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Optimization-Based Energy Disaggregation: A Constrained Multi-Objective Approach

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Abstract: Recently, optimization-based energy disaggregation (ED) algorithms have been gaining significance due to their capability to perform disaggregation with minimal information compared to the pattern-based ED algorithms, which demand large amounts of data for training. However, the performances of optimization-based ED algorithms depend on the problem formulation that includes an objective function(s) and/or constraints. In the literature, ED has been formulated as a constrained single-objective problem or an unconstrained multi-objective problem considering disaggregation error, sparsity of state switching, on/off switching, etc. In this work, the ED problem is formulated as a constrained multi-objective problem (CMOP), where the constraints related to the operational characteristics of the devices are included. In addition, the formulated CMOP is solved using a constrained multi-objective evolutionary algorithm (CMOEA). The performance of the proposed formulation is compared with those of three high-performing ED formulations in the literature based on the appliance-level and overall indicators. The results show that the proposed formulation improves both appliance-level and overall ED results.

Keywords: energy disaggregation; non-intrusive load monitoring; optimization-based energy disaggregation; constrained multi-objective optimization; evolutionary algorithms

MSC: 68T20

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1. Introduction

In the modern world, the residential sector accounts for nearly one-third of global energy consumption [1]. Unlike traditional indirect feedback, such as monthly bills, the provision of appliance-based consumption feedback is projected to result in 12% energy savings per year [2] combined with additional features, such as the identification of faulty and/or energy-inefficient devices [2]. In order to provide appliance-level consumption feedback, it is essential to monitor the power consumption of each appliance directly (intrusive) or indirectly (non-intrusive) referred to as appliance load monitoring (ALM). Therefore, ALM can be classified as intrusive ALM (IALM) or non-intrusive ALM (NIALM) [1]. In IALM, one or more sensors are used to measure the consumption of each appliance, resulting in accurate measurements, but it is costly due to the amount of hardware required. On the other hand, NIALM, or energy disaggregation (ED), employs a single sensor to measure the consumption of the whole house, and appliance-level consumption is estimated using artificial-intelligence-based techniques. In the last few decades, the combined growth of artificial intelligence and smart meters led to an exponential growth of ALM [2–4] because of its capability to promote energy awareness with minimal infrastructure.

Given the aggregated measurements, $y(t)$, from the smart meter [1,2] over time, $t = 1, 2, \ldots, T$, the goal of ED is to estimate the energy consumption, $y_i(t)$, of each device, $i \in 1, 2, \ldots, n$, such that

$$y(t) = \sum_{i=1}^{n} y_i(t) + \sigma(t), \tag{1}$$

where $y(t)$ denotes the aggregate active power (P) [5] and $\sigma(t)$ represents the measurement noise.

From Equation (1), it is evident that ED is an over-parameterized and highly ill-posed problem. Furthermore, ED gets complicated as the number, types, and similarity between the devices increases [1], coupled with measurement errors [2]. Frameworks proposed for ED can be classified as (a) unsupervised or (b) supervised [1,2,6].

Unsupervised ED approaches [7–9] leverage unsupervised and generic learning features; however, they often fail when appliances with similar operating characteristics are featured in the network or when the power rating of one appliance is a linear combination of two or more appliances [10]. Supervised ED frameworks require representative labeled datasets to facilitate training of the components of the model. Furthermore, the type and amount of the training dataset depend on the components present. The challenges associated with machine-learning-based approaches are summarized in [10–14]. Among them, the main challenges are the ones associated with the data required for feature extraction and model training, such as

1. Exponential increase in data requirement as the number of appliances increases.
2. Depending on feature extraction, the sampling rate of data collection needs to be changed.
3. Data are household-specific due to unique device combinations and their usage patterns.
4. Class imbalance is inherent due to infrequent operation of some devices.
5. To incorporate new devices, the processes of data collection and training need to be repeated.

Optimization-based ED approaches alleviate the need for a training process that demands large amounts of data. Contrary to machine learning approaches, optimization-based ED approaches employ simple and readily available information corresponding to electrical devices such as different modes of operation and their associated power ratings. Additionally, new appliances can be integrated easily into the network by appending the appliance-specific information (states and ratings). Given the above information, ED can be formulated as a single-objective or multi-objective optimization problem with/without constraints [4,15–17]. The performances of optimization-based ED algorithms depend on various factors [14]. However, the main ones among them are the objective function(s) and constraints. In other words, the performance strongly depends on how the problem is formulated. In the literature, the objective and constraint functions are based on energy disaggregation error, sparsity of switching events, and some constraints regarding device operation depending on how the problem is formulated. Recently, in [13,18], ED is formulated as a multi-objective optimization problem. However, these formulations are unconstrained and do not consider the device's operation characteristics.

Motivated by the need for more efficient ED problem formulations that take into account the associated constraints in order to realize good ED results, this work formulates ED as a constrained multi-objective problem (CMOP), where sparsity and disaggregation error are considered as the two objectives. In addition, device-specific operational characteristics are considered as constraints. The formulated CMOP is solved using the constrained multi-objective evolutionary algorithm (CMOEA), and its performance is compared with those of state-of-the-art optimization-based ED formulations. The main contributions of this paper are highlighted as follows:

1. A novel constrained multi-objective formulation of energy disaggregation is proposed.
2. In the formulation, sparsity and disaggregation error are considered as the objectives to be optimized.
3. The constraints are formulated based on the device-specific operation characteristics of each appliance.
4. The performance of the proposed CMOP is evaluated using a constraint multi-objective evolutionary algorithm (CMOEA); it compares favorably with other methods in the literature.

