Swarm and Evolutionary Algorithms for Energy Disaggregation: Challenges and Prospects

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Abstract: Energy disaggregation is defined as the process of estimating the individual electrical appliance energy consumption of a set of appliances in a house from the aggregated measurements taken at a single point or limited points. The energy disaggregation problem can be modelled both as pattern recognition problem and as an optimization problem. Among the two, the pattern recognition problem has been considerably explored while the optimization problem has not been explored to the potential. In literature, researchers have attempted to solve the problem using various optimization algorithms including swarm and evolutionary algorithms. However, the focus on optimization-based methodologies, in general, swarm and evolutionary algorithm based methodologies in particular is minimal. By considering the different problem formulations in the literature, we propose a framework to solve the energy disaggregation problem with swarm and evolutionary algorithms. With the help of simulation results using the existing problem formulations, we discuss the challenges posed by the energy disaggregation to swarm and evolutionary algorithm based methodologies and analyse the prospects of these algorithms for the problem of energy disaggregation with some future directions.

Keywords: Energy Disaggregation, Swarm and Evolutionary Algorithms.

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1 Introduction

In the last few decades, an exponential increase in energy demand coupled with dwindling energy resources and environmental impacts such as climate change highlight the importance of energy conservation. It has been investigated that in residential buildings, which accounts for 30% of electrical usage (Zoha, Gluhak et al. 2012), direct feedback including real-time appliance-level consumption can result in an annual energy conservation of 12% (Klemenjak and Goldsborough 2016) compared to overall indirect feedback such as monthly bills. In addition, the fine-grained energy consumption monitoring can enable the house owner – a) learn power consumption of each appliance and replace energy-inefficient faulty and/or older devices with energy-efficient new ones (Klemenjak and Goldsborough 2016); and b) participate in demand response programs by re-scheduling appliances. To provide detailed feedback regarding the appliance-level consumption, the techniques employed are referred to as Appliance Load Monitoring.

Even though it is decades older, a significant growth in ALM research recently can be attributed to the simultaneous advancements in smart meters, artificial intelligence and machine learning methodologies. The classification of ALM (Zeifman and Roth 2011, Zoha, Gluhak et al. 2012, Klemenjak and Goldsborough 2016, Pereira and Nunes 2018) methodologies can be seen in Figure 1.Intrusive Appliance Load Monitoring (IALM) also knows as distributed sensing requires one or more than one sensor per appliance and is more accurate in measuring appliance-specific energy consumption compared to Non-intrusive Appliance Load Monitoring (NIALM). However, NIALM being a single point sensing method just requires only a single meter per house or a building and reduces sensing infrastructure costs by relying on machine learning techniques to obtain appliance-level information. Therefore, researchers including companies (Tang, Wu et al. 2014) have focused in developing NIALM based approaches for realistic environments (Zeifman and Roth 2011). NIALM also referred to as energy disaggregation tries to estimate the energy consumption of each individual appliance present in a network from electric power measurements taken at a single point in the network.

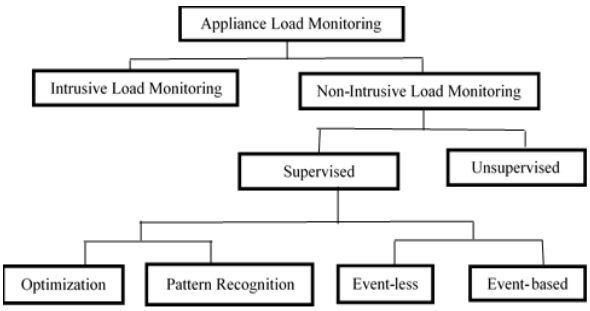

Figure 1. Different methodologies for Appliance Load Monitoring

Energy disaggregation is a highly ill-posed problem similar to the blind source separation problem and gets complicated due to various reasons such as increase in the number and type of devices, similarity the devices and measurement errors etc. Energy disaggregation methodologies can be classified as (Zeifman and Roth 2011, Zoha, Gluhak et al. 2012, Klemenjak and Goldsborough 2016, Pereira and Nunes 2018) – a) supervised approaches; and b) unsupervised approaches. Supervised approaches can be further classified depending on the problem formulation and techniques employed to perform the energy disaggregation. From the classification, it is evident that energy disaggregation can be formulated as an optimization problem. Among the different methodologies, optimization-based methods has not been sufficiently explored.

Recently, swarm and evolutionary algorithms have been successfully applied to solve many challenging real-world optimization problems ranging from power engineering (Palakonda, Awad et al. 2018, Awad, Ali et al. 2019) to agriculture (Uyeh, Mallipeddi et al. 2018). In this paper, we want to demonstrate the applicability of the swarm and evolutionary algorithms for solving the optimization-based energy disaggregation problem. In other words, the contributions can be highlighted as:

- Summarize the literature related to evolutionary algorithms for energy disaggregation
- Highlight the challenges faced by evolutionary algorithms in solving the energy disaggregation optimization problem
- Present prospects of evolutionary algorithms in solving the energy disaggregation problem
- Discuss the different metrics that can be employed to compare the performance of the evolutionary algorithms on energy disaggregation problem

The paper is organized as follows. Section 2 presents a brief literature on energy disaggregation including the different classifications of the algorithms, their advantages and disadvantages. In Section 3, we present a brief summary of evolutionary algorithms and their application to energy disaggregation while Section 4 presents a framework for solving the energy disaggregation problem using evolutionary algorithms. Section 5 discusses the applicability of evolutionary algorithms with experimental results. Section 6 concludes the paper while Section 7 presents some future works for solving energy disaggregation problem using evolutionary algorithms.

2 Energy Disaggregation

From the definition, the goal of energy disaggregation is to partition the aggregated power, P(t) into individual appliance power consumption, $p_i(t)$ and can be mathematically represented as

$$P(t) = p_1(t) + p_2(t) + ... + p_n(t) \qquad (1)$$

where p_i is the power consumption of i-th individual appliance and n is the total number of appliances in the network. The energy disaggregation becomes challenging

1) as the number of devices and types of devices (see (Zoha, Gluhak et al. 2012)) increases.
2) as the similarity between multiple devices increases
3) due to the uncertainty about the number of steady power states for a given device

4) due to the variation of power within each steady power state
5) due to the concurrent switching ON/OFF of multiple devices
6) due to the variable speed devices that show continuous power levels
7) due to measurement errors (10-20% (Klemenjak and Goldsborough 2016)) by the current commercial smart meters.

