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Published in:
Proceedings of IEEE 9th International Power Electronics and Motion Control Conference

Link to article, DOI:
[10.1109/IPEMC-ECCEAsia48364.2020.9367826](https://doi.org/10.1109/IPEMC-ECCEAsia48364.2020.9367826)

Publication date:
2021

Document Version
Peer reviewed version

[Link back to DTU Orbit](#)

Citation (APA):
Han, Z., Lin, Q., & Zhang, Z. (2021). Soft Fault Diagnosis for DC-DC Converters with Wavelet Transform and Fuzzy Cerebellar Model Neural Networks. In *Proceedings of IEEE 9th International Power Electronics and Motion Control Conference* (pp. 1811-1815). IEEE. <https://doi.org/10.1109/IPEMC-ECCEAsia48364.2020.9367826>

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Soft Fault Diagnosis for DC-DC Converters with Wavelet Transform and Fuzzy Cerebellar Model Neural Networks

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Abstract—Identifying the soft faults of converters in power electronic converter is a significant problem for the stable and efficient operation of power systems. This paper proposed a novel soft fault diagnosis method based on wavelet transform and fuzzy cerebellar model neural networks (WT-FCMNN) for DC-DC Converters. First, the multiscale feature extraction is achieved by multilevel signal decomposition to extract the feature information of different frequency ranges signal. Meanwhile, optimal wavelet decomposition scale and feature dimension reduction are used to reduce computational quantity and eliminate redundant information. Then, in order to effectively diagnose soft faults in DC-DC converters, a classifier based on FCMNN is proposed to identify different operating states of the capacitor and power MOSFETs in push-pull circuits. Finally, two common fault diagnosis methods and the proposed FCMNN are performed for circuit fault diagnosis. Compared with the BPNN and SVM, simulation results show that the proposed method has a better generalization, fast diagnosis speed and higher diagnostic accuracy that proves its effectiveness and feasibility in soft fault diagnosis.

Keywords—Soft fault diagnosis, wavelet transform, fuzzy cerebellar model neural networks, DC-DC converter.

I. INTRODUCTION

With the rapid rise of new industries such as new energy generation, industrial motor drive, and electric vehicles, power electronics technology has become the key to energy conversion. Power electronic circuit plays a decisive role in photovoltaic, wind power grid connection, consumer electronics, industrial motors, etc, and its safe operation is the guarantee of equipment normal work. Therefore, it is very important to study the intelligent fault diagnosis method and find the fault in the circuit as soon as possible for the stable operation of the equipment.

DC-DC converters play a vital role in the stable operation of electric vehicles and photovoltaic power generation systems [1]. However, the converter is susceptible to high temperature, over current and over voltage in the long-term operation, which leads to its performance degradation and reduces the efficiency of power systems. Power electronic faults can be divided into

structural faults and parametric faults (soft faults) according to its severity. Structural fault refers to the fault caused by open or short circuit of the device, which will cause the circuit topology to change. Besides, the structural fault usually has obvious fault characteristics, and the current structural fault diagnosis technology has become increasingly mature. The parametric fault is mainly manifested in the degradation of the parameters of the circuit components, which usually does not cause the change of the circuit topology and is difficult to be directly diagnosed by waveform. However, due to the degradation of the device or the change of parameters, the performance of the whole circuit will decline, which can lead to structural failure in serious cases. Therefore, it is necessary to study the soft faults of power electronic circuits to improve the reliability of the whole circuits and provide conditions for fault prediction and health management of power electronic circuits.

Recently, artificial intelligence technologies such as artificial neural networks (ANN) [2], back-propagation neural network (BPNN) [3], and deep learning [5] have been widely used in power electronics fault detection. However, ANN and BPNN take longer to train the model, and the deep neural network has a complex structure and requires a large amount of data. The above methods are not suitable for power electronics fault diagnosis, which is difficult to obtain data and requires fast response.

