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Short-Term Power Meteorological Disaster Risk Assessment Method Based on Sparrow Search Algorithm and Support Vector Machine

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Abstract: Short-term meteorological disasters pose significant operational risks to power systems, making timely and accurate risk assessment crucial for system protection and emergency response. This study proposes a hybrid short-term power meteorological disaster risk assessment model that integrates an Improved Sparrow Search Algorithm (ISSA), a self-attention-enhanced Support Vector Machine (SISSA-SVM), and SA-optimized K-means clustering algorithm (SK-means). ISSA is employed to optimize model parameters and enhance global search capability, while SK-means provides high-quality meteorological scenario classification. SISSA-SVM then performs risk identification with improved representation learning and classification accuracy. Experimental results using ten years of meteorological and power fault data demonstrate that the proposed model converges rapidly, achieves robust fitting performance, and attains a risk identification accuracy of 97.32%. Moreover, in thunder and rainstorm scenarios, the model yields superior recall and markedly lower omission rates than competing methods. These findings indicate that the proposed hybrid model provides an efficient and reliable solution for short-term meteorological disaster risk assessment in modern power systems.

Keywords: K-means; meteorological disaster; power risk assessment; SSA; SVM

1 INTRODUCTION

With the intensification of global climate change, the frequency of meteorological disasters continues to increase. Extreme weather events can severely damage power system facilities, causing large-scale power outages, significant economic losses, and serious threats to production, daily life, and public safety [1]. Therefore, assessing short-term power meteorological disaster risk improves the disaster prevention and mitigation capability of power grids, ensures power supply stability, and reduces economic losses caused by meteorological disasters [2]. However, traditional assessment methods mainly rely on physical derivation, which involves complex computation, high data requirements, and low efficiency, making them unsuitable for handling complex meteorological factors [3]. Hence, it is urgent to develop a more accurate and efficient short-term power meteorological disaster risk assessment method. With rapid advances in computer technology, intelligent algorithms have become a research hotspot in recent years for power meteorological disaster risk assessment models. Intelligent algorithms offer high efficiency, strong objectivity, and reduced dependence on manual analysis. Among them, the Sparrow Search Algorithm (SSA) models the behavioural roles and position update strategies of sparrows, featuring a cooperative and competitive mechanism that enhances search comprehensiveness and adaptability through dynamic parameter adjustment [4]. The Support Vector Machine (SVM) separates positive and negative samples using a hyperplane and demonstrates excellent recognition and generalization performance in small-sample, nonlinear, and high-dimensional problems [5]. This paper improves the SSA structure by integrating the sine-cosine algorithm and Lévy flight strategy, combining the improved SSA with the SVM, and introducing self attention mechanism to establish the correlation between risk and features. In addition, a K-means clustering algorithm is proposed, and its performance is enhanced using the Simulated Annealing (SA) algorithm. Based on these improvements, a short-term power meteorological disaster risk assessment model is constructed to achieve high-precision classification of meteorological scenarios and enhance power risk identification accuracy. The innovative points of the research are as follows:

1. In response to the limitations of standard SSA in optimizing SVM parameters, such as limited global exploration ability and premature convergence, this study introduces the sine cosine algorithm into the SSA algorithm to balance the exploration and development pace. At the same time, the Lévy flight strategy is used to randomly perturb the optimal individual, significantly improving the global and convergence quality of parameter optimization.
2. Research the integration of ISSA algorithm and SVM machine learning algorithm to improve the problem of insufficient identification of key disaster causing factors. On this basis, combined with self attention mechanism, the SISSA-SVM algorithm is obtained, which dynamically learns and weights the importance of different meteorological and power grid characteristics.
3. Research the integration of SA and K-means algorithms, optimize the initial clustering center and iterative process of K-means through SA, and obtain more stable sample cluster partitioning, laying the foundation for subsequent refined risk assessment.
4. Research the integration of SISSA-SVM algorithm and improved K-means algorithm, improve the clustering structure provided by K-means as strong prior knowledge, guide SISSA-SVM for differentiated training of clustering, and enhance the classification efficiency and accuracy of the algorithm.
5. Focusing on the four core characteristics of heterogeneity, interactivity, sparsity, and timeliness in meteorological disaster risk assessment, this study integrated various algorithms and constructed a short-term power meteorological disaster risk assessment model, achieving full chain deep optimization of data intrinsic structure discovery, key feature focus, model parameter optimization, and risk level discrimination, providing a new method for related field research.

2 LITERATURE REVIEW

SSA and SVM are two widely applied artificial intelligence algorithms that can solve complex problems in multiple fields, and numerous scholars have conducted in-depth research on them. SSA can model role behaviors and dynamically adjust algorithm parameters. For example, to solve problems such as automatic skin cancer detection, Balaha H. M. et al. used SSA as a meta optimizer to optimize the hyperparameters of deep learning models, in order to improve the accuracy of automatic skin cancer detection [6]. Salim A. and other scholars have combined clustering algorithms with SSA to enhance the stability and communication performance of cluster head selection in vehicular communication systems [7]. To further improve the performance of SSA, many scholars have introduced optimization strategies. The Zhou X. team integrates butterfly algorithm and Cauchy perturbation to enhance its exploration ability and ability to escape local optima, and successfully applies it to the construction of water quality detection models [8]. The above research indicates that targeted improvement of SSA and its integration with domain specific models can improve practical optimization problems. In classifiers, SVM can accurately segment small sample sizes through hyperplanes, and its performance is highly dependent on parameter selection and feature quality, so it is often combined with optimization algorithms. Li J. et al. addressed the issue of high noise in data processing, improved the anti noise capability of SVM, designed a robust objective function, and solved it using optimization algorithms [9]. Elsedimy E. I. et al. processed data through SVM, extracted optimal features from data using quantum-behaved particle swarm optimization algorithm, and adaptively adjusted algorithm parameters, ultimately constructing a heart disease detection model based on quantum-behaved particle swarm optimization algorithm and SVM [10]. At present, research has highlighted the decisive role of optimizing key parameters of SVM through intelligent algorithms, but there are still limitations such as rigid feature processing and difficulty in adaptively focusing on key feature factors.