The different methodologies proposed in the literature to solve the energy disaggregation problem can be classified as shown in Figure 1. Each of these methodologies have their advantages and disadvantages and cannot accurately disaggregate all types of appliances (Zeifman and Roth 2011, Zoha, Gluhak et al. 2012, Klemenjak and Goldsborough 2016, Pereira and Nunes 2018). Most approaches are based on unique energy consumption patterns of appliances referred to as "appliance signatures", i.e., specific features such as the real/reactive power, current, and voltage of running appliances, to discern and recognize appliance operations from the aggregated load measurements. The appliance identification is highly dependent on load signatures, which are further characterized by the appliance category (TYPES 1~4). A complete survey on the device types, different feature extraction methods, different features, their advantages and disadvantages are summarized in (Hart 1992, Ting, Lucente et al. 2005, Zoha, Gluhak et al. 2012, Klemenjak and Goldsborough 2016) and the current manuscript does not discuss them. The major focus of the paper is on the methodologies and mainly optimization-based methodologies that are covered in the following sections.

a) Supervised Approaches: require labeled data sets to train the different modules present and the amount training data needed depends on the modules present in the algorithm. Depending on the modules present and process adopted, the supervised approaches can be categorized as

1) Event-based approaches and Event-less approaches
2) Pattern recognition-based approaches and Optimization-based approaches

Event-based and Event-less Approaches (Pereira and Nunes 2018): In event-based approaches (Kolter, Batra et al. 2010, Parson, Ghosh et al. 2012), the initial step is to detect and label every appliance transition or power events in the aggregated signal (Pereira and Nunes 2018) using pre-trained supervised or semi-supervised learning. Therefore, event-based approaches require labelled training data that includes a number of power events that occur due to the different appliance transitions. However, event-less approaches (Rahimpour, Qi et al. 2017) do not rely on event detection and classification. Instead, event-less approaches try to match the aggregated power at each time instance with the consumption of a combination of different appliances with the help of statistical (e.g., Bayesian methods) and probabilistic (e.g., Hidden Markov models) machine-learning methods. Hence, the training data required for event-less methods is less compared to the event-based approaches.

Pattern recognition-based Approaches: Starting with initial work of Hart (Hart 1992), most of the energy disaggregation approaches in the literature belong to the class of pattern recognition-based approaches and employ various methodologies such as Artificial Neural Networks (Srinivasan, Ng et al. 2006, Ruzzelli, Nicolas et al. 2010), Hidden Markov Models (Zia, Bruckner et al. 2011), a combination of Support Vector Machines and Gaussian Mixture Models (Srinivasan, Ng et al. 2006, Lin, Lee et al. 2010, Lai, Lai et al. 2013), Naive Bayes classifier (Farinaccio and Zmeureanu 1999, Marchiori, Hakkarinen et al. 2011), Multi-label classification (Tabatabaei, Dick et al. 2017), Committee Decision mechanisms (Liang, Ng et al. 2010, Liang, Ng et al. 2010). However, it is important to note that the performance these approaches depend highly on the feature sets, the type and number of target appliances.

Optimization-based Approaches: Energy disaggregation as an optimization problem, tries to minimize the error between the extracted feature vector of an unknown load to that of known load or a combination of loads from a pool of the appliance. Researchers (Suzuki, Inagaki et al. 2008, Egarter and Elmenreich 2013, Egarter, Sobe et al. 2013, Tang, Wu et al. 2014, Egarter and Elmenreich 2015) have tried different optimization approaches including integer programming and genetic algorithms in order to tackle the energy disaggregation optimization problem. The approaches seem promising with less number of devices and simple ON/OFF devices. It needs to be mentioned here that most optimization-based approaches, unlike pattern recognition-based approaches, employ simple features such as power ratings or current drawn. In other words, they do not employ much of the training data for feature extraction. Therefore, the performance of these approaches is degrades with the increase in the number of devices and the similarity between the devices.

In addition to the general challenges faced by energy disaggregation, following are some of the challenges faced by supervised energy disaggregation approaches:

1) Model construction demands huge amounts of training data that increases with the number of appliances.
2) Depending on the features employed, the training data collection should be performed at high sampling rates for better feature extraction.
3) The combination of devices and their usage pattern (especially multi-state devices) change from user to user. Therefore, the training process needs to be done differently for each house or fine-tuned with the corresponding training data.
4) Rare operation of some devices can create imbalance in the training data.
5) After data collection and training, a subtle change in the supply frequency (i.e., power factor correction) by an energy supplying company can cause a mismatch of appliance profile (Zoha, Gluhak et al. 2012) and the degraded performance.
6) No widely accepted load signatures to aptly model the operation of all appliance categories.
7) Most of the supervised methods are based on off-line training, therefore, adding a new device requires time

consuming process of updating the database and relearning the model parameters.

b) Unsupervised Approaches: Unsupervised approaches try to achieve the energy disaggregation without the need of training data and minimal setup cost. These approaches emphasis on building unsupervised learning features, including clustering algorithms (Gonçalves, Ocneanu et al. 2011), Factorial Hidden Markov Models (Kim, Marwah et al. 2011, Johnson and Willsky 2013), Matching Pursuit (Gonçalves, Ocneanu et al. 2011), Temporal Motif Mining (Shao, Marwah et al. 1700) and Additive Factorial Approximate MAP (AFMAP) (Kolter and Jaakkola 2012). The unsupervised approaches present the following challenges:

1) During the clustering process, different appliances were sometimes clustered together and some appliances were broken down between several clusters due to similarities in terms of consumption levels. Therefore, these methods cannot disaggregate between appliances that are similar.
2) Multi-state devices generate several clusters or a single device is reduced to a summation of two-state appliances (Hart 1992).

