

# GIS Circuit Breaker Mechanical Fault Diagnosis based on Voice-Print

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**Abstract**—In this work, a method is proposed to successfully diagnose mechanical faults in gas-insulated switchgear (GIS) circuit breakers prone to acoustic signal disturbance from significant background noise and challenging feature extraction. Initially, a multi-channel acoustic sensor array is employed to gather the original observation signal of the circuit breaker. The independent component analysis (ICA) method is employed to decompose the observed signal into multiple source signals, and the source signal with the lowest fuzzy entropy is chosen as the feature signal. Subsequently, the multiscale fuzzy entropy (MFE) of the feature signal is computed to generate the sound-print feature of the circuit breaker. Lastly, the fault of the circuit breaker is identified using the extreme learning machine (ELM) algorithm. The experimental results demonstrate that the utilization of acoustic signals as a detection method offers a novel approach for diagnosing mechanical faults in GIS circuit breakers. The suggested approach successfully extracts the sound-print information, resulting in a notable enhancement in fault diagnostic accuracy compared to the conventional method.

**Index Terms**— GIS switchgear circuit breaker; CB fault diagnosis; voice-print; independent component analysis; extreme learning machine.

## I. INTRODUCTION

Gas-insulated switchgear offers the benefits of exceptional dependability and convenient upkeep, making it extensively employed in high-voltage power networks. Circuit breakers are an essential element of GIS and serve to safeguard and regulate electrical systems [1]. Statistically, the primary reason for failures in GIS (Gas Insulated Switchgear) is the mechanical malfunction of circuit breakers [2]. Precisely detecting and recognizing mechanical malfunctions of circuit breakers using efficient techniques is crucial for guaranteeing the secure and steady power transfer. In engineering, the mechanical vibration signal of the circuit breaker is often obtained using a contact sensor. Various algorithms are then employed to evaluate and process the signal, enabling the identification of mechanical faults in the circuit breaker. Reference [3] introduced a fault detection approach for high-voltage circuit breakers that relies on empirical mode decomposition (EMD) and support vector machine (SVM). The hyperparameters of the Support Vector Machine (SVM) were fine-tuned using a genetic approach, resulting in a higher diagnostic accuracy than the conventional classification method. Integrated empirical mode decomposition to break down the original signal into various intrinsic mode functions (IMF) can be employed for fault diagnostic [4].

They then extracted the energy entropy of each IMF as the input for support vector machine (SVM) analysis, successfully identifying the fault mode of the circuit breaker. A fault diagnosis technique that relies on time series parameters and fuzzy C-means clustering (FCM) is presented in [5]. The double threshold approach was employed to extract the vibration event's occurrence time and end time as the feature vector. FCM (Fuzzy C-Means) algorithm was utilized to compute the cluster center of the feature vector, hence achieving precise classification of the circuit breaker fault type.

The circuit breaker produces mechanical vibrations and sound signals while it is being closed or opened. These signals provide essential information about the equipment's status. However, collecting these mechanical vibrations is challenging because the vibration sensor must be inside the GIS device. Furthermore, even a slight displacement of the position can significantly alter the measurement outcome. Consequently, the defect diagnostic technique that relies on mechanical vibration also demands precise placement of the acceleration sensor [6]. The acoustic signal-based detection method [7] offers the benefits of non-contact and real-time detection, making it well-suited for diagnosing mechanical faults in circuit breakers. Empirical Mode Decomposition (EMD) is very useful for extracting the energy entropy of time segments, specifically acoustic signals, as feature vectors. They then utilized Support Vector Machines (SVM) to diagnose various states of circuit breakers. This approach effectively addressed the challenge of fault diagnosis in circuit breakers with little sample data. A technique for detecting mechanical faults in high-voltage circuit breakers using sound waves is described in [8]. The K-S test was employed to identify intervals with significant disparities in sample amplitudes, and a limited number of signal characteristics within these intervals were retrieved to detect the faulty signal.

Currently, acoustic diagnosis methods are predominantly utilized to identify faults in rotating machinery. More research is needed on using acoustic signals to diagnose mechanical faults in GIS circuit breakers. Additionally, the data gathered from a single channel is susceptible to interference from surrounding noise. This research presents a mechanical fault diagnostic technique for GIS circuit breakers that relies on voiceprint analysis. The process begins by utilizing a multi-channel acoustic array to gather signals, followed by applying the ICA algorithm to achieve blind source separation of the original signal. Next, the component with the lowest fuzzy entropy in the source signal is chosen as the feature signal, and the MFE (Multiscale Fuzzy Entropy) of this feature signal is extracted to generate the voiceprint of the circuit breaker. Lastly, the ELM algorithm is employed for state recognition. The experimental findings demonstrate that the suggested approach may accurately detect mechanical malfunctions in circuit breakers.

