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Research on the Circuit Breaker State Judgment Method Based on Ant Colony Optimization Dempster-Shafer Evidence Theory

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Abstract: The paper proposes a method for circuit breaker state judgment based on ant colony algorithm-optimized Dempster-Shafer evidence theory.It can improve the accuracy and robustness of state judgment. As a key device in the power system, the state judgment of circuit breakers is crucial for the safety and stability of the power grid. Existing methods have limitations in handling conflicts and uncertainties of multi-source data, and a single model is difficult to meet the needs of complex data fusion. Therefore, the paper applies the ant colony algorithm to optimize the basic probability assignment in Dempster-Shafer evidence theory to improve the fusion effect of multi-source data. The ant colony algorithm, through its global search and adaptive characteristics, can effectively optimize evidence combination and enhance the accuracy of the fusion results. The experiment used a support vector machine model based on current signals and a decision tree model based on vibration signals for data fusion and discrimination. The results showed that the Dempster-Shafer evidence theory model optimized by the ant colony algorithm achieved a discrimination accuracy of 75% under various circuit breaker conditions. Compared to the Dempster-Shafer evidence theory fusion model, it improved by approximately 8.3%, and compared to the current research's Dempster-Shafer evidence theory and neural network methods, it improved by 5%.. This method has broad application prospects in enhancing the operational stability of power grid equipment and improving fault detection efficiency.

Keywords: accuracy; robustness; multi-source data; basic probability assignment

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1. Introduction

Circuit breakers play a crucial role in power systems, with core functions including circuit protection, current control, and fault isolation. Specifically, circuit breakers can automatically cut off the current in abnormal situations such as short circuits or overloads, preventing equipment damage and fires, and ensuring the safety of the power system [1]. Moreover, circuit breakers can quickly interrupt and restore current during both faults and normal operation, ensuring effective circuit isolation during maintenance or repair, and safeguarding the normal operation of other parts. Through these functions, circuit breakers not only enhance the safety of the power grid but also significantly reduce the risk of fault propagation, ensuring a continuous power supply [2]. The combination of modern circuit breakers and automation systems has achieved remote monitoring and automatic operation, significantly enhancing the flexibility and reliability of the power system [3]. Therefore, circuit breakers have profound significance for the safe operation of

the power grid and are a key component in ensuring the stability and continuous supply of the power system.

Given the significant impact of circuit breakers on the safety of power grid systems, research on circuit breaker status identification technology is particularly necessary [4]. This technology, by real-time monitoring of the operating status of circuit breakers, can accurately identify potential fault issues, thereby enabling proactive maintenance to prevent the spread of faults and the occurrence of power accidents [5]. By implementing circuit breaker condition assessment technology, not only can it effectively reduce power outage time, but it can also significantly lower the economic losses caused by circuit breaker failures, especially in industrial and commercial power usage scenarios. Additionally, this technology improves the operational efficiency of the power grid by enabling targeted maintenance through data analysis, reducing unnecessary maintenance operations, extending the lifespan of circuit breakers, and lowering operational and maintenance costs [6]. With the large-scale integration of smart grids and new energy sources, circuit breaker status identification technology has driven the intelligent and automated management of the power grid, enhancing the grid's self-repair capabilities and rapid fault location abilities [7]. This has provided solid technical support for the efficient and reliable operation of the grid in complex power environments and laid the foundation for the sustainable development of the power grid.

Currently, in the research on circuit breaker state diagnosis, there is not much study on the integration of multi-source data fusion technology. Even when multi-source data fusion is considered, such as [8–10], it is merely a simple application of multi-source data fusion technology and does not involve improvements to the multi-source data fusion technology itself in the corresponding scenarios. This paper studies circuit breaker state identification technology and designs a circuit breaker state identification method based on an improved Dempster-Shafer (D-S) evidence theory using an ant colony algorithm, addressing the issues of poor robustness and stability in single model identification. The main contributions are as follows:

1. Using D-S evidence theory to integrate the support vector machine model based on current signals with the decision tree model based on vibration signals improves the stability of the state discrimination model;

2. By optimizing the basic probability assignment of D-S evidence theory using the ant colony algorithm, the optimal basic probability assignment based on the dataset is obtained, which improves the accuracy of the state discrimination model.

2. Literature Review

According to the circuit breaker state discrimination process, this paper will introduce its research status from two parts: feature data acquisition and state discrimination method.

Accurate state identification of circuit breakers relies on the effective collection and feature extraction of diverse data sets. These data are sourced from internal current, voltage, temperature, and acceleration sensors within the circuit breaker. Feature extraction from these raw data sets typically employs techniques like Fourier transform, wavelet transform, or feature selection algorithms. For example, Ref. [11] uses the discrete Fourier transform as an initialization dictionary for training, and employs the learned dictionary obtained from training to achieve sparse representation of the original signal [12]. The time-frequency analysis method of continuous wavelet transform was combined with the improved Alex Net convolutional neural network model to achieve contact system fault diagnosis, thereby improving the accuracy of fault diagnosis [13]; Using principal component analysis to reduce the dimensionality of the electromechanical joint features, the reduced joint feature vector is used as the input for the circuit breaker fault diagnosis model.

Furthermore, data sources encompass vibration signals, acoustic emission signals, and temperature measurements, among others. The mechanical operations of circuit breakers generate distinct vibration patterns and high-frequency acoustic emission signals. These signals are captured using acceleration and acoustic emission sensors, followed by feature extraction processes. Feature extraction methods for vibration and acoustic emission signals encompass time-domain analysis techniques. For instance, extracting features such as peak, mean, variance, standard deviation, and skewness from vibration or acoustic emission signals provides insights into the overall intensity, fluctuation extent, and symmetry of mechanical impacts. These can be utilized to assess the fundamental condition, stability, and symmetry of the mechanical vibrations within circuit breakers. Frequency-domain analysis involves applying the Fast Fourier Transform [14] to transition vibration or acoustic emission signals from the time domain to the frequency domain, thereby extracting the signal's frequency components. The time-frequency domain analysis method, such as the short-time Fourier transform [15], is well-suited for analyzing the short-term dynamic changes in the vibration signals of circuit breakers. By analyzing the frequency characteristics of each time segment using a sliding window on the vibration signals, the signal's frequency distribution at various times is obtained. Additionally, methods like wavelet transform and Hilbert-Huang transform are employed to identify abrupt fault signals and address transient shocks and localized anomalies. As in [16], using continuous wavelet transform to convert data into a two-dimensional time-frequency map for model training improved the accuracy of fault diagnosis. Envelope extraction involves detecting the envelope of the vibration or acoustic emission signal to extract its envelope curve and analyze the frequency characteristics of the envelope. This method is suitable for identifying impact faults in circuit breakers and is categorized under envelope analysis methods [17]. Using machine learning or deep learning techniques, including principal component analysis and linear discriminant analysis, the most discriminative features can be identified from a multitude of time-domain, frequency-domain, and time-frequency domain characteristics, thereby enhancing discrimination efficiency. As [18] demonstrated, using principal component analysis to reduce the dimensionality of the energy spectrum effectively improved the accuracy of circuit breaker mechanical fault diagnosis. Temperature detection in circuit breakers aids in predicting and preventing issues such as overheating and short circuits, ensuring the equipment's safe operation, and the temperature data, often acquired directly from temperature sensors, can be processed using data preprocessing techniques like dimensionality reduction.

