Evolutionary Algorithms for Energy Scheduling under uncertainty considering Multiple Aggregators

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***Abstract*—The ever-increasing number of electric vehicles (EVs) circulating on the roads and renewable energy production to achieve carbon footprint reduction targets has brought many challenges to the electrical grid. The increasing integration of distributed energy resources (DER) in the grid is causing severe operational challenges, such as congestion and overloading for the grid. Active management of distribution network using the smart grid (SG) technologies and artificial intelligence (AI) techniques can support the grid's operation under such situations. Implementing evolutionary computational algorithms has become possible using SG technologies. This paper proposes an optimal day-ahead resource scheduling to minimize multiple aggregators' operational costs in a SG, considering a high DER penetration. The optimization is achieved considering three metaheuristics (DE, HyDE-DF, CUMDANCauchy++). Results show that CUMDANCauchy++ and HyDE-DF present the best overall results in comparison to the standard DE.**

***Index Terms*—aggregator, electric vehicles, energy resource management, evolutionary algorithms, smart grid, uncertainty**

NOMENCLATURE

η_c	Charging efficiency of ESSs/EVs
η_d	Discharging efficiency of ESSs/EVs
Ω_{DG}^{d}	Set of dispatchable DG units
Ω_{DG}^{nd}	Set of non-dispatchable DG units
$\pi(s)$	Scenario probability
C_{curt}	Load curtailment cost (m.u./MWh)
C_{DG}	Cost of DG generation (m.u./MWh)
C_{ESS^-}	Discharging cost of ESS (m.u./MWh)
C_{EV^-}	Discharging cost of EV (m.u./MWh)
C_{ext}	External supplier cost (m.u./MWh)
C_{imb^+}	Energy exceeded from DG cost (m.u./MWh)
C_{imb^-}	Non-supplied energy cost (m.u./MWh)
E_{BatCap}	Maximum battery capacity of ESSs/EVs (MWh)
E_{MinChr}	Minimum energy required by ESSs/EVs (MWh)
E_{stored}	Energy stored in ESSs/EVs (MWh)
MP	Market price (m.u./MWh)
N_{DG}	Number of DGs
N_e	Number of ESSs
N_k	Number of external suppliers
N_L	Number of loads
N_m	Number of markets
N_s	Number of scenarios
N_v	Number of EVs
$P_{buymin/max}$	Minimum/Maximum buy in the market (MW)
P_{buy}	Power brought from the market (MW)
P_{curt}	Power reduction of load (MW)
$P_{DG_{nd}}$	Forecast of non-dispatchable DG (MW)
$P_{DGmin/max}$	Minimum/maximum active power of dispatchable DGs (MW)
P_{DG}	Active power generation (MW)
$P_{discharge/chargelimit}$	Maximum discharge/charge rate of ESSs/EVs (MW)
P_{DRmax}	Maximum of reduction load (MW)
P_{ESS^+}	ESS power charge (MW)
P_{ESS^-}	ESS power discharge (MW)
P_{EV^+}	EV power charge (MW)
P_{EV^-}	EV power discharge (MW)
P_{ext}	External power supplied (MW)
P_{imb^+}	Exceeded power from DG unit (MW)
P_{imb^-}	Non-supplied power (MW)
P_{load}	Forecast active power of load (MW)
$P_{minlimit/maxlimit}$	Minimum/maximum active power of

This research has received funding from FEDER funds through the Operational Programme for Competitiveness and Internationalization (COMPETE 2020), under Project POCI-01-0145-FEDER-028983; by National Funds through the FCT Portuguese Foundation for Science and Technology, under Projects PTDC/EEI-EEE/28983/2017(CENERGETIC),CEECIND/02814/2017, and UIDB/000760/2020.

	external supplier (MW)
$P_{offermin/max}$	Minimum/Maximum offer in the market (MW)
P_{sell}	Power sold to the market (MW)
T	Number of periods
x_{DG}	Binary representing the state of DG units
$x_{offer/buy}$	Binary representing sell/buy to a market
$x_{supplier}$	Binary of choosing suppliers

I. INTRODUCTION

Today one of the problems that are being widely studied in energy systems is energy resource management (ERM) [1]- [4]. This factor is essential in the context of the smart grid (SG) [5], [6] due to the high penetration of distributed energy resources (DER), mainly electric vehicles (EVs) due to their variable demand, and renewables (wind and solar) also variable and uncertain. This penetration brings a high level of uncertainty and complexity to the grid, causing classic optimization approaches to struggle when solving this highly complex task [7].

Algorithms based on computational intelligence (CI), in this case, evolutionary algorithms (EAs), have proved to be extremely suitable for this type of problems because they offer good solutions in useful time [8], [9]. These algorithms originate from the biological evolution observed in nature through reproduction, recombination, mutation, and selection. They are defined as population-based metaheuristics. Since electrical energy systems are large systems with many variables and constraints, evolutionary computational (EC) based algorithms are adequate because they can generate feasible solutions with low computational effort [10].

