Exploiting flexibility of end-users at DSO-TSO levels acting in dynamic coalitions

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***Abstract*—In this paper, we propose and analyze a coalitional game in which end-users with different characteristics and preferences can cooperate to offer their flexibility to upper-level entities such as the DSO and TSO. We formulate the problem as a cooperative game in which users need to decide the percentage of flexibility they want to offer to DSO and TSO, while searching for the coalition structures that maximize their utilities. Finding the optimal coalition structure that maximizes the sum of pay-offs (i.e., social welfare) is a complex combinatorial problem that cannot be efficiently solved for large instances. Therefore, we evoke the use of computational intelligence algorithms to find near-optimal solutions that can provide higher pay-offs in acceptable times than, for example, the grand coalition and independent coalitions.**

I. Introduction

The large-scale integration of renewable energy sources (RES) is occurring worldwide. However, the distributed generators based on renewable sources, such as solar, wind, among others, carry an inherent variability that introduces several challenges to the planning and operation of distribution networks. The high penetration of this kind of generators may have a positive or negative impact on the regular operation of the distribution networks [1].

The distribution network (DN) design and operation are not adequately prepared to integrate a large number of distributed RES units. As a result, the distribution system operators (DSO) are encouraged to rethink their actions according to the most recent challenges. Consumption flexibility is seen as one of the most promising solutions to counterbalance the variability from the generation side and mitigate several of the problems that are emerging [2]. However, in order to capture the full potential from consumers' flexibility, the coordination between the DSO and the transmission system operator (TSO) is required. In [3], five different mechanisms of coordination between TSO and DSO are presented. In all scenarios, the aggregator is the player that enables flexibility resources aggregation.

The aggregator is, in fact, a player that enables the coordination and cooperation between multiple small-sized resources, including consumers; see e.g. [4], which presents a model for local market trading with different levels of flexibility transaction, using the aggregator as the facilitator of transactions. Coalitional game theory is being increasingly used as an enabler of consumers aggregation process. For instance, in [5], a cooperative game theory model is used to minimize the coalitional energy cost. A framework for smart transactive energy in home-microgrids considering coalition formation and demand-side management is presented in [6]. A coalitional game approach is also used in [7] to address the problem of sharing storage in a smart grid; in [8] to solve the cooperative energy trading of wind turbines and in [9] and [10] to deal with microgrid related problems.

Although coalitional game theoretical models have been studied and applied as a promising way to solve power and energy system problems, the problem of dynamic coalition formation for consumers flexibility considering multiple negotiation opportunities, both at the DSO and TSO level, has not yet been addressed. In this paper, a coalitional game in which end-users can opt to offer their flexibility for local management (DSO level) or upper streaming level (TSO level) is formulated. Consumers are able to choose their coalitions according to the expected benefits, contrarily to the usual approach in which the aggregator dictates the aggregation structure. An evolutionary optimization approach is also introduced to enable reaching decisions in acceptable time frames.

After this introductory section, Section II presents the problem formulation, Section III provides a description of the proposed application of evolutionary computation to find the optimal coalition structures, and Section IV presents the achieved results. Finally, Section V presents the most relevant conclusions of this work.

II. Problem formulation

The flexibility aggregation model proposed in this work aims at capturing the essence of a game in which players, representing energy consumers, are aggregated into two coalition structures to provide a percentage of their flexibility to upper levels of the energy chain. Each coalition is managed by a flexibility aggregator, which will negotiate the consumption flexibility of the members of its coalition structure to the DSO and TSO, respectively.

Figure 1 illustrates the proposed model. We assume that players (consumers) will get payed for their volume of flexibility at the weighted average price among all players of

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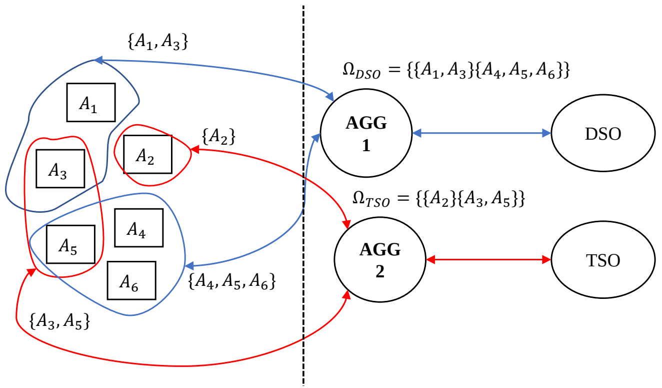

Fig. 1. Coalition formation with multiple options.

