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The Dangerous Feature Identification of Transmission Line Galloping Under Multi-channel Modal State

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Abstract. A rough set combined with an ant colony algorithm is used to extract the non-forced vibration signal from the measured transmission line galloping displacement signal, which is used as the risk feature recognition index. In the real model test, the transmission line's six split line segment shift time history is measured across multiple channels to identify the galloping frequency, vibration mode, and damping ratio of the transmission line. At the same time, MATLAB simulation is employed to verify the algorithm's accuracy and computation time. The results show that the accuracy of the proposed algorithm in identifying the galloping frequency, vibration mode, and damping ratio is 98%, 97.6%, and 98.5%, respectively, with calculation times of 16s, 18s, and 17.5s. Therefore, in multi-channel modal analysis, a rough set combined with the ant colony algorithm can effectively address the problem of dangerous feature identification of transmission line galloping.

Key words. Damping ratio, galloping frequency, hazardous characteristics, multi-channel modal state, transmission line.

1. Introduction

With the continuous expansion of the construction scale of transmission networks, the galloping problem of the transmission line is becoming more and more serious, threatening the safety of the power grid. Transmission line galloping causes changes in vibration form, frequency, motion trajectory, and line damping. How to make an effective judgment scheme according to the changes of the above indicators is an urgent problem to be solved [1].

Currently, methods for evaluating transmission line galloping mainly include numerical simulation, wind tunnel tests, field tests, and other approaches. Japan, the United States, and several other countries have established galloping testing bases, and China in 2010 set up a comprehensive testing facility in Xinmi City, Henan Province [2]. How to observe the galloping process of transmission lines and analyze the galloping characteristics thoroughly remains a key challenge [3]. Domestic researchers tend to rely on single-channel eigenvalue analysis for transmission line galloping, which often overlooks the more detailed insights obtainable through multi-channel comprehensive analysis that combines numerical simulations, wind tunnel tests, and field measurements [4]. This leads to less accurate identification of essential galloping features.

Significant vibrations in multi-line systems often result from the combined effects of gusts and self-excited responses. Single-channel mimicry cannot reliably identify higher-order vibration modes or distinguish between similar frequency components [5]. Additionally, such methods have low accuracy in detecting negative damping effects and struggle to effectively resolve displacement and acceleration signals [6].

To address these limitations, this paper suggests integrating Rough Set Theory with the Ant Colony Optimization (ACO) algorithm. While both methods have been individually applied to signal processing and optimization problems [7], their combined use remains relatively unexplored in the context of power line galloping analysis. The rough set method improves data integrity by filtering noise and grouping semi-structured data. Conversely, the ACO is used to optimize feature identification based on frequency, damping ratio, and modal parameters. This hybrid approach allows for a more reliable early warning system and increases the interpretability of modal interactions across multiple observation channels.

Compared to traditional ACO-based models [8], the inclusion of rough sets addresses the common problems of premature convergence and trapping in local extrema within search processes. Moreover, unlike fuzzy logic-based methods or neural models used in vibration feature recognition [9], the proposed approach offers a more transparent and controllable framework for managing both quantitative and qualitative feature sets.

At the same time, threshold, penalty, and weight constraints are embedded into the model to improve prediction accuracy and feature clustering. The approach not only supports higher computation speed and robustness but also delivers better classification outcomes in identifying galloping modes across different test configurations.

2. The calculation flow and index selection of transmission line galloping under the multi-channel state

Modal identification can test the vibration response of the transmission line by simulating the transmission signal and environment, and identify the galloping characteristics combined with the feedback signal. Multi-channel mode requires a random decrement of data and calculation of eigenvalues [10]. The non-forced vibration signal is obtained by random decrement, and the structural modal parameters are obtained by eigenvalue. In recent developments, researchers have emphasized the significance of using adaptive signal decomposition techniques such as Ensemble Empirical Mode Decomposition (EEMD) and Wavelet Packet Transform (WPT) to preprocess multi-channel vibration data. These methods help isolate relevant signal modes and reduce the influence of environmental noise more efficiently than conventional filtering [11]. By applying adaptive thresholding to the decomposed components, especially when embedded within modal analysis pipelines, these techniques can enhance the clarity of modal characteristics before feeding into a Hankel matrix-based singular value decomposition. This is particularly important when dealing with non-stationary galloping signals that exhibit time-varying modal content.

In the multi-channel modal analysis, the low-channel filter should be used to eliminate the high-frequency noise [12], and the elimination frequency of the filter should be higher than the structural frequency to avoid the attenuation of the effective frequency. Based on the above multi-channel modal analysis, the non-forced vibration signal is separated, the Hankel matrix is constructed, and the singular value analysis is carried out to obtain the optimal control matrix [13], the system matrix and observation matrix, and the corresponding modal parameters. The specific analysis process is shown in Figure 1.

The specific evaluation indicators are obtained based on the relevant domestic literature and foreign research data, as shown in Table 1.