Differential evolution (DE) is an algorithm gaining notoriety within electrical energy systems, given its effectiveness in solving large-scale optimization problems. A reactive power management model using DE algorithm is proposed in [11]. This methodology is applied in multiple IEEE electrical grids and a real Egyptian grid, showing promising results in reducing active power losses and balancing the voltage profile. The work presented in [12] analyzes the use of DE in a 33 bus distribution network (DN) with high penetration of DER and demand response (DR) programs. The authors examine the performance of the algorithm with four state-of-the-art mutation strategies. A comparison between these strategies, other EAs and a deterministic method, is made with over 50 runs of the algorithms. The paper [13] presents optimal day-ahead scheduling for a microgrid using a hybrid search algorithm with DE. A comparison is made with other algorithms in conjunction with DE, such as the artificial immune algorithm with DE, the hybrid genetic algorithm (GA) with DE, the modified DE, and the hybrid particle swarm optimization (PSO) algorithm with DE.

In this paper, the energy resource scheduling of the dedicated resources for the day-ahead is made. Each aggregator (in total five) schedules the resources through a state of the art metaheuristic, the Hybrid-Adaptive Differential Evolution with Decay Function (HyDE-DF) [14], in comparison with two other metaheuristics, to minimize the costs of each (or maximizing its profits). These aggregators are inserted in a smart city (SC) with a 13-bus distribution network (DN) with a high penetration of DER, mainly renewable energy and EVs (2000 EVs will be considered in the simulations). To modelling the uncertainty associated with DER and market prices, many scenarios are generated through Monte Carlo Simulation (MCS) using the probability distribution functions of the forecast error. Finally, the results obtained by the optimization algorithm are analyzed in terms of profits and performance (convergence, timing, and tuning).

This paper is structured as follows. After this first section, Section II represents the problem formulation and the proposed optimization algorithm, presenting the objective function and constraints. Section III presents the case study used in this work, while Section IV presents the results and respective analysis of these results. Finally, the last section presents the main conclusions of this paper and future work.

II. PROPOSED METHODOLOGY

This section details the methodology applied in this paper, according to the problem formulation and optimization model.

Fig. 1 presents the overall diagram of the proposed methodology. The methodology can consider several aggregators (second block of Fig. 1), where each one will seek to satisfy its energy needs from its resources and interaction with the electricity markets. Each aggregator is responsible for certain services, as will be described in section III. It is necessary to provide the various resources of the smart grid as inputs for optimization.

As it is present in the Fig. 1 first block, the data acquisition is made by acquiring data of the total energy production from renewable energy sources (RES), dispatchable distributed generation (DG) from the SG, and demand response programs from the SG. The electricity market is also considered, where wholesale prices are considered. Energy storage systems (ESSs), data from EVs with vehicle-to-grid (V2G) capacities are also considered, and the load consumption from residential buildings and other sources with production capacity (prosumers) is also acknowledged. These aggregators then do the programming of the dedicated energy resources in the context of the previous day for the 24 hours of the following day. Fitness values will be obtained, that is, an average profit that each will have, and an analysis of these results will be made.

A. Problem formulation

Each of the aggregators tries to minimize its costs while maximizing its profits. The proposed objective function for each aggregator is as follows:

$$minimize\ Z = OC - In \tag{1}$$

In (1), OC represents the operational costs, and In represents the aggregators' income. Z is the total cost (or

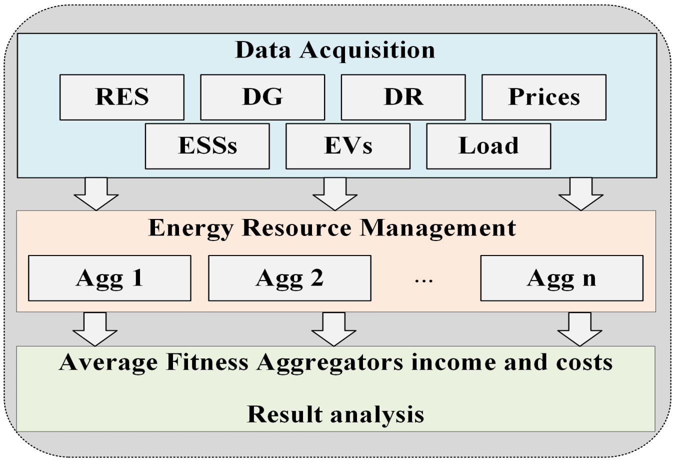

Fig. 1. Diagram representing the proposed methodology.