Accurate assessment of power meteorological disaster risk occupies an important position in power systems. Currently, the theory and application of risk assessment methods have become relatively mature, and many scholars have conducted in-depth research on them. Cao Y. et al. proposed a power safety emergency strategy under heavy rainfall meteorological environment, which distinguished rainfall changes by quantifying power outage risks in distribution networks, calculated power load using the Saint-Venant partial differential equation, and dynamically adjusted emergency plans for distribution networks through progressive hedging acceleration solution algorithm [11]. Aiming at power operation risks under extreme weather, Liu X.'s team proposed a power risk assessment model based on Bayesian neural network, which simulated risk probability through Bayesian neural network and analyzed power historical data using multi-source heterogeneous data, achieving high accuracy in risk assessment [12]. Fu X. et al. proposed a weather impact assessment model in distribution networks based on statistical machine learning, which extracted weather change features through generative adversarial networks and modelled weather-sensitive loads in power and weather using weather generators, achieving accurate assessment of weather impacts in distribution networks [13]. Aiming at power system failures in extreme weather, Atrigna M.'s team proposed a power system failure prediction model based on machine learning methods, which analyzed historical grid failure data using machine learning and predicted grid power outages combined with meteorological information [14]. Yang F. et al. utilized reanalysis technology of meteorological data to assess power system failure problems in extreme weather, reclassified data through machine learning algorithms, quantified power outage-related data, and further assessed grid vulnerability in electrical storms based on meteorological threshold analysis [15]. Despite the continuous improvement of existing methods, there still exists a core contradiction between prediction accuracy and real-time performance when dealing with short-term and sudden power meteorological disasters.

In summary, existing research has made certain progress in power risk assessment, but limitations such as low assessment efficiency still exist. Therefore, in response to the limitations of difficult extraction of key disaster causing factors and low efficiency in parameter tuning in existing optimized SVM, research is being conducted to improve the SSA algorithm and integrate it with SVM algorithm to enhance parameter optimization efficiency and classification accuracy. Self attention mechanism is introduced to strengthen disaster causing factors and establish risk associations. Meanwhile, this study proposed a K-means algorithm optimized by SA algorithm, ultimately constructing a short-term power meteorological disaster risk assessment model, expecting to improve the assessment capability of short-term power meteorological disaster risks to meet the demands of power systems.

3 RESEARCH METHODOLOGY

3.1 Optimization Design of SSA-SVM Integrated Algorithm

With the rapid development of artificial intelligence, computer-based intelligent algorithms provide new technical approaches for short-term power meteorological disaster risk assessment [16, 17]. Traditional algorithms often have high computational costs, strict input data precision requirements, and low assessment efficiency [18, 19]. The SSA simulates sparrow behavior to perform global searches through division and cooperation. However, the basic algorithm tends to fall into local optima in the later stages of iteration, and the decline in population diversity reduces search precision and slows convergence [20, 21]. Therefore, the study introduces the sine cosine algorithm to enhance the algorithm's ability to capture temporal fluctuations and periodic patterns of meteorological elements, while utilizing the Lévy flight strategy to improve the algorithm's exploration efficiency for rare extreme weather events, ultimately achieving global information aggregation. After fusion, the Improved Sparrow Search Algorithm (ISSA) is obtained, and its process is shown in Fig. 1.

As shown in Fig. 1, The ISSA algorithm first randomly initializes the sparrow population, then calculates the fitness value of each individual, and determines the optimal and worst individuals in the current population. During the iteration process, the algorithm divides the population into three roles: discoverer, follower, and alert based on a preset ratio, and uses a differentiated strategy to update their positions. In response to the temporal fluctuations and periodic patterns of meteorological elements, the algorithm introduces the periodic search mode of the sine cosine algorithm to guide discoverers to explore extensively in the solution space, balancing the algorithm's global search and local development capabilities. Followers gather towards better solution areas based on the information provided by discoverers, and population roles can be dynamically adjusted according to fitness to achieve competition and collaboration. In order to enhance the ability to jump out of local optima, the alert adopts the Lévy flight strategy for random long-distance movement, effectively detecting potential optimal areas that may be overlooked, and avoiding optimization getting stuck in local optima that are only effective for common weather patterns. The mathematical expression of sparrow population initialization is shown in Eq. (1) [22].

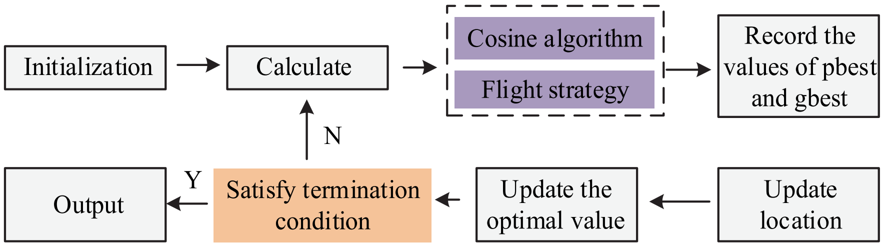


Figure 1 ISSA algorithm flowchart

$$X_{i,j} = lb_j + (ub_j - lb_j) \times rand \tag{1}$$

In Eq. (1), ub_j represents the upper bound of the j-dimensional space, lb_j represents the lower bound of the j-dimensional space, and $rand$ represents a random number between 0 and 1. Algorithm initialization can ensure the uniform distribution of the initial population. In order to further improve the adaptive ability of the algorithm to cope with the complexity of meteorological data during the optimization process, research has been conducted to improve the adaptive weight of the algorithm through the sine cosine algorithm. The adaptive weight factor is expressed in Eq. (2).

$$\lambda = \lambda_{\min} + \frac{(\lambda_{\max} - \lambda_{\min})}{(\lambda_{\max} + \lambda_{\min})} \cdot \cos(t \cdot \pi / iter_{\max}) \tag{2}$$

