

Research on Fault Identification Algorithm for Photovoltaic Grid-Connected Inverter Based on VMD-Wavelet and SVM

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ABSTRACT

With the large-scale application of solar photovoltaic power generation technology, photovoltaic grid-connected inverters, as the core equipment for energy conversion between photovoltaic systems and public power grids, play a crucial role in ensuring the overall benefits of photovoltaic power generation systems. IGBT power switching devices operate under harsh conditions such as high voltage, high current, and high frequency for long periods, resulting in a high probability of open-circuit faults. Moreover, the circuit can still operate during the initial fault period, and external characteristics are not obvious. Traditional diagnostic methods have limited detection accuracy. This paper proposes a fault identification algorithm for photovoltaic grid-connected inverters based on Variational Mode Decomposition (VMD), Wavelet Packet Transform, and Support Vector Machine (SVM). The algorithm uses three-phase output current from the AC side as the fault observation signal, adaptively decomposes the signal into several band-limited modal components using VMD, and determines the optimal modal number using the minimum sample entropy criterion. Three-layer wavelet packet transform is applied to each modal component, and wavelet packet energy of each sub-band is calculated to form a high-dimensional fault feature vector. After normalization, the feature vector is input into a multi-class SVM classifier to complete accurate fault type identification. A simulation model of three-phase two-level photovoltaic grid-connected inverter is built on MATLAB/Simulink platform. 280 sets of sample data are generated for 7 types of working conditions including 6 IGBT single-device open-circuit faults and normal operation. Experimental results show that the proposed method achieves identification accuracy above 98.5% for all fault types, and maintains good robustness and anti-interference ability under low signal-to-noise ratio conditions.

KEYWORDS

Photovoltaic grid-connected inverter; IGBT open-circuit fault; Variational mode decomposition; Wavelet packet energy; Support vector machine

1 Introduction

Solar photovoltaic power generation has developed rapidly due to its clean, pollution-free, and flexible deployment advantages. China's cumulative grid-connected capacity of photovoltaic power generation has ranked first in the world for many consecutive years, and the photovoltaic industry has become a strategic emerging industry supporting sustainable development. As the energy conversion hub of the system, photovoltaic grid-connected inverters undertake the core task of converting DC power to qualified AC power for grid connection. They work under harsh conditions for long periods, and their reliability directly determines the overall system benefits. Related data shows that inverter faults account for 60% of photovoltaic system faults, making them the equipment with the highest fault rate. Among these, IGBT open-circuit faults are the most common and covert. If not diagnosed in time, they can easily cause chain accidents such as device damage and power grid safety issues. Therefore, research on IGBT open-circuit fault diagnosis for inverters has important practical significance. Accurate diagnosis can shorten the maintenance cycle, reduce maintenance costs, ensure stable system operation, improve the economic benefits of photovoltaic power plants, and meet the intelligent operation and maintenance needs of large-scale photovoltaic power plants.

Currently, research on IGBT open-circuit fault diagnosis for photovoltaic inverters has made some progress. Existing methods mainly achieve fault identification based on time-domain and frequency-domain feature extraction combined with traditional classifiers. However, existing research still has obvious deficiencies: traditional feature extraction methods have weak anti-noise interference ability; under actual engineering strong noise environments, fault features are easily submerged by noise, leading to significant decline in diagnostic accuracy; some methods rely on manual experience to select feature extraction parameters, with limited generalization ability, making it difficult to meet fault diagnosis requirements under different working conditions.

To address the above problems, this paper proposes a fault identification algorithm based on VMD-wavelet packet energy features and SVM classifier, aiming to improve diagnostic accuracy in strong noise environments and solve the engineering applicability problems of existing methods.