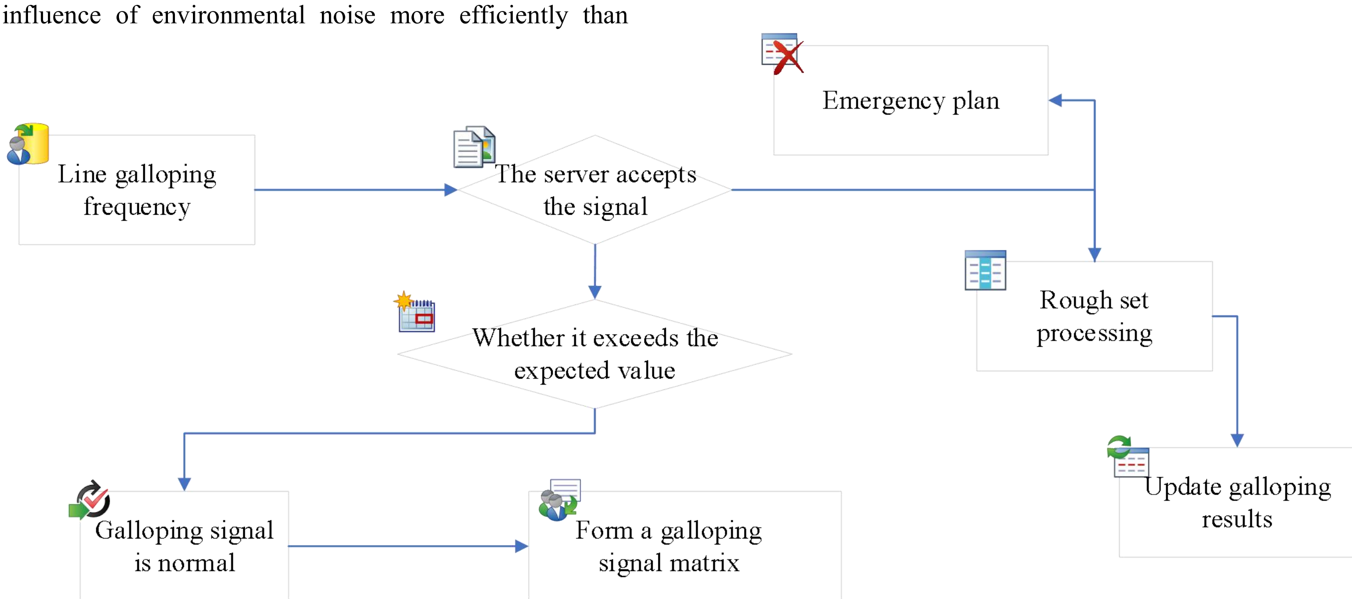

Figure 1. The deal process of transmission line galloping is under multi-channel conditions.

Table 1. Identification index of the galloping hazard of the transmission line.

The Index category		Test points	The Controllability with other indicators
Modality	Single half wave	3	0.23
	Double half wave	2	0.77
	Three half-waves	1	0.57
Non-forced vibration signal	the frequency	3	0.32
	Damping ratio	2	0.43
	Displacement of the measuring point	1	0.44
	Measuring point trajectory	3	0.32
	the direction	2	0.23

Note: the reliability and validity are <0.7.

3. Construction of transmission line galloping model under multi-channel mode

A. The rough set processing of line galloping data

In transmission line galloping analysis, the rough set M method is applied to establish the non-forced vibration signal, perform simulations, and build related databases. The rough set technique then preprocesses the data, filtering it based on structural modal parameters. A threshold ρ and weight ω are set according to the requirements of transmission line galloping [14]. Deviations in test results, denoted as Δx , arise due to environmental factors, materials, and measurement tools. The rough set eliminates irrelevant frequencies using the threshold and weight, avoids local extrema, and enhances the accuracy of the calculated results.

To manage semi-structured and uncertain data in power line monitoring, fuzzy logic principles have been integrated into the preprocessing phase of rough sets. Fuzzy-rough hybrid models enable smoother transitions between attribute granules, leading to more robust decision boundaries for modal identification tasks[15]. This is particularly beneficial when handling directional attributes, where polarity (+/-) and trajectory (“extend”/“shorten”) may become inconsistent due to transient wind conditions or measurement noise. The hybrid approach improves the rule induction phase and increases clustering accuracy in hazard characterization.

The data in the rough set is discrete, so the clustering coefficient should be adjusted to enable continuity analysis. The eigenvalue judgment coefficient λ is used in a rough set to cluster data with a correlation greater than 0.7, helping to further simplify the rapidly changing data. Since the galloping direction, galloping degree, and other data components are semi-structured [16], they need to be standardized. In this paper, attributes are represented as vectors. The rough set facilitates the organized arrangement of feature data, improving pre-processing capabilities. The specific formula is provided below. Therefore, in this paper, applying a rough set and forming feature vectors enhances data processing and continuity analysis, with the results shown in Formula (1).

$$M\{x_1, x_2, \cdots, x_n\} = \sum_{i=1}^{n} \rho x_i + \omega x_{i-1} - \Delta x \quad (1)$$

B. The ant colony algorithm analysis of galloping data

When the galloping situation of the transmission line is complex, the ant colony algorithm should be used for comprehensive analysis. Although the ant colony algorithm can analyze the line galloping data gradually, it cannot perform the analysis of a large amount of data. A rough set can cluster a large amount of data, reduce the overall number of initial data points [17], and improve the calculation speed and accuracy. Therefore, a rough set can improve the ant colony algorithm. The specific recognition scheme is shown in Figure 2.

