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Research on Training-less Metaheuristic-based Energy Disaggregation Considering Mined Load Operational Constraints

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A smart grid is one of the promising paradigms of artificial intelligence of things (AIoT), which enables bidirectional communication between the utility side and the consumer side to achieve demand-side management (DSM) using demand response programs. To achieve effective DSM, energy disaggregation (i.e., nonintrusive load monitoring), a cost-effective virtual sensing technique in appliance-level load monitoring, can disaggregate circuit-level/building-level power consumption into appliance-level power consumption in a practical field of interest. In this paper, we present a training-less metaheuristic-based residential energy disaggregation approach for discerning appliance-level power consumption from power consumption via a combinatorial optimization search based on a genetic algorithm, whereby the algorithm is developed in consideration of time-series load profiling as a penalty term declared and used to incorporate appliance constraints by penalizing constraint violations. The algorithm executed with the penalty term during the evolutionary process for the energy disaggregation purpose can speed up and target accurately its evolutionary convergence. The presented genetic algorithm-based energy disaggregation approach is practically evaluated using a publicly available reference dataset—the electrical-end-use dataset.

1. Introduction

A smart home environment integrates interconnected devices with systems to automate and optimize household functions, thereby enhancing home convenience, energy efficiency, and residential security.[(1–5)] Artificial intelligence of things (AIoT) is a technical combination of AI across IoT technologies to achieve more efficient IoT applications, i.e., AIoT applications, with AI in, for example, such a smart home environment. Real-time intelligent stock management tracking shelf visibility based on retail product detection[(6)] is another application paradigm. Besides a smart home and an intelligent stock management system, a smart grid is also another application paradigm, which has been developed for a traditional power grid to be upgraded and

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optimized for energy efficiency. Energy disaggregation, also called nonintrusive load monitoring, monitors major electrical appliances, such as home appliances/devices as consumer electronics, in a cost-effective and nonintrusive manner to identify appliance-level power consumption for load management. It was first studied by Hart(7) in the early 1980s. Energy disaggregation applied as a virtual sensor methodology dedicated for device-level load monitoring to plug-panel load data has been recognized as an alternative to intrusive load monitoring approaches that utilize deployed plug-load power meters (i.e., smart plugs) in energy management systems (EMSs), such as home EMSs,(8–11) in practical fields of interest. In a smart grid implementing demand-side management (DSM), consumers utilizing an EMS with energy disaggregation have the opportunity to improve their awareness of which of and when their monitored relevant electrical appliances should be operated in response to demand response (DR) signals. Also, the power utility(ies) coming up with DR programs to realize DSM has the opportunity to plan to operate, in an optimal way, the grid addressing ever-increasing electricity demands.(12,13) Energy disaggregation can be applied for applications such as smart home energy efficiency(1) and home activity recognition and safety alerts for the elderly.(14–17)

The technical content behind energy disaggregation can be based on AI including machine learning (ML)(14,18–24) and/or deep learning (DL).(25–30) The challenges to energy disaggregation based on ML/DL model approaches are summarized in the research articles.(31,32) One of the challenges is that the sampling rate is required at a high frequency level for the data collection of electricity signals to be processed for feature extraction/model training (data modeling). Optimization (metaheuristic)-based energy disaggregation approaches can alleviate the need for a model training process that demands large amounts of data.(32) However, not much attention has been paid to metaheuristics used to run energy disaggregation through a combinatorial optimization search incorporating time-series load profiling information. Machlev *et al.*(33) developed and utilized a multi-objective evolutionary algorithm-based energy disaggregation approach to break down the measured circuit-level/building-level power consumption (i.e., mains) into appliance-level power consumption at each data sample; the features/signatures considered and used to identify individual relevant monitored electrical appliances based on combinatorial search were real power (P) and reactive power (Q) (usually/practically, only data of P are available, which are retrieved directly from a smart meter in a field). Similar to the work by Machlev *et al.*,(33) Lin (34) developed and used a multi-objective evolutionary algorithm-based energy disaggregation approach to perform energy disaggregation based on P and Q. Similarly, Hu *et al.*(23) presented and used a parallel-computing-accelerated, genetic algorithm (GA)-based energy disaggregation approach to address the basic energy disaggregation problem(23) [i.e., to perform energy disaggregation at time t (at each time point of mains reading)]; the considered feature/signature to discern the electrical appliances of concern from the mains was their P. Although the three energy disaggregation approaches(23,33,34) are the evolutionary computing-based combinatorial search approaches, they seem impractical for energy disaggregation in that the combinatorial search is required every time intervals and individual relevant concerned electrical appliances may be identical in P and/or Q [an additional feature(s) that can incorporate time-series appliance usage routine information needs to be considered during the combinatorial search). Therefore, in this study, energy disaggregation is declared as a combinatorial optimization problem, which is resolved by GA whose objective function is designed, integrated with a penalty function, and implemented. By incorporating the objective function with the penalty function to search for the optimal feasible solution in energy disaggregation, the algorithm becomes capable of improving its evolutionary convergence. The GA-based energy disaggregation approach described in this paper has been practically validated on a publicly available reference dataset, the electrical-end-use dataset (EEUD),[35] for its feasibility and effectiveness. A constrained multi-objective energy disaggregation method based on an evolutionary algorithm was proposed by Park *et al.*;[32] however, this method was evaluated using simulation data.

This paper is organized as follows. The presented methodology is described in Sect. 2. Sect. 3 showcases the practical evaluation results. Finally, Sect. 4 concludes this paper with a description of future work.

2. Methodology

Figure 1 shows the flowchart of the presented training-less GA-based energy disaggregation methodology considering time-series load profiling based on past trends.

The flowchart consists of 1) a *data preprocessing* step as the preliminary step[34] of energy disaggregation: base load-related information in a practical field of interest (a load monitoring environment) is computed and label data in a structured energy disaggregation dataset to be modeled are determined; 2) a *penalty function design* step for GA energy disaggregation data

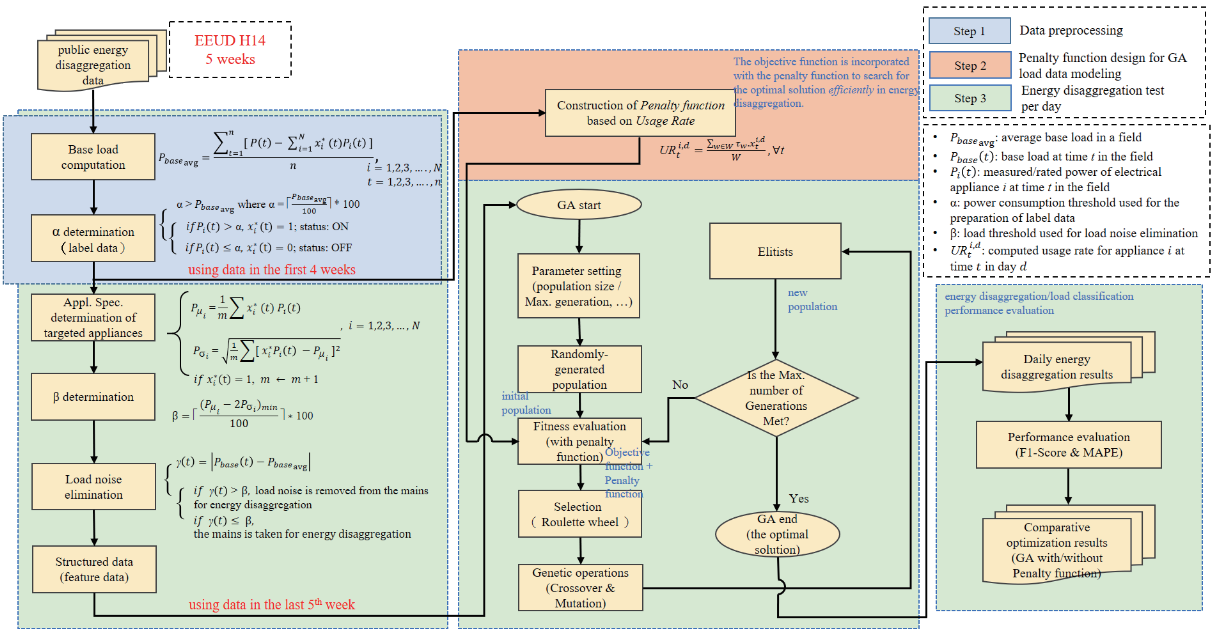


Fig. 1. (Color online) Flowchart of presented training-less GA-based energy disaggregation algorithm considering time-series load profiling.

modeling: a penalty function based on label data determined in the data preprocessing step is designed and implemented in GA evolution where the algorithm can search for the optimal solution efficiently for the energy disaggregation purpose, taking into consideration mined load operational constraints; and 3) a *daily energy disaggregation test* step for appliance recognition: the algorithm with the designed and implemented penalty function integrated in fitness evaluation is utilized to recognize the electrical appliances of concern. The energy disaggregation methodology presented in this paper is an event-less energy disaggregation approach.

The basic (event-less) daily energy disaggregation problem can be formulated as Eq. (1). In this equation, the summation of the superimposed absorptions can be treated as a combinatorial optimization process. The base load-related information required for *power consumption thresholding* to determine label data in the data preprocessing step can be derived from

$$P(t)=\left[\sum_{i=1}^{N}x_i(t)P_i(t)\right]+P_{base}(t),\ t=1,2,3,\ldots,T. \tag{1}$$

In Eq. (1), $P(t)$ stands for total/aggregated real power consumption measured at time t, $P_i(t)$ accounts for real power consumption absorbed by concerned electrical appliance i, $P_{base}(t)$ represents the base load at time t in a load monitoring field, the summation term $\sum_i x_i(t)P_i(t)$ is the superimposed absorptions made and deduced for the energy disaggregation purpose, N is the total number of concerned electrical appliances to be monitored nonintrusively, and $x_i(t)$ is a value of 0 or 1 representing the ON/OFF operational status of appliance i at time t. Energy disaggregation as *virtual sensing* is capable of recognizing the optimal (possible) operational status of each of the concerned electrical appliances $x_i(t) \mid i = 1, 2, ..., N$ at time t when the measured $P(t)$ is given: $[x_1(t), x_2(t), ..., x_i(t), ..., x_N(t)] = F^{-1}(P(t))$, where F^{-1} is an AI model that returns the best N estimates of $x_i(t)$ at time t.

