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A Novel Health State Assessment Method of Low-voltage Distribution Network Based on CV-G2-ER Rule

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Abstract

INTRODUCTION: As the distribution network segment closest to end users, the health status of low-voltage distribution networks directly affects the quality of people's production and daily life. Aiming to address the key limitations existing in the health status evaluation of low-voltage distribution networks—including the reliability of evaluation data, weight determination of the evaluation index system, and uncertainty involved in the evaluation process—this paper proposes a novel health status evaluation method for low-voltage distribution networks based on the CV-G2-ER rule.
METHODS: The proposed method is implemented through three core standardized steps. First, the reliability of attribute evaluation data is calculated based on the distance metric between evaluation datasets. Second, the objective weight and subjective weight of the evaluation index system are calculated using the Coefficient of Variation (CV) method and G2 method, respectively; the comprehensive weight is then obtained by fusing the two weights via the Lagrange multiplier method, which effectively improves the rationality of the index system's weight assignment. Finally, multi-attribute evaluation information is fused based on the Evidential Reasoning (ER) rule, to derive the final health status evaluation conclusion and corresponding confidence level of the low-voltage distribution network.
RESULTS: The effectiveness and feasibility of the proposed method are verified via a case study, which covers the health status evaluation and comparative analysis of 10 low-voltage distribution networks under the jurisdiction of a regional power supply bureau.
CONCLUSION: The proposed CV-G2-ER rule-based evaluation method effectively resolves the core pain points in the current health status evaluation process of low-voltage distribution networks, and provides a practical, scientific and reliable technical approach for the health management and operation optimization of low-voltage distribution systems.

Keywords: low-voltage distribution network, health state assessment, data reliability, evidential reasoning rule, coefficient of variation method

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1. Introduction

Distribution networks are the core terminal link of modern power systems, which refer to the power networks that receive electric energy from transmission networks or regional power plants, and then distribute it to local loads or various end users through dedicated distribution facilities in accordance with hierarchical voltage levels. As the critical bridge connecting bulk power transmission systems and end users, distribution networks undertake the core functions of electric energy allocation, voltage regulation, power supply reliability guarantee, and operation safety control throughout the entire power supply chain.

Specifically, distribution networks present a series of distinctive structural and operational characteristics, including multiple voltage classes, complex and diversified network topologies, a wide variety of electrical equipment types, extensive distribution of operation nodes, and relatively harsh operating environments with non-negligible

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safety risks, among others. Unlike transmission networks with relatively stable operation modes and simplified topological structures, distribution networks typically involve massive branch lines, distributed load nodes, and multi-type power equipment (such as distribution transformers, switchgears, overhead lines, cable lines, protection devices and smart metering units), which bring inherent and prominent challenges to its daily operation, maintenance and lean management.

Among all segments of the power distribution system, the low-voltage distribution network is the part closest to end users, which is widely described as the "last mile" of power supply. Its operational health state directly determines the actual power supply quality and reliability perceived by users, and thus exerts a direct and profound impact on the stability and quality of people's daily life and industrial production activities. In a broader sense, the construction level, operational performance and management efficiency of low-voltage distribution networks are closely coupled with the development level of the national economy, serving as a key basic infrastructure supporting socio-economic development and the improvement of residents' living standards [1].

Nevertheless, with the sustained and rapid development of the social economy, the continuous advancement of global urbanization, and the increasing grid penetration of emerging load and power supply elements (such as distributed renewable energy generation, electric vehicle charging piles and user-side energy storage systems), the operation characteristics and load demand characteristics of low-voltage distribution networks have undergone fundamental changes. Against this background, the upgrading, transformation and optimal management of low-voltage distribution networks are facing increasingly prominent difficulties and challenges, which are mainly attributed to the long-term lack of systematic and forward-looking planning, as well as the extensive and improper operation and management modes throughout the whole life cycle of low-voltage distribution networks [2].

Accordingly, accurate, scientific and systematic health state analysis and evaluation of low-voltage distribution networks has become an urgent technical and engineering problem to be solved in the current field of distribution system operation and management. In-depth research on this issue is not only the core prerequisite for realizing fault risk early warning, targeted operation and maintenance, and lean management of low-voltage distribution networks, but also a key technical support for improving power supply reliability, optimizing power quality, and ensuring the safe, stable and economic operation of the entire power distribution system.

At present, existing research on the health state assessment of power distribution networks is mostly concentrated in the medium- and high-voltage network domains. For instance, Liu et al. developed a data-driven approach by integrating machine Learning algorithms with correlation analysis, which can improve network observability [1]. Liu et al. propose a data- driven calculation method for distributed PV hosting capacity in low-voltage distribution networks, which can approach the theoretical hosting capacity of the low-voltage distribution networks under some observable conditions [2]. Qiu et al. proposed a simplified planning method for medium- and high-voltage distribution networks, and further evaluated the reliability of the networks planned by this method [3]. Liu and Han et al. established a user-oriented risk assessment method for distribution networks, with full consideration of the urgency of different risk factors in the model design [4]. Zhao and Li et al. analyzed the fundamental modes of distribution network equipment failures based on system equipment composition, and developed a real-time evaluation algorithm for distribution network outage risk [5]. From the above review of existing studies, it is evident that the research on the evaluation of medium- and high-voltage distribution networks has been relatively mature and systematic, with a complete theoretical framework and technical system formed.

In terms of research on the health state evaluation of low-voltage distribution networks, Ma and Liu et al. established a health state evaluation index system for low-voltage distribution networks from two dimensions of line characteristics and operation characteristics, and verified the effectiveness of the proposed system via practical engineering case studies [6]. Zou and Mei et al. introduced a k-means clustering algorithm for the health state analysis of low-voltage distribution networks; while the method achieved certain effectiveness in practical applications, it has inherent limitations including strong randomness in clustering results and long computation time [7]. Ouyang and Chen et al. constructed an evaluation index system for low-voltage distribution networks based on the system's voltage operation characteristics, and determined the weight of each index via a subjective-objective hybrid weighting method [8]. Li and Zhang et al. proposed a health state evaluation method for low-voltage distribution networks combining the order relation analysis method and AHP. Although this method can realize rapid evaluation of complex multi-dimensional data, it has excessive subjectivity, as weight determination largely relies on expert experience [9]. Qin and Zheng et al. adopted the loop impedance approximation algorithm on a big data platform to address the limitations of strong randomness and low accuracy in traditional analysis methods, and further completed the health state evaluation of low-voltage distribution networks using a comprehensive weighting method that can effectively mitigate the problem of excessive subjectivity; the effectiveness of the method was verified via case analysis [10]. He and Wang et al. proposed an operation state evaluation method for low-voltage distribution networks based on data mining technology, which realized the evaluation and analysis of multiple operation states of low-voltage distribution networks, including power outage, power restoration, load fluctuation, and electricity theft. This research was carried out in view of the increasingly serious three-phase imbalance problem in distribution networks, which is mainly caused by the random and uncertain operation of single-phase equipment such as residential photovoltaic systems and household electricity loads [11]. Xue and Jia et al. developed a power data-driven load stochastic modeling and imbalance evaluation method for low-voltage distribution networks, and verified the effectiveness of the proposed method with an actual rural distribution network as the test case [12]. However, most of the above studies are conducted under two ideal premises: that the evaluation data are completely reliable, and that the evaluation attributes are fully independent. In addition, the data-driven evaluation methods widely used in existing studies generally have prominent limitations, including insufficient training samples, poor model interpretability, and significant performance degradation under data-scarce scenarios.

