Load Identification of Non-intrusive Load-monitoring System in Smart Home

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Abstract: - In response to the governmental policy of saving energy sources and reducing CO_2, and carry out the resident quality of local; this paper proposes a new method for a non-intrusive load-monitoring (NILM) system in smart home to implement the load identification of electric equipments and establish the electric demand management. Non-intrusive load-monitoring techniques were often based on power signatures in the past, these techniques are necessary to be improved for the results of reliability and accuracy of recognition. By using neural network (NN) in combination with genetic programming (GP) and turn-on transient energy analysis, this study attempts to identify load demands and improve recognition accuracy of non-intrusive load-monitoring results. The turn-on transient energy signature can improve the efficiency of load identification and computational time under multiple operations.

Key-Words: - load identification, artificial neural networks, non-intrusive load monitoring, turn-on transient energy analysis, smart home.

1 Introduction

Smart home provides an integrated service in intelligent residences for health care, human life, residence safety and environment of leisure in a community; for examples, security service, monitoring and management system service, logistics service, medical care service, distance e-learning service, leisure service, e-commerce service, and etc. The quality of human life is gradually emphasized by peoples; the demands of resident services for user's own need are increasing. The smart home is an emphasis on quality of residence. The peoples can enjoy the professional and considerate resident services, medical care with comfortable, carefree residence space and happiness environments in the smart home by using innovative techniques.

Smart home applies some information technologies of computer, communication and consuming electronic products to arrange the demands of electrical equipment and design the space of residence by managing lamplights, air-conditions and energy sources for the management of entrance guard, health care, saving energy and reducing CO_2, and comfortable life. Intelligent life of residence includes digital home, energy source of residence, and health care of residence. Digital home is an application of entertainment and learning. Energy source of residence is an objective of saving energy and reducing CO_2 of residence using some new techniques. Health care of residence is medical cares of members of home using some information technologies, especially for health and safety care for hidden elderly.

The years of mining for petroleum, natural gas and coal are estimated to be 40, 62 and 272 years respectively for the whole world [1]. The energy demands of worldwide quickly increase from the view of energy consumption for 1999 to 2020. The energy consumption growth of petroleum is 2.2% every year. The demand of nature gas is from 23% to 28% for all energy demands of worldwide [2]. The petroleum and nature gas are main energy sources for all peoples of worldwide and they will be not too much for use after the middle of the twenty-first century. The energy crisis will approach for all peoples of world.

In Taiwan, the developments of economics highly depend on energy sources of import. The generating costs of coal-fired unit, oil-fired unit and gas combined-cycle unit in 2001 are more than 30%, 44% and 22% in 1999 respectively. The generating costs continually increase in Taiwan, and then unit prices of electric power are also raised. In energy demands, the amount of residence is increasing 5.93% every year from the view of amount of residence; the demands of electric power are increasing 11.43% every year from the view of power demands for home. The energy demands of home are 0.555% of energy demands of all in Taiwan [3]. The energy demands of home are increasing obviously from analysis of energy demands for the amount of residence and electric power demands.

The methods of saving energy play an important role of reducing costs for the users of high electric power demands. The policy of environmental protection is set positively into action by the government for different country for the problems of warm for the whole world. In contrast to the difficulty of exploitation of energy sources, the sustainable energy sources exploitation, saving energy and reducing CO_2 and protection of environment of earth can be still executed by efficient energy management policies.

In 1990, the real time operating system nucleus house (TRON House) was built by Japanese computer residence research association. The TRON House is a typical smart home. The TRON House can control automatically various sensors and drivers to sense actively the temperature and humidity for inside and outside from home, and control automatically the windows and various electric appliances through different terminal.

From 2004, some information, communication and monitoring technologies are applied in buildings by American National Science Council after executing intelligent construction development project to speed the market trend of smart home. In Europe, the demands of health care are increasing because elderly populations are increased. The intelligent health care services are developed by using information and communication technologies. For instance, the wearable micro device is developed in the CAALYX program in 2008 to detect user's condition for anytime.

In Korea, Smart Home Vision 2007 program was executed from 2003. This program will promote 60% for smart home by investing 2,000 billion dollars during four years to make the output value of intelligent residences for 14,000 billion dollars. In Taiwan, the Center of Innovation and Synergy for Intelligent Home Technology (INSIGHT Center) was built by National Science Council to actively develop the innovative application of intelligent home and promote intelligent home market. In intelligent sustainable management, there are some products include solar energy tracking controllers, the tracer of battery maximum power, energy conservation insulated board, excellent ventilation system and energy conservation and management system, etc.

