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Leveraging Artificial Intelligence for Assessing Metering Faults in Electric Power Systems

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Abstract

Accurate energy metering is essential for reliable power system operation, fair billing, and effective monitoring of electricity consumption. However, detecting faults in electric energy meters remains challenging because conventional inspection practices, including manual testing, operational sampling, and user-reported verification, are time-consuming, labor-intensive, and often limited in dynamic field conditions. This study proposes a deep learning-assisted prediction model (DLPM) for identifying abnormal metering behavior and improving the assessment of energy meter faults in electric power systems. The proposed model learns the relationship between expected and observed meter trajectories, enabling it to detect significant deviations that may indicate measurement errors or operational faults. By automating the analysis of metering discrepancies, the DLPM provides a more consistent and data-driven alternative to traditional fault diagnosis methods. The model supports accurate deviation estimation, improves abnormality recognition, and assists in identifying potential causes of smart meter malfunction. Simulation results demonstrate that the proposed DLPM achieves strong predictive performance, with 99.2% accuracy, 97.8% overall performance, and 98.9% efficiency. In addition, the model records an average consumption deviation of 10.3% and a root mean square error of 11.2%, indicating its effectiveness in supporting intelligent meter fault assessment. These findings suggest that deep learning can enhance the reliability, automation, and diagnostic capability of smart metering systems in modern electric power networks.

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Keywords: Artificial intelligence; Electric energy metering device error; Deep learning methods

1. Introduction

In the power system, the energy meter is the main instrument used to measure electricity consumption and to support the settlement of power exchange [1]. Therefore, the accuracy of the energy meter is directly related to the economic benefits of the smart grid and the fairness of transactions between power suppliers and consumers [2]. However, in many practical situations, meter inspection still depends on periodic testing or offline maintenance after measurement errors exceed the acceptable limits. This practice affects the reliability of electricity supply and increases the cost of operation and maintenance [3]. In recent years, automated metering systems have been increasingly promoted and applied because of their technical advantages in energy metering [4]. These systems collect electricity meter data and real-time operating information, including load curves, power distribution, frozen energy data, demand, voltage, current, and related indicators. Through statistical processing and data analysis, automated metering systems support metering management, line-loss management, and other operational functions [5]. As an important subsystem of the substation metering automation system, the automatic collection, processing, and storage platform for metering stations can monitor metering devices across the network in real time. It also provides statistical data for line-loss analysis and supports the evaluation, transmission, and management of electric energy information [6].

The metering automation system also provides historical data records and query functions. By keeping complete records of abnormal meter-measurement events, metering managers can identify the fault location, trace the changes associated with the fault, and analyze its possible causes [7]. Compared with traditional estimation and correction methods, automated metering systems provide greater benefits, especially when they are integrated with power-loss analysis and related operational data [8]. With the development of smart grids, distributed management systems require more accurate assessment of equipment conditions, which places higher demands on the accuracy of energy metering devices [9]. The measurement accuracy of a smart electric meter is one of the key indicators for evaluating the quality of the meter [10]. It is also closely related to equity and fairness in electricity measurement, which makes it a major concern for power companies and society. In actual operation, the accuracy of measurement may change because of the quality level of the meter itself and the influence of the working environment. When the allowable error range is exceeded, the meter becomes unqualified for accurate measurement [11]. At present, the performance of smart electric meters is commonly evaluated through manual methods, such as sampling inspection, manual reading verification, customer consultation, and other physical checking procedures [12]. Without intelligent real-time monitoring, periodic errors are difficult to detect and handle promptly, which may negatively affect business operation [13]. In addition, smart meter readings contain useful information that can support better management decisions, but current approaches still lack an innovative method for conducting fast, comprehensive, and intelligent analysis [14].

Electric power enterprises are responsible for providing users with safe, stable, economical, and high-quality electricity [15]. With continuous technological and economic development, the power system is being restructured and improved toward greater intelligence and automation [16]. Accurate measurement and calculation of consumer electricity use are essential, and this requires the deployment of intelligent meters to protect the interests of both power suppliers and consumers [17]. Electric energy meters are widely used in urban and rural areas to measure users' electricity consumption in real time [18]. Smart electric meters can display consumer power consumption and then support recharging or payment according to the measurement results [19].

This paper applies artificial intelligence to analyze the remote error behavior of smart electric meters, identify the dynamic pattern of each fault as it occurs in real time, determine the distribution of defects across different states, and diagnose existing problems. Through this approach, working-quality issues can be detected and handled promptly, which can effectively improve enterprise management in product quality, operational supervision, and customer service.

- This research proposes an error-diagnosis analysis approach based on deep learning, which can improve the model's generalization ability and robustness under limited data conditions. The proposed technique can predict electric energy meter faults with higher precision.
- The diagnostic results can guide the rotation and replacement of smart electric meters and support intelligent meter operation and energy-saving management.
- Company resource allocation can be further optimized, and labor costs can be reduced by using the proposed DLPM model.

The remaining sections of the article are organized as follows: Section 2 provides the background and related discussion on electric energy meter error analysis. Section 3 presents the proposed DLPM. Section 4 reports the simulation analysis. Section 5 concludes the paper.

2. Related Work

Zilvinas Nakutis et al. [22] introduced a non-invasive remote monitoring method (NIRMM) for analyzing faults in electric energy meters. The proposed technique satisfies error-monitoring requirements by continuously examining normal consumer electricity consumption patterns without the need to inject an additional test load. In this approach, the meter under examination observes a specific phase of the consumer's total load profile, while a reference indicator measures the magnitude of the power step in synchronization with the supply, enabling direct comparison. The error-analysis process was validated by simulating a 26-state energy distribution grid using publicly available electricity-consumption data. Experimental findings showed that after two to three days, or approximately 170 power steps, the uncertainty of the meter-error estimation stabilized at nearly 0.63%. The authors also demonstrated how the method can be implemented within advanced metering infrastructure by using occupancy-index models and modern energy-meter data collection protocols.