In this paper, the circuit breaker state discrimination algorithm is divided into three categories: machine learning method, deep learning method, and multi-source data fusion.

Machine learning methods are widely used in circuit breaker state discrimination because they can automatically learn features from a large amount of data and make classification and regression judgments on complex states. At present, support vector machine, K-nearest neighbor algorithm, and ensemble learning are commonly used in circuit breaker state discrimination research. For example, Ref. [19] established a circuit breaker state recognition model based on support vector machines and determined the optimal parameters using cross-validation grid search; Ref. [20] used the K-nearest neighbors algorithm to classify the monitored data, achieving live monitoring of electric actuator faults; Ref. [21] proposed a new ensemble learning model that can effectively handle vibration signals and accurately determine fault types; Ref. [22] introduced a random forest model with superior accuracy and anti-interference capabilities for circuit breaker fault diagnosis. In the state discrimination of circuit breakers, data sources usually include multi-source data such as electrical signals, mechanical vibration, temperature, acoustic emission, and partial discharge. There is a complex coupling relationship between these data. A single model is

difficult to capture these complex relationships, and ensemble learning can improve the overall discriminant effect by integrating the results of multiple models. However, integrating multiple models requires high computational resources, especially when dealing with large-scale, high-dimensional data, which takes a long time to train and predict.

Deep learning algorithms have been widely used in the field of state discrimination in recent years, especially for complex signal processing and pattern recognition tasks. It can automatically extract multi-level features to classify and regress complex data. Because of its good classification performance, deep learning algorithms have become a hot topic in circuit breaker state discrimination technology. The widely used convolutional neural network is a neural network that is good at processing images and time series data. It is usually used for the analysis of vibration signals, acoustic emission signals, and image data of circuit breakers. Because of its powerful feature extraction ability, it is very suitable for processing high-dimensional data and complex pattern recognition tasks, but it also requires a large amount of data for training, and the model is more complex, and the computational cost is high. Recurrent neural network is a kind of neural network suitable for processing sequence data, which can model the dynamic process of circuit breaker state changing with time. The commonly used long-term and short-term memory network is one of its variants. As in [23], based on bidirectional long short-term memory neural networks, accurate prediction of the remaining life of circuit breakers was achieved. It can capture the time dependence of the circuit breaker state, and is superior in dealing with complex time series data. It is suitable for processing time series, but it also has large computational overhead and high data volume requirements. It is usually difficult to meet its data requirements in power grid systems.

Multi-source data fusion addresses the limitations of single data sources, such as incomplete information, noise, and bias, by integrating data from various sources. This approach enhances the model's robustness, accuracy, and fault tolerance. Object-wise, multi-source data fusion can be categorized into three types: data-level fusion, feature-level fusion, and decision-level fusion. The common method is the weighted average method, which assigns different weights to each data source and performs a weighted average according to the weights. This method can only handle simple scenarios. Bayesian inference combines the information of different data sources by calculating conditional probability, which is suitable for fusion when the data source is uncertain, but requires prior probability information. D-S evidence theory [24] is more common in uncertain data fusion. Unlike Bayesian methods, it allows the uncertainty of data sources to be processed, and uses trust functions and doubts to synthesize information from different sources. Therefore, it is suitable for multi-source and multi-model fusion, especially in complex decision-making scenarios. In circuit breaker fault diagnosis, only a few researchers have considered multi-source data fusion. Among them, Ref. [8] uses box plots for feature selection, fusion, and reconstruction of multi-source data, and establishes a fault diagnosis model based on machine learning. There is also [9], which proposes a multiple echo state network based on D-S evidence theory, that is, by fusing multiple echo state network models through D-S evidence theory. In addition, there is [10], which designs a modified graph convolution network-trusted multi-source information fusion framework for vibration, current, and acoustic signals. Although these studies have considered multi-source data fusion, they merely represent simple applications of multi-source data fusion methods without optimizing the methods themselves. In this paper, the ant colony algorithm is used to optimize the basic probability distribution of D-S evidence theory. The optimized D-S evidence theory is applied to the decision-making level fusion of circuit breaker state discrimination, which improves the robustness and accuracy of its fusion model. The Section 3 introduces the D-S evidence theory in decision level fusion. The Section 4 is the

content of the Optimization method for basic probability allocation used in this paper. The Section 5 is the specific application of the improved D-S evidence theory based on the ant colony algorithm. The Section 6 is the experimental effect of the improved D-S evidence theory circuit breaker state discrimination model based on the ant colony algorithm. The Section 7 is the conclusion of this paper.

3. D-S Evidence Theory in Decision Level Fusion

D-S evidence theory is a theory proposed by Dempster to deal with uncertain information. It is widely used in multi-source data fusion and decision analysis. Compared with traditional probability theory, D-S evidence theory allows reasoning in the case of incomplete or uncertain information. It is especially suitable for multi-sensor systems and scenes with large uncertainty. Because it can deal with uncertainty and ambiguity, it has excellent performance in various cases of incomplete information in power grid systems.

The D-S evidence theory used in this paper mainly includes the following three parts:

Identification Framework: First, define the set S = {a, b, c...} of objects or events under examination, which consists of n mutually exclusive events, then the identification framework P(S) = {{∅}, {a}, {b},...{a, b},...{S}} consists of 2^n elements.

Basic probability assignment: D-S evidence theory uses basic probability assignment to represent the degree of trust in different assumptions. The basic probability assignment is to assign a total probability value to all possible assumptions. The function m is used to represent the basic probability distribution for each time, as shown in Formula (1):

$$\begin{cases} m(\phi) = 0 \\ \sum_{A \subseteq S} m(A) = 1 \end{cases} \tag{1}$$

This means that the sum of the basic probability distribution of all events equals 1, that is, all hypotheses are complementary, and there is always one hypothesis that is true. Therefore, the sum of the degrees of confidence assigned to all propositions should be equal to 1. In this paper, the basic probability assignment will subsequently be determined by the Ant Colony Optimization algorithm.

Composition rule: The probability assignment value of the combined set is obtained by combining different events, as shown in Formula (2):

$$m(A) = \frac{1}{1-K} * \sum_{B \cap C = A} m_1(B) * m_2(C) \tag{2}$$

Among them, $m_1(B)$ and $m_2(C)$ are probability assignment values from different sources or sensors, and K is the conflict degree, which is used to measure the inconsistency or conflict in the synthesis process. For example, if $m_1(B)$ represents the probability that B is true, and $m_2(C)$ completely excludes B, that is, $B \cap C = \varnothing$, then this conflict will be reflected by K. Specifically, it is calculated based on the degree of conflict between evidence from different sources, as shown in Formula (3):

$$K = \sum_{B \cap C = \varnothing} m_1(B) * m_2(C) \tag{3}$$

That is, the sum of the combined probability values of all mutually exclusive event sets. When K is larger, it indicates that the greater the conflict between the evidence sources, the greater the uncertainty in the synthesis results. When K is close to 1, it indicates that there is a high degree of conflict between the evidence, and the credibility of the synthesis results is reduced. The Dempster combination rule adjusts the final trust allocation through $\frac{1}{1-K}$ to ensure that the synthesized results can still reflect the overall information of the evidence in the case of conflict. In the state identification of the circuit breaker, multiple

sensors will provide different evidence to reflect the state of the circuit breaker, and the evidence of each sensor may be conflicting. For example, when the temperature sensor shows abnormal and the vibration sensor shows normal, the Dempster combination rule can be used to fuse these different pieces of evidence and adjust the fusion result according to the conflict degree K between them. In order to further demonstrate the impact of conflict degree K on the final decision, we assume that the sum of the basic probability distribution values of the empty set and other event sets outside set A is 0.5, that is, the sum of $\sum_{B\cap C=A} m_1(B) * m_2(C)$ and $\sum_{B\cap C=\varnothing} m_1(B) * m_2(C)$ is 0.5. A curve chart showing the variation of $m(A)$ values with K values ranging from 0 to 0.5 was drawn, as shown in Figure 1. This also confirms that as K increases, the conflict between evidence sources becomes greater, and the credibility of the synthesis results decreases.