## II. CIRCUIT BREAKER FAULT DIAGNOSIS METHOD

### A. Independent Component Analysis

ICA is a method for separating mixed signals by removing their complexity and relying solely on the observed signal to get the original source signal [9]. Let the original observed signal collected by the multi-channel acoustic sensor array be recorded as  $R = (r_1, r_2, \dots, r_n)^T$ , and the source signal be recorded as  $S = (s_1, s_2, \dots, s_n)^T$ , then the ICA model can be expressed as

$$R = AS \quad (1)$$

Where:  $A$  is the mixing matrix.

The estimation of the source signal  $S$  can be obtained by unmixing the matrix  $W$

$Y = (y_1, y_2, \dots, y_n)^T$ , that is

$$Y = \hat{S} = WR \quad (2)$$

Selecting a suitable unmixing matrix  $W$  can achieve the separation of independent components. The maximum non-Gaussian estimation method based on negative entropy is an ICA algorithm with strong robustness and fast convergence speed. This method evaluates the mutual independence of components by measuring the non-Gaussianity of the separation results. Its basic steps are as follows:

- Centre and whiten the original signal  $R$ ;
- Let  $l$  be the number of signal channels to be separated, and initialize the number of iterations  $k = 1$ ;
- Randomly select the initial vector  $w_k$ , where  $w_k$  is a vector of the unmixing matrix  $W$ ;
- Use Newton's method to calculate and normalize  $w_k$ , where  $E$  is the mathematical expectation. Since the sound signal is a super-Gaussian signal,  $E$  can be taken;
- Orthogonalize and normalize  $w_k$ ;

- Determine the convergence of wk. If it does not converge, return to the last step otherwise proceed to the next step;
- Let  $k = k + 1$ . If  $k \leq 1$ , return to step 3. Otherwise, the algorithm ends.

### B. Fuzzy entropy and multiscale fuzzy entropy

Fuzzy entropy is a technique used to measure the level of intricacy in time series data. As the series becomes more complex, the entropy value increases. The precise calculating procedure is denoted as reference [10]. Multiscale fuzzy entropy is a technique used to quantify the fuzzy entropy of time series data at several sizes. The system possesses the benefits of noise resilience and anti-interference, enabling it to accurately depict the failure characteristics of mechanical equipment [11]. The primary computational procedure of MFE is as follows.

- Coarse-grained time series  $x(i)$ ,  $1 \leq j \leq N$ , divide  $y(i)$  into  $\tau$  segments, each segment length is  $N/\tau$ , that is

$$z_j^\tau = \frac{1}{\tau} \sum_{i=j}^{j+\tau-1} x_i \quad (1 \leq j \leq N - \tau + 1) \quad (3)$$

Where,  $\tau$  is the time scale factor.

- Compute the fuzzy entropy (FuzzyEn) for each coarse-grained sequence using the given embedding dimension  $m$ , similarity tolerance  $r$ , and fuzzy function gradient  $n$ .

$$MFE(y, \tau, m, r, n) = \text{FuzzyEn}(z_j^\tau, m, r, n) = \lim_{N \rightarrow \infty} [\ln \phi^m(r, n) - \ln \phi^{m+1}(r, n)] \quad (4)$$

The study begins by selecting the component with the lowest fuzzy entropy in the source signal as the feature signal. Then, the Multiscale Fuzzy Entropy (MFE) of the feature signal is computed to generate the voiceprint feature of the circuit breaker. The Fuzzy Entropy definition is as under.

$$H[V] = \int_{-\infty}^{+\infty} S(C_r \{A \geq t\}) dt \quad (5)$$

Where fuzzy variable is denoted by  $V$ , and credibility measure is denoted by  $Cr$ .

