Evolutionary Algorithms applied to the Intraday Energy Resource Scheduling in the Context of Multiple Aggregators

José Almeida
GECAD
Polytechnic of Porto
Porto, Portugal
jorga@isep.ipp.pt

João Soares
GECAD
Polytechnic of Porto
Porto, Portugal
jan@isep.ipp.pt

Fernando Lezama
GECAD
Polytechnic of Porto
Porto, Portugal
flz@isep.ipp.pt

Bruno Canizes
GECAD
Polytechnic of Porto
Porto, Portugal
bmc@isep.ipp.pt

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

***Abstract*—The growing number of electric vehicles (EVs) on the road and renewable energy production to meet carbon reduction targets has posed numerous electrical grid problems. The increasing use of distributed energy resources (DER) in the grid poses severe operational issues, such as grid congestion and overloading. Active management of distribution networks using the smart grid (SG) technologies and artificial intelligence (AI) techniques by multiple entities. In this case, aggregators can support the grid's operation, providing a better product for the end-user. This study proposes an effective intraday energy resource management starting with a day-ahead time frame, considering the uncertainty associated with high DER penetration. The optimization is achieved considering five different metaheuristics (DE, HyDE-DF, DEEDA, CUMDANCauchy++, and HC2RCEDUMDA). Results show that the proposed model is effective for the multiple aggregators with variations from the day-ahead around the 6% mark, except for the final aggregator. A Wilcoxon test is also applied to compare the performance of the CUMDANCauchy++ algorithm with the remaining. CUMDANCauchy++ shows competitive results beating all algorithms in all aggregators except for DEEDA, which presents similar results.**

***Index Terms*—aggregator, energy resource management, local electricity market, metaheuristics, optimization**

I. Introduction

Computational intelligence (CI), an artificial intelligence (AI) field, is increasingly gaining notoriety in electric power systems in contrast to more deterministic methods [1], [2].

With the steady increase in distributed energy resources (DER), especially renewable generation and electric vehicles (EVs), managing energy resources becomes more and more complex with the increasing scale of the problem. CI fits better for solving this problem because electrical energy systems are large systems with many variables and constraints, and they allow obtaining reasonable solutions in useful time with low computational effort and are generally easier to implement than deterministic algorithms [3]. However, deterministic methods can obtain an optimal solution, which guarantees greater certainty in the results. One of the issues that may lead to the application of CI models to the detriment of more deterministic models is the uncertainty associated with DER (solar radiation, wind, the behavior of EV users, among others). This uncertainty can lead to low effectiveness of the more traditional methods [4].

Within CI comes evolutionary computation (EC), becoming one of the fields most integrated into solving energy problems. According to the literature the most popular algorithms already implemented in power system problems are the genetic algorithm (GA) [5], [6], particle swarm optimization (PSO) [7], [8], differential evolution (DE) [9], [10]. With the increase in applying this type of algorithm to solve optimization problems in the energy field, more precisely in resource management, variants of these more efficient algorithms with easier implementation are emerging, as seen in the literature. In [11] a new hybrid-adaptive DE algorithm is proposed to solve an energy resource management problem in the smart grid (SG) context under uncertainty. The authors applied multiple DE mutation strategies, and a new *"DE/target-to-perturbed_best/1"* mutation strategy with an adaptive mechanism that autotunes the crossover probability and mutation factor was proposed. This new algorithm presented the best overall results when compared to the DE. The research in [12] a cellular estimation distribution algorithm is proposed where the crossover and mutation factors are replaced by estimating and sampling the probability distribution learned from the chosen individuals. The algorithm showed excellent results compared to multiple variants of the PSO when solving the energy resource scheduling problem in an uncertain environment with high penetration of renewables and EVs. In [13] multiple variants of the PSO algorithm and other metaheuristics were implemented by the authors for a multi-objective management problem involving profit maximization and $C0_2$ minimization. A weighted PSO which uses Pareto set scheme obtained the best results for both objective functions.

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.

This paper proposes an optimal intraday energy resource scheduling for five different aggregators of different technologies treating it as mixed-inter linear programming (MILP) because network constraints are not considered. Each of the five aggregators manages their resources for the hour-ahead with 15 minute time intervals. A local electricity market (LEM) is considered so the multiple aggregators can meet the power balance constraint. Standard DE algorithm and four new metaheuristics are also used to solve the optimization problem. These four state-of-the-art algorithm are the Hybrid-Adaptive DE with Decay function (HyDE-DF) [14], a cellular estimation distribution algorithm named CUMDANCauchy++ [15], a DE with Estimation of Distribution Algorithm (DEEDA) [16], and a brand new algorithm named Hill Climbing to Ring Cellular Encode-Decode Univariate Marginal Distribution Algorithm (HC2RCEDUMDA) [17] that placed highly in the *"2021 Competition on Evolutionary Computation in the Energy Domain: Smart Grid Applications"* [18]. The results of these algorithms are then compared in the intraday context, and the Wilcoxon statistical test is performed to see the rankings of the algorithms and analyze which performs better.

This paper is organized as follows. Following this, Section II offers the problem formulation as well as the proposed optimization procedure, including the objective function and restrictions. The case study employed in this work is presented in Section III. The outcomes and analysis of these results are shown in Section IV. Finally, the last section discusses the paper's primary conclusions as well as future research.

II. PROPOSED FORMULATION

This section presents the proposed problem formulation in terms of mathematical formulation, algorithm optimization, and uncertainty generation.

