Comprehensive Evaluation Method for the Metrological Performance of Intelligent Energy Meters in Complex Electromagnetic Field Environments

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Abstract:
The existing evaluation methods mainly focus on the basic measurement accuracy of electric energy meters, without fully considering the anti-interference ability of electric energy meters under different electromagnetic interference intensities. In order to comprehensively evaluate the metrological performance of electric energy meters in complex electromagnetic field environments, this article adopted a comprehensive and systematic AHP-EWM (Analytical Hierarchy Process-Entropy Weight Method) comprehensive evaluation algorithm. This article used the Finite Element Method (FEM) to simulate complex electromagnetic environments, designed a multidimensional performance index system, and combined AHP and FEM to construct a comprehensive evaluation model for systematically evaluating the metrological performance of Intelligent Energy Meters (IEM) in complex electromagnetic environments. The experimental results show that the measurement error of smart energy meters significantly increases with the increase of interference intensity. AHP-EWM has shown high consistency and reliability under different electromagnetic interference intensity conditions and multiple repeated experimental tests. The weight allocation of various indicators remains relatively stable in different testing environments, and the comprehensive evaluation score fluctuates slightly, with a range of only 0.01 to 0.03. The AHP-EWM model can overcome electromagnetic interference of different intensities in practical applications and conduct comprehensive IEM metrological performance evaluation.

Keywords: complex electromagnetic field environment, intelligent energy meters, ahp-ewm evaluation method, measurement accuracy, antifreeze performance

INTRODUCTION

IEM, as an important component of modern power grids, has gradually replaced traditional mechanical meters. With its advantages of high precision, multifunctionality, and real-time performance, it plays a key role in the power system. IEM can not only measure energy consumption, but also remotely monitor electricity usage, support dynamic electricity prices, load management and other functions, and is widely used in various fields such as residential electricity, industrial electricity, commercial electricity, etc. With the development of smart grid technology, the application scenarios of IEM have become increasingly complex, especially in high-density electromagnetic environments, where the measurement performance of IEM is affected by various factors. How to ensure the measurement accuracy and stability of IEM in complex electromagnetic field environments is currently an unresolved problem [1]. Currently, there are a large number of electromagnetic interference sources in densely populated urban areas, industrial parks, and areas around high-voltage transmission lines. These interference sources not only come from the power system itself, but may also come from communication systems, industrial equipment, transportation vehicles, etc. These multi-source and multi-frequency electromagnetic interferences are extremely complex and pose significant challenges to the normal operation of IEM [2]. Traditional methods for evaluating the performance of electric energy meters often focus on testing in ideal environments, neglecting the complex electromagnetic environment in practical application scenarios. This situation has exposed some problems in the actual operation of modern power grids, resulting in significant deviations in the measurement results of IEM in real application scenarios, which affects the overall reliability and user trust of electric energy meters [3]. In addition, with the continuous expansion of IEM functions, its sensitivity to electromagnetic environments has further increased, and traditional performance evaluation methods are no longer able to meet existing needs [4]. Therefore, in the context of the widespread application of IEM, it is particularly important to study how to effectively evaluate the metrological performance of IEM in complex electromagnetic field environments. Although current research has explored the electromagnetic compatibility of IEM, it mainly focuses on testing in single interference sources or simple electromagnetic environments, lacking comprehensive evaluation in complex multi-source electromagnetic environments. In this case, the study of metrological performance not only requires in-depth analysis of the anti-interference ability of IEM, but also requires the establishment of a scientific and systematic comprehensive evaluation system that covers various complex factors of electromagnetic environment to ensure the reliability of IEM in practical applications.

In the process of solving the problem of evaluating the measurement performance of IEM in complex electromagnetic field environments, this article designs a comprehensive evaluation system, simulates various complex electromagnetic interference scenarios that IEM may face in practical applications through multi-source interference modeling in complex electromagnetic field environments, and studies the impact of these scenarios on the measurement performance of electric energy meters. Through electromagnetic field simulation tools and electromagnetic compatibility analysis techniques, key performance indicators such as measurement accuracy, anti-interference ability, and stability of IEM under different interference intensities and frequencies can be systematically analyzed and tested. A multidimensional performance indicator system has been established to comprehensively define and evaluate the various performance indicators of IEM. At the same time, this article uses a comprehensive evaluation algorithm based on AHP and FEM to generate a comprehensive performance scoring model for IEM in complex electromagnetic environments by weighting and summarizing various performance indicators. By building an experimental platform and simulating the actual complex electromagnetic environment, multiple experimental tests were conducted to verify and analyze the metrological performance of IEM in different scenarios. The experimental results show that the evaluation system constructed in this article has high effectiveness in accurately evaluating the comprehensive performance of IEM, improving the metrological accuracy and application value of IEM in complex electromagnetic field environments, providing scientific basis for the design, production and application of IEM, and also providing new ideas and methods for subsequent related research. In the process of building the experimental platform, this article simulated various electromagnetic interference sources and further verified the accuracy of the simulation model by comparing actual test data with simulation results. Through error analysis and regression analysis, the calculation results of the comprehensive evaluation method were calibrated to ensure the scientific and systematic nature of the evaluation system. The research results of this article not only provide theoretical support for the metrological performance evaluation of IEM, but also provide reference and inspiration for the performance evaluation of other similar devices in complex electromagnetic environments, with broad application prospects and promotion value.