Shouxiang Wang et al. [23] proposed a stacked convolutional sparse auto-encoder (SCSAE) for compressing intelligent meter data. The proposed structure provides a simple and lightweight auto-encoder design for energy-meter readings. The encoder is constructed using a two-dimensional separable convolutional layer, while both the encoder and decoder rely on transposed convolutional layers. Compared with existing auto-encoder models and conventional compression methods, the proposed structure reduces both reconstruction error and model parameters effectively. In addition, cluster-based indices were used to analyze the relationship between electricity-consumption behavior and compression performance. Case-study results indicated that the proposed method can considerably improve computational efficiency and reduce model size while preserving detailed reconstruction quality. The study also showed that the compression performance can be further improved by grouping consumers according to their electricity-consumption patterns.

Shishir Muralidhara et al. [24] recommended an Internet of Things-based smart energy meter (IoT-SEM) for monitoring energy consumption at the device level. During system testing, energy-consumption information was collected and transmitted through the ThingSpeak platform. The proposed system allows consumers to observe, monitor, and store electricity-usage data. These records help users verify whether their devices are operating within the expected power-rating limits. Moreover, by providing customers with detailed behavioral consumption information, the system encourages conscious energy use and supports the reduction of electricity costs. Therefore, the IoT-SEM framework enables consumers to track long-term energy-consumption patterns, confirm device performance according to energy ratings, and adopt more efficient conservation practices.

Xiangyu Kong et al. [25] investigated the use of Recursive Least Squares (RLS) for online error estimation of electric energy meters. First, the measured data are preprocessed, and abnormal records, such as light-load and no-load data, are removed using a suitable clustering method. This step helps ensure that the estimation data correspond to comparable operating conditions for each user. Then, based on the law of electrical energy conservation, mathematical relationships are established among the substation head meter, user meters, and line losses. After that, a recursive least-squares double-parameter estimation technique is applied to calculate both line loss and electric-meter error. Finally, the study analyzes how dynamic double forgetting factors and constant double forgetting factors affect the accuracy of electric-meter error estimation.

Čegovnik, T. et al. [26] proposed an artificial intelligence-based approach for electricity-consumption prediction. The study presents early results from a commercial project aimed at developing AI models for forecasting next-day electricity use at 15-minute intervals. First, the most relevant features for predicting future consumption were identified for each measuring point and each 15-minute time interval. Then, scripts and databases were developed to collect these features along with historical electricity-consumption data at 15-minute granularity for every measuring point. Finally, three AI prediction models were developed and evaluated. Compared with the top ten observation models reported by the data provider, the proposed predictions produced a relatively high MAPE. The authors also assessed available parallelization strategies in R and reported the computational results obtained using the parallel and foreach R libraries.

Sayed H. A. et al. [27] proposed smart electricity-meter load prediction in Dubai using multiple linear regression (MLR), artificial neural networks (ANN), random forests (RF), and autoregressive integrated moving average (ARIMA). The study considered several research methodologies, including MLR, RF, ANN, and ARIMA, and used electricity-consumption data collected in Dubai. When the analysis was limited to one district, ANN and RF achieved strong predictive accuracy of about 97%, whereas ARIMA reached approximately 93%. In the single-category setting, ANN and RF also showed competitive performance, with an accuracy of nearly 91.02%.

Nutakki M. et al. [28] presented a review of optimization methods and the role of artificial intelligence in residential energy management systems. The study emphasized that smart grids benefit consumers by enabling two-way communication between utilities and end users. To improve grid reliability, both supply-side and demand-side management strategies must be applied. Within decentralized smart grids, home energy management systems (HEMS) play an important role in controlling and optimizing residential electricity use. With technological development, AI-based smart optimization methods have become increasingly important. The article discusses the advantages of AI-driven optimization strategies and explains how they can outperform traditional energy-management approaches.

Richter L. et al. [29] supported the use of artificial intelligence for automating power distribution networks. AI is useful in this context because it helps process large and diverse datasets through prediction and optimization techniques. The study focuses on several stages of the electricity supply chain, including generation, maintenance, preprocessing, analysis, forecasting, optimization, and trading. By considering human interaction, AI adaptability, energy transition, and sustainable development, the authors examine the opportunities and limitations associated with shifting from manual to automated electricity supply chains. Based on the above literature, it is clear that existing models still face important limitations in accuracy, automation, real-time monitoring, and practical deployment. Therefore, this research proposes the DLPM model to improve the precision of error analysis in energy meters. The proposed model is presented in the next section.

3. A Predictive Model Aided Using Deep Learning

The global power system is undergoing a major transformation because of the integration of distributed components, advanced metering infrastructure, communication networks, distributed energy resources, and electric vehicles. These developments aim to improve the reliability, management, energy efficiency, and security of future power systems. Smart electric meters are essential measuring devices used to record consumers' electricity consumption. Any deviation in the measurement accuracy of these meters can directly affect the economic and social benefits of power companies. Therefore, accurate energy measurement is a critical issue that power management departments must carefully control. The metering process should be strictly regulated, stable, and adjustable to ensure reliable billing and fair energy exchange.

The basic error of an electric energy meter changes according to the load current and the load power factor. The relationship between these variables forms the typical error curve of the meter. After factory inspection or verification testing, the basic error of every qualified electric energy meter must satisfy the standards specified in relevant regulations. This ensures that the meter has stable and acceptable error characteristics during normal operation. In an induction energy meter, the rotation of the turntable is mainly affected by the driving torque and braking torque, which are related to the load condition. Therefore, the turntable reading can be considered proportional to the electrical energy load. However, in practice, this relationship is not completely simple. In addition to the main driving and braking torques, several other factors may influence the meter operation, including damping torque, friction torque, parasitic torque, nonlinearity of the current-core magnetization curve, compensation torque, rotational torque effects, voltage variation, frequency variation, and temperature change. When these factors exceed certain limits, the basic error of the meter is immediately affected, and the turntable speed is no longer a strictly linear function of load power.

