ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on Risk Level Assessment Technology for Intelligent Water Immersion Alarms in Power Equipment Based on Machine Learning Classification Algorithms

Mengyuan Huang[1,*], *Guang Wang*[1], *Zihao Feng*[1], *Yi Chen*[1], *Weijian Lin*[1], *Wenchang Lin*[1] *and Weiling Zhang*[1]

[1] Guangdong Power Grid Yunfu Luoding Power Supply Bureau, Yunfu, Guangdong, 527300, China

SUMMARY: *Power equipment serves as a critical component ensuring the stable operation of power systems, undertaking the task of electricity distribution. However, changes in the external environment may impact its normal functioning. Based on this, this paper proposes a risk level assessment model for intelligent water immersion alerts targeting power equipment. First, ArcGIS geographic information systems are employed to collect high-resolution LiDAR data from substations, thereby constructing digital twin data suitable for mirror analysis. Second, building upon the Stacking model within machine classification algorithms, a grid security situation early warning module is constructed. This module integrates geographic, meteorological data, and power equipment information as inputs, primarily serving to predict and warn of water immersion depths for power equipment. Finally, a case study analysis is conducted using a substation in a coastal city as the research subject. Results demonstrate that this model achieves significantly lower prediction errors for water immersion depth compared to benchmark models, with a recall rate of 99.98% for power outage warnings. Dynamic early warnings based on this framework enable power grid enterprises to proactively implement protective measures, mitigating the impact of external environmental changes on the stable operation of power systems.*

KEYWORDS: *machine learning algorithms; power equipment; water immersion early warning; Stacking model; ArcGIS system*

1 Introduction

Over the past decade, global electricity supply has risen steadily year after year. In 2024, worldwide electricity consumption reached approximately 30,000 terawatt-hours, with power usage increasing by 1,100 terawatt-hours—a year-on-year growth of 4.3%. Concurrently, an increasing number of large-capacity, high-output power generation units have been commissioned. This has spurred the development of various advanced and convenient electronic products, continuously elevating people's living standards. Consequently, society's demands for high-quality electricity and reliable power supply systems have also progressively intensified [1-3]. Adverse weather conditions pose significant challenges to the operation and reliability of power facilities. During extreme weather events such as storms, blizzards, typhoons, and heatwaves, power facilities often face risks of damage, outages, and failures, potentially leading to severe safety incidents and economic losses [4, 5]. With the increasing

*huangmengyuan9326@163.com
https://doi.org/10.65102/is2026840
Published: 30 April, 2026

frequency of extreme weather globally, power equipment frequently suffers water immersion incidents after storms due to heavy rainfall, flooding, and leaks [6, 7]. According to an International Energy Agency report, the incidence rate of water immersion incidents in power equipment increased by 12% in 2024 compared to 2023. Therefore, effectively monitoring the operation of power equipment during severe weather has become essential.

Driven by intelligent concepts and technological advancements, traditional power inspections can no longer meet the demands of the new era. Their intelligent evolution is crucial to align with State Grid's “One Strength, Three Excellences” initiative and embrace the Industrial 4.0 era [8-10]. Visual monitoring, intelligent control, and human-machine interaction are all integral components of smart power equipment. The introduction of cutting-edge intelligent devices enables real-time dynamic tracking of environmental parameters and operational status with minimal human intervention. When risks emerge, the system can autonomously issue warnings based on risk assessment levels, significantly enhancing the reliability of power supply systems and driving progress toward greater efficiency, economy, and environmental sustainability [11-15]. In summary, the stable operation of power systems is crucial for national economic and social development, ensuring steady and healthy societal progress. Intelligent monitoring and assessment of power equipment operational risks represent an inevitable trend.

In current water ingress risk monitoring for power equipment, most facilities rely on manual inspections, which are time-consuming, prone to oversight, and suffer from severe inaccuracies in risk classification. Sensor technology has improved the effectiveness of water ingress risk monitoring. Pham and Tran [16] shared a substation water level monitoring and control model that utilizes IoT technology to monitor water level changes in drainage systems in real time and control pump operations accordingly to prevent increased flood risks. Kondalkar et al. [17] developed a highly sensitive and stable humidity sensor for real-time detection of dissolved moisture in power transformer insulating oil. However, humidity sensors exhibit high false alarm rates in high-temperature, high-humidity environments [18]. In contrast, Ansari et al. [19] employed fiber optic sensors to monitor moisture content in internal paper components of operational power transformers, enabling online observation and establishing an effective technique for transformer moisture measurement. However, fiber optic sensors struggle to match the response speed of traditional sensors in dynamic environments, and their measurement accuracy is affected by temperature variations [20].

Additionally, researchers have begun assessing water immersion risks in power equipment. Ke et al. [21] constructed a specific flood model using flood evolution models. Through simulation calculations, they developed a rainfall-flood risk assessment scheme for substations by integrating flood vulnerability curves. For evaluating moisture-induced aging in distribution cables, Hu et al. [22] combined the Analytic Hierarchy Process (AHP) and Entropy Weighting Method to perform weighted calculations of cable performance. They analyzed aging status using an improved radar chart, aging index, aging rate, and curve area calculations, thereby effectively assessing cable moisture conditions.

With the advancement of machine learning algorithms, relevant classification methods have opened new avenues for water immersion risk assessment. Atiq et al. [23] employed machine learning classification and regression models to predict cable health indices. The regression and classification accuracies of the random forest algorithm reached 99.01% and 97.2%, respectively, establishing it as an effective method for evaluating cable health indices. Afzal et al. [24] constructed a probabilistic flood model for power distribution systems in flood-prone environments. They employed Monte Carlo techniques to predict flood overflow locations and introduced reinforcement learning to identify distribution substations at risk of inundation, thereby assessing flood hazards for distribution systems. Tang et al. [25] designed a low-frequency broadband sonar technology for online monitoring of submarine cables. Combined with machine learning for comprehensive cable analysis, this approach effectively detects the degradation level of submarine cables.

As critical infrastructure within power systems, electrical equipment often suffers widespread outages during low-probability, high-risk meteorological disasters. This paper integrates ArcGIS Geographic Information System into power equipment situational awareness. By incorporating substation meteorological data and power equipment data as inputs, it constructs a digital twin model for mirror analysis. A Dataframe-based missing data detection method is designed to ensure the integrity of power equipment water immersion data. Subsequently, algorithms including Random Forest, Support Vector Machine, Extreme Gradient Boosting Tree, and Logistic Regression are selected as learners. By incorporating the Stacking ensemble learning strategy, a power equipment flooding early warning model is constructed. Building upon this foundation, a power system resilience assessment method is proposed. To validate the effectiveness of the aforementioned approach, data simulation is conducted on a substation in a coastal city in China.

2 Situation Awareness Based on Geographic Information Systems

The power system is the most critical public infrastructure in modern society. The daily necessities of life for millions of households and the orderly functioning of the economy and society depend on a reliable power supply. In recent years, as the energy transition accelerates, electricity's share in terminal energy consumption has rapidly increased. Past major blackouts demonstrate that the greater the economy's dependence on electricity, the more severe the losses from widespread power outages. Concurrently, global climate change has led to a noticeable rise in severe natural disasters, posing significant threats to the safe operation of power systems. Therefore, achieving intelligent alerts for power equipment under changing external conditions has become a critical research focus for ensuring stable operation.

2.1 Design of the Flood Situation Awareness Framework

2.1.1 ArcGIS System

ArcGIS is a comprehensive GIS platform product suite developed by ESRI, featuring robust capabilities in map creation, spatial data management, spatial analysis, spatial information integration, and publishing and sharing. It supports not only desktop environments but also mobile platforms, web platforms, enterprise-level environments, and cloud computing architectures. Simultaneously, it provides developers with a rich array of IT-standard-based development interfaces and tools, enabling them to build customized applications[26].