For the daily energy disaggregation test step, we develop and utilize a GA, as the AI model for F^{-1} above, with a penalty function to metaheuristically search for the optimal feasible solution $x_i^*(t)$ of N electrical appliances of concern efficiently [in Eq. (1), load profiling to obtain $P_i(t)$ and $P_{base}(t)$ is performed *a priori*]. The chromosomal representation for encoding $x_i(t)$ in Eq. (1) for the evolutionary process in the GA used to achieve the daily energy disaggregation purpose ($t = 1, 2, 3, \ldots, T, \forall i$) is illustrated in Fig. 2. Here, energy disaggregation is declared as a combinatorial optimization problem, which is formulated as the objective function in Eq. (2) and resolved by the algorithm, considering a penalty function to find $\hat{X}$ [i.e., $\hat{x}_i(t)$], in accordance with the chromosomal design. In the daily energy disaggregation test step, a load noise

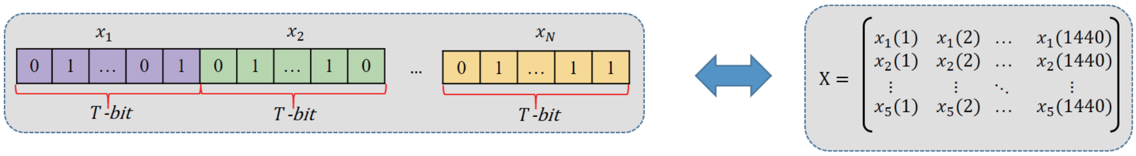


Fig. 2. (Color online) Chromosomal representation encoding $x_i(t)$ for GA in daily energy disaggregation in Eq. (1). Suppose that there are 1440 (= T) time slots in one day and 5 (= N) appliances in a load monitoring field on that day.

elimination principle based on β, which is computed in accordance with Eq. (3), for improved energy disaggregation is considered. GAs, an effective meta-heuristic search technique mimicking biological evolution to conduct a global probabilistic search based on Darwin's natural selection process,[1,36] are stochastic, population-based metaheuristic optimization algorithms. They can metaheuristically search for a global optimal solution to a constrained or unconstrained, discrete or continuous engineering optimization problem. In a GA, the key operations involve *selection* operations, which mimic Darwin's natural selection (Darwinism) and select current chromosomes for further gene recombination, and *genetic operations* comprising 1) *crossover* operations, which combine genetic information from selected parent chromosomes inherited by new offspring to be generated, and 2) *mutation* operations, which provide genetic diversity among population members. The evolutionary process of a GA is based on the principle of biological evolution; the selection operations are the driving force of evolution in the algorithm. In a GA, a population of chromosomes as candidate solutions in a search space is evolved, from generation to generation, through selection and genetic operations such that the solutions can be converged towards a global optimal feasible solution. As exhibited in Fig. 1, in the algorithm involved in the daily energy disaggregation test step, a proportion of an existing population (the initial population containing several hundreds or thousands of chromosomes is generated at random) in its current generation can be reproduced by selection operations and recombined via crossover and mutation operations to breed a new population for the next generation. Here, the selection operations can select chromosomes on the basis of a fitness-based selection scheme; a *fitness function* of Eq. (4), from Eq. (2), can evaluate the chromosomes as the candidate solutions. In the selection operations, the chromosomes with relatively high fitness values are typically more likely to be selected. To improve the *search efficiency*, the algorithm considers a *penalty function* to be designed for the energy disaggregation purpose. The penalty function is expressed as Eq. (5). The design of the penalty function in the penalty function design step will be described later. The scaled penalty function to Eq. (5) is expressed by Eq. (6). Overall, the fitness function developed in conjunction with the penalty function, i.e., Eq. (4) + Eq. (6), in this study is shown in Eq. (7). As depicted in Fig. 1, in the algorithm involved in the daily energy disaggregation test step, the crossover operations enable the exchange of subparts of two chromosomes as the biological recombination between two haploid organisms. Moreover, the mutation operations can randomly alter genes in some chromosomes; arbitrary bits of chromosomes can be changed from their original state to their new state. Lastly, the evolutionary process of the algorithm is repeated from generation to generation until a termination condition is met (for instance, the predetermined maximum number of generations has been reached).

Below, the design of the penalty function, Eq. (5), incorporated, in a weighted-sum manner, with the objective function, Eq. (2), in the algorithm to improve its search efficiency for the achievement (searching for an optimal feasible appliance combination solution) of training-less daily energy disaggregation is described. In this paper, on the basis of the *usage rate* (UR) computation of Eq. (8),[37] the algorithm can quantify time-series predictable load behaviors of relevant monitored electrical appliances that are representative of their operational routines on weekdays. An illustrative example exhibiting the quantified load behavioral routines of an electrical appliance is shown in Fig. 3. As shown in Fig. 3, the electrical appliance can be

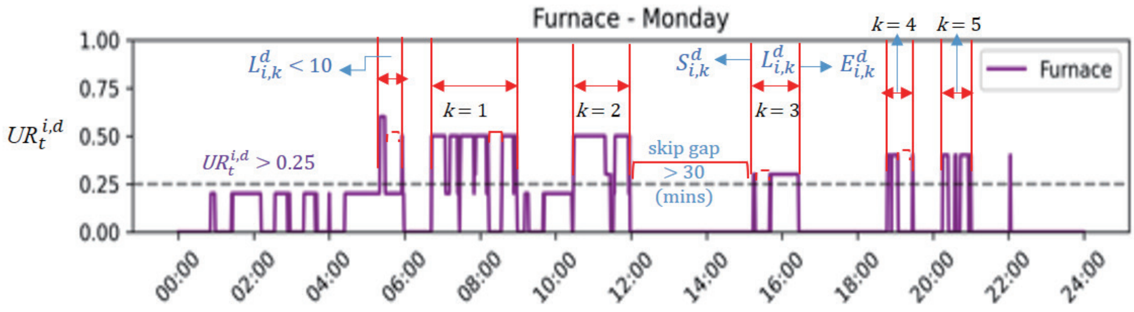


Fig. 3. (Color online) Illustrative example of quantified load behavioral routines of an electrical appliance. The *UR thresholding* is preset as, for example, 0.25. Moreover, the skip gap duration, in time point, among the load operational routine intervals is prespecified by, for instance, at least 30 mins. Both of them can be parameterized for the determination of ($S_{i,k}^d$, $L_{i,k}^d$, $E_{i,k}^d$).

partitioned by *K load operational routine intervals*; each of which can be parameterized by ($S_{i,k}^d$, $L_{i,k}^d$, $E_{i,k}^d$) and used during the evolutionary process as formulated in Eq. (5). ($S_{i,k}^d$, $L_{i,k}^d$, $E_{i,k}^d$) denotes the *start time* (in time point), *duration time*, and *end time* of the quantified operational routine interval k of the appliance (appliance i) on weekday d, respectively. In Eq. (5), $\hat{x}$ is the daily energy disaggregation result, which is estimated by the GA to solve/optimize Eq. (1).

$$Obj(X) = \min(err(X)) \tag{2}$$

In Eq. (2), $\varepsilon rr(X) = \left\| P(t) - P_{base_{avg}} \right| - \sum_{i=1}^{N} x_i(t) P_{\mu_i} \Big|$, where $t = 1,2,3,\ldots,T$. Also, $P_{base_{avg}}$ and P_{μ_i} (with P_{σ_i}) are statistically computed in advance.

$$\beta = \left\lceil \frac{\left(P_{\mu_i} - 2P_{\sigma_i}\right)_{min}}{100} \right\rceil \times 100 \tag{3}$$

In Eq. (3), β is computed in association with appliance specifications of P_{μ_i} and P_{σ_i} of the targeted electrical appliances.

$$f_X = \frac{Obj_{max} - Obj_{chr} + \gamma}{Obj_{max} - Obj_{min} + \gamma} \tag{4}$$

$$Pen(X) = \sum_{i=1}^{N} \sum_{k=1}^{K} \left| \frac{L_{i,k}^d - \sum_{idx=S_{i,k}^d}^{E_{i,k}^d} \hat{x}_{i,k,idx}^d}{L_{i,k}^d} \right| \tag{5}$$

In Eq. (4), k denotes the quantified operational routine interval k of appliance i on weekday d.

$$Pen'_{chr} = \frac{Pen_{max} - Pen_{chr} + \gamma}{Pen_{max} - Pen_{min} + \gamma} \tag{6}$$

$$F(X) = w_1 \cdot f_X + w_2 \cdot Pen'_{chr} \tag{7}$$

In Eq. (6), $w_1 + w_2 = 1$. If $w_1 = 1$ and $w_2 = 0$, the penalty function is not considered during the evolutionary process.

$$UR_t^{i,d} = \frac{\sum_{w \in W} \tau_w \cdot x_{t,w}^{i,d}}{W}, \forall t \tag{8}$$

