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A Cloud-Based Adaptive ConvolutionalNetwork for Real-Time Error Detection in Energy Meter Systems

Chen Xu*[1], Zhang Haomiao[2,] Zhang Chao[3,] Wang Tao [4], Yan Yu[5], Xu Yinzhe[6]
State Grid Ningxia Marketing Service Center (State Grid Ningxia Metrology Center), Yinchuan 750000, Ningxia, China
E-mail: cxhbdl@126.com

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To solve the problem of real-time measurement error detection of intelligent electric meter, this paper proposes a cloud edge collaborative online detection framework based on CNN-GRU mixed depth model and entropy weight scoring mechanism. The system extracts the local variation characteristics by one-dimensional convolution, and uses two-way GRU to model the time-dependent error evolution. Meanwhile, the dynamic threshold score function is introduced to realize the self-adaptive judgment of error alarm. The special data sets R-Elec, I-Load and S-ErrGen covering residential, industrial and rural scenes are constructed, and pre-processed through standardization, sliding window segmentation and statistical cleaning. The experimental results show that the average identification accuracy of the system in the three types of data is 97.6% and the average response time is 0.62 seconds, which is significantly superior to the performance of traditional models (such as RF, SVM, LSTM) in false alarm control and adaptability. The ablation experiments validated the key role of multi-source feature fusion and entropy scoring mechanisms in performance improvement. The research shows that the fusion of lightweight depth model and cloud edge architecture can achieve efficient, low delay and extensible intelligent meter error online detection, and has the practical engineering deployment value.

Povzetek: Sistem uporablja model CNN-GRU s kooperacijo oblak-rob in mehanizmom točkovanja uteži entropije za detekcijo napak pametnih števcev v realnem času. Omogoča učinkovito in prilagodljivo spletno spremljanje za pametna omrežja.

1 Introduction

With the continuous promotion of the construction of new power systems, the accuracy and intelligence of energy metering are becoming key links to support the efficient operation of smart grids. As the core equipment for terminal energy consumption measurement and monitoring, the performance of electric energy meters is directly related to the stability and reliability of multiple links such as power grid scheduling, load forecasting, and electricity bill settlement. Especially in the context of multiple load grid connections and diverse energy consumption behaviors, traditional measurement error detection methods that rely on manual inspection and periodic verification are no longer able to meet the modern power grid's demand for "real-time, accurate, and wide area" monitoring. The decrease in the credibility of measurement data not only affects the fairness of electricity consumption for end-users, but also constrains the operational efficiency of the entire power grid dispatch and management system.

Building an online deviation testing system for electric energy meters based on cloud platforms has become an important implementation method to improve the intelligence of the testing system. By connecting distributed collection modules with cloud computing center processing capabilities, real-time collection and analysis of massive operational data from different regions and types of energy meters can be achieved, enabling dynamic error discrimination, evolution trend tracking, and functional warning testing purposes. This type of system must have high-frequency data processing speed, abnormal model recognition method, and self-feedback mechanism to achieve intelligent measurement maintenance and hierarchical management control. Compared to traditional models, the advantage of data storage and computing elasticity in cloud centers is that they not only improve the overall accuracy and speed of system inspection, but also provide a technological foundation for future widespread applications [4]. In this context, this article proposes an online testing system for measurement errors in power instruments, which is driven by data flow and constructed through multi-dimensional integration and intelligent analysis. The system relies on the integration and distributed deployment of cloud services, combined with a series of core technologies such as extracting the variation law of measurement deviation, identifying the density of abnormal points, and autonomously improving and optimizing the model, to achieve efficient performance monitoring and automatic fault diagnosis of electric energy meters in multiple scenarios [5]. This system has built a more flexible and anti-interference intelligent energy metering system. Accurate measurement deviation can timely detect information such as equipment aging, signal drift, or external interference. It also provides data for the life evaluation of metering devices and builds a visual digital asset management platform for power companies. At the same time, this technology system has good scalability and wide applicability, and can be applied to energy metering in various energy application places, such as industrial parks, residential areas, or commercial buildings, to ensure the security of the energy network and save costs.

In response to the shortcomings of existing error detection technologies for electric energy meters, such as poor real-time performance, poor simulation specificity, and insufficient application scope, this article focuses on the following two key technologies for research: (1) How to design a real-time detection system with the ability to identify errors and analyze error trends, thereby breaking the limitations of traditional pattern based modeling of nonlinear errors and the accuracy and precision of dynamic scene identification? (2) How to use IoT technology to complete the design of a data closed-loop structure for information collection, detection, and feedback, while reducing the hardware investment cost at the end and improving the accuracy of misjudgment recognition, system response speed, and multi table consistency?

For the questions raised in the above research, this article adopts a lightweight fault recognition mode based on CNN and GRU fusion network, and constructs an efficient monitoring system with high recognition accuracy, low missed detection rate, and long-distance deployment using multiple attribute extraction, boundary cooperative calculation, and entropy dynamic judgment methods. The results show that the system has good recognition performance for electricity loads in complex working environments, flexible application characteristics, and wide promotion value. To this end, this paper proposes an error detection model that integrates the lightweight CNN-GRU network and the entropy weight scoring mechanism, and constructs an online detection system based on cloud-edge collaboration. We assume that this model can effectively increase the accuracy of electricity meter error recognition to over 97% without increasing the terminal computing power, control the average response delay within 0.6 seconds, and demonstrate good generalization ability and low false alarm rate under the condition of multi-source data fusion. The experimental verification will be systematically evaluated around the above indicators.

This article will elaborate on the following ideas in the research of the paper: Chapter 2 introduces the current status, development, and limitations of existing fault localization algorithms; Chapter 3 provides a detailed explanation of the design concept and implementation of the main parts of this article; Chapter 4: Testing and Evaluating Test Results Based on Actual Application Scenarios; Chapter 5 discusses how to improve the efficiency and optimal installation location of the device; Chapter 6 discusses the future applications and developments in the power system, as well as summarizes the main content of this article.

2 Related work

Although the importance of energy metering is increasing, it is not easy to accurately identify and improve the accuracy of energy metering in smart grids. Due to the complex and constantly changing environment surrounding the electric energy meter, its errors are not only caused by external electromagnetic interference, nonlinear loads, and harmonics, but also by the aging of its own equipment and insufficient design accuracy [6]. Especially when various types of instruments are used, the voltage they are subjected to is relatively high, and the frequency of input data is relatively high, traditional manual inspection methods can no longer meet the high efficiency and precision requirements of power grid operation. Therefore, researchers have started to study real-time monitoring systems and self-diagnostic systems in order to use digital means to track the changes in errors [7,8].