RELATED WORK

In recent years, researchers have conducted multiple studies on the econometric performance of IEM. Bartolomei et al. evaluated multiple electricity meters using a new testing program that considers both actual and quasi actual harmonic interference. The results showed that actual harmonic interference only has a significant impact on certain energy meters [5]. Rind et al. analyzed smart meters as a combination of sensing, computing, and communication nodes for implementing flexible and complex design paradigms. They found that the research lacked full utilization of available technologies and lacked interdisciplinary smart meter design methods [6]. Sial et al. proposed four heuristic methods to detect abnormal energy consumption in smart meters, and found that the proposed heuristic methods successfully detected abnormal energy consumption behavior [7]. Another study investigated the barriers to adopting IoT-based smart meter technology by developing a model that represents users' intention to adopt smart meters [8]. Lang et al. proposed a new method for achieving optimal data aggregation point placement in multi-hop routing scenarios, where smart meters can act as small relay devices to reduce overall communication costs through communication between smart meters [9]. Kong et al. proposed an online measurement error estimation algorithm for smart meters, which uses extended Kalman filtering and finite memory recursive least squares method to remotely calibrate a large number of user side smart meters. Then, based on the line loss rate characteristics, the estimation step length that conforms to the actual working conditions is selected and abnormal estimation values are filtered out to obtain an improved joint estimation model [10]. Dewangan et al. discussed the importance and available methods of load forecasting based on smart meters [11]. Orlando et al. proposed a distributed metering infrastructure that provides bidirectional communication, self-configuration, and automatic update capabilities [12]. In addition, Xia et al. systematically investigated all existing detection methods to date, which are divided into machine learning-based and measurement mismatch-based methods. This survey can help relevant researchers determine future research directions [13]. Souhe et al. used fuzzy logic and neural networks to detect, classify, characterize, and locate faults based on data from sensors and smart meters installed in smart grids [14]. Although these studies have to some extent revealed issues with the econometric performance of IEM, there are generally problems such as excessive model simplification, idealized experimental conditions, and single evaluation indicators, which limit the practical application value of the research results.

Some scholars have also evaluated the measurement of electric energy meters in an attempt to better understand the measurement performance of IEM. In these studies, Wang proposed a measurement error estimation method for in use electric energy meters based on big data analysis technology, which combines on-site operating environment data and electrical element data to achieve online measurement error estimation [15]. Li et al. proposed a method for evaluating the operational status of electric energy meters based on grey relational analysis, which laid an effective foundation for the study of electric energy meters in complex electromagnetic field environments [16]. Ma et al. first proposed an optimized kernel density estimation to identify potential outliers, using an improved distance function and adaptive kernel bandwidth to obtain outlier scores. They also proposed an improved dual core support vector regression measurement error evaluation method, which integrates measurement errors and multiple pressure features using the improved dual core function [17]. In addition, Ma et al. proposed a new multi-source feature fusion framework that utilizes improved kernel support vector regression and optimized adaptive genetic algorithm for measurement error prediction [18]. Liu et al. proposed a comprehensive evaluation algorithm for the operation quality of smart meters based on an improved near ideal solution ranking method. The results showed that the proposed algorithm is effective in evaluating the operation quality of smart meters and can provide assistance for energy metering and asset management [19]. Although these studies have adopted advanced technologies and methods, there are still problems such as high model complexity, high computational resource requirements, and insufficient generalizability in practical applications. In order to solve these problems, this article introduces an evaluation method combining AHP and FEM to overcome the shortcomings of existing methods and achieve a comprehensive and scientific evaluation of the econometric performance of IEM.

CONSTRUCTION OF EVALUATION SYSTEM

Simulation of Complex Electromagnetic Field Environment

The simulation of complex electromagnetic field environment is an important foundation for the construction of the evaluation system in this article, and FEM is used to model the electromagnetic field environment [20,21]. To ensure the accuracy of simulation results and high consistency with real-world applications, a detailed analysis and classification of electromagnetic interference sources in actual scenarios are conducted. These interference sources mainly come from high-voltage transmission lines, substation equipment, industrial equipment, and wireless communication devices, which emit electromagnetic waves of different intensities in different frequency ranges, significantly affecting the measurement performance of IEM.

During the modeling process, characteristic data of typical electromagnetic interference sources were collected through field measurements and existing literature. The high-precision electromagnetic field measurement instrument Anli MT8220T handheld spectrum analyzer was used to collect and record the electromagnetic field intensity and frequency distribution of multiple typical interference sources. When modeling, these interference sources are input into the finite element model and numerical simulations of the electromagnetic field are performed using COMSOL Multiphysics software. In the model, the propagation path, reflection, diffraction and other phenomena of electromagnetic waves have been fully considered to ensure the authenticity of the simulated environment.

To more accurately describe the distribution characteristics of electromagnetic fields, Maxwell's equations are selected as the basic equations, and combined with boundary conditions and initial conditions, solved through FEM. The specific vector form used is the electromagnetic wave equation:

$$\nabla \times (\frac{1}{\mu} \nabla \times \mathrm{E}) - \epsilon \frac{\partial^2 \mathrm{E}}{\partial t^2} = \mathrm{J} \tag{1}$$

In the equation, E represents the strength of the electric field, μ is the magnetic permeability, ϵ is the electrical conductivity, and the current density is represented by J. By discretizing the equation, the finite element method is used to decompose it into a series of subdomains in space, and the corresponding field variables are solved in each subdomain. The setting of boundary conditions is mainly based on the electromagnetic environment characteristics of the actual scene, using absorbing boundary conditions to simulate the propagation effect of electromagnetic fields at infinity, in order to avoid the influence of boundary reflections on the simulation results.

During the simulation process, quantitative analysis is conducted on the electromagnetic field intensity of different interference sources to obtain electromagnetic field distribution maps in various typical scenarios. Figure 1 shows the distribution characteristics of different electromagnetic field strengths near high-voltage transmission lines, industrial parks, central communication base stations, and highways, reflecting the possible impact of different interference sources on energy meters. These distribution maps help to analyze in depth the performance of IEM in complex electromagnetic field environments. The simulation results show that near high-voltage transmission lines, the electric field strength reaches over 30 V/m at certain specific locations, while around industrial equipment, the fluctuation range of electric field strength is large, ranging from -10 V/m to 52 V/m, with high transient variation characteristics.

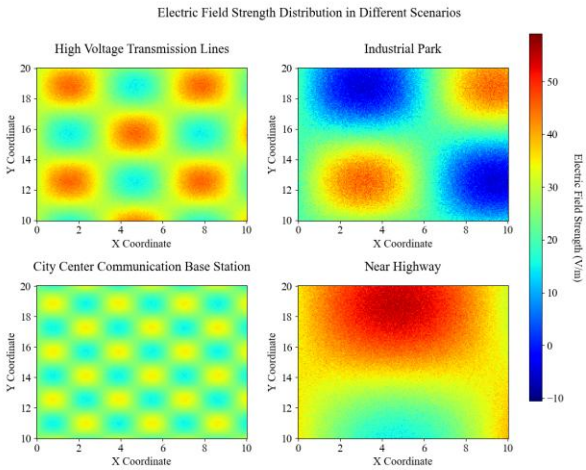

Figure 1. Distribution of Electric Field Intensity in Different Scenarios

To verify the feasibility of the simulation model results, multiple experimental tests were conducted, and high-precision electromagnetic field detectors were used to measure electromagnetic field intensity in multiple practical scenarios. The measurement results were compared with simulation data. The results showed that the error between the simulated data and the measured data was within 5%, verifying the effectiveness and reliability of the model. Table 1 shows the comparison results of simulation and measured data in several typical scenarios.