Currently, the trend of intelligent home is springing up all over the world. Smart home creates tremendous business. The output value of intelligent home in whole world and Taiwan will meet 256 billion US dollars and 333.1 billion NT dollars up to 2015, respectively. The markets of home safety and heath care are the biggest among applications of intelligent home. According to the report from institute of information industry, the output value of monitoring market will be 4.23 US dollars and 14 billion NT dollars in 2011 for worldwide and in 2012 for Taiwan, respectively.

Traditional energy-monitoring instrumentation systems employ meters for each load to be monitored because they tend to be comprehensive, systematic, and convenient. These meters may incur significant time and costs to install and maintain. Furthermore, increasing numbers of meters may influence system reliability. Some research also indicate that the utility of energy-monitoring systems have been questioned by energy-monitoring system practitioners, and future studies of energy-monitoring systems will focus on more significant issues, such as strategies for minimizing the number of instruments using non-intrusive load-monitoring (NILM) system [4]-[6]. Figure 1 shows the NILM system in smart home used to monitor voltage and current waveforms in an electrical service entry powering loads representative of different important load classes. The results of monitoring are used to analyze and identify the ON/OFF status of loads and then to estimate the electric power demands of different loads from time of use, and power. The NILM system is worth to be researched because it can not easily install but reduce the costs of system.

In feature extraction, this paper applies genetic program (GP) to search the best solutions for the optimum of feature input vectors of load pattern recognition system using the operation of reproduction, crossover and mutation. The results of analysis for NILM system can identify various loads of home and to know the condition of use for loads including of the electric power demands, names or items, time of use and overloaded capacities of loads, etc. Figure 2 shows the flowchart for NILM in smart home.

