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RESEARCH ARTICLE

External Risk Assessment for Substations Based on Single and Superimposed Anomaly Risks

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ABSTRACT Substations, as critical components of the power system, are frequently exposed to various external risks during operation. Without timely monitoring and effective evaluation, the risks caused by anomalies can undermine the stability of the mining area's power system, potentially leading to significant production interruptions and safety accidents. However, current research mainly focuses on the substation internal risks. Regrettably, there is currently a lack of implementable external risk assessment methods for substations. To detect substation external risk level effectively, an external risk assessment method for substations based on single and superimposed anomaly risks is proposed. First, the CAVF (Identification credibility C, anomaly area proportion A, anomaly development velocity V and correction factor F) external risk assessment model is constructed, based on the improved PES (Probability, Exposure, Sequel) operational risk assessment method. Next, the collaborative set pair analysis of uncertain AHP (Analytic Hierarchy Process) is used to assign weights to the importance of different anomalies, addressing the differences in the impact of each anomaly and the fuzziness of expert judgment. Then, the IDO (Identity Difference Opposition) contact measure method is adopted to determine the substation external risk level under multiple superimposed anomalies, with the importance weight vector of anomalies. Finally, the substation external risk level is evaluated, comprehensively considering the risks of single and multiple superimposed anomalies. A case in an actual scenario shows the effectiveness of the proposed method, highlighting its significant impact on optimizing maintenance configurations and ensuring the safe operation of substations.

INDEX TERMS Substation, state assessment, external risk levels, CAVF model, IDO contact measure method.

I. INTRODUCTION

Adverse weather conditions such as heavy rain, storms, or extreme temperatures bring several operational challenges for substations in Shanxi Province, China [1], [2], [3], [4], [5]. Meanwhile, geological conditions in mining subsidence areas may lead to settlement and tilting [6], causing stress concentration [7] and subsequently altering the external state of equipment and components. Under a variety of external harsh conditions, essential substation components like insulators, bushings, fuses, and oil pillows may deteriorate [8], [9],which may affect power transmission and potentially lead to risk incidents [10].

To understand and quantify the specific impacts of natural disasters, human errors, equipment failures, or other anomalies on power systems, conducted extensive research is carried out [11], [12], [13], [14], [15]. These studies can be mainly divided into two directions. Firstly, the mechanisms of power system risks under various weather conditions and natural disasters are explored to determine the likelihood of these risks [16], [17]. Second, various related risk factors are considered to quantify the overall risk of power systems. These methods provide theoretical guidance for management, operation, maintenance, and safety decision-making

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processes [18], [19]. However, existing risk assessment methods for electrical equipment primarily focus on overhead transmission lines, cables, and broader power system risks.

There is relatively little research on the risks of substations, which is still in development. The standardized lightning risk assessment process is supplemented by adjusting key risk factors such as fire load function, environmental factors, and Lightning Protection Level (LPL) [20]. The main risk components in substations are highlighted in [21]. The minimal cut set algorithm is used to evaluate seismic risks in substation systems [22], and two risk reduction strategies of seismic reinforcement and adding redundant equipment are proposed. The risk of substation under natural disasters is studied but the influence of comprehensive risk on substation is not fully considered. The external risk assessment of substations involves numerous factors. Substation components interact with external weather and environmental factors, complicating the integration of these multi-source factors into the assessment model. Considering the influence of multiple anomalies comprehensively and integrating them reasonably into the assessment model are still challenges. Therefore, the risks of substations are modeled and analyzed so that some risk assessment methods can be proposed.

The fuzzy Bayesian classification method is used for dynamic flood risk assessment in substations [23]. dynamic risk assessment methods for substation based on the PES risk assessment method are proposed [24], [25]. Furthermore, the PES method lacks mechanisms to adjust risk values in response to varying environmental impacts, leading to potential inaccuracies in risk evaluations [26]. There is currently no clear and explicit method for quantifying values. These methods address the simplicity and rigidity of previous safety operation risk assessment methods. AHP (Analytic Hierarchy Process) is combined with a system risk assessment method, applying the Bellman-Zadeh method for decision-making in fuzzy environments [27]. Additionally, a substation operation risk assessment method based on the triangular fuzzy number AHP method is proposed [28]. However, traditional AHP relies on expert subjective opinions, failing to address the fuzziness and uncertainty of subjective judgments.

To address these problems, a mathematical model method based on element analysis is adopted firstly in this paper. The current threat elements are quantified based on domain knowledge and establishes a mathematical model to assess the substation external risk level. The method can be performed in the absence of a large number of historical accident records. Therefore, it is suitable for substations with complex environments, frequent background changes, and high requirements for information confidentiality. Then, the improved PES operational risk assessment method by establishing the CAVF (Identification credibility C, anomaly area proportion A, anomaly development velocity V and correction factor F) external risk assessment model is proposed. Abnormal risk indicators are quantified, and an external risk assessment model is established under multi-source data interaction. Next, to account for the varying impact of each anomaly and the inherent ambiguity in expert judgment, the collaborative set analysis and uncertainty analytic hierarchy process are employed to assign weights to the importance of different anomalies. Then, the IDO measurement method and weight vector determine the external risk state of substations under multiple superimposed anomalies. Finally, by jointly considering the highest external risk level corresponding to a single anomaly, and the external risk level corresponding to the combined impact of multiple anomalies, the final external risk status of the substation is assessed.

II. EXTERNAL RISK ASSESSMENT MODEL

Leveraging extensive analysis of multifaceted factors and incorporating insights from field experts, a comprehensive external risk assessment model for substations is developed under the framework of multivariate data interaction. Following this, a detailed external risk assessment index system specific to substations is formulated. Subsequently, a robust CAVF external risk assessment model is constructed to systematically evaluate these risks. Finally, the risk levels associated with individual anomalies are meticulously categorized to ensure precise risk identification.

