

Flexibility management model of home appliances to support DSO requests in smart grids

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ABSTRACT

Several initiatives have been taken promoting clean energy and the use of local flexibility towards a more sustainable and green economy. From a residential point of view, flexibility can be provided to operators using home-appliances with the ability to modify their consumption profiles. These actions are part of demand response programs and can be utilized to avoid problems, such as balancing/congestion, in distribution networks. In this paper, we propose a model for aggregators flexibility provision in distribution networks. The model takes advantage of load flexibility resources allowing the re-schedule of shifting/real-time home-appliances to provision a request from a distribution system operator (DSO) or a balance responsible party (BRP). Due to the complex nature of the problem, evolutionary computation is evoked and different algorithms are implemented for solving the formulation efficiently. A case study considering 20 residential houses equipped each with seven types of home-appliances is used to test and compare the performance of evolutionary algorithms solving the proposed model. Results show that the aggregator can fulfill a flexibility request from the DSO/BRP by re-scheduling the home-appliances loads for the next 24-h horizon while minimizing the costs associated with the remuneration given to end-users.

1. Introduction

The global environmental situation has been raising the European Union concern about the impact of the energy sector in this regard. Due to this, several initiatives have been taken for energy sustainability promoting clean energy (i.e., renewable generation) and maximizing the use of local flexibility towards a low carbon, more sustainable, green economy (Soares, Pinto, Lezama, & Morais, 2018a). The transformation of the electrical grid, led by smart grid technologies, promises a series of benefits in the areas of interest, such as efficient energy management and high penetration of renewables. However, such transformation also imposes new challenges in operation and management that should be addressed to exploit its full potential at the different levels of the energy supply chain including distribution networks (Siano, 2014; Spiliotis, Gutierrez, & Belmans, 2016).

A solution to take advantage of smart grid technologies comes with the use of advanced communication capabilities. Such functionalities offer an alternative for demand-side management (DSM) and the implementation of demand response (DR) programs allowing the participation of end-users in solving distribution network problems by the use of flexibility from home-appliances (Elghitani & Zhuang, 2017). Energy

flexibility is typically referred to as the amount of load that can be modified (either shifted, reduced or curtailed) over timescales, and is playing a pivotal role in the new energy market model (Sadeghianpourhamami, Strobbe, & Develder, 2016).

From a residential point of view, flexibility can be provisioned to operators through the use of home-appliances with the ability to modify their profiles (either by reducing or shifting their loads to different periods of the baseline operation). The aggregator emerges as a crucial player in this context, offering a possibility for small consumers of enrolling in DR programs and take advantage of their flexibility (Faria, Spnola, & Vale, 2016). Aggregators, therefore, will pursue an efficient use of the distributed energy resources in the so-called local energy communities. This new local environment envisages a proper definition of processes and participants to allow transactive energy exchanges, addressing local constraints (Graditi, Somma, & Siano, 2018; Lezama et al., 2018a).

In this paper, we develop further the model proposed in Sousa, Lezama, Soares, Ramos, and Vale (2018), by adding an aggregator that manage an energy community of home energy management systems (HEMS), performing a re-schedule of home appliances for flexibility provision. In this way, aggregators can provide flexibility to

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Notation	
Sets	
A	set of appliances with shifting capabilities
B	set of appliances with reduction capabilities
Indices	
t	period
i	appliance index with shifting capabilities
j	appliance index with reduction capabilities
k	duration index of shifting appliances' profiles
Parameters	
N_T	number of periods
N_I	number of appliances with shifting capabilities
N_J	number of appliances with reduction capabilities
$t_{start(i)}$	baseline start period of appliance i
$O_{t(i)}$	operation time profile of appliance i
$P_{A(i,k)}$	load profile power of appliance i at period k
$Int_{start(j,t)}$	intensity of appliance j in period t
$P_{B(j)}$	maximum power capacity of appliance j (kW)
$A_{base(i,t)}$	baseline power of appliance i at period t (kW)
$B_{base(j,t)}$	baseline power of appliances j at period t (kW)
$P_{base(t)}$	aggregated baseline profile of all appliances at period t
	(kW)
$F_{DSO(t)}$	flexibility required by the DSO/BRP in period t (kW)
$C_{DSO(t)}$	penalty for mismatch flexibility request (EUR/kWh)
User-preferences	
$Pref_{A(i)}$	preference for i type A (tuple $[t_{allow(i)}, D_{allow(i)}, C_{A(i)}]$)
$Pref_{B(j)}$	preferences for j type B (tuple $[t_{allow(j)}, D_{allow(j)}, I_{min(j)}, I_{max(j)}, C_{B(j)}]$)
$t_{allow(i)}$	allowed starting time for shifting/reduction of device i/j
$D_{allow(i)}$	allowed interval for shifting/reduction of device i/j
$I_{min(j)}$	minimum allowed intensity reduction for device j
$I_{max(j)}$	maximum allowed intensity increase for device j
$C_{A(i)}$	remuneration for shifting device i (EUR)
$C_{B(j)}$	remuneration for reduction/increase device j (EUR/kWh)
Variables	
$t_{new(i)}$	new starting period of appliance i
$A_{flex(i,t)}$	power of appliance i at period t after shifting (kW)
$Int_{new(j,t)}$	new intensity of appliance j in period t
$B_{flex(j,t)}$	power of appliance j at period t after reduction (kW)
$P_{flex(t)}$	new aggregated demand profile at period t (kW)
$F_{agg(t)}$	flexibility provided by the aggregator at period t (i.e., difference between aggregated baseline and demand profile after shifting and reduction)

distribution system operators (DSO) or balance responsible parties (BRP), re-optimizing the available resources for monetary compensations. Due to the complexity of the mathematical formulation, a swarm intelligence algorithm, the particle swarm optimization (PSO) (Kennedy, 2011), is used to find acceptable solutions for the re-schedule of devices for the day ahead.

The paper is structured as follows: Section 2 reviews some energy management systems based on aggregators, positioning our work in the state-of-the-art. Section 3 presents the description and mathematical formulation of the problem. Section 4 introduces the use of evolutionary computation as an efficient tool for solving the proposed problem. Section 5 presents the case study based on real load profiles of appliances. Results are shown in Section 6, to finally conclude the paper in Section 7.

2. State-of-the-art on aggregation management systems

The transformation of the energy sector is pushing towards a more sustainable energy grid. In this context, energy flexibility becomes of paramount importance to achieve sustainable energy goals, providing an efficient way for balance supply and demand under the increasing variable patterns of energy consumption (including, e.g., renewables and EVs). Prosumers (consumers with production capabilities) have been identified as a possible source of the flexibility that the power grid needs. However, the flexibility that small prosumers can offer individually may not be sufficient to alleviate power grid problems. Therefore, the role of the “aggregator” arises as a solution to gather overall flexibility volumes from small prosumers, giving them the opportunity to gain access to markets and unlock their flexibility value (USEF Foundation, 2015).

The demand response solutions present in a considerable number of countries usually consider resources connected to Medium and High Voltage levels (i.e., industrial loads) (Lipari, Del Rosario, Corchero, Ponci, & Monti, 2018; Paiho et al., 2018). The aggregation of customers and prosumers at LV are scarcely considered in the published works. Therefore, the system requires aggregators to manage the resources

connected at LV level in the most efficient way. The work in Lampropoulos, van den Broek, van der Hoofd, Hommes, and van Sark (2018) identifies opportunities and barriers for flexibility services through aggregators for companies in the Dutch energy system. The study concludes that there are still market, regulatory, technical and social barriers. In addition, policy adaptations are required for the provision of operating reserves. The potential technologies and means to increase the flexibility of the Finnish energy systems is investigated in Paiho et al. (2018). Authors introduce renewable energy data from the country and discuss how flexibility is defined. Technologies to provide flexibility means include energy storage systems, electric vehicles, district heating and cooling, smart meters, demand response, and energy markets.