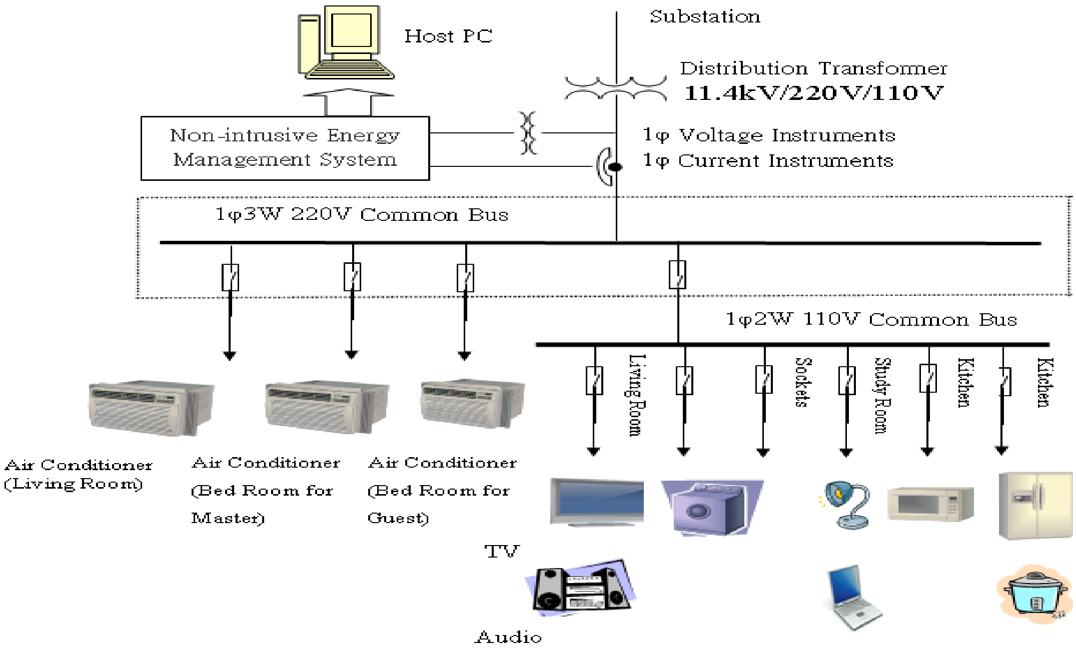

Fig. 1 Non-intrusive load-monitoring system in smart home

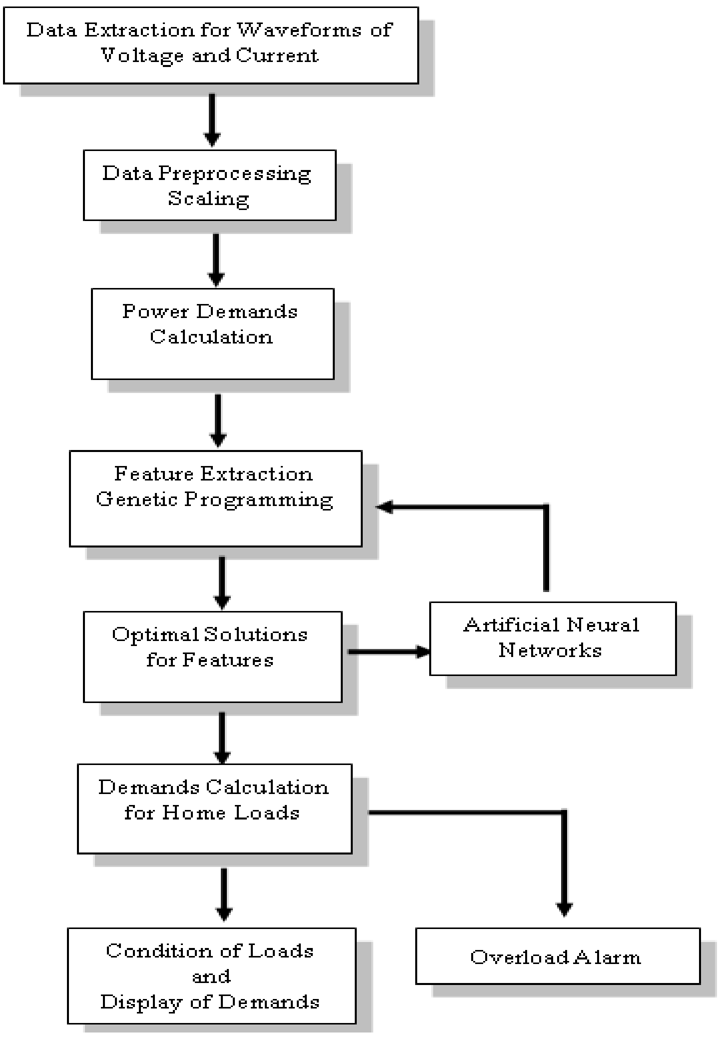

Fig. 2 The flowchart of Non-intrusive load-monitoring system

2 Review of Related Studies

Due to the importance and difference of recognition accuracy of power signatures, several previous studies have addressed the load identification of power signatures in NILM. Hart [7] proposed a load identification method that examined the steady-state behavior of loads. Hart conceptualized a finite state machine to represent a single appliance in which power consumption varied discretely with each step change. The method performs well. However, it has the limitations of the method. For example, small appliances and appliances, which are always on or non-discrete changes in power, should not be chosen as targets for the method [4], [7]. Robertson [8] employed a wavelet transformation technique to classify several unknown transient behaviors for load identification. This technique, however, is expensive for the detection of transients. In addition, the detection of transient behavior can be obscured by the simultaneous transient of other loads [9]. Cole [9], [10] examined a data extraction method and a steady-state load identification algorithm for NILM. The algorithm developed by Cole can be employed for load switching between individual appliances when one or more appliances are switched on or off. This algorithm, however, requires an extended period of time to accumulate real power (P) and reactive power (Q) for sample data. In addition, any appliance power consumption that does not change cannot be recognized [10].

Recently, several papers have proposed new power signature analysis algorithms [11]-[15], load identification methods [16]-[19], and feature selection approaches [20]-[22] to recognize loads and to solve classification problems. For the load identification methods, many papers have been published to improve the performance of recognition using artificial neural networks for the NILM system. For example, Roos *et al.* [5] proposed a detailed analysis of steady-state appliance signatures to recognize industrial electrical loads. This method, however, requires complicated computations for accurate data of power signatures. In addition, Srinivasan *et al.* [19] proposed a neural-network-based approach to identify non-intrusive harmonic source. The method performs well. However, it does not incorporate the various operational modes of each load and operation under different voltage sources. In a practical power system, there exist many harmonics. How harmonics affect the results of the proposed method has been demonstrated by authors in [23]. However, harmonic content is very small for constant linear loads [13], especially for commercial buildings and residences. Therefore, another feature besides harmonics is necessary for power systems, commercial buildings and residences.

To solve the disadvantages for the previously published research, a new method for load identification of the NILM system in smart home is proposed in this paper. This method uses the turn-on transient energy (U_T) analysis and artificial neural networks to improve the recognition accuracy and to reduce computational requirements. The proposed improvement technique is unrelated to operational mode of loads, operation under different voltage sources, and power consumption change. The proposed method can be applied for commercial loads and industrial loads. Moreover, the proposed method can be applied for different loads with the same real power and reactive power. Experimental results show that the proposed method for the NILM system in smart home allows efficient recognition of commercial or industrial loads as well as improvement of computational requirements. Moreover, the turn-on transient energy signature can be used to distinguish different loads with the same real power and reactive power.

3 Data Preparation

Figure 1 schematically illustrates the overall scheme in the NILM system of smart home. One-phase electricity powers the loads, which are representative of important load classes in a residential building. A dedicated computer connected to the circuit breaker panel controls the operation of each load. The local computer can also be programmed to stimulate various end-use scenarios. The work presented in this paper is load recognition using neural networks and the employment of features to estimate the energy consumption of major loads.