profits if negative) for the aggregators. The operational costs can be formulated as:

$$
\begin{aligned}
&OC = \textstyle\sum_{t=1}^{T} \sum_{i\epsilon\Omega^{d}_{DG}} P_{DG(i,t)} \cdot C_{DG(i,t)} \\
&+ \textstyle\sum_{t=1}^{T} \sum_{k=1}^{N_k} P_{ext(k,t)} \cdot C_{ext(k,t)} \\
&+ \textstyle\sum_{s=1}^{N_s} \sum_{t=1}^{T} (\sum_{i\epsilon\Omega^{nd}_{DG}} P_{DG(i,t,s)} \cdot C_{DG(i,t)} \\
&+ \textstyle\sum_{e=1}^{N_e} P_{ESS^-(e,t,s)} \cdot C_{ESS^-(e,t)} \\
&+ \textstyle\sum_{v=1}^{N_v} P_{EV^-(v,t,s)} \cdot C_{EV^-(v,t)} \\
&+ \textstyle\sum_{l=1}^{N_L} P_{curt(l,t,s)} \cdot C_{curt(l,t)} \\
&+ \textstyle\sum_{l=1}^{N_L} P_{imb^-(l,t,s)} \cdot C_{imb^-(l,t)} \\
&+ \textstyle\sum_{i=1}^{N_{DG}} P_{imb^+(i,t,s)} \cdot C_{imb^+(i,t)}) \cdot \pi(s)
\end{aligned} \quad (2)
$$

Eq. (2) considers the cost associated with DG, external suppliers, discharge of ESS and EVs, DR by direct load control programs (curtailable loads). It also finds penalization of non-supplied demand (negative imbalance) and penalization for the excess of DG units' generation (positive imbalance).

As previously mentioned, each aggregator is responsible for a specific service in the DN; that is, certain parameters of (2) become zero and disappear according to each one's specific purpose.

On the other hand, all the aggregators can receive their incomes from market transactions as follows:

$$
In = \sum_{s=1}^{N_s} \sum_{t=1}^{T} (\sum_{m=1}^{N_m} (P_{buy(m,t)} - P_{sell(m,t)}) \cdot MP_{(m,t,s)}) \cdot \pi(s) \quad (3)
$$

Where in (3) it is considered that the aggregators go to the marketplace to bid or buy energy resources.

The objective function of the proposed aggregators is constrained as follows:

1) Power balance: The active power balance constraint in each periods t for each scenario s is given by:

$$
\begin{aligned}
&\textstyle\sum_{i\epsilon\Omega^{d}_{DG}} P_{DG(i,t)} + \sum_{k=1}^{N_k} P_{ext(k,t)} \\
&+ \textstyle\sum_{i\epsilon\Omega^{nd}_{DG}} (P_{DG(i,t,s)} - P_{imb^+(i,t,s)}) \\
&+ \textstyle\sum_{l=1}^{N_L} (P_{imb^-(l,t,s)} + P_{curt(l,t,s)} - P_{load(l,t,s)}) \\
&+ \textstyle\sum_{v=1}^{N_v} (P_{EV^-(v,t,s)} - P_{EV^+(e,t,s)}) \\
&+ \textstyle\sum_{e=1}^{N_e} (P_{ESS^-(e,t,s)} - P_{ESS^+(e,t,s)}) \\
&- \textstyle\sum_{m=1}^{N_m} (P_{buy(m,t)} - P_{sell(m,t)}) = 0 \qquad \forall t, \forall s
\end{aligned} \quad (4)
$$

Again some of these terms are zero depending on the aggregator, for example for the load aggregators proposed the EV, and non-dispatchable DG terms are zero in this equation.

2) Dispatchable generation and external suppliers: The maximum and minimum values for the external supplier and DG units in each period t can be formulated as:

$$
P_{DGmin(i,t)} \cdot x_{DG(i,t)} \leqslant P_{DG(i,t)} \qquad \forall t, \forall i\epsilon\Omega^{d}_{DG} \quad (5)
$$

$$
P_{DG(i,t)} \leqslant P_{DGmax(i,t)} \cdot x_{DG(i,t)} \qquad \forall t, \forall i\epsilon\Omega^{d}_{DG} \quad (6)
$$

$$
P_{minlimit(k,t)} \cdot x_{supplier(k,t)} \leqslant P_{ext(k,t)} \qquad \forall t, \forall k \quad (7)
$$

$$
P_{ext(k,t)} \leqslant P_{maxlimit(k,t)} \cdot x_{supplier(k,t)} \qquad \forall t, \forall k \quad (8)
$$

3) Non-dispatchable generation: The renewable generation aggregator is the only aggregator subject to this constraint where:

$$
P_{DG(i,t,s)} = P_{DG_{nd}(i,t,s)} \qquad \forall t, \forall i\epsilon\Omega^{nd}_{DG}, \forall s \quad (9)
$$

4) Eenergy storage systems: The battery balance constraint for each ESS is characterized as follows:

$$
\begin{aligned}
E_{stored(e,t,s)} = {} & E_{stored(e,t-1,s)} + \eta_{c(e)} \cdot P_{ESS^+(e,t,s)} \\
& - \tfrac{1}{\eta_{d(e)}} \cdot P_{ESS^-(e,t,s)} \qquad \forall e, \forall t, \forall s
\end{aligned} \quad (10)
$$

