DSO contract market for demand response using evolutionary computation

Eduardo Lacerda, Fernando Lezama, Joao Soares
GECAD, Polytechnic of Porto, Portugal
{1192196, flz, jan}@isep.ipp.pt

Zita Vale
Polytechnic of Porto, Portugal
zav@isep.ipp.pt

***Abstract*—In this article, a cost optimization problem in local energy markets is analyzed considering fixed-term flexibility contracts between the DSO and aggregators. In this market structure, the DSO procures flexibility while aggregators of different types (e.g., conventional demand response or thermo-load aggregators) offer the service. We solve the proposed model using evolutionary algorithms based on the well-known differential evolution (DE). First, a parameter-tuning analysis is done to assess the impact of the DE parameters on the quality of solutions to the problem. Later, after finding the best set of parameters for the "tuned" DE strategies, we compare their performance with other self-adaptive parameter algorithms, namely the HyDE, HyDE-DF, and vortex search algorithms. Results show that with the identification of the best set of parameters to be used for each strategy, the tuned DE versions lead to better results than the other tested EAs. Overall, the algorithms are able to find near-optimal solutions to the problem and can be considered an alternative solver for more complex instances of the model.**

I. INTRODUCTION

The increased use of renewable energy sources (RES) has a fundamental role in the search for a more sustainable world. The European Union (EU) expects, through its objectives for energy and climate to 2030, the growth of RES participation of more than 50 % of energy production. This expansion is disturbing the electric system as a whole, demanding a redesign that allows a better management of distributed resources [1].

In this context, demand response (DR) programs and new market structures at the local level of the supply chain, the local energy markets (LEM), seem to be adequate alternatives to take advantage of the flexibility and active participation of end-users. Flexibility is usually defined as the possibility of modifying generation or consumption patterns reacting to price or activation signals and ultimately contributing to the power system stability in a cost-effective manner [2]. In a general view, the distribution system operator (DSO) can procure flexibility from market agents to solve problems that arise while doing its function of guaranteeing the free flow of energy, avoiding energy imbalance, realizing the congestion management, voltage and frequency control, and others functions as the ones described in [3]. In such a new environment, the role of the aggregators is crucial because they are responsible for the acquisition of consumers/prosumers flexibility, aggregating it as a product that can be traded with other market players (e.g., DSO or the TSO). Among the loads able to be aggregated and provide up regulation, thermostatically controlled loads hold different aspects (e.g., thermal inertia and steady-state operation), compared to conventional loads, that makes them suitable for this task. However, the operation of these loads requires a special attention to their steady-state operation because any deviation of power requires the energy to return to the previous operation state (i.e, load reduction must be followed by load increase and vice-versa). This characteristic is known as rebound effect [4], and due to this, aggregators of this type of loads offer their flexibility products in the shape of asymmetric blocks.

This paper uses the model proposed in [5], where two types of DR services, conventional and scheduled, are used to provide flexibility to the DSO. A fixed-term contract market with duration of one month is defined between the DSO and aggregators in which a conventional service is available for load reduction every day whereas a scheduled service is activated only a percentage of the days according to external signals from the DSO. The problem in [5] is solved by linear optimization methods using GAMS software. This approach, however, could be limited if more complex instances of the model are considered (such as with models including nonlinearities related to network constraints or uncertainty of parameters). Therefore, in this first study, we propose the use of a more flexible approach to solve the problem based on evolutionary computation (EC). EC encompasses a set of algorithms for optimization that are tolerant to imprecision, uncertainty, and approximation [6].

In this paper, we apply different DE-based algorithms [7], [8]. We use two distinct DE strategies, namely DE/rand/1 and DE/target-to-best/1. The study methodology is based in [9] where the best set of parameters of the algorithm are found using a tuning methodology. After that, a comparison with other self-adaptive parameter evolutionary algorithms (EAs), namely the Vortex Search (VS) [10], the Hybrid-Adaptive Differential Evolution (HyDE), and the HyDE with decay function (HyDE-DF), is provided to assess the performance of algorithms.

II. PROBLEM FORMULATION

This section is divided in two parts. The first part presents the LEM model and the market participants, whereas the

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second part presents the mathematical formulation.

A. Market Structure

In the market model proposed by Kok et al. [5] the DSO procures flexibility while DR aggregators offer this type of product. Considering a competitive market context, the best combination of bids and offers must be found so the equilibrium price is reached and the participants adapt their products in order to decrease the costs and maximize profits. The services are settled trough fixed term contracts which expose the obligations of both parts. The aggregators must provide fixed quantities of flexibility every day besides the reserved flexibility that eventually can be requested by the DSO through an external signal. The DSO is responsible for the stable and reliable energy supply, and its duty is to utilize the flexibility available to solve network issues. A representation of the model is shown in Fig. 1.

