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A Comprehensive Evaluation Model for the State of Electric Energy Metering Devices Based on Fuzzy Analytic Hierarchy Process

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Accurately evaluating the status of electric energy metering devices is the foundation for ensuring their stable operation on smart grids, and is conducive to the development of equipment management towards refinement and intelligence. This article proposes a comprehensive evaluation model through the fuzzy analytic hierarchy process (F-AHP), which is characterized by establishing a multi-index system and taking into account subjective opinions and objective data, thereby improving the scientificity of its evaluation and enhancing its anti-interference ability. It starts with establishing a hierarchical structure, dividing the functions of indicators such as structural reliability, measurement accuracy, communication stability, and environmental adaptability. Then, based on the fuzzy decision matrix assignment, the importance of each indicator is calculated, and the assignment and overall score of the indicators are obtained, completing the quantitative evaluation of the health of the measuring device. In the experimental verification, 50 typical electric energy metering device samples were selected for state evaluation modeling. The average CI value of the model was 0.016, the coefficient of variation CV was 0.069, and the accuracy of state recognition reached 92.5%. The evaluation results have high stability, can effectively identify boundary fuzzy samples, and have strong robustness and practical value. The results indicate that the evaluation model proposed in this article can better solve multiple practical cases and the overall evaluation error does not exceed 5%; Compared with traditional AHP and weighted average method (WAM), this model performs better in state recognition accuracy and boundary blurring processing ability. Simultaneously conducting noise experiments and sensitivity analysis, and proving that the model has high stability and reliability under various abnormal conditions.

Povzetek: F-AHP model z večkazalčno hierarhijo izboljša ocenjevanje stanja merilnih naprav, združuje subjektivne in objektivne podatke ter krepi robustnost. Na 50 vzorcih doseže 92,5-odstotno točnost, nizko varianco ter boljšo prepoznavo mejnih primerov.

1 Introduction

With the development of smart grids, the position of energy metering devices in the operation and production of power grid enterprises is becoming increasingly important. They not only serve as the basic unit of measurement for billing and metering, but also perform important tasks such as data collection, load monitoring, and equipment status recognition, playing an important role in ensuring the quality of power supply and serving customer rights. With the rapid development of smart grids and the increasing number of connected devices, it is essential to accurately grasp the operating status of metering devices and be able to detect risks early. However, traditional evaluation methods often rely on human visual inspection or judgment based on a single factor, and cannot provide sufficient measurement scales. The proportion of weights is too subjective and the definition is not clear enough, which cannot adapt to the operation of large-scale equipment.

Different factors can affect the operating status of energy metering devices, such as installation location, wear and tear of components, data transmission quality, power supply quality, and changes in grid noise. There are not only quantitative factors that can be quantified to a single value, but also qualitative evaluation factors that cannot be directly quantified. Whether the instrument interface docking is reasonable is an indicator that cannot be directly measured. Historical data shows that the trend of error rate changes has a strong human explanatory factor. Therefore, it is not easy to simultaneously balance "orderliness" and "fuzziness" using only traditional analytic hierarchy process or fuzzy mathematics methods. To more accurately and comprehensively characterize the overall working status of electric energy metering, it is necessary to establish a performance evaluation model with clear hierarchy and measurement fuzzy acceptability requirements [3]. This article establishes a comprehensive performance evaluation model using the fuzzy analytic hierarchy process to design a specific evaluation system model for electric energy metering devices in real-world operating scenarios. This model is based on a multi-dimensional evaluation index system and integrates professional knowledge and real-time data. After establishing a fuzzy judgment matrix, determining weights, and conducting consistency checks, it forms a comprehensive evaluation model with clear hierarchy, reasonable weights, and practical effectiveness, thus changing the shortcomings of traditional methods that cannot cope with fuzziness and human factors. Through this model, equipment managers can achieve quantitative diagnosis of equipment operating status, identify operational defects, and assist in developing differentiated maintenance and repair plans.

The structure of this article is arranged as follows: Chapter 2 provides an overview of the research status of existing power measurement equipment status evaluation; Chapter 3 further elaborates on the design ideas and construction methods of the proposed model; Chapter 4 mainly presents the implementation methods and evaluation process of the model; Chapter 5 provides a discussion of an example and presents a comparative analysis of the example, as well as an analysis of the practicality and robustness of the model; The final chapter six provides a comprehensive summary of the research content and prospects for future development directions.

2 Related work

Although energy metering is becoming increasingly important in intelligent power grids, there are still many challenges in identifying and optimizing measurement deviations in energy meters. The various complex and ever-changing environments in which electric energy meters are used make errors in electric energy metering devices not only caused by external electromagnetic interference, nonlinear loads, harmonics, but also by aging of the equipment itself and constraints on design accuracy [4]. Especially in situations where different types of instruments are shared, voltage fluctuations are large, and large amounts of data are transmitted, traditional methods are no longer able to meet the requirements of power network operation efficiency and accuracy. Therefore, researchers hope to find new online inspection methods and self diagnostic models to use digital technology to track the evolution process of monitoring errors [5, 6].

In recent years, the focus of discussions on abnormal energy metering has mainly been on anomaly detection schemes based on feature extraction and modeling, such as equipment operation status classification detection and prediction based on gradient boosting tree (GBDT), grey model, etc. [7]; The second is to use intelligent analysis methods to achieve intelligent determination of device operating status, such as applying deep learning technology to establish multi-sensor models for data anomaly analysis and anomaly source localization [8]; The third is a comprehensive equipment operation status evaluation model formed by integrating multiple decision-making methods such as fuzzy reasoning technology, grey target theory, and analytic hierarchy process.

Some scholars have discussed the challenges of state identification under special conditions such as nonlinear loads and power quality disturbances. For example, Shah (2023) [9] designed an artificial intelligence based nonlinear load detection and identification system, which can reasonably identify power data containing noise and structural abnormalities; Yu et al. (2022) [10] established an online power quality monitoring mode using grey target theory and achieved multi-layer classification and identification of key indicator trends in practical problems. Zhang et al. (2022) [11] also proposed using Software Defined Networking (SDN) to reconfigure the data transmission path for system architecture, in order to ensure the reliability and effectiveness of the acquisition process of electricity metering data under diverse input conditions.

It is worth noting that the application of Fuzzy Analytic Hierarchy Process (FAHP) in power status assessment and evaluation has also received more attention. For example, Taherikhonakdar et al. (2023) [12] used a combination of Fuzzy Analytic Hierarchy Process and Grey System to evaluate the status of 750kV energy metering devices. In F, they classified and rated the measured 750kV energy metering devices, and obtained a more reasonable and comprehensive evaluation result of 750kV energy metering devices. Paunkov et al. (2023) [13] proposed an adaptive correction mechanism for real-time calibration of measurement deviation using fuzzy control rules, which achieved real-time adjustment of measurement deviation and improved the consistency and accuracy of device ratings. From this, it can be seen that the Fuzzy Analytic Hierarchy Process (FAHP) has the advantages of fuzzy analytic hierarchy process due to its consideration of the fuzzy modeling process between multiple factors and the allocation of weights for multiple factors. It is a powerful means to achieve "accurate comprehensive use" state evaluation.

