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Feature Extraction of Non-Intrusive Load-Monitoring System Using Genetic Algorithm in Smart Meters

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Abstract— **This paper proposes non-intrusive load-monitoring (NILM) techniques using artificial neural networks (ANN) in combination with genetic algorithm (GA) to identify load demands and improve recognition accuracy of non-intrusive load-monitoring results. The feature extraction method of genetic algorithm can improve the efficiency of load identification and computational time under multiple operations. After comparing various training algorithms and classifiers in terms of artificial neural networks due to various factors that determine whether a network is being used for pattern recognition, the back propagation artificial neural network (BP-ANN) classifier is adopted in the load identification process. Additionally, in combination with electromagnetic transients program (EMTP) simulations and measurements on site, extracting the features of power signatures can lead to accurate load identifications and is a significant feature in smart meters.**

Keywords- artificial neural network; genetic algorithm; smart meters; feature extraction; non-intrusive load-monitoring techniques.

I. INTRODUCTION

Traditional load-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 researches also indicate that the utility of load-monitoring systems has been questioned by load-monitoring system practitioners, and future studies of load-monitoring systems will focus on more significant issues, such as strategies for minimizing the number of instruments using non-intrusive load-monitoring (NILM) system [1]-[3].

In this study, a NILM can be programmed to recognize more appliances. This should increase its ability to recognize appliances by using the optimal signatures model or the features of the appliance. To develop such a NILM system, a number of load recognition techniques have been proposed.

However, some appliances have transient features and steady-state features with quite different indications and meaning at different times, particularly in an industrial plant. These appliances have no sufficient features to be identified whether the load is starting or operating, or if these features are only steady-state features or transient features. These features [4-9], when selected, have been proven to enhance the capability of a NILM system to distinguish among industrial loads or different loads with the same real power (P) and reactive power (Q) under multiple operations using the turn-on transient energy feature (U_T) and traditional steady-state power features by analyzing the physical industrial load characteristics.

Figure 1 schematically illustrates the overall scheme in the NILM system. Three-phase or single-phase electric loads represent important load classes in an industrial or commercial building. A meter data management system (MDMS) connected via wireless to the smart meter/ NILM manages and recognizes the operation status, load quality and power demand of each load. The client computers can also read all information from MDMS by Internet and Web systems. The computer supported cooperative work presented in this paper is load recognition using artificial neural networks and the employment of those features to estimate the energy consumption of major loads.

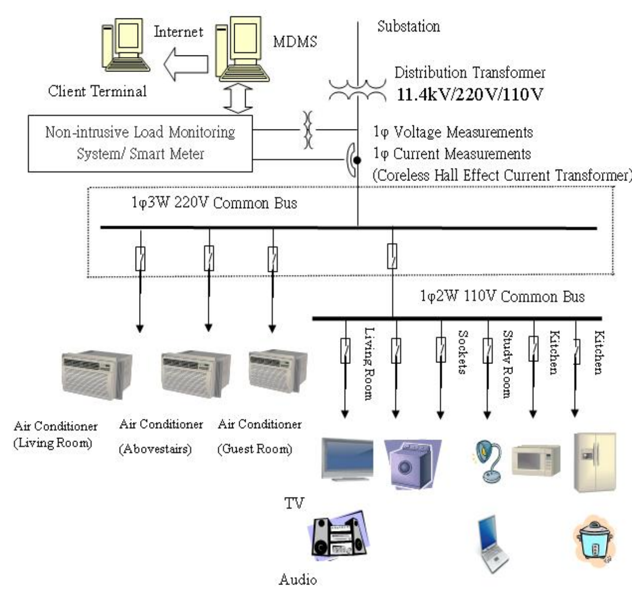

Figure 1. Smart meter and load identification system for a NILM system

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The NILM system is worth to be researched because it cannot be easily installed but can reduce the costs of system. In feature extraction, this paper employs the genetic algorithm (GA) to find the optimum solution of feature input vectors of load pattern recognition system using the operation of reproduction, crossover and mutation. The NILM system can identify various loads of a home and the status of them including electric power demands, names or items, time of use and overloaded capacities of loads, etc. Fig.2 shows the flowchart of NILM in smart meters.