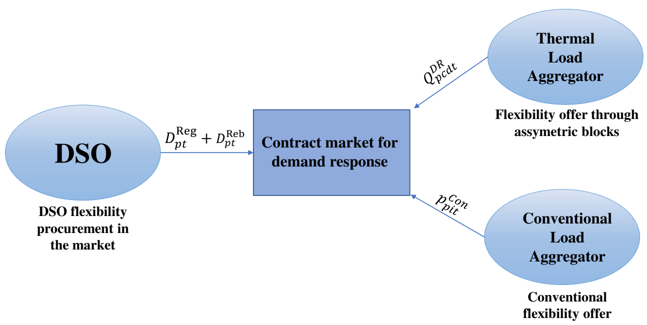


Fig. 1: Market Model Representation

Scheduled and Conditional are the two types of services that can be concerted by both parts. In these two services, the aggregators offer their flexibility for trading before the Market Clearing. The information that must be provided by the DSO before the Market Clearing is the period in which it demands flexibility and the probability of activating the conditional service. Taking this into consideration, it was defined in [5] that, for each type of service $p \in P$, the maximum quantity of available flexibility must be declared for every period t before the Market Clearing.

The aggregators function in this model is to put the available flexibility from customers in their portfolio as a product that can be of interest to agents in the energy market. The aggregated flexibility comes from its customers who have the most diverse profiles. One of these profiles is related to thermostatically controlled loads whose operation is different from other types of load because the temperature of a certain space must be maintained within a pre-established level. Thus, two types of agents participate in the market, namely thermo-load aggregators $c \in C$ and conventional aggregators $i \in I$. Conventional aggregators are able to offer for each service p and time step t an amount of load reduction p_{pit} that is less to its maximum allowed P_{pit}. This flexibility can be contracted and partially used by DSO. The thermo-load aggregators, due to their rebound characteristics, offer their products in the form of asymmetric blocks, which must be completely used (not partially), considering that the load reduction/increase is followed by an increase/reduction to reach the stable point. Each block is identified by $d \in D$ and its response at each time t is identified by the parameter Q_{pcdt}^{DR}.

B. Mathematical Model

The optimization function of this study is related to minimizing the system overall costs through the best combination of bids and offers for DR described by (1):

$$\text{minimize} \sum_{p \in P} RC_p + \sum_{p \in P} \mathbb{P}_p DC_p \tag{1}$$

This optimization problem can be modelled as a mixed integer linear problem defined through functions (1) to (9d). Regarding the objective function, the dummy variables RC and DC are arranged, which are the reserve costs (or capacity costs) and the dispatch costs respectively. The reserve costs defined in (2) refer to fixed costs and are not dependent on the number of times the service is activated. It represents the market costs associated with DSO and aggregator operation. Regarding aggregators, the main cost is associated with the choice to reserve flexibility for the DSO-level instead of participating in another markets (e.g., at the TSO-level). For the DSO, the benefits of its market share are counted as a decrease in the overall cost of the system.

$$\begin{aligned} RC_p = & \sum_{i \in I} \sum_{t \in T} C_{pit}^{\text{R,Con}} p_{pit} + \sum_{c \in C} \sum_{d \in D} C_{pcd}^{\text{R,DR}} r_{pcd} + \\ & \sum_{t \in T} C_{pt}^{\text{R,Reb}} s_{pt} - C_p^{\text{R,DSO}} z_p \qquad \forall p \in P. \end{aligned} \tag{2}$$

The first term of the Eq. (2) refers to the cost associated with conventional aggregators, where $C_{pit}^{\text{R,Con}}$ is equal to the reserve component cost (cost / kW) for unit i to meet service p at time t, and the upward regulation (load reduction) is given by p_{pit}. DR cost in the second term is related to the total cost of the asymmetric blocks offered by each aggregator c, where $C_{pcd}^{\text{R,DR}}$ is the cost of the block d and r_{pcd} is the number of blocks offered. The third term of the Eq. (2) corresponds to the rebound cost, this being the cost to DSO for the allowed rebound of the aggregators $c \in C$, $C_{pt}^{\text{R,Reb}}$ is the cost per kW of rebound, and s_{pt} is the amount of total rebound at each time t. The last term refers to the benefit to the DSO of activating the service (this term is negative because it decreases the total cost of the system). $C_p^{\text{R,DSO}}$ refers to the benefit of DSO while z_p is a binary variable that indicates which of the services has been selected.

The dispatch cost refers to the second term of Eq. (1) and is defined as (3):

$$\begin{aligned} DC_p = & \sum_{i \in I} \sum_{t \in T} C_{pit}^{\text{D,Con}} p_{pit} + \sum_{c \in C} \sum_{d \in D} C_{pcd}^{\text{D,DR}} r_{pcd} + \\ & \sum_{t \in T} C_{pt}^{\text{D,Reb}} s_{pt} - C_p^{\text{D,DSO}} z_p \qquad \forall p \in P. \end{aligned} \tag{3}$$

where the terms are similar to those of equation (2) considering different parameter values associated with the costs. The use of this flexibility is dependent on a DSO activation signal and is not mandatory for all days and periods. Thus, associated with the DC is the term $\mathbb{P}_p$ which indicates the daily probability of activation of the service p. This probability of activation is previously established by the DSO before the Market Clearing.