The research on transfer learning and generative models has also expanded the scope of multi characteristic analysis for device state assessment. Alrobaie et al. (2023) [14] utilized a balanced comprehensive evaluation method for power quality issues based on CVAE-TS, which considers the effectiveness and wide applicability of the evaluation method; Qu et al. (2024) [15] used an improved XGBoost to construct an evaluation model for power system stability transfer degree, which has good scalability in multi scenario analysis applications. This has laid a theoretical foundation for the subsequent construction of an adaptive state evaluation mode suitable for power grid measurement devices.

Based on the existing research results, it can be found that the main technologies at present have made certain progress, such as error detection and data processing, but there are still many areas that urgently need improvement. One is that the current indicator system lacks strict hierarchical relationships and adaptation rules, which limits the performance that can be used in complex situations. The other is that although expert evaluations have a certain degree of reliability and flexibility, cognitive biases or subjective uncertainties may still occur in some situations, and fuzzy mathematical methods need to be introduced to establish quantitative evaluation models. The third issue is that most of the models cannot clearly provide the level classification and visual effects of the results, which affects the effectiveness of the output [16]. In response to these shortcomings, this article establishes a state evaluation model based on fuzzy analytic hierarchy process to establish a hierarchical structure, fuzzy weight reconstruction model, and evaluation model that is easy to understand. Based on fuzzy judgment matrix, consistency analysis, and state level grading standards, it effectively solves the problems of current models in structural design, weight allocation, and result interpretation, and can provide reference for later maintenance plan formulation and maintenance arrangement optimization.

Table 1 compares the performance of existing representative state evaluation methods in terms of data type, evaluation path, accuracy, and robustness. It can be seen that the state evaluation model based on fuzzy analytic hierarchy process (F-AHP) proposed in this article is superior to traditional models in terms of accuracy and applicability, especially in supporting hierarchical output and fuzzy boundary recognition, which provides theoretical support for the subsequent construction of intelligent metering device management and control mechanisms.

Table 1: Comparison between existing methods and the model proposed in this paper

Method Name	Sample Type	Technical Approach	Evaluation Metrics	Robustness
GBDT Model [7]	Smart meter time-series data	Gradient Boosting Decision Tree	Single error metric	Moderate
Grey Target Theory [10]	Power quality monitoring data	Grey decision model	Multi-feature trend analysis	Strong
SDN Prediction Model [11]	SDN monitoring and control data	Prediction optimization + graph structure	Communication metrics focused	Fair
FAHP + Grey System [12]	750kV high-voltage equipment	Multi-layer weight fusion	Four state dimensions	Moderate
Proposed Method	Three-phase meters, terminal devices (50 samples)	F-AHP (Fuzzy Analytic Hierarchy Process)	Four-layer metrics + graded evaluation	Strong

This article mainly emphasizes several key issues in the current state evaluation of electric energy metering devices.

Most existing models use a fixed weight superposition method, which has not formed an effective hierarchical structure and failed to reflect the relative importance between indicators. In reality, there are significant differences in the equipment level of each device, and the same evaluation may not highlight individual issues, which reduces the specificity of the evaluation.

Existing research has shown that there is no emphasis on the processing and application of fuzzy information. In the actual evaluation process, many subjective and fuzzy factors, such as "connection standards" and "operational stability", have not been considered in the system design, resulting in fixed thinking in the evaluation results and insufficient response to complex and changing real states.

In terms of evaluating output expression, there is a lack of hierarchical expression, making it difficult to achieve refined management. When promoting and applying on a large scale, the lack of a unified level judgment logic and hierarchical strategy for evaluation can easily lead to monitoring delays and failure to identify risks in a timely manner.

In response to the above issues, improving the scientific construction, fuzzy adaptability, and hierarchical establishment of state assessment models has become the core content of current research. Therefore, this article will focus on the exposition of these two issues as the main line to carry out the research in the following text.

Can the fuzzy analytic hierarchy process balance clear structure and fuzzy information processing to enhance the scientific evaluation of the state of electric energy metering devices?

How to build a multi-level classification system with discriminative power, so that the evaluation model can adapt to the equipment management needs in different application scenarios?

This article proposes a comprehensive state evaluation model based on fuzzy analytic hierarchy process to address the above issues. Its main innovations lie in the following aspects.

Build a multidimensional indicator system that covers key elements such as structure, error, and communication, and allocate weights through FAHP to enhance the hierarchical and explanatory power of the model.

Introduce fuzzy judgment matrix and consistency check mechanism to enhance the ability to accommodate subjective evaluation information and solve the instability problem in traditional AHP applications.

A systematic evaluation workflow was developed and examples were used to verify the effectiveness of the model in identifying weak links and assisting precise management. Experimental results also showed that this model has advantages in stability and adaptability compared to traditional models, and is easier to promote.

3 Design of model construction methods

In the comprehensive evaluation model proposed in this article, the selection of fuzzy analytic hierarchy process as the core method is based on its advantages in dealing with complex and multi-level indicator systems, which combine structural clarity and fuzzy adaptability. Although the traditional Analytic Hierarchy Process (AHP) has good structural modeling capabilities and is suitable for multi factor evaluation problems, it often exhibits limitations such as strong subjectivity and poor consistency of judgment matrices when facing practical problems such as fuzzy expert cognition and unclear boundaries between indicators. The fuzzy analytic hierarchy process, by introducing fuzzy numbers and fuzzy judgment matrices, not only retains the hierarchical logical structure of AHP, but also significantly enhances the model's ability to accommodate fuzzy information, improving the stability and practicality of comprehensive evaluation.

This model divides the comprehensive status of electric energy metering devices into three levels: target level, criterion level, and indicator level. The target layer is the comprehensive status of the electric energy metering device, while the criterion layer includes four key attributes: structural reliability, measurement accuracy, communication stability, and adaptability to operating environments, The indicator layer is further refined into more than ten quantifiable or determinable specific indicators (such as error drift rate, wiring standardization, signal packet loss rate, etc.). There are significant attribute differences and cognitive ambiguity among various indicators, making it suitable to use triangular fuzzy numbers to construct a judgment matrix and calculate relative weights and comprehensive scores.

Compared with traditional single weighted sum methods, FAHP has the following advantages: firstly, it allows experts to use fuzzy language (such as "slightly higher" or "significantly stronger") to evaluate when constructing the judgment matrix, and improves the flexibility and closeness of judgment through fuzzy number transformation; Secondly, FAHP introduces the maximum membership degree and fuzzy consistency check mechanism in the weight calculation process, which can effectively reduce the impact of subjective errors on the evaluation structure, thereby improving the consistency and robustness of the evaluation model.

