Online verification and management scheme of gateway meter flow in the power system by machine learning

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At present, in the process of calibrating electric energy meters, manual meter reading and dismantling inspection or regular sampling inspection by professionals are often used. To improve the work efficiency and verification accuracy, this research integrates machine learning (ML) into the scheme of online verification and management of gateway meter flow in the power system. First, the Faster-Region Convolutional Neural Network (Faster-RCNN) model and the Single Shot MultiBox Detector (SSD) model are applied to the recognition system of dial readings. Then, the collected measurement data is preprocessed, and it is excluded under light load conditions. Next, the estimation error model and the solution equation of the electricity meter are established based on the preprocessed data. The operation error of the electricity meter is estimated and the estimation accuracy is checked by the limited memory recursive least squares algorithm (LMRLSA). Finally, combined with the remote verification results, the business assistant decision-making is carried out. A total of 528 images of meter readings are selected to test the proposed dial reading recognition system, and the accuracy of the test is 98.49%. In addition, the influence of various parameters on the error results of the electricity meter is also explored. The results demonstrate that when the memory length ranges from 600 to 1200 and the line loss error is less than 5%, the accuracy of the electricity meter error estimation is the most suitable. Meanwhile, to avoid over-checking, the measurement data at light load should be removed as much as possible. Experiments manifest that the proposed algorithm can properly eliminate the influence of old measurement data on the error parameter estimation, and improve the accuracy of the error parameter estimation value. The memory length is adjusted to ensure the real-time performance of the electricity meter error estimation, and realize the function of online monitoring. This research has certain reference significance for realizing the online verification and management of gateway meter flow in the power system.

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Abstract: At present, in the process of calibrating electric energy meters, manual meter reading and dismantling inspection or regular sampling inspection by professionals are often used. To improve the work efficiency and verification accuracy, this research integrates machine learning (ML) into the scheme of online verification and management of gateway meter flow in the power system. First, the Faster-Region Convolutional Neural Network (Faster-RCNN) model and the Single Shot MultiBox Detector (SSD) model are applied to the recognition system of dial readings. Then, the collected measurement data is preprocessed, and it is excluded under light load conditions. Next, the estimation error model and the solution equation of the electricity meter are established based on the preprocessed data. The operation error of the electricity meter is estimated and the estimation accuracy is checked by the limited memory recursive least squares algorithm (LMRLSA). Finally, combined with the remote verification results, the business assistant decision-making is carried out. A total of 528 images of meter readings are selected to test the proposed dial reading recognition system, and the accuracy of the test is 98.49%. In addition, the influence of various parameters on the error results of the electricity meter is also explored. The results demonstrate that when the memory length ranges from 600 to 1200 and the line loss error is less than 5%, the accuracy of the electricity meter error estimation is the most suitable. Meanwhile, to avoid over-checking, the measurement data at light load should be removed as much as possible. Experiments manifest that the proposed algorithm can properly eliminate the influence of old measurement data on the error parameter estimation, and improve the accuracy of the error parameter estimation value. The memory length is adjusted to ensure the real-time performance of the electricity meter error estimation, and realize the function of online monitoring. This research has certain reference significance for realizing the online verification and management of gateway meter flow in the power system.

Keywords: Machine learning; Faster-RCNN model; SSD model; Limited memory recursive least squares algorithm; Dial reading identification; Online verification; Line loss; Light load condition

1. Introduction

At present, the main way for power companies to verify the accuracy of the gateway meter flow of the power system (hereinafter referred to as the total meter) is to carry out dismantling inspection or regularly carry instruments and equipment to the site for periodic sampling inspection by professionals [1]. With the expansion of the power grid, China has more than 500 million meters in operation. The existing verification mode has high work intensity, a long verification period and low management efficiency, and it is difficult to meet the requirements of condition maintenance and replacement of smart meters [2]. To realize the transformation of smart meters from regular verification to state verification and ensure the accuracy of measurement, it is imperative to explore an efficient and accurate online remote verification and management solution for the operation of the total meter.

The existing online remote verification methods for smart meters based on measurement data analysis mainly include ordinary least squares inversion and weighted recursive least squares. However, the solution accuracy and practicability of the method are not high, and it is easily affected by factors such as the user's power consumption level, the number of user meters, and data quality [3]. Wang et al. (2020) proposed the idea of the error analysis of the electricity meters based on advanced meter infrastructure (AMI) measurement data, without using external standard instruments, only by comparing the existing meters in the cluster to calculate the error [4]. However, this method fails to consider the influence of the algorithm such as the number of measurement periods, the number of meters in the station area, and the out-of-tolerance of a single low-voltage user meter on the model results. The Marketing Department of State Grid Corporation of China has carried out research on the state inspection plan of the electricity

meters. Through four triggering methods: family defects, online monitoring, on-site inspection, and regular triggering, the operation state of the electricity meters is scored, and corresponding inspection strategies are generated according to the scoring results [5]. The relevant research results qualitatively divide the electricity meter into several states, and the analysis results are relatively rough, and it is impossible to realize the remote accurate verification of the electricity meter.

To simplify the verification method of the total meter and improve the verification accuracy, an online verification and management scheme of gateway meter flow in the power system by machine learning (ML) is proposed. Firstly, the automatic meter reading is realized through the scheme of the dial reading recognition system of the Faster-Region Convolutional Neural Networks (Faster-RCNN) model and the Single Shot MultiBox Detector (SSD) model. Secondly, the automatic meter reading data is used to estimate the operation error of the electricity meter based on the limited memory recursive least squares algorithm (LMRLSA). The error estimation results of the electric meter are verified and analyzed, and the online remote verification results of the electric meter are combined to make business decision-making. Finally, the system is verified and tested, which proves that the proposed scheme is scientific and feasible. The research has certain reference significance for realizing remote intelligent online meter reading and verification management of the electricity meter.

2. Design of the Scheme

2.1 Faster-RCNN model and SSD model

The Faster-RCNN model was proposed in 2015. The main feature of this model is that the model is large in size and has a strong ability to extract features. Therefore, the Faster-RCNN model is used to identify the specific readings of the dial image, but its running speed is relatively slow [6]. The network structure of the model is shown in Figure 1:

Figure 1 The network structure of the Faster-RCNN model

First, when a picture is input, and the picture is adjusted to a fixed size. Then, the feature map is obtained by processing the convolutional neural network (CNN). Next, the candidate box is generated by the Region Proposal Networks (RPN), and the candidate box and feature map generated by the RPN are input into the Regions of interest (ROI) pooling layer to obtain a fixed-size proposal feature map. Finally, the candidate box is classified and regressed through the fully connected layer to obtain a more accurate target frame [7,8].

The SSD model is characterized by relatively small size, high accuracy in detecting large targets, and the advantage of fast detection [9]. Therefore, the SSD model is adopted to detect the effective reading area of the dial image. The core of the SSD model is to predict the category score and offset of the candidate box. Simultaneously, candidate boxes of different sizes can be obtained by predicting on feature maps of different scales [10]. The network structure of the SSD model is shown in Figure 2:

Figure 2 The network structure of the SSD model

The SSD model is different from the Faster-RCNN model in object detection. The Faster-RCNN model first generates candidate regions through RPN, then classifies these candidate regions and calculates location information through regression. However, the SSD model obtains a series of candidate regions on the feature maps of different scales, and each point on the feature maps of different scales corresponds to different positions of the original image, so high-precision detection results can be obtained [11, 12].

2.2 Realization of image recognition function

In this research, model training is done on Google's open-source TensorFlow framework. As an excellent development framework for ML, TensorFlow provides developers with a large number of mature model implementation solutions. For object detection tasks, TensorFlow provides the TensorFlow Object Detection API open-source framework in its models' subproject. This framework has been widely used in Google's computer vision applications. An open-source framework is adopted, which can easily build, train, and deploy object detection models [13-15]. In the electricity meter reading recognition, two models are mainly trained, the first is the SSD model trained to detect the effective reading area of the electricity meter screen, and the second is the Faster-RCNN model trained to identify the readings in the effective reading area. The specific training process of the SSD model is shown in Figure 3:

Figure 3 The specific training process of the SSD model

When training the SSD model, first, the input meter image is resized, the height of the image is uniformly set to

500px, and the width is scaled proportionally. Then, LabelImg software is used to label the effective reading area of the image screen, a training sample set is constructed, and an XML format file is generated. Next, the generated XML format files and images are converted into TFRecord format files. Finally, the pre-trained model is read and the TFRecord format file is used for model training, resulting in the desired SSD model [16-18].

The training process of the Faster-RCNN model is shown in Figure 4:

Figure 4 The training process of the Faster-RCNN model

For the Faster-RCNN model trained to identify the readings in the effective reading area, the effective reading area is firstly processed in grayscale, and then the brightness is adjusted, which can solve the problem that some images are too bright or too dark, and reduce the complexity of identifying the readings in the effective reading area. Secondly, LabelImg software is also used to label the numbers in the area, generate an xml format file, and convert it into a TFRecord format file. Finally, the model is trained to obtain the desired Faster-RCNN model [19-21]. The specific training steps for the two models are shown in Figure 5:

Figure 5 The training steps for the models

2.3 Analysis of measurement data

The Faster-RCNN model and the SSD model are used to collect the electricity metering information of the total meter and sub-meters according to the pre-set time, and after the collection and summary, the user's electricity consumption information is transmitted to the master station, and the electricity consumption data is automatically copied and collected. The obtained measurement data is preprocessed, and then the estimation model and solution method are established through the preprocessed data. The estimation accuracy is checked, and finally, the purpose of online verification and business assistant decision-making is realized [22,23]. The specific process is shown in Figure 6:

Figure 6 The process of scheme

The time series of original measurement data is preprocessed by the improved fuzzy C-means clustering technology, and the measurement data under light load conditions is excluded as the input variable of the online remote verification model [24]. Among them, the specific steps of preprocessing time series of the original measurement data based on the improved fuzzy C-means clustering are as follows:

Step 1: Determine the weighting index w and the iteration termination parameter Ɛ according to the ratio of the increment of the electricity meter reading and the range of the electricity meter less than 0.1.

Step 2: Determine the number of clusters and cluster centers, sequentially select measurement data samples and substitute them into the hill-climbing function, as shown in the following equation (1):

$$\hat{M}^1(x_r) = \sum_{j=1}^{n} e^{-\alpha \| x_j - x_r \|^2} \quad (1)$$

In equation (1), x_j is the jth sample, and n is the total number of samples. x_r is the rth sample, which is the cluster center. $\hat{M}^1(x_r)$ is the hill-climbing function when the rth sample is taken as the cluster center, α is a positive number. If $x_r = x_1{}^*$, where $x_1{}^*$ is a sample in the sample set, get the first hill-climbing function to get the maximum value $\hat{M}_{max}^{\ 1} = \max(\hat{M}^1(x_1{}^*))$, $x_1{}^*$ can be taken as the first cluster center [25]. When looking for other cluster centers, to eliminate the influence of $x_1{}^*$, the revised tth hill-climbing function is shown in the following equation (2):

$$\hat{M}^t(x_r) = \hat{M}^{t-1}(x_r) - \hat{M}_{max}^{t-1} \sum_{j=1}^{n} e^{-\beta \| x_j - x_{t-1} \|^2} \quad (2)$$

In equation (2), $\hat{M}^t(x_r)$ is the new hill-climbing function, $\hat{M}^{t-1}(x_r)$ is the hill-climbing function of the previous step, and $\hat{M}_{max}^{t-1}$ is the maximum value of the hill-climbing function of the previous step. The process of finding cluster centers ends when $\hat{M}_{max}^{\ t} / \hat{M}_{max}^{\ 1} \le \delta$, where δ is the convergence coefficient of the classification, which can be 0.001 [26]. The total number of iterative clustering before judging convergence is the classification number c of fuzzy clustering. In each clustering process, the sample with the largest value of the hill-climbing function is $x_t{}^*$.

