A Novel Feature Extraction Method for the Development of Nonintrusive Load Monitoring System based on BP-ANN

Yu-Hsiu Lin
Graduate Institute of Automation Technology
National Taipei University of Technology
Taipei, Taiwan
e-mail: t6618001@ntut.edu.tw

Men-Shen Tsai
Graduate Institute of Automation Technology
National Taipei University of Technology
Taipei, Taiwan
e-mail: mstsai@ntut.edu.tw

***Abstract*—The novel feature extraction method for nonintrusive load monitoring (NILM) systems was proposed in this paper. In order to monitoring the status of each load, a sensor is installed for each load traditionally. The status of the load is transmitted to the main controller such that the status of each load can be monitored. On the other hand, the NILM is able to detect the status of loads by analyzing the current signals that is picked-up by a current sensor installed at the main electrical panel.**

Traditional NILM methods used real power, reactive power, harmonic contents of power signatures and transient energy to determine the status of appliances. These methods are very complex and require a lot of computation. In this paper, a novel method that integrates artificial intelligent recognition technique and load current acquisition method for NILM is proposed. The proposed method uses time-domain information. This approach is different from traditional NILM methods. The proposed method is able to detect the energization and de-energization of loads by applying back-propagation neural networks (BP-ANNs). The overall correct rate for this method is above 98.75%. This result shows that the proposed method is able to determine the operation status of loads with proper robustness.

Keywords-Feature extraction; Back-propagation neural network; Nonintrusive load monitoring; Power signatures

I. INTRODUCTION

Detection of the usage of loads in a house is an import problem recently due to higher cost of fossil energy. In order to conserve the energy, several polices were proposed by the government. The most important step to conserve the energy is realizing how the energy is used in a house. The easiest way of detection the usage of energy can be achieved by installing sensors for each load. The sensors send the power usage information to the control device in order to keep track the usage of energy for each device. However, this method requires a large amount of sensors. On the other hand, the nonintrusive load monitoring (NILM) method requires a set of current and voltage sensors that are installed at the main electrical panel. By analyzing the current and voltage waveforms, the power usage of each load can be detected. Compared with traditional technique, the NILM has several advantages, e.g., easier to install, lower cost, lower energy consumption, etc. Several methods that implement NILM were proposed [1-10].

In this paper, a new method that is different from other NILM methods is proposed. The method integrates load current acquisition method and artificial recognition technique. The transient wave form as well as steady-state wave form is acquired. The features are extracted from the acquired wave forms. A pattern recognition system is used. A real scenario is used to test the robustness of the proposed method. The results of the test show that the proposed method is able to identify different loads when they are operated at the same time.

The organization of the paper is as following. First, the existing methods and power wave form features used by these methods are discussed. The proposed NILM method is discussed in Sec. 3. The laboratory test and experimental results are shown in Sec. 4. A popular recognizer that is used for load usage recognitions are also discussed in Sec. 4. The results and conclusions are discussed in Sec. 5.

II. THE CHARACTERISTICS OF POWER WAVE FORMS

Two major research topics on NILM were focused on the usage of steady-state and transient analysis. For the steady-state analysis, an NILM system was developed by the Electric Power Research Institute (EPRI) [1]. The system uses the variations of real and reactive power to detect the status of loads based on the $\triangle P$-$\triangle Q$ plane. Although this method had been applied to some regular houses with acceptable performance, several problems were pointed out by papers [2-4]. In papers [5, 6], nonlinear loads not only consumes real and reactive power, they also introduce harmonics to the power lines. This harmonics can be used as features to detect different loads. Besides the usage of steady-state analysis, the research team led by Steve Leeb pointed out that the transient wave forms are different for different loads due to the differences of physical characteristics [2, 3, 7, 8]. Therefore, the transient characteristics can also be used for the load recognition. Besides the discovery of the transient characteristics, they also found that these transient wave forms have complete or partial repeatability. By applying short-term Fast-Fourier Transform (frequency domain), the

978-1-4244-5567-6/10/$26.00 ©2010 IEEE 3CA 2010

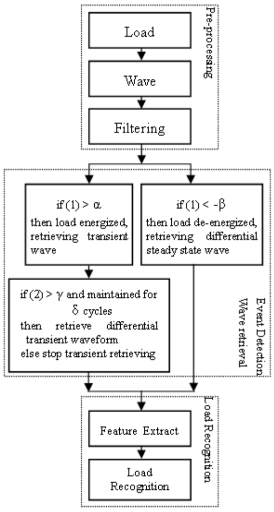

Figure 1. Flow of nonintrusive load monitor system.

