

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

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Introduction

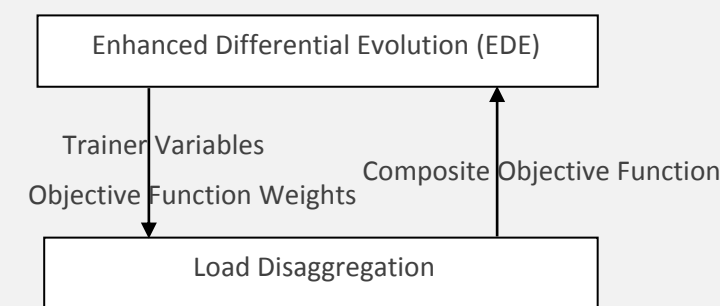
Non-intrusive load disaggregation or NALM is the resolution of overall demand profile of a household into individual signatures of appliances switched on at a particular instant or within a specified time period, without any intrusive physical sensors on individual appliances.

Manual-Setup refers to a one-time intrusive calibration period for all appliances under consideration prior to normal operation.

This study generalizes a bi-level prediction methodology originally introduced in [4] (for short-term load forecast of microgrids) and appropriates it for self-regulation of MS-NALM systems.

The strategy, illustrated below, applies enhanced differential evolution, 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 in the lower level. A brief review of various design choices follows.

Proposed Strategy



Feature Space

Choice of feature space has implications on generalization of classifier training, performance of disaggregation.

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.

Other metrics like orthonormal vectors from SVD applied to current waveform or traditional power metrics are compared for capacity of differentiation in [3].

Chosen shape features of the V-I trajectory for this study are:

Looping Direction, Area Enclosed, Non-linearity of Mean Curve, Self-Intersections, & Slope of Middle Segment [3].

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.

A generalized NALM system usually realizes a parallel execution of single-algorithm methods (multi-class classification, distance minimization, pattern recognition) and uses committee decision methods (CDMs) to achieve the best performing of 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.

Performance Optimization

Following passage describes the algorithm for parameter search, 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 relative to fitness of original population.

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

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

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

such that $\text{OF}_k(X)$ 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 in a general purpose, large scale NALM system such as proposed in [6], and

Introduce additional selectivity of in search for optimal system parameters (in terms of critical performance constraints on disaggregator for a subset of appliances)

Choice of objective function is such as to both selectively optimize performance of appliance classes in question and dynamically adapt to degree of convergence of the population of training parameters.

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) or 'genes' for k th trainer and l th iteration, $X_{vw}^i(k)$, $k = 1, 2, \dots, N$ are randomly initialized in the beginning, 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_k s 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.

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

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

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:

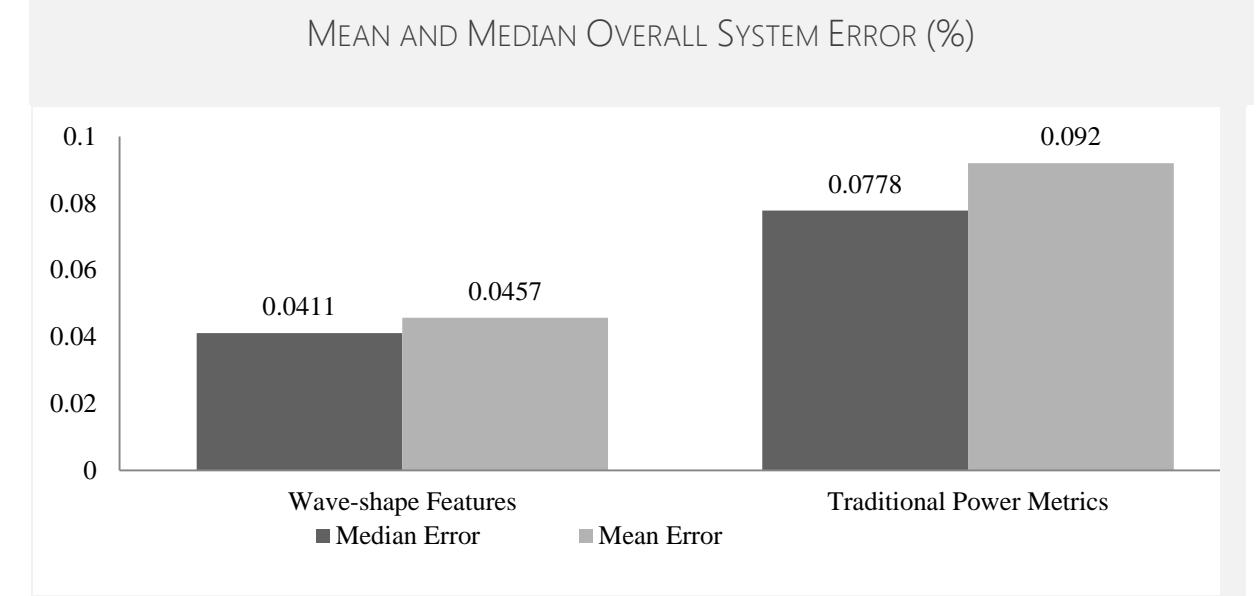
$$x_{vw}^{i+1}(k) = \begin{cases} u_{vw}^i(k) & \text{if rand} < \text{Fitness Function}(U) \\ x_{vw}^i(k) & \text{if rand} \geq \text{Fitness Function}(U) \end{cases}$$

