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Remote Estimation of Measurement Error of Smart Meters based on AMI

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Abstract **– A remote calibration method of measurement error of smart meter, which has the characteristics of large quantity and difficult calibration one by one on site, is studied in this paper. First of all, we introduce the principle of estimation the measurement error of smart meter by using a large number of data collected by smart meter to the information center under the structure of Advanced Metering Infrastructure. Then, the relationship between reading of summary meter and sub-meters and line loss estimation is given. Finally, the influence of line loss estimation on the measurement error remote estimation of smart meter is analyzed and show the solution of the model can be solved by the mature iterative method.**

Keywords –Remote Calibration, AMI, Smart Meter, Line Lose

I. INTRODUCTION

Smart meter is an important part of smart grid, and it is also the basis of power grid operation control and trade settlement between power supply and power supply. The measurement results are directly related to the safety of power grid and whether the trade settlement between the two sides is fair and reasonable, so it is particularly important to determine the operation error state of smart meter [1-3].

Advanced Metering Infrastructure (short for AMI) is the basic link of smart grid. Its main function is to collect the system information with time scale, and to connect the users with the load to support the operation of the power grid[1, 4-6]. With the development of AMI and smart meter which can record and transmit electricity data, power supply company can accumulate a large amount of active power, voltage, current, power factor, positive and negative power grid state data from ever meter.

The measurement data collected by AMI should not only exist in the database, but should be utilized. With the help of the rich communication and computing storage resources of AMI, the data should be processed and excavated deeply to realize its value.

Generally speaking, load forecasting is carried out using system level data and with little or no information at lower levels, such as, substation level, feeder level, transformer level, or residential level. It is the consensus of academic and industrial researchers to use high-voltage level data for load forecasting, one can see [7, 8]. Based on the emergence of AMI structure and the application of a large number of intelligent meters, it is possible to carry out more accurate load forecasting through a large number of household load data [4, 6, 9-16].

In fact, the main direction of these applications is to use AMI data to load forecasting. Although the data of smart electric meter based on AMI structure have made some progress in load forecasting, there are few applications in other fields.

The traditional power grid metering system realizes the reliability of electric energy metering through the verification of the initial installation of electricity meter, regular calibration, periodic replacement and so on. These steps are particularly complex for meters with huge number, and require lots of costs [6].

In fact, the electric energy flowing through the summary meter should be the sum of all the sub-meters (household meters) and the loss on the line in AMI structure. On the basis of this principle, the research of remote estimation of measurement error of smart meters is possible by using a large number of electric energy metering data of smart meters.

In this paper, the remote estimation of measurement error of smart meters is theoretically explored by using the data of sub-meters and the summary meter data in different time in a region. The relationship between the summary meter, sub-meters and the line lose based on AMI structure is analyzed. Then the influence of line loss on the accuracy of measurement error estimation of each meter in the model is analyzed.

The proposed method provides a theoretical basis for the measurement error verification of large-scale smart meters.

II. ESTIMATION MODEL OF MEASUREMENT ERROR

In AMI system, the structure of summary meter and sub-meters in a region can be shown in Fig. 1, where M represents the smart meter, subscript represents the summary meter within the area, the number i form 1 to n means the label of sub-meters.

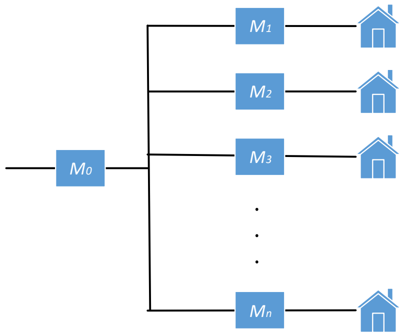

Fig. 1. Physical structure of smart meter based on AMI structure

The specific power transfer can be described by the following equation:

$$\sum_{i=1}^{n} E_i^j = E_0^j - L^j \tag{1}$$

where $i = 0,1,2,\cdots,n$, $j = 0,1,2,\cdots,m$, $m > n$, E_i^j represents the real electric energy flowing through the i -th meter M_i during the j -th measurement, L^j represents all power line losses during the j -th measurement, mainly includes leakage loss, line loss, power consumption of sub-meters M_1 to M_n , etc.

The energy value given by (1) is the real energy value in theory. In reality, the electrical energy used by householder is measured by the increment of smart meter readings. Denote δ_i as the relative measurement error of meter M_i . Then, the increment of smart meter reading can be expressed by the real flow of energy as

$$O_i^j = (1+\delta_i) E_i^j$$

where O_i^j express the increment of the reading of meter M_i during the j -th measurement.

Next, the real energy flow E_i^j in (1) of meter M_i during the j -th measurement can be expressed as

$$E_i^j = \epsilon_i O_i^j \tag{2}$$

where $\epsilon_i = \dfrac{1}{1+\delta_i}$ represents the ratio of the real energy flowing through the meter M_i to the reading increment.