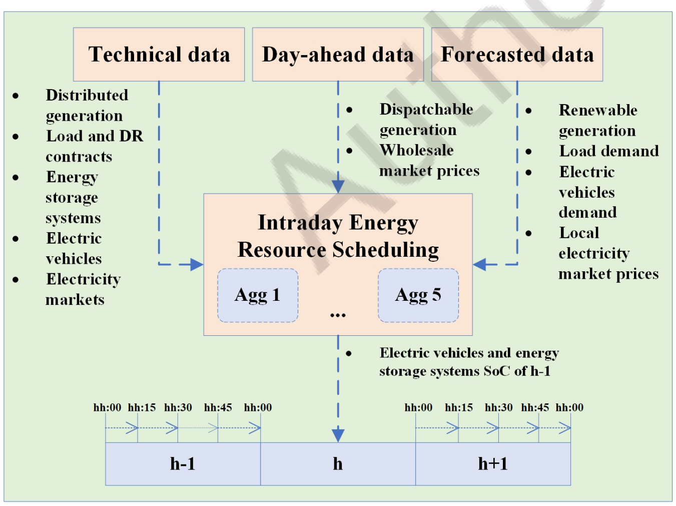

Fig. 1. Proposed intraday energy resource scheduling model.

Fig. 1 shows a diagram of resource schedule planning in the hour-ahead meaning. The technical data including the distributed generation needed for the renewable generation aggregator, load and demand response (DR) contracts for the load aggregators, EV data for the EV aggregator, and other shared resources. Hour-ahead forecasted the hour-ahead ERM model requires data, and the contracts closed in the day-ahead time horizon are also injected in the intraday model. For the next four time slots, projections are prepared using a 15-minute time slot resolution, where the EV and energy storage systems (ESSs) state of charge (SoC) of the hour $h-1$ is given in as the initial SoC of the hour h.

A. Mathematical model

Each aggregator seeks to keep its costs as low as possible while increasing its earnings. Here a minimization problem is proposed as $minimize\ OC$ where OC are the operational costs that each aggregator has and is given by:

$$OC = \sum_{t=1}^{T} \begin{bmatrix} \sum\limits_{i \in \Omega_{DG}^{d}} P_{DG(i,t)} \cdot C_{DG(i,t)} + \\ \sum\limits_{k=1}^{N_k} P_{ext(k,t)} \cdot C_{ext(k,t)} \end{bmatrix} \cdot \Delta t + \sum_{s=1}^{N_s} \sum_{t=1}^{T} \begin{bmatrix} \sum\limits_{i \in \Omega_{DG}^{nd}} P_{DG(i,t,s)} \cdot C_{DG(i,t)} + \\ \sum\limits_{e=1}^{N_e} P_{Disch(e,t,s)} \cdot C_{Disch(e,t)} + \\ \sum\limits_{v=1}^{N_v} EV_{Disch(v,t,s)} \cdot EVC_{Disch(v,t)} + \\ \sum\limits_{l=1}^{N_l} P_{Curt(l,t,s)} \cdot C_{Curt(l,t)} + \\ \sum\limits_{r=1}^{N_r} P_{ENS(r,t,s)} \cdot C_{ENS(r,t)} + \\ \sum\limits_{i=1}^{N_i} P_{GCP(i,t,s)} \cdot C_{GCP(i,t)} + \\ \sum\limits_{m=1}^{N_m} \left(P_{Buy(m,t)} - P_{Sell(m,t)}\right) \cdot MP_{(m,t,s)} + \\ \sum\limits_{l=1}^{N_{le}} \left(M_{Buy(le,t)} - M_{Sell(le,t)}\right) \cdot LM_{(le,t,s)} \end{bmatrix} \cdot \Delta t \cdot \pi(s) \quad (1)$$

where the number of periods is represented by the symbol T (four 15-minute periods), the set of dispatchable generation is referred to as Ω_{DG}^{d}. The number of external suppliers is given as N_k, and the total number of scenarios is N_s. N_e represents the number of ESSs. The number of EVs is called N_v, and the number of loads is N_l. N_r represents the number of resources where energy is not supplied (ENS), and N_i is the number of distributed generators. The symbol N_m denotes the number of wholesale (WS) markets, and the number of LEM is N_{le}. The active power generation is given by P_{DG} (MW), P_{ext} is the external power supplied (MW). P_{Disch} represents the ESS power discharge (MW), EV_{Disch} is the EV discharge power (MW). The power reduction of load l is given by P_{curt} (MW), P_{ENS} represents the non-supplied demand, in periods t of resource r (MW), and the excess of DG units' i generation is P_{GCP} (MW). P_{Buy} represents power purchased from the market (MW), P_{Sell} represents power sold to the market (MW), and M_{Buy} and M_{Sell} reflect power purchased and sold in the LEM (MW), respectively. C_{DG} represents the cost of distributed generation (m.u./MWh), C_{ext} represents the cost of an external supplier (m.u./MWh), and C_{Disch} represents the cost of ESS discharging (m.u./MWh). The cost of EV discharge is EVC_{Disch} (m.u./MWh), and the load curtailment cost is C_{Curt} (m.u./MWh). The cost of energy not supplied is represented by C_{ENS} (m.u./MWh), whereas the penalty for excess energy is represented by C_{GCP} (m.u./MWh). The WS electricity market price is MP (m.u./MWh), while the LEM price is LM (m.u./MWh). Finally, for each scenario, $pi(s)$ is the scenario probability.

It's worth noting that each aggregator is in charge of a specific service in the DN; as a result, certain parameters of (1) become zero and disappear depending on the aggregator's special purpose. For example, for the load aggregators, the EV term and renewable energy term disappear.