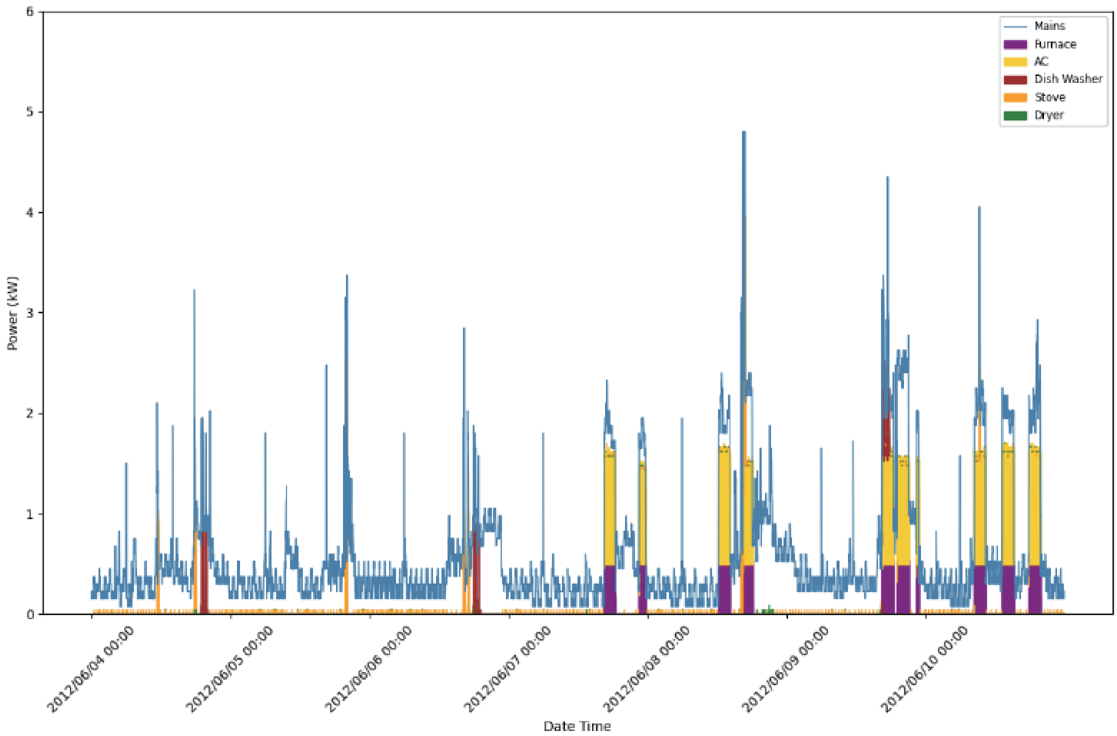
In Eq. (8), $x_{t,w}^{i,d}$ represents the historical ON/OFF operational status of appliance i at time t on weekday d of week w and takes a value of {0, 1}, where 0 indicates the OFF status and 1 indicates the ON status. In addition, the $x_{t,w}^{i,d}$ values are weighted chronologically by weights τ_w.

In this paper, the F_1-*score* described in detail below is used as the performance metric to show the feasibility and effectiveness of the presented training-less daily energy disaggregation methodology. Equation (9) shows the F_1-*score* used to evaluate the load classification performance of the presented methodology for the energy disaggregation purpose. In Eq. (9), being the harmonic mean of precision and recall, precision is the ratio of the total number of correctly classified positive data instances to the total number of classified positive data instances; recall, i.e., sensitivity or hit rate, is the ratio of the total number of correctly classified positive data instances to the total number of actual positive data instances. As shown by Eq. (9), a classifier that throws no false positive predictions has a precision of 1.0, and one throwing no false negative predictions has a recall of 1.0. F_1-*score* reaches the best value at 1.0 (perfect precision and recall).

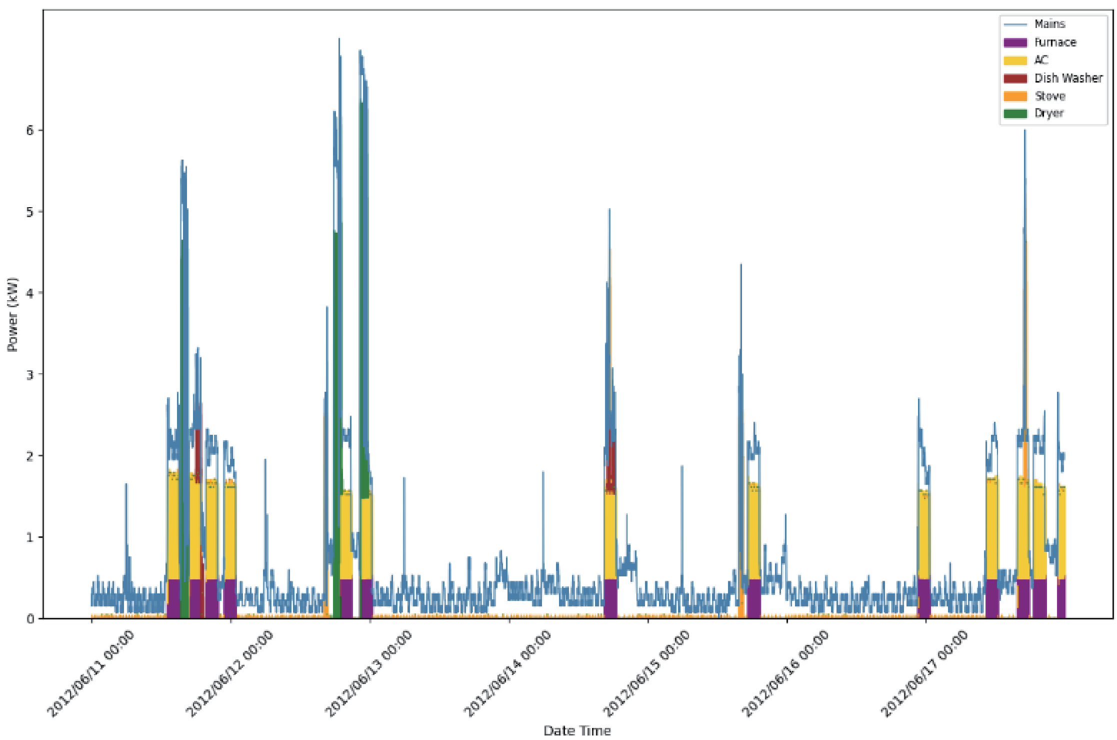
$$F_1\text{-}score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{9}$$

3. Practical Evaluation Results

Now, practical evaluations are carried out to validate the validity of the presented training-less daily energy disaggregation methodology applied to the publicly available EEUD dataset.(35) Figure 4 shows the considered historical 5-week power consumption data in House 14 from the dataset, which is considered, preprocessed, and used to experimentally validate the load classification performance of the presented methodology [data in the first four weeks (from 2012/06/04 00:00 to 2012/07/01 23:59) are used to construct the penalty function of Eq. (5) using the computed URs of Eq. (8); data in the last 5th week (from 2012/07/02 00:00 to 2012/07/08 23:59) are used to validate the training-less daily energy disaggregation performance]. In the

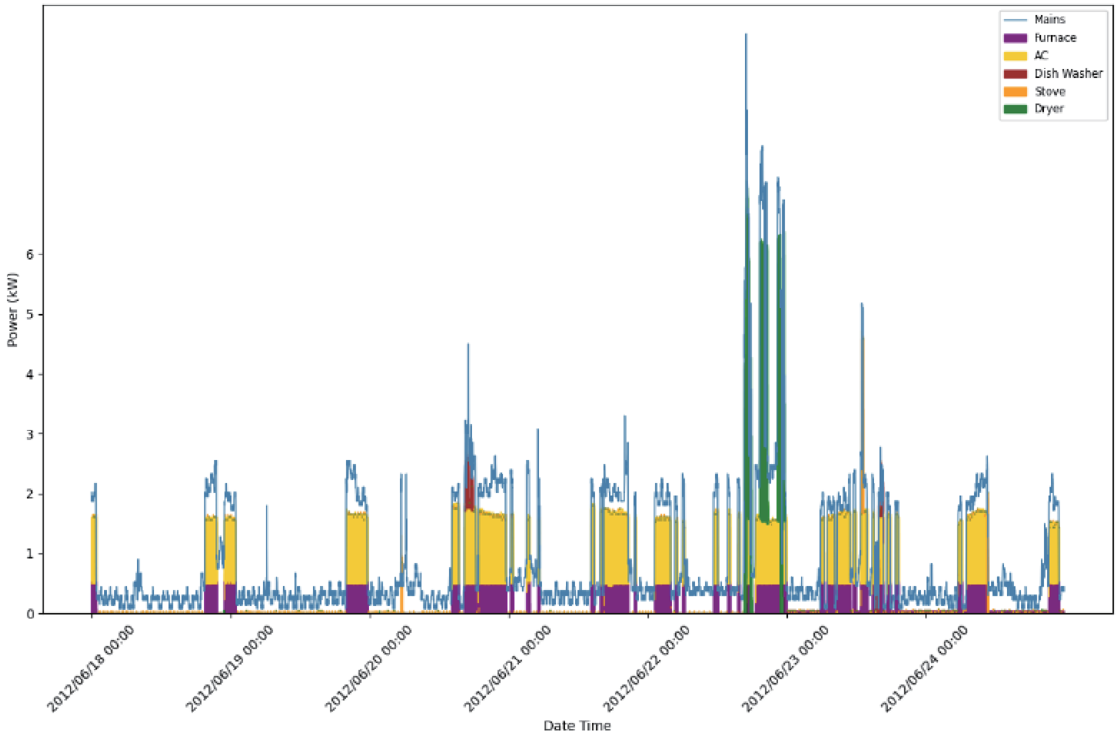


(a)