The remainder of the paper is organized as follows. In Section 2, a review of the different formulations of optimization-based ED existing in the literature is presented. Section 3 presents the formulation proposed in the current work, where ED is formulated as a constrained multi-objective problem (CMOP). Section 4 presents the simulation results and a comparison with state-of-the-art optimization-based ED algorithms.

2. Literature Review on Optimization-Based Energy Disaggregation

Electrical devices, generally, operate in one of the predefined modes that are associated with estimated power-consumption levels, as depicted in Table 1. Given the information on the number of devices (n) in the network, the operational modes, and the associated power consumption corresponding to each device, ED can be formulated as an optimization problem as a constrained/unconstrained single or multi-objective problem [16]. In the literature, most of the optimization-based ED algorithms [15,19,20] represent ED as a binary optimization problem where a device i with l_i non-off modes is decomposed into l_i virtual two-state (on/off $(1/0)$) devices. For appliance i, let $P_i = \left[p_i^1, \dots, p_i^{l_i}\right]^T$ represent a power rating corresponding to l_i virtual devices. Then, for n devices, the power rating corresponding to the $m = \sum_{i=1}^{n} l_i$ virtual devices is given by an $(m \times 1)$ vector $P = [P_1, P_2, \dots, P_i, \dots, P_n]^T$. At time t, the operational status of m virtual on/off devices is given by the binary vector

$$S(t) = \left[s_1^{(1)}(t), \dots; s_1^{(l_1)}(t), \dots, s_i^{(1)}(t), \dots, s_i^{(l_i)}(t), \dots, s_n^{(1)}(t), \dots, s_n^{(l_n)}(t)\right]^T, \quad (2)$$

where $s^{(j)}(t) = \{0, 1\}$ for j $= \{l_1, l_2, \dots, l_n\}$.

Table 1. Details of appliances, their modes of operation with associated power ratings, and their power deviations [4].

No. of Appliances	Appliance	Maximum No of Modes	Power Rating (p)			Power Deviation (Θ)		
n		l_i	p_i^1	p_i^2	p_i^3	Θ_i^1	Θ_i^2	Θ_i^3
D1	LCD-Dell	1	25	-	-	5	-	-
D2	LCD-LG	1	22	-	-	5	-	-
D3	Coffee Maker	3	700	900	1100	100	100	100
D4	iMac	2	35	50	-	5	10	0
D5	Desktop	2	40	50	-	15	20	-
D6	Server	1	130	-	-	20	-	-
D7	Water Cooler	3	65	380	450	5	10	10
D8	Laptop	3	15	30	70	5	10	10
D9	Microwave	3	1000	1200	1700	100	100	100
D10	Printer	3	400	700	900	50	80	100
D11	Refrigerator	2	115	350	-	15	10	-

The aim of any ED algorithm is to find the operational state of each device in the network at each time instance given by $(S(t))$, so that estimated power consumption $\hat{y}(t)$ resembles the aggregated measurements, $y(t)$, from the smart meter [1,2], over time $t = 1, 2, \dots, T$. In addition, $\hat{y}(t)$ is a combination of $\hat{y}_i(t)$, where $i = 1, 2, \dots, n$. Therefore, during the estimation of $(S(t))$, the estimation of $\hat{y}_i(t)$, where $i = 1, 2, \dots, n$, should match the true power-consumption levels of the individual appliances.

In order to approximate $(S(t))$, the intuitive and the most commonly employed objective function in optimization-based ED is the least-square error between $y(t)$ and $\hat{y}(t)$, as shown below [15,19,20].

$$\text{minimize} f = \sum_{t=1}^{T} (y_i(t) - \hat{y}_i(t))^2, \tag{3}$$

where $\hat{y}(t) = S(t)^{T} P$.

To handle optimization-based energy disaggregation, as formulated in (3), integer programming [17], mixed integer programming [19], evolutionary algorithms [4,15,16,21], etc., have been employed. The search space associated with the binary optimization problem given by (3) increases drastically with the increase in the number of devices and their associated operational modes. Furthermore, the energy disaggregation given by (3) is over-parameterized. Hence, the solutions obtained may fail to represent the practical operation of an appliance. The different issues associated with optimization-based ED algorithms are summarized in [14]. In other words, it is essential to improve the problem formulation considering additional objectives and/or constraints.

Due to the binary representation of the ED problem, where appliance i with l_i non-off operating modes is represented as l_i virtual devices, during the estimation of S, the appliance i might operate in more than one of the possible modes, which is impractical. To address this problem, the authors of [19] considered an inequality constraint that forces the device to operate in only one of the l_i modes or switches off all the l_i two state devices.

As shown in Table 1, the power rating of one on/off device can be similar to those of others, or the power rating of one device can be represented as a linear combination of multiple devices. This results in a situation where there exist multiple possible solutions for a given aggregate value. To address this issue, in [19], it has been experimentally demonstrated that choosing a combination of appliances with the lowest number of devices being on at a given time would result in better performance.

