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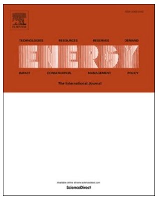

Residential load shifting in demand response events for bill reduction using a genetic algorithm

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ABSTRACT

Flexible demand management for residential load scheduling, which considers constraints, such as load operating time window and order between them, is a key aspect in demand response. This paper aims to address constraints imposed on the operation schedule of appliances while also participating in demand response events. An innovative crossover method of genetic algorithms is proposed, implemented, and validated. The proposed solution considers distributed generation, dynamic pricing, and load shifting to minimize energy costs, reducing the electricity bill. A case study using real household workload data is presented, where four appliances are scheduled for five days, and three different scenarios are explored. The implemented genetic algorithm achieved up to 15% in bill reduction, in different scenarios, when compared to business as usual.

1. Introduction

Residential load usage optimization is a great opportunity to reduce electricity bill. Such optimization should include the participation in Demand Response (DR) events and locally available Distributed Generation (DG) [1,2]. In fact, electricity prices have also been increasing in the past months, it is estimated that electricity prices in 2022 will rise up to 15% in Germany and 14% in France, which raises the need for energy cost optimization [3,4]. According to Ref. [5], Renewable Energy Resources (RERs) account for 25% of 2018's electricity production and are expected to account for 40% globally by 2040. This change in RERs usage can be explained by the increasing awareness in the general public of the negative impacts of fossil fuels on the environment and the link between energy consumption and pollution [6]. As a result, an increasing number of households around the globe have been searching for intelligent systems capable of not only provide monetary savings but also minimize energy usage, primarily through RERs such as photovoltaic energy, in an effort to contribute to a better lower-carbon future by tackling climate change [7,8]. Transactive energy, when applied to smart grids, aims to provide solutions to regulate the rate of generation in both the grid and the demand side of the network, rather than only the consumption side [9].

DR can be described as a change in energy consumption such that the energy demand compares to the energy that can be provided during that time. It can consider a series of stimuli, such as a change in the price of energy or the payment of incentives to consumers who engage in the DR events [10,11]. Furthermore, the usage of DR can increase the flexibility of a power and energy system [12].

A specific type of DR is load shifting, which can be described as shifting loads from peak demand periods to off-peak periods in order to reduce peak energy demand, thus influencing the load curve and reducing energy costs while also improving reliability [13]. Residential consumers can minimize their energy consumption through intelligent systems that participate in DR programs through load shifting [14].

Computational algorithms for load shifting are fundamental to solve complex load demand scheduling problems that require energy consumption and cost optimization. As a result, problems that integrate DG based on renewable energy, dynamic pricing, and high energy-consuming appliances have a big room for potential monetary and energy savings when faced with DR events.

This paper aims to address gaps of the works cited in the related literature section (Section II) by considering both load flexibility with DR participation and bill reduction, taking into account the usage of DG based on renewable energy (e.g., photovoltaic energy), dynamic energy market pricing, and constraints imposed on the operation schedule of appliances (e.g., order between loads and operating time windows). Additionally, it is proposed an innovative approach to Genetic Algorithm (GA) crossovers, which allows higher chances of producing crossed individuals that respect all the imposed constraints in the

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Nomenclature

A	Variables
$EDema(p,a)$	Energy consumption of appliance in period
FI	Fitness value of an individual
B	Parameters
a	Appliance index
A	Total number of available appliances in the operation schedule
$E(p)$	Available distributed generation in period
$EPri(p)$	Energy price in period
p	Specific period
P	Total number of available periods in the operation schedule of appliances
plower	Lower bound period of an interval
pupper	Upper bound period of an interval
$REC^{max}_{Demand(p)}$	Maximum retail energy consumption in period
$REC^{max}_{Demand(plower,pupper)}$	Maximum retail energy consumption in an interval from period to period

operation schedule of appliances.

This paper structure is divided into six main sections. This first introductory section presents a contextualization to the objective of the paper. Section 2 shows state-of-the-art demand response programs with genetic algorithms. Section 3 presents the proposed methodology for load shifting using a genetic algorithm. Section 4 will present in detail the implementation of the proposed solution. Section 5 provides a case study to validate the proposed solution, and finally, the conclusions are presented in section 6.

2. Related literature

The related literature in this subject includes the usage of approaches supported by linear programming [1,2,12,15], and [16], reinforcement learning [17], particle swarm optimization algorithms [18], tabu search [19], and several approaches on GA. In fact, the authors have selected GA to implement in the proposed method in this paper, since GA is capable of providing semi-consistent good solutions and is both highly flexible for problem modeling (e.g., the addition of constraints) and execution time [20,21].

GA is an evolutionary algorithm inspired by natural selection that uses a metaheuristic search-based optimization algorithm. Furthermore, due to the randomness of the mutation operators, GAs have a chance of escaping local optimums and, therefore, although not always, finding the global optimum [22].

Regarding GA driven to DR participation [23], uses demand-side management (DSM) GA strategy that aims to shift household appliances in order to minimize daily energy costs but also guarantee user comfort, by considering a user's appliance usage habits. In addition, it can adapt to multiple users with different habits and the DSM is able to avoid power surges, through power threshold control. The system in Ref. [24] can do load shifting based on the objective function of load shaping in DSM by using a GA. It focuses on controlling power demand during electricity peak hours on residential, industrial, and commercial areas, through flexible load shifting. It achieves this by shifting loads to off-peak hours, however, it only considers energy consumption and not energy costs. Reference [25] also uses a similar GA approach, minimizing the Peak to Average Ratio (PAR), but in this case, it also considers reducing the overall energy cost. While many works already focus on this topic, the highlight of this approach is that it is capable of shifting a large number of shiftable appliances while maintaining low executing times and good results. A proposed hybridization of two optimization algorithms, bacterial foraging, and a GA, is also noteworthy [26] since it also aims to reduce the energy bill and PAR. The emphasis of the work is on day-ahead Real-Time Pricing (RTP) and the performance of the proposed GA-based hybrid model.