The problem constraints are similar to [19] including the LEM contraints and can be summarized as: the power balancing constraint specifies that the quantity of created power must match the amount of consumed power at any given time t; limits on dispatchable generation and power generation from external suppliers in each time t; DR constraint gievn by the maximum amount reduction of load l in period t; the non-dispatchable generation constraint; constraints on energy storage systems include the battery balance of each ESS, the maximum charge and discharge limitations for each ESS, the maximum battery capacity limit for each ESS, and the minimum amount of stored energy that must be guaranteed at the conclusion of the period t, and each ESS cannot charge/discharge in the same period t; constraints related to the EV battery that are similar to the ESS constraints such as EV power balance, charge and discharge limits for each EV over a given time t, battery capacity limits for each EV, and the minimum energy stored necessary at the conclusion of instant t equal to the ESSs, and each EV cannot charge/discharge at the same period t; offer and bidding limits in the WS and LEM markets, where values are bargained in the day-ahead time horizon for each hour in the WS market (four 15 minutes time slots).

B. Metaheuristics

Multiple algorithms were used to solve the intraday optimization problem, including the DE algorithm and four new evolutionary algorithms (EAs).

1) DE: For this problem, the DE algorithm with a mutation strategy *"DE/rand/1/bin"* was used. Only one difference vector (random solutions) is required for mutation, and binomial crossover is used. The mutation operator of the used strategy can be given by:

$$\vec{m}_{i,G} = \vec{x}_{r1,G} + F(\vec{x}_{r2,G} - \vec{x}_{r3,G}) \tag{2}$$

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: The HyDE-DF algorithm [14] uses the mutation strategy *"DE/target-to-perturbed_best/1"*, the same as the normal hybrid-adaptive DE paired with a decay factor δ_G. This factor is initially one and gradually decreases as the number of iterations increases as given in $\delta_G = e^{(1-\frac{1}{a^2})}$ with $a = (GEN - G)/GEN$ where GEN are the maximum number of iterations, and G is the latest iteration being run. The mutation operator of the HyDE-DF algorithm is as follows:

$$\vec{m}_{i,G} = \vec{x}_{i,G} + \delta_G \cdot [F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G})] + F_i^2(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \tag{3}$$

where $\vec{x}_{r1,G}$, $\vec{x}_{r2,G}$ are different from $\vec{x}_{i,G}$, which is the current target vector, and $\vec{x}_{best}$ is the best solution found. F_i^1, and F_i^2 are two scaling factors within the range [0,1] independent for each individual i. $\epsilon = \mathcal{N}(F_i^3, 1)$ represents a random perturbation factor, with 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 generation following a self-adaptive mechanism. 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.

3) DEEDA: The DEEDA algorithm [16] in an initial phase uses the standard DE algorithm to obtain a partial solution. After an Estimation of Distribution Algorithm (EDA), normal and Cauchy distributions are used to find the global solution. Combining these two different algorithms helps the optimum solution to be guided on a correct global scale.

4) CUMDANCauchy++: CUMDANCauchy [15] is a cellular EA that uses the Normal and Cauchy distributions to develop a new solution. To handle the uncertainty associated with DN resources, CUMDANCauchy++ is an upgrade to the prior technique. This algorithm uses a mechanism of comparison of s_{best} and $global_{best}$, that is, if the fitness of x individuals is less than the fitness of this $global_{best}$, this parameter is then updated with the best value found in the fitness of these individuals.

5) HC2RCEDUMDA: HC2RCEDUMDA is a brand new algorithm that combines hill climbing and a ring cellular encode-decode UMDA (RCEDUMDA) [17]. This algorithm uses a cellular estimation of distribution algorithm similar to CUMDANCauchy. The search space is reduced by transforming continuous variables to categorical variables and then inverting the process, basically using an encoding-decoding method. This algorithm also estimates an univariate marginal distribution $p(x) = \prod_{i=1}^{l} p(x_i)$ from the neighborhoods' best individuals. A scaling method is used for the $p(x_i)$ to generate new individuals according to the probability of distribution used.

C. Solution encoding

The initial solution generated by the metaheuristic is initialized randomly between the maximum and minimum limits specified for each variable. Fig. 2 shows the vector representation of the developed solutions for the hour-ahead.

Individual 1	D1	D2	D3	D4
Individual 2	D1	D2	D3	D4
Individual 3	D1	D2	D3	D4
...	...	...	...	
Individual NP	D1	D2	D3	D4

Group of variables		
Name	**Type**	**Bounds**
Dispatchable power generation	Continuous	[DApower]
Non-dispatchable power generation	Continuous	[minPower,maxPower]
Dispatchable power generation binaries	Binary	[DAbin]
Non-dispatchable power generation binaries	Binary	0,1
EVs charge/discharge	Continuous	[-maxDischarge,maxCharge]
Demand response	Continuous	[0,maxReduce]
ESSs charge/discharge	Continuous	[-maxDischarge,maxCharge]
WS market	Continuous	[DAbuy/sell]
LEM	Continuous	[-maxBuy,maxSell]

Fig. 2. Solution encoding.

Each solution per individual is represented by sequentially repeating a group of variables for all periods of the optimization hour, in this case, four periods (15 minutes each). All variables in this group are of the continuous type except for the binary variables associated with the state of the generators. This state is 0 if it is not connected to the grid and 1 if it is. For the intraday case, the dispatchable DG and WS market do not vary, and their bounds are equal to the values obtained in day-ahead.

In the group of variables belonging to the non-dispatchable generation that includes PV and wind generation, it is essential to note that this generation cannot be controlled; hence even if it is included in the vector solution, the variables relating to renewable generation will have a specific, and thus unchangeable, the value depending on the scenario.