To achieve intelligent early warning for water immersion of power equipment, this paper leverages the ArcGIS Geographic Information System to collect high-resolution LiDAR data of substation areas. Through data processing, it acquires water immersion information for power equipment, thereby enabling situational awareness of water immersion conditions. The software required for this system includes ArcGIS Desktop, ArcSDE, and ArcGIS Server. ArcGIS Desktop, a desktop software product within the ArcGIS family, supports editing, creating, and analyzing geographic information. It provides a suite of tools for data collection and management, visualization, spatial modeling and analysis, advanced cartography, and feature creation and management. It supports both single-user and multi-user editing and enables complex automated workflows.

2.1.2 Frame Structure

Situation awareness forms the foundation of situational awareness technology, requiring comprehensive detection and acquisition of critical elements and information related to power equipment risks to prepare for intelligent flood warning and assessment of power equipment. Figure 1 illustrates the ArcGIS-based situational awareness framework for power equipment flood risk. (1) Power equipment structure, line parameters, geographic coordinates, and grid resources for withstanding heavy rainfall and recovery can be obtained from power authorities. (2) Real-time rainfall data acquisition for power equipment. Utilizing meteorological data from real-time monitoring stations, combined with rainfall models, predicts rainfall trajectory, intensity, and maximum rainfall rate changes. It estimates the next rainfall center location and maximum rainfall intensity, extrapolates their broken-line paths point-by-point, and promptly calibrates based on actual monitoring data.

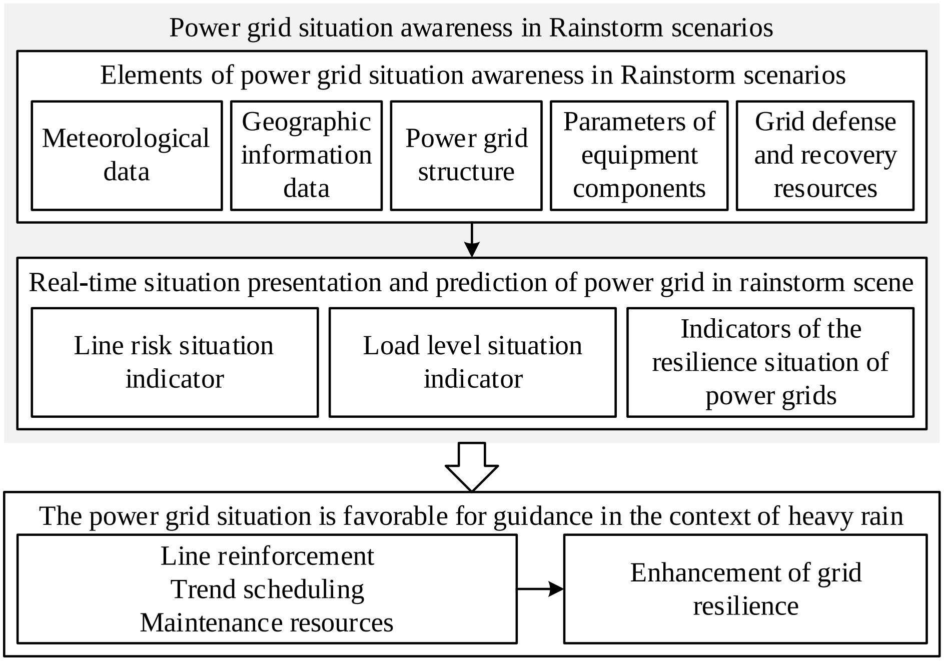


Figure 1: The power equipment water risk posture perception framework

2.2 Flood Situation Awareness Function Design

2.2.1 Information Collection Module

Digital twin technology is a method for establishing mathematical models of real-world objects' information and data through digital means on an information platform. This section focuses on applying digital twin technology to collect and preprocess data from substations. Given that substation operations involve complex power networks and numerous electrical devices, data must be gathered and analyzed from diverse perspectives and levels to ensure efficient and safe substation operation. This encompasses, but is not limited to, electrical parameters such as voltage, current, and temperature, as well as information on equipment status and operational environments.

$$U_i = U_{i,x} + U_{i,y} \tag{1}$$

Here, U_i represents the total energy of the substation as a whole, $U_{i,x}$ denotes the discrepancy between the calculated energy and the actual value for each zone within the substation, and $U_{i,y}$ indicates the actual energy state within each zone.

When processing point cloud data, it is common to encounter a significant amount of useless information mixed within the data, such as noise and redundant data points. These can adversely affect the quality and accuracy of data processing. To enhance data processing efficiency and result accuracy, this section proposes a data filtering mechanism. The purpose of this mechanism is to remove unnecessary noise and redundant points, resulting in cleaner and more accurate final processed data. The data preprocessing workflow is as follows:

First, to filter out valid data, a distance threshold is set. Only data points separated by distances exceeding this threshold are retained. This approach eliminates points that are too close together, potentially lacking independence or accuracy. Next, considering the presence of noise in substation data, digital twin technology is employed for data preprocessing. Digital twin technology simulates real-world objects through virtual models, effectively removing noise and enhancing data precision and quality. Finally, this preprocessed, high-quality data is used to construct a 3D model of the substation, making the model more closely resemble the actual substation environment. Such a 3D model plays a crucial role in improving the accuracy of water ingress early warning for electrical equipment within the substation.

2.2.2 Information Processing Module

Through the combined application of ArcGIS and digital twin technology, data related to water immersion in electrical equipment can be obtained. However, such data may be incomplete during collection, and simple data preprocessing alone cannot effectively ensure data integrity. Therefore, this paper proposes a Dataframe-based method for detecting missing data and provides a more reasonable estimation for missing values. The specific steps are as follows:

(1) Input the dataset D_1 to be processed and consolidate it into an $n \times m$ matrix, where n represents the number of data points and m represents the dimension of each data point. Each element is denoted as x_{ij} (where i represents the row number and j represents the column number). Then:

$$D_1 = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{2}$$

(2) Define an $n \times m$ zero matrix Z_0 Starting from the first row and first column of the matrix, i.e., $i=1, j=1$, sequentially examine the rows and columns of the dataset matrix in space. Determine whether each dimension $x_i(0<i \le n, i \in N)$ of each data point $x_i(0< j \le m, j \in N)$ is empty. If x_i is determined to be empty, is empty, mark the i th row and j th column of the dataset matrix as "F", i.e., $x_{ij} = F$, and assign the value 1 to the i th row and j th column of matrix Z, i.e., $Z[i, j] = 1$, indicating that x_{ij} is missing. Otherwise, it is not filled.

For a more intuitive illustration, consider a 6×4 dataset $D_1^{'}$. Suppose dataset $D_1^{'}$ contains 6 data points, each with 4 attribute dimensions. Based on the distribution of $D_1^{'}$, missing values occur in the 1st and 5th data points. That is:

$$D_i' = \begin{bmatrix} 1.4 & 3.7 & & 0.4 \\ 3.2 & 3.8 & 5.6 & 0.2 \\ 2.1 & 3.5 & 6.1 & 0.3 \\ 1.3 & 3.1 & 6.2 & 0.4 \\ 2.1 & 6.1 & & \\ 1.6 & 3.4 & 5.2 & 0.1 \end{bmatrix} \tag{3}$$

(3) Repeat step (2) until the entire dataset D_1 has been inspected. At this point, the Z matrix is fully annotated, providing a spatial visualization of the dataset's missing value distribution. Annotated cells indicate data points with missing values in the corresponding dimension. Accordingly, after inspecting dataset D_1', the resulting D_1' and its Z' matrix are:

$$D' = \begin{bmatrix} 1.4 & 3.7 & F & 0.4 \\ 3.2 & 3.8 & 5.6 & 0.2 \\ 2.1 & 3.5 & 6.1 & 0.3 \\ 1.3 & 3.1 & 6.2 & 0.4 \\ 2.1 & 6.1 & F & F \\ 1.6 & 3.4 & 5.2 & 0.1 \end{bmatrix} \tag{4}$$

$$Z[i, j] = \begin{cases} 1, & D_1'[i, j] = F \\ 0, & \text{other} \end{cases} \tag{5}$$

The aforementioned missing value detection method can identify the locations of missing data points within a dataset and the number of missing attributes. Based on this detection method, multiple concepts of missingness are proposed. By calculating the missingness of the dataset according to the detection results, the overall degree of missingness across the entire dataset can be objectively and comprehensively reflected.