Constraint (4) defines the amount of power that each aggregator i can offer for up regulation in each time t and service p, this being defined as the upper limit P_{pi}^{Con}.

$$p_{pit} \leq P_{pi}^{\text{Con}} z_p \qquad \forall p \in P, i \in I, t \in T. \tag{4}$$

Aggregators c might offer many asymmetric blocks with different structures knowing that at least one of them must be activated. So a variable called m_{pcd} is defined to indicate which block d offered for service p and aggregator c is selected. Equation (5) guarantees that at least one block is selected.

$$\sum_{d \in D} m_{pcd} \leq z_p \qquad \forall p \in P, c \in C. \tag{5}$$

Equation (6) guarantees that only one of the services will be cleared by the market.

$$r_{pcd} \leq B_{pcd}^{DR} \qquad \forall p \in P, c \in C, d \in D. \tag{6}$$

The amount of total rebound possible is not unlimited as it could cause problems for the DSO. In this way, a limit of s_{pt} rebound to a maximum D_{reb} is defined by the DSO. Equation (7) guarantees this restriction.

$$s_{pt} \leq D_{pt}^{\text{Reb}} z_p \qquad \forall p \in P, t \in T. \tag{7}$$

Constraint (8) defines a minimum amount of response required by the DSO for each period. That is, in each period the combination of bids from conventional units and the asymmetric blocks must match or exceed the requirement of the DSO D_{pt}^{Reg} considering the rebound effect at each time step:

$$\sum_{i \in I} p_{pit} + \sum_{c \in C} \sum_{d \in D} Q_{pcdt}^{\text{DR}} r_{pcd} \geq D_{pt}^{\text{Reg}} z_p - s_{pt} \qquad \forall p \in P, t \in T. \tag{8}$$

Finally, variables are bounded according to Eqs. (9a) - (9d):

$$p_{pit} \geq 0 \qquad \forall p \in P, i \in I, t \in T. \tag{9a}$$
$$r_{pcd} \in Z_+ \qquad \forall p \in P, c \in C, d \in D. \tag{9b}$$
$$m_{pcd} \in 0,1 \qquad \forall p \in P, c \in C, d \in D. \tag{9c}$$
$$z_p \in 0,1 \qquad \forall p \in P. \tag{9d}$$

III. Evolutionary algorithms

EC is a sub-field of computational intelligence (CI) that includes different algorithms for global optimization inspired by evolutionary processes [11]. Typically, the so-called EAs are population-based meta-heuristics that evolve an initial set of candidate solutions (i.e., a population or swarm) over iterations. A given fitness function measures the improvement of solutions in the evolutionary process. Thus, at each iteration, new solutions are generated using particular operators and introduced into the population depending on their fitness value (i.e., replacing solutions with low performance). By doing this, it is expected that the population gradually evolves towards a promising area of the search space following the principles of natural/artificial selection [11].

A. Encoding of Individuals

The encoding of individuals (solutions to the problem) plays a key role in applying EAs. An individual is typically a vector containing the necessary variables for evaluating the objective function in Eq. (1). Several variables are used in the optimization problems in energy systems, leading to vectors $\vec{x}$ of high dimension. In the case of the analyzed DSO-Contract market, some variables must be evaluated to obtain the lowest system overall cost. For instance, in this problem encoding, the individual includes information about the selected service Z_p (notice that this integer variable Z_p makes a mapping from the binary variable z_p already telling you the selected service as an integer value) with N_P being the number of available services; the power values of conventional aggregators p_{pit} at each time t and service p with N_I being the number of conventional aggregators; and the selected block by thermo-load aggregators m_{pc} (notice that this variable makes a mapping from the binary variable m_{pcd} already telling you the selected block as an integer value), with N_C being the number of thermo-load aggregators and N_D being the number of available blocks. This results in a dimension of individuals equal to $1 + (t * N_I * N_P) + N_C$. Three groups of variables can be identified in the individual structure. The 1st position corresponds to the selected service Z_p; the following group of variables corresponds to the reduction of load for each conventional aggregator, period, and service p_{pit}; and the last group indicates the selected block for each thermo-load aggregator and service m_{pc}. For instance, for the case study considered in this article, we have 2 conventional aggregators (i.e., $N_I = 2$), 2 thermo-load aggregators (i.e., $N_C = 2$), 12 periods (i.e., $T = 12$), 3 services (i.e., $N_P = 3$); thus, the dimension of the solution vector is $1+(t{*}N_I{*}N_P)+N_C = 75$.

Lower bounds and upper bounds of variables related to the parameters established in the case study and real technical restrictions are set to put pressure on generating feasible solutions. Thus, the selection of service is defined as an integer value in the range $Z_p = [1, N_p]$; the up-regulation values offered by conventional aggregators i are bounded in the p_{pit}=[0,P_{pit}^{CONn}] range; and the chosen block by thermo-load aggregator is an integer in the range $m_{pc} = [0, N_m]$. Random solutions are generated as an initial population with values between the defined bounds.

Since the problem has restrictions that are hardly perceived and solved by the algorithm, penalties are applied in case one of these restrictions is not satisfied. In the proposed problem, these repair techniques refer to the fulfillment of the requirements proposed by the DSO regarding the amount

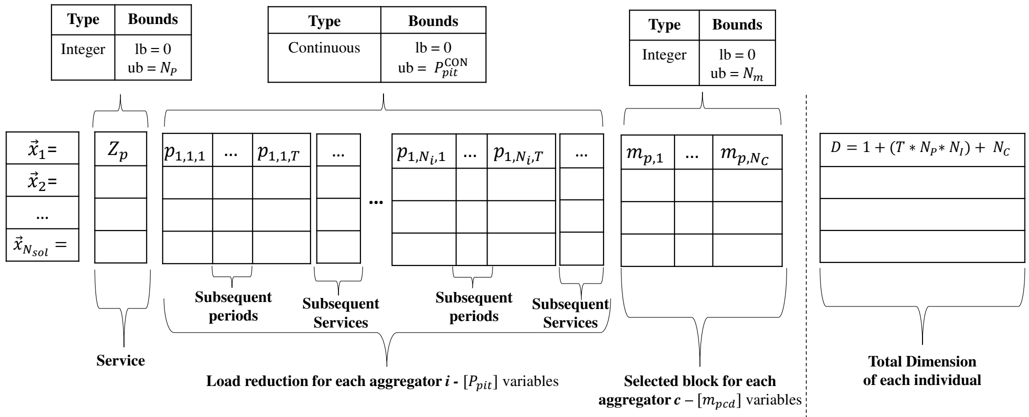


Fig. 2: Solution Encoding and lower/upper bounds of variables.