Currently, the smart meters provide high-frequency data. In other words, consecutive measurements of $y(t)$ are obtained at significantly shorter intervals (say 10 s). Therefore, minimizing the least-square error (3) alone may result in frequent appliance switching (on/off). To enforce temporal sparsity, in [3], ED is expressed as a constrained single-objective problem. In this framework, Sparse Switching Event Recovering (SSER), the goal is to minimize the total number of on/off switchings (4) subject to power-limit constraints given by (5).

$$\text{minimize} TSE(\triangle S) = \sum_{j=1}^{m} \sum_{t=1}^{T} \left| \triangle S^{(j)}(t) \right|, \tag{4}$$

subject to

$$S'(t)(P - \Theta) \leq y(t) \leq S'(t)(P + \Theta). \tag{5}$$

where $S = [S(1), ..., S(i), ..., S(T)]$ is the $(m \times T)$ matrix. $\left(\Theta = [\Theta_1, \Theta_2, \ldots, \Theta_m]^T\right)$ is the approximate power deviation variation corresponding to each power state $\left(P = [P_1, P_2, \ldots, P_m]^T\right)$. $TSE(.)$ denotes the total switching events in $\triangle S$ given by

$$\triangle S = S.D,$$

where differential matrix (D) of size $T \times (T-1)$ is given by:

$$D = \begin{bmatrix} -1 & & & & \\ 1 & -1 & & & \\ & 1 & \ddots & & \\ & & \ddots & -1 & \\ & & & 1 & -1 \\ & & & & 1 \end{bmatrix}$$

In other words, corresponding to each operational mode, the deviation from the rated power (Θ) is assumed to be provided. It is challenging to estimate (Θ) corresponding to every operational mode resulting in serious degradation in the performance [3].

The over-parameterized formulation in Equation (3) is regularized in [22], which is referred to as sparse optimization (Sopt), as shown below.

$$\begin{aligned} &\text{minimize} f = \sum_{t=1}^{T} (y(t) - \hat{y}(t))^2 + \\ &\Rightarrow \lambda_1 \sum_{i=1}^{n} \sum_{t=1}^{T} \left\| \begin{bmatrix} w_i^{(1)}(t) \\ . \\ . \\ . \\ w_i^{(l_i)}(t) \end{bmatrix} \odot \begin{bmatrix} s_i^{(1)}(t) \\ . \\ . \\ . \\ s_i^{(l_i)}(t) \end{bmatrix} \right\|_1 + \\ &\Rightarrow \lambda_1 \sum_{i=1}^{n} \sum_{t=1}^{T} \left\| k_i \begin{bmatrix} s_i^{(1)}(t) - s_i^{(1)}(t-1) \\ . \\ . \\ . \\ s_i^{(l_i)}(t) - s_i^{(l_i)}(t-1) \end{bmatrix} \right\|_\infty , \end{aligned} \tag{6}$$

subject to

$$\sum_{j=1}^{l_i} s_i^{(j)}(t) = 1, i = 1, \ldots, n, and\ \ t = 1, \ldots, T \tag{7}$$

The equality constraint (7) is to enforce that continuous operating devices operate in at least one of the l_i non-off states. In (6), the penalty terms are expected to provide the temporal sparsity. However, the performance significantly varies based on the non-negative weight vector $[w_i^{(1)}(t), \ldots, w_i^{(l_i)}(t)]^T$ and hyperparameters (λ_1, λ_2, and $k_i(i = 1, \ldots, n)$).

Recently, ED is modeled as a multi-objective optimization problem in [18], where objectives are

$$\text{minimize} \begin{cases} f_1 = |y(t) - \hat{y}(t)| \\ f_2 = \phi_o d_o(s(t), s(t-1)) + \phi_s d_s(s(t), s(t-1)), \end{cases} \tag{8}$$

where function $d_s(s(t), s(t-1))$ represents the number of mode changes, and function $d_o(s(t), s(t-1))$ represents the number of on/off changes. Generally, solving a multi-objective optimization problem leads to a number of trade-off solutions where each solution is a prospective energy disaggregation. Therefore, it is essential to select a solution from the set to estimate the power consumption profile of devices. In [18], a decision-maker (DM) function defined by the following equation is employed to select the optimal ED solution from the set of trade-off solutions.

$$DM = f_1(s(t)) + \left[(1 + f_2(s(t))) \sqrt{|f_1(s(t)) - f_1(s(t-1))|} \right] \tag{9}$$

In [13], it was observed that minimization of least-square error (f_1 in (8)) maximizes the sum of the variations in switching events (f_2 in (8)) and vice versa. This is because of the featured inherent noise and similarity between the appliances in terms of power ratings. In other words, minimization of least-square error and total variation of switching events are conflicting. In [13], the problem is solved as a multi-objective problem. However, instead of employing the decision function, once the trade-off set is obtained, a solution where the disaggregated individual device operations match the practical device operation is selected (using some reference signals). The reference signals are considered to available or given by the manufacturer. In addition, in [13], the ED is solved as an discrete optimization problem instead of binary optimization problem where the state matrix (S) is represented as

$$SP = \begin{bmatrix} sp_1(1) & \cdots & sp_1(T) \\ \vdots & \ddots & \vdots \\ sp_n(1) & \cdots & sp_n(T) \end{bmatrix} \tag{10}$$

where SP is a state matrix of size $n \times T$ and $sp_i(t)$ is the consumption of device i = 1, 2,. . . , n at time instance t = 1, 2, . . . , T. The objective functions considered are

$$Minimize : E = \sum_{t=1}^{T} (y(t) - \sum_{i=1}^{n} sp_i(t))^2 \tag{11}$$

$$Minimize \begin{matrix} \sum_{i=1}^{n} \sum_{t=2}^{T} [(sp_i(t) \neq sp_i(t-1))(sp_i(t)sp_i(t-1) \neq 0)] \\ + \\ \sum_{i=1}^{n} \sum_{t=2}^{T} [(sp_i(t) \neq sp_i(t-1))(sp_i(t)sp_i(t-1) = 0)] \end{matrix} \tag{12}$$

Equation (11) is similar to f_1 in (8), and Equation (12) is similar to f_2 in (8). In addition, to effectively solve the multi-objective ED using the multi-objective evolutionary algorithm, problem-specific mutation and crossover operators were proposed.

