Electric Power Systems Research 133 (2016) 241–248

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A nonintrusive load identification method for residential applications based on quadratic programming

Shunfu Lin [a], Lunjia Zhao [a], Fangxing Li [b], Qingqiang Liu [a], Dongdong Li [a], Yang Fu [a,*]

[a] Dept. of EE, The Shanghai University of Electric Power, Shanghai 200090, China
[b] Dept. of EECS, The University of Tennessee, Knoxville, TN 37996, USA

ARTICLE INFO

Article history:
Received 4 July 2015
Received in revised form 8 November 2015
Accepted 12 December 2015
Available online 12 January 2016

Keywords:
Appliance identification
Load signature
Nonintrusive load monitoring (NILM)
Quadratic programming

ABSTRACT

The decomposition of household power consumption is highly desired for scheduling household appliances and reducing home energy consumption. This paper presents a novel nonintrusive load identification method based on quadratic programming. Extensive simulation and laboratory tests have demonstrated that the proposed technique can provide adequate load identification accuracy for residential energy monitoring such that it is suitable for nonintrusive load monitoring (NILM) systems in residential and commercial buildings.

1. Introduction

With the development of smart grid and increasing awareness of energy conservation, the decomposed data at individual load levels in households or buildings is more desired for load scheduling and demand response programs [1]. Past research works indicated that the visualization of home electricity use can reduce 4–15% of power consumptions [2]. Two approaches are available to monitor the energy consumption of each appliance in residential dwellings: the traditional approach is to employ separate sensors (i.e., smart plugs) for each load to be monitored. While this may provide accurate measurement of each appliance with a smart plug, this does have the disadvantages of high hardware cost and additional complexity of communication network (e.g., for smart plugs to communicate with each other). In contrast, a newer approach is to employ intelligent algorithms to break down the total power consumption, which is called nonintrusive load monitoring (NILM) technique. In general, the traditional approach with separate sensors can be viewed as a high-end solution for accurate measurement, while the new NILM approach can be viewed as a low-cost solution to provide rough energy consumption profiles for customer's awareness of energy consumption and future guideline of appliance scheduling.

NILM was addressed originally at MIT by Hart [3] in the 1980's, and has attracted many interests [4–16] in recent years due to the fast development of smart metering technologies. NILM employs a centralized monitoring device installed at the main breaker level, combined with intelligent load identification technologies to break down the operational information and power consumption of each appliance. NILM can be useful for homeowners and building managers to monitor energy consumption on an appliance-by-appliance basis without having to install dedicated sensors. Large companies (e.g., Intel and Belkin) and small firms (e.g., Onzo in the US and Navetas in the UK) have initiated aggressive research and development efforts in energy monitoring with NILM data [4]. A novel senor embedded with NILM for home energy use monitoring was also developed by a research team at University of Alberta [5].

The original and extended NILM methods by MIT [3] use low-frequency hardware devices that only provide steady, coarse, and macroscopic signatures such as active and reactive power (P–Q). Recently, most researchers have agreed that the high-frequency hardware installation, which is capable of providing not only the conventional steady signatures but the microscopic transient signatures, can reach high accuracy of appliance detection and identification. The microscopic signatures include harmonics, transient power, and geometrical properties of *V–I* curves, and so on [6–10].

Several intelligent algorithms have been proposed for appliance identification by researchers in the past a few years. In [14], the artificial neural network (ANN) was used to identify the appliance by simply teaching the ANN to learn specific features. In [15,16], the

* Corresponding author. Tel.: +86 133 7189 6889.
E-mail address: mfudong@126.com (Y. Fu).

http://dx.doi.org/10.1016/j.epsr.2015.12.014
0378-7796/© 2016 Published by Elsevier B.V.