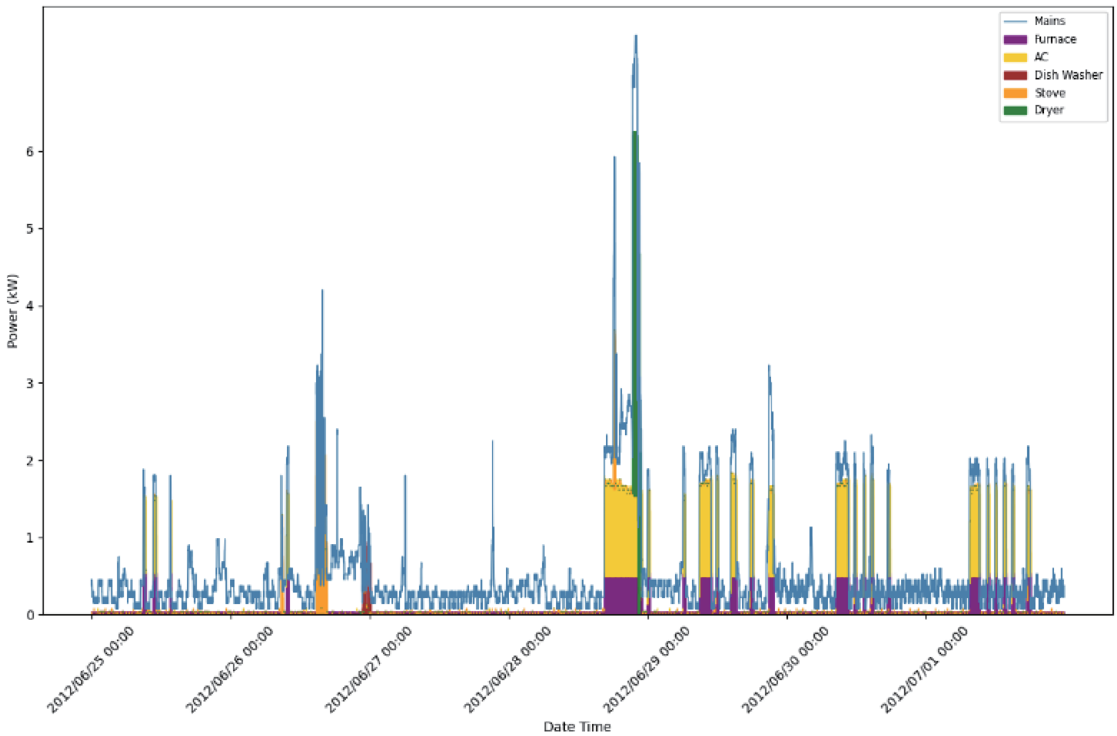


(b)

Fig. 4. (Color online) Considered historical 5-week power consumption data in House 14 from EEUD: (a) 1st week, (b) 2nd week, (c) 3rd week, (d) 4th week, and (e) 5th week of [circuit-level (i.e., building-level) vs appliance-level] power consumption profiles. The data rate (Δt) is 1 min.

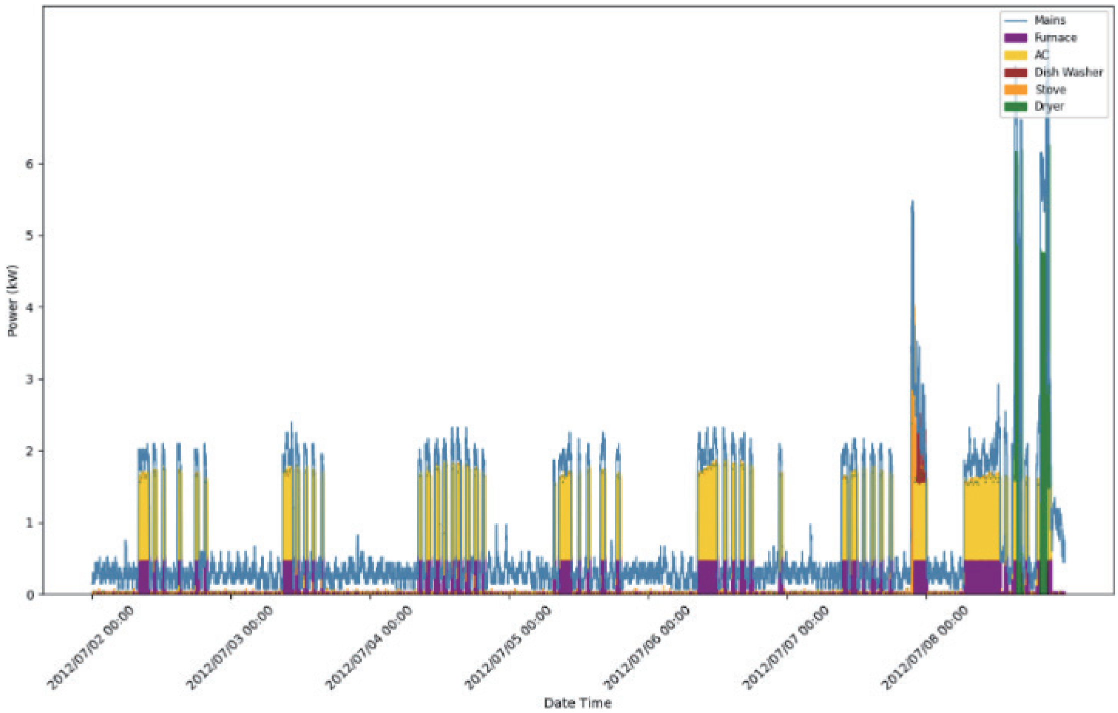


(c)



(d)

Fig. 4. (Color online) (Continued) Considered historical 5-week power consumption data in House 14 from EEUD: (a) 1st week, (b) 2nd week, (c) 3rd week, (d) 4th week, and (e) 5th week of [circuit-level (i.e., building-level) vs appliance-level] power consumption profiles. The data rate (Δt) is 1 min.



(e)

Fig. 4. (Color online) (Continued) Considered historical 5-week power consumption data in House 14 from EEUD: (a) 1st week, (b) 2nd week, (c) 3rd week, (d) 4th week, and (e) 5th week of [circuit-level (i.e., building-level) vs appliance-level] power consumption profiles. The data rate (Δt) is 1 min.

house environment, the relevant major electrical appliances to be monitored nonintrusively from the mains include a furnace, an air conditioner (AC), a dishwasher, a stove, and a dryer.

Before performing training-less daily energy disaggregation to the mains data in the last 5th week, the GA in Fig. 1 quantifies the load operational behavioral routines, i.e., URs, of the monitored appliances from their past trends, in accordance with Eq. (8). Figure 5 shows the quantified load operational behavioral routines of each monitored electrical appliance operated in the load monitoring field from Monday through Sunday, where, corresponding to Eq. (8), $\tau_1 = 0.1$, $\tau_2 = 0.2$, $\tau_3 = 0.3$, and $\tau_4 = 0.4$. Table 1 shows the parameterized results of the partitioned load operational routine intervals from the quantified behavioral routines (Sunday), which are used to improve the search efficiency of the algorithm that optimizes Eq. (7) for the training-less daily energy disaggregation purpose.

Subsequently, the algorithm performs training-less daily energy disaggregation to the considered data in the last week [referring to Fig. 4(e)]. Parameters are prespecified for the algorithm as follows. The population size is 500. The initial population is created randomly in bit strings as chromosomes whose total length is 7200 (the total number of appliance combinations is 2^{7200}). The roulette selection mechanism is employed to the fitness function of Eq. (7) to evaluate each of the chromosomes as candidate solutions during the evolutionary process. The multipoint (10-point) crossover operator is used; the crossover fraction of the population to be evolved is 0.8. The bit-wise multipoint (10-point) mutation operator is applied; the mutation rate