III. Case Study

The proposed methodology previously shown is applied to the case study that this section describes.

Five different aggregators are proposed in this case study. Each aggregator has to manage various types of resources, resources that are integrated into a 13-bus distribution network (DN) inserted in a smart city with varying types of loads, high penetration of EVs, and renewables like Fig. 3 shows [20]. The considered aggregators are divided as follows:

- Aggregator 1: Service loads (hospital, fire station, and shopping mall);
- Aggregator 2: Residential loads;
- Aggregator 3: Office loads;
- Aggregator 4: Renewable production;
- Aggregator 5: EVs.

Aggregator 1 consists of 3 loads, aggregator 2 has 15 loads of residential buildings, and aggregator 3 has seven office buildings, making 25 types of loads present in the network. In terms of renewable production, aggregator 4 has two wind generation farms and 13 photovoltaic parks. For the last aggregator, a total of 2000 EVs are considered for the simulations performed. The data for each EV was obtained from an EV trip simulator tool present in [21] used to simulate the uncertainty associated with EV trips.

For the uncertainty, 5000 scenarios were produced, which were then reduced to 150 scenarios for day-ahead scheduling

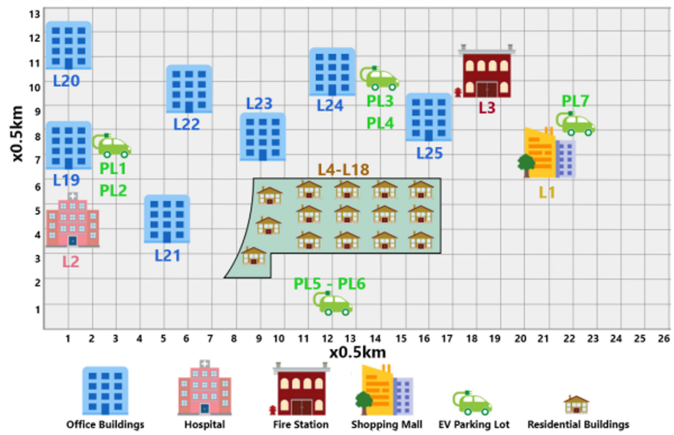

Fig. 3. Smart city schematic [20].

using a technique present in [22]. In the intraday, 150 new scenarios were produced from the scenario with the highest probability in the day-ahead. A normal distribution function was applied to the uncertain resources from this scenario with a 5% variation to inject into the provided hour-ahead model using these generated scenarios. This circumstance is not ideal, and it may cause a minor change in the obtained results when using the same technique used for the day-ahead. The overall demand and renewable generation forecasted by the proposed method for four aggregators is shown in Fig. 4. From aggregator 1 to 3, the range for the total demand is given, and full renewable power is demonstrated in aggregator 4.

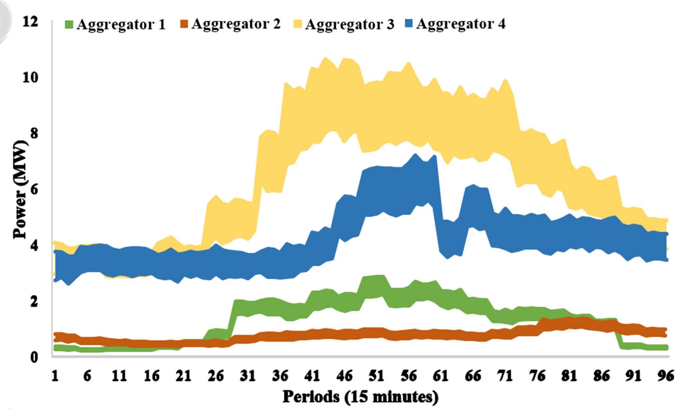

Fig. 4. Total demand and renewable generation forecast for each aggregator in the intraday time horizon.

Fig. 5 shows the prices used in intraday marketplaces for these aggregators' resource optimization. Compared to the LEM, which changes the prices in the range depicted in Fig. 5, the external supplier and wholesale (WS) market prices are fixed and do not alter. Because the LEM is often more expensive than the WS market due to its proximity to the retail market, the price gap between the two markets was calculated at 25% with a 5% variation like previously mentioned. The considered percentage was small because it turned out that the higher this percentage is, the more the algorithm will try to sell the excess in the market to earn a higher profit which often caused a decrease in costs from day-ahead to intraday, which is not supposed to happen. The LEM is regarded to have 20% the capacity of the WS market.

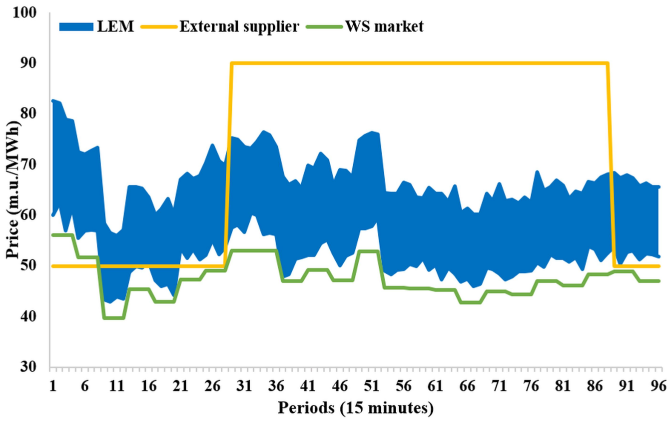

Fig. 5. External supplier, WS market, and LEM prices for the intraday time horizon.