The maximum discharge and charge limit for each ESS is as follows:

$$
P_{ESS^-(e,t,s)} \leqslant P_{dischargelimit(e,t)} \qquad \forall e, \forall t \quad (11)
$$

$$
P_{ESS^+(e,t,s)} \leqslant P_{chargelimit(e,t)} \qquad \forall e, \forall t \quad (12)
$$

Each ESS has a maximum battery capacity limit and a minimum energy stored required at the end of each period t that can be represented as:

$$
E_{stored(e,t,s)} \leqslant E_{BatCap(e)} \qquad \forall e, \forall t, \forall s \quad (13)
$$

$$
E_{stored(e,t,s)} \geqslant E_{MinChr(e,t)} \qquad \forall e, \forall t, \forall s \quad (14)
$$

5) Electric vehicles: The constraints presented here are only applied to the EV aggregator. The battery balance constraint for each EV is given by:

$$E_{stored(v,t,s)} = E_{stored(v,t-1,s)} + \eta_{c(v)} \cdot P_{EV^{+}(v,t,s)} - \frac{1}{\eta_{d(v)}} \cdot P_{EV^{-}(v,t,s)} \qquad \forall v, \forall t, \forall s \tag{15}$$

The maximum discharge and charge limit for each EV is as follows:

$$P_{EV^{-}(v,t,s)} \leqslant P_{dischargelimit(v,t)} \qquad \forall v, \forall t \tag{16}$$

$$P_{EV^{+}(v,t,s)} \leqslant P_{chargelimit(v,t)} \qquad \forall v, \forall t \tag{17}$$

The maximum EV battery capacity limit and a minimum energy stored required at the end of each period t that can be represented as:

$$E_{stored(v,t,s)} \leqslant E_{BatCap(v)} \qquad \forall v, \forall t, \forall s \tag{18}$$

$$E_{stored(v,t,s)} \geqslant E_{MinChr(v,t)} \qquad \forall v, \forall t, \forall s \tag{19}$$

6) Demand response: Only the three load aggregators are subject to this constraint. The demand response program incorporated in this problem was a direct load control method given by:

$$P_{curt(l,t,s)} \leqslant P_{DRmax(l,t)} \qquad \forall l, \forall t, \forall s \tag{20}$$

7) Electricity market: The markets offers (sell), and bidding (buy) constraints can be given by the following equations:

$$P_{sell(m,t)} \leqslant P_{offermax(m,t)} \cdot x_{offer(m,t)} \qquad \forall m, \forall t \tag{21}$$

$$P_{sell(m,t)} \geqslant P_{offermin(m,t)} \cdot x_{offer(m,t)} \qquad \forall m, \forall t \tag{22}$$

$$P_{buy(m,t)} \geqslant P_{buymin(m,t)} \cdot x_{buy(m,t)} \qquad \forall m, \forall t \tag{23}$$

$$P_{buy(m,t)} \geqslant P_{buymin(m,t)} \cdot x_{buy(m,t)} \qquad \forall m, \forall t \tag{24}$$

The market cannot sell and buy energy in the simultaneously, so $x_{offer(m,t)}$, and $x_{buy(m,t)}$ are two binary variables where:

$$x_{offer(m,t)} + x_{buy(m,t)} \leqslant 1 \qquad \forall m, \forall t \tag{25}$$

B. Evolutionary algorithms

The three EAs used in this problem are DE, HyDE-DF and CUMDANCauchy++.

1) DE: DE optimizes a problem through the combination of existing solutions and new solutions created by it. This algorithm keeps the solutions that best fit the problem in question or present better fitness. This algorithm's steps are: first, a solution is generated (target vector), then trough mutation a donor vector is generated and through recombination, a trial vector is generated. This algorithm presents several mutation strategies. For the problem in question the strategy used was *"DE/rand/1/bin"*, representing the binomial crossover. The expression of the donor vector is given by:

$$\vec{m}_{i,G} = \vec{x}_{r1,G} + F(\vec{x}_{r2,G} - \vec{x}_{r3,G}) \tag{26}$$

Where $\vec{x}_{r1,G}$, $\vec{x}_{r2,G}$, and $\vec{x}_{r3,G}$ are three random individuals from the population that differ from each other, and F is the scaling factor.

2) HyDE-DF: HyDE-DF [1] [14] uses the mutation operator *"DE/target-to-perturbed_best/1"* with a decay factor δ_G. This factor decreases gradually according to the number of iterations. The main operator of the HyDE-DF algorithm is calculated as follows:

$$\vec{m}_{i,G} = \vec{x}_{i,G} + \delta_G \cdot [F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G})] + F_i^2(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \tag{27}$$

Where $\vec{x}_{r1,G}$, $\vec{x}_{r2,G}$ are different from $\vec{x}_{i,G}$, the current target vector, and $\vec{x}_{best}$ is the best solution found. F_i^1, and F_i^2 are two scale factors within the range [0,1] independent for each individual i, where $\epsilon = \mathcal{N}(F_i^3, 1)$ which represents a random perturbation factor, from normal distribution with mean value of F_i^3, and standard deviation 1. F_i^1, F_i^2, and F_i^3 are updated each iteration following the self-adaptive parameter mechanism of jDE algorithm [9]. δ_G is necessary to decrease the influence of the term $F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G})$ responsible for the fast convergence to the best individual in the population. In an initial phase, the algorithm presents a greater diversity. It is said that there is greater exploitation following the best solution. Small adjustments are made in the decay function in the final phases so that smaller jumps are made in the research space, and there is greater local exploration.