In Eq. (2), λ is the weight factor, $\lambda_{\max}$ is the maximum weight, $\lambda_{\min}$ is the minimum weight, t is the number of iterations, and $iter_{\max}$ is the maximum iteration count. In the early stages of iteration, larger λ are endowed with stronger global exploration capabilities, which is crucial for multiple potential optimal regions corresponding to various disaster modes. As the iteration progresses, the weights decay, driving the algorithm to focus on the optimal region for deep search to improve the accuracy of the final classifier. The Lévy flight strategy used to enhance the algorithm's ability to escape local optima is calculated using Eq. (3).

$$F(x) = 0.01 \cdot \frac{r_1 \cdot \sigma}{\sqrt[\varsigma]{|r_2|}} \tag{3}$$

In Eq. (3), F represents the Lévy flight, r_1 and r_2 are discrete values between 0 and 1, and ς is a constant. The ISSA performs global optimization on short-term power meteorological disaster data and optimizes algorithm parameters, but it cannot classify the data. The SVM classifies data through a hyperplane to predict risk [23, 24]. Therefore, the ISSA and SVM are integrated to form the ISSA-SVM hybrid algorithm, which is applied to short-term power meteorological disaster risk assessment for rapid short-term risk analysis. The operation process of the ISSA-SVM algorithm is shown in Fig. 2.

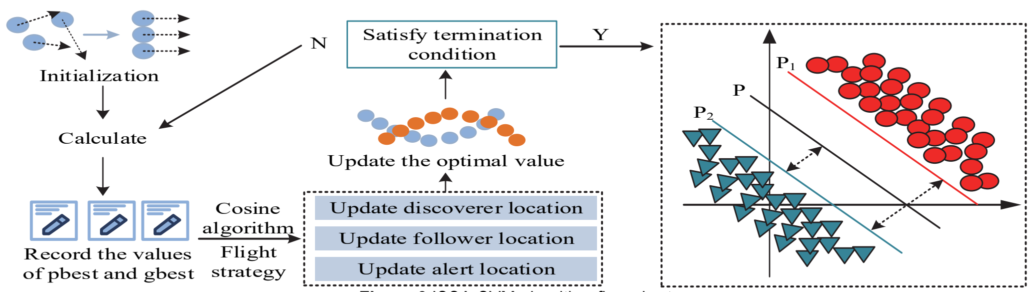


Figure 2 ISSA-SVM algorithm flow chart

As shown in Fig. 2, The ISSA algorithm first maps the key parameters of the SVM to be optimized to particles in the search space, initializes the population, and randomly generates multiple sets of candidate parameter combinations within the parameter domain. The population is divided into discoverers, followers, and warners. The positions of discoverers and followers are updated, and they compete with each other. The algorithm further updates the position of the alert person to obtain the optimal values for both the individual and the global. Finally, determine whether the maximum number of iterations has been reached as the termination condition. If it has not been reached, return to recalculate the fitness and proceed to the next iteration. If it has been reached, output the globally optimal position and output the SVM hyperparameters with the best performance. The position update of discoverers is expressed in Eq. (4).

$$X^{t+1}_{i,j} = \begin{cases} X^{t}_{i,j}\exp(\dfrac{-i}{\alpha \cdot Max\_iter}) & \text{if} \quad R_2 < ST \\ X^{t}_{i,j} + QL & \text{if} \quad R_2 \geq ST \end{cases} \tag{4}$$

In Eq. (4), $X^{t}_{i,j}$ represents the i-th sparrow position in j - dimensional space, Max_iter is the maximum number of iterations, α is a random number between 0 and 1, R_2 is the warning value, ST is the safety value, Q is a normally distributed random number, and L is a matrix. The position update of followers is expressed in Eq. (5).

$$X^{t+1}_{i,j} = \begin{cases} Q \cdot \exp(\dfrac{X^{t}_{worse} - X^{t}_{i,j}}{i^2}) & i > n/2 \\ X^{t+1}_{p} + \left|X^{t}_{i,j} - X^{t+1}_{p}\right| & i \leq n/2 \end{cases} \tag{5}$$

In Eq. (5), X^{t}_{worse} and X^{t+1}_{p} represent the worst and best positions, respectively. Sparrows in poor positions migrate to new areas, while sparrows in better positions continue searching nearby. Followers move toward the optimal position. The position of the sparrow population is determined by Eq. (6).

$$X = [c_1, c_2, c_3, ..., c_d]^T, c_i = [c_{i1}, c_{i2}, c_{i3}, ..., c_{id}] \tag{6}$$

In Eq. (6), X represents the position information, c is a variable, and d denotes the spatial dimension. The data classification equation in SVM is expressed in Eq. (7).

$$Y_i(\omega X_i + b) - 1 \geq 0, i = 1, 2, ..., n \tag{7}$$

In Eq. (7), X_i and Y_i represent the horizontal and vertical classification coordinates, ω represents the classification margin, and i represents the number of data samples. Although the ISSA-SVM algorithm enables deep data mining and precise classification, the convergence curve of its optimization process is prone to non-stationary fluctuations. Therefore, in order to enhance the representation ability of high-dimensional meteorological features and the interpretability of risk discrimination, the ISSA-SVM algorithm is further optimized by combining self attention mechanism, aiming to specifically improve the feature interaction modeling and dynamic weight allocation problem in meteorological risk classification. The study named the hybrid algorithm SISSA-SVM algorithm, and its running process is shown in Fig. 3.