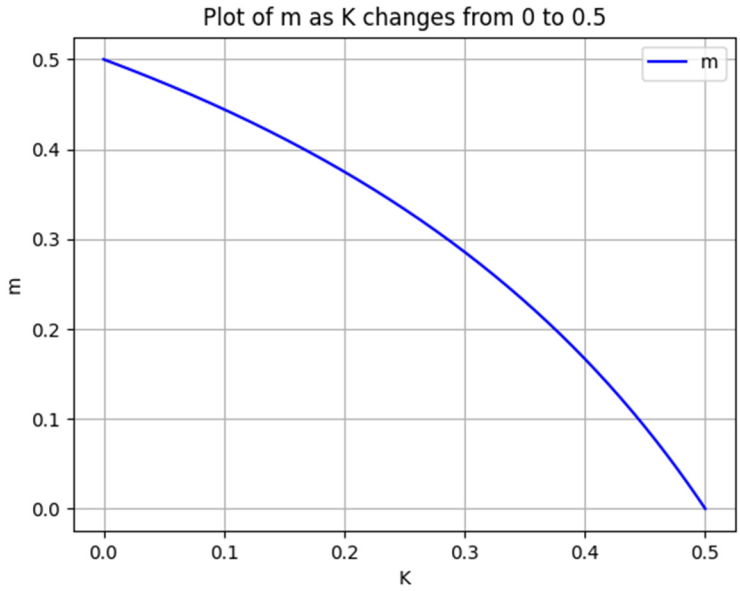


Figure 1. Probability assignment value versus conflict degree K variation curve.

This paper will apply the D-S evidence theory, based on the aforementioned assumptions, to the decision layer fusion in circuit breaker status discrimination. It can fully utilize the advantages of various models, handle conflicts and uncertainties in multi-source data, thereby improving the accuracy, robustness, and stability of circuit breaker status diagnosis. Machine learning Each model may perform well under certain conditions, but due to the limitations of the model and the complexity of the sensor data, a single model may not provide the most accurate results. Therefore, integrating the output of these models at the decision-making level can make better use of the advantages of each model and reduce the risk of misjudgment of a single model. In power grid systems, circuit breakers require real-time monitoring and rapid response. The D-S evidence theory, through its dynamic decision-making capabilities, can fuse the outputs of multiple models within real-time data streams to generate real-time circuit breaker status diagnostic results. This is of great significance for quickly identifying faults and taking emergency measures.

The process of its action is first to transform the model output into evidence. Each machine learning model gives its judgment results according to the input data, such as the sensor data of the circuit breaker, such as 'normal circuit breaker', 'circuit breaker failure', etc. These results are regarded as evidence of a certain state, and the basic probability distribution is used to represent the degree of support of each model for different states. Then, using Dempster's combination rule, D-S evidence theory can fuse evidence from different machine learning models to obtain a comprehensive probability assignment. The fusion process takes into account the credibility of each model. In addition, the weight of

inconsistent evidence is adjusted by the conflict degree K to ensure that the fusion result is more robust. Finally, according to the trust allocation after fusion, the D-S evidence theory can give a comprehensive judgment result for the state of the circuit breaker. This result can be the most likely state among multiple states.

4. Optimization Method for Basic Probability Allocation

In the state identification of circuit breakers, the fusion effect of D-S evidence theory depends on the basic probability distribution. Therefore, this paper proposes to use the ant colony algorithm to determine the global optimal basic probability distribution for the purpose of maximizing the accuracy of fusion results, which can improve the efficiency and accuracy of evidence fusion, especially when dealing with complex multi-source data. The ant colony algorithm includes four parts: ant, pheromone, heuristic information, and objective function. Ants are used to simulate individuals and are responsible for exploring solutions and updating probability values. The pheromone is used to guide the ant's search direction, and the strength of the pheromone indicates the quality of different solutions. Heuristic information provides additional guidance in the search process to help ants choose a better path. The objective function, the final circuit breaker state discrimination accuracy, is used to evaluate the quality of the solution found by each ant.

The process of determining the basic probability distribution of D-S evidence theory by ant colony algorithm is shown in Figure 2.

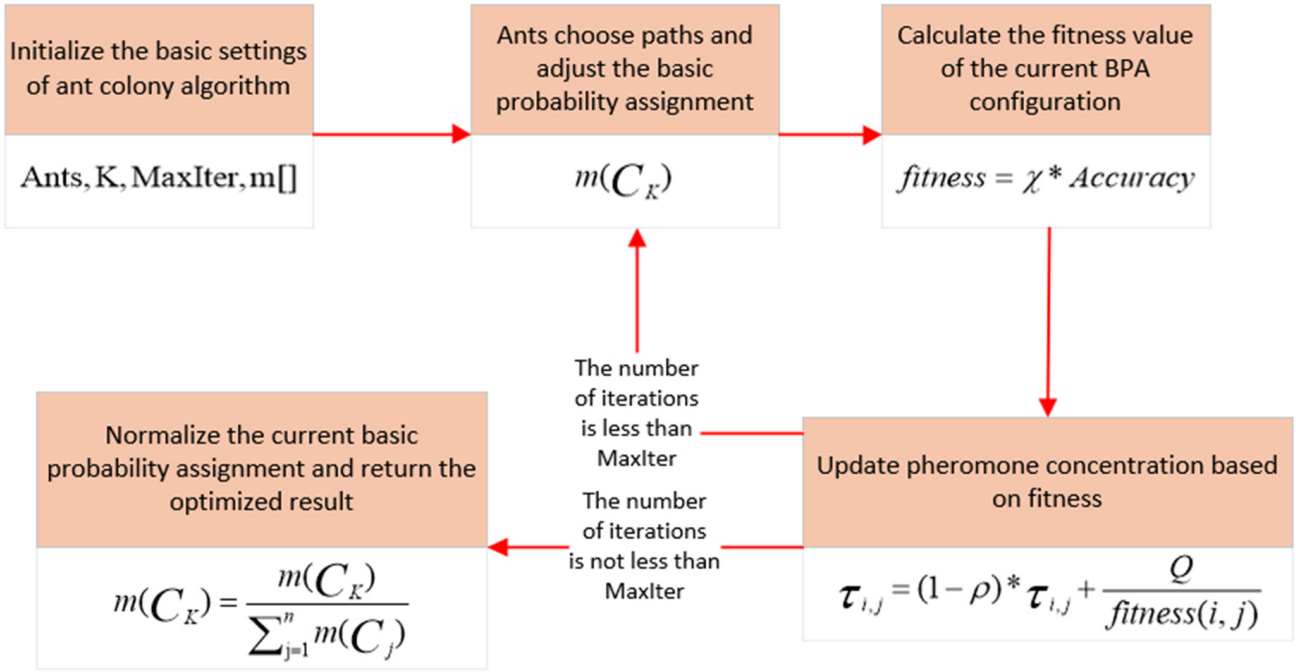


Figure 2. Flow chart of Basic Probability Distribution Optimization using Ant Colony Algorithm.