Put (2) into (1), one can obtain the following equation:

$$\sum_{i=1}^{n} \epsilon_i O_i^j = \epsilon_0 O_0^j - L^j . \tag{3}$$

Then, by (3) and the data collection of m , $m > n$ reading increments, the power transfer in a region based on AMI can be expressed as

$$\mathbf{Ax} = \mathbf{b} \tag{4}$$

where $\mathbf{A} \in \mathbb{R}^{m\times n}$ represents m times reading incremental data matrix of sub-meters M_1 to M_n sent by the communication module of smart meters, $\mathbf{x} \in \mathbb{R}^n$ represents the ratio of the real energy to the reading increment of M_1 to M_n , $\mathbf{b} \in \mathbb{R}^m$ represents the vector of m times difference between the total electric energy flowing through the region and the total loss in the region. Specifically, it can be expressed as

$$\mathbf{A} = \begin{pmatrix} O_1^1 & O_2^1 & \cdots & O_n^1 \\ O_1^2 & O_2^2 & \cdots & O_n^2 \\ \vdots & \vdots & \ddots & \vdots \\ O_1^m & O_2^m & \cdots & O_n^m \end{pmatrix}, \mathbf{x} = \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{pmatrix}, \mathbf{b} = \begin{pmatrix} \epsilon_0 O_0^1 - L^1 \\ \epsilon_0 O_0^2 - L^2 \\ \vdots \\ \epsilon_0 O_0^m - L^m \end{pmatrix}, \tag{5}$$

respectively.

By calculating the solution $\mathbf{x}$ of equation (4), the measurement relative error of meter M_1 to M_n in the region can be determined.

In the next section, the influence of the estimation accuracy of line loss $L^i, i = 1,2,\cdots,m$ on the estimation of measurement error of meters is analyzed.

III. INFLUENCE OF LINE LOSS ESTIMATION ACCURACY

Denote by $C(J,\mathbb{R}^n)$ the metric space of vector-value continuous functions from $J \to \mathbb{R}^n$ endowed with the norm $\|z\| = \sqrt{\sum_{i=1}^{n} |z_i(t)|^2}$. For $A:\mathbb{R}^n \to \mathbb{R}^n$, we consider its matrix norm $\|\mathbf{A}\| = \max_{\|z\|=1} \|\mathbf{A}z\|$ generated by $\|\cdot\|$.

Assuming that the energy measured by the summary meter is accurate, and in fact, the measurement accuracy of the summary meter is also much higher than that of the household sub-meters. Therefore, the error $\mathbf{b}$ in formula (5) depends only on the estimation of line loss.

Denote the estimation error of $\mathbf{b}$ is $\Delta\mathbf{b}$, and then we can rewrite (4) as

$$\mathbf{A}(\mathbf{x} + \Delta\mathbf{x}) = \mathbf{b} + \Delta\mathbf{b} \tag{6}$$

where $\Delta\mathbf{x}$ represents the perturbation of the solution $\mathbf{x}$ with the influence of $\Delta\mathbf{b}$.

Due to (4) and (6), one can obtain $\mathbf{A}\Delta\mathbf{x} = \Delta\mathbf{b}$, that is to say,

$$\Delta\mathbf{x} = \mathbf{A}^{-1}\Delta\mathbf{b}. \tag{7}$$

Taking norm for (7), we have

$$\|\Delta\mathbf{x}\| \le \|\mathbf{A}^{-1}\| \cdot \|\Delta\mathbf{b}\| \tag{8}$$

according to the basic properties of norm.

By (4), we can obtain

$$\|\mathbf{A}\| \cdot \|\mathbf{x}\| \le \|\mathbf{b}\| \tag{9}$$

Next, by (8) and (9), we have

$$\frac{\|\Delta\mathbf{x}\|}{\|\mathbf{A}\| \cdot \|\mathbf{x}\|} \le \frac{\|\mathbf{A}^{-1}\| \cdot \|\Delta\mathbf{b}\|}{\|\mathbf{b}\|}$$

and then one can obtain the effect of $\mathbf{b}$ depended on line loss on the measurement error $\mathbf{x}$

$$\frac{\|\Delta\mathbf{x}\|}{\|\mathbf{x}\|} \le \|\mathbf{A}\| \cdot \|\mathbf{A}^{-1}\| \frac{\|\Delta\mathbf{b}\|}{\|\mathbf{b}\|} \tag{10}$$

where $\|\mathbf{A}\| \cdot \|\mathbf{A}^{-1}\|$ is also represented as the condition number of matrix $\mathbf{A}$.

IV. CONCLUSIONS

This paper explores a new application direction of smart meter data under AMI structure. Make full use of the meter power data sent by the smart meter to the data center, provides a new research idea for on-line analysis of measurement error of large-scale smart electric meter. Then the main factors affecting the measurement error of smart meter are analyzed. This specific model can be solved by using the iterative method of linear equations, the least square method, which is now more mature.

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