Furthermore, in Ref. [27], a multi-objective GA for peak load shaving is proposed that focuses on incorporating Photovoltaic (PV) generation and energy storage to minimize energy waste further. Also similar, a multi-level DSM system using GA is proposed in Ref. [28], which utilizes RERs and energy storage to reduce peak load demand and increase RER usage. The highlight of the work is that it considers using multiple energy sources from an island, such as solar, wind, tidal, and wave. Finally, reference [29] focuses on a GA for direct-load control, providing the users with the ability to control when a load could start and finish (i.e., scheduling window) as well as its power. Also, it considers RER usage and storage but not energy costs (e.g., electricity prices). The work aims to reduce battery discharging energy and conventional power generation in DR events.

Regarding home energy management systems [30], proposes a solution that aims at reducing monetary expenses through load shifting, by considering both electricity prices (flexible and time of use tariff) and RER usage. A Binary Particle Swarm optimization was used to accomplish such results. In Ref. [31], a GA for load shifting is proposed, focusing on the uncertainty of market prices, renewable energy production, and load demand. The solution was tested for DR programs with industrial, commercial, and house loads.

When compared to other works in the literature, such as the work in Ref. [32], which focuses on a trading strategy optimization for cost savings, the present work innovates in some key features. The cited work considers demand response programs and RER usage, features already provided in the present work, however, it lacks the flexibility to provide users with the ability to choose when a load could start and finish, a feature included in the present work. Also, in Ref. [33] it is proposed an innovative direct load control for air conditioners that aims to reduce energy usage and manage peak loads while also taking into account dynamic pricing and real-time demand response incentives. Accordingly, the present work also considers dynamic pricing and demand response incentives, with the latter feature allowing not only the introduction of monetary incentives but also the limitation of load energy in peak hours, if need be, a feature not covered in the cited work. Moreover, a multi-objective approach for cost-peak optimization in residential areas of loads is proposed in Ref. [34]. It considers demand response participation, user comfort, by enabling users to choose their preferred loads operating time window, and a variety of constraints, such as order of execution between loads and limiting the maximum load consumption in a given time. However, it does not consider the usage of RER, and as such the present proposed solution not only includes all the features mentioned in the cited work but also enables the usage of distributed generation, by utilizing available RERs. The hybrid mechanism proposed in Ref. [35] allows for the combination of real-time pricing and incentives while also participating in demand response programs to minimize energy costs and peak load. When compared to the present work, the cited work does not take into account available RER, constraints imposed in the grid, and non-shiftable loads.

Accordingly, looking at the references mentioned above, GAs have been largely used in home energy management systems for load shifting and in the context of DR programs incorporated with issues such as bill reduction, dynamic pricing, DG, and user comfort. However, many of these works only address one to two problems at a time, which, when applied to real-world applications, there is much to be desired in terms of optimization. In addition, some of the works mentioned use standard implementations of GA, with many of these works using the GA library from MATLAB. The present work in this paper aims to handle all of these issues and more, study the trade-offs between them, as well as implement a novel GA without the use of an already existing library. To achieve this, a GA approach is proposed that aims to reduce electricity bill while also considering:

- Demand response programs, through the limitation of load energy in peak hours;
- Dynamic pricing, by shifting loads to off-peak periods, where electricity bills are lower;
- Distributed Generation usage, by efficiently utilizing RERs (e.g., photovoltaic) to minimize electricity usage;
- User comfort, by providing users with the ability to choose when a load could start and finish, according to their appliance usage habits;
- Scheduling constraints, by allowing the proposed solution to respect imposed constraints on the loads. For instance, order between loads (e.g., clothes can only be dried after they are washed);
- Non- and Shiftable loads, for a more realistic and reliable load schedule.

Furthermore, due to the number of possible constraints, a new crossover method is proposed that aims to reduce invalid individuals (i.e., that do not respect all imposed constraints) when multiple constraints are imposed in the operation schedule of appliances.

3. Load shifting optimization methodology

The proposed methodology aims to achieve a bill reduction optimization capable of participating in DR events. It uses an intelligent search-based algorithm, a genetic algorithm, to find a low energy cost operation schedule for appliances. The solution proposed in this paper considers DG (e.g., photovoltaic generation), dynamic pricing, and constraints imposed on the operation schedule of appliances to minimize electricity bill. Also, as long as the customer is flexible enough, the system is robust enough to adapt to a large range of DG amount, selecting the most convenient flexible resources. Fig. 1 represents the proposed methodology, where users must first provide the available appliances and their respective energy profile as well as all the non- and shiftable loads to be included in the operation schedule of appliances. Furthermore, regarding the loads, users also need to describe the comfort constraints (i.e., load order, load operating time window, and load collision constraints) to be imposed on the operation schedule of appliances. Loads operating time windows can be linked to the user's daily consumption behavior and/or preferred times in order to minimize unnecessary adjustments in the user's consumption behavior, while also maximizing monetary savings. These can either be added manually by the user or automated using Internet of Things technology [36]. Retailer energy (i.e., electricity prices) and distributed generation (e.g., PV availability) must also be provided to the scheduler. After obtaining all the aforementioned data, an operation schedule of appliances, that aims at reducing the electricity bill, is provided by the scheduler. However, if a demand response program occurs, a new operation schedule of appliances, using the same data, is scheduled, but with the added energy limit constraint in order to comply with the DR program.