The various modules in the diagram correspond to the initialization, ant colony search, fitness calculation, pheromone update, and result return in sequential order.

The initialization involves setting parameters such as the number of ants A, the maximum number of iterations B, and the number of events K, and initializing the probability value array M to store the probability values for each event.

Ant colony search is the process where all ants search simultaneously. Each ant selects a path based on available data, chooses the current algorithm model for judgment, and updates the probability value after obtaining the judgment result. For each sample i, if the prediction result $pred_A[i]$ of model A matches the true label y[i], the corresponding event's

probability value is increased; otherwise, the probability value remains unchanged. The update of each model's event probability value is shown in Formula (4):

$$\mathrm{m(C_k)} = \begin{cases} \mathrm{m(C_k)} + 1, & \text{if } test_A[i] = \mathrm{y[i]} \\ \mathrm{m(C_k)}, & \text{if } test_A[i] \neq \mathrm{y[i]} \end{cases} \tag{4}$$

Fitness calculation refers to updating pheromone concentration based on the current fitness, and its calculation method is shown in Formula (5):

$$\text{fitness} = \chi * \text{Accuracy} \tag{5}$$

Among them, fitness is the fitness, χ is the fitness factor, and $\chi > 0$. Accuracy are the model classification accuracies after fusion based on the current basic probability distribution values. Therefore, the higher the fusion model classification accuracy, the greater the fitness value.

Pheromone update refers to updating the pheromone concentration based on fitness, and the update method is shown in Formula (6):

$$\tau_{i,j} = (1 - \rho) * \tau_{i,j} + \frac{Q}{fitness(i,j)} \tag{6}$$

Among them, $\tau_{i,j}$ is the pheromone concentration on the path from i to j, ρ is the pheromone evaporation factor, and $0 < \rho < 1$. Q are constants greater than zero used to control the amount of pheromone update. $fitness(i,j)$ is the fitness of the path from i to j.

Normalization means that after each ant colony search is completed, the probability values need to be normalized and returned as the optimized basic probability distribution results to the D-S evidence theory fusion model for multi-source data fusion, ensuring that their sum is 1, thus satisfying the definition of basic probability distribution. The normalization formula is shown in Formula (7):

$$\mathrm{m(C_k)} = \frac{\mathrm{m(C_k)}}{\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{m(C_j)}} \tag{7}$$

The ant colony algorithm has a unique advantage in optimizing the basic probability distribution in D-S evidence theory. Because of its unique search mechanism, adaptability, conflict handling ability, and parallel computing characteristics, it often performs well in the fusion of complex multi-source data. Compared with other optimization algorithms, it is more suitable for dynamic and complex environments and helps to improve the accuracy and efficiency of circuit breaker state discrimination. Compared with the ant colony algorithm, the genetic algorithm relies on selection, crossover and mutation operations. Although it can explore a larger space, it may face premature convergence when dealing with complex problems. Particle swarm optimization searches through collaboration and learning between individuals and groups, but it may not be flexible enough to deal with multi-peak problems. Simulated annealing controls the search by gradually lowering the temperature, but when the solution space is large, it may lead to a slower search speed.

5. Application of Circuit Breaker State Discrimination Based on the Ant Colony Algorithm Improved D-S Evidence Theory

There are some obvious defects and challenges in the current research on the state identification of circuit breakers. In order to solve these problems, we propose a circuit breaker state discrimination model based on the ant colony algorithm to improve D-S evidence theory. In multi-source data fusion, data from different sensors or models

may have conflicts and inconsistencies, which leads to a decrease in the accuracy of the discriminant results. D-S evidence theory can effectively deal with these conflicts, but it needs to optimize the basic probability distribution to enhance its performance. Existing machine learning models are often difficult to adapt to changing operating conditions when facing complex power systems. Traditional methods have poor flexibility in dealing with dynamic data and are difficult to cope with real-time state changes. The ant colony algorithm can provide the ability of dynamic adjustment and improve the adaptability of the model. Through the dynamic optimization of the ant colony algorithm and the conflict processing of D-S evidence theory, it not only improves the accuracy and robustness, but also improves the adaptability of the system to the complex power environment, and provides more reliable support for the security and stability of the smart grid.

The support vector machine model and the decision tree model used in this paper each have their own advantages. The support vector machine excels at handling high-dimensional, nonlinear data, while the decision tree model can make intuitive decisions through rules. By combining these two models, we can better leverage their respective strengths, enhancing the system's robustness and accuracy. Moreover, this paper does not simply apply D-S evidence theory to multi-source data fusion; it also optimizes the basic probability assignment through the ant colony algorithm, which can reduce manual adjustments and experience-driven processes, thereby enhancing the system's automation and adaptability.

It should be noted that this paper uses the improved D-S evidence theory based on the ant colony algorithm to fuse the model, which is the support vector machine circuit breaker state discrimination model based on current signals and the decision tree circuit breaker state discrimination model based on vibration signals. The process of the circuit breaker state discrimination method based on the ant colony algorithm to improve D-S evidence theory is shown in Figure 3, which includes six steps.