Each aggregator has to manage their respective resources, power bought from the external supplier, and energy bought/sold in the marketplaces. Two energy storage systems (ESSs) were also considered and are attributed to all aggregators. Also are integrated into the DN four capacitors but are not considered in this problem, so they are set to zero. Table I presents the data of the energy resources associated with each aggregator, where a distinction is made from the aggregators, prices of the resources, capacity, forecasted values from the renewables and loads, and the number of units corresponding to each resource.

TABLE I
ENERGY RESOURCES INFORMATION OF EACH AGGREGATOR.

Energy resources		Aggregators	Prices (m.u./MWh) min–max	Capacity (MW) min–max	Forecast (MW) min-max	Units
Capacitors		1-5	0–0	0.00–0.00		4
Photovoltaic		4	150–150		0.00–0.94	13
Wind		4	130–130		0.60–2.80	2
External Supplier		1-5	50–90	0.00–30.00		1
Storage	Charge	1-5	110–110	0.00–1.25		2
	Discharge		90–90	0.00–1.25		
Electric Vehicles	Charge	5	0–0	0.01–0.13		2000
	Discharge		90–90	0.01–0.09		
Demand Response	Reduce program 1	1	100–100	0.01–1.21		3
	Reduce program 2	2	100–100	0.01–0.08		15
	Reduce program 3	3	100–100	0.28–0.1.11		7
Load type 1		1	0–0		0.01–2.23	3
Load type 2		2	0-0		0.01-0.13	15
Load type 3		3	0-0		0.31-1.88	7
Market buy and sell		1-5	39.66–56.08	0.00–10.00		1
Local Market buy and sell		1-5	42.97–82.61	0.00–2.50		1

Multiple metaheuristics were used to solve the proposed energy management model, and Table II shows the parameters chosen for each algorithm. For all metaheuristics, the population size (NP) and the maximum number of iterations was 20, and 250 respectively, taking into consideration the number of objective function evaluations [19]. The crossover probability (Cr) and scaling factor (F) are the following parameters, which are necessary for the first three displayed algorithms. The subpopulation size is given by p, and the number of selected individuals is provided by s. α represents the additional occurrence used in the scaling method of the HC2RCEDUMDA algorithm. The number of elitist individuals is represented by l. The neighborhood ratio is given by r. Finally, k is the number of codes used in the HC2RCEDUMDA metaheuristic.

TABLE II
PARAMETERS OF THE EAS.

Parameter	DE	HyDE-DF	DEEDA	CUMDANCauchy++	HC2RCEDUMDA
NP	20	20	20	20	20
Max iterations	250	250	250	250	250
Cr	0.50	0.50	0.50	-	-
F	0.30	0.30	0.30	-	-
p	-	-	16	16	-
s	-	-	2	2	3
α	-	-	-	-	0.009
l	-	-	-	-	3
r	-	-	-	-	3
k	-	-	-	-	7

The experiments were run on a machine with an AMD Ryzen 5 3600 processor with 3.6 GHz and 16GB of RAM running Windows 10 and MATLAB 2018a.

IV. RESULTS

The findings of applying the proposed methodology to the case study reported in Section III are shown in this section.

A total of 456 variables compose aggregator 1 in the day-ahead problem compared to 80 variables in the hour-ahead model. For aggregator 2, the number of variables was 744 in the day-ahead and 128 in the intraday time horizon. Aggregators 3 and 4 presented a total of 552 and 1,128 variables, respectively, in the day-ahead context. A total of 96 variables and 192 variables are in the intraday problem for aggregators 3 and 4. The aggregator 5 presented 48,384 variables in the day-ahead problem and 8,068 in the hour-ahead problem.

Table III shows the best-obtained results using CI for the day-ahead problem for one trial showing the time it took the metaheuristic to run the simulation. In [19] with CUMDAN obtained the best scheduling results for the day-ahead but for this case with different external supplier costs, and EV charging/discharging costs HyDE-DF presented better results in comparison to this algorithm as shown in Table III. It shows each proposed aggregator's cost when scheduling their resources for the next 24 hours.

The overall objective function results from the 20 trials for the 150 scenarios are shown in Table IV. Due to the scale of the numbers acquired in the various aggregators for the objective function, the table provides the minimum and maximum cost values, the average costs, and standard deviation in monetary units and percentages, and the increased percentage when comparing the intraday results with the day-ahead.

The average costs presented in Table IV are calculated by adding up the average prices of the optimization done for each hour for a total of 24 hours. Regarding the increase percentage it can be seen that for the first, thrid and fourth aggregators, the latest algorithm presents the best variation results despite being the slowest of all the metaheuristics tested. For aggregator 2, the DE is the one that gives the slightest variation compared to the day-ahead results. It can be concluded that for the last aggregator, the tested EAs did not obtain good results with HyDE-DF having the less variation value with 19.78% which is still not ideal. DE and HC2RCEDUMDA present a significant amount of penalties in the solution; that is, they could not find a solution that satisfied the power balance constraint.

When it comes to the optimization time for the first four aggregators the metaheuristics present similar values but for the last aggregator which is the aggregator with the most variables CUMDANCauchy is the fastest. From the standard deviation results DEEDA and CUMDAN present great percentages with values varying slightly between runs.

TABLE III
DAY-AHEAD OBJECTIVE FUNCTION RESULTS AND OPTIMIZATION TIME.

