July - August 2020
ISSN: 0193-4120 Page No. 3674 - 3681

Remote Estimation Method for Running Error of Smart Meters Based on Genetic Optimization LM Algorithm

Liang Chen[1], Youpeng Huang[1], Tao Lu[1], Sanlei Dang[1], Zhengmin Kong[2*]
[1] Meteorology Center of Guangdong Power Grid Co. Ltd., Guangzhou, China.
[2] School of Electrical Engineering and Automation, Wuhan University, Wuhan, China.
Email: zmkong@whu.edu.cn

Article Info Volume 83
Page Number: 3674 - 3681
Publication Issue:
July - August 2020

Article History
Article Received: *25 April 2020*
Revised: *29 May 2020*
Accepted: *20 June 2020*
Publication: *10 August 2020*

Abstract

To solve the problems of high work intensity, long verification cycle and low management efficiency in the current way of smart meter verification, a remote estimation method for the running error of smart meters based on the genetic optimization LM algorithm is proposed in this paper. Firstly, the relationship between the running error of smart meters and the electricity consumption is deeply analyzed based on the measurement data of various users. Then, the genetic optimization LM algorithm is applied to estimate the running error of smart meters. Finally, the performance of the proposed algorithm is tested with the real measurement data of a power grid. The results show that an accurate estimation for the running error of smart meters can be achieved when the measurement data is sufficient.

Keywords: *smart meter, AMI data, running error, remote estimation, Genetic algorithm, LM algorithm*

1.INTRODUCTION

With the development of the Ubiquitous Electric Internet of Things, smart meters have become extremely important sensor terminals in the sensing layer of the smart grid due to their high accuracy and versatile features [1, 2]. The smart meters are responsible for precise energy measurement tasks, laying the foundation for the realization of digital smart grid functions. In addition to electricity billing, the measurement data from smart meters can also be used for other advanced applications such as electricity consumption behavior analysis [3], demand response strategy design [4] and electricity market pricing [5]. However, the above-mentioned applications are dependent on the accurate measurement of smart meters. The measurement accuracy of smart meters not only directly affects the actual interests of consumers, but also affects the operation of the power company [6].

In theory, it is a very difficult task to judge the status of each running smart meter to timely identify the ones with error overruns or faults and replace them as soon as possible. A large-scale replacement without screening will waste a lot of manpower and material resources [7]. The current

July - August 2020
ISSN: 0193-4120 Page No. 3674 - 3681

monitoring method for measurement accuracy of energy meters in the world is to spot check on users periodically [8]. This method is time-consuming and cannot fully detect the failed meters, let alone monitor all running meters on the network.

With the widespread use of advanced metering infrastructure (AMI) in smart grids, power companies have accumulated a mass of electricity measurement data [9, 10]. Based on these data, different methods for abnormal electricity metering analysis are considered in recent studies. Reference [11] proposed an autonomous error algorithm based on the reading of energy meter cluster in the tree topology. However, this method requires a large amount of data and has poor real-time performance. Furthermore, it can only obtain the average error under a certain load distribution. Reference [12] proposed a remote estimation method for measurement error of energy meters based on the limited memory recursive least square algorithm. In this method, the measurement data of similar operation state are screened out according to the power consumption level of users, and the line loss of the distribution area is calculated based on the power flow analysis. However, this method excludes the measurement data under light load, and the accuracy of error estimation is dependent on the accuracy of line loss calculation. With the massive data of AMI, Reference [13] introduced the concept of weighted average of relative measurement error and optimized the linear equations of measurement error estimation. A remote abnormal measurement point diagnosis model was then proposed. However, the calculation result of this model is sensitive to many factors such as the electricity consumption environment and users' electricity consumption. The research [14, 15] tried to find abnormal measurement points from the perspective of line loss management, and established an intelligent diagnosis model of line loss based on the collected data.