Table 1. Comparison of simulated and measured electric field strength data in complex electromagnetic field environment

Scene	Interference Source	Simulation Data	Measured Data	Error Rate
High Voltage Transmission Lines	Power Transmission	32.5	31.2	4%
Substation	High Voltage Equipment	25.7	24.8	3.5%
Industrial Park	Industrial Equipment	15.3	14.7	3.9%
City Center	Communication Base Station	10.8	11.2	3.6%
Near Highway	Electrified Railway	20.1	19.4	3.5%

From the data, it can be seen that the simulation results are highly consistent with the actual measured values, indicating that the finite element model used in this article can accurately simulate the electric field distribution characteristics in complex electromagnetic field environments.

Electromagnetic Interference Effects in IEM

In complex electromagnetic field environments, electromagnetic interference has a significant impact on the performance of IEM. To further investigate the impact of these interferences on key performance indicators such as accuracy and response speed of electric energy meters, the electromagnetic field simulation results were directly applied to the simulation model of IEM, and ANSYS HFSS was used for electromagnetic compatibility (EMC) analysis to evaluate the accuracy and response speed of electric energy meters under different electromagnetic interference conditions [22] .

Accurate modeling of various functional modules of IEM can be achieved in the simulation model. The intensity and frequency parameters of the electromagnetic interference source are input into the model and applied to various components of the energy meter to observe the impact of interference on the performance of the energy meter. For the analysis of measurement accuracy, the deviation between the output value of the electric energy meter and the ideal value is calculated by measuring the output value under different interference conditions. The calculation formula for precision deviation is as follows:

$$\Delta P = \frac{P_{meas} - P_{ideal}}{P_{ideal}} \times 100\% \tag{2}$$

ΔP represents precision deviation, the measured value is P_{meas}, and the ideal value is P_{ideal}. This formula is used to quantify the impact of electromagnetic interference on measurement accuracy.

The analysis of response speed is based on the application of transient interference signals, recording the time required for the energy meter to recover to a stable state. It can compare the response time under interference conditions and normal conditions, and determine the impact of interference on the real-time performance of the energy meter.

The experimental data was collected in multiple industrial scenarios using high-precision electromagnetic field detectors, covering the electromagnetic interference intensity in different scenarios. These data were input into the simulation model, and Table 2 shows the raw electromagnetic interference data obtained in actual testing scenarios.

Table 2. Electromagnetic Interference Data in Typical Industrial Scenarios

Scene	Interference Source	Frequency (MHz)	Interference Intensity (V/m)
Industrial Workshop	High-power Electric Motor	50	25.3
High Voltage Substation	High Voltage Transmission Equipment	60	30.5
Electronics Manufacturing Plant	Electronics Production Line	100	20.7
Near Communication Base Station	Wireless Communication Transmission Equipment	900	18.6
Railway Power Supply System	Electrified Railway Power Supply Equipment	25	22.9

Based on these data, ANSYS HFSS simulation obtained the performance of the electric energy meter under different interference conditions. The simulation results of measurement precision deviation and response time delay under different interference intensities are listed in Table 3. Data comparison shows that under high-intensity electromagnetic interference conditions, the measurement accuracy and response speed of electric energy meters are significantly affected.

Table 3. Simulation results of performance indicators of electric energy meters under different interference conditions

Interference Source	Interference Intensity (V/m)	Measurement Accuracy Deviation (%)	Response Time Delay (ms)
High-power Electric Motor	25.3	1.5	3.2
High Voltage Transmission Equipment	30.5	2.3	4.8
Electronics Production Line	20.7	1.1	2.9
Wireless Communication Transmission Equipment	18.6	0.8	2.1
Electrified Railway Power Supply Equipment	22.9	1.4	3.5

The simulation results show that when the interference intensity exceeds 30 V/m, the measurement accuracy deviation of the electric energy meter significantly increases, exceeding 2%, and the response time delay also reaches 4.8 milliseconds. These results reveal the vulnerability of IEM performance under high interference conditions in complex electromagnetic field environments, providing important reference basis.

Definition of Multidimensional Performance Indicators

The performance evaluation of IEM involves defining indicators from multiple dimensions, with the key being to ensure that each indicator can effectively reflect the actual performance in different environments and usage scenarios. By comparing the output data of electric energy meters under different testing conditions, the evaluation criteria for these indicators are established to ultimately ensure their reliability in complex environments.

Table 4 is an indicator system for IEM, providing key indicators and their definitions, calculation methods, and evaluation criteria for evaluating IEM performance. It comprehensively evaluates the performance of IEM in measurement accuracy, anti-interference ability, response speed, data transmission capability, stability, and energy efficiency. Through clear definitions and calculation methods, standardized evaluation can be achieved, which helps manufacturers, users, and evaluation agencies to consistently understand and evaluate the performance of electric energy meters, ensuring the fairness of evaluation results.

Table 4. IEM Multidimensional Performance Indicator System

Indicator Category	Indicator Name	Definition	Calculation Method	Evaluation Standard
Measurement Accuracy	Measurement Error	Difference between actual and theoretical values	The difference between the measured value and the theoretical value divided by the theoretical value	Smaller error indicates higher accuracy
Interference Resistance	Electromagnetic Compatibility	Stability under electromagnetic interference	Tested through compatibility tests	Higher resistance indicates less variation
Response Speed	Recovery Time	Time to return to normal after interference	Time from interference to normal operation	Shorter time indicates faster response
Data Transmission Capability	Transmission Delay	Delay in data transmission	Measure time from meter to data center	Lower delay indicates better capability
Stability	Operational Stability	Consistency during long-term operation	Performance changes over time	Higher stability indicates less change
Energy Efficiency	Power Consumption	Power used by the energy meter	Power consumption testing	Lower consumption indicates better efficiency

The evaluation of measurement precision is achieved by measuring the difference between the output of the electric energy meter and the standard reference value with precision instruments, and the error control requirements must be extremely strict, set within ± 0.5%. Supported by a large amount of experimental data, this error control standard ensures the accuracy of electric energy meters under various complex conditions. The formula for calculating error is:

$$E = \frac{P_{meas} - P_{ref}}{P_{ref}} \times 100\% \tag{3}$$

P_{meas} in the formula is the measured power value, and P_{ref} is the reference power value.