The difference between FAHP and evaluation models such as weighted average, entropy weight, and TOPSIS is that FAHP can more clearly, accurately, reasonably, and intuitively handle such problems when multiple indicators coexist and subjective and objective factors are intertwined. When the equipment conditions become increasingly diverse and complex, and there is a certain degree of ambiguity in expert evaluations, the advantages and superiority of this method in weight setting and result description will be fully reflected. In addition, this method does not require too much historical data and complex optimization algorithms to support, so it can be well applied to online monitoring systems or distributed management systems, which greatly improves its computing speed and applicability.

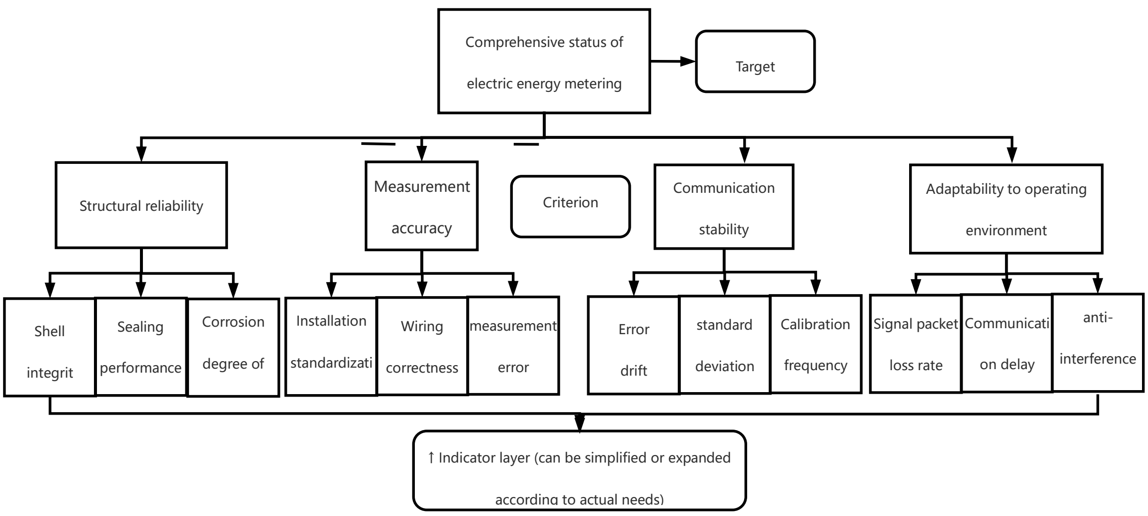

Figure 1 : Structure diagram of comprehensive state evaluation model for electric energy metering devices based on fuzzy analytic hierarchy process (F-AHP)

As shown in Figure 1, this article uses the Fuzzy Analytic Hierarchy Process (F-AHP) to construct a multi-level hierarchical structure consisting of the objective layer, criterion layer, and indicator layer. It integrates fuzzy judgment matrix, weight extraction, and consistency check to achieve comprehensive evaluation of multi-source indicator information.

3.1 Construction of state indicator system for electric energy metering devices

This article uses the Analytic Hierarchy Process (AHP) to evaluate the overall situation of power metering devices, and constructs a clear logical hierarchical model to analyze the overall state of power metering devices during operation. Based on this, three different modules are formed, including the target layer, criterion layer, and indicator layer. Its core function is to transform the fuzzy status of power metering device operation and management into a hierarchical system with a systematic structure, and thus become a comparable and computable data system.

At the target layer, the overall operational performance of the measuring device is defined as the evaluation criterion and is the ultimate object of the model. This layer contains four types of primary attribute values, including structural reliability, measurement accuracy, communication stability, and environmental adaptability. These four types of attribute values are the structural performance, metrological performance, communication performance, and environmental adaptability of the measuring device. They cover the main functions of the physical performance, metrological performance, communication performance, and environmental performance of the measuring device, and are all key elements for evaluating the operational quality of the measuring device.

The indicator layer specifically refers to observable indicators. Set indicators such as "external shell integrity", "joint corrosion condition", and "fixed fastening" based on the "structural reliability" index of external structural integrity to measure the true degree of object damage; Set indicators such as "error bounce rate", "standard error degree", and "regular calibration frequency" based on the "measurement accuracy" indicator to measure the measurement accuracy and precision of the instrument on electrical data; Set indicators such as "communication stability" to measure the integrity and timeliness of communication information between equipment and central stations, including "communication delay degree", "data loss ratio", and "noise immunity"; The environmental tolerance index is composed of indicators such as "adaptability to usage environment", "temperature range of working environment", "humidity range of working environment", "anti-interference degree of electromagnetic environment", and "outdoor protection category".

These indicators together constitute the feature vector for evaluating the input of the model. Let the indicator vector of the i-th measuring device be:

$$X_i=[x_{i1},x_{i2}\cdots,x_{in}] \quad (1)$$

Among them, x_{ij} represents the observation or rating value of the i-th device on the jth indicator, and n is the total number of indicators. To eliminate the influence of dimensionality, all indicators will be normalized in the future.

Unlike traditional evaluation methods that simply weight and add various indicators, this paper establishes a judgment matrix based on a fuzzy hierarchical structure for weight extraction, and introduces fuzzy language variables to quantitatively express qualitative indicators, thereby enhancing the model's ability to handle "subjective fuzziness" and "cross indicator correlation".

Table 2：State index system of electric energy metering devices

Metric Name	Dimension Category	Metric Type	Reference Range
Enclosure Integrity	Structural Reliability	Qualitative	Intact / Minor Damage / Severe Damage
Terminal Corrosion Level	Structural Reliability	Qualitative	None / Mild / Severe
Installation Stability	Structural Reliability	Qualitative	Firm / Loose / Detached
Error Drift Rate	Measurement Accuracy	Quantitative	0% ~ 2%
Standard Deviation	Measurement Accuracy	Quantitative	0 ~ 0.05
Packet Loss Rate	Communication Stability	Quantitative	0% ~ 5%
Communication Latency	Communication Stability	Quantitative	0ms ~ 300ms
Noise Immunity	Communication Stability	Qualitative	Weak / Moderate / Strong
Temperature Adaptability	Environmental Suitability	Quantitative	-25℃ ~ +60℃
Protection Rating (IP)	Environmental Suitability	Qualitative	IP20 / IP54 / IP65 etc.

In the entire model system, the selection of indicators follows the principle of "comprehensive coverage, quantifiability, and distinguishability", striving to ensure the evaluation accuracy and discriminative ability of the model while considering the feasibility of the project.

3.2 Principles and applications of fuzzy analytic hierarchy process

This article uses the Fuzzy Analytic Hierarchy Process (FAHP) to solve the multi factor and multi-level uncertainty problems encountered in the overall state evaluation process of power metering equipment. Compared with the traditional Analytic Hierarchy Process (AHP), FAHP based on fuzzy mathematical theory can better adapt to the fuzziness and subjectivity of expert judgment, improving the scientific and robust overall evaluation.