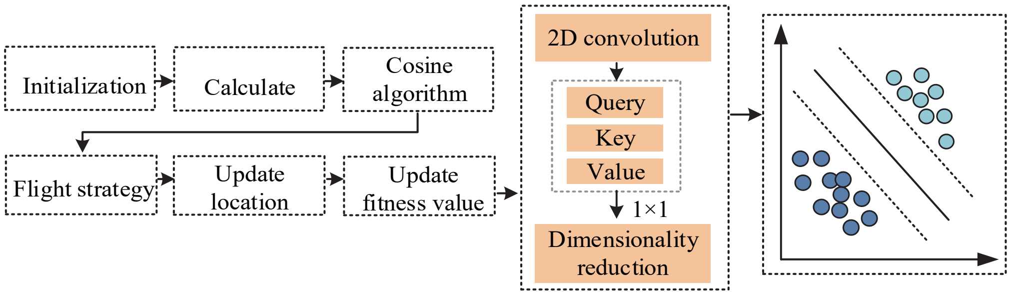


Figure 3 SISSA-SVM algorithm flow chart

As shown in Fig. 3, the SISSA-SVM algorithm first initializes the sparrow population, calculates fitness values, and determines the best and worst individuals. The sine-cosine algorithm and Lévy flight strategy are used to update the positions of discoverers, followers, and warners in real time, obtain the optimal SVM parameters. At the same time, in order to directly improve the model's ability to distinguish meteorological risk features, the algorithm introduces a self attention mechanism to dynamically reconstruct the input features. By calculating the correlation weights between features, establish the interaction relationship between different meteorological elements, and highlight key disaster causing factors based on the current sample. During the feature transformation process, the original one-dimensional feature vector $x \in \mathbb{R}^d$ is mapped to a two-dimensional structure suitable for further analysis, where d is the total number of features. Subsequently, the subsequent 1x1 convolution is used to compress and adjust the weights of the two-dimensional features across channels, in order to simplify the operation and stabilize the output. The resulting data are input into the SVM, where the classifier performs data preprocessing and classification. The mathematical expression for self-attention computation is shown in Eq. (8).

$$Attention(Q, K, V) = soft\max(\frac{QK^T}{\sqrt{d_k}})V \tag{8}$$

In Eq. (8), Q, K, and V represent the query, key, and value, respectively, and $\sqrt{d_k}$ denotes the scaling factor.

3.2 Short-Term Power Meteorological Disaster Risk Assessment Model with SK-Means

The SISSA-SVM algorithm improves the data collection capability for short-term power meteorological disaster risk, but its classification ability for meteorological scenarios is limited. This weakness reduces the precision and efficiency of risk assessment. The K-means algorithm can quickly and effectively identify potential meteorological scene cluster structures from unlabeled data, but traditional K-means algorithms are highly sensitive to the initial center, and different initial values may lead to vastly different final clustering results and fall into different local optimal solutions. In meteorological disaster data, this may not be able to stably identify the real disaster scenario patterns, resulting in unreliable subsequent evaluation data. By simulating physical annealing, SA can escape from local optima and achieve the goal of searching towards the global optimal region, which helps to discover cluster centers affected by sparse extreme event samples. Therefore, for the meteorological environment classification problem of SISSA-SVM algorithm, the study combines SA and K-means to form the SK-means algorithm. The SK-means algorithm groups power meteorological disaster data quickly and simply, calculates similarity to classify meteorological disaster scenarios, and further enhances risk assessment capability. The similarity calculation in the SK-means algorithm is shown in Eq. (9).

$$CluSim = \min(D(i, j)) \tag{9}$$

In Eq. (9), i and j represent two cluster centers, and D represents the Euclidean distance. The workflow of the SK-means algorithm is shown in Fig. 4.

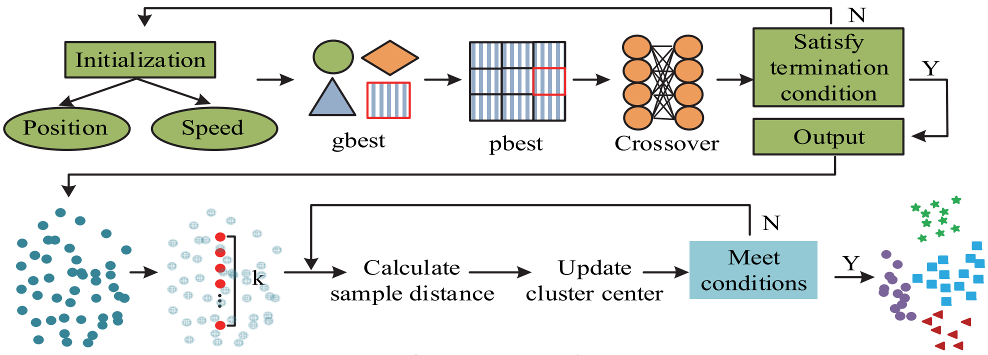


Figure 4 SK-means algorithm flow chart

As shown in Fig. 4, SK-means divides the similarity of meteorological, power grid, and geographic features of samples in an unsupervised manner. First, SA to initialize particle positions and velocities, then updates to generate new particles. The global and individual optimal values are obtained through calculation. The crossover operation helps particles escape local optima and achieve global optimization. The algorithm then checks whether the termination condition is met; if satisfied, it outputs the result, otherwise it returns for reinitialization. Next, the K-means clustering algorithm is applied. It iteratively calculates the distance of each sample, assigns the nearest samples to a cluster, and relocates the cluster centers to reclassify samples. This process repeats until the termination condition is reached, and the final clustering result is produced. The acceptance criterion in the crossover operation is expressed in Eq. (10).

$$\min(1, E^{-(F_1 - F_2)/T_h}) > rand[0,1] \tag{10}$$

In Eq. (10), E represents the energy value, F_1 and F_2 represent the fitness before and after crossover, and T_h denotes the annealing temperature. The annealing operation is expressed in Eq. (11).

$$T_{h+1} = CT_h \tag{11}$$

In Eq. (11), C represents the sum of c_1 and c_2. K-means clustering often applies the expectation-maximization algorithm to converge to the optimal solution, which is shown in Eq. (12).

$$C_k = \left\{ x_i : \left\| x_i - \mu_k \right\|^2 \le \left\| x_i - \mu_j \right\|^2, \forall j \ne k \right\} \tag{12}$$

In Eq. (12), C_k represents the set of k clusters, $\left\| x_i - \mu_k \right\|^2$ is the squared Euclidean distance, and μ_j denotes the cluster center of cluster j. The study integrates SK-means with SISSA-SVM to form the SK-SISSA-SVM algorithm. Its structure is shown in Fig. 5.