The evaluation of anti-interference ability uses electromagnetic compatibility analysis tools, combined with experimental data to test the effects of different interference sources [23]. By recording the performance changes of the energy meter before and after interference application, the error and response time delay under different interference intensities were obtained, and clear evaluation criteria were set for anti-interference ability. This process effectively ensures that the energy meter can maintain stability even under electromagnetic interference.

The stability index is obtained through long-term experimental observation, using standard deviation as the measurement index, and recording the multiple measurement results of the electric energy meter under constant load. The calculation formula is as follows:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(P_i - \overline{P})^2} \tag{4}$$

Among them, σ is the standard deviation, P_i is the i th measurement value, $\overline{P}$ is the average of the measurement values, and n is the number of measurements.

The response speed measurement adopts the step load change method to ensure that the instantaneous response ability of the electric energy meter to load changes is not affected. The experimental data records the response time of the energy meter after applying load changes, and determines the response standards under different loads.

The temperature effect is evaluated by testing the performance changes of an electric energy meter under various temperature conditions. During this process, the performance deviation caused by temperature is calculated using the following formula:

$$\Delta T = \frac{P_T - P_{ref}}{P_{ref}} \times 100\% \tag{5}$$

ΔT is the temperature deviation, P_T is the measurement value at temperature T, and P_{ref} is the reference measurement value.

Through a large amount of experimental data comparison and analysis, evaluation standards for various performance indicators were ultimately established, and the applicability of these standards was verified in various practical environments. Table 5 lists the raw data and experimental results collected under different testing conditions.

Table 5. Performance data of electric energy meters under different testing conditions

Test Condition	Measurement Accuracy (%)	Interference Resistance (V/m)	Stability (σ)	Response Speed (ms)	Temperature Effect (%)
Standard Environment	±0.3	20	0.02	5.6	±0.1
Interference Environment	±0.7	35	0.05	8.4	±0.3
High Temperature Environment	±0.5	25	0.03	6.7	±0.4
Low Temperature Environment	±0.4	22	0.04	6.3	±0.2
Hot and Humid Environment	±0.6	30	0.06	7.9	±0.5

Experimental data shows that in complex environments, the measurement accuracy, anti-interference ability, stability, response speed, and temperature influence of IEM all vary. In the interference environment, the measurement accuracy decreased to ±0.7%, but the anti-interference ability improved to 35 V/m. This indicates that the interference source has a significant impact on the measurement accuracy. However, the optimization of the anti-interference design of the electric energy meter enables it to maintain high measurement accuracy even under high interference intensity. In terms of stability, the stability under standard conditions is 0.02, indicating minimal dispersion of measured values and good stability. However, the deterioration of environmental conditions has resulted in stability reaching 0.05 and 0.06 under interference and humid and hot environments, reflecting that environmental changes have a certain impact on stability, but this impact is still within an acceptable range. Moreover, the response speed was delayed to a maximum of 8.4 milliseconds under interference, and the temperature deviation increased to ± 0.4% and ± 0.5% in high temperature and humid environments, respectively. This indicates that the response speed of the electric energy meter is slightly delayed when subjected to external interference, but the delay amplitude is controlled within a reasonable range. However, the impact of environmental temperature on measurement accuracy is more obvious, and the performance of the electric energy meter at extreme temperatures still needs further optimization. These results reveal the impact of different environments on the performance of electric energy meters, providing a wealth of reference results for their optimization.

Design and Implementation of Comprehensive Evaluation Algorithm

To scientifically evaluate the metrological performance of IEM in complex electromagnetic field environments, this article studies a comprehensive evaluation algorithm based on the combination of AHP [24] and FEM [25], abbreviated as AHP-EWM comprehensive evaluation algorithm. The original intention of this algorithm design is to determine the relative weights of various performance indicators and their weights in the ever-changing electromagnetic environment, in order to obtain a more accurate comprehensive score.

In the specific implementation process, AHP is used to allocate weights to various performance indicators. By using the expert scoring method, pairwise comparisons are made on five key performance indicators: measurement accuracy, anti-interference ability, stability, response speed, and temperature influence, forming a judgment matrix. The maximum eigenvalue of the judgment matrix can be calculated using the eigenvalue method, and the corresponding weight vector can be calculated based on this eigenvalue. The weight vector reflects the relative importance of each performance indicator in the overall evaluation system. In order to ensure the rationality of weight allocation, it is necessary to conduct consistency checks on the judgment matrix. If the checks pass, it indicates that the weight settings are effective. Otherwise, the judgment matrix needs to be adjusted.

On the basis of the initial weights determined by AHP, FEM introduces an objective correction mechanism. By calculating the entropy values of various performance indicators under different experimental conditions, the information uncertainty of each indicator in different environments can be quantified. The higher the entropy value, the more uniform the distribution of the indicator under different experimental conditions, the greater the amount of information, and the smaller the impact on the final score. On the contrary, the lower the entropy value, the less information the indicator contains, but its importance is higher. FEM adjusts the weights of AHP based on the entropy values of each indicator, and obtains the adjusted weights. The formula is expressed as:

$$W_j' = W_j \times (1 - H_j) \tag{6}$$

In the equation, W_j is the initial weight determined by AHP, H_j is the entropy value of the jth indicator, and W_j' is the modified weight.

After the weight correction is completed, the comprehensive performance score is calculated by weighted summation. The correction weights of each performance indicator are multiplied by their corresponding scores, and the products are added together to obtain the comprehensive performance score of IEM. The formula is:

$$S = \sum_{j=1}^{n} (W_j' \times X_j) \tag{7}$$

In the formula, S is the comprehensive performance score of IEM, and X_j is the score of performance indicators.