Different aggregator models have been adopted in the literature aiming at the aggregation of flexibility and energy for different goals. Optimization is usually adopted in large part of the works available in the literature. A load aggregator for the portfolio of energy consumers is presented in Roos, Ottesen, and Bolkesjø (2014). The aggregator solves an optimization model with the objective to gather flexibility from the loads and storage to minimize the total consumption costs. The optimization model includes a detailed representation of the physical system at each consumer, however shifting load of appliances and their detailed profiles are not included. The study concludes that it is possible a potential reduction of 4% in the portfolio energy cost, despite batteries are yet not a compelling investment due to its inefficiency and high costs. Optimal bidding strategy for aggregators is proposed in several works as a tool to obtain the best possible bidding strategy to participate in wholesale and local energy markets. The most common works are for day-ahead wholesale energy market. The work proposed in Di Somma, Graditi, and Siano (2018) presents an optimization model provided for the participation of an aggregator in the day-ahead market in the presence of demand flexibility. The model is based on a stochastic MILP considering uncertainties of intermittent generation facilities and market price with the goal to find the optimal bidding strategies while maximizing the expected profit. Prieto-Castrillo, Shokri Gazafroudi, Prieto, and Corchado (2018) analyses customers demand flexibility in a

local power trading scenario through an Ising spin-based model. The authors analyze the system on a large scale, considering the accumulated benefit of all the actors involved, and also from the perspective of total aggregation. In the maximum flexibility scenario, the total aggregation profit increases with the number of aggregators, suggesting that a higher number of interactions in the low level are to the involved players. The Energy Box Aggregator – EBAG, is presented in Carreiro, Oliveira, Antunes, and Jorge (2015). This aggregator represents a mediator between the system operator (SO) and the end-user, enabling the coordination of large-scale flexibility with the in-house deployed devices. The EBAG aims at gathering demand-side flexibility provided by clusters of end-users to make it available for system service requirements, by lowering or increasing the power demand in each period of a given planning horizon. This enables the load/supply balancing, avoiding peaks, coping with the intermittent nature of renewable energy sources (RES). At the same time, the model increases the overall system efficiency by offering an alternative to supply investments on reserve and peak generation. It uses a multi-objective optimization model that maximizes the aggregators profits, considering the revenues from the SO and payments made to end-user clusters, while minimizing the inequity between the load flexibility provided by each cluster. The authors from Jacobsen et al. (2015) designed an architecture based on an ICT platform, which provides management, forecasting, aggregation and load scheduling of numerous end-users. It is a scalable infrastructure enabling the participation of the residential level in DR programs, with an aggregator at the core operation. The infrastructure was validated with a large-scale simulation considering 200.000 households. The study concludes that the remuneration schemes given to end-users would lead to a more secure and sustainable supply. Wu, Shahidehpour, Alabdulwahab, and Abusorrah (2016) develops a stochastic optimization model aiming at the aggregation of EVs flexibility for ancillary services. This aggregator also considers conditional value at risk to measure uncertainties associated with EVs bidding process. A bi-level problem is then transformed to a MILP problem that can be solved with mathematical programming with equilibrium constraints. The work in Abapour, Mohammadi-Ivatloo, and Hagh (2019) propose that DR aggregators compete together to offer their DR services to the network operator and in this way provide compensation for customers. The proposed DR program is based on price elasticity and customer benefit function and the Nash equilibrium idea is used to solve the problem. The profit of the network operator is increased by 7 percent. The work in Spinola, Faia, Faria, and Vale (2017) presents an approach to address aggregation of distributed resources using clustering techniques. With the combination of metaheuristics and clustering techniques, the aggregator can guarantee the number of resources and amount of energy for each group for the day-ahead operation. In Henrquez, Wenzel, Olivares, and Negrete-Pincetic (2018), a model to determine the optimal operation of a DR aggregator is presented in the context of wholesale electricity markets. The aggregator portfolio includes load curtailment and flexible loads. This approach also considers the uncertainty of market prices and balancing requirements that impact the aggregator activities. In Olivella-Rosell et al. (2018), a market-based mechanism was developed for aggregators, showing the needed interactions between local market stakeholders, as well as inputs/outputs of operation algorithms from the participants. It is claimed that a local market may contribute to postponing grid upgrades, reduce energy costs and increase grid capacity.

Table 1 depicts the most related works from the selected literature review where our proposal is highlighted. Our paper proposes an aggregator placed between prosumers and the DSO/BRP to gather the flexibility from residential houses in an attempt to match the DSO flexibility requests with day-ahead anticipation. The contributions to the state-of-the-art are as follows:

- (1) Consideration of shifting and real-time reduction/increase ability of energy appliances in the aggregator/DSO flexibility model.

Table 1
Summary of most related works.

Ref.	Devices considered in the approach	Planning horizon and interval	Optimization algorithm	DSO player	Comments
Lipari et al. (2018)	Electric energy storage	Day-ahead intervals of 15 min	Not specified	Yes	There is no actual coordination of flexibility volume inside the residential houses; Only volumes are passed to the automation management system.
Roos et al. (2014)	Electric energy storage	Day-ahead 1 h interval	Deterministic mixed integer linear programming (MILP)	No	The study considers participation in wholesale and tertiary regulation market but the DSO entity is not.
Di Somma et al. (2018)	Combined heat and power (CHP), auxiliary boilers (AB), PV, absorption chiller (AChil), heat pumps (HPs), batteries, and thermal energy storage	Day-ahead 1 h interval	Stochastic optimization model using MILP approach	No	Flexibility is provided by clusters of local energy systems considering interactions of various energy carriers (e.g., gas, electricity, heat, and cooling). DSO is not considered.
Prieto-Castrillo et al. (2018)	Shiftable-Loads in general not specifically detailed	Day-ahead 1 h interval	Linear programming	Yes	The aggregators buy and sell power from DSO. Flexibility is explored in the shifting loads but the power profiles are not take into account. Social welfare increases when flexibility increases.
Henrquez et al. (2018)	Load reduction, shift and fixed loads. General but not detailed.	Day-ahead 1 h interval	Mixed-integer linear programming	No	Bi-level formulation solved as MILP. The aggregator is considered to be a strategic participant in the real-time market. The portfolio is composed of various contracts of load curtailment and flexible loads that can be executed for hourly load change
Olivella-Rosell et al. (2018)	Electric vehicles and batteries, shiftable loads, generators	Day-ahead intervals of 15 min	Not specified	Yes	This work enable multiple participants to compete for selling or buying flexibility. DSO is considered as a stakeholder. The optimization method and scalability of approach is not specified.
Proposed work	Real-time devices (Lighting, TV, Desktop, Air Conditioner, Washing) and shifting devices (Machine, Tumble Dryer, Dish Washer)	Day-ahead intervals of 15 min	Metaheuristics (PSO, DE, VS, Hybrid Adaptive DE (with and without Decay Function))	Yes	The proposed work includes a vast number of state-of-the-art EC methods to address a challenging problem: Aggregator-DSO consideration.

- (2) Consideration of detailed consumption profiles for shifting and real-time reduction/increase devices.
- (3) Consideration of duration time and start time for each appliance (baseline profile).
- (4) Scalable optimization approach using evolutionary computation methods (metaheuristics) that can scale to thousands of appliances/devices.
- (5) Monetary compensation for shifting devices using an activation scheme instead of the volume transacted.

At the best of our knowledge these contributions are yet not reported or scarce. The details and assumptions made for this work are explained in the following section.

3. Problem description

In this section, we introduce the framework and some assumptions made in our model. After that, we provide the mathematical formulation as an optimization model to minimize the aggregator's costs due to flexibility provision.

3.1. Aggregator flexibility provision to DSO/BRP

In a previous work (Sousa et al., 2018), we considered modern HEMS installed at the end-users side for managing appliances with shifting capabilities in response to a flexibility request from an aggregator. The HEMS was able to optimize the shifting time of a variety of appliances and re-schedule them to maximize the monetary compensation received for the flexibility provision. In this paper, we extend that model in the following way (Fig. 1):

- We focus on the perspective of an aggregator in charge of a HEMS with different devices with DR capabilities.
- Two types of devices are considered for DR, namely devices which consumption can be shifted to a different period, and devices with real-time control capabilities (Basit, Sidhu, Mahmood, & Gao, 2017).
- The aggregator is prepared to respond to a flexibility request from a DSO or a BRP, who pays monetary compensation for each power unit (p.u.) of flexibility provisioned.
- The aggregator makes use of a flexibility management system to re-schedule some appliances and match, as close as possible, the flexibility curve procured by the DSO.
- End-users have the capability of registering devices for flexibility provision and configuring their preferences regarding allowed shiftable times, expected remuneration due to flexibility activation,

- a priority of the available devices for activation, among others.
- We assume that the required infrastructure for achieving such management and control (e.g., smart metering systems, communication lines, HEMS) is available (Lezama, Palominos, Rodríguez-González, Farinelli, & de Cote, 2017).
- Both, the DSO/BRP and the aggregator, have access to forecast baseline power consumption provided by a third party (the baseline represents normal consumption in case no DR is activated) (USEF Foundation, 2015).