of up-regulation requested in critical periods and also the maximum amount of rebound allowed, adding the contribution of all aggregators c and i.In the up-regulation periods for each time t, the contributions of all aggregators are added together, and subsequently, a penalty per kW/h different from that required by the DSO is applied. This penalty is described by (10). In rebound periods, the total amount of rebound in the period is shown by the s_{pt} variable. When this amount exceeds the allowed D_{reb}^{pt} a penalty is applied per kw/h exceeded, this penalty is described by (11). Finally, the fitness function of the problem becomes (12) by adding the repairs related to the unfeasibility of solutions.

$$g_1 = |(D_{pt}^{Reg} - P_{pit})| \tag{10}$$

$$g_2 = \begin{cases} |(D_{pt}^{Reg} - s_{pt})| & \text{if } s_{pt} > D_{pt}^{Reg} \\ 0 & \text{if } s_{pt} \leq D_{pt}^{Reg} \end{cases} \tag{11}$$

$$F(\vec{x}) = f(\vec{x}) + \sum_{j=1}^{J} g_i * R \tag{12}$$

Now that we defined the encoding of individuals and the fitness function, we can apply some EA to solve the problem. In this paper, we have chosen two differential evolution (DE) variants, one single-based solution heuristic called vortex search (VS) algorithm [10], and two self-adaptive versions of DE called HyDE and HyDE-DF (selected due to their success in many applications and easy implementation [12], [13]).

B. Differential Evolution

Differential Evolution (DE) algorithms are part of a wide range of EAs whose study and application has been growing and developing continuously. As described in more detail in [14], DE uses a population of individuals where G is the generation number and the number of individuals per generation corresponds to $i = [1...NP]$. The most common method used in the creation of the population is a random initialization between bounds of variables. Recombination and mutation operators are used to create new solutions and will be explained in the following subsections. After this, the individuals with the best fitness are selected and the rest are discarded in order to obtain better results each time in later generations.

The recombination and mutation operators contain two parameters (F and Cr) that are fundamental for the good performance of the algorithm. In addition to these two, the NP parameter also has a great value, with only these three being the parameters of the algorithm. F is the mutation constant and is related to the control of the mutation force, Cr is the recombination constant and is linked to diversity in the mutation process. At the same time, NP defines the population size.

In the evolutionary computing process, four steps occur sequentially: the strategy used to create the mutation of individuals, the recombination of individuals, the performance validation of solutions, and the selection of individuals with the best fitness. In the first step, all $\vec{x}_{i,G} \in Pop$ individuals are evaluated at each generation. The individual under evaluation is called the target vector $\vec{x}_{i,G}$. Using the mutation operator, a mutant individual $\vec{m}_{i,G}$ is created for each target vector. The mutation operator varies in different applications (here, we call them strategies). In this work, we analyze two different strategies, the DE/rand/1 and DE/target-to-best/1. The other three steps and strategies are explained in the following subsections. It is possible to obtain a complete explanation of the algorithm and state-of-the-art of some DE strategies in [14].

1) Mutation Operator Strategies: The DE/rand/1 strategy operator is shown in Eq. (13). This is the standard DE mutation operator model where three random individuals of the current population, different from each other and from the target vector, make a linear combination in order to generate $\vec{m}_{i,G}$. Unlike the previous strategy, the DE/target-to-best/1 strategy acts in order to favor the convergence capabilities of the algorithm using information related to the best individual found in the evolutionary process. The strategy operator is described in Eq. (14).

$$\vec{m}_{i,G} = \vec{x}_{r1,G} + F(\vec{x}_{r2,G} - \vec{x}_{r3,G}) \tag{13}$$

$$\vec{m}_{i,G} = \vec{x}_{i,G} + F(\vec{x}_{best,G} - \vec{x}_{i,G}) + F(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \tag{14}$$

2) Recombination Operator: The recombination operator is applied to create the trial vector $\vec{t}_{j,i,G}$, which corresponds to the combination between the target vector $\vec{x}_{i,G}$ and the mutant individual $\vec{m}_{i,G}$ according to Eq. (15). In this step, Cr corresponds to the probability of choosing each element from $\vec{m}_{i,G}$. Rnd is an integer between [1,D] that guarantees that at least one of the individuals in $\vec{m}_{i,G}$ will be selected to form the new population.

$$\vec{t}_{j,i,G} = \begin{cases} \vec{m}_{j,i,G} & \text{if } (rand_{i,j}[0,1] < \text{Cr}) \vee (j = \text{Rnd}) \\ \vec{x}_{j,i,G} & \text{otherwise} \end{cases} \tag{15}$$