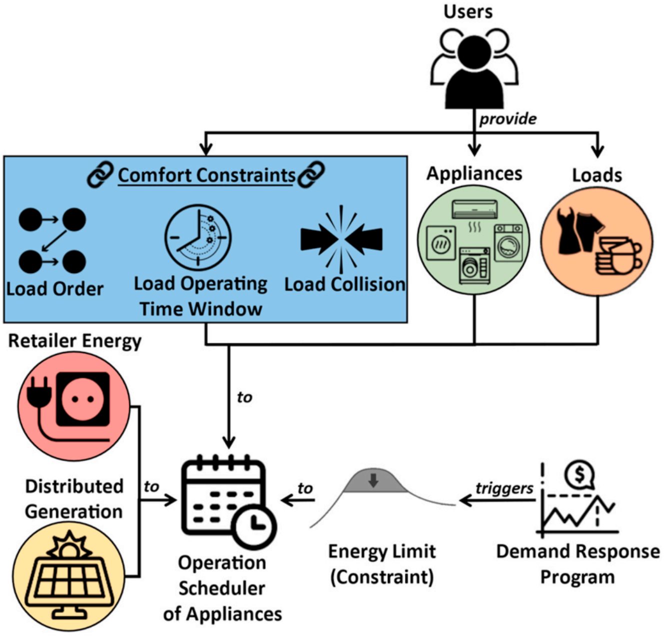

Fig. 1. Proposed load shifting optimization.

A set of concepts describes the domain model of the proposed solution for load shifting:

- **Appliance -** An appliance describes a specific household appliance (e.g., air conditioner, dishwasher, washing machine, clothes dryer);
- **Load -** A load represents an instance of using an appliance. It includes information on the duration of such instance and respective consumption;
- **Retailer energy –** Represents the electricity bought to a retailer at dynamic market prices;
- **Distributed generation –** On-site generated electricity (e.g., photovoltaic);
- **Load order –** Is a user comfort constraint that represents order between loads (e.g., load A can only start after load B is done);
- **Load operating time window –** Is a user comfort constraint that specifies when a load operation is able to start and must be finished (e.g., load A can only start at 7:00 and must be completed by 15:00);
- **Load collision –** Is a user comfort constraint that describes collision interactions between loads (e.g., load A and load B cannot be executing at the same time);
- **Energy limit –** Is the maximum consumption allowed in a given moment. It can be imposed by user preference or by specification of a DR program. (e.g., between 12:00 and 16:00 the net consumption, the retailer energy, must not surpass 5000 kWh).

The proposed solution uses the notion of periods, representing an abstract concept of time; it can be seen as intervals in time. For instance, we can consider 5 s, 10 min, or 1 h, and it is up to the user to decide. All input data must follow the same notion of periods stipulated by the user (e.g., if the load profile's length is specified on a 1-min basis, then the prices and forecasts of the energy market must also be provided in 1 min), ensuring data consistency.

Regarding the validation of the comfort and energy limit constraints in the operation scheduler of appliances, these are done during the execution of the GA.

Considering as an example the operation schedule of appliances in Fig. 3 and the load order constraint that a completed washing machine load must precede every clothes dryer load. To validate the mentioned load order constraint, the algorithm needs to check, considering Fig. 3, that "L7" (clothes dryer load) has at least one preceding washing machine load, in this case, "L5". Afterward, "L8" (clothes dryer load) is validated, in this case, there are two preceding washing machine loads, "L5" and "L6", however, since "L5" is already associated with "L7", the only available remaining washing machine load for "L8" is "L6". Therefore, if all clothes dryer loads have at least one associated washing machine load that is preceding, the load order constraint is successfully validated.

The operating time window constraint is validated by the algorithm by checking whenever or not a load is operating within the stipulated lower and upper bound periods. For example, considering Fig. 3 and the lower and upper periods of 1 and 6, respectively, for the load operating time window of "L3", the algorithm checks first when the load starts, which is in period 1, respecting the constraint, and then checks when the load finished, which is also respecting the constraint since it is in period 4, before the stipulated upper bound of 6.

For the load collision constraint, taking into account Fig. 3 and the collision of loads between the dishwasher and the washing machine, the algorithm checks in each period, if there are loads executing at the same time from the mentioned appliances. For instance, in periods 1 and 2, considering the aforementioned appliances, only "L5" (washing machine load) is executing while in periods 3 to 5 is "L1" (dishwasher load), and the same happens for "L6" (washing machine load) and "L2" (dishwasher load), where these loads are not executing in the same periods. Therefore, in a load collision constraint as long as the loads that can collide are not executing at the same time, the constraint is respected.

The validation of the energy limit constraint can be decomposed into two major equations. The maximum Retail Energy Consumption in a period (REC) is obtained through eq. (1):

$$\sum_{a=1}^{A}{=}_{1} E_{Demand(p,a)} {}^{-} E_{DG(P)} \leq REC^{\max}_{Demand(p)} \forall p \in 1..p \tag{1}$$

Afterward, the energy limit constraint is validated using the maximum Retail Energy Consumption in an Interval (RECI) is represented eq. (2):

$$\sum_{p=p_{lower}}^{p_{upper}} \left(\left(\sum_{a=1}^{A} E_{Demand(p,a)} - E_{DG\left(p\right)\leq} RECI^{\max}_{Demand\left(p_{lower},p_{upper}\right)} \right.\right. \tag{2}$$

4. Genetic algorithm approach

Implementing a bill reduction load shifting system using a GA is divided into four main phases: the creation of the initial population, the breeding of individuals (i.e., crossover), maintaining genetic diversity (i.e., mutation), and the selection of the individuals for the next generation, as shown in Fig. 2.

5. Initial population

The algorithm starts with creating an initial random population, able to comply with all the imposed constraints. It begins by populating with individuals, representing a possible operation schedule of appliances. Duplicated individuals in the population are removed and replaced with another random individual that is not a duplicate. In this way, each individual represents one possible operation schedule of appliances. Then, loads are randomly assigned to each appliance within the load operating time window (e.g., clean load dishes need to be done tomorrow between 9:00 and 17:00). An individual can be seen as a matrix, where each line represents the operation schedule of an appliance, and each column represents the periods, as shown in Fig. 3 where each load is represented by "L" plus a numeric identifier. This approach greatly helps with constraint validation.

