Sustainable Cities and Society 74 (2021) 103218

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

An efficient optimization approach for flexibility provisioning in community microgrids with an incentive-based demand response scheme

Md Juel Rana *, Kamrul Hasan Rahi, Tapabrata Ray, Ruhul Sarker

School of Engineering and Information Technology, University of New South Wales, Canberra, ACT 2600, Australia

ARTICLE INFO

Keywords:
Demand response
Flexibility management
Residential appliances
Community microgrid
Memetic algorithm
Bi-objective optimization

ABSTRACT

Flexibility provisioning through demand response (DR) programs has emerged as an efficient tool for the economic and reliable management of electricity grids. In this work, an incentive-based DR model of a community microgrid (CMG) is considered, where an aggregator provides flexibility to the CMG. The objective of the aggregator is to minimize the cost of flexibility management that comprises the incentives paid to the residential users for shifting demands and penalty payments to the CMG operator for violating contractual commitments. Instead of attempting to minimize the total cost as single objective minimization, we adopt a two-stage optimization approach, wherein a bi-objective formulation is used in the first stage and a single objective formulation is used in the next. The bi-objective formulation enhances diversity and preserves promising solutions during the course of the search. An evolutionary algorithm is used to solve the bi-objective formulation and the obtained solution is improved in the next stage using local search conforming to a memetic algorithm paradigm. The performance of the proposed algorithm is investigated through statistical analysis and comparison with existing algorithms. The proposed algorithm reduces the peak-to-average ratio of CMG load by 3.97% with at least 27.94% cost saving compared to the state-of-the-art algorithms.

1. Introduction

Community microgrids (CMGs) have emerged as an intelligent entity of smart grids due to their improved reliability and efficiency (Rana et al., 2020). CMGs serve a community of energy consumers by utilizing their local electricity generation from renewable sources (such as solar or wind) and non-renewable sources (such as micro-turbines and/or other fossil-fuel based generators). Maintaining supply-demand balance in CMGs is still very challenging due to the uncertainty associated with the renewable energy generation and variability in the demand from the customers (Rana et al., 2021). The simplest way to balance this energy mismatch is to vary the energy generated which in turn could require installation of new energy generation/storage facilities. An alternative would be to incentivise the end-users to motivate them to change their energy usage through a demand response (DR) program (Elghitani and Zhuang, 2018) commonly referred as flexibility provisioning. This approach has gained significant interest since it allows for more efficient energy management without the need for any additional generation/storage infrastructure. In most of the related works, DR was employed from the perspective of the system operator (SO). However, the application of DR for flexibility provisioning within microgrids has not been studied adequately. For efficient operation within microgrids, one can procure flexibility from small end-users (who can not participate in the DR program directly) through a DR aggregator. Incentive-based DR (IBDR) has been employed successfully in many studies (Eissa, 2018; Lamprinos et al., 2016; Luo et al., 2019) for economic operation of the power system. Therefore, this research focuses on the optimal flexibility provisioning of DR aggregator through IBDR in the context of a community microgrid. The residential end-users in the CMG participate with the aggregator operating on a IBDR scheme i.e., the end users receive incentive for modifying their energy profiles. The optimization problem considered in this paper minimizes the aggregator's net cost which is the sum of the incentive payments made to the end-users and penalty paid to the CMG for failing to provide the required flexibility under the IBDR scheme. The optimal modification of aggregated end-users' energy profile turns into a complex large-scale problem from the aggregator perspective. The performance of the mathematical programming based algorithms used to solve such problems degrades with the increase in the problem dimension. In this context, population-based stochastic algorithms which are also known as meta-heuristics such as EAs (evolutionary algorithms) are often effective. Although EAs can

* Corresponding author.
E-mail addresses: m.rana@student.unsw.edu.au (M.J. Rana), k.rahi@student.adfa.edu.au (K.H. Rahi), t.ray@adfa.edu.au (T. Ray), r.sarker@adfa.edu.au (R. Sarker).

https://doi.org/10.1016/j.scs.2021.103218
Received 24 April 2021; Received in revised form 23 June 2021; Accepted 28 July 2021
Available online 8 August 2021
2210-6707/© 2021 Elsevier Ltd. All rights reserved.

Nomenclature

Acronym

MA_b	Memetic algorithm with bi-objective EA
MA_s	Memetic algorithm with single-objective EA
CMG	Community microgrid
CMGO	Community microgrid operator
DR	Demand response
IBDR	Incentive-based demand response
PAR	Peak-to-average ratio
PBDR	Price-based demand response
SO	System operator

Parameter

C_{dev}^{CMGO}	Penalty rate for any deviation in requested flexibility
C_i^{shift}	Expected remuneration for shiftable appliance i
C_k^{reglt}	Expected remuneration for regulatable appliance k
$I_{base,k,t}$	Base intensity of power consumption (%) for regulatable appliance k at time t
$I_{\min,k}/I_{\max,k}$	Allowed minimum/maximum intensity (%) for regulatable appliance k
N_{reglt}	Number of regulatable appliances
N_{shift}	Number of shiftable appliances
$P_{base,i}^{shift}$	Baseline profile of shiftable appliance i
$P_{base,k}^{reglt}$	Baseline profile of regulatable appliance k
P_{base}	Accumulated baseline profile of all appliance
$P_{flex,t}^{CMGO}$	Flexibility requested by CMGO
$p_{i,t}^{shift}$	Power consumption of shiftable appliance i at time t
p_k^{reglt}	Maximum power of regulatable appliance k
T_H	Time horizon
$t_{base,i}^{start}$	Baseline starting time of the appliance i
t_{pref}^{start}	Preferred starting time of appliance from end-users
$w_{i/k}^{opr}$	Operating window of the appliance i/k

Variable

$C_{penalty}$	Penalty cost incurred on the aggregator
C_{rem}	Remuneration paid to the appliances
F	Net cost of the aggregator
$I_{new,k}$	New intensity of power consumption (%) for regulatable appliance k
$P_{flex,t}^{agg}$	Flexibility procured by the aggregator
P_{flex}^{dev}	Deviation between flexibility procured and flexibility requested
$P_{new,i/k}$	Modified profile of the appliance i/k
$t_{new,i}^{start}$	New starting time of the appliance i
i	Index of shiftable appliances
k	Index of regulatable appliances
t	Index for time slots

handle larger problem size, they often require a higher computational budget to reach the optimal region of the search space. Therefore, to solve the problem efficiently, an effective memetic algorithm (MA) is proposed that delivers near-optimal solutions utilizing the given computational budget. The proposed MA applies a two-stage process, where the first stage evolves the solutions using a bi-objective EA towards the improved region (near optimum), while the second stage is driven by the intensification of the search locally (through a gradient descent based optimizer using standard MATLAB *fmincon* function) from the best-obtained location so far in the first stage. The bi-objective EA is incorporated in the proposed MA to expedite the overall convergence of the algorithm. The main purpose of the developed algorithm is to solve the flexibility management problem of the aggregator more efficiently. The performance of the proposed optimization approach is investigated and compared with other state of the art algorithms through detail statistical analysis. The contributions of this work can be summarized as follows:

- Flexibility provisions for CMG from residential end-users under the IBDR scheme is proposed.
- Flexibility management of DR aggregator is formulated as a bi-objective problem as opposed to the traditional single-objective approach.
- Proposed algorithm can provide near-optimal solution with a limited computational budget.
- Numerical experiments with statistical analysis and comparison with state-of-the-art algorithms corroborate the efficacy of the proposed formulation and the algorithm.

The remainder of the work is organized as follows. The background of DR programs and related works are discussed in Section 2. Section 3 provides the system overview, mathematical problem formulation and rationale for the proposed optimization approach. Section 4 presents the proposed algorithm. In Section 5, experimental results are presented and analyzed to validate and evaluate the performance of the proposed solution approach. Finally, the conclusions are drawn in Section 6.

2. Background and related works

2.1. Background

The term *flexibility* in a more generic sense refers to the modification of end users' demand profile in response to the energy generation or electricity market price variations (El Geneidy and Howard, 2020). The DR program is the underlying element that offers flexibility and there are two forms of DR in use i.e. a price-based DR (PBDR) and an incentive-based DR (IBDR). In the former, the electricity price is varied so that the end-users reduce their consumption during periods of higher price and vice versa. In the latter, the end-users receive incentives for changing their energy usage profile based on agreed conditions with the system operator (SO) or aggregators (third-party) (Lamprinos et al., 2016). Since price-based DR is not dispatchable, it offer less flexibility to the system operator. Furthermore, the end-users are exposed to the risk of price-volatility of the wholesale electricity market. The natural risk aversion tendency limits participation of end-users to such DR programs (Yu et al., 2016). In contrast, incentive-based DR is attractive from the SO perspective as it can achieve the required flexibility by dispatching DR resources. Besides, it is also lucrative for the end-users since they get instant rewards for modifying their energy usage profile (Eissa, 2018). In the US, incentive-based DR led to 93% reduction in peak load (Asadinejad and Tomsovic, 2017). In IBDR programs, the aggregator plays a vital role as a mediator/broker between the end-users and the SO. The aggregator can negotiate with the SO effectively on behalf of the end-users and SO can directly deal with the aggregator instead of individually managing a large number of end-users (Gkatzikis et al., 2013). In this work, we consider flexibility provisioning by an aggregator relying on a incentive based demand response program.