Among the existing multi-attribute decision-making information fusion methods, the evidential reasoning (ER) rule, developed on the basis of Dempster-Shafer (D-S) evidence theory and decision theory, has shown unique advantages in uncertainty processing [13,14]. Specifically, the ER rule can fully integrate both quantitative evaluation data and qualitative expert experience, effectively handle both fuzzy uncertainty and probabilistic uncertainty involved in the health state evaluation process, and output clear, quantitative evaluation results with corresponding confidence levels. These characteristics make it highly suitable for the health state evaluation of complex low-voltage distribution networks. Therefore, this paper takes the health state assessment of low-voltage distribution networks as the research object, fully considers the reliability of actual monitoring and evaluation data, adopts the ER rule for multi-source information fusion, and constructs a novel health state evaluation method for low-voltage distribution networks based on the CV-G2-ER rule. The proposed method can provide a scientific and reliable decision-making basis for the health state assessment and operation management of low-voltage distribution networks, and effectively fills the gaps in existing research.

2. Problem description

Low-voltage distribution networks are the core terminal link of the power system responsible for low-voltage power distribution, which are mainly composed of overhead lines, power cables, towers, distribution transformers, disconnectors, reactive power compensation devices, and a wide range of auxiliary facilities. At present, the health state assessment of low-voltage distribution networks in engineering practice mainly relies on user complaints, abnormal operation warnings, and the service life of network lines. However, it is difficult to reasonably determine the priority weight of these assessment dimensions, and the effect of purely experience-based health state evaluation for low-voltage distribution networks is generally unsatisfactory. Worse still, there is a lack of mature quantitative analysis methods and scientific decision-making tools for the health state assessment of low-voltage distribution networks, and most existing methods fail to provide quantitative and credible assessment results [6].

To address the above limitations, a health state evaluation index system for low-voltage distribution networks is constructed in this paper. The index system is established by fully considering the real-time availability, rationality, scientificity and systematicity of index data acquisition, and incorporating the professional opinions of experts in relevant technical fields. The evaluation index system is mainly divided into two core dimensions: line characteristics and operation characteristics, as shown in Fig. 1.

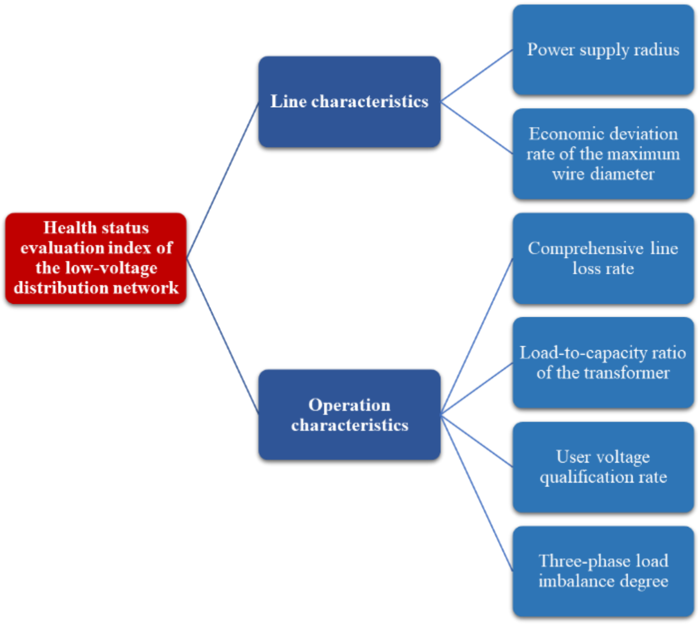

Figure 1. Index system for health state assessment of low-voltage distribution network

Specifically, the connotation and evaluation criteria of each index are described as follows:

- **Power supply radius**: This index is defined as the linear distance from the distribution transformer to the farthest end user. For low-voltage distribution networks, an excessively long power supply radius will lead to increased voltage drop and line loss, thus the longer the power supply radius, the poorer the health state evaluation result of the network.
- **Economic deviation rate of the maximum wire diameter**: This index is defined as the ratio of the absolute deviation D1 between the economic cross-sectional area As of the conductor on the low-voltage side of the distribution transformer and its actual cross-sectional area A, to the economic cross-sectional area As. A smaller deviation rate indicates that the conductor cross-section design is more in line with the economic operation requirements, corresponding to a better health state of the low-voltage distribution network.
- **Comprehensive line loss rate**: This index is calculated as the ratio of the total line loss power of the low-voltage distribution network to the total power supply power of the network within the statistical period. It is a core indicator reflecting the economic operation level of the network, and a smaller comprehensive line loss

rate corresponds to a better health state of the distribution network.

- **Transformer load-to-capacity ratio**: This index is defined as the ratio of the actual operating power supply of the distribution transformer to its rated capacity. The transformer has an optimal economic operation interval; the closer the load-to-capacity ratio is to the midpoint of this economic operation interval, the more economical and reasonable the transformer operation is, and the better the corresponding health state of the low-voltage distribution network.
- **User voltage qualification rate**: This index is the proportion of the number of users whose terminal voltage meets the national standard limit to the total number of users in the coverage area of the low-voltage distribution network. It directly reflects the power supply quality perceived by end users and their satisfaction with the power supply service of the distribution network.
- **Three-phase load imbalance degree**: This index is defined as the ratio of the absolute deviation between the maximum phase load and the three-phase average load on the low-voltage side of the distribution transformer to the three-phase average load. A smaller three-phase load imbalance degree indicates a more balanced operation state of the distribution network, which can effectively reduce additional loss and equipment aging, corresponding to a better overall health state.