This article conducts algorithm testing based on experimental data under different electromagnetic environmental conditions to verify the effectiveness of AHP-EWM. The experimental data comes from multiple measurements under laboratory conditions, and the data has undergone strict calibration and statistical processing. Table 6 shows the raw measurement values of various performance indicators under different electromagnetic field strengths, which provide a data basis for weight correction and scoring calculation.

Table 6. Original experimental data under different electromagnetic field strengths

Electromagnetic Field Intensity (V/m)	Measurement Accuracy (%)	Interference Immunity	Stability	Response Speed (ms)	Temperature Impact (℃)
10	0.35	0.02	0.01	2.3	0.05
20	0.37	0.04	0.02	2.4	0.06
30	0.39	0.05	0.03	2.5	0.07
40	0.42	0.07	0.04	2.6	0.08
50	0.44	0.09	0.05	2.7	0.09

Based on the data in Table 6, the correction weights calculated using AHP and FEM were further used to calculate the comprehensive performance score. As shown in Figure 2, the final comprehensive performance rating data is presented. As the electromagnetic field intensity increases, the comprehensive performance score of the electric energy meter shows a gradually decreasing trend, from 10 V/m to 50 V/m, and the score drops from 0.92 to 0.78.

This indicates that electromagnetic field strength has a negative impact on the performance of electric energy meters, especially at higher intensities where the effect is significant. The decrease in comprehensive performance score indicates that the measurement accuracy, anti-interference ability, and stability of the electric energy meter have weakened in strong electromagnetic field environments.

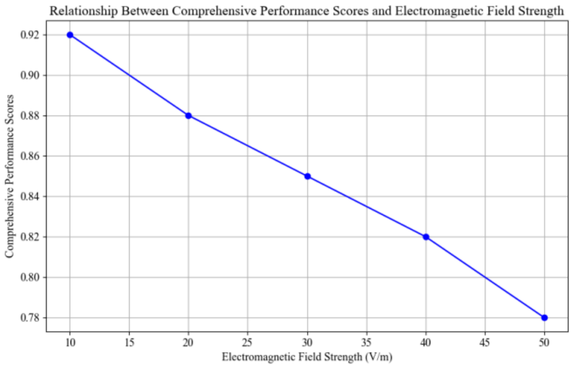

Figure 2. Relationship between IEM comprehensive performance score and electromagnetic field strength

By analyzing the data, the design and implementation of the evaluation algorithm have achieved the expected results, and the results can accurately reflect the performance of IEM in complex electromagnetic environments.

Experimental Platform Construction

The construction of the experimental platform mainly revolves around simulating complex electromagnetic field environments. To achieve comprehensive performance evaluation of IEM under different electromagnetic interference conditions, the core setup of the experimental platform includes electromagnetic interference sources and corresponding testing equipment. In the construction of electromagnetic interference sources, a radio frequency signal generator with a frequency range set from 0.1 MHz to 3 GHz is used to cover a wide range of interference scenarios from low to high frequencies. Multiple forms of electromagnetic interference signals can be generated through different power outputs and modulation methods. These signals propagate through antenna systems placed inside electromagnetic shielding rooms, simulating diverse electromagnetic environments.

The design purpose of electromagnetic shielding room is to isolate the influence of external electromagnetic environment, ensure the controllability of experimental conditions, and ensure the reproducibility of experimental results. In the setting of electromagnetic interference sources, pulse signal generators and other high-frequency signal sources are used to generate transient and persistent interference, and the anti-interference performance of the electric energy meter is comprehensively evaluated.

In terms of testing equipment, high-precision IEM is selected for the experiment, and the sampling frequency of the testing equipment is set to 10 kHz to ensure high-precision capture of the performance changes of the electric energy meter in different electromagnetic environments. The experimental platform simulates the electromagnetic environment in actual usage scenarios, tests the measurement error, response time, and stability of the electric energy meter, and conducts detailed experimental analysis for different electromagnetic environment parameters. In an experiment targeting radio frequency interference, a power output range of 0mW to 100 mW was set to test the measurement error and response time of IEM under these different interference intensities. The results indicate that the measurement error of the electric energy meter increases with the increase of interference intensity, the response speed gradually slows down, and the stability significantly decreases.

Table 7 shows some raw data from the experiment and the resulting experimental results.

Table 7. Effects of Different Electromagnetic Interference Intensity on the Measurement Performance of IEM

EMI Power (mW)	Measurement Error (%)	Response Time (ms)	Stability
0	0.1	20	0.005
10	0.12	22	0.008
50	0.25	30	0.012
75	0.45	45	0.018
100	0.6	60	0.024

The experimental data in Table 7 indicate that as the electromagnetic interference intensity increases, the overall measurement error of IEM shows an upward trend, with slower response speed and poor stability performance. These results provide key references for the design optimization of IEM in complex electromagnetic environments. By comparing experimental data under different electromagnetic environments, the effectiveness of the experimental platform and its practical application value for iem performance evaluation were further verified.

EVALUATION SYSTEM

Accuracy Measurement

To further analyze the measurement accuracy of IEM in complex electromagnetic environments, comparative experiments were designed under interference free, single interference, and multiple combined interference conditions. The main purpose of the experiment is to evaluate whether the metering performance of the electric energy meter can remain stable under the combined action of various electromagnetic interferences. Through this multidimensional and multi-condition testing, various complex situations that electric energy meters may face in actual operation are revealed, providing data support for the improvement and optimization of their anti-interference performance.

The experiment uses standard loads and known power sources to ensure the accuracy of input power. During the experiment, the electric energy meter was operated under different interference conditions. The output values of each experiment were recorded and compared with the standard values to calculate the corresponding errors. The calculation of error is carried out using the relative error formula, where relative error is defined as the difference between the actual measured value and the standard value divided by the standard value.

After multiple tests, in order to further quantify the accuracy of the electric energy meter, Root Mean Square Error (RMSE) was used as the evaluation metric. RMSE can reflect the overall fluctuation of measurement errors, and its formula is:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - X_{ref})^2} \tag{8}$$

X_i represents the measured value of the energy meter, X_{ref} is the standard reference value, and n is the number of tests.