To sum up, although there have been some research results in the field of abnormal analysis of energy metering, the existing methods have a poor real-time and accuracy performance. The estimation accuracy of energy meters is not only affected by the authenticity and reliability of collected data, but also limited by the performance of the adopted optimization algorithm. In Reference [16], a method of using the Levenberg-Marquardt (LM) algorithm to optimize the parameters of error estimation model was considered and proved to be effective. However, this method is easy to fall into the local optimum. To avoid this, this paper proposes a genetic optimization LM algorithm for remote error estimation of smart meters. This method deeply analyzes the relationship between the running error of smart meters and the electricity consumption according to the measurement data of the sub-station area. On this basis, the genetic optimization LM algorithm is used to remotely analyze the running error of smart meters. The performance of the proposed method is tested with the measurement data of a real distribution sub-station area. The results show that this method can significantly improve the accuracy of error estimation, thus providing guidance for the online status assessment and rotation of smart meters.

2.NETWORK TOPOLOGY ANALYSIS OF SUB-STATION AREA

Generally, there are two types of smart meters in a typical distribution sub-station area. One is the high-precision smart meter (hereinafter referred to as the total-meter) installed under the distribution transformer in the sub-station area, which is used to measure the electricity consumption of all users in the sub-station area. The other one is the smart meter (hereinafter referred to as a sub-meter)

July - August 2020
ISSN: 0193-4120 Page No. 3674 - 3681

installed on each user side, which is used to measure the power consumption of a single user. The connection between the total-meter and the sub-meters is radial. That is, one total-meter is connected to m sub-meters (shown in Figure 1).

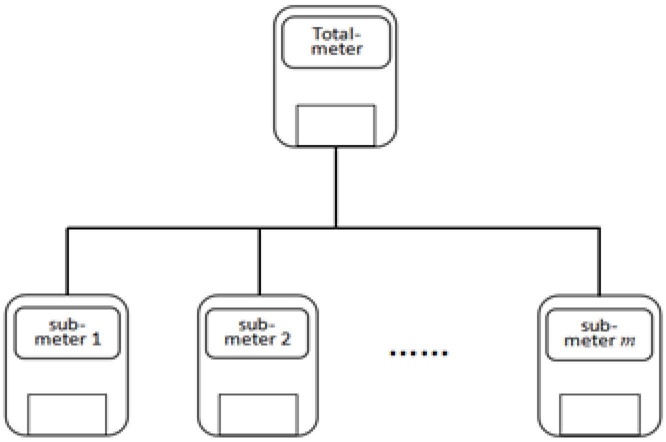

Figure 1. Electrical topological structure diagram of a typical distribution sub-station area.

The measurement accuracy of the total-meter is usually much higher than that of the sub-meter, so the total-meter is set as a standard meter without measurement error. The reading of the total-meter can be regarded as the electricity consumption of the entire sub-station area. In addition, the power loss in the process of energy transmission from the total-meter to the sub-meter and the measurement error of sub-meters cannot be ignored. Based on the law of conservation of energy, the relationship between the reading of the total-meter and that of the sub-meters can be obtained. That is, in any measurement period, the reading of the total-meter is equal to the sum of the readings of sub-meters plus the total line loss during the period and the measurement errors of sub-meters, i.e., "total meter reading" - "energy loss" = "sum of sub-meter readings" + " sum of sub-meter metering errors".

3.MATHEMATICAL MODEL FOR RUNNING ERROR ANALYSIS OF SMART METERS

As shown in Figure 1, the topological structure of smart meters in a sub-station area is tree-like. We assume that there is a total-meter M_0 and *m* sub-meters M_i $(i=1,2,\cdots,m)$ in a sub-station area. During a measurement period *t*, the actual energy consumption associated with M_0 and M_i are $\overline{y}_0$ and $\overline{x}_i$ $(i=1,2,\cdots,m)$, respectively. Considering the power loss w_{L}, the relationship between $\overline{y}_0$ and $\overline{x}_i$ can be written as

$$\overline{y}_0=\sum_{i=1}^{m}\overline{x}_i+w_{\mathrm{L}} \tag{1}$$

During the measurement period *t*, we denote the reading increments of the total-meter and *i*th sub-meter as y_0 and x_i, respectively. Generally, all the smart meters in use have running errors. Since the error of the total-meter is much smaller than that of the sub-meter in practice, we assume the running error of the total-meter M_0 be 0（$y_0=\overline{y}_0$）. The relative error δ_i of the *i*th sub-meter is defined as

