Non-invasive Power Load Monitoring Method Based on Cloud Edge Collaboration

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Abstract. With the large-scale penetration of renewable energy, the safe and stable operation of power grid and economic dispatch are facing great challenges. How to realize accurate perception of internal load characteristics of power users is an important technical difficulty to support power demand side management. For this reason, this article is based on extensive IOT technology in electricity, and a non-invasive power load monitoring method (NILM) based on cloud edge collaboration is proposed. Through the two-level architecture of “edge identification” and “cloud correction”, the method effectively overcomes the contradiction between the weak computing capability of edge terminal and the heavy communication pressure of cloud master station. The experimental results show that the method can effectively improve the accuracy and reliability of traditional NILM method by considering the influence of external factors.

1. Introduction

In the proportion of energy consumption, electric energy is an important form of energy consumption in social production and life. Therefore, advocating energy conservation and emission reduction is the basis of current energy conservation work. Some studies have shown that under the circumstance of introducing feedbacks of electricity consumption information, the residential load will have greater energy saving potential. However, the traditional load detection method is usually based on the intrusive way, which increases the cost of sensors for users. On the other hand, the measuring points of the monitoring system is fixed and does not have flexible extensibility. Compared with invasive power load identification method, non-invasive power load identification is the direct extraction of electric current, voltage information at the power entrance of house. The identification algorithm is adopted to manage for situation of electrical equipment, which can avoid too much of the sensor installed in electric equipment, but also contribute to understanding of the user load. Therefore, it can guide power users to reasonably arrange the time and methods of using electricity, support the power grid to adjust the peak-valley difference, reduce the power grid loss, achieve energy saving and reduce consumption, and enhance users’ awareness of power saving.

In this paper, a non-invasive power load monitoring method (NILM) based on cloud edge collaboration is proposed. Through the two-level architecture of “edge identification” and “cloud correction”, the method effectively overcomes the contradiction between the weak computing capability of edge terminal and the heavy communication pressure of cloud master station. The experimental results show that the method can effectively improve the accuracy and reliability of traditional NILM method by considering the influence of external factors.
2. The principle of cloud edge collaboration NILM

The principle of NILM based on cloud edge collaboration mainly includes two parts, one is “edge primary identification”, the other is “cloud secondary correction”. The detailed principle is shown in figure 1.

1) In the “edge primary identification” part, the data import module refers to extracting useful information related to the data set that is known to be collected. The data preprocess module is to analyse digital signals such as voltage, current, power and other raw data. Then, the useful feature vectors are extracted, and a reasonable load decomposition model is established.

2) In the “cloud secondary correction” part, the communication data correction module adjusts the data missing items and abnormal data in the communication process. The cloud data fusion module can effectively integrate external data such as climate and consumption level, and make a secondary correction to the edge identification results to obtain the final power load identification results.

3. The process of edge identification

Electrical equipment typically consists of two states: start and stop. When the equipment is started, the power value at the power inlet will suddenly increase. Therefore, we can consider that the total power value data of power load is a one-dimensional time series. On the one hand, it has uncertainties, such as circuit loss and random interference; on the other hand, under certain conditions, time series has an obvious change trend. At this point, for some equipment that are normally open for a certain period of time, the amplitude change is always zero. So we use the percentile method to remove the normally open device signal \( a_y(t) \). Firstly, \( th \) is used to represent the normally open threshold.

\[
th = \text{The 50\% percentile of input sequence} \tag{1}
\]

The percentile is calculated as follows:

1) The \( T \) values of the observed value sequence \( y_t, t = 1, 2, \ldots T \) are arranged from large to small, and \( y_t \) represents the \( t \)th value in the sequence.

2) To calculate the exponent, suppose \( (T + 1)P = j + g \), \( j \) is integral part and \( g \) is fractional part.

