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Leveraging Artificial Intelligence for Assessing Metering Faults in Electric Power Systems

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Abstract

Operations sampling inspections, manual verification, user applications, and other labor-intensive methods are commonly used for energy meter error analysis in the power industry. Accurate fault detection in electric energy meters is crucial for achieving reliable measurements. The fundamental issue with on-site testing of electrical energy metering equipment is the characteristics of electric power meters under dynamic settings. This research develops a deep learning-assisted prediction model (DLPM) to address the problem of inaccurate energy power meters. Electricity is measured precisely, and the meters can pinpoint the most consequential deviations between the predicted and actual trajectories. The results of this research point to the widespread adoption of a consistent and autonomous method for analyzing discrepancies in energy meters. Compared to the traditional way, this technology considerably improves the electric intelligent meter deviance computation, providing exact data assistance for analysis and diagnostics of the source of the electric smart meter abnormality. The simulation results show that the suggested DLPM model has better prediction accuracy (99.2%), performance (97.8%), efficiency (98.9%), average consumption (10.3%), and root mean square error (11.2%) than the state-of-the-art.

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1. Introduction

In the energy system, the energy meter is the principal tool for measuring power and the basis for compensating power exchanges [1]. The accuracy of the energy meter directly connects to the smart grid's economic advantages and the consumers' trade fair [2]. In contrast, regular tests are still occupied on most of the meter or offline conservation when the estimation faults surpass the limitations, which distresses the consistency of the electricity supply and raises the price of operations and preservation [3]. An automated metering system has been promoted and applied in recent years with better methodological benefits in energy metering [4]. Data on the measure of electricity meters and the instantaneous data, including power diagram, power-sharing, freezing power, demand, voltage, current, etc., are acquired employing statistics and analysis of the different data, the management of an automated measuring system (measurements, line losses management) and other [5]. A subsystem of the computerized sub-station measurement system, the automatic collecting, processing, and storage system of the metering stations, can monitor the whole network effect measurement device in real time, providing statistics for line loss and analysis for evaluating and transferring electrical energy information [6].

Historical data records and query functions come in the metering automation system. A thorough record of an error meter measurement event for measuring management may check the fault site; changes to the fault recorded, and cause analysis [7]. The automated measuring system offers a higher benefit than the standard projection correction approach [8] combined with integration during a power loss. With the advent of intelligent grids, more accurate requirements for distributed management systems that estimate device conditions place increased demands on energy metering equipment accuracy [9]. The measurement correctness of the smart electric meter is an essential pointer to estimating the electric energy meter quality [10]. It concerns the measurement of equity and fairness. The company and society are apprehensive. In the current operational procedure, the measurement's accuracy changes due to the effect of the electricity meter quality level and the working environment. The allowed variance range is surpassed, and the measurement without qualifications is carried out [11]. Checking a sample of operations, manually verifying readings, consulting with customers and other such physical methods are the norm for evaluating the efficiency of electric smart meters that have been used in succession at present [12]. Errors in the peri are harder to find and address without intelligent real-time tracking, which is bad for business [13]. Smart meter readings also include information that may serve as a foundation for improved managerial decision-making. It does not have a creative method for conducting a thorough and rapid inquiry [14].

Electric power enterprises should deliver persons safe, stable, cost-effective, and high-quality electricity [15]. The power system is continuously restructuring and enhancing based on technological and economic advancement and is emerging towards intelligence and automation [16]. It is crucial to accurately measure and compute the consumer's use, which necessitates the deployment of intelligent meters [17] to protect the interests of both power providers and consumers. Urban and rural regions use electric energy meters to evaluate users ' power in real-time [18]. Smart electric meters can show the consumer's power consumption and then recharge or pay consistent with the measurement finding information [19].

The paper uses AI to understand the remote analysis error of smart electric meters, the dynamic pattern of each fault as it occurs in real time, the scope of defects across states, and the diagnosis of existing problems. It can be promptly determined, deal with working quality issues, efficiently enhance the firm's management levels in product management and quality, and consumer quality service levels.