2 System Modeling and Fault Analysis of Photovoltaic Grid-Connected Inverter

2.1 Topology Structure and Working Principle

The three-phase two-level photovoltaic grid-connected inverter adopts a two-stage topology. The main circuit

includes photovoltaic array, Boost boost converter, DC bus capacitor C_{dc} , three-phase bridge inverter circuit, LCL filter, and public power grid. The system adopts double closed-loop control (see Figure 1). The front-stage Boost converter raises the photovoltaic voltage to the level required for grid connection using the perturbation observation method for Maximum Power Point Tracking (MPPT) control, which can quickly track the maximum power point of the photovoltaic array under different illumination and temperature conditions, ensuring the front-stage output voltage remains stable at the level required for grid-connected inversion. The rear-stage three-phase bridge inverter circuit consists of six IGBTs (VT1~VT6) and antiparallel freewheeling diodes (VD1~VD6). The upper and lower bridge arm IGBTs conduct complementarily to achieve DC to three-phase AC inversion. After being filtered by the LCL filter to suppress high-frequency harmonics, the power is connected to the grid.

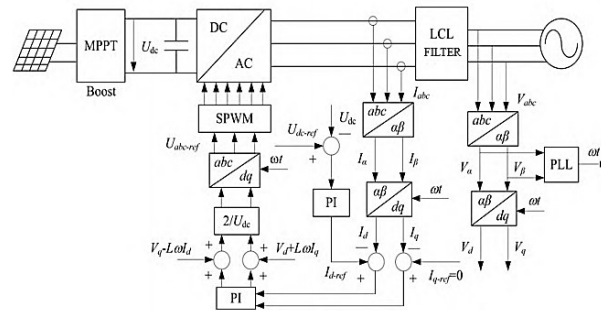


Figure 1 Double closed-loop control strategy block diagram of photovoltaic grid-connected inverter

Table 1 Main Parameters of Simulation Model

Parameter Name	Symbol	Value
Inverter Rated Power	P	100 kW
Switching Frequency	f_s	10 kHz
Inverter Side Filter Inductance	L_1	0.8 mH
Grid Side Filter Inductance	L_2	0.2 mH
Filter Capacitor	C_1	100 μ F
DC Bus Capacitor	C_{dc}	3300 μ F
Grid Line Voltage	U_g	380 V
Grid Rated Frequency	f	50 Hz

2.2 IGBT Open-Circuit Fault Mechanism Analysis

2.2.1 Single-Device Open-Circuit Fault Current Characteristics

The three-phase two-level inverter consists of six IGBTs (VT1~VT6). An open-circuit fault of any power device will cause characteristic distortion of the corresponding phase current. Taking the upper bridge arm VT1 open-circuit fault as an example: during normal operation, when $i_a > 0$, the forward current flows through VT1; when $i_a < 0$, the negative current flows through freewheeling diode VD1 or lower bridge arm VT2. After VT1 open-circuit, the forward current path for $i_a > 0$ is cut off, and the current can only continue through the lower bridge arm freewheeling diode VD2. Since the conduction direction is opposite to the forward direction of i_a , the positive half cycle of phase-a current is missing. However, when $i_a < 0$, the negative current can still flow normally through VD1 or VT2, so the negative half cycle is not affected. Figure 2 shows the three-phase current output waveforms before and after VT1 open-circuit fault.

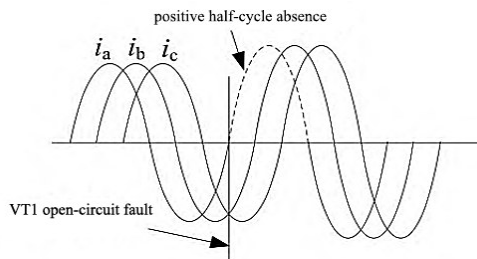


Figure 2 Three-phase current output waveforms before and after VT1 open-circuit fault

2.2.2 Fault Type Classification and Working State Encoding

According to the fault location, single-device open-circuit faults of VT1~VT6 and normal operation are divided into 7 working states, as shown in Table 2. From the symmetry of the three-phase inverter circuit topology, it can be seen that: open-circuit faults of upper bridge arm devices (VT1, VT3, VT5) cause the positive half cycle of the corresponding phase current to be missing, while open-circuit faults of lower bridge arm devices (VT2, VT4, VT6) cause the negative half cycle

to be missing. The three-phase current characteristics corresponding to each fault are significantly different, providing good physical separability for fault feature extraction and classification identification.