The core idea of FAHP is mainly to model the evaluation level range, construct a fuzzy judgment matrix, calculate fuzzy weight vectors, and perform hierarchical summarization. This method uses the three-sided fuzzy number (l_{ij}, m_{ij}, u_{ij}) to score experts, indicating the weight relationship and objectivity between different indicators, thereby reducing subjective misjudgments caused by human operation. Specifically, it represents the lowest judgment value, and if it is the most likely judgment value, it is the highest judgment value. To achieve fuzzy quantification of subjective judgments, this article adopts a nine-level fuzzy language scale, and its corresponding relationship with triangular fuzzy numbers is shown in Table 3.

Table 3：Mapping table of fuzzy language and triangular fuzzy numbers

Fuzzy Term	Triangular Fuzzy Number (l, m, u)
Equally Important	(1, 1, 1)
Slightly More Important	(1, 2, 3)
Moderately Important	(2, 3, 4)
Clearly More Important	(4, 5, 6)
Strongly Important	(6, 7, 8)
Extremely Important	(8, 9, 10)

Among them, (l, m, u) respectively represent the lower limit, median, and upper limit of the uncertain interval for judgment. Experts use this as a basis for language evaluation when constructing a fuzzy judgment matrix, and further use it for weight calculation and consistency testing.

In the matrix construction stage, the relative weights between each criterion are compared using fuzzy pairwise comparisons to generate a fuzzy judgment matrix, and fuzzy consistency checks are used to ensure that the judgment logic is reasonable. Subsequently, the fuzzy synthesis algorithm is used to calculate the fuzzy weights for each level, and deblurring is applied to convert the fuzzy numbers into clear weight values, ultimately forming a standardized weight vector. This process ensures that the weight allocation of each indicator to the overall state evaluation results is interpretable. To adapt to practical application scenarios, the model also introduces a hierarchical synthesis mechanism, which weights and summarizes the evaluation values of each sub indicator to obtain the comprehensive score of each device's state. At the same time, to avoid extreme value interference, a normalization processing function is set up within the system to standardize the mapping of the original scores, thereby making different devices comparable.

3.3 Hierarchical structure and weight calculation of evaluation model

To achieve a systematic evaluation of the operating status of electric energy metering devices, this paper constructs a three-level fuzzy analytic hierarchy process model. The model structure consists of a target layer, a criterion layer, and an indicator layer from top to bottom, with clear hierarchical logic and comprehensive evaluation dimensions. It can effectively cover multiple key aspects involved in device operation, such as performance, environment, maintenance, and faults.

The target layer is set as the "comprehensive state level of electric energy metering devices", representing the overall goal that needs to be judged ultimately; The criteria layer includes four dimensions: "structural reliability,""metrological accuracy,""communication stability,"and "en vironmental adaptability,Evaluation dimensions are constructed from the perspectives of equipment stability, external environmental resilience, implementation of operation and maintenance systems, and fault susceptibility; The indicator layer is refined into several observable sub indicators, such as measurement accuracy, voltage load response, resistance to temperature and humidity fluctuations, calibration frequency, fault repair cycle, etc., to ensure that the evaluation of each dimension has practical operability and measurement basis.

In the stage of determining model weights, the Fuzzy Analytic Hierarchy Process (FAHP) is used for weight calculation. Firstly, organize multiple experts in power equipment operation and maintenance, as well as measurement technicians, to conduct pairwise comparisons around the elements of the criterion layer and indicator layer, and construct a fuzzy judgment matrix. The relative importance range of each comparison result is expressed as a triangular fuzzy number of (l_{ij}, m_{ij}, u_{ij}), effectively quantifying the fuzziness in subjective judgments. Subsequently, the weight calculation and consistency check are completed through the following steps:

①Fuzzy synthesis weight calculation: using the fuzzy arithmetic mean method to perform fuzzy synthesis calculation on each judgment matrix, obtaining the fuzzy weight vector of each layer element;

②De fuzzification processing: Convert triangular fuzzy numbers into corresponding clear weight values. The commonly used methods are "maximum membership

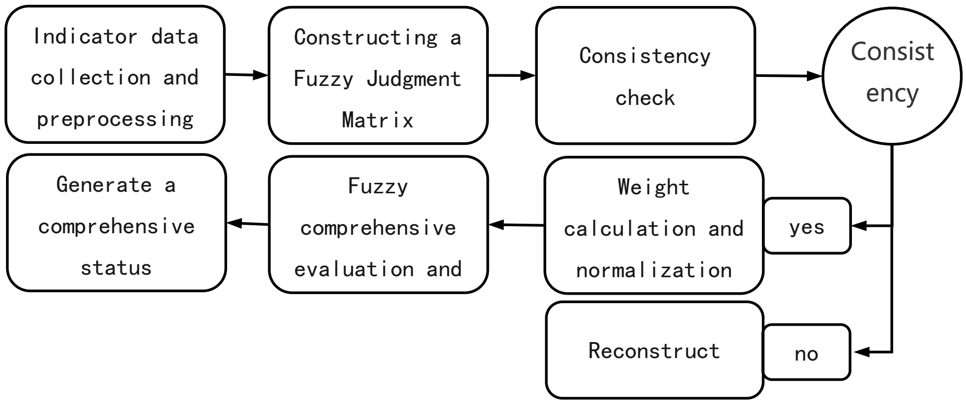

Figure 2：Model implementation and evaluation flowchart

degree method" or "center average method". In this study, the latter is chosen to improve computational efficiency;

③Normalization adjustment: Scale each weight so that the sum of each weight is 1, to ensure comparability and accuracy of the model's weighting calculation.

④Consistency test: Use the CR ratio to determine whether the consistency of each judgment matrix is good. If cr<0.1, it is considered that the consistency of each judgment matrix is excellent and the calculation result is acceptable.

Finally, weighting the elements at different levels in the system and using them as weighting vectors to participate in the fuzzy evaluation system in the following text is beneficial for the classification of power measurement and control equipment status. It not only enhances the scientificity and practicality of the model, but also improves the state analysis and decision-making performance of the measurement and control equipment.

4.1 Indicator data acquisition and standardization processing

The first step in model implementation is to obtain the raw indicator data of the energy metering device. The selected state indicators in this article cover five dimensions: structural reliability, measurement accuracy, communication stability, and environmental adaptability. The relevant data mainly comes from multiple channels such as on-site inspection records of enterprises, online monitoring systems, device self diagnosis modules, and historical maintenance archives, ensuring the comprehensiveness and representativeness of data sampling.