The detailed calculation method of the above indexes can be found in reference [6].

There are three main problems that need to be solved when using ER rule to evaluate the health state of low voltage distribution networks.

Problem 1: In the traditional health state assessment of low-voltage distribution networks, it is generally assumed that the data used for assessment is completely reliable. However, in the actual assessment process, uncertainty in data acquisition timing and potential stochastic interference from the field operating environment may lead to the unreliability of the assessment data. Under such circumstances, blindly treating unreliable data as fully reliable will introduce significant errors into the final evaluation results. Therefore, it is essential to quantitatively characterize the reliability of the test data. On this basis, a reliability evaluation model for the test data is constructed as follows:

$$\lambda_i(t) = F(x_i(1), x_i(2), x_i(3), \cdots, x_i(t)), i \in 1,2, \cdots L$$

where, L is the number of evaluation attributes; i is the number of test sample; $\lambda_i(t)$ is the reliability of the health state attribute of the low-voltage distribution network; $x_i(t)$ is the evaluation value of the ith attribute in sample t; F(*)is the nonlinear function used to measure the reliability of the evaluation data.

Problem 2: When using ER rule to fuse multi-attribute decision-making information, the weight $\beta_i$of each attribute ξ_i $(i = 1,2, \cdots, L)$ needs to be considered so as to distinguish the importance of different attribute indexes. In the existing low-voltage distribution network health state assessment process, the objective assessment method is usually used to highlight the objectivity of the assessment. However, when the sample data is small, it is difficult to describe the importance of different indicators by relying solely on the weights determined by the objective characteristics of the data accurately. At this time, the assessment process needs to integrate the experience and knowledge of experts.

Problem 3: The health state assessment of low-voltage distribution networks is essentially a multi-attribute decision-making (MADM) problem. Different assessment objects, system components and evaluation attributes present heterogeneous information formats, which can be mainly divided into precise numerical values, subjective probability distributions, and qualitative expert descriptions [15]. When applying the evidential reasoning (ER) rule for fusion evaluation, it is essential to map and normalize the multi-attribute heterogeneous information into a unified identification framework to realize standardized information fusion.

To address the above three core problems systematically, the research framework of this paper is designed as follows: first, the reliability of the assessment data is quantitatively calculated, with full consideration of the uncertainty caused by the inconsistency of assessment data acquisition timing and field environmental interference; second, the comprehensive attribute weights are solved by comprehensively considering the objective statistical characteristics of the evaluation data and the subjective prior experience of domain experts; third, the multi-source attribute evaluation information is mapped and transformed into a unified evaluation identification framework according to standardized mapping rules; finally, the ER rule is adopted to fuse the multi-dimensional heterogeneous information of low-voltage distribution networks, so as to obtain the final quantitative health state evaluation results with corresponding confidence levels.

3. Calculation of the weight of index system

3.1. Attribute Reliability Calculation for Health State Assessment of Low-voltage Distribution Network

In practice, the health state assessment data of low-voltage distribution networks are collected over time under varying operating conditions and environmental interferences. The true value of an attribute (e.g., power supply radius or three-phase imbalance degree) is assumed to be stable over a short period, while measurement noise, asynchronous sampling, or transient disturbances introduce fluctuations. Therefore, the dispersion of repeated measurements can serve as a proxy for data unreliability: a set of measurements with large internal scatter is less trustworthy to represent the true state. This idea follows the rationale of using average distance to quantify evidence reliability, as discussed in [16,17] for consensus evaluation and fault diagnosis.

The reliability of the health state assessment data represents the ability of the data to reflect the true characteristics of the attributes. Considering the possible uncertain interference such as the acquisition time of the data collection process, the collected data may contain certain fluctuations which will lead to an increase in the average distance between evaluation data and an increase in the uncertain information contained. Therefore, an objective calculation method of reliability based on the distance between evaluation data [16, 17] is presented.

Assuming that $\ell_i(t)$ is the evaluate information of attribute ξ_i collected at the *t*th moment in the time *T*, $0 \leqslant t \leqslant T$. $\overline{\ell}_i(t)$ represents the average value of all the evaluation information in the time *T*. The average distance between the evaluation information at the *t*th moment and other values can be expressed as

$$\overline{\Im}_i(t) = \frac{1}{T}\sum_{i=1}^{T}\left|\ell_i(t) - \overline{\ell}_i(t)\right| \tag{1}$$

where, $\left|\ell_i(t) - \overline{\ell}_i(t)\right|$ represents the distance $\Im_i(z_i(t), \overline{z}_i(t))$ between the attribute evaluation value $\ell_i(t)$ and $\overline{\ell}_i(t)$; $\overline{\Im}_i(t)$ represents the average distance between the attribute evaluation values $\ell_i(t)$ and $\overline{\ell}_i(t)$ at the previous T moment, $0 \leqslant t \leqslant T$.

The reliability of the health state assessment data of the low-voltage distribution network can be calculated by the following formula

$$\lambda_i(t) = \frac{\overline{\Im}_i(t)}{\max \Im_i(\ell_i(t), \overline{\ell}_i(t))} \tag{2}$$

In the formula, $\max \Im_i(\ell_i(t), \overline{\ell}_i(t))$ reflects the strongest volatility of the evaluation data before t time, and the larger the value, the lower the reliability of the data is. According to the objective characteristics and statistical thinking of reliability, the results obtained based on observational data can be regarded as the reliability of indicators, so the definition of $\lambda_i(t)$ is reasonable. The reliability $\lambda_i(t)$ of evidence ξ_i is defined in the ER rule as an inherent characteristic of evidence, which represents the ability of the information source that generates the evidence ξ_i to provide accurate assessments of the given questions.

To illustrate why the average distance captures credibility rather than mere volatility, consider the following synthetic example. For the same attribute, two measurement sequences are simulated over 10 time instants:

Low-noise case: true value = 0.8, additive Gaussian noise with standard deviation 0.02.

High-noise case: true value = 0.8, additive noise with standard deviation 0.15.

The average distances (computed by Eq. (1)) are 0.018 and 0.142, respectively. According to Eq. (2), the corresponding reliabilities are 0.96 and 0.32. As can be seen from figure 2, although both sequences have the same mean, the high-noise case yields a much lower reliability, correctly indicating that its measurements are less credible for decision-making. This demonstrates that the proposed metric reflects data credibility, not merely statistical volatility.