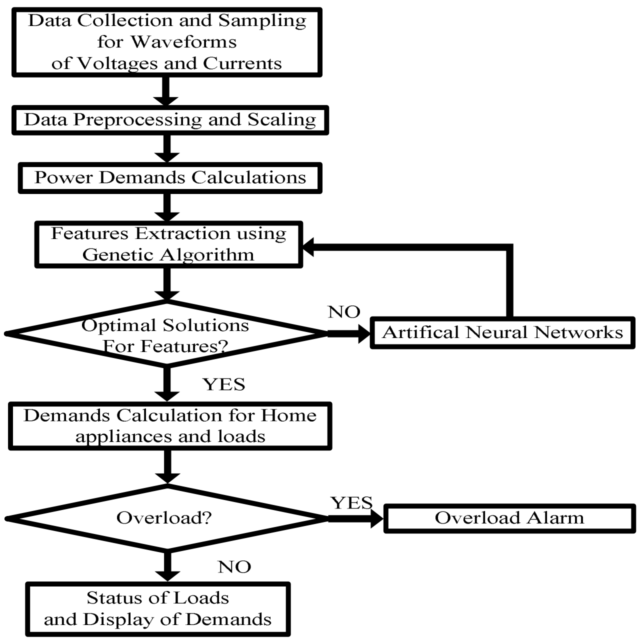

Figure 2. The flowchart of non-intrusive load-monitoring system

This paper is organized as follows. The architecture of smart meters is addressed and described in Section 2. The proposed methods for feature extraction and identification of load patterns are described in Section 3. Based on the feature extraction technique, GA, and the load recognition method, BP-ANN, a series of experiments such as software simulations and measurements on site are analyzed and discussed in Section 4 to prove the feasibility of the proposed method in this paper. The conclusions and further works are stated in Section 5.

II. SMART METERS

Due to pressure of global resources and environmental pollution, the market competition of electric power, and increasing requirement of users on the reliability and quality of electric power, the future power grid must be more suitable for various kinds of power loads and power demand management.

The development of renewable energy resources and innovative approaches in energy conservation become top priorities of government officials and politicians worldwide. The installation of Advanced Metering Infrastructure (AMI) is looked upon as a bridge to the construction of smart grids. The AMI system includes smart meters, communication infrastructure, and Meter Database Management System (MDMS). Smart meters can provide functions to acquire real-time energy consumption information including time-of-use rates, maximum demand, load curve, real time pricing, and power quality. Smart meters can be used to transmit real time detailed power consumption data and to output event data to local AMI, customer information center, power consumption information center, and event information center for clients. In addition, smart meters can also show the information of power changes and power efficiency, with clear data and analysis in order to remind the user to adjust the use of time of a load, or to replace more economical electrical house appliances. It can be applied to monitor even final house appliances and a useful system for client management. Collection of energy consumption data from all clients on a regular basis allows the utility companies to manage electricity demand more efficiently and also to advise the clients about the cost efficient ways to use their appliances. Fig. 3 illustrates the architecture of smart meters in an AMI system.

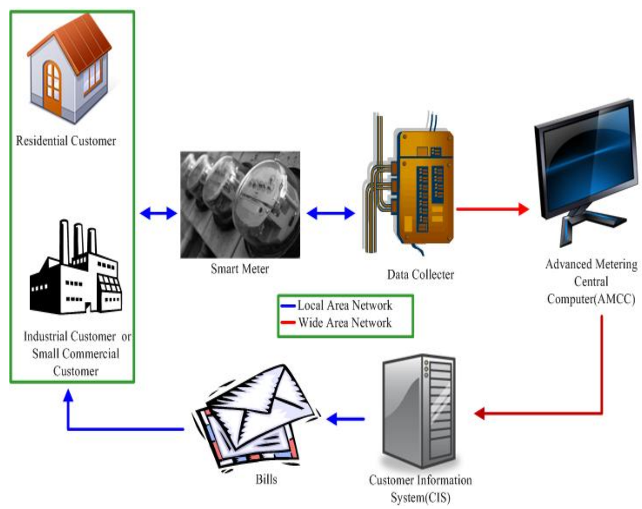

Figure 3. The architecture of smart meters in an AMI system

III. PROPOSED METHODS

A. Genetic Algorithm

Genetic Algorithm starts with a population of encoding candidate solutions for an optimization problem. In a genetic algorithm, strings, which encode candidate solutions to an optimization problem, evolves better solutions. Solutions which are selected to form new generations are selected according to their fitness; the more suitable they are, the more likely they can be reproduced. This is repeated until some condition is satisfied, for example, the number of populations or improvement of the best solution [10].