3 Evolutionary Algorithms for Energy Disaggregation

The initial attempt to solve the optimization-based energy disaggregation problem using evolutionary algorithms was made in (Egarter and Elmenreich 2013, Egarter, Sobe et al. 2013, Egarter and Elmenreich 2015). In these papers, the problem is formulated as a knapsack problem with the following objective function

$$e(t) = argmin|P(t) - \sum_{n=1}^{N} p_n \cdot a_n(t)| \qquad (2)$$

where, $e(t)$ is the error between the measured, $P(t)$ and estimated aggregated power; N is the number of appliances; $a_n(t) \in [0,1]$ represents the status of n-th appliance at time t (0 and 1 indicate OFF and ON, respectively) and p_n is the power consumed by the n-th device. The initial work in (Egarter, Sobe et al. 2013) is limited to ON/OFF devices assuming the devices are operating with constant time duration and constant magnitude, which is not realistic. An extended work considering appliances that can draw varying power magnitudes and varying usage duration was reported in (Egarter and Elmenreich 2013). In addition, they proposed preprocessing step and evolutionary operators such as: Time-duration mutation, Power-magnitude mutation, Repeating-signal mutation, and Periodic-signal mutation. In (Egarter and Elmenreich 2015), a more detailed analysis comparing with six different metaheuristics (General Evolutionary Algorithm, Differential Evolution, Particle Swarm Optimization, Simulated Annealing, Cuckoo Search and Firefly Optimization) with two different datasets – 1) appliance set with similar power states and 2) appliance set with unique power states was performed. The experimental results of the preliminary study considering only ON/OFF devices yields the following conclusions (Egarter and Elmenreich 2013, Egarter, Sobe et al. 2013, Egarter and Elmenreich 2015):

1) The influence of the metaheuristic is not significant, or all the metaheuristics algorithms provide the similar solutions
2) Detection accuracy can reach 100% depending on the number of devices and type of the devices. In other words, with less number of devices and with less similarities in the power states of the devices the performance can be higher.
3) The higher the number of devices and number of states per device (the size of the database), the lower the detection accuracy. In other words, the similarity between the power states of different devices, the possible representation of a high power state by a combination of two or more low power states and noise effects effect the performance of the algorithm.

Recently, in (Tang, Wu et al. 2014), an optimization model based on the sparsity of appliance activities referred to as Sparse Switching Event Recovering (SSER) optimization was proposed. In SSER, the objective is to minimize the total variation of ON/OFF switching events subjected to power limit constraints taking into account the power deviations in each power state. In this model, multi-state appliances are split into multiple virtual devices where each device has only two states (ON/OFF). In SSER, the objective function to identify the states of N appliances in a time interval t = 1 to T can be formulated as

$$\text{Minimize:} \quad TV(\Delta S) = \sum_{n=1}^{N} \sum_{t=1}^{T} |\Delta S_t^{(n)}| \qquad (3)$$

$$\text{Subject to: } X - S^T (P + \Theta) \leq 0$$

$$S^T (P - \Theta) - X \leq 0$$

where X is the measured aggregated signal

S is the state matrix given by $S = \begin{bmatrix} s_1^{(1)} & \cdots & s_T^{(1)} \\ \vdots & \ddots & \vdots \\ s_1^{(N)} & \cdots & s_T^{(N)} \end{bmatrix}$

$P = [P_1, P_2, \ldots, P_N]^T$ is a vector with the rated powers of N devices

$\Theta = [\Theta_1, \Theta_2, \ldots, \Theta_N]^T$ is a vector with the power deviation of N devices

TV (.) denotes the total variation of the sparse event matrix (ΔS) given by $\Delta S = S.D$

where D is a differential matrix with size of T-by-(T - 1) as follows: $D = \begin{bmatrix} -1 & & & \\ 1 & -1 & & \\ & 1 & \ddots & \\ & & \ddots & -1 \\ & & & 1 \end{bmatrix}$

The event matrix $\Delta S_t^{(n)} \in \{-1, 0, 1\}$, where 1 or -1 indicates a switching ON or OFF of n-th appliance at time t,

while 0 indicates no switching. From the experimental analysis, it has been concluded that the performance of SSER is better than Least Square Estimation (LSE) and Hidden Markov Models (HMM). In addition, it was concluded that the algorithmic performance is robust to the estimation errors in the power deviation (Θ). However, the performance of the algorithm is very sensitive to the power deviation (Θ) depending on the number of devices and type of devices.

In the limited research related to optimization-based energy disaggregation, the two different objective functions considered are shown in equations 2 and 3. In addition, the current optimization-based approaches employ simple features such as power ratings (Egarter and Elmenreich 2013, Egarter, Sobe et al. 2013, Tang, Wu et al. 2014, Egarter and Elmenreich 2015) or the current ratings (Suzuki, Inagaki et al. 2008). The first objective function shown in equation (2) tries to find the combination that better minimize the absolute error at each time instance but does not consider the device operation requirements such as continuity etc. In other words, due to the nature of the objective the possibility of combination of devices operating at time (t – 1) and t can be entirely different which is not realistic in household appliance operation. The second objective function in equation (3) considers the continuity of device operation by minimizing the total number of variations (TV). In addition, the minimization of total variations (TV) depends on the power deviation (Θ). If Θ is larger then the possibility of satisfying the constraints in equation (3) with minimum number of total variations (TV) is possible and can result in huge difference between the measured and estimated aggregated signals (E). Therefore, the amount of power deviation (Θ) strongly effects the absolute error minimization (E) at each time instance.

4 Proposed Framework for Evolutionary Algorithm based Energy Disaggregation

As mentioned in the previous section, in (Egarter and Elmenreich 2013, Egarter, Sobe et al. 2013, Tang, Wu et al. 2014, Egarter and Elmenreich 2015), the multi-state devices are split into multiple simple ON/OFF devices. However, in the proposed framework we represent a device with m operating states having {0, 1, …, m} modes where 0 is the OFF state.

Therefore, in the proposed framework, the objective function in equation (2) can be modified to minimize the error over a time interval t = 1 to T as follows

$$\text{Minimize} \quad E = \sum_{t=1}^{T}\left(P(t) - \sum_{n=1}^{N}\left(P_n\left(S_t^n\right)\right)\right) \qquad (4)$$

where the aim is find the optimal state matrix $S^* = \begin{bmatrix} s_1^{(1)} & \cdots & s_T^{(1)} \\ \vdots & \ddots & \vdots \\ s_1^{(N)} & \cdots & s_T^{(N)} \end{bmatrix}$

s_i^j represents the state of j-th device at i-th time instance and $s_i^j \in [0\ m_j]$ where m_j is the maximum number of operating states of the j-th device.

