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An Adaptive Gradient Descent Method for Error Estimation of Electric Meters

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Article Info
Volume 83
Page Number: 1539 - 1549
Publication Issue:
July-August 2020

Article History
Article Received:*06 June 2020*
Revised: *29 June 2020*
Accepted: *14July 2020*
Publication: *25July 2020*

Abstract

Error verification of electric meters in the power industry is usually manually conducted through standard meters. With the continuous improvement of real-time data collection technology, data of power systems available for analysis is becoming more abundant. In this paper, we propose an adaptive gradient descent method for error estimation of electric meters based on large amount of data. In order to improve the accuracy of estimation results, we first adopt a clustering algorithm for light load data detection and elimination. Then we provide a detailed description of the remote estimation model for the running error of electric meters. According to the simulation experiments, results obtained by the proposed method can well match the true value of electric meter's running error. This method can effectively reduce the maintenance cost of on-site calibration of electric meters, and can also provide a reference for the service of electric meters.

Keywords:*smart meter, AMI data; running error, remote estimation, Adaptive Gradient Descent Algorithm*

1.INTRODUCTION

Smart grid is a modern power supply system that monitors, protects, and optimizes the operation of its interconnected components, including smart meters. Accurate and reliable energy measurement methods are necessary to ensure the reliability of power supply, from power generation, transmission to distribution and power consumption [1-3]. In addition, measurement accuracy has an important impact on various power data analysis [4,5]. Thus we need take measures to obtain the status of metering devices in a timely manner, and estimate the reliability and accuracy of the devices [6-8]. The running error of electric meters is a key indicator for measuring the performance quality of the electric meters. At present, evaluation of the running error of electric meters is generally carried out by manual operations (sampling inspection, user review, etc.) in the actual operating process. Recently, with the development of communication technology, smart meters can transmit online electricity consumption information remotely in real time [9-11]. Related works based on operation data analysis of smart electric meters have become increasingly mature [12-14]. The application of data analysis techniques to the calculation of electric meters' error has certain practical significance [15-18].

In the field of remote evaluation for electric meter's operating error, many institutions at home and abroad have carried out related theoretical and practical research in order to solve the problems caused by the traditional manual calibration method [19-21]. Some researchers have studied the method of calculating running error of each electric meter based on electricity information collection, processing, and real-time monitoring [22-24]. For example, Guo used the AMI measurement data to propose an autonomous error algorithm of the electric meter cluster, and discussed the accuracy class of any electric meter [25]. Qiao et al. deduced a method for calculating running errors based on multiple linear regression models, and explored the application of artificial intelligence technology in this regard [26]. On the basis of the above problems, Yang et al. proposed a new iterative method for line loss estimation, and they deeply studied the data distribution of electric meters' calculation errors [27].

How to judge the status of each running electric meter so that individuals with faults or errors exceeding the limits can be found in time and replaced is a very difficult problem in theory. Although the above works have achieved certain results in remote diagnosis for running errors of electric meters, research on remote error calculation of electric meters is still in its infancy, with poor applicability in actual working conditions. For example, power loss in the network is a non-negligible part which requires real-time electric data. Irrational calculation of the power loss will aggravate inaccuracy of the estimation error and cause misjudgement. In addition, the effectiveness of solving algorithm should also be considered to ensure that the results are optimal. Therefore, it is important to take all the above factors into account for high accuracy and practicality of the error estimation method, and then truly implement remote analysis and calculation of electric meter's error.

In this paper, we establish an error analysis model on the basis of [24], and propose an adaptive gradient descent method for estimating the running error of electric meters based on massive measurement data. The energy flow equation of the experimental area is established based on the principle of energy conservation with fixed loss and variable line loss taken into account. Considering the calculation accuracy, we use the fuzzy C-means clustering algorithm to pre-process the original data and eliminate abnormal data under light load conditions. For solution of the error analysis model, traditional least square method has its own limitations, including problems as data saturation, rank missing and so on. Therefore, we propose an adaptive gradient descent method to find the optimal solution of this problem, which makes full use of data and guarantees convergence. Adopting the proposed method to study and estimate the running errors of the electric meters in the experimental area, the maintenance efficiency of the smart meters is greatly improved and the operating costs are reduced. The accuracy and real-time performance of remote estimation will help find suspected abnormal measurement points in time by technical means, and overcome the current heavy workload of manual investigation.