The GA evaluates each candidate according to the fitness function. In a pool of randomly generated candidates, of course, most will not work at all, and these will be deleted. However, purely by chance, a few may hold promise, they may show activity, even if only weak and imperfect activity, toward solving the problem. The flow chart of GA is illustrated in Fig.4. To solve optimization problems, some techniques are inspired by natural evolution, such as initial population encoding, fitness evaluation, reproduction and selection, crossover and mutation.

1) Initial population encoding

To generate randomly population of n chromosomes, the chromosome should in some way contain information about the solution which it represents. In binary encoding, every chromosome is a string of bits, where each bit represents a different object, and the value of the binary bit represents whether or not the object is a solution? The chromosome then could look like this:

Chromosome 1 11110001101010

Chromosome 2 11000111000100

Binary encoding gives many possible chromosomes even with a small number of alleles. On the other hand, this encoding is often not natural for many problems and sometimes corrections must be made after crossover and/or mutation.

2) Fitness evaluation

The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. A fitness function is a particular type of objective function that assigns the optimality of a solution in a genetic algorithm so that the particular chromosome may be ranked against all the other chromosomes. Optimal chromosomes, or at least chromosomes which are more optimal, are allowed to breed and mix their datasets by any of several techniques, to produce a new generation that will be even better.

3) Reproduction and selection

For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. A new solution is created which typically shares many of the characteristics of its "parents". New parents are selected for each new child, and the process continues until a new population of solutions of appropriate size is generated.

Individual solutions are selected through a fitness-based process, where fitter solutions are typically more likely to be selected. Certain selection methods evaluate the fitness of each solution and preferentially select the best solutions. Other methods rank only a random sample of the population, as this process may be very time-consuming.

4) Crossover

Table 1 shows that crossover selects genes from parent chromosomes and creates a new offspring. The simplest way to do this is to choose randomly some crossover point. Everything before this point is copied from a first parent and then everything after a crossover point copied from the second parent.

Crossover can be rather complicated and depends on encoding of chromosome. Specific crossover made for a specific problem can improve performance of the genetic algorithm.

TABLE I. THE RESULTS OF OFFSPRING AFTER CROSSOVER

Chromosome 1	11110001101010
Chromosome 2	110001**11000100**
Offspring 1	111100**11000100**
Offspring 2	11000101101010

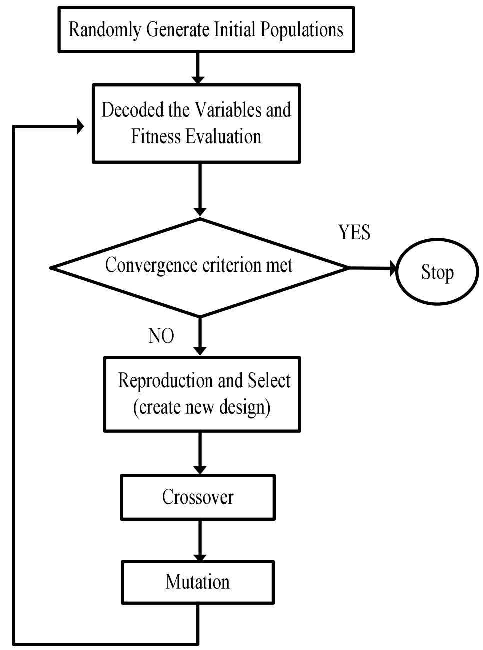

Figure 4. The flow chart of genetic algorithm

5) Mutation

After a crossover is performed, mutation takes place. This is to prevent all solutions in a population from falling into a local optimum of the problem. Mutation changes the new offspring randomly. For binary encoding, we can switch a few randomly chosen bits from 1 to 0 or from 0 to 1. Mutation can be demonstrated as Table 2.

TABLE II. THE RESULTS OF OFFSPRING AFTER MUTATION

Chromosome 1	111**1**0001101010
Chromosome 2	110001**1**1000**0**100
Offspring 1	111***0***0011000100
Offspring 2	110001***0***110***1***010

B. Artificial Neural Networks

Pattern classifiers partition a multidimensional space into decision regions that indicate the class to which any input belongs [6]. Many classification techniques have been created for load recognition. The parametric and learning-supervised classifier has been applied to identify the electrical patterns of commercial and industrial appliances because the distribution of these patterns is very complex without any formulation, and large loads can be labeled easily and clearly.