In recent years, research on energy metering errors has mainly focused on three technical paths: first, error analysis methods based on feature extraction and modeling, which often analyze the formation mechanism and propagation path of errors by establishing mathematical models or statistical inference systems; The second is to integrate artificial intelligence and machine learning error recognition algorithms to improve the sensitivity and generalization ability of error detection on a data-driven basis; The third is to combine the system integration framework of edge computing and cloud platform to realize remote operation and maintenance and performance optimization of large-scale meters. In terms of traditional models, Hong (2024) [9] effectively revealed the complexity of error sources by constructing harmonic analysis models, distortion identification algorithms, and a distortion rate quantification system under nonlinear loads. The low-cost wireless smart meter design framework proposed by Sousa et al. (2023) [10] balances error monitoring and power quality acquisition, and achieves structural integration under the smart grid architecture. At the same time, Lindani (2023) [11]. attempted to use a dual channel data acquisition method for identifying electricity theft, which expanded the safety function of intelligent metering beyond error detection

With the development of artificial intelligence technology, machine learning based error detection methods are increasingly receiving attention. For example, Yuan et al. (2022) [12] constructed an error detection model based on random forests, demonstrating stable performance in small sample environments. Wals et al. (2024) [13] proposed a smart meter lifespan prediction method based on health index, introducing a device degradation evaluation dimension for error detection. In addition, Vasylets et al. (2022) [14] proposed a mathematical correction model for the uncertainty of energy metering under low load conditions, and made preliminary progress in identifying edge characteristics. It is worth mentioning that image recognition technology has gradually been integrated into the field of energy meter error detection. As described by Yang et al. (2024) [15], cloud edge collaboration mechanism helps to enhance system deployment flexibility and delay control capability, and is suitable for large-scale distributed energy systems. and Xiaofeng et al. (2024) [16] further integrated maximum likelihood method and decision tree model to achieve structured analysis of errors. An end-to-end error evaluation model based on deep neural networks have also been proposed. Huang et al. (2024) [17] constructed an error recognition framework that integrates multi-layer convolution, significantly improving the accuracy and robustness of recognition. However, existing research still faces many limitations. On the one hand, most models are based on specific operating conditions or small sample experiments, making it difficult to maintain stability in the widespread deployment of multiple regions and types of meters. On the other hand, Xu et al. (2024) [18] demonstrated the effectiveness of the XGBoost and CNN-GRU structures in short-term load forecasting for temporal feature extraction and anomaly modeling. In addition, Zhao et al. [2024][19] combined CNN-GRU with factor graph structure to achieve error correction in GNSS signal loss scenarios, demonstrating the stability of the fusion model in strong interference environments. In recent years, some scholars have also begun to pay attention to the dynamic evolution modeling of error characteristics driven by big data. Wang (2023) [20] proposed a cloud-based method for identifying energy consumption in big data, which achieved innovative breakthroughs in data mining and error trend tracking, providing path support for error optimization.

Table 1：Comparison of the performance and applicability of the methods and related research in this paper

Author & Year	Technical Approach	Application Scenario	Accuracy	Response Delay	Identified Issues
Yu, 2022 [12]	Random Forest (RF)	Small residential loads	92.4%	>1.1s	No temporal modeling capability
Jun, 2022 [13]	Health index + Random Forest	Aging equipment degradation	89.7%	1.2s	Lacks modeling of anomaly trends
Gu, 2023 [15]	Image recognition + difference calc	Visual meter comparison	85.6%	High image processing latency	Poor real-time performance, high deployment cost
This paper	CNN + GRU + Entropy-weighted scoring model	Multi-scenario heterogeneous devices	97.6%	0.62s	—

Based on the accuracy measurement methods of some important power metering devices in recent years (Table 1), establish a research path for the research methods and technologies in this paper. It can be seen that traditional methods have accuracy limitations in identifying nonlinear errors, and some machine learning methods lack temporal characteristics or are limited in their application fields. However, our CNN-GRU combination research approach demonstrates greater flexibility and judgment in feature extraction, temporal characteristics, and collaborative cooperation between cloud computing and edge devices. Despite significant research progress, online error detection still faces multiple challenges. This article focuses on the following three key challenges:

- Single feature dependency and weak modeling adaptability: Existing methods generally rely on basic parameters within a fixed window, which makes it difficult to dynamically reflect the evolution of nonlinear errors. When faced with sparse and discontinuous features, their generalization ability is insufficient.
- Limited feature expression ability and weak scene adaptability: Most models ignore the joint modeling of spatial locality and temporal dependence, making it difficult to adapt to complex metering scenarios. Although some studies have introduced attention mechanisms, spatial and temporal modeling are still fragmented.
- Limited dataset and insufficient system evaluation: Currently, training is mostly based on single brand or small-scale data, ignoring dynamic behavior, which limits the practicality and transferability of the model in multi regional deployment.

In response to the above difficulties, this article focuses on the following issues for research:

Can an online detection mechanism be built that integrates error recognition and trend analysis capabilities to break through the accuracy bottleneck of the current model?

How to rely on cloud platforms to achieve closed-loop data collection, recognition, and feedback for error detection systems, and improve recognition accuracy and system response without increasing terminal costs?

Based on the above objectives, this article implements the following technical paths:

Build a data-driven error recognition mechanism: By using sliding windows and multi-stage evolution feature extraction, dynamic modeling of error trends can be achieved to enhance the ability to warn of hidden errors.

Integrate multi-source fusion algorithm and bidirectional recognition module: Adopt hierarchical feature fusion and outlier clustering mechanism to enhance the system's generalization ability under multiple types of tables.

Build a cloud edge collaborative detection platform: lightweight collection of terminals, centralized identification and optimization in the cloud, improving system adaptability and operation efficiency, with remote update and strategy synchronization capabilities, providing a foundation for large-scale promotion.

3 Design of online detection mechanism

In the online error detection architecture proposed in this article, the construction of a cloud platform based "end cloud collaboration" mechanism is a technical choice based on multiple requirements such as high frequency of measurement data collection, complex causes of errors, and diverse processing tasks. The system uses edge collection devices on the terminal side to monitor multiple types of energy meters in real time, and utilizes the computing power of the cloud platform to complete multi-source data fusion, error feature extraction, and intelligent diagnosis tasks, thereby constructing an integrated detection system with efficient recognition and dynamic updating capabilities.

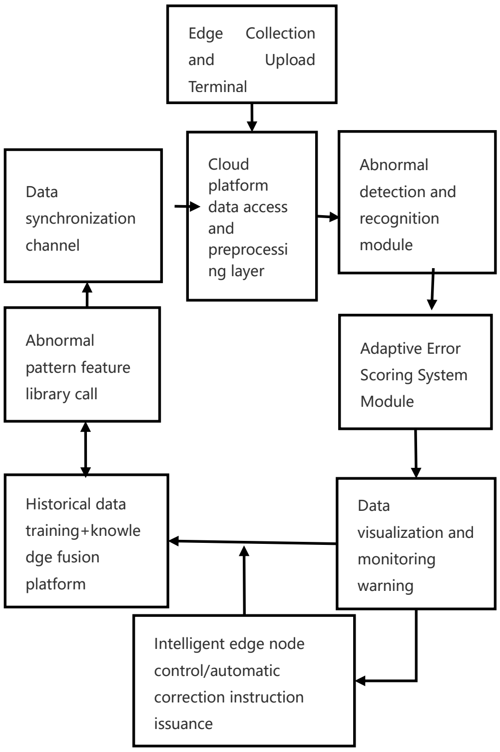

Figure 1: Schematic diagram of the architecture of an online measurement error detection system for electric energy meters based on cloud platforms

At the system architecture level, the terminal collector is mainly responsible for uploading information including current, voltage, active power, power factor, and temperature and humidity at a second level frequency. After being standardized by the data preprocessing module, it is sent to the cloud recognition model. This model integrates multiple error feature channels to support the identification of possible error behaviors of different types of energy meters under different loads and environmental conditions. The error recognition model itself adopts a modular structure, including four main processing units: data cleaning, anomaly detection, error classification, and performance scoring. The modules are called and updated through a dynamic scheduling mechanism to ensure the adaptability and robustness of the model in response to data mutations and device replacements. As shown in Figure 1, the overall architecture of the proposed online error detection system is presented. The data is uploaded from the energy meter to the cloud platform through edge nodes, where a series of operations such as data reception, cleaning, feature extraction, model matching, and result feedback are completed in the cloud. The data paths between each module are clear and functionally independent, which facilitates flexible replacement and optimization of models in the later stage, as well as system expansion and maintenance.