To ensure that the basic error of an induction power meter remains within the required standard range, an error-adjustment mechanism is usually installed inside the meter. By adjusting these components, the basic error of the smart electric meter can be controlled within the allowable limits. Generally, the basic error of an energy meter is mainly determined by the load current and the power factor, while other operating conditions are allowed to vary only within a limited range specified in the technical requirements of energy meters. However, the actual external operating conditions of a meter often differ from standard technical conditions. For example, the alternating-current frequency in the main grid may differ from the rated frequency. Similarly, the grid voltage and the temperature at the meter installation location may vary over a wide range. These environmental changes influence the measurement error of the electric energy meter. The error caused by such external condition variations is commonly referred to as the additional error of the energy meter.

Many factors may contribute to power meter error, so they should be carefully investigated during any error analysis. For this reason, it is necessary to collect comprehensive information related to electric energy meter errors. In most cases, measurement errors are mainly caused by variations in voltage, current, and temperature. The energy meter management unit usually stores these data in a relational database that can be extracted and processed. Since electricity consumption accumulates over time and depends on current flow, both voltage and current behavior are important for meter-error analysis. In addition, ambient temperature continuously changes during long-term meter operation, affecting both the voltage and current characteristics of the power meter. In practice, however, such information is often not stored securely or completely. Therefore, temperature data related to energy meter error must be collected using suitable pre-acquisition and acquisition devices before performing accurate error analysis. Within the field of artificial intelligence, support vector machines, neural networks, and various hybrid deep learning methods have achieved notable results in error prediction and estimation.

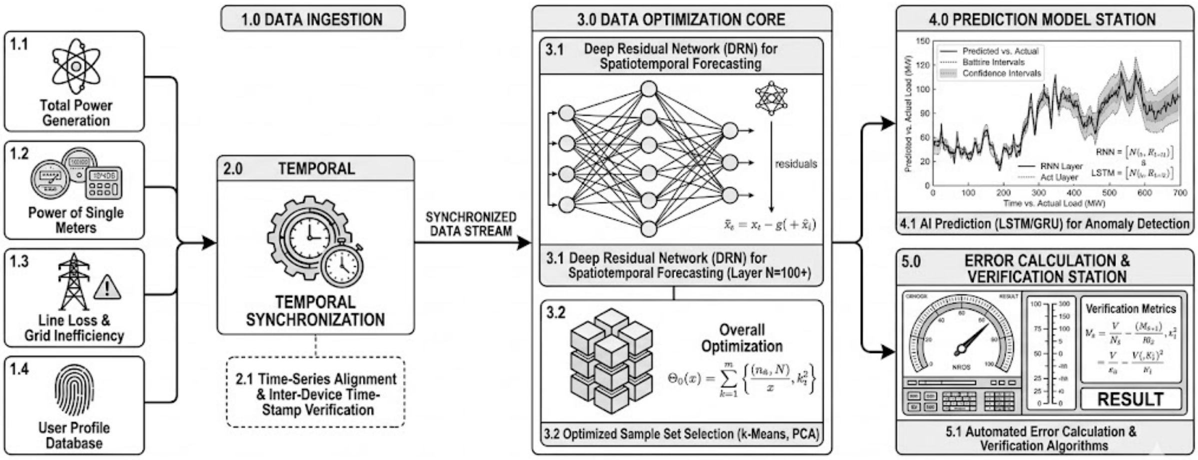

Figure 1. Error Calculation based on proposed DLPM model.

The error-computation process of the proposed DLPM model is illustrated in Figure 1. The operational error of each electric energy meter can be estimated by using multiple linear regression methods, based on the statistical relationship among the total meter power in the station area, the power values of individual user meters, and the corresponding line loss within the station area. In this process, time synchronization between the user meter and the station master meter is a critical requirement. Because smart meters may have clock deviations, the clock of each electric energy meter should be aligned with the relevant meters in the same station area. This synchronization ensures that the calculated operating error and line loss of the electric energy meters are reliable.

First, this paper applies carrier-based precise time technology using the existing electric information acquisition network. This procedure is used to analyze the clock-deviation distribution and the load-stability condition of the station area. Then, a time interval with relatively stable load behavior is selected for calculation, which helps reduce the influence of clock deviation on the error-estimation results. In this study, the clock deviation is controlled within an acceptable range, and the relationship between line loss and user-meter power is then analyzed.

According to the conventional line-loss calculation method, the line-loss ratio of a station area is related to the total metered power of that station. Therefore, the measured power can be used to estimate and control daily line loss. However, line loss is also affected by the actual current-flow path in the distribution network. For this reason, high precision is required when analyzing the error of an electric energy meter. The station bus loss and the load distribution of each customer in the station area must also be considered. When analyzing meter error, the correlation should be evaluated under relatively stable load-distribution conditions. Otherwise, excessive interfering variables may lead to inaccurate or misleading results.

To improve the reliability of the error-estimation process, the data foundation should identify a group of load samples that have similar and independent electricity-load distributions. This provides a more dependable basis for assessing meter errors. As shown in Figure 1, the DLPM-based error-analysis process begins by collecting data from the station area itself, including total meter power, user-meter power, household-meter relationships, and related operational information. After data collection, time synchronization is performed to ensure that all measurements are aligned before the error-analysis process is conducted.

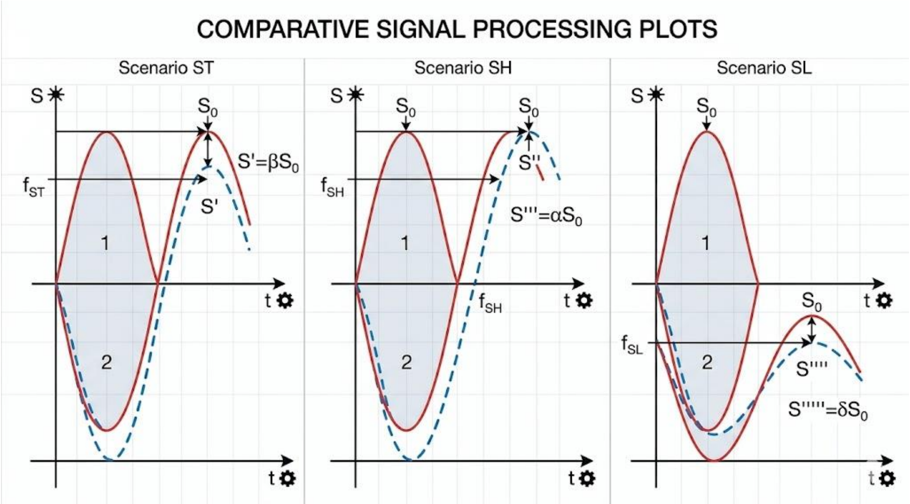

Figure 2. (a) Energy under the temperature's impact error ratio, (b) Energy under the humidity's impact error ratio, (c) Energy under the load's impact error ratio.