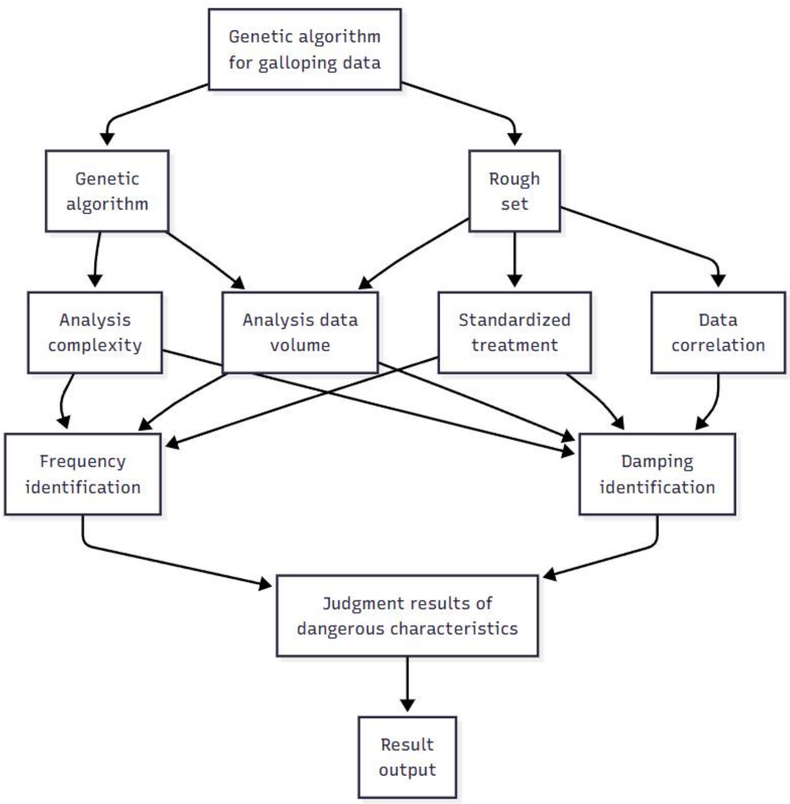

Figure 2. The risk feature identification of transmission line galloping under multi-channel mode.

Figure 2 shows that a rough set should be used to identify dangerous features of transmission line galloping. Then, each identification index should be analyzed with an ant colony algorithm [18]. Meanwhile, the frequency and damping should be comprehensively examined, and the identification results should be output.

C. *The galloping hazard feature recognition model based on rough set and ant colony algorithm*

Construction of the objective function of line galloping. It is assumed that the dangerous feature identification target of galloping is x, i is the number of dangerous features, j is the channel mode, and x_{ij} is the dangerous feature of any transmission line. The calculation results are shown in Formula (2).

$$\min F_{obj} = \sum_j \left(p \cdot f\left(x_{ij}, x_{ij-1}\right) \cdot S_{ij} + \phi\left(y_{ij}\right)\right) \quad (2)$$

Where, S_{ij} Is the judge effect of the j channel mode, $\varsigma\left(y_{ij}\right)$ is the impact rate of j channel mode on line galloping, and T is the dangerous feature identification process of line galloping, the calculation results are shown in Formula (3).

$$\varsigma\left(y_{ij}\right) = x_i y_{ij-1}^2 \quad (3)$$

The galloping state can be classified into types, such as a stable state $\left(a_i\right)$, a single half wave $\left(b_i\right)$, a double half wave, and a three-half wave. Classification is performed by comparing observed characteristics derived from the multi-channel analysis against thresholds and patterns defined by industry standards $\left(B_b\right)$ and refined by adjustment coefficients $\left(C_i\right)$ to account for specific line properties and environmental factors.

$$H\left(y_{ij}\right) = \prod \sum_{i=1}^{T} B_{b_i} \cdot c_i \quad (4)$$

Among them, the galloping judgment standard is the industry standard, which is represented by B_b. According to the adjustment coefficient of the line, the whole data of the line is obtained, and the adjustment coefficient is generally less than 0.3, and the constraint standard is improved. At the same time, the upper limit and the lower limit of the constraint are set. The specific calculation is shown in Formula (5)

$$Z\left(X, H\right) = S'_{ij} \cdot \sum_{\min \approx 0}^{\infty} \frac{\max\left(X, H\right)'}{\min\left(X, H\right)'} \cdot f\left[x_{ij}\left(1 - x_{ij-1}\right)\right] \quad (5)$$

Among them, the maximum value judgment function of galloping amplitude is $\max\left(X, H\right)$, the minimum value judgment function is $\min\left(X, H\right)$, the optimal constraint function is $f\left[x_{ij}\left(1 - x_{ij-1}\right)\right]$, and the constraint condition adjustment function is S'_{ij}.

D. *The construction of hazard feature identification matrix under multi-channel mode*

The efforts of a rough set on the algorithm mainly focus on three areas: improving the standard data, changing the direction of the data, and optimizing the data matrix. Therefore, the primary changes of a rough set are twofold: standardizing the data and optimizing the number matrix, as shown in Formula (6).

$$\left|E\right| = Z() \times \sqrt{\begin{cases} \sum_{i,j=0}^{n} x_{ij}, y_{ij} \\ \sum_{i=0}^{n} S_i^{H(2\pi/2)\left(x_{ij}, y_{ij}\right)} \end{cases}} \quad (6)$$

The joint matrix of galloping amplitude $\underline{x_{ij}}$ and the galloping frequency is $\underline{y_{ij}}$, and $\bigcup_{i,j=1}^{n} X_{ij}, H_{ij} = U$. U represents the adjustment coefficient of the matrix $\left|E\right|$, which is mainly the numerical change of the adjustment X_{ij}, H_{ij}.

Assuming that the abnormal galloping data changes sound, the abnormal data set V should be constructed as shown in Formula (7).

$$V = \left\{1, \cdots v_{11}, v_{12} \cdots v_{ij}\right\} \quad (7)$$

The abnormal data set V is constructed to form a corresponding matrix u, and its calculation process is shown in Formula (8).

$$\mathrm{u} = \alpha \begin{bmatrix} u_{11} & \cdots & \cdots & u_{1j} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ u_{i1} & \cdots & \cdots & u_{ij} \end{bmatrix} \quad (8)$$

After determining the control relationship u_{ij} between the data, the rough set function should be calculated, as shown in Formula (9).

$$\min F\left(u_{ij}, v_i\right) = \alpha \cdot \sum_{i=1} \beta \cdot \sum_{j=1} u_{ij}^{\tau}\left(x_{ij} - v_i\right) \quad (9)$$

Where, τ is the degree of control between X_{ij} and H_{ij}. The calculation of v_i Frequency variation Center as shown in formula (10).

$$v_i = \frac{x_{ij}}{\sum_{i=1} u_{ij}^{\tau}\left(x_{ij} - v_i\right)} \alpha \cdot \sum u_{ij}^{\tau}\left(x_{ij} - v_i\right) \quad (10)$$