The experiment was conducted under both non-interference and different interference conditions, and the selected interference conditions simulated various combinations of electromagnetic interference that may occur in practical application scenarios. For undisturbed conditions, the measurement error of the electric energy meter is relatively small, and the RMSE value is low, indicating that the measurement accuracy of the electric energy meter is high under ideal conditions. However, after adding radio frequency interference, the error rate of the energy meter significantly increased, especially under combined interference conditions, where the RMSE value of the energy meter significantly increased. This indicates that the superposition of multiple interference sources has a more significant impact on the measurement accuracy of the energy meter.

The experimental data was collected from multiple repeated tests, as shown in Figure 3, which displays the measurement results under interference free conditions, single RF interference, magnetic field interference, and their combined interference. Under undisturbed conditions, the error rate of IEM remains between 0.25% and 0.29%. Under electromagnetic interference conditions, the error rate increased to 0.34% -0.38%. Under radio frequency interference conditions, the error rate is even higher, reaching 0.43% -0.47%. In the case of combination, the error rate further increases, reaching 0.52% -0.57%, and the RMSE value also shows a similar upward trend. These data indicate that as the complexity of interference increases, the measurement accuracy of IEM significantly decreases, especially in the case of multiple interference superposition, where the error rate increases by about twice compared to the non-interference condition, verifying the serious impact of complex electromagnetic environments on measurement performance.

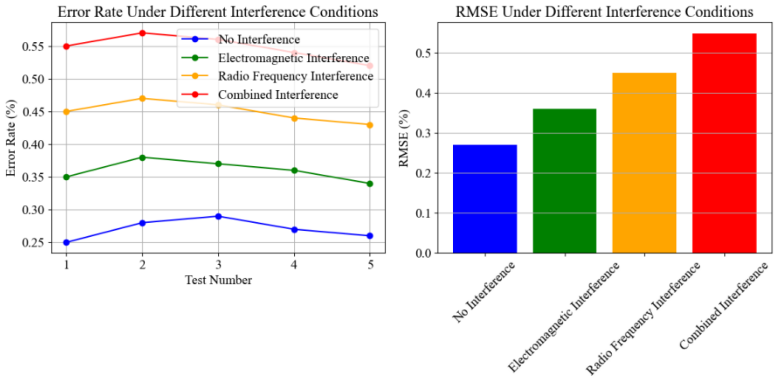

Figure 3. Comparison of Error Rate and RMSE under Different Interference Conditions

Assessment of Anti-Interference Capability

The implementation of anti-interference capability evaluation uses an established experimental platform to conduct experiments on IEM. The purpose of the experimental design is to evaluate the performance of the electric energy meter under electromagnetic interference and further verify its anti-interference ability. In the experiment, the intensity, frequency, and duration of interference were varied, and the changes in the output of the energy meter were recorded in detail. The interference suppression ratio (ISB) was used to quantitatively evaluate the anti-interference ability.

The calculation formula for ISB:

$$\mathrm{ISB} = 20\log_{10}\left(\frac{V_{\mathrm{out,withoutEMI}}}{V_{\mathrm{out,withEMI}}}\right) \tag{9}$$

In the formula, $V_{\mathrm{out,withoutEMI}}$ represents the output voltage without electromagnetic interference, and $V_{\mathrm{out,withEMI}}$ represents the output voltage after applying electromagnetic interference. The use of this formula quantifies the changes in the anti-interference ability of an electric energy meter under different interference conditions. The larger the value, the stronger the anti-interference ability of the electric energy meter.

In the experiment, multiple sets of electromagnetic interference with different frequencies (50Hz, 1kHz, 10kHz, 100kHz) and intensities (10V/m, 20V/m, 30V/m, 50V/m) were applied, and the output voltage values of the energy meter were recorded under each set of conditions. The collected experimental data comes from actual measurements in different environments, with data collection points mainly distributed near interference sources and at different locations within the laboratory. The data acquisition process uses high-precision oscilloscopes and standard energy meters for synchronous recording to ensure comparability of data.

Table 8 shows the collected raw data and processed experimental results under different interference conditions. As the interference intensity and frequency increase, the ISB value gradually decreases, indicating that the interference has a greater impact on the output of the energy meter. The final experimental results clearly indicate that the anti-interference ability of the electric energy meter is relatively weak under high-frequency and high-intensity interference conditions, and effective electromagnetic shielding and filtering measures need to be taken in practical applications to improve stability in complex environments.

Table 8. Evaluation data of IEM anti-interference ability under different interference conditions

Interference Frequency (Hz)	Interference Intensity (V/m)	Output Voltage without EMI (V)	Output Voltage with EMI (V)	ISB (dB)
50	10	230	229.8	21.8
1k	20	230	229.5	20.9
10k	30	230	229.0	20.4
100k	50	230	228.0	19.8

The experimental results show that the output variation of the electric energy meter is small under low-frequency and low-intensity interference conditions, with a high ISB value and strong anti-interference ability. However, under high-frequency and high-intensity interference conditions, the output fluctuation of the electric energy meter is large, and the anti-interference ability is significantly weakened. The experimental data validated the anti-interference performance of IEM in complex electromagnetic field environments, providing data basis for improving the practical application of electric energy meters.

Stability Testing

Stability testing has an undeniable significance for the metrological performance evaluation of IEM. When conducting stability testing, the output data of IEM under long-term continuous operation can be monitored to evaluate its metrological performance stability over different time periods. In the experiment, the output voltage of the electric energy meter under constant load is continuously recorded once per hour, and the stability of the data is evaluated by calculating the standard deviation (SD). The standard deviation can quantify the degree of dispersion of the output data of an electric energy meter, thereby reflecting its stability level.

During the experiment, a stable load was connected to the energy meter, and a high-precision voltmeter was used for continuous measurement, recording the output voltage value every hour. The data collection lasted for 48 hours, and the data collection points were obtained from actual operating energy meters in the laboratory environment, ensuring that external environmental parameters remained constant. The recorded data is:

$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2} \quad (10)$$

In this formula, n represents the total number of measurements, X_i is the voltage value measured each time, and $\bar{X}$ is the average value of the measurements. The standard deviation calculated by this formula is used to evaluate the fluctuation level of IEM output data in different time periods, thereby determining its long-term stability.