3.1 Data Acquisition

The main parameters to be acquired are the voltage and current of aggregated loads. To compile data for training purposes, either every load of interest or a representative sample of the loads should be monitored. Taking 256 samples of each cycle is sufficient and hence the sampling frequency is approximately 15 kHz.

3.2 Data Preprocessing

Neural network training can be made more efficient if certain preprocessing steps are performed on the network inputs. Before training, it is often useful to scale the inputs and targets so that they always fall within a specified range. The approach for scaling network inputs and targets is to normalize the mean and standard deviation of the training set, normalizing the inputs and targets so that they will have zero mean and unity standard deviation. After the network has been trained, these vectors should be used to transform any future inputs that are applied to the network. These can be computed by

$$P_n = (P - meanp) / stdp \tag{1}$$

and

$$t_n = (t - meant) / stdt \tag{2}$$

where the matrices P and t are respectively the original network inputs and targets, the matrices P_n and t_n represent respectively the normalized inputs and targets. The vectors *meanp* and *stdp* contain the mean and standard deviations of the original inputs, and the vectors *meant* and *stdt* contain the means and standard deviations of the original targets.

4 Power Signature Problems and Turn-on Transient Energy Algorithms

4.1 Problems of Power Signatures

In multiple operations, a class shows that any configuration can be one or many loads. In other words, a class may be a combination of more than one load. In general, an appliance may have many load representations and a load may involve many physical components. For example, a dryer has two loads, a motor and a heater. A refrigerator has only one load, a compressor, but has different physical components for refrigerating and freezing.

Most appliances are distinguishable by unique power signatures that can be observed from voltage and current waveforms supplied to the appliance, or from processed reproductions of these signals such as the delivered real power and reactive power or harmonics [5]. According to the switch continuity principle, steady-state signatures, for example, real power and reactive power, are additive when two signatures occur simultaneously. In contrast to steady-state properties, transient properties are not additive [4]. Distinguishing different loads may be problematic when they have equivalent real power and reactive power but no harmonic components, and/or when the sums of real power and reactive power of two load types are equal to that of another load during multiple load operations. Therefore, classifications are more complicated, especially when identifying different loads with the same real power and reactive power.

4.2 Turn-on Transient Energy Algorithms

The transient properties of a typical electrical load are mainly determined by the physical task that the load performs [24, 25]. Transient energy may assume different forms in consumer appliances, depending on the generating mechanism [7]. Estimating current waveform envelopes at the utility service entry of a building, for example, allows accurate transient event detection in the NILM [24]. Load classes performing physically different tasks are therefore distinguishable by their transient behavior [24, 25]. Since the envelopes of turn-on transient instantaneous power are closely linked to unique physical quantities, they can serve as reliable metrics for load identification. Two different appliances consuming identical levels of real power and reactive power may have very different turn-on transient currents. Analysis of these transient currents can accurately determine which of the two is actually present in the load.

In general, the transient behavior of many important loads is sufficiently distinct to identify load type. The long characteristic switching-on transient, the less substantial switching-on transient, the short but very high-amplitude switching-on transient, and the long two-step switching-on transient are the principal values measured in pump-operated appliances, motor-driven appliances, electronically fed appliances, and fluorescent lighting, respectively [26].

However, the transient is the dominant state directly after load inception. Figure 3 plots the turn-on real-power transient of each load for an NILM system at the entry of an electrical service. In Figs. 3(a) and 3(b), these loads are respectively a 119-W dehumidifier and a 590-W vacuum cleaner. The turn-on real-power transients differ from each other because the motor is started and operated using different methods. In Fig. 3(c), this load is an oven of an R-L linear load with real power and reactive power equivalent to that of a 590-W vacuum cleaner. The real-power transient is quickly increased and then back to the normal rated power.

The one-phase turn-on transient energy is determined as follows.

$$V(k) = v(k) - v(k-1) \tag{3}$$

$$I(k) = (i(k) + i(k-1))/2 \tag{4}$$

$$U_T = U_{1\phi,transient} = \sum_{k=0}^{K} V(k)I(k) \tag{5}$$

where $V(k)$ is derivative of transient voltage for sample k; $I(k)$ is average transient current for sample k; $v(k)$ is voltage sampled for sample k;

$v(k-1)$ is voltage sampled for sample k-1; $i(k)$ is current sampled for sample k; $i(k-1)$ is current sampled for sample k-1; K is number of samples, k=1, 2, …K.

The three-phase turn-on transient energy is computed as follows:

$$U_T = U_{3\phi,transient} = \Sigma\left(Va(k)\cdot Ia(k) + Vb(k)\cdot Ib(k) + Vc(k)\cdot Ic(k)\right) \tag{6}$$

where $V_a(k), V_b(k), V_c(k)$ are derivatives of transient voltage in phases a, b, and c for sample k; $I_a(k)$, $I_b(k)$, $I_c(k)$ are the average value of transient current in phases a, b, and c for sample k.