3 Water Inundation Early Warning Based on Stacking Fusion

As critical infrastructure underpinning the lifeline of the national economy and the orderly functioning of society, the secure and stable operation of power systems and reliable electricity supply are essential prerequisites for sustaining daily production and life. However, intensified climate change in recent years has led to an increase in extreme weather events, resulting in frequent large-scale power outages caused by water-induced failures in electrical equipment. In response, this chapter employs machine learning classification algorithms and leverages the Stacking ensemble learning approach to construct a water immersion early warning model for electrical equipment. The objective is to achieve rapid and effective intelligent early warning of water immersion in electrical equipment, thereby better ensuring stable operation under changing external environmental conditions.

3.1 Stacking Fusion Model Construction

3.1.1 Stacking Model

For the problem of intelligent early warning assessment of water immersion in power equipment, machine learning models carry risks of overfitting and underfitting, presenting new challenges for such assessment models. Stacking ensemble learning can conveniently address this issue to a certain extent. Common ensemble learning methods include Bagging, Boosting, and Stacking. Bagging and Boosting typically employ the same base learner, whereas Stacking generally combines multiple distinct base learners to construct the model [27].

Figure 2 illustrates the framework of the Stacking ensemble learning model. Stacking is a two-layer model comprising a set of base learners and a meta-learner. The first layer consists of two or more base learner models. While incorporating more base learners improves learning performance, it increases model complexity and training time. The meta-learner in the second layer differs from the base learners, typically employing simple linear algorithms. This design prevents redundancy and overfitting caused by excessive model complexity. Base learners first generate preliminary predictions, which are then passed to the meta-learner. By integrating and learning from the outputs of the base learners, the meta-learner further optimizes the overall model performance, thereby enhancing accuracy.

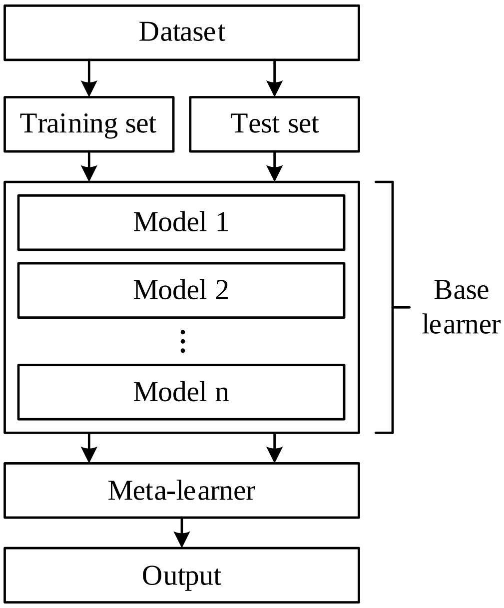


Figure 2: Stacking the ensemble learning model framework

Building a Stacking ensemble learning model primarily involves three steps:

(1) Data partitioning. Using cross-validation, the training dataset is evenly split into n subsets. In each iteration, one subset is sequentially selected as the validation set, while the remaining n-1 subsets are combined as the training set. This process is repeated n times, corresponding to the first through nth rounds of cross-validation.

(2) Training and prediction of base learners. Within each fold of cross-validation, the n-1 subsets are input into each model of the base learners for training. After training, these models are used to predict the current fold's validation set and the entire test set. Upon completing n-fold cross-validation, the prediction results from each fold's training set are aggregated to form a new training set. Simultaneously, the average of the prediction results from each fold's test set is taken to obtain a new test set.

(3) Meta-Learner Training and Prediction. The meta-learner is trained using the new training set generated by the first layer of base learners. By utilizing the outputs of base learners as its input, the meta-learner captures both the predictive capabilities and feature interactions of the base models. After training, the meta-learner makes predictions on the new test set to produce the final prediction results.

3.1.2 Selection of Base Learners and Meta-Learners

To achieve intelligent early warning for water immersion in electrical equipment, this paper selects Random Forest (RF), Extreme Gradient Boosting Tree (XGBoost), and Support Vector Machine (SVM) as base learners. By leveraging their respective strengths in handling diverse, nonlinear, and sparse data, the overall model's accuracy is enhanced. Logistic Regression (LR) is selected as the meta-learner to effectively integrate predictions from different base models, thereby improving the overall model's performance and generalization capability [28].

(1) RF is an ensemble learning method that enhances prediction accuracy by constructing multiple decision trees and aggregating their outputs. In power equipment early warning assessment, RF handles diverse data types—including topography, equipment information, and meteorological/hydrological data—to evaluate equipment risks. By randomly selecting samples and features, this model increases diversity and effectively mitigates overfitting risks.

(2) XGBoost is a decision tree-based ensemble learning algorithm primarily used for classification and regression problems. In power equipment flood warning evaluation, XGBoost analyzes data from multiple factors—terrain, power equipment information, meteorology, etc.—to progressively add decision trees for predicting flood risks. It continuously optimizes the model to reduce prediction errors, thereby enhancing the accuracy and reliability of flood warning evaluations.

(3) SVM is a supervised learning algorithm suitable for both classification and regression problems. In power equipment flood warning evaluation, SVM effectively handles both linear and nonlinear relationships, performing well with high-dimensional data and small sample sizes.

(4) LR serves as a foundational component for various classification algorithms, featuring low computational complexity and interpretability, which helps mitigate model overfitting risks. Additionally, LR possesses feature selection capabilities that can better correct biases in the training set introduced by multiple algorithms in the first layer. Therefore, selecting the LR algorithm as the meta-learner for the Stacking ensemble learning model offers greater competitiveness.

3.1.3 Stacking Fusion Framework

The modeling steps for the water immersion early warning model for power equipment based on multi-feature fusion within the Stacking ensemble learning framework are as follows:

(1) First, the original dataset is split into a training set X and a test set T at a 7:3 ratio. The Synthetic Minority Over-sampling Technique (SMOTE) algorithm is applied to over-sample the minority class data in the training set X. The synthesized new samples are added to the training set to form a new training set X'.

(2) Extract physical features from the training set X' and test set T, perform feature selection, and use the selected feature values as feature vectors to form the feature training set X_1 and test set T_1. Train the CNN model using the training set X'. Employ the trained model as a feature extractor to further extract information features from the feature training set X^* and test set T, forming the training set X_2 and test set T_2.

(3) Perform normalization on the feature training sets X_1, X_2 and the test sets T_1, T_2 respectively. Employ a five-fold cross-validation method to reconstruct the training sets X_1, X_2

by dividing them into five equal training subsets: $X_i = \{S_{11}, S_{12}, S_{13}, S_{14}, S_{15}\}$ and $X_2 = \{S_{21}, S_{22}, S_{23}, S_{24}, S_{25}\}$. The X_1 data is used to train and validate the base classifiers SVM and RF, while the X_2 data is used to train and validate the base classifiers SVM and RF.

