Research on Brake Energy Recovery System Based on Uncertain Stacked Auto Encoder Method

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Abstract. Aiming at the problem of real-time and poor reliability caused by the complex control algorithm of braking energy recovery system of electric vehicle, the uncertainty optimization theory is introduced into the SAE sample data preprocessing stage to establish the uncertainty SAE control parameter prediction model. The simulation results show that the real-time and reliability of the proposed method meet the system requirements, and the prediction accuracy of the control parameters is high.

1. Introduction

Electric vehicle brake system includes friction brake system and electromagnetic brake system, and the electromagnetic brake system performs brake energy recovery while providing brake torque. Brake energy recovery technology is one of the key technologies for increasing the driving range and improving economy of electric vehicles. Determining the proportion of electromagnetic braking force distribution is the key and thorny point in the research of braking energy recovery. In [1], based on the multidisciplinary optimization method, a braking force distribution control algorithm is proposed to enable the electric vehicle to achieve the optimal braking energy recovery efficiency while meeting the braking requirements during braking processes. However, the control algorithm is relatively complicated, resulting in poor real-time and reliability of control parameter calculation output.

Aiming at this problem, based on the braking force distribution control algorithm, the uncertainty optimization is introduced into the SAE sample data pre-processing stage, and a control parameter prediction model based on the uncertainty SAE method is proposed. The method controls input and output parameters of the algorithm for uncertainty optimization as sample data. SAE extracts deep features of sample data through forward propagation and backpropagation architectures. The simulation results show that the real-time, reliability and prediction accuracy of the uncertain SAE method meet the requirements of the braking energy recovery system.

2. Uncertainty SAE method

In this paper, the uncertainty optimization theory is introduced into the SAE sample data pre-processing stage. When the interference factors are difficult to eliminate, the key parameters are improved to minimize the influence of uncertain factors, so that the prediction results meet the performance requirements and guarantee the stability of the system. The uncertainty SAE method consists of two parts: data pre-processing and SAE model. The data pre-processing stage optimizes and normalizes the data. The SAE model performs pre-processed data for feature learning and outputs prediction results. The structure of the uncertainty SAE method is shown in the figure below.
3. Prediction of control parameters based on uncertain SAE method

3.1. Sample data construction and pre-processing.
In the braking condition, the optimal braking force distribution coefficient $a$ is related to the braking strength $z$, the battery SOC value $s$, and the vehicle speed $v$. In order to ensure the randomness and validity of the sample data, the Latin hypercube design is adopted for various brake working conditions, in the case of $(z, s, v)$, to DOE discrete sampling. That is, 9000 samples are taken, three variables are divided into four independent subspaces, and equal probability sampling is performed in each subspace, and the elements in the obtained three sets of data are randomly combined to obtain sample data $X = [x_1, x_2, \ldots, x_{9000}]$, wherein $x_i = [z_i, s_i, v_i]$. The control algorithm model is built in Matlab/Simulink, with $X$ as the input variable and the output optimal braking force distribution coefficient $A = [a_1, a_2, \ldots, a_{9000}]$ as the tag value.

In order to meet the reliability requirements of the control system, two-level nesting optimization is used in the data pre-processing stage to optimize the uncertainty of the sample data and tag values. As shown in Figure 1, the ASA algorithm is used for deterministic optimization in the inner layer module. Based on the Monte Carlo simulation technology, the reliability analysis is performed on the outer module, and the optimal brake distribution coefficient satisfying the reliability analysis is normalized, then saved to the database.

3.2. Network construction.
The Matlab/Simulink simulation model outputs a control parameter every 85ms online, which cannot meet the 20ms real-time control requirements of the braking energy recovery system. According to the SAE model theory, the trained SAE model outputs more accurate prediction values in a shorter time than traditional prediction techniques. It can be seen from the above analysis that the uncertainty SAE method has three output variables of $z$, $s$, and $v$, and outputs a braking force distribution prediction coefficient $\hat{a}$. Among them, the number of hidden layers and hidden nodes is determined by the complexity of sample data and control algorithm, and the optimal network structure needs to be determined by experiments.

The number of hidden layers in the SAE network, the number of hidden nodes and sparse parameters will affect the model prediction accuracy and sample training time. In order to determine the optimal model structure, improve the prediction accuracy, reduce the sample training time, determine the parameters of the model through experimental methods. When the number of hidden layers is 5, 6, and 7, and the number of hidden nodes is 5, 10, and 15, the iteration is performed 25
times, 50 times, and 100 times respectively to observe the prediction accuracy. When the number of hidden layers in the model is 6, and the number of hidden nodes is 10, the model prediction error rate is the lowest. When the sparse parameter is set to vary from 0.1 to 0.7, the sparse parameter is between 0.3 and 0.5, and the model has the best prediction accuracy. In summary, the SAE model parameters are shown in the following table:

| Parameter | Input Parameter | Output Parameter | Hidden Layers | Hidden Nodes | Sparse Parameter | Output Time |
|-----------|-----------------|------------------|---------------|--------------|-----------------|-------------|
| Value     | 3               | 1                | 6             | 10           | 0.4             | 5.2ms       |

4. Simulation results and analysis

In order to evaluate the prediction accuracy of the uncertainty SAE method, the following evaluation indicators were established:

\[ S_a = \frac{|a - \hat{a}|}{a} \times 100\% \] (1)

\[ \hat{P_F} = \int_{-\infty}^{\infty} I[g(x) \leq 0] \cdot f(x)dx \] (2)

Where \( S_a \) is the predicted relative error; \( a \) is the actual optimal value; \( \hat{a} \) is the predicted optimal value; \( \hat{P_F} \) is the failure probability estimate; \( K \) is the number of sample points; \( x_i \) is the \( i \) sample point that is randomly distributed.

Based on the above-mentioned uncertainty SAE method, 9000 sets of sample data and tag values are used as training data, and 1000 sets of sample data are randomly selected as error test sets, and the prediction relative error and reliability are calculated based on equations (1) and (2). The results are shown in Figure 2 and Figure 3.

It can be seen from Fig. 2 and Fig. 3 that the relative error distribution of the prediction parameters is between -5.1% and 5.2%, and the maximum failure probability is not more than 2.4%. And after many experiments, the output prediction parameter time is controlled within 5-10ms. Therefore, the uncertainty SAE method has higher prediction accuracy and reliability level, and can meet the requirements of electric vehicle braking energy recovery system.

![Fig. 2 Predictive parameter \( \hat{a} \) relative error](image)
5. Conclusion
Based on the uncertainty optimization theory and SAE theory, the uncertainty SAE method is proposed, which can improve the reliability of prediction parameters, and the prediction accuracy and real-time level are higher, which provides a new idea for parameter control problem in electric vehicle braking energy recovery system. Based on the uncertainty SAE method, the braking force distribution coefficient prediction model is built and simulated.

The simulation results show that the uncertainty SAE method has higher control precision and reliability, and can meet the real-time requirements of electric vehicle energy recovery system.

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