3.2. Mathematical formulation

The problem can be modeled as a Mixed-Integer Non-Linear Programming (MINLP) in which the aggregator strives to match a flexibility request from the DSO/BRP, paying a remuneration to the households participating in the DR program according to their preferences and the modification of their baseline profile.

In our model, let $A = \{1, \dots, N_f\}$ be the set of all appliances with shifting capabilities, and $B = \{1, \dots, N_r\}$ be the set of all appliances with reduction capabilities registered in the aggregator's EMS. Each appliance with shifting capabilities is characterized by tuple $A_i = [t_{start(i)}, O(i), p_{A(i,k)}] \in A$, where $t_{start(i)}$ represents the baseline starting period of functioning program of appliance i , $O(i)$ is the time duration of a given program of appliance i , and $p_{A(i,k)}$ is the power profile of a given functioning program of appliance i defined in the interval $k = [1, \dots, O(i)]$. On the other hand, each appliance with real-time control capabilities is characterized by a tuple $B_j = [p_{B(j)}, Int_{start(j,t)}] \in B$, where $p_{B(j)}$ is the maximum power of appliance j , and $Int_{start(j,t)}$ is the baseline intensity of appliance j in time t .

It is assumed that users have access to a HEMS interface in which they can configure their preferences. A tuple $Pref_{A(i)} = [t_{allow(i)}, D_{allow(i)}, C_{A(i)}]$ is defined by the user, specifying the starting allowed time $t_{allow(i)}$, the window duration $D_{allow(i)}$ for aggregator's control access, and the expected remuneration $C_{A(i)}$ (in EUR) to be received if device i is shifted in the allowed window. With these parameters, the shifting periods of devices type A are constrained by the user as:

$$t_{allow(i)} \leq t_{new(i)} \leq t_{allow(i)} + D_{allow(i)} \tag{1}$$

where $t_{new(i)}$ is the new starting period of appliance i . Similarly, a tuple $Pref_{B(j)} = [t_{allow(j)}, D_{allow(j)}, I_{min(j)}, I_{max(j)}]$, defines the allowed periods where intensities of appliances of type B can modified (i.e., $t_{allow(j)}, D_{allow(j)}$), the maximum allowed reduction/increase of consumption of such devices (i.e., $I_{min(j)}, I_{max(j)}$), and the expected remuneration $C_{B(j)}$ (in EUR/kWh) to be received for the amount of power reduction/increase of device j in the allowed window. Thus, the

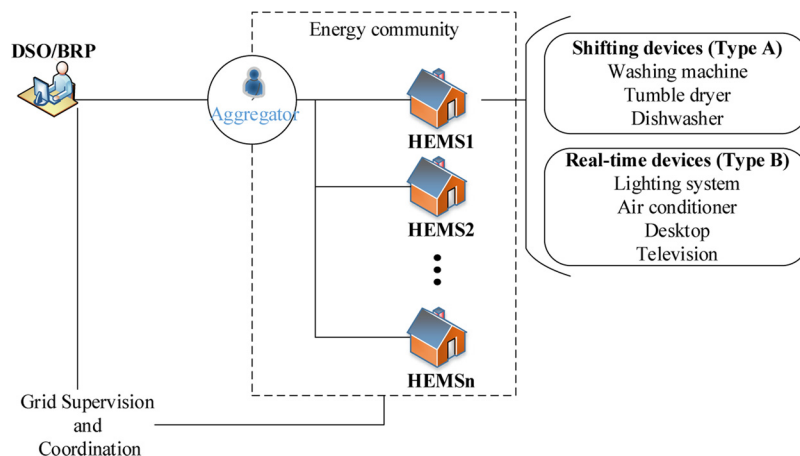


Fig. 1. The problem description considers a distribution network in which an aggregator is in control of the management of devices with DR capabilities. The users register voluntarily for participation in flexibility provision receiving monetary compensation if their baseline profile is modified.

modification of power profiles of devices type B are constrained by the user as follows:

$$I_{\min(j)} \leq \text{Int}_{\text{new}(j)} \leq I_{\max(j)} \quad (2)$$

$$\text{Int}_{\text{new}(j,t)} = \begin{cases} \text{Int}_{\text{new}(j,t)} & \text{if } t_{\text{allow}(j)} \leq t \leq t_{\text{allow}(j)} + D_{\text{allow}(j)} \\ \text{Int}_{\text{start}(j,t)} & \text{otherwise} \end{cases} \quad (3)$$

where $\text{Int}_{\text{new}(j,t)}$ is a variable in the range $[0,1]$ for each $t \in N_T$ defining a modification (in percentage) of the baseline profile.

The flexibility provisioned by the aggregator (i.e., $F_{\text{agg}(t)}$) is defined as the difference between the baseline profile, and the new scheduled profile as follows:

$$F_{\text{agg}(t)} = P_{\text{base}(t)} - P_{\text{flex}(t)} \quad (4)$$

where $P_{\text{base}(t)}$ is the baseline profile and $P_{\text{flex}(t)}$ is the resulting profile after re-scheduling appliances. Notice that a third party should determine the baseline since it represents the expected power consumption of the appliances if no re-schedule or modification is performed. It is assumed that the aggregator has the information regarding the baseline consumption of each household, and it uses this information to determine the flexibility offer.

Eqs. (5)–(7) are used to represent the baseline profile:

$$P_{\text{base}(t)} = \sum_{i=1}^{N_I} A_{\text{base}(i,t)} + \sum_{j=1}^{N_J} B_{\text{base}(j,t)} \quad (5)$$

$$A_{\text{base}(i,t)} = \begin{cases} P_{A(i,t-t_{\text{start}(i)}+1)} & \text{if } t_{\text{start}(i)} \leq t \leq t_{\text{start}(i)} + O_{t(i)} - 1 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

$$B_{\text{base}(j,t)} = P_{B(j)} * \text{Int}_{\text{start}(j,t)} \quad (7)$$

where Eq. (5) captures the aggregated power of all appliances at a given time t . Eq. (6) captures the power of shifting appliance i at a given time t , $t_{\text{start}(i)}$ is the baseline starting period of operation, and $O_{t(i)}$ is the number of periods of the operation program of device i (e.g., considering 15 min periods, a washing machine can start its baseline operation at $t_{\text{start}} = 5\text{--}1:00$ am, and have a duration of operation program of $O_{t(i)} = 9\text{--}135$ min). Eq. (7) captures the baseline power of appliance j at time t considering intensity $\text{Int}_{\text{start}(j,t)}$ being a number in the range $[0,1]$ (representing a percentage of the consumption). Notice that variables $t_{\text{start}(i)}$ and $\text{Int}_{\text{start}(j,t)}$ are input parameters to represent baseline consumption patterns.

On the other hand, the aggregator is in charge of determining new starting periods $t_{\text{new}(i)}$ for the appliances with shifting capabilities and new intensities $\text{Int}_{\text{new}(j,t)}$ for the appliances with reduction capabilities. Eqs. (8)–(7) represents the determination of the new consumption profile:

$$P_{\text{flex}(t)} = \sum_{i=1}^{N_I} A_{\text{flex}(i,t)} + \sum_{j=1}^{N_J} B_{\text{flex}(j,t)} \quad (8)$$

$$A_{\text{flex}(i,t)} = \begin{cases} P_{A(i,t-t_{\text{new}(i)}+1)} & \text{if } t_{\text{new}(i)} \leq t \leq t_{\text{new}(i)} + O_{t(i)} - 1 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

$$B_{\text{flex}(j,t)} = P_{B(j)} * \text{Int}_{\text{new}(j,t)} \quad (10)$$

where Eq. (8) represents the new consumption profile after determining optimal starting periods $t_{\text{new}(i)}$ (Eq. (9)) and intensities $\text{Int}_{\text{new}(j,t)}$ (Eq. (10)) for all the appliances managed by the aggregator.