2.2. Related works

Numerous studies have been reported in the literature on incentive-based DR programs with aggregators offering required flexibility to the system operators. In Luo et al. (2019), an incentive-based DR was considered for a virtual power plant (VPP) with an aim to minimize the operating cost of the VPP, while preserving customers' interests. The customers were grouped based on their preferred incentive rates and the problem was formulated as a non-linear programming problem and solved with LINGO optimizer (a software package for linear and non-linear programming). The operation of a community-based residential microgrid was optimized using a multi-agent system in Morsali et al. (2020). The DR model was formulated as a mixed-integer problem and solved using a gradient descent (GD) algorithm. Multiple competitive aggregators have also been considered in Abapour et al. (2020) in an attempt to achieve greater flexibility. In Nguyen and Le (2015), the profit of a microgrid (MG) aggregator was maximized by procuring flexibility from customers through incentive-based DR. Stochastic programming was employed to solve the optimization problem. A non-cooperative game model was used in Gregori et al. (2016) to maximize the profits of connected MGs and DR aggregators. The DR aggregators maximized their profits by trading flexibility with MGs by shifting the usage of appliance loads of its customers. Different meta-heuristic techniques have also been employed to optimize DR problems. In Xu et al. (2019), an incentive-based demand-side management strategy with a micro-market module was proposed for non-controllable loads within an university campus. A self-crossover genetic algorithm (GA) was proposed to optimize the DR program. Hybridization of IBDR and PBDR have also been considered in Kim et al. (2021) to reduce peak loads and improve the reliability of microgrids. Particle swarm optimization (PSO) was used to optimize the MG operation with DR. However, in the design of IBDR, penalty cost associated with customers' failure to satisfy predefined terms was ignored. Evolutionary algorithms (such as differential evolution, PSO and vortex search) have also been employed in Lezama et al. (2020) to maximize the profit of the DR aggregator in providing flexibility to the SO through scheduling home appliances of its customers. The profit of the aggregator is maximum when its cost (sum of the remuneration paid to the customers and the penalty for the mismatch of flexibility sought by the SO) is minimum. The problem has been formulated as a single-objective minimization task combining both parts of the cost function. Other meta-heuristic algorithms employed for DR applications include non-dominated sorting genetic algorithm II (NSGA-II) (Devia et al., 2021), discrete harmony search (DHS) algorithm (Chauhan and Saini, 2017), simulated annealing (SA) algorithm (Qian et al., 2013), teaching learning-based optimisation (TLBO) algorithm (Derakhshan et al., 2016) and hybrids (Waseem et al., 2020) etc.

3. System overview and problem formulation

The overview of the considered CMG and mathematical problem formulation of the IBDR program is presented in this section.

3.1. System overview

A community microgrid is connected to the utility grid through point-of-common-connection (PCC) as shown in Fig. 1. The CMG serves the energy consumers with the energy from the local generations and energy purchased from the utility grid. The CMG gathers flexibility from its consumers via IBDR to reduce energy purchase from the utility grid during peak hours, while ensuring reliable supply. In other words, the CMG operator targets to improve peak-to-average ratio (PAR) of its aggregated load through flexibility management. The CMG can also utilize the obtained flexibility to provide ancillary services to the utility grid. Existing DR programs mostly cater to large industrial/commercial customers as they are capable of significantly modifying the demand. An aggregator can also provide significant flexibility to the community microgrid operator (CMGO) by managing the energy usage of its large number of residential consumers. The aggregator receives payment from the CMG operator for the flexibility provided.

However, the aggregator is also penalized by the CMGO for any

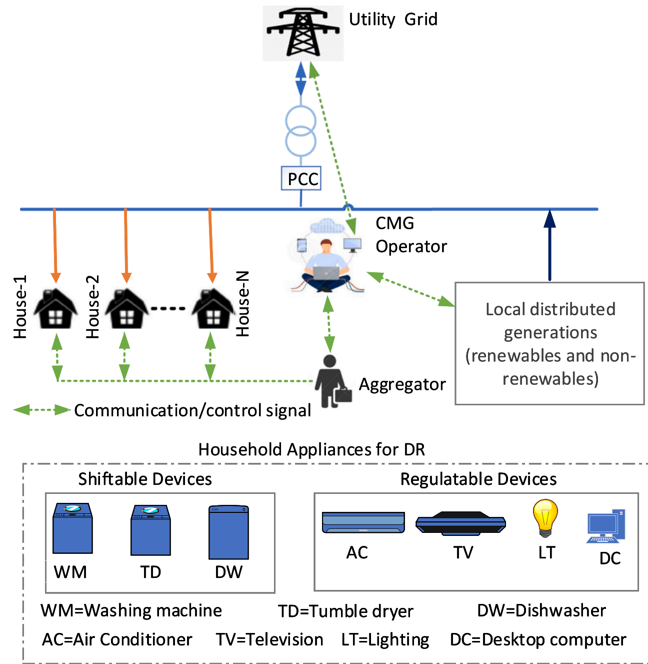

Fig. 1. Proposed IBDR in the community microgrid.

mismatch between the delivered and the sought flexibility. The aggregator in turn pays its residential consumers incentives to alter their energy profile to meet the required flexibility.

Two types of household appliances have been considered for flexibility provisioning: shiftable devices and regulatable devices. The appliances for which the power consumption can not be controlled but their starting time can be delayed/shifted falls in the first category. The second category consists of regulatable appliances for which power consumption can only be regulated.

The end-users can specify their preferences (such as allowed delay for switching on a device, expected remuneration etc.) when they participate in the DR program.

3.2. Formulation of optimization problem

The objective is to minimize the net cost of the aggregator that comprises of the incentive payments to the residential customers and the penalty paid to the CMG operator. In the following subsections, we first present the details of the model followed by the single and bi-objective formulation of the problem. The rationale for the bi-objective formulation is also discussed in details.

3.2.1. Mathematical model

Let, D=$\{d^{shift}, d^{reglt}\}$ be the set of all appliances from the households participating in the DR program where $d^{shift} = \{1, 2, \ldots N_{shift}\}$ and $d^{reglt} = \{1, 2, \ldots N_{reglt}\}$ represent the set of shiftable and regulatable appliances, respectively. Number of shiftable and regulatable appliances are denoted by N_{shift} and N_{reglt}. The end-users receive financial incentives from the aggregator for any modification in their base profile. The base profile denotes the power consumption of the appliances without DR over the time horizon (T_H). For the daily profile (24 h), a time resolution of 15 min would lead to T_H of 96 time-slots. The base profile of the shiftable devices i is characterized by their starting time ($t^{start}_{base,i}$), appliances' operating window in time slots (w^{opr}_i) and power consumption ($p^{shift}_{i,t}$) in each of the time slots within the operating window. The base profile of the shiftable appliances can be calculated as in (1).

$$P^{shift}_{base,i,t} = \begin{cases} p^{shift}_{i,t-t^{start}_{base,i}+1} & if\ t^{start}_{base,i} \le t \le t^{start}_{base,i} + w^{opr}_i - 1 \\ 0 & else \end{cases} \quad (1)$$

As the start times of the regulatable appliances can not be shifted, the base profile of any regulatable appliance k is characterized by its maximum rated power (p^{reglt}_k) and base intensity of power consumption ($I_{base,k,t}$). The intensity of consumption refers to the percentage of peak power consumed by the appliance. Therefore, the base profile of the regulated appliances can be represented as in (2).

$$P^{reglt}_{base,k,t} = p^{reglt}_k I_{base,k,t} \quad (2)$$

The aggregated base-profile for all appliances can be obtained from (3) by combining individual base-profile of (1) and (2).

$$P_{base,t} = \sum_{i=1}^{N_{shift}} P^{shift}_{base,i,t} + \sum_{k=1}^{N_{reglt}} P^{reglt}_{base,k,t} \quad (3)$$

In this study we assume that the aggregator has access to the base-profile for each type of appliances. The aggregator runs an optimization algorithm to meet the flexibility needs of the CMGO by modifying the base-profile according to the end-users' preferences. It is also assumed that the end-users can submit their preferences of appliance operation through the home energy management system. The decision variable for optimizing operation of shiftable appliances is the modified/new starting time ($t^{start}_{new,i}$). The end-users' submitted preferences include preferred starting time ($t^{start}_{pref,i}$), allowed time window for aggregator to control the appliance (TW^{agg}_i) and expected remuneration (C^{shift}_i) for any shifting of appliance i within the allowed time window. The shifting of appliances from the base-profile is constrained by user preferences as follows:

$$t^{start}_{pref,i} \le t^{start}_{new,i} \le t^{start}_{pref,i} + TW^{agg}_i \quad (4)$$

$$t^{start}_{pref,i} + TW^{agg}_i \le T_H - w^{opr}_i \quad (5)$$

Equation (4) describes that the new starting time of the appliance can be any time between preferred starting time and end time for the allowed time window. The Eq. (5) indicates that the upper limit for the new starting time of the appliance i must be within the considered time horizon that can accommodate its operating window w^{opr}_i.