(4) Taking the SVM algorithm as an example, sequentially select one subset S_{1i} from X_1 as the validation subset, while the remaining four training subsets are used for model training. The prediction results for the validation subset are denoted as α_{1i}, and the prediction results for the test set τ_1 are denoted as β_{1i}. Repeating this training cycle five times yields predictions for all validation subsets: $\{\alpha_{11}, \alpha_{12}, \alpha_{13}, \alpha_{14}, \alpha_{15}\}$. By sequentially concatenating the five validation results column-wise, we obtain a column vector matching the length of the X' labels Y_{train}, denoted as A_{SVM}. Similarly, the predictions for the test set T_1 are represented as $\{\beta_{11}, \beta_{12}, \beta_{13}, \beta_{14}, \beta_{15}\}$ corresponding to the test set T_1 and taking their sum and average yields a column vector B_{SVM} matching the length of the test set τ.

(5) For the base classifiers RF and XGBoost, repeat steps (3) and (4) sequentially. Output the column vectors $A_{RF}, A_{XGBoost}$ corresponding to the training set and the column vectors $B_{RF}, B_{XGBoost}$ corresponding to the test set. This completes the first layer of feature transformation for all data from input features to output features.

(6) Integrate $A_{SVM}, A_{RF}, A_{XGBoost}$ with the labels Y_{train} of the training set X' to form a new sample training set, denoted as the meta-training set $X_3 = \{(A_{SVM}, A_{RF}, A_{XGBoost}, Y_{train})\}$. Similarly, integrate $B_{SVM}, B_{RF}, B_{XGBoost}$ with the labels Y_{test} from the test set T to form a new sample test set, the meta-test set, denoted as $T_3 = \{(B_{SVM}, B_{RF}, B_{XGBoost}, Y_{test})\}$. Using X_3 to model and train the meta-classifier LR, and testing with T_3, yields the final classification results and recognition accuracy.

3.2 Flooding Early Warning and Resilience Assessment

3.2.1 Water Immersion Early Warning Process for Power Equipment

This paper employs a deterministic early warning approach to deliver warning information, dividing the warning process into two stages: water depth prediction and inundation risk warning. This provides multi-perspective references for disaster prevention and control tasks of power equipment. Figure 3 illustrates the water inundation warning flowchart for power equipment, where A represents the output matrix after k iterations of cyclic training.

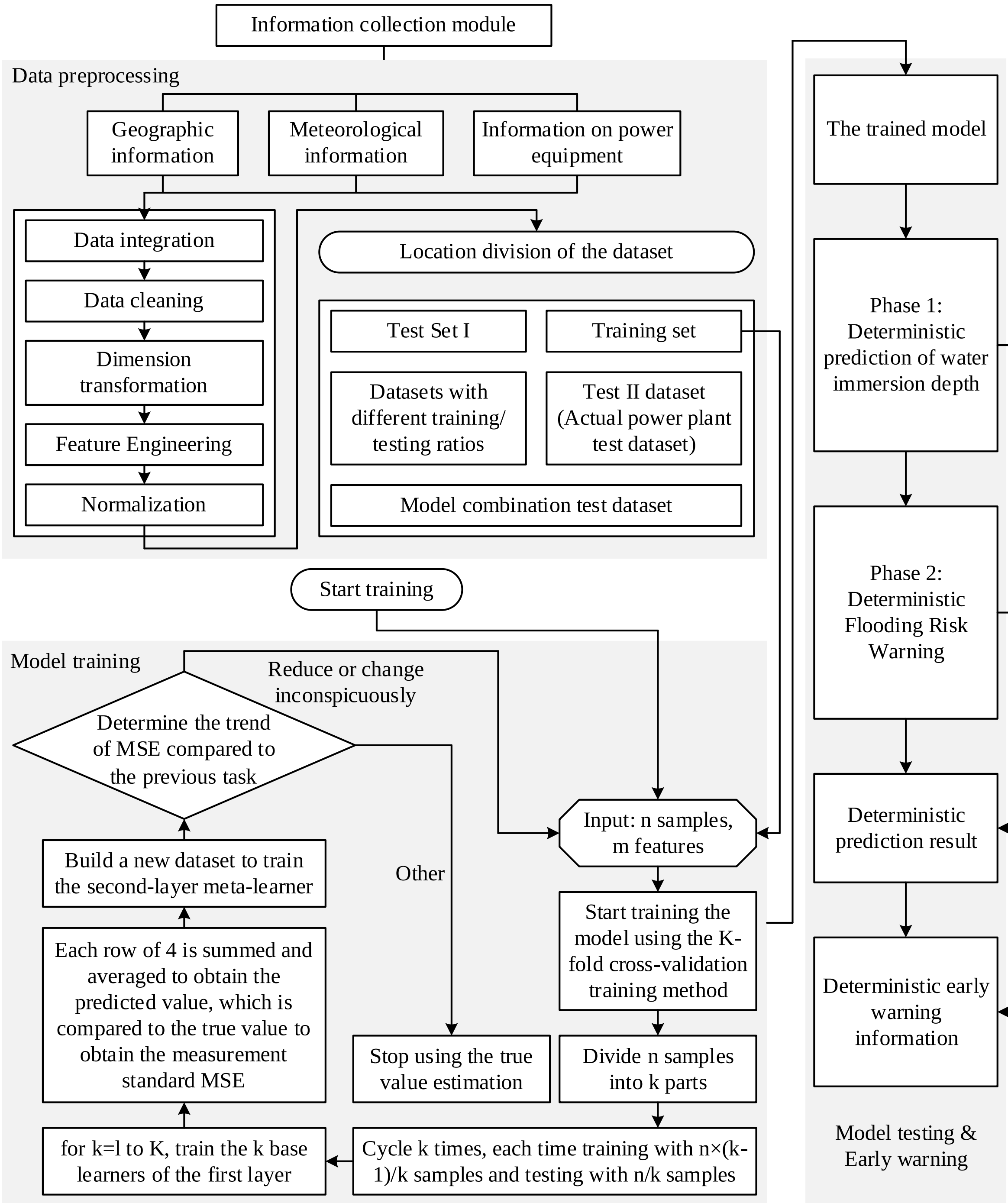


Figure 3: Early warning process for water immersion in power equipment

In the context of intelligent flood warning for electrical equipment, the model inputs comprise data essential for flood disaster alerts, including meteorological information, electrical equipment details, and geographic data. The model outputs the predicted flood depth. Training results are evaluated in two dimensions: model prediction accuracy and risk level warning.

First, the error between the model's predicted flood depth and the actual value is calculated, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), thereby determining the model's inherent prediction accuracy. Subsequently, based on the predicted power station flooding conditions and the actual flooding conditions, the warning accuracy metrics are calculated: Accuracy (ACC), Precision (PRE), Recall (REC), and F1 score. After inputting the specific test set for the warning phase, the model outputs are compared against the power plant's rated flood depth. If the predicted depth is below the rated flood depth, it is assessed as “no risk”; if above, it is assessed as “risk present.” The “no-risk rate” for the warning test set data is calculated, representing the proportion of samples classified as “no risk” out of the total sample size.

3.2.2 Power System Resilience Assessment Methods

Figure 4 shows the trapezoidal curve of the power system performance function before and after an extreme event, illustrating the behavior of the power system when subjected to such events.