Relationship between dangerous eigenvalues of galloping on different lines as shown in formula (11).

$$u_{ij}=\frac{\left(\frac{1}{\Delta x_{ij}}\right)^{1/(\tau-1)}}{\sum_{i=1}\left[\frac{1}{\Delta x_{ij}-v_i}\right]^{1/(\tau-1)}}\quad(11)$$

Weight assignment should be carried out for abnormal galloping amplitude values to form a galloping data list until all data analysis is finished. Matrix construction is carried out to ensure that the judgment results conform to abnormal values, and it is combined with weights to form the output of comprehensive judgment. For the galloping of the same line, continuous monitoring should be carried out to form corresponding data sets, and the optimal data content X and the optimal frequency H should be output. The abnormal data that meets the evaluation criteria should be selected to complete the data judgment. If there is no abnormal data, it means that there is no abnormal value in galloping, and normal monitoring can be carried out. Therefore, each transmission line will form a fixed abnormal data set, giving corresponding weights $w_i=1/n_i$, and compare the data sets to complete the analysis of the whole regional power grid and establish the data set of the power grid $D=\{X\}$ Cut-off constraint is H , then any cut-off constraint in X is u_i , $u_i=\{X_i\times H_i\}$. The control between the cut-off constraint and the Actual hazard judgment is shown in formula (12).

$$r_i(H)=\frac{\sum\rho\left[r_i[F]_D\right]}{\rho(u_i)}+\zeta\quad(12)$$

The galloping warning calculation of any line is shown in Formula (13).

$$\sigma(X,H)=r_i(H)-\Delta r_i(H)\quad(13)$$

The calculation process of weight assignment between different lines is shown in Formula (14).

$$W_i=\sigma(X_i,H_i)/\sum_k\sigma(X_k,H_k)\quad(14)$$

Among these weights, the weight associated with galloping amplitude is mainly used to identify the characteristics across different line amplitude values. Continuous monitoring of the same line involves forming data sets over time, identifying the optimal features (X) and frequency parameters (H) for analysis. Data points meeting evaluation criteria (potentially involving thresholds related to the constraint setting in Formula 5) are selected for hazard judgment. If no abnormal data is detected, regular monitoring continues. Each transmission line develops a set of detected "abnormal" data and corresponding weights, allowing for a comprehensive analysis across the regional power grid.

To further refine the output judgment mechanism, the model can incorporate reinforcement learning techniques where weight adjustments are dynamically updated based on reward functions derived from system accuracy or alarm performance. For example, recent studies have shown the benefits of using Deep Q-Networks (DQN) in online power system monitoring to adaptively reconfigure sensor weighting schemes and threshold limits in real time [19]. This feedback-driven approach ensures that the galloping identification model stays adaptive and responsive to emerging fault patterns or environmental changes, reducing false positives and improving real-time warning accuracy.

E. The actual hazard judgment results output of the genetic algorithm matrix

The integrated RS+ACO model produces the final hazard judgment results. This involves synthesizing the information obtained from the RS-processed data, the ACO's optimization of feature combinations, and the calculated warning indices and weights. The process requires constraining the analysis to the relevant monitoring data, comparing data across different lines, and integrating additional factors like voltage, current, and power flow to provide a comprehensive risk assessment. Assuming that the normalized values of different factors are k_i, the calculation is shown in Formula (15).

$$H(y_{ij})_k=v_i\prod_k\lambda\sum_{i=1}^{T}A_{ai}+B_{bi}+C_{ci}\quad(15)$$

The normalized values of different factors (k_i) are calculated and combined with the identified hazard characteristics. This combination involves standard values (A_{ai},B_{bi},C_{ci}) representing different states, processed values (v_i) , and specific constraints or iterations (k) . The rough set ensures data continuity before this final combination step, preparing the data for clustering or direct output. The final early warning indicator (XH_l , as attempted to be represented in Formula 16) is calculated by combining the various elements processed by RS and ACO, including judge effects (S_{ij}), weights (W_i), feature values (x_{ij}), and reference values based on standards and coefficients, taking into account different cut-off constraints (H_l).

F. Different cut-off constraints have different effects on dangerous eigenvalues

For the shortcomings of risk factors in transmission line galloping, multi-channel simulation and rough value filling should be carried out to complete the whole early warning analysis, and the specific calculation is shown in Formula (16).

$$X_{H_i} = S_{ij} \cdot \frac{w_i \varsigma\left(y_{ij}\right) \cdot x_{ij}\left(1 - x_{ij-1}\right)}{\max\left\{v_i \lambda \cdot \left(B_{b_i} + C_{c_i}\right)\right\}} \quad (16)$$

where, H_i is a different cut-off constraint and λ is the Iteration coefficient.

The calculation steps of the Actual hazard judgment results. The specific steps are as follows:

Step1. Construct a rough set of the impact of such exercise on dangerous eigenvalues, and form $X = \left\{x_{11}, x_{12}, \cdots, x_{ij}\right\}$ and $H = \left\{h_{11}, h_{12}, \cdots, h_{ij}\right\}$ sets.

Step2. The dataset is constrained. The Frequency variation Center V of the data is calculated, the weights of Cut off constraint and the dangerous eigenvalues are obtained, and the iterative operation is carried out. If the calculation results X and H are greater than $\max\{\}$ [20], the results shall be included in the calculation results; otherwise, they shall be eliminated. If the calculation result is less than $\min\{\}$, the result shall be included in the calculation result.

Step3. When all the Hazard characteristic index $H\left(y_{ij}\right)_k$ are traversed, output X_{H_i}, otherwise, repeat step 2.