In the case of regulatable appliance k, the decision variable is the new intensity of power consumption ($I_{new,k,t}$). The user preferences for these appliances include preferred time for initiating/altering consumption ($t^{start}_{pref,k}$), allowed time window for the aggregator to control the appliance (TW^{agg}_k), allowed maximum/minimum intensity ($I_{\min,k}$ /$I_{\max,k}$), and expected remuneration (C^{reglt}_k) for any modification of appliance intensity within the allowed time window. The new intensity of consumption of the regulatable appliances is constrained by the following equations.

$$I_{\min,k} \le I_{new,k,t} \le I_{\max,k} \quad (6)$$

$$I_{new,k,t} = \begin{cases} I_{new,k,t} & if\ t^{start}_{pref,k} \le t \le t^{start}_{pref,k} + TW^{agg}_k \\ I_{base,k,t} & else \end{cases} \quad (7)$$

The new starting time of shiftable appliances ($t^{start}_{new,i}$) and new intensity of regulatable appliances ($I_{new,k,t}$) can be used to determine the modified profile of the appliances. The new aggregated profile can be obtained using (8)–(10).

$$P^{shift}_{new,i,t} = \begin{cases} p^{shift}_{i,t-t^{start}_{new,i}+1} & if\ t^{start}_{new,i} \le t \le t^{start}_{new,i} + w^{opr}_i - 1 \\ 0 & else \end{cases} \quad (8)$$

$$P^{reglt}_{new,k,t} = p^{reglt}_k I_{new,k,t} t \in w^{opr}_k, w^{opr}_k \in T_H \quad (9)$$

$$P_{new,t} = \sum_{i=1}^{N_{shift}} P^{shift}_{new,i,t} + \sum_{k=1}^{N_{reglt}} P^{reglt}_{new,k,t} \quad (10)$$

The flexibility procured by the aggregator is the difference between the aggregated base-profile and the new/modified profile of the appliances as presented in (11). Also, the deviation of flexibility provisioned by aggregator from the flexibility requirement of CMGO is calculated in (12).

$$P^{agg}_{flex,t} = P_{base,t} - P_{new,t} \quad (11)$$

$$P^{dev}_{flex} = \sum_{t=1}^{T_H} \left| P^{agg}_{flex,t} - P^{CMGO}_{flex,t} \right| \quad (12)$$

The aggregator pays the remuneration to the end-users based on changes to their energy usage by the shiftable and regulatable devices according to the new scheduled profiles as presented in (13)-(14). The total remuneration cost (C_{rem}) paid to the end-users is given by (15). The aggregator also needs to pay a penalty imposed by the CMGO if $P^{dev}_{flex} > 0$.

$$C^{shift}_{rem,i} = \begin{cases} C^{shift}_i & if\ t^{start}_{base,i} \ne t^{start}_{new,i} \\ 0 & else \end{cases} \quad (13)$$

$$C^{reglt}_{rem,k} = C^{reglt}_k \sum_{t=1}^{T_H} \left| P^{reglt}_{base,k,t} - P^{reglt}_{new,k,t} \right| \quad (14)$$

$$C_{rem} = \sum_{i=1}^{N_{shift}} C^{shift}_{rem,i} + \sum_{k=1}^{N_{reglt}} C^{reglt}_{rem,k} \quad (15)$$

The net cost of the aggregator is the sum of the remuneration paid to the end-users and the penalty cost paid to the CMGO. Therefore, the objective of the aggregator is to minimize the net cost (F) for the flexibility provision.

3.2.2. Single objective formulation

The single-objective formulation of the minimization problem can be written in compact form as in (16) (Lezama et al. 2020).

$$\begin{aligned} \min_{\vec{x}} \quad & F = C_{rem} + C^{CMGO}_{dev} P^{dev}_{flex} \\ s.t \quad & \\ & (4) - (6) \end{aligned} \quad (16)$$

where $\vec{x}$ denotes the vector of decision variables combining $t^{start}_{new,i}$ and $I_{new,k,t}$. C^{CMGO}_{dev} is the penalty factor (weight factor) in € /kWh set by the CMGO for any mismatch of flexibility collected by the aggregator and the required flexibility. The choice of this penalty factor in the single-objective formulation (16) affects the course of search.

3.2.3. Bi-objective formulation

In the bi-objective formulation, the remuneration paid to the end-users and penalty cost paid to the CMGO are considered as two different objectives. Both objectives are minimized simultaneously to reduce the net cost of the aggregator for the flexibility provisions. The bi-objective formulation of the optimization problem can be presented as in (17).

$$\begin{aligned} \min_{\vec{x}} \quad & F = \{f_1, f_2\} \\ s.t \quad & \\ & (4) - (6) \end{aligned} \quad (17)$$

$$f_1 = C_{rem} \quad (18)$$

$$f_2 = C_{penalty} = C^{CMGO}_{dev} P^{dev}_{flex} \quad (19)$$

Where f_1 and f_2 represent the two objectives, namely, remuneration cost (C_{rem}) and penalty cost ($C_{penalty}$), respectively. The value of f_1 and f_2

can be obtained using (15) and (19).

3.2.4. Rationale for bi-objective formulation

As discussed earlier, the objective of this paper is to minimize the net cost (F) of the aggregator in procuring flexibility services for the CMGO. It is well known that EAs evolve a set of solutions over the generations/iterations towards the optimal solution. While doing so, the optimizer can follow different trajectories as shown in Fig. 2. For the sake of illustration, let's assume, the initially generated point is A and the optimum point is B and both points are depicted in a two-dimensional objective space (i.e., objectives f_1 and f_2) where B implies minimum values in both objectives.

Also, let's assume that A and B are the opposite corner points of a two-dimensional space. This means that the shortest distance (according to the triangle inequality theorem) which can be travelled from A to reach B must be along the hypotenuse (i.e., straight trajectory AEB) of the triangle ΔADB. This further implies that all other lines of search trajectory in the space $\square ADBC$ must be greater than AEB, while both ACB as well as ADB form the longest trajectories. This indicates that the convergence rate will be maximum only if the search trajectory follows the path AEB. Since F is correlated with both f_1 and f_2 as stated above (F decreases when f_1 and f_2 decrease and vice-versa), trajectory AEB involves equal weights (in the normalized scale), while minimizing F along this path. Note that the weight of f_1 and f_2 in F varies due to the values of C_{dev}^{CMGO} in (19) as well as remuneration rates (C_i^{shift} and C_k^{reglt}) in (13)-(14). The weight will create bias in the course of search i.e. objective with a higher weight will get priority and vice versa. This might happen often when minimization of net cost (F) is considered in the optimization process. In that case, search is diverted towards any trajectory in the upper/lower triangular space (i.e., two extreme conditions are ACB and ADB) based on weight of f_1 and/or f_2. Such a scenario in turn consumes a higher evaluation budget to identify the near-optimal solution. In contrast, bi-objective formulation of (17) considers f_1 and f_2 as two separate objectives which are minimized simultaneously and such a consideration will inherently force a search along the most preferred shortest path as illustrated in Fig. 2.

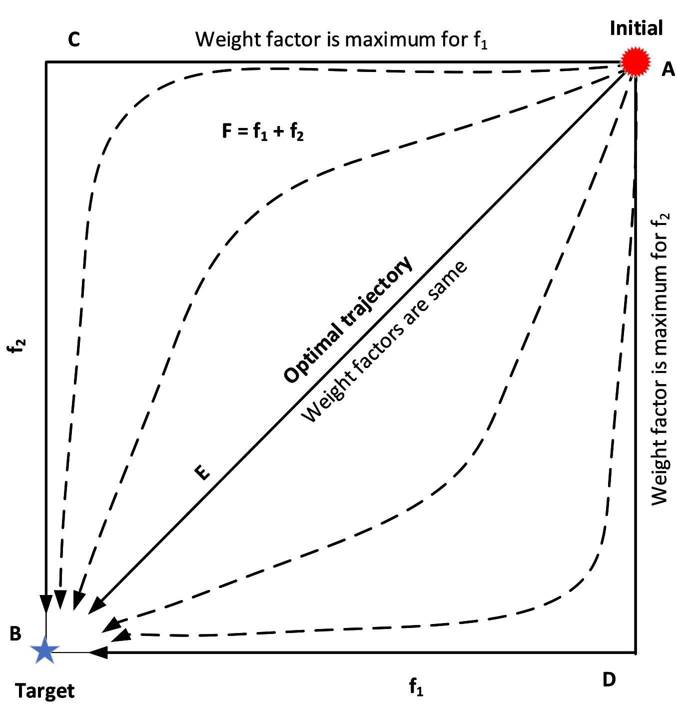

Fig. 2. Trajectory of the solution process in the objective space.