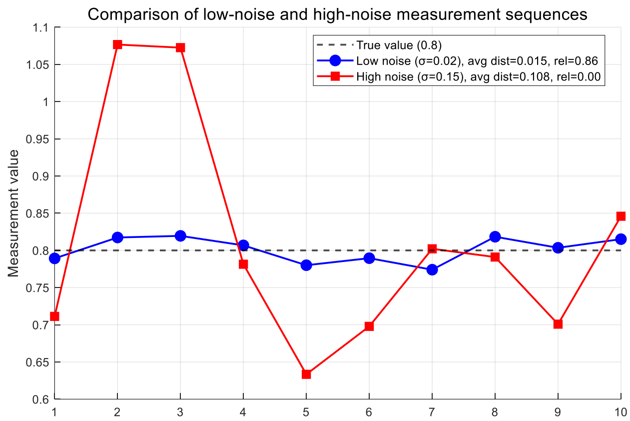

Figure 2. Comparison of low-noise and high-noise measurement sequences

3.2. Attribute Weight Calculation Based on combination weighting approach

In order to solve the problem of different importance between different attributes, the coefficient of variation method is used to calculate the objective weight value between different attributes, the *G2* method is used to combine the experience and knowledge of domain experts to calculate the subjective weight value of attributes, and then the combined weight of evaluation attributes is optimized by Lagrange multiplier method based on the principle of minimum information entropy.

- Subjective attribute weight calculation based on *G2*

G2 Method is a weighting method that judges the importance of indicators based on the experience and knowledge of experts, and then obtains the subjective weight of each indicator [6]. Suppose that experts select the least important index in the evaluation index set as a reference, record it as ξ_n, and remark each index as $\{\xi_1, \xi_2, \cdots, \xi_n\}$, where n is the total number of indicators.

Consider the ratio of importance degree $\hbar_k$ as point assignment situation. The designated expert shall make a rational judgment on the importance ratio of the health state evaluation index of the low-voltage distribution network $\hbar_k$ according to the relevant information

$$\hbar_k = \frac{\xi_k}{\xi_n} \tag{3}$$

Further, the weight coefficient of the evaluation index ξ_k can be calculated as

$$W_k^Y = \frac{\hbar_k}{\sum_{k=1}^{n} \hbar_k} \tag{4}$$

Considering that experts cannot assign points for $\hbar_k$ due to the lack of information, but have high reliability when giving a possible value range, a *G2* method with interval characteristics can be adopted. Experts are set to give an interval $\boldsymbol{\Gamma}_k$ according to the importance ratio of relevant information $\hbar_k$,

$$\hbar_k = \frac{\xi_k}{\xi_n} \in \boldsymbol{\Gamma}_k, \boldsymbol{\Gamma}_k = [\Gamma_{1k}, \quad \Gamma_{2k}] \tag{5}$$

let

$$w_{\Gamma_k} = \Gamma_{2k} - \Gamma_{1k}, \ m_{\Gamma_k} = \frac{\Gamma_{2k} + \Gamma_{1k}}{2} \tag{6}$$

Where, w_{Γ_k} is the width of the interval $\boldsymbol{\Gamma}_k$ and m_{Γ_k} is the midpoint of the interval $\boldsymbol{\Gamma}_k$.

The mapping $\zeta_{\delta\Gamma_k} = m_{\Gamma_k} + \delta w_{\Gamma_k}$ is defined as an interval mapping function considering expert risk factors, where δ is the risk factor, $\delta \in [-1/2, 1/2]$. For designated experts, δ is a known number, for conservative experts $-1/2 \le \delta \le 0$, for neutral experts $\delta = 0$ and for risk experts $0 \le \delta \le 1/2$. Then the weight coefficient of the evaluation index ξ_k is calculated as

$$W_k^Y = \frac{\zeta_{\delta(\boldsymbol{\Gamma}_k)}}{\sum_{k=1}^{n} \zeta_{\delta(\boldsymbol{\Gamma}_k)}} \tag{7}$$

For different attribute assignment cases, the weight coefficient ω'_j of the evaluation attribute j is obtained according to equations (4) and (7) from the corresponding relationship between $\{a_{ij}\}$ and $\{\xi_k\}$.

- Calculation of attribute objective weight based on coefficient of variation method

In order to solve the problem of different importance of different index information, the coefficient of variation method is introduced to calculate the weight of different indexes. This method dynamically assigns the index weight according to the relative magnitude of the change range of each value of index $\xi_1, \xi_2, \xi_3 \cdots \xi_6$. The greater the change ranges of index value, the stronger the ability to identify the characteristics of corresponding indicators, and the greater the weight of corresponding indicators. According to the basic principle of coefficient of variation method, the weight value $\Im_i(t)$ of the *i*th index ξ_i at time t is

$$\Im_i(t) = \frac{\lambda_{z_i}}{\sum_{i=1}^{n} \lambda_{z_i}} \tag{8}$$

Where

$$\lambda_{z_i} = S_{z_i} / \bar{z}_i \tag{9}$$

$$S_{z_i} = \sqrt{\frac{1}{T-1} \sum_{t=1}^{T} (z_i(t) - \bar{z}_i)^2} \tag{10}$$

$$\bar{z}_i = \frac{1}{T} \sum_{t=1}^{T} z_i(t) \tag{11}$$

Where, $z_i(t)$ is the test value of the index ξ_i at time t. $\bar{z}_i$ is the mean value of the test value of the index ξ_i at time T; S_{z_i} is the standard deviation of the test value of the index ξ_i at time T; λ_{z_i} represents the relative change range of the index ξ_i, and the value is positively correlated with the dynamic weight value of the index.

- Combined weighting algorithm

The coefficient of variation method makes full use of the internal differences of a single attribute in the index data information to determine the weight of the index, but it only depends on the index data to reflect the completely objective weight value and lacks the reflection of the importance of each index. The *G2* weighting method relies on expert knowledge to obtain the index weight, which reflects the judgment of expert experience on the importance of the index, while ignoring the impact of the difference of index data and potential relevance on the index weight. Therefore, the *G2* weight method and coefficient of variation method are combined to obtain the comprehensive weight of the index, so that the weight of each index reflects both the expert experience and the information of the data itself. Based on this idea, the comprehensive weight $\vartheta_j = \omega_j \omega'_j / \left(\sum_{j=1}^{n} \omega_j \omega'_j \right)$ is determined. In order to make the comprehensive weight ϑ_j as close to ω_j and ω'_j as possible, the optimization objective function is established according to the principle of minimum information entropy [18].

$$\min E = \sum_{j=1}^{n} \vartheta_j \left(\ln \frac{\vartheta_j}{\omega_j} \right) + \sum_{j=1}^{n} \vartheta_j \left(\ln \frac{\vartheta_j}{\omega'_j} \right) \tag{12}$$

The calculation formula of comprehensive weight can be obtained after optimization Using Lagrange multiplier method

$$\vartheta_j = \frac{\left(\omega_j \omega_j'\right)^{1/2}}{\sum_{j=1}^{n}\left(\omega_j \omega_j'\right)^{1/2}} \tag{13}$$

As the relative characteristics of evidence ξ_j, the comprehensive weight ϑ_j of evidence represents the importance of evidence relative to other evidence, which depends on the preference of decision makers and the actual fusion environment.