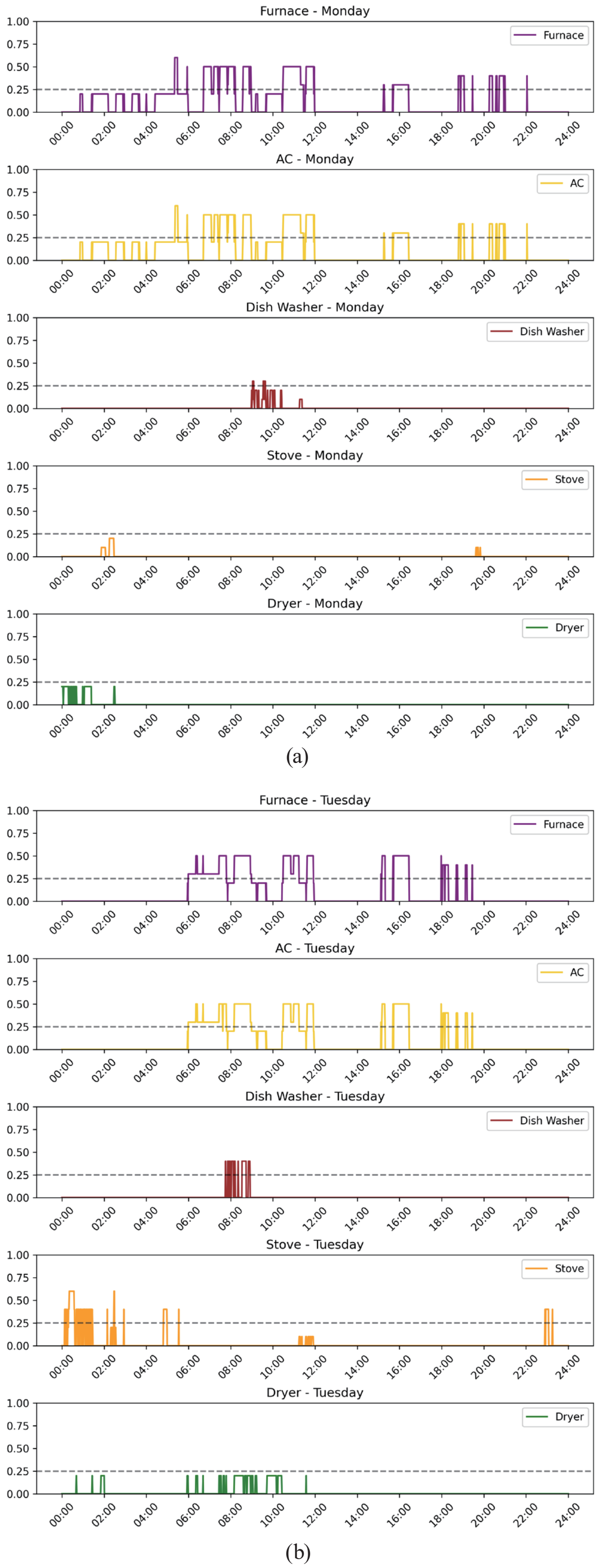
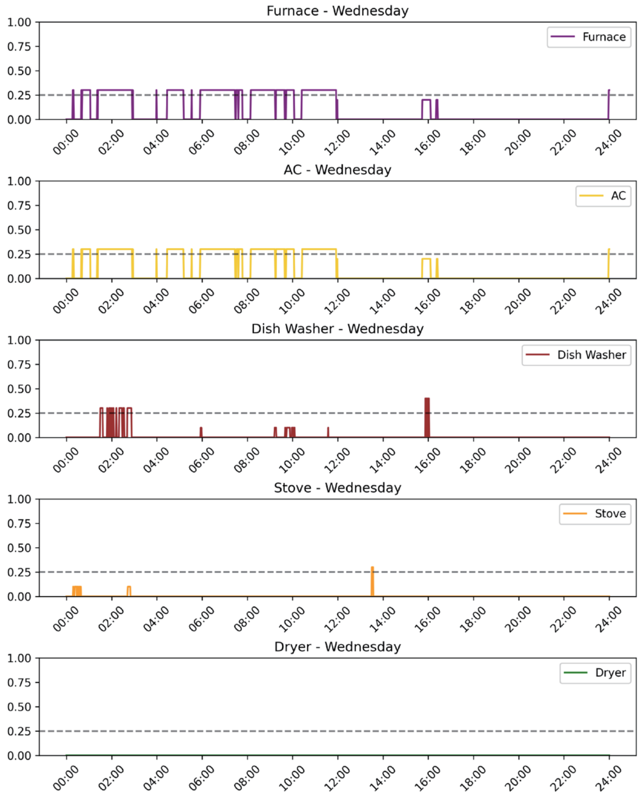
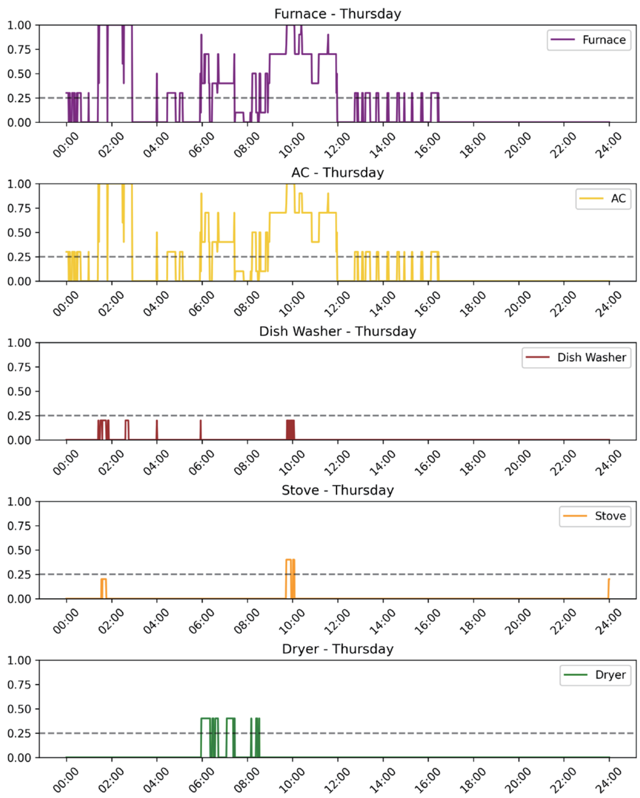


Fig. 5. (Color online) Quantified load operational behavioral routines of monitored electrical appliances operated on (a) Monday, (b) Tuesday, (c) Wednesday, (d) Thursday, (e) Friday, (f) Saturday, and (g) Sunday from past trends.

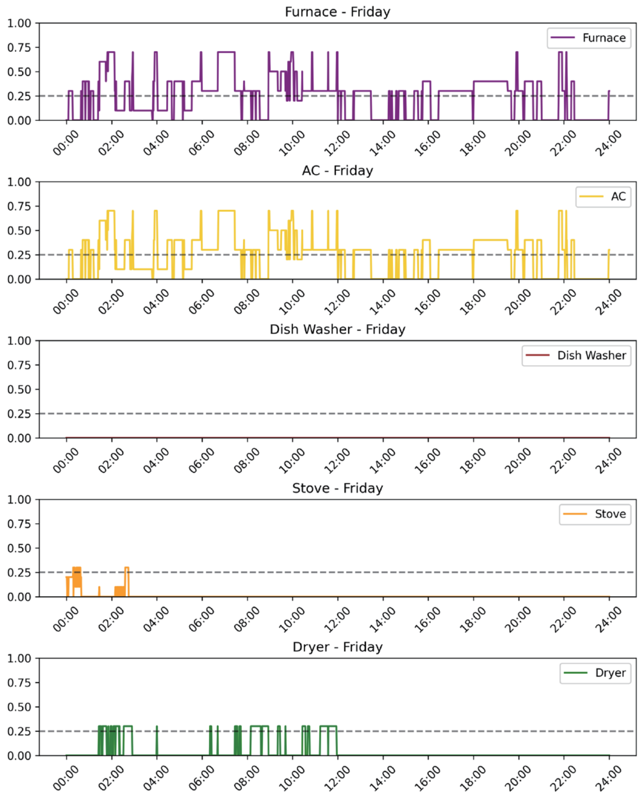


(c)

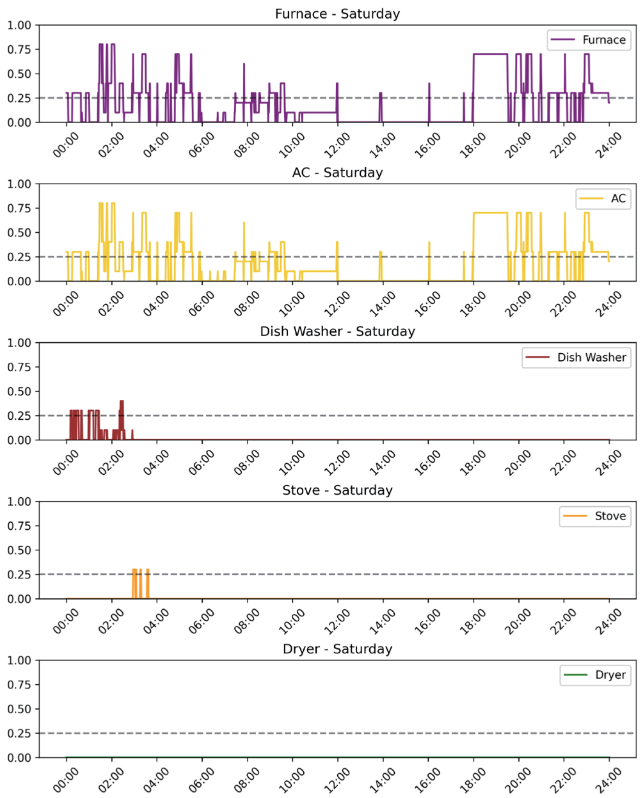


(d)

Fig. 5. (Color online) (Continued) Quantified load operational behavioral routines of monitored electrical appliances operated on (a) Monday, (b) Tuesday, (c) Wednesday, (d) Thursday, (e) Friday, (f) Saturday, and (g) Sunday from past trends.

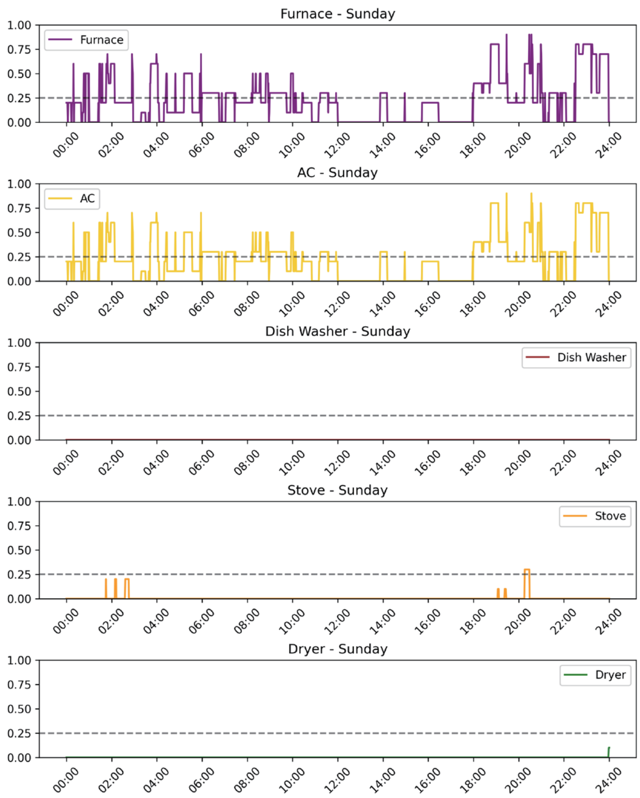


(e)



(f)

Fig. 5. (Color online) (Continued) Quantified load operational behavioral routines of monitored electrical appliances operated on (a) Monday, (b) Tuesday, (c) Wednesday, (d) Thursday, (e) Friday, (f) Saturday, and (g) Sunday from past trends.