3) Boundary Verification: Mutation and recombination processes can generate solutions that do not respect the problem's constraints and are therefore not feasible. Thus, the boundary verification occurs according to (16)

$$\vec{t}_{j,i,G} = \begin{cases} \vec{x}_{j,lb} & \text{if } \vec{t}_{j,i,G} < \vec{x}_{j,ub} \\ \vec{x}_{j,b} & \text{if } \vec{t}_{j,i,G} > \vec{x}_{j,ub} \end{cases} \tag{16}$$

4) Selection: The selection occurs by comparing the fitness values of the objective function between the trial vector $\vec{t}_{j,i,G}$ and the target vector $\vec{x}_{i,G}$ in which the best individual is selected to compose the population of the next generation $Pop_{i,G+1}$. This selection is described by Eq. (17).

$$Pop_{i,G+1} = \begin{cases} \vec{t}_{t,G} & \text{if } f(\vec{t}_{i,G}) \leq f(\vec{x}_{i,G}) \\ \vec{x}_{i,G} & Otherwise \end{cases} \tag{17}$$

The other tested algorithms, which are self-adaptive parameter metaheuristics, are briefly explained in the following subsections.

C. Vortex Search

Vortex search (VS) is classified as a single-solution based metaheuristic with a similar framework compared with other EAs. Therefore, VS generates N_{vs} neighbor solutions at each iteration using a multivariate Gaussian distribution around the initial single-solution. After that, those N_{vs} solutions are evaluated in the fitness function (i.e., in Eq. 12), and the single-solution is updated with the best solution found. The iterative process is repeated until a stop criterion set by the user is met [10]. The advantage of applying VS algorithm lies in its simplicity and effectiveness and the fact that no associate parameters (apart from the number of neighbor solutions N_{vs} and iterations) need to be set or tuned.

D. HyDE

Hybrid-adaptive DE (HyDE) is a self-adaptive EA proposed in [12] and inspired in the DE. HyDE incorporates different ideas from other EAs, such as an operator called "DE/target-to-$perturbed_{best}$/1" (which is a modification of the DE/target-to-best/1 strategy [8] with a perturbation of the best individual inspired by the evolutionary PSO [15]), and the parameters self-adaptive mechanism of DE [16]. HyDE main operator is defined as:

$$\vec{m}_{i,G} = \vec{x}_{i,G} + F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G}) + F_i^2(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \tag{18}$$

where F_i^1 and F_i^2, are scale factors in the range $[0, 1]$ independent for each individual i, and $\epsilon = \mathcal{N}(F_i^3, 1)$ is a perturbation factor equivalent to a random number taken from a normal distribution with mean F_i^3 and standard deviation 1. F_i^1, F_i^2 and F_i^3 are updated at each iteration following the same rule of jDE algorithm (see Sect. III.B of [12]).

E. HyDE-DF

HyDE with decay function (HyDE-DF) is an improved version of HyDE used for function optimization [13]. It incorporates a decay function to perform a transition in the iteration process from the main operator of HyDE (Eq. 18) to the basic operator of DE (Eq. 13):

$$\vec{m}_{i,G} = \vec{x}_{i,G} + \delta_G \cdot [F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G})] + F_i^2(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \tag{19}$$

where δ_G factor is used to gradually decrease the influence of the term $F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G})$ responsible for the fast convergence towards the best individual in the population. Therefore, δ_G is a function that decreases its value from $1 \rightarrow 0$ at each iteration mitigating the influence towards x_{best}, and taking advantage of the inherent DE exploitation capabilities in later stages of the evolutionary process:

$$\delta_G = e^{1-1/a^2}; \qquad \text{with} \qquad a = (GEN - G)/GEN \tag{20}$$

where a is a value that linearly decreases from $1 \rightarrow 0$. Such a decrease value of a is proportional to the number of generations GEN. The transition implemented in HyDE-DF allows an enhanced phase of exploration in the early stage of evolution and stresses the exploitation in later stages of the optimization. To remark that HyDE-DF achieved third place (out of 36 algorithms) in the 100-digit challenge in CEC/GECCO 2019 [13].

We do not include a more detailed explanation of the selected EAs for space limitations, but the reader can consult the cited references to that end.

IV. Case Study and Results

In this case study, the tests were divided into two parts. In the first part, the impact of DE parameters, using the DE/rand/1 and DE/target-to-best/1 strategies, was evaluated to know how these yield better performance. In the second part. After that, results obtained from the optimization problem were collected and compared with other algorithms such as VS and HyDE and HyDE-DF.

A. Case Study Description

For this study, a market with 5 participants, the DSO and four aggregators, was considered. Among these aggregators, two of them aggregate conventional loads ($i1$ and $i2$), and the other two thermostatically controlled loads ($c1$ and $c2$). $i1$ and $i2$ offer flexibility without rebound effect while $c1$ and $c2$ offer flexibility in the form of asymmetric blocks. The DSO controls the market with monthly contracts. In this case study, the DSO demands flexibility in the periods between 17:00 and 18:00 hours, searching to reduce the peak consumption in this time of the day. Also, it was defined that the period of one hour before and one hour after the period that the DSO requires flexibility is allowed for a rebound effect, i.e., thermostatically load aggregators might increase their consumption within these periods. Three DR services were considered in this case study, one of which is Scheduled (denoted by $Sched$) and the other two Conditional (denoted by $Cond1$ and $Cond2$). As described, the Schedule service must be delivered every day (i.e., $\mathbb{P} = 1$), whereas conditional services $Cond1$ and $Cond2$ are dependent on a DSO activation signal and are activated with a probability of $\mathbb{P} = 0.30$ and $\mathbb{P} = 0.45$ respectively.

