Research on intelligent Diagnosis method of Electric vehicle Charging Fault based on artificial intelligence expert system

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Abstract. To realize charging electric vehicle safety, this paper studies the latest artificial intelligence learning algorithm, combined with the characteristics in the process of electric vehicle charging, based on the deep learning algorithm of charge-discharge failure correlation method, combining with the characteristics of the expert system, design of electric vehicle charging process of the fault intelligent diagnosis system structure, characteristic information database, knowledge base, reasoning machine, and for battery, charging pile, power supply equipment failure correlation between the integration of online diagnosis, which can effectively improve the electric car battery safety, promote the healthy development of electric vehicles.

1. Introduction

In recent years, automobile fault diagnosis technology has developed rapidly, and the fault diagnosis expert system usually studied is an expert system based on instance, rule or behavior [1]. Literature [2] proposes a method to realize on-board diagnosis on an on-board bus. The Beijing Institute of Technology uses communication cards to collect communication data of ev messages, so as to realize detection and diagnosis of vehicle state and fault information [3]. Literature [4] designs the vehicle fault code and its data flow based on the protocol, and introduces remote server and handheld terminal to realize remote fault diagnosis of vehicles. Literature [5] has carried out studies on fault diagnosis and fault-tolerant control strategy development, fault diagnosis and bench test. At present, there is a lack of a more suitable fault diagnosis method for ev charging evaluation.

This paper designs relevant modules for intelligent fault diagnosis in the charging process of electric vehicles, and makes integrated online diagnosis for fault correlation among batteries, charging piles and power supply equipment.
2. Fault correlation processing technology based on deep learning algorithm

![Diagram showing data processing flow]

Firstly, the fault diagnosis data in the charging and discharging process of electric vehicles are preprocessed: null value processing, data dimension reduction and discretization processing.

Figure 1. Figure with FP-growth algorithm diagnosis process for EV charging and discharging.
Association rules for symptoms and faults will be obtained as a result of the algorithm. The optimized FP-Growth algorithm diagnosis process was established, as shown in the figure1.

3. Research on integrated online Diagnosis modeling technology of Electric Vehicle Charge-discharge Fault based on artificial Intelligence expert system

3.1. System structure
The expert system is composed of feature information base, knowledge base, reasoning machine, explanation machine, knowledge acquisition mechanism and human-computer interaction interface. In order to obtain the unified form of fault symptom information, the fault symptom information after feature extraction is required to form a feature information database.

3.2. Feature information base
The main task of feature information base is to realize the fusion of diagnostic information from multiple channels. The structure of the feature information base is shown in the figure below.

![Feature information base diagram](image)

Figure 2. Figure with information library system diagram.

There are two forms of diagnostic information: data information and non-data information. Different feature extraction methods and feature extraction algorithms are adopted for these information, so that the processed information has two attributes: feature value and state.

3.3. Knowledge base system
The representation is as follows:

IF \((T1 \& T2) | (T3 * \text{Const} > T4)\); THEN failure mode
The rules in the rule library are in the form of IF prefixes, THEN postfixes. In the rules, T1, T2, T3 and T4 are the number of the feature information in the feature information base.

3.4. Fault tree
Fault tree is a special inverted logical causal diagram. The correct establishment of fault tree is the key to fault tree analysis (FTA). The establishment of fault tree requires an in-depth understanding of the tree building system, and the process of tree building promotes the in-depth understanding of the system.

3.5. Reasoning machine
Inference machine is mainly divided into two parts: one part is rule inference part. The other part is fault tree reasoning part. Regular operation adopts analytic expression. For example, a regular expression is as follows:

\[ T_1 \& (T_2 > T_3) | T_4 | T_3 \]

When performing rule analysis, firstly compare whether the eigenvalue of T2 is greater than the eigenvalue of T3, if greater than (T2 > T3) part is true, if less than or equal to (T2 < T3) part is false. During the logical operation, the state of each feature information is calculated according to the logical operation rules.

The qualitative analysis of fault tree mainly adopts the following steps:
1. Generate the minimum cut set for each fault mode according to the Fussell method, put the minimum cut set of each fault mode into the possible fault library, and simplify the minimum cut set merged into the library. The same is true for non-failure modes.
2. Remove the cut set in the possible fault library contains the cut set in the impossible fault library.
3. Calculate the confidence of the residual cut set. For example, in a certain fault mode, n minimum cut sets are left after the above steps, and the relation between each cut set is or, the fault mode is calculated according to the compatible event probability calculation formula:

\[ P(T) = P(K_1 \cup \cdots \cup K_n) = \sum_{i=1}^{n} P(K_i) - \sum_{i=1}^{n} \sum_{j=1}^{n} P(K_i, K_j) + \cdots + (-1)^{n-1} P(K_1, \cdots, K_n) \]

Where, T is a fault mode, which represents the ith minimum cut set in the fault mode. When the failure rate of the top event is very small, it converges quickly, so the probability of the failure mode can be approximated as follows:

\[ P(T) \approx \sum_{i=1}^{n} P(K_i) \]

Then the confidence degree of each fault cause in the fault mode is:

\[ P_i = \frac{P(K_i)}{\sum_{i=1}^{n} P(K_i)} \]

3.6. Integrated online diagnosis
In the comprehensive evaluation index, the second-level index of each evaluation factor is

\[ U_1 = \{u_{11}, u_{12}, u_{13}\} \]
\[ U_2 = \{u_{21}, u_{22}, u_{23}\} \]
\[ U_3 = \{u_{31}, u_{32}, u_{33}\} \]