4. Proposed memetic algorithm

The proposed approach relies on a two-stage solution process. In the first stage, a population-based stochastic algorithm (an evolutionary algorithm (EA) in this case) is used with the bi-objective formulation to identify promising regions of the search space. From the set of trade-off solutions identified at the end of stage one, the solution with the best aggregate cost measure is selected. A gradient based local search using the single-objective formulation is used in the second stage with the starting solution being the one selected from the first stage. The computational budget is equally divided among the stages in this study for simplicity. The EA consists of components for initialization, evolution, evaluation and environmental selection, while the local search is based on a gradient based optimizer (default *fmincon* function in MATLAB). The combination of the proposed population based search and the local search conforms to a memetic algorithm paradigm. The pseudo-code of the approach is presented in Algorithm 1 and steps are discussed later in this section. The codes of the proposed memetic algorithm can be downloaded from Code.

4.1. Solution encoding

The first step relates to an encoding process where decision variables of the problem are represented as a chromosome. The decision variables of the problem under consideration are the new starting times (t_{new}^{start}) of the shiftable appliances and the new intensity levels (I_{new}) of power consumption of the regulatable appliances. The solution vector concerning the shiftable appliance can be presented as in (20).

$$\vec{x}_{shift} = \left[t_{new,1}^{start}, \ldots, t_{new,i}^{start} \ldots t_{new,N^{shift}}^{start}\right] \tag{20}$$

Where $i = 1, 2, \ldots, N^{shift}$ denotes the index of shiftable appliances.

Similarly, the solution vector for the regulatable appliances can be presented as in (21).

$$\vec{x}_{reglt} = \left[I_{new,1,1}, \ldots, I_{new,k,t}, \ldots, I_{new,N^{reglt},w^{opr}}\right] \tag{21}$$

Where $k = 1, 2, \ldots, N^{reglt}$ represents the index of regulatable appliances. Time-slots of the operating window for the respective regulatable appliances are denoted by $t = 1, 2, \ldots, w^{opr}$. The decision variables for both types of appliances are concatenated to form a single solution vector for the optimization problem as in (22).

$$\vec{x} = \left[\vec{x}_{shift}\ \vec{x}_{reglt}\right] \tag{22}$$

The upper and lower bound of these decision variables are set as per end-users preferences for the respective appliances.

4.2. Stage one

In this stage, an evolutionary algorithm is used to deal with the bi-objective formulation of the problem. A set of initial solutions are generated randomly within the specified variable bounds for the encoded decision variables. Then, the current parent set of solutions are used to generate offspring solutions using crossover and mutation operations. In doing so, we have used popularly known simulated binary crossover (SBX) and polynomial mutation approach (Deb and Agrawal, 1995) in this study. Prior to both operations, the parent solutions are selected following binary tournament (Deb et al., 2002) strategy to maximize the likelihood of elite parents used in recombination. The offspring solutions are then evaluated. With the newly evaluated offspring solutions and also all solutions that have been evaluated so far, the best set of N solutions are identified based on non-dominated sorting and carried forward as parents for the next generation. The process continues until half of the computing budget is exhausted and the set of non-dominated solutions based on all evaluated solutions are considered as an output from stage one.

Require: $NFE_{\max}$ (maximum number of function evaluations), N (population size), crossover and mutation parameters.
Output: The best point found at the end of evaluation budget.

$NFE = 0$, $j = 0$. // Initial generation
Initialize $(P_N{}^j)$. // Initial set of solutions
Evaluate $(P_N{}^j)$ and update NFE.
Store the evaluated solutions in archive $\mathcal{A}$.
Rank $(P_N{}^j)$ based on merits of (f_1) and (f_2). // Following non-dominated sorting (Deb, Pratap, Agarwal, & Meyarivan, 2002)
while $(NFE \leq NFE_{\max})$ **do**
    if $(NFE \leq \frac{1}{2} \times NFE_{\max})$ **then**
        $C_N{}^j$ = **Evolve** $(P_N{}^j)$. // Following SBX crossover and PM (Deb & Agrawal, 1995)
        Evaluate $(C_N{}^j)$ and update NFE.
        Update the archive; $\mathcal{A} \longleftarrow (\mathcal{A} \cup C_N{}^j)$.
        Rank $(\mathcal{A})$ based on f_1 and f_2 merits. // Following non-dominated sorting (Deb et al., 2002)
        $P_N{}^{j+1} \longleftarrow$ **Reduce** $(\mathcal{A})$. // Environmental selection
        $j = j + 1$.
    else
        Find the best solution so far based on total fitness $(F = f_1 + f_2)$ merit.
        Run a local search from the current best. // Using *fmincon* as the GD based optimizer .
        Evaluate the locally improved solution and update NFE.
        Update the archive $\mathcal{A}$ with locally evaluated solutions.
    end if
end while

Algorithm 1. Proposed memetic algorithm with bi-objective EA (MA_b).

4.3. Stage two

While the EA used in stage one delivers a set of trade-off solutions, there is a need to accelerate the search especially when the overall computing budget is limited. Memetic algorithms are a popular choice in such circumstances, where a local search is usually conducted following a population-based search. In our proposed approach, we first identify the solution with the best aggregate measure (F) and initiate a local search using a gradient-based optimizer (fmincon with default MATLAB settings have been used in this study) with the aggregate measure (F) as the objective. The default settings include 'SQP' (sequential quadratic programming) as the active set algorithm where step tolerance as well as optimality tolerance limit were set to default ($1e-6$ respectively). The local search is allocated to use half the overall computing budget in this study. At the end of the local search, the best solution in terms of F (i.e., minimum net cost) is reported.

5. Results and discussion

In this section, the performance of the proposed approach is investigated using numerical experiments.

5.1. System data

For the numerical experiments, 20 similar residential end-users, who registered their appliances for DR, have been considered. It is assumed that all the registered residential end-users have both shiftable and regulatable appliances. The registered shiftable appliances in each household includes washing machine (WM), tumble dryer (TD), and dishwasher (DW). On the other hand, regulatable appliances registered for DR consists of air-conditioning (AC) unit, television (TV), lighting system (LT), and desktop computer (DC). The typical power consumption profile and operating window of the appliances is presented in Figs. 3 and 4. The baseline profile of each appliances in the end-users' premises are created across a 24 h period with 15 min intervals (i.e. 96 time-slots). The overall load profile in the CMG as well as the accumulated baseline profile of both shiftable and regulatable appliances is shown in Fig. 5. The preferred shifting time window of the shiftable appliances is generated using uniform random function in the range of 0–64 time-slots; likewise, the preferred intensity of regulatable appliances is varied between 0 to 40% of the appliance power. For different participation of the end-users, the remuneration paid for shifting appliances is modelled as ±30% of 0.2 €. On the other hand, the expected remuneration of the regulatable appliances is considered to be ± 30% of 0.09 € /kWh. The penalty cost imposed on the aggregator by CMGO for any deviation in the requested and supplied flexibility is assumed as 0.2 € /kWh. It is assumed that by registering appliances in the IBDR scheme, the end-users provide aggregator direct control over their appliances and aggregator respects user preferences while controlling these appliances. The off-peak and peak periods of energy consumption are considered as 02:00-06:00 and 18:00-21:00 hours, respectively.

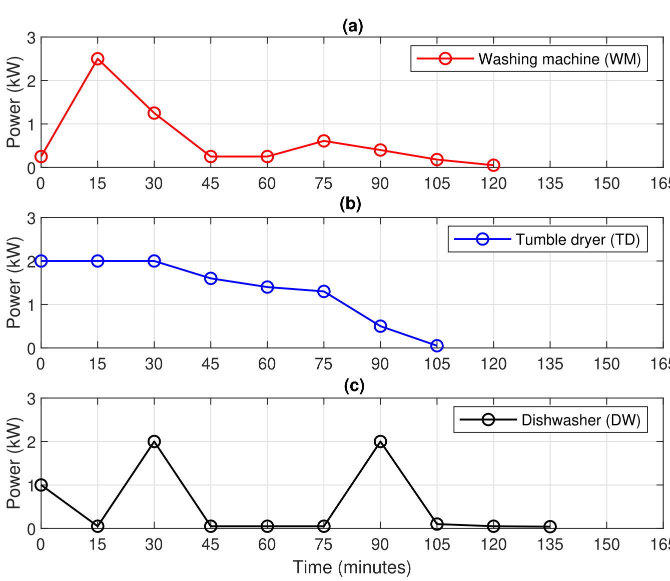

Fig. 3. Operating window and typical power consumption profile of shiftable appliances (a) WM (b) TD (c) DW.