Based on the review, it can be concluded that to improve the performance of optimization-based ED algorithms, novel problem formulations in terms of objectives and constraints are very crucial. Hence, more efficient formulations and algorithms are needed to address the ED problem.

3. Energy Disaggregation as a Constrained Multi-Objective Optimization Problem

In [13], the ED problem is formulated as an unconstrained multi-objective optimization problem given by Equations (11) and (12). In the second objective related to temporal sparsity (12), the sum of appliance on/off switching is combined with appliance state switching. It is to be remembered that the appliance on/off switching and appliance state changing strongly depend on the type of device. For instance, a refrigerator is a continuous operational device that rarely switches on/off and also switches operational modes with less frequency. However, a printer is a device that is regularly switched on/off, and during a certain period of operation, the number of state switches is high compared to the number in devices such as refrigerators. In other words, it is essential to take the device-specific operational constraints into account. In this work, appliance-specific operational constraints are incorporated, and ED is formulated as a constrained multi-objective optimization problem (CMOP). It is solved using a constrained multi-objective evolutionary algorithm (CMOEA). The appliance-specific operational constraints include a number of state switches per unit time of operation. This is specific to devices and the way in which they are designed to be operated. In addition, this information can be easily obtained from the manufacturer or through some data collection regarding how the particular device is operated in a network.

In the current framework, the objectives considered are same as (11) and (12). However, the minimization of (11) and (12) is subjected to n constraints, one corresponding to each device, represented as follows.

$$\frac{\sum_{t=2}^{T}[(sp_i(t) \neq sp_i(t-1))(sp_i(t)sp_i(t-1) \neq 0)]}{\sum_{t=1}^{T}[(sp_i(t) \neq 0)]} \leq b_i \qquad i = 1, \ldots., n \tag{13}$$

In the constraints given by (13), the left-hand side represents the number of state switching events corresponding to a device per unit time of operation in a prospective energy disaggregation vector. The right-hand side b_i represents the numerical value specific to the device. In other words, continuously operating devices such as refrigerators have low values of b_i, as the number of state switches is significantly low for a large period of operation. On the other hand, for devices such as a coffee maker, the number of state switching events is significantly higher over a shorter period of time. It has to be remembered that obtaining the values of b_i corresponding to device operation is not difficult to do.

To solve the CMOP defined by (11)–(13), any existing state-of-the-art CMOEA can be employed. However, in the current work, I_{SDE^+} [23], which is an evolutionary multi-objective algorithm, is used. I_{SDE^+} is effective at handling multi-objective problems with a variety of landscapes and is computationally efficient. I_{SDE^+} is combined with superiority of feasible (SF) to handle the constraints. In addition, to effectively solve the ED problem formulated as a CMOP, application-specific variation operators (crossover and mutation) proposed in [13] are employed. The overall framework used to solve the ED, formulated as a CMOP—CMOEA (I_{SDE^+} with superiority of feasible)—is shown in Algorithm 1.

Algorithm 1: General framework of the CMOEA employed to solve the ED formulated as a CMOP.

1 **Input**: N (population size)
2 $\boldsymbol{P} \leftarrow$ Initialization
3 $\boldsymbol{ISDE+} \leftarrow$ Evaluation (P)
4 **while** *predefined termination criteria not satisfied* **do**
5 $\quad \boldsymbol{M} \leftarrow$ Mating selection (P, N, ISDE+)
6 $\quad \boldsymbol{O} \leftarrow$ Variation (M, N)
7 $\quad \boldsymbol{Q} \leftarrow \mathrm{P} \cup \mathrm{O}$
8 $\quad \boldsymbol{ISDE+} \leftarrow$ Evaluate (Q)
9 $\quad [\boldsymbol{P}, \boldsymbol{ISDE+}] \leftarrow$ Environmental selection $(Q, N, ISDE+)$
10 **end**
11 **Output**: P

In the proposed framework, the CMOEA starts with random initialization of a set of solutions (N) for the given ED problem, where each prospective solution is represented as shown in (10). The ISDE+ indicator value that depends on the two objectives given by ((11) and (12)) and constraint violation given by (13) is evaluated for individual solution candidates in the population (as outlined in line 2 of Algorithm 1). Later, mating selection is carried out, in which the population members with superior ISDE+ values are prioritized in a probabilistic manner (line 4 in Algorithm 1). The solutions selected during mating selection (M) are then used to produce new solutions, namely, the offspring population (O) (line 5 in Algorithm 1). The process of producing new solutions using the solutions and their objective values in the population is referred to as variation. In the current work, we employ the problem-specific variation operators proposed in [13]. The population (P) and offspring population (O) are combined (Q) (line 6 in Algorithm 1) and evaluated (line 7 in Algorithm 1). Finally, environmental selection is performed, where the best NP candidates of Q are chosen to be the population (P) for the next generation (line 8 in Algorithm 1). The steps mating selection, variation to produce new solutions, evaluation, and environmental selection (Algorithm 1, lines 4–8) are repeated until a predefined stopping criterion is met. After the termination, the final population (P) which contains trade-off solutions that satisfy the objectives and constraints are considered as the output. In other words, each solution in the trade-off set represents a possible ED. From the set of trade-off solutions, the solution with the lowest value of disaggregation error is selected as the best possible energy disaggregation result.

