Appliance Recognition Based on Continuous Quadratic Programming

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Abstract. The detailed information of residents' electricity consumption is of great significance to the planning of the use of electrical appliances and the reduction of electrical energy consumption. On the basis of analyzing the characteristics of residents' load, through the event detection of changes in the status of electrical appliances, using binary planning to solve the idea of global optimal solution, using the constraints of 0-1, proposed a continuous binary planning model. Based on the proposed load identification algorithm, personal power consumption data can be subdivided into load levels. The test results show that the recognition accuracy can be obtained by selecting the appropriate load identification index. The algorithm can be applied to non-intrusive load monitoring systems in residential buildings.
Keywords: Load Signature; Nonintrusive Load Monitoring; Load Identification; Quadratic Programming.

1 Introduction

At present, residential electricity monitoring systems are mainly divided into two major categories: The first category is discrete monitoring, that is, the installation of discrete sensors (such as smart plug Seats) Monitor the operating status of each appliance and obtain information on the power consumption of the appliance; however, discrete monitoring systems have high hardware costs, complex communication networks, and inconvenient maintenance. The other type is centralized. The client installs the monitoring equipment to obtain the family's total power consumption information. Non-intrusive load monitoring (NILM) refines the total power usage information to the load level to obtain the power usage of each appliance. Centralized residential electricity monitoring .The hardware cost of the measurement system is low, the communication network is simple and easy to maintain.

NILM technology was proposed by Professor Hart of the Massachusetts Institute of Technology in the early 1980s [1]. Its algorithm is based on the steady-state macro load characteristics obtained by low-frequency hardware, such as active or reactive power. In recent years, many scholars have conducted more research work in the field of NILM technology. Many companies have also invested in NILM technology research and product development [2, 3]. In [4, 5], it introduced a variety of non-intrusive methods, non-intrusive methods can be divided into steady state analysis (mainly based on low-frequency hardware) and transient analysis methods (based on high-frequency sampling hardware). Steady-state analysis mainly monitors active power and reactive power. When the current changes and exceeds the set threshold, the difference between active power and reactive power changes is calculated [6]. Harmonic analysis can identify some ambiguous cases, especially non-linear loads [7, 8]. Relevant studies have shown that the higher load identification accuracy can be obtained by adopting the steady-state macro characteristics and transient micro-characteristics of residential load obtained by high-frequency hardware. In [9], it proposed a method based on S-transform for residents' load feature extraction that can take into account the signal characteristics in both time and frequency domains. A resident load identification method was also proposed based on BP neural network, which can greatly reduce the computational complexity. In [10], it proposed a load identification method based on genetic algorithm.

This paper innovatively proposes a new identification algorithm—non-intrusive load identification algorithm based on 0-1 quadratic programming. The algorithm can be integrated in the monitoring device or sensor on the home side to identify the open status of the device according to different load identification characteristics.

2 Background

2.1 The Features of Load Signature

The load characteristics are electrical characteristics that are unique to consumers when they consume electricity [11]. The load characteristics of different electrical equipment may have large or small differences, such as different active and reactive power consumptions of different equipment; current curves and harmonic content of linear load and nonlinear load are different; electric and non-electrical Load VI characteristics are different. Based on the voltage and current signals monitored by the residents' homes, the load can be calculated Characteristics of indicators for the identification of residents of electrical appliances. Common residents' load characteristics [12] mainly include the following types.

A Load signature is fined as the electrical behavior of an individual appliance of equipment when it is in operation. Each home application contains unique features in its consumption behavior. The behavior is limited to what can be monitored at a point of interest (smart socket used in this paper).These variables normally include cur-rent, voltage and power measurements. Millions of electrical appliances in operation today. With an increasing number of electrical appliances, it is infeasible and impractical to obtain a complete database for all equipment. Therefore, we focus on developing a set of generalized and critical features that can be extracted from conventional measurements. The authors have divided two forms of load signature [13]. The first is called snapshot form and another is called delta form.

Snapshot Form - In this form, the signature is the instantaneous snapshot of the load behavior taken at any fixed time intervals. This signature is generally a compo-site load with many load signatures mixed in it.

Delta Form - The form tells the difference between two sequential snapshot form load signatures. If the time interval is small enough, we regard the delta form signature as a single appliance's load behavior more likely than composite load.

Feature extraction is used to capture features around the event points. Nowadays, the researchers study steady-state and transient feature .The features can be divided into two types according to the sampling frequency: steady-state features and transient - state features.