(g)

Fig. 5. (Color online) (Continued) Quantified load operational behavioral routines of monitored electrical appliances operated on (a) Monday, (b) Tuesday, (c) Wednesday, (d) Thursday, (e) Friday, (f) Saturday, and (g) Sunday from past trends.

is 0.1. An elitist strategy that guarantees the survival of two top chromosomes from the current population to the next population is also used. Finally, the maximum number of generations is 5000.

Figure 6 shows the obtained evolutionary trajectory of the GA (Sunday) with ($w_1 = w_2 = 0.5$) or without ($w_1 = 1$ and $w_2 = 0$) the penalty function. Figure 7 reveals the global optimal objective value of 455.198 W obtained by the GA with the penalty function producing the final penalty score of 0.096. This reveals that the algorithm improves its efficiency in searching for the global optimal feasible solution to the addressed training-less daily energy disaggregation problem (i.e., in disaggregating the mains data while considering the appliance operational constraints) (Sunday). Figure 8 shows the *operational routineness* (Sunday) indicated in the shaded areas for each of the relevant monitored appliances to be optimized to Eq. (1); the effectiveness of the algorithm that considers the penalty function to improve the search efficiency is also revealed. The appliance classification results obtained by the algorithm with or without the penalty function (Sunday) are reported in Table 2. As reported in Table 2, the GA with the penalty function outperforms the GA without the penalty function in appliance classification.

Table 3 reveals the complete evaluation results (from Monday to Sunday) obtained by the algorithm, with and without the penalty function, performing the energy disaggregation task. As revealed in Table 3, the presented training-less daily (7-day) energy disaggregation

Table 1
Parameterized results of partitioned load operational routine intervals from quantified behavioral routines to relevant monitored electrical appliances (Sunday).

<table>
<tr><th></th><th></th><th colspan="6">K load operational routine intervals (Sunday)</th></tr>
<tr><th></th><th></th><th>interval 1 ($k = 1$)</th><th>interval 2 ($k = 2$)</th><th>interval 3 ($k = 3$)</th><th>interval 4 ($k = 4$)</th><th>interval 5 ($k = 5$)</th><th>interval 6 ($k = 6$)</th></tr>
<tr><td rowspan="3">Furnace ($i = 1$)</td><td>operation time</td><td>00:45–02:07</td><td>03:42–10:28</td><td>11:14–11:58</td><td>13:52–14:10</td><td>17:35–19:30</td><td>20:13–23:57</td></tr>
<tr><td>$S_{i,k}^d - E_{i,k}^d$ (in time points)</td><td>45–127</td><td>222–628</td><td>674–718</td><td>832–850</td><td>1055–1170</td><td>1213–1437</td></tr>
<tr><td>available duration time points $L_{i,k}^d$</td><td>41</td><td>209</td><td>24</td><td>19</td><td>93</td><td>165</td></tr>
<tr><td rowspan="3">AC ($i = 2$)</td><td>operation time</td><td>00:46–02:07</td><td>03:42–10:28</td><td>11:14–11:58</td><td>13:52–14:10</td><td>17:35–19:30</td><td>20:13–23:57</td></tr>
<tr><td>$S_{i,k}^d - E_{i,k}^d$</td><td>46–127</td><td>222–628</td><td>674–718</td><td>832–850</td><td>1055–1170</td><td>1213–1437</td></tr>
<tr><td>available duration time points $L_{i,k}^d$</td><td>40</td><td>206</td><td>24</td><td>19</td><td>93</td><td>164</td></tr>
<tr><td rowspan="3">Dish-washer ($i = 3$)</td><td>operation time</td><td colspan="6" rowspan="3">—</td></tr>
<tr><td>$S_{i,k}^d - E_{i,k}^d$</td></tr>
<tr><td>available duration time points $L_{i,k}^d$</td></tr>
<tr><td rowspan="3">Stove ($i = 4$)</td><td>operation time</td><td>20:16–20:34</td><td colspan="5" rowspan="3">—</td></tr>
<tr><td>$S_{i,k}^d - E_{i,k}^d$</td><td>1216–1234</td></tr>
<tr><td>available duration time points $L_{i,k}^d$</td><td>13</td></tr>
<tr><td rowspan="3">Dryer ($i = 5$)</td><td>operation time</td><td colspan="6" rowspan="3">—</td></tr>
<tr><td>$S_{i,k}^d - E_{i,k}^d$</td></tr>
<tr><td>available duration time points $L_{i,k}^d$</td></tr>
</table>

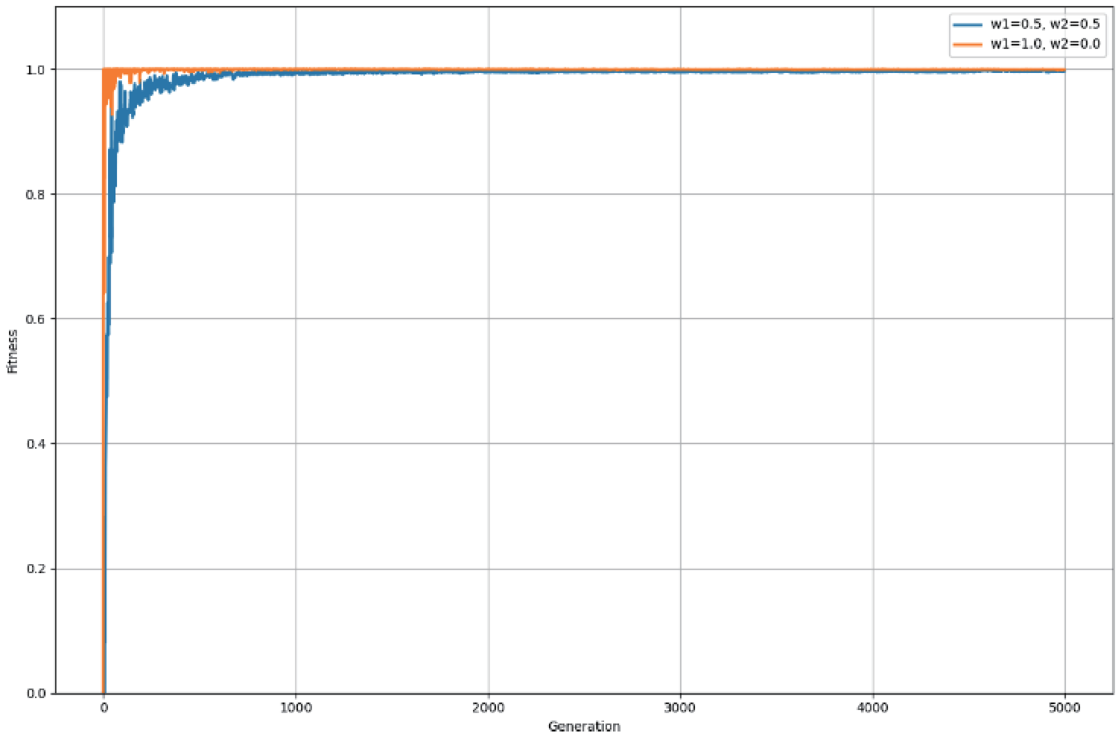
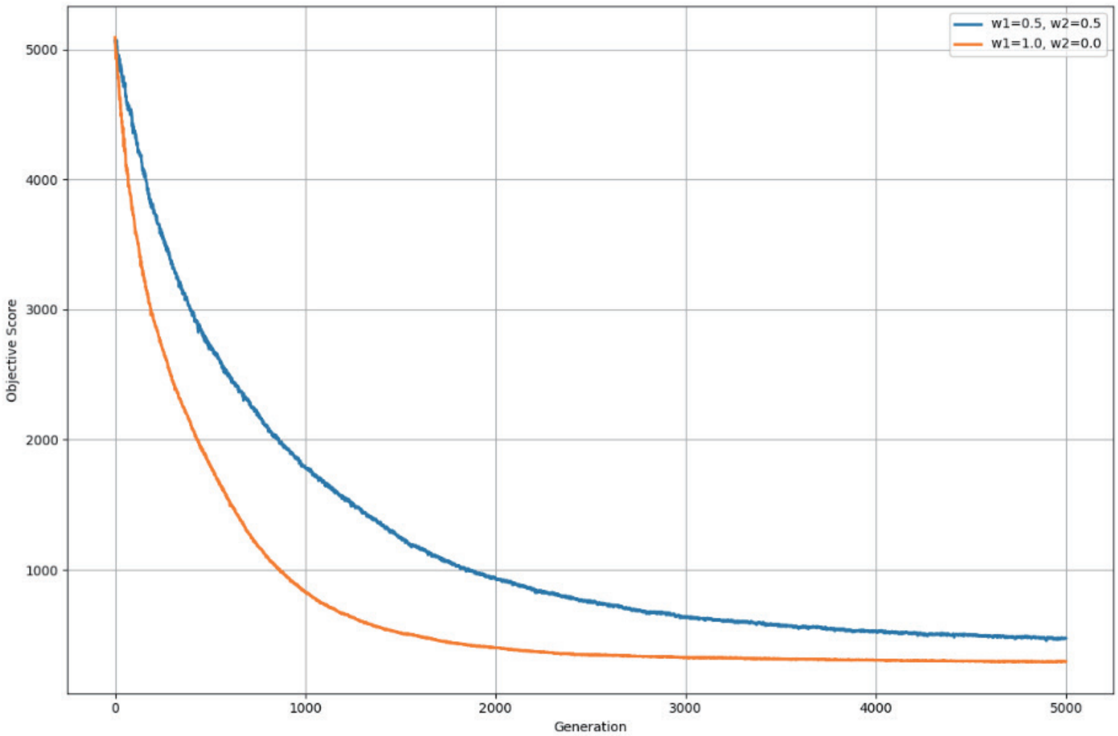
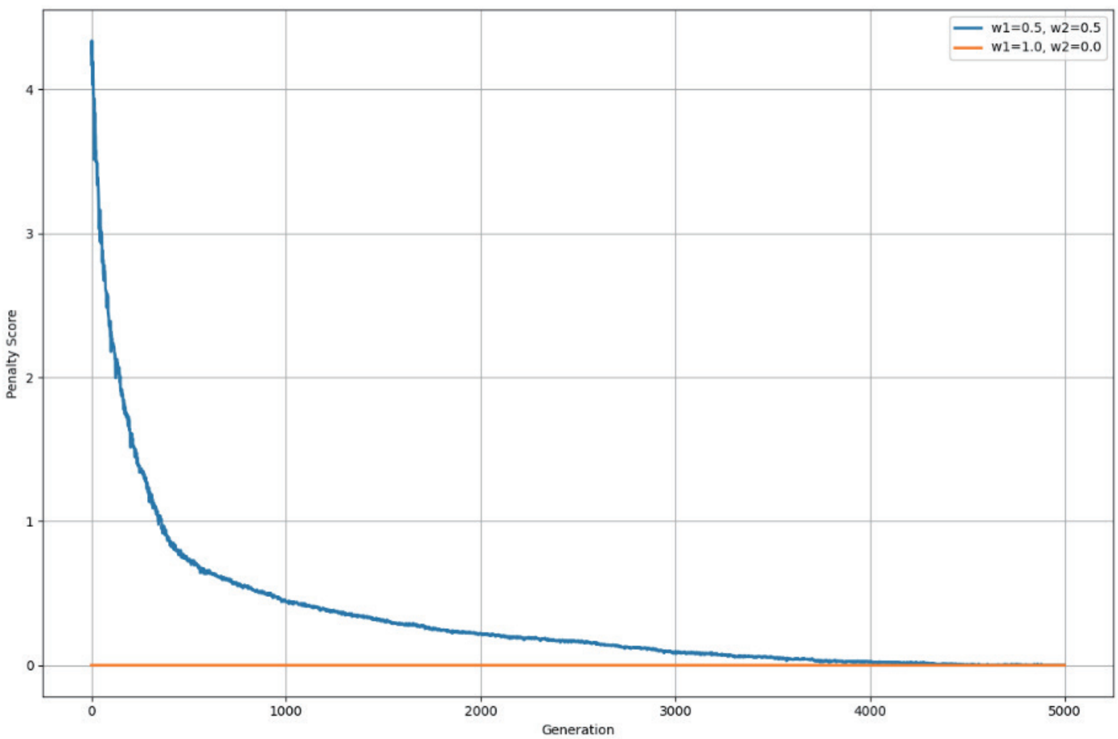