Aggregators	Costs (m.u.)	Penalties (m.u.)	Time (s)
1	1508.84	0.00	13.31
2	985.62	0.00	14.08
3	7793.99	0.00	15.12
4	8641.38	0.00	13.78
5	906.80	0.00	397.09

Fig. 6 shows the total costs of all aggregators obtained by each metaheuristic for the hour-ahead problem. For comparison between all intraday optimizations, a constant value of 19,836.63 m.u. is also shown for the overall price of the day ahead optimization. The HyDE-DF algorithm produced the slightest variation compared to the day-ahead, with a total value of 19,053.97 m.u., a minor drop of 782.66 m.u (3.95%). The overall costs of the DEEDA and CUMDANCauchy++ algorithms were similar, with DEEDA's total cost of 18,962.99 m.u. and CUMDANCauchy's total cost of 18,963.34 m.u. In this case, DEEDA showed the lowest prices in the entire system, presenting the best value in terms of operational costs with a 4.40% reduction. The worst overall expenses were HC2RCEDUMDA and DE, with the former having a 17.89% increase over the previous day and the latter having a total value of 21,865.94 m.u (10.23%). DE and HC2RCEDUMDA gave these prices due to the last aggregator when the expenses escalated enormously due to the imposed penalties.

A small example of the convergence of each algorithm for a population size of 20 is shown in Fig. 7. The first aggregator is tested in the 24th hour of the optimization. CUMDAN-Cauchy++ offers the best conversion compared to the other algorithms, but it is possible to observe that the solution in both CUMDAN and HC2RCEDUMDA can still be improved. This circumstance could indicate that the parameters employed; notably, the number of iterations and the objective function evaluation limit, were not the most optimal. In contrast, the fitness of DE, HyDE-DF, and DEEDA seem to stabilize. This last algorithm shows an increase in fitness around generation 50. This peak shows the transaction in the algorithm from the DE to the EDA.

A Wilcoxon test was also applied to the intraday results considering a sample of 20 trials with 24 hours each. The base

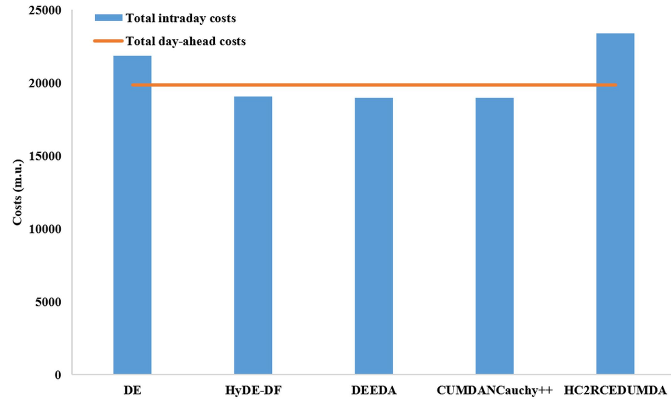

Fig. 6. A comparison of the day-ahead total costs with the overall intraday costs generated by each EA.

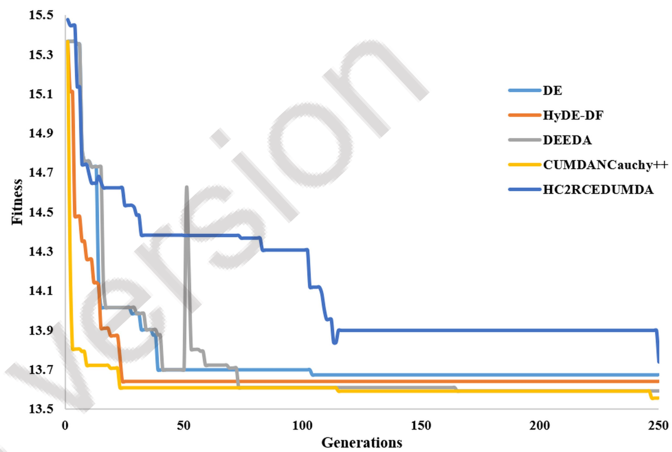

Fig. 7. Convergence of the considered EAs using NP= 20 for the last hour of the intraday problem of the first aggregator.

algorithm for comparison with the others was the CUMDAN-Cauchy++ algorithm represented in Table V. The Wilcoxon test was applied to each set of results of the five aggregators. Table V shows the signal ranking of the statistical test. For all aggregators, it can be determined that CUMDANCauchy++ outperforms HC2RCEDUMDA and HyDE-DF. CUMDAN-Cauchy also outperforms DE in all aggregators, with the exception of the fourth, where they have identical results. DEEDA is only outperformed in the first aggregator; in the remaining aggregators, both algorithms perform similarly.

V. CONCLUSIONS

This work proposes an optimal intraday energy resource scheduling for multiple aggregators considering the high penetration of distributed energy resources in a DN. The intraday problem considers an hour-ahead model with four 15 minute periods and transactions on a LEM to meet the energy balance equation.

The optimization problem was solved using a variety of metaheuristics to schedule their available resources. Each of the five aggregators must consider the constraints in the day-ahead management and the previous optimization hour, and

TABLE IV
OVERALL INTRADAY OBJECTIVE FUNCTION RESULTS AND OPTIMIZATION TIME BY THE TESTED METAHEURISTICS.