CMNN has good local approximation ability, strong generalization ability, faster learning speed, and is widely used in the research of control systems [6]-[7]. In recent years, CMNN has also been used as a classifier to solve classification problems [8]. In addition, the wavelet transform method is developed from the limitations of the Fourier transform method when analyzing non-stationary or time-varying signals [9]-[11]. It is a very effective time-frequency analysis method.

Based on the above analysis, this paper proposes a soft fault diagnosis method based on WT and FCMNN, which is used to study the diagnostic performance of different soft faults in push-pull DC-DC circuits.

II. FAULT DIAGNOSIS METHOD BASED ON WT-FCMNN

A. Wavelet transform

Multi-level signal decomposition is achieved by multi-resolution analysis (MRA) based on discrete wavelet transform (DWT) to obtain different levels of decomposition coefficients [12]. DWT has been widely studied as a new method to decompose signals into different frequency intervals to analyze non-stationary signals. More importantly, MRA has better time scale representation for discrete signals with different decomposition scales.

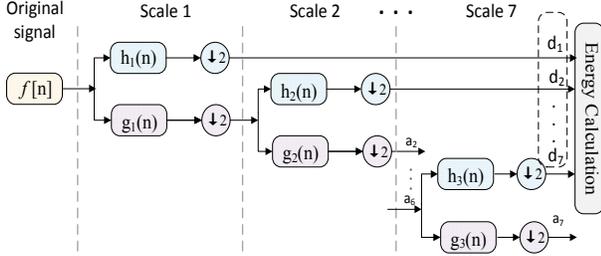


Fig. 1 The feature extraction process of DWT-based seven-leave MRA

As shown in Fig.1, the original signal is decomposed into different levels of detailed coefficients d_j and approximate coefficients a_j by a high-pass filter $h_j(n)$ and a low-pass filter $g_j(n)$, respectively [13]. In order to decompose the signal, a scaling function $\Phi_{j,k}(t)$ and a wavelet function $\Psi_{j,k}(t)$ are needed:

$$\phi_{j,k}(t) = 2^{-\frac{j}{2}} \phi(2^{-j}t - k) \quad (1)$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}} \psi(2^{-j}t - k) \quad (2)$$

where $\Psi_{j,k}(t)$ is associated with the detailed coefficient d_{jk} of level j and related to the high-pass filter coefficient $g(n)$, respectively. The detailed coefficients d_{jk} are as follows:

$$d_{jk} = \sum_n g(n-2k)a_{j-1,n} \quad (3)$$

The detail coefficients and approximate coefficients obtained by wavelet transform decomposition of the original signal are not suitable as the input of the classifier directly. Wavelet energy has unique characteristics for different fault locations. By calculating the wavelet energy with each scale, a very effective diagnostic tool can be constructed [14]. In this paper, the wavelet energy of each layer after signal decomposition is used as the characteristic parameter of the neural network fault diagnosis. The definition of wavelet energy at each scale is as follows:

$$E_j = \sum_{k=1}^{q_j} |d_{jk}|^2 \quad (4)$$

where q_j is the length of wavelet coefficients at scale j .

B. FCMNN classifier

To distinguish the state of capacitors and power MOSFETs in push-pull circuits, a Gaussian ambiguity function FCMNN classifier is designed. The wavelet energy described in the previous section is used as the input of the classifier.

The proposed FCMNN classifier consists of five different spaces, and its structure is shown in Fig.2. The following is the specific introduction of different spaces.