3) CUMDANCauchy++: CUMDANCauchy [15] is a cellular EA with the learning processes of the normal distribution and cauchy to generate a new solution. CUMDANCauchy++ is an improvement of the previous algorithm to address the uncertainty associated with DN resources. Here the global optimum is updated with the best individual of a given generation if K individuals' fitness is less than the global optimum found so far.

C. Monte Carlo Simulation

The aggregators in the considered model face uncertainty in originating from various resources, through the forecasted errors of market prices, renewables, and EV trip behavior (random driving patterns of EV users, and charging behavior). Here the MCS, through massive random sampling, will

[1] https://fernandolezama.github.io/CodesImple

obtain numerical results; that is, it repeats successive simulations a high number of times to calculate heuristic probabilities. It builds a possible product model through a probability distribution, normal distribution, for any variable with uncertainty. Then it recalculates the results using a set of values between minimum and maximum.

The scenarios (x^s) can be represented as the following:

$$x^s(t) = x^{forecasted}(t) + x^{error,s}(t) \qquad \forall t, \forall s \tag{28}$$

Where $x^{forecasted}$ is the error associated with the forecast. This parameter can be positive or negative. $x^{error,s}$ has a normal distribution function with a zero-mean noise, and standard deviation σ.

III. Case Study

This section presents the case study that served to apply the methodology developed for this work. For this case study, a medium voltage (MV) DN of a SC located in the BISITE laboratory, Salamanca, Spain, was used (schematic is shown in Fig. 2).

This DN is composed by 25 load points of multiple types, namely:

1) 1375 homes;
2) 7 office buildings;
3) 1 Hospital;
4) 1 Fire station;
5) 1 Shopping mall;

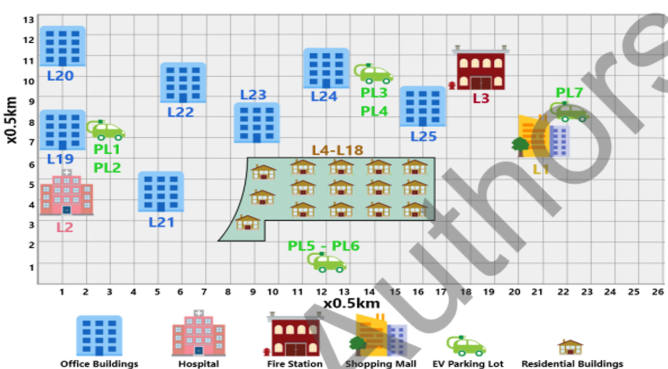

Fig. 2. Distribution network schematic [16].

It has one substation of 30MVA, a total of 15 DG units (2 wind farms and 13 PV parks), and four capacitor banks of 1Mvar. The SC in question has seven charging stations so that the EV can charge their batteries, four slow charging stations of 7.2kW for each connection point, and the fast charging lots of 50kW for each connection point. All the technologies mentioned can be seen in the single-line diagram of the 13-bus 30-kV. High penetration of EVs and renewables was considered in this case study. Multiple aggregators were considered for this case study. To be precise, five aggregators, each with different aggregated customers [17]. The aggregators are divided as follows:

- Aggregator 1: Hospital, fire station and shopping mall;
- Aggregator 2: Residential buildings;
- Aggregator 3: Office buildings;
- Aggregator 4: DG (wind and PV);
- Aggregator 5: EVs.

A large number of EVs was considered in the simulations, precisely 2000 EVs. The data of each EV for the optimization model were obtained through an Electric Vehicle Scenario Simulator Tool available in [18]. For this simulator, the various parameters for the six-vehicle model types (four battery EVs (BEVs) and two plug-in hybrid EVs (PHEVs)) presented in Table I. This table also shows the vehicle class and its description according to [19]. Table II presents the distribution values considered for each vehicle class. By multiplying these values by the total number of vehicles, one can conclude that simulations were performed with 10 Le7 cars, 1740 M1, 200 N1, and 50 N2. The distribution of the previously mentioned EV types is presented in Table III. It was considered a 67% share for BEVs and a 33% share for PHEVs, corresponding to the current percentages of the global EV car stock in the world for each type [20].