### C. Extreme Learning Machine

The Extreme Learning Machine is an algorithm for a single hidden layer feedforward neural network. The node parameters of the input layer and the hidden layer are stochastically generated and do not require any adjustments. It offers the benefits of rapid training speed and exceptional identification accuracy. Given that the sample

$(V, T) = \{(v_i, t_i)\}$  ( $i = 1, 2, \dots, N$ ), where  $v_i$  is the input sample,  $t_i$  is the sample label, and  $N$  is the number of samples, the output of ELM is

$$f_L(v_j) = \sum_{i=1}^L \beta_i g(w_i v_i + b_i) = t_j, \quad (j = 1, 2, \dots, N) \quad (6)$$

The variables in the equation are defined as follows:  $L$  represents the number of nodes in the hidden layer,  $\beta_i$  represents the connection weight between the  $i$ -th node in the hidden layer and the output layer,  $P(x)$  represents the feature mapping function (typically the Sigmoid function),  $a_i$  represents the connection weight between the input layer and the  $i$ -th node in the hidden layer, and  $b_i$  represents the bias of the  $i$ -th node in the hidden layer.

Therefore, the output matrix of the network is

$$H\beta = T \quad (7)$$

Where:  $H$  is the hidden layer output matrix.

$$H = \begin{bmatrix} P(a_1, b_1, v_1) & \cdots & P(a_L, b_L, v_1) \\ \vdots & \ddots & \vdots \\ P(a_1, b_1, v_N) & \cdots & P(a_L, b_L, v_N) \end{bmatrix}_{N \times L} \quad (8)$$

The output weight  $\beta$  can be obtained by solving equation (6) using the least squares method, that is,

$$\hat{\beta} = H^\dagger T \quad (9)$$

Where:  $H^+$  is the generalized inverse matrix of  $H$ .

#### D. Diagnostic Process

In summary, the proposed circuit breaker mechanical fault diagnosis process based on the ICA-MFE-ELM algorithm is as follows:

- Use the ICA method to perform blind source separation on the circuit breaker acoustic signal to obtain multi-dimensional source signal  $y_i$  ( $i = 1, 2, \dots, n$ );
- Calculate the fuzzy entropy of all  $y_i$  and select the signal  $y_m$  with the smallest entropy as the feature signal;
- Calculate the MFE of the feature signal  $y_m$  as the circuit breaker sound-print feature;
- Use ELM to identify the mechanical fault of the circuit breaker.

### III. EXPERIMENTAL VERIFICATION AND RESULT ANALYSIS

#### A. Experimental data collection

The illustration of the experimental setup is shown in Figure 1. The experiment uses a specific type of 66 kV GIS equipment. An arc will be generated between the contacts when the GIS circuit breaker breaks the circuit. The high temperature of the arc can easily cause contact erosion as shown in Figure 2, resulting in mechanical failures such as switch refusal of the circuit breaker [12]. To collect fault information, the experiment designed two working conditions: normal contact and contact erosion.

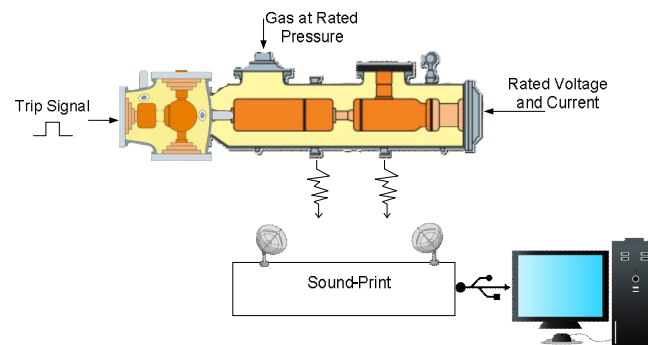


Figure 1. Illustration of experimental setup



Figure 2. Sample photos of deteriorated contact

The data acquisition device is the acoustic imaging device sound CAM of Ruishen Electronic Technology, which is equipped with an acoustic array composed of 64 acoustic sensors. The frequency response range of the sensors is 20 Hz~25 kHz, and the maximum measurable sound pressure level is 125 dB. The circuit breaker to be tested is placed parallel to the acoustic array, and the test distance is 2.1 m. During the experiment, the circuit breaker sound signal is synchronously sampled at a sampling rate of 48 kHz.

The experiment collected 16 s of sound data from before closing to after opening of the circuit breaker. To reduce the signal processing time, 0.5 s of data near the closing and opening action signals were intercepted as the original signal. Figure 3 is the waveform of the original sound signal. It can be seen from the figure that the sound signals in the two states contain a lot of background noise, which is challenging to distinguish directly.