1) Forward computation:

a) Input Space: Each input variable I_i is quantified into n_e discrete regions according to a given control space.

b) Association memory space: In this space, several elements can be accumulated as a block:

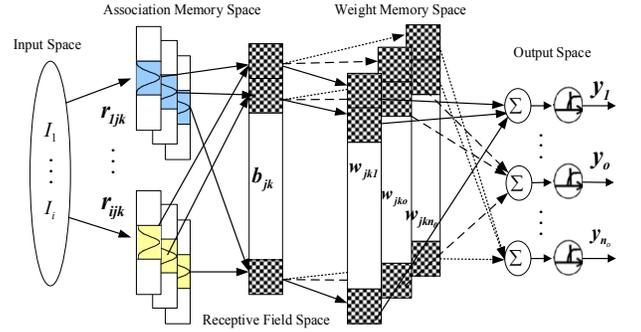


Fig. 2 Structure of a FCMNN classifier

$$f_{ijk}(I_i) = \exp\left[-\frac{(I_i - m_{ijk})^2}{v_{ijk}^2}\right], \quad j=1,2,\dots,n_j, \quad k=1,2,\dots,n_k \quad (5)$$

where m_{ijk} and v_{ijk} are the mean and the variance of the j -th layer and k -th block for the i -th input, respectively.

c) Receptive-Field Space: this space is composed of multiple input fields and defined as:

$$r_{jk} = \prod_{i=1}^{n_i} f_{ijk} = \exp\left[\sum_{i=1}^{n_i} -\frac{(I_i - m_{ijk})^2}{v_{ijk}^2}\right] \quad (6)$$

d) Weight memory space: Each location of Receptive-Field space corresponds to the adjustable value of a specific weight memory space, which can be expressed as:

$$\mathbf{W}_o = [w_{11o}, \dots, w_{1n_k o}, w_{21o}, \dots, w_{2n_k o}, w_{n_j 1o}, \dots, w_{n_j n_k o}]^T \in R^{n_j n_k \times 1} \quad (7)$$

e) Output space: The output of FCMNN is expressed as:

$$b_o = \sum_{j=1}^{n_j} \sum_{k=1}^{n_k} (w_{jko} \cdot r_{jk}) \quad (8)$$

$$y_o = 1 / [1 + \exp(-b_o)], o = 1, 2, \dots, n_o \quad (9)$$

2) Backward parameter adjustment:

The weights of FCMNN are adjusted by using back-propagation (BP), and the cost function is:

$$E(k) = \frac{1}{2} \sum_{o=1}^{n_o} (t_o(k) - y_o(k))^2 \quad (10)$$

where $t_o(k)$ and $y_o(k)$ are the o -th target output and FCMNN output, respectively. According to the cost function $E(k)$ and the BP updating algorithm, the parameter updating law can be obtained as follows:

$$\alpha(k+1) = \alpha(k) + \Delta\alpha(k) \equiv \alpha(k) + \eta \left(-\frac{\partial E(k)}{\partial \alpha} \right) \quad (11)$$

where $\alpha = [m_{ijk}, v_{ijk}, w_{ijk}]^T$ and $\eta = \text{diag} [m_{ijk}, v_{ijk}, w_{ijk}]$ are the parameter vector and learning-rate matrix for m_{ijk} , v_{ijk} and w_{ijk} , respectively. $\partial E(k)/\partial \alpha$ is defined as:

$$\frac{\partial E(k)}{\partial \alpha} = \left[\frac{\partial E(k)}{\partial m_{ijk}}, \frac{\partial E(k)}{\partial v_{ijk}}, \frac{\partial E(k)}{\partial w_{jko}} \right]^T \quad (12)$$

Using the chain rule to calculate the gradient of the cost function:

$$\begin{aligned} \Delta m_{ijk} &= -\eta_m \frac{\partial E(k)}{\partial m_{ijk}} = -\eta_m \frac{\partial E}{\partial y_o} \frac{\partial y_o}{\partial b_o} \frac{\partial b_o}{\partial r_{jk}} \frac{\partial r_{jk}}{\partial f_{ijk}} \frac{\partial f_{ijk}}{\partial m_{ijk}} \\ &= -\eta_m \sum_{o=1}^{n_o} (t_o - y_o) \cdot y_o \cdot (1 - y_o) \cdot w_{jko} \cdot r_{jk} \cdot 2 \cdot \frac{I_i - m_{ijk}}{v_{ijk}^2} \end{aligned} \quad (13)$$