4. Simulation Results and Analysis

To evaluate the performance of the proposed framework, we considered some instances of ED problems from the benchmark suite proposed in [14]. Specifically, we selected instances I_1, I_{12} and I_{18}, which are problem instances that feature cases where almost all devices are in operation, the power rating of one appliance is a linear combination of multiple appliances, and simultaneous switching of appliances with similar states or multiple devices whose linear combinations are similar to each other. These instances were chosen because they represent the different challenges posed by optimization problems formulated as ED.

Furthermore, as shown in [14], the performances of ED algorithms must be evaluated by a number of metrics, including both appliance-level and overall performance metrics. Therefore, we employ standard metrics such as per-appliance accuracy (AC_i), estimated energy fraction index (EEFI) $(\hat{h}_i)$, and relative squared error (RSE_i) at the appliance level; and overall accuracy (ACC), overall state prediction accuracy (SPA), and fraction of total energy assigned correctly (FTEAC) at the overall level to compare the performance of the proposed framework with the baseline results from the literature. A better-performing ED algorithm is expected to have higher values for overall performance indicators—ACC, SPA, and FTEAC. Among the appliance-level indicators, AC_i is expected to be higher, and RSE_i is expected to be lower. However, $(\hat{h}_i)$ is expected to be as close as possible to (h_i).

All the simulations were performed in MATLAB 2020a installed on a PC with 64-bit Windows 10, a 3.30 GHz CPU, and 24 GB of RAM. Based on the aforementioned problem instances and metrics, we first evaluated the ED performance with and without the constraints defined by Equation (13). In Tables 2–4, the effects of the appliance-specific constraints on the energy disaggregation performance are evaluated considering problem instances I_1, I_{12}, and I_{18}. Tables 5–7, present a comparative analysis of the proposed framework with state-of-the-art energy disaggregation frameworks, such as ALIP [19], MONILM [18], and SOPT [22].

In Tables 2–4, it can be observed that with respect to most of the devices, the energy disaggregation performance with constraints is better than that without constraints in most of the per-appliance metrics. In addition, a similar observation can be made with respect to overall performance metrics, such as SPA and FTEAC. However, in instance I_{12}, the ACC of the proposed framework with constraints is less, but the performance is drastically improved in terms of SPA. This is because the use of constraints helped the framework perform better on D_{11}, which was in operation for significant amount of time and consumed significant amount of power (h). Therefore, it justified the use of appliance-specific constraints defined by (13).

Table 2. Effect of appliance-specific constraints on the performance of energy disaggregation considering the I_1 problem instance.

No of Appliances	AC_i		h	$\hat{h}_i$		RSE_i	
n	**Without**	**With**	**Ground Truth**	**Without**	**With**	**Without**	**With**
D1	1	1	0.05	0.0584	0.0542	0	0
D2	0.94	0.94	0.0328	0.0514	0.0477	0.4669	0.4469
D3	1	1	0	0	0	0	0
D4	0.8570	0.9072	0.0728	0.1074	0.0680	0.1589	0.0994
D5	0.5394	0.8796	0.0734	0.0149	0.0867	1	0.0713
D6	0.9358	0.9358	0.2267	0.3039	0.2816	0.0766	0.0766
D7	0.5809	0.7407	0.3025	0.1359	0.2147	0.6718	0.4313
D8	0.6825	0.7576	0.0489	0.0933	0.0398	0.1001	0.3891
D9	1	1	0	0	0		
D10	0.5423	0.5	0.0759	0.0987	0	1	1
D11	0.9823	0.9711	0.1158	0.1359	0.2074	0.3824	2.0084
Overall Metrics							
				Without		With	
Overall Energy Disaggregation Accuracy (ACC (%))				87.6556		90.7188	
State Prediction Accuracy (SPA (%))				56.4899		64.899	
Fraction of Total Energy assigned correctly (FTEAC)				0.7749		0.8222	

Table 3. Effect of appliance-specific constraints on the performance of energy disaggregation considering the I_{12} problem instance.

No of Appliances	AC_i		h	$\hat{h}_i$		RSE_i	
n	**without**	**With**	**Ground Truth**	**Without**	**With**	**Without**	**With**
D1	1	1	0.0501	0.0550	0.0650	0.0876	0.0060
D2	1	1	0	0.0523	0		
D3	1	1	0	0	0		
D4	0.7218	0.8644	0.0706	0.1101	0.0867	0.1256	0.3309
D5	0.8285	0.5618	0.0797	0.1174	0.0259	1	0.1811
D6	0.9167	0.9150	0.2567	0.2896	0.3134	0.0826	0.0777
D7	0.7303	0.5945	0.2779	0.2738	0.1548	0.7184	0.5988
D8	0.5214	0.6224	0.0204	0.1018	0.0552	2.2408	8.0803
D9	1	1	0	0	0		
D10	0.5	0.5	0.0061	0	0.0000	1	1
D11	0.5	0.9601	0.2387	0	0.2989	0.1101	1.0000
Overall Metrics							
				without		With	
Overall Energy Disaggregation Accuracy (ACC (%))				89.4814		86.1355	
State Prediction Accuracy (SPA (%))				33.6869		60.2778	
Fraction of Total Energy assigned correctly (FTEAC)				0.7512		0.8172	

Table 4. Effect of appliance-specific constraints on the performance of energy disaggregation considering I_{18} problem instance.