Curve 1 represents the actual input signals, whereas Curve 2 represents the signals affected by a certain fault ratio. It is assumed that the degradation variable of the electric energy meters is initially at the first stage. During operation, the meters gradually degrade along their corresponding dimensions, but the degradation path is uncertain. When the three variables are disturbed or contaminated at fSTf_{ST}fST, fSHf_{SH}fSH, and fSLf_{SL}fSL under similar operating points, the discrete electric energy can be expressed as follows:

$S = \sum_{j=0}^{M}\left(\beta_j + \alpha_j + \delta_j\right) S_0$ (1)

In equation (1), $\beta_j$indicates the energy measurement error coefficients affected by f_{ST}, α_jAre the measurement error coefficients affected by f_{SH} , and $\delta_j$caused by f_{SL} . The range of β_j 's, α_j 's and δ_j 's values are: $-1 \le \beta_j \le 1, -1 \le \alpha_j \le 1, -1 \le \delta_j \le 1$. When $\beta_j + \alpha_j + \delta_j = 1$, the accuracy measure of energy meters is unaffected, representing that the impact of every degradation performing variable on the energy meter error is balancing.

To streamline the model, the three degradation variablesf_{ST}, f_{SH} and f_{SL} are fused into one degradation variable, specifically the Energy's measurement error ratef_S. The three aspects impact energy meters at a similar period, which affects the degradation variable.f_S. The degradation progression can be described as follows:

$f_S(t) = h\left(\text{Temp }(t), \text{Hum}(t), \text{Load}(t)\right)$ (2)

In the above equation (2), $\mathrm{Temp}\ (\mathrm{t})$denotes a function of temperature over a period, $\mathrm{Hum}(\mathrm{t})$ denotes a function of humidity and $\mathrm{Load}(\mathrm{t})$Of load. Let:

$$\varepsilon = \mathrm{f_S}(\mathrm{t})$$

$$\beta = \left(\mathrm{Temp}\ (\mathrm{t}), \mathrm{Hum}(\mathrm{t}), \mathrm{Load}(\mathrm{t})\right) \quad (3)$$

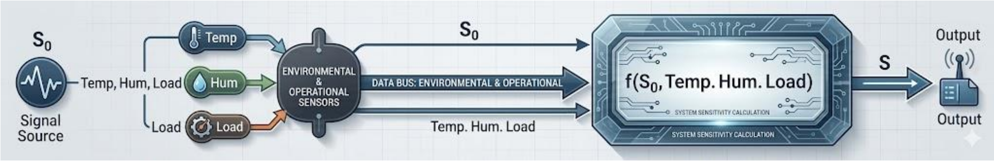

Figure 3. Equivalent schematic model of energy metering system

Figure 3 demonstrates the equivalent schematic diagram of the energy-metering model. The humidity, temperature, and load degradation acting parameters can lead to the energy meter's error. Thus, the degradation variables of the energy meter involve the subsequent three portions: the energy meter error rate under the impact of temperature, the meter error rate under the effects of humidity, and the error rate under the effect of loads.

The solution of the expression (2) is B, and then presentation (3) can be transcribed as:

$$\varepsilon = B\beta \tag{4}$$

Expression (4) is described as the variable degradation calculation of energy meters, where εindicates the degradation variable, βdenotes the degradation performing variable, and solutionsmatrices$B$indicate degradation networks under the degradation performing variables. The estimation error ratio of the meter is utilized as the assessed restraint:

$$\eta_S = \frac{S - S_0}{S_0} \tag{5}$$

In the above equation (5), η_S, signifies the average energy measurement errors. A model for evaluating energy meter errors is established using the equations (4) and (5).

Data sample rates need to be standardized to ensure accurate timing. Every data type requires allocation with standardization processing to integrate the parameters' dimensions and weights. Due to the humidity and temperature not changing, the first-order linear interpolation technique can enlarge humidity and temperature data. Captivating the temperature information handling as an instance, supposing that sampling temperatures of$j$ and $i$are$T(j)$ and $T(i)$, the information increases to Mperiods. When the data is extended, the interruption series among the temperature sampling value is shown in the following equation (6):

$$T(j + l) = \begin{cases} T(j) + \frac{T(i) - T(j)}{M} \cdot l & l = 1,2,K,M-1 \\ T(i) & l = M \end{cases} \tag{6}$$

Humidity information is dealt with similarly, and the humidity and temperature sampling rates after treatment are the same as that of load.

Supposing that the series of the variable is $\{S_1, S_2, \ldots, S_m, S_{m+1}\}$, its high variation gradient with the technique of standardization is described in equation (7) :

$$\Delta S = \max\{\Delta S_j\}(j = 1,2,3, \ldots m, m+1) \tag{7}$$

The variable series is dealt with differential standardized as in equation (8):

$$S_j = \frac{S_{j+1} - S_j}{\Delta S} \tag{8}$$

The expression (5) can be rewritten as the standardized form:

$$\Delta\varepsilon = A \cdot \Delta\beta \tag{9}$$

The above word (9) $\Delta\varepsilon$indicates the differential standardized degradation variable, $\Delta\beta$ is the standardized differential degradation acting variable, and Adenotes the respective standardized degradation networks.