$$\begin{aligned} \Delta v_{ijk} &= -\eta_v \frac{\partial E(k)}{\partial v_{ijk}} = -\eta_v \frac{\partial E}{\partial y_o} \frac{\partial y_o}{\partial b_o} \frac{\partial b_o}{\partial r_{jk}} \frac{\partial r_{jk}}{\partial f_{ijk}} \frac{\partial f_{ijk}}{\partial v_{ijk}} \\ &= -\eta_v \sum_{o=1}^{n_o} (t_o - y_o) \cdot y_o \cdot (1 - y_o) \cdot w_{jko} \cdot r_{jk} \cdot 2 \cdot \frac{(I_i - m_{ijk})^2}{v_{ijk}^3} \end{aligned} \quad (14)$$

$$\begin{aligned} \Delta w_{jko} &= -\eta_w \frac{\partial E(k)}{\partial w_{jko}} = -\eta_w \frac{\partial E}{\partial y_o} \frac{\partial y_o}{\partial b_o} \frac{\partial b_o}{\partial w_{jko}} \\ &= \eta_w (t_o - y_o) \cdot y_o \cdot (1 - y_o) \cdot r_{jk} \end{aligned} \quad (15)$$

III. EXAMPLE AND RESULT ANALYSIS

A. Push-pull DC-DC converter

A push-pull converter is a type of dc-dc converter that can efficiently convert a lower DC voltage to a higher voltage. In this paper, a push-pull dc-dc converter is built on the PSIM software, as shown in Fig.3. The input voltage of 36V DC is converted to the output voltage of 400V DC, and the switching frequency is 50khz. It is worth noting that the symbols VD and VT in Fig.3 represent a diode and a power MOSFET, respectively.

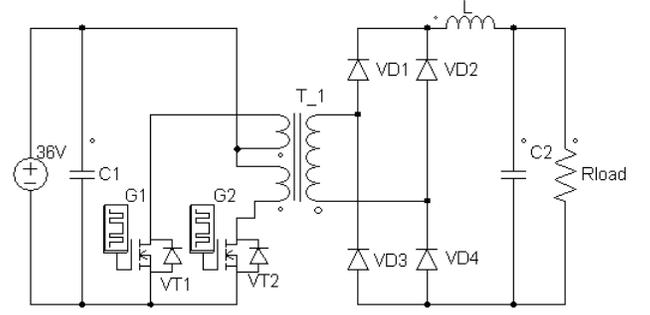


Fig. 3 push-pull DC-DC converter circuit

B. Fault mode setting

Due to the aging of the components, the performance of the push-pull converter will gradually degrade. When the capacitor and the power MOSFET are degraded, the capacitance of the capacitor and the on-resistance of the power MOSFET will change. In this paper, seven kinds of working modes of the main circuit, recorded as F1 to F7, are considered, as shown in Table I. F1 to F3 and F4 to F7 are different working modes of the capacitor and power MOSFETs.

TABLE I. FAULT MODE SETTING

Fault classification	Fault type	Fault mode
F1	C_f1	The normal operation(Capacitor)
F2	C_f2	Capacitance decreased by 20%-50%
F3	C_f3	Capacitance decreased by 50%-80%
F4	MOS1_f1	The normal operation (MOS1)
F5	MOS1_f2	R_{on1} increased by 20%-80%
F6	MOS2_f1	The normal operation (MOS2)
F7	MOS2_f2	R_{on2} increased by 20%-80%

In the case of a capacitor, capacitance tolerance is 20%. In other words, when the change in capacitance is less than 20%, we confirm that the capacitor is in the normal working state. Similarly, if the R_{on} change of power MOSFET is less than 20%, the power MOSFET is considered to be in the normal working state.