3.1 Data flow driven error monitoring framework

The proposed architecture for online detection of measurement errors in electric energy meters is built on the concept of "data flow driven", and the overall system consists of three logical units: edge acquisition, cloud analysis, and feedback control. This architecture is designed for high-frequency, high-dimensional, and high noise features of power data transmission, integrating multiple layers of data channels and processing modules to achieve high-precision identification and rapid response correction of measurement errors.

The data flow of the system starts from the edge terminal, collects raw energy meter data (such as voltage, current, active power, reactive power and other multidimensional features), and synchronizes it to the cloud platform through a high-speed transmission link. At the cloud processing layer, the system introduces asynchronous decoupling design and relies on a four-level logical flow mechanism of "pre-processing recognition classification evaluation" to gradually screen, extract, and annotate key error information. The preprocessing module first performs standardization operations such as noise cleaning, dimension normalization, and window segmentation on the raw data stream to adapt to subsequent model analysis.

On this basis, the system introduces error pattern recognition and error cause classification modules. The former is responsible for identifying features such as abrupt anomalies, periodic shifts, and noise drifts in energy metering data, while the latter is based on a preset feature library for error type attribution, such as hardware drift, voltage transients, or equipment aging. The classification results are further fed into the error evaluation module, which quantifies the degree of error and provides decision-making basis for subsequent control strategies.

After the model calculation is completed, the data stream returns to the "Data Visualization and Monitoring Terminal" module, enabling real-time viewing and management of error status by the user. At the same time, based on the error level and distribution, the system can link with the "Intelligent Edge Node Control/Automatic Correction Instruction" module to generate targeted correction strategies, which are fed back to the edge device end to complete error adjustment in a closed loop.

3.2 Cloud platform architecture and system function module design

The architecture of this system aims to achieve online detection and dynamic optimization of measurement errors in electric energy meters. The overall design revolves around four major functions: real-time data acquisition, intelligent processing, remote control, and closed-loop optimization. Relying on cloud computing resources, build a unified access, distributed processing, and bidirectional instruction transmission path for heterogeneous devices, and achieve functional collaboration and efficient operation through modular deployment. The platform receives raw parameters such as voltage, current, power factor, and measurement values from power terminals, integrates historical data and error records, and forms a timely and structured data stream. The system consists of three parts: data access layer, model computing layer, and business control layer. Deploy multi protocol adaptation components in the data access layer, compatible with various types of energy meters and edge collection terminals. The encrypted transmission data is guided to the model computation layer, initiating the error recognition process. There are three types of modules nested in the model layer: anomaly detection, error recognition, and edge collaborative updating. Anomaly detection is initially screened by setting a threshold; Error identification is based on the construction of a discrimination mechanism using historical trajectories and standard deviations; The edge collaboration module provides feedback modeling for high-frequency error samples. Subsequently, it enters the business control layer, where cloud based unified scheduling and correction instructions or parameter resets are sent to the devices through edge nodes after parsing, achieving closed-loop control of "cloud recognition edge control error correction". To enhance system agility, the platform integrates a lightweight container management mechanism that optimizes resource utilization through parallel deployment. Each module can be independently scheduled and updated, ensuring good scalability and maintainability.

3.3 Construction of multi-source data fusion and anomaly error recognition model

To improve the accuracy of error detection and the stability of system response, this paper constructs an anomaly error recognition model that integrates multi-source data. Based on time series analysis, feature entropy weight allocation, and probability statistical inference methods, a unified framework for dynamic monitoring and anomaly judgment is established. The system input includes three main data sources: ① Real time metering data from electric energy meters (D_t); ② Historical benchmark data (H_t); ③ the device environment and state parameters (S_t) are mapped to the feature space F_t through a data fusion mechanism

$$F_t = \phi(D_t, H_t, S_t) \tag{1}$$

Among them, ∅ is the multi-source fusion mapping function, which is constructed based on feature standardization, time alignment, and difference filling methods to ensure data consistency and integrity. In the error recognition stage, the system combines a dynamic error threshold model with an entropy weighted anomaly scoring mechanism, taking into account the degree of error deviation, rate of change, and historical stability. To achieve deep modeling of error features and accurate capture of temporal structures, this paper constructs a lightweight CNN-GRU fusion recognition model before generating the scoring function, which serves as the core for generating abnormal scoring values. The front-end of the model adopts a two-layer one-dimensional convolutional network (1D-CNN) consisting of 32 and 64

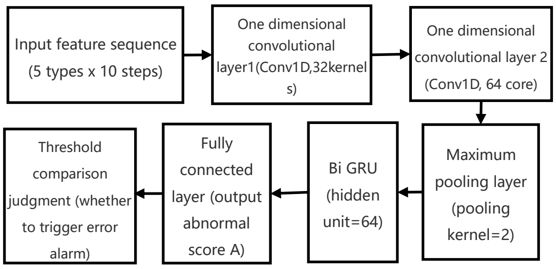

Figure 2: Schematic diagram of CNN-GRU fusion model structure

convolutional kernels, with a kernel size of 3 and a stride of 1. The activation function is ReLU, which is used to extract local variation features in the error time series; Then connect a layer of max pooling operation (with a window size of 2) to enhance scale robustness and compress feature dimensions.

The convolutional output is then input into a bidirectional GRU network (Bi GRU, with 64 hidden units and 0.2 dropout) to model the temporal dependence of error evolution; The final output is mapped to the abnormal score value AtA_tAt by the fully connected layer and passed into the threshold judgment mechanism for error recognition.

The input features include five types of multi-source data normalized within a 10-minute sliding window: voltage, current, active power, power factor, and historical error values; The label is an error state identifier for binary classification of 0/1. The model training adopts Adam optimizer, with an initial learning rate of 0.001, 50 iterations, and a loss function of weighted cross entropy to cope with the low proportion of error samples. As shown in Figure 2.