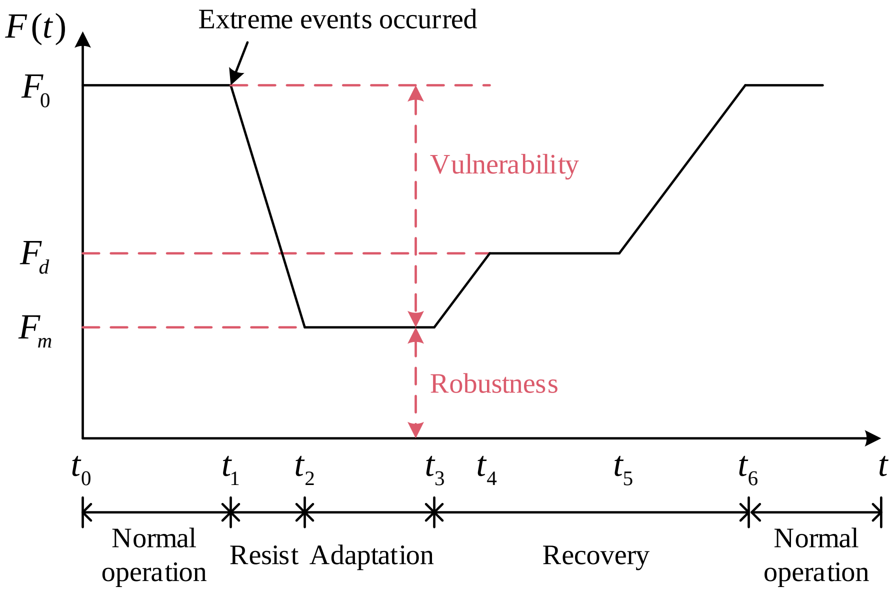


Figure 4: Schematic diagram of power system resilience curve

In the figure, $F(t)$ represents the variation of the system's functional performance across different stages, while F_0 denotes the system's performance during normal operation, typically corresponding to the power supply level for system loads. The figure illustrates that the evolution of extreme events comprises four distinct phases:

(1) Normal Operation Phase $t_0 \sim t_1$: The system maintains safe and stable operation prior to the extreme event, with performance sustained at F_0.

(2) Mitigation phase $t_1 \sim t_2$: Active mitigation measures are implemented after the extreme event, partially sustaining the load while system performance declines to F_m.

(3) Adaptation phase $t_2 \sim t_3$: Emergency coordination measures are implemented to adapt to the extreme event, reducing load fluctuations and stabilizing system performance at F_m.

(4) Recovery phase $t_3 \sim t_6$: System performance is restored through network reconfiguration, component repairs, and other measures. Due to potential damage to power infrastructure during extreme events, the process from initial disruption to full performance recovery often spans hours or even days.

After clarifying the results of the power equipment flooding warning, this paper further conducts a resilience assessment of the power system based on these findings. The paper uses load curves to describe system functionality and calculates the power supply deficit for each scenario. The grid resilience index is calculated using the probability of fault scenarios occurring and the corresponding area of deficit in the load curve, defined as:

$$AR=\sum_{n=1}^{N}\lambda_n\times Im_n=\sum_{n=1}^{N}\lambda_n\times E\left[\frac{\int_0^{T_0}L(t)dt}{\int_0^{T_0}TL(t)dt}\right]=\sum_{n=1}^{N}\lambda_n\times E\left[\frac{\int_0^{T_0}TL(t)dt-RES_n}{\int_0^{T_0}TL(t)dt}\right] \tag{6}$$

In the equation, λ_n represents the occurrence probability of scenario n, N denotes the number of selected fault scenarios, Im_n indicates the power supply deficiency level of scenario n, and T_0 signifies the duration of extreme weather impact on the distribution network. $L(t)$ denotes the actual load curve during large-scale failures caused by extreme weather, $TL(t)$ represents the target load curve under fault-free system operation, and RES_n indicates the missing area of the load curve.

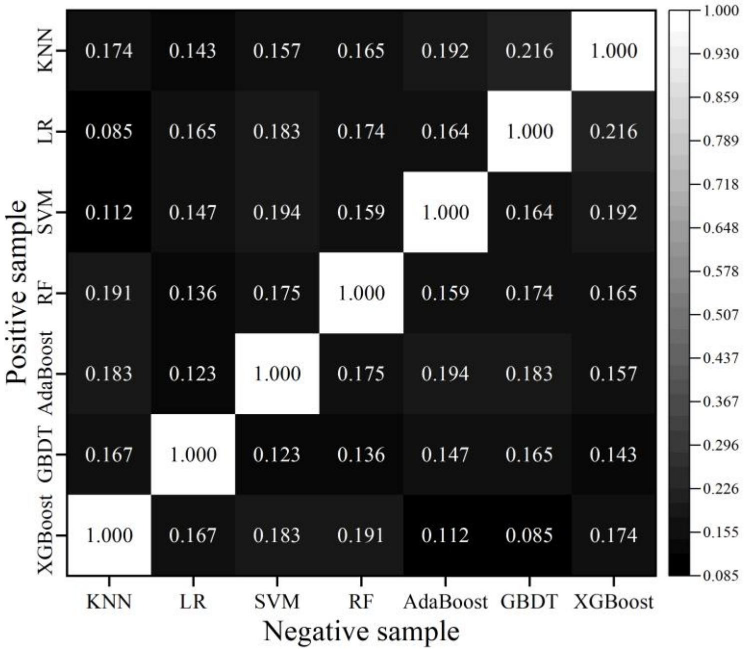
4 Water Immersion Early Warning and Resilience Assessment for Power Equipment

As critical infrastructure underpinning socioeconomic development and public welfare, power system failures not only inflict substantial economic losses on society but also severely disrupt normal human activities. With the increasing frequency of large-scale blackouts worldwide, enhancing the resilience of power systems to recover from disturbance events has become an urgent priority. This chapter conducts case studies on the water inundation early warning model for power equipment developed in the preceding sections. It further explores changes in the resilience of power systems following water inundation alerts, aiming to promote the stable operation of both power equipment and the broader power system.

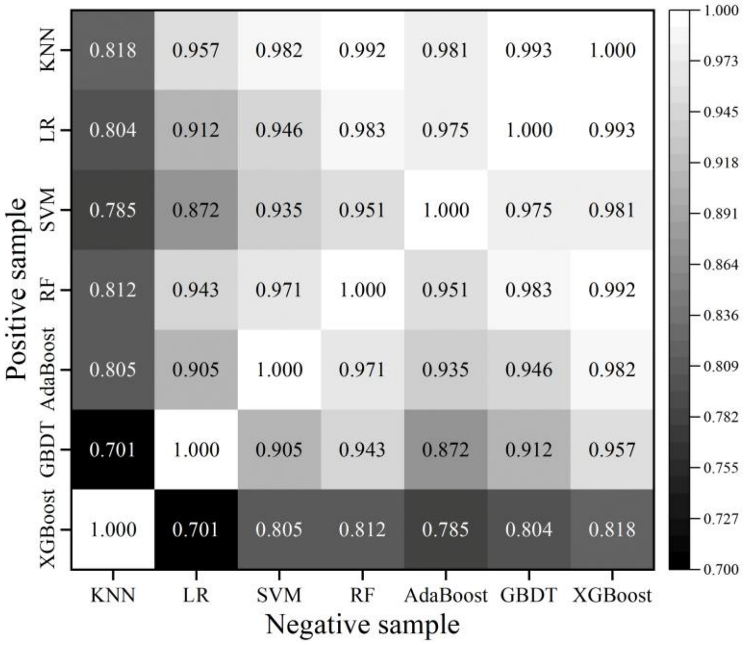
4.1 Power Equipment Water Immersion Early Warning Simulation

(1) Learner Selection

For stacking ensemble learning, the greater the diversity among different learners, the more room for improvement by the meta-learner, resulting in better classification performance. Therefore, after selecting classifiers with superior classification performance, it is also necessary to examine the diversity among these learners and choose those with the greatest differences whenever possible. Based on this, this paper selects Double Failure (DF) and Q-statistics as evaluation metrics to measure learner diversity in the ensemble from different perspectives. Figure 5 presents the diversity metrics for various learners on the UCI dataset, with Figure 5(a) and (b) showing DF values and Q values, respectively. Due to significant differences in training mechanisms between AdaBoost and GBDT compared to other learners, their DF and Q values are substantially lower than those of other learners. Additionally, GBDT exhibits relatively poorer classification performance compared to RF, SVM, and XGBoost. Therefore, RF, SVM, and XGBoost are selected as the base learners for the single-learner models.



