A Newly Designed Method for On-Line Error Estimation of Smart Meter

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Abstract. The method of manual verification of smart meters used at the current stage usually suffers from high cost, poor efficiency, and small coverage. A new method is presented to solve the error of energy meter by iteration. Firstly, the daily electricity data is collected and sifted through to classify the data for light-load and no-load meters. Then, by applying the outlier line-loss rate treatment method, it can obtain the invariable-loss & line-loss rate & the suspected out-of-tolerance meter and their initial values. After that, the meter error, invariable-loss, and line-loss rate can be calculated by the improved meter error estimation model. Based on the computed results, the data with relatively high and low line-loss rate are removed. It is to guarantee that the line-loss rate of data is within a small range. The sifted process removes the outliers and avoids the mis-deletion of the valid data, which improves the calculation accuracy. The proposed method proves to be effective in out-of-tolerance meter search by verifying the data from two different scale distribute-electricity transformer districts (DETDs) and comparing with the traditional least-squares method (LSM). The algorithm is easily applicable to small computation burdens.

1 Introduction

With the development of the smart grid, big data technology has been widely applied in the power industry, which leads to a massive utilization of smart meters. The accuracy of smart meter is related to the economical interests of users and public service providers, thus attracting considerable attention to error detection of running smart meters [1-3]. Traditional detection methods largely rely on manual operation, which is unable to meet the needs of a large number of smart meter error detection. Online error estimation has been proposed by taking advantage of operating data. Kochneva et al. [4] proposed a test equation method to detect the meter errors based on the state estimation theory. But, it requires a large number of statistical samples. Ukočius et al. [5] adopted the global maximization of the system error objective function to estimate the meter's error. Two random global extremum search techniques (genetic algorithm & pattern search) and nonlinear programming solver were used to further validate the reliability of the evaluated solution. Zhou et al [6] analyzed the influence of the current transformer and secondary circuit on the operating error in the view of the energy meter structures. Due to the randomness and ambiguity of the different factors of the error change, a new method is proposed in [6] for energy measurement error estimation based on membership cloud and
dynamic time warping. Lin et al. [7] utilized wavelet decomposition to decompose the
dynamic error sequence into a component group, then applied the optimized extreme
learning machines to predict each component individually. After the prediction results were
obtained through reconstruction, the dynamic error can be estimated. However, no practical
verification is conducted in it. In [8], Zhang et al. proposed an error estimation method
based on a parametric regression model. It estimated the dynamic error by pre-processing
the differential normalized data and then approximating the degradation characteristics of
the meter by the feed-forward neural network. However, the estimation results fail to meet
the realistic situation successively in a relatively long period.

In summary, although the outstanding achievements have been reached technically in
meter error computation, it is of great necessity to improve the accuracy and reliability of
error prediction. A new method is proposed to solve the problem of meter errors iteratively.
It applies the big data mining technology for online error detection in real-time, which
ensures fast and accurate detections and improves reliability.

This study is organized as follows. Section 2 introduces the principle of error estimation
of smart meters and proposes specific improvement methods on traditional estimation
models. Section 3 proposes a method for finding outlier line-loss rate data and analyzes the
rationality of the method. Section 4 explains the steps for iteratively solving the meter error.
Section 5 verifies the proposed method through two examples. Section 6 concludes.

2 Error estimation of smart meter

2.1 Traditional model

The energy measurement devices in the distribute-electricity transformer district (DETD)
usually consist of a main-meter and several sub-meters. The traditional method to find out
abnormal meters is to use the historical electricity data of the meters in operation, and
calculate the error of the meter based on the electricity data. Then the error-coefficient is
used to find out the suspicious out-of-tolerance meters. Finally, on-site verification is
carried out to confirm the operating status of the meters [10].

![Figure 1. Classical calculation model of meter error.](image)

The calculation model of meter error is investigated in Fig. 1. It is assumed that the
measurement errors may exist in sub-meters while the main-meter displays correctly. The
total electric energy includes the electric energy of sub-meters, line-loss electric energy,
invariable-loss electric energy, etc. The invariable-loss electric energy is the core-loss of
the transformers of voltage and current. In a certain DETD, the daily invariable-loss electric energy is fixed. The line-loss electric energy is closely related to the load, which fluctuates with the load in real-time. There are real and error components in the electric energies of the meter. That is, the above-related quantities follow the relations below:

\[ W_z = \sum_{i=1}^{m} W_i(1 + \epsilon_i) + W_g + \beta W_z \]  

(1)

where \( W_z \) is the total electric energy; \( W_i \) and \( \epsilon_i \) are the electric energy and estimated error-coefficient of the sub-meter \( i \); \( W_g \) is the invariable-loss electric energy; \( \beta \) is the line-loss rate and \( m \) is the number of the sub-meters. The estimated error-coefficient in Equation (1) is relevant to the real error-coefficient and the verification process is as follows.