3) When \( g = 0 \), the percentile of \( P \) is \( y_t \). Otherwise, when \( g \neq 0 \), the percentile of \( P \) is \( gy_j + (1 - g)y_{(j+1)} \).
In this paper, we set $P=0.5$ to remove normally open device information. The hundreds digit value can be calculated through equation (1), and the normally open sequence value can be obtained through equation (2). Finally, the changed part $v_y(t)$ can be obtained through equation (3).

\[
a_y(t) = \begin{cases} 
  th & \text{if } y(t) > th \\
  0 & \text{else} 
\end{cases} 
\]

\[
v_y(t) = y(t) - a_y(t)
\]

On this basis, we preprocessed and identified the total power data values of six families. In a certain period of time, we sampled the total power data values every 5 seconds, and then removed the power values of normally open devices. The total power data waveform in family 1 and the power data sequence waveform after remove the normally open device signal are shown in figure 2.

4. The process of cloud identification
Due to the large number of loads in the residential electricity network, the calculation amount of load composition in the judgment of mixed load is large, and the optimization process of genetic algorithm is efficient and fast, which can greatly reduce the calculation amount. Therefore, genetic optimization algorithm is adopted to modify the load identification results in the cloud in this paper. See figure 3 for the specific realization process.
Figure 3. Cloud identification realization process.

1) Obtain the load data of residents, calculate the active power and current effective values, and normalize the data to eliminate dimensional influence for the convenience of subsequent calculation.

2) Design the coding mode, formulate the corresponding fitness function, and determine the experimental parameters of the genetic algorithm.

3) Randomly generate the combined value of two load characteristics and change it into a chromosome after coding; Random characteristic combination value is generated until the number of chromosomes reaches the set target and the initial population is formed.

4) Carry in the encoded chromosome to calculate the fitness function of the chromosome, eliminate part of the load characteristic combination value according to the set probability, and the remaining chromosomes generate new chromosomes through a series of operations such as replication, crossover and mutation.

5) Judge the fitness function of the population, and the chromosome with strong adaptability will be selected. The selection was repeated until the chromosome with the optimal fitness was screened out, and the combination of load characteristics was obtained according to the chromosome, so as to achieve the purpose of load identification.

5. The result of cloud edge collaboration
Table 1 shows the average absolute difference between the four categories of equipment decomposed by six families using NILM based on “cloud edge coordination” (NILM-CEC) and “local identification” (NILM-LI) respectively. In the first family, we use NILM-CEC design model of
equipment, and the absolute difference of load identification is below 5%, and the average absolute difference is 2.75%. Meanwhile, the absolute difference of NILM-LI is less than 13%, and the average absolute difference is 7%. In family 4, the absolute difference between device 3 and device 4 is the same, but comparing device 1 and device 2, NILM-CEC method still works better. In family 2, 3 and 5, although the absolute difference of one kind of equipment using method A for load identification is slightly smaller, in general, the average absolute difference of method B is smaller and the accuracy of the algorithm is higher. In family 6, although the absolute difference between device 2 and device 3 after using NILM-CEC method for load identification is relatively large, from the overall analysis data of 6 families, the effect of NILM-CEC method for load identification is generally better.

| Family | Equipment 1 | Equipment 2 | Equipment 3 | Equipment 4 | Average absolute difference |
|--------|-------------|-------------|-------------|-------------|-----------------------------|
| Family 1 | 4% | 3% | 13% | 3% | 5% | 3% | 6% | 2% | 7% | 2.75% |
| Family 2 | 0% | 0% | 13% | 10% | 10% | 9% | 17% | 18% | 10% | 9.25% |
| Family 3 | 1% | 6% | 7% | 1% | 9% | 2% | 10% | 6% | 67.9% | 3.75% |
| Family 4 | 7% | 3% | 21% | 11% | 21% | 21% | 16% | 16% | 162.5% | 12.75% |
| Family 5 | 9% | 1% | 0% | 0% | 2% | 12% | 17% | 7% | 7% | 5% |
| Family 6 | 3% | 3% | 13% | 23% | 8% | 21% | 9% | 1% | 82.5% | 12% |

### 6. Conclusion
In this paper, a non-invasive power load monitoring method (NILM) based on cloud edge collaboration is proposed. Through the two-level architecture of “edge identification” and “cloud correction”, the method effectively overcomes the contradiction between the weak computing capability of edge terminal and the heavy communication pressure of cloud master station. The experimental results show that the method can effectively improve the accuracy and reliability of traditional NILM method by considering the influence of external factors.

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