4. The cases of dangerous characteristics identification of transmission line galloping

A. The research data of dangerous characteristics

The data of 8 characteristic identification indicators in Table 1 are collected as samples in the real transmission line comprehensive test base, and they are analyzed using MATLAB software. The testbed consisted of a scaled transmission line segment. This segment was a supported beam with dimensions approximately 6.5 cm in length, 6 cm in width, and 0.8 cm in thickness, made of material selected to simulate the scaled mechanical properties of a conductor bundle. Key material properties included an elastic modulus of 2.10×10^5 Pa, Poisson's ratio of 0.29, and a density of 7.92×10^{-6} Kg/m³.

The test setup used controlled excitation methods to generate vibrations that mimic wind-induced galloping and self-excited oscillations. This involved both applying controlled forces and base excitation. A signal generator produced excitation signals, including white noise, to replicate the random nature of turbulent wind. The vibration exciter, which applied forces to the line segment, was mechanically isolated from the test frame to reduce external vibrations and ensure measurements reflected only the response of the line segment itself.

Piezoelectric sensors were strategically placed along the line segment (six split line segments, as mentioned in the abstract) to enable multi-channel measurement of displacement and acceleration signals. Data collection was conducted at a sampling rate of 20 kHz, which is sufficient to capture the dynamics of the induced vibrations.

The measurements captured the transmission line's response under controlled excitation, providing data on displacement, frequency, damping ratio, and mode shape characteristics. While conducted under controlled lab conditions, the experimental setup inherently involved some level of noise from sensors and the mechanical system. The white noise excitation introduced a controlled form of variability. The multi-channel measurements allowed for the observation of spatial variations in vibration along the line, which is crucial for identifying different modal states. The data collected over 8 hours, partitioned into 1-hour segments for analysis, are summarized in Table 2.

Table 2. The judge's content of the test.

Identification index	1~2h	2~3h	3~4h	4~5h	5~6h	6~7h	7~8h
The frequency	300	303	292	302	309	310	299
Damping ratio (%)	24.3	26.2	28.4	26.4	27.2	28.4	27.4
Displacement of measuring point (cm)	32.8	34.1	31.4	33.8	32	33.2	34.3
Measuring point trajectory (Lengthen and shorten)	extend	shorten	extend	shorten	extend	extend	extend
the direction (+ -)	+	+	+	+	+	+	+

B. The Accuracy of Hazard Feature Identification under Multi-channel Mode

Accuracy is essential for identifying the dangerous traits of transmission line galloping. Combining the rough set with the ant colony algorithm enhances the local search strategy and improves the accuracy of the calculation results. The specific evaluation outcomes are shown in Figure 3.

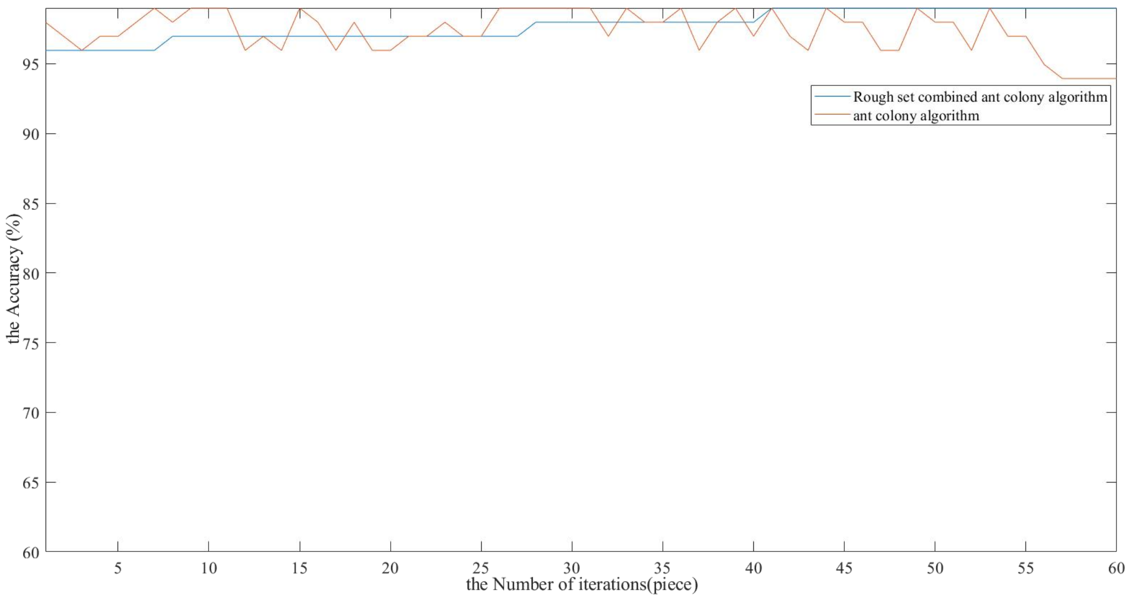

Figure 3. The judge's accuracy of dangerous eigenvalues.

The analysis results above indicate that the algorithm proposed in this paper has high accuracy and stability for detecting the danger of galloping lines, suggesting that the calculation method for the galloping line is sound. Additionally, regarding numerical fluctuations, the algorithm demonstrates low volatility, supporting early warning for galloping. Overall, this paper concludes that the algorithm is reliable and precise, capable of supporting the detection of amplitude galloping in transmission lines and improving danger prediction. The enhanced performance and stability are mainly due to the effectiveness of the rough set in pre-processing raw data, improving data continuity, and structuring inputs for the ACO algorithm.

The change of the dance amplitude of the previous algorithm fluctuates wildly, mainly due to the lack of continuity of the values. Still, the rough set of the algorithm proposed in this paper can better carry out numerical simulation and calculation and improve the stability of the calculation results [21].

C. The Index Analysis of Transmission Line under Multi-channel Mode

Taking frequency and damping rate as the primary indicators, it is found that the accuracy of different indicators exceeds 95%, and their variation remains relatively stable. This is because rough set pre-processes transmission line galloping data and enhances initial data processing capabilities. The system matrix, structure matrix, and observation matrix built using rough set methods can eliminate redundant data, maintain stability during calculations, and improve the accuracy of results. The findings are shown in Figure 4.