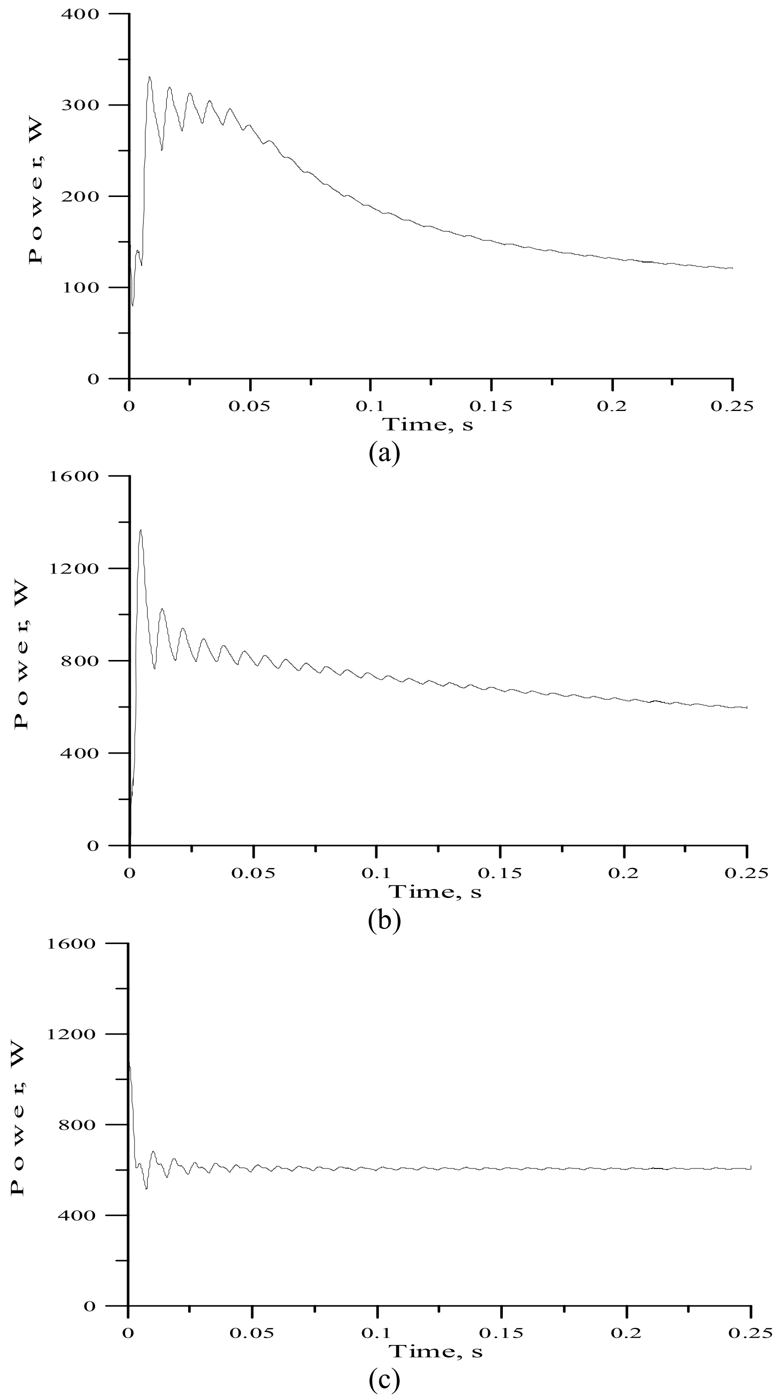

Fig. 3 Turn-on real-power transient for a NILM system, (a) a 119-W dehumidifier; (b) a 590-W vacuum cleaner; (c) an oven of an R-L linear load with real power and reactive power equivalent to that of a 590-W vacuum cleaner.

5 Load Identification by Artificial Neural Network

Pattern classifiers partition multidimensional space into decision regions indicating to which class any input belongs [27]. Many classification techniques have been developed for load identification. The non-parametric and learning-supervised classifier is adopted for electrical patterns of commercial or industrial appliances because the distribution of these patterns is quite complicated without any formulation, and the larger loads can be easily and clearly labeled.

Most back-propagation (BP) neural network applications employ single- or multi-layer perceptron networks using gradient-descent training techniques, with learning by back propagation. These multi-layer perceptrons can be trained with supervision using analytical functions to activate network nodes ("neurons") and by applying a backward error-propagation algorithm to update interconnecting weights and thresholds until proper recognition capability is attained. In the present study, the back-propagation classifier is generally used as a trainable classifier. "Classification" in this context denotes a mapping from a feature space to the set of class labels – the names of commercial or industrial load combinations.