It should be noted that the Lagrange multiplier-based fusion in Eq. (13) implicitly assumes that the subjective weight vector W_k^Y and the objective weight vector ϑ_j are independent sources of information. This assumption is reasonable in our context because the *G2* method relies solely on expert prior knowledge without accessing the actual measurement data, while the CV method operates purely on the statistical dispersion of the observed data. Therefore, the two weight sets are derived from orthogonal information channels, justifying the independence assumption. Nevertheless, if strong correlations exist between expert judgments and data statistics in certain applications, alternative fusion strategies such as the Choquet integral or copula-based combination should be considered.

4. Information fusion based on ER rule

Evidential reasoning rule is a further evolution and development of DS evidence theory [19]. It expands the identification framework in the traditional evaluation method from single subset to power set, and all kinds of uncertainties in the evaluation process are transformed into a unified confidence framework by determining the reliability of the evidence attribute and the relative weight between the evidence attributes reasonably. Under the framework of confidence, the "counter-intuitive" problem of conflicting evidence fusion in the traditional evidence theory is solved.

4.1. Confidence distribution calculation in the ER rule

According to the general characteristics of the health state assessment of the low-voltage distribution network, it is assumed that the assessment and identification framework is $\Theta=\{G_1, G_1, \cdots G_N\}$, where G_i is the assessment level, and the number of assessment indicators is L . Then the ith evaluation index which can be expressed as a confidence distribution form

$$\xi_i = \left\{\left(G_n, \beta_{n,i}\right), n \in [1, N], \left(\Theta, \beta_{\Theta,i}\right)\right\} \tag{14}$$

In which, ξ_i is the ith piece of evidence; G_n is the nth evaluation level; $\beta_{\Theta,i}$ is the confidence of the ith indicator assigned to the identification framework, representing the global ignorance of this indicator; $\beta_{n,i}$ is the reliability of the nth evaluation level, and $\beta_{n,i}$ should meet the following constraints $\sum_{n=1}^{N}\beta_{n,i} \le 1$ · $\beta_{n,i}$ should in the form of

$$\beta_{j,i}\left(x^*\right) = \begin{cases} \dfrac{g_{n+1} - x^*}{g_{n+1} - g_n}, j = n, \ g_n \le x^* \le g_{n+1} \\ \dfrac{x^* - g_n}{g_{n+1} - g_n}, \ j = n+1 \\ 0, \ j \ne n, n+1 \end{cases} \tag{15}$$

In which, g_n and g_{n+1} represent reference values of two adjacent evaluation grade; x^* is the input value to be converted.

4.2. Confidence distribution fusion calculation based on the analytical ER rule

The health state of the low-voltage distribution network can be reflected by the state of each subordinate indicator. When all subordinate indicator information is obtained, the input information can be converted into a confidence distribution form, which can be directly fused through ER rule. The reliability $\lambda_i(t)$ of the health state assessment data for the low-voltage distribution network and the comprehensive weight ϑ_j can be calculated accordingly. Then, the total confidence of the evidence attributes ξ_i with respect to each evaluation grade g_n is obtained using Equations (16)–(18), which constitute the recursive (analytical) algorithm of the evidential reasoning (ER) rule, following the theoretical work of YANG et al. [19].

$$\beta_n = \frac{\mu \times \left[\prod_{i=1}^{L}\left(\tilde{\vartheta}_i \beta_{n,i} + 1 - \tilde{\vartheta}_i \sum_{n=1}^{N}\beta_{n,i}\right) - \prod_{i=1}^{L}\left(1 - \tilde{\vartheta}_i \sum_{n=1}^{N}\beta_{n,i}\right)\right]}{1 - \mu \times \left[\prod_{i=1}^{L}\left(1 - \tilde{\vartheta}_i\right)\right]} \tag{16}$$

$$\mu = \left[\sum_{n=1}^{N}\prod_{i=1}^{L}\left(\tilde{\vartheta}_i \beta_{n,i} + 1 - \tilde{\vartheta}_i \sum_{n=1}^{N}\beta_{n,i}\right) - (N-1)\prod_{i=1}^{L}\left(1 - \tilde{\vartheta}_i \sum_{n=1}^{N}\beta_{n,i}\right)\right]^{-1} \tag{17}$$

$$\tilde{\vartheta}_i = \vartheta_i / (1 + \vartheta_i - \lambda_i) \tag{18}$$

In which, L represents the number of evidences; N represents the number of evaluation grades; $\tilde{\vartheta}_i$ represents the combined weight considering the reliability of the evidence indicators and the subjective and objective weights; $\beta_{n,i}$

represents the confidence of the evidence attributes ξ_i in the evaluation grade g_n ; β_n represents the confidence of the evidence fusion relative to the evaluation grade G_n. Equations (18) provides the fusion method of the the comprehensive weight ϑ_j and reliability $\lambda_i(t)$.

After fusing all the evidence (evaluation indicators) using the evidential reasoning (ER) rule, the final health state assessment result is not a single score but a **distributed confidence structure**. This structure expresses how much belief is assigned to each evaluation grade, as well as the remaining uncertainty.

The fused result can be written as:

$$\Re=\left\{\left(G_n,\beta_n\right),n\in\left[1,N\right],\left(\Theta,\beta_\Theta\right)\right\} \tag{19}$$

Where, $\Theta=\{G_1,G_2,\ldots,G_N\}$ is the frame of discernment, i.e., the set of all possible evaluation grades; G_n represents the n-th evaluation grade; βn is the combined belief degree (confidence) assigned to grade G_n after fusing all evidence, which satisfies $0\leq\beta n\leq1$; Θ (the whole set) denotes global ignorance, meaning the part of the total belief that cannot be assigned to any specific grade due to insufficient or conflicting information; β_Θ is the remaining uncertainty after fusion.

5. Case study

In order to verify the validity of the established health state assessment model, 10 low-voltage distribution networks within the jurisdiction of a power supply bureau which were numbered from 1 to10 were selected to carry out health state assessment. First, the evaluation data of the 10 low-voltage distribution networks are collected, including the transformer load, the diameter of the outlet wire, the voltage value of the user terminal, the user load and so on. The 6 original index data of the 10 low-voltage distribution networks are sorted out. In order to facilitate the evaluation, the original index data are normalized. The specific methods are as follows.