The information source, the metric utilized in the model, and the data distribution can be initialized. The desensitized data have been gathered from two residential regions. The master meters in both the B and A residential areas also took real-time voltage and current readings every 15 minutes. All the information in this paper has been harmonized in corresponding records after data pre-processing and cleaning. After the data cleaning, the formulation to compute the residual measurement fault (containing the transmission power loss) for one day is shown below:

$$E = S_{master} - \sum_{j=1}^{m} S_{sub_j} \tag{10}$$

As inferred from equation (10), where E symbolizes the daily residual error among the master meters and S_{sub_j}, S_{master}signifies the daily reading of master meters and S_{sub_j} Denotes the reading of jth submeters over m submeter on that day. In the raw information, the faults between the submeters and master meters are minor; most of the comparative faults do not surpass 2%, which specifies the high accuracy of the gathered data. Besides, these meters are new at the data-gathering period, so it is presumed that there are no erroneous meters.

In this paper, the residual neural network's building block has been defined,

$$x = F\left(y, \{S_j\}\right) + y \tag{11}$$

As shown in equation (11), where $y$denotes input vectors, and $x$indicates the output vectors of the deliberation layers. The function $F\left(y, \{S_j\}\right)$, this signifies the remaining mapping to be learned.

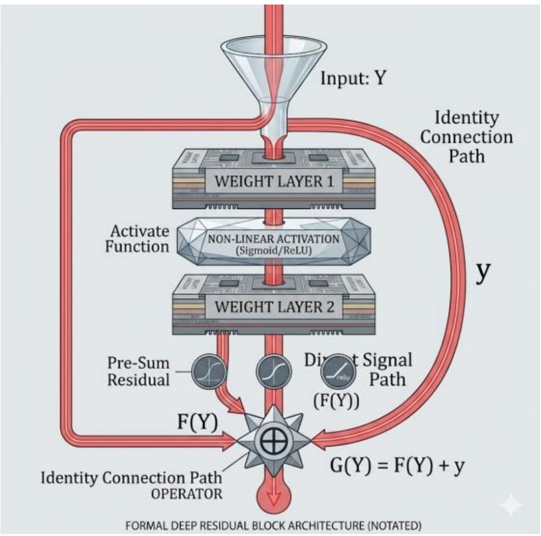

Figure 4. Residual Network

Figure 4 shows the residual network. This study focuses on behaviours connecting to the shortcut networks map in the residual network rather than increasing the state-of-the-art for the residual network. In this part, core structures of residual networks, residual blocks, are first defined. Then, this study analyses the propagation progression in the residual network to evaluate how it must be enhanced. Next, backward-propagation is used for fine-tuning. If training targets are preserved as a multi-class issue, the difference between the forecasted result and the original findings is provided:

$$K = \frac{1}{2}\sum_{j=1}^{c}\left\|\hat{x}_j - x_j\right\|^2 = \frac{1}{2}\sum_{j=1}^{c}\sum_{j=1}^{c}\left\|e_j\right\|^2 \tag{12}$$

As discussed in equation (12), where c is the number of classifications. $\hat{x}_j$ denotes the actual value of samples andx_j, $i$ndicates the class forecasted by networks.

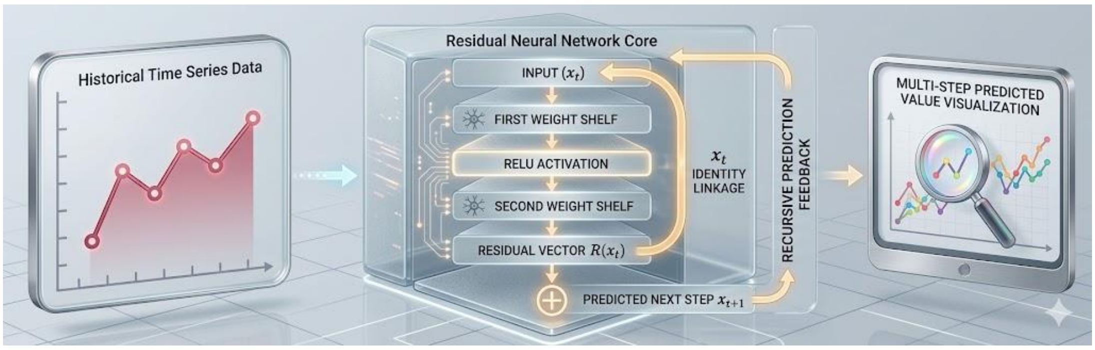

Figure 5. Load Forecasting based on Residual Network

Figure 5 shows the load forecasting based on the residual network. A load-predicting time series has been utilized as input to the Residual network model. It is handled in various layers of residual network models, and lastly, the output is in terms of error between actual load demand and forecasted values. For the forward propagation of the simplified residual networks, the set $y_1, y_2, \dots y_n$, arrives at input layers first. After that, the connection weight s_{ji}^1 is computed to determine$w_1^1, w_2^1, \dots w_m^1$, as inputs of the first hidden layers, and $\theta\,(w_j)$ is computed by its activation functions$\theta\,()$. In hidden layers to which the shortcut assembly is auxiliary, the input of the kth hidden layers are$w_j^1 = \sum_{j=1}^{m} \theta\left(w_j^{k-1}\right) \cdot \omega_{ji}^k + \theta_j^{k-1}$. The output of the final networks is the output. $\hat{x}_j$ Of the last layers. For the backward-propagation of single residual blocks, the gradient of K for the final linking weightss_{ji}^m Is computed in equation (13):

$$\frac{\partial K}{\partial \omega_{ji}^m} = \frac{\partial K}{\partial w_j^m} \cdot \frac{\partial w_j^m}{\partial \omega_{ji}^m}$$

$$= \gamma_j^m \cdot \frac{\partial\left(\sum_{i=1}^{c} \theta\left(w_j^m\right)\omega_{ji}^m\right)}{\partial \omega_{ji}^m}$$