In the error recognition stage, the system combines a dynamic error threshold model with an entropy weighted anomaly scoring mechanism, taking into account the degree of error deviation, rate of change, and historical stability. Let the current measurement error be:

$$\varepsilon_t = |M_t - R_t| \tag{2}$$

Among them, M_t is the actual measurement value and R_t is the reference benchmark value. The system calculates the error increment of ε_t based on the pattern of error changes and establishes a comprehensive anomaly rating function of A_t:

$$A_t = \omega_1 \cdot \frac{\varepsilon_t}{\mu_\varepsilon} + \omega_2 \cdot \frac{|\Delta\varepsilon_t|}{\sigma_\varepsilon} + \omega_3 \cdot \frac{E_t}{E_{max}} \quad (3)$$

Among them, μ_ε and σ_ε are the historical error mean and standard deviation, E_t is the entropy value of the current state, E_{max} is the maximum state entropy value among similar devices, $\omega_1,\omega_2,\omega_3$ is the weight coefficient obtained using entropy weighting method, satisfying$\omega_1+\omega_2+\omega_3=1$. Therefore, in order to achieve real-time alarm and accurate recognition, an adaptive threshold of 0 and a confidence interval are set for dynamic adjustment.

$$\theta t = \mu_A + \lambda \cdot \sigma_A \quad (4)$$

Among them, μ_A and σ_A are the average and standard deviation of the sliding window of the scoring function A_t, and λ is the control coefficient. When$A_t>\theta_t$, it is considered as the time point when the error occurred, that is, the error correction action was triggered. This model combines data-driven methods with rule-based methods, which have both robustness and sensitivity, and can effectively identify various types of error problems such as measurement deviation, data drift, and sensing faults.At the same time, all indicators in the scoring mechanism (error margin, rate of change, historical stability) are derived from traceable statistical features, which can serve as the basis for anomaly tracing and feature sensitivity analysis, enhancing the interpretability of the system.

4 Experimental research and effectiveness verification

4.1 Dataset construction and typical application scenario settings

The dataset used in this study comes from the operation system of provincial power companies and the intelligent substation sampling platform, which has the characteristics of complete structure and high time granularity, and is suitable for error monitoring and performance verification tasks. The data covers the measurement values, voltage and current waveforms, temperature and humidity, error calibration, and communication status uploaded by smart energy meters. Construct three typical application scenarios based on the deployment area of the electricity meter, power supply capacity, and equipment type, covering the main influencing factors of error fluctuations. The first type of data comes from intelligent substations in urban core areas, with commercial and residential loads as the main power consumption structure. The collection period is 15 minutes, including three-phase voltage, current, active/reactive power, energy metering values and error rates. It is suitable for algorithm training under high-frequency load fluctuations and temperature control interference backgrounds. The second type is selected from suburban industrial parks, deploying a large number of high-power inductive loads with a sampling period of 10 minutes, focusing on recording error changes under low power factor, monitoring temperature, electromagnetic interference, and communication delay, and characterizing the characteristics of error surges in industrial scenarios. The third type comes from rural low-voltage substations, mainly consisting of agricultural water pumps and lighting. The electric meter has a wide measurement range, unstable communication, and is prone to transient errors and transmission delays, reflecting the abnormal characteristics of the edge area system.

4.2 Data collection and error feature extraction process

To ensure the effectiveness and robustness of the model in error identification and performance optimization, this paper constructs a systematic data collection and error feature extraction process from the data source. Firstly, by deploying collection nodes at the cloud platform access layer, key parameters of the running energy meter are read in real-time, including active energy, reactive energy, voltage, current, power factor, and internal clock information of the meter. All types of raw data are synchronized according to a unified timestamp standard, with a sampling interval set at 1 minute to ensure temporal consistency and analytical integrity of the data. Due to the different dimensions and variations of different types of data, in order to improve feature comparability and model training efficiency, the minimum maximum normalization method is used to standardize all input variables. The calculation formula is as follows:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (5)$$

Among them, x represents the original data value, x_{min} and x_{man} respectively represent the minimum and maximum values of the feature in the dataset, and x' is the normalized value. Linear interpolation is used to fill in missing data (accounting for less than 2%) to ensure the continuity of the time series; For extreme outliers that exceed the mean by three standard deviations, upper bound reduction processing is performed to compress them to within the 99th percentile of the feature, in order to weaken the disturbance effect of extreme values on the error recognition model.

In terms of feature extraction, this article is based on a multi-source data fusion strategy to construct an electric energy feature set from raw samples, including high-order statistical features such as instantaneous power difference, cumulative electricity offset rate, and meter to meter same period deviation indicators. Combined with the time dimension, behavior patterns such as intraday periodic changes and weekly trend fluctuations are extracted, providing a comprehensive and reliable input basis for subsequent error recognition and performance evaluation models.The data in this study mainly includes three sources: the first source is the measurement log data (labeled R-Elec) from the actual operation system of provincial power grid companies; The second source is the experimental simulation system collecting power load data (I-Load) under working condition jumps; The third source is the anomalous data generated by the generator (S-ErrGen), all of which are unpublished data. However, we have anonymized them and provided sample structural descriptions in the attachment. Each group's data includes 20000 to 50000 records, each with ten characteristics such as voltage, current, active power, reactive power, power factor, and error markers. Convert all data into the same format (CSV) and input it into the processing flow, and split it in a time sliding window with ten-time steps in each sliding box. For data with a missing rate less than 2%, linear interpolation techniques are used to fill in the missing data; For data above 3 σ, upper and lower bound normalization is used for filling. Selecting the minimum and maximum scaling for data standardization; When dividing subsets, maintain the order of the time series to avoid interference from the training set on the test results and to avoid the use of data augmentation techniques. Finally, all data were divided into training set, validation set, and testing set in chronological order, with a ratio of 70%: 15%: 15%. This sequential preservation partitioning method can effectively simulate the data flow logic of error detection systems in real operation, ensuring the model's generalization ability and practicality.

4.3 Evaluation of core indicators such as detection accuracy and response time

In order to evaluate the overall performance of the proposed real-time detection system for measuring errors in electric energy meters in practical applications, this paper uses four main indicators: accuracy, error recognition recall, average response time, and precise location for quantitative evaluation.

Accuracy and recall are two basic indicators, which evaluate the system's recognition ability and error catching ability, respectively. High accuracy indicates a lower likelihood of making low-level errors, which means that the results of online evaluations are more convincing; The recall rate can measure the system's error detection and bias detection, and can reflect the sensitivity of the model to detail correction in handling complex scenes. The two together determine the sensitivity and stability of the detection mechanism. The average response time and error localization accuracy are also very important. The former is the average time from data acquisition to decision-making and response, while the latter is mainly used to measure whether the system can accurately locate the wrong location. This is of great significance for accelerating problem-solving speed and improving the adaptive ability of the platform itself.