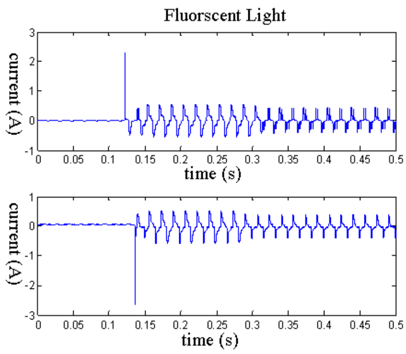

Figure 2. The current waves at different energize angles.

pattern matching scheme utilizes a least-squares fit (time domain) for the load recognition. In [4, 9, 10], the steady-state information such as real power, reactive power, total harmonic distortion, and the turn-on transient energy are used as input features to the recognizer. These papers also applied the coefficient of variations to verify the repeatability of transient energy.

III. Nonintrusive Load Monitor System

The proposed NILM integrates load current acquisition and artificial intelligent recognition. The flow chart of the proposed is shown in Fig. 1.

A. *Flow of Nonintrusive Load Monitor System*

In Fig. 1, the system is formed by three large function blocks: pre-processing, event detection and wave retrieval and load recognition. Details descriptions of these function blocks are described in the following sections.

B. *Feature Extraction*

In order to identify the features for different loads, a system shown in Fig. 7 is developed to control the energized the load at different angles that are 22.5 degrees apart. The load currents are acquired. As discussed in [2-4, 7, 9, 10], the transient currents of different loads shows uniqueness and repeatability. Some acquired wave forms are shown in Fig. 2 and Fig. 3.

1) *Transient Feature Extraction*

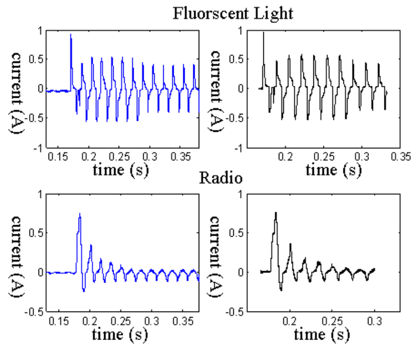

Figure 3. Transient current waveform for different loads.

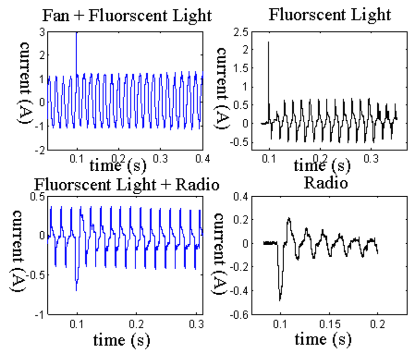

Figure 4. Transient waveform for multiple loads.

The energizing and de-energizing state of loads can be detected by applying (1). The transient acquisition period is determined using (2). The event detection and acquisition flow are shown in the "Event Detection and Wave Retrieval" block in Fig. 1. The key problem of wave form retrieval is the period of transient wave forms. When a load is turned on, the current wave transient period will maintain for a certain period of time. After this period, the steady-state wave will take place. The waveform changes are shown in Fig. 3 and Fig. 4. In Fig. 3, the transient for single operation load scenarios is shown. The transient wave is retrieved and shown on the right column. Multiple load scenarios are shown in Fig. 4. In these scenarios, a load was turn on in advance. A second load is energized after the first load is operated in the steady-state. The transient wave forms of the second load can also be retrieved.

$$\Delta[I_{intensity}] = |(I_{intensity})_{k+1} - (I_{intensity})_k| \qquad (1)$$

where $I_{intensity} = \frac{\sum_{j=1}^{N} |i(j) - mean(i)|}{N}$, $i(j)$ represent the j-th sampling point, N is the total sampling points, k is the number of sampling cycles, and mean(i) represents the average current value for each sampling cycle.

$$\Delta[I'_{intensity}] = |(I'_{intensity})_{k+1} - (I'_{intensity})_k| \qquad (2)$$

where $I'_{intensity} = \log(\sum_{j=1}^{N} (i(j) - mean(i))^2)$.