Steady-State Features- There are Power step feature, steady current waveform feature, V-I trajectory feature, harmonic feature and so on.

Transient-State Features- There are transient power waveform feature, starting current waveform feature, voltage noise feature and so on.

Due to the different type load waveform of similar equipment is different, so it is necessary to establish the load data set of commonly used household appliances, appliance load data acquisition using universal smart meters, and according to its manufacturer, type and mode are stored in the data set, the user can according to their own conditions to determine the decomposition of data sets, and through use a separate electric appliance will add to the unknown data of electrical load data.

On the other hand, current harmonics can also describe the non-linear load characteristics of non-sinusoidal currents. Harmonics are used in combination with active and reactive power [14] to improve the performance of the detection algorithm, but harmonic analysis requires waveforms. High frequency sampling. Study in [15] shows that parallel electrical operation has unique steady-state harmonics for their respective combinations.

Wave signature. Although this method is well-suited for identifying the load of on/off appliances and normally open appliances, load identification requires consideration of the available harmonic signature data sets for all possible combinations of equipment.

V-I trajectory characteristics: Research in [16] proposed a new method using V-I trajectories to classify groups of appliances. V-I trajectories use normalized current and voltage values to divide each appliance. The V-I trajectories classify the appliances into eight groups, each providing further subdivisions. Using a unique curve to establish the classification of appliances, studies have shown that V-I trajectory-based methods are more effective than existing methods based on power consumption measurements.

3 Event Detection Algorithm

Event detection refers to the use of edge detection algorithm to extract load change events on the total energy consumption curve and collect a series of features before and after the event point for subsequent load decomposition. The causes of load events are: (1) changes in the state of one or more devices; (2) noise; (3) normal operation of devices with continuously changing power consumption without a change in state. For the first reason, the event detection algorithm needs to reduce the missed rate of real events; for the latter two reasons, the event detection algorithm needs to reduce the false detection rate of "false events".

Before the event detection, the original load curve needs to be smoothed and filtered to eliminate some spikes and outliers, thereby reducing the false detection rate and the missed detection rate of load events. Research work in [17] proposed a method of total variation regularization, which can remove noise at low signal-to-noise ratios and preserve important details such as signal edges. Its principle is that signals that may contain pseudo-details have a high total variation, so the absolute gradient integral of the signal is high. Research work in [18] recorded a rapid electrical status switching event as a triangle, recording a steady state electrical work event as a rectangle. Research work in [19] proposed that the residual method is used to detect events included in the household energy consumption curve. This method uses the window to calculate the average of the active power energy consumption curves of the initial and final samples, and compares the difference between the two and the prior The set threshold is compared. If it is greater than the threshold, electrical events will be detected and recorded. Research work in [20] proposed generalized likelihood ratio detection, which is an on-line edge detection method based on the change of average value. The purpose is to find out the value jump of load waveform at a certain moment. The jump is often due to changes in the state of the appliance.

We call the process of changing the on-state, off-state, and state of the electricity load as the occurrence of a switching event, which is a transient event. The problem of transient events such as the change of the status of the load or status of the electrical appliances used for general detection can be categorized as point-of-change monitoring. Change point monitoring has many use scenarios, most of which are used in the detection of machine faults and monitoring of various signal mutations. The basic definition of a change point is that in a sequence or process, when a statistical characteristic changes at a certain moment due to the influence of system factors, we call this point in time a change point. Change point identification uses a statistical method to estimate the position of the change point, which is defined as follows:

Assuming there is such a data set, each data observation value is independent of each other. If at any moment, one or more variables in the model suddenly change, there is a time point before the data point. Load a distribution after which the dataset is loaded with another distribution, which is the change point of the dataset.

Change point identification uses certain statistical indicators or statistical methods to monitor the status of the time series to accurately and accurately estimate the change point location. In the 1970s, many statisticians invested in the research field of variable point problems, and achieved some results. Some methods for estimating and detecting change points have also been developed and improved, such as cumulative flat methods and methods, iterative cumulative flat methods, and methods. Maximum likelihood method, etc. This paper use a sliding bilateral CUSUM of electrical load switching event detection algorithm. CUSUM automatic detection algorithm for transient events, accumulates sample data information, and improves the accuracy of detection of small offsets by accumulating small offsets in the sliding window process.

