PFC fault detection method for EV wireless charging system based on hidden Markov model

Changfu Xu¹, Bin Bo¹, Ruoyin Wang*, Ming Zhang³, Jiayuan Xu¹
¹State Grid Jiangsu Electric Power Co., Ltd. Research Institute, 211100 Nanjing, China
²School of Electrical Engineering, Southeast University, 210096 Nanjing, China

Corresponding author: 379152942@qq.com

Abstract. The PFC device serves as an important bridge between rectifier module and high-frequency inverter module in the wireless charging system of electric vehicle (EV). Once this device fails, it will not only have a serious impact on the power grid, but also cause irreversible damage to the back-end high-frequency inverter module. Traditional fault diagnosis methods are difficult to meet the requirements of complex systems. In this paper, HMM which has unique advantages in training model and fault identification is used for fault diagnosis of PFC device of EV wireless charging system. Firstly, the model is initialized and the initial values of HMM are determined. Then, Baum-Welch algorithm is used for iterative training. Finally, Viterbi algorithm is used for fault diagnosis. The test results show that the PFC fault diagnosis accuracy of EV wireless charging system using HMM is about 25% higher than the traditional method, and the recognition speed is significantly improved.

1. Introduction
EV wireless charging technology is a new type of electric vehicle energy supply[1]. Traditional way of EV charging mainly contact recharging by cable, it is easy to produce contact spark. Therefore, the emergence of wireless charging technology effectively eliminates these disadvantages. Therefore, when the PFC fails, it not only has a serious impact on the power grid, but also cause irreversible damage to the back-end high-frequency inverters. Therefore, a fast and accurate fault diagnosis method is urgently needed to minimize the damage to the wireless charging system of EV when it breaks down. When the circuit of power electronic device fails, it is necessary to carry out detection and analysis in time to effectively complete the troubleshooting and overhaul[2]. McArthur used multimedia technology to diagnose the fault of switching power supply independently[3]. Xi. Zhang et al. used the voltage measurement value to detect the fault of the capacitive voltage transformer.[4] Song Xiaolan et al. introduced expert system into radar power diagnosis[5]. W.J. Wang et al. designed a method for diagnosing the gradual fault of the line electronic transformer[6]. This paper intends to diagnose the fault of PFC devices in the wireless charging system of electric vehicles. The commonly used fault diagnosis methods are as follows(1) Fault Tree Diagnosis[7], Although it is intuitive, the process of fault modeling is very complex, and the workload is too large for the case of a large number of fault states. (2) Neural Network Method [8], it combines some advantages of self-learning, but the speed of modeling is still slow. (3) Based on expert experience [9], this method makes full use of the experience of experts in a certain field, but it has great limitations and low accuracy.
In this paper, the boost chopper circuit is chosen as the PFC topology in the wireless charging system of EV. The hidden Markov model (HMM) in Markov theory is introduced to train and diagnose the failure model of the PFC device. HMM is a model based on statistical theory[10], which has made great achievements in the field of speech recognition[11]. In recent years, HMM has also shown its superiority in the field of fault diagnosis. In [12], HMM is used in bearing fault detection; In [13], HMM is used in power system fault detection; In [14] HMM is used in motor fault state detection; In [15-16] HMM is used to fault detection in mechanical speed-up and speed-down process.

2. Classification of fault types Margins
Before the fault diagnosis of the PFC device of the EV wireless charging system, we need to summarize and classify the possible faults of the PFC device. In this paper, the boost chopper circuit is selected as the basic topology of PFC, as shown in figure 1. The possible failures of PFC are numbered, as shown in table 1.

![Figure 1. Basic topology of PFC device in EV wireless charging system](image)

### Table 1. Fault status number

| Number | Fault status     | Number | Fault status                |
|--------|------------------|--------|----------------------------|
| 1      | C aging          | 5      | C and MOSFET aging         |
| 2      | C invalid        | 6      | C aging MOSFET invalid     |
| 3      | MOSFET aging     | 7      | C invalid MOSFET aging     |
| 4      | MOSFET invalid   | 8      | C and MOSFET invalid       |

3. Hidden Markov Model
Hidden Markov Model (HMM) is a statistical Model that can be used to describe a Markov process with hidden unknown parameters. A HMM contains five basic elements, which constitute a sequence, where:

(1) \( N \): represents the number of hidden states in the model; (2) \( M \): represents the number of observable states in the model; (3) \( \pi \): represents the initial state probability distribution in the model; (4) \( A \): represents the transition probability matrix of hidden states in the model, \( A = \{ a_{ij} \} \); (5) \( B \): represents the probability matrix of observable states in the model. We use the abbreviated form \((\pi, A, B)\).

