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Online Calibration for Smart Meters

Fangxing Liu[1,2],Chengbin Liang[2,3] Qing He[2]

[1] *Harbin Institute of Technology, Harbin, P. R. China*
[2] *National Institute of Metrology, Beijing, P. R. China*
[3]*Hunan University, Changsha, P. R. China*
Email: liufx@nim.ac.cn

Abstract **– Smart Meters have been deployed in different countries around the world during the past decade. Also, smart meter has been considered as the key element in the smart grid and substantial smart meter data analytics academic research have been conducted. A popular application for massive smart meter data analytics is monitoring smart meter running statues. Online calibration for is a novel method which compute meter errors through analysing meter data. This paper presents a comprehensive survey and basic model of smart meter online calibration. Meanwhile, we discuss low voltage electricity system model, data collection, novel learning algorithm issues and research trend of the remoting calibration method.**

Keywords – smart meter data analytics, online calibration, low voltage system, smart meter

I. INTRODUCTION

Smart meter is an important terminal of smart grid and it is not the same as traditional electricity meter. In addition to the basic function of metering electricity, smart meter has two-side communication and multiple measurement model. It also contains multiple data transmission modes and the anti-stealing function, etc. The smart meter represents the development direction of the intelligent terminal of the energy-saving smart grid in the future.

The widespread popularity of smart energy meter enables a massive of electricity data to be collected, such as consumption data, voltage, current. In china, 460 million smart meter have been installed while the deployed smart electricity meter in US and UK beyond 70 million and 2.9 million [1].

Smart meter data analytics became a hot research filed. Many novel methods and algorithms have been developed on application of energy data analytics. The aspect of analysing energy data includes consumer profiling, load forecasting, electricity pricing, irregularities identification, metering and real-time operations. Consumption data analytics could help to build consumer behaviour and then forecast their consumption [2]. The energy data shows the peak and troughs of daily electricity consumption and form the pricing strategy according to the energy usage character. Abnormal data could be detected through the insight relationship of energy usage data. Also, online data analytics will help to monitor the equipment through collecting data constantly.

II. ONLINE CALIBRATION

In many countries, the smart meter calibration were conducted in professional laboratory. If a meter need to detected, the electrician should remove the meter from site and install a new one, then send the removed meter the professional agencies to test its metrological character. It's a time-consuming and labor cost process when the smart meter number is large. Many smart meters were designed to be used more than 10 years. In this way, energy company sets specific years to replace energy meters such as China Smart Gird remove meters at the eighth year in order to reduce the testing costs. Also, some energy operator conducts random sampling to pick up part of meters to test their performance, then to infer the quality of all meters. The deficiency of those methods are it can't measure the working statues of all meters, so it's difficult to make decision whether the smart meter should continue to use or need to be removed.

Online Calibration for smart meter is a novel method that to compute meter errors by processing data from smart meter. Due to the increased digitization of smart meter, multiple types of energy data can be stored and transmitted to energy data centre. Those data type contain energy consumption, voltage, current, time, location, installation condition. Those data contain huge information related to the energy meter, power system and remoting measurement is one application for those energy data.

This Section gives a brief introduction to online calibration for smart meters. The low voltage system is a topological structure system where there is a mater meter followed by some submeters (Figure1). The central data centre collected meter data from smart meters through communication system. A mater meter is installed at the end of low voltage transformer, then a cluster of submeters deployed. The energy first pass through the mater meter then flow to energy-consuming house. Each house has at least one submeter. The master energy consumption equals the sum of submeters energy usage during the same time under ideal conditions. This can be written in equation [1].

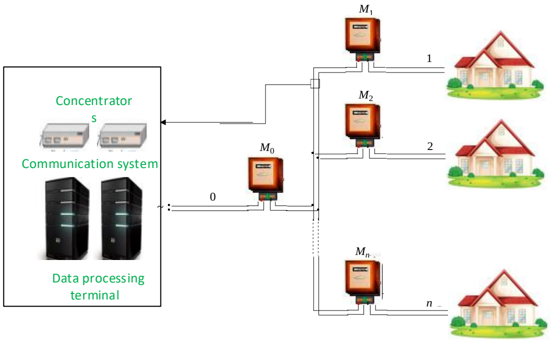

Figure 1 Low Voltage System Structure

$$\sum_{j=1}^{n} E_{j,i} = E_{0,i} \tag{1}$$

Where $E_{j,i}$ is the ture energy data of submeter j at time slot i. $E_{0,i}$ is the master meter energy consumption at time j. However, the meter has relative error which is not the ture energy data. So equation (1) can be rewritten as equation (2).

$$\sum_{j=1}^{n} \frac{e_{j,i}}{1+\varepsilon_j} + E_j = \frac{e_{0,i}}{1+\varepsilon_0} \tag{2}$$

Where ε_i is the relative error of meter i, $e_{j,i}$ and $e_{0,i}$ are the meter energy reading of submeter and mater meter respectively. The relative error of meter j is denoted by ε_j.The energy lossess during period E_j.We pick up at least i time slots data and constuct the equation. This can be written as equation (3).