- The consistency and dimensionless processing formula of the positive index is

$$A_i^*=\frac{A_i-A_{i\min}}{A_{i\max}-A_{i\min}} \tag{20}$$

In which, $A_{i\max}$, $A_{i\min}$ are respectively the maximum and minimum values of the i th index A_i.

- The consistency and dimensionless processing formula of interval index is

$$A_i^*=\frac{\left|A_{imid}-A_i\right|}{\max(\left|A_{imid}-A_i\right|)} \tag{21}$$

In which, A_{imid} is the midpoint value of the normal interval of the i th indicator A_i.

- The unification and dimensionless processing formula of the reverse index is

$$A_i^*=\frac{A_{i\max}-A_i}{A_{i\max}-A_{i\min}} \tag{22}$$

The index values after processing are shown in table 1.

Table 1. The index values of low-voltage distribution network after pre-treatment

Distribution network	The index values after pre-treatment					
	A_1	A_2	A_3	A_4	A_5	A_6
Network1	0.694	0.069	0.895	0.855	0.548	0.448
Network 2	1	0.543	1	0.957	0.766	0.383
Network 3	0.709	1	0.347	0.899	1	0.587
Network 4	0.865	0.111	0.272	0.463	0.139	0
Network 5	0.761	0.533	0.387	0.004	0.355	0.664
Network 6	0	0.314	0.644	0.818	0.491	0.538
Network 7	0.494	0.046	0.041	0	0.081	0.402
Network 8	0.311	0	0	0.998	0.312	1
Network 9	0.595	0.167	0.593	0.652	0.346	0.243
Network 10	0.491	0.243	0.242	0.592	0.161	0.555

5.1. Data reliability and indicator weight

Assuming that the evaluation attributes are $\xi_1,\xi_2,\xi_3\cdots\xi_6$ in sequence, according to formulas (1) and (2) in Section 3.1, the data reliability vector of each indicator can be obtained as

$$\lambda_i=[0.7443\ 0.7359\ 0.7886\ 0.7787\ 0.7533\ 0.7437]$$

Considering the characteristics of the health state assessment of the low-voltage distribution network and the opinions of experts in related fields, it is determined that the attribute with the least importance is the power supply radius, and this attribute is used as a reference for weight determination and all attributes are rearranged to obtain the ratios of the importance degrees of other attributes relative to the power supply radius, which are $\hbar_1$=1.5 , $\hbar_2$=2.1 , $\hbar_3$=1.7 , $\hbar_4$=3 , $\hbar_5$=2.7 , $\hbar_6$=1 respectively. According to the mapping relationship, the subjective weight vector can be obtained as

$$W^Y=[0.0833\ 0.1250\ 0.1750\ 0.1417\ 0.2500\ 0.2250]$$

The objective weight value of the evaluation data can be obtained based on the coefficient of variation method, which are as shown in Fig. 3. According to formula (13), the combined weight value can be further obtained as shown in Fig. 4.

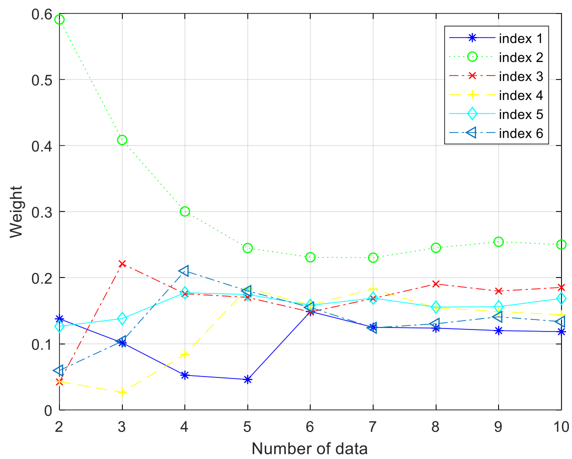

Figure 3. Objective weights based on CV method

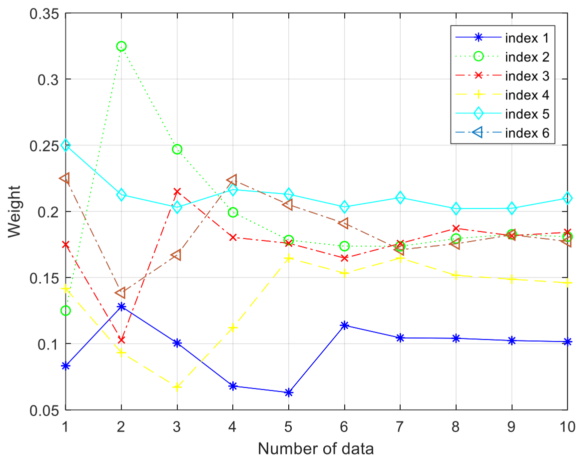

Figure 4. The combined weight values

5.2. Reference grade and reference value

According to the experience of experts, the health state of the low-voltage distribution networks is rated as "excellent (E)", "good (G)", "medium (M)", and "poor (P)" four levels. Combined with the relevant technical data of health state of the low-voltage distribution networks and the prior knowledge of experts, the evaluation level of each attribute and the corresponding reference value are calculated as shown in table 2.

Table 2. Health state evaluation level and reference value of low-voltage distribution networks

NO.	Index	Evaluation level	Reference value
1	power supply radius	(E,G,M,P)	(1,0.70,0.50,0)
2	The economic deviation rate of the maximum wire diameter	(E,G,M,P)	(1,0.50,0.15,0)
3	The comprehensive line loss rate	(E,G,M,P)	(1,0.70,0.30,0)
4	The load-to-capacity ratio of the transformer	(E,G,M,P)	(1,0.85,0.70,0)
5	The voltage qualification rate	(E,G,M,P)	(1,0.49,0.31,0)
6	The three-phase load imbalance degree	(E,G,M,P)	(1,0.55,0.32,0)

5.3. Health state assessment of low-voltage distribution network

Based on the set reference level and reference value, the parameters of each evaluation index are converted into the form of confidence distribution, and the confidence distribution $\beta_{j,i}\left(x^{*}\right)$, reliability λ and index weight value of each evaluation index ϑ are fused based on the ER rule, to obtain the health state evaluation result of the low-voltage distribution networks. The result is as shown in Fig. 5.