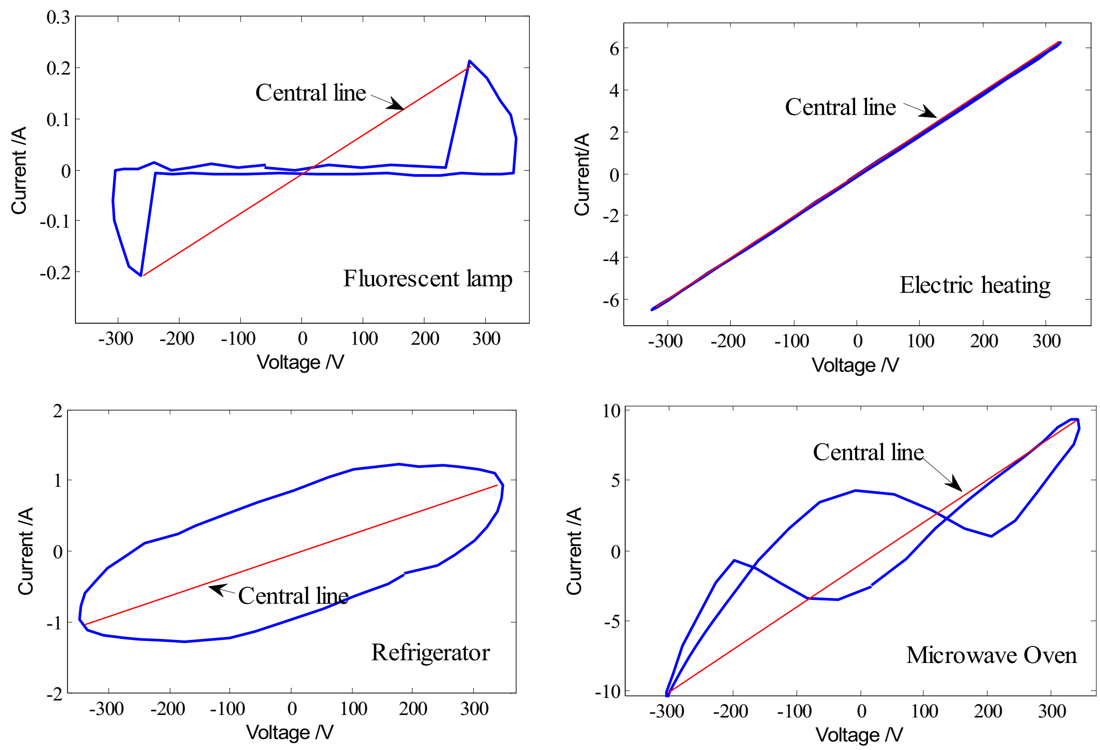

Fig. 1. Processing procedure of the recording data.

neural network was also used for the electrical appliance identification. The previous works in the literature based on intelligent systems which are based on a large amount of training from operational data. This training effort work will hinder the industrial application of the NILM technologies. There are still no complete available NILM solutions till now such that further research is still needed [4].

This paper presents an intelligent algorithm based on quadratic 0–1 programming for the residential appliance identification. The algorithm can be applied into the monitors or sensors installed at the main breaker of a residential home. A simulation experiment platform in laboratory was built up for testing the proposed algorithms. Ten different types of home appliances are employed in laboratory tests to verify the identification accuracy. The test results validate that the identification accuracy of the proposed algorithm is around 90%.

2. Residential load signatures

The following signal signatures extracted for the voltage and current signals are employed in this paper.

2.1. Current waveform signatures

Three signal signatures can be extracted from a current waveform as follows:

$$I_{\mathrm{rms}} = \sqrt{\frac{1}{n}\sum_{k=0}^{n} i(k)^2} \tag{1}$$

$$I_p = \max(i(k)) \tag{2}$$

$$I_{\mathrm{CF}} = \frac{I_p}{I_{\mathrm{rms}}} \tag{3}$$

where I_{rms}, I_p and I_{CF} are the root mean square value, peak magnitude and crest factor, respectively, of the current waveform.

2.2. Current harmonic signatures

The harmonic components can be calculated by the discrete Fourier transform. The total harmonic distortion (THD) is written as

$$\mathrm{THD}_I = \sqrt{\frac{\sum_{h=2}^{H} I_h^2}{I_1}} \tag{4}$$

Typical harmonic orders (e.g., 2nd, 3rd, and 5th) as well as the THD can be used for appliance identification. The typical order harmonics can be computed with the common discrete Fourier transform (DFT).

2.3. Active and reactive power signatures

The active and reactive power are calculated by the following two equations, respectively:

$$P = \sum_{k=0}^{\infty} P_k = \sum_{k=0}^{\infty} U_k I_k \cos(\Phi_k) \tag{5}$$

$$Q = \sum_{k=0}^{\infty} Q_k = \sum_{k=0}^{\infty} U_k I_k \sin(\Phi_k) \tag{6}$$

2.4. Geometrical properties of V–I curves

Fig. 1 shows the *V–I* curves of four typical appliances such as a fluorescent lamp, an electric heating unit, a refrigerator and a microwave. The central line is the straight line between the maximum and minimum point of the current amplitudes. The slope of the central line is adopted as a signal signature for appliance identification. In addition, the enclosed envelope area of the *V–I* curve can be also used for identification.