In order to maximize the aggregator profits, the objective function can be modelled as the minimization of the remuneration to be paid to the households plus a penalty for the mismatch of flexibility procured by the DSO/BRP:

$$\text{Minimize } f = \left(\sum_{i=1}^{N_I} \text{Rem}_{A(i)} + \sum_{j=1}^{N_J} \text{Rem}_{B(j)} \right) + C_{\text{DSO}} \cdot F_{\text{match}} \quad (11)$$

$$\text{Rem}_{A(i)} = \begin{cases} C_{A(i)} & \text{if } t_{\text{start}(i)} \neq t_{\text{new}(i)} \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Rem}_{B(j)} = C_{B(j)} \cdot \sum_{t=1}^{N_T} |B_{\text{base}(j,t)} - B_{\text{flex}(j,t)}|$$

$$F_{\text{match}} = \sum_{t=1}^{N_T} |F_{\text{agg}(t)} - F_{\text{DSO}(t)}|$$

where the first term of Eq. (11) corresponds to the monetary compensation paid for shifting device i (a flat payment $C_{A(i)}$ in EUR is considered despite how many periods the device is shifted); the second term corresponds to the remuneration given for the modification of the baseline profile of devices type B (where $C_{B(j)}$ is a compensation paid in EUR/kWh modification); and the third term corresponds to a penalty, C_{DSO} in EUR/kWh, paid for the mismatch between the flexibility procured by the DSO ($F_{\text{DSO}(t)}$) and the flexibility provided by the aggregator ($F_{\text{agg}(t)}$) in each period t .

4. Evolutionary computation as optimization method

Due to the combinatorial nature and complexity of the problem (which also can turn into a large-scale optimization problem when a large number of devices is considered), we evoke the use of evolutionary computation (EC) as a solver (Soares, Pinto, Lezama, & Morais, 2018b). EC includes algorithms for global optimization inspired by evolutionary processes. Typically, evolutionary algorithms (EA) are population-based solvers that act over an initial set of candidate solutions (i.e., a population or swarm) that is iteratively updated. A given fitness function measures the performance of solutions. Every iteration, new solutions are generated and introduced into the population, replacing solutions with low performance in the fitness function. Thus, following the principles of natural/artificial selection, it is expected that the population will gradually evolve towards a promising area of the search space (Soares et al., 2018b).

Many approaches have been developed in the field of EC (e.g., particle swarm optimization (PSO), differential evolution (DE), and all their variants, just to mention a few). In fact, EAs can target different problems by defining an encoding of solutions (i.e., a way to represent solutions to the problem typically in the form of vectors) and a fitness function to evaluate the performance of such solutions. Therefore, how to encode individuals for this problem, the fitness function, and the EC approaches used to solve the optimization problem, are introduced in this section.

4.1. Encoding of solutions for flexibility provision

One fundamental aspect of population-based algorithms is the encoding of the solutions. Depending on the problem, particles/vectors must contain all the information associated with a solution and should be evaluated in a fitness function in order to measure their performance.

For the specific problem tackle in this paper, a given solution \vec{x} must contain all the new starting periods of appliances with shifting capabilities (type A) and the new intensities of real-time appliances (type B).

The information related to appliances type A can be encoded in a vector:

$$\vec{x}_{\text{shift}} = [t_{\text{new}(1)}, t_{\text{new}(2)} \dots t_{\text{new}(N_I)}] \quad (12)$$

where \vec{x}_{shift} contains the decision variables $t_{\text{new}(i)}$ corresponding to the new starting period of appliance $i \in A$.

On the other hand, new intensities for appliances type B should be defined for all of their operation periods and are encoded as:

$$\vec{x}_{\text{int}} = [(\text{Int}_{\text{new}(1,1)}, \dots, \text{Int}_{\text{new}(1,N_T)}), (\text{Int}_{\text{new}(2,1)}, \dots, \text{Int}_{\text{new}(2,N_T)}), \dots, (\text{Int}_{\text{new}(N_j,1)}, \dots, \text{Int}_{\text{new}(N_j,N_T)})] \quad (13)$$

where \vec{x}_{int} contains the decision variables $\text{Int}_{\text{new}(j,t)}$ representing the new intensity of the j th appliance in the operation period t .

The two vectors can be concatenated in a solution in the form $\vec{x} = (\vec{x}_{\text{shift}}, \vec{x}_{\text{int}})$, containing all the new shifting periods and intensities. Such vector \vec{x} can be therefore evaluated in the fitness function equivalent to objective function Eq. (11).

Infeasible solutions are avoided since variable boundaries are kept within the ranges in each iteration.

4.2. Evolutionary algorithms

Now that we defined the encoding of individuals and the fitness function, we can basically apply any EA to solve the problem. In this paper, we have chosen differential evolution (DE) and two of its variants HyDE and HyDE-DF (due to its success in many applications and easy implementation (Das & Suganthan, 2011)), an improved version of the well-known Particle swarm optimization (PSO) (Soares, Ghazvini, Silva, & Vale, 2016), and a single-solution evolutionary algorithm called vortex search (VS) (Dogan & Olmez, 2015).

- **Differential evolution (DE):** DE uses a population (Pop) of individuals $\vec{x}_{j,i,G} = [x_{1,i,G}, \dots, x_{D,i,G}]$, where G is the generation number, and $i = [1, \dots, \text{NP}]$ is the number of individuals in the population, to optimize a function with D variables (i.e., the dimension of the problem). In the initialization stage, NP solutions are generated randomly within lower and upper ranges of decision variables $[x_{\text{lb},j}, x_{\text{ub},j}]$. DE follows the general iterative form of EAs by creating new solutions, applying a mutation and recombination operator, and performing elitist selection (solutions with better fitness survive for the next generation) in each iteration. The mutation and recombination operators of the DE/rand/1 algorithm are defined as:

$$\vec{t}_{j,i,G} = \begin{cases} \vec{m}_{j,i,G} & \text{if } (\text{rand}_{i,j}[0, 1] < \text{Cr}) \vee (j = \text{Rnd}) \\ \vec{x}_{j,i,G} & \text{otherwise} \end{cases} \quad (14)$$

where $\vec{m}_{i,G} = \vec{x}_{r1,G} + F(\vec{x}_{r2,G} - \vec{x}_{r3,G})$, and $\vec{x}_{r1,G}, \vec{x}_{r2,G}, \vec{x}_{r3,G} \in \text{Pop}$ are three random individuals from the Pop, mutually different from each other. F and Cr are the mutation and recombination parameters of DE, usually set in the range $[0, 1]$. The fitness function, (i.e., Eq. (11)), is used to evaluate the performance of new individuals. A detailed explanation of DE can be found in Das, Abraham, Chakraborty, and Konar (2009), Lezama, Soares, Faia, Pinto, and Vale (2018).

- **HyDE and HyDE-DF:** Hybrid-adaptive DE (HyDE) is a new self-adaptive version of DE proposed in Lezama, Soares, Faia, et al. (2018). HyDE uses an operator known as DE/target-to-perturbed_{est}/1 that modifies the well-known DE/target-to-best/1 strategy (Das & Suganthan, 2011) with a perturbation of the best individual (inspired by the evolutionary PSO (Miranda & Fonseca, 2002)), and the self-adaptive mechanism of jDE (Brest, Greiner, Boskovic, Mernik, & Zumer, 2006). The main operator of HyDE is defined as follows:

$$\vec{m}_{i,G} = \vec{x}_{i,G} + F_1^1(\epsilon \cdot \vec{x}_{\text{best}} - \vec{x}_{i,G}) + F_1^2(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \quad (15)$$

where F_1^1 and F_1^2 are scale factors in the range $[0, 1]$ independent for each individual i , and $\epsilon = \mathcal{N}(F_1^3, 1)$ is a random perturbation factor taken from a normal distribution with mean F_1^3 and standard deviation 1. F_1^1, F_1^2 and F_1^3 are updated each iteration following the same rule of jDE algorithm (see Sect. III.B of Lezama, Soares, Faia, et al. (2018)). HyDE with decay function (HyDE-DF) is an improved version of HyDE used for function optimization (Lezama, Soares, Faia, & Vale, 2019). It incorporates a decay function to perform a transition in the iteration process from the main operator of HyDE (Eq. (15)) to the basic operator of DE/rand/1. This transition allows an enhanced phase of exploration in the early stage of evolution and stress the exploitation in later stages of the optimization.