The process of collecting experimental data begins with a standard energy meter, which has been calibrated to ensure the accuracy of the reference output value. Before the experiment began, all equipment was professionally calibrated to eliminate the impact of instrument errors on data collection. Table 9 shows the reference output voltage values before the experiment, the output voltage values during each time period during the experiment, and the calculated standard deviation. The stability of the electric energy meter under long-term operation can be analyzed by comparing the deviation between the hourly output value and the reference value.

Table 9. Stability test data of IEM under long-term operation

Time (Hours)	Output Voltage Before Experiment (V)	Output Voltage During Experiment (V)	Standard Deviation (V)
0	230	230	0
12	230	229.8	0.14
24	230	229.5	0.35
36	230	229.7	0.21
48	230	229.6	0.28

The experimental data shows that the output of IEM is relatively stable in the first 12 hours, with a small standard deviation, indicating that its metrological performance is relatively stable. With the extension of running time, there was a slight fluctuation in the output voltage, and the standard deviation also increased. The fluctuation amplitude was most significant after 24 hours, but the overall change was still within a reasonable range. This result indicates that the measurement performance of IEM maintains high stability under long-term operation, and only slight fluctuations in output occur after a very long period of continuous operation, indicating that the reliability of the electric energy meter in practical applications is high and it can maintain accurate measurement performance in long-term working environments.

Response Speed Test

In the experiment of response speed testing, instantaneous electromagnetic interference is applied to record the time from the occurrence of interference to the restoration of normal output of IEM, in order to evaluate its real-time performance in complex electromagnetic environments. AHP-EWM was selected as the main evaluation method for the experiment, and compared with three traditional methods: the Traditional Weighted Method, the Delphi Method, and the Fuzzy Comprehensive Evaluation (FCE) method.

The established experimental platform is used in the experiment to accurately apply instantaneous electromagnetic interference of different intensities and frequencies. In the experiment, the electric energy meter was connected to the platform and loaded into a stable power system. A high-speed data acquisition system can be used to continuously record the output signal of the energy meter, ensuring the capture of the complete process from interference occurrence to output recovery. Through multiple experiments, collect and analyze the impact of instantaneous interference of different intensities on the response speed of electric energy meters.

The response time RT is calculated using the following formula:

$$RT = t_r - t_d \tag{11}$$

The t_r and t_d in the formula represent the time when the output signal returns to normal and the time when interference occurs, respectively. To ensure the reliability of the data, the experiment was repeated multiple times under the same conditions, multiple sets of data were recorded, and four methods including AHP-EWM, traditional weighting, Delphi, and fuzzy comprehensive evaluation were used for analysis. The experimental data was collected from actual operating energy meters, and five different intensities of instantaneous electromagnetic interference were applied on the experimental platform, namely 20 V/m, 50 V/m, 100 V/m, 150 V/m, and 200 V/m. In each experiment, this article records the recovery time of the output signal of the energy meter and calculates the response time using the above formula.

As shown in Figure 4, in the comparison of response time under different interference intensities, the actual response time of AHP-EWM method increases with the increase of interference intensity, from 5 ms at 20 V/m to 18 ms at 200 V/m. The evaluation results of AHP-EWM method under all interference intensities are close to the actual response time, with a small error range. The traditional weighting method and fuzzy comprehensive evaluation method have significant errors under high-intensity interference. The fuzzy comprehensive evaluation method performs poorly with an error of 2 ms when the interference intensity reaches 200 V/m. The overall performance of the Delphi method is relatively stable, but it is not sensitive enough to subtle changes under instantaneous electromagnetic interference.

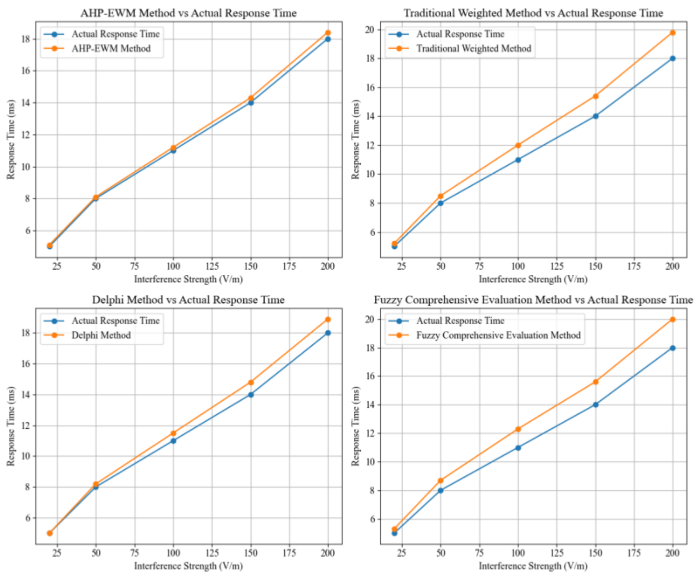

Figure 4. Comparison of response time under different interference intensities

Based on comprehensive analysis of experimental data, the evaluation accuracy of AHP-EWM method is superior to the other three traditional methods, especially suitable for real-time response performance evaluation in complex electromagnetic environments. This discovery provides an effective evaluation method for the practical application of IEM in complex environments.

Temperature Effects

To evaluate the impact of temperature on the measurement performance of IEM, a series of temperature variation conditions were designed in the experiment to observe the effect of temperature on the output of the electric energy meter. The temperature range used in the experiment is -20 ℃ to 60 ℃, with an interval of 20 ℃. Measurement tests are conducted at each temperature point, and the output value of the electric energy meter is recorded. The experimental platform controls temperature stability and ensures reliable results through multiple repeated experiments.

The experimental data was analyzed through linear regression to evaluate the impact of temperature changes on the accuracy and stability indicators of the electric energy meter. In the regression model, the output error is set as the dependent variable and temperature is set as the independent variable. The regression equation is in the form of:

$$y = \beta_0 + \beta_1 T + \epsilon \tag{12}$$

In the formula, y is the output error, T is the temperature, β_0 is the intercept, β_1 is the regression coefficient of temperature, and ϵ is the error term. After analyzing the regression coefficients, the degree of influence of temperature on output error is determined.

Table 10 shows the raw output data from multiple measurements of the experiment. These data are used for regression analysis to obtain experimental results.