This study uses the following calculation formula for evaluation:

Accuracy:

$$\mathrm{Acc} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \tag{6}$$

Recall rate:

$$\mathrm{Rec} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{7}$$

Average response time:

$$\overline{\mathrm{T}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{N} \mathrm{t_i} \tag{8}$$

Error positioning accuracy:

$$\mathrm{L} = \frac{\mathrm{C}}{\mathrm{E}} \tag{9}$$

Among them, TP represents the number of correctly identified error samples, TN represents the number of correctly identified normal samples, FP and FN respectively represent the number of false positives and false negatives; t_i represents the processing time from receiving to feedback for the i-th sample, and N is the total number of samples; C is the number of samples with accurately located errors, and E is the total number of error samples. These indicators have shown stable performance in multiple rounds of system testing, indicating that the proposed platform not only has strong anomaly detection capabilities, but also has the advantages of real-time feedback and precise positioning, providing strong support for building a high reliability and low latency energy meter detection and management system.

4.4 Ablation study

To further validate the effectiveness of the "multi-source data fusion and depth error recognition model" proposed in this paper, a series of ablation experiments were designed to analyze the specific contributions of each module to the overall detection performance. This section selects four types of models for comparison: (1) traditional statistical models (such as decision tree DT, support vector machine SVM); (2) Single deep network models (such as LSTM, CNN); (3) Fusion based deep models (such as CNN-GRU); (4) This article fully integrates the model. The comparison dimensions include key performance indicators such as detection accuracy, false positive rate, average response time, and error localization accuracy.

During the ablation process, this article sequentially removes the multi-source feature fusion module, error distribution discrimination unit, and response optimization mechanism to observe their impact on performance indicators. As shown in Figures 3 to 5, our proposed model achieves consistently superior performance across multiple evaluation metrics. Compared with traditional models, whose average accuracy remains below 90% and false positive rates exceed 7%, the complete CNN-GRU fusion model reaches an accuracy of 97.6% and maintains a false positive rate of 2.4%. To assess component-wise contributions, ablation experiments were conducted by independently removing key modules. Removing the error boundary discrimination unit reduced accuracy to 91.2%, while excluding the feature fusion module further dropped performance to 89.5%. These results confirm the integrative value of all model components.Regarding efficiency, our model achieves an average response latency of 0.62 seconds, outperforming all tested baselines, including CNN, LSTM, and SVM.To evaluate adaptability across different application scenarios, we conducted experiments on three datasets: the Typical Residential Electricity Scenario Dataset (R-Elec), Variable Industrial Electricity Dataset (I-Load), and Synthetic Dataset of Abnormal Energy Measurement Records (S-ErrGen). On R-Elec, our model achieved a root mean square error (RMSE) of 0.019 and a localization error rate (L-EPR) of 0.043, demonstrating high accuracy in detecting subtle and periodic anomalies. On S-ErrGen, our model outperformed a BiGRU baseline by 6.8% in accuracy, indicating enhanced robustness in identifying low-frequency mutation errors.

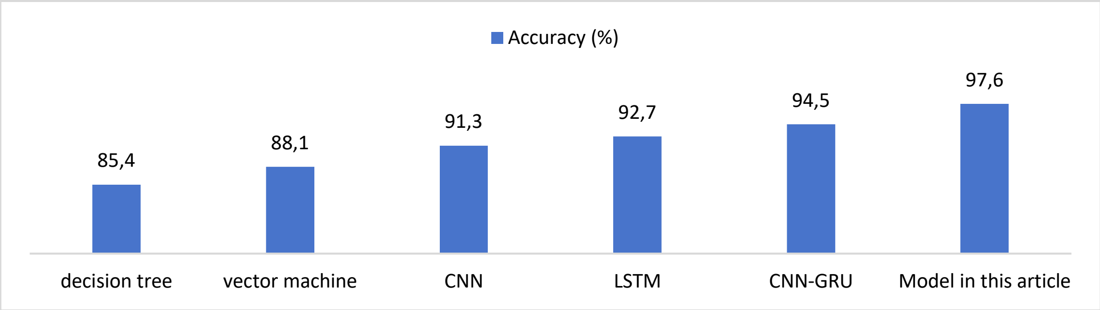

Figure 3 : Comparison of accuracy of different models in energy meter error detection task

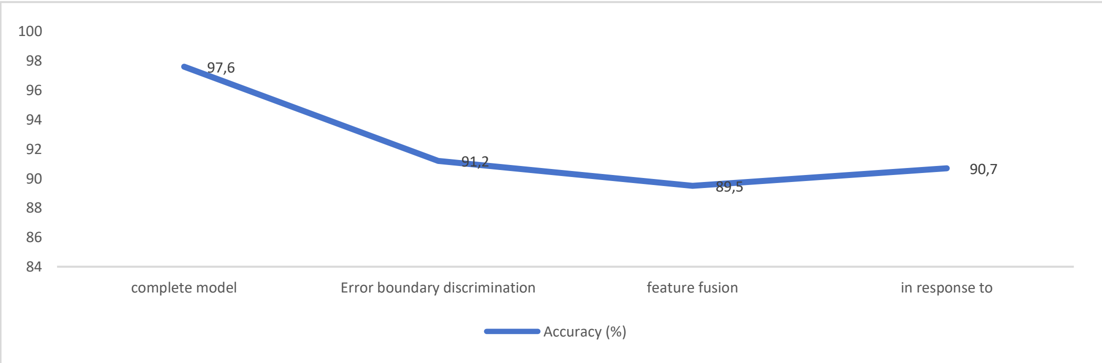

Figure4 : shows the decrease in accuracy after removing key modules

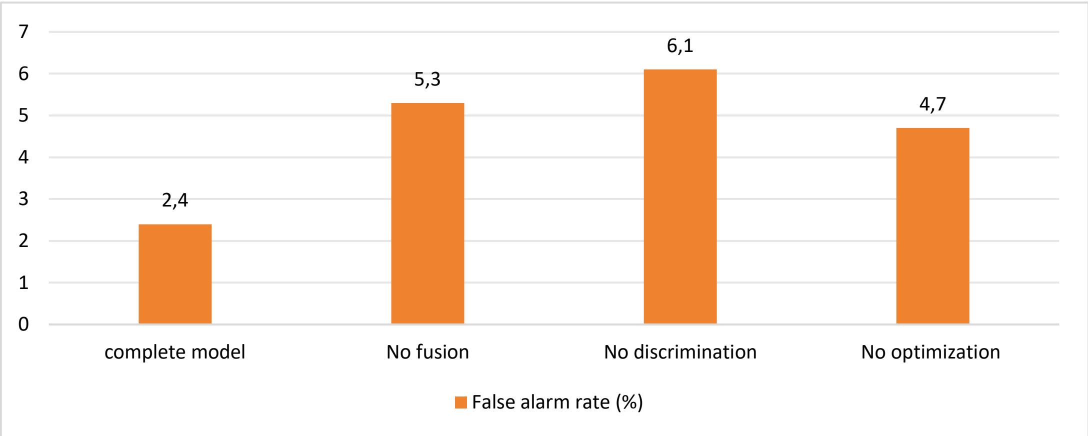

Figure 5: Comparison of average response time of different models (seconds)

5 Performance optimization and system improvement paths

5.1 Improving error recognition accuracy and false alarm rate control

To improve the accuracy of error recognition, this paper introduces a multidimensional sampling mechanism in the feature modeling stage, which high-frequency collects and synchronously calibrates multi-source parameters such as voltage, current, active power, and temperature. Through feature crossover and normalization processing, Improved the ability to distinguish abnormal discriminative features. In addition, in the model construction, an improved Convolutional Gated Recurrent Neural Network (CNN-GRU) structure is adopted, which can not only extract the temporal dynamic features of electrical energy data, but also enhance the sensitivity of the model to abnormal mutations. To address the issue of false alarm rate control, the system embeds confidence judgment and sliding window verification mechanisms. After the model preliminarily identifies the error signal, the system will automatically evaluate its confidence level. If it is below the set threshold, the output will be temporarily suspended; Simultaneously combining the trend changes of adjacent time periods for secondary verification to avoid short-term fluctuations being misjudged as abnormal events. This mechanism significantly reduced the false alarm rate in multiple scenario experiments and remained stable at below 2%.