In the current framework, the SSER is formulated as follows:

$$\text{Minimize:} \quad TV(\Delta S) = \sum_{n=1}^{N}\sum_{t=1}^{T}\left|\Delta S_t^{(n)}\right| \qquad (5)$$

$$\text{Subject to: } X - \sum_{n=1}^{N} P_n(S_t^n) + \Theta_n(S_t^n) \leq 0$$

$$X - \sum_{n=1}^{N} P_n(S_t^n) - \Theta_n(S_t^n) \geq 0$$

where $P_n = [P_{n,1}, P_{n,2}, \ldots, P_{n,mn}]$ is a vector with the rated powers of N devices and m_n is the maximum number of states for devices. $\Theta_n = [\Theta_{n,1}, \Theta_{n,2}, \ldots, \Theta_{n,mn}]$ is a vector with the power deviation of N devices. However, it has to be noted that the ΔS matrix considers only the ON/OFF as in the above section and not the change between other modes.

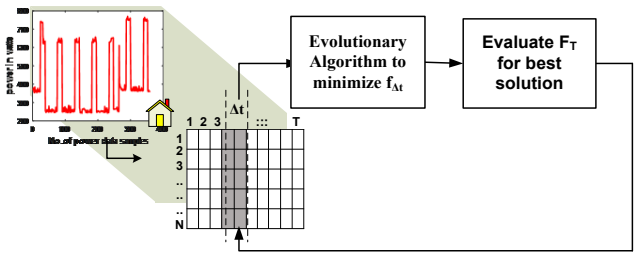

Figure 2. Proposed Framework for Evolutionary Algorithm based Energy Disaggregation

Both the objective functions described in equations 4 and 5 are linearly separable. Therefore, the optimization over the time interval t = 1 to T can be separated in to simple time blocks for effective energy disaggregation. The schematic diagram of the proposed framework employing the objective functions described in equations 4 and 5 is shown below. As shown in Figure 2, the states of N devices corresponding to the aggregated signal for the time t = 1 to T is represented in the form of a matrix of size N-by-T. Then, we take the aggregated signal of a small time interval (Δt) to be optimized by the evolutionary algorithm. To find the optimal states of the devices in the duration of Δt, the objective function (equations 4 or 5) is evaluated using the aggregated signal of that time interval referred to as $f_{\Delta t}$. After obtaining the optimal solution for the time interval (Δt) the solution replaces the corresponding vector in the N-by-T matrix only if it is better on the objective function evaluated over the entire time interval t = 1 to T, referred to as F_T. As mentioned in the Introduction, the aim of energy disaggregation is to perform the disaggregation of the total power consumption as it comes and provide a real-time tracking of appliance-level power consumption. The proposed framework is in accordance with the goal as it disaggregates the aggregated signal overall small time (Δt) horizons.

5 Experimental Setup and Results

In this Section, we try to analyze the advantages and disadvantages of the two objective functions described in equations 4 and 5, referred to as Case 1 and Case 2, respectively. For the experimental analysis, we employ the dataset provided in (Tang, Wu et al. 2014). The dataset

contains aggregated signal and individual devices operation data for 7 days. The experiments reported in the current study correspond to Day 3. To analyze the two objectives described in equations 4 and 5, we used two instances – a) 6 devices (Instance 1) and b) 11 devices (Instance 2). The details about the devices, the number of states, the power levels and the deviations are provided in Table 1.

In the current work, we employ a simple evolutionary algorithm for optimization. To produce the offspring population, the parents are selected based on Roulette Wheel selection. From the combination of parent and offspring population, the better half of the individuals are selected for the next generation. To perform crossover, we employed to operators referred to as time-based crossover and device-based crossover. In time-based crossover, the states of devices during a time index t are exactly copied from one individual to the other. In device-based crossover, the states of a device in an individual are entirely copied into the other individual. These two operators provide a better convergence. The population size and maximum number of generations employed are set as 100 and 250, respectively for Instance 1, while population size of 250 and maximum generations of 500 were employed for Instance 2. In both the instances, the crossover (pc) and mutation probabilities (pm) are set as 0.8 and 0.3, respectively. The flowchart of the evolutionary algorithm employed in the current work is presented in Figure 3.

Table 1. Details of Datasets – Instance 1 (6 devices in Gray) and Instance 2 (11 devices)

No. of Appliances	Appliance	Maximum No. of modes	Power rating(P)			Power deviation(Θ)		
n		m_n	$P_{n,1}$	$P_{n,2}$	$P_{n,3}$	$\Theta_{n,1}$	$\Theta_{n,2}$	$\Theta_{n,2}$
1	Coffee maker	3	700	900	1100	100	100	100
2	iMac	2	35	50	-	5	10	0
3	Water cooler	3	65	380	450	5	10	10
4	Microwave	3	1000	1200	1700	100	100	100
5	Printer	3	400	700	900	50	80	100
6	refrigerator	2	115	350	-	15	10	-
7	LCD-Dell	1	25	-	-	5	-	-
8	LCD-LG	1	22	-	-	5	-	-
9	Desktop	2	40	50	-	15	20	-
10	Server	1	130	-	-	20	-	-
11	Laptop	3	15	30	70	5	10	10

In general, the common components present in most energy disaggregation algorithms are – event detection, event classification and energy estimation. Based on the different algorithmic components, there are measures to quantitatively evaluate each algorithmic component and the overall performance. Therefore, the metrics can be classified as – Event Detection metrics, Event Classification metrics, Energy estimation metrics and Overall metrics. A detailed summary of the different performance metrics is presented in (Pereira and Nunes 2018). In this work, we employ the overall metrics such as Energy Disaggregation Accuracy (EDA) and State Prediction Accuracy (SPA) (Tang, Wu et al. 2014). In addition, we also report the total number of deviations (TV) and total absolute error between the measured and estimated aggregated signal (E).

$$\text{EDA} = 1 - \frac{\sum_{n=1}^{N} \left\| X^{(n)} - S^{*} P_n \right\|_1}{\left\| X \right\|_1} \quad (6)$$

$$\text{SPA} = 1 - \frac{\sum_{n=1}^{N} \left\| S^{*} - \hat{S} \right\|_1}{N.T} \quad (7)$$

where X is the measured aggregated signal, is the estimated state matrix obtained through optimization, is the actual state matrix, N is the number of devices and T is total time interval over which the disaggregation is performed. EDA measures the efficiency of the algorithm in assigning correct power values to corresponding appliances while SPA measures the efficiency of the algorithm in estimating the states of appliances (Tang, Wu et al. 2014). It should be noted that an algorithm with a higher SPA, can have a low EDA if a low duration, high power device is wrongly identified.