A. ESTABLISH AN EVALUATION INDEX SYSTEM

PES operational risk assessment method is a semi-quantitative external risk assessment method proposed in the Technical Standard of Operational Hazard Identification and Risk Assessment of China Southern Power Grid Company. The assessment model of this method is shown in (1).

$$R_F = P_F \times E_F \times S_F \tag{1}$$

where, R_F represents the external risk value of the evaluated electrical equipment. P_F denotes the likelihood of accidents caused by threat factors. E_F stands for the frequency of personnel exposure to threat factors. S_F indicates the varying degrees of severity of accidents caused by threat factors.

For the external risk assessment of substations, it is defined as a combination of four types of visible anomalies: casing cracking, insulator string drop, oil pillow oil seepage, and fuse tube drop. Various factors, including weather conditions, the interaction of external damage sources, and fault elimination time intervals, are considered. Additionally, the experience of field experts is incorporated for a more comprehensive analysis. The substation external risk assessment index system is illustrated in Fig. 1.

B. CAVF EXTERNAL RISK ASSESSMENT MODEL

1) IDENTIFICATION CREDIBILITY C

A confidence score is generated for each boundary box and mask is generated. The identification credibility C for each type of anomaly is defined as the confidence score produced by the MSAI++ framework. If the framework identifies an anomaly with a high confidence score, it is considered likely that the anomaly will occur in the substation. When the confidence level of the critical anomaly bounding box is greater than 0.6, it is selected as the identification result of the fuse

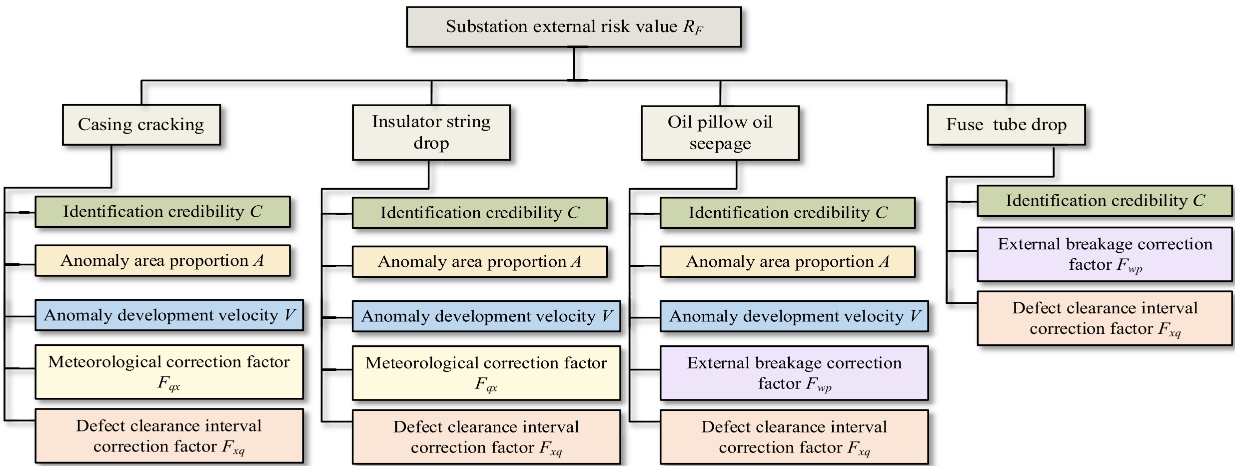

FIGURE 1. Substation external risk assessment index system.

tube drop anomaly. Then, the corresponding confidence score is generated. For bounding boxes with overlapping anomalies after filtering, Non-Maximum Suppression (NMS) is used to eliminate redundancy. Constrained by the confidence threshold (0.6) and the Intersection of Union (IoU) threshold of NMS (0.5), the confidence scores of various anomaly identification results are converted into corresponding identification credibility C in the form of intervals, as shown in Table 1.

TABLE 1. Score quantification table of identification credibility *C*.

Anomaly Confidence	Identification Confidence C Score	Corresponding Description
(0.9, 1]	9	The identification results are highly reliable
(0.8, 0.9]	8	The identification results are reliable
(0.7, 0.8]	7	The identification results are preliminarily reliable
(0.6, 0.7]	5	The reliability of the identification results is low

2) ANOMALY AREA PROPORTION A

The anomaly area proportion A is used to quantify the impact of the anomaly area at a specific time point on the external risks of the substation. For three types of warning anomalies, the identified pixel mask area can reflect the actual severity of the anomaly to some extent. The larger the area, the more serious the potential safety hazard in the substation. Casing cracking and insulator string drop may cause flashover in humid weather, leading to immediate electrical failures. Therefore, even if the area is small, it should be considered a higher risk. Oil pillow oil seepage is usually a gradual accumulation process. Small areas of oil leakage may not immediately cause malfunctions, but large areas of oil leakage can lead to fires. The anomaly area proportion A score is quantitatively divided based on the risk impact of three types of anomalies. For fuse tube drops, precise pixel-level identification is unnecessary. When such anomalies are detected, the power supply may be temporarily interrupted, and a higher value should be assigned in the A-score quantification. Based on the opinions of on-site experts, the quantitative results of the anomaly area proportion A are shown in Table 2.

TABLE 2. Score quantification table of anomaly area proportion *A*.

Anomaly Type	Anomaly Area Proportion A (%)	Anomaly Area Proportion A Score	Corresponding Description
Fuse tube drop	-	9	Instantaneous occurrence, equipment anomalies urgent
Casing cracking, Insulator string drop	(40, 100]	8	Anomalous region significance
	(30, 40]	7	Large anomaly area
	(15, 30]	6	Moderate anomaly area
	(0, 15]	3	Anomalous area minuscule
Oil pillow oil seepage	(50, 100]	8	The oil seepage area is extensive
	(40, 50]	7	The oil seepage area is large
	(25, 40]	6	Oil infiltration area is moderate
	(0, 25]	3	The oil seepage area is small

3) ANOMALY DEVELOPMENT VELOCITY V

The anomaly development velocity V measures the trend of this anomaly over a period. Considering that 24 hours is a relatively complete cycle, the development and changes of anomalies can be observed within a certain period. Thus, the anomaly development velocity can be assessed by comparing the abnormal area growth ratio Δ_{A24h}, which reflects the change in the warning abnormal area in the current image compared to the image from 24 hours prior. If the area of the same warning anomaly in the substation expands by a sufficient proportion within one day, the development velocity of such anomaly is considered fast enough, and the corresponding threat to the overall mobile substation is also higher. Based on the opinions of experts, the quantitative results of the anomaly development velocity V are shown in Table 3.