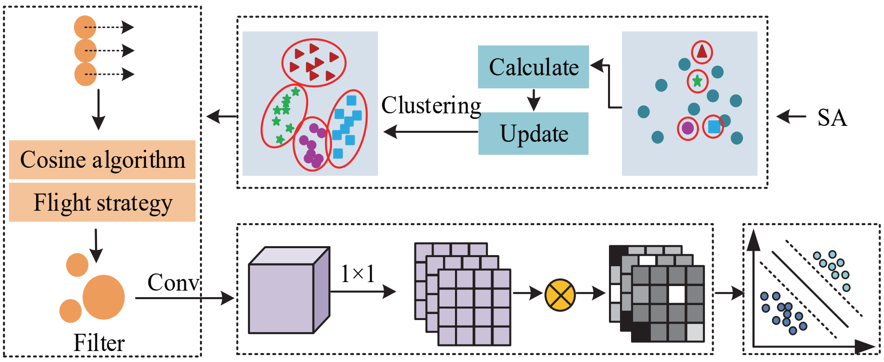


Figure 5 SK-SISSA-SVM algorithm flow chart

As shown in Fig. 5, the SK-SISSA-SVM algorithm initializes parameters using SA, generates optimal parameter values through crossover and annealing operations, and avoids module interference and data error problems. The data processed by SA are then input into K-means. In K-means, the Euclidean distance is iteratively calculated to divide samples into clusters. The cluster centers are relocated to reclassify the samples, and this process is repeated until the clustering results are obtained. Then, the algorithm calculates fitness values, determines the best and worst individuals in the population, and updates the positions of discoverers, followers, and warners. The self-attention mechanism is used to obtain the global optimal parameters. Finally, the resulting data are input into the SVM, where the classifier performs preprocessing and classification. The constraint condition in SVM classification is shown in Eq. (13) [25].

$$\min \Phi(\omega)=\frac{\|\omega\|^2}{2} \tag{13}$$

In Eq. (13), Φ represents the nonlinear mapping. The Lagrangian function constructed in SVM is expressed in Eq. (14).

$$L(\omega)=\frac{\|\omega\|^2}{2}-\sum_{i=1}^{n}\alpha_i[Y_i(\omega X_i+b)-1] \tag{14}$$

In Eq. (14), α_i denotes the Lagrange multiplier. The SVM classification function is expressed in Eq. (15).

$$f(X)=\operatorname{sgn}[\sum_{i=1}^{n}\alpha_i Y_i(X\cdot X_i)+b] \tag{15}$$

The SK-SISSA-SVM algorithm enables comprehensive collection and accurate classification of short-term power meteorological disaster risk data. Based on this algorithm, the study constructs a short-term power meteorological disaster risk assessment model, named SK-SISSA-SVM. The operational process of this model is shown in Fig. 6.

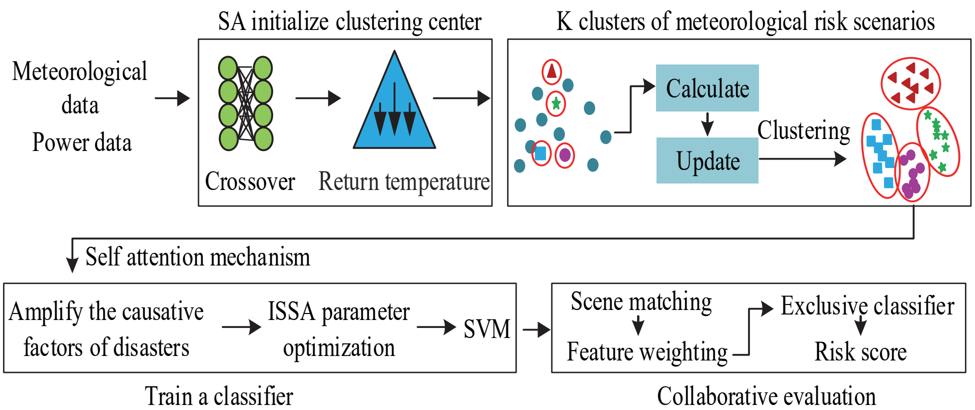


Figure 6 SK-SISSA-SVM model operation flow chart

As shown in Fig. 6, meteorological data and short-term electricity data are input separately in the SK-SISSA-SVM model. Firstly, the K-means algorithm is used to optimize the initial center using SA. Based on the similarity of meteorological and spatial features of the samples, all historical data is divided into K mutually exclusive clusters. Each cluster represents a scenario with unique meteorological patterns and risk characteristics, and the historical average failure rate of each cluster is calculated as the inherent risk level of the meteorological scenario. By analyzing the correlation between features and risks through self attention mechanism, a cluster specific feature weight vector is generated to amplify key disaster causing factors. By using the improved ISSA algorithm, the optimal SVM parameters are obtained on the weighted feature space, thereby training a highly adapted exclusive classifier. Finally, the most similar clusters are obtained through scene matching, and feature weights are used to dynamically weight the features, focusing on key risk signals. Input the weighted features into the corresponding classifier to obtain a preliminary risk probability prediction value, combine it with the inherent risk baseline of the scene to obtain the final risk score, and map it to the risk level.

4 RESULTS AND DISCUSSION

4.1 Performance Verification of SK-SISSA-SVM Algorithm

To verify the effectiveness of the SK-SISSA-SVM short-term power meteorological disaster risk assessment algorithm, the study compared it with four short-term power meteorological disaster risk assessment algorithms: Gorilla Troops Optimizer (GTO), Chaos Particle Swarm Optimization (CPSO), and Aquila Optimizer-Random Forest (AO-RF). The experiment selected Windows11 Ubuntu 18.04 as the operating system, Intel (R) Xeon (R) Platinum as the processor, MATLAB as the simulation software, and Adam as the optimizer. The algorithm learning rate was set to 0.0005, with iteration times within 100. Power operation data during meteorological disasters in the north-western region of Henan Province from 2014 to 2024 were selected as the dataset. There are a total of 43800 valid samples, the proportion of faulty samples is about 0.8%, each containing meteorological characteristics, power grid operation characteristics, geographic and equipment vulnerability characteristics, and temporal characteristics. The study clearly divides the disaster causing weather into five categories: thunder and lightning, gale, rainstorm, icing and mountain fire.