- This research proposes an error diagnosis analysis approach based on DL, which can improve the model's simplification capacity and strength under limited data conditions. The effect of an electric energy meter fault may be predicted with more precision using the proposed technique.
- The results of diagnostic investigations may guide the implementation of smart electric meter rotation and removal and support the meter's intelligent operations and energy saving.
- Company resource allocations may be optimized more and labour expenses can be reduced using the proposed DLPM model.

The remaining sections of the article are structured as follows: The second section provides context for discussing electric energy meter error analysis. In the third segment, DLPM is proposed. Analysis via simulation was performed in Part 4. Portion 5 is the final portion of the study paper.

2. Related Work

Zilvinas Nakutis et al. [22] proposed the non-invasive remote monitoring technique (NIRMM) for fault analysis of electric energy meters. Error monitoring requirements are met by real-time study of normal consumer power usage patterns without injecting additional load. The under-scrutiny meter notices a certain phase of the consumer's overall electricity use profile. The reference indicator measures the size of the power step in sync with the supply, allowing for a direct comparison. The method's error analysis mimics the 26-state energy distribution grid using public data on energy usage. After 2 or three days (or around 170 power steps), the uncertainty of the error meter estimate settles at around 0.63 percent, as has been demonstrated experimentally. The technique implementation scenarios in the advanced measurement infrastructure using occupancy index models are achieved using state-of-the-art energy meter information collecting protocols.

Shouxiang Wang et al. [23] proposed the stacked convolutional sparse auto-encoder (SCSAE) for intelligent meter data compression. At first glance, readings from energy meters reveal a simple and lightweight auto-encoder structure. Both the encoder and the decoder are built on the idea of converting layers that have been transposed; the encoder is based on a 2D separable convolutional layer. Reconstruction errors and parameters are reduced effectively compared to the current auto encoder and conventional methods, allowing for the reconstruction of the proposed structure. Additionally, the correlation between energy usage and compression is revealed using cluster-based indices. Evidence from case studies suggests that the proposed approach has the potential to drastically expand the model's size and computational efficiency while simultaneously reducing reconstruction mistakes and preserving the highest levels of detail. In addition, the compression effect may be further improved by grouping electricity consumption rules into account by consumers.

Shishir Muralidhara et al. [24] recommended the Internet of Things-based intelligent energy meter (IoT-SEM) to monitor device-level energy consumption. Energy spending information was extracted and transferred over the

ThingSpeak channel during the system testing. Consumers may observe, monitor, and record statistics on usage. This record can assist them in making sure that their devices function well in their projected power ratings. In addition, with their behavioural consumption figures supplied for customers, they may deliberately cut energy use and minimize energy expenses. This consumption helps customers ensure that their gadgets operate according to the energy rating, allows them access to energy consumption patterns developed over time, and contributes to conscious and energy-efficient conservation.

Xiangyu Kong et al. [25] studied Recursive Least Squares (RLS) for online error estimation of electric meters. First, the measured information is prepared and aberrant information such as light and null load data are removed with a suitable clustering technique to display the estimated data from each user's comparable operating conditions. The following equations relate to the electric head in the substation and electric meters and line losses for every user depending on the legislation on electrical energy conservation. The recursive least-flowing double-parameter technique is then utilized to calculate the line loss and the fault of electric meters. Lastly, the impacts on estimated electric meter inaccuracy accuracy are explored by the double dynamics forgetting elements and double constant ignoring parts.

Čegovnik, T. et al. [26] proposed Electricity consumption prediction using artificial intelligence. In this study, researchers show early findings from a commercial effort to develop 15-minute AI models that predict tomorrow's power use. First, we determined the most important features for predicting future electricity consumption at each 15-minute interval and each measuring point. Then, we developed scripts and databases to collect data about these features and the past electricity consumption at 15-minute granularity for each measuring point, and finally, we developed three AI models. Compared to the models for the top ten observations (as reported by the data provider), our predictions have a very high MAPE. We have also presented an assessment of available parallelization strategies in R and detailed the outcomes of computational research conducted with the aid of the parallel, parallel, and for each R library.