The rest of this paper is organized as follows. In Section 2, we introduce the framework of error estimation and data pre-processing algorithm. The mathematical principle and its solving algorithm for the remote error estimation of electric meter clusters in the experimental area are described in detail in Section 3. In Section 4, we provide the implementation of the proposed method and accuracy verification. Finally, we draw some conclusions from our results in Section 5.

2.INFORMATION COLLECTION OF ELECTRIC METERS AND DATA PRE-PROCESSING

2.1 Framework for Remote Error Estimation of Electric Meters

The proposed remote error estimation method for electric meters is based on the analysis of large-scale electric meters' measurement data. The implementation of this method includes data acquisition, pre-processing, model calculation, accuracy analysis and other steps. Specifically, firstly, we obtain the total power of the on-site area and the users' electricity consumption from the

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electricity consumption information collection system. Next, we adopt a clustering algorithm to pre-process the acquired data so as to eliminate abnormal measured data such as null data and light load data. Then, we analyse the power relationship of the on-site area and provide a detailed model of remote error estimation. Then the model can be solved by the conventional regression analysis algorithm to obtain the running error of each smart meter. It is worth mentioning that the reasonability of the model and the effectiveness of the algorithm will directly affect the accuracy of error estimation. At last, we conduct some verification experiments to assess the performance of error estimation. This process is illustrated in Figure 1.

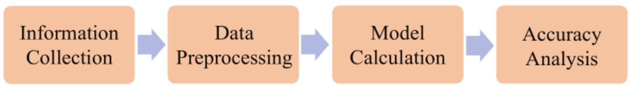

Figure 1. Scheme of the data based error estimation model.

2.2 Electric Information Collection

The original measurement data is mainly obtained from the AMI-based smart meter data acquisition system. Although the collection system's architectures are slightly different in different regions, they share the same typical physical architecture as shown in Figure 2. The traditional power information collection system mainly includes three parts: master station, communication network, and terminal execution. The master station layer plays a supervisory role and is responsible for collecting users' power consumption automatically. The communication layer establishes an information transmission channel between the master station layer and the user terminal equipment to transmit all data in the power consumption process in real time. Through the communication layer, the computer equipment in the master station receives various types of power information data (electricity quota, electrical power, loss, etc.) from the terminal execution (electric meters). On the contrary, the execution layer processes according to the command from the master station. Each electric meter can take multiple measurements at different times, and the master station then records the readings of all electric meters in the entire network.

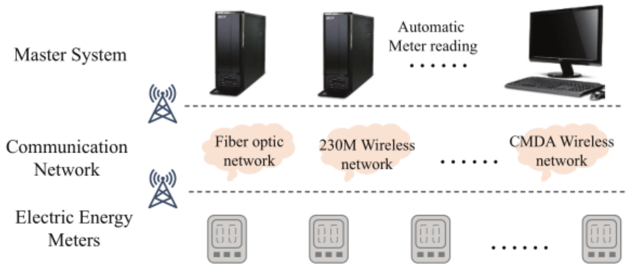

Figure 2. Physical architecture of the electric information collection system.

2.3 Data Pre-processing to Eliminate Abnormal Data

The electricity information collection system can usually provide measurement data under different operating conditions. Among these data, there may exist data in light load conditions when the running load current is below 5% to 10% of the rated current. Light load affects the submersible performance of smart meters and the working state of current transformers, causing great effects on the accuracy of smart meter measurement. Estimating the running error of electric meters with light load data included will result in relatively high inaccuracy. Thus, in order to ensure high accuracy level for error estimation of electric meters, the measurement data at light load needs to be removed.