Standardize all continuous features using Z-score and match the corresponding spatiotemporal grid meteorological data forward based on the time of power fault recording. The study defines short-term warning as a warning advance of 0-12 hours and uses fault density as a continuous risk label. The study used the time forward method to train the model using data from January 1, 2014 to December 31, 2019. The data from January 1, 2020 to December 31, 2021 was used as the validation set, and the data from January 1, 2022 to December 31, 2023 was divided into a test set. In order to analyze the comprehensive performance of SK-SISSA-SVM algorithm, the training and testing precision of SK-SISSA-SVM, GTO, CPSO, and AO-RF algorithms in short-term power meteorological disaster risk assessment were evaluated. The results are shown in Fig. 7.

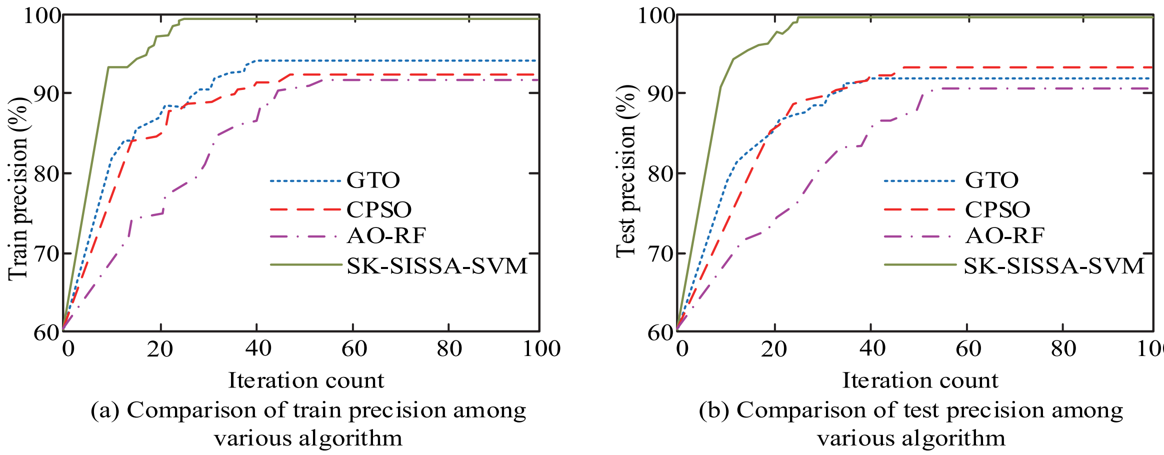


Figure 7 Results of training precision and testing precision for each algorithm

As shown in Fig. 7a, the training precision of the SK-SISSA-SVM algorithm rapidly increases with the number of iterations, reaching 98.89% at the end of each iteration. The trend and precision values are significantly higher than those of the comparison algorithm. As shown in Fig. 7b, the testing precision of the SK-SISSA-SVM algorithm rapidly improved, reaching the highest value of 99.17% at 24 iterations, which is better than the comparison algorithm. In summary, the training precision and testing precision of the SK-SISSA-SVM algorithm have synchronously increased to a high level, indicating that the algorithm has good performance. This is mainly attributed to the SSA algorithm's ability to simulate sparrow behavior, achieve global search, and improve accuracy. To further analyze the operational performance of the SK-SISSA-SVM algorithm in short-term power meteorological disaster risk assessment, the study compared the fitting degree and loss value of the four algorithms for risk assessment, and the obtained results are shown in Fig. 8.

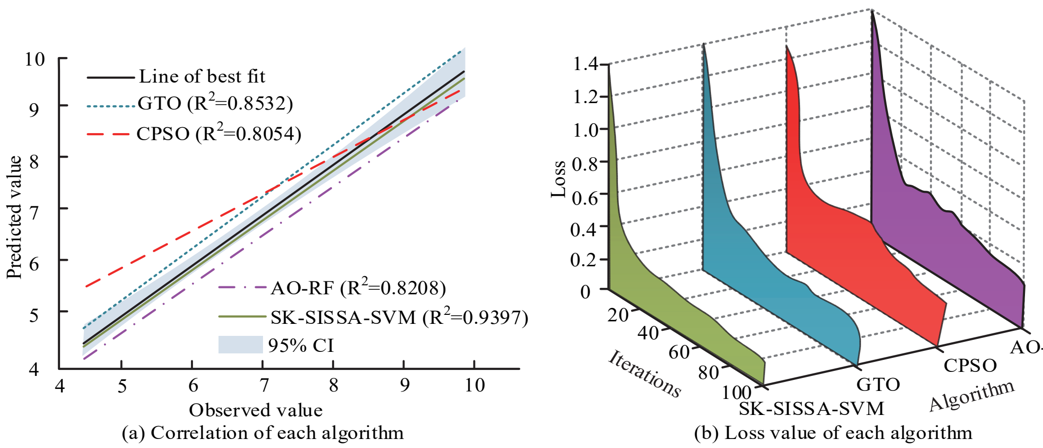
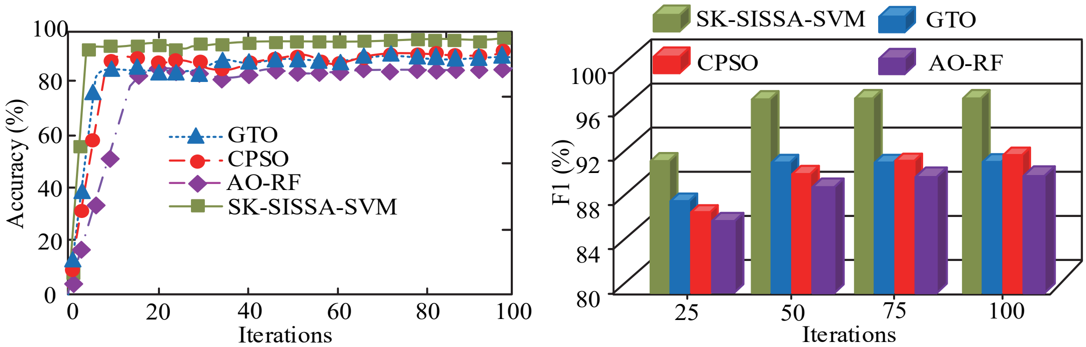