Sayed proposed smart electricity meter load prediction in Dubai, H. A. et al. [27] using MLR, ANN, RF, and ARIMA. We suggest several different research methodologies, including multiple linear regression (MLR), random forests (RF), artificial neural networks (ANN), and automated regression integrated moving averages (ARIMA). This investigation used information on the amount of electricity utilized in Dubai. Working with just one district, ANN and RF achieved outstanding accuracy of approximately 97%, whereas ARIMA only achieved around 93%. The ANN and RF models are competitive for use in a single-category setting, with an accuracy of roughly 91.02 percent.

A review of optimization methods and the function of AI in residential energy management systems was proposed by Nutakki M. et al. [28]. An intelligent grid is useful for consumers because it facilitates two-way communication between the utility and end users. Supply- and demand-side management (DSM) techniques must be implemented to increase grid dependability. Home energy management systems (HEMS) are crucial in the decentralized smart grid. As technology has advanced, AI-driven smart optimization strategies have evolved. This article discusses the benefits of AI-based optimization tactics and their advantages over other methods.

Richter L. et al. [29] advocated using AI to automate the power distribution network. AI technology is helpful because it aids people in dealing with diverse data in bulk and processing it using prediction and optimization methods. Our study focuses on the phases of the Electricity Supply Chain that involve the creation, upkeep, pre-processing, analysis, forecasting, optimization, and trade. Focusing on human interaction, AI adaptability, the energy transition, and sustainable development, we examine potential outcomes and restrictions for the move from manual to automated Electricity Supply Chains. The preceding analysis suggests significant problems with the currently accepted models. Therefore, in this research, we propose the DLPM model to enhance the precision of error analysis in energy meters. The proposed model is briefly discussed in the next section.

3. A Predictive Model Aided by Deep Learning (DLPM)

The power system worldwide is going via a revolutionary conversion due to the integration of different distributed elements, improved metering infrastructure, communication infrastructures, distributed energy resources, and electric vehicles to enhance future power system's reliability, management, energy efficiency, and security—smart electric meters are measuring devices utilized to estimate the consumer's electricity utilization. The variation in the meter of the electricity meter significantly affects the social and economic advantages of the company. Precise energy measurement is an issue that departments of power management must address. Strictly regulated and adjustable must be the measuring procedure. With the load power factor and load current, the fundamental deviation of the energy meter varies. There is a link curve between both, which is the typical error curve. Following factory inspection or verification process testing, the basic errors of every certified electric energy meter will fulfil the standards stated in the rules, thereby assuring the electric energy component's proper and stable error characteristics. The braking and driving torque in proportion to the load under all load situations solely affects the turntable. The turntable readings may be concluded to be related to the electrical energy load. This load is the functioning standard of the power meter, although it is a complex issue. Besides those two principal moments, suppression torques, friction, parasitic, current core magnetization curves not linearity and compensatory torques and the impact of the rotational torque, even the electrical voltage, and frequency of the energy meter. When the temperature and other factors reach certain values, the power meter's basic inaccuracy is instantly impacted, and the turntable speed is no longer a linear function of the load power.

An error-adjusting mechanism is often installed within the meter to ensure the inductive power meter's basic defect meets all standards. Modifying these components may make the smart electric meter's fundamental inaccuracy within the acceptable range. The basic error of the energy meter is often determined by only the charge current and the power factor. At the same time, the other conditions may only vary within a restricted range, which is expressly described in the technical circumstances of energy meters; hence, electric energy meters are used to establish a basic inaccuracy. The outside circumstances for the energy meter generally differ from the technical conditions. The conditions are different. FOR EXAMPLE, the AC frequency in the main is typically different from the esteemed frequencies. The grid and temperature voltages of the electrical energy meter's installation table may differ, and the scope and scope will be extensive. The change in these environmental variables will affect the electrical energy meter inaccuracy. The magnitude of this shift is then known as the energy meter extra error.