5.1. Crossover

Each genetic generation begins with the crossover procedure applied to the previous generation. First, individuals are randomly crossed in pairs from the population pool, for each pair, composed of parent 1 (i.e., individual 1) and parent 2 (i.e., individual 2). Then, the solution of each parent is passed to the child (i.e., the associated appliances and used periods). Every load passed alternates between parents (e.g., adds load according to parent 1, then parent 2, then parent 1, and so on). Each pair of parents produces two children, one by beginning the crossover with parent 1 and another with parent 2.

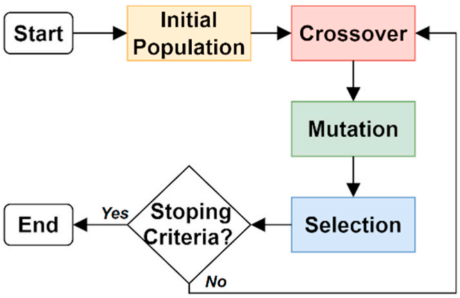

Fig. 2. Flowchart of the proposed genetic algorithm.

Appliance/Period	1	2	3	4	5	6	7	8	9	10
Dishwasher			L1	L1	L1			L2	L2	L2
Air Conditioner	L3	L3	L3	L3			L4	L4	L4	L4
Washing Machine	L5	L5				L6	L6			
Clothes Dryer				L7	L7	L7		L8	L8	L8

Fig. 3. Appliance matrix of an individual.

If a given operation schedule of appliances (related to a given child) does not respect constraints, it is discarded.

The most commonly used crossover approaches (e.g., cutting points) are not much effective when dealing with matrix individuals and complex constraints [11]. Therefore, in the present paper, a more deterministic crossover approach was chosen, where loads are passed to the child alternating between parents from a load list sorted by loads' execution time. The chosen crossover approach allows for a higher chance of producing valid children.

5.2. Mutation

Using the crossover approach can lead to local optimum. A mutation procedure is a way to overcommit. In this paper, the mutation is applied to some individuals from the population obtained in the crossover. According to the percentage of mutation, the algorithm decides which individuals are to be mutated, defined as an optimization control parameter. When a mutation is applied to an individual, then one randomly chosen load is moved by one period, either to the left or right, also randomly chosen.

If the mutated individual does not comply with all constraints, the mutation is reversed, and another load that has not yet been tried for mutation is randomly chosen.

5.3. Selection

In the selection phase, the algorithm selects which individuals inherit to the next generation from a population pool composed of the old and new populations (i.e., the initial population of the previous generation and the crossed and mutated population, respectively). Furthermore, any duplicates in the resulting unified population are eliminated. Finally, each individual is evaluated according to the Fitness Individual (FI), according to eq. (3).

$$FI = \frac{1}{\sum_{p=1}^{p}\left(\left(\left(\sum_{a=1}^{A} E_{Demand(p,a)} - E_{DG}\left(p\right)\right) {}^{*}Eprice\left(p\right)\right)\right.} \tag{3}$$

Both and are used to navigate the operation schedule of appliances matrix, such as the and cartesian coordinates, respectively. In general, the fitness equation can be seen as the inversion of the total energy cost from the operation schedule of appliances, which is determined by the energy balance (consumption – generation) multiplied by the respective energy price. Therefore, higher fitness values represent lower energy costs and thus better individuals to inherit.

After each individual is evaluated, the algorithm selects the n (defined by the user) best individuals (i.e., elite selection), based on the input data, to be inherited to the next generation. Additionally, any remaining individuals (i.e., population size – elite size) are obtained from non-elite tournaments. This type of tournament randomly selects two individuals from the remaining population to compete with each other using their fitness scores, obtained through eq. (3). The higher the fitness score, the higher the chance of an individual being selected; therefore, even the individual with the highest fitness score is not always inherited to the next generation. Furthermore, this approach avoids local maximums since a lower fitness individual could lead to better individuals, and the best individuals are already guaranteed to inherit through elite selection.

After the selection phase, a new generation begins with the population obtained from this selection, and all the procedures mentioned above are repeated. Since the GA always works with good operation schedules, the overall evolution of the GA always trends to create more operation schedules that comply with the DR event.

Finally, when a stop condition is met (e.g., by the number of generations, algorithm execution time, fitness score stagnation, or fitness score reached), the individual with the lowest energy cost operation schedule of appliances generated by the GA is extracted and used as the operation schedule of appliances found by the algorithm.

6. Results and discussion

This section presents the results and discussion of a case study that highlights the benefits of the proposed solution. The case study used is based on a household with four appliances to be scheduled for five days that has available PV energy. While the proposed solution is able to provide the schedule for far more days (e.g., for a whole week or a longer period), only five days were considered to better demonstrate the obtained results. Also, the five days represent concrete consumption days, with specific days for flexibility. The solution proposed in this paper was implemented using the Python programming language. No GA libraries were used in the implementation since no library was appropriate for adding complex constraints to the proposed solution.