$$\delta_i=\frac{x_i-\overline{x}_i}{\overline{x}_i}, \tag{2}$$

where $\overline{x}_i$ and x_i are the actual power flowing through the *i*th sub-meter and the reading increment of the *i*th sub-meter, respectively. According to (2), we can get

$$\overline{x}_i=\frac{x_i}{1+\delta_i}. \tag{3}$$

Let

$$\varepsilon_i=\frac{1}{1+\delta_i}, \tag{4}$$

then (1) can be rewritten as

TEST Engineering & Management

July - August 2020
ISSN: 0193-4120 Page No. 3674 - 3681

$$y_0 = \sum_{i=1}^{m} x_i \varepsilon_i + w_{\rm L} \quad . \tag{5}$$

In practice, the power loss includes the line loss, the leakage loss and other losses. The line loss is the heat loss caused by the line current, which can be described by (6). Here, r_l is the resistance of line l that can be calculated according to the nature of the line and $I(\tau)$ is the real-time current during the measurement period *t*. Under the condition that the topology of the sub-station area, the length of the line, the working current and the voltage of each sub-meter are measurable, the line loss of the sub-station area can be obtained by weighting the total length from the total-meter to each sub-meter,

$$w_{\rm L} = \sum_{l=1}^{m} \int_0^t I^2(\tau) r_l d\tau \quad . \tag{6}$$

Other losses such as the leakage loss and the equipment loss are fixed losses that are not related to the topology of the sub-station area. The calculation of the leakage loss requires the leakage conductance, which is related to the material's property parameters and is difficult to obtain. In order to simplify the model, we assume that the fixed loss is an independent constant ε_0. Based on the above analysis and assumptions, we denote $y = y_0 - w_{\rm L}$ and rewrite (5) as

$$y = \sum_{i=1}^{m} x_i \varepsilon_i + \varepsilon_0 \tag{7}$$

The formula (7) is the remote estimation model for analyzing the running error of smart meters in this paper. Obviously, the estimation accuracy is related to the accuracy of calculating the line loss and the method for solving the equation (7).

4.REMOTE ESTIMATION FOR THE RUNNING ERROR OF SMART METERS BASED ON THE GENETIC OPTIMIZATION LM ALGORITHM

The LM algorithm is a parameter optimization algorithm, which seeks an approximate solution of unknown parameters through iterative optimization calculation. The algorithm procedure is as follows.

Step 1: Take the initial point p_0 and set the threshold constant α , $k=0$, λ_0=10^{-3}, ν=10 (or other values larger than 1). Calculate

$$\alpha_0 = \|a - f(p_0)\| . \tag{8}$$

Step 2: Calculate the *Jacobi* matrix $\mathbf{J}_k$, and

$$\bar{\mathbf{N}}_k = \mathbf{J}_k^{\rm T} \mathbf{J}_k + \lambda_k \mathbf{O} \tag{9}$$

with the identity matrix O.

Construct incremental normal equations

$$\bar{\mathbf{N}}_k \sigma_k = \mathbf{J}_k^{\rm T} \alpha_k . \tag{10}$$

Step 3: Solve the incremental normal equation to get σ_k.

(1) If

$$\|a - f(p_k + \sigma_k)\| < \alpha_k ,$$

then let

$$p_{k+1} = p_k + \sigma_k ; \tag{11}$$

if also $\sigma_k < \alpha$, then stop the iteration and output the result. Otherwise, let

$$\lambda_{k+1} = \nu \lambda_k , \tag{12}$$

go to **Step 2**;

(2) If

$$\|a - f(p_k + \sigma_k)\| \ge \alpha_k ,$$

then resolve the incremental normal equation to get σ_k and back to **Step 1**.

The genetic algorithm is a heuristic search algorithm used to solve optimization problems in the field of artificial intelligence. It is a kind of evolutionary algorithm. The algorithm process is as follows.

