will be Will continue to jump to point C. This cycle continues until the optimal solution falls on point D. At this point, the cycle continues. Point D still has a certain probability to jump to point E. However, due to the idea of shifting to low energy, point E will eventually jump back to point D, so as to achieve the goal of seeking the global optimum.

![Simulated Annealing Theory Analysis Diagram](image)

**Fig. 2.** Simulated annealing theory analysis diagram

The algorithm first needs to initialize the parameters, including the initial temperature, the lower temperature limit, the temperature degradation rate, the number of iterations, the objective function and the initial solution. It should be noted that the temperature degradation rate should not be set too high, otherwise the algorithm will fall into a local optimal solution; The degradation rate should be moderate. If the degradation rate is too fast, the optimal solution may be skipped when searching. If the degradation rate is too slow, the search time will be too long. After performing the initialization step, the initial solution is brought into the objective function to form the current function value, and the difference between the current function value and the current temperature value is calculated. If this value is less than 0, the solution corresponding to the current function value is updated to the solution after the loop is solved. If it is not less than 0, the solution corresponding to the current function value is updated to the solution after the loop with a certain probability according to the idea, and every cycle Use the temperature degradation rate to update the current temperature once until the end of the cycle. After the end of the cycle, the optimal solution of the cycle can be obtained. The specific implementation process of the algorithm is shown in Figure 3:
4. PF-SA METHOD ANALYSIS

The optimization algorithm for SOH estimation of lithium-ion batteries based on PF-SA first obtains the posterior probability distribution of SOH through the observation model in the particle filter, and gradually approximates the true value of the parameter by continuously iteratively updating the weights, that is, the simulated annealing algorithm is used to filter the particle. The re-sampling stage is improved, and the weights of particles are updated, so that the particles can be quickly optimized, the calculation efficiency is improved, and the results quickly converge. The specific process of the improved algorithm is shown in Figure 4:
5. SIMULATION VERIFICATION ANALYSIS

This article uses battery data from battery manufacturers as the test object to evaluate the accuracy of this method. The true value of SOH of the battery cell is calculated by Equation 3.

\[ SOH = \frac{R - R_0}{R_e - R_0} \]  

(3)

Among them, R is the current internal resistance of the battery; \( R_e \) is the internal resistance at the end of the battery life, and \( R_0 \) is the internal resistance when the battery is out of the field.

The following two prediction methods, particle filter and simulated annealing optimized particle filter, are used to analyze the health of the battery, and the effectiveness of the two methods is verified through actual data.

5.1 Particle filter predictive analysis

The experimental data takes the internal resistance data of 25 single batteries randomly collected by BMS. Use these internal resistance data to calculate the true value of the SOH sample and use the PF algorithm The SOH of each single cell yields sample estimates. The number of iterations in the algorithm is set to 100, and the predicted result is compared with the actual calculated result in the matlab environment. For the convenience of observation, the 25 real values and 25 predicted values are plotted as graphs. The comparison result is shown in Figure 5:
It can be seen from the figure that the particle filter algorithm alone will have a large error in predicting the SOH of the battery, and further optimization is needed.

5.2 PF-SA algorithm analysis
In order to reduce the prediction error of PF as much as possible, it is introduced into the idea of simulated annealing, and the predicted value of SOH sample is calculated based on the 25 battery internal resistance data randomly selected in the BMS. The comparison between the predicted value and the real value of the optimization algorithm in the matlab environment is shown in Figure 6:

The number of calculation iterations of PF and SA are both set to 100, in which the number of particles in PF is set to 100, the initial temperature in SA is set to 1000°C, and the lower limit of temperature is 10°C and the annealing rate is 0.98. Experiments show that the error between the estimated state value and the actual measured value of the improved prediction algorithm is within 2%, which verifies the accuracy of the algorithm.
6. CONCLUSION
This paper proposes a strategy for battery SOH estimation. The SOH of the battery is estimated by PF, and the particle weight in the PF is optimized by the SA algorithm. After 38.4V200Ah lithium battery charge and discharge test data, the effectiveness of this method is verified. Because the evaluation strategy adopted in this article is only verified on one type of lithium battery, there are limitations, and the method needs to be further optimized.

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