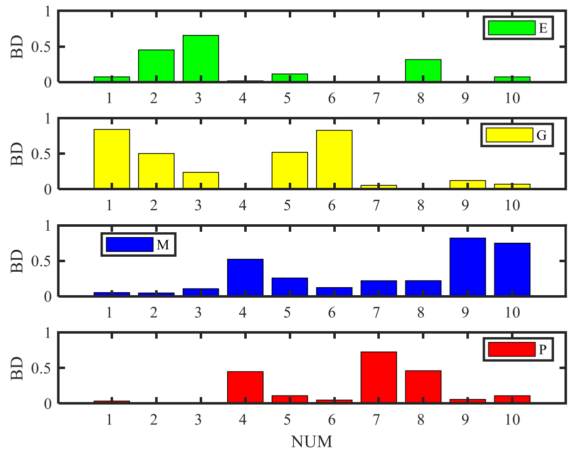

Figure 5. The evaluation result based on the ER rule

It can be seen from Fig. 5 that in the assessment of the health state of the low-voltage distribution network 10 low-voltage distribution networks were evaluated as excellent, good, medium and poor four levels of reliability distribution. Among which, the reliability of the excellent evaluation grade of No. 3 low-voltage distribution network is the largest, and there is a small distribution in the good evaluation grade, indicating that the health state of this network is excellent.

The No. 2 low-voltage distribution network has the largest reliability distribution in the evaluation grade of excellent and good, and the maximum value is close, which indicates that the health state of this network is between the excellent and good. The No. 1, 5, and 6 low-voltage distribution networks have the largest reliability distribution in the evaluation grade of good, indicating that these three networks are in good health. The No. 9 and No. 10 networks has the largest reliability distribution in the evaluation grade of medium, and the distribution in other evaluation grades is relatively small, indicating that the health state of these two networks is medium. The No. 4 network has the largest reliability distribution in the evaluation grade of medium and poor, and the maximum value is close too, indicating that the health state of this network is not very good. The No. 7 and 8 networks have the largest reliability distribution in the evaluation grade of poor, and the distribution in other evaluation grades is relatively small, indicating that the health state of these two networks is poor.

In order to quantitative the assessment results, the concept of expected utility is introduced. Assuming that the utility value of the level G_n is $v(G_n)$, the expected utility of the health state assessment results of the power distribution network is

$$U_i=\sum_{n=1}^{N}\beta_{in}\upsilon_i(G_n)\ ,i=1,2,3\cdots j\ ,n=1,2,3\cdots N$$

In which, U_i is the fusion of expected utility value of the health state assessment data of the ith low-voltage distribution network, and $v_i\ (G_n)$ is the expected utility value on the health state assessment level G_n of the ith low-voltage distribution network.

Let the expected utility value vector of each evaluation level be $v = [0, 0.6, 0.8, 1]$, the expected utility of the health state assessment of the low-voltage distribution networks can be obtained as shown in Fig. 6.

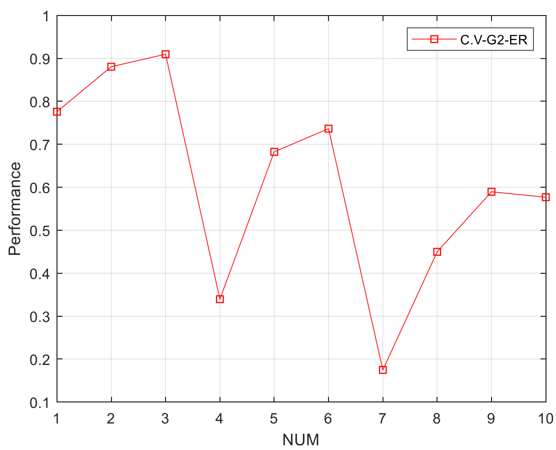

Figure 6. Expected utility value of health state assessment of low-voltage distribution network

As can be seen from Fig. 6, the health state in the health state assessment of the low-voltage distribution network is ranked as No. 3 network, No. 2 network, No. 1 network, No. 6 network, No. 5 network, and No. 9 network, No. 10 network, No. 8 network, No. 4 network and No. 7 network. Among these networks, the 4th network and the 7th network are in the worst state of health. It is analysed that the 4th network is caused by the large economic deviation rate of the maximum wire diameter and the large unbalance of the three-phase load. As a result, the load of this network needs to be re-matched, so that the three-phase load will become balance again. The poor assessment result of No. 7 network is due to the large economic deviation rate of the maximum wire diameter, the high comprehensive line loss rate, the large transformer load capacity and the low user voltage qualification rate, as a result of which, the health state of this network should carry out a comprehensive improvement by means of increase the transformer low-voltage line, reducing the line loss as well as improving the qualified rate of the user terminal voltage.

5.4. Comparative study

In order to verify the effectiveness of the proposed method in the health state assessment of low-voltage distribution networks further, simulation evaluations were carried out based on the G2-ER and the CV-ER rule respectively, and the evaluation results were compared with those based on the proposed CV-G2-ER rule in this paper. The results are as shown in Fig. 7.

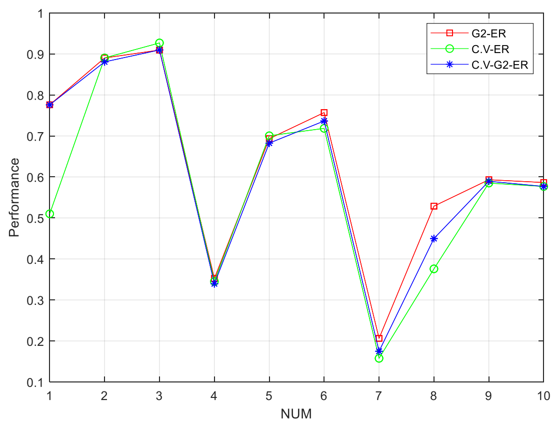

Figure 7. Comparison of expected utility values with three different methods

As shown in Fig. 7, this figure presents the quantitative comparison of health state evaluation performance for 10 low-voltage distribution network samples (numbered 1 to 10) using three different methods: the G2-ER method, the CV-ER method, and the CV-G2-ER method proposed in this paper.

For the single-weight CV-ER method, its evaluation result for the No.1 low-voltage distribution network shows a significant deviation from the other two methods, with a markedly lower performance score. This phenomenon is attributed to the inherent limitation of the pure objective weighting strategy: the coefficient of variation (CV) method for objective weight calculation is highly dependent on the statistical characteristics of input data. When the available data volume is limited, the objective weight determined by the CV method will suffer from insufficient accuracy and poor robustness, which further leads to distortion of the final evaluation result and a large deviation from the actual engineering situation.