Where, U1 is the power battery, U11 is the power battery health, U12 is the number of battery failures, and U13 is the number of gross errors in battery data transmission. U2 is the charging pile, U21 is the health degree of the charging pile, U22 is the number of faults of the charging pile, and U23 is the number of gross errors in data transmission of the charging pile. U3 is the power supply facility, U31 is the health degree of the power supply facility, U32 is the number of failures of the new energy device, and U33 is the number of gross errors of transmission of the new energy device.
According to the empirical method of expert decision, the weight coefficient matrix is given
\[
W = \begin{bmatrix}
W_1 & W_2 & W_3
\end{bmatrix}^T = \begin{bmatrix}
w_{11} & w_{12} & w_{13} \\
w_{21} & w_{22} & w_{23} \\
w_{31} & w_{32} & w_{33}
\end{bmatrix} = \begin{bmatrix}
0.713 & 0.159 & 0.128 \\
0.685 & 0.181 & 0.134 \\
0.676 & 0.186 & 0.138
\end{bmatrix}
\]  \hspace{1cm} (6)

Among them, \( W_1 = \begin{bmatrix} 0.713, 0.159, 0.128 \end{bmatrix}, W_2 = \begin{bmatrix} 0.685, 0.181, 0.134 \end{bmatrix}, W_3 = \begin{bmatrix} 0.676, 0.186, 0.138 \end{bmatrix} \).

Select the set of five evaluation levels, i.e.
\[ V = \{ v_1, v_2, v_3, v_4, v_5 \} \]  \hspace{1cm} (7)

Where, \( V1 \) is absolutely safe, \( V2 \) is safe, \( V3 \) is general, \( V4 \) is dangerous and \( V5 \) is very dangerous.

Determine the single-factor evaluation results for the \( i \)-th level indicator \( U_i \).
\[
R_i = \begin{bmatrix}
r_{i1} & r_{i2} & \cdots & r_{i3} \\
r_{i1} & r_{i2} & \cdots & r_{i5} \\
r_{i1} & r_{i2} & \cdots & r_{i5}
\end{bmatrix}
\]  \hspace{1cm} (8)

The single factor evaluation results are found according to the single health degree, the number of short-term failures and the number of gross errors of the power battery, charging pile and power supply facility (Taiwan converted new energy device) respectively. The specific results are as follows:

1. **Single health assessment list**

   Table 1. Single health assessment list.

   | Single health real-time input \( u_{11}(u_{21}) (u_{31}) \) | Ranger | \( r_{11}(v_1) \) | \( r_{12}(v_3) \) | \( r_{13}(v_3) \) | \( r_{14}(v_4) \) | \( r_{15}(v_5) \) |
   |------------------|------|-------------|-------------|-------------|-------------|-------------|
   | \( >90\% \)      | 0.9 | 0.1         | 0           | 0           | 0           |
   | \( 80\%-90\% \)  | 0.7 | 0.1         | 0.1         | 0.1         | 0           |
   | \( 70\%-80\% \)  | 0.5 | 0.1         | 0.2         | 0.1         | 0.1         |
   | \( 60\%-70\% \)  | 0.1 | 0.2         | 0.3         | 0.2         | 0.2         |
   | \( <60\% \)      | 0   | 0           | 0.1         | 0.2         | 0.7         |

2. **Evaluation list of short-term failure occurrence times**

   Table 2. Evaluation list of short-term failure occurrence times.

   | Occurrence times \( u_{12}(u_{22}) (u_{32}) \) | Times | \( r_{11}(v_1) \) | \( r_{12}(v_3) \) | \( r_{13}(v_3) \) | \( r_{14}(v_4) \) | \( r_{15}(v_5) \) |
   |------------------|------|-------------|-------------|-------------|-------------|-------------|
   | \( 0 \)          | 0.9 | 0.1         | 0           | 0           | 0           |
   | \( 1 \)          | 0.8 | 0.1         | 0.1         | 0           | 0           |
   | \( 2 \)          | 0.5 | 0.3         | 0.1         | 0.1         | 0           |
   | \( 3 \)          | 0.1 | 0.2         | 0.4         | 0.2         | 0.1         |
   | \( 4 \)          | 0   | 0.1         | 0.3         | 0.4         | 0.2         |
   | \( 5 \)          | 0   | 0           | 0           | 0.3         | 0.5         |
   | \( 6 \) or above | 0   | 0           | 0           | 0.1         | 0.9         |

3. **Evaluation list of gross error times**

   Table 3. Evaluation list of gross error times.

   | Occurrence times \( u_{13}(u_{23}) (u_{33}) \) | Times | \( r_{11}(v_1) \) | \( r_{12}(v_3) \) | \( r_{13}(v_3) \) | \( r_{14}(v_4) \) | \( r_{15}(v_5) \) |
   |------------------|------|-------------|-------------|-------------|-------------|-------------|
   | \( 0 \)          | 0.9 | 0.1         | 0           | 0           | 0           |
   | \( 1 \)          | 0.8 | 0.1         | 0.1         | 0           | 0           |
   | \( 2 \)          | 0.5 | 0.3         | 0.1         | 0.1         | 0           |
(4) Output
Query the processing mode of the warning level in the 3D table and output after the call.

4. conclusion
This paper proposes a fault correlation processing method based on deep learning algorithm and designs an intelligent fault diagnosis scheme for the charging process of EV. The fault correlation among battery, charging pile and power supply equipment is analyzed to make an integrated online diagnosis, which can effectively improve the charging safety of EV.

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