3.1 Load identification algorithm

Quadratic programming is a very classic optimization problem, including convex quadratic programming and non-convex quadratic programming. In this type of problem, the goal is a quadratic function of the variable whose constraint is the linear inequality of the variable. Assuming that the number of quantifiers is d and the number of constraints is m, the mathematical expression model of the standard quadratic programming is as follows:

$$minf(x)=\frac{1}{2}x^{T}Qx+c^{T}x \tag{1}$$

Common quadratic programming problem solving methods are: (1) ellipsoid method (2) interior point method (3) Lagrange method (4) gradient projection method. In real life, the switching events of the electrical appliances are mutually exclusive, either closed or open. Therefore, we think of the use of binary programming to solve mutually exclusive planning problems and constraints on the mutual exclusion of functions to apply to load decomposition. For the constraints of quadratic programming, we decided to introduce 0-1 nonlinear constraints, and its model becomes a quadratic programming problem with constraints of 0 and 1. The mathematical model has the following expression:

$$\begin{cases} \min g = Y'^{T}Y' - 2Y'^{T}\varphi\overrightarrow{X} + \frac{1}{2}(\overrightarrow{X}\varphi^{T}2\varphi\overrightarrow{X}) \\ x_i = \{0,1\} \end{cases} \tag{2}$$

Based on the above basic principles of quadratic programming, this paper proposes a non-intrusive load decomposition algorithm based on quadratic programming. 0 and 1 as constraints of the operating state of an appliance. The specific algorithm idea is: Known characteristic matrix of all electrical loads in the power system.

$$\varphi=\begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdot & \varphi_{1N} \\ \varphi_{21} & \varphi_{22} & \cdot & \varphi_{2N} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \varphi_{\mathrm{M}1} & \varphi_{\mathrm{M}2} & \cdot & \varphi_{\mathrm{MN}} \end{bmatrix} \tag{3}$$

N is the number of loads in the power system. For a multi-state electrical appliance such as an air conditioner, each working state is regarded as an electrical load processing, and thus N is greater than the actual number of electrical appliances in the electrical power system. M is the number of types of extracted load features.

The actual measured data extracted to identify the feature vector is Y:

$$Y' = \left[y'_1, y'_2, \ldots y'_{\mathrm{M}}\right]^{T} \tag{4}$$

Then the relational expression of Y and Y' is

$$Y' = Y + \varepsilon = \varphi\overrightarrow{X} + \varepsilon \tag{5}$$

Then the equation is transformed into the following model to find the minimum value.

$$\min g = Y'^{T} Y' - 2Y'^{T} \varphi\overrightarrow{X} + \frac{1}{2}(\overrightarrow{X}\varphi^{T} 2\varphi\overrightarrow{X}) \tag{6}$$

Since the constraints are 0-1 planning problems, the solution to the above planning problem can only be a discrete method. The discrete algorithm is to solve the integer programming directly from the discrete characteristics of the design variables. Most of the traditional discrete methods belong to combinatorial algorithms, such as exhaustive methods and implicit enumeration methods. Such algorithms can accurately find the global optimal solution of the problem, but with the increase of the scale of the problem, the calculation cost is very high. The other is a discrete heuristic algorithm, such as a genetic algorithm. The main disadvantage of this approach is that it does not handle constraints well, and it is prone to premature convergence problems. The continuous method does not have the above problem equation (1), so the above problem is transformed into a continuous method for solving.

$$\begin{cases} \min g = Y'^{T} Y' - 2Y'^{T} \varphi\overrightarrow{X} + \frac{1}{2}(\overrightarrow{X}\varphi^{T} 2\varphi\overrightarrow{X}) \\ \sum_{i=1}^{N} a_i (x_i - x_i^{2}) = 0 \end{cases} \tag{7}$$

The actual measured data extracted to identify the feature vector is Y' :

$$Y' = \left[y'_1, y'_2, \ldots. y'_{\mathrm{M}} \right]^{T} \tag{8}$$

Then we are asking for the vector of the state of the work of each appliance:

$$\overrightarrow{X} = [x_1, x_2, x_3, x_4, \ldots. x_N]^{T} \tag{9}$$

where $\vec{X}$ is the state vector of the appliance, where the values can only be 0 and 1.

Processing procedure of the recording data First, when the installation of the monitoring device is completed, it needs to be established. Household appliance identification indicator database for the whole family, database construction .This is done by manual registration. When the test starts, from the data Reading the identification index of each appliance in the library and establishing the identification index matrix. Detects switch events using the CUSUM algorithm when detected on off event, according to the acquired voltage, current signal acquisition switch Change the amount of signal before and after the piece, extract the value of each identification index, and establish the difference.

The value matrix Y' by solving matrix $\vec{X}$ in equation (7), you can identify at the moment, the switch state has changed.