$$= \gamma_j^m \cdot \theta\left(w_j^{m-1}\right) \tag{13}$$

The equation 13 can now be defined as, $\gamma_j^k = \frac{\partial K}{\partial w_j^k}, k = \{1,2,..m\}$and γ_j^m It is computed as follows in equation(14):

$$\gamma_j^m = \frac{\partial K}{\partial w_j^m}$$

$$= \partial 1/2 \sum_{j=1}^{c} \left\|\hat{x}_j - x_j\right\|^2$$

$$= \left|\hat{x}_j - x_j\right| \cdot \frac{\partial \hat{x}_j}{\partial w_j^m}$$

$$= e_j \cdot \theta'\left(w_j^m\right) \tag{14}$$

The hidden layer of the simplified residual networks has similar structures, so the connection weight among the hidden layer will have the same gradient formulations as in equations (15) and (16):

$$\frac{\partial K}{\partial \omega_{ji}^k} = \gamma_j^k \cdot \theta\left(w_j^{k-1}\right) \tag{15}$$

$$\gamma_j^k = \theta'\left(w_j^k\right) \sum_{ji}^{k+1}\left(\omega_{ji}^{k+1} + 1\right) \quad k = 1,2,3, \dots 13 \tag{16}$$

The gradients of$K$ for the first connection weightss_{ji}^1will be in equation (17) :

$$\frac{\partial K}{\partial \omega_{ji}^1} = \gamma_j^1 y_j \tag{17}$$

$$\gamma_j^1 = \theta'(w_i^1) \sum_{i=1}^{m} \gamma_j^2 \left(\omega_{ji}^2 + 1\right)$$

The following equation can denote w_j^0 as equal to y_j And (8) can be rewritten as (18) :

$$\frac{\partial K}{\partial \omega_{ji}^1} = \gamma_j^1 \cdot w_j^0 \tag{18}$$

Thus, the connection weight for the sum of the gradients of residual blocks (of m layers) can be provided by equation (19):

$$\frac{\partial K}{\partial \omega_{ji}^1} = \gamma_j^1 \cdot \theta\left(w_j^{k-1}\right),\ k = 1,2,3, \dots 16 \tag{19}$$

Likewise, the gradient formulation of plain networks can be given by:

$$\frac{\partial K}{\partial \dot{\omega}_{ji}^1} = \dot{\gamma}_j^1 \cdot \theta\left(\dot{w}_j^{k-1}\right),\ k = 1,2,3, \dots 16 \tag{20}$$

As inferred from equation (20), where $\dot{\omega}_{ji}^{1}$, $\dot{\gamma}_{j}^{1}$, and $\dot{w}_{j}^{k-1}$, are the respective variables of the plain network. Compared to current models, the suggested DLPM model improves prediction accuracy, performance, and efficiency while decreasing the average consumption ratio and root mean square error rate.

4. Analytical Simulation

The experimental results of the proposed DLPM model are evaluated using several performance indicators, including prediction accuracy, estimation error, real error, overall performance, efficiency, average consumption, and root mean square error rate. For the simulation analysis, the Electrical Fault Detection and Classification dataset [30] is used. Transmission lines are essential components of the electrical power network. In recent decades, the demand for electricity and the need for reliable supply have increased significantly, making transmission lines more important for transferring electrical energy from generation units to consumers. Modern power systems also depend on high-capacity power plants and interconnected grid structures, where synchronized generating stations and geographically distributed networks operate together. In such systems, rapid fault diagnosis and the timely activation of protection devices are necessary to maintain stability and prevent serious failures. Accurate identification and classification of transmission-line faults are therefore important for clearing faults as quickly as possible. Artificial neural networks (ANNs) are well suited for this task because of their strong pattern-recognition ability. They can detect abnormal fault patterns and classify different types of electrical faults effectively. A dependable protection scheme should operate accurately under different system conditions and infrastructure states, ensuring that faults are detected and isolated without delay.

(i) Prediction Accuracy Ratio

The accuracy of electric energy meters in recording electricity consumption is a key indicator of their operational reliability. When the measurement error exceeds the allowable tolerance range, the meter can no longer provide qualified and precise measurements. Therefore, improving the quality-control process of energy meters is essential for reducing measurement errors and ensuring fair electricity billing. After a defined service period, random sampling inspection can be used to identify inaccurate or faulty meters. Once abnormal smart meters are detected, they can be repaired, recalibrated, or replaced. This process improves the accuracy and timeliness of managing non-standard energy metering devices. Compared with traditional manual inspection, the proposed approach reduces labour requirements, provides higher computational accuracy, and shortens the inspection cycle. It also uses mathematical statistical methods to process and analyze the collected meter data in a centralized manner. The prediction accuracy of the proposed DLPM model is presented in Figure 6.

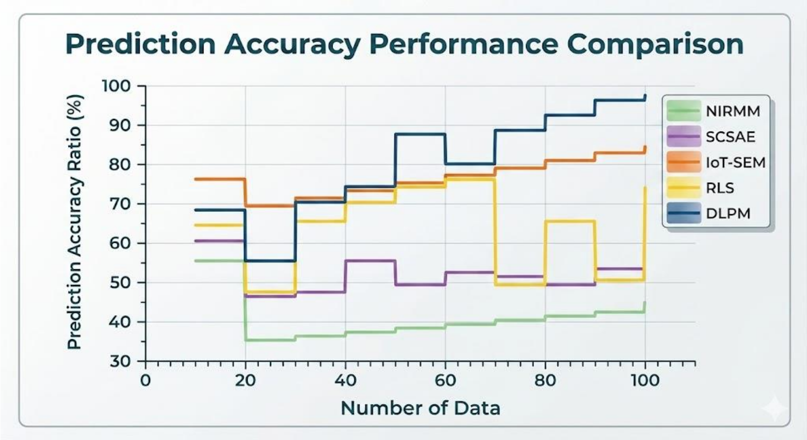

Figure 6. Prediction Accuracy Ratio

(ii) Performance Ratio

The performance of intelligent electric energy metering may degrade during operation, which can directly affect the measurement accuracy of the energy meter. Most condition-estimation systems for energy equipment are based on comprehensive models, where several variables are used to describe the operating state of dynamic devices. Therefore, when a condition-estimation system is applied, each relevant parameter should be measured and analyzed. Theoretical studies indicate that energy meter performance can be influenced by several factors, including environmental temperature and humidity, electrical variables such as frequency, harmonics, and load, communication disturbances, vibration, electromagnetic fields, and power-grid events such as interruptions and voltage drops. The performance ratio of the proposed DLPM method is presented in Figure 7.