No of Appliances	AC_i		h	$\hat{h}_i$		RSE_i	
n	**Without**	**With**	**Ground Truth**	**Without**	**Proposed**	**Without**	**Proposed**
D1	0.7583	1	0.0652	0.0363	0.0696	0.4833	0.0000
D2	0.6561	0.94	0.0056	0.0349	0.0612	5.4466	8.2330
D3	1	1	0	0	0		
D4	0.5	0.8730	0.0848	0.0000	0.1135	1	0.1172
D5	0.6138	0.5354	0.1076	0.0504	0.0142	0.7165	1.0000
D6	0.9408	0.9408	0.2939	0.3658	0.3617	0.0586	0.0586
D7	0.6373	0.6373	0.1684	0.1468	0.1658	0.6727	0.7272
D8	0.6687	0.7534	0.0926	0.0422	0.0497	0.4666	0.3115
D9	1	1	0	0	0		
D10	0.5	0.5	0.0277	0.00000	0.0000	1	1
D11	0.9809	0.9744	0	0.32356	0.1644	0.9485	0.1166

Overall Metrics		
	without	With
Overall Energy Disaggregation Accuracy (ACC (%))	88.4347	88.8737
State Prediction Accuracy (SPA (%))	53.4091	54.0657
Fraction of Total Energy assigned correctly (FTEAC)	0.7293	0.8333

In Tables 5–7, it can be observed that the performance of the proposed framework, in terms of SPA and FTEAC, is better than the state-of-the-art methods for instances I_1 and I_{18}, but slightly worse for I_{12}. However, in ACC, the performance of the proposed framework is worse. As mentioned in the literature [13], this is not a concern, because a high value of ACC does not signify superior performance, as each mode of the device is represented with a discrete value, and thus achieving an ACC close to 100% is not possible. In other words, even accurate energy disaggregation does not result in an ACC close to 100%. Therefore, the performance of the proposed framework seems to be superior for instances I_1 and I_{18}. However, for instance I_{12}, the performance of ALIP seems better than that of the proposed framework. For instance I_{12}, nearly 80% of the total energy is consumed by continuously operating devices, such as D_6, D_7, and D_{11}. In ALIP, an equality constraint is specifically employed to handle continuously operating devices, resulting in superior performance.

Table 5. Comparison of the proposed framework with the state-of-the-art methods in terms of energy disaggregation on the I_1 problem instance.

No of Appliances	AC_i				h	$\hat{h}_i$				RSE_i			
n	**ALIP**	**MONILM**	**SOPT**	**Proposed**	**Ground Truth**	**ALIP**	**MONILM**	**SOPT**	**Proposed**	**ALIP**	**MONILM**	**SOPT**	**Proposed**
D1	0.6648	0.8722	0.8403	1	0.05	0.0169	0.0381	0.0348	0.0542	0.6704	0.2556	0.3194	0
D2	0.6162	0.841	0.94	0.94	0.0328	0.0144	0.0359	0.045	0.0477	0.9208	0.5983	0.4469	0.4469
D3	1	1	1	1	0	0.0221	0.0131	0.0233	0	-	-	-	-
D4	0.6612	0.8093	0.8073	0.9072	0.0728	0.0387	0.0714	0.1023	0.0680	0.614	0.2651	0.1778	0.0994
D5	0.6663	0.8039	0.8226	0.8796	0.0734	0.0403	0.0842	0.1023	0.0867	0.6019	0.2493	0.2055	0.0713
D6	0.9358	0.8605	0.5012	0.9358	0.2267	0.2663	0.2113	0.0007	0.2816	0.0764	0.2175	0.9972	0.0766
D7	0.7923	0.7633	0.9194	0.7407	0.3025	0.2307	0.1895	0.286	0.2147	0.3687	0.4554	0.1109	0.4313
D8	0.5763	0.4203	0.4363	0.7576	0.0489	0.0398	0.095	0.0898	0.0398	1.0479	2.1133	1.9037	0.3891
D9	1	1	1	1	0	0.0057	0	0	0	-	-	-	-
D10	0.6593	0.7096	0.664	0.5	0.0759	0.055	0.0307	0.0358	0.0000	0.8208	0.4959	0.6601	1
D11	0.9656	0.8919	0.9767	0.9711	0.1158	0.2729	0.232	0.242	0.2074	2.2818	2.5971	1.2418	2.0084

Overall Metrics				
	ALIP	MONILM	SOPT	Proposed
Overall Energy Disaggregation Accuracy (ACC (%))	99.8051	99.6126	96.5757	90.7188
State Prediction Accuracy (SPA (%))	60.0758	49.899	42.2475	64.899
Fraction of Total Energy assigned correctly (FTEAC)	0.7785	0.7769	0.7011	0.8222

Table 6. Comparison of the proposed framework with state-of-the-art methods in terms of energy disaggregation in the I_{12} problem instance.