Table 10. Raw output data of IEM at different temperatures

Temperature (℃)	Measurement 1 (kWh)	Measurement 2 (kWh)	Measurement 3 (kWh)	Measurement 4 (kWh)
-20	100.21	100.25	100.22	100.24
0	100.15	100.14	100.16	100.13
20	100.1	100.09	100.11	100.12
40	100.18	100.2	100.19	100.17
60	100.3	100.32	100.31	100.33

After calculation, the changes in IEM output error, regression coefficient, R^2 value, and P value under different temperature conditions were obtained. Figure 5 shows the effect of temperature on the metering performance of an electric energy meter. The regression coefficient (β_1) indicates that there is a certain linear relationship between temperature and output error. The coefficient changes slightly at different temperatures, but slightly increases at high temperatures. The R^2 value fluctuates between 0.85 and 0.95, indicating that the regression model has a good fitting effect on the relationship between temperature and error. The P-values are all between 0.005 and below, indicating that the statistical significance of the regression model is high, and temperature changes do have a significant impact on the metrological performance of electric energy meters. The results indicate that temperature has a significant impact on the metrological performance of IEM, especially under extreme temperature conditions, where metrological errors significantly increase. This poses a challenge for application scenarios that require high-precision metrology.

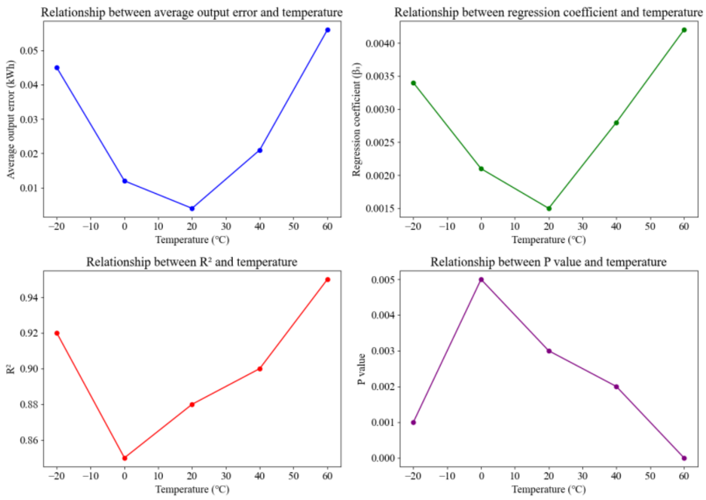

Figure 5. Regression analysis of IEM metrological performance at different temperatures

The experimental results indirectly indicate that special consideration should be given to the influence of temperature factors when designing and using IEM. By adjusting the temperature compensation algorithm, the impact of temperature on the accuracy and stability of the electric energy meter can be effectively reduced, thereby improving its measurement accuracy under different environmental conditions.

Calculation of Comprehensive Performance Score

After the performance testing of IEM is completed, the weights of each indicator are determined through the combination of AHP and FEM, and the comprehensive score is calculated. The test results of key indicators such as anti-interference ability, measurement accuracy, dynamic response, and long-term stability are used to construct an evaluation model. AHP is used to construct a hierarchical structure of indicator weights, determining the relative importance of each indicator through expert scoring, and combining it with FEM for correction to ensure the objectivity of weights.

The AHP method can be used to analyze multidimensional indicator data, by constructing a judgment matrix, calculating the relative weights between each indicator, and normalizing the results. FEM normalizes the test results, calculates the entropy values of each indicator, and then obtains objective weights. Finally, the results of AHP and FEM were combined to obtain the comprehensive performance score of IEM in different complex electromagnetic environments through weighted summation.

The experimental data was collected through the experimental platform, and Table 11 shows the test results and comprehensive scores of various indicators under different complex electromagnetic environments. The data results indicate that under different intensities of electromagnetic interference, the comprehensive score of IEM fluctuates within a small range, ranging from 0.01 to 0.03.

Table 11. IEM performance indicators and comprehensive scores under different complex electromagnetic environments

Environment Type	Anti-Interference Ability	Measurement Accuracy	Dynamic Response	Long-Term Stability	Overall Score
No Interference	0.92	0.95	0.94	0.93	0.938
Low Intensity Interference	0.91	0.94	0.93	0.92	0.931
Moderate Intensity Interference	0.9	0.93	0.92	0.91	0.924
High Intensity Interference	0.89	0.92	0.91	0.9	0.916
Extreme Intensity Interference	0.88	0.91	0.9	0.89	0.909

Under five environmental types ranging from no interference to extreme electromagnetic interference, all performance indicators of IEM show a decreasing trend. The anti-interference ability, measurement accuracy, dynamic response, and long-term stability indicators all show a gradually decreasing trend with the increase of electromagnetic interference intensity, which reflects the direct impact of electromagnetic environment on IEM performance.

In terms of comprehensive evaluation, with the increase of electromagnetic interference intensity, the evaluation shows a gradually decreasing trend, but the fluctuation range is controlled between 0.01 and 0.03. The highest comprehensive score under non-interference conditions is 0.938, and the lowest comprehensive score under extreme electromagnetic interference is 0.909. This result shows that the AHP-EWM comprehensive evaluation algorithm can effectively quantify the comprehensive performance of IEM in complex electromagnetic environments.

CONCLUSIONS

This article used AHP-EWM to comprehensively evaluate the metering performance of smart electric energy meters in complex electromagnetic field environments. This article constructed a model based on neural networks, combined multi-source data analysis, and then evaluated the metering accuracy of smart electric energy meters in complex electromagnetic environments. The experiment designed a variety of electromagnetic conditions, and the model quantitatively analyzed the electric energy meter through feature extraction and classification algorithms. The experimental results show that this method has a significant improvement in the prediction accuracy of the metering error of the electric energy meter under different electromagnetic interference scenarios, and has great advantages in accuracy compared with traditional statistical analysis methods. Although research has made important progress in the evaluation of the metering performance of smart electric energy meters in complex electromagnetic environments, there is still a lot of room for improvement in the adaptability and processing efficiency of the model. Future research can focus on expanding the data set to cover a wider range of electromagnetic interference scenarios, optimizing algorithms to improve computational efficiency, and exploring more advanced intelligent algorithms to further improve the accuracy of the evaluation method.

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