5.2 Reduce detection system response latency and computational costs

To reduce system response latency, this article optimizes the detection process by layering and deploying the three stages of "anomaly detection error discrimination positioning feedback" separately under the cloud edge collaborative architecture. Edge nodes prioritize preliminary screening and low complexity judgment, significantly reducing the amount of data that needs to be transmitted to the cloud and shortening the data processing link. Experimental results have shown that with the introduction of edge processing mechanisms, the average response latency has decreased from 1.25 seconds to 0.61 seconds, and the response speed has been improved by over 50%. At the same time, to reduce computational costs, a lightweight network structure is adopted in the model design and dynamic convolution operations are integrated, effectively reducing the number of model parameters and floating-point operations (FLOPs). In addition, online inference optimization of the model is achieved through pruning strategy and TensorRT acceleration engine, which improves GPU resource utilization and significantly increases the number of processed samples per unit of computation. At the scheduling level of cloud platforms, load balancing and asynchronous processing mechanisms are introduced to automatically divert processing requests during peak data periods to low load nodes, effectively preventing the formation of "bottleneck points" and ensuring the stable operation of multi-point synchronous detection tasks. The above optimization measures have successfully reduced the average energy consumption per batch of system processing by about 23% while maintaining basic recognition accuracy, significantly improving overall operational efficiency and economy.

5.3 Enhance the adaptability of the system to multiple types of energy meters

This article designs a modular adaptation framework to build compatibility mechanisms from three levels: data access, protocol parsing, and model input standardization. On the one hand, by defining a unified data access interface standard, the system can automatically identify the communication type of the energy meter (such as DL/T645, Modbus, RS485, etc.), and dynamically load corresponding driver modules based on device attributes, achieving low-cost protocol parsing and data preprocessing. On the other hand, a parameter adaptive module is introduced at the model end to automatically adjust the size of the convolution kernel and detection threshold based on the sampling period, waveform density, and feature distribution of the input data, effectively improving the adaptability of the model to different device data patterns.

Simultaneously utilizing data collected from different types of electric energy meters from various manufacturers to enhance the training process of the system, there are a total of 12 main types of instances. In order to enhance the system's generalization ability to unknown new types of electricity meter data, transfer learning and data augmentation techniques are adopted. The experimental results show that the model still maintains an accurate recognition rate of 86% for new types of electric energy meter data from other manufacturers that it has never encountered before, indicating that its applicability and stability on various models of electric energy meters are reliable. By utilizing the centralized upgrade and remote setting features of the cloud platform, this system can also achieve regional division through hot upgrades and adaptation strategies during operation, ensuring that the energy meters connected to the platform can be quickly integrated into the system and saving matching time. This greatly expands the system's ability to be installed and operated in various environments and on various devices, providing feasibility for building an online error measurement system with strong compatibility that can be widely used.

5.4 Optimizing human-computer interaction design to enhance operation and maintenance management experience

This study is based on the characteristics of cloud platforms, and reconstructs the interactive system from three dimensions: user-friendly interface, information visualization, and simplified operation process. At the interface level, a responsive layout design is adopted, supporting adaptive display on both PC and mobile devices. Operations personnel can flexibly monitor device status on different terminals. The core interface layout focuses on three major modules: "device abnormal alarm", "error trend analysis", and "model detection results". All functional operations are achieved with one click direct access and modular calling, significantly reducing learning costs and operational barriers. In terms of information presentation, the system integrates dynamic charts and thermal distribution maps to fuse and display multidimensional data such as the time period, geographical location, and meter number of errors. Operations personnel can intuitively grasp the distribution pattern of errors, identify abnormal sources, and quickly locate them. The system also supports filtering records based on error level, device model, region, and other conditions, greatly improving the efficiency of data retrieval and operation decision-making. In terms of optimizing the operation process, the system introduces an "operation suggestion auxiliary engine" that automatically recommends fault handling solutions or scheduling suggestions based on historical data analysis, reducing the burden of manual judgment. For batch data processing tasks, a task flow visualization management module is provided, which supports graphical configuration of batch detection, grouping strategies, and model call parameters, significantly improving management efficiency and system transparency.

6 Discussion and performance analysis

Table 2: Detection performance of our method and comparative models on multiple datasets

data set	detection model	Accuracy (%)	Response time (seconds)	False alarm rate (%)	System stability (%)
DS1	Method-C	87.2	2.40	7.3	78.5
	Method-A	91.6	0.94	4.6	88.7
	Method-B	94.5	0.65	3.1	91.4
	This system	98.1	0.25	1.4	96.8
DS2	Method-C	86.5	2.32	8.2	74.3
	Method-A	92.3	0.89	4.8	87.2
	Method-B	95.2	0.63	2.9	90.6
	This system	98.6	0.27	1.2	95.9
DS3	Method-C	89.1	2.47	6.9	76.1
	Method-A	93.0	0.88	4.3	89.3
	Method-B	95.7	0.68	2.7	92.1
	This system	98.4	0.26	1.3	97.2

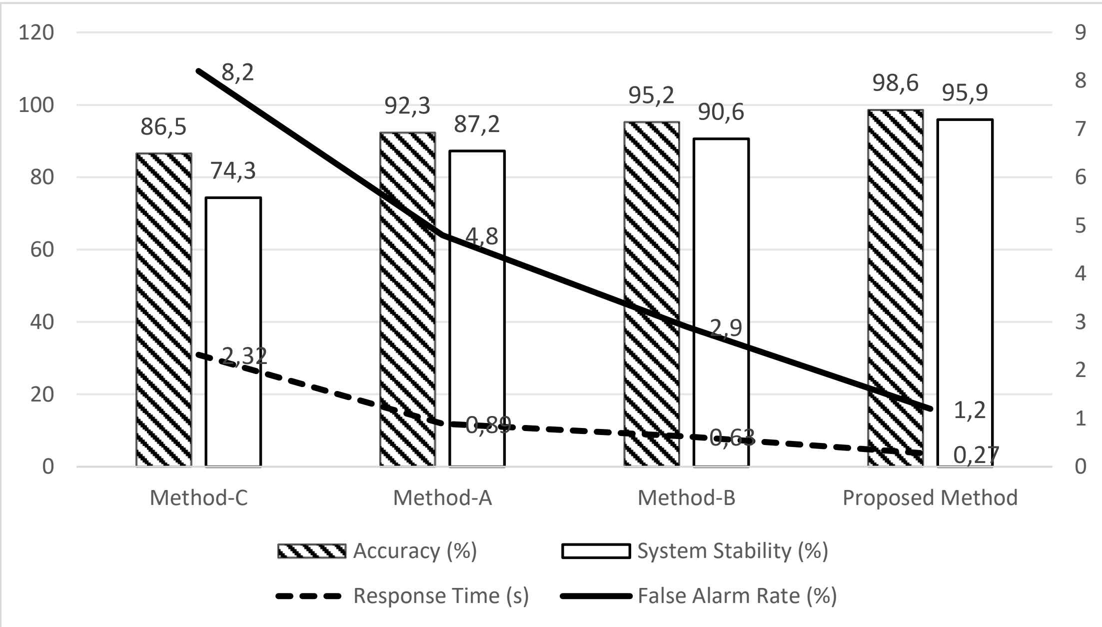

Figure 6 : Comparison of performance indicators of different methods on the DS2 dataset