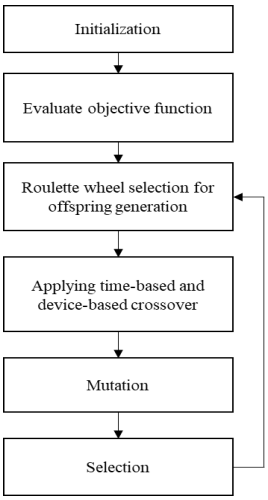

Figure 3. Flowchart of the evolutionary algorithm employed in the current work

Each of the simulations are performed 30 times and the mean and standard deviation values of performance indicators, EDA, SPA, E and TV are summarized for every one hour and are shown in Tables 2 and 3. For each hour statistical significance t-test with a significance level of 0.05 is performed on each indictor. To evaluate the effect of the power deviation (Θ) on the performance of the algorithm, we multiplied it with a factor ρ. In other words, ρ in Tables 2 and 3, indicate that the simulations consider a power deviation of ρ.Θ. The ρ values considered are 0.1 and 0.3.

According to results of Tables 2 and 3, in Case 1 the objective function is to minimize the absolute error (E) between the measured and estimated aggregated signals as in equation (4). Therefore, the algorithm is able to reduce the absolute error (E) and average absolute error (E) for Case 1 is better than Case 2 in both the Instances as shown in Tables 2 and 3. In addition, as the number of devices increases, the performance of the algorithm in Case 1 degrades drastically in terms of both EDA and SPA. This is mainly due to nature of the objective function. In Case 1, as the number of devices increases the number of different possible combinations to minimize the absolute error (E) at given time instance increase exponentially.

Table 2. Performance comparison of different Cases in terms of performance indicators for different hours on Instance 1