Step 3: The membership matrix is calculated, as shown in equation (3):

$$\begin{cases} x_r = \dfrac{\sum_{j=1}^{n}(u_{rj})^w x_j}{\sum_{j=1}^{n}(u_{rj})^w}(1 \le r \le c) \\ u_{rj} = \left[\sum_{k=1}^{c}\left(\dfrac{\| x_j - x_r \|}{\| x_j - x_k \|}\right)^{2/(w-1)}\right]^{-1}(1 \le r \le c, 1 \le j \le n) \end{cases} \tag{3}$$

In equation (3), u_{rj} represents the membership degree of the jth sample with respect to the rth cluster center, w is the weighting index, and the value range is [1, +∞), and the value of w determines the fuzzyness of the final clustering effect. This method is taken as 1.8.

Step 4: The objective function is calculated, which is the weighted sum of squares of distances from each sample to all cluster centers, as shown in the following equation (4):

$$J_w(\mathbf{U},\mathbf{V}) = \sum_{j=1}^{n}\sum_{r=1}^{c} u_{rj}^{w} \| x_j - x_r \|^2 \tag{4}$$

Taking equation (4) as the iterative equation, when the two iteration errors $\Delta J_w(\mathbf{U},\mathbf{V})$ before and after the objective function are less than the termination parameter Ɛ, the clustering ends. The light load condition has been eliminated from the time series of the original measurement data, and the data preprocessing is completed.

After the data is preprocessed, an equation for solving the meter error is established. The remaining measurement data are sorted in chronological order to form the total and sub-meter matrices of the measurement data respectively, which are used as input samples for the error solution of the LMRLSA [27]. Based on the law of energy conservation, in any measurement period, the reading of the total meter is equal to the sum of the true values of each user sub-meter plus the sum of the line losses in this period [28]. For any tth measurement period, the relationship between the total meter and the sub-meter readings is shown in the following equation (5):

$$y_0(t) = \sum_{i=1}^{m} z_i(t)\left(1 + \xi_i(t)\right) + w_{\text{loss}}(t) \tag{5}$$

In equation (5), $y_0(t)$ is the reading increment of the total meter in the measurement period, $z_i(t)$ is the reading increment of the ith sub-meter in the measurement period, and $\xi_i(t)$ is the error of the ith sub-meter in the measurement period. $z_i(t)\left(1 + \xi_i(t)\right)$ is the power value actually consumed by the ith sub-meter in the measurement period, and $w_{\text{loss}}(t)$ is the power consumption of all lines in the measurement period, m is the total number of all sub-meters. The Levenberg-Marquardt (LM) algorithm is used to optimize the multi-layer feedforward neural network model to calculate the line loss [29]. Then, $1 + \xi_i(t)$ in equation (5) is represented by $\theta_i(t)$, and a set of measurement data series is formed by each unit measurement period $z_i(t)$ and the solution obtained $y(t)$. The equation (5) is written in matrix form, and the following equation (6) is obtained:

$$\begin{cases} y(t) = \boldsymbol{Z}(t)\hat{\boldsymbol{\theta}}(t) \\ \hat{\zeta}(t) = \hat{\boldsymbol{\theta}}(t) - \boldsymbol{I} \end{cases} \tag{6}$$

In equation (6), $\boldsymbol{Z}(t) = \left[z_1(t), z_2(t), \cdots, z_m(t)\right]$ represents the measurement data matrix of each user's sub-meter in tth periods; $\hat{\boldsymbol{\theta}}(t) = \left[\theta_1(t), \theta_2(t), \cdots, \theta_m(t)\right]^T$ refers to the error parameter matrix to be estimated by each user's sub-meter in the tth measurement period, and $\theta_i(t)$ denotes the operating error parameter of the ith meter to be found in the tth measurement period. $\hat{\zeta}(t) = \left[\hat{\zeta}_1(t), \hat{\zeta}_2(t), \cdots, \hat{\zeta}_m(t)\right]^T$ is the remote estimated value of the operating error of the electricity meter in the tth measurement period. After the equation is established, the operation error of the electricity meter is estimated through the LMRLSA. Specific steps are as follows:

Step 1: The initial value $\hat{\boldsymbol{\theta}}(0,0)$ and $\boldsymbol{P}(0,0) = \alpha I$ are selected, where each element of $\hat{\boldsymbol{\theta}}(0,0)$ is 0 or a smaller number, $\boldsymbol{P}(0,0) = \alpha I$, α is a large enough positive number, usually between 10^5 and 10^{10}, and I is the unit matrix. L represents the memory length, and T refers to the latest measurement period. Compare T and L. If T≤L, go to Step 2; if T>L, go to Step 3.

Step 2: When T≤L, the ordinary Recursive Least Squares (RLS) algorithm is used to obtain the initial parameter estimate $\hat{\boldsymbol{\theta}}(0, L-1)$, its corresponding $\boldsymbol{P}(0, L-1)$ and the gain matrix $\boldsymbol{K}(0, L-1)$, and use it as the initial quantity of the LMRLSA. The specific process is as follows:

a. After the previous t measurements, the matrix equation can be obtained as shown in equation (7):

$$\hat{\boldsymbol{\theta}}(t) = \left(\boldsymbol{Z}(t)^T\boldsymbol{Z}(t)\right)^{-1}\boldsymbol{Z}(t)^T\boldsymbol{Y}(t) \tag{7}$$

In equation (7), $\boldsymbol{Z}(t) = \begin{bmatrix} z_1(1) & z_2(1) & \cdots & z_m(1) \\ z_1(2) & z_2(2) & \cdots & z_m(2) \\ \vdots & \vdots & \ddots & \vdots \\ z_1(t) & z_2(t) & \cdots & z_m(t) \end{bmatrix}$ is the sub-meter matrix，$\boldsymbol{Y}(t) = \begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(t) \end{bmatrix}$ is the total meter matrix. It is assumed that $\hat{\boldsymbol{\theta}}(t-1)$ has been calculated in the $t-1$ recursion. Before the tth recursion, the time series

of the new total and sub-meter measurement data collected are respectively $y(t)$ and $\boldsymbol{Z}(t)=[z_1(t),z_2(t),\cdots,z_m(t)]$. All the measurement data of each user sub-meter measured in the previous t times are represented by $\boldsymbol{Z}_t$, and all the measurement data of the total meter measured in the previous t times are represented by $\boldsymbol{Y}_t$. For the previous t-1 measurements, they are represented by $\boldsymbol{Z}_{t-1}$, $\boldsymbol{Y}_{t-1}$ respectively. Based on the measurement data collected in the previous t-1 measurement and the previous t measurement, the estimation result of the meter error parameter is shown in the following equation (8):

$$\begin{cases}\hat{\boldsymbol{\theta}}(t-1)=\left(\boldsymbol{Z}_{t-1}^{\ T}\boldsymbol{Z}_{t-1}\right)^{-1}\boldsymbol{Z}_{t-1}^{\ T}\boldsymbol{Y}_{t-1}\\ \hat{\boldsymbol{\theta}}(t)=\left(\boldsymbol{Z}_t^T\boldsymbol{Z}_t\right)^{-1}\boldsymbol{Z}_t^T\boldsymbol{Y}_t\end{cases} \tag{8}$$

b. The inverse **P**(t) of the covariance matrix of the measurement data is shown in equation (9):

$$\begin{aligned}\boldsymbol{P}(t)&=\left(\boldsymbol{Z}(t)^T\boldsymbol{Z}(t)\right)^{-1}\\&=\left(\left[\boldsymbol{Z}_{t-1}^{\ T},\boldsymbol{Z}^T(t)\right]\begin{bmatrix}\boldsymbol{Z}_{t-1}\\ \boldsymbol{Z}(t)\end{bmatrix}\right)^{-1}\\&=\left(\boldsymbol{Z}_{t-1}^{\ T}\boldsymbol{Z}_{t-1}+\boldsymbol{Z}^T(t)\boldsymbol{Z}(t)\right)^{-1}\\&=\left[\boldsymbol{P}^{-1}(t-1)+\boldsymbol{Z}^T(t)\boldsymbol{Z}(t)\right]^{-1}\\&=\left[\boldsymbol{I}-\frac{\boldsymbol{P}(t-1)\boldsymbol{Z}^T(t)\boldsymbol{Z}(t)}{1+\boldsymbol{Z}(t)\boldsymbol{P}(t-1)\boldsymbol{Z}^T(t)}\right]\boldsymbol{P}(t-1)\end{aligned} \tag{9}$$

c. The estimated value of the error parameter of each user's sub-meter is expressed as $\hat{\boldsymbol{\theta}}(t)$, and its calculation is shown in the following equation (10):

$$\begin{aligned}\hat{\boldsymbol{\theta}}(t)&=\left(\boldsymbol{Z}_t^T\boldsymbol{Z}_t\right)^{-1}\boldsymbol{Z}_t^T\boldsymbol{Y}_t\\&=\boldsymbol{P}(t)\left[\boldsymbol{Z}_{t-1}^{\ T},\boldsymbol{Z}^T(t)\right]\begin{bmatrix}\boldsymbol{Y}_{t-1}\\ y(t)\end{bmatrix}\\&=\boldsymbol{P}(t)\left[\boldsymbol{Z}_{t-1}^{\ T}\boldsymbol{Y}_{t-1}+\boldsymbol{Z}^T(t)y(t)\right]\\&=\boldsymbol{P}(t)\left[\boldsymbol{P}^{-1}(t-1)\hat{\boldsymbol{\theta}}(t-1)+\boldsymbol{Z}^T(t)y(t)\right]\\&=\boldsymbol{P}(t)\left\{\left[\boldsymbol{P}^{-1}(t)-\boldsymbol{Z}^T(t)\boldsymbol{Z}(t)\right]\hat{\boldsymbol{\theta}}(t-1)+\boldsymbol{Z}^T(t)y(t)\right\}\\&=\hat{\boldsymbol{\theta}}(t-1)+\boldsymbol{P}(t)\boldsymbol{Z}^T(t)[y(t)-\boldsymbol{Z}(t)\hat{\boldsymbol{\theta}}(t-1)]\end{aligned} \tag{10}$$

d. The defined gain matrix is expressed as $\boldsymbol{K}(t)$, as shown in the following equation (11):

$$\boldsymbol{K}(t)=\frac{\boldsymbol{P}(t-1)\boldsymbol{Z}^T(t)}{1+\boldsymbol{Z}(t)\boldsymbol{P}(t-1)\boldsymbol{Z}^T(t)} \tag{11}$$

e. Combined with equation s (8) to (11), when T≤L, the error check of the smart meter is shown in the following equation (12):

$$\begin{cases}\boldsymbol{P}(t)=\boldsymbol{P}(t-1)[I-\boldsymbol{K}(t-1)\boldsymbol{Z}(t)]\\ \hat{\boldsymbol{\theta}}(t)=\hat{\boldsymbol{\theta}}(t-1)+\boldsymbol{K}(t)[y(t)-\boldsymbol{Z}(t)\hat{\boldsymbol{\theta}}(t-1)]\end{cases} \tag{12}$$