TABLE 3. Score quantification table of anomaly development velocity V.

Anomaly Type	24h Anomaly Area Growth Ratio Δ_{A24h}(%)	Anomaly Development Velocity V Score	Corresponding Description
Fuse tube drop	-	9	Instantaneous, can cause an accident very quickly
Casing cracking, Insulator string drop, Oil pillow oil seepage	>50	9	The anomaly develops very fast
	(40, 50]	8	Unusually rapid development
	(30, 40]	7	Abnormally fast development
	(20, 30]	6	Abnormally stable development
	(10, 20]	4	Anomalies develop more slowly
	<10	2	Abnormally slow development

4) CORRECTION FACTOR F

a: METEOROLOGICAL CORRECTION FACTOR F_{qx}

The influence of temperature and humidity on flashover of dusty insulating bushings and insulators is determined in [29], as shown in (2).

$$V_{fo} = \frac{0.386 \cdot 760(273+20)100 \cdot V_{sl}}{(273+T_{wd})^2(100-H_{sd})} \tag{2}$$

where, V_{fo} is the flashover voltage under current conditions (kV), V_{sl} is the flashover voltage under standard conditions (kV), T_{wd} is the current ambient temperature (°C), and H_{sd} is the current relative humidity (%).

From the perspective of the impact of temperature and humidity on flashover voltage, the meteorological correction factor F_{qx} is introduced to adjust the final risk value of substation. The meteorological correction factor F_{qx} is defined as in (3):

$$F_{qx} = \delta(V_{av} - V_{fo})/V_{av} \tag{3}$$

where, V_{av} is the flashover voltage (kV) under the conditions of average annual temperature and average annual relative humidity, and δ is the conversion coefficient from flashover voltage to anomaly development, taking 0.1. By substituting the corresponding value, equation (4) is obtained. Temperature $T_{wd} \in [-25, 40]$ (°C), relative humidity $H_{sd} \in [0, 70]$ (%), and meteorological correction factor $F_{qx} \in [-11.40, 5.97]$ (%) are taken as constraint conditions.

$$F_{qx} = 0.1 - \frac{5^*(273+8)^2}{(273+T_{wd})^2(100-H_{sd})} \tag{4}$$

b: EXTERNAL BREAKAGE CORRECTION FACTOR F_{wp}

Referring to the "Guidance for electrical safety risk assessment and risk reduction in multiple application workplace" (GB/T 41092-2021) and the "National safety technical code for electric equipment" (GB 19517-2023), the external breakage correction factor F_{wp} is specifically quantified, as shown in Table 4. If there is an external breaking source in the early warning area with a radius of 200 pixels, the external breakage correction factor F_{wp} is 5%. If no anomaly is detected, the radius will be expanded to 300. If an external breaking source is identified in the newly defined warning area, the external breakage correction factor F_{wp} will be 4%. Each time the two types of anomalies of oil pillow oil seepage and fuse tube drop are identified, the radius of the warning area is successively expanded according to the first column in Table 4, and the value of the external failure correction factor F_{wp} is assigned. If no external break source appears after the traversal is complete, the two types of exceptions are considered unaffected by external interference, and the value of F_{wp} is 0.

TABLE 4. Score quantification table of external breakage correction factor F_{wp}.

Warning Area Radius (pixel)	External Breakage Correction Factor F_{wp}
200	5%
300	4%
400	3%
500	2%
600	1%

5) DEFECT CLEARANCE INTERVAL CORRECTION FACTOR F_{XQ}

The defect clearance interval correction factor F_{xq} for the defect clearance interval is determined using the defect clearance time interval as the benchmark, based on the opinions of the on-site operation and inspection members, as shown in Table 5. In areas with short gap elimination intervals, the time for anomaly development is relatively limited, allowing the risk to be controlled in a timely manner. A small defect clearance interval correction factor F_{xq} should be assigned to constrain the final risk value, about 0.6. On the contrary, for the region with a long interval, the timeliness of risk control is not as good as the former, and the correction factor F_{xq} is too large, about 0.8.

TABLE 5. Score quantification table of defect clearance interval correction factor F_{xq}.

Scenes	Defect Clearance Interval	Defect Clearance Interval Correction Factor F_{xq}
Working section Contact road	10 days	0.6
Auxiliary line Coal preparation area	30 days	0.8

C. SINGLE ANOMALY RISK CLASSIFICATION

Based on the CAVF external risk assessment model, the external risk value RF corresponding to each type of anomaly is determined as shown in (5).

$$R_F = C \times A \times V \times (1 + F) \times F_{xq} \tag{5}$$

where, C represents the identification credibility, A denotes the anomaly area proportion, V signifies the anomaly development velocity, and F_{qx} is the fault elimination interval correction factor. When casing cracking or insulator string drop anomalies occur, F is the meteorological correction factor F_{qx}; when oil pillow oil seepage or fuse tube drop anomalies occur, F is the external breakage correction F_{wp}.

Based on the calculation of the single anomaly external risk value obtained from (4) and combined with field experts' opinions, using the method of percentile segmentation, the external risks of substations with single anomalies occurring under various circumstances can be divided into five levels: *a, b, c, d, e*. These respectively correspond to "extremely dangerous," "highly dangerous," "moderately dangerous," "low-level danger," and "relatively safe" severity levels.

