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Fault Tolerant Strategy of Abnormal Battery Discharge

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Abstract

To solve the problem of abnormal battery discharge in the operation of electric vehicles, a method of fault tolerance based on data driven is proposed. First, based on the relation between transient voltage and the aging degree, battery SOC estimation model is built through LS-SVM method. Then, the fault-tolerant control scheme is put forward, which aims at abnormal discharge of power battery. When known battery exception occurs, the corresponding model control law is implemented to achieve fault tolerance control. When the unknown abnormal battery fault occurs, using dynamic data circulation way, the unknown exception model is rapidly established implementing system fault tolerant control for unknown exception. Finally, the accuracy of the method is verified by the simulation, which shows that this method is good for the fault tolerance of known and unknown faults.

Keywords*: power battery; fault diagnosis; fault tolerant control; LS-SVM*

1. Introduction

Because of zero emissions, high efficiency and energy saving features, electric car has become the mainstream in the development of new energy vehicles. As the energy source of the new energy vehicles, the key technology of power battery has attracted people's attention. Actual electric vehicle operating environment is complex and changeable. As the heart of the electric car, power batteries are subject to waves, vibration, and the influence of real-time traffic conditions and practical operation, which leads to the decline in the performance of the power battery. When abnormal discharge phenomenon occurs, their characteristics and properties are hidden in the data. If it cannot be timely and effective detected and processed, it can lead to damage of the battery and malfunction of the electric vehicle, or even causes the huge loss of personnel and property. In order to reduce the frequent occurrence of abnormal battery discharge, it is necessary to study fault diagnosis and fault tolerance of power battery [1-11].

At present there are many methods for the fault diagnosis of the battery, the authors in the literature [1] propose a multiple classifier which bases on binary tree support vector machine (SVM) fault diagnosis method, through the fuel battery system as the research object, taking the failure after normal preprocessing parameters as the input into the support vector machine (SVM), a typical fault becomes the output to complete the fault diagnosis of the fuel battery system. In the literature [2], the author starts from the characteristics of battery charging and discharging, and the main problems encounters in the use, fault content are analyzed in detail, and it combines the theory and method of the existing expert system, obtaining relevant information through the network server and the collected battery status information data for analysis and processing, so it finishes the fault diagnosis of the battery. In the literature [3], the author puts forward the fuzzy mathematics theory, using fuzzy comprehensive evaluation method, building fuzzy diagnosis matrix, and according to the development process of expert system

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development, joining the artificial fault exclusion function in the inference part, so that the system has more accurate data to improve the accuracy of fault diagnosis.

Abroad, there are many research results in the battery fault diagnosis, in the literature [6], the authors put forward a kind of active discrete event system framework. The system model is composed of an automaton (finite state machine) with the state output, and the system is applied to the fault diagnosis of the battery system. In literature [7], the authors propose an adaptive fault diagnosis technology for lithium ion battery, by using the equivalent circuit method to construct multiple nonlinear fault model, the way of Extended Karman Filter estimate that the terminal voltage generate a residual signal in each model, using the residual signal generation technique to determine the calibration failure probability in multiple model adaptive estimation. In literature [8], the authors propose a method which bases on support vector machine (SVM) to estimate the battery state of charge, mainly though the weighted least squares support vector machine method establishes in relation to the battery voltage, current and battery voltage, and puts forward the method of iterative model.

2. Abnormal Power Battery Discharge Fault Tolerant Strategy

In this paper, the design of power battery fault tolerant system is composed of monitoring mechanism and controller, monitoring mechanism include SOC model library and the decision-making mechanism. SOC model library contains normal model and the known model, they are the basis of the decision-making mechanism; Decision-making mechanism calculated monitoring indexes. Though analyzing the results determine which SOC of battery's discharge mode, So as to adjust the parameters of the model. Controller regroup and restructure Law of Control[12-14]. Fault tolerant system structure is shown in Figure 1.