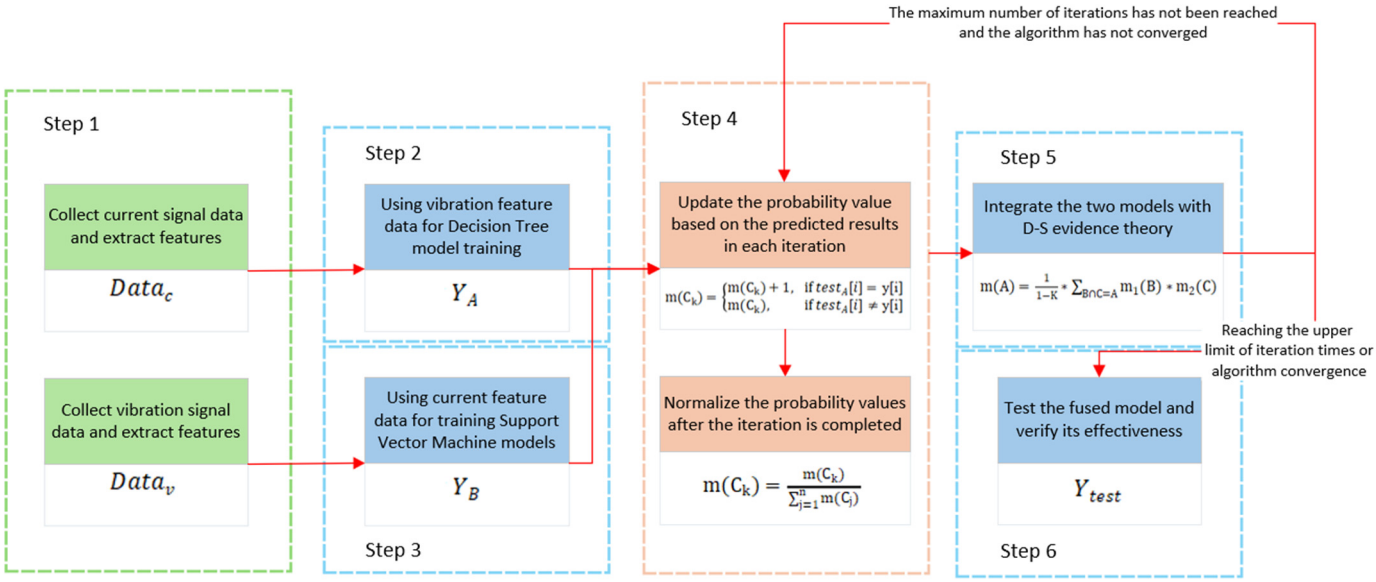


Figure 3. Flow chart of circuit breaker state discrimination method based on the ant colony algorithm improved D-S evidence theory.

Among them, the green part represents the data acquisition module, which in this experiment refers to the labeled simulated data after extracting features from the circuit breaker current signal and vibration signal; the blue part is the main circuit breaker state identification model module, including machine learning model training and D-S evidence theory fusion; the yellow part is the optimization module of D-S evidence theory, which

uses ant colony algorithm to optimize the basic probability assignment of D-S evidence theory. The first step is to collect data and extract features, that is, to collect current signal data and vibration signal data from the current sensor and the acceleration sensor, and extract relevant features to obtain datasets $Data_c$ and $Data_v$ respectively. The second step is to use the current feature data for training the support vector machine model and obtain the result Y_A, that is, using the current feature data extracted from the current sensor as the training dataset for the support vector machine model, which is used for circuit breaker state discrimination. The third step is to use the vibration feature data for training the decision tree model and obtain the result Y_B. This means using the vibration feature data extracted from the accelerometer sensor as the training dataset for the decision tree model, which is also used for circuit breaker state judgment. Steps two and three can be carried out simultaneously. The fourth step involves using the ant colony algorithm to determine the basic probability assignment of the D-S evidence theory. The probability value update formula is Formula (4) in Section 4, and the normalization processing formula is Formula (5). The effectiveness of the D-S evidence theory for multi-source data fusion depends on the basic probability assignment, so the ant colony algorithm is needed to determine the globally optimal basic probability assignment. The fifth step is to perform D-S evidence theory fusion on the two models. The basic probability assignment obtained from the ant colony algorithm is used to fuse the support vector machine model and the decision tree model. The fusion formula is the same as Equation (2) in Section 3, and the fused circuit breaker status identification results are obtained. If the number of iterations of the ant colony algorithm reaches the upper limit or the results have converged, proceed to the sixth step; otherwise, return to step four to continue using the ant colony algorithm to adjust the basic probability distribution; step six involves testing the fused model to obtain the result Y_{test} and verify its effectiveness. After determining the final globally optimal basic probability distribution, use the real-time extracted circuit breaker current feature data and vibration feature data as the test dataset. Finally, obtain the test results of the fused model and conduct a comparative analysis with the support vector machine model and the decision tree model.

Specifically, the ant colony algorithm in the above process improves the ant colony algorithm in the D-S evidence theory as shown in Algorithm 1.

Algorithm 1 Ant colony algorithm

```
Input: ant_count, max_iterations, event_count, initial_probabilities, delta_value;
Output: BPA;
Initialize BPA[event_count] = initial_probabilities
Initialize Pheromone[event_count] = initial_pheromone
iteration = 0
while iteration < max_iterations:
    for each ant i from 1 to ant_count:
        classification_result = model_classification(input_data)
        for each event j from 1 to event_count:
            if classification_result == true_label:
                BPA[j] += delta_value(classification_result)
            end if
        end for
    end for
    total_sum = 0
    for each event j from 1 to event_count:
```

Algorithm 1 *Cont.*

```
            total_sum += BPA[j]
        end for
        for each event j from 1 to event_count:
            BPA[j] = BPA[j]/total_sum
        end for
        for each event j from 1 to event_count:
            Pheromone[j] += BPA[j]
        end for
        iteration += 1
end while
```

Among them, ant_count is the number of ants, max_iterations is the maximum number of iterations, event_count is the number of events, and initial_probabilities is the initial probability value. Delta_value is a function used to calculate the incremental value. In this paper, the accuracy of the circuit breaker state discrimination result is incrementally calculated. In Algorithm 1, the 3rd to 5th behaviors initialize the basic probability assignment and pheromone array. The whole iterative process of the ant colony algorithm from line 6 to line 26. From line 7 to line 14, the state of each ant is judged, and the basic probability assignment array of the corresponding event is updated. Lines 15 to 21 normalize the updated basic probability assignment array. Lines 22 to 24 update the pheromone array according to the current basic probability distribution data. In addition, some algorithms of D-S evidence theory are given as shown in Algorithm 2.

Algorithm 2 D-S evidence theory

```
Input: pred_A, pred_B, probability_values_A, probability_values_B;
Output: final_decision
Initialize num_classes = 4
Initialize m = np.zeros((num_classes, num_classes))
K = 0.0
m[pred_A, pred_A] += probability_values_A[pred_A]
m[pred_B, pred_B] += probability_values_B[pred_B]
for each class i:
    for each class j:
        if i != j:
            K += m[i, j] * m[j, i]
        end if
    end for
end for
for each class A:
    for each class B:
        if A != B:
            m_combined[A, B] = (m[A, A] * m[B, B])/(1 − K)
        end if
    end for
end for
m_combined_sum = np.sum(m_combined, axis = 1)
m_combined_sum /= np.sum(m_combined_sum)]
final_decision = np.argmax(m_combined_sum)
```

Among them, pred_A is the prediction result of algorithm A, pred_B is the prediction result of algorithm B, probability_values_A is the probability value of algorithm A, and probability_values_B is the probability value of algorithm B. Algorithm A refers to the support vector machine algorithm based on current signals, and algorithm B refers to the decision tree algorithm based on vibration signals. Lines 3 to 5 initialize the number of categories, the basic probability distribution matrix, and the degree of conflict. Line 6 and line 7 calculate the basic distribution probability. From line 8 to line 14, the conflict degree K is calculated. From line 15 to line 21, the combination probability value is calculated. The 22nd and 23rd behaviors are normalized. The 24th behavior selects the category with the highest probability value.