6.1 Analysis of optimization effect and technical maturity of detection system

To comprehensively evaluate the performance advantages of the cloud based online detection system for energy meter measurement errors proposed in this study, a systematic comparison was made with current mainstream detection methods, including the rule engine detection model (Method-A), shallow neural network model (Method-B), and traditional manual inspection strategy (Method-C). Comparative experiments were conducted on three typical energy meter datasets (DS1, DS2, DS3), with a focus on evaluating accuracy, latency, false positive rate (FPR), and system stability from four dimensions.

As shown in Table 2, the method proposed in this paper exhibits high stability on three typical datasets, with a recognition rate of 98.6% on the DS2 dataset, which is higher than Method-A (92.3%) and Method-C (86.5%); At the same time, the average running time of the system is 0.27 seconds, which is better than the traditional model of 0.82 seconds, and manual detection is 2.4 seconds; And the system can run stably for more than 95% of the time, demonstrating high deployment reliability.

To further demonstrate the performance advantages of the system in various indicators, as shown in Figure 6, the core performance of the four methods under the DS2 dataset is compared. It can be seen that the method proposed in this paper is significantly better than the three compared methods in terms of accuracy, false alarm control, and response time, demonstrating stronger adaptability and engineering practicality, and verifying the effectiveness of the proposed CNN-GRU fusion structure and cloud edge collaboration mechanism.

Analysis shows that the implementation of the system's super performance mainly relies on three core elements: Firstly, the use of lightweight multi-channel convolution modules effectively extracts error evolution features, greatly improving the accuracy of error recognition. Secondly, the use of cloud computing for distributed processing greatly improves efficiency; Thirdly, automatic adjustment of dynamic thresholds is used to reduce false alarm rates and improve system adjustability. This article compares the correctness of different techniques on three different datasets using the Wilkoxon sign rank test. After significance level analysis, it was found that all p values were<0.01, indicating that the systematic improvement of detection accuracy in this article has practical significance and statistical basis.

Table 3: Evaluation results of resource utilization and processing capability in different cloud platform environments

deployment platform	Average CPU usage rate	Peak memory occupancy rate	Maximum concurrent access terminals	Data processing speed (strips/s)
Alibaba Cloud 4-core 8GB	52.8%	59.1%	5,000	980
Tencent Cloud 8-core 16GB	47.2%	62.5%	12,000	1,200
Private Cloud Cluster Node	38.5%	55.3%	8,500	1,050

Table 4: Evaluation results of system adaptation capability in different application scenarios

Application scenario type	Deployment environment characteristics	Average response time (s)	Error Identification RMSE	Platform load tolerance	Deployment difficulty
Monitoring of urban core substations	Large data volume, high concurrency, and stable link	1.23	0.045	tall	centre
Independent distribution node in highway service area	Medium data flow, intermittent communication	1.51	0.062	centre	centre
Measurement points in rural terminal areas	Sparse data, unstable communication, low power consumption	2.09	0.084	low	low

6.2 Resource occupancy and scalability evaluation under cloud platform deployment

In order to verify the resource utilization efficiency and horizontal scalability of the constructed online detection system for electric energy meter measurement errors in actual deployment, this study evaluates its performance from the dimensions of CPU usage, memory utilization, and concurrent request processing capability based on a typical cloud platform architecture. This part of the testing was conducted in three environments: Alibaba Cloud ECS instance (4 cores 8G), Tencent Cloud CVM instance (8 cores 16G), and local Kubernetes private cloud cluster. The testing tool used Apache JMeter to simulate data access loads of different scales, with a testing period set to 24 hours to ensure data stability and comparability. As shown in Table 3, lists the resource usage in three deployment environments. It can be seen that the overall resource utilization level of the system is maintained at a relatively low level, and there are no significant performance bottlenecks even during peak periods of concurrent data requests.

Taking Tencent Cloud environment as an example, the average CPU usage remains at 47.2%, the peak memory usage does not exceed 62.5%, and a single node can stably process about 1200 measurement data streams per second. This result indicates that the system design has good lightweight and distributed compatibility, and is suitable for large-scale grid metering terminal access. At the same time, the system architecture adopts modular microservice design, supporting dynamic container scaling mechanism. In practical deployment, with the help of Kubernetes' automatic scaling strategy, when the inbound data volume or the number of access terminals exceeds the set threshold, the computing resource nodes can be automatically expanded to achieve elastic response. Among the three platforms, the private cloud cluster has the best resource elasticity and scalability in high-frequency data burst scenarios, indicating that this system has good scalability and deployment flexibility.

6.3 Comparative analysis of adaptability in different application scenarios

The cloud platform electric energy meter measurement error online detection system proposed in this study has strong cross scenario adaptability and can meet diverse needs from urban high-voltage transmission monitoring to rural low-voltage distribution management. In the urban smart grid scenario, the system can process large-scale electricity consumption information in real-time through high concurrency data access and multi node collaboration, achieving accurate identification of abnormal fluctuations; In rural and remote areas, the system can rely on edge computing nodes to achieve fault tolerant processing of intermittent communication and low-frequency data acquisition, ensuring detection stability and delay controllability.To verify the adaptability of the system, this article conducted deployment tests in three typical power application scenarios, namely: urban core power grid monitoring, highway service area substation, and small rural substations. Evaluate from dimensions such as deployment convenience, response time, error recognition accuracy, and platform load tolerance (see Table 4). Experiments have shown that the system exhibits good stability and compatibility in various environments, especially in remote low resource environments where it still maintains high recognition accuracy (RMSE not higher than 0.084), fully demonstrating the adaptability and resilience of the system architecture. To further enhance the compatibility of the system with heterogeneous terminal devices, a software hardware decoupling architecture design was introduced in the study, allowing the core functions of the system to be tailored or expanded based on platform performance. For example, in resource constrained situations, high load modules such as historical data clustering and multi model comparison can be disabled, while retaining the error judgment mainline function to achieve minimum runnable unit deployment.