Initially, 5000 scenarios were generated for renewable generation, load consumption, market price variations, and parking lots. The maximum standard deviation values for the considered uncertainty variables (load consumption, electricity market price, parking lots capacities, parking lots charge, and discharge) are 15%, 10%, 35%, 35%, and 35%, respectively. The minimum values are 8%, 6%, 20%, 20%, and 20%, respectively. Random values are generated for the standard deviation (or error) between these limits for these parameters. Fig. 3 shows the average of the exact standard deviation (%) for the forecast of the DG technologies (wind, and PV) considered in this case study over 24 hours. The initial scenarios were then reduced to 150 scenarios using GAMS/SCENRED [2] through a technique developed in [21].

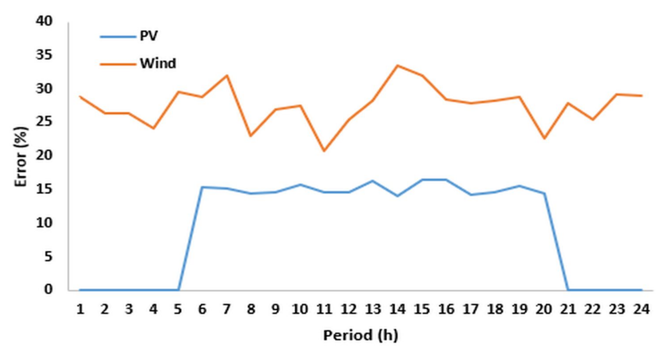

Fig. 3. Average forecast error for generation technologies.

When it comes to the optimization algorithms, Table IV presents the values of the parameters for DE, HyDE-DF, and CUMDANCauchy++ algorithms. The first parameter that the table shows is the population size (NP). The maximum number of iterations is the following parameter. This parameter is calculated regarding the maximum number of objective

[2] https://www.gams.com/latest/docs/T_SCENRED.html

TABLE I
VEHICLE MODEL DEFINITIONS.

Model ID	Vehicle type	Vehicle class	Description	Battery capacity (kWh)	Slow charging rate (kW)	Fast charging rate (kW)	Average economy (kWh/km)	Average usage (km/day)	Average speed (km/h)	Tank capacity (liters)
1	BEV	L7e	Passenger car	6.10	3.60	0.00	0.06	20.00	30.00	0.00
2	BEV	M1	Passenger car	40.00	6.60	50.00	0.16	38.00	34.00	0.00
3	BEV	N1	Commercial van	33.00	7.40	0.00	0.19	56.00	32.00	0.00
4	BEV	N2	Light truck	82.80	7.20	50.00	0.65	136.00	16.00	0.00
5	PHEV	M1	Passenger car	8.90	3.30	0.00	0.11	20.00	16.00	43.00
6	PHEV	N1	Commercial van	13.60	3.70	0.00	0.26	20.00	16.00	54.00

TABLE II
EV CLASSES DISTRIBUTION.

Vehicle class	Share (%)
L7e	0.50
M1	87.00
M2	0.00
M3	0.00
N1	10.00
N2	2.50
N3	0.00

TABLE III
EV TYPE DISTRIBUTION.

Vehicle types	Share (%)
BEV	67
PHEV	33

function evaluations (OFE) given by [NP*Max Iterations] considered in the model. The next parameters are the crossover probability (Cr) and the scaling factor (F), set to 0.5 and 0.3, respectively. These parameters were also considered for the standard DE. CUMDANCauchy++ does not need the Cr and F parameters. NP and the number of iterations were equal for this algorithm to what is in the table.

TABLE IV
PARAMETERS OF THE EAS.

Parameter	DE	HyDE-DF	CUMDANCauchy++
NP	10		
Max iterations	500		
Cr	0.50		-
F	0.30		-

All the experiments performed were implemented in MATLAB 2018a in a computer with an AMD Ryzen 5 3500U processor with 16GB of RAM running Windows 10.

IV. RESULTS AND DISCUSSION

This section presents the results obtained when applying the proposed methodology to the case study shown in Section III.

Table V presents the overall fitness results obtained in the 20 trials for the 150 scenarios. The table shows the minimum and maximum cost values and the average and standard deviation in monetary units and percentages due to the size of the values obtained in the various aggregators for the objective function.

It is possible to analyze from Table V that the DE algorithm presents the worst results, followed by HyDE-DF, and CUMDANCauchy++ presents the best results for all aggregators. HyDE-DF has the slowest computational time of the three except for the first aggregator due to the exploitation and exploration techniques adopted by this algorithm previously explained. In the last and fifth aggregator, the EV aggregator, the DE presents the worst results than the other two by a more significant margin. CUMDANCauchy++ and HyDE-DF have similar results, with CUMDANCauchy having a much lower time in comparison. For this aggregator, the number of variables increases dramatically (100 times more than some other aggregators) due to the high number of considered vehicles. In other words, it can be concluded that for a more significant number of resources, the last two algorithms are better concerning the DE due to better techniques for exploration and exploitation of the research space for the HyDE-DF and the learning processes of the CUMDAN algorithm.