Metaheuristic	Aggregators	Avg. costs (m.u.)	Std. costs (m.u.)	Min. costs (m.u.)	Max. costs (m.u.)	Avg. penalties (m.u.)	Avg. Time (s)	Increase (%)
DE	1	1481.98	4.98 (0.34%)	1476.32	1495.86	0.00	2.05	-1.78
	2	978.19	9.25 (0.95%)	963.07	997.97	0.00	2.46	-0.75
	3	7473.07	51.52 (0.69%)	7387.53	7591.33	0.00	1.98	-4.12
	4	8525.54	0.94 (0.01%)	8525.30	8529.41	0.00	2.16	-1.34
	5	3478.17	49.20 (1.41%)	3386.13	3576.12	100.00	61.44	283.57
HyDE-DF	1	1479.70	3.33 (0.23%)	1474.88	1487.31	0.00	2.05	-1.93
	2	945.11	4.08 (0.43%)	938.80	953.85	0.00	2.03	-4.11
	3	7371.48	23.60 (0.32%)	7336.56	7423.03	0.17	2.03	-5.42
	4	8527.98	6.27 (0.07%)	8526.27	8542.75	0.00	2.20	-1.31
	5	727.42	4.74 (0.65%)	720.35	737.78	0.00	64.73	-19.78
DEEDA	1	1472.92	0.00 (0.00%)	1472.92	1472.93	0.00	1.97	-2.38
	2	934.22	0.00 (0.00%)	934.22	934.23	0.00	2.20	-5.22
	3	7317.24	0.18 (0.00%)	7316.98	7317.59	0.67	2.20	-6.12
	4	8525.32	0.09 (0.00%)	8525.30	8525.70	0.00	2.36	-1.34
	5	713.26	0.00 (0.00%)	713.26	713.26	0.00	46.01	-21.34
CUMDANCauchy++	1	1472.92	0.01 (0.00%)	1472.92	1472.95	0.00	2.27	-2.38
	2	934.22	0.00 (0.00%)	934.22	934.22	0.00	2.07	-5.22
	3	7317.35	0.27 (0.00%)	7317.13	7318.29	0.67	2.12	-6.12
	4	8525.31	0.06 (0.00%)	8525.30	8525.57	0.00	2.17	-1.34
	5	713.26	0.00 (0.00%)	713.26	713.27	0.00	41.69	-21.34
HC2RCEDUMDA	1	1516.88	25.30 (1.67%)	1479.81	1575.26	0.00	24.07	0.53
	2	1052.76	18.49 (1.76%)	1019.28	1088.99	0.00	22.89	6.81
	3	7984.65	157.49 (1.97%)	7713.67	8320.24	0.50	23.78	2.45
	4	8532.67	14.32 (0.17%)	8525.99	8579.71	0.00	22.19	-1.26
	5	4349.15	66.70 (1.53%)	4234.71	4469.32	235.00	89.39	379.61

TABLE V
RESULTS FROM THE WILCOXON SIGNED-RANK TEST.

		DE	HyDE-DF	DEEDA	HC2RCEDUMDA
Agg 1	**CUMDAN**	'+'	'+'	'+'	'+'
Agg 2		'+'	'+'	'='	'+'
Agg 3		'+'	'+'	'='	'+'
Agg 4		'='	'+'	'='	'+'
Agg 5		'+'	'+'	'='	'+'

the uncertainty associated with the intraday time horizon. The critical aspect is that there is no significant variation from what has already been scheduled in day-ahead into whats is sequentially scheduled in the intraday. Still, there is usually a slight increase/decrease in costs. HC2RCEDUMDA presented the best solution for the first aggregator (0.53% increase) and the third and fourth aggregators, with DE having the slightest variation when it comes to the second aggregator with only a 0.75% decrease. It can be concluded that, especially for the EV aggregator (aggregator 5), the adopted mechanism is weak because there are huge variations up to almost 400% when the comparison is made with the day-ahead. In some cases, there are associated penalties of 235.00 m.u. for HC2RCEDUMDA and 100 m.u. DE. A deterministic method could be a better alternative mainly due to the low number of variables present in the hour-ahead model.

CUMDANCauchy++ has been compared to the other algorithms through a statistical test, i.e., DE, HyDE-DF, DEEDA, HC2RCEDUMDA. We can conclude through this paper that the CUMDANCauchy++ algorithm is very competitive in this problem, having a better statistical performance than all other algorithms for all aggregators, except DEEDA, which has similar performance. This algorithm and the DEEDA algorithm present a similar performance on most simulations due to the learning processes used to generate a new solution by estimating Normal and Cauchy distributions.

REFERENCES

[1] A. Bartolini, G. Comodi, F. Marinelli, A. Pizzuti, and R. Rosetti, "A Matheuristic Approach for Resource Scheduling and Design of a Multi-energy System:," in *Proceedings of the 8th International Conference on Operations Research and Enterprise Systems*, Prague, Czech Republic, 2019, pp. 451–458. doi: 10.5220/0007574104510458.

[2] S. Leonori, A. Martino, F. M. Frattale Mascioli, and A. Rizzi, "Microgrid Energy Management Systems Design by Computational Intelligence Techniques," *Applied Energy*, vol. 277, p. 115524, Nov. 2020, doi: 10.1016/j.apenergy.2020.115524.

[3] G. Graditi, M. L. Di Silvestre, R. Gallea, and E. Riva Sanseverino, "Heuristic-Based Shiftable Loads Optimal Management in Smart Micro-Grids," *IEEE Trans. Ind. Inf.*, vol. 11, no. 1, pp. 271–280, Feb. 2015, doi: 10.1109/TII.2014.2331000.

[4] M. Hedayati-Mehdiabadi, K. W. Hedman, and J. Zhang, "Reserve Policy Optimization for Scheduling Wind Energy and Reserve," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 19–31, Jan. 2018, doi: 10.1109/TPWRS.2017.2707568.

[5] Y.-Y. Hong and P.-S. Yo, "Novel Genetic Algorithm-Based Energy Management in a Factory Power System Considering Uncertain Photovoltaic Energies," *Applied Sciences*, vol. 7, no. 5, p. 438, Apr. 2017, doi: 10.3390/app7050438.