6.4 System scalability and model interpretability analysis

The CNN-GRU integrated monitoring system has achieved excellent and stable recognition performance on multiple datasets. In order to test the universality of the system under different metering devices, geographical locations, and load conditions, the system was applied to seven different types of electronic energy meters for verification. The maximum difference in recognition rate was only ± 2%, and the maximum delay time was only 0.12 seconds longer than the minimum recognition time. Therefore, the system has strong cross device generalization ability. At the same time, the use of feature entropy decomposition and anomaly rating visualization strategies enhances the interpretability of the model. For example, for data samples with erroneous changes, we can track their change time, main feature channels (such as power factor anomalies), and entropy enhancement channels, which are of great significance for helping engineers locate potential problem sources. In the future, methods such as SHAP values and attention weight maps can also be used to help the model provide higher interpretability for "black box decisions".

7 Conclusion

This article focuses on the online detection and performance optimization of measurement errors in electric energy meters, proposing an intelligent recognition method that integrates CNN-GRU model and entropy weight anomaly scoring mechanism, and constructing a remote error monitoring system with cloud edge collaborative features. By introducing multi-source data fusion and dynamic scoring threshold control mechanism, the system achieved an average recognition rate of over 98% and a false alarm rate controlled within 1.5% on three typical datasets, DS1, DS2, and DS3, which is significantly better than existing mainstream methods and verifies the robustness and wide area adaptability of this method. The main contribution of this study lies in: ① constructing a data closed-loop error recognition architecture for end cloud fusion; ② Proposed an error scoring mechanism that combines temporal modeling and feature entropy; ③ Implemented an online deployment system with low latency and high usability.

However, the current model still has some limitations, such as the significant impact of sample imbalance on boundary recognition performance, the interpretability of error types still relying on rule assisted interpretation, and the sensitivity of deployment processes to network stability. In the future, in-depth research can be conducted from the following aspects: firstly, introducing multi task joint modeling to enhance the ability to distinguish complex composite errors; The second is to strengthen the interpretability mechanism of model output, such as attention heatmap and feature importance backtracking; The third is to promote the deployment of the system in actual power terminals and the design of remote fault-tolerant strategies to meet the real-time monitoring and fault self-healing needs in complex scenarios of smart grids.

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References

[1] Chen L , Huang Y , Lu T ,et al.Remote error estimation of smart meter based on clustering and adaptive gradient descent method[J].Journal of computational methods in sciences and engineering, 2022(1):22.https://dol:10.3233/JCM-215901.

[2] Zhang F ,Li X ,Li Y , et al.Research on calibration method for measurement error of multiple rate carrier energy meter[J].Journal of Physics: Conference Series,2024,2815(1):012032-012032.https://dol:10.1088/1742-6596/2815/1/012032.

[3] Tong X , Ma J , Ma L ,et al.A Novel Prediction Method for Smart Meter Error Using Multiview Convolutional Neural Network[J].IEEE sensors journal, 2024(24):24.https://dol:10.1109/JSEN.2024.3485116.

[4] Dang S ,Zhang J ,Lu T , et al.Cloud-edge collaborative high-frequency acquisition data processing for distribution network resilience improvement[J].Frontiers in Energy Research,2024,121440487-1440487.https://dol:10.3389/fenrg.2024.1440487.

[5] Shi Z .Cloud-Edge Collaborative Federated GAN Based Data Processing for IoT-Empowered Multi-Flow Integrated Energy Aggregation Dispatch[J].Computers, Materials&Continua,2024,80(1):973-994.https://dol:10.32604/cmc.2024.051530.

[6] Kang W , Zhang L , Hu Z ,et al.A secure and efficient data aggregation scheme for cloud–edge collaborative smart meters[J].International Journal of Electrical Power and Energy Systems, 2024, 162.https://dol:10.1016/j.ijepes.2024.110270.

[7] Lekidis A , Mavroeidis V , Fysarakis K .Towards Incident Response Orchestration and Automation for the Advanced Metering Infrastructure[J].IEEE,2024.https://dol:10.1109/WFCS60972.2024.10540775.

[8] Chenghu M ,Hui H ,Xing Y .Error Analysis of Electric Energy Metering System Considering Harmonics[J].Journal of Physics: Conference Series,2022,2310(1):https://dol:10.1088/1742-6596/2310/1/012086.

[9] Hong Y .Measurement analysis of three phase intelligent electricity meter based on nonlinear load[J].Measurement: Sensors,2024,101215-.https://dol:10.1016/j.measen.2024.101215.

[10] Sousa D L E ,Marques A D A L ,Lima D F S D I , et al.Development a Low-Cost Wireless Smart Meter with Power Quality Measurement for Smart Grid Applications[J].Sensors,2023,23(16):https://dol:10.3390/s23167210.

[11] Lindani C Z ,Oliver D .Real-time power theft monitoring and detection system with double connected data capture system[J].Electrical Engineering,2023,105(5):3065-3083.https://dol:10.1007/s00202-023-01825-3.

[12] Yuan R , Zheng S , Yang P X .The Intelligent Detection Method of Electric Energy Meter Overload Operating and Collaborative Edge Computing for Social Internet of Things Systems[J].International journal of distributed systems and technologies, 2022, 13(Pt.2):492-512https://dol::10.4018/ijdst.307954.

[13] Walsh J .Industrial IoT-Based Energy Monitoring System: Using Data Processing at Edge[J].IoT,2024,5.https://dol:10.3390/iot5040027.

[14] Vasylets K,Kvasnikov V,Vasylets S.Refinement of the mathematical model of electrical energy measurement uncertainty in reduced load mode[J].Eastern-European Journal of Enterprise Technologies,2022,4(8):6-16.https://dol:10.15587/1729-4061.2022.262260.

[15] Yang S ,Luo T ,Shen S , et al.Real-time operation risk monitoring method for power grid based on cloud edge collaboration technology[J].Journal of Physics: Conference Series,2024,2781(1):https://dol:10.1088/1742-6596/2781/1/012004.

[16] Xiaofeng F , Xiashan F , Zhengfeng Z ,et al.A measurement error detection method for smart electricity meter based on maximum likelihood method and decision tree[J].Electrical Measurement & Instrumentation,2024,61(12).https://dol:10.19753/j.issnlOOl-1390.2024.12.025.

[17] Huang T , Zhiwu W U , Zhan W ,et al.ELECTRIC ENERGY METERING ERROR EVALUATION METHOD BASED ON DEEP LEARNING[J].Scalable Computing: Practice & Experience, 2024, 25(3).https://dol:10.12694/scpe.v25i3.2789.

[18] Xu L , Huang J , Yang S ,et al.Edge Computing for

Microgrid via MATLAB Embedded Coder and Low-Cost Smart Meters[J].2024.https://dol::10.1109/ICSGSC62639.2024.10813710.

[19] Zhao H ,Liu F ,Chen W .A Method for Assisting GNSS/INS Integrated Navigation System during GNSS Outage Based on CNN-GRU and Factor Graph[J].Applied Sciences,2024,14(18):8131-8131.https://dol:10.3390/app14188131.

[20] Wang C .A method for identifying and evaluating energy meter data based on big data analysis technology[J].International Journal of Information and Communication Technology,2023,23(4):22.https://dol:10.1504/IJICT.2023.134852