Step 3: When T>L, the specific solution process of the LMRLSA module is directly entered, as follows:

a. When a new set of data of the latest measurement period T is added, based on the measurement data of the L+1 group of smart meters from the T-Lth to the Tth and the recursive calculation results of the previous T-1 times, the calculation process of the inverse matrix $\boldsymbol{P}(T-L,T)$ of the covariance of the measurement data is shown in equation (13):

$$\begin{aligned}\boldsymbol{P}(T-L,T)&=\left(\boldsymbol{Z}(T-L,T)^T\boldsymbol{Z}(T-L,T)\right)^{-1}\\&=\left(\boldsymbol{Z}(T-L,T-1)^T\boldsymbol{Z}(T-L,T-1)+\boldsymbol{Z}^T(T)\boldsymbol{Z}(T)\right)^{-1}\\&=\left[\boldsymbol{P}^{-1}(T-L,T-1)+\boldsymbol{Z}^T(T)\boldsymbol{Z}(T)\right]^{-1}\\&=\left[\boldsymbol{I}-\frac{\boldsymbol{P}(T-L,T-1)\boldsymbol{Z}^T(T)\boldsymbol{Z}(T)}{1+\boldsymbol{Z}(T)\boldsymbol{P}(T-L,T-1)\boldsymbol{Z}^T(T)}\right]\boldsymbol{P}(T-L,T-1)\\&=[\boldsymbol{I}-\boldsymbol{K}(T-L,T)\boldsymbol{Z}(T)]\boldsymbol{P}(T-L,T-1)\end{aligned} \tag{13}$$

In equation (13), the sub-meter reading matrix from T-Lth to T times is shown in equation (14):

$$\begin{aligned}\boldsymbol{Z}(T-L,T)&=[\boldsymbol{Z}(T-L),\boldsymbol{Z}(T-L+1),\cdots,\boldsymbol{Z}(T)]^T\\&=\begin{bmatrix}z_1(T-L) & z_2(T-L) & \cdots & z_m(T-L)\\ z_1(T-L+1) & z_2(T-L+1) & \cdots & z_m(T-L+1)\\ \vdots & \vdots & \ddots & \vdots\\ z_1(T) & z_2(T) & \cdots & z_m(T)\end{bmatrix}\end{aligned} \tag{14}$$

b. $\boldsymbol{K}(T-L,T)$ is defined as the gain matrix, as shown in equation (15):

$$\boldsymbol{K}(T-L,T)=\frac{\boldsymbol{P}(T-L,T-1)\boldsymbol{Z}^{T}(T)}{1+\boldsymbol{Z}(T)\boldsymbol{P}(T-L,T-1)\boldsymbol{Z}^{T}(T)} \tag{15}$$

c. The estimated value of the error parameter of the meter is calculated, as shown in equation (16):

$$\begin{aligned}\hat{\boldsymbol{\theta}}(T-L,T) &= [\theta_1,\theta_2,\cdots,\theta_m]^T\\ &= \left(\boldsymbol{Z}(T-L,T)^T\boldsymbol{Z}(T-L,T)\right)^{-1}\boldsymbol{Z}(T-L,T)^T\boldsymbol{Y}(T-L,T)\\ &= \boldsymbol{P}(T-L,T)\left[\boldsymbol{Z}(T-L,T-1)^T\boldsymbol{Y}(T-L,T-1)+\boldsymbol{Z}^T(T)y(T)\right]\\ &= \boldsymbol{P}(T-L,T)\left[\boldsymbol{P}(T-L,T-1)^{-1}\hat{\boldsymbol{\theta}}(T-L,T-1)+\boldsymbol{Z}^T(T)y(T)\right]\\ &= \hat{\boldsymbol{\theta}}(T-L,T-1)+\boldsymbol{K}(T-L,T)\times[y(T)-\boldsymbol{Z}(T)\hat{\boldsymbol{\theta}}(T-L,T-1)]\end{aligned} \tag{16}$$

Among them, the total meter reading matrix is expressed as: $\boldsymbol{Y}(T-L,T)=[y(T-L),y(T-L+1),\cdots,y(T)]^T$.

d. According to the above analysis, when a new set of T-th measurement data is added, the solution of the LMRLSA is shown in the following equation (17):

$$\begin{cases}\boldsymbol{K}(T-L,T)=\dfrac{\boldsymbol{P}(T-L,T-1)\boldsymbol{Z}^T(T)}{1+\boldsymbol{Z}(T)\boldsymbol{P}(T-L,T-1)\boldsymbol{Z}^T(T)}\\ \boldsymbol{P}(T-L,T)=[I-K(T-L,T)\boldsymbol{Z}(T)]\boldsymbol{P}(T-L,T-1)\\ \hat{\boldsymbol{\theta}}(T-L,T)=\hat{\boldsymbol{\theta}}(T-L,T-1)+\boldsymbol{K}(T-L,T)\times[y(T)-\boldsymbol{Z}(T)\hat{\boldsymbol{\theta}}(T-L,T-1)]\end{cases} \tag{17}$$

e. to keep the memory length L unchanged, the measurement data of a group of smart meters in the *T*th is added, and the measurement data of the T-Lth time needs to be removed. Based on the measurement data from the $T-L+1$th to the L sets of T-th and the calculation result obtained by equation (17), the LMRLSA can be obtained when the measurement data of the T-Lth is excluded. The solution of the LMRLSA is expressed as the following equation (18):

$$\begin{cases}\boldsymbol{K}(T-L+1,T)=\dfrac{\boldsymbol{P}(T-L,T)\boldsymbol{Z}^T(T-L)}{1-\boldsymbol{Z}(T-L)\boldsymbol{P}(T-L,T)\boldsymbol{Z}^T(T-L)}\\ \boldsymbol{P}(T-L+1,T)=[I+K(T-L+1,T)\boldsymbol{Z}(T-L)]\boldsymbol{P}(T-L,T)\\ \hat{\boldsymbol{\theta}}(T-L+1,T)=\hat{\boldsymbol{\theta}}(T-L,T)-\boldsymbol{K}(T-L+1,T)\times[y(T-L)-\boldsymbol{Z}(T-L)\hat{\boldsymbol{\theta}}(T-L,T)]\end{cases} \tag{18}$$

Step 4: Based on the actual data, the calculation example analysis is carried out, and the online verification and analysis of the estimation error result of the electricity meter is carried out, which includes the following contents:

a. Determine the ratio of the total number of electricity meters and the sample size;

b. Stratify according to the electricity consumption level of each user, thereby determining the number of smart meter samples drawn from each layer;

c. The sum of the number of smart meters drawn from each layer should be equal to the sample size;

d. For the number that cannot be rounded, find its approximate value;

e. After the actual values of the extracted error parameters of smart meter are measured on-site by stratified sampling, the Mean Absolute Percent Error (MAPE) and the Root Mean Square Error (RMSE) are used as judgments basis. In the process of remote error verification of smart meter, the smaller the MAPE value and the RMSE value, the higher the accuracy of the estimated error parameters [30]. If the total number of samples drawn on site is p, MAPE and RMSE can be expressed by the following equations (19) and (20):

$$MAPE=\frac{1}{p}\sum_{i=1}^{p}\frac{\left|\hat{\theta}_i-\theta_i\right|}{\theta_i}\times 100\% \tag{19}$$

$$RMSE=\sqrt{\frac{1}{p}\sum_{i=1}^{p}\left(\hat{\theta}_i-\theta_i\right)^2} \tag{20}$$

In equations (19) and (20), θ_i is the actual error of the meter in the detected area, and $\hat{\theta}_i$ is the estimated value of θ_i.

After that, a hierarchical processing mechanism for abnormal situations in low-voltage areas can be established. Combined with the obtained results of the operation error of the smart meter, the degree of operation error of the electricity meter, the proportion in the batch, the reason for the out-of-tolerance of the operation meter, the abnormal level and other factors are analyzed to replace the status of smart meters, and perform services such as electricity theft and electric leakage online detection [31,32].

3. Experimental Results and Analysis

3.1 Verification of image recognition effect

The TensorFlow Object Detection API provides the corresponding eval.py script to verify the trained model. Running the script can verify the test set and generate the corresponding log file. Then, the log file is read through TensorBoard and the verification effect of the model is displayed. The specific display effect is shown in Figure 7 and Figure 8:

Figure 7 The SSD model detects the effective reading area of the electricity meter

Figure 8 The Faster-RCNN model identifies the specific readings of the electricity meter

The proposed step-by-step image recognition method is verified using the test data set, and the accuracy of recognition is calculated according to the recognition results. The specific verification scheme is shown in Figure 9.

Figure 9 Verification scheme

The verification scheme uses the Remote Procedure Call (RPC) image recognition interface implemented by the system for verification. Then, the recognition service of the image recognition terminal through the RPC interface is called to obtain the recognition reading results, and compare the recorded results with the correct readings. Finally, the recognition accuracy is counted. 528 electric meter images are used for testing. After testing and verification, the recognition accuracy is 98.49%.

3.2 Validation of remote verification methods

To verify the effectiveness of the proposed method, this experiment takes the actual electricity meter measurement data of a city in China from February to May 2021 as the object for analysis, and the frequency of the data collection is 15min. The research area contains 1 total meter and 195 user sub-meters. Through data preprocessing, no-load or light-load data is filtered out, and measurement data sets of different periods are obtained as analysis samples. The value of the memory length L is set to 1000, and the recursive estimation curve of the operation error of the smart meter solved by this method is shown in Figure 10:

Figure 10 The recursive estimation curve of the operation error of the electricity meter

Figure 10 denotes that there are 5 meters in the research area with extremely large errors, and the estimated error parameters of the remaining meters are all within the allowable range of normal errors. Taking any data in a measurement period, the estimated error value of the electricity meter in this period can be obtained, as shown in Figure 11:

Figure 11 The estimation error value of the electricity meter in a certain period

Figure 11 indicates that most of the error rates of the user sub-meters in the selected power distribution area are within the allowable range of normal errors. User sub-meters No. 48, 65, 112, 135, and 181 have errors out of tolerance. The error rate of the No. 48 meter is 4.2885%, the error rate of the No. 65 meter is 6.9741%, the error rate of the No. 112 meter is -14.1072%, the error rate of the No. 135 meter is 3.9381%, and the error rate of the No. 181 meter is 4.5189%. The user profile information obtained by the user information collection system can accurately locate the electricity customer information corresponding to the number of the smart meter whose error is out of tolerance, and collect the information of the smart meter. Based on the obtained potential out-of-tolerance meter information, through further analysis and verification, the specific reasons for the out-of-tolerance error of the smart meter are confirmed. For example, a positive error indicates that the electricity meter is aging and damaged, and a negative error indicates that the electricity meter is artificially destroyed, and there is electricity stealing behavior.