4. Fault diagnosis of PFC device using HMM
PFC fault diagnosis with HMM is usually divided into two parts: model training and fault diagnosis. Firstly, the corresponding fault model is trained for each fault:

(1) Measure the inductance current \( I_1 \), output current \( I_2 \) and output voltage \( U \) under each fault state of the PFC device, and take them as the fault characteristic parameters to form the observation state sequence \( O = [I_1, I_2, U] \) of HMM;
(2) Build the HMM model $\lambda$. The hidden state is set as 4, the initial state probability is set as $\pi = [1 0 0 0]$, and the state transition matrix $A$ is set as:

$$A = \begin{bmatrix} 0.5 & 0.5 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0.5 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

(1) the probability matrix $B$ of the observed state is set as:

(2) Use Baum-Welch algorithm to iterate parameters to convergence.

Define a probability:

$$\vartheta_{t}(i, j) = P(O_{t}, q_{t} = \theta_{j}, q_{t+1} = \theta_{j} \mid \lambda)$$

(3) It is given by the backward variable:

$$\vartheta_{t}(i, j) = \left[ a_{t}(i) a_{t}(o_{t+1}) b_{t+1}(j) \right] / P(O \mid \lambda)$$

(4) The probability of being in state $\theta_{i}$ at time $t$ is:

$$\theta_{t}(i) = P(O_{t}, q_{t} = \theta_{j} \mid \lambda) = a_{t}(i) \beta_{t}(i) / P(O \mid \lambda)$$

(5) Define $\sum_{j=1}^{N} \vartheta_{t}(i, j)$ is the expected value of the transition from state $\theta_{i}$ to state $\theta_{j}$, $\gamma_{t}(i)$ is the conditional probability of being in state $\theta_{i}$ at time $t$, sum them up:

$$\gamma_{t}(i) = \sum_{j=1}^{N} \vartheta_{t}(i, j)$$

(6) The model reevaluation formula is obtained:

$$\pi_{t} = \gamma_{1}(i)$$

(7)$$a_{t} = \frac{\sum_{j=1}^{T-1} \vartheta_{t}(i, j)}{\sum_{i=1}^{T} \gamma_{i}(t)}$$

(8)$$b_{t} = \frac{\sum_{j=1}^{T} \gamma_{t}(j) o_{t} \delta_{t}}{\sum_{i=1}^{T} \gamma_{t}(i)}$$

(9) Repeat the above steps to train the HMM of each fault states. In our research, multiple training samples are used for model training, considering the common characteristics of multiple data sets, that is, we define $H$ training samples, which means there are $H$ observable state sequences $O^{(1)}, O^{(2)}, \ldots, O^{(H)}$, which satisfy the following requirements:

$$P(O \mid \lambda) = P(O^{(1)} \mid \lambda) P(O^{(2)} \mid O^{(1)}, \lambda) \cdots P(O^{(H)} \mid O^{(H-1)}, \lambda)$$

$$P(O^{(1)} \mid \lambda) = P(O^{(2)} \mid \lambda) P(O^{(3)} \mid O^{(2)}, \lambda) \cdots P(O^{(H)} \mid O^{(H-2)}, \lambda)$$

$$\vdots$$

$$P(O^{(H)} \mid \lambda) = P(O^{(H+1)} \mid \lambda) P(O^{(H+2)} \mid O^{(H)}, \lambda) \cdots P(O^{(1)} \mid O^{(H-1)}, \lambda)$$

(10) Introduce the weight coefficient $\varepsilon$ :
\[ 
\varepsilon_1 = \frac{1}{H} \cdot P(O^1 | \omega, \lambda) \cdot \ldots \cdot P(O^N | \omega, \lambda) \\
\varepsilon_2 = \frac{1}{H} \cdot P(O^2 | \omega, \lambda) \cdot \ldots \cdot P(O^N | \omega, \lambda) \\
\vdots \\
\varepsilon_n = \frac{1}{H} \cdot P(O^n | \omega, \lambda) \cdot \ldots \cdot P(O^N | \omega, \lambda) 
\] (11)

Replace \( P(O | \omega) \) in equations (7), (8) and (9) with the following formula:
\[ 
P(O | \omega) = \sum_{k=1}^{n} \varepsilon_k \cdot P(O^k | \lambda) 
\] (12)

The fault model training is completed to ensure that there is a corresponding HMM for each fault. The next step is to use the trained hidden markov model for PFC fault diagnosis. In this paper, Viterbi algorithm is used for fault diagnosis.