July - August 2020
ISSN: 0193-4120 Page No. 3674 - 3681

a) Initialization: Set the counter of generation as $t=0$ and choose the maximum number of generation *T*. Randomly generate *M* individuals as the initial population $P(0)$.

b) Evaluation: Calculate the fitness *F* of each individual in the population $P(t)$ as

$$F=\sum_{j=1}^{n}\left|y_j-y_{Pj}\right|. \tag{13}$$

c) Selection: Apply the selection operator to the population. Its purpose is to directly select the optimized individuals to breed a new generation or to generate new individuals through pairing and crossover to breed the next generation. This operation is based on assessing the fitness of individuals in the population.

d) Crossover: Apply the crossover operator to the population. The crossover operator plays a core role in the genetic algorithm.

e) Mutation: Apply the mutation operator to the population. That is, to alter one or more gene values in a chromosome from its initial state.

Through selection, crossover and mutation, the population $P(t)$ generates the next generation population $P(t+1)$.

f) Termination: If $t=T$, stop the algorithm and output the individual with the smallest fitness during the evolution process.

This paper uses the genetic optimization LM algorithm to solve the error remote estimation model (7). Firstly, the line loss w_L is calculated with the branch resistance r_l of the line *l* and the real-time current $I(\tau)$ during the measurement period *t*. While the line loss is known, there are *m* running error parameters ε_i and a fixed error parameter ε_0 to be solved in the model (7). Then the genetic algorithm is applied to seek an optimal value of these $m+1$ parameters, which is used as the initial input to the LM algorithm. The values of ε_i and ε_0 are obtained by the iteration process of the LM algorithm. Finally, the relative error δ_i of each sub-meter is derived based on (4).

5.EXPERIMENT RESULTS

In order to verify the effectiveness of the proposed method, we use a sub-station with 80 users under a certain area of Guangdong Power Grid as the experimental area. Each user's smart meter is independent of each other, and there is an area meter that can calculate the power consumption of the entire sub-station area. In this experimental area, we collect 260 sets of real-time data in different time periods. Before estimating the running error, we preprocess the collected data. The data sets with an acquisition success rate less than 100% are cleared, resulting in 238 sets of usable data. Meanwhile, the users with zero electricity consumption or with the days of zero consumption exceeding 60% of the total days are excluded, which remains 60 users finally. After the data preprocessing, we use the genetic algorithm to select the optimal value of parameters for the initialization of the LM algorithm. The maximum number of generation is set as T=20. At the beginning, the minimum fitness of the population declines with the number of generation. After 13 generations, the minimum fitness of the population remains unchanged and thus the population reaches the optimal. The selection process is shown in Figure 2.

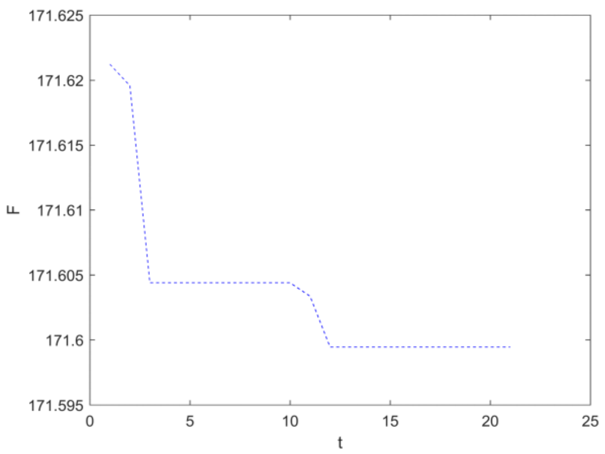

Figure 2. Fitness curve of the genetic algorithm.

The selected parameters by the genetic algorithm are then inputted into the LM algorithm as the initial value to estimate the running error of smart meters. The estimation results are shown in Figure 3. As observed in this figure, the proposed algorithm can quickly identify the meter in abnormal operation (with a running error greater than 2%).

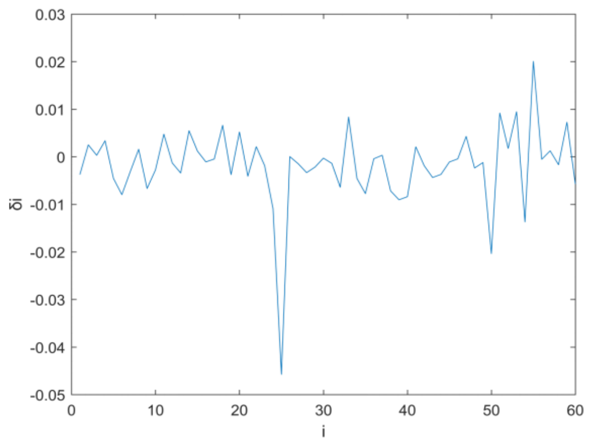

Figure 3. Estimated running errors of smart meters.