Table I shows the reserve and dispatch cost for blocks of thermo-load aggregators and for kW for conventional aggregators.

TABLE I: Reserve and dispatch cost for aggregators.

c	d	$C^{\mathbf{R,DR}}_{pcd}$ (€/bk)	$C^{\mathbf{D,DR}}_{pcd}$ (€/bk)	$B^{\mathbf{DR}}_{pcd}$ (bk)
c1	d1,d2	150	55	2
c1	d3,d4	150	55	1
c2	d1-d4	150	60	1
p	i	$C^{\mathbf{R,Con}}_{pit}$ (€/kW)	$C^{\mathbf{D,Con}}_{pit}$ (€/kW)	$P^{\mathbf{Con}}_{pit}$ (kW)
$Sched$	i1	2	4.0	50
$Sched$	i2	2	4.1	50
$Cond1$	i1	1	4.0	50
$Cond1$	i2	1	4.1	50
$Cond2$	i1	1	4.0	50
$Cond2$	i2	1	4.1	50

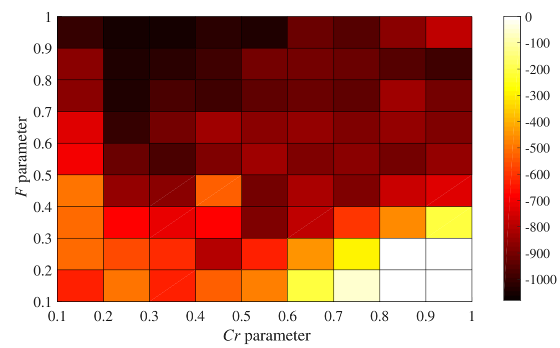
The benefit of the DSO clearing the market using any of the services in the reserve term is $C^{\text{R,Res}}_{p} = 400$€. In the dispatch term, the DSO benefit is of $C^{\text{D,Res}}_{p} = 2400$€ when the $Sched$ service is cleared, and $C^{\text{R,Res}}_{p} = 4000$€ when $Cond1$ or $Cond2$ are cleared. The costs of the rebound effect was $C^{\text{R,Reb}}_{pt} = 0$€ in the reserve term and $C^{\text{R,Reb}}_{pt} = 1$€ in the dispatch term. Lastly, the service requirement of the DSO is set to $D^{\text{Reg}}_{pt} = 100$kW of up-regulation in hours 17:00-17:59 (i.e., periods 5 to 8), and the allowed rebound has a limit of $D^{\text{Reb}}_{pt} = 25$kW in hours 16:00-16:59 (periods 1 to 4) and 18:00-18:59 (periods 9 to 12).

B. Parameters Tuning

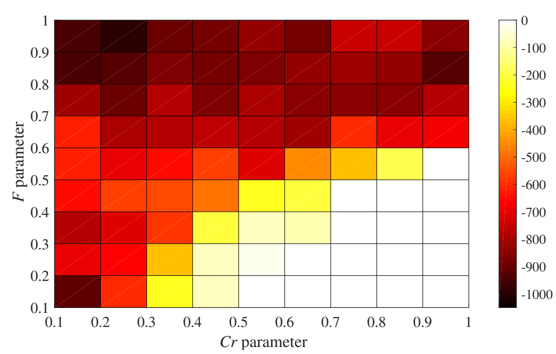
Tests were carried out to identify the best combination of parameters F, Cr, NP and G for DE/rand/1 and DE/target-to-best/1. Three tests were performed: the first related to the parameters F and Cr, the second to NP parameter, and the third related to the number of generations G.

In the first experiment, F and Cr were varied from 0.1 to 1 in steps of 0.1, and results were obtained with all possible combinations. In these tests, the number of population and generations were fixed $NP = 30$ and $G = 4000$, and 10 trials were carried out for each test. Figures 3(a) and 3(b) show the HeatMaps for the results found with each combination of parameters F and Cr in terms of fitness. In these HeatMaps, the darkest points refer to better fitness values (i.e., lower values of overall costs in Eq. (1)). It was chosen to represent all values greater than 0 by the white color for visualization purposes. Figure 3(a) shows the HeatMap related to the DE/rand/1 strategy. It can be seen that lower F values lead to much worse fitness values, while lower Cr values have better fitness. Figure 3(b) shows the HeatMap related to the DE/target-to-best/1 strategy. The evaluation of its results is similar to the previous strategy. Table II presents the best values of F and Cr found in the tuning of parameter and their average fitness, execution time and standard deviation along the 10 trials.

Using the best values of F and Cr from Table II, the second



(a)



(b)

Fig. 3: Heatmap of analyzed DE strategies. [a] DE/rand/1. [b] DE/target-to-best/1.

TABLE II: Best DE tuning of F and Cr values.