Table 2 Inverter Working State Encoding

Working State	State Code
Normal Operation (No Fault)	0
VT1 Open-Circuit Fault	1
VT2 Open-Circuit Fault	2
VT3 Open-Circuit Fault	3
VT4 Open-Circuit Fault	4
VT5 Open-Circuit Fault	5
VT6 Open-Circuit Fault	6

3 Fault Feature Extraction Method Based on VMD-Wavelet Packet

3.1 Variational Mode Decomposition Theory

3.1.1 VMD Basic Principle

Variational Mode Decomposition (VMD) was proposed by Dragomiretskiy and Zosso in 2014. It is a non-recursive adaptive signal decomposition method that can adaptively decompose the original signal into K band-limited Intrinsic Mode Functions (IMFs) with different center frequencies. Its core is solving the constraint optimization problem through iteration to address the mode mixing and endpoint effects of Empirical Mode Decomposition (EMD), with better noise robustness and decomposition accuracy.

The constraint optimization problem of VMD is:

$$\min_{\{u_k\}, \{\omega_k\}} \sum_k \left\| \frac{\partial}{\partial t} \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \quad (1)$$

$$\text{s.t. } \sum_k u_k(t) = f(t) \quad (2)$$

Where: $f(t)$ is the original fault signal; $u_k(t)$ is the k-th modal component; ω_k is the center angular frequency of the k-th mode; $\delta(t)$ is the unit impulse function; $*$ denotes convolution operation; ∂t is the partial derivative operator with respect to time.

The alternating direction method of multipliers (ADMM) is used for iterative solution.

3.1.2 Optimal Modal Number Determination Based on Sample Entropy

VMD decomposition effect is highly sensitive to the preset modal number K: when K is too small, each modal component carries insufficient fault information; when K is too large, over-decomposition occurs, increasing noise interference and significantly increasing computational load. This paper uses the minimum sample entropy mean criterion to adaptively determine the optimal modal number K, thereby eliminating manual experience interference in parameter selection.

3.2 Wavelet Packet Energy Feature Extraction and Overall Process

3.2.1 Wavelet Packet Transform Principle

Wavelet Packet Transform (WPT) is a more refined full-band uniform multi-resolution analysis method than wavelet transform. Each level of decomposition simultaneously decomposes both high-frequency and low-frequency components. After p levels of decomposition, 2^p sub-band signals are obtained. Its high-frequency refinement capability can accurately capture the current frequency band energy abnormalities caused by IGBT open-circuit faults, providing high-discriminability features for the classifier.

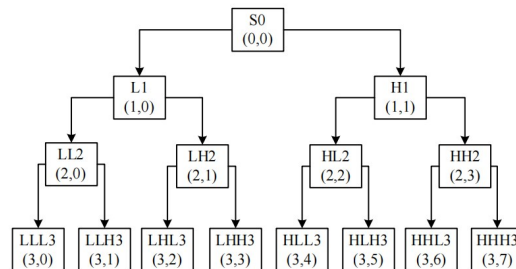


Figure 3 Three-level wavelet packet decomposition tree structure

3.2.2 Overall Feature Extraction Process

Combining VMD decomposition and wavelet packet transform, the overall fault feature extraction process is as follows:

- (1) Collect three-phase currents I_a, I_b, I_c ;
- (2) According to the minimum sample entropy mean criterion, adaptively select the optimal K in the range $K=2\sim7$, combined with penalty factor $\alpha=2000$ to complete VMD decomposition, obtaining K IMF components;
- (3) Use db3 wavelet basis to perform 3-level wavelet packet decomposition on each IMF component, obtaining 8 sub-bands, calculate the energy of each frequency band, and construct an 8-dimensional energy sub-vector for each mode;
- (4) Concatenate all K energy sub-vectors to obtain a $K \times 8$ -dimensional fault feature vector;
- (5) Normalize the feature vector to $[0,1]$, eliminate dimension differences, and input to SVM for fault identification.