- **Particle swarm optimization (PSO):** PSO (Soares et al., 2016) belongs to the class of swarm intelligence (SI), in which particles

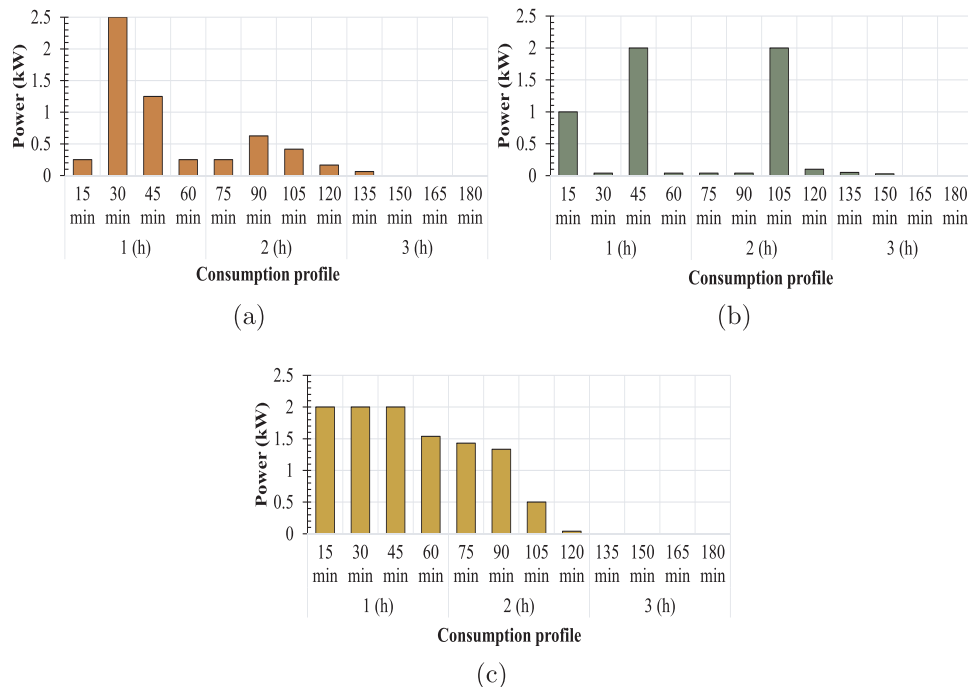


Fig. 2. Typical consumption profiles of appliances with shifting capabilities (each 15 min). (a) Washing Machine (9 periods = 2.25 h) (b) Tumble Dryer (8 periods = 2 h). (c) Dishwasher (10 periods = 2.5 h).

(solutions to the problem) coordinate their actions by modifying their position towards the optimum value. Particles are evaluated in the fitness function and improve their position in each iteration (similar to the iterative process in EAs).

- Vortex search (VS): VS is classified as a single-solution based metaheuristic, although it has an analogous framework to the EAs as well. In each iteration, N given number of neighbor solutions are generated using a multivariate Gaussian distribution around the initial solution. Those N solutions are evaluated in the fitness function, and the single-solution is updated with the best solution found. The iterative process is repeated until a stop criterion is met (Dogan & Olmez, 2015).

We do not included a detailed explanations of the selected EAs since it is not the main scope of this work, but the reader can consult the cited references for further details.

5. Case study

In the case study, we assume that the aggregator has direct control of some of the household devices that users voluntarily register through flexibility contracts and under specific preferences that can be configured in their HEMS. Different from Sousa et al. (2018), in addition to shifting devices, in this work, real-time devices are also considered. The main difference between these two types of appliances is explained below (Basit et al., 2017):

1. Shifting devices: Fully-programmed devices which consumption program can be shifted (scheduled) at a later or previous time when, for instance, an incentive is offered to the user for such modification. Devices with this characteristic fit well for flexibility provision purposes.
2. Real-time devices: real-time devices are considered those in which the load consumption can be slightly modified in a period (either in down-regulation or up-regulation). These devices present a low degree of flexibility, depending on the basic needs and the priority of the consumers.

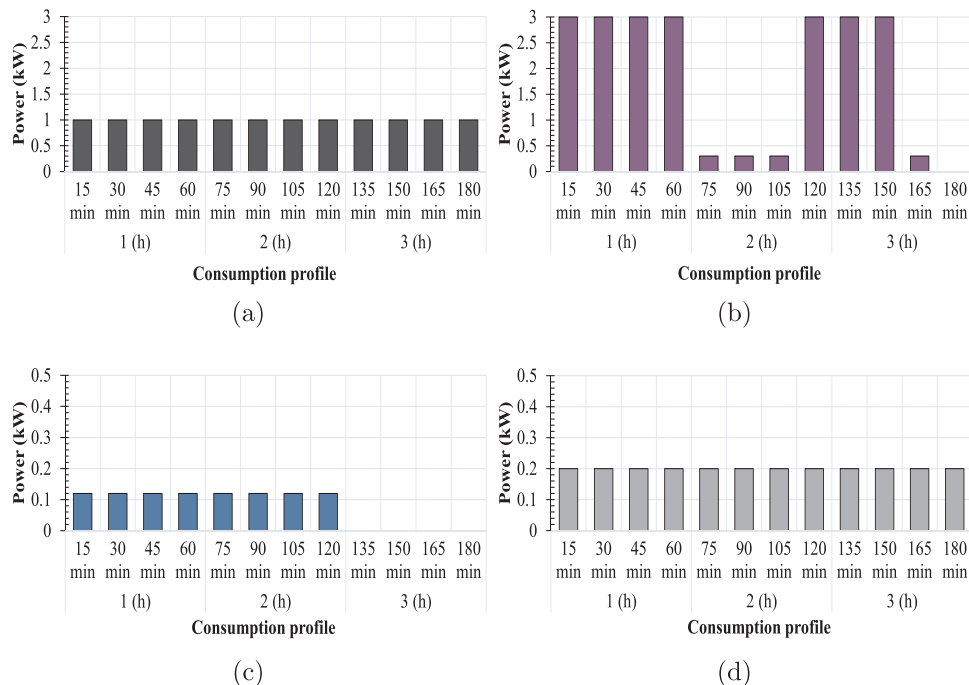


Fig. 3. Typical consumption profiles of appliances with real-time reduction capabilities (each 15 min). (a) Lighting system (12 periods = 3 h). (b) Air conditioner (11 periods = 2.75 h). (c) Desktop (8 periods = 2 h). (d) Television (12 periods = 3 h).

Table 2
Individual (and aggregated) consumption of one (and 20) houses equipped with the considered appliances.

Appliance	Type	Peak power (kW)	Energy (kWh)	Remuneration (EUR)
Washing machine	Shifting	2.5	5.77	± 30% of 0.2
Tumble dryer	Shifting	2	10.84	± 30% of 0.2
Dish washer	Shifting	2	5.34	± 30% of 0.2
Lighting system	Real-time	1	12.00	± 30% of 0.09
TV	Real-time	0.2	2.40	± 30% of 0.09
Desktop	Real-time	0.12	0.96	± 30% of 0.09
Air conditioner	Real-time	3	22.20	± 30% of 0.09
Aggregated (one house)		10.82	59.51	
Aggregated (20 houses)		216.4	1190.20	

The case study considers houses equipped with appliances belonging to one of the above categories. Expressly, we assume houses with the following appliances: (A) shifting devices with profiles showed in Fig. 2: washing machines, tumble dryers, and dishwashers; (B) real-time devices with typical consumption showed in Fig. 3: lighting devices, air conditioner, computer desktop and televisions. A brief description and the characteristic consumption profile of these devices is summarized in Stammering et al. (2008).