6.1. Case study

The case study used in this paper uses real household workload data, locally generated PV data, and energy market prices provided by Refs. [1,16]. The house case study is presented in Fig. 4. Energy prices reflect a double tariff: on-peak hours, between 8:15 and 22:00, 0.1879 EUR/kWh; off-peak prices are 0.101 EUR/kWh. The workload data represents five full days (i.e., from 0:00 to 23:59) of business as usual (BAU) workload, which is to be optimized energy cost-wise (i.e., reduce electricity bill) by the proposed algorithm. Three load shifting optimization scenarios are explored: scenario "A," which represents standard load flexibility; scenario "B," which describes low load flexibility; and scenario "C," which is characterized by having high load flexibility. The case study uses 15 min for all loads and energy data, thus having a total number of available periods of 480. The case study considers four different appliances and a culmination of them (e.g., HI-FI, microwave, television, and fridge) consuming energy and are not considered to be able to shift, denominated as "*Other*." The four appliances considered are an air conditioner, a dishwasher, a washing machine, and a clothes dryer. Fig. 5 represents the energy profiles of one load, from start to finish, for each appliance. Therefore, the case study uses four different loads: an air conditioner load with a duration of five and a half hours, the dishwasher with an execution time of one and a half hours, a washing machine with a profile of one and a half hours, and the clothes dryer with 1 h. Also, for this case study, each load for each appliance is executed three times. Non-shiftable appliances, denominated as the load "*Other*," it has the energy profile represented in Fig. 6, for each day considered in the case study.

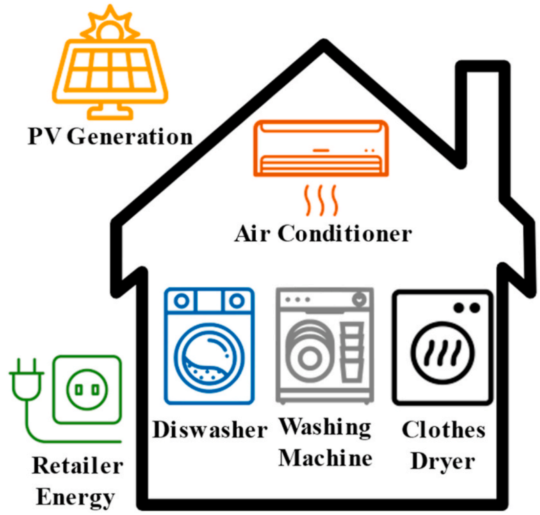

Fig. 4. Case study house scenario.

The case study uses two constraints: load order and load operating time window. The order constraint was applied so that a completed washing machine load must precede every clothes dryer load. The operation schedule execution time ranges considering both the BAU and load shifting scenarios for the load operating time window constraint are represented in Table 1.

The BAU scenario aims to simulate the regular user consumption when no electricity bill reduction is taken into account. Therefore, it does not prioritize DG usage and low energy price periods. The operation schedule of appliances for the BAU scenario is shown in Fig. 7. In this scenario, generated PV, provided by photovoltaic panels, is poorly used, as most appliances execute in low PV availability periods. Furthermore, as complemented by Fig. 11, some loads are positioned in high demand periods, where energy price is highest. Therefore, there is a significant margin of improvement for the BAU scenario, as loads on both low PV availability and high energy price periods could be shifted for electricity bill savings. For this scenario, the overall total electricity bill is 119.26 EUR.

6.2. Results scenario A

The load shifting scenario with standard load flexibility, also denominated as scenario "A," contrarily to the BAU scenario, clearly demonstrates, through Fig. 8, that the proposed solution utilizes generated PV as much as possible, thus reducing the demand for external energy suppliers. Also, the black arrows represent the imposed order constraint; thus, all constraints are respected. For this case study, the overall total electricity bill from the load shifting scenario "A" is 104.05 EUR, thus improving 12.7% from the BAU scenario.

Fig. 11 represents the energy consumption from both scenarios (i.e., BAU and scenario "A"), available PV, and energy market prices. Apart from high generated PV usage from the algorithm in the load shifting scenario, the higher the energy prices, the lower the energy consumed, thus loads are being shifted to reduce electricity bill. Also, it is noteworthy that on day 4, even though there is available PV, the algorithm

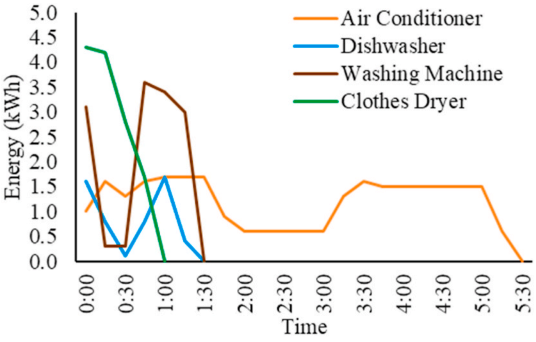

Fig. 5. Appliances energy profiles.

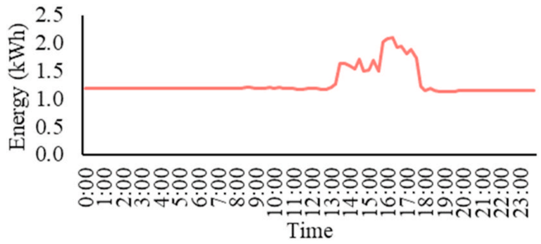

Fig. 6. Non-shiftable appliances energy profile in a day.

chose instead to shift loads to lower energy price periods. Due to high energy prices and high consumption, the available PV would not cover the high costs. The cost (i.e., electricity bill) difference between both scenarios (load shifting “A" − BAU) is represented in Fig. 12. It demonstrates bill reductions mainly at the end of days 1, 2, and 3. The overall electricity bill reduced is 15.21 EUR.

6.3. *Results scenario B*

Scenario “B" describes a load shifting scenario with low load flexibility than scenario “A.” The operation schedule of appliances and available PV for scenario “B" are represented in Fig. 9, showing less generated PV utilization when compared to scenario “A.” This could be related to having lower flexibility and thus not shifting loads to periods with available PV. Nonetheless, when complemented with Fig. 11, it is clear that even though the algorithm could not shift loads to available PV periods, it instead shifted them to lower energy price periods. For example, there are huge energy consumptions around the dawn of days 4 and 5, where energy price is at its lowest. Furthermore, there is also some consumption in the mornings of days 2 and 3, just before on-peak hours. The overall total electricity bill of scenario “B" is 108.68 EUR, thus improving 8.9% from the BAU scenario.