There might be several factors contributing to the power meter error. Therefore, it's important to investigate them as part of any error study. Therefore, collecting information on all-electric energy meter errors is necessary. Inaccuracy in energy meter readings is mostly caused by tension, current, and temperature variations. The energy meter administration unit stores this data in a simple extract and process-relational database. Imagine that electricity accumulates and dissipates with the passage of time and current. The voltage and current in the power meter are affected by the ambient temperature, which fluctuates constantly due to the constant use of the electric energy meter. In actuality, the information is not stored safely. The temperature data respective to the energy meter error must be obtained to analyse the energy meter error meter needs pre-acquisition and acquisition device installation. Within artificial intelligence, support vector machines, neural networks, and different hybrid methods based on DL have generated predominantly notable findings concerning error prediction and estimation.

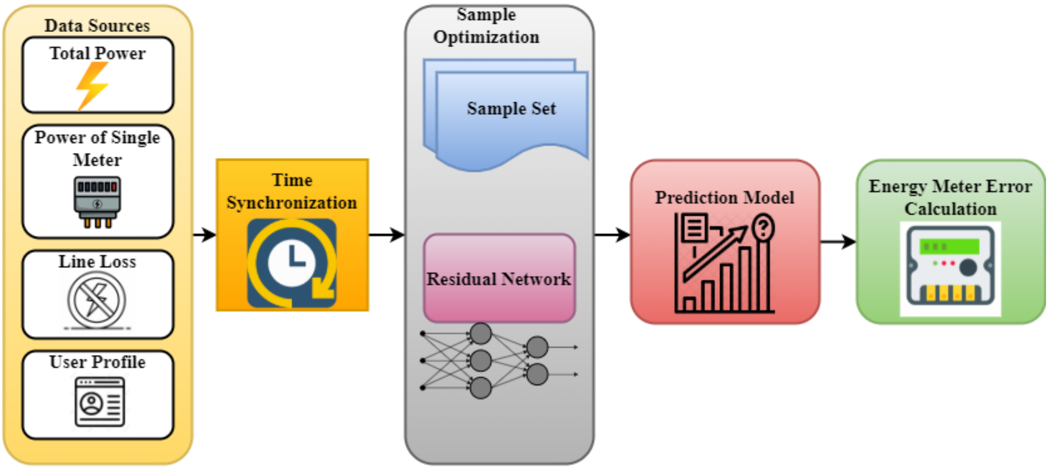

Figure 1: Error Calculation based on proposed DLPM model.

The suggested DLPM model's error computation is depicted in Figure 1. Numerous linear regression approaches may be used to determine the operational inaccuracy of each electric meter thanks to the statistical relationship between the power of overall meters in the station region and the various meters and the line loss in the station region. Harmonization of timestamps between the user table and the base station table is an important connection to keep in mind. Given the variance in innovative meter clocks, the electric power meter clock should be unified with the watch of the relevant tables of the region to provide time harmonization to guarantee a reliable operating fault and line losses of electrical energy meters. First, the paper uses the carrier-precise time technology based on the residual electrical information collection network to cycle the clock variation distribution and the station area load stability, select the time with a comparatively steady load for calculating, and decrease the effect of clock skews. This paper calculates clock deviation within a controlled range: line losses and consumer table power relationship. The standard line losses approach states that the station's line loss ratio is associated with the station's total meter power. This metered power may be used to control daily line losses—however, the line losses are tied to the path that the current passes through. High precision and accuracy are required to analyses the inaccuracy of the energy controller. The bus losses of the station and loads-dissemination of every customer at the station must thus be considered. When investigating energy meter error, the correlation must be carried out under relatively constant load distribution; otherwise, too many confounding variables would generate misleading findings. A more trustworthy assessment of mistakes is made possible by a data foundation's identification of a set of load samples with the same independent dispersion of the electric load distribution. Figure (1) depicts an error analysis of a deep learning model. Before anything else, the station itself is used as a data source for things like total meter powers, user table powers, household table relation, etc., and time synchronization is guaranteed.