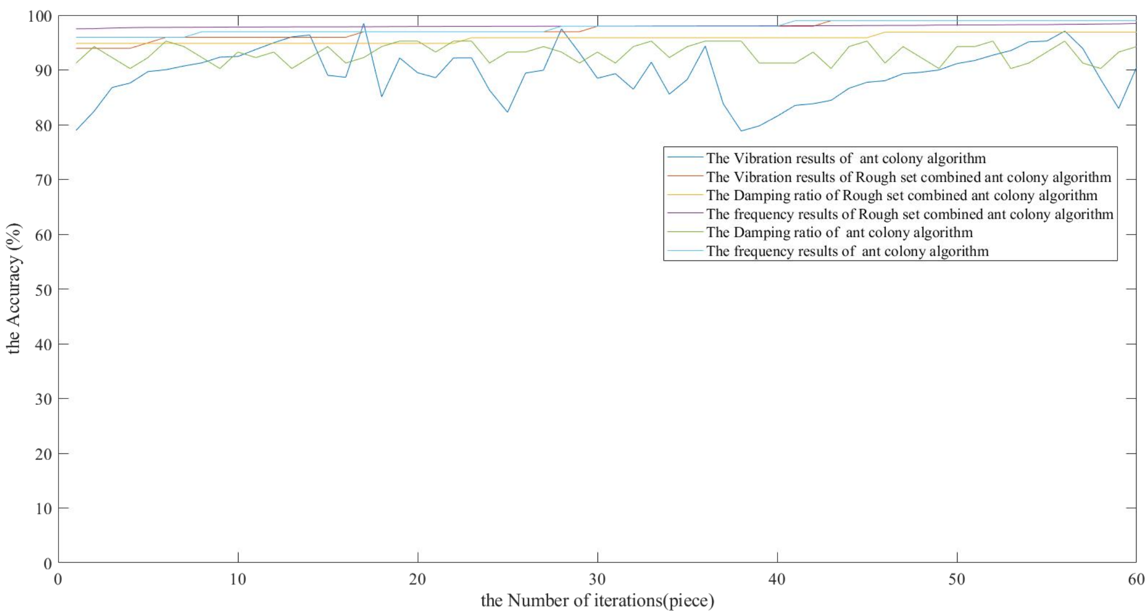

Figure 4. The actual hazard judgment results.

As can be seen from Figure 4, the change of different hazard feature identification indicators is stable without significant change. This shows that the rough set has better pre-processing of feature identification indicators, the aggregation degree of indicators is improved, and the optimization of the evaluation of different indicators is realized.

Table 3.The judge's time of test(seconds).

	Identification index	Single half wave	Double half wave	Three half-waves
The rough set combined ant colony algorithm	the frequency	16.2	18.3	17.6
	Damping ratio	16.1	17.9	17.2
	Vibration	16.4	18.1	17.8
The ant colony algorithm	the frequency	13.1	15.2	11.2
	Damping ratio	13.5	15.1	11.5
	Vibration	13.2	15.3	11.4
Differences in the comparison of results (p)		0.024	0.025	0.015

As can be seen from Table 3, there are significant differences in the dance frequency and vibration of the two methods (p=0.024, 0.025, and 0.015). The method proposed in this paper is shorter in terms of test time, mainly because it can pre-process the data and improve the data processing capacity. At the same time, the galloping results of the transmission line were compared for early warning and simulation tests, and the specific results are as follows.

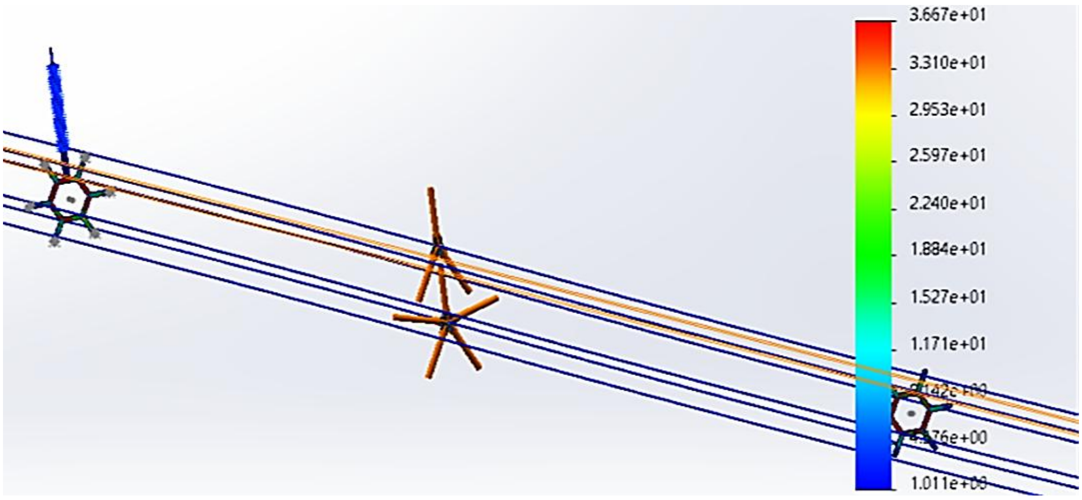

Figure 5a. The rough set combined ant colony algorithm.