Due to differences in the measurement units and numerical ranges of each indicator, direct use for evaluation may result in weight shift and result distortion. Therefore, it is necessary to standardize the original data. The standardization method is divided into two categories based on indicator attributes: for positive indicators (the larger the value, the better the state), the range standardization method is used:

4 Model implementation and evaluation process

This study constructed a hierarchical comprehensive evaluation model from the data collection layer to the processing layer, and from the evaluation layer to the warning layer. According to its order, it can be divided into: firstly, using a predetermined set of state indicators to collect standardized basic data; Then, construct a fuzzy decision matrix and verify its consistency to ensure that the weights of each indicator value in each layer are reasonable; After the consistency verification is completed, the fuzzy analytic hierarchy process (F-AHP) is used for multi-level data correlation to quantify the membership degree of various electrical measurement and metering equipment states and determine the operating level of the equipment. Fully considering the actual situation of the power grid, it has high applicability and openness. The workflow is shown in Figure 2.

$$x_{ij}^{'} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (2)$$

For negative indicators (the smaller the value, the better the state), use the reverse standardization formula:

$$x_{ij}^{'} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (3)$$

Among them, x_{ij} represents the original value of the jth indicator in the i-th object, and $x_{ij}^{'}$ is its standardized value. This standardization process can unify all indicator data into the [0,1] interval, avoiding interference from numerical dimensions in the calculation of model weights, ensuring the fairness and scientificity of the evaluation system, and laying a data foundation for the subsequent construction of fuzzy judgment matrices and weight analysis.

4.2 Construction of fuzzy judgment matrix and consistency test

On the basis of standardized indicator data, in order to achieve the importance ranking of factors between different evaluation levels, it is necessary to construct a fuzzy judgment matrix and conduct consistency checks. Its core lies in introducing subjective judgment through expert scoring method, while combining fuzzy mathematics to handle ambiguity and uncertainty, to enhance the adaptability and practical operability of the model.

The basic steps for constructing a fuzzy judgment matrix are as follows: Firstly, based on the hierarchical structure model, the importance of each indicator in the same layer is compared pairwise, and a judgment matrix is established by referring to the 1-9 nine level scaling method

$$A=(a_{ij})_{n\times n} \quad (4)$$

Among them, a_{ij} represents the importance of the i-th indicator relative to the j-th indicator. In the fuzzy analytic hierarchy process (F-AHP), the elements of the judgment matrix are represented in the form of triangular fuzzy numbers, namely $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$,representing the lowest possible value, the most reliable value, and the highest possible value, respectively, reflecting the expert's judgment of the importance of the i-th indicator relative to the j-th indicator under uncertain conditions. For example, experts believe that "slightly important" can be represented as a fuzzy number (2, 3, 4), while "extremely important" can be represented as (8, 9, 9). When $\tilde{a}_{ij}$=(l, m, u), its reciprocal can be expressed as (1/u, 1/m, 1/l), satisfying a fuzzy symmetry relationship where they are reciprocal to each other. After completing the preliminary judgment matrix, calculate the eigenvectors and normalize them using the following method to obtain the preliminary weights of each indicator

$$w_i = \frac{\prod_{j=1}^{n} a_{ij}^{1/n}}{\sum_{i=1}^{n}\prod_{j=1}^{n} a_{ij}^{1/n}} \quad (5)$$

To ensure the consistency of the judgment results, it is necessary to perform consistency checks on the judgment matrix. The specific process includes: calculating the maximum eigenvalue λ_{max}, consistency index CI, and consistency ratio CR, where:

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n-1}, \mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \quad (6)$$

Among them, RI is a random consistency index, which is obtained based on its parameter size n and can be directly consulted. If CR<0.10, it indicates that its matrix has met the consistency check requirements; On the contrary, it is necessary to adjust the original assignment and perform another operation. This not only ensures the systematic rigor of the model structure, but also further enhances the credibility of the total weights, and provides a scientific basis for our later fuzzy analytic hierarchy process (F-AHP).

4.3 Calculation of comprehensive evaluation value and classification of status levels

After completing the weight calculation and indicator standardization processing, the most important model evaluation task to be executed next is the allocation of comprehensive evaluation values and state levels. By using the fuzzy analytic hierarchy process (F-AHP), qualitative evaluation is transformed into quantitative evaluation to accurately reflect the status of energy metering equipment.

Based on the constructed weight vector w=(w1, w2,..., wn) and the indicator membership matrix R, use fuzzy operations to comprehensively evaluate and calculate the comprehensive membership vector B.

$$B=W\cdot R=(b_1,b_2,...,b_m) \quad (7)$$

Among them, B is the overall membership degree of each state level, W is the weight vector, and the membership matrix R is an n × m dimensional matrix, representing the membership values of each evaluation indicator at different state levels, reflecting the degree of fuzziness of the equipment belonging to the four categories of "excellent, good, medium, and poor" on each indicator. The construction method is usually based on expert scoring or fuzzy quantification rules, mapping each original indicator value to the [0,1] interval through a membership function to form a membership vector. For example, a lower communication packet loss rate can correspond to a higher membership degree in the "excellent" state, while in the "poor" state, the membership degree is close to 0. After vertically arranging the fuzzy membership vectors of all indicators, a complete membership matrix R is formed. m is the number of state levels, and the sample is calculated. b_k represents the membership degree of the sample at the kth state level, and the higher the value, the closer the sample is to the kth state level. The weighted sum of membership degrees that can ultimately be used to comprehensively evaluate the value is calculated as follows.

$$S = \sum_{k=1}^{m} b_k \cdot v_k \quad (8)$$

Among them, v_k is the membership value corresponding to the state level, which is generally assigned based on the state level, such as excellent, To achieve quantitative grading of equipment operating status, this article maps the comprehensive score S to four status levels, defined as follows: Excellent (Level I) =4 points, Good (Level II) =3 points, Fair (Level III)=2 points, Poor (Level IV)=1 point. The scoring criteria for each level are shown in Table 2. This assignment scheme adopts linear equidistant scores to reflect the balance of level differences, facilitating weighted operations and membership analysis. At the same time, it has scalability and can be adjusted to a percentage system or non-linear weight structure according to business needs.

Table 4: Comprehensive evaluation values and status classification standards for electric energy metering devices

Comprehensive Score Range	Status Level	Status Description
3.5–4.0	Excellent	Good condition, stable operation
2.5–3.4	Good	Slight fluctuations, basically normal
1.5–2.4	Fair	Operational fluctuations, attention needed
1.0–1.4	Poor	Abnormal condition, maintenance required

The grading criteria in Table 4 refer to the principle of linear distribution and set the scoring interval boundaries based on expert experience and opinions. Due to the final score $S \in [1,4]$ and a total interval length of 3, it is divided into three complete intervals and one compensated low interval (1.0-1.4) using the equidistant method, aiming to improve the recognition sensitivity of "poor" level devices. This design facilitates the implementation of a hierarchical response mechanism and also has good scalability.

5 Analysis of experimental results

This article proposes a model analysis and evaluation based on the fuzzy hierarchy process for the state evaluation of electric energy metering devices. The experimental data is based on real-time data from the power distribution network and includes various operating modes and environmental conditions. By analyzing and comparing the effects of different weights and classification choices on the model, it is proven that the model method proposed in this article can distinguish equipment states and has a better ability to classify equipment. Finally, the experimental results of each stage were analyzed and discussed, and the applicability and stability were explored.