Based on the actual working conditions of the research area, the optimal value range of the memory length L is analyzed. The value of the memory length L in the proposed method is related to the frequency of the measurement data collected by the electricity meter in the area. The estimation error value of the electricity meter with different memory length L values is shown in Figure 12:

Figure 12 The estimation error value of the electricity meter with different memory length

Figure 12 refers that when L=100, the estimation error value of a normal smart meter seriously deviates from its actual error value, because the number of recursive estimation equations is in an underdetermined state when it is less than the number of error parameters to be estimated. The results cannot be applied. When L=400, the number of measurements is greater than the number of error parameters to be estimated, and the estimation error value begin to converge. However, the estimation error value of some normal smart meters are still in the out of tolerance range, and the estimation effect is not ideal. When L=1000, the estimation error value of each electricity meter is close to a certain value, and a more accurate estimation of the error parameters of the smart meter is obtained, and the estimation effect is ideal. When the value of L is large, although the error can also be estimated parameters, it takes a long time and reduces the efficiency of online analysis. Therefore, based on the actual working conditions of the research area, to ensure the accuracy of the estimated value and the real-time performance of the solution analysis, the recommended value of L ranges from 600 to 1200.

In this research, the line loss is considered in the calibration of the electricity meter, so if the calculation error of the line loss is large, it will also affect the estimation result of the operation error of the electricity meter. When the calculation errors of the line loss are 1%, 5%, 8%, and 10%, respectively, the comparison of the estimation error value of each electricity meter is shown in Figure 13:

Figure 13 The estimation error value of electricity meters under line losses of different errors

Figure 13 shows that when the error of the line loss calculation result is within 5%, it has little effect on finding the out-of-tolerance electricity meter in the area, and the out-of-tolerance electricity meter can be accurately found, and the effect is ideal. when the error of the line loss calculation result is about 8%, although the out-of-tolerance meter can be found, the estimation error of the normal electricity meter is higher than its actual error value. There is a situation of wrong detection, and the estimation effect is not good. When the error of the line loss calculation result is more than 10%, the obtained out-of-tolerance meter has the situation of missed detection and wrong detection, and the estimation effect is poor. The above analysis manifests that the line loss should be calculated as accurately as possible to reduce the influence of the line loss on the estimation results of the operating error of the electricity meter. Based on the current existing technical methods, it is necessary to ensure that the calculation accuracy of the line loss is within 5%.

Data preprocessing is required to exclude data under light load conditions. The following analysis is made for the light load condition. Based on the measurement data obtained by clustering under the light load condition, the proposed algorithm is used to estimate the operation error of the smart meter. The results are shown in Figure 14:

Figure 14 Estimation error value of electricity meter without excluding light load condition

Figure 14 means that when the measurement data under light load is used to remotely estimate the operating error of the electricity meter, it is impossible to determine the out-of-tolerance meter, and most of the estimation error of the electricity meter belong to the out-of-tolerance range. There are two main reasons: 1. The pulse generated by the smart meter at light load is irregular, which will cause creeping phenomenon; 2. At light load, the proportion of excitation loss and iron loss of the current transformer (CT) increases, which affects the error characteristic of the CT and makes it enter the nonlinear region. At this time, there is no corresponding relationship between the error and the load, and it is difficult to accurately compensate the error. Therefore, in the process of data preprocessing, the measurement data at light load should be removed to the greatest extent to ensure the accuracy of the estimation error of each user's smart meter and prevent over-checking.

4. Conclusion

With the continuous expansion of the scale of China's power grid, the number of electricity meters is also increasing. The purpose is to simplify the verification method of the electricity meter and improve the work efficiency while ensuring the calibration accuracy. Firstly, it is proposed to realize automatic meter reading through the Faster-RCNN model and the SSD model, and the collected metering information is aggregated and sent to the master station. Secondly, the original measurement data is preprocessed in the master station, and the measurement data under light load conditions is excluded. Thirdly, the estimation error model and the solution equation of the electricity meter are established based on the preprocessed data. The operation error of the electricity meter is estimated and the estimation accuracy is checked by the LMRLSA. Combined with the remote verification results, the business assistant decision-making is carried out. Finally, by the test of image recognition effect, it is verified that the image recognition system based on the proposed Faster-RCNN model and the SSD model has an accuracy rate of 98.49%. Through the test of remote verification effect, it is proved that the proposed algorithm can properly eliminate the influence of the old measurement data on the error parameter estimation, improve the accuracy of the error parameter estimation value, and ensure the real-time error estimation of the meter by adjusting the memory length. It can realize the function of online monitoring whether there is electricity stealing or leakage by the recursive estimation curve. moreover, by analyzing the influence of parameters on error results, it demonstrates that when the memory length ranges from 600 to 1200 and the line loss error is less than 5%, the accuracy of the electricity meter error estimation is most suitable. Meanwhile, to avoid over-checking, the measurement data at light load should be removed as much as possible. Due to limited energy, the proposed solution has not yet been completed for the development of the back-end, resulting in very inconvenient data operations on the back-end. It will be improved in the future to improve the operation experience. This research has certain reference significance for realizing intelligent remote online meter reading, verification and management of electricity meters.

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Figure 1

The network structure of the Faster-RCNN model

The Faster-RCNN model is used to identify the specific readings of the dial image, but its running speed is relatively slow.

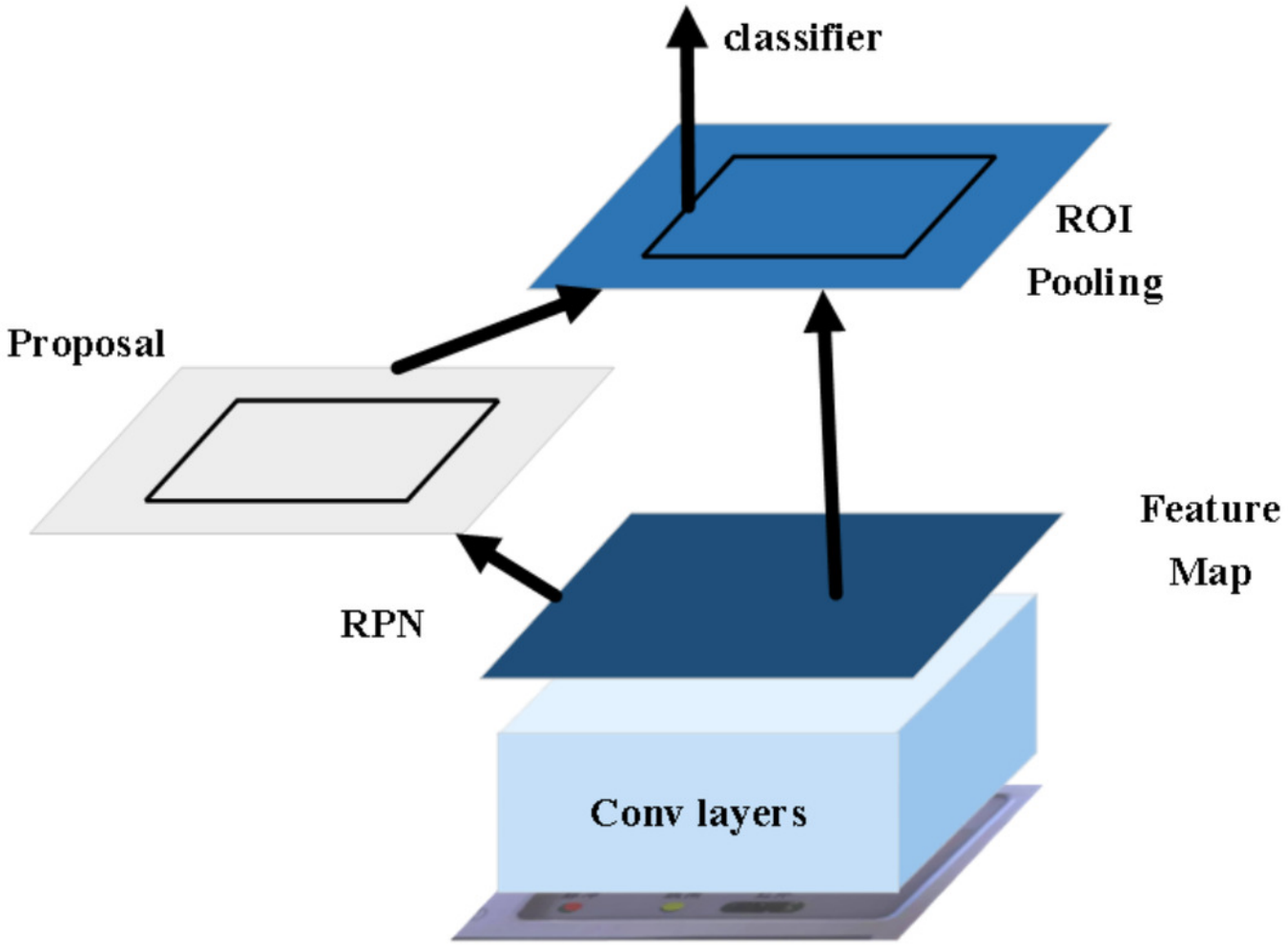

Figure 2

The network structure of the SSD model

The core of the SSD model is to predict the category score and offset of the candidate box. Simultaneously, candidate boxes of different sizes can be obtained by predicting on feature maps of different scales.