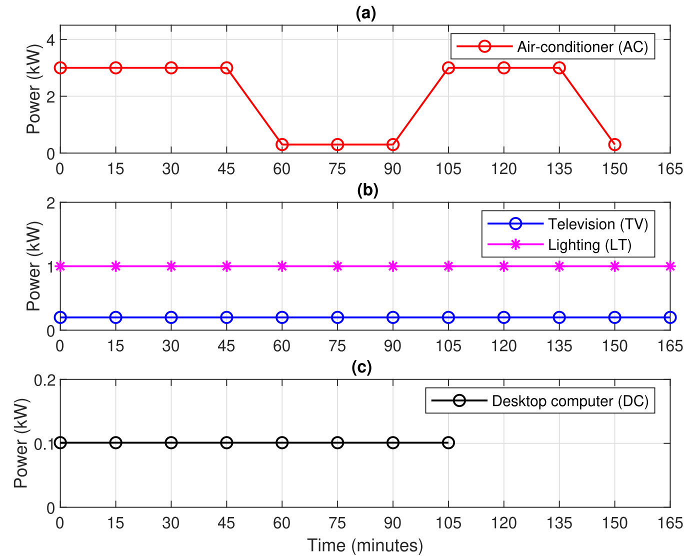

Fig. 4. Operating window and typical power consumption profile of regulatable appliances (a) AC (b) TV and LT (c) DC .

The flexibility requirement of the CMG varies according to the period of operation as shown in Fig. 6. Data regarding household appliances and their baseline consumption profiles are taken from Lezama et al. (2020).

5.2. Experimental setup

In this subsection, the results obtained from the proposed approach is

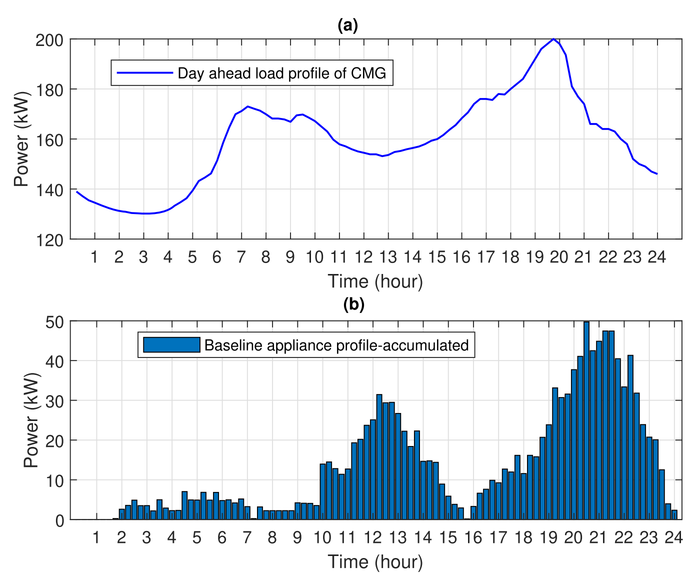

Fig. 5. Load profile (a) overall load in the CMG (b) accumulated baseline power consumption profile from both shiftable and regulatable appliances.

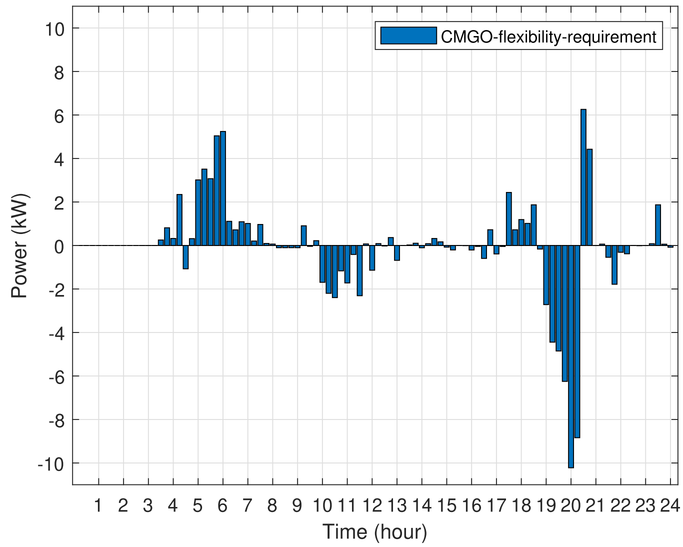

Fig. 6. Flexibility requirement from the CMGO.

Table 1
Fitness value obtained from single-objective approach.

Algorithm	Best (€)	Worst (€)	Average (€)	Median (€)	STD
PSO	16.59	20.69	18.26	18.35	0.94
DE_{rand}	16.18	18.11	17.18	17.22	0.43
$DE_{current-to-best}$	6.57	8.59	7.80	7.88	0.53
HyDE	8.93	10.65	9.89	9.91	0.41
HyDE-DF	8.17	10.05	9.16	9.14	0.43
VS	5.48	7.70	6.67	6.64	0.57
Proposed MA_s	5.12	8.48	6.56	6.41	0.80

presented, analyzed and compared with the state-of-the-art algorithms. The simulation was conducted for 31 independent runs to carry out statistical analysis. A computational budget of 1e5 function evaluations were allocated to all algorithms. The total number of decision variables of the considered problem is 940. The population size, crossover probability, and mutation probability for the proposed algorithm were set to 100, 1, and 0.1, respectively. Two variants of the proposed algorithm, namely, memetic algorithm with single-objective EA (MA_s) and memetic algorithm with bi-objective EA (MA_b) were used to solve the problem. The performance of MA_s was investigated against the state-of-the-art algorithms; then, the effectiveness of the proposed MA_b was assessed with MA_s and the best performer among the state-of-the-art algorithms. All the simulation studies were programmed and implemented in the MATLAB (R2018a) environment on a computer equipped with 3.20 GHz Intel Core i7 processor and 16 GB of RAM.

Table 2
Fitness value obtained from the proposed memetic approach with bi-objective EA.

Algorithm	Best	Worst	Average	Median	STD
Proposed MA_b	3.81	6.76	5.22	5.19	0.58
Proposed MA_s	5.12	8.48	6.56	6.41	0.80
Avg. savings (%)	-	-	20.43	-	-

5.3. Results with single-objective approach

The single-objective approach aims to minimize the total cost of the aggregator for managing flexibility provision for the CMG. The minimization problem was solved using the MA embedded with single-objective EA (i.e., MA_s). Additionally, for the sake of comparison, the problem was solved employing different state-of-the-art algorithms that include PSO, vortex search (VS) and different variants of DE. The variants of DE include DE_{rand}, $DE_{current-to-best}$, hybrid adaptive DE (HyDE) and HyDE with decay function (HyDE-DF). The implementations of the above algorithms were taken from Lezama et al. (2020).The obtained net cost of the aggregator using the proposed MA_s and the state-of-the-art algorithms are presented in Table 1. The results show that the VS produced minimum net cost of the aggregator among the state-of-the-art algorithms with a median fitness value of 6.64€. Although the proposed MA_s exhibits a higher standard deviation, it outperformed all the state-of-the-art algorithms in terms of fitness value. The convergence plots for the median run of the state-of-the-art algorithms and MA_s are shown in Fig. 7. From the convergence plots, it can be observed that $DE_{current-to-best}$ and VS algorithms converged to better fitness values compared to the other state-of-the-art algorithms. Although both $DE_{current-to-best}$ and the VS algorithm had almost similar convergence during early stages of the search process, VS algorithm outperforms $DE_{current-to-best}$ eventually. On the contrary, the proposed MA_s employing an evolutionary search process achieved faster

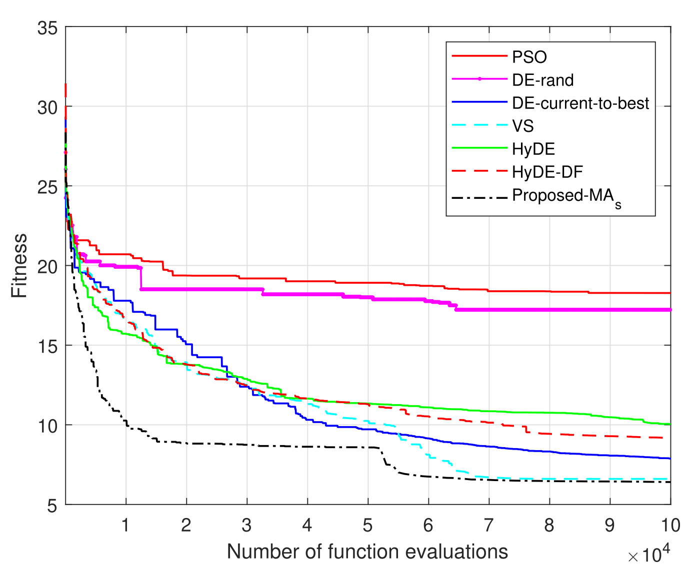

Fig. 7. Convergence plots for median run of the algorithms in single-objective approach.