Figure 8 Comparison of fit and loss value results

As shown in Fig. 8a, the coefficient of determination (R^2) of the study algorithm was 0.9397, which was higher than the GTO, CPSO, and AO-RF comparison algorithms. The fitting degree of the study algorithm approached 1, indicating that the study algorithm had strong explanatory capability. The 95% confidence interval was very narrow and close to the best fit line, indicating that the study algorithm had high stability. As shown in Fig. 8b, in the first 10 iterations of the SK-SISSA-SVM algorithm, the loss value declined rapidly. In the range of 20-80 iterations, the decline speed of the loss value slowed down, and finally at 100 iterations the loss value was 0.12. The decline trend and loss value of the study algorithm were both superior to other comparison algorithms. In summary, the study results indicated that the study algorithm could significantly reduce data loss and possessed operational reliability, because the algorithm's introducing self attention mechanism to correlate input features and enhanced reliability. To further demonstrate the risk identification effect of the SK-SISSA-SVM algorithm, the study tested its risk identification accuracy and F1 value against the GTO, CPSO, and AO-RF algorithms, and the obtained results were shown in Fig. 9.

As shown in Fig. 9a, the risk identification accuracy of the SK-SISSA-SVM algorithm rose sharply in the range of 0-5 iterations, and after reaching 93.72%, the increase was relatively moderate. Subsequently, the accuracy reached 97.32% at 100 iterations, which was superior to the comparison algorithms. As shown in Fig. 9b, the F1 scores of the SK-SISSA-SVM algorithm were all above 90%, significantly higher than the comparison algorithms, further verifying that the study algorithm achieved the optimal balance between classification precision and recall rate. Comprehensively, the study algorithm had better accuracy and robustness in risk identification, because the study algorithm utilized cross operation and temperature reduction processing to generate optimal parameter values, avoiding module confusion and data error problems.

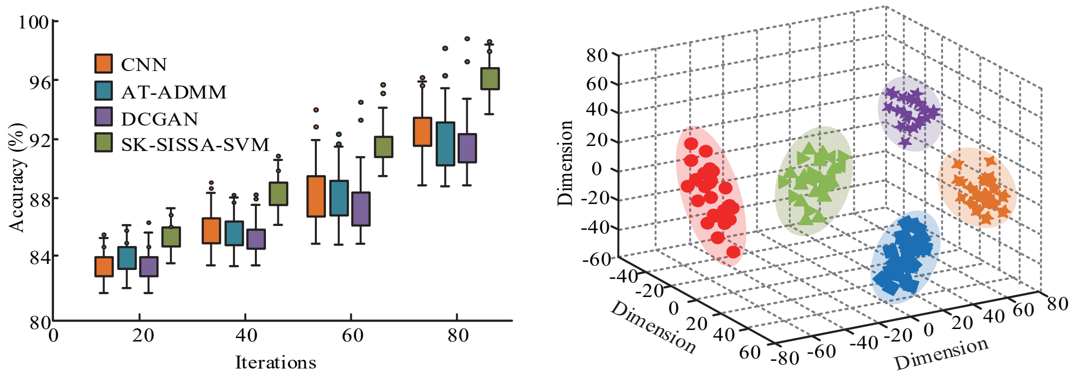


(a) Accuracy of each algorithm (b) F1 of each algorithm

Figure 9 Recognition accuracy and F1 score test results

4.2 Application Analysis of Short-Term Power Meteorological Disaster Risk Assessment Model

After verifying the performance of the SK-SISSA-SVM algorithm, to further evaluate the performance of the finally constructed short-term power meteorological disaster risk assessment model based on the SK-SISSA-SVM algorithm, the study compared it with typical models of Convolutional Neural Network (CNN) and compared its practical application effects with mainstream short-term power meteorological disaster risk assessment models such as Adaptive Alternating Direction Method of Multipliers (AT-ADMM) and Deep Convolutional Generative Adversarial Network (DCGAN). The experiment selected a processor of Intel (R) Xeon (R) Platinum, graphics card of RTX 4090, and memory of 8G. The learning rate was set to 0.001, and the iteration times were set to 100. To explore the meteorological disaster scenario classification performance of the SK-SISSA-SVM model, the study analyzed the meteorological classification effects of SK-SISSA-SVM, CNN, AT-ADMM, and DCGAN models, and the obtained results are shown in Fig. 10.



(a) Accuracy comparison of each model (b) SK-SISSA-SVM model classification results

Figure 10 Visual analysis of classification effects

As shown in Fig. 10a, the classification accuracy of the SK-SISSA-SVM model rose rapidly with the increase of iteration times. At 80 iterations, the accuracy was 96.09%, with a maximum value of 96.97% and a minimum value of 95.23%, all higher than the comparison models. As shown in Fig. 10b, the study model accurately classified meteorological disaster scenarios into five categories: lightning, strong wind, rainstorm, icing, and wildfire. The classification boundaries of the five scenarios were clear, with good aggregation degree and clear distinction. In summary, the SK-SISSA-SVM model possessed superior scenario classification accuracy, because the clustering algorithm in the model achieved accurate classification by iteratively calculating similarity and relocating data centers. To further analyze the risk assessment capability of the model, the study compared the short-term power meteorological disaster risk assessment correctness of the four models, and the obtained results are shown in Fig. 11.

As shown in Fig. 11a, the study model could accurately assess risk conditions, with only very few samples not correctly identified, and its assessment correctness rate was 95.33%. As shown in Figs. 11b, c, and d, although the three comparison models CNN, AT-ADMM, and DCGAN could roughly identify risks, the number of incorrect samples was significantly greater than the study model, with assessment correctness rates of 90.01%, 88.67%, and 90.57% respectively. The assessment correctness of the study model was significantly higher than the comparison models. In summary, this indicated that the SK-SISSA-SVM model possessed superior short-term power meteorological disaster risk assessment performance, because the Lagrangian function constructed in SVM could achieve assessment accuracy. In order to further explore the actual evaluation performance of SK-SISSA-SVM model, the study conducted tests on the four models for the missing report rate, power failure prediction accuracy, prediction recall rate, response time, receiver operating characteristic area under curve (ROC-AUC) indicators of risk assessment in the lightning and rainstorm meteorological environment, and the results are shown in Tab. 1.