\( \Delta W_i \) is defined as the sum of line-loss electric energy and invariable-loss electric energy. \( \Delta W \) is defined to be the sum of line-loss electric energy, invariable-loss electric energy, and the error of electric energy. \( W_i \) is the real electric energy of sub-meter \( i \). \( \epsilon_i \) is the real error-coefficient of sub-meter \( i \), and \( W_r \) is the error of electric energy. According to the electric energy calculation model, they can be expressed as:

\[ \Delta W_i = W_z - \sum_{i=1}^{m} W_i \]  

(2)

\[ \Delta W = W_z - \sum_{i=1}^{m} W_i \]  

(3)

\[ W_r = \sum_{i=1}^{m} W_i \cdot \epsilon_i = \sum_{i=1}^{m} W_i' - \sum_{i=1}^{m} W_i \]  

(4)

The error of electric energy can be obtained from Equation (2)-(4), that is,

\[ \Delta W - \Delta W_i = -\sum_{i=1}^{m} W_i + \sum_{i=1}^{m} W_i' = \sum_{i=1}^{m} W_i' \epsilon_i \]  

(5)

Then the following equation can be deducted from Equation (5).

\[ \sum_{i=1}^{m} W_i'(1 - \epsilon_i') = \sum_{i=1}^{m} W_i \]  

(6)

That is, for each sub-meter, \( W_i' \) can be expressed as:

\[ W_i' = \frac{W_i}{1 - \epsilon_i'} \]  

(7)

Since \( W_i' \epsilon_i' \) is equal to \( W_i \epsilon_i \), the relationship between estimated error \( \epsilon_i \) and real error \( \epsilon_i' \) is:
\[ \epsilon = \frac{\epsilon_i}{1 - \epsilon} \]  

(8)

In other words, once the estimated error is obtained, the real error can also be obtained according to Equation (8).

1.2 Model improvement

Since there are many parameters in Equation (1), it is impractical to accurately calculate the line-loss electric energy, invariable-loss electric energy, and the error-coefficient of all the meters individually by simply using daily electricity data. In fact, the least square method (LSM) is usually applied to estimate the parameters without considering the line-loss electric energy. However, it largely influences the accuracy of error estimation, which may result in misidentification. Hence, the original model is improved in this study and the line-loss electric energy is included in the calculation, so as to improve the accuracy of error computation. From Equation (1) - (7), it can be obtained that:

\[ \Delta W = \beta W_z + W_g + \sum_{i=1}^{m} \frac{\epsilon_i}{1 - \epsilon_i} W_i \]  

(9)

which can be written as

\[ \frac{\Delta W}{W_z} = \beta + \frac{W_g}{W_z} + \sum_{i=1}^{m} \frac{\epsilon_i}{W_i} \]  

(10)

In a DETD where daily electricity data is larger than the number of sub-meters, the following Equations can be obtained according to Equation (10).

\[
\begin{bmatrix}
\Delta W_1 \\
W_{z1} \\
\Delta W_2 \\
W_{z2} \\
\vdots \\
\Delta W_n \\
W_{zn}
\end{bmatrix}
= 
\begin{bmatrix}
1 & 1 & W_i(1) & W_i(2) & \ldots & W_i(m) \\
1 & W_{z1} & W_{z1} & W_{z1} & \ldots & W_{z1} \\
1 & W_{z2} & W_{z2} & W_{z2} & \ldots & W_{z2} \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
1 & W_{zn} & W_{zn} & W_{zn} & \ldots & W_{zn}
\end{bmatrix}
\begin{bmatrix}
\beta \\
W_g \\
\epsilon_1 \\
\epsilon_2 \\
\vdots \\
\epsilon_n
\end{bmatrix}
\]

(11)

where \( \frac{\Delta W_i}{W_{zi}} \) is the ratio of the sum of electric energy error, invariable-loss, and line-loss to the electric energy of main-meter on day \( i \). \( \frac{W_i(j)}{W_{zi}} \) is the ratio of sub-meter \( j \) electric energy to electric energy of main-meter on day \( i \).