Hr	Case1				Case2							
					ρ = 0.1				ρ = 0.3			
	EDA	SPA	E	TV	EDA	SPA	E	TV	EDA	SPA	E	TV
1	96.56 (1.02)	99.14 (0.23)	817.00 (25.59)	52.33 (3.72)	92.07 (1.44)	98.32 (0.29)	809.27 (26.22)	19.93 (4.08)	73.96 (27.26)	95.08 (4.54)	1070.60 (393.57)	32.13 (6.64)
2	94.79 (0.90)	98.78 (0.23)	1265.00 (37.59)	45.47 (10.76)	93.37 (1.24)	98.57 (0.27)	1294.87 (32.36)	9.87 (5.03)	62.45 (37.12)	94.16 (5.34)	1720.87 (490.88)	13.70 (7.81)
3	96.96 (0.09)	99.93 (0.02)	702.20 (11.84)	32.80 (2.43)	96.46 (0.45)	99.84 (0.08)	703.53 (11.51)	4.17 (2.07)	62.54 (35.04)	94.52 (5.49)	1205.37 (512.60)	10.60 (6.26)
4	93.65 (1.48)	98.90 (0.23)	778.73 (18.68)	47.20 (4.92)	93.22 (1.36)	98.83 (0.23)	778.40 (16.84)	6.00 (1.39)	54.99 (32.10)	92.79 (5.10)	1351.33 (476.03)	10.73 (5.13)
5	96.04 (0.76)	99.25 (0.13)	817.03 (23.33)	46.47 (2.86)	95.67 (0.86)	99.16 (0.15)	819.33 (23.77)	8.47 (1.25)	78.72 (31.54)	96.32 (5.25)	1077.30 (499.44)	11.33 (4.96)
6	96.11 (0.04)	99.40 (0.09)	906.43 (14.45)	20.80 (2.14)	96.11 (0.03)	99.38 (0.07)	905.30 (10.87)	2.00 (0.00)	84.67 (13.58)	97.80 (1.73)	1051.96 (179.24)	6.67 (4.11)
7	62.05 (5.81)	92.92 (1.00)	758.50 (61.10)	46.87 (17.70)	51.78 (3.44)	91.13 (0.56)	763.43 (32.00)	23.53 (4.64)	29.12 (6.56)	87.22 (0.95)	956.23 (95.87)	22.13 (6.74)
8	4.57 (2.07)	78.43 (0.90)	1167.14 (16.12)	134.57 (69.34)	1.82 (0.23)	79.11 (0.11)	1185.77 (30.49)	34.07 (4.88)	2.90 (2.01)	77.76 (1.96)	1270.50 (117.82)	39.60 (12.05)
9	49.67 (3.68)	84.01 (2.51)	1539.47 (15.39)	192.27 (70.87)	45.39 (2.47)	85.47 (0.49)	1561.97 (20.07)	40.23 (7.57)	17.63 (6.66)	80.85 (0.88)	1925.83 (77.51)	38.47 (9.31)
10	66.85 (10.05)	76.49 (3.98)	1464.27 (46.84)	491.77 (66.41)	54.51 (11.06)	72.94 (5.37)	1588.90 (72.08)	177.97 (17.90)	49.07 (13.39)	70.68 (6.87)	2398.13 (170.62)	124.13 (19.19)
11	87.44 (3.89)	88.58 (0.68)	1988.00 (28.53)	229.43 (21.42)	71.61 (5.86)	83.20 (1.47)	2022.63 (36.05)	108.43 (11.46)	23.91 (5.09)	68.81 (0.85)	2974.27 (68.06)	84.03 (6.05)
12	40.11 (6.66)	81.85 (1.13)	1582.87 (36.37)	301.77 (37.51)	26.88 (7.36)	79.84 (1.13)	1724.97 (62.84)	117.40 (9.67)	28.84 (7.14)	80.89 (1.43)	2035.20 (97.09)	94.00 (8.88)
13	70.92 (4.83)	85.63 (1.82)	1624.17 (37.49)	290.53 (32.49)	69.25 (5.37)	85.46 (1.72)	1720.50 (66.83)	121.13 (15.59)	45.61 (19.32)	81.90 (3.99)	2497.07 (285.02)	110.87 (11.40)
14	63.23 (6.45)	93.36 (0.80)	1326.00 (22.63)	182.40 (17.84)	58.04 (8.11)	92.50 (1.02)	1351.00 (37.05)	95.63 (10.85)	55.57 (9.72)	92.59 (1.16)	1560.00 (64.09)	83.03 (9.32)
15	61.91 (6.31)	91.00 (1.54)	1355.83 (12.12)	178.47 (23.59)	27.12 (6.05)	85.17 (1.33)	1422.67 (23.05)	38.27 (8.35)	20.34 (4.38)	84.05 (0.84)	1507.93 (36.14)	28.13 (10.55)
16	76.52 (4.50)	94.23 (0.77)	936.77 (5.92)	110.53 (14.40)	59.79 (3.21)	91.75 (0.48)	958.87 (18.73)	36.00 (9.47)	39.54 (10.42)	89.25 (1.42)	1171.50 (64.04)	31.53 (9.41)
17	87.43 (6.84)	94.13 (2.34)	1857.63 (24.85)	106.03 (63.31)	87.93 (6.06)	95.20 (0.89)	1926.03 (49.99)	19.87 (6.88)	73.01 (8.36)	93.17 (1.12)	2027.17 (65.16)	27.67 (6.69)
18	3.50 (4.08)	78.37 (0.98)	1639.60 (26.71)	174.00 (87.97)	-3.32 (2.10)	78.35 (0.43)	1633.10 (15.59)	50.20 (7.83)	-1.04 (3.39)	78.97 (0.77)	1718.84 (57.39)	40.13 (5.75)
19	78.67 (4.77)	93.57 (0.57)	1232.97 (29.65)	197.07 (17.78)	73.85 (5.26)	89.12 (1.46)	1277.43 (25.03)	104.13 (10.22)	31.47 (6.60)	79.03 (1.48)	2080.80 (99.89)	68.80 (7.78)
20	95.59 (1.09)	99.57 (0.13)	788.33 (11.61)	32.00 (4.10)	95.40 (1.26)	99.51 (0.16)	783.10 (11.87)	5.40 (2.36)	65.75 (19.75)	94.21 (3.31)	1150.67 (265.54)	24.77 (5.18)
21	97.09 (0.56)	99.62 (0.12)	843.07 (12.13)	17.73 (3.85)	96.98 (0.63)	99.61 (0.13)	845.90 (24.27)	3.33 (2.25)	86.37 (8.17)	98.12 (1.06)	946.40 (95.59)	11.97 (4.14)
22	94.52 (1.81)	99.44 (0.17)	647.60 (4.47)	31.07 (5.93)	93.39 (1.57)	99.33 (0.15)	648.47 (5.77)	4.40 (1.50)	63.01 (30.29)	95.18 (4.09)	1069.60 (390.61)	7.30 (3.80)
23	92.49 (2.83)	97.18 (0.32)	1100.00 (20.79)	73.93 (15.34)	92.26 (3.64)	97.04 (0.40)	1092.23 (16.36)	19.20 (6.12)	33.90 (38.65)	89.76 (5.08)	1645.60 (398.13)	22.50 (4.15)
24	90.15 (1.63)	97.39 (0.48)	654.57 (9.21)	69.67 (8.07)	80.56 (3.41)	95.89 (0.35)	665.90 (14.13)	31.33 (7.58)	36.55 (30.77)	90.59 (4.10)	1276.30 (340.62)	14.73 (3.78)
Overall	78.32 (0.87)	92.54 (0.27)	1158.04 (23.05)	129.38 (25.19)	71.32 (0.88)	91.44 (0.31)	1186.81 (28.49)	45.04 (6.62)	48.51 (4.04)	87.65 (0.68)	1570.39 (222.54)	39.95 (7.46)

But in Case 2 the performance is very sensitive to the power deviation controlled by ρ. Because of the larger power deviation (ρ=0.3), the algorithm concentrates on the minimization of the total deviation (TV) and estimated signal at each time instance can be quite different from the original aggregated value. In other words, as the power deviations (ρ) of the devices are larger, then the possibility of the absolute error (E) between the measured and the estimated aggregated signal can shoot up at the expense of minimizing TV. Therefore, in Case 2, it can be observed that as the power deviation (ρ) increases, TV decreases, E increases.

To show the effect of the power deviation on the disaggregation performance of the algorithm, we present the pie charts of the ground truth, Case 1, Case 2 (ρ=0.1) and Case 2 (ρ=0.3) for hour 3 in Figure 4. From the pie charts, it is evident that as the ρ values or as the power deviation increase the possibility of a high power device (Printer) replacing other devices (Water Cooler) increases, resulting a lower EDA. In other words, as the power deviation is increased, the possibility of high power devices replacing the low power devices occurs and as result the performance of the algorithm (SPA and EDA) decreases. In Table 2, the reduction in EDA is more evident as the high power device replaces low power devices. A similar observation can be made in Hour 5.

Table 3. Performance comparison of different Cases in terms of performance indicators for different hours on Instance 2

