Fault diagnosis of DC-DC module of V2G charging pile based on Fuzzy Neural Network

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Abstract. Aiming at the problem of fault diagnosis of switching devices in DC / DC module of V2G charging pile, a diagnosis method based on fuzzy neural network is proposed. The method combines fuzzy mathematics with neural network, adopts 4-layer forward network and a step degree optimization algorithm, uses the self-learning and self-adaptive ability of neural network, adjusts the parameters of fuzzy set membership function in real-time, and trains a set suitable for V2G charging Fault diagnosis algorithm of DC / DC module of electric pile. Simulation results show that the fault diagnosis algorithm based on fuzzy neural network can effectively diagnose faults.

1. Introduction

With the deepening of the global energy crisis, new energy vehicles have been greatly applied¹, but the large number of electric vehicles and renewable energy access to the grid has brought a huge impact on the reliability, security and economic operation of the grid. Through V2G (Vehicle-to-Grid) technology, the problems such as insufficient grid operation adequacy, low efficiency, seriously limited renewable energy acceptance capacity, inflexible charging and discharging of electric vehicles, and uneconomical use can be alleviated to varying degrees²³. Therefore, V2G technology has become a research hotspot in many countries. With the gradual increase in the number of V2G charging piles, its fault problems are gradually exposed, which has aroused people's attention.

In many parts of the charging pile, the charging module is the most critical and the highest failure probability component. Moreover, the fault characteristics of the charging module are not obvious, and the fault components are difficult to identify, which leads to the staff to spend time and energy in the maintenance of the charging module. Therefore, it is of practical and economic significance to study the fault process of charging module and extract the fault feature vector which can be used to locate the fault components. In reference⁴, wavelet packet energy spectrum method was used to extract fault features of three-phase input current of charging module, and neural network method was used for fault pattern recognition. In reference⁵, the fault diagnosis theory and method of DC charging pile are studied. On this basis, the fault diagnosis knowledge base is established, and a fault diagnosis expert system based on fault tree is developed. However, there is no specific fault diagnosis strategy for V2G charging pile.

Aiming at the DC-DC module of V2G, the fuzzy neural network (FNN) technology is adopted in this paper, which overcomes the shortcoming that neural network can't deal with fuzzy data of boundary classification well, and can learn and adjust constantly based on fuzzy reasoning to deal with imprecise or uncertain fuzzy information.
2. Analysis of main topology and fault mode of V2G charging pile

The V2G charging pile is composed of two parts: the front stage bidirectional AC / DC converter and the later stage DC / DC converter. The system structure is shown in Figure 1. The former AC / DC converter generally adopts voltage source three-phase full-bridge PWM converter (VSC), which can operate in four-quadrant conditions and input different active and reactive power commands to realize active and reactive power compensation of power grid[6].

![Figure 1. System structure of V2G charging point.](image)

The fault diagnosis object of this paper is the post-stage structure of V2G charging pile, double active bridge converter (DAB). The circuit topology is shown in Figure 2, in which S1, S2, S3 and S4 are power side switching devices, Q1, Q2, Q3 and Q4 are load side switching devices. The function of the structure is to adjust the charging voltage, charging current or charging power to the electric vehicle according to the system command. The control method adopted here is dual-phase-shifting control, and the output current of DAB circuit is controlled to be constant value, that is, the charging pile works in the working mode of constant current charging.

![Figure 2. Circuit diagram of V2G charging pile DC / DC module.](image)

The most common fault types in charging module are short circuit and open circuit of components. After short circuit fault occurs, most of them will change into open circuit under the action of protection circuit. Since the probability of two or more devices failure at the same time is very small, only single device open circuit is studied. In the case of dual-phase-shift control, the two switches connected to the same bridge arm at the power supply side have the same function, so the fault characteristics are similar. At the same time, in order to distinguish the fault state from the normal working state, the normal working state is regarded as a special fault state, and the fault types are divided into the following five types:

1. Normal working state;
2. Switch device S1 or S2 failure;
3. Switch device S3 or S4 failure;
4. Switch device Q1 or Q4 failure;
5. Switch device Q2 or Q3 failure.

3. Fault feature information extraction

According to the circuit in Figure 2, the simulation model is constructed, DC power supply \( V_{dc} = 700 \text{V} \), nominal battery voltage \( E_0 = 360 \text{V} \). The control method adopts dual phase-shifting control. The
initial control power supply is used to charge the battery. The charging current is 50A. When 0.225s, the battery is controlled to feed back the electric energy to the power supply side, and the feedback current is 40A. The battery terminal voltage curves under five kinds of fault conditions were collected, and a representative sample was selected as the initial training sample for each fault type. That is to form a set of samples containing five curves.