III. ANALYZE THE IMPORTANCE OF DIFFERENT ANOMALIES IN SUBSTATIONS

In the actual scenario, multiple anomalies may arise, and different anomalies have different impacts on the whole substation. To comprehensively evaluate the external risks facing the substation, it is necessary to assign importance to all kinds of anomaly first-level indicators first. To comprehensively evaluate the external risks facing the substation, this paper uses the uncertain AHP method of cooperative set pair analysis to assign weight to the importance of four types of anomalies, enabling a more precise determination of the relative significance of each anomaly type.

A. BUILD HIERARCHY

To ensure that substation external risks are fully assessed, a hierarchical structure model is constructed in this paper. The model can characterize the level of substation external risks based on the measurability and comprehensiveness of evaluation criteria, including the destination layer, criterion layer, and scheme layer. Among them, the criterion layer consists of four types of anomalies that affect the substation external risks. The hierarchical structure model is shown in Fig. 2.

B. DETERMINISTIC JUDGMENT MATRIX

To deeply analyze the operational anomalies or power supply incidents of substations caused by various anomaly situations, four experts were invited for detailed discussion and analysis. These experts include the Director of the Operation and Inspection Center of the Power Supply Company, the Chief and Technician of the Substation Operation and Inspection Team, the Deputy Chief, and the Safety Production Manager. They independently rated the importance of four anomaly indicators: casing cracking, insulator string drop, oil pillow oil seepage, and fuse tube drop. This resulted in the uncertain interval judgment matrix $A^{(K)}(k = 1{,}2{,}3{,}4)$, as shown in (6)

$$A^{(1)} = \begin{bmatrix} [1,1] & [3,4] & [\frac{1}{7},\frac{1}{6}] & [\frac{1}{8},\frac{1}{7}] \\ [\frac{1}{4},\frac{1}{3}] & [1,1] & [\frac{1}{8},\frac{1}{6}] & [\frac{1}{9},\frac{1}{8}] \\ [6,7] & [6,8] & [1,1] & [\frac{1}{3},\frac{1}{2}] \\ [7,8] & [8,9] & [2,3] & [1,1] \end{bmatrix},$$
$$A^{(2)} = \begin{bmatrix} [1,1] & [2,4] & [\frac{1}{5},\frac{1}{4}] & [\frac{1}{8},\frac{1}{6}] \\ [\frac{1}{4},\frac{1}{2}] & [1,1] & [\frac{1}{7},\frac{1}{5}] & [\frac{1}{8},\frac{1}{7}] \\ [4,5] & [5,7] & [1,1] & [\frac{1}{4},\frac{1}{3}] \\ [6,8] & [7,8] & [3,4] & [1,1] \end{bmatrix}$$
$$A^{(3)} = \begin{bmatrix} [1,1] & [2,3] & [\frac{1}{6},\frac{1}{5}] & [\frac{1}{7},\frac{1}{6}] \\ [\frac{1}{3},\frac{1}{2}] & [1,1] & [\frac{1}{7},\frac{1}{6}] & [\frac{1}{8},\frac{1}{6}] \\ [5,6] & [6,7] & [1,1] & [\frac{1}{3},\frac{1}{2}] \\ [6,7] & [6,8] & [2,3] & [1,1] \end{bmatrix},$$
$$A^{(4)} = \begin{bmatrix} [1,1] & [2,4] & [\frac{1}{7},\frac{1}{6}] & [\frac{1}{8},\frac{1}{6}] \\ [\frac{1}{4},\frac{1}{2}] & [1,1] & [\frac{1}{7},\frac{1}{6}] & [\frac{1}{8},\frac{1}{7}] \\ [6,7] & [6,7] & [1,1] & [\frac{1}{2},1] \\ [6,8] & [7,8] & [1,2] & [1,1] \end{bmatrix} \tag{6}$$

C. CALCULATE INDEX WEIGHT

The weight of experts is assessed based on their credibility, due to differences in engineering experience. Expert credibility is determined by both overall similarity and local differences [30].

1) CALCULATE OVEROLL SIMILARITY

The uncertain interval judgment matrix $A^{(k)}$ is decomposed into row vectors $(a_{11}, \cdots, a_{n1}, a_{12}, \cdots, a_{n2} \cdots a_{1n}, \cdots, a_{nn}, b_{11}, \cdots, b_{n1}, b_{12}, \cdots, b_{n2}, \cdots, b_{1n}, \cdots, b_{nn})_{1\times 2n^2}$. The decomposed row vectors of $A^{(l)}$, and $A^{(k)}$ are $\partial = (\partial_i)$ and $\ell = (\ell_i)$ respectively. The similarity between the two vectors

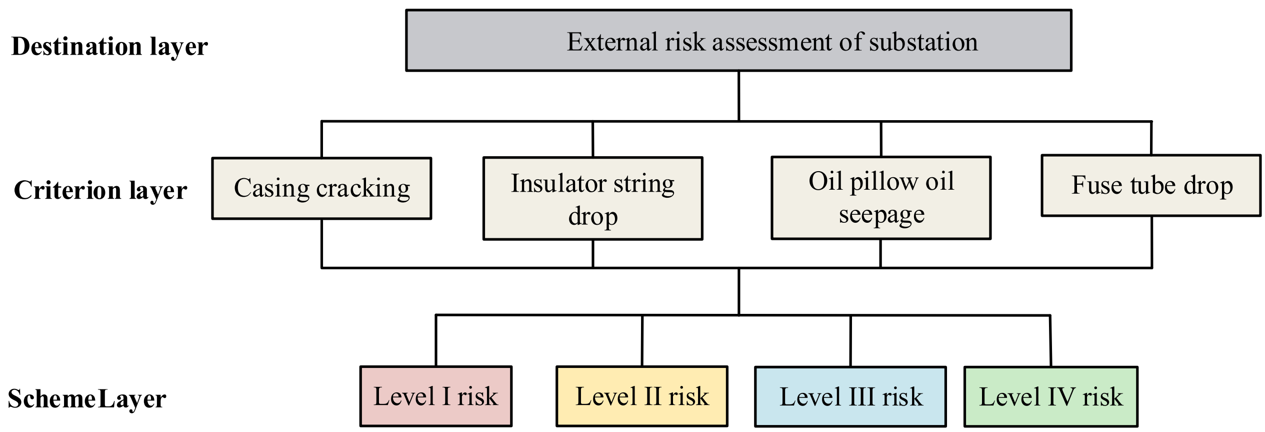

FIGURE 2. Hierarchical structure model of substation external risk assessment.