Table V also shows that aggregators 3 and 4 present the higher costs of the five considered. This situation occurs because aggregator 3 presents the highest total load of the load aggregators considered increasing the costs due to the energy that it needs to buy in the market when the generation supplied does not satisfy the demand. For the fourth aggregator, the renewable generation aggregator, the sale of energy in the market is not enough to bring profit to this aggregator. The renewable generation is considerably high, and the costs associated with this type of generation are more expensive than the market value of energy purchase.

Fig. 4 shows the costs for all system aggregators for the best solution found by DE (Fig. 4a), HyDE-DF (Fig. 4b) and CUMDANCauchy++ (Fig. 4c) of the 20 runs (minimum value). This figure also shows the total average system costs for these results. It can be seen that the system costs are higher when the optimization is done through DE with a total of 4210.33 m.u.. These costs decrease when HyDE-DF (3736.58 mu.u.) and CUMDANCauchy++ (3707.86 m.u.) are applied to the optimization. This situation is mainly due to aggregator five, in which the last two algorithms obtained a higher cost reduction, as can be seen in the figures. CUMDANCauchy++ presents better overall costs as presented.

The convergence of each algorithm is also analyzed. For this case, it was only considered the fitness of the 20 trials for

TABLE V
OVERALL OBJECTIVE FUNCTION RESULTS AND OPTIMIZATION TIME BY THE TESTED EAS.

EA	Aggregators	Avg. costs (m.u.)	Std. costs (m.u.)	Min. costs (m.u.)	Max. costs (m.u.)	Time (min)
DE	**1**	1526.48	23.72 (1.55%)	1485.50	1584.34	17.92
	2	1051.04	9.45 (0.90%)	1029.48	1066.59	14.29
	3	7760.04	64.89 (0.84%)	7585.82	7855.03	16.29
	4	8657.76	26.66 (0.31%)	8626.69	8737.95	16.41
	5	2395.83	35.05 (1.46%)	2324.17	2473.02	271.77
HyDE-DF	**1**	1418.95	10.44 (0.74%)	1400.14	1445.71	19.35
	2	916.05	9.99 (1.09%)	901.90	938.81	26.54
	3	7048.96	16.86 (0.05%)	7031.28	7109.19	27.41
	4	8655.60	15.91 (0.18%)	8632.17	8693.75	24.01
	5	717.76	1.31 (0.18%)	717.40	723.28	268.84
CUMDANCauchy++	**1**	1381.73	3.95 (0.29%)	1373.93	1389.60	24.10
	2	881.63	4.43 (0.50%)	873.86	889.94	18.40
	3	7007.46	5.31 (0.08%)	6998.03	7015.25	13.50
	4	8599.65	3.15 (0.04%)	8595.77	8605.91	13.75
	5	707.53	5.22 (0.74%)	697.73	715.05	171.89

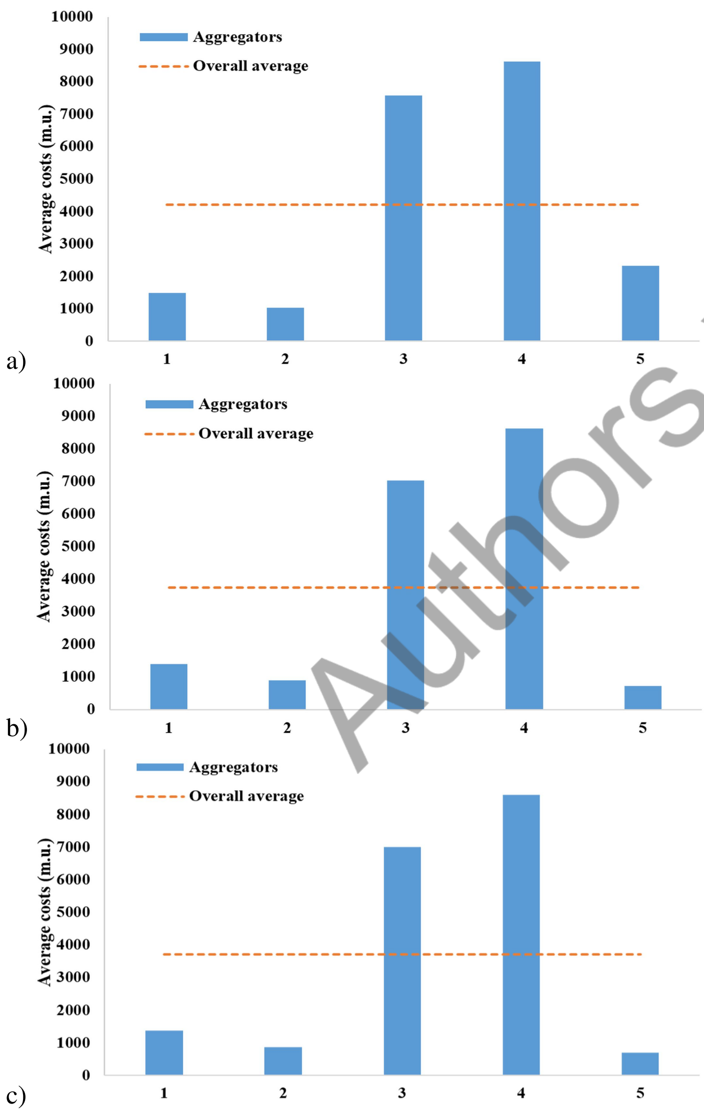

Fig. 4. Overall costs of each aggregator for the best solution found with a) DE; b) HyDE-DF; c) CUMDANCauchy++.