The cost difference between the BAU and “B" scenarios is shown in Fig. 13. Similar to scenario “A,” it demonstrates electricity bill savings at the end of days 1, 2, and 3. However, it is noteworthy that there is a huge bill increase on the noon of day 2, meaning that loads were shifted to these periods instead. The overall electricity bill reduced is 10.58 EUR.

6.4. *Results scenario C*

The load shifting scenario “C" aims at simulating scenario “A" but with much higher load flexibility, allowing loads to be shifted to available PV periods that previously could not. Fig. 10 represents the operation schedule of appliances for scenario “C,” which shows when compared to scenario “A,” that scenario “C" utilizes PV generation much more efficiently, having the majority of its loads in these periods. Moreover, through Fig. 11, we can conclude that almost every load not using PV generation is in off-peak hours. Therefore, due to PV availability and energy price optimization coupled with very flexible loads, scenario “C" can further minimize electricity bills than scenario “A,” reaching an overall total electricity bill of 101.70 EUR. Compared to the BAU scenario, scenario “C" has an improved bill reduction of 14.7%.

Fig. 14 represents the cost difference between scenarios BAU and “C.” As already stated in scenarios “A" and “B,” “C" also has electricity bill reductions at the end of days 1, 2, and 3. This similar occurrence in the three scenarios implies that, when taking into account Fig. 7, the

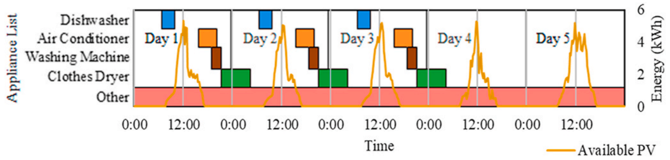

Fig. 7. Business as usual operation schedule of appliances.

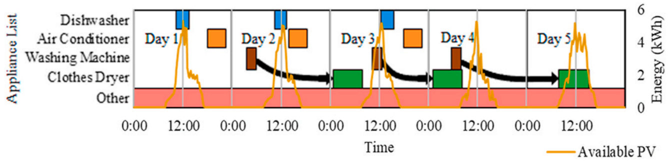

Fig. 8. Load Shifting Operation Schedule of Appliances for Scenario A, black arrows represent the order constraint “Washing Machine” then “Clothes Dryer."

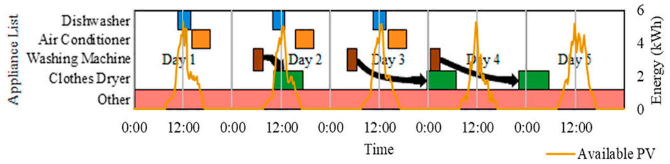

Fig. 9. Load Shifting Operation Schedule of Appliances for Scenario B, black arrows represent the order constraint “Washing Machine” then “Clothes Dryer."

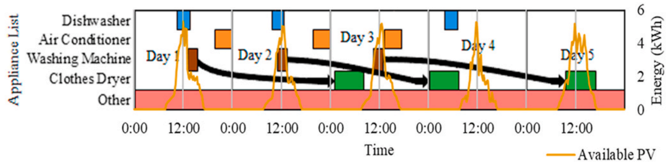

Fig. 10. Load Shifting Operation Schedule of Appliances for Scenario C, black arrows represent the order constraint “Washing Machine” then “Clothes Dryer."

Table 1
Load operating time window.

Load	BAU	Scenario A (Standard Flexibility)		Scenario B (Low Flexibility)		Scenario C (High Flexibility)	
		Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Dishwasher “1″	7:00 Day 1	9:00 Day 1	17:00 Day 1	9:00 Day 1	14:00 Day 1	9:00 Day 1	7:00 Day 2
Air Conditioner “1″	16:00 Day 1	14:00 Day 1	22:30 Day 1	14:00 Day 1	20:00 Day 1	13:00 Day 1	00:00 Day 2
Washing Machine “1″	19:00 Day 1	0:00 Day 2	17:00 Day 2	0:00 Day 2	8:00 Day 2	9:00 Day 1	7:00 Day 2
Clothes Dryer “1″	21:30 Day 1	19:00 Day 2	17:00 Day 3	10:00 Day 2	7:00 Day 3	9:00 Day 2	23:59 Day 3
Dishwasher “2″	7:00 Day 2	9:00 Day 2	17:00 Day 2	9:00 Day 2	14:00 Day 2	9:00 Day 2	7:00 Day 3
Air Conditioner “2″	16:00 Day 2	14:00 Day 2	22:30 Day 2	14:00 Day 2	20:00 Day 2	13:00 Day 2	00:00 Day 3
Washing Machine “2″	19:00 Day 2	0:00 Day 3	17:00 Day 3	0:00 Day 3	8:00 Day 3	9:00 Day 2	7:00 Day 3
Clothes Dryer “2″	21:30 Day 2	19:00 Day 3	17:00 Day 4	10:00 Day 3	7:00 Day 4	9:00 Day 3	23:59 Day 4
Dishwasher “3″	7:00 Day 3	9:00 Day 3	17:00 Day 3	9:00 Day 3	14:00 Day 3	9:00 Day 3	7:00 Day 4
Air Conditioner “3″	16:00 Day 3	14:00 Day 3	22:30 Day 3	14:00 Day 3	20:00 Day 3	13:00 Day 3	00:00 Day 4
Washing Machine “3″	19:00 Day 3	0:00 Day 4	17:00 Day 4	0:00 Day 4	8:00 Day 4	9:00 Day 3	7:00 Day 4
Clothes Dryer “3″	21:30 Day 3	19:00 Day 4	17:00 Day 5	10:00 Day 4	7:00 Day 5	9:00 Day 4	23:59 Day 5
Other	0:00 Day 1	0:00 Day 1	23:59 Day 5	0:00 Day 1	23:59 Day 5	0:00 Day 1	23:59 Day 5