is inversely proportional to the cosine of the angle between them, as shown in (7).

$$\gamma_{lk} = \cos\theta = \frac{\sum_{i=1}^{2n^2} \partial_i \ell_i}{\sqrt{\sum_{i=1}^{2n^2} \partial_i^2}\sqrt{\sum_{i=1}^{2n^2} \ell_i^2}} \tag{7}$$

In (7), $0 \le \gamma_{lk} \le 1$, when $\partial_i = \ell_i$, $\gamma_{lk} = 1$.

$$\gamma_k = \sum_{l=1, l\neq k}^{q} \gamma_{lk} \tag{8}$$

where γ_k is the sum of similarities between $A^{(k)}$ and other uncertain interval judgment matrices. The overall similarity λ_k between the k-th expert decision and those of other expert can be obtained post-normalization, as shown in (9).

$$\lambda_k = \frac{\gamma_k}{\sum_{k=1}^{q} \gamma_k} \tag{9}$$

2) CALCULATE LOCAL DIFFERENCE

The total difference between the k-th expert decision and the mean of all expert decisions is obtained, by equating the decomposed row vector of $A^{(k)}$ to $(h_j)_{1\times 2n^2} = (h_1, h_2, \cdots, h_{2n^2})$, as shown in (10).

$$\sigma_k = \sum_{j=1}^{2n^2} \left| h_j^{(k)} - \frac{1}{q}\sum_{i=1}^{n} h_j^{(i)} \right| \tag{10}$$

The local difference between the k-th expert decision and other expert decisions is obtained post-normalization, as shown in (11).

$$\delta_k = \frac{\sigma_k}{\sum_{k=1}^{q} \sigma_k} \tag{11}$$

3) CALCULATE COMPREHENSIVE RELIABILITY

The comprehensive reliability α_k of experts is dynamically weighted, by integrating both the overall similarity and local difference, as shown in (12).

$$\alpha_k = \begin{cases} \lambda_k & \sum_{i=1}^{q} \lambda_i \delta_i = 1 \\ \dfrac{\lambda_k (1-\delta_k)}{1-\sum_{i=1}^{q} \lambda_i \delta_i} & \sum_{i=1}^{q} \lambda_i \delta_i \neq 1 \end{cases}, k = 1, 2, \cdots, q \tag{12}$$

Based on (7)-(12), the overall similarity, local difference and comprehensive reliability for the four experts are computed. The results are shown in Table 6.

TABLE 6. Comprehensive reliability calculation results.

Index	Director of Transportation Inspection Center	Monitor	Vice Monitor	Responsible Person for Security Production
Overall similarity	0.2508	0.2489	0.2506	0.2497
Local difference	0.2714	0.2993	0.1854	0.2439
Comprehen sive reliability	0.2436	0.2325	0.2722	0.2517

As is shown in Table 6, the overall similarity and local difference among the four experts are similar, indicating the reliability of the results. Therefore, the final weight assigned to each expert is as follows:

$$\alpha_k = (\alpha_1, \alpha_2, \alpha_3, \alpha_4) = (0.2436, 0.2325, 0.2722, 0.2517) \tag{13}$$

IV. ASSESS SUBSTATION EXTERNAL RISK LEVEL BASED ON IDO CONNECTIVITY MEASUREMENT

The substation may be affected by multiple superimposed anomalies, with anomalies interacting and escalating risks.

However, accurately accounting for these interactions is challenging, and the highest risk level of single anomaly is often overlooked. Therefore, the IDO correlation measurement is adopted to assess the comprehensive correlation of substation external risks under multiple superimposed anomalies, enabling an accurate assessment of the substation external risk level.

A. DETERMINATE SINGLE ANOMALY CORRELATION DEGREE

Multiple anomalies often occur simultaneously in practical scenarios. The substation external risk level under multiple superimposed anomalies is categorized into five distinct levels in this paper: A, B, C, D, and E, representing "extremely dangerous", "highly dangerous", "moderately dangerous", "low-level dangerous", and "relatively safe", respectively. To encompass all single anomalies, the global minimum and maximum values are calculated based on the risk classification of each single anomaly. Consequently, the critical value of the single anomaly comprehensive risk is obtained.

The IDO correlation measurement method is used to determine the set pair correlation between the actual risk values of each single anomaly and their respective risk levels. The method enables a more in-depth assessment of the external risk posed by multiple superimposed anomalies. The values range between -1 and 1. A value of 1 indicates identity when the anomaly is at a specific level. A value of -1 indicates opposition when the anomaly spans two or more levels. A value in the range $(-1, 1)$ indicates a difference when the anomaly is at an adjacent level.