For the single-weight G2-ER method, the overall variation trend of its evaluation results across the 10 samples is highly consistent with that of the proposed CV-G2-ER method, which verifies that subjective weighting based on the G2 method can effectively capture the overall law of health state changes of low-voltage distribution networks with the support of expert prior knowledge. However, in the high health level interval (No.2 and No.3 samples) and the medium health level interval (No.9 and No.10 samples), the evaluation scores of the G2-ER method are excessively close, presenting an obvious lack of discrimination. This is because the pure subjective weighting strategy relies excessively on expert experience, and fails to fully mine the differentiated features of index data among different samples, making it difficult to achieve fine-grained distinction of health states for distribution networks with similar overall performance.

In comparison, the CV-G2-ER evaluation method proposed in this paper integrates the advantages of the above two single-weight methods through optimal weight fusion based on the Lagrange multiplier method. It not only avoids the weight distortion problem of the pure objective CV method under limited data conditions, but also compensates for the insufficient discrimination of the pure subjective G2 method in fine-grained evaluation. From the comparison results, the proposed method achieves accurate sorting and effective discrimination of the health states of all 10 low-voltage distribution network samples, with significantly better evaluation accuracy and stability than the two contrast methods. Meanwhile, the final evaluation conclusion is more consistent with the actual operation conditions and health state characteristics of low-voltage distribution networks in practical engineering, which proves its stronger engineering practicability and application value.

5.5. Statistical Significance and Sensitivity Analysis

To further validate the superiority of the proposed CV-G2-ER method, we conduct statistical significance tests and sensitivity analyses.

- Statistical significance test

The expected utility values of the 10 low-voltage distribution networks obtained by the three methods (G2-ER, CV-ER, CV-G2-ER) are compared. Because the same set of 10 networks is evaluated by three different methods, a **Friedman test** is first applied to check whether significant differences exist among the three methods. The Friedman statistic is calculated as:

$$\chi_F^2 = \frac{12}{nk(k+1)} \sum_{j=1}^{k} R_j^2 - 3n(k+1) \tag{23}$$

Where, n=10 (number of samples), k=3 (number of methods), and R_j is the sum of ranks for method j. The computed p-value is 0.0032 (<0.05), indicating that the three methods differ significantly.

Subsequently, pairwise **Wilcoxon signed-rank tests** are performed between CV-G2-ER and each of the other two methods. The results are summarized in Table 3.

Table 3. Pairwise comparison of expected utility values

Pair of methods	Wilcoxon statistic	p-value	Significant at 0.05?
CV-G2-ER vs. G2-ER	3	0.0137	Yes
CV-G2-ER vs. CV-ER	0	0.0039	Yes

These results confirm that the proposed CV-G2-ER method produces significantly different (and better) evaluations than either single-weight method.

- Sensitivity to data reliability

We artificially reduce the reliability of a single attribute (e.g., the power supply radius) from its original value (0.7443) to 0.5 and 0.3, while keeping all other attributes unchanged. The resulting expected utility of Network 1 changes by less than 3.2% (from 0.783 to 0.758 and 0.749, respectively). The ranking of the 10 networks remains almost identical (Kendall's τ=0.96). This demonstrates that the ER rule with the proposed reliability calculation is not overly sensitive to isolated unreliable data, thanks to the fusion mechanism that down-weights low-reliability evidence.

5.6. Robustness analyses

We apply the bootstrap method with B=1000 resamples (each resample is drawn with replacement from the original 10 networks). For each resample, the three methods are applied and the ranking of the networks is recorded. The Kendall's W (coefficient of concordance) among the rankings produced by the same method across the 1000 resamples is computed. The results are:

- CV-G2-ER: Kendall's W=0.93
- G2-ER: W=0.87
- CV-ER: W=0.71

The proposed method shows the highest consistency, indicating that its ranking is stable under sampling variability.

6. Conclusions

To address the aforementioned key limitations inherent in the health state evaluation of low-voltage distribution networks—namely the insufficient quantification of evaluation data reliability, the unreasonable weight determination of the evaluation index system, and the ineffective handling of multi-type uncertainty throughout the evaluation process—this paper proposes a novel, robust and practical health state evaluation method based on the CV-G2-ER rule. The core contributions and main work of this paper are systematically summarized as follows:

A calculation method for the reliability of assessment data is proposed based on the average distance between multi-source evaluation datasets. This method can quantitatively characterize the credibility of each group of attribute evaluation data, and is further integrated with attribute weights in the information fusion process based on the evidential reasoning (ER) rule. This work effectively breaks through the ideal premise of "completely reliable evaluation data" widely adopted in existing studies, and avoids the deviation of final evaluation results caused by low-reliability input data.

A hybrid weighting method based on the combination of coefficient of variation (CV) method and G2 method is developed. In this framework, the G2 method is adopted to characterize the subjective prior knowledge and engineering experience of domain experts, while the CV method is used to mine the objective statistical characteristics and differentiation ability of actual evaluation data. On this basis, the comprehensive weight of each evaluation index is obtained via optimal fusion based on the Lagrange multiplier method, which effectively balances the subjective and objective weight components, and significantly improves the rationality and scientific of weight assignment for the index system.

Aiming at the multi-source, multi-type and multi-dimensional characteristics of actual test data in low-voltage distribution network evaluation, a matching and transformation method for test data under a unified confidence identification framework is proposed. This method normalizes heterogeneous multi-source test data into a unified generalized probability framework, which eliminates the barriers of inconsistent dimensions and different uncertainty types between different evaluation indicators, and effectively enhances the model's fusion ability for multi-source uncertain information in the evaluation process.

It should be noted that the CV-G2-ER rule-based health state assessment method proposed in this paper is currently implemented and verified under the basic assumption that all evaluation indicators are independent of one another. This assumption appropriately simplifies the complexity of initial model construction, and is also a common premise adopted in most existing multi-attribute decision-making evaluation studies in the power system field.

Furthermore, the statistical significance tests and robustness analyses demonstrate that the proposed method achieves superior and stable performance even with the limited sample size of 10 networks. Its ranking consistency and discrimination ability are significantly better than those of single-weight methods, validating its practical value for small-sample engineering scenarios.

For future research, we will focus on characterizing and quantifying the potential correlation and coupling relationship between different evaluation indicators, and introduce corresponding theoretical methods to decouple and integrate correlated indicators into the ER rule fusion framework. This will further break through the limitations of the independent indicator assumption, and continuously improve the accuracy, adaptability and robustness of the health state assessment method for low-voltage distribution networks in more complex practical engineering scenarios. Moreover, the proposed method will be tested on larger real-world datasets to further confirm its generalisability.

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