A study on Demand Side Response (DSR) aggregators, carried out by Curtis (2017), revealed that customers need a minimum of 200 kW of DSR potential to be assessed as financially viable. Therefore, taking into account the consumption profiles of the considered appliances, it would be necessary to aggregate 20 clients with similar dwellings to achieve the required power. Therefore, we have created 20 profiles for each type of device using a randomized function with uniform distribution, 5% around the standard profiles showed in Figs. 2 and 3. Table 2 presents the consumption and type of appliances considered in this work. A total peak consumption of around 217 kW is achieved, considering 20 houses with similar appliances. For the creation of the baseline profiles (i.e., the starting periods $t_{start(i)}$ of appliances A_i and B_j in the formulation of Section 3.2), we distributed randomly 10% of the

appliances from period 1 to 40 (i.e., 00:00 to 10:00 h), 30% of the appliances from period 41 to 56 (i.e., 10:00 to 14:00 h), 10% of the appliances from period 56 to 76 (i.e., 14:00 to 19:00 h), and the remaining 50% between periods 76 to 88 (i.e., 19:00 to 22:00 h). With this distribution of devices, we aim at creating an initial baseline profile matching a typical daylight consumption profile. Fig. 4 shows the baseline profile, corresponding to a vector $P_{\text{base}(t)}$. $P_{\text{base}(t)}$ contains 96 values of power consumption corresponding to the aggregated power of all the appliances for the next 24 h in 15 min interval.

To simulate the preferences of shifting devices, a randomized uniform function was used to generate allowed windows in the range of 0 to 64 periods (16 h), and the expected remuneration was assumed to be $\pm 30\%$ of 0.2 EUR to simulate different participation of users. On the other hand, a randomized uniform function was used to generate allowed intensity modification ranges between 0 and 0.4 (i.e., from 0 to up to 40% of the device power), and the expected remuneration was assumed to be $\pm 30\%$ of 0.09 EUR/kWh modified.

Our model is built upon the idea that a DSO/BRP might be interested in buying flexibility from an aggregator. This idea has been explored in other works, such as the USEF framework (USEF Foundation, 2015), in which aggregator and DSO have a contractual relationship for the trade of flexibility. Following this, in our case study, we have considered the request for flexibility by a DSO (for the day ahead) showed in Fig. 5. For the simulation, the flexibility request is represented as an input vector $F_{\text{DSO}(t)}$ with 96 values (corresponding to 24 h in 15 min interval) representing power values either for up-regulation (increase in consumption) or down-regulation (decrease in consumption).

While several assumptions can be made for the creation of the baseline and the flexibility requested by the DSO, the case study was designed to have enough diversity on the prices and consumption over the day, reflecting users behaviour according to typical patterns (For instance, following the low voltage tariffs in Portugal on-line: <https://www.edpsu.pt/pt/tarifasehorarios>).¹

5.1. Algorithm settings

We have compared the performance of five EAs to solve the flexibility provision optimization problem proposed in Section 3. The algorithms are the well-known DE (Price, Storn, & Lampinen, 2006), the more recently proposed HyDE and HyDE-DF (Lezama et al., 2019; Lezama, Soares, Faia, et al., 2018), an improved PSO (Soares et al., 2016), and the VS (Dogan & Olmez, 2015). The selected algorithms are population-based approaches with similar mechanisms,² performing a number of function evaluations (FE) equal to the size of the population in each iteration. Thus, the size of population/neighbour solutions was set to 20, with a budget of $2e5$ iterations for all the algorithms.

The parameters for each algorithm were chosen according other studies. For DE, the mutation factor and recombination constant (F and Cr) were set to the recommended values 0.9 and 0.5 respectively (Price et al., 2006). HyDE and HyDE-DF (Lezama, Soares, Faia, et al. (2018) are self-adaptive parameter versions, but initial values for F^i and Cr were set to 0.9 and 0.5 as well. VS algorithm does not have any parameter to configure (Dogan & Olmez, 2015).

6. Results and discussion

The algorithms and experiments were implemented in MATLAB

¹ The case study data, as well as the simulation platform, can be found in <https://fernandolezama.github.io/publication>. Therefore, the study can be easily replicated, and the analysis of further scenarios is left as further work.

² VS is not strictly speaking a population-based approach but evaluates in each iteration a given number of neighbour solutions, which results in the same number of FE per iteration as the other algorithms.

2018a in a computer with Intel Xeon(R) E5-2620v2@2.1 GHz processor with 16GB of RAM running Windows 10. Due to the stochastic nature of EAs, 30 trials have been performed to validate the overall performance of the algorithms. The mean, standard deviation, and the best values were recorded for each algorithm.³

6.1. EAs performance comparison and convergence

We have compared the performance of algorithms regarding their convergence capabilities and minimization cost for the aggregator. Table 3 presents the minimum, maximum, mean, and standard deviation (std) values of the fitness (Eq. (11)) obtained by the tested algorithms. The table also presents the average remuneration (Rem_{AndB} paid by the aggregator to users) and penalties (DSO_{mismatch} paid by the aggregator to the DSO due to the mismatch of flexibility), as well as the average time required by the algorithms to find a solution.

It can be seen that all the algorithms attain acceptable solutions to the problem requiring similar optimization time. Apart from PSO, DE_{current-to-best}, HyDE, HyDE-DF, and VS have similar average fitness value. This can also be explained due to the sensitivity of parameters inherent to PSO. Further studies to tune the parameters (or the use of self-adaptive versions, can be suggested as an interesting avenue of research. The best minimum and average fitness were found with VS, while HyDE obtained the best std value.

We also analyze the convergence of the algorithms, to validate their performance and robustness finding good solutions. Fig. 6 shows the average convergence achieved by the tested algorithms. It can be seen that, while PSO and DE_{rand} have similar convergence curves, DE_{rand} attains a final average fitness similar to the other tested algorithms. In fact, all DE_{current-to-best}, HyDE, HyDE-DF, and VS have similar convergence curves and fitness value.

To provide further insights into the resulting profiles, remuneration and match of flexibility, in the next subsection we analyze the best solution found by DE_{rand} (one of the best among all the solutions found).

6.2. Baseline profile and re-scheduled profile for flexibility provision.

As we specified in Eq. (11), the model should find an optimal re-scheduling of devices to modify the baseline profile (showed in Fig. 4) and make a match with the flexibility requested by the DSO (showed in Fig. 5).

Fig. 7 shows the baseline profile (light blue color) and the modified profile (dark blue) after applying the optimization model. It can be noticed that the consumption is reduced in peak hours (red circles in periods 10–14 and 19–23), following the request of flexibility. The shift in consumption also has an impact during non-peak hours (red circle in period 5–7), presenting an increase of power in the early hours of the days. It is important to point out that this modification will only occur if the procured flexibility is activated by the DSO. A contractual agreement for the remuneration and settlement rules must exist between the aggregator and the DSO to this end.

To appreciate the match of flexibility obtained by the aggregator, Fig. 8 shows the flexibility requested by the DSO (light blue colour) and the flexibility provisioned by the aggregator after the re-scheduling of devices. It can be noticed that the aggregator can find a new schedule of devices that can match to a certain degree the request made by the DSO. It is essential to point out that the modification of the baseline schedule, from the perspective of the aggregator, implies a change from the optimal scheduling of appliances (assuming that the aggregator is equipped with the technology to perform an optimal energy resource

³ For the sake of reproducible research, case study data and complete experimentation files can be found in <https://fernandolezama.github.io/publication>.