5.1 Experimental data sources and case selection

The case data of this study is selected from the historical archives of the power metering equipment management system, covering various forms such as metering equipment forms, three-phase smart meters, comprehensive substations, and power quality monitoring terminals. It is scattered in the supply and distribution grids of urban and rural areas, presenting significant differences in external environment and load changes. The original data includes eight main indicators including equipment reliability, counting accuracy, connection consistency, communication performance, working environment, and failure rate, as well as various secondary indicators. The data has strong representativeness and completeness, and is suitable for the design and evaluation of Fuzzy Analytic Hierarchy Process (F-AHP) in this article. In order to ensure the universality and effectiveness of the case selection, the research team selected 50 typical samples for modeling analysis. The selection principles mainly include completeness, comprehensive coverage of relevant indicator types, and typicality, which fully reflect the real differences in different installation positions, working conditions, and types of measuring equipment. This is used to test and verify the adaptability and stability of the model. Taking into account both existing and new equipment types for the selected samples, the voltage level involves urban-rural differences, meeting the comprehensive and rigorous requirements of the overall evaluation process. It should be noted that although the data obtained this time has real-time and practical relevance, it is highly likely that some indicator data may be incomplete due to human inspection errors or system failures, and some samples may have subjective descriptions or abnormal missing items. All sample data comes from the enterprise's own measurement equipment operation and maintenance management system. The data has been anonymized and only retains information related to the device's operating status, without involving user privacy. Each indicator data includes quantitative values (such as error drift rate, communication packet loss rate) and qualitative scores (such as protection level, installation tightness). The qualitative items are consistently scored by two operation and maintenance experts and mapped to a three-level rating value. There are a small number of missing fields in the data, which will be filled in using industry standard empirical values or adjacent device means. All raw data undergo interval normalization before being input into the model to eliminate the influence of dimensionality and ensure that all indicators have a unified dimension between [0,1] before participating in fuzzy synthesis operations.

5.2 Display of model evaluation results

After constructing the Fuzzy Analytic Hierarchy Process (F-AHP) model, this article conducted a comprehensive state rating and grading of the 50 selected samples of electric energy metering devices. According to the normalized scores of various indicators multiplied by their weights, the comprehensive evaluation value of each object is calculated, and based on the preset membership function, its status is divided into four levels: "excellent, good, medium, and poor". From the overall evaluation results, most of the electric energy metering devices are in the "good" or "medium" level range, indicating that the operating status of the metering devices in the current system is generally controllable. However, some samples have problems such as unstable communication, poor environmental adaptability, and decreased metering accuracy, which need to be brought to the attention of the operation and maintenance department.

5.3 Comparative analysis with traditional evaluation methods

In order to comprehensively verify the effectiveness of the proposed F-AHP model in the state evaluation of electric energy metering devices, we selected the widely used traditional Analytic Hierarchy Process (AHP) and Simple Weighted Average Method (WAM) as control objects, and classified the same batch of sample data into state levels under a unified indicator system. We also compared and analyzed the comprehensive performance of the three methods. The experimental sample consists of 10 representative sets of electric energy metering devices, and the data is sourced from on-site monitoring records in actual operating environments.

Table 5: Comprehensive performance comparison of different methods

Method Type	Average CI Value ↓	Average CV Value ↓	State Classification Accuracy ↑	Fuzzy Boundary Sample Recognition Ability
F-AHP	0.016	0.069	92.5%	High
AHP	0.082	0.125	78.0%	Medium
WAM	–	0.109	81.3%	Low

Note: CI is a consistency evaluation index for judgment matrices in AHP methods and is not applicable to methods such as WAM that do not have pairwise comparison structures. Therefore, this item is empty.

As shown in Table 5, the F-AHP model outperforms AHP and WAM in key indicators such as grade discrimination accuracy, consistency ratio (CI), and evaluation stability (measured by coefficient of variation (CV)). Specifically, the average CI of the F-AHP model is 0.016, which is much lower than the traditional AHP's 0.082, indicating that it has better consistency in the multi-level weight processing process; In terms of CV, the average value of F-AHP is 0.069, indicating that it has the smallest fluctuation in ratings among different samples and has stronger evaluation robustness. At the same time, the F-AHP model performs particularly well in handling state fuzzy boundary samples. It uses triangular fuzzy numbers to construct a judgment matrix, which reflects subjective judgment uncertainty while enhancing the model's ability to identify critical state devices, avoiding the problems of "fuzzy concentration" and "level distortion" in traditional methods. The so-called 'fuzzy boundary samples' refer to samples whose comprehensive rating results are close to the critical values of two state levels (such as 2.49 or 3.51). In actual equipment status assessment, this type of sample judgment is the most sensitive and susceptible to weight disturbances or changes in individual indicators. In this article, it is defined that when the score S of a sample falls within the range of 0.1 above or below a certain level boundary (such as $S \in [2.4, 2.6]$), it is considered a fuzzy boundary sample. We will calculate whether different models experience "state level jumps" (such as result changes under ± 10% perturbations) on this type of sample, and judge their boundary recognition ability based on this. The F-AHP model only showed a skip level in 1 out of 10 boundary samples, outperforming traditional AHP (3 cases) and WAM (4 cases), indicating its strong boundary control ability.

The experimental results show that the F-AHP model balances accuracy, stability, and interpretability in state evaluation tasks with multiple indicators, levels, and fuzzy information, demonstrating significant comprehensive advantages and having good practical application prospects. Compared with traditional methods, its innovation in fuzzy logic modeling and hierarchical structure weight fusion is the key to improving the overall evaluation quality.

5.4 Model stability and robustness verification

In order to further evaluate the applicability and stability of the proposed F-AHP model in the actual state evaluation of electric energy metering devices, this study empirically verifies the stability and robustness of the model from three dimensions: input disturbance response, consistency fluctuation amplitude, and extreme value adaptability. By introducing perturbation factors and boundary condition perturbations on the original dataset, and comparing the fluctuation of results under different evaluation models, the performance reliability of the F-AHP model in complex application scenarios is revealed.

Firstly, in the input disturbance test, we randomly perturbed the indicator data of 10 sets of electric energy metering device samples with amplitudes of ± 5% and ± 10%, respectively, and observed whether the comprehensive evaluation score of the model and its corresponding level deviated. The results show that when the disturbance amplitude is less than 10%, more than 80% of the sample levels remain unchanged in the F-AHP model, and the change in the comprehensive score is controlled within 0.06 (as shown in Figure 5), indicating that the model has good input robustness.