After the transient current wave forms are retrieved, (3), (4), and (5) are used to calculate the maximum value, average value, and RMS value respectively. The transient period, E_t, is measured from the detection of an operation of a load until $\Delta[I'_{intensity}]$ is less than pre-specified thresh-

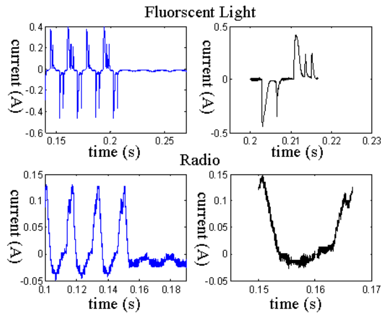

Figure 5. Single load steady-state current.

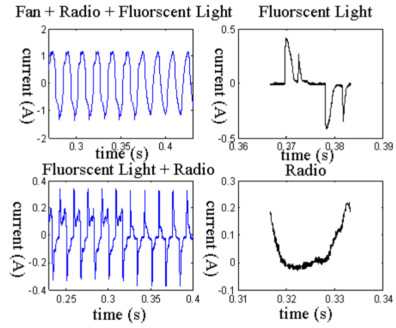

Figure 6. Multiple loads steady-state current.

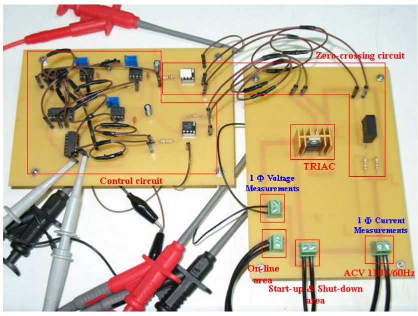

Figure 7. The control circuit.

hold, γ. These four features are used as the inputs for load recognition system.

$$I_{peak} = \max_{j \in N} |i(j)| \quad (3)$$

$$I_{avg} = \frac{\int_{t_0}^{t_0+E_t} i(t)dt}{E_t} \quad (4)$$

$$I_{rms} = \sqrt{\frac{\int_{t_0}^{t_0+E_t} i^2(t)dt}{E_t}} \quad (5)$$

2) Steady-state Feature Extraction

When a de-energizing event is detected, the current wave forms before and after the event are used for comparing. The maximum, average, and RMS values of current differences are used for the recognition system. Fig. 5 and Fig. 6 show the steady-state current difference for single load and multiple loads scenarios. The two diagrams show that the wave forms can be extracted successfully in both scenarios.

3) Load Monitor System

The proposed load monitor system performs pattern identification based on a known classified database. The back-propagation artificial neural networks (BP-ANNs) [11] are used for pattern identification.

IV. Experimental Results

In this section, the proposed system is used to recognizing different loads including fan, fluorescent light and radio. The load currents of these three types of loads are measured in advanced. These measurements are performed at different locations and time. During the recognition process, only single load is energized or de-energized. The picture of control circuit is shown in Fig. 7. Loads are connected to the mark of "ACV110V/60Hz" in Fig. 7. The current is measured at this point.

In this experiment, 108 single load current measurements are performed. 69 of the measurements are used for training; while the remaining 39 measurements are used for verification. An additional of 41 multiple load current measurements are also performed for testing.

A. Experimental 1: Load Energizing Test

For the BP-ANN, a 4-6-3 configuration is used. The tan-sigmoid function is used for the activation function of the hidden and output layers. The batched steepest descent technique is used to train the BP-ANN. An error goal of 1e-5, learning rate of 0.1, momentum of 0.2, and learning epoch of 3000 are used during the training.

The training and test results are shown in Table I. The total recognition rates of 100% and 98.75% are obtained for both phases.

B. Experimental 2: Load De-energizing Test

For this experimental, the BP-ANN structure is changed to 3-5-3. The learning rate and momentum are changed to 0.3 and 0.2 respectively. The training and test results are shown in Table II. The results for both phases can correctly recognition the de-energization operation of load.

From the results of test 1 shown in Table I, the recognition rate for the radio has lowest value of 94.44%; the fluorescent light has recognition rate of 100%; and the fan has recognition rate of 100%. In the other words, only one datum is misclassified by the BP-ANN. For the test2, both phases are able to recognize the de-energized load correctly.