(a) DF value



(b) Q value

Figure 5: Diversity measurement of seven learners

The type of meta-learner is crucial for Stacking ensemble learning, as it can both reduce the bias of individual learners and ensure sufficient generalization capability to mitigate overfitting. Therefore, for the binary classification task of water immersion early warning for power equipment, a meta-learner must be selected to combine multiple heterogeneous base learners. Since the predictions of base learners vary and each has its own strengths and weaknesses, choosing an appropriate meta-learner is essential to achieve optimal classification performance in the final Stacking ensemble. Thus, based on the selected base learners, this paper trained the initial seven compared learners as meta-learners. The average values of the metrics ACC, F1, and AUC, along with the average runtime, were verified on the mixed dataset. The specific results are shown in Table 1.

After selecting the base learners, when the meta-learners were KNN, LR, SVM, RF, AdaBoost, GBDT, and XGBoost respectively, the stacked ACC and F1 scores all exceeded 94%. This demonstrates that meta-learners can fully leverage the strengths of different base learners. However, for the binary classification task of power equipment water immersion early warning, to maximize the strengths of the base learners, the meta-learner should be selected to achieve the optimal ensemble outcome. As shown in the table, when LR serves as the meta-learner, the Stacking ensemble model performs best, yielding the highest ACC, F1, and AUC values. Table 1 shows that except for LR, ensemble learners as meta-learners exhibit longer runtime than single learners. Notably, AdaBoost and GBDT as meta-learners exceed 720 seconds, attributed to their more complex internal structures. However, when LR serves as the meta-learner, the runtime is only 434.05 seconds—shorter than when any single learner is used as the meta-learner. This demonstrates that employing LR as the meta-learner reduces the model's complexity.

Therefore, the water immersion early warning model for power equipment based on multi-hyperclassifier fusion Stacking ensemble learning ultimately adopts LR as the meta-learner. This approach not only maximizes avoidance of misclassifications and missed detections but also enables rapid and precise detection of water immersion depth. Thus, selecting the optimal meta-learner achieves the best classification performance for this model, thereby assisting power supply enterprises in power equipment maintenance.

Table 1: Selection of meta-learners

Meta-learners	ACC/%	*F*1/%	AUC/%	Time/s
Stacking-KNN	92.08	96.38	83.51	543.12
Stacking-LR	97.35	97.28	96.75	434.05
Stacking-SVM	94.42	94.98	94.48	493.48
Stacking-RF	95.27	94.51	96.22	543.27
Stacking-AdaBoost	95.38	94.37	96.08	763.35
Stacking-GBDT	95.41	94.72	95.34	721.62
Stacking-XGBoost	95.62	95.78	96.37	458.83

(2) Flood Depth Prediction

This paper utilizes meteorological information, equipment operation data, micro-topography data, and real-time damage reports provided by meteorological and power authorities. Employing a geographic coordinate system within the ArcGIS Geographic Information System, it constructs a geographic information model and digital twins for 278 low-lying substations in a coastal city in China. Collected data includes meteorological parameters such as typhoon paths, wind speeds and forces, central pressure, surrounding sea depths, and precipitation; electrical equipment parameters including design wind speeds and maximum allowable water immersion heights; and geographic information encompassing elevation, slope aspect, slope gradient, slope position, and surface conditions.

Prediction results from specific datasets were compared against power station rated water immersion levels. A Stacking ensemble model combining RF, SVM, and XGBoost was constructed and evaluated against other AI models. Water immersion depth prediction errors are shown in Table 2. The data in the table indicates that compared to numerous classical machine learning models, the Stacking ensemble learning model constructed in this paper achieves the lowest prediction error across different datasets for power equipment flood warning. Its MSE, MAE, RMSE, and standard deviation of prediction error (STD) are all significantly smaller in magnitude than those of other models. Moreover, the confidence interval half-width derived from the prediction results of this model is narrower, indicating higher accuracy in water immersion early warning for power equipment.

Table 2: Prediction error of flooding depth

Model	Dataset A				Dataset B			
	MSE	MAE	RMSE	STD	MSE	MAE	RMSE	STD
Stacking	1e-06	0.0003	0.0027	0.0038	0.0001	0.0024	0.0151	0.0115
MLP	0.0048	0.0537	0.0713	0.0506	0.1833	0.2248	0.4218	0.4194
GBDT	0.002	0.0004	0.0144	0.0143	0.1064	0.2125	0.3264	0.2928
KNN	0.0015	0.0012	0.0352	0.0351	0.0389	0.0814	0.1924	0.1943
AdaBoost	0.0437	0.0948	0.2048	0.1767	0.2814	0.4543	0.5348	0.4503
RF	0.0001	0.0002	0.0164	0.0164	0.1315	0.2214	0.3627	0.1237
SVM	0.0008	0.0005	0.0311	0.0315	0.0061	0.0531	0.2537	0.1368
XGBoost	0.0012	0.0148	0.0408	0.0428	0.1713	0.2738	0.4123	0.2443

(3) Model Performance Comparison

The Stacking ensemble model designed in this paper was compared with individual machine learning models. Using ACC, Macro-F1, and REC as evaluation metrics, the performance comparison results of the Stacking ensemble model versus three primary learners on the power equipment water immersion data test set are shown in Figure 6.

As shown in the figure, the proposed Stacking ensemble model achieves accuracy improvements of 24.29%, 6.43%, 9.28%, and 3.95% over the single machine learning models (LR, SVM, RF, and XGBoost), respectively. When applied to power equipment water immersion early warning, the designed Stacking ensemble learning model achieved a maximum recall rate of 99.98%, surpassing the best-performing SVM model by 7.51 percentage points. Additionally, it avoided the low precision issues observed in the XGBoost model for certain equipment scenarios, significantly mitigating the impact of sample imbalance. The Stacking ensemble learning model demonstrated outstanding performance across all three metrics. Therefore, leveraging the Stacking ensemble learning strategy enables the integration of multiple machine learning algorithms to achieve precise water immersion early warning for power equipment after determining the immersion depth. This provides reliable, forward-looking results for power supply companies to conduct emergency repairs and ensure the stable operation of the power system.

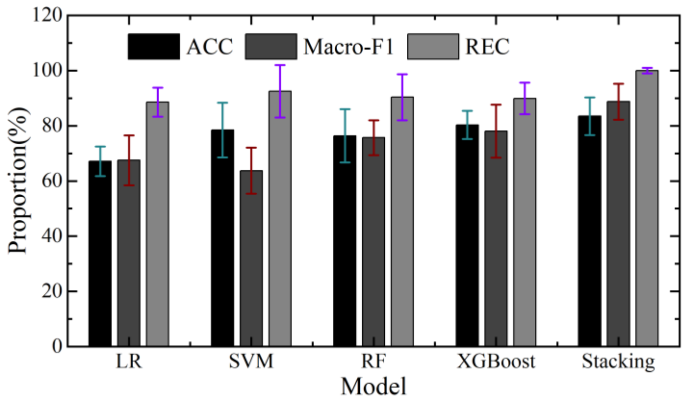


Figure 6: Performance comparison results of the model

(4) Model Stability

The previous subsection applied the Stacking ensemble learning model proposed in this paper to identify water immersion conditions in electrical equipment, achieving high recognition accuracy. Another crucial metric for evaluating model performance is stability, which reflects the model's generalization capability by measuring how its recognition performance changes when the data distribution undergoes perturbations within a training set of the same size. The most common method for assessing model stability is cross-validation, an approach also adopted in the Stacking phase of the ensemble learning model in this paper.

To analyze the stability of the model designed in this paper, ten-fold cross-validation was employed. This involves dividing the original dataset into ten equal parts, denoted as K1 to K10. First, models were trained using data from K2 to K10 and then predicted on K1. Similarly, models were trained using data from K1 and K3 to K10 and predicted on K2, and so on, to obtain predictions across the entire original dataset. Analyzing the fluctuation in accuracy across these ten folds reveals the model's stability.