1) Training algorithms and performance index function

Over-fitting is a typical problem that occurs during artificial neural network training. Bayesian regularization (mean square error, MSE) typically provides better generalization performance than early stopping because Bayesian regularization does not require a validation dataset to be separated from the training dataset. On the other words, the input training data uses all training datasets. This advantage is particularly important when the dataset is small.

The typical performance index function used for training a feedforward neural network is the mean sum of squares of network errors, also called MSE, which is the average squared error between network outputs and target outputs.

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

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

2) Multi-layer feed-forward neural network

The fast algorithms that compare gradient descent and gradient descent with momentum fall into two main categories for back propagation artificial neural network (BP-ANN). The first category comprises heuristic techniques. The second category comprises standard numerical optimization techniques such as the conjugate gradient technique, the quasi-Newton technique and the Reduced Memory Levenberg–Marquardt (LM) algorithm [11].

Most BP artificial neural network applications utilize single- or multilayer perceptron networks by using gradient-descent training methods combined with learning via back propagation. These multi-layer perceptrons can be trained under supervision using analytical functions to activate network nodes (“neurons”) and by applying a backward error-propagation algorithm to update interconnecting weights and thresholds until a sufficient recognition capability is achieved. In this study, the BP classifier is used as a trainable classifier for a multi-layer feed-forward neural network (MFNN). “Classification” in this context is a mapping from a feature space to a set of class labels, which are the names of loads.

A supervised MFNN is generally divided into three layers: input, hidden, and output layers. These neurons are connected by links with weights that are selected to meet the desired relationship between input and output neurons. These weights must be trained with existing input－output pairs using a suitable algorithm. An appropriate momentum and learning rate should be utilized during training. The MFNN in this study is utilized to identify loads in the NILM system. The input, output, and hidden layers of the BP-ANN are as follows:

a) Input layer: power signature information, including real powers and/ or reactive powers, for an electrical service entry serves as inputs.

b) Output layer: the number of output neurons is the same as the number of individual loads identified. Each binary bit serves as a load indicator for ON/OFF status.

c) Hidden layer: only one hidden layer is used in this study.Some heuristics have been developed that can determine the number of neurons in a hidden layer [12]. The common number of neurons in a hidden layer is the sum of the number of neurons in an input layer and that in an output layer.

IV. EXPERIMENTAL RESULTS

A. Study Environments

Each entry in the results 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 10000.

B. Results

1)Case Study 1, EMTP Simulation: In case study 1, a simulated NILM system monitors the voltage and current waveforms in a three-phase electrical service entry powering representative loads in an industrial building. The neural network algorithm in the NILM system identifies three loads of the 480-V common bus with steady-state signatures observed during operation. These loads include a 160-hp induction motor, a 123-hp induction motor driven by line frequency variable-voltage drives, and a bank of loads supplied by a six-pulse thyristor rectifier for A.C. power.

Table 3 shows that values for recognition accuracy of load identification in multiple operations are higher than 97% for features with real power and reactive power (PQ) regardless of whether GA is employed or not. However, the recognition accuracy of load in multiple operations is less than 72% for features with real power (P), or reactive power (Q) without GA method. But, the recognition accuracy of load recognition is higher than 97% for features with real power (P), reactive power (Q), or real power and reactive power (PQ) with GA.

In computation time, the time of training when the feature extraction uses GA algorithm is less than that of the feature extraction without using GA.

TABLE III. THE RESULTS OF LOAD IDENTIFICATION IN CASE STUDY 1

Methods	GA-without			GA		
Power Feature	P	Q	PQ	P	Q	PQ
Recognition Accuracy In Training (%)	71.8	56.4	100	100	100	100
Recognition Accuracy In Test (%)	57.9	47.4	100	97.4	97.4	97.4
Computation Time (s)	7.17	8.25	7.80	4.80	4.82	4.81

2)Case Study 2, Experiment: The NILM system in case study 2 monitors the voltage and current waveforms in a three-phase electrical service entry powering representative loads in a laboratory. The neural network algorithm in the NILM system identifies three actual loads on a 220-V common bus with steady-state signatures. These loads include a three-phase R-L linear load, a one-phase 0.2-hp induction motor, and a three-phase 1-hp induction motor.

