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Literature Review of Power Disaggregation

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***Abstract*—There are mainly two classes of approaches in power disaggregation, including Intrusive Load Monitoring (ILM) and Nonintrusive Load Monitoring (NILM). This paper presents the literature review on the NILM approaches. NILM is a process for detecting changes in the voltage and current going through a house, deducing what appliances are used in the house, as well as their individual energy consumption, with a single set of sensors. Different strategies and approaches for NILM systems have been developed over the past thirty years. This paper reviews the current state of the algorithms and systems of NILM. The paper points out that NILM can be utilised presently on available commercial devices and provides meaningful feedback. Our vision on the future of NILM is also summarized.**

I. INTRODUCTION

THE idea of Non-Intrusive Load Monitoring (NILM) developed since the 1980s is to facilitate electric utilities in the collection of appliance end use data. The key idea of this technology is that changes in the on-off status of an appliance can be detected by step changes in the total power consumption. Instead of bringing sensors to the individual appliances, the aggregate load is disaggregated by signal analysis and pattern recognition techniques implemented in software [1, 2]. The following sections will present the related works in more details.

II. NONINTRUSIVE DISAGGREGATION SYSTEMS

There exist many nonintrusive disaggregation systems. This section reviews the advance in the area.

Marceau's computer program has two modes: sampling and evaluation [3]. In the sampling mode, the operating characteristics of each end use are determined from data collected over a period of several days using at least one current sensor per appliance. In the evaluation mode, only the main electric entrance of the house is monitored, and the electric signal is analyzed to disaggregate the total energy consumption. The errors in estimating the energy shares of three major end uses (water heater, baseboard heater and refrigerator) are less than 10% for most evaluation scenarios. In the system, after data downloaded from data recorders (Current convert to demand), four main components are included: 1. Work out appliance operating characteristics from each appliance file. 2. Filters data in total house hold demand input file. 3. Attributes changes in the whole household demand to specific appliances. 4. Calculates the energy consumption of major household appliances and saves data.

This nonintrusive load disaggregation computer program is incorporated into an Energy Monitoring and Management System (EMMS). An EMMS will continuously monitor and quantify the real long term energy impact of renovations, purchases, aging appliances and changes in occupant behavior, increase the home owner's awareness of actual energy performance and provide helpful recommendations to the home owner for improving the house's energy performance.

Another algorithm is designed to analyse rough data from ordinary electricity meters and has been tested with simulated and real data from different domestic homes in 2004 [4]. The analyzed real data was collected with an optical sensor clamped on the already installed electricity meter in domestic homes. The genetic algorithm offers a variety of parameters to be tuned to improve the detection of appliances or to assimilate data sources of different applications, and the results show that patterns of chief consumer load devices could be detected.

Later, Warit Wichakool [5] has demonstrated the method to extract the fundamental current harmonic of the uncontrolled, three-phase rectifier load using a linear combination of higher ac-side harmonics. The proposed estimator does not require the complete knowledge of circuit parameters and the system's operating point. The experimental results demonstrate that the switching-function based VSD (variable speed driver) power estimator shows significant improvement over the empirically based estimator in resolving the VSD power consumption under small variations in the input voltage. The proposed algorithm enables NILM to work with a larger set of loads. Furthermore, the estimator also shows the ability to track multiple VSDs and rectifier loads together without an additional sensor. This method could be adapted to track other nonlinear loads as well.

The value of physical simplicity should not be overlooked. Complex arrays of monitoring sensors tend to increase the difficulty and the cost of installation, particularly for short-term or temporary monitoring. Larger arrays of less-expensive sensors may diminish overall reliability and require the collation of data streams from different points. Steven R. Shaw [6] minimizes the sensor requirement and provides a flexible platform for diagnostic and control monitoring for almost any electromechanical system or plant. The NILM is quick to install and physically reliable because of its relative hardware simplicity. The NILM's ability to associate observed electrical waveforms with the operation of particular devices makes it a perfect foundation for diagnostic and power quality monitoring systems using state and parameter estimation techniques.

Out of the reviewing on the current available NILM systems, it can be seen that collecting detailed energy consumption data reliably and efficiently is challenging. Sub-metering with separate hardware is expensive, time-consuming, and not designed for home deployment. Software-based disaggregation would benefit from an appliance signature library to save users from explicitly identifying all appliances in the home, but such a convenience depends on the alignment of power metrics from different meters, which is not necessarily possible. Therefore, we propose focusing on the software side of the solution. Hardware will keep improving as time passes, and obtaining high frequency samples for current and voltage waveforms will become less costly. In addition to that, we envision using other sensor data to enhance recognition (e.g., light intensity, relative humidity). From this, the next phase of research can begin: development of a NILM system using sensor fusion and automated event categorization [7].