Each user's power consumption in measurement period t is expressed as

$$E_i = U_i I_i \cos\varphi \cdot t, \qquad (1)$$

where U_i and I_i represent the average voltage and average current during t respectively, and $\cos\varphi$ represents the power factor. As the voltage and power factor remain almost constant for each user, we can use E_i / E^* (E^* is the range of the energy meter) to approximate I_i / I^* (I^* is the rated current). Thus E_i / E^* is chosen to characterize the operating condition of electric meter i. Suppose we have n sets of measurements for each user, and we take $E=[E_1,E_2,\ldots,E_m]$ (m is the number of electric meters in the system) to describe each measurement result of the whole system. In this paper, the original measurement data sequence $E(1),E(2),\ldots E(n)$ is preprocessed by fuzzy C-means clustering algorithm [28-31] to screen out data groups in similar operating conditions, and then the measurement data under light load conditions is removed[32]. The specific flow of the algorithm is shown as follows.

Input: Electric meters' measurement data $E(1),E(2),\ldots,E(n)$

Output: Cluster centre C and membership matrix U

Step 1: Given the iteration termination parameter ε.
Step 2: Use the mountain climbing method to determine the number of clusters and initialize cluster centre C_0 and membership matrix U_0.

Step 3: Update the clustering centres C and membership degree matrix U.
Step 4: If

$$\Delta J(C,U)\le\varepsilon, \tag{2}$$

then **return** Final cluster centre C and membership matrix U.

Else

Proceed to **step 3.**

Based on the above algorithm, we classify the operating conditions of each measurement. Then we use threshold processing to determine the cluster centre under light load conditions ($E/E^*<0.1$). And we can get the light load data group of each light load cluster centre from the membership matrix. After removing these data, we obtain the reliable data used for running error estimation.

3.METHOD FOR ESTIMATING ELECTRIC METER'S RUNNING ERROR

3.1Establishing an Estimation Model of Running Error

The electric meters cluster topology of a treelike distribution network is shown in Figure 3. Suppose there is a regional meter M_0 and m sub-meters $M_i\,(i=1,2,\ldots,m)$ for users in the on-site area. Corresponding, the actual power consumption through the electric meters during a certain period is respectively $\bar{y}_0$ and $\bar{x}_i\,(i=1,2,\ldots,m)$. A consumer's load profile or power consumption profile tends to remain the same over a period of time. According to the law of conservation of energy illustrated above, at any sampling period, the actual energy flowing into the on-site area is equal to the actual power flow from the district. Namely, during any time interval, the algebraic sum of increments of all throughputs going through the electric meter cluster should be zero. With power loss (w_{loss}) taken into consideration, the power relationship of the station area can be expressed as the following equation.

$$\bar{y}_0=\sum_{i=1}^{m}\bar{x}_i+w_{loss}. \tag{3}$$

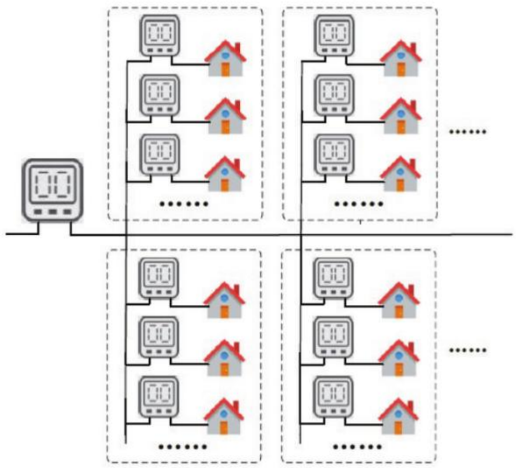

Figure 3. The electric meters cluster topology of a treelike distribution network.

Suppose the readings of electric meters during measurement period t are y_0 and $x_i\,(i=1,2,\ldots,m)$. As we all know, there is a certain running error when the electric meter is in operation. Since the error level of the regional meter M_0 is generally

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significantly lower than the meters of users in actual conditions, it is assumed that the running error of M_0 is known and zero (i.e. $y_0 = \bar{y}_0$). The relative error of i user's electric meter measurement δ_i is expressed by the following equation

$$\delta_i = \frac{x_i - \bar{x}_i}{\bar{x}_i} \times 100\%, \quad (4)$$

where $\bar{x}_i$ is the real power flowing through the electric meter i and x_i is the reading value of electric meter. According to the definition of relative error, we can get

$$\bar{x}_i = \frac{x_i}{1+\delta_i}. \quad (5)$$

Suppose $\varepsilon_i = \frac{1}{1+\delta_i}$, the power relationship of equation (4) can be written as

$$y_0 = \sum_{i=1}^{m} x_i \varepsilon_i + w_{loss}. \quad (6)$$

In the practical application of the above principle, the total power loss of the on-site area includes line loss, leakage and other methods. Line loss is the thermal loss caused by the current flowing through the lines in the cluster of electric meters, which is expressed in equation (7). r_l is the branch resistance of line l, which can be calculated according to the characteristics of the wire and $I(\tau)$ is the real-time current in time period t As the system topology, trace length, working current and voltage of the sub-meter can be measured, the line loss of the system can be calculated according to the weight of the total length of the regional meter to each sub-meter [33].

