An Evaluation of VI-Trajectory based Load Signature for Non-Intrusive Load Monitoring

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***Abstract*—Choice of load signature or feature space is one of the most fundamental design choices for various characterizations of non-intrusive load monitoring or energy disaggregation problem (classification, pattern recognition). This paper evaluates appliance load signatures based on VI-trajectory - the mutual locus of canonical instantaneous voltage and current waveforms - for overall precision and robustness of prediction in DE-optimized classifiers used for disaggregation of household energy use into constituent appliance signatures. Benchmark dataset employed for evaluation is REDD (reference energy disaggregation dataset - MIT CSAIL).**

***Index Terms*—Non-intrusive Load Monitoring; Smart grids; energy disaggregation; REDD**

I. Introduction

Monitoring of end user device loads can have significant benefit in energy conservation applications. Savings of up to 20% have been reported in household where total energy usage of the household is visualized in realtime for the users. Monitoring of devices has even more application in suggestive demand side management, integration of distributed generation and renewable energy and in micro-grids operations and in reactive demand response. To monitor end user device loads, the state of the art is to install sensors on the devices and collect the data through some wireless means -usually using ZigBee protocol. However, this not only is costly but also has security and privacy issues.

Non-intrusive load monitoring (NILM) provides a viable solution[**?**]. NILM identifies loads of individual devices without intrusive sensors placed on the user premises and in most cases disaggregated the total load of the house into load components of individual devices. Since automated metering infrastructure installations are already underway in many regions, the cost of such monitoring will be minimal.

Various algorithms have been proposed to identify and monitor loads of individual devices [citation for some pre 2009 survey]. However, recent studies of Lian and colleagues and Lam and colleagues on load signature curves and their relationship with device usage has provided a new avenue for research. This taxonomy of loads based on load signature curves has been used for load disaggregation by various researchers and has been shown as a good way for load monitoring. In this paper we apply this taxonomy to build a non-intrusive load monitoring infrastructure.

In this paper we evaluate the effectiveness of a two-dimensional load signature defined by the mutual locus of instantaneous voltage and current waveforms (referred to as the VI-trajectory in introductory work [3]). Our goal is precision and robustness of prediction in non-intrusive load monitoring applications. For the scope of this study NILM is characterized as a multi-class classification problem.

To solve this multi-class classification problem we have used a hybrid EDE-NN algorithm. This EDE-NN algorithm applies enhanced differential evolution (EDE) algorithm for parameter search to optimize the neural network classification framework. The algorithm has previously been used for short term load forecasting of micro-grids however, to our knowledge we are the first one to apply such a hybrid system for this problem.

We have evaluated this algorithm on Reference Energy Disaggregation Data Set (REDD) collected by computer science and artificial intelligence (CSAIL) laboratory at MIT, USA. This data consists of whole-home and device specific electricity consumption data for 119 days for a 10 houses. For each monitored house, REDD provides the whole home electricity signal at a frequency of15kHz and up to 20 plug-level monitors in the home, recorded at 1 Hz. Since REDD to date is the largest publicly available data set of such kind, we use this data as a benchmark for evaluation of our NILM application.

Our results show that the VI-trajectory has a marked better prediction accuracy of wave-shape features (WS) derived from VI-trajectory compared to other benchmark load signatures. We also show that the hybrid EDE-NN classifier performs better than the state of the art algorithms for NILM specifically those applied to REDD.

The paper is organized in the following way: Section II details these various design choices. Section III presents the numerical results illustrating the superior prediction accuracy of wave-shape features (WS) derived from VI-trajectory compared to other benchmark load signatures.

II. Proposed Strategy

Structure of the proposed setup is depicted below, followed by an evaluation of various design choices.

A. Review of Various Design Choices for Load Signature (LS)

Choice of feature space has implications on generalization of classifier training, performance of disaggregation. Research in [3] assesses the relative feasibility of traditional power metrics, metrics based on wave-shape and most significant orthonormal vectors of current waveform for establishing taxonomy of electrical appliance signatures. Traditional power metrics like real and reactive RMS power consumed (P, Q), total odd and even harmonic distortion of current (ToHD, TeHD) have concrete engineering meanings that detail operating characteristics of the appliance in question; however, they often allow for appliances of very different nature (for instance, motor-driven, power electronic and resistive) to be identified within the same appliance class when chosen as the feature space for classification. An alternative choice would be to apply singular value decomposition (SVD) on a matrix containing cycle-by-cycle current waveform and consider the most significant orthonormal vectors. Extracted vectors are characteristic of current wave-shape; however, they do have obvious engineering meanings. Metrics based on shape of V-I trajectory (mutual locus of voltage and current waveforms) allow for appliances of similar operating characteristics to be grouped closer, hence less fuzziness in dataset, should allow the training algorithm to generalize better to unknown examples and the disaggregation to improve overall accuracy. Chosen wave-shape metrics for this study are Looping Direction, Area Enclosed, Non-linearity of Mean Curve, Self Intersections and Slope of Middle Segment *Looping Direction, Area Enclosed, Non-linearity of Mean Curve, Self Intersections and Slope of Middle Segment*[3].