Define variable \( \sigma_i(i) \)
\[ 
\sigma_i(i) = \max_{q_i \in Q_i} P(q_i, q_2, \ldots, q_t, o_i, \ldots, o_t | \lambda) 
\] (13)

Initialize :
\[ 
\sigma_1(i) = \pi_i b_1(o_i) \\
\varphi_1(i) = 0, 1 \leq i \leq N 
\] (14)(15)

Iteration :
\[ 
\sigma_t(i) = \max_{1 \leq j \leq N} [ \sigma_{r-1}(i) a_{r,j} ] b_j(o_t), 2 \leq t \leq T, 1 \leq j \leq N 
\] (16)
\[ 
\varphi_t(i) = \arg \max_{1 \leq j \leq N} [ \sigma_{r-1}(i) a_{r,j} ], 1 \leq t \leq T, 1 \leq j \leq N 
\] (17)

Termination :
\[ 
P' = \max_{1 \leq i \leq N} [ \sigma_T(i) ] 
\] (18)

5. Simulation verification
The training diagram of setting the convergence error as \( 1 \times 10^{-5} \), 10 fault states is shown in figure 2. The number of iteration steps required for training under different fault models is shown in table 2. The trained HMM is used to identify the measured characteristic parameters, finally calculate \( P(Q | O, \lambda) \). The model with the largest \( P(Q | O, \lambda) \) is the fault diagnosis result. The calculation results are shown in table 2. The maximum value of each column is marked in red.
In order to verify the effectiveness of circuit state recognition using HMM, it is compared with other traditional pattern recognition methods. Table 3 shows the results obtained using different methods.
Table 3. Diagnosis results of different methods

| Diagnostic methods | HMM | BP neural network | SVM |
|--------------------|-----|-------------------|-----|
| Fault number       |     |                   |     |
| 1                  | 100%| 78%              | 89% |
| 2                  | 100%| 91%              | 76% |
| 3                  | 100%| 60%              | 81% |
| 4                  | 100%| 72%              | 75% |
| 5                  | 100%| 85%              | 83% |
| 6                  | 100%| 66%              | 72% |
| 7                  | 100%| 81%              | 77% |
| 8                  | 100%| 73%              | 61% |
| 9                  | 100%| 76%              | 81% |
| 10                 | 100%| 66%              | 79% |

6. Conclusion
HMM can process dynamic processes well. This paper introduces a HMM method for fault diagnosis of PFC device of EV wireless charging system. Firstly, initialize the HMM. Then, Baum-Welch algorithm is used to train the fault model. Finally, Viterbi algorithm is used to identify the fault. The results show that it is feasible and effective to use HMM to diagnose the PFC device fault of EV wireless charging system. Compared with the traditional fault diagnosis method, HMM has a much higher recognition rate. Therefore, it is of great theoretical and practical value to apply HMM to the fault diagnosis of PFC device of EV wireless charging system.

This work was supported by State Grid Corporation Science and Technology Project Funding "Serial design and equipment development of wireless charging system for electric vehicles".

7. References
[1] Li B, Liu C and Chen QC 2013 Wireless charging technology for electric vehicle EPET. 32 p 81
[2] He J 2018 Detection methods and techniques for electronic circuit faults EW. 15 p 95
[3] Zhang X, Zhou WH and Zhou YY 2011 Application of voltage measurement value in fault detection of capacitive voltage transformers EPET. 30 p 19
[4] Mcarthur S, Strachan S and Jahn G 2004 The design of a multi-agent transformer condition monitoring system IEEE Trans. PS. 19 p 1845
[5] Song XA and Li ZH 2004 Application of fault diagnosis expert system based on relational database in radar power supply Journal of hehai university. 18 p 23
[6] Wang WJ and Yin H 2018 Fault diagnosis method of line electronic transformer EPET
[7] Zhang K, Li GY and Han FZ 2017 Fault tree method and improved elevator fault diagnosis model of PSO-PNN network Science and technology of safe production in China. 13 p 175
[8] Qiao DW 2016 Neural network identification of rotating rectifier faults in brushless synchronous generator Journal of wenzhou vocational and technical college. 16 p 44
[9] Yu XG 2016 Study on fault diagnosis expert system of electronic injection engine CT. p 212
[10] Roy P, Bhunia A and Das A 2016 HMM-based Indic handwritten word recognition using zone segmentation Pattern Recognition p 1057
[11] Jin JM, Liu J and Liu Runsheng 2003 Application of HMM based speech recognition technology in embedded system Electronic technology application. 29 p 12
[12] Lu RH, Duan S and Yang SY 2009 Diagnosis method of bearing fault audio signal based on CGHMM, Computer engineering and applications Computer engineering and applications. 45 p 223
[13] Luo XL 2006 Fault diagnosis method and system research of large-scale transformer hidden Markov model (HMM) Zhejiang University
[14] Yu TJ, Chen YT and Chen TF 2014 Research on motor fault diagnosis based on HMM Journal of railway science and engineering p 103
[15] Xiong JW 2016 Research on mechanical fault diagnosis method based on infinite factor hidden Markov model Nanchang Aviation University
[16] Gao QY, Yang JF and Wang HQ 2015 Early fault pattern recognition of bearing based on HMM and wpt-acf CMEEME.