The electricity data in one DETD in different period are linearly independent due to the uncertainty of real-time power load. The estimated error-coefficient can be calculated by Equation (11) once the collected daily electricity data exceeds than the number of sub-meters.
3 Processing of outlier line-loss data

3.1 Culling of outlier line-loss date

It can be seen from Section 2 that the line-loss rate varies with loads. Therefore, the measurement error estimation will be largely influenced due to the uncertain load fluctuation. However, the line-loss rate used in Equation (12) is constant, which is not the case in reality. In order to make the results more accurate, it is necessary to calculate the daily line-loss rate to remove the data of outlier line-loss rate. For this purpose, $\alpha W_z$ is defined to be the total relative error electric energy.

$$\alpha W_z = \sum_{i=1}^{m} T_i W_i$$  \hspace{1cm} (12)

where $\alpha$ is the total relative error-coefficient. Equation (9) is rewritten as

$$\Delta W = (\beta + \alpha) W_z + W_g = \theta W_z + W_g$$  \hspace{1cm} (13)

where $\theta$ is defined as the mixed line-loss rate.

In Equation (13), $W_g$ is unknown. So Equation (13) is rewritten as follows.

$$W_g = \Delta W - \theta W_z$$  \hspace{1cm} (14)

It is clear that the line-loss rate has fluctuation. Even if the total electric energy is the same, the value of $\Delta W$ under different line-loss rate is also different. From Equation (12), it can be seen that the error of electric energy mainly depends on the daily electricity consumption of the meter with a large error out-of-tolerance. If the line-loss electric energy is ignored, it can be seen that the daily electric energy of the out-of-tolerance meter will also affect the value of $\Delta W$ according to Equation (13). Considering the actual residents’ electricity consumption habits, $\theta$ is roughly equal in the case of the same $W_z$ and $\Delta W$. Therefore, once the data is selected reasonably, $W_g$ can be obtained from Equation (14).

There is usually not too many meters out of tolerance in one DETD in the maintenance cycle. Besides the proportion of error electric energy in the total electric energy is far less than the line-loss electric energy. That is, the total relative error-coefficient is very small. In other words, the coefficient $\alpha$ is far less than $\beta$, so $\theta \approx \beta$.

Line-loss rate on day $i$ is estimated as

$$\beta \approx \theta_i = \frac{\Delta W_i - W_g}{W_{zi}}$$  \hspace{1cm} (15)

In case of an extreme situation, such as the out-of-tolerance meter with large error-coefficient was found in the DETD, if $\alpha$ is not much less than $\beta$, then the Equation (15) will not be valid. At this time, the line-loss rate needs to be corrected. The steps of line-loss rate correction are as follows:

1. Sifting the sample of electric energy, and then select the sample with abnormal ratio of $\frac{\Delta W_i}{W_{zi}}$. 

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(2) Mark the suspected out-of-tolerance meter with large error-coefficient one by one and preliminarily determine its error-coefficient $\varepsilon_i$.

(3) Carry out line-loss rate correction, and use the data obtained in the first two steps to get Equation (16) with respect to Equation (13).

$$\beta \approx \theta = \frac{\Delta W - W_g - \sum_{i=1}^{k} W_i \varepsilon_i}{W_z}$$ (16)

where $k$ is the number of suspected out-of-tolerance meter with large error-coefficient.

During the normal life cycle of electricity meters, it is of low proporbility to find two or more out-of-tolerance meters with large error-coefficient in DETD. In extreme cases, when there are two meters with large error-coefficients of one positive and one negative in the DETD, the errors of electric energy may get cancelled. But, after data filtering, reasonable data can be selected to initially determine the error-coefficient. Besides, the line-loss rate can be corrected according to Equation (16).

According to the calculated daily line-loss rate distribution, more accurate error-coefficient can be obtained by removing the data with outlier line-loss rate. Here, the culling rule is defined as: data of $\delta \%$ of line-loss rate before and after sorting is removed, and the intermediate value is retained.

### 3.2 Rationality analysis

The $W_g$ fitted by Equation (14) is taken as the initial value of the line-loss rate calculation model. However, it is the average of multiple sets of data fitting, which is not accurate enough. Therefore, it is necessary to discuss the rationality of the calculation model in the case of imprecision.