4 Support Vector Machine Fault Classification Model

4.1 Optimal Classification Hyperplane Solution

Support Vector Machine (SVM) is a supervised learning method based on the Structural Risk Minimization (SRM) principle of statistical learning theory. The core is to find the optimal classification hyperplane in high-dimensional space to maximize the margin between different sample classes. While ensuring classification accuracy, it improves generalization ability.

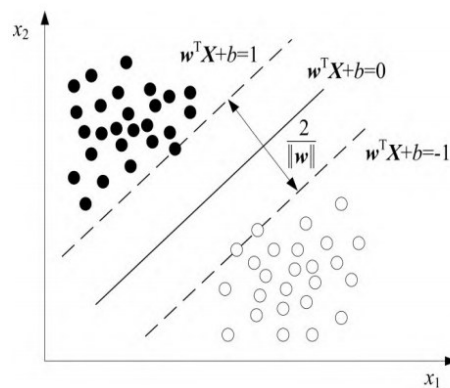


Figure 4 SVM classification principle schematic

4.2 Kernel Function Selection and Characteristic Analysis

The selection of kernel function has a decisive influence on SVM classification performance. Different kernel functions map the original feature space to different high-dimensional feature spaces, resulting in decision boundaries of different shapes. The expressions and characteristics of commonly used inner product kernel functions are shown in Table 2.

Table 2 Comparison of Common SVM Inner Product Kernel Functions

Kernel Type	Expression	Main Characteristics
Linear Kernel	$K(x,xi) = x \cdot xi$	Global, simple computation
Polynomial Kernel	$K(x,xi) = [(x \cdot xi) + 1]^r$	Global, high-order feature interaction
Gaussian Kernel (RBF)	$K(x,xi) = \exp(-g x-xi ^2)$	Local, sensitive to kernel parameters
Sigmoid Kernel	$K(x,xi) = \tanh(\beta \cdot x \cdot xi + c)$	Neural network analogy

5 Simulation Experiment and Result Analysis

5.1 Simulation Model Construction and Normal Working Condition Verification

According to the double closed-loop control strategy in Chapter 2, a three-phase two-level photovoltaic grid-connected inverter simulation model is built in MATLAB/Simulink. The clock module is used to set the fault occurrence time, and the switch module is used to switch IGBT control signals (PWM signal for normal conduction, low level for single-device open-circuit) to simulate various single-device open-circuit faults. Under standard working conditions ($S=1000 \text{ W/m}^2$, $T=25^\circ\text{C}$), simulation shows: DC bus voltage stabilizes at about 600 V, three-phase grid-connected currents are in-phase with the same frequency and smooth waveform, I_d is constant, and current Total Harmonic Distortion (THD) is 1.43%, meeting the national standard GB/T 37408-2019 grid connection requirements ($\leq 5\%$). This verifies the effectiveness of the simulation model and control strategy.

5.2 Single-Device Open-Circuit Fault Simulation Results

5.2.1 Fault Waveform Analysis

Set VT1 open-circuit fault to occur at 0.02 s. The three-phase current waveforms after the fault are shown in Figure 5. The positive half cycle of phase-a current is missing, and phase-b and phase-c currents show sinusoidal waves but with amplitude increased to about 1.15 times. This result is consistent with the theoretical analysis in Chapter 2, verifying the correctness of the fault mechanism.

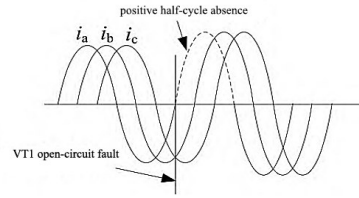
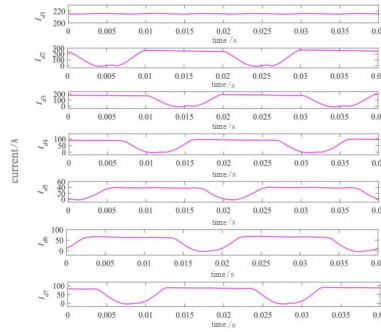


Figure 5 Three-phase output current waveforms under VT1 open-circuit fault

Figure 6 Rotating current I_d waveforms under 7 working states

5.2.2 VMD Decomposition and Optimal Modal Number Determination

Taking the I_d signal under VT1 open-circuit fault state as an example, calculate the SE mean for different modal numbers in the range $K=2\sim 7$. The SE mean corresponding to each K value is shown in Table 3.