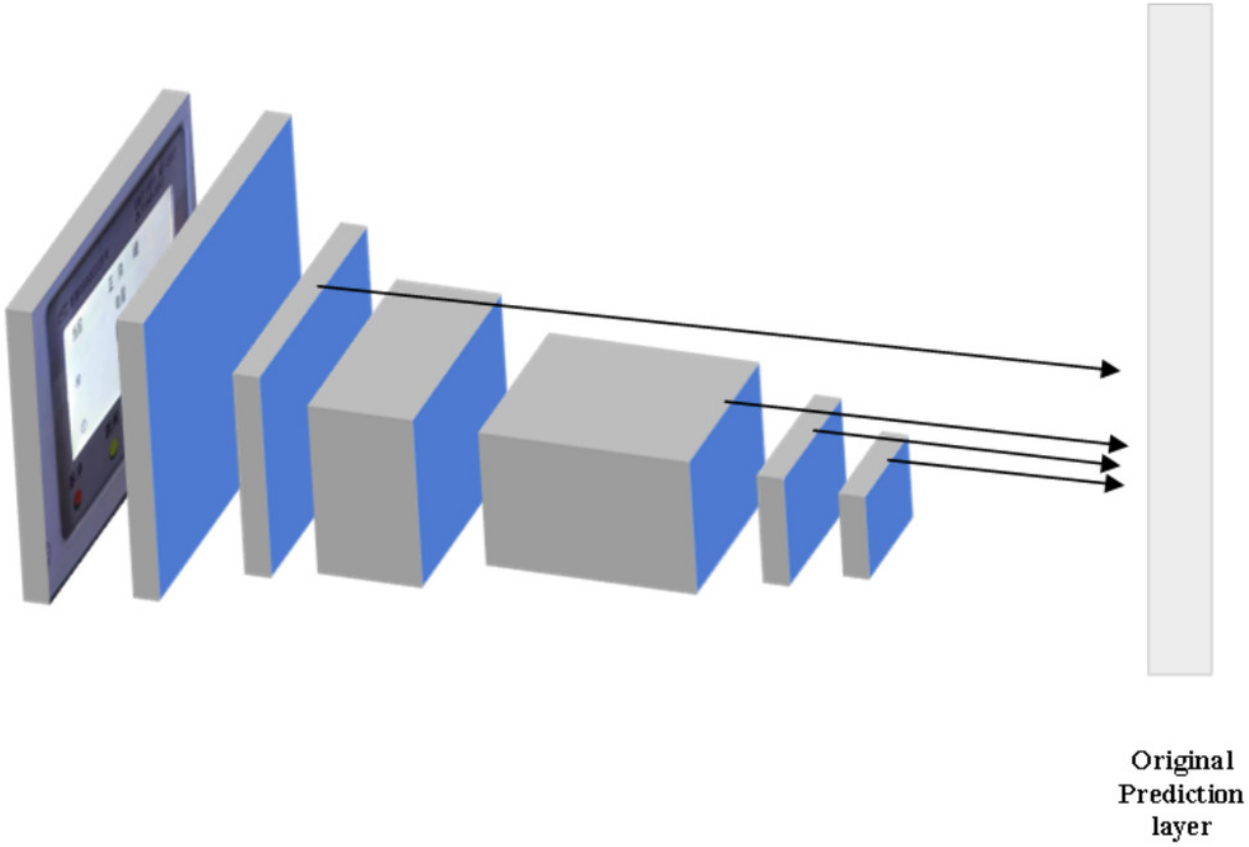

Figure 3

The specific training process of the SSD model

When training the SSD model, first, the input meter image is resized, the height of the image is uniformly set to 500px, and the width is scaled proportionally. Then, LabelImg software is used to label the effective reading area of the image screen, a training sample set is constructed, and an XML format file is generated. Next, the generated XML format files and images are converted into TFRecord format files. Finally, the pre-trained model is read and the TFRecord format file is used for model training, resulting in the desired SSD model.

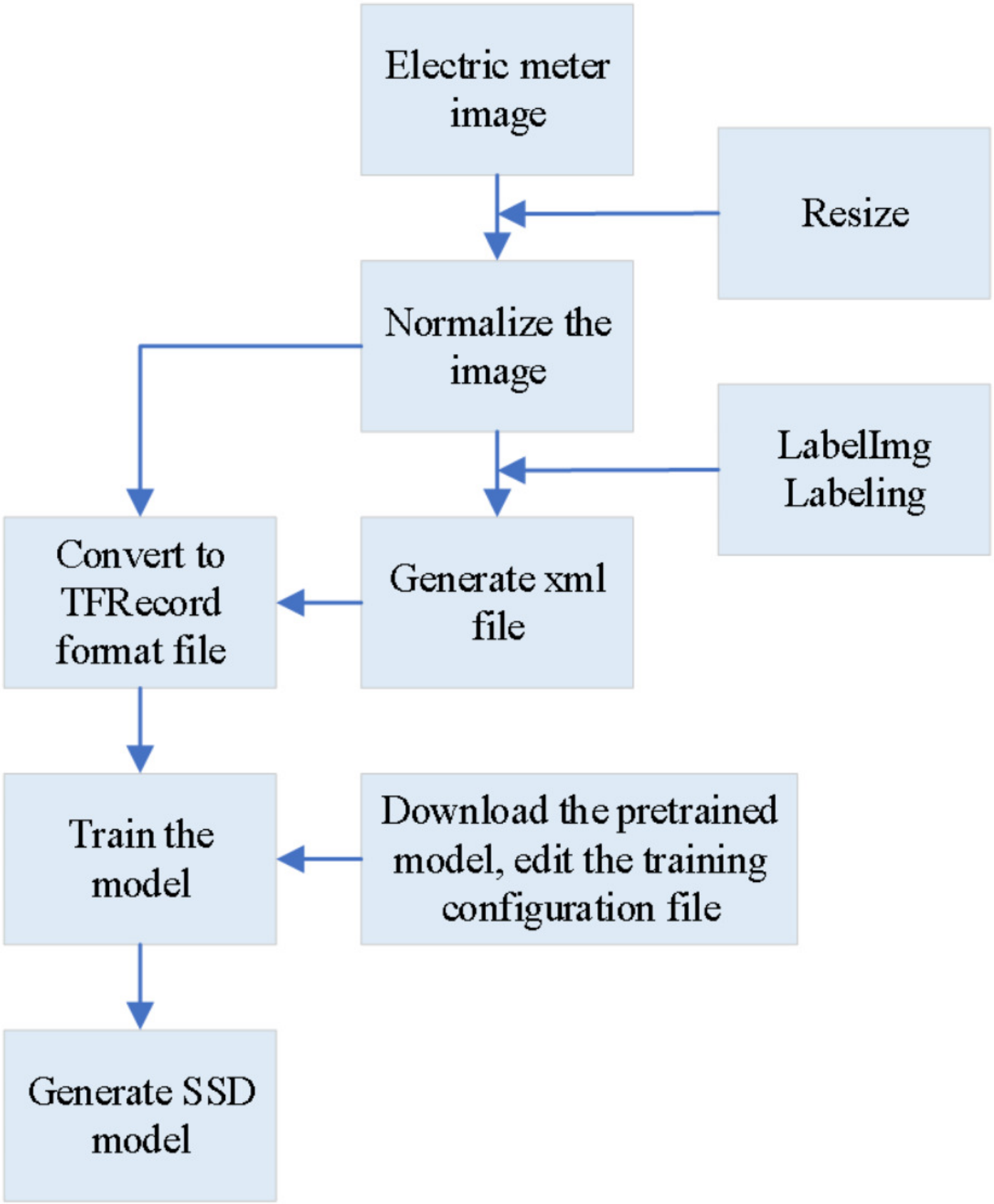
Electric meter image
Resize
Normalize the image
LabelImg Labeling
Convert to TFRecord format file
Generate xml file
Train the model
Download the pretrained model, edit the training configuration file
Generate SSD model

Figure 4

The training process of the Faster-RCNN model

For the Faster-RCNN model trained to identify the readings in the effective reading area, the effective reading area is firstly processed in grayscale, and then the brightness is adjusted, which can solve the problem that some images are too bright or too dark, and reduce the complexity of identifying the readings in the effective reading area. Secondly, LabelImg software is also used to label the numbers in the area, generate an xml format file, and convert it into a TFRecord format file. Finally, the model is trained to obtain the desired Faster-RCNN model.

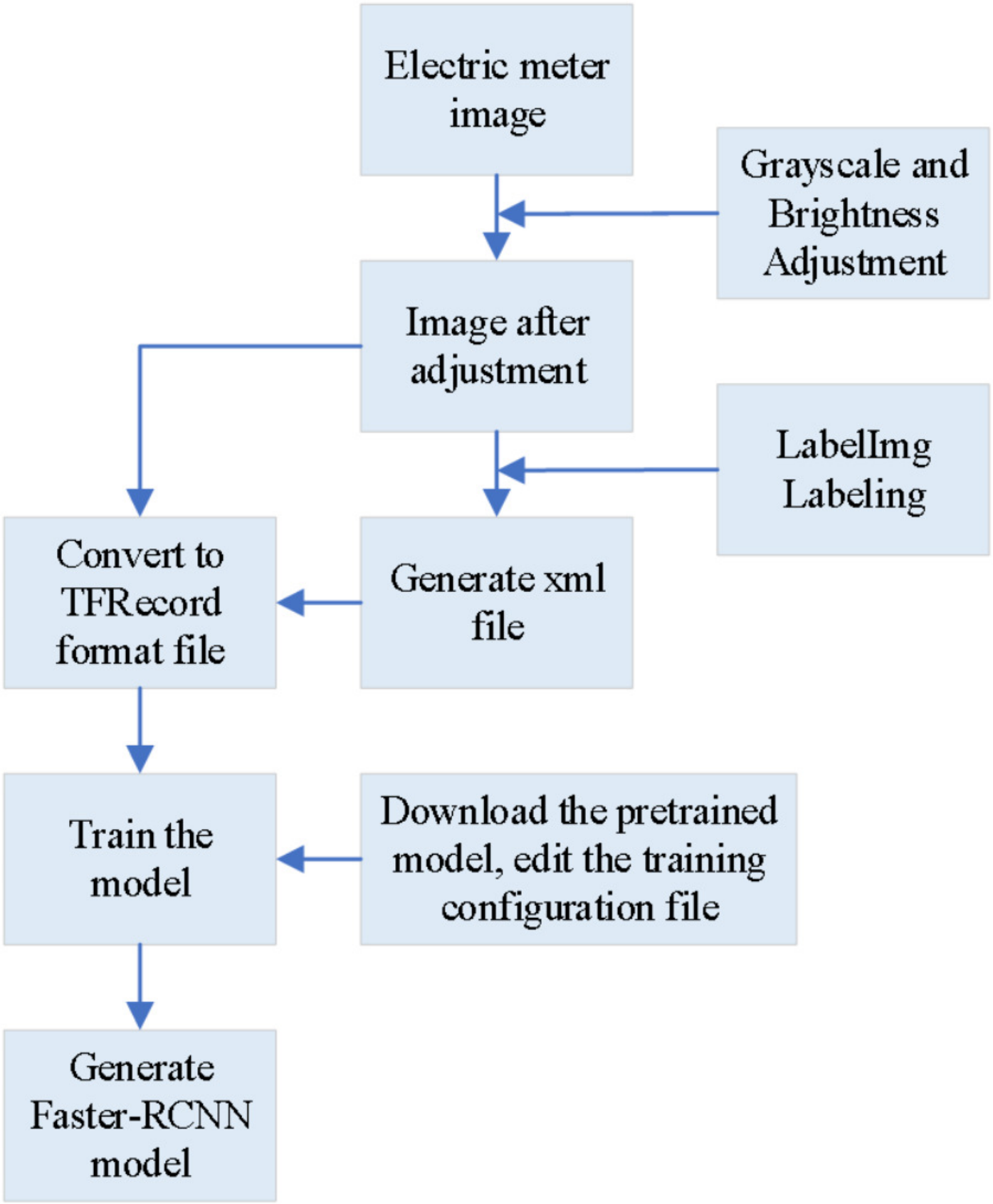
Electric meter image
Grayscale and Brightness Adjustment
Image after adjustment
LabelImg Labeling
Convert to TFRecord format file
Generate xml file
Train the model
Download the pretrained model, edit the training configuration file
Generate Faster-RCNN model

Figure 5

The training steps for the models

The specific training steps for the two models.