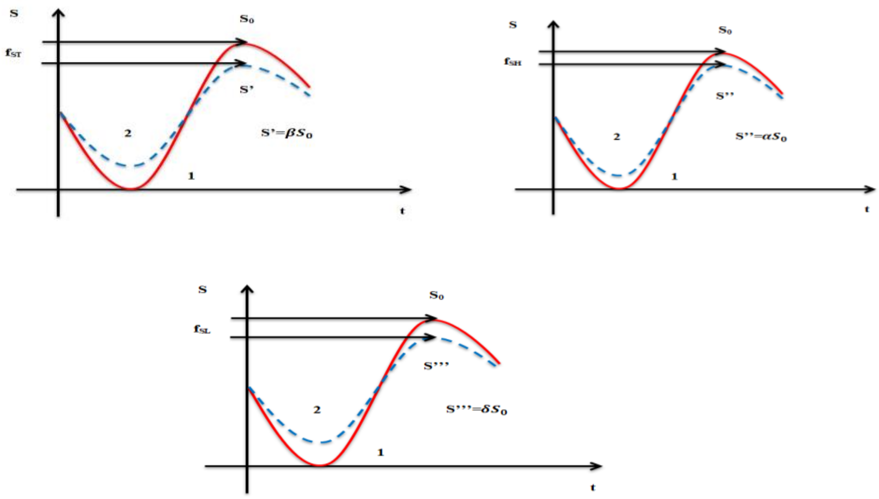

Figure 2: (a) Energy under the temperature's impact error ratio, (b) Energy under the humidity's impact error ratio, (c) Energy under the load's impact error ratio.

Curve 1 denotes real input signals, and curve 2 indicates signs with a fault ratio. They are supposing that the degradation variable of the energy meters is at the first period. During operations, they are degrading in their corresponding dimension, and the way is indeterminate. When 3variables are contaminated to f_{ST}, f_{SH} and f_{SL} Similar points, the discrete electrical Energy is:

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

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

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

$$\varepsilon = f_S(t)$$

$\beta = (\text{Temp }(t), \text{Hum}(t), \text{Load}(t))$ (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 $\{S_1, S_2, \dots, S_m, S_{m+1}\}$, its high variation gradient with the technique of standardization is described in equation (7)：

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

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,

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

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

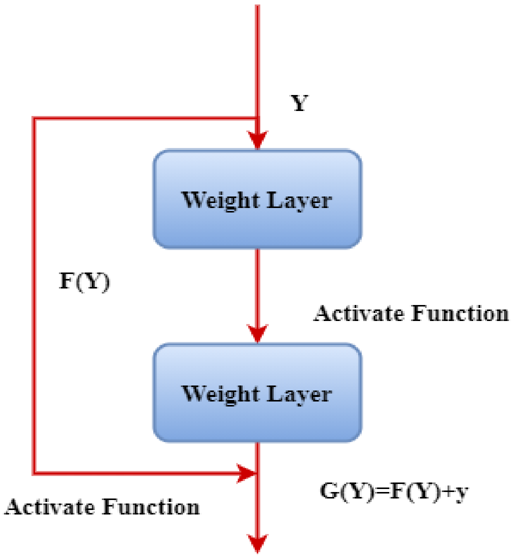

Figure 4: Residual Network

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.

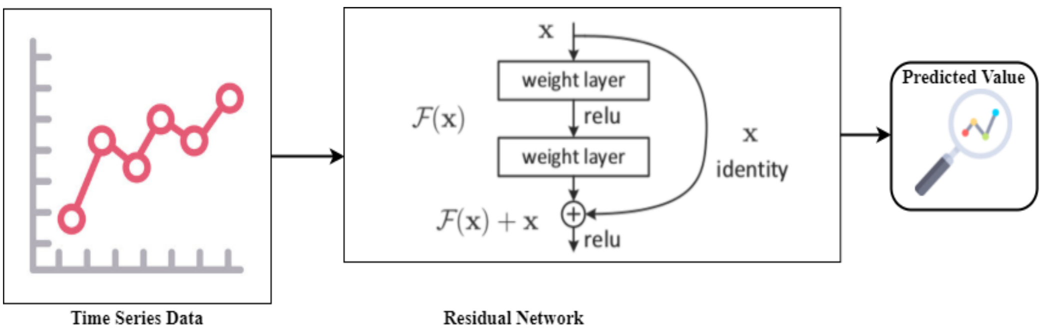

Figure 5: Load Forecasting based on Residual Network

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):