The set pair connectivity of the substation external risk level under multiple superimposed anomalies for each single anomaly, is as follows:

Level E - relatively safe:

$$\tau_i[E] = \begin{cases} 1 & R_{Fi} \in [0, R_{Ft1}] \\ 1 - \dfrac{2(R_{Fi} - R_{Ft1})}{R_{Ft2} - R_{Ft1}} & R_{Fi} \in (R_{Ft1}, R_{Ft2}] \\ -1 & R_{Fi} \in (R_{Ft2}, R_{Ft5}] \end{cases} \tag{14}$$

Level D - low-level dangerous:

$$\tau_i[D] = \begin{cases} 1 - \dfrac{2(R_{Ft1} - R_{Fi})}{R_{Ft1} - R_{Ft0}} & R_{Fi} \in [0, R_{Ft1}] \\ 1 & R_{Fi} \in (R_{Ft1}, R_{Ft2}] \\ 1 - \dfrac{2(R_{Fi} - R_{Ft2})}{R_{Ft3} - R_{Ft2}} & R_{Fi} \in (R_{Ft2}, R_{Ft3}] \\ -1 & R_{Fi} \in (R_{Ft3}, R_{Ft5}] \end{cases} \tag{15}$$

Level C - moderately dangerous:

$$\tau_i[C] = \begin{cases} -1 & R_{Fi} \in [0, R_{Ft1}] \\ 1 - \dfrac{2(R_{Ft2} - R_{Fi})}{R_{Ft2} - R_{Ft1}} & R_{Fi} \in (R_{Ft1}, R_{Ft2}] \\ 1 & R_{Fi} \in (R_{Ft2}, R_{Ft3}] \\ 1 - \dfrac{2(R_{Fi} - R_{Ft3})}{R_{Ft4} - R_{Ft3}} & R_{Fi} \in (R_{Ft3}, R_{Ft4}] \\ -1 & R_{Fi} \in (R_{Ft4}, R_{Ft5}] \end{cases} \tag{16}$$

Level B - highly dangerous:

$$\tau_i[B] = \begin{cases} -1 & R_{Fi} \in [0, R_{Ft2}] \\ 1 - \dfrac{2(R_{Ft3} - R_{Fi})}{R_{Ft3} - R_{Ft2}} & R_{Fi} \in (R_{Ft2}, R_{Ft3}] \\ 1 & R_{Fi} \in (R_{Ft3}, R_{Ft4}] \\ 1 - \dfrac{2(R_{Fi} - R_{Ft4})}{R_{Ft5} - R_{Ft4}} & R_{Fi} \in (R_{Ft4}, R_{Ft5}] \end{cases} \tag{17}$$

Level A - extremely dangerous:

$$\tau_i[A] = \begin{cases} -1 & R_{Fi} \in [0, R_{Ft3}] \\ 1 - \dfrac{2(R_{Ft4} - R_{Fi})}{R_{Ft4} - R_{Ft3}} & R_{Fi} \in (R_{Ft3}, R_{Ft4}] \\ 1 & R_{Fi} \in (R_{Ft4}, R_{Ft5}] \end{cases} \tag{18}$$

where $\tau_i[A]\sim\ \tau_i[E]$ are the connection degree between the i-th anomaly and the substation external risks categorized as A-E level under multiple superimposed anomalies. R_{Fti} is the critical value of the single anomaly comprehensive risk. R_{Fi} is the risk value calculated by the CAVF assessment model for the i-th anomaly.

The correlation degree of the substation external risk level under multiple superimposed anomalies are shown in Table 7, where n is the number of anomalies in the scenario to be assessed.

TABLE 7. Correlation degree of substation external risk levels under single anomalies relative to multiple anomalies.

Anomaly Number	Single Anomaly Correlation				
	E	D	C	B	A
1	$\tau_1[E]$	$\tau_1[D]$	$\tau_1[C]$	$\tau_1[B]$	$\tau_1[A]$
2	$\tau_2[E]$	$\tau_2[D]$	$\tau_2[C]$	$\tau_2[B]$	$\tau_2[A]$
…	…	…	…	…	…
n	$\tau_n[E]$	$\tau_n[D]$	$\tau_n[C]$	$\tau_n[B]$	$\tau_n[A]$

B. ASSESS EXTERNAL RISK LEVEL

Firstly, the importance weight vectors w^* for the multiple superimposed anomalies are filtered. Secondly, the importance weight vectors w^{**} for each anomaly in the current assessment scenario are obtained. Thirdly, these vectors are normalized to w^{**}_{avg}. Using the correlation degree in Table 7 and the obtained w_{avg}^{**}, the comprehensive correlation degree of substation external risk level for multiple superimposed anomalies is calculated:

$$\tau[\zeta] = \sum_{i=1}^{n} w_{avg}^{**} \tau_i[\zeta] \tag{19}$$

where $\tau[\zeta]$ is the comprehensive correlation degree of the substation external risk level for all anomalies in the current assessment scenario, $\zeta = A, B, C, D, E$.

Based on the principle of maximum connectivity, the substation external risk level under multiple superimposed anomalies is determined by the level for the maximum value of $\tau[\zeta]$.

$$\tau[k] = \max\{\tau[\zeta]\} \tag{20}$$

The final substation external risk level is determined by assessing both the highest external risk level of the single anomaly and the external risk level of the multiple superimposed anomalies. The risk levels are conducted using a four-level method, as shown in Fig. 3. The arrow indicates the increasing severity of risk levels. The vertical direction indicates the highest external risk level of the single anomaly, whereas the horizontal direction indicates the external risk level of the multiple superimposed anomalies. The risk levels are color-coded as follows: Red indicates an extremely high-risk level (I), necessitating urgent monitoring and immediate inspection of anomalies. Yellow indicates a high hazard level (II), requiring intensive supervision and prompt resolution of detected anomalies. Blue indicates a medium risk level (III), requiring periodic inspections and enhanced safety management. Green indicates a low risk level (IV), and routine monitoring is deemed adequate. Cases Ae, Ad, Ac, and Be are non-existent based on the calculations. Therefore, they are left blank in the figure.

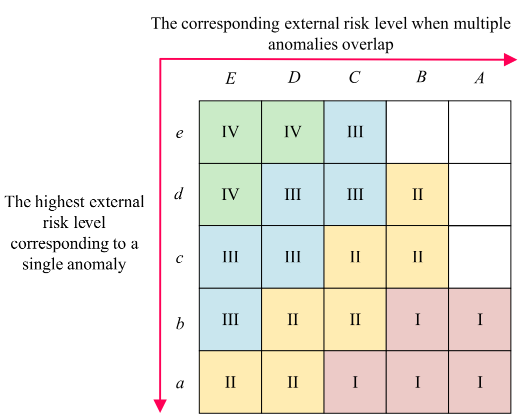

FIGURE 3. The final substation external risk level.