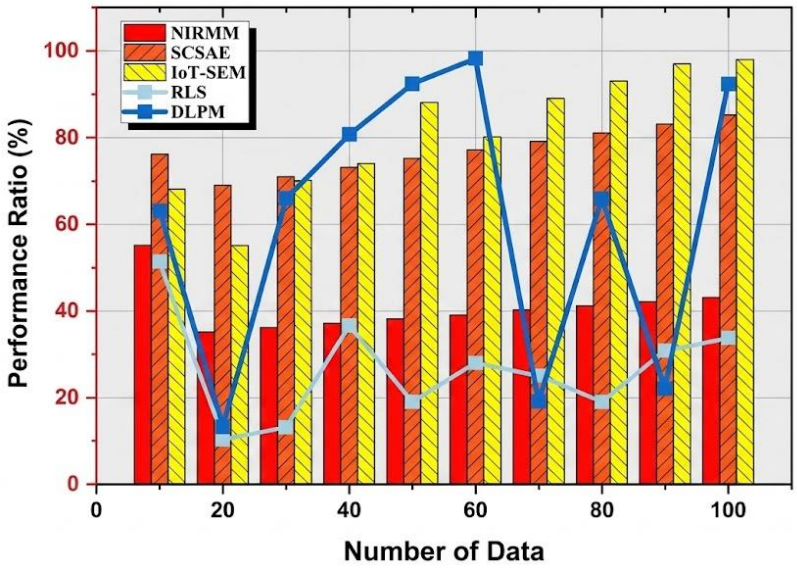

Figure 7. Performance to Cost Ratio

(iii) Error in Estimation vs. Actual Error

The least-squares method can be used to estimate the model and evaluate its variables mathematically. Predicting or measuring the dependent variable based on the optimal combination of multiple independent parameters is more accurate and efficient than relying on a single independent parameter. The standard error represents the difference between the actual value and the value predicted by the model. One of the key advantages of the proposed DLPM model is its improved accuracy in forecasting energy meter errors. The comparison between the predicted error and the actual error is presented in Figure 8.

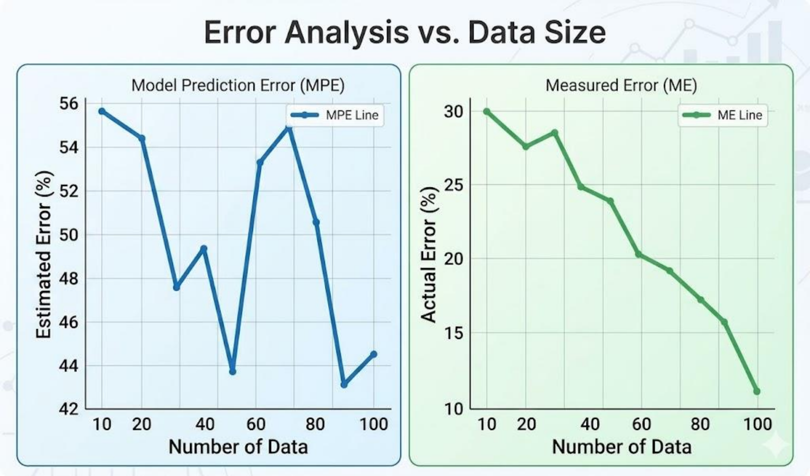

Figure 8. Estimated Error and Actual Error

(iv) Efficiency Ratio

Energy efficiency is an important indicator for reducing energy consumption while maintaining a stable service level and acceptable comfort for residential users. Estimating the power and energy consumption of appliances can also support predictive maintenance, helping to improve operational efficiency and safety during load operation. Training a deep learning model usually requires considerable computational resources. Therefore, the objective is to optimize the learning model parameters efficiently and complete the training process within a reasonable time using an effective computing configuration. To evaluate training-time efficiency, this study defines an experimental throughput metric, measured as the number of processed samples per training period using the same input datasets for smart meter error calculation. Figure 9 shows the efficiency ratio of the proposed DLPM model.

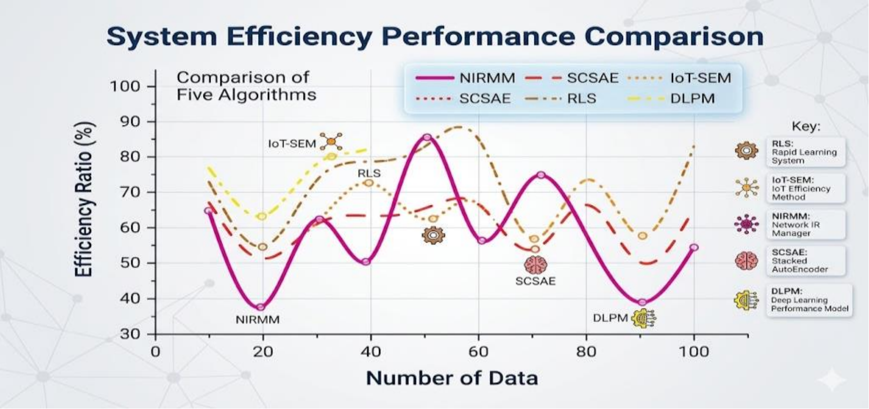

Figure 9. Efficiency Ratio

(v) Average Consumption Ratio

This study aims to measure and analyze household power consumption using energy meter data. As electricity demand continues to increase, greater attention should be given to understanding consumption patterns over time. Therefore, analyzing and measuring electricity usage trends is important for improving intelligent power distribution, supporting energy-saving strategies, and predicting electric energy meter errors. For many small households, installing energy meters can help reduce electricity bills by making consumption more visible and easier to manage. Meter performance can also be checked by switching on appliances one at a time and observing the meter response. If the meter does not respond properly when an appliance is operating, either the appliance may be faulty or the meter may have an accuracy problem. If the meter continues to move unexpectedly, it may indicate inaccurate measurement or hidden power consumption. Figure 10 shows the average consumption ratio.