III. NONINTRUSIVE DISAGGREGATION ALGORITHMS&METHODS

There are mainly three categories of nonintrusive disaggregation algorithms and methods. This section reviews the advance in the area.

A. Wavelet transforms

The integral wavelet transform is the integral transform defined as

$$\left[W_{\psi} f\right](a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} \overline{\psi(\frac{x-b}{a})} f(x) dx$$

The wavelet coefficients C_{jk} are then given by

$$c_{jk} = [W_{\psi} f](2^{-j}, k_2^{-j})$$

where $a = 2^{-j}$ is called the binary dilation or dyadic dilation, and $b = k_2^{-j}$ is the binary or dyadic position.

In Chan's paper [8], fuzzy numbers are used for harmonics signature recognition. They have made use of new developments in wavelets so that each type of current waveform polluted with power harmonics can be well represented by a normalized energy vector consisting of five elements. Furthermore, a mixture of harmonics load can also be represented by corresponding vector. Mathematics and algorithms for arriving at the vectors form a strong foundation for real-time harmonics signature recognition, in particular useful to the restructuring of the whole electric power industry.

Beside, the importance of harmonics signature recognition and the existing problem of harmonics pollution in the electric power distribution system have been discussed. A new method of identifying harmonics signature of different types of non-linear loads has been developed involving discrete wavelet transforms. Each type of load is well represented by five levels of wavelet decomposition. The result is the creation of a normalized energy vector for each type of load, each vector consisting of five elements. These five elements can characterize a particular type of load. Intelligent and automatic signature recognition can be achieved in future with the aid of artificial neural networks. Then optimized harmonics compensation can be carried out even under a noisy environment due to the rejection of level-1 wavelet coefficient which represents the higher frequency component. It is hoped that this method can be further developed to identify and analyze transient disturbance within a power system when non-periodic waveforms are involved [8].

The MIT's method [1] can relatively easy detect and track the on-off appliances, but has apparent problems in detecting multi-state and variable-load appliances. For example, the appliances consuming similar power such as a computer and an incandescent bulb, may not be separated [13].

Another computational algorithm for estimating the amplitudes of non-stationary power system harmonics waveforms is presented by Norman. It is based on Complex Continuous Wavelet Transform (CCWT) by using a modified Complex Morlet Wavelet (CMW).

A WT-based waveform reconstruction algorithm is proposed to reconstruct the harmonic waveforms from the complex CWT (Continuous Wavelet Transform) coefficients for identifying the amplitude variations of the non-stationary harmonics over the estimation period. The proposed algorithm makes use of a modified Complex Morlet Wavelet suggested in the paper. The WT-based reconstruction algorithm is time-invariant and therefore is able to preserve the time and phase information of the harmonic waveform. The proposed WT- based waveform reconstruction algorithm has been tested vigorously by both synthesized waveforms and field harmonic waveforms for its effectiveness. DWT is also used to reconstruct the synthesized signals and it was found that the proposed algorithm is better than DWT in waveform reconstruction [9].

B. Neural Networks

The use of neural network classifiers to evaluate back propagation (BP) and learning vector quantization (LVQ) for feature selection of load identification in a non-intrusive load monitoring (NILM) system is proposed by Chang [10]. To test the performance of the proposed approach, data sets for electrical loads were analyzed and established using a computer supported program-Electro-magnetic Transient Program (EMTP) and onsite load measurement. Load identification techniques were applied in neural networks. The efficiency of load identification and computational requirements was analyzed and compared using BP or LVQ classifiers method. This paper revealed some contributions below. The turn-on transient energy signatures can improve the efficiency of load identification and computational time under multiple operations. The turn-on transient energy has repeatability when used as a power signature to recognize industrial loads in a NILM system. Moreover, the BP classifier is better than the LVQ classifier in the efficiency of load identification and computational requirements.

There are different representations of load patterns for individual operation and multiple operations. In individual operation, a class shows that the representation is only one load. In multiple operations, a class shows that the representation can be one or many loads. In other words, a class may be a combination of more than one load. Therefore, classifications are more complicated for multiple operations.

These features cannot be adequately measured only from steady-state parameters in multiple operations, that is, real power and reactive power. In other words, it is difficult in steady-state power to identify each load, when the sums of real power and reactive power of two loads types are equal to that of another load. In contrast to steady-state properties, transient properties such as the turn-on transient energy can play an important role. Combining transient and steady-state signatures is necessary to improve recognition accuracy for NILM.

In the individual operation, back propagation classifier requires less computational requirements than learning vector quantization classifier. In multiple operations, the computational requirements cannot compare with the back propagation classifier and the learning vector quantization classifier, for the algorithm of LVQ classifier cannot converge until the number of maximum iterations.