Hr	Case1				Case2							
					ρ = 0.1				ρ = 0.3			
	EDA	SPA	E	TV	EDA	SPA	E	TV	EDA	SPA	E	TV
1	33.73 (13.91)	51.00 (4.33)	243.91 (9.24)	1691.03 (138.55)	23.71 (26.18)	51.23 (8.60)	1148.18 (74.09)	70.63 (31.11)	19.24 (22.91)	51.84 (11.25)	3246.68 (387.99)	32.27 (12.58)
2	34.34 (16.40)	50.78 (5.26)	270.50 (13.12)	1681.00 (141.53)	27.37 (23.01)	54.28 (10.73)	1102.77 (111.94)	84.30 (39.80)	15.56 (23.82)	52.12 (10.99)	3349.80 (430.16)	29.83 (13.75)
3	33.19 (14.18)	51.30 (6.29)	255.23 (18.78)	1602.67 (187.12)	25.07 (22.07)	51.28 (10.45)	1215.87 (108.79)	77.07 (45.82)	28.57 (23.91)	49.82 (10.81)	3305.57 (317.98)	26.93 (14.20)
4	37.45 (14.02)	53.06 (3.83)	242.77 (10.79)	1729.77 (106.57)	30.73 (25.90)	56.18 (9.99)	1137.47 (100.96)	69.57 (45.59)	26.07 (20.28)	55.25 (8.81)	3443.23 (425.97)	21.07 (10.92)
5	32.62 (14.71)	51.02 (4.18)	247.17 (10.16)	1627.60 (94.56)	19.92 (21.25)	52.52 (6.78)	1162.10 (89.63)	71.80 (33.37)	22.62 (27.58)	48.14 (11.04)	3434.97 (407.97)	31.43 (14.22)
6	43.37 (13.99)	54.79 (5.75)	226.17 (11.96)	1535.27 (125.48)	31.63 (16.54)	53.96 (8.49)	1105.60 (68.35)	55.17 (35.27)	33.11 (18.88)	53.12 (11.91)	2891.52 (427.54)	25.70 (17.30)
7	30.14 (9.98)	50.18 (4.24)	255.56 (14.76)	1637.10 (121.40)	7.92 (28.08)	49.57 (11.90)	1080.58 (73.75)	65.13 (38.02)	0.92 (26.70)	48.22 (12.42)	3512.35 (504.29)	23.40 (15.45)
8	35.03 (13.95)	50.86 (3.44)	233.26 (10.61)	1806.67 (124.06)	18.37 (31.12)	50.37 (10.73)	1164.43 (94.45)	69.73 (19.29)	18.40 (32.63)	50.01 (12.51)	3282.65 (334.68)	32.23 (17.85)
9	34.65 (10.05)	51.22 (4.14)	243.23 (13.54)	1687.27 (156.15)	27.88 (21.05)	52.65 (7.25)	1135.13 (102.79)	73.50 (38.95)	28.94 (24.16)	49.86 (10.78)	3253.70 (340.03)	35.50 (14.14)
10	57.81 (8.69)	48.66 (3.07)	283.97 (13.71)	1928.10 (109.95)	50.55 (11.63)	50.21 (7.80)	1436.67 (92.97)	168.10 (33.96)	45.90 (16.68)	48.82 (10.60)	4263.27 (337.14)	86.73 (14.16)
11	47.17 (10.48)	51.88 (3.43)	274.27 (11.58)	1812.47 (107.92)	40.37 (25.51)	52.66 (8.02)	1384.40 (162.36)	147.20 (43.40)	35.41 (24.19)	47.73 (9.31)	4057.10 (362.15)	79.67 (11.31)
12	48.81 (10.38)	53.42 (2.79)	292.07 (13.50)	1918.97 (110.66)	33.75 (16.89)	55.04 (6.17)	1377.53 (102.20)	183.43 (54.31)	33.33 (14.96)	54.53 (6.29)	4149.60 (317.96)	88.83 (16.44)
13	52.29 (10.13)	49.63 (3.43)	283.63 (14.90)	1931.00 (98.85)	36.18 (13.32)	53.37 (6.81)	1520.33 (90.21)	191.67 (22.87)	39.47 (15.08)	56.28 (9.66)	4512.00 (312.38)	98.93 (10.60)
14	50.81 (10.89)	55.13 (4.14)	267.63 (12.02)	1785.43 (88.00)	38.29 (14.22)	52.49 (6.46)	1185.27 (53.17)	140.77 (33.40)	34.12 (14.71)	52.29 (8.95)	3514.47 (254.91)	63.90 (13.26)
15	51.37 (9.64)	58.01 (2.63)	251.80 (10.46)	1653.13 (89.04)	43.71 (23.34)	61.08 (10.00)	1235.43 (106.09)	86.47 (27.71)	35.01 (26.64)	59.64 (13.20)	3648.70 (313.61)	24.97 (12.20)
16	55.17 (14.88)	57.95 (4.89)	268.03 (12.28)	1627.43 (105.46)	41.65 (16.26)	61.20 (9.41)	1229.97 (72.78)	79.17 (32.98)	41.34 (24.88)	61.55 (13.49)	3620.93 (264.07)	26.97 (12.33)
17	51.12 (16.48)	57.04 (5.85)	271.07 (16.05)	1625.17 (179.63)	58.67 (25.76)	70.69 (13.22)	1153.00 (63.08)	81.00 (54.04)	51.0 (25.79)	60.68 (12.30)	3385.03 (310.56)	27.93 (20.76)
18	47.66 (10.75)	51.86 (3.32)	262.24 (9.82)	1706.30 (119.76)	36.38 (22.38)	56.81 (6.46)	1328.27 (98.08)	81.23 (24.75)	31.12 (21.74)	53.98 (10.02)	3903.13 (494.87)	34.43 (11.51)
19	52.12 (9.25)	53.94 (3.00)	276.40 (16.05)	1828.80 (104.66)	39.75 (17.58)	56.23 (9.71)	1374.47 (97.35)	157.13 (33.38)	40.07 (17.32)	56.06 (11.15)	4200.93 (386.56)	75.20 (17.68)
20	44.26 (11.35)	55.87 (3.81)	256.83 (12.52)	1718.00 (137.81)	27.52 (22.57)	56.54 (8.39)	1210.40 (77.62)	55.70 (31.25)	31.65 (22.27)	58.01 (9.72)	3317.63 (472.60)	29.50 (21.20)
21	58.73 (9.19)	59.23 (3.13)	227.20 (11.62)	1583.67 (120.43)	43.89 (11.79)	57.83 (6.18)	1210.40 (79.68)	46.90 (28.45)	42.44 (15.93)	58.25 (9.16)	3389.33 (304.16)	17.80 (9.64)
22	42.64 (12.10)	54.12 (5.22)	245.43 (14.51)	1700.57 (161.24)	25.59 (19.07)	53.55 (8.67)	1205.80 (73.45)	59.67 (28.58)	27.49 (20.06)	57.14 (10.98)	3345.60 (264.74)	20.80 (8.13)
23	38.15 (14.02)	55.59 (3.17)	273.83 (12.58)	1794.37 (83.65)	22.30 (25.06)	57.77 (7.87)	1207.77 (95.53)	109.23 (52.72)	28.95 (28.48)	60.98 (9.16)	3355.17 (363.96)	43.87 (17.69)
24	30.00 (13.81)	52.81 (5.02)	260.80 (12.09)	1675.47 (175.65)	23.61 (21.20)	55.71 (11.16)	1101.63 (102.32)	88.83 (50.27)	24.98 (25.42)	53.52 (12.73)	3344.00 (525.29)	28.43 (19.93)
Overall	48.17 (2.48)	53.30 (0.71)	258.88 (12.78)	1720.30 (124.50)	46.55 (4.77)	51.20 (1.72)	1225.56 (91.31)	96.39 (36.63)	46.42 (5.80)	54.24 (2.85)	3571.97 (369.23)	41.93 (14.46)