6. Experiments

In order to reflect the superiority of the circuit breaker state discrimination method based on the ant colony algorithm to improve D-S evidence theory, we conducted simulation experiments using labeled simulated data extracted from circuit breaker current signals and vibration signals. This dataset is divided into two types: current signal feature data and vibration signal feature data, with current data being two-dimensional features and vibration data being one-dimensional features. Both datasets have 120 data points, corresponding to four circuit breaker states, with 30 data points for each state. In the experiment, we used 50% of the data as training data and 50% as test data. Based on the training data, train the circuit breaker state discrimination model based on support vector machines and the circuit breaker state discrimination model based on decision trees. Subsequently, perform D-S evidence theory fusion improved by the ant colony algorithm to obtain the circuit breaker state discrimination model based on D-S evidence theory improved by the ant colony algorithm. The test results obtained from the test data are shown in Table 1. The accuracy of the circuit breaker state discrimination model based on the support vector machine is 68.3%, the accuracy of the circuit breaker state discrimination model based on the decision tree is 55%, the accuracy of the circuit breaker state discrimination model using the method support vector machine and decision tree methods based on D-S Evidence Theory Fusion is 66.7%, the accuracy of the circuit breaker state discrimination model using the method based on D-S evidence theory and neural networks is 70%, and the accuracy of the circuit breaker state discrimination model based on the ant colony algorithm improved D-S evidence theory is 75%.

Table 1. Test set accuracy results table of each model.

	State0	State1	State2	State3	Entirety
Support Vector Machine	20%	53.3%	100%	100%	68.3%
Decision Tree	40%	53.3%	73.3%	53.3%	55%
Support vector machine and decision tree methods based on D-S evidence theory fusion	46.7%	66.7%	73.3%	80%	66.7%
Method based on D-S evidence theory and neural networks	46.7%	40%	100%	93.3%	70%
Ant colony algorithm improves D-S evidence theory	40%	73.3%	86.6%	100%	75%

It can be seen that the overall accuracy of the circuit breaker state discrimination model based on the ant colony algorithm improved D-S evidence theory is significantly higher than that of the two individual models, support vector machine and decision tree. This is because through the D-S evidence theory, the output of different models can be reasonably integrated, and more credible comprehensive results can be generated according

to their accuracy and confidence, which effectively improves the operation stability and maintenance efficiency of electrical equipment.

The specific experimental results are shown in Figure 4. Among them, green represents the test dataset labels, red represents the classification results of the support vector machine, orange represents the classification results of the decision tree, blue represents the classification results of the ant colony algorithm improves D-S evidence theory method, and blue represents the classification results of the ant colony algorithm improves D-S evidence theory method.

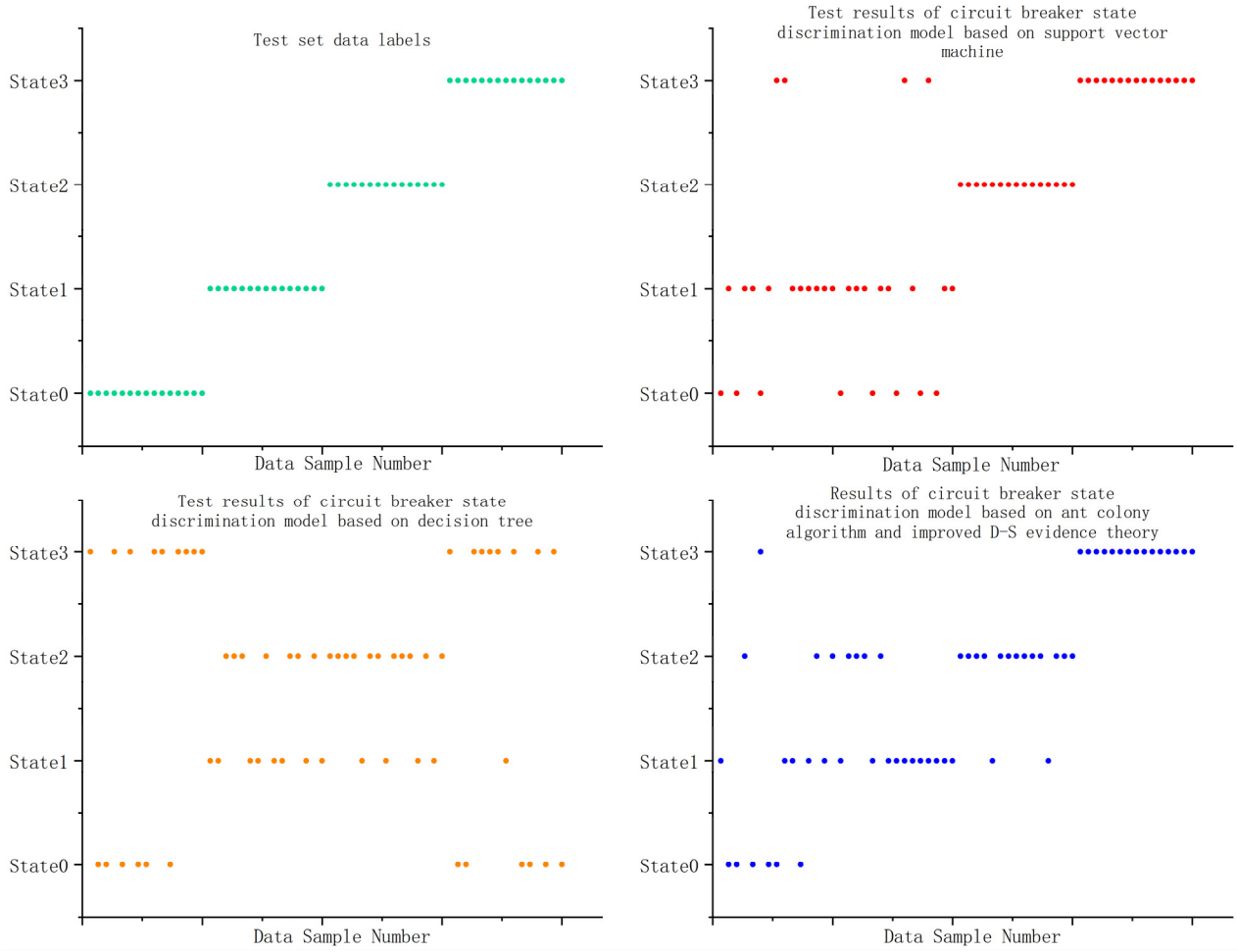


Figure 4. Comparison chart of ant colony algorithm improves D-S evidence theory with two single models.

This paper also highlights the improvements brought by the ant colony algorithm to the model proposed in this paper by comparing it with methods that do not use the ant colony algorithm to optimize D-S evidence theory. Additionally, this paper compares it with a method based on D-S evidence theory and neural networks from the paper [25], as shown in Figure 5. Among them, green represents the test dataset labels, orange represents the classification results of the method based on D-S evidence theory and neural networks, blue represents the classification results of the ant colony algorithm improves D-S evidence theory method, and red represents the classification results of the support vector machine and decision tree methods based on D-S evidence theory fusion. It can be seen that the blue image is closest to the green image, so the proposed ant colony algorithm improves D-S evidence theory method in this paper performs better than other methods in classification. However, to more clearly demonstrate the improvement of the proposed ant colony algorithm improves D-S evidence theory method compared to

other methods, we have plotted the state of each support vector machine and decision tree methods based on D-S evidence theory fusion, method based on D-S evidence theory and neural networks, and ant colony algorithm improves D-S evidence theory, as well as the overall average classification accuracy bar chart, as shown in Figure 6. Among them, method A, B, and C correspond to support vector machine and decision tree methods based on D-S evidence theory fusion, the method based on D-S evidence theory and neural networks, and ant colony algorithm improves D-S evidence theory, respectively. It is clear that the ant colony algorithm improves D-S evidence theory method proposed in this paper has the highest overall classification accuracy compared to support vector machine and decision tree methods based on D-S evidence theory fusion and method based on D-S evidence theory and neural networks. Additionally, due to the influence of various factors on the model training process of the proposed method, its time complexity is difficult to represent with a mathematical formula, making it challenging to compare mathematically from the perspective of complexity. Therefore, we directly compare the actual running times of the two methods. The total running time of the method based on D-S evidence theory and neural networks is 2.33 s, while the total running time of the proposed ant colony algorithm improves D-S evidence theory method is only 1.09 s. It can be seen that ant colony algorithm improves D-S evidence theory method has improved computational efficiency to some extent.