$$\begin{bmatrix} e_{1,1} & e_{2,1} & \cdots & e_{i,1} \\ e_{1,2} & e_{2,2} & \cdots & e_{i,2} \\ \vdots & \vdots & \ddots & \vdots \\ e_{1,i} & e_{2,i} & \cdots & e_{n,i} \end{bmatrix} \bullet \begin{bmatrix} \frac{1}{1+\varepsilon_1} \\ \frac{1}{1+\varepsilon_2} \\ \vdots \\ \frac{1}{1+\varepsilon_n} \end{bmatrix} = \begin{bmatrix} \frac{e_{0,1}}{1+\varepsilon_0} - E_1 \\ \frac{e_{0,2}}{1+\varepsilon_0} - E_2 \\ \vdots \\ \frac{e_{0,i}}{1+\varepsilon_0} - E_i \end{bmatrix} \tag{3}$$

The time slot n is no less than the submeter number. The solution of equations is the relative error.

This is the basic theory of online meter calibration that compute meter relative error through its data.

III. RESEARCH ISSUES

The basic idea of online calibration has been introduced in session II and it will be perfect measurement method under the condition that all data and system structure should be available and clearly formulated. However, the real low voltage system is a complex energy network and smart meter data quality is not as good as expected. There are several issues in mart meter online calibration application.

A. Data Collection Issues

In order to construct and solve the equation successfully, all data should be collected in the same time period. The more data, the more accurate result. In some energy system, the data were transmitted one time a day, while in another system meter data were collected every 15 minutes. In a 200 submeter system, an equation requires at least 200 sets data. If we filter low quality data, it needs more data. It is a long period for a system that store only one set data a day. Online calibration requires aggregation for a long time in a low-frequency data collection system.

Data consistency is also an important aspect should be concern. In the framework of remote testing, the data collected from master meter and submeters should have the same period. In the real data collection, part of submeter fail to receive the signal to send data immediate and transmit the delayed data to control centre. Those nonsynchronous data will affect the validity of online calibration model.

Data collection is an important foundation part of remoting calibration. This is an issue that the analyst hardly to solve in mathematical way. It’s necessary to confirm the synchronization of data.

B. Energy system issues

In the normal low voltage system, a master meter followed by some submeters. In power system, the voltage and current are three-phase. Submeter are single-phase energy meter in the real energy system. In the energy structure model, all submeters are in same phase so that the master meter energy equals the sum of submeters’. However, the real energy system may mix the submeter in different phase. There are at least two phases submeter connected on branch of a master meter. The mater meter does not match the total sum submeters. The equation doesn’t work that will influence the solve error significantly. A number of literature attempt to identify the topology structure such as principal component analysis, graph-theoretic interpretation [3-5].

The proposed method involves the application of and its to infer the steady state network topology from smart meter energy measurements.

C. Abnormal data issues

Abnormal data always exist in power system. Power theft and some miss-quality data caused by environment will generate abnormal data. The master meter have record the energy flow data while the submeter did not collect the really energy consumption because of energy theft. Those abnormal data will break the equality relationship and damage the meter error solution.

Electricity theft is a worldwide problem and utilities have attempted to address the problem by analysing smart metering. Supervised learning method is an effective approach to detect the abnormal data. Clustering-based feature extraction approach and SVM algorithm is used in abnormal data analytics [6-8]. To train a abnormal data detector and then input the real data to classify and determine the bad data.

A pre-processing of smart meter data will be a great help to complete the online error computing

D. Energy losses issues

Energy losses is every common in the energy network. Most energy losses happened on the power line and the equipment self-consumption. In the low voltage system, the smart meter self-consume is fixed. More energy waste on the power line. The more accurate estimation is, the more effective the online calibration is. However, the length of power line from each master meter to submeter is hardly to measure. Also, the current is an average number during a period and energy losses couldn't be accurately compute and measure.[9]

Smart meter readings available for a low voltage system line losses estimation [10,11]. A loss factor is usually used to esitmate losses by multiplying the peak load.

The deviation energy losses estimation will bring much trouble to the remoting meter calibration.

E. Analysis Methods

Solving the equation is one of the most effective method for online calibration under complete smart meter data. However, some data sets contain the interference information that influence the equation solving. More algorithms have been proposed to reduce the effect of disturbed data.

New technologies involve computer science, particularly in machine learning. Cluster and regularization theory were used to analysis online smart meter error[12]. Deep learning is popular in among smart grid data analytics. Transfer learning and incremental learning has also been used in smart meter analytics technologies [13].

Machine learning is a powerful method in data analytics. When introduce one algorithm to solving a problem, the meaning and physical implication should be taken into consideration carefully.

IV. CONCLUSIONS

In this paper, we have explained the online calibration of smart meter, including online calibration principle and some issues in application. Online calibration is a promising metrological method in the future with the development of data acquisition and data analytics. Smart meter data analytics on remoting calibration is an emerging research area which has huge application and economic value. We hope that this paper can provide readers a picture and insights of online calibration.

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