In Instance 1, the overall performance with ρ = 0.1 is significantly better than the overall performance with ρ= 0.3. However, as the number of devices increases, the overall performance with ρ= 0.3 is better than ρ = 0.1. Therefore, the appropriate selection of the power deviation plays a significant role. In both Case 1 and Case 2, in certain time instances (Hours 8 & 18) SPA is better. However, EDA is quite low because one of the devices (Printer) replaces another devices (Water cooler) that has similar power states as shown in Figure 5. As mentioned in the earlier sections this is a common problem in most disaggregation methods.

From the results, it can be observed that the average error of Case 1 is less than Case 2. In addition, in Case 2, the average error is less when power deviation is less. This is because of the nature of the objective function employed for the optimization. In Case 2, as the power deviation is reduced the absolute error is reduced because the constraints force the estimated signal at each time instance to be close to the measured aggregated value. However, TV is in Case 1 is larger than in Case 2 as in Case 1 the objective is to minimize the absolute error (E) and not restriction on the number of total variations is enforced. In addition, in Case 2, the TV decreases as the power deviation increases. This is due to the relaxation of the constraints. This is also evident in the Figures 4 and 5.

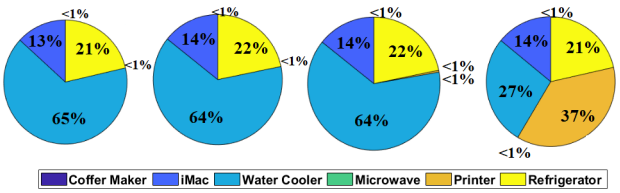

Figure 4. Pie charts of Ground Truth, Case 1, Case 2 (ρ = 0.1) and Case 2 (ρ=0.3) on Instance 1 for hour 3

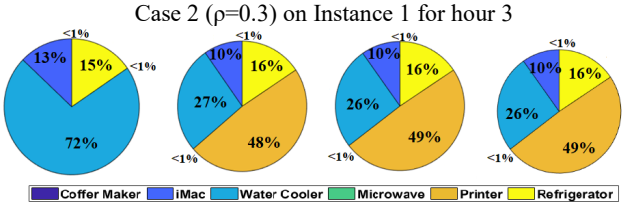

Figure 5. Pie charts of Ground Truth, Case 1, Case 2 (ρ = 0.1) and Case 2 (ρ=0.3) on Instance 1 for hour 8

6 Conclusion

In this paper, we discussed the challenges posed by the current problem formulation of energy disaggregation to swarm and evolutionary algorithm. In addition, from the different problem formulation by literature, we proposed a framework for evolutionary energy disaggregation. Pursuant to the simulation results in the previous section, it is evident that the evolutionary algorithms were able to optimize the objective functions with/without constraints. In addition, it is clear that our proposed framework is practical (feasible) for using in NILM systems. In the last few decades, the advancements in evolutionary algorithm literature has reached the capability of solving even complex optimization problems. However, the applicability of swarm and evolutionary algorithms to energy disaggregation optimization is limited by the appropriate objective and constraint formulation.

7 Future works

From the simulation results, the degraded performance of the evolutionary algorithms with respect to the energy disaggregation is due to the limitations in the problem formulation including objective function and constraints. In other words, the current problem formulation and the constraints do not actually represent the problem and need to include the following aspects:

1. The objective function should take into account the uncertainties in the data measurement into account.

2. Constraint related to device operation can be placed. For instance, a proper operation of a device last for a significant amount of time. Therefore, the sparsity constraint can be placed over a small duration of time.

3. A constraint on the number of switching instances at given time instance can be placed.

4. In pattern recognition based methods, the algorithm is provided with lot of training data and correlation between the devices, which plays a crucial role in some instances, can be implicitly learnt. However, in the case of optimization-based approaches the correlation between devices needs to be explicitly incorporated in the form of constraints.

5. Identifying devices with similar states is generally not possible without the feedback from the user. The problem formulation should facilitate the interaction between the user and the algorithm. For instance, the information such as "time of the day" as well as the "appliance usage duration" from the user can be included to enhance the performance of disaggregation algorithm (this information can change depending on the day and the house). With the advancement in interactive evolutionary algorithms, it is possible to incorporated user information into the optimization process.

Some advantages of optimization-based approaches compared to pattern recognition-based approaches:

1. Pattern recognition-based approaches require huge amount of training data to learn. During the training process the time-based correlation between devices is implicitly learnt by the algorithm. However, the process cannot be controlled by the user and the user is not sure if the learning process incorporated the information. However, in case of optimization-based approaches the correlation can be modelled as a constraint and the level of constraint satisfaction can be observed by the user.

2. After, the final disaggregation is done and the user want to provide some feedback regarding the process (for instance, the Printer is identified in the place of Coffee machine) and the user wants to provide the feedback. This can be easily done with interactive evolutionary algorithms. In other words, with advancement of interactive evolutionary algorithms, it is possible for the humans to interact with the system to specify some information about how many times a device is operated etc. This is not easy in supervised machine learning algorithms as the algorithm mainly learns from the data.

3. The current challenge in applying swarm and evolutionary algorithms to energy disaggregation is hindered by the absence of exact problem formulation. Therefore, once the appropriate objective functions and constraints are identified then advanced evolutionary algorithms in the literature (Awad, Ali et al. 2018, Biswas, Suganthan et al. 2018, Awad, Ali et al. 2019, Cai, Wang et al. 2019, Cai, Zhang et al. 2019) can be employed to effectively solve the energy disaggregation optimization problem.

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