To verify the estimation accuracy of the proposed algorithm, the relative error R_i between the estimated running error (δ_i) and the true running error ($True_i$) of the smart meter is presented in Figure 4. Here,

$$R_i = \frac{\delta_i - True_i}{True_i} \times 100\% \tag{14}$$

From Figure 4, the proposed algorithm has a good performance on estimation accuracy with a small relative error less than 10% [17].

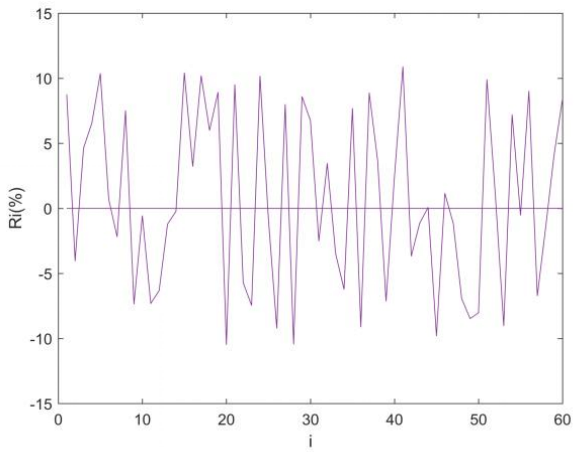

Figure 4. Relative error of the estimated running error.

To further verify the effectiveness of the proposed algorithm in this paper, the least squares (LS) algorithm and the classical LM algorithm are introduced for comparison. The running errors of smart meters under three different algorithms and their true values are presented in Figure 5. It can be seen that the proposed genetic optimization LM algorithm has a better performance than both the LS algorithm and the classical LM algorithm. In addition, we introduce two indexes, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) to quantitatively evaluate the performance of three algorithms. The definitions of two indexes are given in (14) and (15), respectively. The values of MAPE and RMSE for each algorithm are listed in Table 1. According to Table 1, the proposed genetic algorithm has a smaller value of both MAPE and RMSE, which further proves its better performance on estimating the running error of smart meters.

July - August 2020
ISSN: 0193-4120 Page No. 3674 - 3681

$$\mathrm{MAPE} = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\delta_i - True_i}{True_i} \right| \tag{15}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\delta_i - True_i)^2} \tag{16}$$

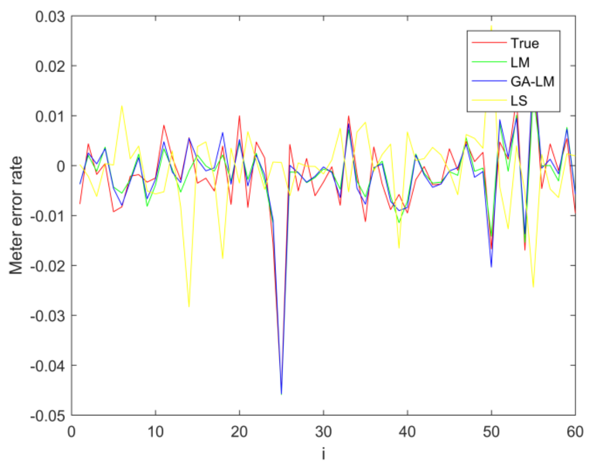

Figure 5. Estimated running errors under different algorithms.

Table 1. The values of MAPE and RMSE under different algorithms

Algorithm	MAPE	RMSE
LS	221.2	0.0143
LM	113.7	0.0036
Genetic optimization LM	104.8	0.0031

6.CONCLUSION

This paper presents a remote estimation method for the running error of smart meters based on the genetic optimization LM algorithm. This method takes consideration of the power loss of the sub-station area and is able to estimate the running error of smart meters remotely. The proposed genetic optimization LM algorithm combines the latest developments in data processing and parameter estimation, and makes full use of the massive measurement data, which is more adaptable than the traditional methods of solving linear equations with fewer data sets. The performance of the proposed method is demonstrated by the experiments in a real sub-station area. With the high accuracy of running error estimation, the proposed method will provide great convenience for the operation monitoring of smart meters and is also beneficial for the construction of smart grid. However, this method only obtains the average value of running errors during the measurement period. In practice, the running error of smart meters may change with time. How to estimate the instantaneous value of running error deserves further studies in the future.