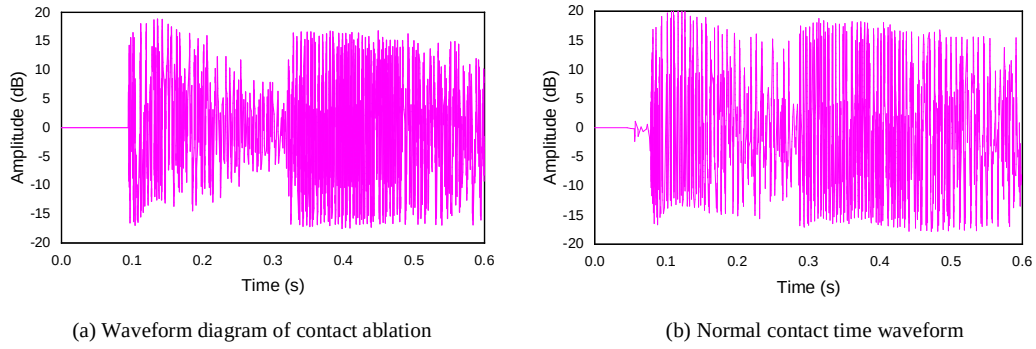


Figure 3. Oscillography of the recorded sound signal

### B. Feature signal selection

First, the ICA algorithm is used to process the original signal. The input is the original sound signal of 32 channels, and the output is 32 groups of source signals. Secondly, the component with the smallest fuzzy entropy in the source signal is taken as the feature signal. According to the definition of fuzzy entropy, three parameters, namely, embedding dimension  $m$ , fuzzy function gradient  $n$ , and similarity tolerance  $r$  must be determined before calculation. According to the characteristics of the sound sequence in this study, the longer data required, so  $m = 4$ ,  $n = 2$  or  $3$ ,  $r = 0.15SD \sim 0.25SD$  ( $SD$  is the standard deviation of the signal data) are selected after careful consideration. Since selecting smaller parameters can obtain more detailed information in the data,  $n = 2$  and  $r = 0.15SD$  are selected in this study. Figure 4 is the waveform of the selected feature signal.

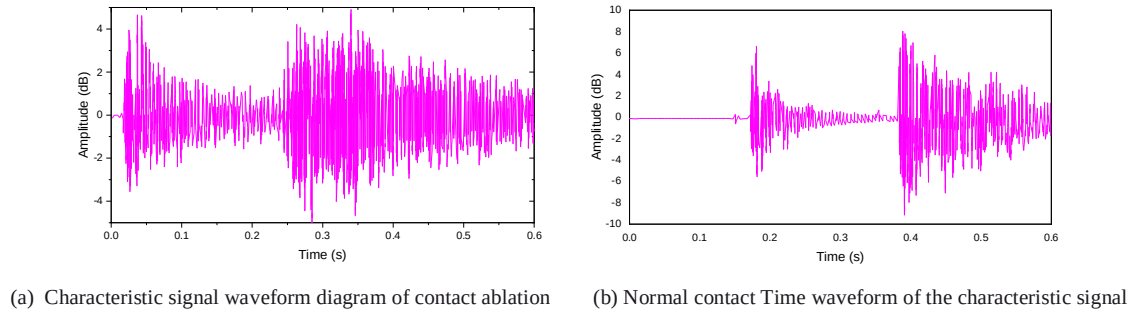


Figure 4. Time waveform of oscillography of original signals

Thirty-five groups of acoustic signal samples of contact ablation and contact normal were randomly selected to compare the entropy changes of the signals before and after ICA processing. The entropy values of the original signal and the characteristic signal are shown in Figure 5. From Figure 5, it can be seen that the two types of states of the circuit breaker cannot be distinguished based on the entropy value of the original signal, while the entropy values of the characteristic signals of different states are clearly distinguished after ICA processing. However, because the fuzzy entropy of a single scale is easily disturbed by noise, it is difficult to reflect the essential characteristics of the circuit breaker signal fully, so it is necessary to extract its voiceprint features from multiple scales.