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

$$\gamma_{j}^{k} = \theta'\left(w_{j}^{k}\right) \textstyle\sum_{ji}^{k+1}\left(\omega_{ji}^{k+1} + 1\right) \quad k = 1,2,3, \ldots 13 \tag{16}$$

The gradients of$K$ for the first connection weightss_{ji}^{1}will 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):

$$\frac{\partial K}{\partial \omega_{ji}^{1}} = \gamma_{j}^{1} \cdot \theta\left(w_{j}^{k-1}\right),\ k = 1,2,3, \ldots 16 \tag{19}$$

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

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

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

Prediction accuracy, estimation error, real error, performance, efficiency, average consumption, and root mean square error rate are only a few of the metrics on which the suggested DLPM model's experimental findings are based. Here, the Electrical Fault detection and classification dataset [30] is used for the simulation analysis. The transmission line plays a key role in the electrical network. Since the demand for electricity and its reliability has increased dramatically in recent decades, transmission lines have become increasingly important in moving electricity from generators to consumers. High-capacity electrical generating power plants and the grid concept—synchronized electrical power plants and geographically spatially distributed grids—needed rapid fault diagnosis and the activation of preventive devices to ensure system stability. Recognizing and correctly classifying transmission line issues is a prerequisite for clearing them as rapidly as feasible. Artificial neural networks (ANNs) excel in pattern recognition, making them useful for detecting faulty patterns and classifying errors. A reliable protection plan will perform flawlessly regardless of the system's state or the electrical infrastructure.

(i) Prediction Accuracy Ratio

The precision with which electric energy meters record consumption is a major factor in determining the reliability of such devices. When the allowable variation range is exceeded, the measurement loses its precision and becomes unqualified. Improved quality control for energy meters will reduce measurement error, and after a fixed number of years in service, random sampling will reveal the inaccuracy; faulty smart meters may then be replaced. Irregular meters improve the precision and timeliness of non-standard energy measurement tools. Less labour is needed, high computing accuracy and rapid check cycles are all advantages of this method, which employs mathematical statistics to advance the collected data centrally. The proposed DLPM model's predictive accuracy, as seen in Figure 6, is shown below.

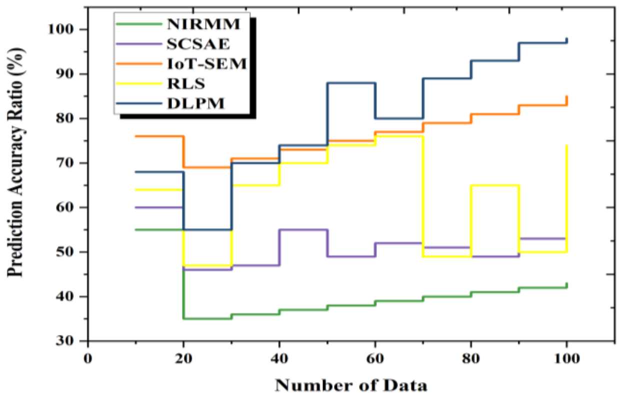

Figure 6: Prediction Accuracy Ratio

(ii) Performance Ratio

The intelligent electrical energy metering performance deteriorates during the operation, affecting the accuracy of the energy meter. Most energy equipment's condition estimating systems and approaches have a comprehensive model. There are generally numerous variables defining the state of dynamic equipment or models. Every parameter must be measured when a state estimating system is implemented. The theoretical study proposes that several facets distress the energy meter performance, including the humidity and temperature of the environment; electrical variables like frequencies, harmonics, and load; communication and vibration irregularities; electromagnetic fields; and power grid actions like interruption and pressure losses. The recommended DLPM method's performance ratio is shown in Figure 7.