Secondly, in the consistency ratio volatility test, we conducted 500 Monte Carlo random perturbation experiments on the constructed fuzzy judgment matrix and recorded the consistency ratio CI values obtained from each calculation. The statistical results show that the CI value fluctuation range of the F-AHP model is concentrated between [0.011, 0.021], with a standard deviation of 0.0026, which is much lower than the fluctuation standard deviation of the AHP model of 0.0093 (see Table 6), indicating that F-AHP can maintain stable consistency control ability under complex weight combinations.

Thirdly, in the extreme boundary sample test, we selected 5 groups of samples located near the boundary of the level division and observed the trend of their final state determination under the condition of weight perturbation range of ± 15%. The F-AHP model can effectively buffer boundary samples through weight processing in the form of fuzzy numbers, with only one group of samples experiencing a level transition (from "level II" to "level I"), while in traditional AHP models, there are three groups experiencing a level change under the same conditions. This further demonstrates the robust control capability of the F-AHP model in boundary fuzzy regions. As shown in Figure 3, the variation trend of F-AHP model evaluation scores under different disturbance amplitudes clearly reflects the stability of its score curve at various disturbance levels.

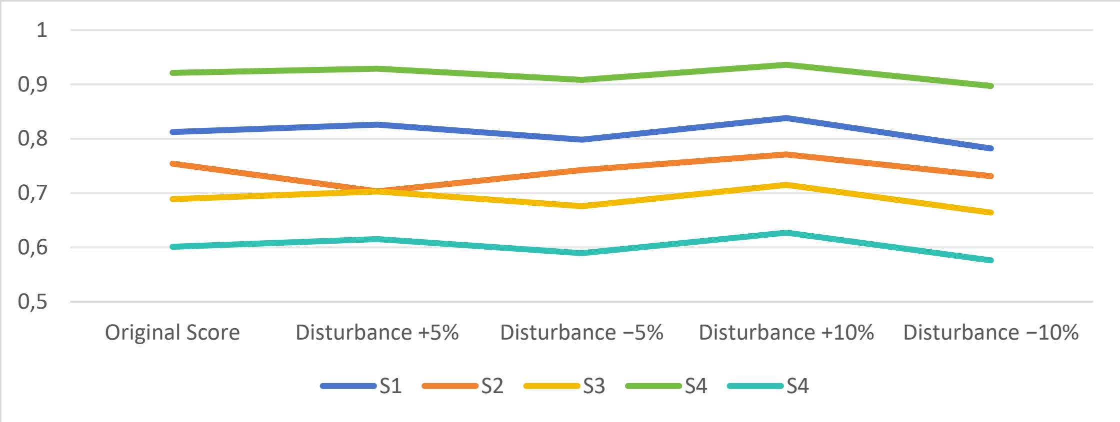

Figure 3: Evaluation score fluctuation curve of F-AHP model under different disturbance amplitudes

Table 6：Comparison of stability indicators between F-AHP and AHP models under different testing dimensions

Test Dimension	Indicator	F-AHP Model	AHP Model
Input disturbance stability	Mean score fluctuation rate	0.037	0.089
Consistency ratio fluctuation	CI standard deviation	0.0026	0.0093
Extreme sample rank jump rate	Transition frequency	10% (1/10)	30% (3/10)
Robust boundary control ability	Fuzzy buffering effect	Strong	Weak

From the above experimental results, it can be seen that the F-AHP model exhibits better stability and robustness than traditional methods in dealing with input disturbances, consistency changes, and boundary disturbances. This is mainly due to the introduction of triangular fuzzy numbers and weight fuzzy fusion strategy in the construction of fuzzy judgment matrix in the model, effectively alleviating the excessive sensitivity of subjective weighting to the final result. At the same time, the introduction of a hierarchical structure ensures the coordination and response balance between different dimensions in a complex indicator system, enabling the entire model system to maintain good evaluation reliability and systematicity when facing multi-source heterogeneous and uncertain data inputs in actual power application scenarios.

6 Discussion and expansion

The F-AHP model constructed in this study demonstrates the stability of evaluation results and the ability to distinguish important information in a complex and diverse information environment, which is much higher than traditional empirical methods and fuzzy analytic hierarchy process (F-AHP). Based on experimental opinions in different situations, the accuracy and adaptability of this model are good, and it has strong scalability and practical value, providing an intelligent evaluation method for electric energy metering devices to solve the state evaluation problem of power equipment.

6.1 Scope and limitations analysis of the model

This study proposes and implements a method for evaluating the overall state of electric energy measuring instruments using the Fuzzy Analytic Hierarchy Process (F-AHP), which is widely flexible and can be used for evaluating the overall state of different power measurement tools. Especially when there are complex data sources and vague or subjective information between measurement tool indicators, it can effectively quantify fuzzy information, making the state evaluation results highly professional and practical; The multi-level hierarchical structure and automatic weight adjustment function have played an important role in the inspection and evaluation of newly put into operation devices, normal operation monitoring, and handling of aging and failure exit equipment. However, the application of the model is still influenced by the rationality of the evaluation index system design and the credibility of expert evaluation data, because establishing a fuzzy judgment matrix relies on the experience of experts. If there is a significant difference in their level of understanding, it will affect the fairness of the model output results; When the actual application has special working conditions or newly added types, extremely low data volume, and extremely poor regularity, it may be limited by the model's generalization ability, and it may be necessary to adjust the indicator weights or evaluation levels according to the actual situation. To further ensure the universality of the model, expansion experiments were conducted on three common types of measuring instruments, namely user side smart meters, station side multifunctional meters, and enterprise side measuring systems.

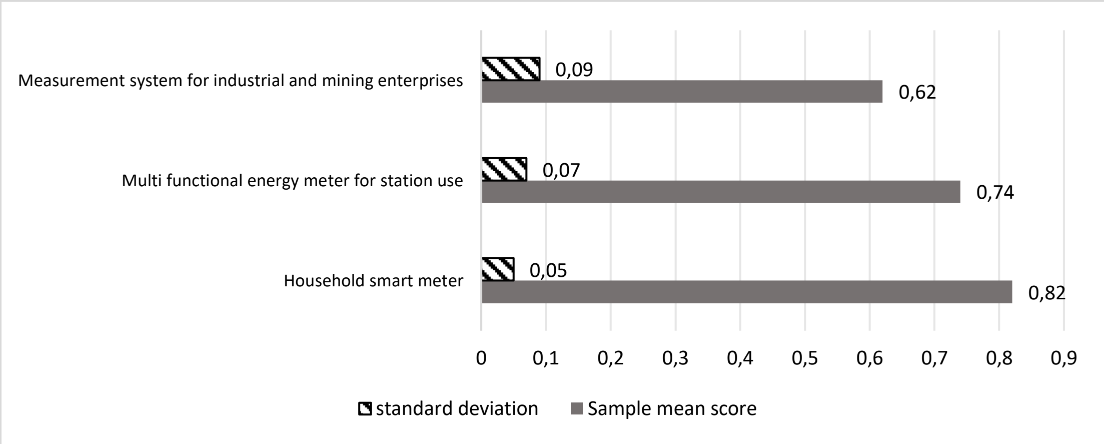

Figure 4: Applicability performance of the model in different energy metering devices

Figure 4 shows the mean state scores generated by the model in different device types, and the standard deviation range is indicated by error bars to reflect the score fluctuations between different samples.