[6] R. Faia, T. Pinto, Z. Vale, J. M. Corchado, J. Soares, and F. Lezama, "Genetic Algorithms for Portfolio Optimization with Weighted Sum Approach," in *2018 IEEE Symposium Series on Computational Intelligence (SSCI)*, Bangalore, India, Nov. 2018, pp. 1823–1829. doi: 10.1109/SSCI.2018.8628773.

[7] J. Soares, H. Morais, T. Sousa, Z. Vale, and P. Faria, "Day-Ahead Resource Scheduling Including Demand Response for Electric Vehicles," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 596–605, Mar. 2013, doi: 10.1109/TSG.2012.2235865.

[8] J. Soares, M. A. Fotouhi Ghazvini, M. Silva, and Z. Vale, "Multi-dimensional signaling method for population-based metaheuristics: Solving the large-scale scheduling problem in smart grids," *Swarm and Evolutionary Computation*, vol. 29, pp. 13–32, Aug. 2016, doi: 10.1016/j.swevo.2016.02.005.

[9] F. Lezama, L. E. Sucar, E. M. de Cote, J. Soares, and Z. Vale, "Differential evolution strategies for large-scale energy resource management in smart grids," in *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, Berlin Germany, Jul. 2017, pp. 1279–1286. doi: 10.1145/3067695.3082478.

[10] P. Chandra, A. Das, C. Das, A. Naskar, B. Ganguly, and S. Paul, "Differential Evolution Algorithm Based Energy Management of Residential Microgrid Under Appliance Scheduling DSM," in *2020 IEEE VLSI DEVICE CIRCUIT AND SYSTEM (VLSI DCS)*, Kolkata, India, Jul. 2020, pp. 50–55. doi: 10.1109/VLSIDCS47293.2020.9179893.

[11] F. Lezama, J. Soares, R. Faia, T. Pinto, and Z. Vale, “A New Hybrid-Adaptive Differential Evolution for a Smart Grid Application Under Uncertainty,” in *2018 IEEE Congress on Evolutionary Computation (CEC)*, Rio de Janeiro, Jul. 2018, pp. 1–8. doi: 10.1109/CEC.2018.8477808.

[12] Y. Martínez-López, A. Y. Rodríguez-González, J. M. Quintana, A. Moya, B. Morgado, and M. B. Mayedo, “CUMDANCauchy-C1: a cellular EDA designed to solve the energy resource management problem under uncertainty,” in *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, Prague Czech Republic, Jul. 2019, pp. 13–14. doi: 10.1145/3319619.3326743.

[13] J. Soares, N. Borges, Z. Vale, and P. B. Oliveira, “Enhanced Multi-Objective Energy Optimization by a Signaling Method,” *Energies*, vol. 9, no. 10, p. 807, Oct. 2016, doi: 10.3390/en9100807.

[14] F. Lezama, J. Soares, R. Faia, and Z. Vale, “Hybrid-adaptive differential evolution with decay function (HyDE-DF) applied to the 100-digit challenge competition on single objective numerical optimization,” in *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, Prague Czech Republic, Jul. 2019, pp. 7–8. doi: 10.1145/3319619.3326747.

[15] Y. Martínez-López, A. Y. Rodríguez-González, J. M. Quintana, M. B. Mayedo, A. Moya, and O. M. Santiago, “Applying some EDAs and hybrid variants to the ERM problem under uncertainty,” in *Proceedings of the 2020 Genetic and Evolutionary Computation Conference Companion*, Cancún Mexico, Jul. 2020, pp. 1–2. doi: 10.1145/3377929.3398393.

[16] Y. Martínez-López, J. Madera, A. Moya, M. Bethencourt, and A. Y. R. González, “DEEDA Differential Evolutionary and Estimation of Distribution Algorithm,” p. 2.

[17] A. Y. Rodríguez-González, S. Barajas, R. Aranda, Y. Martínez-López, and J. Madera-Quintana, “Ring cellular encode-decode UMDA: simple is effective,” in *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, Lille France, Jul. 2021, pp. 1–2. doi: 10.1145/3449726.3463278.

[18] F. Lezama, J. Soares, B. Canizes, Z. Vale, and R. Romero, “CEC/GECCO 2021 Competition Evolutionary Computation in Uncertain Environments: A Smart Grid Application,” p. 18.

[19] J. Almeida, J. Soares, B. Canizes, F. Lezama, M. A. Ghazvini Fotouhi, and Z. Vale, “Evolutionary Algorithms for Energy Scheduling under uncertainty considering Multiple Aggregators,” in 2021 IEEE Congress on Evolutionary Computation (CEC), Kraków, Poland, Jun. 2021, pp. 225–232. doi: 10.1109/CEC45853.2021.9504942.

[20] B. Canizes, J. Soares, Z. Vale, and J. M. Corchado, “Optimal distribution grid operation using DLMP-based pricing for electric vehicle charging infrastructure in a smart city,” *Energies*, vol. 12, no. 4, 2019.

[21] J. Soares, B. Canizes, C. Lobo, Z. Vale, and H. Morais, “Electric Vehicle Scenario Simulator Tool for Smart Grid Operators,” *Energies*, vol. 5, no. 6, pp. 1881–1899, Jun. 2012, doi: 10.3390/en5061881.

[22] N. Growe-Kuska, H. Heitsch and W. Romisch, ”Scenario reduction and scenario tree construction for power management problems,” *2003 IEEE Bologna Power Tech Conference Proceedings*, Bologna, Italy, 2003, pp. 7 pp. Vol.3-.