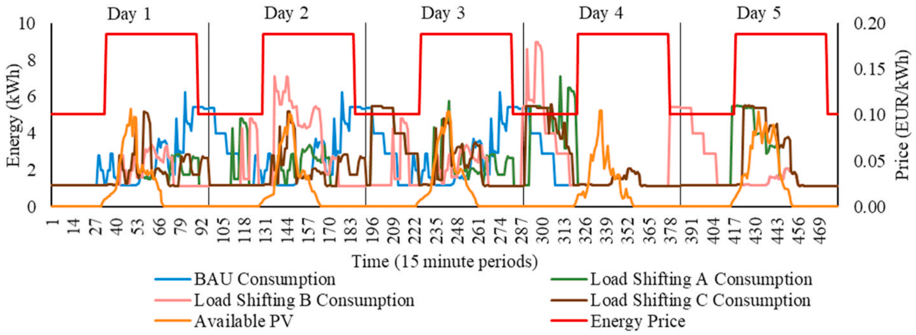

Fig. 11. Energy consumption, energy price, and available PV.

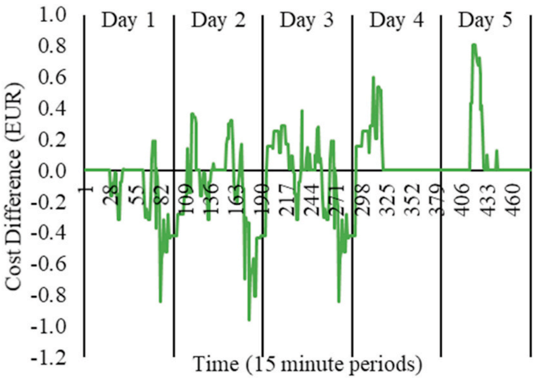

Fig. 12. Scenario A cost difference (load shifting A − BAU).

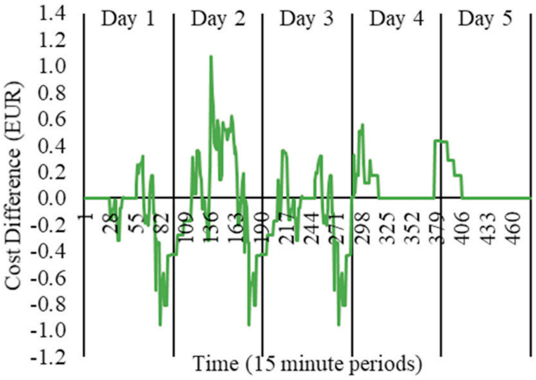

Fig. 13. Scenario B cost difference (load shifting B − BAU).

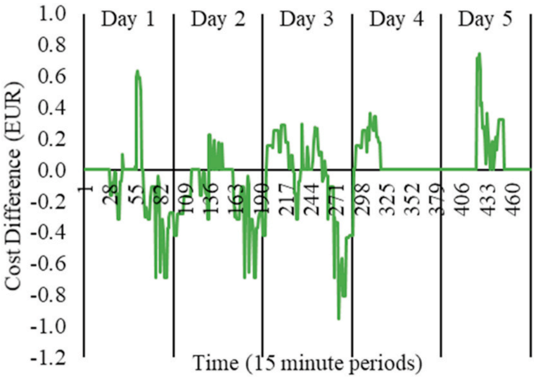

Fig. 14. Scenario C cost difference (load shifting C − BAU).

clothes dryers are highly inefficient at 21:30 of days 1, 2, and 3. Also noteworthy from Fig. 14 is that electricity bill increases are more or less balanced between the five days, except for bill spikes at noon of days 1 and 5. Therefore, when given more flexibility, the proposed solution can efficiently balance the loads' electricity bills among its available scheduling days. The overall electricity bill reduced is 17.56 EUR.

6.5. *Discussion*

The electricity bill of each scenario and their bill difference with the BAU scenario and overall bill reduction percentage is represented in Table 2. Results show that the proposed solution effectively reduces electricity bills, allowing household consumers to save up 10.58 to 17.56 EUR on five days. Subsequently, if applied to a whole month, it can save 65.60 to 108.87 EUR on bills. Furthermore, even though scenario "B" is the least flexible when comparing bill reductions, it still pulls an overall electricity bill reduction of 8.9%. Also, it is noteworthy that there are diminishing returns when increasing load flexibility. For instance, from scenario "B" to scenario "A," there is an improvement of 3.8%, while from scenario "A" to scenario "C," there is only a gain of 2.0%. Therefore, the algorithm is already effective enough for consumers to use it with their standard loads' schedules without sparing more time to save more money since there are diminishing returns.

For this case study, load shifting scenario "A," the GA was executed for 30 min, equivalent to around 634 generations. The performance of the proposed GA can be seen through the cost of the best individual of each genetic generation, as shown in Fig. 15. The results imply a good performance since they follow a decreasing logarithmic function. However, they do not represent a perfect logarithmic function because we also have to consider the number of constraints applied since they limit the number of available solutions. It is noteworthy that, for this case study, only 187 genetic generations were needed to achieve a good solution, thus demonstrating that the algorithm only needed about 9 min to find a good solution, lower than the stipulated 30 min of execution time.

The GA in scenario "B" was also executed for 30 min, having 783 genetic generations. The cost evolution of the best individual in the GA can be seen in Fig. 16. Results show that the GA has bad performance since the cost does not follow a decreasing logarithmic function. However, we must consider that this scenario has the lowest load flexibility compared to the other scenarios, making it very difficult for the algorithm to find a reasonable solution (i.e., a solution that respects all

Table 2
Scenario bill.