5.1 Recognition Accuracy, Speed, and Memory Comparison with different Classifier

In this section we perform a number of benchmark comparisons of the various classifiers; for examples, back-propagation, probabilistic neural network (PNN), and learning vector quantization (LVQ). Probabilistic neural networks are a radial basis function network (RBF) suitable for classification problems. When an input is presented, the first layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a competitive transfer function of the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes [24]. Learning vector quantization is a method for training competitive layers in a supervised manner. A competitive layer automatically learns to classify input vectors. However, the classes that the competitive layer finds are dependent only on the distance between input vectors. If two input vectors are very similar, the competitive layer probably will put them in the same class [25].

The following table, Table 1, lists data of power signatures, some characteristics of the networks, and training processes for three different classifiers. Table 2 summarizes the results of recognition accuracy and computation time for the example of a MILM system in the previous section. In each case, the network is trained until the mean square error is less than 0.0001. The fastest classifier for this problem is the probabilistic neural networks. It is over fifteen times and four times faster than the next fastest classifier BP for training and testing, respectively. However, the back-propagation neural network demonstrates higher recognition accuracy than the probabilistic neural networks. In addition, the number of weights and biases in the BP network is less than the PNN network (23 versus. 358). The BP classifier is suited for this type of problem.

5.2 Training Algorithms and Performance Index Function

The faster algorithms fall into two main categories for the back-propagation neural network [28]. The first category uses heuristic techniques, which were developed from an analysis of the performance of the standard steepest descent algorithm. One heuristic modification is the momentum technique. There are two more heuristic techniques; for example, variable learning rate back-propagation (GDX) and resilient back-propagation (RP).

The second category of fast algorithms uses standard numerical optimization techniques. There are three types of numerical optimization techniques for neural network training. The first is the conjugate gradient technique; Scaled Conjugate Gradient algorithm (SCG) and Powell –Beale Restarts algorithm (CGB), the second is the quasi-Newton technique; BFGS algorithm (BFG) and One-Step Secant algorithm (OSS), and the third technique is the Reduced Memory Levenberg-Marquardt algorithm (LM).

The typical performance index function that is used for training feed forward neural networks is the mean sum of squares of the network errors also called mean square error (MSE). It is the average squared error between the network outputs and the target outputs.

$$F = MSE = \frac{1}{N}\sum_{i=1}^{N} e^2(i) = \frac{1}{N}\sum_{i=1}^{N} ((t(i) - a(i))^2 \quad (7)$$

where the variable N is the number of training samples, the variable t is the target output, and variable a is the network output.

It is very difficult to know which training algorithm will be the fastest for a given problem. This depends on several factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition or function approximation. A number of benchmark comparisons of the various training algorithms were discussed [28]. Figure 4 shows the comparison of convergence speed of different training algorithms for the example of a MILM system in the previous section. A 1-4-3 network, with a tan-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer, is used to identify loads of the NILM system. In each case, the network is trained until the mean square error is less than 0.0001. This is demonstrated in the figure 4, which plots the mean square error versus epochs (repetitions) for several representative algorithms. Typically, one epoch of training is defined as a single presentation of all input vectors to the network. The network is then updated according to the results of all those presentations. Here the error in the Levenberg-Marquardt algorithm decreases much more rapidly with epoch than the other algorithms shown. The Levenberg-Marquardt algorithm is able to drive the mean square error to a lower level than the other algorithms. The fastest initial convergence algorithm for this problem is the Levenberg-Marquardt algorithm, although the BFGS quasi-Newton algorithm is as fast.

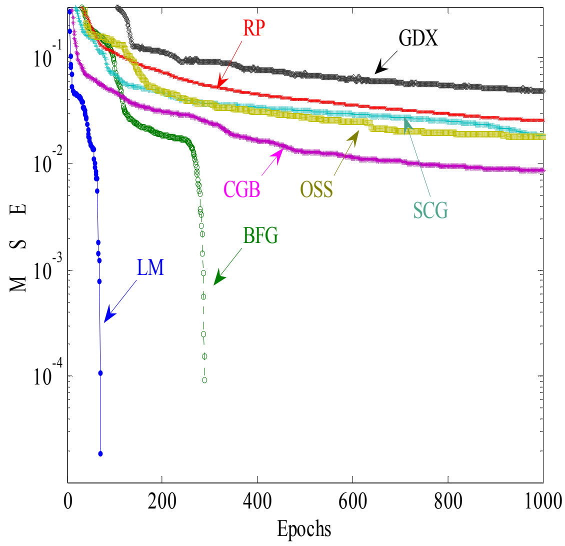

Fig. 4 Convergence speed comparison for the different training algorithms

Table 1. List of different classifiers for Artificial Neural Networks

Classifier	Power signature	Network structure	Error goal	Maximum epoch
BP	U_T	1-4-3	0.0001	1000
PNN	U_T	1-39-7	--	--
LVQ	U_T	1-14-7	0.0001	1000