No of Appliances	AC_i				h	$\hat{h}_i$				RSE_i			
n	**ALIP**	**MONILM**	**SOPT**	**Proposed**	**Ground Truth**	**ALIP**	**MONILM**	**Proposed**	**SOPT**	**ALIP**	**MONILM**	**SOPT**	**Proposed**
D1	0.6949	0.9018	0.5	1	0.0501	0.0197	0.0434	0.0650	0	0.6133	0.2598	1	0.0060
D2	1	1	1	1	0	0.016	0.0356	0	0.029	-	-	-	-
D3	1	1	1	1	0	0.0042	0	0	0	-	-	-	-
D4	0.6332	0.8008	0.833	0.8644	0.0706	0.0364	0.0861	0.0867	0.0942	0.6694	0.2413	0.1654	0.3309
D5	0.6292	0.8163	0.8243	0.5618	0.0797	0.0347	0.0933	0.0259	0.1087	0.6795	0.2202	0.1911	0.1811
D6	0.9465	0.8697	0.9127	0.9150	0.2567	0.2833	0.2337	0.3134	0.2613	0.0126	0.1836	0.0878	0.0777
D7	0.8121	0.7788	0.5	0.5945	0.2779	0.2571	0.2289	0.1548	0	0.3326	0.3994	1	0.5988
D8	0.5574	0.6015	0.527	0.6224	0.0204	0.0416	0.0849	0.0552	0.0887	2.511	6.8094	6.1865	8.0803
D9	1	1	1	1	0	0	0.0061	0	0.0061	-	-	-	-
D10	0.5	0.5	0.5	0.5	0.0061	0.0218	0.046	0.0000	0	2.44	4.04	1	1
D11	0.8915	0.6184	0.7128	0.9601	0.2387	0.2961	0.1436	0.2989	0.39	0.5494	0.9286	1.2979	1

Overall Metrics				
	ALIP	MONILM	SOPT	Proposed
Overall Energy Disaggregation Accuracy (ACC (%))	99.6766	99.5509	97.2710	86.1355
State Prediction Accuracy (SPA (%))	65.8081	47.0202	54.2929	60.2778
Fraction of Total Energy assigned correctly (FTEAC)	0.8697	0.8561	0.666	0.8172

Table 7. Comparison of the proposed framework with state-of-the-art methods in terms of energy disaggregation in the I_{18} problem instance.

No of Appliances	AC_i				h	$\hat{h}_i$				RSE_i			
n	**ALIP**	**MONILM**	**SOPT**	**Proposed**	**Ground Truth**	**ALIP**	**MONILM**	**SOPT**	**Proposed**	**ALIP**	**MONILM**	**SOPT**	**Proposed**
D1	0.6389	0.8139	0.9903	1	0.0652	0.0181	0.0409	0.064	0.0696	0.7222	0.3722	0.0194	0.0000
D2	0.5852	0.7129	0.94	0.94	0.0056	0.0179	0.047	0.0571	0.0612	3.4572	7.5177	8.1831	8.2330
D3	1	1	1	1	0	0.0065	0	0.0065	0	-	-	-	-
D4	0.6079	0.7868	0.7338	0.8730	0.0848	0.033	0.1168	0.1277	0.1135	0.7384	0.2318	0.292	0.1172
D5	0.6226	0.8231	0.8591	0.5354	0.1076	0.0412	0.1046	0.1305	0.0142	0.6951	0.207	0.1219	1.0000
D6	0.9408	0.8385	0.9041	0.9408	0.2939	0.3392	0.2591	0.31	0.3617	0.0586	0.2731	0.1332	0.0586
D7	0.7751	0.8421	0.6236	0.6373	0.1684	0.2041	0.1655	0.024	0.1658	0.521	0.3469	0.7221	0.7272
D8	0.5641	0.7003	0.682	0.7534	0.0926	0.0319	0.0857	0.0501	0.0497	0.8537	0.5692	0.4666	0.3115
D9	1	1	1	1	0	0	0	0	0	-	-	-	
D10	0.7638	0.7491	0.6947	0.5	0.0277	0.0261	0.0232	0.0464	0.0000	0.5213	0.4129	1.2459	1
D11	0.9483	0.8001	0.9369	0.9744	0	0.3222	0.157	0.1995	0.1644	1.401	0.8337	0.535	0.1166

Overall Metrics				
	ALIP	MONILM	SOPT	Proposed
Overall Energy Disaggregation Accuracy (ACC (%))	98.8239	99.3654	95.3903	88.8737
State Prediction Accuracy (SPA (%))	55.2778	50.4545	46.9949	54.0657
Fraction of Total Energy assigned correctly (FTEAC)	0.7723	0.8655	0.8117	0.8333

5. Conclusions and Future Work

In this work, ED was formulated as a constrained multi-objective optimization problem, where the objectives are minimizing energy disaggregation error and temporal sparsity, and constraints related to the practical operation of the devices were proposed. Specifically, in the proposed formulation, the constraints make sure that each device operation during the ED process adheres to the associated practical operational characteristics. Results from the experiments conducted in this work show that the incorporation of the constraints enhanced the ED performance in various metrics (appliance-level and overall) compared to the case where the constraints were not considered. Furthermore, when compared with state-of-the-art ED algorithms, the proposed constrained multi-objective framework was able to demonstrate superior performance.