The fault feature information is extracted by subsection method, and the original data is divided into 8 intervals according to time or value, so as to better capture the fault features with weak difference between each section and the whole sample. The statistical characteristics of voltage maximum value, mean value, variance and section numerical integration are extracted for each interval, so that each curve corresponds to a feature vector with a length of $4 \times 8 = 32$.

Too many feature number selection will not only greatly increase the complexity of calculation, but also through the observation of all 32 features, it can be found that there are some big differences between the same feature of different samples, while some almost have no difference. In this paper, we calculate the average weight of each feature by ReliefF algorithm, and select the most effective feature for distinguishing different samples. The fruit is shown in Figure 3.

![Figure 3. Fault feature selection results.](image)

It can be seen from Figure 3 that the features with average weight greater than 0.15 are from large to small, feature 17, 21, 9, 29, feature 9 and feature 17 are voltage mean and variance in charging start-up phase, and feature 21 and feature 29 are voltage variance and numerical integration in control strategy switching stage, which shows that the four features are better than other features in distinguishing various modes.

4. Training and recognition of fuzzy neural network

Fuzzy neural network uses fuzzy theory to fuzzify the input fault symptom information to form the fault training sample input network, thus changing the weight and threshold value of the network, making the network have stronger expression ability, data processing ability and stable reasoning ability. This paper combines fuzzy theory and neural network to design a four-layer feedforward fuzzy neural network, as shown in Figure 4.

4.1. Construction of fuzzy neural network

The first layer is the input layer, which can transfer the pre-selected voltage data features to the second layer of the network. $P_1, P_2, P_3$ and $P_4$ are the input eigenvectors, and the number of nodes is the number of feature vectors 4, which are feature 9, feature 17, feature 21 and feature 29, respectively.
Figure 4. Schematic diagram of four-layer fuzzy neural network structure.

which fuzzies the input variables by membership function. Each node represents a fuzzy set, which is used to represent the membership values of each fuzzy set. Each input parameter corresponds to three fuzzy sets, which are respectively used to represent the input parameter values "high (H)", "normal (n)" and "low (L)". The membership function of system input variables is Gaussian membership:

$$A_k^j = e^{-\frac{(r-d_{kj})^2}{2\sigma^2}} \quad k = 1, 2, 3; j = 1, 2, 3$$

$d_{kj}$ is the center parameter of the function and $\sigma_{kj}$ is the width of each center.

The third layer is the rule layer, in which each neuron represents a fuzzy rule, which is used to match the antecedents of fuzzy rules. The sum of activation degrees of all rules is 1 through normalization operation. The algorithm for calculating each activation degree is as follows:

$$r_m = \frac{\min(A_k^1, A_k^2, \cdots, A_k^j)}{\sum_{j=1}^{R} \min(A_k^1, A_k^2, \cdots, A_k^j)} \quad j \in \{1, 2, 3\}, k = 4$$

$R$ is the number of rules formulated by expert experience.

The fourth layer is the network output layer. The output of the system is represented by the confidence degree of five typical faults. The confidence degree represents the possible degree of the fault, which is described by four fuzzy subsets: $A = 0.8$, $B = 0.6$, $C = 0.5$, $D = 0.3$. The confidence levels $F_1, F_2, F_3, F_4, F_5$ of module failure are obtained by the following formula:

$$F_n = \sum_{m=1}^{R} c_{nm} r_m \quad n = 1, 2, \cdots, 5; m = 1, 2, \cdots, R$$

$c_{nm}$ is the center value of the $m$-th membership function of $F_n$.

Then, the parameters of $c_{nm}$, $\sigma_{kj}$ and $d_{kj}$ are optimized by a step degree optimization algorithm, and the parameter learning algorithm is:\[9\]:

$$c_{nm}(n+1) = c_{nm}(n) - \alpha \frac{\partial E}{\partial c_{nm}(n)}$$

$$d_{kj}(n+1) = d_{kj}(n) - \alpha \frac{\partial E}{\partial d_{kj}(n)}$$

$$\sigma_{kj}(n+1) = \sigma_{kj}(n) - \alpha \frac{\partial E}{\partial \sigma_{kj}(n)}$$

$\alpha$ is the learning rate.

4.2. Training of fuzzy neural network

In this paper, four kinds of fault characteristic parameters and five kinds of fault modes are fuzzily expressed, and six fault diagnosis rules are formulated by combining with expert experience knowledge, as shown in Table 1.
Table 1. Fault diagnosis rules.

| Characteristic parameter | Fault type |
|--------------------------|------------|
|                         | P1  | P2  | P3  | P4  | F1  | F2  | F3  | F4  | F5  |
| H                       | L   | H   | H   |     | A   | D   | D   | B   | B   |
| H                       | L   | H   | N   |     | A   | D   | C   | D   |     |
| L                       | H   | L   | L   |     | D   | A   | D   | D   | D   |
| N                       | H   | H   | N   |     | D   | D   | A   | D   | D   |
| N                       | L   | N   | H   |     | C   | D   | D   | B   | A   |
| N                       | L   | H   | H   |     | B   | D   | D   | A   | B   |

The learning samples of fault diagnosis system are determined according to the above table, as shown in Table 2.