Method	(F,Cr)	Fitness Ave. ± Std	Time/Run (sec) Ave. ± Std
DE/rand/1	(1.0 , 0.2)	-1080.2 ± 6.4	565.5 ± 41.4
DE/target-to-best/1	(1.0 , 0.1)	-1049 ± 100.1	562.3 ± 14.4

test was accomplished to analyze the influence of the NP parameter. Thus, we varied NP with a step size of 10 in the range $10 < NP < 100$. The value of the generations was varied according to $Gen = 120000/NP$ so that the number of function evaluations remains the same and the comparison was performed fairly. Figure 4(a) shows the variation in the fitness value referring to the assessment of NP for each of the strategies using the optimal combination of F and Cr for DE/rand/1. With these results, it is possible to observe that for both cases, the value of the objective function improves as the population increases up to NP = 70. After this point, the NP increase interferes negatively in obtaining a better fitness. Figure 4(b) shows the variation in the fitness value using the optimal combination of F and Cr for DE/target-to-best/1. It is possible to observe the same behavior from the other test, with NP = 70 being the value with the best performance.

After that, using the optimal values of F and Cr, and setting $NP = 70$, the number of generations was varied in the range [500 5000] with a 500 step size. Figures 5(a) and 5(b) show the results of these experiments demonstrating that for both cases, increasing such parameter up to 3500 generations results in an improvement of the fitness value. However, going further than 3500 generations impacts negatively on the performance of the algorithm.

Finally, after tuning the parameters, their ideal values were established to carry out the final tests of the case study. Regarding the DE/rand/1 algorithm, the values found were $F = 1.0$, $Cr = 0.1$, NP = 70 and G = 3500, while for the DE/target-to-best/1 algorithm the only difference occurs in the parameter $Cr = 0.2$.

C. Performance Analysis

In this subsection, the best values of F and Cr found for the two DE algorithms are used to compare against other algorithms. The number of generations is set to 3500, and the number of individuals to NP= 70 for all the algorithms so that the objective function is evaluated the same number of times. VS, HyDE, and HyDE-DF do not have any parameter to be tuned. Figure 6 shows the convergence of all the algorithms over generations. As expected throughout the iterations, the results become more negative as this is a minimization function that aims to reduce the overall cost. The convergence rate is similar for both tuned DE strategies, both quickly

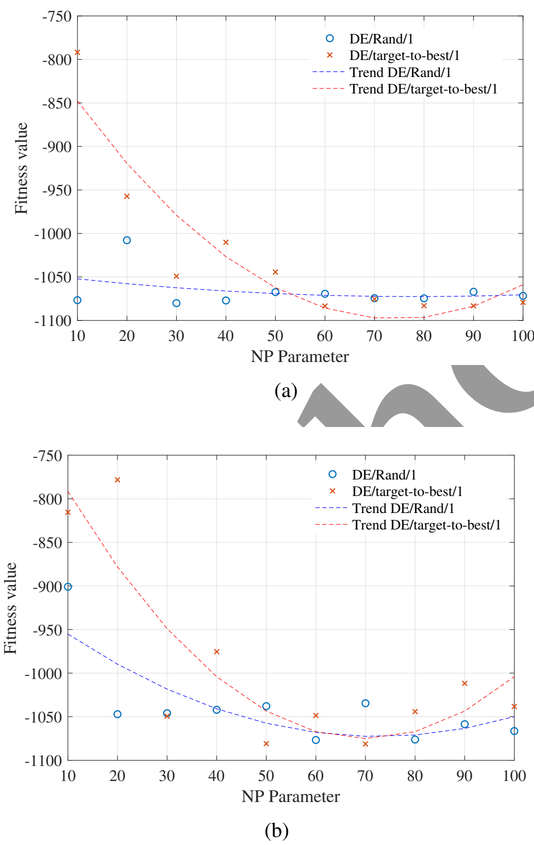


Fig. 4: Fitness variation in function of NP parameter. [a] with $F = 1$ and $Cr = 0.2$. [b] with $F = 1$ and $Cr = 0.1$.

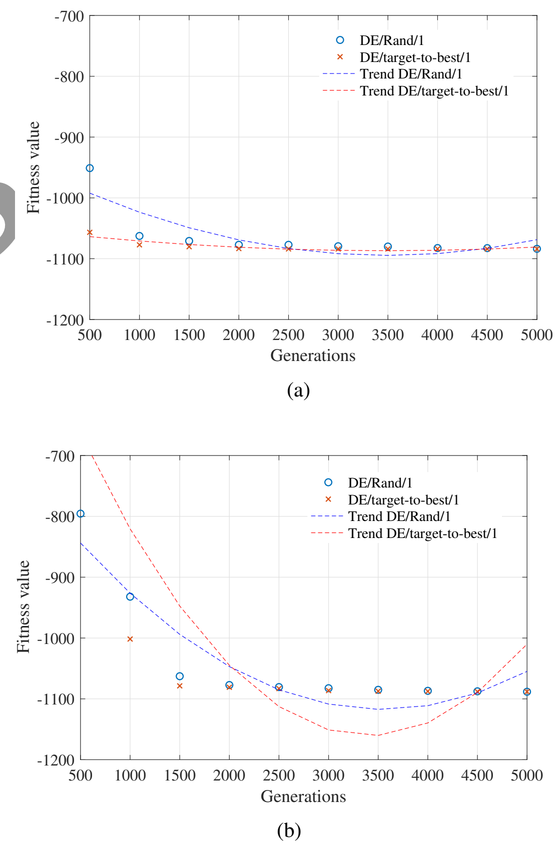


Fig. 5: Fitness variation in function of G parameter. [a] with $F = 1$ and $Cr = 0.2$. [b] with $F = 1$ and $Cr = 0.1$.