Table 4 shows that values for recognition accuracy of load identification in multiple operations are higher than 97% for features with real power and reactive power (PQ) even if GA is not employed. However, the recognition accuracy of load recognition in multiple operations is less than 64% for features with reactive power (Q) without GA method. But, the recognition accuracy of load recognition is higher than 94% for features with real power (P), reactive power (Q), or real power and reactive power (PQ) with GA.

TABLE IV. THE RESULTS OF LOAD IDENTIFICATION IN CASE STUDY 2

Methods	GA-without			GA		
Power Feature	P	Q	PQ	P	Q	PQ
Recognition Accuracy In Training (%)	97.8	64.1	100	100	97.4	100
Recognition Accuracy In Test (%)	81.6	57.9	97.4	97.4	94.7	98.4
Computation Time (s)	8.34	8.51	8.70	7.95	3.29	8.06

3)Case study 3, EMTP Simulation for Different Loads with the Same Real Power and Reactive Power: In case study 3, the NILM system monitors voltage and current waveforms in a three-phase electrical service entry powering a collection of loads representing the major load classes in a commercial building. The neural network algorithm in the NILM system identifies three loads operating on a 220-V common bus with steady-state signatures. 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 5 shows that values for recognition accuracy of load identification in multiple operations are less than 69% for features with real power (P), reactive power (Q), or real power and reactive power (PQ) when GA is not employed. However, the recognition accuracy in multiple operations is higher than 84% for features with real power (P), reactive power (Q), or real power and reactive power (PQ) when GA is used. Those loads cannot be identified by real power, reactive power, or real power and reactive power features when the features cannot be extracted because the second load and the third load are different loads with the same real power and reactive power, similarly for the combination of the first and second loads and the combination 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, reactive power, or real power and reactive power features.

In computation time, the time of training when the feature extraction uses GA is also less than that when the feature extraction does not utilize GA.

TABLE V. THE RESULTS OF LOAD IDENTIFICATION IN CASE STUDY 3

Methods	GA-without			GA		
Power Feature	P	Q	PQ	P	Q	PQ
Recognition Accuracy In Training (%)	43.6	38.5	69.2	97.4	94.9	98.6
Recognition Accuracy In Test (%)	44.1	34.2	42.1	86.8	84.2	91.0
Computation Time (s)	8.28	8.32	8.55	8.05	8.12	8.03

4)Case study 4, Experiment for Different Loads with the Same Real Power and Reactive Power: In case study 4, the NILM system is used to monitor voltage and current waveforms in a one-phase electrical service entry powering representative loads in a laboratory. The neural network algorithm in the NILM system identifies three actual loads on a 110-V common bus with steady-state signatures. 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 6 shows that values for recognition accuracy of load identification in multiple operations are less than 49% for features with real power (P), reactive power (Q), or real power and reactive power (PQ) when GA is not employed. But, the recognition accuracy of load recognition in multiple operations is higher than 86% for features with real power (P), reactive power (Q), or real power and reactive power (PQ) when GA is used. The test recognition for those loads in multiple operations is also quite low when using only real power, reactive power, or real power and reactive power features if the feature extraction method does not employ GA. The reason is the same as that for the previous case. 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 using only features of real power, reactive power, or real power and reactive power without GA. Second, the GA method can improve load identification, especially for different loads with the same real power and reactive power.

In computation time, the time of training when the feature extraction uses GA method is also less than that of the feature extraction without GA.

TABLE VI. THE RESULTS OF LOAD IDENTIFICATION IN CASE STUDY 4

Methods	GA-without			GA		
Power Feature	P	Q	PQ	P	Q	PQ
Recognition Accuracy In Training (%)	41.0	43.6	48.7	92.6	94.6	97.8
Recognition Accuracy In Test (%)	26.3	36.8	39.5	86.6	90.8	89.2
Computation Time (s)	8.15	8.27	8.26	7.63	8.19	7.99

V. CONCLUSIONS AND FUTURE WORKS

The NILM system employs genetic algorithm and artificial neural network to improve the efficiency of load identification and computational time. The experimental results reveal that the recognition accuracy is not high and uncertain about the distribution of power features for only real power or reactive power without feature extraction of GA. However, the recognition accuracy and computational time can be improved after using GA, especially for the identification of different loads with the same real power and reactive power.

In the future works, some other methods of feature extraction will be compared to analyze the efficiency of load identification and computational time with the genetic algorithm.

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