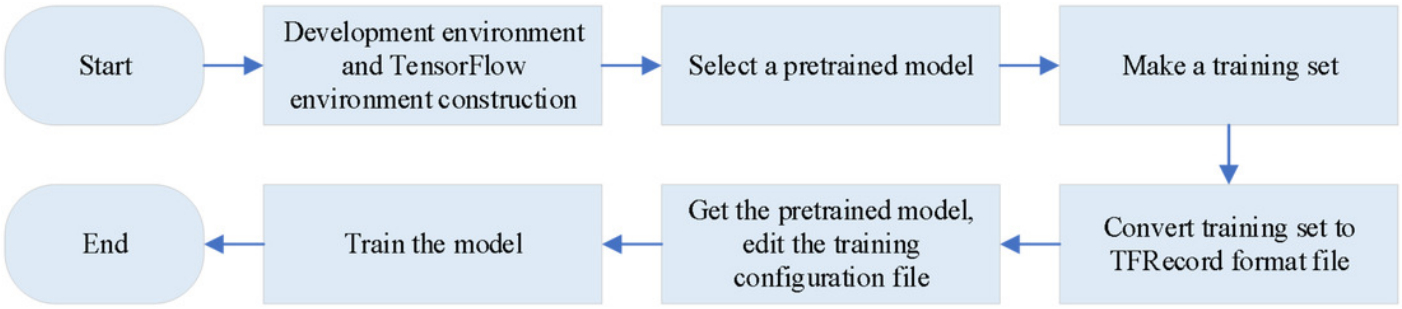

Figure 6

The process of scheme

The Faster-RCNN model and the SSD model are used to collect the electricity metering information of the total meter and sub-meters according to the pre-set time, and after the collection and summary, the user's electricity consumption information is transmitted to the master station, and the electricity consumption data is automatically copied and collected. The obtained measurement data is preprocessed, and then the estimation model and solution method are established through the preprocessed data. The estimation accuracy is checked, and finally, the purpose of online verification and business assistant decision-making is realized.

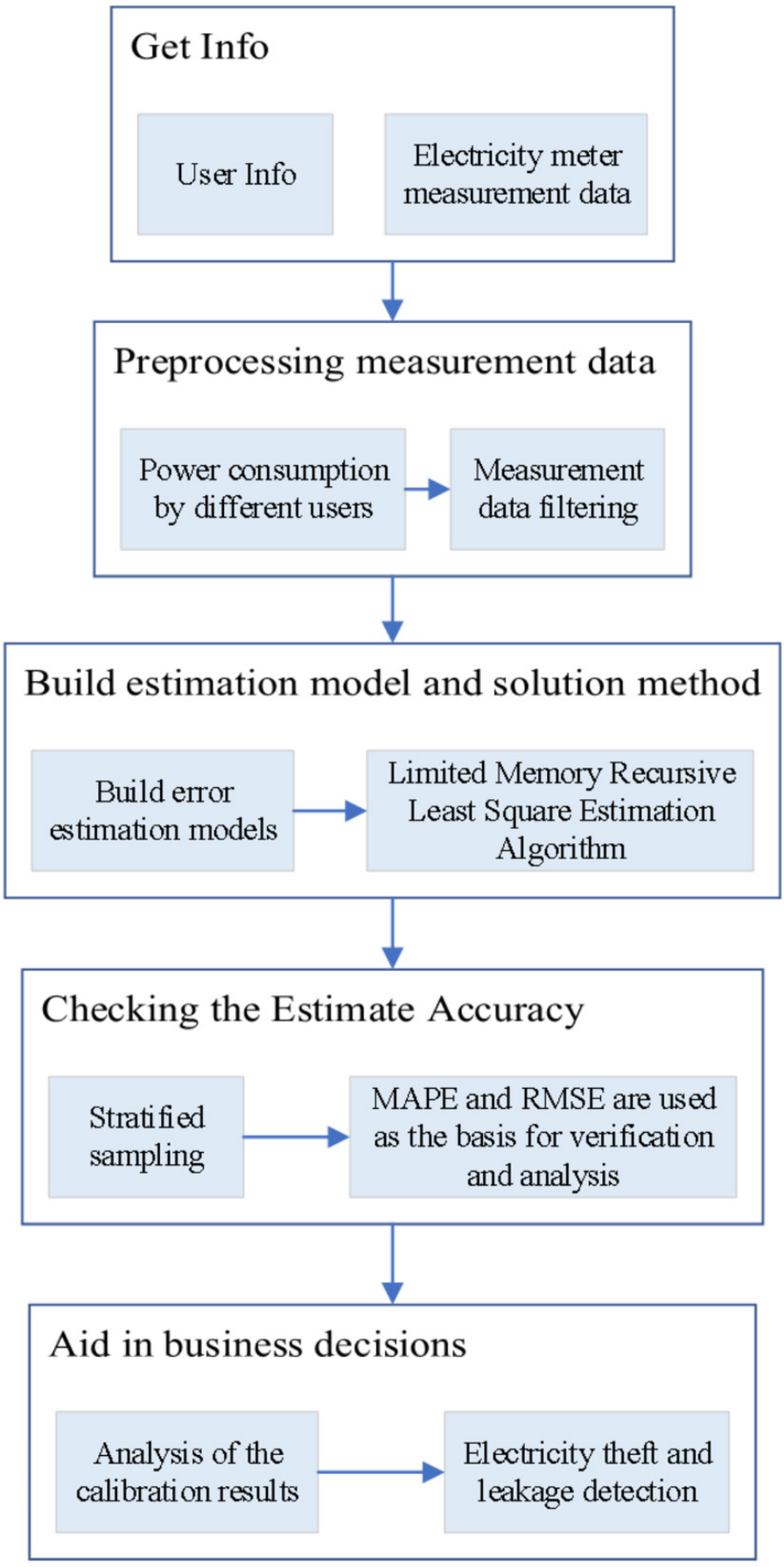
Get Info
User Info
Electricity meter measurement data
Preprocessing measurement data
Power consumption by different users
Measurement data filtering
Build estimation model and solution method
Build error estimation models
Limited Memory Recursive Least Square Estimation Algorithm
Checking the Estimate Accuracy
Stratified sampling
MAPE and RMSE are used as the basis for verification and analysis
Aid in business decisions
Analysis of the calibration results
Electricity theft and leakage detection

Figure 7

The SSD model detects the effective reading area of the electricity meter

The TensorFlow Object Detection API provides the corresponding eval.py script to verify the trained model. Running the script can verify the test set and generate the corresponding log file. Then, the log file is read through TensorBoard and the verification effect of the model is displayed.

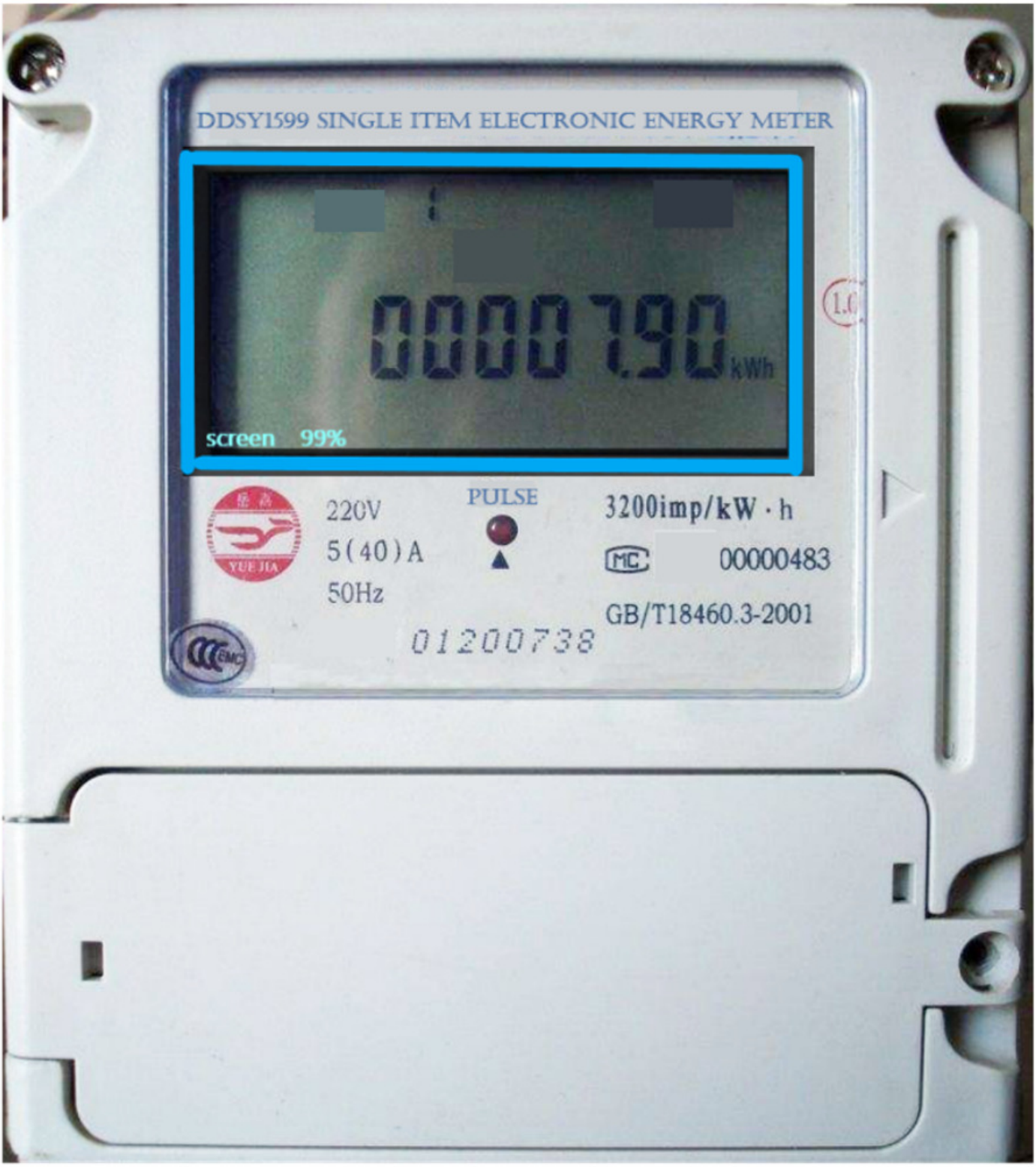
DDSY1599 SINGLE ITEM ELECTRONIC ENERGY METER
0000790 kWh
screen 99%
220V
5(40)A
50Hz
PULSE
3200imp/kW · h
00000483
GB/T18460.3-2001
01200738