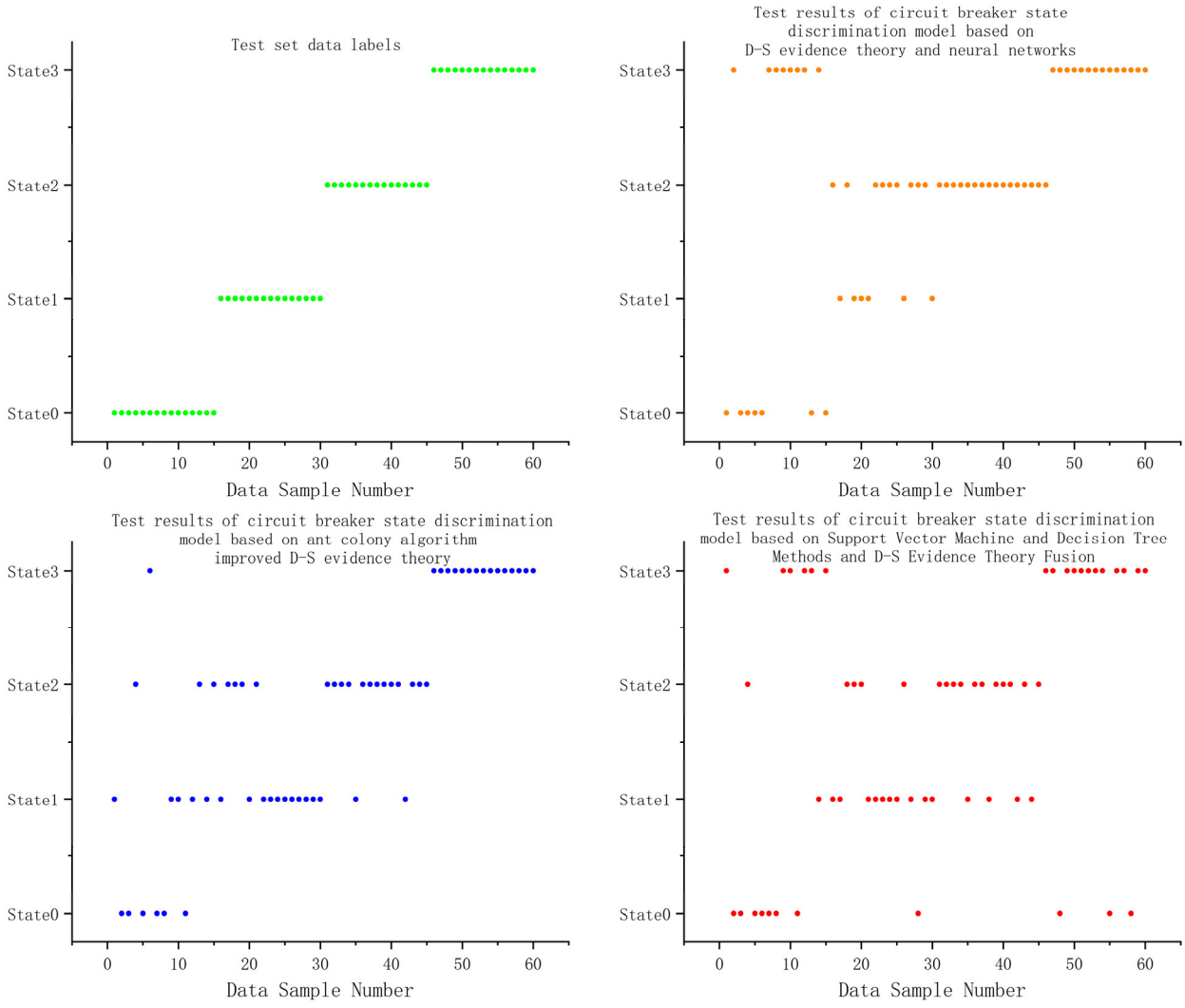


Figure 5. Comparison chart of various circuit Breaker status determination methods.

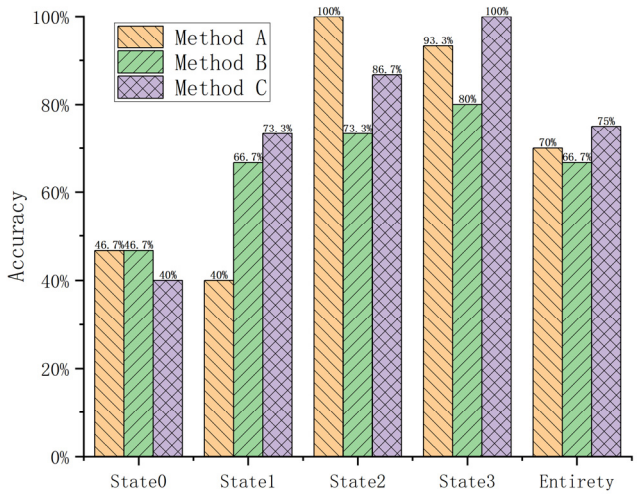


Figure 6. Bar chart of the accuracy of various circuit breaker status identification methods.

From the overall experimental results, it can also be seen that the circuit breaker state discrimination model based on the ant colony algorithm improved D-S evidence theory has the highest overall discrimination accuracy under various circuit breaker states. Therefore, it can be concluded that the circuit breaker state discrimination method based on the ant colony algorithm improved D-S evidence theory improves the robustness and stability of circuit breaker state discrimination to a certain extent, and improves the accuracy of circuit breaker state discrimination on the basis of ensuring its calculation efficiency. This experiment is only used to illustrate the feasibility and advantages of the circuit breaker state discrimination method based on the ant colony algorithm to improve D-S evidence theory. This method can also be extended to the fusion of other data and other algorithm models.

7. Conclusions

Based on the existing research on circuit breaker state discrimination, this paper proposes a circuit breaker state discrimination model based on the ant colony algorithm to improve D-S evidence theory. The ant colony optimization algorithm is used to optimize the basic probability distribution of D-S evidence theory. This method effectively responds to the challenges of uncertainty and conflicting information generated by multiple prediction models. And the final experimental results show that the optimization of the ant colony algorithm can bring about an 8.3% increase in the accuracy of the circuit breaker state identification model, and a 5% increase in accuracy compared to existing methods. Therefore, the combination of the ant colony algorithm and D-S evidence theory significantly enhances the ability to identify the state of the circuit breaker, especially by avoiding the limitations of a single model and improving accuracy. Future explorations can apply this method to other fields that require reliable decision-making under uncertainty, such as fault diagnosis of transformers, switchgear, and other electrical equipment.