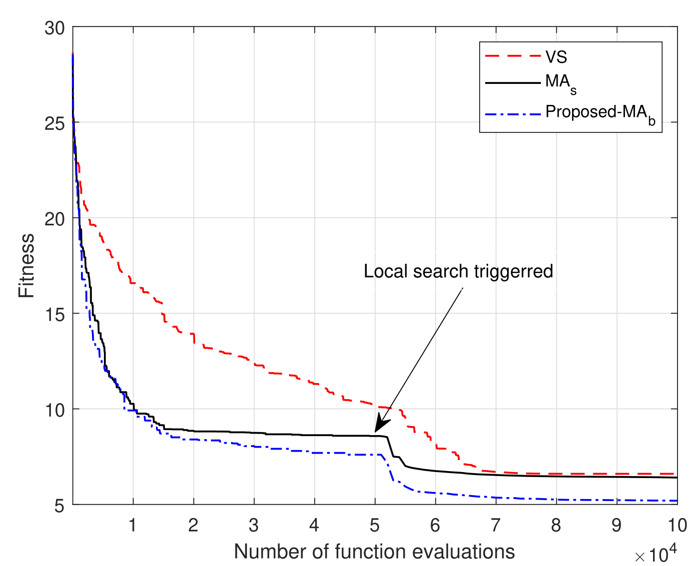

Fig. 8. Convergence comparison of the proposed MA_b, MA_s and state-of-the art algorithm.

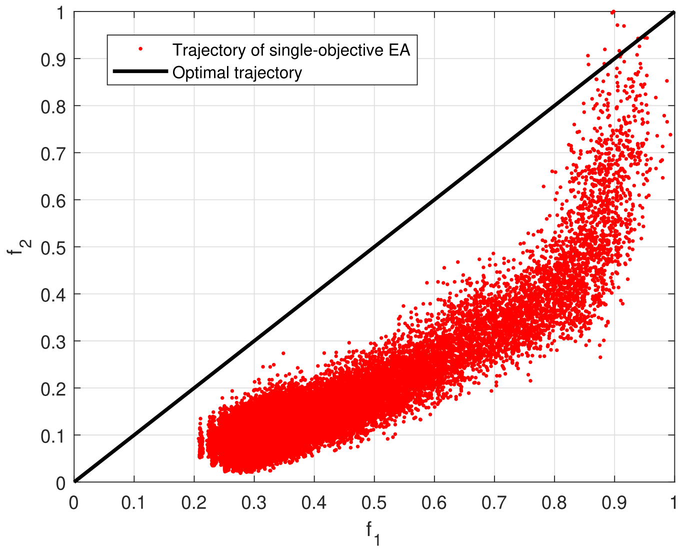

Fig. 9. Trajectory of single-objective EA of MA_s in the normalized objective space.

convergence than the state-of-the-art algorithms during the early stages. However, improvement in the fitness value stalled between the number of function evaluations 2e4 to 5e4. Local search (LS) was then applied after 5e4 function evaluations to further improve the fitness value. The impact of LS is evident from the final fitness value which places MA_s as the top performer ahead of all the state-of-the-art algorithms.

5.4. Results with bi-objective approach

In the bi-objective approach, the goal is to minimize the net cost of the aggregator by simultaneously reducing remuneration cost and penalty cost. The results obtained from 31 runs of the proposed MA_b is presented in Table 2. It is evident from the results that MA_b identifies solutions with better net cost. It shows that the aggregator can save on average 20.43% employing the bi-objective approach than the single-objective strategy (i.e., MA_s). The lower standard deviation (i.e. 0.58) of the obtained results compared to the MA_s indicates the robustness of the proposed MA_b.

To further analyze the performance, the convergence plots of the

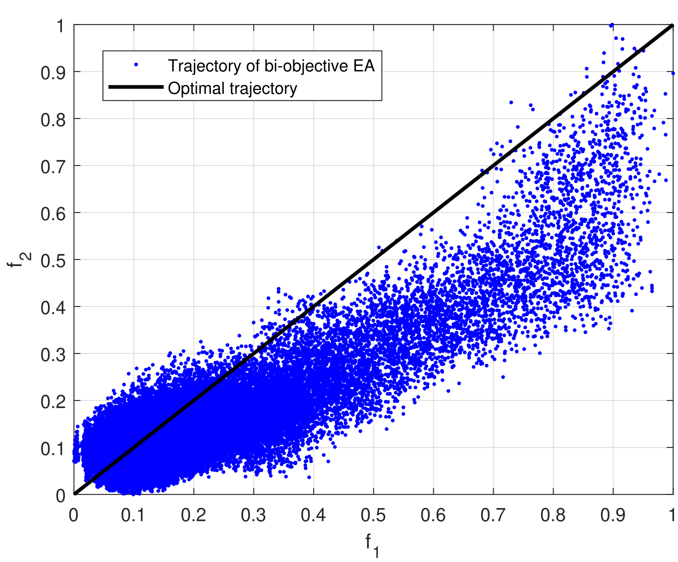

Fig. 10. Trajectory of proposed bi-objective EA of MA_b in the normalized objective space.

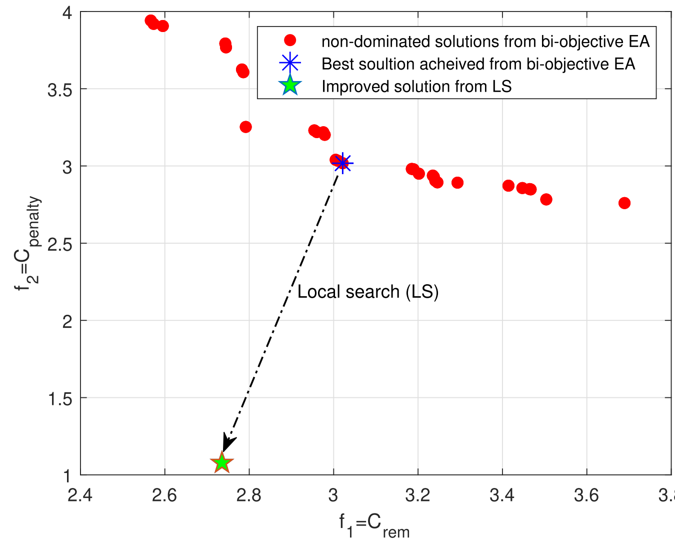

Fig. 11. Non-dominated solution set of EA and final solution from local search (LS) using proposed MA_b.

Table 3
Wilcoxon sign test of the proposed MA_b versus single-objective algorithms for 31 runs.

Comparison	Better	Similar	Worse	p-value
MA_b vs. PSO	31	0	0	1.17e-06
MA_b vs. DE_{rand}	31	0	0	1.17e-06
MA_b vs. $DE_{current-to-best}$	31	0	0	1.17e-06
MA_b vs. HyDE	31	0	0	1.17e-06
MA_b vs. HyDE-DF	31	0	0	1.17e-06
MA_b vs. VS	30	0	1	1.92e-06
MA_b vs. MA_s	28	0	3	6.57e-06

Table 4
Friedman test for all algorithms.

Category	Algorithms	Mean rank
Proposed	MA_b	1.13
	MA_s	2.52
State-of-the-art	PSO	7.77
	DE_{rand}	7.23
	$DE_{current-to-best}$	3.81
	HyDE	5.87
	HyDE-DF	5.10
	VS	2.58

median run for the proposed MA_b, MA_s and the VS algorithm (best performer among the state-of-the-art-algorithms) are shown in Fig. 8. From the convergence plots, it can be inferred that the single-objective approaches (MA_s and VS) converge to almost similar fitness values (although MA_s slightly outperformed VS). However, significant improvement in the convergence of fitness value is attained by adopting the bi-objective formulation that confirms the effectiveness of the proposed MA_b.

5.5. Performance analysis of the proposed algorithm

5.5.1. Convergence comparison

The purpose of this subsection is to validate the principle discussed in Section 3.2.4 which hypothesizes that a bi-objective formulation can lead to better fitness values than the single-objective approach given an

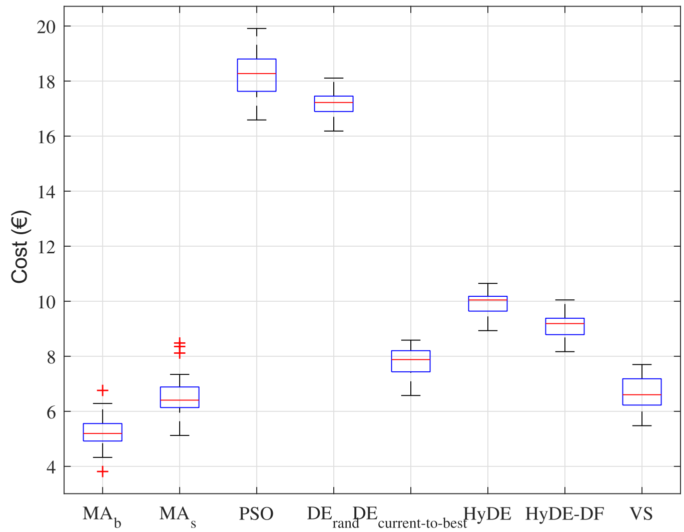

Fig. 12. Box plots for all algorithms.

Table 5
Comparison of computational time between proposed algorithm and state-of-the-art-algorithms.