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References

1. Zoha, A.; Gluhak, A.; Imran, M.A.; Rajasegarar, S. Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey. *Sensors* **2012**, *12*, 16838–16866. [CrossRef]
2. Zeifman, M.; Roth, K. Nonintrusive appliance load monitoring: Review and outlook. *IEEE Trans. Consum. Electron.* **2011**, *57*, 76–84. [CrossRef]
3. Tang, G.; Wu, K.; Lei, J.; Tang, J. Plug and play! a simple, universal model for energy disaggregation. *arXiv* **2014**. arXiv:1404.1884.
4. Tang, G.; Wu, K.; Lei, J.; Tang, J. A simple model-driven approach to energy disaggregation. In Proceedings of the 2014 IEEE International Conference on Smart Grid Communications (SmartGridComm), Venice, Italy, 3–6 November 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 566–571.
5. Laughman, C.; Lee, K.; Cox, R.; Shaw, S.; Leeb, S.; Norford, L.; Armstrong, P. Power signature analysis. *IEEE Power Energy Mag.* **2003**, *1*, 56–63. [CrossRef]
6. Pereira, L.; Nunes, N. Performance evaluation in non-intrusive load monitoring: Datasets, metrics, and tools—A review. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2018**, *8*, e1265. [CrossRef]
7. Gonçalves, H.; Ocneanu, A.; Bergés, M. Unsupervised disaggregation of appliances using aggregated consumption data. In Proceedings of the 1st KDD Workshop on Data Mining Applications in Sustainability (SustKDD), San Diego, CA, USA, 21 August 2011.
8. Johnson, M.J.; Willsky, A.S. Bayesian Nonparametric Hidden Semi-Markov Models. *J. Mach. Learn. Res.* **2013**, *14*, 673–701.
9. Winkler, P.; Le Ray, G.; Pinson, P. Unsupervised Energy Disaggregation: From Sparse Signal Approximation to Community Detection. *IEEE Trans. Smart Grid* **2019**, 1–8. Available online: http://pierrepinson.com/docs/Lerayetal2019-unsupnilm.pdf (accessed on 19 June 2022).
10. Hart, G. Nonintrusive appliance load monitoring. *Proc. IEEE* **1992**, *80*, 1870–1891. [CrossRef]
11. Srinivasan, D.; Ng, W.; Liew, A. Neural-network-based signature recognition for harmonic source identification. *IEEE Trans. Power Deliv.* **2006**, *21*, 398–405. [CrossRef]
12. Tsai, M.S.; Lin, Y.H. Modern development of an Adaptive Non-Intrusive Appliance Load Monitoring system in electricity energy conservation. *Appl. Energy* **2012**, *96*, 55–73. [CrossRef]
13. Ghorbanpour, S.; Pamulapati, T.; Mallipeddi, R.; Lee, M. Energy disaggregation considering least square error and temporal sparsity: A multi-objective evolutionary approach. *Swarm Evol. Comput.* **2021**, *64*, 100909, . [CrossRef]
14. Ajani, O.S.; Kumar, A.; Mallipeddi, R.; Das, S.; Suganthan, P.N. Benchmarking Optimization-Based Energy Disaggregation Algorithms. *Energies* **2022**, *15*, 1600. [CrossRef]
15. Egarter, D.; Elmenreich, W. EvoNILM: Evolutionary appliance detection for miscellaneous household appliances. In Proceedings of the GECCO ’13 Companion, Amsterdam, The Netherlands, 6–10 July 2013.
16. Ghorbanpour, S.; Pamulapati, T.; Mallipeddi, R. Swarm and evolutionary algorithms for energy disaggregation: challenges and prospects. *Int. J. Bio Inspired Comput.* **2021**, *17*, 215–226. [CrossRef]
17. Suzuki, K.; Inagaki, S.; Suzuki, T.; Nakamura, H.; Ito, K. Nonintrusive appliance load monitoring based on integer programming. In Proceedings of the 2008 SICE Annual Conference, Tokyo, Japan, 20–22 August 2008; pp. 2742–2747. [CrossRef]
18. Machlev, R.; Belikov, J.; Beck, Y.; Levron, Y. MO-NILM: A multi-objective evolutionary algorithm for NILM classification. *Energy Build.* **2019**, *199*, 134–144. [CrossRef]
19. Bhotto, M.Z.A.; Makonin, S.; Bajić, I.V. Load Disaggregation Based on Aided Linear Integer Programming. *IEEE Trans. Circuits Syst. II Express Briefs* **2017**, *64*, 792–796. [CrossRef]
20. Shen, Q.; Wang, X. An analysis of the optimization disaggregation algorithm in the estimation related to energy consumption of appliances in buildings. *Appl. Math. Comput.* **2014**, *234*, 506–519. [CrossRef]
21. Egarter, D.; Sobe, A.; Elmenreich, W. Evolving Non-Intrusive Load Monitoring. In Proceedings of the 16th European Conference, EvoApplications 2013, Vienna, Austria, 3–5 April 2013.
22. Piga, D.; Cominola, A.; Giuliani, M.; Castelletti, A.; Rizzoli, A.E. Sparse Optimization for Automated Energy End Use Disaggregation. *IEEE Trans. Control Syst. Technol.* **2016**, *24*, 1044–1051. [CrossRef]
23. Pamulapati, T.; Mallipeddi, R.; Suganthan, P.N. I_{SDE}+—An Indicator for Multi and Many-Objective Optimization. *IEEE Trans. Evol. Comput.* **2018**, *23*, 346–352. [CrossRef]