$$w_{line\_loss} = \sum_{l=1}^{m} \int_0^t I^2(\tau) r_l d\tau \ . \quad (7)$$

While other power losses as leakage loss and equipment loss are fixed losses not related to the topology of the power grid. Calculation of actual total leakage loss needs leakage conductance, which is related to the material property parameters and cannot be obtained. In [27], some basic assumptions for fixed loss in the on-site area are proposed in order to reasonably model the actual situation. Here we adopt the assumption that the fixed loss in the station area is an independent constant ε_0 to simplify our problem. Based on the above analysis and assumption, suppose $y = y_0 - w_{line\_loss}$, we can rewrite equation (6) as

$$y = \sum_{i=1}^{m} x_i \varepsilon_i + \varepsilon_0. \quad (8)$$

We establish the mathematical model equation (8) of remote estimation for the running error of electric meters. Obviously, the accuracy of error estimation results is related to the accuracy of line loss calculation and the effectiveness of solution method of equation (8).

3.2Error Estimation Algorithm

In the case when electric meters' error maintain a relatively stable state within a certain sampling time, the unknown parameters in equation (8) can be fitted based on the data of multiple samplings, and then the relative error of each energy meter in the station area can be obtained. The error estimation problem can be transformed into a parameter fitting problem of a multiple linear regression model. Specifically, a set of parameters $\hat{\theta} = \left[\hat{\theta}_0, \hat{\theta}_1, \ldots, \hat{\theta}_m\right]$ is estimated based on multiple sets of measured values x, y with $\hat{\theta}$ infinitely approximate the value of parameter $\varepsilon = [\varepsilon_0, \varepsilon_1, \ldots, \varepsilon_m]$ in equation (8), which is described in mathematical form as

$$y = \sum_{i=1}^{m} x_i \hat{\theta}_i + \hat{\theta}_0. \quad (9)$$

Based on above analysis, the relative error of electric meter i can be obtained as

$$\hat{\delta}_i = \frac{1}{\hat{\theta}_i} - 1. \quad (10)$$

Given the pre-processed data point set $(x(j), y(j)),\ j = 1, 2, \ldots, n$, which means that we have n sets of data under normal running condition (where $x(j) = [x_1(j), x_2(j), \ldots, x_m(j)]$). For any parameter $\hat{\theta}$, we can calculate residual and the loss function is

$$J(\hat{\theta})=\frac{1}{2n}\sum_{j=1}^{n}\left(y(j)-\sum_{i=1}^{m}x_i(j)\hat{\theta}_i-\hat{\theta}_0\right)^2. \qquad (11)$$

Our goal of parameters estimation is to obtain $\hat{\theta}^*=\arg\min\left\{J\left(\hat{\theta}\right)\right\}$. We can solve the above problem by traditional least square method. While when the amount of data n is very large, the symmetric matrix is n-dimensional times n-dimensional and it will cause high complexity of the solving process. Besides, the power consumption of users in the on-site area is in a similar condition, causing the data matrix not a full rank matrix. In short, considering problems as data saturation, traditional least square method is not applicable in this issue. Thus the gradient descent algorithm is chosen to solve the above parameters estimation issue as an optimization problem. As the direction of gradient is the fastest changing direction of the loss function, we can finally reach the minimum. The specific flow of the algorithm is shown in the following.

Input : Data point set $(x(j),y(j)),\ j=1,2,\ldots,n$

Output : Estimated parameter $\hat{\theta}$

Step1: Algorithm related parameters $\hat{\theta}$, algorithm termination distance ξ and step size α are initialized. With prior knowledge, we initialize all $\hat{\theta}$ to 1, the step size to 0.1, and then optimize them when tuning.