Table 2. Recognition accuracy, speed, and memory comparison for different classifiers

Classifier	Power signature	Function	Recognition accuracy (%)	Time (Seconds)
BP	U_T	Training	100	4.16
		Test	100	0.45
PNN	U_T	Training	100	0.27
		Test	92.1	0.11
LVQ	U_T	Training	87.18	91.4
		Test	86.8	0.17

6 Turn-on Transient Energy Repeatability

Most loads observed in the field have repeatable transient profiles or at least repeatable sections of transient profiles [12]. The load survey reveals that non-linearity in the constitutive relationships of the elements comprising a load model and/or in the state equation describing a load tends to produce interesting and repeatable observable turn-on transient profiles suitable for use in identifying specific load classes [29, 30]. Because of the varying transients (which often depend on the exact point in the voltage cycle at which the switch opens or closes), data sets for load identification must provide accurate repeatability of the turn-on transient energy signatures.

As Figures 5 and 6 demonstrate, the turn-on transient profiles exhibit repeatable measured current waveforms in one phase at voltage phase 0° and 90° for the turn-on transient of a three-phase 300-hp induction motor. The turn-on characteristic of a load clearly increases in complexity over time. Closer investigation of the load turn-on is thus required before the characteristics can be used as a distinguishing feature of a load. This information, collected via non-intrusive monitoring, can be used to answer important questions using the statistical validity of power measurements.

Determination of whether or not turn-on transient energy content is repeatable would be useful in developing a turn-on transient energy signature. As Eq. 8 shows, the average value of the sample data (x_i) for the turn-on transient energy of each load is $\overline{x}$. The standard deviation (S) of the turn-on transient energy for each load is computed according to Eq. 9 for all loads monitored in isolation. An experiment is then used to demonstrate that the statistical validity of the turn-on transient energy for each load is repeatable in terms of the coefficient of variation (C.V.) according to Eq. 10.

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i , \tag{8}$$

where the variable x_i is the sample data for the turn-on transient energy of each load, and the variable n is the number of sample.

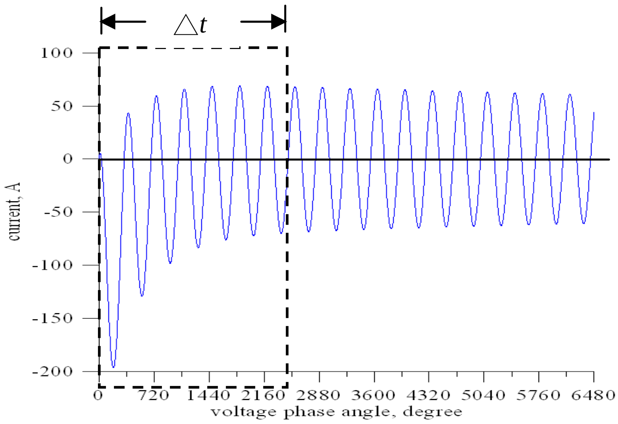

Fig. 5 Current waveform at voltage phase 0° for the turn-on transient

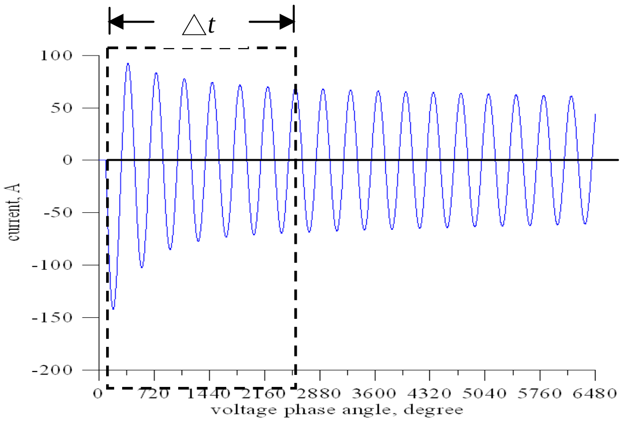

Fig. 6 Current waveform at voltage phase 90° for the turn-on transient

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \ , \tag{9}$$

and

$$\mathrm{C.V.} = \frac{S}{\bar{x}} \ . \tag{10}$$

where the variable $\bar{x}$ is the average value of the sample data, and the variable S is the standard deviation of the turn-on transient energy for each load.

7 Experimental Results

7.1 Case Study Environment

Each entry in the table represents 10 different trials, where different random initial weights are used in each trial. In each case, the network is trained until the mean square error is less than 0.0001 or the maximum of epoch is 3000.