Fig. 6. (Color online) Obtained evolutionary trajectory (Sunday).



(a)



(b)

Fig. 7. (Color online) Obtained (raw) objective value of (a) 324.442 W versus 455.198 W, where (b) a final penalty score of 0.096 was obtained (Sunday).

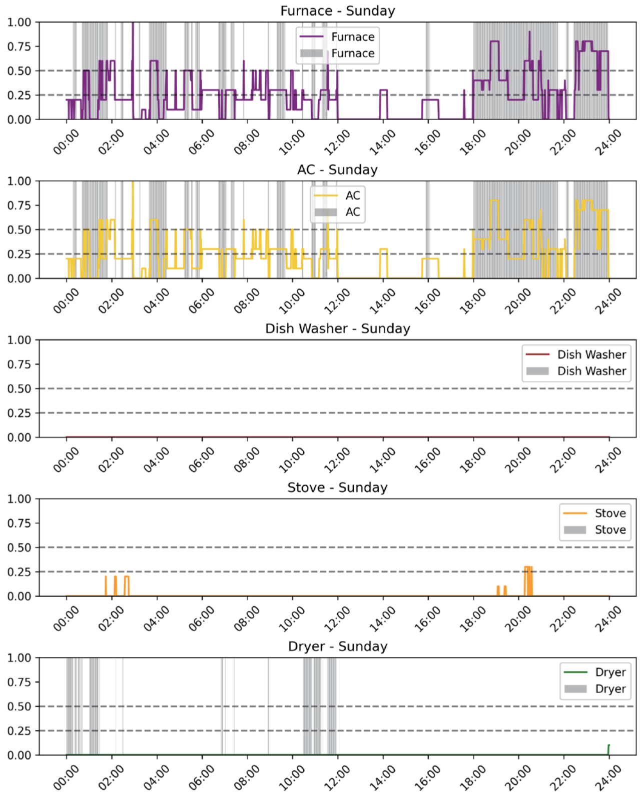


Fig. 8. (Color online) Revealed operational routineness (shadowed areas) of relevant monitored electrical appliances to be optimized to Eq. (1) considering their operational constraints during evolutionary computing (Sunday).

Table 2
Appliance classification results obtained by GA with and without penalizing appliance operational constraint violations (Sunday).

Load		GA with penalty function					GA without penalty function				
		Accuracy	Precision	Recall	F_1-*score*	Support	Accuracy	Precision	Recall	F_1-*score*	Support
Furnace	Off	0.77	0.91	0.70	0.79	894	0.70	0.73	0.82	0.77	894
	On		0.65	0.88	0.75	546		0.63	0.50	0.56	546
	weighted avg.	—	0.81	0.77	0.78	1440	—	0.69	0.70	0.69	1440
AC	Off	0.88	0.93	0.88	0.90	898	0.80	0.78	0.94	0.86	898
	On		0.82	0.89	0.85	542		0.86	0.57	0.69	542
	weighted avg.	—	0.89	0.88	0.88	1440	—	0.81	0.80	0.79	1440
Dish-washer	Off	0.81	1.00	0.81	0.90	1440	0.80	1.00	0.80	0.89	1440
	On		—	—	—	—		—	—	—	—
	weighted avg.	—	1.00	0.78	0.88	1440	—	1.00	0.80	0.89	1440
Stove	Off	0.96	1.00	0.95	0.97	1440	0.87	1.00	0.88	0.93	1440
	On		—	—	—	—		—	—	—	—
	weighted avg.	—	1.00	0.95	0.97	1440	—	1.00	0.88	0.93	1440
Dryer	Off	0.96	0.97	1.00	0.98	1308	0.96	0.97	1.0	0.98	1308
	On		0.93	0.64	0.76	132		0.96	0.66	0.78	132
	weighted avg.	—	0.96	0.96	0.96	1440	—	0.97	0.97	0.96	1440

Table 3
Complete evaluation results obtained by GA with or without penalizing appliance operational constraint violations (from Monday to Sunday).

Load		Monday					Tuesday				
		Accuracy	Weighted avg				Accuracy	Weighted avg			
			Precision	Recall	F_1-score	Support		Precision	Recall	F_1-score	Support
Furnace	GA with penalty function	0.70	0.82	0.71	0.74	1440	0.73	0.88	0.73	0.77	1440
	GA without penalty function	0.89	0.88	0.89	0.88	1440	0.86	0.86	0.86	0.86	1440
AC	GA with penalty function	0.80	0.85	0.81	0.80	1440	0.89	0.91	0.89	0.90	1440
	GA without penalty function	0.91	0.92	0.91	0.90	1440	0.93	0.93	0.93	0.92	1440
Dish-washer	GA with penalty function	0.88	1.00	0.88	0.94	1440	0.82	1.00	0.82	0.90	1440
	GA without penalty function	0.92	1.00	0.92	0.96	1440	0.92	1.00	0.92	0.96	1440
Stove	GA with penalty function	0.98	1.00	0.98	0.99	1440	0.98	1.00	0.97	0.99	1440
	GA without penalty function	0.95	1.00	0.95	0.98	1440	0.96	1.00	0.97	0.98	1440
Dryer	GA with penalty function	1.00	1.00	1.00	1.00	1440	0.99	1.00	0.99	1.00	1440
	GA without penalty function	1.00	1.00	1.00	1.00	1440	0.99	1.00	1.00	1.00	1440

Load		Wednesday					Thursday				
		Accuracy	Weighted avg				Accuracy	Weighted avg			
			Precision	Recall	F_1-score	Support		Precision	Recall	F_1-score	Support
Furnace	GA with penalty function	0.75	0.77	0.75	0.76	1440	0.75	0.81	0.75	0.77	1440
	GA without penalty function	0.84	0.83	0.84	0.83	1440	0.88	0.87	0.88	0.88	1440
AC	GA with penalty function	0.85	0.84	0.85	0.84	1440	0.87	0.88	0.87	0.87	1440
	GA without penalty function	0.87	0.89	0.88	0.86	1440	0.91	0.91	0.91	0.90	1440
Dish-washer	GA with penalty function	0.83	1.00	0.82	0.9	1440	0.87	1.00	0.87	0.93	1440
	GA without penalty function	0.89	1.00	0.89	0.94	1440	0.92	1.00	0.92	0.96	1440
Stove	GA with penalty function	0.95	1.00	0.95	0.97	1440	0.96	1.00	0.96	0.98	1440
	GA without penalty function	0.94	1.00	0.94	0.97	1440	0.95	1.00	0.95	0.98	1440
Dryer	GA with penalty function	0.99	1.00	0.99	1.00	1440	0.99	1.00	0.99	0.99	1440
	GA without penalty function	1.00	1.00	1.00	1.00	1440	1.00	1.00	1.00	1.00	1440

Table 3
(Continued) Complete evaluation results by GA with or without penalizing appliance operational constraint violations (from Monday to Sunday).