C. ASSESS FOR SUBSTATION EXTERNAL RISK LEVEL COMBINED SINGLE AND SUPERIMPOSED ANOMALIES

The assessment process for the substation external risk level involves several key steps, as shown in Fig. 4. Firstly, an external risk assessment model is developed, incorporating meteorological conditions, interaction with external sources, and time intervals for defect elimination. Secondly, the uncertain AHP with collaborative set pair analysis is used to assign weights to the importance of the four anomalies. Next, the comprehensive correlation degree of external risks across all levels under multiple superimposed anomalies is calculated using the IDO correlation measure. Finally, the highest external risk level of a single anomaly and the external risk level under multiple superimposed anomalies are integrated to assess the substation external risk level.

V. EXAMPLE VERIFICATION ANALYSIS

To validate the effectiveness of the external risk assessment method proposed in this paper, a randomly selected image sample with anomalies is analyzed. The sample, captured at 8:30 am on October 8, 2022, is shown in Fig. 5 (a). The monitoring location is situated along a connecting road within a transportation area. Fig. 5 (b) shows the anomaly identification results of the sample.

A. DETERMINE THE EXTERNAL RISK VALUE OF A SINGLE ANOMALY

1) CALCULATE THE SCORE OF IDENTIFICATION CREDIBILITY C

In this sample, three types of anomalies are identified: casing crack, insulator string drop, and oil pillow oil seepage. A total of four electrical components are involved. The anomalies are sequentially numbered 1 through 4, from left to right. The identification results are shown in Table 8.

TABLE 8. Identification results of the sample to be assessed.

Anomaly Number	Anomaly Type	Anomaly Confidence Level
1	Insulator string drop	0.76
2	Casing crack	0.78
3	Casing crack	0.83
4	Oil pillow oil seepage	0.74

According to Table 1, the score of identification credibility C for each single anomaly is as follows: $C_1 = 7$, $C_2 = 7$, $C_3 = 8$, $C_4 = 7$.

2) CALCULATE THE SCORE OF ANOMALY AREA PROPORTION A

The overall mask segmentation results for the anomaly correspond to the area of each mask, are shown in Table 9.

According to Table 2, the score of anomaly area proportion A for each single anomaly is as follows: $A_1 = 3$, $A_2 = 6$, $A_3 = 3$, $A_4 = 6$.

3) CALCULATE THE SCORE OF ANOMALY DEVELOPMENT VELOCITYV

The current scene and the anomaly identification results for the substation are shown in Table 10, including the anomaly

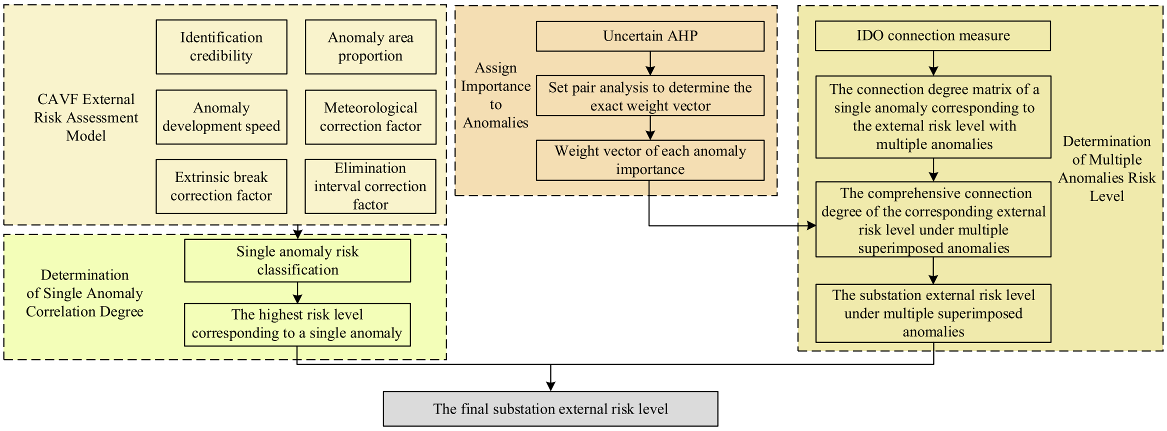

FIGURE 4. **The assessment process for substation external risk.**

(a) A sample with the anomaly

(b) The current scene anomaly identification results

FIGURE 5. **Graph of the sample to be assessed.**

mask area 24 hours ago (8:30 am on October 7, 2022) and the 24-hour anomaly area growth ratio ΔA_{24h}.

According to Table 3, the score of anomaly development velocity V for each single anomaly is as follows: $V_1 = 4$, $V_2 = 9$, $V_3 = 2$, $V_4 = 9$.

TABLE 9. **Areas of each mask and the anomaly area proportion.**

Anomaly Number	Anomaly Mask Area	Overall Mask Area of Components	Anomaly Area Proportion
1	3546	41951	8.45%
2	6246	40763	15.32%
3	3087	48076	6.42%
4	167299	540950	30.93%

TABLE 10. **Areas of each mask and the growth ratio of anomaly area.**

Anomaly Number	Current Anomaly Mask Area m_{Ba}	Anomaly Mask Area 24 Hours Ago $m_{Ba,24h}$	24-Hour Anomaly Area Growth Ratio ΔA_{24h}
1	3546	3188	11.23%
2	6246	3332	87.46%
3	3087	2837	8.81%
4	167299	104198	60.56%

4) CALCULATE THE SCORE OFCORRECTION FACTOR F

For casing crack and insulator string drop, the meteorological correction factor F_{qx} is adjusted based on temperature and humidity impacts on flashover. According to the local meteorological department's website, the weather conditions on October 8, 2022 are 3.5 °C and 31% relative humidity. Substituting these values into (4), the meteorological correction factor F_{qx} is calculated to be 2.52%, indicating $F_{qx1} = F_{qx2} = F_{qx3} = 2.52\%$.