Scenario	Bill (EUR)	Bill Difference from BAU	Bill Reduction (%)
BAU	119.26	0	0%
Scenario A	104.05	15.21	12.7%
Scenario B	108.68	10.58	8.9%
Scenario C	101.70	17.56	14.7%

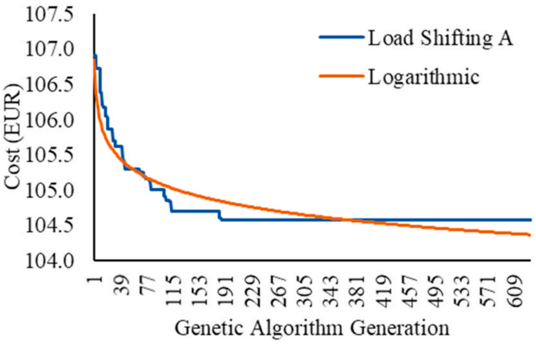

Fig. 15. Cost per generation of the genetic algorithm in scenario A.

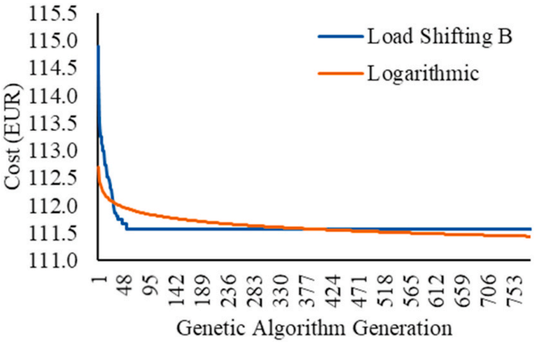

Fig. 16. Cost per generation of the genetic algorithm in scenario B.

imposed constraints) and one with better fitness values. As a result, from Fig. 16, it is unclear if the GA had a good performance. Nonetheless, let's only consider the difference between the first and last best individuals, which amounts to 6.21, an improvement of 5.41%, and compare it to 2.67% from scenario "A" and 7.27% from scenario "C." We can conclude that scenario "B" has similar bill reduction as the other scenarios, thus implying that it has a good GA performance. Furthermore, the best solution found by the GA was at generation 54; therefore, the algorithm only needed around 2 min of execution time to find a good solution for scenario "B."

Scenario "C" has a total of 1149 genetic generations from 30 min of GA execution time. Compared to the other scenarios, the high number of genetic generations is that, due to the high load flexibility in the scenario, there is a wider variety of reasonable solutions, thus reducing the need for repair or exclusion of invalid solutions. The cost of the best individual per generation of the GA, shown in Fig. 17, clearly demonstrates a high performance from the GA, with the cost evolution of scenario "C" almost being a decreasing logarithmic function. To achieve such a good solution, the GA used 588 generations, equivalent to around 15 min of execution time.

Through the convergence analysis of the GA, by using different scenarios, we can conclude that the proposed solution, when confronted with lower load flexibility scenarios, has worse fitness evolution. In contrast, higher load flexibility scenarios reach an almost perfect convergence function.

It is worth noting that, when comparing qualitatively to other works such as in Refs. [23–25], and [31] which can achieve up to 29.0%, 21.9%, 26,7%, and 28.2% in monetary savings, respectively, the proposed solution seems to have limited bill reduction capabilities, achieving only 14.7% in bill reduction. However cited works, while also having different case studies, do not consider the ability to choose when a load could start and finish, forcing users to adjust their daily consumption behavior. Also, many of these works do not consider constraints imposed on the operation schedule of appliances, such as load order or collision. On the other hand, the works proposed in Refs. [26, 30] had improvements of 10.0% and 6.1%, respectively, from their BAU scenario, lower than the proposed solution obtained results, while at the same time not having the same level of flexibility and constraint application as the proposed solution.

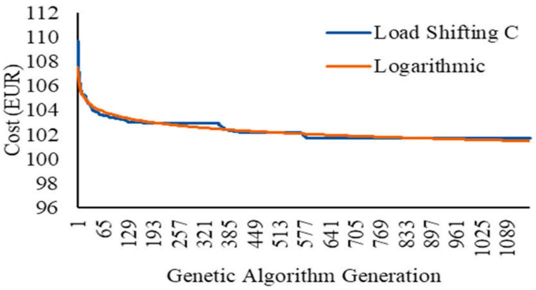

Fig. 17. Cost per generation of the genetic algorithm in scenario C.

7. Conclusions

With the increasing challenge of climate change, households need to start managing energy resources more effectively, mainly high energy-consuming appliances. Through incentives and changes in energy prices, participation in DR programs can be a good solution to the problem.

Accordingly, the solution proposed in the present paper aims to use a GA to participate in DR events and minimize electricity bill in the operation schedule of appliances through flexible load shifting. Furthermore, it considers DG, dynamic pricing, and constraints imposed on the loads.

The results obtained in the presented case study highlight the effectiveness of the proposed solution in allocating loads to reduce electricity bills when considering four different appliances, PV generation, a bi-hourly tariff, and two imposed constraints. Given the results, loads were shifted to off-peak periods of lower energy prices or high PV availability periods, reducing the overall electricity bill.

While there are still many challenges ahead that need to be overcome in order to tackle climate change, this paper's ambition is to contribute to the reduction of energy and electricity bills in households. It aims to promote a more sustainable future by incentivizing users to change their daily consumption behaviors and invest in DG to gain significant bill reductions.

Author contributions

Bruno Mota: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. Pedro Faria: Conceptualization, Formal analysis, Methodology, Validation, Writing – review & editing. Zita Vale: Conceptualization, Investigation, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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