Using a dataset from transformer scenarios in substations as the analysis subject, we compare the recognition results of the Stacking ensemble learning model designed in this paper with those of single models (SVM, RF, XGBoost, LR) under 10-fold cross-validation. The evaluation metric adopts the average F1 score, which simultaneously considers missed detections and false positives. Specifically, it represents the average F1 score for each model's recognition rate of water immersion warnings. The test results are shown in Figure 7. It is evident that ensemble models (RF, XGBoost) exhibit lower variability compared to traditional models (LR, SVM), demonstrating the stability advantage of ensemble learning. Concurrently, the Stacking ensemble model shows the smallest fluctuation in power equipment water immersion warning results, achieving an average F1 score of 0.992. This confirms that the designed power equipment water immersion warning model possesses high stability and accuracy.

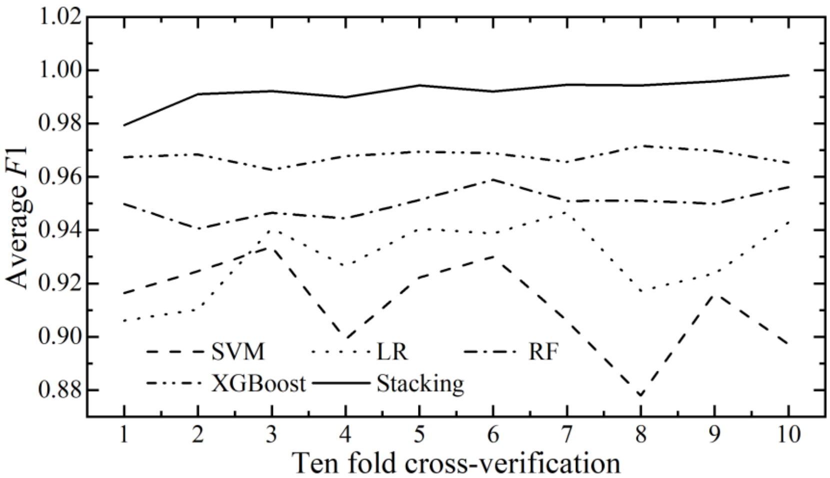


Figure 7: Ten fold cross-verification recognition results

4.2 Power System Resilience Assessment Analysis

Based on the water immersion warning results for power equipment, combined with the previously outlined calculation methods and procedures for power system resilience assessment indicators, simulations were conducted to model the evolution of water immersion risks affecting power equipment. During a single simulation cycle, four distinct scenarios of cascading accident chains were considered. After accounting for the power system's recovery process, the corresponding performance evolution curves for these four scenarios are shown in

Figure 8. The resilience metrics for the system under each fault chain are calculated based on the system performance change curves, with specific results presented in Table 3. In the table, V1, S, T, V2, AR, C denote the system performance degradation rate, system performance degradation magnitude, derated operation duration, system performance recovery rate, resilience metric, and lost load capacity, respectively.

Figure 8 reveals that the trends in system performance changes during a single simulation run exhibit similarities. This is because the timing of performance degradation and recovery is determined by the sampling results of component failures and restoration events. Within a single sampling round, these results share similarities. Through multiple simulation rounds, high-risk accident chains in the system can be comprehensively covered. The resilience metrics across different accident chains in the table reveal that accident chains 1 and 2 exhibit similar evolutionary processes. The minimal differences in the (V1, S, T, V2) metric values indicate the validity of these metrics and their applicability to specific fault evolution sequences. The AR for a single accident chain is derived from the product of its occurrence probability and cumulative lost load. This single-chain AR quantifies the risk level of that specific chain. For the entire system, the average AR value across multiple simulations measures the system's resilience under that round of extreme weather conditions. A lower value indicates a reduced risk level for that accident chain. The (V1, S, T, V2) metric and the AR metric complement each other, reflecting power system resilience from two perspectives: specific accident manifestations and comprehensive power loss risk.

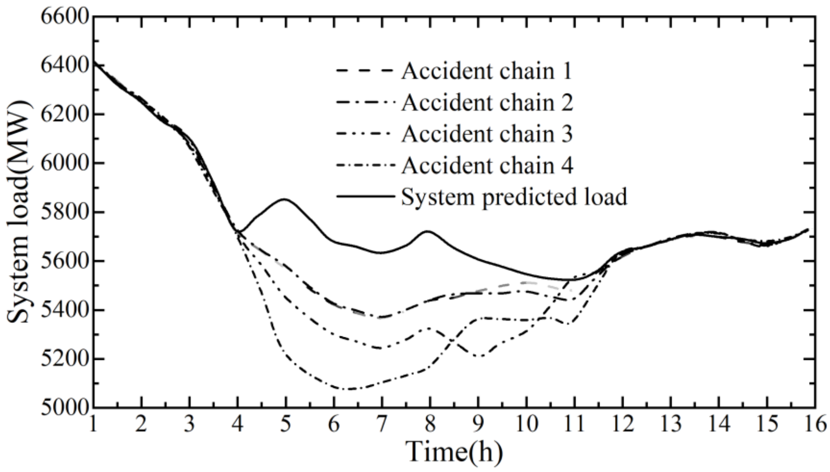


Figure 8: System's function curve of different fault chains

Table 3: Resilience index under different fault chains

Code	Probability	V1	S	T	V2	AR	C(MW·h)
1	$2.51*10^{-6}$	91.7	272.6	5	39.8	0.0029	1157.8
2	$8.86*10^{-6}$	88.3	266.7	5	37.5	0.0095	1074.3
3	$8.31*10^{-5}$	116.14	351.7	5	51.4	0.1366	1643.6
4	$5.12*10^{-5}$	242.6	485.3	4	78.6	0.1136	2218.7

5 Conclusion

This paper constructs a water immersion situation detection model for power equipment based on the ArcGIS system. By incorporating multiple machine learning algorithms and employing Stacking ensemble learning, an intelligent early warning model for power equipment water immersion is designed. Simulation results demonstrate that the proposed model achieves superior prediction accuracy for water immersion depth compared to benchmark models, with an overall early warning recall rate reaching 99.98%. Furthermore, simulations were conducted to assess the system resilience of power equipment post-flooding. Results from multiple simulation rounds align closely with the actual resilience recovery patterns observed in power systems. This research offers a novel approach to ensuring the stable operation of power equipment and grids, serving as an effective method to prevent power system failures during extreme weather events.

About the Author

Mengyuan Huang, born in 1993 in Yuncheng City, Shanxi Province, is a postgraduate student of Taiyuan University of Technology. He is currently working in Guangdong Power Grid Yunfu Luoding Power Supply Bureau, where his main research direction is the application of artificial intelligence technology in new power systems.

Guang Wang, born in 1980 in Suizhou City, Hubei Province, is a master's student at South China University of Technology. He currently works at Guangdong Power Grid Yunfu Luoding Power Supply Bureau, where his main research direction is the application of big data and large model technology in power grid management.

Zihao Feng, born in 1999 in Jingmen City, Hubei Province, graduated from Donghua University of Technology and is currently working in Guangdong Power Grid Yunfu Luoding Power Supply Bureau, where his main research direction is the application of big data analysis technology in new power systems.

Yi Chen, born in 1985 in Qinzhou City, Guangxi Province, graduated from Wuhan University and is currently working at Yunfu Power Supply Bureau of Guangdong Power Grid Co., LTD. Main research direction is the application of new energy storage intelligent technology in new power system.

Weijian Lin, born in 1993 in Zhaoqing City, Guangdong Province, is a master's student of North China Electric Power University. He currently works at Guangdong Power Grid Yunfu Luoding Power Supply Bureau, where his main research direction is the application of digital twin technology in new power systems.