Step 2: Determine the gradient of the current position loss function

$$\frac{\Delta J\left(\hat{\theta}\right)}{\Delta\hat{\theta}_i}=\frac{1}{n}\sum_{j=1}^{n}\left(\sum_{i=1}^{m}x_i(j)\hat{\theta}_i+\hat{\theta}_0-y(j)\right)x_i(j). \qquad (12)$$

Step 3: If all the gradient descent distances

$$\frac{\Delta J\left(\hat{\theta}\right)}{\Delta\hat{\theta}_i}<\xi, \qquad (13)$$

then the algorithm terminates, and the current $\hat{\theta}$ is the optimal result $\hat{\theta}^*$, **return** $\hat{\theta}$.

Else

Update all $\hat{\theta}$ as

$$\hat{\theta}=\hat{\theta}-\alpha\frac{\partial J}{\partial\hat{\theta}}. \qquad (14)$$

After the updating process is completed, proceed to **step 2**.

A key point in gradient descent optimization is the setting of the learning rate. If the learning rate is too small, the convergence speed will be slow. While if it is too large, it will cause training shock and may diverge. Another key point is that the process of gradient descent may fall into the local minimum. For global convergence and fast converging speed, we propose an adaptive learning rate [34] for gradient descent algorithm as follows, where η is the initial learning rate, ε is a constant with small value, and t indicates the number of iterations.

$$\hat{\theta}(t+1)=\hat{\theta}(t)-\frac{\eta}{\sqrt{\sum_{\tau=1}^{t}\Delta J\left(\hat{\theta}\right)_\tau+\varepsilon}}\Delta J\left(\hat{\theta}\right)_t. \qquad (15)$$

The above algorithm can estimate each parameter $\hat{\theta}_i$ based on n measured group data, and then the running error of each electric meter $\hat{\delta}_i$ can be obtained.

3.3 Accuracy Check

In order to analyse the accuracy of the running error of electric meter estimated by the proposed method, check for the error estimation needs to be performed. With the actual value of the electric meter's error in the experimental area measured by the stratified sampling method for comparison, the Mean Absolute Percent Error (MAPE) and Root Mean Square Error (RMSE) can be used for accuracy judgment. During the remote estimation of the electric meter error, the smaller MAPE and RMSE value indicates higher accuracy of the estimated error.

$$\mathrm{MAPE}=\frac{1}{m}\sum_{i=1}^{m}\frac{\left|\hat{\delta}_i-\delta_i\right|}{\left|\delta_i\right|}\times 100\%,$$
$$\mathrm{RMSE}=\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(\hat{\delta}_i-\delta_i\right)^2}, \qquad (16)$$

where m represents the number of energy meters and δ_i represents the actual error of energy meter i.

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4.CASE ANALYSIS

We first remove the data under abnormal working conditions according to the data pre-processing method in **Section 2**, and then we use the data under normal working conditions to perform following estimation.

In order to verify the effectiveness the proposed method, we choose a distribution system with 68 users as experimental area. Each user's electric meter is independent with each other. There is a regional meter to calculate the power consumption of the entire system. In the actual operation process, we collect 300 sets of real-time data at different time periods for estimation. The estimated error of each meter is shown in Figure 4(a). Based on the results in Figure 4(a), we can quickly identify meters in abnormal operation (relative error greater than 2%). Besides, we also present a probability distribution chart of the estimated errors of the users' electric meters in the system. From Figure 4(b), we can evaluate the conditions of electric meters in the entire system and determine whether most electric meters in the system are in a normal working state. We can see from Figure 4(b) that the running errors of electric meters in the experimental area follow a normal distribution. Most of the running errors of electric meters are at low level (less than 1%).