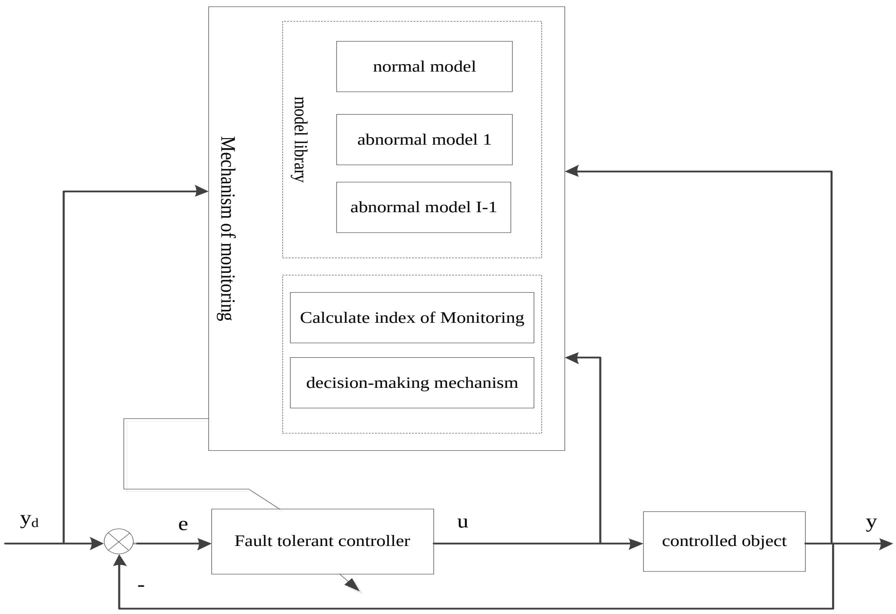

Figure 1. Fault Tolerant System Structure

2.1. The Establishment of SOC Model Library Base on LS-SVM

In a closed chamber, the battery is discharged, and the operating voltage, current and temperature of the battery are measured and recorded every 10 to 20s. The State of Charge of the battery can be calculated based on the current and time integral, this can also get the full charge of the initial capacity and then know the State of Health[15]. Based on the relationship between transient voltage and State of Charge, Releasing the relationship between transient voltage and State of Health. Finally, the 80 sets of data obtained from the experiment are used to train the sample data to carry on the simulation experiment, and obtain the corresponding curve, as is shown in Figure 2.

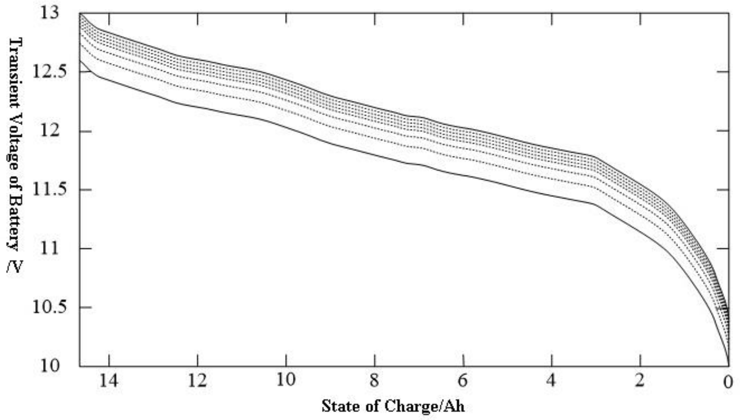

Figure 2. Transient Voltage and the Residual Capacity in the Aging Condition of Different Batteries

In Figure 2, the bottom curve is the battery discharge curve with the State of Health of 84.6%, the top curve is 97% of the State of Health. It can be seen that the State of Health and transient voltage which have a certain relationship, and the State of Health is related to battery capacity, so it can obtain the relationship which are between the battery's State of Health and the battery 's terminal voltage[16]. It is shown in Figure 3.

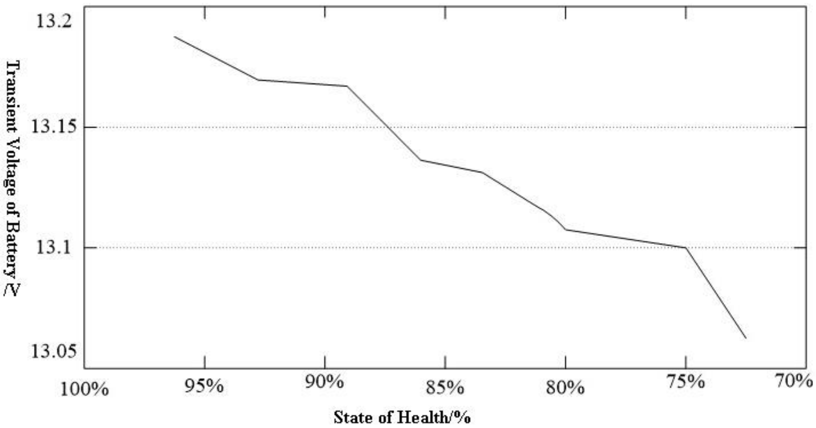

Figure 3. The Relationship Between the Change of The Voltage and The Aging Condition of the Battery