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Conflicts of Interest: Authors Qian Zhang, Zhi Liu, Zhilan Zhang, Lei Guo, and Yan Wang were employed by State Grid Hubei Electric Power Co., Ltd., Xiaogan Power Supply Company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that this study received funding from the Science and Technology Project of State Grid Hubei Electric Power Co., Ltd., Xiaogan Power Supply Company.

References

1. Rodrigues, R.; Du, Y.; Antoniazzi, A.; Cairoli, P. A review of solid-state circuit breakers. *IEEE Trans. Power Electron.* **2020**, *36*, 364–377. [CrossRef]
2. Taherzadeh, E.; Radmanesh, H.; Javadi, S.; Gharehpetian, G.B. Circuit breakers in HVDC systems: State-of-the-art review and future trends. *Prot. Control Mod. Power Syst.* **2023**, *8*, 38. [CrossRef]
3. Qian, Z.; Qi, X.; Wang, S.; Cao, W.; Han, S.; Zhu, F. The Research and Application on the Intelligent Control System of the GIS Circuit Breaker. In Proceedings of the 2021 International Conference on Power System Technology (POWERCON), Haikou, China, 8–9 December 2021; pp. 1759–1763.
4. Wu, Y.; Cao, N.; Yu, Q. State evaluation of circuit breakers based on improved fuzzy comprehensive evaluation method. *J. Phys. Conf. Ser.* **2021**, *1748*, 022013. [CrossRef]
5. Bento, A.R.F.; Bento, F.; Cardoso, A.J.M. A review on Hybrid Circuit Breakers for DC applications. *IEEE Open J. Ind. Electron. Soc.* **2023**, *4*, 432–450. [CrossRef]
6. Abbasi, A.R. Fault detection and diagnosis in power transformers: A comprehensive review and classification of publications and methods. *Electr. Power Syst. Res.* **2022**, *209*, 107990. [CrossRef]
7. Moreno Escobar, J.J.; Morales Matamoros, O.; Tejeida Padilla, R.; Lina Reyes, I.; Quintana Espinosa, H. A comprehensive review on smart grids: Challenges and opportunities. *Sensors* **2021**, *21*, 6978. [CrossRef]
8. Zhao, X.; Lv, S.; Guan, X.; Liu, W.; Wang, H.; Li, X.; Ma, C.; Lu, Y. Research on Mechanical Fault Diagnosis Method of Circuit Breakers Based on Fusion of Multi-Source Signal Data. In Proceedings of the 2024 7th International Conference on Energy, Electrical and Power Engineering (CEEPE), Yangzhou, China, 26–28 April 2024; pp. 477–484.
9. Li, X.; Chen, H.; Xie, F.; Cao, C.; Wang, S.; Shuai, C. Hybrid Model of Multiple Echo State Network Integrated by Evidence Fusion for Fault Diagnosis of a High-Voltage Circuit Breaker. *IEEE Trans. Consum. Electron.* **2024**, *70*, 5269–5277. [CrossRef]
10. Zhang, K.; Li, H.; Cao, S.; Lv, S.; Yang, C.; Xiang, W. Trusted multi-source information fusion for fault diagnosis of electromechanical system with modified graph convolution network. *Adv. Eng. Inform.* **2023**, *57*, 102088. [CrossRef]
11. Qi, H. Research on Fault Diagnosis of High Voltage Circuit Breaker Based on Compressed Sensing Theory. Master's Thesis, Lanzhou Jiaotong University, Lanzhou, China, 2022.
12. Li, Q. Research on Mechanical Fault Diagnosis Method for Universal Circuit Breakers Based on Convolutional Neural Networks. Master's Thesis, Hebei University of Technology, Tianjin, China, 2020.
13. Sun, Y. Research on Mechanical Fault Diagnosis Method of High Voltage Circuit Breaker Based on Electric-Vibration Signal Combination. Master's Thesis, School of Electrical and Electronic Engineering, Beijing, China, 2023.
14. Lin, J. Research on Mechanical Fault Diagnosis Method for Circuit Breakers Based on Vibration Signals. Master's Thesis, Shandong University, Jinan, China, 2019.
15. Li, C.; Chu, J.; Long, X.; Yang, A.; Yuan, H.; Rong, M.; Wang, X. Online Monitoring Method for Electrical Life of High-Voltage SF6 Circuit Breakers Based on Contact Vibration Characteristics of Arc Contacts. *Trans. China Electrotech. Soc.* **2024**, *39*, 4883–4895.
16. Chen, C. Research on Mechanical Fault Diagnosis Method of Air Circuit Breakers Based on Machine. Master's Thesis, Chongqing Jiaotong University, Chongqing, China, 2024.
17. Chen, Z. Research on Fault Diagnosis Method for Mechanical Components of Circuit Breakers Based on ANFIS. Master's Thesis, Hebei University of Science and Technology, Shijiazhuang, China, 2022.
18. Peng, Y.; Wang, L.; Pan, N.; Chen, J.; Pang, J.; Zhou, X.; Huang, Y. Mechanical Fault Diagnosis of Circuit Breaker Based on Wavelet Packet Energy Spectrum and Support Vector Machine. *Mech. Electr. Eng. Technol.* **2023**, *52*, 159–163.
19. Liu, W.; Zhang, G.; Liu, Y.; Yang, J.; Zhao, K.; Wang, J. Mechanical Status Identification of High Voltage Circuit Breakers Based on Principal Component Analysis and Support Vector Machines. *High Volt. Appar.* **2020**, *56*, 267–272+278.
20. Liu, T.; Wang, L.; Zhang, J.; Yang, F.; Duan, J. Design of On-Line Fault Monitoring System for Circuit Breaker Electric Operating Mechanism. *Lamps Light.* **2022**, *09*, 99–101.
21. Si, J.; Tursunjiang, K.; Fan, X.; Gao, W.; Zhu, W. Fault diagnosis of high-voltage circuit breaker based on SO-PAA-GAF and AdaBoost ensemble learning. *Power Syst. Prot. Control* **2024**, *52*, 152–160.
22. Xu, K.; Chen, P.; Liu, J.; Zhang, Y.; Cao, P.; Huang, J. Application of Improved Random Forest Method in Mechanical Fault Diagnosis of Circuit Breakers. *Meas. Detect. Tech.* **2021**, *43*, 112–114.

23. Li, J.; Wang, Q.; Fan, Y.; Shi, S.; Peng, Z.; Cao, P.; Xu, P. Research on Whale Optimization Algorithm-bidirectional Long-short-term Memory Neural Network for Prediction of Machinery Remaining Useful Life of Circuit Breaker. *High Volt. Eng.* **2024**, *50*, 250–262.
24. Wang, L.; Li, B.; Wu, Y.; Xu, Z.; Li, Y. Partial Discharge Detection Technology of Open Circuit Breakers Based on D-S Evidence Theory. *Guangdong Electr. Power* **2023**, *36*, 77–83.
25. Zhang, J.; Wu, Y.; Xu, Z.; Din, Z.; Chen, H. Fault diagnosis of high voltage circuit breaker based on multi-sensor information fusion with training weights. *Measurement* **2022**, *192*, 110894. [CrossRef]

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