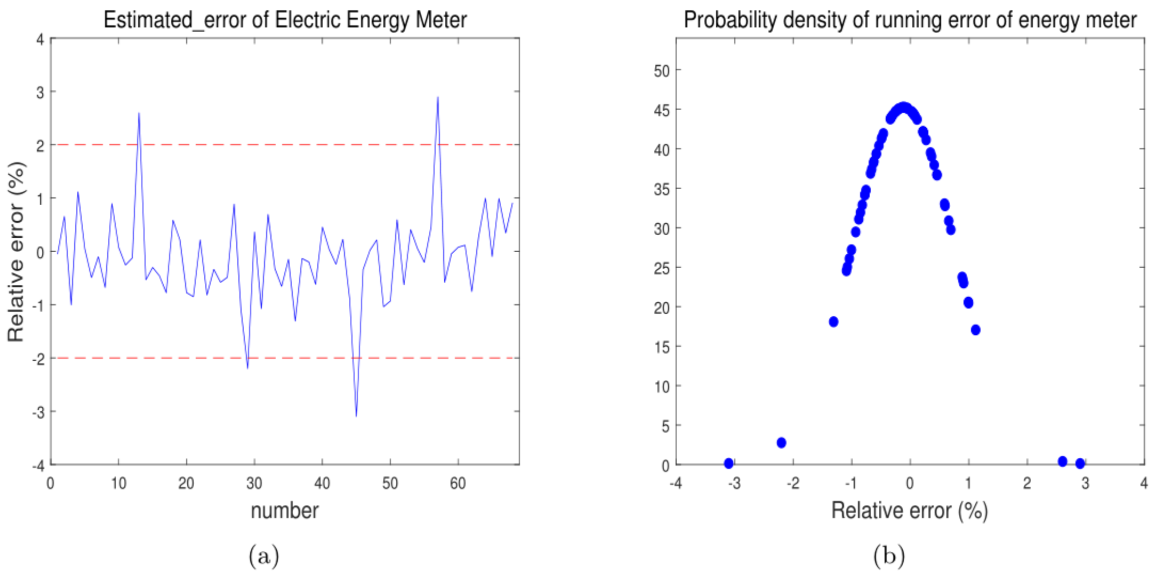

Figure 4. Estimated errors of electric meters and probability density of estimated errors.

To verify the accuracy of the proposed algorithm in this paper, we present the estimated error of each electric meter with different strategies in Figure 5(a). And we also provide the true value of running error as a reference. We select the traditional least squares algorithm (LS) and batch gradient descent algorithm (BGD) for comparison with our adaptive gradient descent algorithm (AdaGD). From Figure 5(a), we can see that the adaptive gradient descent algorithm proposed in this paper and the traditional least squares algorithm can better match the true error, while the batch gradient descent algorithm is not very accurate with more misjudgements. In addition, in order to provide a more intuitive representation of the accuracy under each strategy, we show the MAPE and RMSE value of each strategy in Figure 5(b), from which we can clearly see the proposed adaptive gradient descent algorithm holds higher accuracy in error estimation.