4 Load Identification Algorithm Testing and Analysis

In order to test the accuracy of the quadratic programming-based algorithm proposed in the previous section, a test platform was set up in the laboratory and five kinds of electrical equipment such as desk lamps, air conditioners, induction cookers, refrigerators, and dishwashers were selected as test objects. In the parallel access power system, a digital sensor is installed at the total power consumption to collect signals. Collecting separately (1) only one power load state changes at a time, and other power loads are off at that time. (2) Only one load changes at a time, and this load changes. When the status changes, other power loads are in the running state.

The first load characteristic values are used to build a database of load characteristics for five loads, and then 60 sets of electricity consumption data for each load are collected.

Table 1. Recognition accuracy of single identify indicator

application	features	accuracy	application	features	accuracy
light	H	93	Electric-heat	H	92
	PQ	92		PQ	94
	V-I	90		V-I	93
	P	94		P	94
oven	H	92	Washer-dryer	H	93
	PQ	94		PQ	92
	V-I	96		V-I	89
	P	94		P	90
Microwave oven	H	93			
	PQ	92			
	V-I	90			
	P	89			

In order to test the impact of the type of electrical equipment in the power system on the accuracy of algorithm identification, this article has increased the types of electrical equipment used, increased the number of electrical equipment such as computers and television sets, and allowed testing of electrical equipment. Type C is changed from 4 to 10, and the test results are shown in the following table 2:

Table 2. Recognition accuracy of single identify indicator

application	features	accuracy	application	features	accuracy
4	H	95	8	H	93
	PQ	96		PQ	94
	V-I	96		V-I	96
	P	94		P	94
6	H	94	10	H	95
	PQ	95		PQ	96
	V-I	96		V-I	95
	P	94		P	94

The following conclusions can be drawn from Tables 1 and Tables 2. The continuity of the secondary planning is ideal for recognition, and it can be used to identify non-intrusive power systems because the number of types of power equipment is relatively large. In the load monitoring system, centralized monitoring of electrical equipment is realized.

When only one load changes at a certain moment, and this load state changes, the other test steps of the algorithm are as follows: (1) According to the load characteristic value proposed in Chapter 3 of this paper. To construct a database of load characteristics for five types of loads; (2) Use window sliding tantalizations and monitoring of the moments of turning on and off of electrical equipment to process data and extract feature data of unknown power load equipment. The results are shown in Table 3.

Table 3. Recognition accuracy of identify application

application	features	accuracy	application	features	accuracy
lighting	H	90	Electric-heat	H	92
	PQ	93		PQ	96
	V-I	91		V-I	95
	P	92		P	93
oven	H	91	Washer-dryer	H	90
	PQ	94		PQ	92
	V-I	92		V-I	91
	P	93		P	90
Microwave oven	H	91			
	PQ	92			
	V-I	90			
	P	92			

In order to verify that the type of electrical equipment in the power system has no influence on the accuracy of the algorithm identification, this article has added the types of electrical equipment, increased the number of electrical equipment such as computers and televisions, and made electrical equipment for testing. The type of C is changed from 4 to 10, and the test results are shown in the following table:

Table 4. Recognition accuracy of identify application

application	features	accuracy	application	features	accuracy
4	H	91	8	H	91
	PQ	93		PQ	92
	V-I	92		V-I	93
	P	92		P	94
6	H	91	10	H	92
	PQ	93		PQ	93
	V-I	91		V-I	94
	P	92		P	92

Although the continuous 0-1 quadratic programming identification algorithm is less effective than other non-loaded ones in the presence of other loads, the recognition effect and accuracy are ideal, and the algorithm recognition effect reaches the level of practical application. The algorithm has a certain anti-jamming capability, and the number of identified types is relatively large, which is suitable for application in non-intrusive load monitoring systems in residential households, and realizes centralized monitoring of electricity consumption by resident users.

5 Conclusion

This article describes a method for identifying appliances using the ELM Binary Plan. It can not only identify known devices based on device power data, but also identify unknown devices. This method greatly improves the speed and accuracy of recognition. It can be seen that the similarity of the same type of electrical appliances is very high, and the type of electrical appliances is also different after extracting the characteristics with large differences. However, this article also has some deficiencies. Taking multi-state electrical appliances as an example, this method cannot achieve high accuracy. Fortunately, this will increase the accuracy of future multi-national appliance identification. This method is easy to use, meets the needs of smart homes, and has a good development prospect.

Acknowledgements

This work has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 701697.

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