In this paper, using the least squares support vector machine (SVM) algorithm, the input are battery's State of Health and the battery's terminal voltage. The output is State of Charge. 80 sets of data collected by the experiment as training the total sample, randomly selecting 10 sets of data that are not repeated to form a subset of the sample. Receiving a total of eight subset of samples which have empty intersection. Take seven sample sets for the training sample set, the remaining one for validation sample set. Each sample subset validate the performance indicators such as formula (1).

$$V_l = \frac{1}{10}\sum_{j=1}^{10}(y_j^{\nabla} - f(x_j^{\nabla}))^2$$

$$= \frac{1}{10}\sum_{j=1}^{10}\left(y_j^{\nabla} - \begin{bmatrix} 1 \\ \Omega_1^{\nabla} \\ \vdots \\ \Omega_{70}^{\nabla} \end{bmatrix}^T \begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_1,x_1)+\frac{1}{2\gamma} & \cdots & K(x_1,x_{70}) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(x_{70},x_1) & \cdots & K(x_{70},x_{70})+\frac{1}{2\gamma} \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_{70} \end{bmatrix} \right)^2 \quad (1)$$

Among them, i=1, 2,…, 8, j=1, 2,…,10; $\Omega = K(x,y)$, $\Omega^{\nabla} \in R^{70\times 1}$, $\Omega_i^{\nabla} = K(x_i, x_j^{\nabla})$, $i = 1,2,...,70$; y_j^{∇} is validation sample.

8 samples of the subset of the total validation performance indicators such as the formula (2).

$$V = \frac{(V_1 + V_2 + \cdots + V_8)}{8} \quad (2)$$

In this paper, the parameters and the fitness function is determined by repeat sample .Finally, simulation experiments to estimate the SOC as shown in Figure 4. LS-SVM algorithm accurate estimate of the relative average error is 0.066, the absolute maximum error is 0.112.

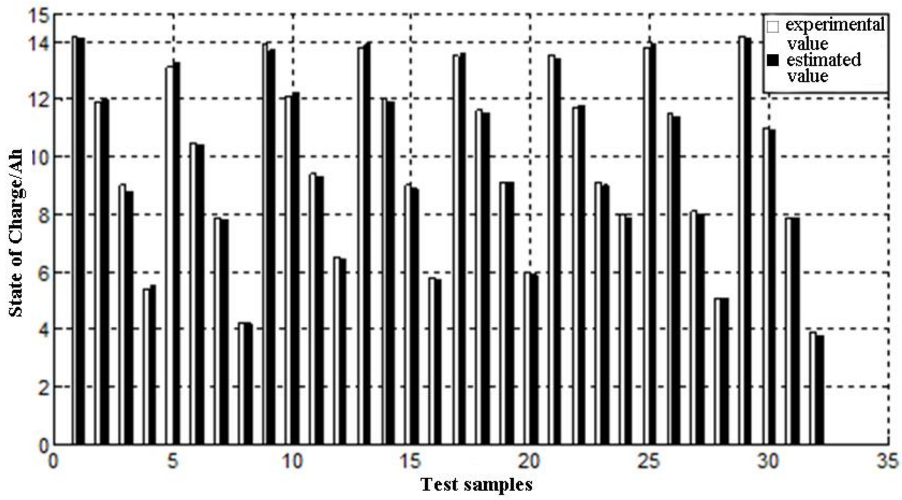

Figure 4. The Comparison Between Estimated Values And The Experimental Values

2.2. Decision-Making Mechanism Design

Decision-making mechanism is to determine whether the system is abnormal, and the corresponding model selection mechanism according to the abnormal happens. This design decision-making mechanisms of system operation from a performance perspective view, a measure is used to determine whether the system is an exception occurs, it is the system performance tolerance index Q_c; another indicator is used to identify abnormal patterns, it is the model mismatch index Q_i, the following algorithm is that it uses two indicators:

Step 1, Calculating $Q_c(k)$ and $Q_c(k)$, according to the real-time data at k time;

Step 2, Analyzing $Q_c(k)$ exceeds the threshold Q_{cT} . When $Q_c(k)$ is less than or equal to Q_{cT} , maintaining the same control model, go to step 6; when $Q_c(k)$ is greater than Q_{cT} , the battery is abnormal discharge, go to step 3.