Wenchang Lin, born in 1997 in Yunfu City, Guangdong Province, graduated from South China University of Technology and is currently working at Guangdong Power Grid Yunfu Luoding Power Supply Bureau. Research interests include artificial intelligence technology applications in cyberspace security.

Weiling Zhang, born in 1993 in Yunfu City, Guangdong Province, is an undergraduate student of Guangdong University of Science and Technology. She currently works at Guangdong Power Grid Yunfu Luoding Power Supply Bureau, focusing on the research direction of intelligent transmission application of Internet of Things data in new power systems.

References

[1] Li, H., Li, B., Luo, Z., Li, H., Zhao, Y., Wang, T., & Sun, Y. (2022). Power supply reliability enhancement for low-voltage distribution area with power quality improvement function. IEEE Access, 10, 130619-130631.

[2] Wan, D., Wang, H., Hu, G., & Zheng, Z. (2024, July). Design and Analysis of Key Equipment for Large Capacity Power Systems. In International Conference on Intelligent

Robotics and Applications (pp. 72-85). Singapore: Springer Nature Singapore.

[3] Song, J., Hur, K., Lee, J., Lee, H., Lee, J., Jung, S., ... & Kim, H. (2020). Hardware-in-the-loop simulation using real-time hybrid-simulator for dynamic performance test of power electronics equipment in large power system. Energies, 13(15), 3955.

[4] Shield, S. A., Quiring, S. M., Pino, J. V., & Buckstaff, K. (2021). Major impacts of weather events on the electrical power delivery system in the United States. Energy, 218, 119434.

[5] Banasik, K. A., & Chojnacki, A. (2025). Influence of atmospheric conditions represented by wind, precipitation and air temperature on the intensity of failures of medium-voltage power lines. Przegląd Elektrotechniczny, 101.

[6] Yifan, L., Yao, Y., Lin, Y., Yanpeng, H., Ao, T., Fuzeng, Z., & Licheng, L. (2018, November). The Study of Extremely Heavy Rainfall Effect on Power System Insulation Equipment Based on Electric Field Simulation. In 2018 International Conference on Power System Technology (POWERCON) (pp. 461-467). IEEE.

[7] Zhang, Z., Wang, T., Li, J., Feng, J., Guan, C., & Yan, Y. (2023, August). Research on power grid equipment disaster loss model based on" strong wind and heavy rain" combined disaster. In 2023 2nd International Conference on Smart Grids and Energy Systems (SGES) (pp. 29-33). IEEE.

[8] Zhou, Z., Zhang, C., Xu, C., Xiong, F., Zhang, Y., & Umer, T. (2018). Energy-efficient industrial internet of UAVs for power line inspection in smart grid. IEEE Transactions on Industrial Informatics, 14(6), 2705-2714.

[9] Qian, G., Zhang, J., Deng, Z., Huang, Q., & Hu, L. (2023, December). Research on Intelligent Inspection Method of Multi-robot Joint Inspection of Power Equipment under New Energy Access. In 2023 13th International Conference on Power and Energy Systems (ICPES) (pp. 295-299). IEEE.

[10] Tian, L., Mao, M., Hou, B., & Ma, G. (2025). Research of Power Inspection Based on Intelligent Algorithm. IAENG International Journal of Computer Science, 52(4).

[11] Wang, E., Meng, X., Yu, J., Wang, J., & Yin, L. (2025). An unmanned intelligent inspection technology based on improved reinforcement learning algorithm for power large-area multi-scene inspection. Scientific Reports, 15(1), 24933.

[12] Martinez, C., Sampedro, C., Chauhan, A., Collumeau, J. F., & Campoy, P. (2018). The Power Line Inspection Software (PoLIS): A versatile system for automating power line inspection. Engineering applications of artificial intelligence, 71, 293-314.

[13] Liang, M., Liu, L., Liang, W., Mi, W., Ye, K., & Gao, J. (2024). Intelligentization helps the green and energy-saving transformation of power industry-evidence from substation engineering in China. Scientific Reports, 14(1), 8698.

[14] Qingshan, M. A., Yuwei, S. U. N., Weichao, D. E. N. G., Xinchun, Y. U., Jianbao, Z. H. U., & Zhongyi, W. A. N. G. (2020). Power equipment risk assessment based on health and importance. Journal of Electrical Engineering, 15(4), 144-152.

[15] Huang, H., & Davis, K. (2018, October). Power system equipment cyber-physical risk assessment based on architecture and critical clearing time. In 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm) (pp. 1-6). IEEE.

[16] Pham, N. L., & Tran, T. P. (2023). Flooding Prevention in High Voltage Substations Using IoT based System. JST: Smart Systems and Devices, 33(2), 35-42.

[17] Kondalkar, V. V., Ryu, G., Lee, Y., & Lee, K. (2019). Development of highly sensitive and stable humidity sensor for real-time monitoring of dissolved moisture in transformer-insulating oil. Sensors and Actuators B: Chemical, 286, 377-385.

[18] Korotcenkov, G., Simonenko, N. P., Simonenko, E. P., Sysoev, V. V., & Brinzari, V. (2023). Based Humidity Sensors as Promising Flexible Devices, State of the Art, Part 2: Humidity-Sensor Performances. Nanomaterials, 13(8), 1381.

[19] Ansari, M. A., Martin, D., & Saha, T. K. (2019). Investigation of distributed moisture and temperature measurements in transformers using fiber optics sensors. IEEE transactions on power delivery, 34(4), 1776-1784.

[20] Warren-Smith, S. C., Schartner, E. P., Nguyen, L. V., Otten, D. E., Yu, Z., Lancaster, D. G., & Ebendorff-Heidepriem, H. (2019). Stability of grating-based optical fiber sensors at high temperature. IEEE Sensors Journal, 19(8), 2978-2983.

[21] Ke, X., Lou, L., Xu, R., & Peng, J. (2025). A flood hazard cause classification model for substation flood prevention case text. Electric Power Systems Research, 249, 112002.

[22] Hu, H., Li, X., Wang, Z., & Jia, Z. (2024). Moisture Degradation Characteristics and Multi-Performance-Based Status Assessment Method of Distribution Cables. IEEE Transactions on Power Delivery, 39(6), 3017-3027.

[23] Atiq, S., Moeen, M., Siddique, A., Aslam, W., & Alsufiani, K. D. (2025). Machine Learning-Based Health Index Prediction for XLPE Power Cables: Enhancing Reliability and Cost-Effective Maintenance. Energy Science & Engineering.

[24] Afzal, S., Mokhlis, H., Illias, H. A., Bajwa, A. A., Mohamad, H., Mansor, N. N., ... & Ramasamy, A. K. (2025). Modeling impact of urban flash floods on power distribution system using Monte Carlo technique and reinforcement learning. Ain Shams Engineering Journal, 16(3), 103325.

[25] Tang, W., Brown, K., Mitchell, D., Blanche, J., & Flynn, D. (2023). Subsea power cable health management using machine learning analysis of low-frequency wide-band sonar data. energies, 16(17), 6172.

[26] Sk Tahsin Hossain,Tan Yigitcanlar,Kien Nguyen & Yue Xu. (2025). Platform urbanism for resident safety: A real-time predictive microclimate risk monitoring and alert system. Urban Climate,61,102445-102445.

[27] Mohit Choubey,Rahul Kumar Chaurasiya & J.S. Yadav. (2025). Robust electric load forecasting through ensemble learning: A stacking approach with empirical mode decomposition and transfer learning. Computers and Electrical Engineering,126,110511-

110511.

[28] Chengyi Cai,Hui Liu & Zhu Duan. (2025). Dynamic stacking ensemble hybrid model for enhanced short-term photovoltaic power forecasting with self-organizing maps and advanced deep learning. Energy Reports,13,4280-4298.