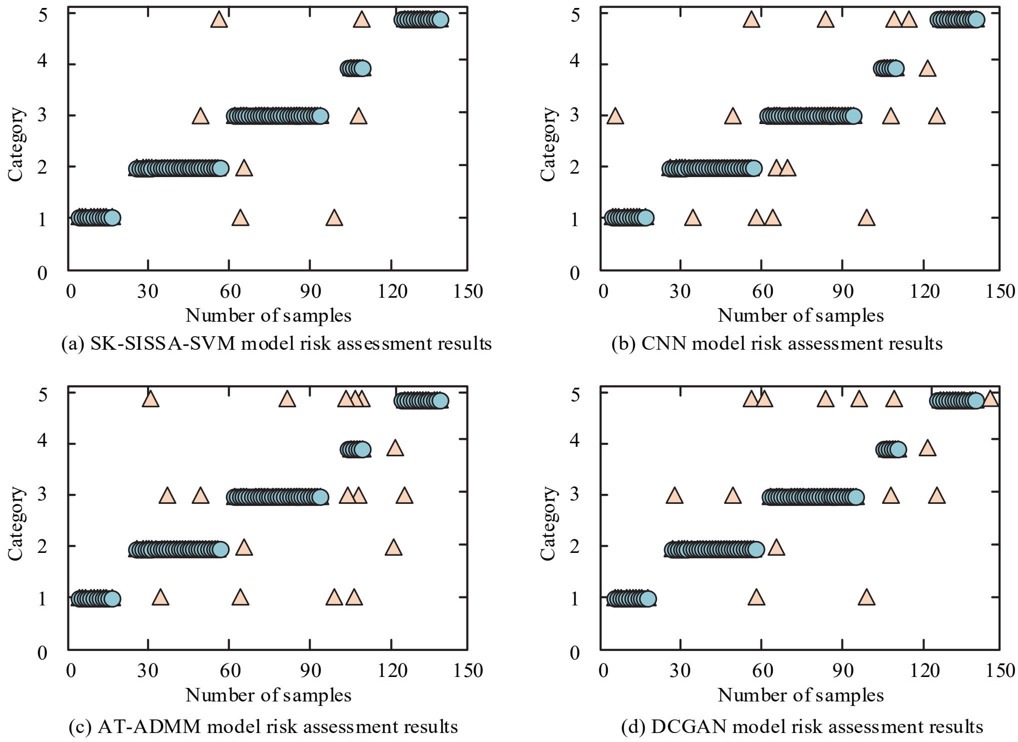


Figure 11 Comparison of disaster risk assessment accuracy

Table 1 Prediction accuracy and recall experimental results

Meteorological scenario	Model	Underreporting rate / %	Accuracy / %	Recall / %	Time / ms	ROC-AUC
Thunder	CNN	6.95*	86.21*	81.20*	58.61*	0.8452*
	AT-ADMM	10.21**	84.65*	80.36*	35.47	0.8963*
	DCGAN	4.13*	90.25*	89.44*	152.98**	0.9120*
	SK-SISSA-SVM	1.36	94.84	94.21	35.36	0.9748
Rainstorm	CNN	7.02*	84.62*	81.74*	57.12*	0.8366*
	AT-ADMM	9.64**	87.63*	85.20*	41.58	0.8756*
	DCGAN	5.47*	80.69*	76.31*	128.14**	0.8178*
	SK-SISSA-SVM	1.03	94.77	93.68	37.84	0.9633

Note: * indicates $p < 0.05$ compared to the research model, * * indicates $p < 0.01$

As shown in Tab. 1, in lightning weather environments, the SK-SISSA-SVM model has a false alarm rate, power fault prediction accuracy, and prediction recall rate of 1.36% (95% CI: [0.98%, 1.74%]), 94.84% (95% CI: [93.2%, 96.5%]), and 94.21% (95% CI: [92.6%, 95.8%]), respectively, which are superior to the other three comparative models ($p < 0.05$). In the rainstorm meteorological environment, the missing report rate of SK-SISSA-SVM model is 1.03% (95% CI: [0.70%, 1.36%]), which is significantly lower than that of the comparison model. The power failure prediction accuracy and prediction recall rate are 94.77% (95% CI: [93.1%, 96.4%]) and 93.68% (95% CI: [91.9%, 95.5%]), which are significantly better than that of the comparison model ($p < 0.05$). The SK-SISSA-SVM model proposed in the study, after introducing scene clustering and attention mechanisms, has a complexity on the same level as the AT-ADMM model, and is significantly better than the CNN classic model and DCGAN model ($p < 0.05$). In addition, the ROC-AUC of the research model in the lightning and rainstorm meteorological environment is significantly better than that of the comparison model ($p < 0.05$). The above results indicate that the research model exhibits superior performance in practical risk assessment applications, mainly due to the aggregation of meteorological and power data by the model and the accurate assessment of risks using SVM.

5 CONCLUSION AND FUTURE WORK

This study presents a hybrid meteorological disaster risk assessment framework that combines ISSA, SK-means clustering, and a self-attention-augmented SVM classifier. The proposed SK-SISSA-SVM model leverages global optimization, adaptive clustering, and enhanced feature representation to improve the accuracy and efficiency of short-term risk assessment in power systems. Experimental results demonstrate that the model outperforms several conventional optimization and learning approaches, achieving higher risk identification accuracy, improved robustness, and lower omission rates under thunderstorm and rainstorm conditions.

Despite these promising results, the current work remains limited by the use of a single regional dataset, the absence of multi-source weather features, and a lack of evaluation under highly complex or mixed disaster scenarios. Future research should expand the dataset across multiple climatic regions, incorporate additional environmental and grid operational indicators, and explore probabilistic and interpretable learning frameworks to better support decision-making in real-world grid monitoring environments. Strengthening these aspects will enhance the model's generalizability and practical applicability for utility-scale meteorological disaster management.

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