Step 3, Analyzing 1 exceeds the threshold 2. When 1 is less than or equal to 2, using model S application from the model library, go to Step 4; when 1 is greater than 2, the battery has a new unusual situation, go to step 5.

Step 4, Operating model and setting new control law, completing new control law of recombination, go to step 6.

Step 5, Using self-tuning algorithm model program for online identification and control law reconfiguration, get new exception model exist in the model database, so the number of model i plus 1.

Step 6, k = k + 1, repeating steps 1 through 5.

2.3. Tolerant Controller Design

From Q_c and Q_i the system will appear three kinds of working state: Working status 1 (LQ_c, LQ_i) is the normal work of the system state (Q_c and Q_i do not exceed the standard); working status 2 (HQ_c, LQ_i) is that system occurs a known abnormal state of the system (Q_c exceed the standard, Q_i do not exceed the standard), it completes fault-tolerant though recombining model control law in Call Library. Working status 3 (HQ_c, LQ_i) is that system occurs an unknown and abnormal state (Q_c and Q_i exceed the standard), this time should to be remodel new control law online which base exception model calculation. Working state of fault tolerant system which base on exception condition is as shown in Figure 5.

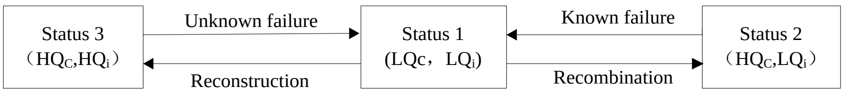

Figure 5. Three States Of Monitoring Decision-Making Mechanism And Transformation Process

When an unknown exception occurs, it combines effectively the LS-SVM modeling method and local linear predictive control algorithm. Using less data in a short period of time to establish high-precision model for fault tolerance system. Fault-tolerant algorithm of dynamic data-driven is as follows:

Step 1, Initialization, the model of the system which at current time operates mode in advance sets a constant number, and marks this as a complement to the constant model library;

Step 2, Comparing the existing model which is unknown and abnormal with the existing models in the model database, and finding the model mismatch which is the most close to the current model. It calculates $Q_{i\min}(k) = \min(|y_{sm}(k) - y(k)|)$, $y_{sm}(k)$ is the predicted value of the current time of each model, $s \in S = \{0,1,2,...,I\}$, S is the existing model in model library, $y(k)$ is actual output value for system in the current time, Q_{imin} indicates model mismatch which is close to abnormal and current pattern, this model as a predictive model of fault-tolerant control process of transition;

Step 3, Using data of abnormal patterns to match that step 2 obtains the model, until the end of $Q_i(k) < Q_{iT}$, and the modeling of unknown model saves in the model library.

Step 4, Prediction models of Step 2 use predictive control algorithm of local linear approximation, thus the system will be over fault-tolerant;

3. Simulation and Analysis

Considering the experimental simplicity and predictive control algorithm's convenience, the parameters are selected as $Q_{cT} = 0.006, Q_{iT} = 0.44$, predicted step P=1, and controllable step L=1.Taking a constant and current SOC models of C/3 as the normal discharge model, Using the SOC model which switches the discharge though the constant and current C/3 C/2 as the abnormal model, Here it is assumed that the mode which changes the discharge though C/3 and C is unknown and abnormal. In order to verify the fault tolerance of the known and unknown anomalies. Setting the system in normal working condition, when the time is 1000s, system occur a known exception, when the time is 2000s, system occur an unknown exception. The system response curve, the performance tolerance index curve and the model mismatch degree index curve are as shown in Figure 6-8.