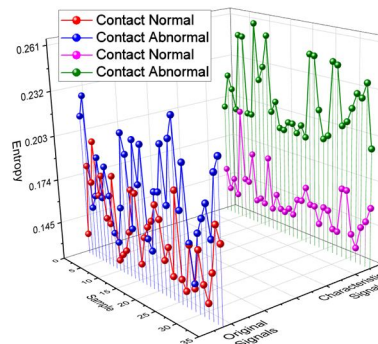


Figure 5. Disorder values for original signals and characteristic signals

### C. Voiceprint feature extraction

The MFE method is used to extract the voiceprint properties of the circuit breaker. Twelve distinct scale factors  $\tau$  are used to compute the fuzzy entropy of the characteristic signal. The multiscale fuzzy entropy of various states are listed in table 1. The table illustrates that the entropy value of contact ablation increases as the scale increases, suggesting that the sequence is relatively complex and contains significant information at multiple scales. Eventually, it becomes stable. On the other hand, the entropy value of normal contact initially increases but starts to decrease when  $\tau$  reaches 6. This indicates that the entropy value of the characteristic signal of normal contact is unstable at a larger scale. Thus, the scale factors  $\tau$  are selected as 1, 2, 3, 4, and 5, and the multiscale fuzzy entropy of the characteristic signal is extracted as the voiceprint feature of the circuit breaker. The experiment involved the collection of 400 sets of data, consisting of 200 sets of contact ablation and 200 sets of normal contacts. Figures 6 and 7 display the voiceprints of contact ablation and normal, respectively.

TABLE I. MULTISCALE FUZZY ENTROPY (MFE) OF DIFFERENT SCALE FACTOR

| Scale Factor<br>( $\tau$ ) | Multiscale fuzzy entropy (MFE) |                  |
|----------------------------|--------------------------------|------------------|
|                            | Contact Normal                 | Contact Ablation |
| 1                          | 0.118                          | 0.171            |
| 2                          | 0.162                          | 0.235            |
| 3                          | 0.190                          | 0.266            |
| 4                          | 0.205                          | 0.288            |
| 5                          | 0.222                          | 0.308            |
| 6                          | 0.243                          | 0.316            |
| 7                          | 0.232                          | 0.325            |
| 8                          | 0.223                          | 0.325            |
| 9                          | 0.214                          | 0.330            |
| 10                         | 0.205                          | 0.325            |
| 11                         | 0.200                          | 0.320            |
| 12                         | 0.205                          | 0.325            |

Four groups of distinctive signals were randomly selected to analyze the voiceprint features in two different states. The comparison of voiceprints in different states may be observed in Figure 8. The graphic clearly demonstrates that the MFE of different states varies dramatically with the changing of the scale factor. The multiscale fuzzy entropy approach is highly effective in extracting the voiceprint properties of the circuit breaker.

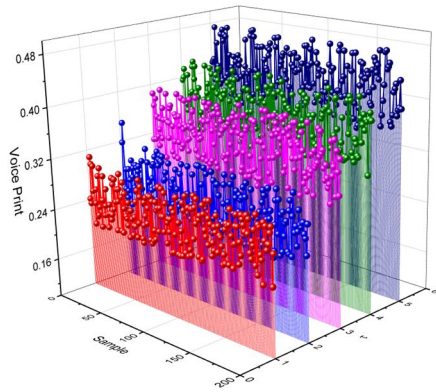


Figure 6. Contact ablation voice-print

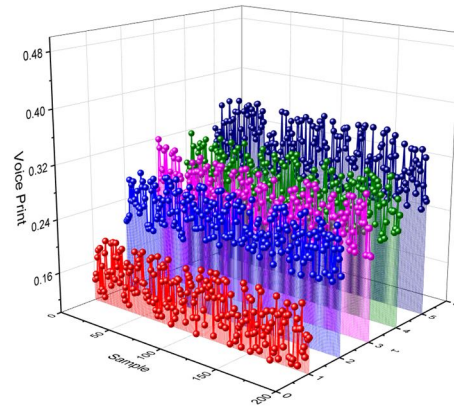


Figure 7. Normal contact Voice-print

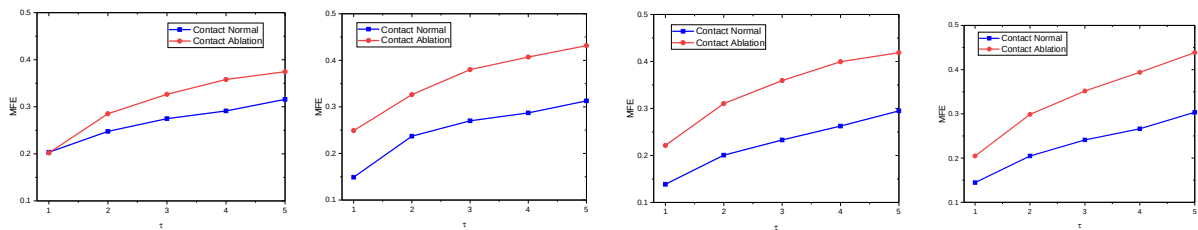


Figure 8. Contact voice-prints in different samples

#### D. Fault identification

The ELM algorithm is employed to ascertain the fault type of the circuit breaker contact, utilizing a total of 200 samples for each state. The training set, validation set, and test set are allocated in a ratio of 3:1:1. With a hidden layer node count of  $L=10$ , the training accuracy can exceed 99%, while the test accuracy can achieve 98.06%.