Table 2. Learning samples.

| Characteristic parameter | Fault type |
|--------------------------|------------|
|                         | P1   | P2   | P3   | P4   | F1   | F2   | F3   | F4   | F5   |
| 389.85                  | 2.5925| 1.8744| 8727.1 | 0.8  | 0.3  | 0.3  | 0.6  | 0.6  |
| 389.84                  | 2.5895| 1.9050| 8726.1 | 0.8  | 0.3  | 0.5  | 0.5  | 0.3  |
| 389.01                  | 2.8741| 1.6867| 8721.6 | 0.2  | 0.8  | 0.2  | 0.2  | 0.3  |
| 389.35                  | 2.9279| 1.8472| 8724.9 | 0.3  | 0.3  | 0.8  | 0.3  | 0.3  |
| 389.70                  | 2.6681| 1.8300| 8728.2 | 0.5  | 0.3  | 0.3  | 0.6  | 0.8  |
| 389.73                  | 2.6881| 1.8423| 8728.5 | 0.6  | 0.3  | 0.3  | 0.8  | 0.6  |

Using the learning samples determined in Table 2, take random numbers with learning rate between [0,1]. After 200 times of training, the network error value is about 0.06386 and remains stable. The network error change curve and the membership function distribution of one of the input parameters are shown in Figure 5.

Figure 5. Training results of fuzzy neural network

4.3. Example of fault diagnosis

Under the input disturbance of the system, 20 groups of battery terminal voltage data under five fault modes are collected, and the above four eigenvectors are extracted and input into the trained fuzzy neural network for fault diagnosis. The diagnosis results are shown in Table 3.

Table 3. Diagnosis results.

| Fault status | Number of samples | Number of correct results | Accuracy |
|--------------|-------------------|---------------------------|----------|
| F1           | 20                | 20                        | 100%     |
| F2           | 20                | 20                        | 100%     |
| F3           | 20                | 20                        | 100%     |
| F4           | 20                | 19                        | 95%      |
| F5           | 20                | 19                        | 95%      |
In the fault diagnosis of DC / DC module of V2G charging pile, only two groups of fault samples are identified, and the correct rate is 98%. This proves the effectiveness of the fuzzy neural network designed in this paper for the fault diagnosis of DC / DC module of V2G charging pile.

5. Conclusion

In this paper, the fuzzy neural network algorithm is applied to the fault detection of the DC / DC module of the V2G charging pile. After verification, the correct rate of fault diagnosis reaches 98%, which can realize the effective fault location. However, there are still some problems to be further studied:

In this paper, the fault diagnosis of the switch devices in the DC-DC module of V2G charging pile is only carried out, and the fault diagnosis of the switch devices in the former AC / DC module is not involved, and will continue to be improved in the future.

In this paper, the diagnosis of eight switch devices in the circuit is divided into four groups, the recognition effect between groups is good, and how to distinguish the fault situation of two switch devices in the group needs further research.

References
[1] Dong Yang. Report on the development of charging infrastructure in China 2019-2020[R]. Beijing: EVCIPA, 2020.
[2] Xiaotao Z, Cruden A, Infield D, et al. Assessment of Vehicle to grid power as power system support[C]. 2009 Proceedings of the 44th International Universities Power Engineering Conference (UPEC), Glasgow, 2009: 1-5.
[3] Shi Ruifeng, Li Shaopeng. Review on Studies of V2G Problem in Electric Vehicles[J]. Proceedings of the CSU-EPSA, 2019,31(06):28-37.
[4] Kang Ning. Research on feature extraction of charging module of DC charging pile[D]. Beijing Jiaotong University,2019.
[5] Yang Shasha. Research on DC charging pile fault diagnosis expert system based on fault tree[D]. Beijing Jiaotong University,2019.
[6] Liu Xiaofei. Research on electric vehicle V2G system and charging and discharging control strategy[D]. Harbin Institute of Technology,2015.
[7] Jiang Baining. Research on feature selection algorithm in machine learning[D]. Ocean University of China,2009.
[8] Tian Jian. Fault diagnosis method for railway switch point based on fuzzy neural network[D]. Beijing Jiaotong University,2015.
[9] Zhang Siyang, Kuang Fangjun, Xu Weihong. Bearing fault diagnosis based on wavelet packet decomposition and fuzzy neural network[J]. Journal of Hunan University of Science & Technology(Natural Science Edition), 2010,25(02):28-31.