For oil pillow oil seepage, the external breakage correction factor F_{wp} is applied, considering interference from external sources. With a warning area radius of 400 pixels, the pixel difference between the front and rear images is 6788, which exceeds 5625. It indicates external damage within the warning area. According to Table 4, the external breakage correction factor F_{wp} is 3%, that is, $F_{\mathrm{wp4}} = 3\%$. Given that the assessment sample is situated along a transportation area connecting road, the defect clearance interval correction factor F_{xq} is 0.6.

5) DETERMINE THE RISK VALUE OF A SINGLE ANOMALY

According to (5), the calculated values are as follows: $R_{\mathrm{F1}} = 51.67$, $R_{\mathrm{F2}} = 232.52$, $R_{\mathrm{F3}} = 29.53$, $R_{\mathrm{F4}} = 233.60$. The results are shown in Table 11.

TABLE 11. Quantitative summary of indicators and single anomaly risk value.

Anomaly Number	C	A	V	F_{qx}	F_{wp}	F_{xq}	R_F
1	7	3	4	2.52%	-	0.6	51.67
2	7	6	9	2.52%	-	0.6	232.52
3	8	3	2	2.52%	-	0.6	29.53
4	7	6	9	-	3%	0.6	233.60

B. DETERMINE THE EXTERNAL RISK STATE UNDER MULTIPLE SUPERIMPOSED ANOMALIES

According to (14) to (18), the correlation degree of substation external risks from levels A to E under multiple superimposed anomalies for each single anomaly, is calculated. The results are shown in Table 12.

TABLE 12. Matrix of set pair association degrees for various anomalies.

Anomaly Number	The Correlation Between External Risk Levels				
	E	D	C	B	A
1	1	-0.2358	-1	-1	-1
2	-0.6313	1	0.6313	-1	-1
3	1	-0.5633	-1	-1	-1
4	-0.6494	1	0.6494	-1	-1

According to (13), the final accurate weight vector for the importance of various anomalies is $w^* = (0.0946, 0.0497, 0.3430, 0.5127)$. For the current assessment scenario, the importance weight vector is $w^{**} = (0.0497, 0.0946, 0.0946, 0.3430)$ and normalized to $w^{**}_{avg} = (0.0854, 0.1626, 0.1626, 0.5894)$. Using the set pair connectivity matrix in Table 12 and w^{**}_{avg}, the comprehensive connectivity of substation external risks across all levels is calculated following (19), as shown in Table 13.

Based on the principle of maximum connectivity, the substation external risk level under the multiple superimposed anomalies is determined to be D-level. It belongs to low-level danger.

TABLE 13. Comprehensive correlation degree when multiple anomalies are superimposed.

Comprehensive connectivity					Rating
$\tau[E]$	$\tau[D]$	$\tau[C]$	$\tau[B]$	$\tau[A]$	
-0.2374	0.6403	-0.5281	-1	-1	Low level danger

C. DETERMINE THE FINAL EXTERNAL RISK STATE OF THE SUBSTATION

The external risk levels corresponding to anomalies 1, 2, 3, and 4 are "e", "c", " e", and "c", respectively. For a single anomaly, the highest risk level is "c", indicating moderate danger. Based on the D-level obtained previously, and Fig. 3, the final substation external risk level is III. This level belongs to the medium risk level, requiring periodic inspections and enhanced safety management.

According to the investigation of equipment accident records, a power supply interruption occurred on the transportation area connecting road on October 16, 2022. The incident is attributed to oil pillow oil seepage based on consultations with on-site experts. It resulted in a decrease in oil levels, transformer overheating, and activation of the protective device. Through the verification and analysis of the above examples, the real-time substation external risk level is determined effectively by the proposed method. By implementing risk management and response measures based on these assessment results, malignant power supply accidents can be prevented, thereby enhancing power supply safety, optimizing resource allocation, and improving operation and maintenance plans.

VI. CONCLUSION

Currently, substations are still exposed to various internal and external risks, and assessing the substation external risk level remains challenging. To address this problem, an external risk level assessment method for substations is proposed by integrating both single and superimposed anomaly risks in this paper. The conclusions are as follows:

1) The improved PES risk assessment method is proposed, along with the establishment of the CAVF external risk assessment model. This model encompasses: identification credibility C, anomaly area proportion A, anomaly development velocity V, meteorological correction factor F_{qx}, external breakage correction factor F_{wp}, and defect clearance interval correction factor F_{xq}. The concept of external anomaly risk in substations is clarified, and the correction of risk values by environmental factors is considered. Risk values are standardized quantitatively.

2) The collaborative set pair of uncertain AHP to assign weights the importance of different anomalies is used in this paper. This method effectively addresses the weighting of various anomalies, quantifies the impact of multiple superimposed anomalies and handles the inherent uncertainty

in expert judgments, and significantly enhances the accuracy of risk assessments.

3) The IDO connection measurement method is adopted to comprehensively assess the interconnections between multiple anomalies. This method effectively couples the risk levels of both single and superimposed anomalies, ultimately determining the substation external risk level. The case shows that the substation external risk level based on the proposed method aligns with accident ledger records, validating its effectiveness. This method is significant for ensuring power supply safety, optimizing operation and maintenance configuration.

The external risk assessment for substations is a relatively challenging topic and should be closely integrated with engineering practice. The proposed method in this paper combines on-site expert experience, considers external environmental influences, quantifies various anomalies, reduces subjectivity in judgment, and improves the accuracy of assessment. Through case verification, it can be deployed in actual on-site production, providing robust technical support for efficient and precise substation operation and maintenance. Monitoring data on electrical parameters, construction personnel activity records, and equipment interaction data will be further combined to enhance the applicability and accuracy of the assessment plan, thereby improving operational safety in complex environments.

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