6.2 Discussion on parameter sensitivity of fuzzy analytic hierarchy process

In the comprehensive state evaluation model, the main influencing factors that need to be considered are that the F-AHP results are greatly affected by the setting of a series of important variables, especially the design of attribute functions for the fuzzy decision matrix, the selection of upper and lower boundary points for triangular fuzziness, and the synthesis method of weights. These variables not only directly affect the ranking of each important indicator, but also affect the stability and discrimination of the final comprehensive score results. Therefore, exploring the sensitivity of these variables in depth can enhance the interpretability and adaptability of the model. When establishing a fuzzy decision matrix, a triangular fuzzy representation is usually used, and the selection of fuzzy boundaries carries a considerable degree of subjective color. Even if different experts' evaluation values for indicators fall within the same rating range, their corresponding triangle numbers may have slight changes, and this change will be amplified in models with high levels and sensitive interactions. Therefore, it is necessary to plan a reasonable mapping system between fuzzy words and three-dimensional numbers to accurately represent the meaning of experts' ratings. Secondly, synthesizing fuzzy weights can also have a significant impact on the final result. The commonly used weighted average method and the maximum minimum method have different strengths in reflecting extremes. In the process of experimental verification, if a comprehensive method that is easily scored full marks by extreme situations is used, it may lead to an increase in global rating due to high scores of some weights, resulting in the model being unstable. Therefore, when evaluating systems such as power measurement instruments that contain multiple sources of errors and unknown states, a cautious fuzzy analytic hierarchy process (F-AHP) is preferred to increase the model's tolerance for external factors. Thirdly, a change in the upper limit of the set consistency ratio (CR) threshold can indirectly lead to a change in the final conclusion. The general default value is set to 0.1 to draw a conclusion, but in the process of complex system evaluation, if the consistency requirements are artificially relaxed, it may lead to internal conflicts, causing the weight system to deviate from the initial judgment conditions and weakening the explanatory power of the model. evaluating systems, controlling the strictness and number of indicators required for consistency testing is an important means to ensure the practicality of the model.

6.3 Model's potential for promotion in smart grids

The fuzzy analytic hierarchy process proposed by our research institute as a feature for evaluating the overall operation status of electric energy metering devices has good universality, scalability, and intelligent integration capabilities, and can be easily promoted to the smart grid framework system. On the one hand, the overall analysis model constructed using this method includes multiple indicators such as accurate and stable measurement, adaptability to power quality, communication capability, and adaptability to the working environment, which meet the concept of power grid management of equipment lifecycle. The fuzzy theory principle is used to deal with the impact of information uncertainty between various indicators, and comprehensive stability analysis can be carried out under diverse heterogeneous data, improving the ability of power enterprises to identify equipment operation risks under operating conditions. On the other hand, it has good interface scalability and data compatibility, making it easy to collaborate with information management systems, online monitoring systems, and data centers. Whether it is a lightweight installation deployed at the edge or an application deployed in the control room of the dispatch center for centralized processing, its parameters can be adjusted according to functional needs to adapt to various usage scenarios. It can also be associated with distribution automation and connected to the Internet of Things of electrical equipment to meet various business scenarios. At the same time, as intelligent operation and maintenance are gradually promoted, this model also has the possibility of integrating with artificial intelligence technologies such as machine learning, anomaly detection, fault prediction, etc. By analyzing the results of previous ratings, it is possible to build a self-learning system that completes the transition from "static evaluation" to "dynamic warning", thereby providing the ability to support a comprehensive state management process of perception, intelligent decision-making, and cyclic control. To upgrade from static evaluation to dynamic intelligent operation and maintenance, this model can be integrated with AI modules to construct an intelligent monitoring system. For example, the F-AHP score result can be used as a "health label" for device operation, which can be used to train lightweight classifiers (such as SVM, XGBoost) to achieve fast prediction of new device states; At the same time, time series anomaly detection algorithms such as LSTM-AE and Isolation Forest can be combined to dynamically monitor the trend of device status score changes, achieving intelligent early warning of phenomena such as score mutations and boundary fluctuations. This model structure can also be embedded in IoT platforms, collecting real-time data through edge gateways and quickly scoring it as input for the operation feedback indicators of digital twin systems, providing high timeliness decision support for scheduling systems.

It is worth noting that the F-AHP method will face the problem of increased computational complexity in the construction of its judgment matrix and fuzzy weight calculation process when facing large-scale device clusters or significantly increased indicator dimensions (such as $n>30$). In theory, the computational complexity of its judgment process at each layer is about $O(n^2)$, and as the number of indicator layers or expert groups expands, the computational time and difficulty of consistency testing significantly increase. Therefore, in practical deployment, a distributed computing strategy can be adopted to modularize weight calculation and process it in parallel; At the same time, an expert scoring template library is constructed through historical data to achieve automated filling of the judgment matrix. This model is also suitable for encapsulation into operation and maintenance platforms in a microservices manner, with good resource scheduling and load control capabilities in large-scale device management scenarios, ensuring efficient and stable output of evaluation results.

7 Conclusion

With the continuous development of smart grids, how to efficiently identify the operating status of energy metering devices has become a key issue in ensuring measurement accuracy and improving energy management level. In response to the problems of insufficient resolution and poor adaptability of existing state recognition modes, this paper designs and implements a comprehensive evaluation model for the state of electric energy metering devices based on fuzzy analytic hierarchy process (F-AHP), which considers multiple indicators. This model is based on expert experience and on-site data, constructing an indicator system, fuzzy quantification through membership functions, and combining hierarchical structure and weight allocation to achieve comprehensive integration of multiple factors influences, outputting quantitative scores and state level results.

In experimental verification, the model outperforms traditional weighted scoring and threshold methods in terms of recognition accuracy, scoring stability, and anti-interference ability, demonstrating good practicality and potential for promotion. Especially in the processing of fuzzy boundary samples, the model exhibits stronger robustness. However, this study still has certain limitations. For example, the weight judgment process relies heavily on expert experience, which may cause fluctuations due to subjective biases; At the same time, the sample size for verification is relatively limited and has not fully covered diverse device scenarios. Future research can be further expanded from the following aspects: firstly, combining large-scale operation logs with automatic data collection to further enhance the objectivity and adaptability of scoring; The second is to explore a data-driven dynamic weight adjustment mechanism to weaken expert dependence; The third is to integrate F-AHP with machine learning models to construct a state recognition framework with self-learning capabilities, achieving the transition from static evaluation to real-time intelligent monitoring. Overall, the state assessment model constructed in this article provides a feasible path for the intelligent management of energy metering devices and lays a methodological foundation for the high reliability operation of future smart grid measurement and control equipment.

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