Stopping criterion	Algorithm	Avg. computation time (second)	Median fitness
Max. number of function evaluation	MA_b	229.73	5.19
	PSO	88.68	18.35
	VS	87.86	6.64
	DE_{rand}	91.64	17.22
	$DE_{current-to-best}$	86.00	7.88
	HyDE	91.88	9.91
	HyDE-DF	101.09	9.14
Max. computation time	PSO	250	17.88
	VS	250	7.68
	DE_{rand}	250	15.97
	$DE_{current-to-best}$	250	7.18
	HyDE	250	8.32
	HyDE-DF	250	8.47

equal computational budget. The better fitness of the bi-objective approach is due to its capability to effectively follow the optimal trajectory during the course of search. To illustrate this point, the trajectory of the evolutionary search process of both the single-objective (i.e., in MA_s) and proposed bi-objective formulation (i.e., in MA_b) are shown in Figs. 9 and 10, respectively.

It can be seen that the search process was biased towards minimizing f_2 in the beginning while f_1 was prioritized in the later stages. On the other hand, the trajectory of the proposed bi-objective EA (shown in Fig. 10) closely follows the optimal trajectory. At the end of the evolutionary search process, a local search was applied to the final non-dominated solution with the lowest net cost (F). The application of local search further minimized the cost as illustrated in Fig. 11.

5.5.2. *Statistical analysis*

To verify the consistency, the performance of the proposed algorithm (MA_b) was compared to the state-of-the-art algorithms using multiple statistical tests The objective values achieved from 31 independent run of all algorithms were taken as the samples for the tests. Two non-parametric tests (Wilcoxon sign test and Friedman test) are conducted. The Wilcoxon sign test was performed using 5% significance level of the samples and the obtained results are presented in Table 3. The results show that the proposed MA_b outperformed all other algorithms in most of the trials. Furthermore, the p values of the tests are less than 0.05 which indicates a significant difference between the obtained results from the proposed algorithm when compared with other algorithms. The results from Friedman test is presented in Table 4, which shows that the proposed MA_b is ranked first among all other algorithms. Additionally, boxplots for all algorithms is shown in Fig. 12 which confirms the superiority of performance of the proposed algorithm.

5.5.3. *Analysis of computational time*

The obtained results presented in Tables 1 and 2 are based on the stopping criteria of maximum number of function evaluations which was set to 1e5 for all algorithms. The average computational time required by each algorithm and corresponding median fitness values is presented in Table 5. The results show that using equal number of function evaluations, the proposed MA_b produced better fitness value. However, the computational time for the proposed algorithm was higher than other algorithms. The additional computational time arises from the initialization of local search optimizer (i.e.fmincon) in the MATLAB environment. The required computational time for the proposed MA_b is

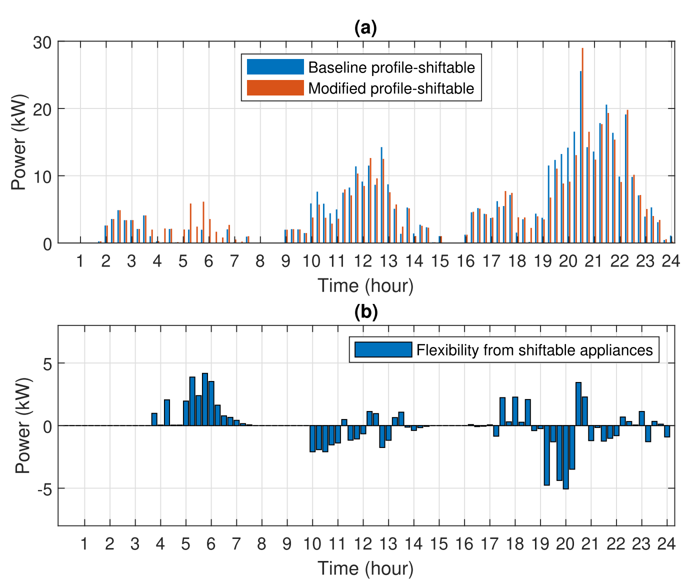

Fig. 13. (a) Baseline vs modified profile (b) flexibility procured from shiftable appliances.

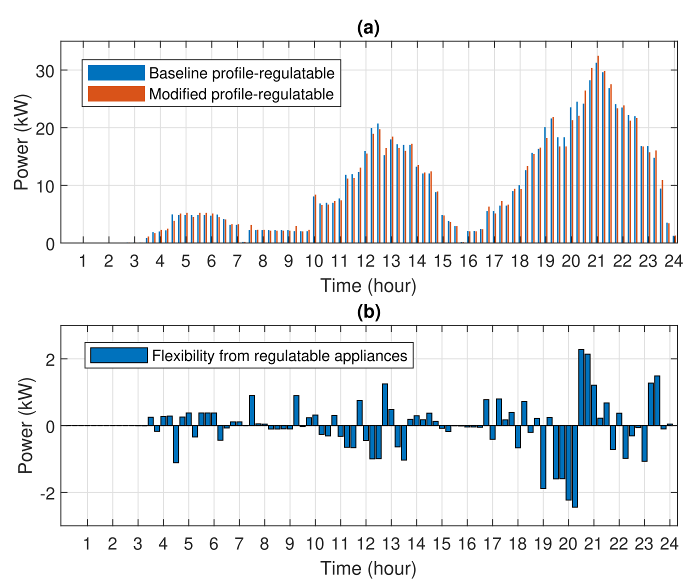

Fig. 14. (a) Baseline vs modified profile (b) flexibility procured from regulatable appliances.

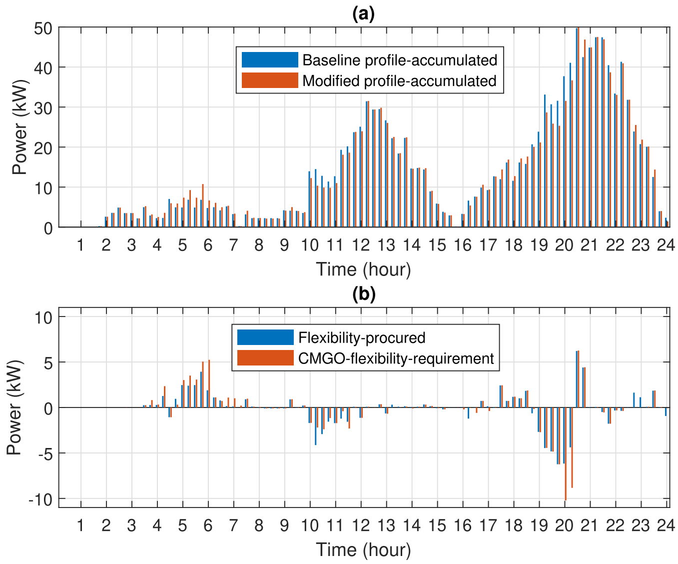

Fig. 15. (a) Baseline vs modified profile of all appliances appliances (b) flexibility requirement vs flexibility procured by aggregator.

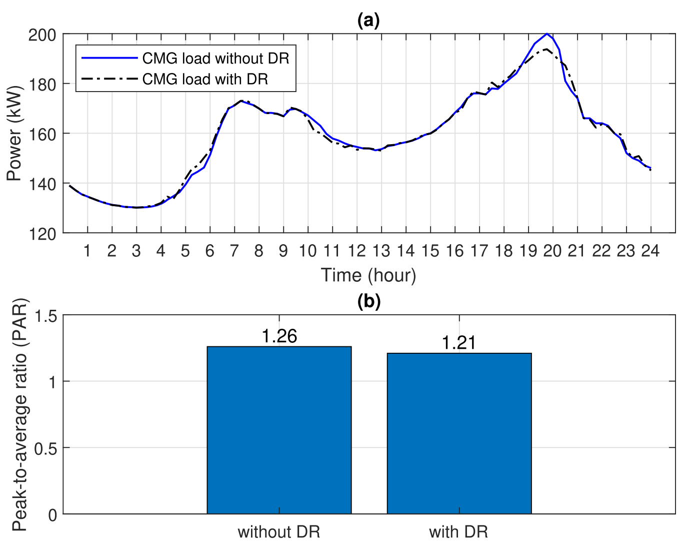

Fig. 16. Impacts of DR with the proposed approach (a) CMG load profile (b) PAR of CMG load.

reasonable from the perspective of the day-ahead flexibility management problem considered in this work where cost minimization is of primary concern. Nevertheless, for fair comparison, state-of-the-art the algorithms were run with the stopping criteria of maximum computational time of 250 s. The fitness values of the algorithms obtained using maximum computational time is shown in Table 5. The results reveal that even with increased computational time allocation, the state-of-the-art algorithms failed to reach the fitness value achieved with the proposed algorithm. This establishes the computational efficiency of the proposed algorithm.

5.6. Analysis of the obtained results

The aggregator modifies the consumption profile of the appliances. The resulting modified profile of the appliances should follow the flexibility requirement as close as possible to avoid penalty from the CMGO. The modified profile of the shiftable appliances with regards to the baseline profile and flexibility offered by the shiftable appliances are shown in Fig. 13(a)-(b) respectively. It can be seen that the power consumption of the modified profile was reduced around 19:00-20:00 and increased around 05:00-06:00. Accordingly, the flexibility from shiftable appliances was maximum during these periods. This occurred due to the shifting of some appliances from peak periods to off-peak periods.