Table 3 Sample Entropy Mean of VMD Modal Components under Different K Values

K Value	Sample Entropy Mean
2	0.0887
3	0.1041
4	0.0951
5	0.0737
6	0.1169
7	0.2496

5.3 SVM Fault Diagnosis Result Analysis

5.3.1 Comparison Analysis of Different Kernel Functions

Input the VMD-wavelet packet energy feature matrix of 280 samples (7 classes $\times$ 40 groups) into SVM. Four inner product kernel functions: Linear, Quadratic Polynomial, Cubic Polynomial, and Gaussian are used to construct SVM models.

Table 4 Diagnosis Accuracy under Different Inner Product Kernel Functions and Cross-Validation Ratios (%)

CV Ratio	Linear	Quadratic	Cubic	Gaussian
5%	95.8	97.2	96.4	68.0
10%	96.2	97.9	95.9	69.4
15%	95.5	97.6	96.7	68.4
20%	96.0	98.3	96.5	67.2
25%	96.4	98.5	96.3	69.7
30%	95.3	97.9	96.0	68.4
35%	96.0	98.6	96.8	68.8

Table 5 AUC Indicators for Quadratic SVM (25% CV)

Normal	VT1	VT2	VT3	VT4	VT5	VT6
1.00	1.00	0.99	0.98	0.99	0.99	0.99

5.3.2 Comparison of Different Feature Extraction Schemes

To further verify the superiority of VMD-wavelet packet features, four comparison schemes are designed.

Table 6 Comparison of Diagnosis Accuracy for Different Feature Extraction Schemes

Feature Extraction Scheme	Dimension	Accuracy (%)
Scheme A: Time-domain Statistics	13-dim	93.6
Scheme B: VMD Time-domain Features	$K \times 13$ -dim	95.3
Scheme C: Direct Wavelet Packet	8-dim	95.9
Scheme D: VMD-Wavelet (This Paper)	$K \times 8$ -dim	98.5

5.4 Anti-Noise Performance Verification

In actual photovoltaic grid-connected systems, inverter detection signals are easily affected by thermal noise and electromagnetic interference. Anti-noise capability is key to evaluating the engineering practicality of fault diagnosis methods.

Table 7 Comparison under Different SNR Conditions (%)

Scheme	SNR=30dB	SNR=20dB	SNR=15dB	SNR=10dB
Scheme A	93.6	91.2	87.5	82.4
Scheme D (This Paper)	98.5	96.1	93.8	90.7

6 Conclusions

This paper proposes and verifies an IGBT single-device open-circuit fault identification algorithm for photovoltaic grid-connected inverters based on VMD-wavelet packet energy features and SVM classifier. For 7 working states (normal and VT1~VT6 single-device open-circuit), 280 groups of simulation samples are constructed to complete systematic research from fault mechanism, feature extraction, classification model to comparative verification. The main conclusions are as follows: In terms of fault mechanism, it is clarified that upper bridge arm IGBT open-circuit causes the positive half cycle of corresponding phase current to be missing, while lower bridge arm open-circuit causes the negative half cycle to be missing, providing physical basis for feature extraction. In terms of feature extraction, the minimum sample entropy criterion is used to adaptively select the optimal $K=5$ for VMD decomposition to suppress mode mixing. Then three-layer wavelet packet is used to extract 8-dimensional energy features, constructing a 40-dimensional fault feature vector. The fault separability is better than traditional time-domain and single wavelet packet features. In terms of classification model, Quadratic Polynomial kernel SVM performs best, achieving 98.6% accuracy under 35% cross-validation, with each fault AUC higher than 0.98, showing strong generalization ability.

In terms of robustness, the proposed scheme improves accuracy by about 5 percentage points compared to pure time-domain feature schemes, and maintains 90.7% accuracy under strong noise SNR=10 dB, 8.3 percentage points higher than the comparison scheme, demonstrating good engineering applicability.

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