$W_g'$ is defined to be the real invariable-loss electric energy, $W_g^{(1)}$ is the initial invariable-loss electric energy calculated by Equation (14), $\theta_i$ and $\theta_i'$ are the approximate and real mixed line-loss rate of sub-meter $i$, respectively. Through line-loss rate correction, the coefficient $\alpha$ is far less than $\beta$, so assume that $\beta_i \approx \theta_i$.

$$\theta_i = \frac{\Delta W - W_g^{(1)}}{W_z}$$ (17)

$$\theta_i' = \frac{\Delta W - W_g'}{W_z}$$ (18)

Deviation of mixed line-loss rate is:

$$\theta_i' - \theta_i = \frac{W_g^{(1)} - W_g'}{W_z}$$ (19)

If $W_z$ is larger and the difference between $W_g'$ and $W_g^{(1)}$ is smaller, the deviation of mixed line-loss rate will be smaller. Since the invariable-loss electric energy is composed of the core-loss of voltage and current transformer. When the electric energy sample is sufficient, the difference between the first calculated invariable-loss electric energy and the
real-loss electric energy is usually less than 0.5kwh. The total daily electric energy in the large DETD is basically greater than 1000kwh, so the deviation of mixed line-loss rate is less than 0.05%. Even in some DETD with a small number of meters, that is, the total daily power consumption is less than 1000kwh, the deviation of mixed line-loss rate will be larger, but the overall mixed line-loss rate still has a similar deviation rate. If it is processed according to the above line-loss rate cull rules, it will also get the data with the relatively centralized line-loss rate distribution. In a word, the application of abnormal line-loss rate calculation model will make the calculation of meter error more accurate.

4 Solve the error of energy meter iteratively

4.1 Data pre-processing

The following problems exist in the operation of smart meters. Firstly, the fluctuation of voltage and current and the load harmonic will lead to the heating of sampling circuit and the change of frequency characteristics. Secondly, the measurement error of meter will increase sharply under light-load and no-load condition. All of these may make the error temporarily exceed the standard error. Therefore, it is necessary to mark these possibly misleading electric energies before applying the proposed method to calculate the meter error-coefficient. Note that the data to be marked is mainly that of light-load and no-load.

When the amount of data is large, it is better to be classified by the method of clustering rather than manual marking. The data can be divided into three categories, that is, light-load, no-load, and normal-load. Data from the meters of light-load and no-load are also processed. When the results show that some light-load and overloaded meters are out-of-tolerance, the results can be ignored. That is to say, the light-load and over-load meters are not considered as the out-of-tolerance meters.

4.2 Error estimation of meter iteratively

Failure to delete all the outlier data may occur if the threshold $\delta$ is small, which may result in the inaccurate calculation. Besides, misdeletion of the valid data should be avoided as well. Therefore, the line-loss rate and error-coefficients of meters are calculated iteratively. Each time a part is culled, the outlier data is gradually culled through multiple iterations. The error estimation flow of smart meter is shown in Fig. 2, where $j$ is the number of iterations, $n$ is the number of iteration termination, $\beta^{(0)}$ is the initial line-loss rate, $W^{(0)}$ is the initial invariable-loss, $\beta^{(j)}$ and $W^{(j)}$ are the line-loss rate and invariable-loss electric energy calculated in the $j$th iteration, $\alpha_k$ is the error-coefficient of light-load meter or no-load meter, and $\alpha_i$ is the error-coefficient of meter $i$. The procedures are as follow.

S1: Set the initial value of $W^{(0)}$, $\beta^{(0)}$ and $\epsilon_i$, $W^{(0)}$ can be calculated according to Equation (14). $\beta^{(0)}$ is the average value of line-loss rate calculated by Outlier line-loss rate cull model. $\epsilon_i$ is the error-coefficient of the suspected out-of-tolerance meter. Generally speaking, if the size of the DETD is larger, the initial values of $W^{(0)}$ and $\beta^{(0)}$ will also be larger.

S2: Carry out iterative calculation according to Equation (11), and get the first iterative calculation result.

S3: Judge the error of light-load and no-load meters. If it is judged to be out-of-tolerance meter, S4 will be executed; otherwise, S5 will be executed.
S4: Correct the error value of light-load and no-load meters obtained in the last iteration.

S5: Update the line-loss rate, invariable-loss electric energy and error-coefficient of each meter calculated by iteration.

S6: Judge the updated parameter \( j \). if the number of iterations exceeds \( n \), the final result will be output. Otherwise, execute S7.

S7: Use the outlier line-loss rate judgment model to calculate the line-loss rate of each sample.