Figure 8

The Faster-RCNN model identifies the specific readings of the electricity meter

The specific display effect

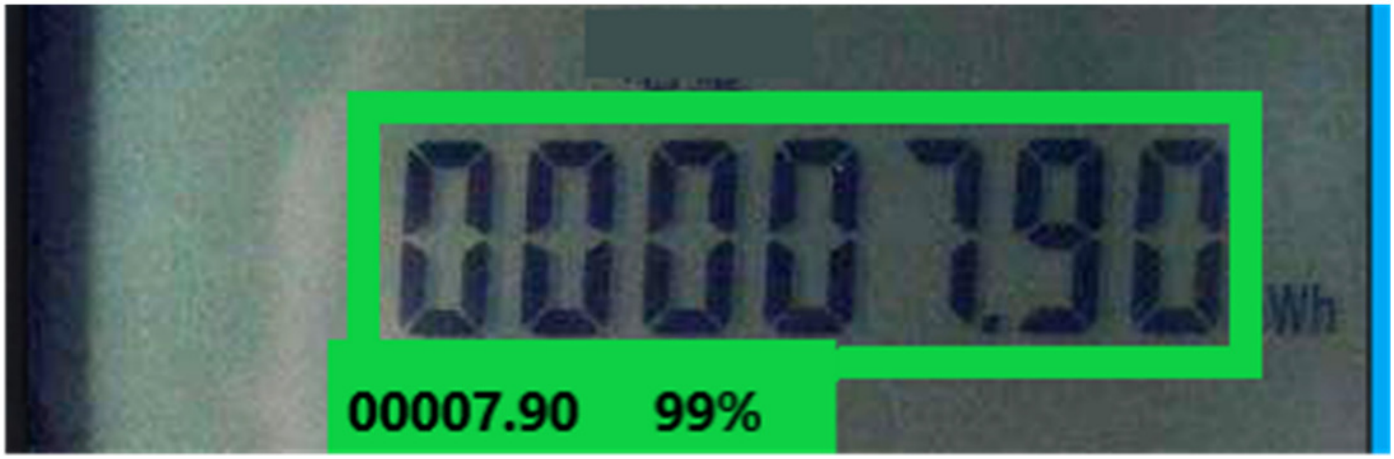

Figure 9

Verification scheme

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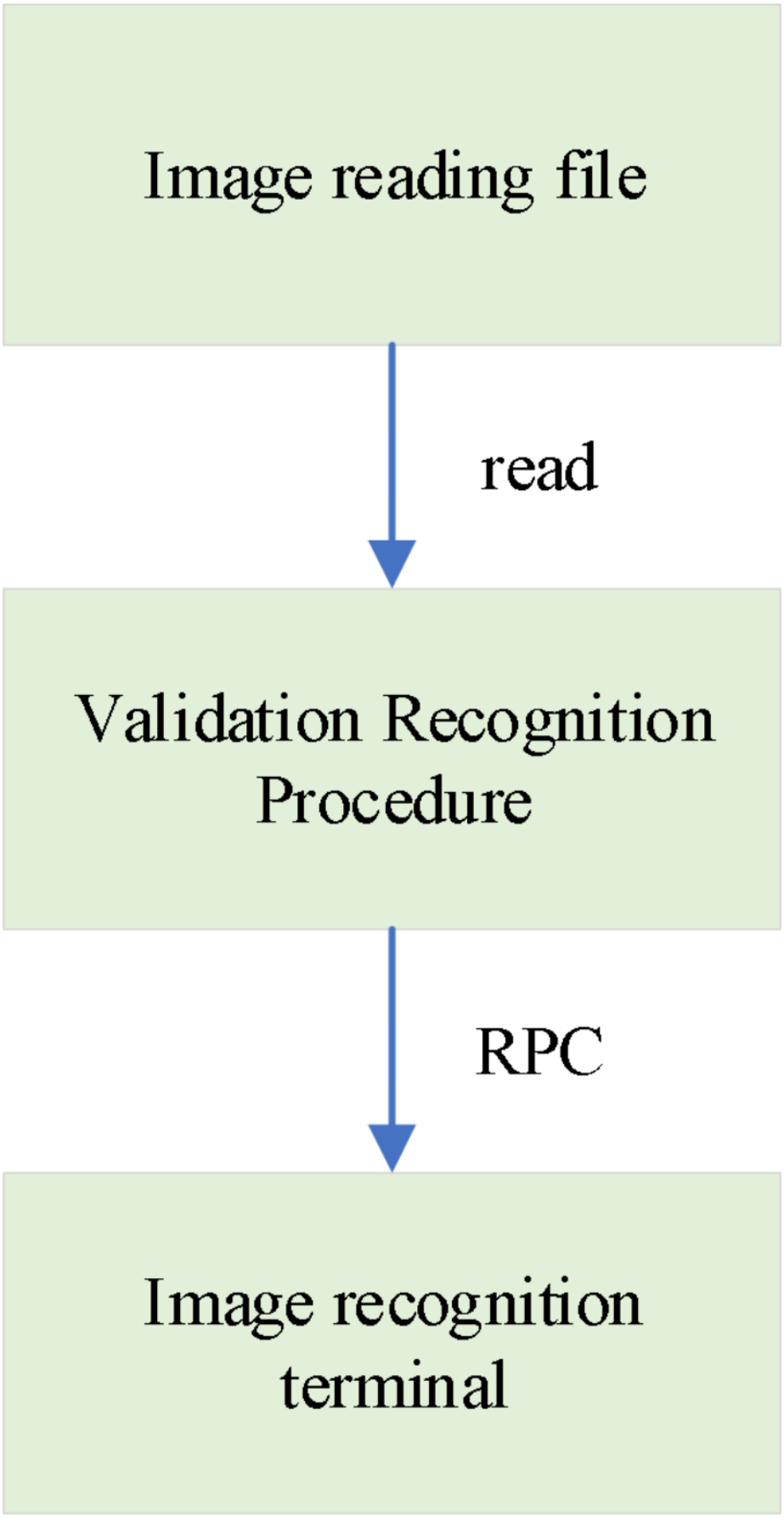
Image reading file
read
Validation Recognition Procedure
RPC
Image recognition terminal

Figure 10

The recursive estimation curve of the operation error of the electricity meter

there are 5 meters in the research area with extremely large errors, and the estimated error parameters of the remaining meters are all within the allowable range of normal errors.

