Bi-level Characterization of Manual-Setup Residential Non-Intrusive Demand Disaggregation using Enhanced Differential Evolution

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ABSTRACT

Renewed interest in formalization of non-intrusiveload monitoring algorithms in recent years has been compounded by inroads into efficient optimization and global search strategies. This work attempts to characterize the manual-setup nonintrusive load disaggregation problem on a household scale using a bi-level strategy composed of an enhanced variant of differential evolution as the optimizing algorithm for a highly adaptive disaggregation in the lower level. Enhanced DifferentialEvolution (EDE) offers efficient convergence compared to itsparent stochastic global search strategy, differential evolution (DE); Coupled with generalized metrics to gauge the selectivity of search for optimal training attributes allows for a highly flexible dissolution of the overall demand profile into its constituent steady-state appliance signatures. Accuracy and efficiency is evaluated forthe proposed strategy.

Keywords

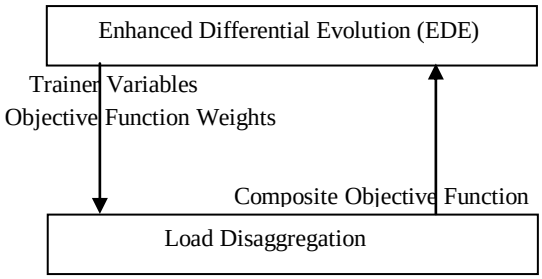
Load monitoring, non-intrusive, differential evolution, manual-setup, bi-level.

1. INTRODUCTION

Non-intrusive load disaggregation or NALM on a household scale, is the resolution of the overall demand profile (ODP) of the household into individual signatures ofappliances switched on at a particular instant or within aspecified time period, without any intrusive physical sensors on individual appliances. The term 'Manual-Setup' refers to a one-time intrusive calibration period for all appliances under consideration prior to normal operation. Since beingproposed in [1], perspectives in NALM have explored natureof requisite signatures ([1]-[3]), composition of learning algorithms proposed to differentiate between signatures [7]-[8]; as well as optimization methods and platforms for large-scale NALM systems ([6]). This work attempts to characterize manual-setupNALM by proposing a generalization of a bi-level prediction methodology originally introduced in [4] for short-term load forecast of microgrids. The strategy uses enhanced differential evolution (EDE), a variant of differential evolution providing efficient convergence and specialized global search along with limited control variables in initial setup to optimize the accuracy of disaggregation (assessed with various signature classifications, including traditional power metrics and VI-trajectory based signatures). Primary training structure for pattern recognition for signatures under consideration is ANN, trained in parallel corresponding to either various classes of appliances in accordance with taxonomies reviewed in [3] or individual appliances. Proposed generalization introduces accuracy metrics that allow for additional control on selectivity of search for optimal system parameters (in terms of critical performance constraints on disaggregator for a subset of appliances), or to cater for the need of gauging sensitivity of disaggregation towards certain appliances in a general-purpose large-scale NALM system such as proposed in [6]. The characterization also provides an analytic framework for systems as [6] to assess the relative performance of various optimization methods (EDE, PSO, GA etc.) in terms of efficiency and accuracy of resultant load monitors as well as to provide feedback on possible discrepancies in signature database, underfitting or overfitting in ANN training etc. .

2. STRATEGY

As introduced in earlier section, the structure of proposed setup is depicted below:



2.1 Enhanced Differential Evolution (EDE)

Differential Evolution (DE) is a heuristic, population-based global search strategy that, as demonstrated in [5], offers more relative certainty and efficiency of convergence for minimization problem for non-linear continuous space functions. EDE is an enhanced variant of DE proposed in [4] whereby instead of an empirical recombination rate for populations of system parameters, a new fitness function is described that weighs the fitness of mutant population relative to fitness of original population, cumulative validation error being the metric for fitness or the objective function corresponding to population of the current iteration.

$$\text{Fitness of Mutant Population} = \frac{\frac{1}{\text{OF(U)}}}{\frac{1}{\text{OF(X)}} + \frac{1}{\text{OF(U)}}}$$

U represents 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 requiring heavily parallelized implementations of various training structures, the objective function represented by OF(X) can be generalized as follows:

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

such that $\mathrm{OF}_k(\mathrm{X})$ represents the objective function corresponding to trainers for one of the various appliances or classes of appliances under consideration.

2.2 Generalized Metrics

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 parallelized implementation. These constants introduce additional flexibility for gauging the constraints on sensitivity of disaggregation towards a subset of appliances. Additionally, if treated as system variables and searched for together with training parameters for ANN in our case, discrepancies in these constants serve as an indicative of overfitting or underfitting in the disaggregator training or of possibly redundant or irrelevant features in a subset of the signature database.

The generalized fitness function for original and mutant populations in the differential evolutionary search would then be:

$$\text{Fitness of Original Population} = \frac{\sum_{k=1}^{\mathrm{N}}(\alpha_k \mathrm{OF}_k(\mathrm{X}))}{\sum_{k=1}^{\mathrm{N}}(\alpha_k \mathrm{OF}_k(\mathrm{X})) + \sum_{k=1}^{\mathrm{N}}(\alpha_k \mathrm{OF}_k(\mathrm{U}))} \quad (1)$$

$$\text{Fitness of Mutant Population} = \frac{\sum_{k=1}^{\mathrm{N}}(\alpha_k \mathrm{OF}_k(\mathrm{U}))}{\sum_{k=1}^{\mathrm{N}}(\alpha_k \mathrm{OF}_k(\mathrm{X})) + \sum_{k=1}^{\mathrm{N}}(\alpha_k \mathrm{OF}_k(\mathrm{U}))} \quad (2)$$

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 parallelized implementation. Usual suspects for $\mathrm{OF_k}$ are weighted mean error (WME), relative prediction error frequency and F-score. The constants introduce additional flexibility for gauging the constraints on sensitivity of disaggregation towards a subset of appliances. Additionally, if treated as system variables and searched for together with training parameters for ANN in our case, discrepancies in these constants serve as an indicative of overfitting or underfitting in the disaggregator training or of possibly redundant or irrelevant features in a subset of the signature database.

2.3 Overall Framework

A brief summary of the overall proposed NALM 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, $X_{vw}^{\,i}(k), k = 1,2,\dots,N$ are randomly initialized, a total of M individuals $(v = 1,2,\dots,M)$ and G genes per individual for each trainer$(w = 1,2,\dots,G)$. Assuming α_ks are known, each individual in the mutant population $U_{vw}^{\,i}(k)$ is determined by a linear combination of genes from three randomly chosen individuals in the original population.

$$U_{vw}^{\,i}(k) = X_{aw}^{\,i}(k) + F \times \left(X_{bw}^{\,i}(k) - X_{cw}^{\,i}(k)\right)$$

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

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

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

The process is continued until maximum number of iterations is reached.

3. ASSESSMENT

Assessment of proposed strategy with two appliance signature databases, REDD and SSE01 (a custom signature database developed locally) is currently underway. A general-purpose NALM simulator proposed in [6] is the simulation environment where signatures in used are of two basic categories [3]: traditional power metrics, Prms, Qrms, THD as well as metrics based on VI-trajectory: *asymmetry of trajectory* (asymmetry of current waveform in half-cycles), *curvature of mean line* (non-linearity of current response), *area enclosed by trajectory* (magnitude of phase difference between voltage and current waveforms) and *slope of middle segment of trajectory* (minimal slope characteristic of power-electronic loads).

4. REFERENCES

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