TABLE I. Training and Test Results of BP-ANN

(a). Test1 experimental training results

CM	Training (Single Loads)					
	Fan	Fluorescent Light	Radio	Fan	Fluorescent Light	Radio
Fan	19	0	0	100	0	0
Fluorescent Light	0	24	0	0	100	0
Radio	0	0	26	0	0	100
Total Recognition Rate (%)	100					

(b). Test1 experimental test results

CM	Testing (Single Load with multiple load differential values)					
	Fan	Fluorescent Light	Radio	Fan	Fluorescent Light	Radio
Fan	32	0	0	100	0	0
Fluorescent Light	0	30	0	0	100	0
Radio	0	1	17	0	5.56	94.44
Total Recognition Rate (%)	98.75					

TABLE II. TRAINING AND TEST RESULTS OF BP-ANN

(a). Test2 experimental training results

CM	Training (Single Loads)					
	Fan	Fluorescent Light	Radio	Fan	Fluorescent Light	Radio
Fan	25	0	0	100	0	0
Fluorescent Light	0	21	0	0	100	0
Radio	0	0	23	0	0	100
Total Recognition Rate (%)	100					

(b). Test2 experimental test results

CM	Testing (Single Load with multiple load differential values)					
	Fan	Fluorescent Light	Radio	Fan	Fluorescent Light	Radio
Fan	26	0	0	100	0	0
Fluorescent Light	0	33	0	0	100	0
Radio	0	0	21	0	0	100
Total Recognition Rate (%)	100					

V. CONCLUSIONS

The proposed method is applied to an actual system with multiple operations of loads. The BP-ANN provides adequate performance for recognizing the energizing and de-energizing of loads. The proposed system has following advantages:

1) The feature computation is based on time domain information. The computation burden is much lighter than traditional methods.

2) The proposed method is able to determine the energizing and de-energizing status of loads in multiple load operation situations. The recognition process does not affected by the location and time.

REFERENCES

[1] S. Drenker and A. Kader, "Nonintrusive Monitoring of Electric Loads," IEEE Computer Applications in Power, Oct. 1999, pp. 47-51.

[2] C. Laughman, K. Lee, R. Cox, S. Shaw, S.B. Leeb, L. Norford, and P. Armstrong, "Power Signature Analysis," IEEE Power & Energy Magazine, March/April 2003, pp. 56-63.

[3] A. Shrestha, E.L. Foulks, R.W. Cox, "Dynamic load shedding for shipboard power systems using the non-intrusive load monitor," IEEE Electric Ship Technologies Symposium, 20-22 April 2009, pp. 412-419.

[4] H.H. Chang, C.L. Lin, H.T. Yang, "Load Recognition for Different Loads with the Same Real Power and Reactive Power in a Non-intrusive Load-morning System," Computer Supported Cooperative Work in Design, 12th International Conference on CSCWD 2008, 16-18 April 2008, pp. 1122-1127.

[5] A. Cole and A. Albicki, "Nonintrusive Identification of Electrical Loads in a Three-Phase Environment Based on Harmonic Content," IEEE Conf. on Instrumentation and Measurement Technology, 1-4 May, 2000, pp. 24–29.

[6] Y. Nakano, H. Murata1, K. Yoshimoto1, S. Hidaka, M. Tadokoro, and K. Nagasaka, "Non-Intrusive Electric Appliances Load Monitoring System Using Harmonic Pattern Recognition - Performance Test Results at Real Households," 4th International Conference on Energy Efficiency in Domestic Appliances and Lighting, Jun. 2006, pp. 477-488.

[7] S.B. Leeb, S.R. Shaw, and J.L. Kirtley Jr., "Transient Event Detection in Spectral Envelope Estimates For Nonintrusive Load Monitoring," IEEE Trans. on Power Delivery, Jul. 1995, pp. 1200–1210.

[8] S.R. Shaw, S.B. Leeb, L.K. Norford and R.W. Cox, "Nonintrusive Load Monitoring and Diagnostics in Power Systems" IEEE Transactions on Instrumentation and Measurement, July 2008, pp. 1445-1454.

[9] H.T. Yang, H.H. Chang, C.L. Lin, "Design a Neural Network for Features Selection in Non-intrusive Monitoring of Industrial Electrical Loads," Computer Supported Cooperative Work in Design, 11th International Conference on CSCWD 2007, Melbourne, Vic., 26-28 April 2007, pp. 1022-1027.

[10] H.H. Chang, C.L. Lin, L.S. Weng, "Application of artificial intelligence and non-intrusive energy-managing system to economic dispatch strategy for cogeneration system and utility," Computer Supported Cooperative Work in Design, 13th International Conference on CSCWD 2009, 22-24 April 2009, pp.740-745.

[11] C.-T. Lin and C.S. George Lee, Neural fuzzy systems: A neuro-fuzzy synergism to intelligent systems, Pearson Education Taiwan Ltd., Taiwan, August 2003.