C. Selection of fault characteristic parameters

Before WT is applied to feature extraction, select the optimal mother wavelet and decomposition scale to achieve efficient feature extraction is preferred. With the proper choice of the mother wavelet, WT is a good tool for signal analysis and fault feature extraction. Due to the Daubechies series wavelets have the characteristics of good orthogonality and sensitivity to irregular signals, the 'db3' wavelet is chosen in this paper.

For the choice of decomposition scale, it is better to use a higher decomposition level to avoid missing some characteristics of the signal. However, a higher number of decomposition layers means a larger amount of calculation. Selecting a better number of decomposition layers can well avoid missing signal characteristics and speed up the diagnosis.

The method of data-independent selection (DIS) was utilized to determine the optimal levels of decomposition.

According to the conditions of the DIS, the optimal number of decomposition levels n_{Ls} of the signal is given by:

$$n_{Ls} = \text{floor}\left(\frac{\log(f_s / f)}{\log(2)}\right) + 2 \quad (16)$$

where floor() means to take an integral part of the calculation result.

According to the DIS methods, the optimal number of leaves of wavelet transform is 7. Thus, this paper uses 7-scale wavelet decomposition for feature extraction to analyze the performance of the proposed FCMNN classifier.

IV. SIMULATION RESULTS AND ANALYSIS

Each fault state is shown in Table I is simulated by the circuit simulation software PSIM and each fault contains 100 samples. The high-side voltage signal V_g is sampled as an information source for circuit fault diagnosis, and it is decomposed into seven-layer wavelet coefficients to obtain the fault feature vector wavelet energy.

After many experiments, the optimal 3-dimensional feature vector is selected from the 7-dimensional feature vector as the characteristic parameter of fault diagnosis. This reduces the interference of the irrelevant information in the characteristic parameters to the diagnosis, realizes the dimension reduction processing of the characteristic parameters, and finally reduces the time of the fault diagnosis.

To analyze the performance of the proposed fault diagnosis method, 80 sets of the samples in each working mode are selected randomly as the training data, and the remaining 20 sets are used as the test data. Therefore, the number of training sample groups is 560, and the number of test sample groups is 140.

FCMNN classifier is constructed by MATLAB software. In the initial parameter setting of FCMNN classifier, the learning rates are 0.1, the weights are randomly selected from (-1,1). To ensure ideal classification performance, all of the parameters of FCMNN classifier are determined by several trials. The output fault label of FCMNN is set to: $C_f1 = \{0, 0, 1\}$, $C_f1 = \{0, 1, 0\}$, $C_f1 = \{0, 1, 1\}$, $MOS1_f1 = \{1, 0, 0\}$, $MOS1_f2 = \{1, 0, 1\}$, $MOS2_f1 = \{1, 1, 0\}$, $MOS2_f2 = \{1, 1, 1\}$. The fault label in the final output is to be converted to decimal numbers.

The common method based on BPNN is also discussed for comparison. A three-layer BP neural network is constructed. To get the best classification results, the number of hidden layers was determined as 12 by trial and error. The sigmoid transfer function is used and the output fault label of the BPNN classifier is the same as FCMNN.