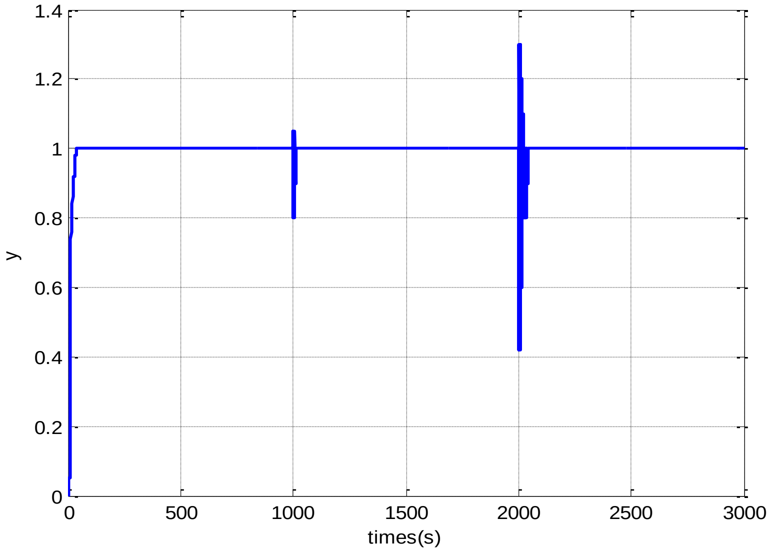

Figure 6. The System Response Curve Of A Known And An Unknown Exception

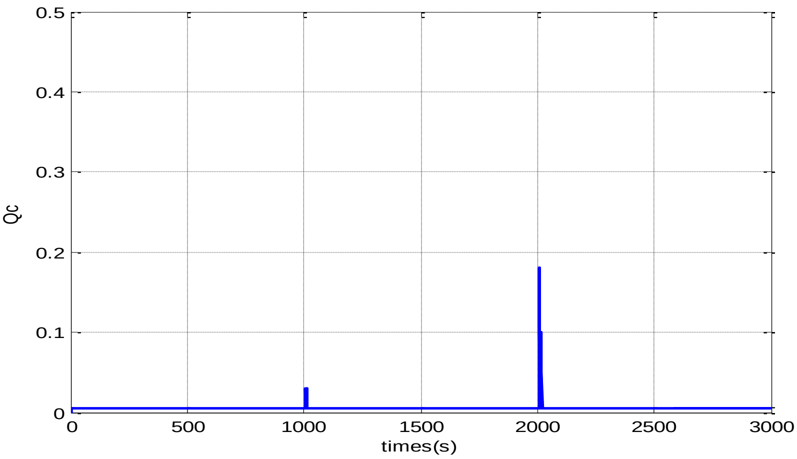

Figure 7. The Performance Tolerance Index Curve Of A Known And An Unknown Exception

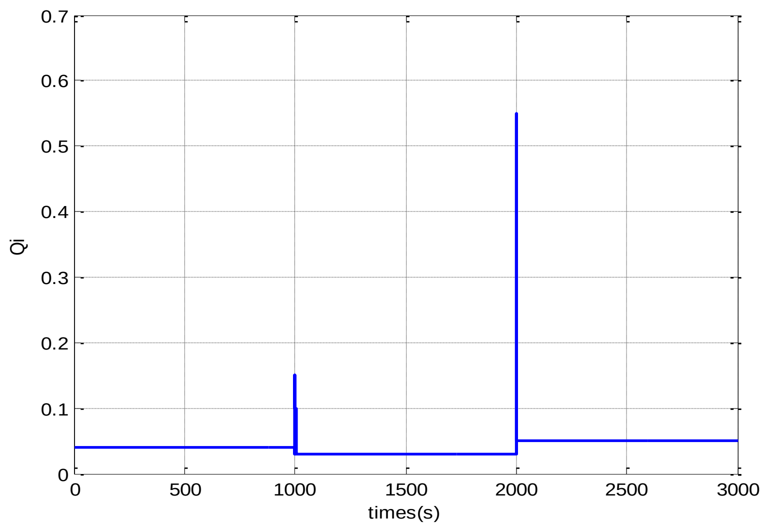

Figure 8. The Model Mismatch Degree Index Curve Of A Known And An Unknown Exception

From the Figure we observe:

1. When the time is 1000s, from Figure 6 can be seen an anomaly on the system response curve, from Figure 7 and 8 can be seen that Qc exceeds the set threshold, although Qi rises but do not exceed the threshold, Based on this, decision-making mechanism is determined to occur a known exception, and calls the model database already exists in the abnormal model, carries on the optimized control to make the system return to normal.

2. When the time is 2000s, Q_c and Q_i are super threshold and occur unknown abnormal, Abnormal data are collected by binding loop of algorithm to build a new model, then the new model is used as the basic model of optimal control, and then the system returns to normal state.

4. Conclusion

In this paper, the abnormal discharge of power battery is studied. The LS-SVM algorithm of battery SOC estimation model is designed, and the simulation verifies the feasibility and accuracy of the model. Further, the design scheme for battery of abnormal discharge is putting forward, which contains the SOC model's establishment and control decision-making mechanism. Fault tolerant control method of power battery is proposed using the dynamic data of cycle algorithm. Unknown anomaly model is rapidly established, and fault-tolerant control for unknown abnormalities is achieved in the system. Finally, feasibility of the fault-tolerant method is proved by experiments.

Acknowledgements

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