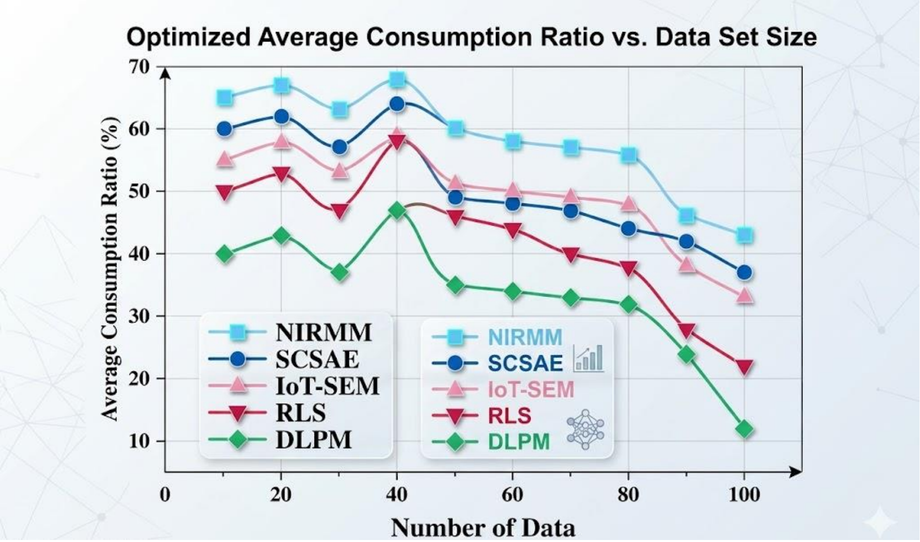

Figure 10. Average Consumption Ratio

(vi) Deviation from the Mean Square

Mean absolute error measures the difference between the predicted values and the actual values. It provides a direct indication of the average prediction error. Compared with other error functions, it is less affected by very large errors. Mean square error and root mean square error describe the dispersion of prediction errors. Because they use squared error values, they are more sensitive to large deviations, making high errors more noticeable in the evaluation. Therefore, these three metrics can be used together to assess the performance of the prediction model from different perspectives.

$$RMSE = \sqrt{\frac{1}{m}\sum_{j=1}^{m}\left(x_j - x_j'\right)} \qquad (21)$$

As shown in Equation (21), mmm represents the number of samples, xjx_jxj denotes the jjj-th actual value, and xj′x'_jxj′ denotes the corresponding jjj-th predicted value. The root mean square error (RMSE) is used to evaluate the difference between the predicted and actual values. The RMSE results are presented in Figure 11.

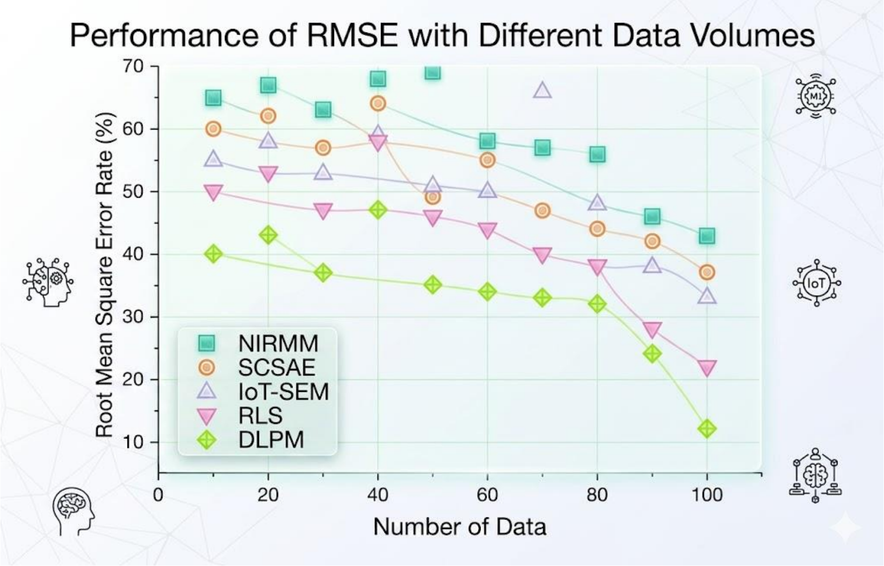

Figure 11. Deviation from the Mean Square

Compared with existing methods, including non-invasive remote monitoring methods (NIRMM), stacked convolutional sparse auto-encoder (SCSAE), Internet of Things-based smart energy meter (IoT-SEM), and Recursive Least Squares Method (RLS), the proposed DLPM model achieves better prediction accuracy, performance, and efficiency. At the same time, it reduces the average consumption ratio and root mean square error rate.

5. Conclusion

Error analysis in smart electric meters requires high accuracy and precision, especially because meter errors are often influenced by line-loss factors. Therefore, this study proposes a deep learning-based approach to optimize and analyze smart meter errors according to load states in identical and independently distributed regions. Line loss is affected by several factors, including three-phase load balancing, customer power distribution within the station service area, and station topology. Even under stable line-loss conditions, the presence of too many variables may distort the analysis results. The deep learning-based error diagnosis method proposed in this study can accurately predict the effect of electric energy meter faults, improve learning effectiveness, and enhance the model’s generalization ability and robustness under limited sample conditions. The experimental results show that the proposed DLPM model achieves a prediction accuracy ratio of 99.2%, a performance ratio of 97.8%, an efficiency ratio of 98.9%, an average consumption ratio of 10.3%, and a root mean square error rate of 11.2%, outperforming other commonly used methods.

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