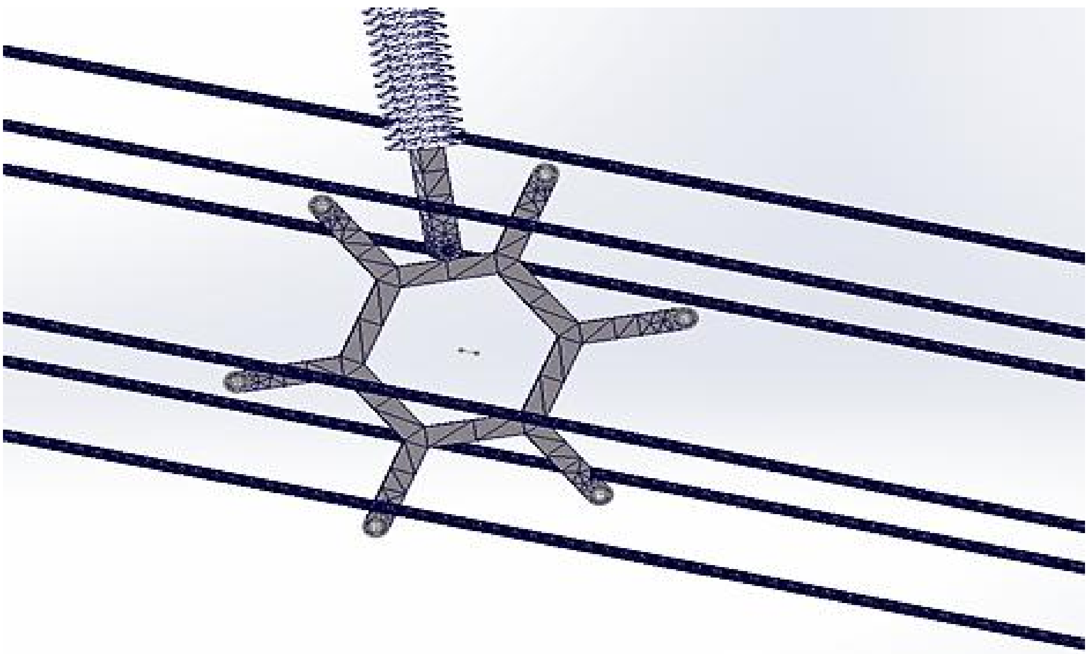

Figure 5b. The ant colony algorithm.

Figure 5. The test results of different methods of line dance

As shown in Figure 5a and 5b, the proposed algorithm performs well in testing for line dance and detects two galloping transmission lines. In comparison, the ant colony algorithm fails to identify the galloping lines. Additionally, the recognition performance of the proposed algorithm is superior.

D. The Amplitude Between Different Indicators

The amplitude of vibration serves as a key indicator of galloping severity. Its precise identification, obtained from the multi-channel non-forced vibration signal after filtering, is essential for a thorough hazard analysis. Amplitude measurement accurately captures the combined effects of factors such as environmental conditions, measurement noise, and the complex interactions of modal responses. Typically, higher amplitude values indicate a greater risk. Figure 6 shows a comparison of the vibration amplitude over time calculated with the standalone ACO algorithm versus a simulated response.

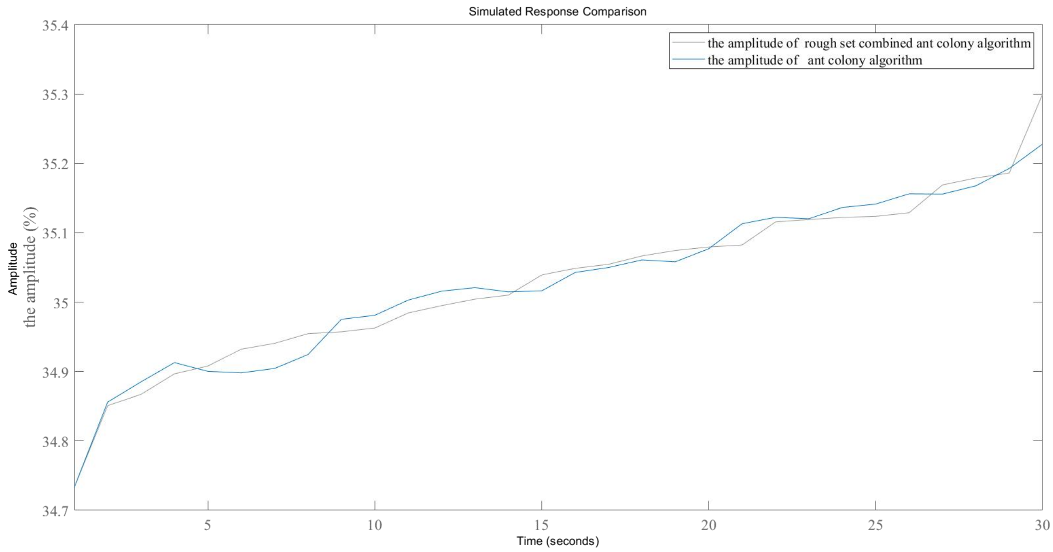

Figure 6. The coupling of the dangerous eigenvalue regimen and the dangerous eigenvalues.

In Figure 6, it can be seen that the fit of the calculation results in this paper is better and shows an upward trend. This indicates that the algorithm proposed here can more accurately match the multi-dimensional line amplitude and produce the overall calculation results. The fit of previous algorithms is poor, fluctuating up and down, which suggests a lack of adjustment signals, especially constraints, during the fitting process. Therefore, the fit value demonstrates that the calculations in this paper are reasonable, produce better results, and maintain accuracy. The process of calculating the fit value shows that this algorithm performs better, highlighting the important role of weight and constraint conditions in maintaining the rationality of the fit, as shown in Figure 7.