ACKNOWLEDGEMENTS

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

REFERENCES

[1] F. Liu, C. Liang and Q. He, Remote malfunctional smart meter detection in edge computing environment. IEEE Access, 2020, 8, pp. 67436-67443.

[2] Z. Zhou, J. Gong, Y. He, and Y. Zhang, Software defined machine-tomachine communication for smart energy management. IEEE Commun. Mag., 2017, 55(10), pp. 52-60.

[3] L. Zheng, W. Hu, and Y. Min, Raw wind data preprocessing: A data-mining approach. IEEE Trans. Sustain. Energy, 2015, 6(1), pp. 11-19.

[4] X Yin, H Liu, C Yin, et al., The error model of the smart meter under the influence of low temperature . International Conference in Communications, Signal Processing, and Systems Springer, Singapore, 2017, pp.1909-1915.

[5] S. E. Collier, The emerging enernet: Convergence of the smart grid with the internet of things. IEEE Ind. Appl. Mag., 2017, 23, pp. 12-16.

[6] N. Bui, A. P. Castellani, P. Casari, and M. Zorzi, The internet of energy: A web-enabled smart grid system. IEEE Network, 2012, 26, pp. 39–45.

[7] Ž. Nakutis, S. Rinaldi, P. Kuzas and R. Lukočius, A method for non-invasive remote monitoring of energy meter error using power consumption profile. IEEE Transactions on Instrumentation and Measurement, 2020, early access.

[8] B. A. Rodrigues Filho, N. S. Nonato, A. D. Carvalho, A risk analysis approach applied to field surveillance in utility meters in legal metrology. Journal of Physics, 2018, 975, pp. 1-5.

[9] C. J. Bandim, J. J. Alves, A. V. Pinto Jr., et al., Identification of energy theft and tampered meters using a central observer meter: a mathematical approach. IEEE PES Conference and Exposition in Transmission and Distribution, 2003, pp. 163-168.

[10] J. Peppanen, M. J. Reno, R. J. Broderick, et al., Distribution System Model calibration with big data from AMI and PV inverters. IEEE Transactions on Smart Grid, 2016 7(5), pp. 2497-250.

[11] S. C. Yip, K. S. Wong, W. P. Hew, et al., Detection of energy theft and defective smart meters in smart grids using linear regression. International Journal of Electrical Power & Energy Systems, 2017, 91, pp. 230-240.

[12] X. Kong, Y. Ma, X. Zhao, et al., A Recursive Least Squares Method with Double-Parameter for Online Estimation of Electric Meter Errors. Energies, 2019, 12(5), pp. 1-16.

[13] A. Korhonen, Verification of energy meters using automatic meter reading data. Named Entities Workshop. Association for Computational Linguistics, 2012, pp. 12-20.

[14] Y. Cheng, J. Du, J. Xiao, et al., Application of variable weight fuzzy analytic hierarchy process in evaluation of electric energy meter. IEEE Advanced Information Technology, Electronic and Automation Control Conference, 2017, pp. 1985-1989.

[15] D. N. Nikovski, Z. Wang, A. Esenther,et al., Smart meter data analysis for power theft detection . Machine Learning and Data Mining in Pattern Recognition. Springer Berlin Heidelberg, 2013.

[16] J. Zhao, L. Mili, R. C. Pires, Statistical and Numerical Robust State Estimator for Heavily Loaded Power Systems. IEEE Transactions on Power Systems, 2018, 33(6), pp. 6904-6914.

[17] L. Yao, Y. Hu, J. Wu, et al., Error analysis and compensation for Non-Integer-Period sampling in energy metering of smart substation. Zhejiang Electric Power, 2015, 34(09), pp. 1-5.