S8: Cull the data of outlier sample and enter a new iteration, that is, continue to execute S2.

5 Example analysis

The experimental samples are provided by the power grid measurement department of Fujian Province, China. In this example, the electricity data in two urban residential DETDs are used to verify the effect of the proposed method, and the least square method (LSM) based on the traditional calculation model is applied for comparison [11]. There are 17 sub-meters in the first DETD with the electricity data collected within 283 days, which is referred to as district 1. There are 109 sub-meters in the second DETD with the electricity data collected within 283 days, which is referred to as district 2. \( \delta \) is set to 10, and the
initial line-loss rate of the first and second district is 1% and 2%, respectively. The number of iterations depends on the size of the DETD. The size of the DETD is larger, the number of iterations will also be larger. For the first DETD, $n$ is 2, for the second DETD, $n$ is 3.

| Method       | Out-of-tolerance meters |
|--------------|-------------------------|
| LSM          | 14                      |
| Proposed method | $1^{\text{st}}$ iteration | - |
|              | $2^{\text{nd}}$ iteration | - |

**Table 1.** Calculation results of district 1.

**Figure 3.** Error-coefficient distribution in district 1. (a) Result of LSM; (b) Result of $1^{\text{st}}$ iteration; (c) Result of $2^{\text{nd}}$ iteration.

The error-coefficient distribution and calculation results in district 1 are shown in Fig. 3 and Table 1, respectively. It is clear that the calculation result of the LSM indicates that the sub-meter of No. 14 is out-of-tolerance meter, with the error-coefficient of 0.045. However, after two iterations, no out-of-tolerance meter is found in the proposed method. In fact, there is no out-of-tolerance meters in this DETD, so the performance of the proposed method is more accurate than that of the traditional method. In addition, it can be seen from Fig. 3 that the error-coefficient calculated by the LSM is larger than that of the proposed method. Besides, the deviation from the real error is larger. The reason is that the traditional method does not filter the electricity data and remove the abnormal line-loss rate samples, which causes a great interference to the error estimation. Besides, the solution of LSM is optimal, and the result is not necessarily reasonable. For example, the line-loss rate and the value of invariable-loss electric energy obtained by the solution are both 0, which is obviously inconsistent with the actual situation. In the proposed method, the last result is used as the initial value for the next iteration calculation. It can be seen that after the sample selection, the calculation results are only slightly different from that of the initial iteration, but closer to the real error. The comparison of the two iterations shows that the cull of outlier samples not only makes the calculation of line-loss rate more accurate, but also makes the results of electricity calculation model more precise.

The error-coefficient distribution before and after subtracting the out-of-tolerance meters in district 2 is depicted in Fig. 4 and Fig. 5, respectively. The calculated results are shown in table 2. The real out-of-tolerance meter is NO. 2, but the LSM diagnosed nine meters. When the proposed method is applied, in the first iteration, nine meters were sifted through by culling the samples with line-loss rate less than 1.5% and more than 3.1%. In the second iteration, the samples with line-loss rate less than 2% and more than 3% were culled, and two out-of-tolerance meters were further selected. After three iterations, error-coefficient calculated were more and more accurate. Finally, the meter of No. 2 was screened out to be out-of-tolerance, which is consistent with the real situation.
Table 2. Calculation results of district 2.

| Method      | Out-of-tolerance meters |
|-------------|--------------------------|
| LSM         | 2, 10, 11, 12, 24, 25, 29, 51, 87 |
| 1st iteration | 2, 11, 12, 19, 23, 24, 27, 45, 85 |
| Proposed method | 2, 85 |
| 3rd iteration | 2 |

Figure 4. Error-coefficient distribution in district 2. (a) Result of LSM; (b) Result of 1st iteration; (c) Result of 3rd iteration.

Figure 5. Error-coefficient distribution in district 2 after subtracting out-of-tolerance meters. (a) Result of 1st iteration; (b) Result of 2nd iteration; (c) Result of 3rd iteration.

6 Conclusion

A new online error estimation method was proposed for smart meters in this study. The classical calculation model of electricity error was improved. By calculating the line-loss electric energy, the result is more accurate than LSM. In addition, the outlier data was removed to avoid large line-loss rate deviation by calculating the line-loss rate iteratively in the distribute-electricity transformer district (DETD). Finally, the daily electricity data within a small range of line-loss rate can be obtained to estimate the error of each meter in the DETD.

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