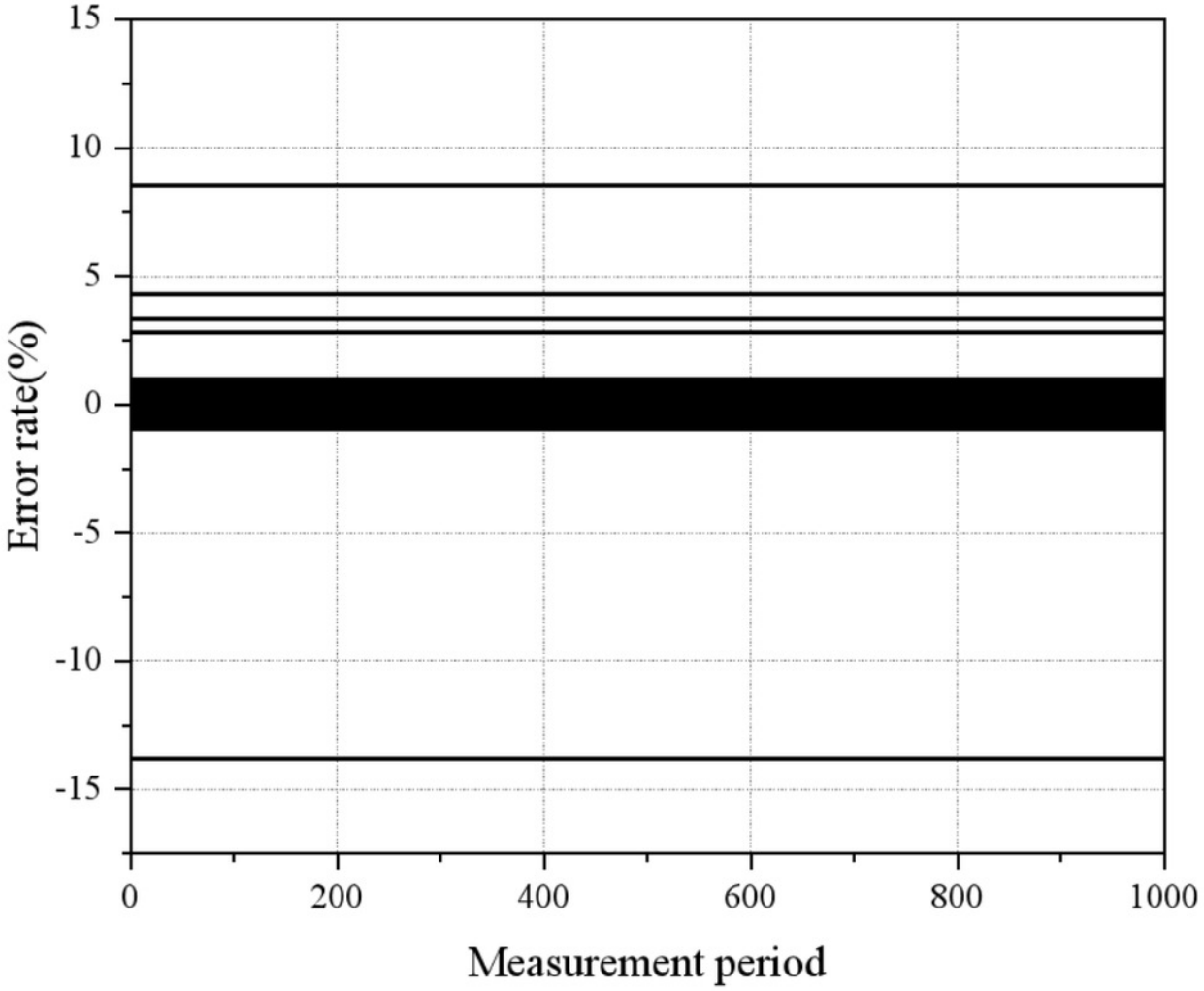

Figure 11

The estimation error value of the electricity meter in a certain period

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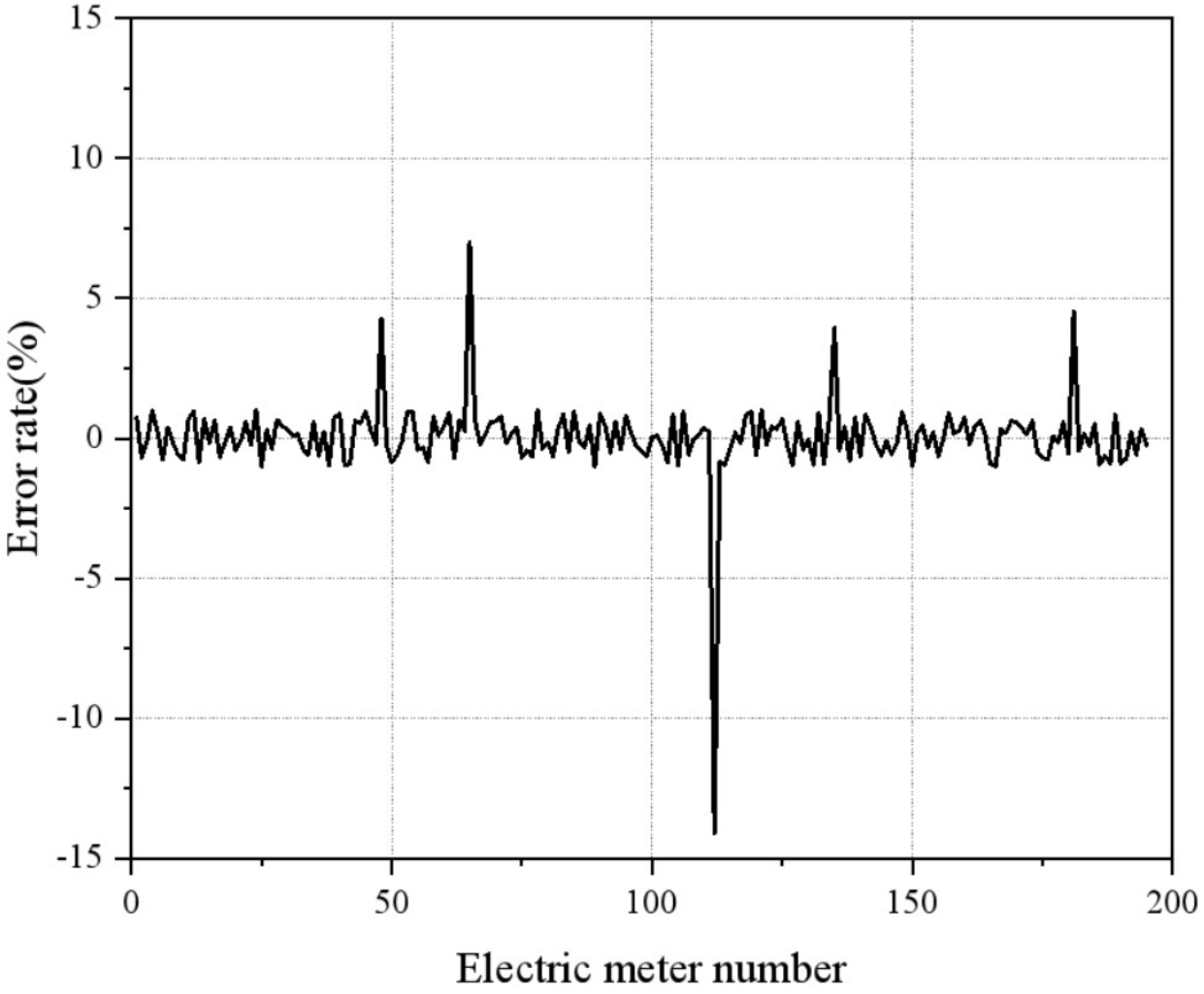

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The estimation error value of the electricity meter with different memory length

When L=100, the estimation error value of a normal smart meter seriously deviates from its actual error value, because the number of recursive estimation equations is in an underdetermined state when it is less than the number of error parameters to be estimated. The results cannot be applied. When L=400, the number of measurements is greater than the number of error parameters to be estimated, and the estimation error value begin to converge. However, the estimation error value of some normal smart meters are still in the out of tolerance range, and the estimation effect is not ideal. When L=1000, the estimation error value of each electricity meter is close to a certain value, and a more accurate estimation of the error parameters of the smart meter is obtained, and the estimation effect is ideal. When the value of L is large, although the error can also be estimated parameters, it takes a long time and reduces the efficiency of online analysis. Therefore, based on the actual working conditions of the research area, to ensure the accuracy of the estimated value and the real-time performance of the solution analysis, the recommended value of L ranges from 600 to 1200.

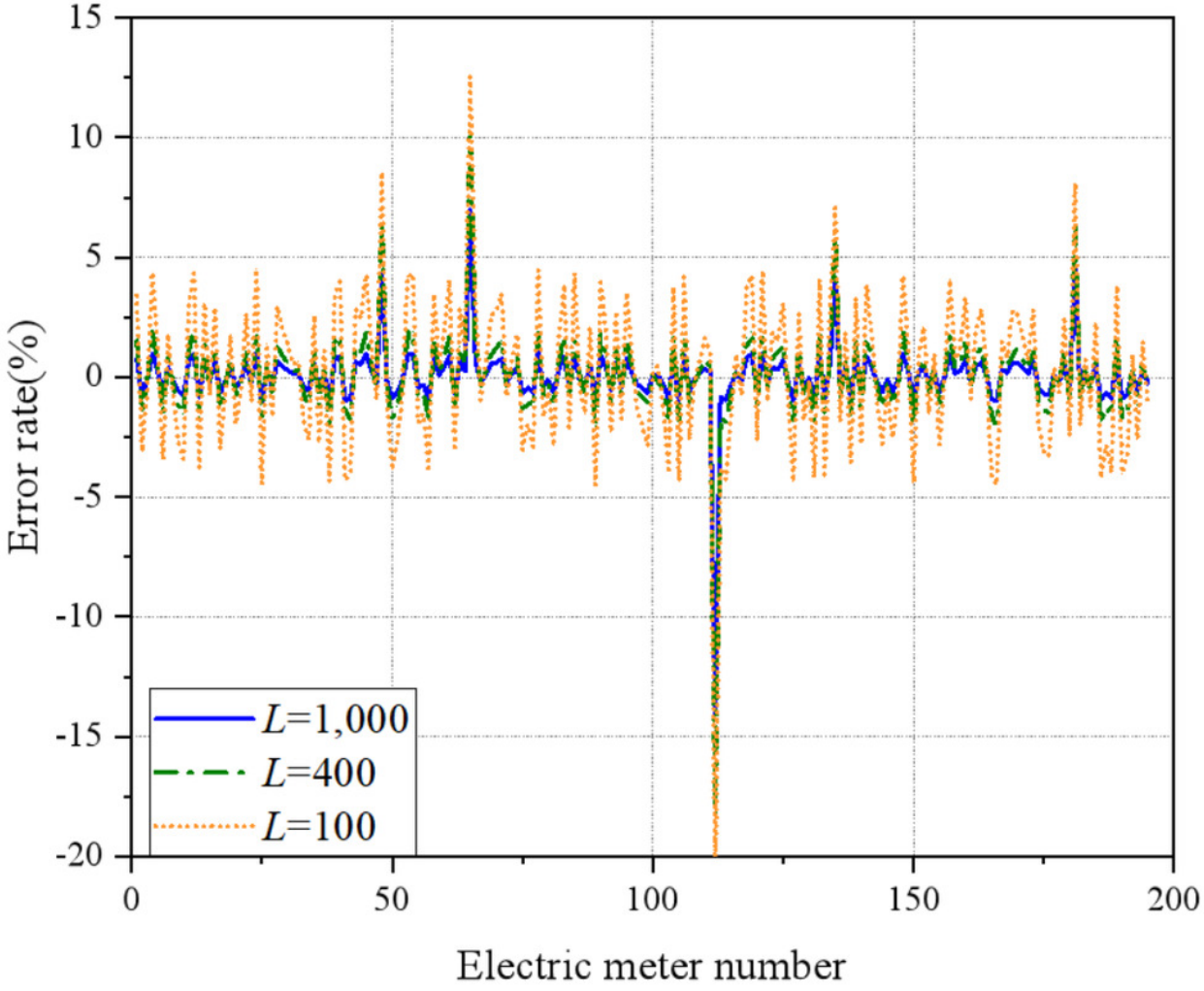
15
10
5
0
-5
-10
-15
-20
Error rate(%)
0
50
100
150
200
Electric meter number
L=1,000
L=400
L=100

Figure 13

The estimation error value of electricity meters under line losses of different errors

When the error of the line loss calculation result is within 5%, it has little effect on finding the out-of-tolerance electricity meter in the area, and the out-of-tolerance electricity meter can be accurately found, and the effect is ideal. when the error of the line loss calculation result is about 8%, although the out-of-tolerance meter can be found, the estimation error of the normal electricity meter is higher than its actual error value. There is a situation of wrong detection, and the estimation effect is not good. When the error of the line loss calculation result is more than 10%, the obtained out-of-tolerance meter has the situation of missed detection and wrong detection, and the estimation effect is poor.

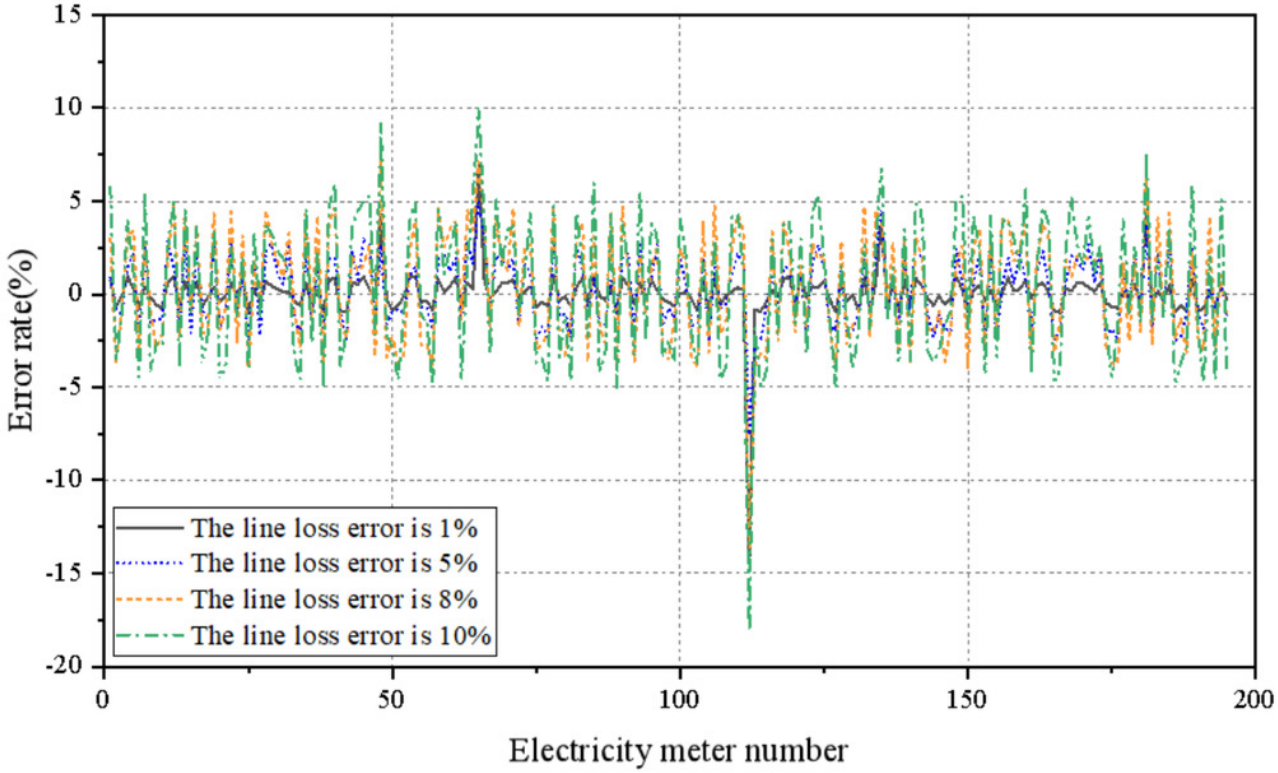

Figure 14

Estimation error value of electricity meter without excluding light load condition

When the measurement data under light load is used to remotely estimate the operating error of the electricity meter, it is impossible to determine the out-of-tolerance meter, and most of the estimation error of the electricity meter belong to the out-of-tolerance range.