On the other hand, as shown in Fig. 14, the maximum flexibility provided by the regulatable appliances (around 2 kW) is less than that of the shiftable appliances. As before, the maximum flexibility occurs during peak hours. The reason behind the higher flexibility from shiftable appliances is that the shifting of any appliances from one time period to another contributes twice in flattening the overall load curve; whereas, the regulatable appliances helps in modifying the consumption at any specific period only.

The accumulated modified profile and procured flexibility from all appliances is shown in Fig. 15. From Fig. 15(a) it can be observed that overall consumption was reduced around peak periods, while it increased around off-peak periods; this conforms to the modification of the usage of individual appliances. Furthermore, Fig. 15(b) reveals that the flexibility requirement was met most of the time except during a few time slots.

Table 6
Peak-to-average-ratio (PAR) of CMG load achieved with median run of the algorithms.

Category	Algorithm	PAR	% Cost increase (w.r.t. MA_b)
Proposed	MA_b	1.21	0
State-of-the-art	PSO	1.23	253.56
	DE_{rand}	1.23	231.79
	$DE_{current-to-best}$	1.22	51.83
	HyDE	1.22	90.94
	HyDE-DF	1.22	76.11
	VS	1.22	27.94

5.6.1. Impact of DR on the CMG load profile

The overall load profile of the CMG is modified due to the procured flexibility by the aggregator as shown in Fig. 16(a). The flexibility requirement set by the CMGO was higher around peak hours. Accordingly, the modified load of the CMG was reduced during peak hours (around 19:00-20:00). On the other hand, the modified load of the CMG was increased slightly around 05:00-06:00 (i.e. off-peak hours). Consequently, the peak-to-average ratio (PAR) of the CMG load profile was reduced by 3.97% as shown in Fig. 16(b). The lower value of PAR is conducive to the economic and reliable operation of the CMG. Similar values of PAR were also achieved employing the state-of-the-art algorithms but with the expense of higher cost of flexibility management. Table 6 shows the percentage increase in the median value of flexibility management cost using state-of-the-art algorithms with respect to (w.r.t.) the cost incurred with the proposed MA_b. For almost similar PAR value, the most economical one (i.e., VS) among the state-of-the-art algorithms incurs 27.94% additional cost for the flexibility management. This confirms the effectiveness of the proposed optimization scheme. Although the impact of achieved flexibility in the overall load profile of the CMG is not that prominent, more benefits can be harnessed by motivating more end-users for increased participation in the DR program.

6. Conclusions and future work

In this work, an optimization approach is proposed for flexibility provisioning from residential end-users participating in an incentive-based demand response scheme. The gathered flexibility is utilized to improve the peak-to-average ratio of the community microgrid load profile. A two-stage optimization approach is proposed wherein in the first, a bi-objective formulation is used with incentive payments and penalty payments being minimized. In the second stage, a local search is used to minimize the total cost as a single objective. We refer to this algorithm as a memetic algorithm with bi-objective considerations in stage one (MA_b). The problem is also solved using memetic algorithm (MA_s) where the aggregate/total cost is used as a single objective in stage one. The performance of the proposed algorithm is validated through detail statistical analysis and comparison with six different state-of-the-art algorithms.

The obtained results from numerical experiments show that the proposed MA_s outperforms all the state-of-the-art algorithms in minimizing the net cost of the aggregator for flexibility management. The proposed bi-objective form (MA_b) delivered better performance when compared with MA_s or any other state-of-the-art algorithms. The simulation results reveal that using the proposed MA_b instead of MA_s, the aggregator can reduce the average cost for flexibility management by 20.43%. The analysis of the underlying search trajectories and convergence validates the rationale for better performance of the proposed bi-objective algorithm (MA_b). The utility of the local search is also reflected in the obtained results. Additionally, the statistical tests confirm the consistency of the proposed algorithm.

The proposed optimization approach allowed the aggregator to meet the flexibility requirement by optimally modifying the baseline profiles of the appliances. From the perspective of the CMG, a 3.97% reduction in the peak-to-average-ratio (PAR) of the CMG load profile was achieved using the proposed approach. For the achieved PAR value the proposed optimization approach results in at least 27.94% cost saving compared to the state-of-the-art algorithms

The success of the DR program depends on the strategies that motivate the participation of a large number of end-users. To harness more benefits for CMG from DR programs, this work can be extended by devising effective DR strategies which may include introducing multiple aggregators and interconnected CMGs as well hybrid DR program combining both PBDR and IBDR. Some of these directions are currently being pursued by the authors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abapour, S., Mohammadi-Ivatloo, B., & Hagh, M. T. (2020). A Bayesian game theoretic based bidding strategy for demand response aggregators in electricity markets. *Sustainable Cities and Society, 54*, 101787.

Asadinejad, A., & Tomsovic, K. (2017). Optimal use of incentive and price based demand response to reduce costs and price volatility. *Electric Power Systems Research, 144*, 215–223.

Chauhan, A., & Saini, R. P. (2017). Size optimization and demand response of a stand-alone integrated renewable energy system. *Energy, 124*, 59–73.

Deb, K., & Agrawal, R. B. (1995). Simulated binary crossover for continuous search space. *Complex Systems, 9*(2), 115–148.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation, 6*(2), 182–197.

Derakhshan, G., Shayanfar, H. A., & Kazemi, A. (2016). The optimization of demand response programs in smart grids. *Energy Policy, 94*, 295–306.

Devia, W., Agbossou, K., & Cardenas, A. (2021). An evolutionary approach to modeling and control of space heating and thermal storage systems. *Energy and Buildings, 234*, 110674.

Eissa, M. (2018). First time real time incentive demand response program in smart grid with "i-Energy" management system with different resources. *Applied Energy, 212*, 607–621.

El Geneidy, R., & Howard, B. (2020). Contracted energy flexibility characteristics of communities: analysis of a control strategy for demand response. *Applied Energy, 263*, 114600.

Elghitani, F., & Zhuang, W. (2018). Aggregating a large number of residential appliances for demand response applications. *IEEE Transactions on Smart Grid, 9*(5), 5092–5100.

Gkatzikis, L., Koutsopoulos, I., & Salonidis, T. (2013). The role of aggregators in smart grid demand response markets. *IEEE Journal on Selected Areas in Communications, 31*(7), 1247–1257.

Gregori, M., Matamoros, J., & Gregoratti, D. (2016). Demand response aggregators in microgrid energy trading. *2016 IEEE global conference on signal and information processing (globalSIP)* (pp. 921–925).

Kim, H. J., Kim, M. K., & Lee, J. W. (2021). A two-stage stochastic p-robust optimal energy trading management in microgrid operation considering uncertainty with hybrid demand response. *International Journal of Electrical Power & Energy Systems, 124*, 106422.

Lamprinos, I., Hatziargyriou, N. D., Kokos, I., & Dimeas, A. D. (2016). Making demand response a reality in europe: Policy, regulations, and deployment status. *IEEE Communications Magazine, 54*(12), 108–113.

Lezama, F., Soares, J., Canizes, B., & Vale, Z. (2020). Flexibility management model of home appliances to support DSO requests in smart grids. *Sustainable Cities and Society, 55*, 102048.

Luo, Z., Hong, S., & Ding, Y. (2019). A data mining-driven incentive-based demand response scheme for a virtual power plant. *Applied Energy, 239*, 549–559.

Morsali, R., Thirunavukkarasu, G. S., Seyedmahmoudian, M., Stojcevski, A., & Kowalczyk, R. (2020). A relaxed constrained decentralised demand side management system of a community-based residential microgrid with realistic appliance models. *Applied Energy, 277*, 115626.

Nguyen, D. T., & Le, L. B. (2015). Risk-constrained profit maximization for microgrid aggregators with demand response. *IEEE Transactions on Smart Grid, 6*(1), 135–146.

Qian, L. P., Zhang, Y. J. A., Huang, J., & Wu, Y. (2013). Demand response management via real-time electricity price control in smart grids. *IEEE Journal on Selected Areas in Communications, 31*(7), 1268–1280.

Rana, M. J., Zaman, F., Ray, T., & Sarker, R. (2020). Heuristic enhanced evolutionary algorithm for community microgrid scheduling. *IEEE Access, 8*, 76500–76515.

Rana, M. J., Zaman, F., Ray, T., & Sarker, R. (2021). Real-time scheduling of community microgrid. *Journal of Cleaner Production, 286*, 125419.

Waseem, M., Lin, Z., Liu, S., Sajjad, I. A., & Aziz, T. (2020). Optimal GWCSO-based home appliances scheduling for demand response considering end-users comfort. *Electric Power Systems Research, 187*, 106477.

Xu, F., Wu, W., Zhao, F., Zhou, Y., Wang, Y., Wu, R., … Jiang, S. (2019). A micro-market module design for university demand-side management using self-crossover genetic algorithms. *Applied Energy, 252*, 113456.

Yu, M., Hong, S. H., & Kim, J. B. (2016). Incentive-based demand response approach for aggregated demand side participation. *2016 IEEE international conference on smart grid communications (smartgridcomm)* (pp. 51–56).