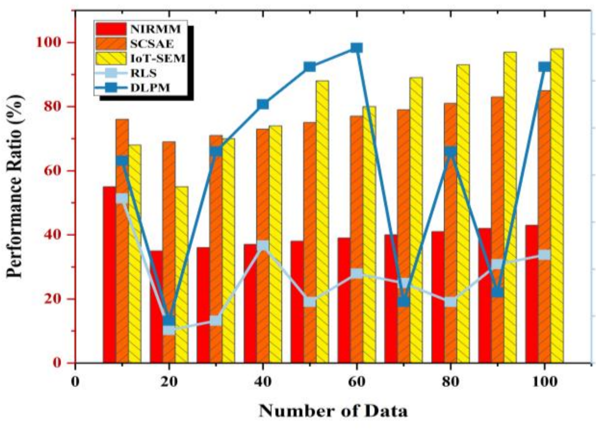

Figure 7: Performance to Cost Ratio

(iii) Error in Estimation vs. Actual Error

The least-squares technique can estimate the model and model variables to be mathematically tested. Forecasting or measuring the dependent parameter utilizing the optimum routing of independent manifold parameters is more efficient and accurate than predicting or assessing with only one separate parameter. The standard error is a variation between the true x value and the model's prediction. Improved accuracy in energy meter error forecasting is one of the many advantages of the proposed DLPM model. The predicted error and the actual error are shown in Figure 8.

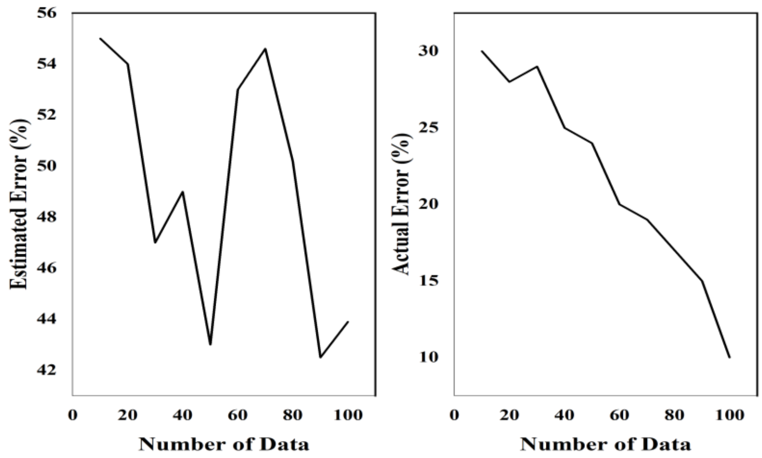

Figure 8: Estimated Error and Actual Error

(iv) Efficiency Ratio

Energy efficiency is one of the primary measures for decreasing energy consumption while preserving a constant service or acceptable comfort level for household customers. Another advantage of determining appliances' power and energy consumption would be the main in predictive maintenance for conserving efficiency and safety in load operations. Many computational resources are needed while training the deep learning model. The goal is to compute the learning model's variables and achieve it quickly with effective computing configuration. Thus, to assess training time effectiveness, this study defines an experimental throughput metric as the number of processing examples per training period for the same input datasets for smart meter error calculation. Figure 9 signifies the efficiency ratio of the suggested DLPM model.

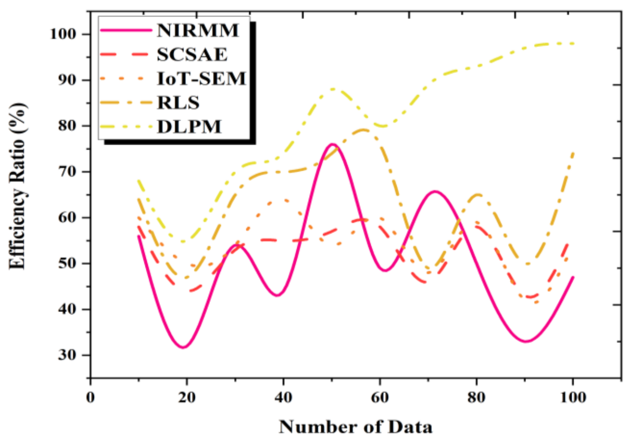

Figure 9: Efficiency Ratio

(v) Average Consumption Ratio

This study aims to measure and examine power consumption utilizing energy meter information by various households. As power consumption increases daily, more concentrates must be on understanding consumption trends, i.e., analysis and measurement of consumption over a period are needed. Consequently, power consumption trends of intelligent electricity distribution are deliberated and examined, leading to an advanced notion for saving the restricted electrical energy resource and predicting the electric energy metering error. For many smaller households, installing energy meters means they see a decrease in their bills straightaway. If the meter rests, turn on one appliance periodically and check the meter. The appliance could be defective if the meter fails to move very speedily. If the meter is still moving, it is not very accurate. Figure 10 shows the average consumption ratio.