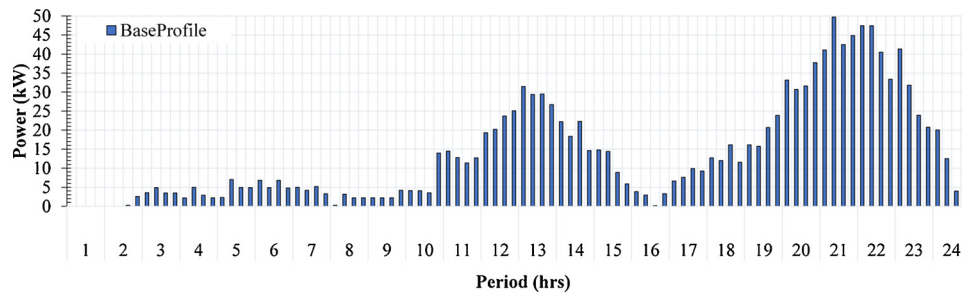


Fig. 4. Baseline consumption profile of all considered appliances. Peak consumption hours are identified approximately between hours 10:00 to 14:00 and 19:00 to 23:00.

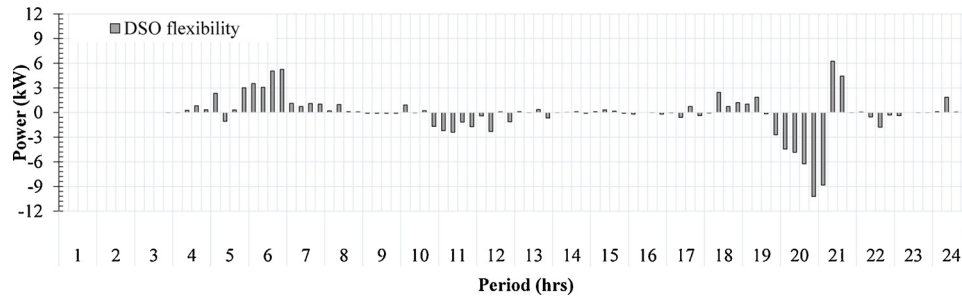


Fig. 5. Flexibility required by the DSO for the next 24 h in 15 min interval. Positive values represent an increase in consumption, while negative values represent a reduction.

Table 3
Statistical values obtained by the algorithms related to fitness, remuneration, penalties and time.

	Fitness (EUR)				Agg cost (EUR)		Time (min)
	Min	Max	Mean	Std	Rem _{Aand B}	DSO _{mismatch}	
PSO	13.77	16.59	15.34	0.86	9.07	6.27	144.23
DE _{rand}	4.91	10.55	7.66	1.34	4.27	3.39	146.40
DE _{current-to-best}	5.81	8.01	6.91	0.55	5.86	1.05	148.09
VS	3.93	8.07	6.76	0.78	5.78	0.98	149.91
HyDE	6.68	8.36	7.64	0.44	6.72	0.92	146.23
HyDE-DF	6.36	8.63	7.53	0.63	6.65	0.87	147.72

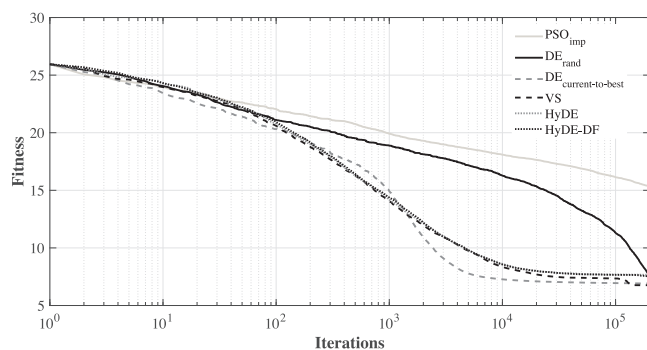


Fig. 6. Average convergence of the tested EAs. HyDE-DF achieved the best results, followed by VS algorithm.

management of devices). Therefore, the aggregator must achieve such modification using the devices with the lowest price to reduce the compensation for the flexibility provisioned. In fact, thanks to the design of the fitness function, the aggregator is willing to pay some penalty mismatch when the overall total cost is reduced (for instance, if the price for shifting or reduction/increase is high).

Finally, we analyze the impact of the flexibility for each type of devices (i.e., the flexibility provision of shiftable and real-time devices). The difference in the contribution of flexibility plays a crucial role in

determining the compensation between the appliances participating in the DR programme.

Fig. 9 shows the baseline and re-scheduling profiles (Fig. 9a), as well as the flexibility provision (Fig. 9b), with shifting appliances. The same information is showed in Fig. 10 related to real-time devices. It can be noticed that the contribution of shifting devices is higher than the one provided by real-time devices. For instance, the peak flexibility provided for reduction by shifting devices reaches 6 kW of power around hour 20 (see Fig. 9b).

On the contrary, real-time devices only provide the flexibility of around 1 kW of power (see Fig. 10b). This can be explained for two main reasons: (1) shifting devices contribute twice to the modification of the baseline profile by reducing the load in the original period where they were scheduled, and increasing the load in the period where they are shifted; (2) the aggregator only needs to pay $\pm 30\%$ of 0.2 EUR for the shift of the profile to any other period allowed by the user, which can be more beneficial than paying a compensation in EUR/kWh (as it happens with real-time devices). In spite of that, real-time devices have a better degree of control in the sense that a reduction/increase in its operation can be performed in a specific period without affecting the scheduled energy in the future. Therefore, the contribution of real-time devices can be used to avoid further the penalty mismatch.

We have performed an additional experiment to analyze the impact of the penalty imposed by the DSO (parameter C_{DSO} in Eq. (11)) for the mismatch of flexibility provisioned. To this end, we have varied the

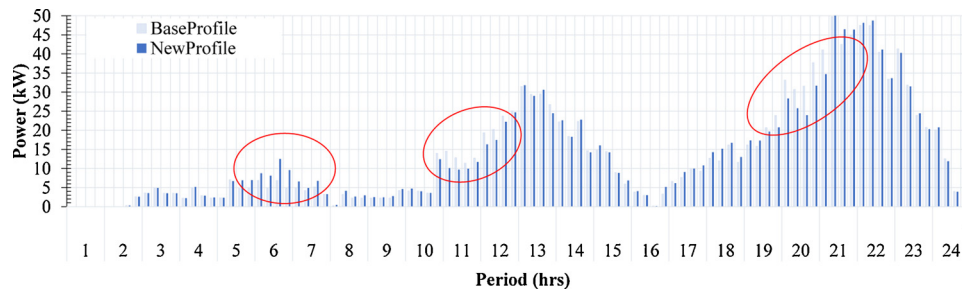


Fig. 7. Baseline profile and new profile after re-scheduling of devices to match the flexibility request. It can be noticed that appliances' consumption is reduced during peak hours, and increased during non-peak hours (marked with red circles in the figure).

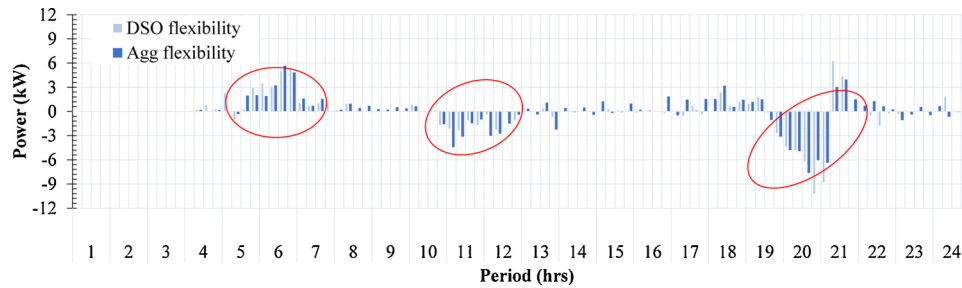


Fig. 8. Flexibility required by the DSO and flexibility provision after re-scheduling. The flexibility cannot be completely matched, so penalties are imposed to the aggregator.