In order to assess the efficacy of the proposed approach, the algorithm utilized in this investigation is contrasted with alternative fault diagnosis approaches that rely on sound signals. The following are the comparison algorithms.

- The sound signal is analyzed and reconstructed using singular spectrum analysis (SSA). The noise component is eliminated, and the reconstructed signal's time domain and frequency domain characteristics are collected. The fault classification is achieved by combining SVM [13]. The Support Vector Machine (SVM) utilizes a Gaussian kernel function. Through cross-validation, the optimal penalty coefficient ( $c$ ) is discovered to be 2.3, and the kernel function width ( $g$ ) is found to be 24.25.
- A complete and efficient classifier involves advanced classification methods and a representative feature set of data attributes. But undue complexity in a classifier and an unnecessarily expanded data attribute list for a classification application can add computational cost. Furthermore, when data attributes are overly complex, vague, or lack unique definitions, the interpretability and performance of even the simplest classifier can be impaired.

For a low-complexity, data-informed application, time and frequency features incorporated with KNN may contribute to the practicability of the KNN classifier and represent the solution to classification, where TFFs with KNN processing only need a very short computation delay and provide competitively high classification performance that is close in accuracy to the application's more complex counterparts. [14]

- Time series analysis has played a dominant role since ancient times. As time series forecasting inevitably involves uncertainty arising from the non-linear application of complex functions, a well-performed pooling theory of disciplines sheds light on this holistic system. Over the past few decades, many mathematical and statistical techniques have been developed to better understand time-relevant usage in various fields. This provides a basis for both methodological advancement and application interest. Due to their potential contribution to various domains and their empirical appeals, researchers have made new contributions to these topics across various disciplines. Such an analytic basis motivates us to introduce in this study two new time-series analysis techniques to operators in various fields. Specifically, we will consider two important applications of the multiscale permutation entropy-back propagation neural network model. [15] Four key facts of the study must be highlighted. First, inspired by the huge success of the permutation entropy measure of time series in the fields of non-linear time series, modeling and the characteristics of time series analysis are recognized as data mining challenges. MPE as a non-linear time series analysis technique combines dimensions for the attributes of permutation order to extract accurate and effective information from historical standardized time series to solve the practical application. Second, while very simple nowadays, hand-designed stock trading strategies relying on judgment will have great importance on Wall Street. Third, represented and indicated by the statistical learning theories applied to various scientific problems, diverse experimental results show that the MPE-BPNN drawn from hybrid models provides an attractive measure of advantages in time series analysis.
- The MFE in the proposed method is replaced by multiscale permutation entropy (MPE). The diagnostic accuracy of different algorithms is shown in Table 3. As can be seen from the table, the fault diagnosis accuracy of the proposed method (ICA-MFE-ELM) is significantly higher than that of other algorithms. MFE introduces a fuzzy function to change the entropy value continuously and smoothly. The fuzzy entropy has a specific anti-interference ability when the signal fluctuates, or the baseline drifts. Since the experimental signal is a non-stationary signal, the fuzzy entropy can better extract the characteristics of the signal than the permutation entropy.

TABLE II. ACCURACY OF DIFFERENT ALGORITHMS

| Algorithm   | Correct rate (%) | Computational Time (Seconds) |
|-------------|------------------|------------------------------|
| SSA-SVM     | 87.92            | 15.26                        |
| TFF-KNN     | 84.96            | 17.21                        |
| MPE-BPNN    | 79.01            | 12.33                        |
| ICA-MPE-ELM | 91.11            | 7.8                          |
| ICA-MFE-ELM | 98.06            | 6.5                          |

#### IV. CONCLUSION

A voiceprint-based GIS circuit breaker mechanical fault diagnosis method is presented, which can effectively reduce noise interference and extract fault features. This method uses ICA to analyze the GIS circuit breaker signal collected by the acoustic array to obtain a multi-dimensional source signal, selects the characteristic signal according to the fuzzy entropy principle, and calculates its MFE as the voiceprint feature. Finally, ELM is used to realize fault identification. The experimental results show that the fault diagnosis accuracy of the proposed method is above 98%, which is significantly improved compared with other methods.

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