B. Training Structures, Disaggregation Framework

Choice of training structure is a function of the characterization of the learning problem subscribed to and the feature space used. With discrete features calculated beforehand - traditional power metrics or wave-shape features - linear search with Euclidean distance would suffice. Treating the disaggregation as a pattern recognition problem however, we can use an artificial neural network to learn complex features of the current wave (CW) shape or of instantaneous admittance waveform (IAW) [2]. Even with features calculated before-hand, a single neural network can be used to perform multi-class classification, so as to derive a single complex, non-linear hypothesis function that works as a composite classifier. A generalized NALM system usually realizes a parallel execution of all of these methods and uses committee decision methods to achieve the best of performance among all deployed algorithms; this provably results in better overall accuracy compared to single algorithm methods [6]. Computation overhead incurred by such a framework might imply limitations on realization, deployment and service period; for instance, a minimal, scalable realization for event-based operation would necessarily exploit software and preferably hardware parallelization and provisions would be needed to account for near simultaneous switching events.

C. Performance Optimization

Following passage reviews the algorithm for parameter search ([4], [11]), with special reference to DE and EDE. Differential Evolution (DE) is a heuristic, population-based global search strategy that, offers more relative certainty and efficiency of convergence for minimization problem for non-linear continuous space functions [5]. EDE is an enhanced variant of DE proposed in [4] whereby instead of an empirical recombination rate (RR) for populations of system parameters, a new fitness function is described that weighs the fitness of mutant population (f) relative to fitness of original population,

$$f = \frac{\frac{1}{OF(U)}}{\frac{1}{OF(X)} + \frac{1}{OF(U)}}$$

Urepresents the mutant population of training parameters, X, the original population, OF, the objective function corresponding to a set of ANN training parameters. In large-scale NALM systems with heavily parallelized implementations of various training structures, the objective function represented by $OF(X)$ can be generalized as follows:

$$OF(X) = \sum_{k=1}^{N} (\alpha_k OF_k(X))$$

such that $OF_k(X)$ represents the objective function corresponding to classifiers for one of the various appliances or classes of appliances under consideration. The constants α_k represent the relative weights of various OFs such that choice of these constants would reconcile the minimization of individual OFs for the composite classifier. These constants introduce additional flexibility for gauging the constraints on sensitivity of disaggregation towards a subset of appliances.

A brief summary of the overall proposed strategy is described as follows. Populations of system variables (number of hidden layer neurons in case of ANN, recombination rate in case of DE/GA or velocity constant in EA) or 'genes' for k^{th} trainer and i^{th} iteration, $X^i_{vw}(k), k = 1, 2, \ldots, N$ are randomly initialized in the beginning, a total of M individuals $(v = 1, 2, , M)$ and G genes per individual for each trainer $(w = 1, 2, \ldots, G)$. Assuming α_ks are known, each individual in the mutant population $U^i_{vw}(k)$ is determined by a linear combination of genes from three randomly chosen individuals in the original population.

$$U^i_{vw}(k) = X^i_{aw}(k) + F \times (X^i_{bw}(k) - X^i_{cw}(k))$$

$$a \neq b \neq c \neq v, F > 0$$

Fitness functions of original and mutant populations are determined from (1) and (2). Each gene in $X^{i+1}_{vw}(k)$ is determined as follows:

$$x^{i+1}_{vw}(k) = \begin{cases} u^i_{vw}(k) & \textit{if rand} < \textit{Fitness Function (U)} \\ x^i_{vw}(k) & \textit{if rand} \geq \textit{Fitness Function (U))} \end{cases}$$

The process is continued until maximum number of iterations is reached [11]. In case of DE, an empirical combination rate (RR) replaces the fitness function described; rest of the strategy stays the same. EDE thus has a self-regulating RR. In a composite classifier, one choice is that performance optimization of each class can be carried out in parallelized fashion (requiring N replicas of above algorithm) such that for selected values of k,

$$\left| OF_k - \frac{1}{N} \right| < \varepsilon$$

An alternative choice would be to use a single objective function following the above rule; simplest instances would be for selected values of k, $\Sigma_k \left| OF_k - \frac{1}{N} \right|$ or $\Sigma_k \left(OF_k - \frac{1}{N} \right)^2$, depending on the penalty required as error grows and whether OF can adapt to degree of convergence of parameters like with the basic case of $max_k OF_k$. More sophisticated objective functions that allow for both dynamic adaptation and selective minimization can be constructed.

III. Assessment

A. Evaluation Framework