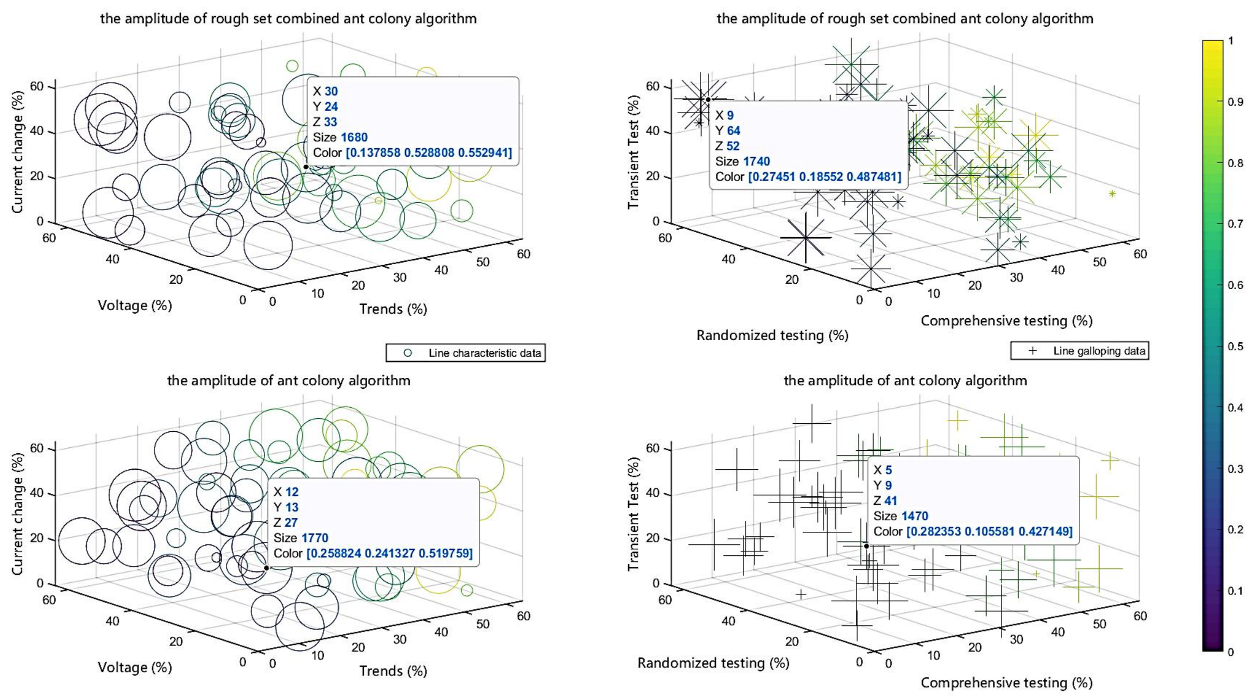

Figure 7. The controllability of the dangerous eigenvalue regimen and different indices of the dangerous eigenvalue.

As shown in Figure 7, the five indicators have improved amplitude control. The combination of rough set and ant colony algorithm achieves better amplitude because of the combined results of threshold, weight, and system matrix.

5. Conclusions

This paper proposes a joint algorithm combining rough set and ant colony methods to address the problem of inaccurate identification of dangerous characteristics in transmission line galloping. The algorithm analyzes the identification of damping, frequency, and other indices. Simultaneously, thresholds, weights, and other constraints are set to prevent local extremum issues during calculation. MATLAB simulation results demonstrate that the proposed algorithm achieves 98%, 97.6%, and 98.5% accuracy in judging galloping frequency, vibration mode, and damping ratio, respectively. The calculation times are 16s, 18s, and 17.5s, respectively, indicating the method's effectiveness. This improvement is due to the clustering process of the rough set, the practical constraints imposed by thresholds and weights, and the elimination of redundant data from the structure, control, and observation matrices. The simulation also shows that the hazard feature recognition model developed can perform multi-channel modal analysis, with results surpassing those of a single ant colony algorithm and offering higher accuracy.

The improved performance results from several factors: The rough set effectively handles data inconsistencies, noise, and redundancy through filtering, clustering, and standardization, providing a clean and organized input for ACO. Enhanced Optimization: The data space enables ACO to perform a more efficient and accurate search for the best feature combinations indicating danger. Robust Framework: Using constraints based on industry standards and adjustment coefficients, along with matrices derived from processed modal parameters, ensures stability and reliability in the calculation process.

While the proposed method shows notable improvements, there are areas for future work: Individual Index Analysis: The current work concentrates on the combined effect of indicators. Future research should involve more detailed differentiation analysis of how each specific risk characteristic index (e.g., frequency deviation versus damping change) influences the overall hazard assessment. Experimental Details and Robustness: Although experimental data was utilized, providing a more detailed discussion of noise levels, sensor errors, and their effects on the algorithm—potentially including reporting mean accuracy and standard deviation over multiple runs or testing under varying simulated noise levels—would enhance the experimental validation. Comparing against additional baseline methods (e.g., classical modal analysis techniques) under challenging scenarios would also add value. Integration with Monitoring Systems: Future efforts could focus on integrating this hazard identification method with existing SCADA systems or digital twin models of the transmission network for continuous, automated monitoring and early warning. This would involve defining the data pipeline from sensors to the algorithm and incorporating the outputs into a power grid management system.

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Appendix A

Table A: Key Variables and Their Significance

Variable	Significance
x_{ij}	Value of dangerous feature i for channel/line j.
y_{ij}	Galloping characteristic data (e.g., frequency, damping) for channel/line j.
S_{ij}	The "judge effect" or contribution score of channel j to feature i.
$\phi(y)_{ij}$	The "impact rate" or weight of channel j's characteristics on the overall galloping state.
B_b	Reference value based on industry standards.
C_i	Adjustment coefficient for feature i.
X	Overall dangerous feature identification target/metric.
H	A set of hazardous characteristics or parameters.
u_{ij}	Element of the matrix u representing relationships or processed data.
v_i	Frequency variation center for feature i.
t	Degree of control or relationship strength.
$\sigma(X,H)$	Calculated galloping warning index based on features X and hazard levels H.
W_i	Weight assigned to line or feature i.
λ	The clustering coefficient is used in Rough Set processing.
ρ, w	Threshold and weight parameters used in Rough Set filtering.
v_{id}	Maximum amplitude value (or other relevant reference value).
H_l	A specific cut-off constraint.