The EMTP simulation is invaluable for testing pattern recognition samples and allows the rapid development and implementation of successful prototypes. The NILM system employs an adaptive algorithm of the turn-on transient energy for start-up analysis to improve the efficiency of load identification and computational time. The testing recognition accuracy can be relatively at a very high rate for back propagation classifier, in multiple operations. Furthermore, the BP classifier is far better than the LVQ classifier, in the efficiency of load identification and computational requirements [10].

It is known that artificial neural networks (ANNs) can be an effective technique to help to predict the fault, when it is provided with characteristics of fault currents and the corresponding past decisions as outputs. This paper describes the use of particle swarm optimisation (PSO) for an effective training of ANN and the application of wavelet transforms for predicting the type of fault. Through wavelet analysis, faults are decomposed into a series of wavelet components, each of which is a time-domain signal that covers a specific octave frequency band.

An application of a PSO-based perceptron approach for prediction of fault type with the help of WT was presented by J. Upendar. The optimisation algorithm is demonstrated to be able to provide model-free estimates in deducing the output from the input. Various case studies have been studied including the variation of fault distance, inception angle and fault resistances. Both PSO-based perception approach and BPNN (back-propagation neural network) method have been implemented. The performance shown demonstrates that the proposed technique gives a very high accuracy (99.912%) in classification of the power system faults. It is demonstrated from the training and verification simulation that the prediction results of fault type are more accurate, when compared with the conventional BP-based perceptron and SVM methods. Therefore the PSO-based perceptron approach can be used as an attractive and effective approach for classification algorithm of power system faults [11].

Adaptive Resonance Theory (ART) is a theory developed by Stephen Grossberg and Gail Carpenter on aspects of how the brain processes information. It describes a number of neural network model which use supervised and unsupervised learning methods, and address problems such as pattern recognition and prediction. This work presents a methodology to analyze electric power systems transient stability for first swing using a neural network based on adaptive resonance theory (ART) architecture, called Euclidean ARTMAP neural network, which combines two slightly modified ART-1 or ART-2 units into a supervised learning structure where the first unit takes the input data and the second unit takes the correct output data, then used to make the minimum possible adjustment of the vigilance parameter in the first unit in order to make the correct classification.

The proposed neural network will have a precision increment when the continuous training is intensified. This is the principal proposal of this paper, i.e., a neural network proposal that achieves the improvement as the time passes, including new topologies of the electrical network. This is the principal contribution of this paper when compared to the specialized literature. Therefore, the electrical power system operation can incorporate a new methodology to analyze the transient stability with an adequate precision.

Afterwards, from the analysis effectuated considering the topologies provided, the neural network will search the incremental knowledge acquisition without overspending the computational costs, and therefore the analysis can be realized with a computational time compatible for applications in real time.

C. Support Vector Machine

Support Vector Machine (SVM) has been widely used in different areas [14]. SVM is a classifier, it gives a set of training examples, each marked as belonging to one of two categories. The SVM training algorithm builds a model that predicts whether a new example falls into one category or the other. Intuitively, an SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible [15]. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

SVM deliver state-of-the-art performance in real-world applications such as text categorization, hand-written character recognition, biosequences analysis, image classification, etc. It is now established as one of the standard tools for machine learning and data mining. The SVM decision function is defined as follows:

$$f(y) = \sum_{i=1}^{N} \alpha_i K(x_i, y) + b$$

Here, y is the unclassified tested vector, x_i are the support vectors and α_i their weights, and b is a constant bias. K(x,y) is the kernel function introduced into SVM to solve the nonlinear problems by performing implicit mapping into a high-dimensional feature space [16].

Rachid Kadouche and his colleagues presented [17] their ongoing work on the house occupant prediction issue based on daily life habits in smart houses. Most of their works are based on supervised learning technical. They used SVM to build behavior classification model for learning the user's habits, analysed the publicly available dataset from the Washington State University Smart Apartment Testbed. Particularly, they evaluated the grooming, having breakfast, and bed to toilet activities [17]. Their experimental results showed that the user can be recognized with a high precision which means that each user have his own way to perform activities. As future work, the users' patterns which allow a person to be discriminated and recognized among a group performing altogether activities in the same environment without using intrusive technologies are being studied.

IV. Conclusions

NILM is being used more extensively in classification and disaggregation of power signals. However, no complete NILM solution suits all types of household appliances is available. One solution to solve this problem is using data fusion technologies, such as Dampster Shafer [18]. It can combine solutions from different methodologies together to provide the most reliable results. Disaggregated energy loads are then used to realize demand side management [19, 20].

We foresee that the development of algorithms and improvement of software are the future of NILM, although it is also optimistic on the enhancing of the hardware such as audits.

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