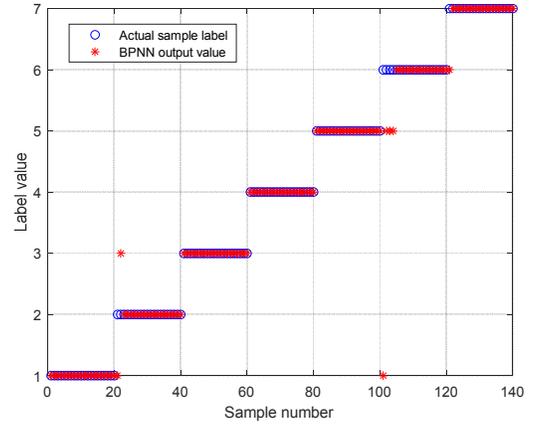


Fig. 4 The fault diagnosis results of BPNN

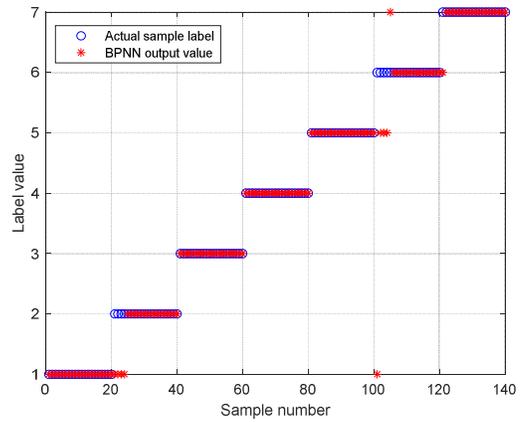


Fig. 5 The fault diagnosis results of SVM

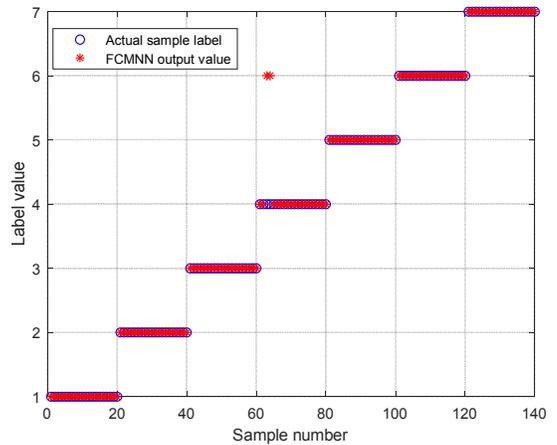


Fig. 6 The fault diagnosis results of FCMNN

The diagnosis results of BPNN are shown in Fig.4, in which the classification accuracy is 95.00%. The diagnosis results of SVM are shown in Fig.5, in which the classification accuracy rate is 92.85%. It can be seen from the fault diagnosis results of BPNN and SVM that the misclassification is mainly concentrated in F2 and F6, in which the fault F2 is mainly

misdiagnosed as F1 and F6 is mainly misclassified as F5. Meanwhile, the fault diagnosis results of FCMNN are shown in Fig.5. The diagnosis accuracy of FCMNN is 98.57% from Fig.6, which means that only two test samples cannot be correctly identified and classified. It can be seen from this that FCMNN has better fault diagnosis performance than BPNN and SVM.

TABLE II. TEST SET ACCURACY FOR EACH FAULT MODE UNDER FOUR CASES

Methods	BPNN	SVM	FCMNN
F1	100%	100%	100%
F2	90%	80%	100%
F3	100%	100%	100%
F4	90%	100%	90%
F5	100%	100%	100%
F6	80%	75%	100%
F7	95%	95%	100%

The diagnosis results for each fault mode of three methods are shown in Table II. From Table II, it can be seen that FCMNN can still maintain 100% classification accuracy on fault F2 and F6 with the poor performance of BPNN and SVM. Meanwhile, two test samples of fault F4 were misdiagnosed. In addition, when the number of training iterations is 1000, the average fault diagnosis time of FCMNN is 10.59s, less than 17.60s of BPNN.

V. CONCLUSION

To solve the problem of DC-DC converter fault diagnosis, a new method based on WT and FCMNN to study the soft fault of the DC bus capacitor and power MOSFETs in push-pull DC-DC converter has been proposed in this paper. Wavelet transform using optimal decomposition scale and artificial selection of feature vectors is used for fault feature extraction. Moreover, FCMNN has better uncertain information processing ability and adaptive learning ability than traditional neural networks due to it combines fuzzy rules with cerebellar model neural networks. Simulation results verify the excellent diagnostic performance of the proposed method. The proposed method has higher diagnostic accuracy and faster diagnosis speed than the traditional fault diagnosis method BPNN and SVM. In addition, our method is also applicable to soft fault diagnosis of other systems.

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