the first aggregator to reduce computational time. As shown in Section III the NP value is 10, and the maximum number of iterations is equal to 500. These numbers maintain the number of evaluations of the objective function, limited to 5000 OFE for this case study.

Fig. 5 shows the convergence of the three algorithms used for a population size equal to 10. It is possible to conclude that the DE shows the worst convergence in comparison. CUMDAN gives the better convergence, having achieved the best fitness in all iterations. Through Fig. 5 it can be seen that only HyDE-DF seems to stabilize with the others not yet stabilized in a value for fitness because they can still obtain better results. This situation may mean that the parameters used have not been the most appropriate, namely the number of iterations and the limit for the OFE.

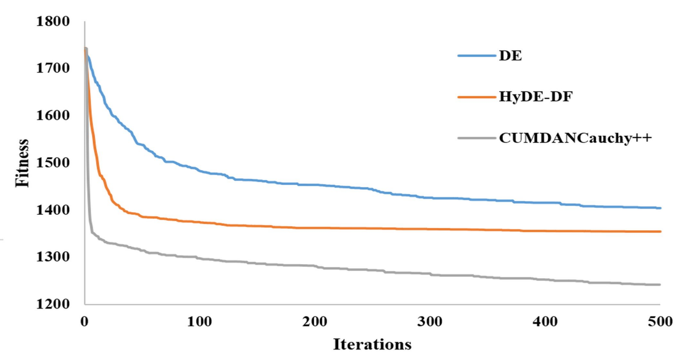

Fig. 5. Average convergence of the first aggregator for the considered EAs using $NP = 10$.

Finally, the NP parameter is studied for each algorithm, keeping the OFE equal for all simulations. Fig. 6 shows the variation of the costs int the objective function for each algorithm for a NP between 10 and 100. It is possible to analyze that when NP is 20, better results are obtained mainly in DE, and CUMDANCauchy++ which makes the calculated average of costs for these algorithms lower in comparison to other NP values even though the HyDE-DF algorithm obtains its best results when the population size is equal to 10.

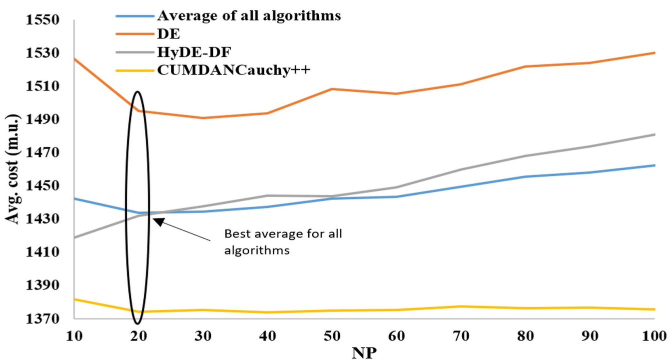

Fig. 6. Sensibility of the NP parameter for the first aggregator for each algorithm.

V. Conclusions

This paper presented an optimal model for the day-ahead resource management in a DN considering multiple aggregators and high penetration of renewables and EVs.

Multiple metaheuristics were used to solve the optimization problem. All five considered aggregators applied this optimization model to schedule their available resources. The optimization problem proposed here tries to find a global minimum for the costs associated with these entities. These costs vary from aggregator to aggregator, as shown in the results. This situation is due to each aggregator having different types of clients; in the equation presented for the costs, certain parameters result in a null value depending on the aggregator. For example, four of the aggregators, as they are load aggregators have no costs associated with the renewables, i.e., these values are zero in the mentioned equation.

It was possible to conclude through the results obtained that the fourth aggregator has the highest costs; since it is the DG aggregator with high generation costs compared to the others that don´t have these costs. Finally, we can conclude that both CUMDANCauchy++ and HyDE-DF algorithms presented the best performance due to their adaptive (HyDE-DF) and learning (CUMDANCauchy++) processes in the exploration and exploitation of the research space when compared to the basic DE, mainly when the number of resources increased dramatically.

The simulations are engaging for the future of the power grid with the inevitable integration of multiple aggregators in the aggregation of certain technologies like this paper presented. These aggregators have to optimize the scheduling of these resources for cost minimization/profit maximization to provide their customers with the best possible service.

As future work involving this case study, we intend to make these simulations for different time horizons in intraday. In this situation, it is also intended to apply other metaheuristics in this problem.

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