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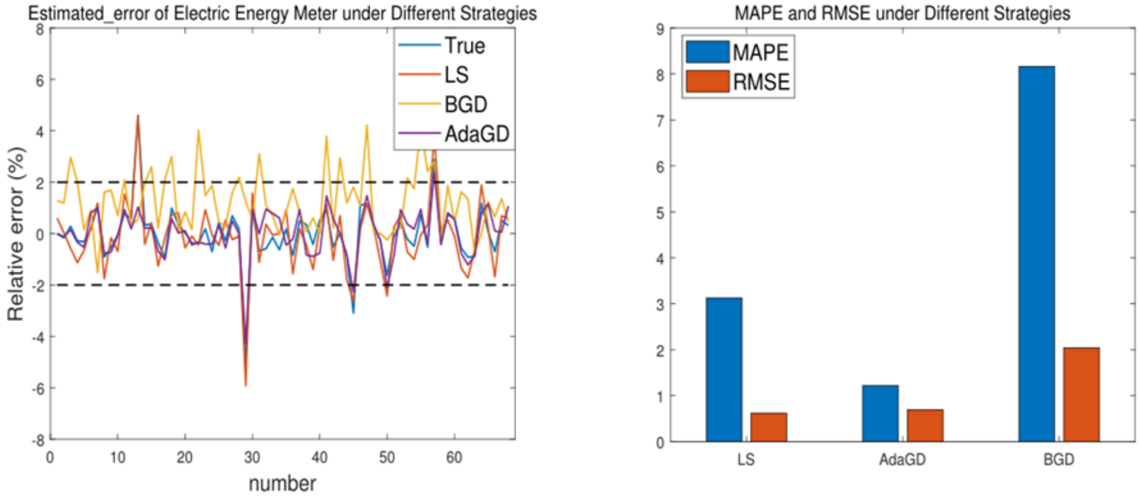
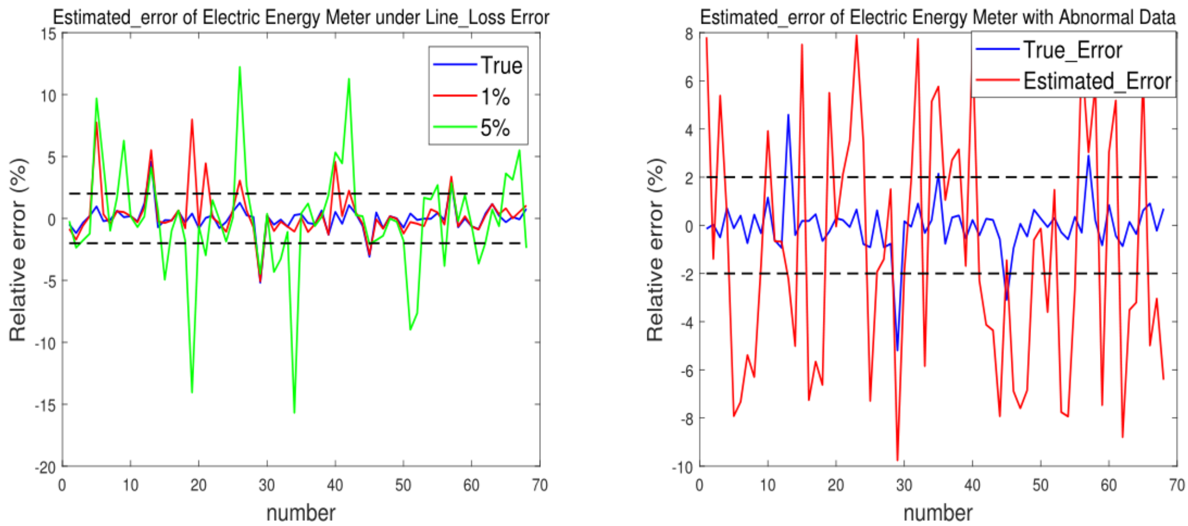


(a) (b)

Figure 5. Accuracy of different estimation strategies.

Due to the poor quality of the network parameters of the distribution network and the inaccuracy of the network parameters, it is difficult to obtain line loss accurately. We take the line loss calculation error into account in this part. In Figure 6(a), we present the estimated error of electric meters with 1% and 5% line loss calculation error. From Figure 6(a), we find that with the increase of the line loss calculation error, the misjudgement of the running error of the electric meters will also increase. Thus we need to ensure that the accuracy of the line loss calculation is high enough in practical applications. On the other hand, data under light load conditions will also affect the accuracy of the electric meter's running error estimation results. In Figure 6(b), almost all electric meters' estimated errors display large deviation from actual value with abnormal data included in estimation, which indicates that it is necessary to remove measurement data under light load condition.



(a) (b)

Figure 6. Estimated error under impact of different measurement data quality.

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5.CONCLUSION

This paper proposes an adaptive gradient descent method that can estimates the running error of electric meters remotely based on massive data, taking into account the situation of power loss in the on-site area. The algorithm proposed in this paper combines the latest developments in data processing, parameter estimation, etc., and makes full use of a large amount of data, which is more adaptable than the traditional method of solving linear equations with fewer sets of data. In addition, we consider the influence of different external factors as abnormal data and take measures to improve accuracy. Experiments proved that the estimation result of this method has high accuracy. The data-based estimation method for running error of electric meters can provide great convenience for the monitoring of the operation of electric meters, which is helpful to the construction of the smart grid. However, this method only estimates the average error of electric meters during the measurement period. In real situation, the operation error of electric meters may change with the different load. The subsequent work needs to consider the change of the load.

ACKNOWLEDGEMENTS

The authors acknowledge the Foundation of China Southern Power Grid Company Limited (Grant: GDKJXM20185871).

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