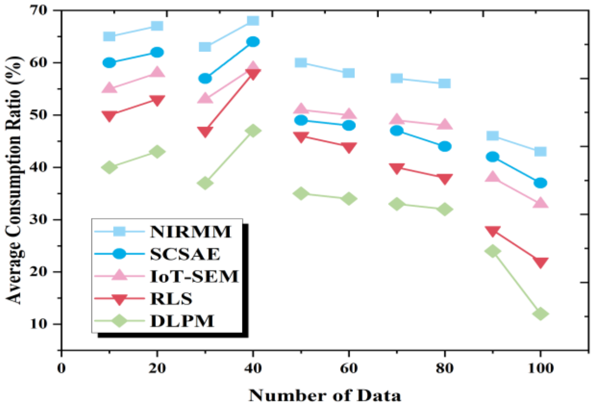

Figure 10: Average Consumption Ratio

(vi) Deviation from the Mean Square

The mean absolute error measures the dissimilarity between the estimated and actual values. This function is more vital for big mistakes than the other functions. Mean square error and Root mean square error reflect the system's dispersion and are sensitive to high faults due to the squared errors, creating them further amplified. These three functions can be utilized to estimate the performance of a predicting model from different viewpoints.

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

As shown in equation (21), where m denotes the size of samples, $x_j$indicates the jth actual values and x_j' Are the jth predicted values? The root mean square error (RMSE) is seen in Figure 11 below.

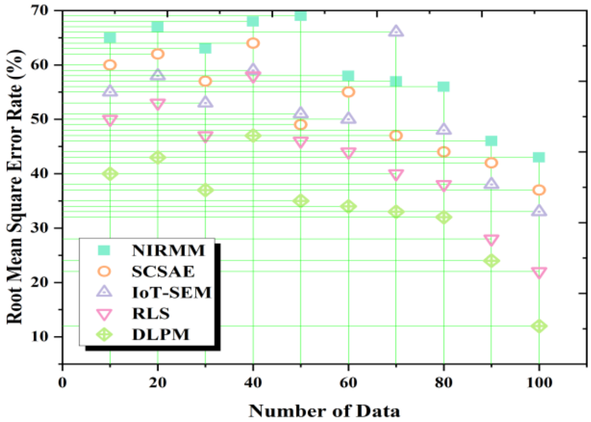

Figure 11: Deviation from the Mean Square

When compared to other existing non-invasive remote monitoring methods (NIRMM), stacked convolutional sparse auto-encoder (SCSAE), Internet of Things-based intelligent energy meter (IoT-SEM), and Recursive Least Squares Method (RLS) models, the proposed DLPM model improves prediction accuracy ratios, performance ratios, and efficiency ratios while decreasing average consumption ratios and root mean square error rate.

5. Conclusion

Error analysis requires high accuracy and precision, often produced by line loss factors; therefore, deep learning is proposed to optimize and analyses errors in smart electric meters based on the load states of identical and independently dispersed regions. Three-phase load balancing, power distribution to all customers in the station's service area, and station topology all impact line loss. Too many variables will skew the results, even in consistent line loss circumstances. The error diagnosis analysis method based on DL suggested in this study can profoundly forecast the effect of electric energy meter fault, guarantee the learning influence, and enhance the simplification capability and strength of the model in the scenario of fewer sample spaces. The experimental results show the suggested DLPM model improves the prediction accuracy ratio of 99.2%, the performance ratio of 97.8%, the efficiency ratio of 98.9%, the average consumption ratio of 10.3%, and the root mean square error rate of 11.2% when compared to other popular methods.

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