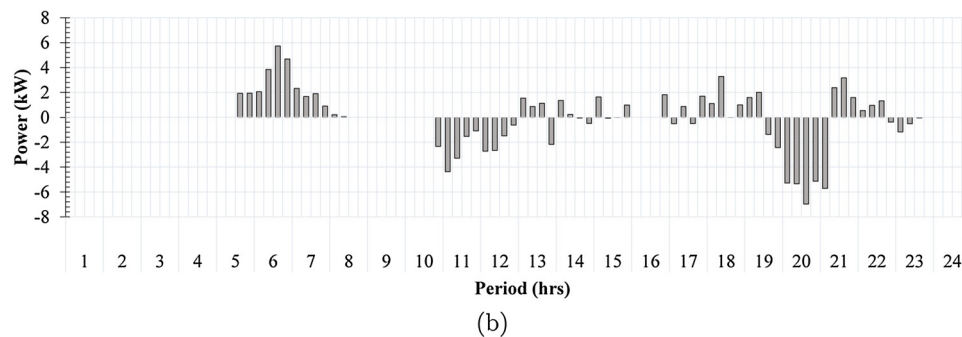
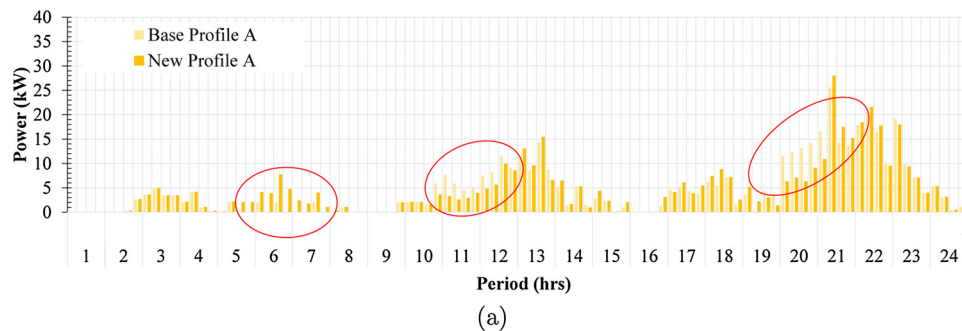
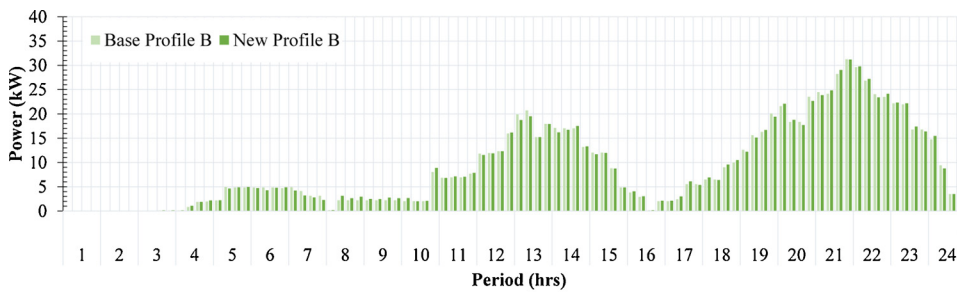


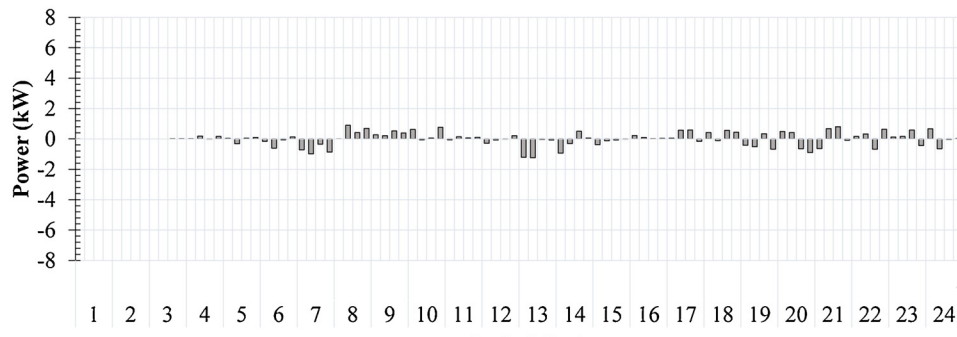
Fig. 9. Baseline, re-scheduling, and flexibility provision. (a) Baseline devices type A and re-scheduling. (b) Flexibility provision devices type A.

penalty cost from 0.05 to 1 EUR and have run the optimization process using VS algorithm (the one that got the lower fitness value in our previous experiments). Also, the experiment is used to appreciate the amount of flexibility provided and remuneration received by each type of devices. Table 4 presents the flexibility provisioned by the aggregator (quantified by the type of appliances used), as well as the remuneration and penalties paid by the aggregator. It can be noticed that, when the penalty imposed by the DSO is lower than the required payment for flexibility activation (i.e., 0.05 EUR), the aggregator prefers to pay the associated penalty and collect almost no flexibility. In fact, when the penalty is 0.05 EUR, the aggregator reduces the flexibility of devices

type B to 0, which makes sense since the activation cost of real-time devices is set to $\pm 30\%$ of 0.09 EUR/kWh (a higher price than the penalty to be paid). When the penalty costs are higher than the activation cost of type B devices (i.e., 0.1 and above), the flexibility is used. Also, it can be noticed that the total amount of flexibility collected by the aggregator overpassed the flexibility request by the DSO in some cases (e.g., in our case study, the flexibility requested corresponds to 109.77 kW in total). This can be explained by the fact that the aggregator must increase the consumption with some devices and at the same time decrease the consumption with others to achieve a match of flexibility that reduces the penalties (See, for instance, Figs. 9b and 10b



(a)



(b)

Fig. 10. Baseline, re-scheduling, and flexibility provision. (a) Baseline devices type B and re-scheduling. (b) Flexibility provision devices type B.

Table 4

Flexibility and aggregator cost variation in function of the imposed DSO penalty. It can be noticed that the optimization solution adapts the remuneration costs and selection of flexibility accordingly.

C_{DSO} (EUR/kWh)	Flexibility (kW)			Aggregator cost (EUR)			
	A_{flex}	B_{flex}	Total	Rem _A	Rem _B	Penalty	Total
0.05	21.67	0.00	21.67	0.16	0.00	1.18	1.34
0.1	32.47	35.39	67.86	0.35	0.72	1.23	2.30
0.2	99.15	44.67	143.82	4.55	1.10	0.85	6.50
0.4	117.87	51.60	169.46	7.44	1.45	1.72	10.61
0.6	113.27	54.69	167.96	8.20	1.57	2.84	12.61
0.8	114.14	47.91	162.05	9.06	1.50	2.53	13.09
1	115.71	44.66	160.37	8.86	1.48	4.23	14.57

between hours 6–8, where the aggregator increases the consumption with some devices type A, and at the same time, decreases the consumption with devices type B to achieve a better match of flexibility). A possible approach to solve this issue is the use of market-based strategies, in which the intermediary between end-users and DSO is eliminated. However, such solution represents a more challenging decentralized optimization approach worth to be explored in future work.

7. Conclusions

In this paper, it has been proposed a mathematical model to assist an aggregator in the management of appliances for flexibility provision. Applying the proposed model, the aggregator is able to match a flexibility request from the DSO while reducing the costs for the re-scheduling of house appliances. Different devices have been considered in this work, namely classified into two types, appliances with shifting capabilities (type A) and with real-time reduction/increase energy capabilities (type B). The formulation results in a large-scale non-linear problem so that the use of swarm intelligence and evolutionary computation is evoked as an optimization tool. Different algorithms, including PSO, DE, VS, and other variants, are used to provide near-optimal solutions to the problem. Results showed that the aggregator is

able to find a match between the flexibility provisioned and the flexibility procured by the DSO, and at the same time reduce remuneration costs paid to users for the flexibility of devices. However, several assumptions have been made in the model to achieve the reported results. For instance, the monetary values (and contractual relationships) between DSO-aggregator-users have been simplified to fixed rates over the simulation, so the variability of these rates and their impact over the optimization time horizon is a venue for further research. Moreover, it was shown that under this model, the aggregator achieves an acceptable match of the flexibility curve by using an extra amount of resources (for instance, increasing the load of some devices and decreasing the load of others in the same period). This effect should be mitigated in future research to fully profit from the available flexibility. For instance, the problem can be transformed into a multi-objective optimization formulation aiming at matching the flexibility curve while considering different remuneration approaches and the reduction of such costs. Decentralized and market-based approaches to select the most suitable devices for the flexibility provision is also worth to be explored in future research.

Conflicts of interest

The authors declare no conflicts of interest.

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