Experimental datasets were generated by preprocessing the data on the voltage and current waveform of the total load. Each final sample consists of 4,608 data samples obtained over a period of 0.3s. Each example of the power feature includes a voltage variation from − 5% to +5% at 1% intervals, yielding eleven examples of power feature for each scenario and $(2^N - 1) \times 11$ raw data for $2^N - 1$ scenarios given N loads in a power system network. To confirm the inferential power of the neural networks, the raw data examples are categorized into $((2^N - 1) \times 11)/2$ learning and test datasets, respectively. The full input dataset comprises a $((2^N - 1) \times 11) \times 4608$ matrix as both the training dataset and the test dataset. Notably, the learning data and test data are selected randomly from all data. A neural network simulation program was designed using MATLAB. The program was run to identify load on an IBM PC with an Intel 1.5GHz Pentium M CPU.

7.2 Case Study Results

7.2.1 Case Study 1: EMTP Simulation

In case study 1, the NILM system monitors voltage and current waveforms in a one-phase electrical service entry powering a collection of loads representative of the major load classes in a commercial building. The neural network algorithm in the NILM system identifies three loads with transient signatures operating on a 220-V common bus. These loads include a 2.6-hp induction motor, a 4.7-hp induction motor, and an R-L linear load with real power and reactive power equivalent to that of a 4.7-hp induction motor.

Table 3 shows that values for the training and test recognition accuracy of load identification in multiple operations are all 100% for feature with the turn-on transient energy (U_T). However, the training and test recognition accuracy of load identification in multiple operations are only 58.97% and 39.47%, respectively, for features with real power and reactive power (PQ). Those loads cannot be identified by real power and reactive power features because the second load and the third load are different loads with the same real power and reactive power, as are combinations of the first and second loads and combinations of the first and third loads. In other words, test recognition for those loads in multiple operations is quite low when using only real power and reactive power features.

7.2.2 Case Study 2: Experiment

In case study 2, the NILM system is used to monitor voltage and current waveforms in a one-phase electrical service entry powering representative loads in the laboratory. The neural network algorithm in the NILM system identifies three actual loads with transient signatures on a 110-V common bus. These loads include a 119-W dehumidifier, a 590-W vacuum cleaner, and an R-L linear load with real power and reactive power equivalent to that of a 590-W vacuum cleaner.

Table 4 shows that values for the training and test recognition accuracy of load identification in multiple operations are also all 100% for feature with the turn-on transient energy (U_T). However, the accuracy of training and test recognition of load identification in multiple operations are only 51.28% and 39.47%, respectively, for features with real power and reactive power (PQ). The test recognition for those loads in multiple operations is also quite low when using only real power and reactive power features. The reason is the same as that for the previous section. In other words, the presence of different loads with the same real power and reactive power can be confirmed in two ways. First, test recognition in multiple operations is quite low when only using features of real power and reactive power. Second, the turn-on transient energy for the features can improve load identification, especially for different loads with the same real power and reactive power.

Table 3. The results of load identification in case study 1

	Features		PQ		U_T	
	Number of training	Number of test	Training	Test	Training	Test
1	5	6	5	5	5	6
2	6	5	2	0	6	5
3	6	5	3	0	6	5
1+2	5	6	1	0	5	6
1+3	5	6	0	0	5	6
2+3	6	5	6	5	6	5
1+2+3	6	5	6	5	6	5
Number of features	39	38	39	38	39	38
Recognizable number			23	15	39	38
Recognition accuracy (%)			58.97	39.47	100	100
Time (Sec.)			29.5704	0.4938	4.6862	0.4937
Number of epochs			3000		458.6	
Number of neurons for layers			2-5-3		1-4-3	

Table 4. The results of load identification in case study 2

	Features		PQ		U_T	
	Number of training	Number of test	Training	Test	Training	Test
1	5	6	5	5	5	6
2	6	5	1	0	6	5
3	6	5	1	0	6	5
1+2	5	6	1	0	5	6
1+3	5	6	0	0	5	6
2+3	6	5	6	5	6	5
1+2+3	6	5	6	5	6	5
Number of features	39	38	39	38	39	38
Recognizable number			20	15	39	38
Recognition accuracy (%)			51.28	39.47	100	100
Time (Sec.)			29.1968	0.483	1.5345	0.4782
Number of epochs			3000		68.5	
Number of neurons for layers			2-5-3		1-4-3	

8 Conclusions

The results of analysis for NILM system can identify various loads of home and to know the condition of use for loads including of the electric power demands, names or items, time of use and overloaded capacities of loads, etc. The users of home can be reminded to save energy by these results. Besides, some related policies of saving energy, reducing CO_2, health and safety care for hidden elderly and the efficiency of electric appliances can be established and planed by these results of smart home.

Based on experimental results and EMTP simulation of NILM, the transient power signature for load identification in NILM can be applied extensively to any case for smart home. ANN and turn-on transient energy analysis are useful tools for improving load recognition accuracy and reducing computation time in a NILM system for smart home.

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