Load		Friday					Saturday				
		Accuracy	Weighted avg				Accuracy	Weighted avg			
			Precision	Recall	F_1-*score*	Support		Precision	Recall	F_1-*score*	Support
Furnace	GA with penalty function	0.75	0.79	0.75	0.76	1440	0.74	0.76	0.74	0.74	1440
	GA without penalty function	0.82	0.82	0.82	0.81	1440	0.85	0.85	0.85	0.84	1440
AC	GA with penalty function	0.87	0.87	0.87	0.87	1440	0.84	0.84	0.84	0.84	1440
	GA without penalty function	0.88	0.90	0.88	0.87	1440	0.86	0.88	0.86	0.85	1440
Dish-washer	GA with penalty function	0.85	1.00	0.85	0.92	1440	0.84	0.95	0.84	0.88	1440
	GA without penalty function	0.88	1.00	0.88	0.94	1440	0.88	0.95	0.88	0.91	1440
Stove	GA with penalty function	0.95	1.00	0.95	0.98	1440	0.93	0.98	0.93	0.95	1440
	GA without penalty function	0.94	1.00	0.94	0.97	1440	0.92	0.97	0.92	0.94	1440
Dryer	GA with penalty function	0.97	1.00	0.97	0.99	1440	0.99	1.00	0.98	0.99	1440
	GA without penalty function	1.00	1.00	1.00	1.00	1440	0.98	1.00	0.98	0.99	1440

Load		Sunday				
		Accuracy	Weighted avg			
			Precision	Recall	F_1-*score*	Support
Furnace	GA with penalty function	0.77	0.81	0.77	0.78	1440
	GA without penalty function	0.70	0.69	0.70	0.69	1440
AC	GA with penalty function	0.88	0.89	0.88	0.88	1440
	GA without penalty function	0.80	0.81	0.80	0.79	1440
Dish-washer	GA with penalty function	0.81	1.00	0.78	0.88	1440
	GA without penalty function	0.80	1.00	0.80	0.89	1440
Stove	GA with penalty function	0.96	1.00	0.95	0.97	1440
	GA without penalty function	0.87	1.00	0.88	0.93	1440
Dryer	GA with penalty function	0.96	0.96	0.96	0.96	1440
	GA without penalty function	0.96	0.97	0.97	0.96	1440

methodology (GA with/without the penalty function) is capable of identifying the appliances nonintrusively with a satisfactory level of classification performance. The daily mean absolute percentage error (MAPE; %)[8] results obtained through the presented training-less daily (7-day) energy disaggregation methodology are summarized in Table 4. As seen in Table 4, the average daily MAPE obtained is improved by 9%, from 23% (GA without the penalty function) to 14% (GA with the penalty function). In the literature, Machlev *et al.* developed a multi-objective evolutionary algorithm, MO-NILM,[33] for energy disaggregation. In MO-NILM method 1, only P is considered as the feature used for the energy disaggregation purpose. In MO-NILM method 2, P and Q are considered as the features used as the two objectives for the energy disaggregation purpose. In their study,[33] data from the Reference Energy Disaggregation Dataset (REDD) house 1 and Almanac of Minutely Power dataset (AMPds) were used for the classification performance evaluation of the algorithm including MO-NILM methods 1 and 2, where AMPds was collected from a house in Canada over a period of one year. Table 5 shows the settings for the four considered scenarios in that study. Garcia-Marrero *et al.*[38] presented an on-line, real-time robust NILM approach based on a finite-state machine (FSM) model, which only requires aggregated P and uses the appliance's state probabilities to estimate the power consumption of each monitored appliance. Similarly, in the article, the authors chose REDD house 1 to evaluate the classification performance of their NILM approach; the considered data length for five appliances to be monitored was 96 h. Table 6 shows the resulting performance evaluation results (F_1-*score*) in the literature used as the

Table 4
Obtained daily MAPE results (from Monday to Sunday).

MAPE		Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	MAPE
Furnace	GA with penalty function	91%	138%	18%	59%	33%	15%	31%	47%
	GA without penalty function	31%	11%	34%	31%	35%	38%	24%	52%
AC	GA with penalty function	51%	31%	16%	26%	9%	2%	13%	10%
	GA without penalty function	47%	44%	52%	43%	47%	51%	35%	49%
Dish-washer	GA with penalty function	—	—	—	—	—	342%	—	342%
	GA without penalty function	—	—	—	—	—	189%	—	189%
Stove	GA with penalty function	—	—	—	—	—	241%	—	241%
	GA without penalty function	—	—	—	—	—	254%	—	254%
Dryer	GA with penalty function	—	—	—	—	—	—	35%	35%
	GA without penalty function	—	—	—	—	—	—	36%	36%
daily MAPE	GA with penalty function	27%	39%	8%	25%	20%	10%	1%	—
	GA without penalty function	33%	34%	28%	33%	26%	21%	9%	—

Note that for MAPE, less than 10% means that data are highly accurately estimated; 10–20% indicates that data are well estimated; 20–50% shows that data are reasonably estimated; greater than 50% implies that data are inaccurately estimated.

Table 5
Summary of considered evaluation scenarios in the study.[33]

Scenario	Dataset	Number of appliances	Length (h)
1	REDD House 1	6	6 (from 2011/4/18 22:33:53)
2	REDD House 1	9	48 (from 2011/5/14 21:18:53)
3	AMPds	7	600 (25 days) (from 2012/4/24 12:18:00)
4	AMPds	6	600

Note that, besides Machlev *et al*., Garcia-Marrero *et al*.[38] chose data from REDD House 1 to validate their NILM approach, where the number of appliances to be monitored was five and the data length was 96 h. Also, note that the methodology presented in this paper was applied and evaluated on REDD House 1 (96 h). Moreover, it was applied and evaluated on EEUD House 14; the house contained the five appliances to be monitored nonintrusively for 168 h (7 days) (totally, 5-week data from 2012/06/04 00:00 to 2012/07/08 23:59 were considered). Finally, note that, besides Machlev *et al*.,[33] Park *et al*.[32] proposed a constrained multi-objective energy disaggregation method utilizing an evolutionary algorithm; however, the method was evaluated using simulation data.

Table 6
Performance evaluation results (F_1-*score*) from the literature.

Scenario 1		Scenario 2		Scenario 2′[31]		Scenario 2″ (this study)	
Load	MO-NILM 1	Load	MO-NILM 1	Load	FSM-NILM	Load	Present work
Oven	0.892	Oven	0.5714	Oven	~0.82	Oven	0.95
Refrigerator	0.7876	Refrigerator	0.6585	Refrigerator	~0.78	Refrigerator	0.61
Dishwasher	0.894	Dishwasher	0.4906	Dishwasher	~0.40	Dishwasher	0.86
Microwave	0.7421	Microwave	0.533	Microwave	~0.70	Microwave	0.95
Kitchen outlet	0.253	Bathroom gfi	0.1886	Bathroom gfi	—	Bathroom gfi	—
Washing dryer2	—	Kitchen outlet	0.1	Kitchen outlet	—	Kitchen outlet	—
—		Washing dryer2	0.6648	Washing dryer2	~0.90	Washing dryer2	0.99
		Lighting1	0.743	—		—	
		Lighting2	0.503				
Avg.	0.824	Avg.	0.6287	Avg.	~0.72	Avg.	0.87

Scenario 3			Scenario 4	
Load	MO-NILM 1	MO-NILM 2	Load	MO-NILM 2
Basement	0.826	0.913	Dishwasher	0.452
Dishwasher	0.617	0.840	Dryer	0.621
Dryer	0.230	0.969	Heat pump	0.881
Fan thermostat	0.888	0.929	Kitchen fridge	0.876
Heat pump	0.937	0.993	Oven	0.147
Kitchen fridge	0.829	0.958	Washing machine	0.271
Oven	0.438	0.662	—	
Avg.	0.844	0.938	Avg.	0.768

Note that the FSM-model-based NILM approach[38] presented by Garcia-Marrero *et al.* is weak for appliances with similar/identical/equivalent P values. Also, note that the metric in this paper is based on the weighted average F_1-*score*. A weighted average F_1-*score* is used to compute the mean of per-class $F1$-*score*s, where the score of each class is weighted by its support. In addition, the penalty function can be designed in accordance with the appliance characteristics (α_a, l_a, β_a) with a slack parameter δ_a[8] to appliance a and used to improve the appliance classification performance.

benchmark in our study. As seen from the benchmark values in Table 6 and our results in Table 3, the feasibility and effectiveness of the presented energy disaggregation methodology compared to the existing similar work—the MO-NILM algorithm in the study[(33)] and the FSM model-based NILM approach in the article[(38)], the possibility of addressing similar NILM datasets has been proven.

4. Conclusions

A smart grid in which DSM is achieved via DR schemes is a promising use-case of AIoT based on information and communications technology. Energy disaggregation is a cost-effective load monitoring approach, which serves as a virtual sensor technology for load monitoring. It is capable of disaggregating acquired circuit-level/building-level power consumption into appliance-level power consumption for DSM such as residential DSM. In this paper, we have presented a training-less metaheuristic-based daily energy disaggregation methodology that was experimentally validated on the publicly available EEUD. It is necessary to improve the search efficiency of the metaheuristic algorithm (GA here) in appliance classifications for the energy disaggregation purpose. As a result, we have designed a penalty function. The penalty function considers the appliance operational routineness and is incorporated with the objective function during the evolutionary computing/combinatorial optimization process. To conclude, the presented methodology, whose resulting appliance classification performance and MAPE results were improved as reported in this paper, is able to classify relevant electrical appliances of concern in a nonintrusive and training-less manner. Energy disaggregation that recovers the energy consumption of individual appliances from aggregated mains signals can be conducted and integrated for appliance scheduling in a smart home environment.[(1,8)] In this study, we assume each relevant monitored electrical appliance as an appliance having two-state (On/Off) operational transitions. Relevant monitored electrical appliances having multistate operational transitions can be characterized and identified, which will involve a straightforward revision of the chromosomal representation design, fitness function formulation, and the load behavior profiling consideration reported herein. In the future, on the basis of the energy disaggregation methodology proposed in this paper, the energy disaggregation methodology will be able to identify electrical appliances having multistate operational transitions. Also, rolling-horizon load monitoring by the energy disaggregation methodology will be investigated.

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