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

Assessment

The framework illustrated earlier is used to optimize and assess the generalized NALM system in a residential setting. Sequences of switching events are simulated, each of these events are uniformly probable at any given instant of time [6]. Load dynamics and electrical noise are accounted for. Neural networks are trained using Levenberg-Marquardt (LM) method. The dataset established (a total of 20 identified operating states) uses a good mix of appliance signatures from classes identified in the taxonomies reviewed in [3].

Overall system accuracies for EDE under preliminary evaluation (moderate SNR, perfect recall) are as follows.



Overall prediction accuracy exceeds those achieved with generalized NALM systems implementing CDMs [6]. More comprehensive evaluation with REDD [11] is underway.

References

- [1] G.W. Hart, "Non-intrusive load monitoring," *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870-1891, Dec 1992.
- [2] J. Liang, S.K.K. Ng, G. Kendall and J.W.M. Cheng, "Load signature study part 1: basic concept, structure and methodology," *IEEE Trans. Power Delivery*, vol. 25, no. 2, pp. 551-560, April 2010.
- [3] H.Y. Lam, G.S.K. Fung, and W.K. Lee, "A Novel Method to Construct Taxonomy of Electrical Appliances Based on Load Signatures," *IEEE Trans. Consumer Elec.*, vol.53, no.2, pp.653-660, May 2007.
- [4] N. Amjady, F. Keynia and H. Zareipour, "Short-term load forecast of microgrids by a new bilevel prediction strategy," *IEEE Trans. Smart Grid*, vol.1, no.3, pp.286-294, Dec. 2010.
- [5] R. Storn and K. Price, "Differential Evolution - A simple and efficient heuristic for global optimization over continuous spaces," *Journal of Glob. Optimization*, vol. 11, no. 4, pp. 341-359, Dec. 1997.
- [6] J. Liang, S.K.K. Ng, G. Kendall and J.W.M. Cheng, "Load Signature Study - Part II: Disaggregation Framework, Simulation and Applications," *IEEE Trans., Power Delivery*, vol.25, no.2, pp.561-569, April2010.
- [7] H. W. Lai, G.S.K. Fung, H.Y. Lam and W.K. Lee, "Disaggregate Loads by Particle Swarm Optimization Method for Non-intrusive Load Monitoring," *International Conference on Electrical Engineering*, July 2007.
- [8] Suzuki, K., Inagaki, S., Suzuki, T., Nakamura, H. and Ito, K. , "Nonintrusive appliance load monitoring based on integer programming," *SICE Annual Conference*, pp.2742-2747, Aug. 2008.
- [9] A. Qing, *Differential Evolution, Fundamentals and Applications in Electrical Engineering*, Wiley, 2009.
- [10] S. Shaw, S. Leeb, L.K. Norford and R. Cox, "Nonintrusive load monitoring and diagnostics in power systems," *IEEE Trans. Instrument. & Measurement*, vol.57, no.7, July 2008.
- [11] J. Zico Kolter and Matthew J. Johnson, "REDD, A public dataset for energy disaggregation research," *Proceedings of the SustKDD workshop on Data Mining Applications in Sustainability*, 2011.
- [12] M. Bergs, E. Goldman, H. Scott Matthews and L. Soibelman. "Enhancing Electricity Audits in Residential Buildings with Non-Intrusive Load Monitoring," *Journal of Industrial Ecology: Special Issue on Environmental Applications of Information and Communication Technologies*, vol. 14, no. 5, pp. 844-858, 2010.
- [13] K.D. Lee, "Electric Load Information System based on Non-Intrusive Power Monitoring," Ph.D. dissertation, Dept. Mech. Eng., Massachusetts Institute of Technology, 2003.
- [14] S. Leeb, "A Conjoint Pattern Recognition Approach to Non-Intrusive Load Monitoring," Ph.D. dissertation, Dept. Elec. Eng. & Comp. Sci., Massachusetts Institute of Technology, 1993.