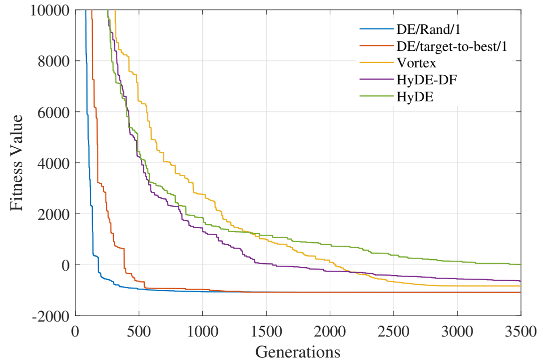


Fig. 6: Average convergence for each algorithm over 10 runs

converging and achieving its best value near to the generation 500 (and with DE/rand/1 being a little bit faster than DE-target to best/1). Both algorithms converge to very close results: the average convergence fitness found by DE/target-to-best/1 of -1087.38 and by DE/rand/1 of -1080.9 in generation 3500. VS, HyDE and HyDE-DF converged to worse solutions compared to the tuned versions of DE algorithms. However, it can be noticed self-parameter tuning algorithms have a slower convergence behavior, and that might achieve better results in the long term. At the end of the generations, the fitness value for VS was -739.9, for HyDE-DF it was -649.2, and for HyDE it was 9.9. These three algorithms do not need any tuning, which is an advantage when dealing with new instances of the problem.

Table (III) show the results in terms of the mean and standard deviation values obtained in the 10 trials for each algorithm. In addition to the fitness value, the RC (Reserve Cost) and DC (Dispatch Cost) are also presented. Regarding fitness, it was possible to observe that DE/rand/1 and DE/target-to-best/1 obtained superior results to the other tested algorithms, with results of -1080.09 and 1087,38, respectively. The VS and HyDE-DF algorithms had similar results but were not close to the tuned DE algorithms results. HyDE algorithm obtained the worst performance, not even obtaining negative overall costs (i.e., not obtaining profits). Regarding the DE/rand/1 and DE/target-to-best/1 time, they also obtained the best results per trial, with their average time being 9.00 and 8.60 seconds, respectively, while the other algorithms took around 12 seconds.

TABLE III: Comparison of results for each algorithm.

Method	Fitness	Reserve Cost	Dispatch Cost
DE/rand/1	-1080,1 ± 3,3	148,8 ± 1,0	-2731,0 ± 5,59
DE/target-to-best	-1087,4 ± 2,6	145,8 ± 0,8	-2740,4 ± 4,7
Vortex	-739,0 ± 230,3	220,5 ± 85,0	-2431,1 ± 494,0
HyDE-DF	-649,2 ± 153,7	178,3 ± 66,3	-2545,7 ± 481,8
HyDE	9,9 ± 160,7	250,9 ± 131,6	-2081,1 ± 829,6

Finally, Figure (7) graphically illustrates the best result obtained among all trials and algorithms. The figure shows the scheduling of the provided flexibility services. The result

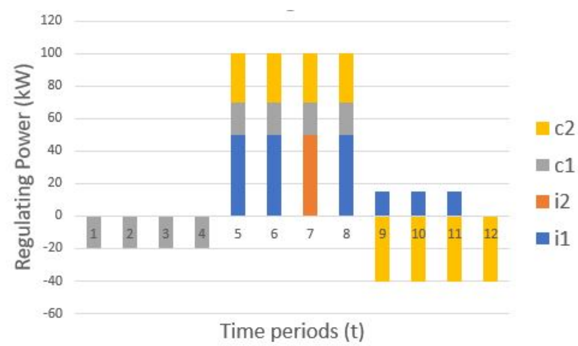


Fig. 7: Upward and Downward Regulation

showed corresponds to the one found by the DE/target-to-best/1 algorithm in its 3rd trial, which fitness is -1091,7 with $RC = 145,3$ and $DC = -2749$. In this trial, a conditional service $Cond2$ was selected in the contract market clearing. The blocks selected of the thermostatically controlled load aggregators were block 1 for aggregator $c1$ and block 2 for aggregator $c2$. Also, aggregator $i1$ was cleared in both up-regulation and rebound period, while aggregator $i2$ was activated in just one period of up-regulation.

V. Conclusions

In this paper, different DE strategies were used to execute a flexibility contract market in a proposed LEM model. Tests of DE parameters, F, Cr and NP, were accomplished to verify their influence in the obtained results and subsequently to use the best combination of them. With this analysis, it can be seen that the choice of parameters significantly impacts the results obtained. Also, it can be concluded that each DE strategy has a different set of optimal parameters that lead to good performance. After that, DE algorithms were compared with other algorithms, namely VS, HyDE and HyDE-DF, to compare the results obtained and the convergence time to the best solutions. In the comparison, better fitness values were obtained with the tuned DE strategies than with the self-parameter tuning algorithms, with similar execution times for all of them. Despite its good performance, the tested algorithms were not able to reach the optimal fitness value found by the linear method. Therefore, as future work, the model should be enhanced considered more realistic elements, such as network constraints or larger instances of the problem (e.g., more aggregators involved). This might introduce uncertainty and non-linearities to the model, and EAs can find their value in solving such models more efficiently.

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