the coalition they belong to. Besides, players can be part of either both types of coalitions (see, for instance, A_2 and A_3 in the Figure) or just one depending on the percentage of flexibility they are able to offer to a given market. Upon that, we assume that players are interested in: (i) belong to coalitions in which their relative volume of flexibility is high (in this way, users expect to have a higher chance of being chosen when the flexibility aggregator needs to use some flexibility among its members); (ii) forming the lowest number of different coalitions as possible (to reduce the competition in the market, and thus avoid a potential reduction of the return prices); and (iii) being part of a coalition with as much diversity among the players as possible to reduce internal competition. Diversity refers to external characteristics, for instance: the volume of flexibility, the type of consumer (residential, industry, commerce, etc.), the expected price, previous participation in flexibility provision, flexibility profile (e.g., times at which the volume is available).

These preferences can be quantified, by attaching values to the possible outcomes Ω_{DSO} and Ω_{TSO} of the game G. In general terms, an outcome Ω is defined as (CS, x), representing a coalition structure CS together with a payoff vector x, with a value associated to each coalition. Moreover, each member i of the coalition structure has an associated utility value calculated with a function $u_i : \Omega \rightarrow R$. In this work, we define the utility of player i as the sum of utilities obtained from its participation in Ω_{DSO} and Ω_{TSO}:

$$u_i(\Omega) = u_i(\Omega_{DSO}) + u_i(\Omega_{TSO}) \qquad \forall i \in N \tag{1}$$

where $u_i(\Omega_{DSO})$ and $u_i(\Omega_{TSO})$ represent the possible incomes that an agent can generate by selling its flexibility to one market or another while taking into account the preferences mentioned above. Formally, we define:

$$u_i(\Omega_{DSO}) = I_{(i,DSO)} * Q_{(i,DSO)} \qquad \forall i \in N \tag{2}$$

$$I_{(i,DSO)} = V_{(i,DSO)} * \left(\frac{\sum_i M_i * V_{(i,DSO)}}{\sum_i V_{(i,DSO)}} \right) \tag{3}$$

$$Q_{(i,DSO)} = w_1 \frac{V_{(i,DSO)}}{\sum_{i=1}^{T_c} V_{(i,DSO)}} + w_2 \frac{1}{N * C} + w_3 D_c \tag{4}$$

where $I_{(i,DSO)}$ represents the incomes that player i gets for the volume of flexibility $V_{(i,DSO)}$ multiplied by the volume-weighed average price. On the other hand, $Q_{(i,DSO)}$ in Eq. (4) captures the preferences of player i regarding its relative volume of flexibility (first term), reducing the total number of coalitions (second term), and increasing the diversity of the coalition it belongs to (third term).

The calculation of $u_i(\Omega_{TSO})$ follows the same logic of Eq. (2)-(4) considering flexibility and prices for the TSO. Overall, we search for maximizing the utilitarian social welfare over all the coalitions defined as:

$$\text{maximize} : USW = \sum_{i \in N} u_i(\Omega) \tag{5}$$

where $u_i(\Omega)$ includes the utilities that player i obtains from the DSO and TSO aggregators (eq. 1). Notice that other social welfare criteria, such as the egalitarian social welfare, can be easily adapted to the formulation.

III. Finding the Optimal Coalition Structures Using Evolutionary Computation

In our framework, we are interested in finding coalition structures to participate at the DSO and TSO levels maximizing the utilitarian social welfare. In fact, the optimal CS search problem is a combinatorial problem with an exponential search space depending on the number of players in the game [11]. In addition, players also need to determine the volume of flexibility they will provide to each type of coalitions, which increases the complexity of the problem.

Deterministic approaches proposed to solve the CS search problem systematically searching the space and a bound on the value of the optimal structure [12]. However, deterministic approaches exhaustively search the entire space of CS, which is unpractical due to the exponential relationship between the size of the search space and the number of players. While from the theoretical point of view, having guarantees on the CS searching procedure is relevant, from the practical point of view, we are interested in finding effective and efficient CS despite a large number of players in the system.

Therefore, we evoke the use of evolutionary computation to find near-optimal solutions to the problem in practical applications. Despite no guarantees on finding the optimal CS can be provided due to the stochastic nature of evolutionary algorithms (EA), this class of algorithms has been successfully applied in large-scale NP-complete combinatorial optimization problems including finding near-optimal coalitional structures [13], [14].

We utilize a variant of the differential evolution (DE) [15], the recently proposed Hybrid-adaptive DE with decay function (HyDE-DF) [16]. HyDE-DF is a population-based solver that acts over an initial set of candidate solutions (i.e., a population) that is iteratively updated through mutation and

TABLE I
AGENTS CHARACTERISTICS AND PREFERENCES

Player ($i \in N$)	Characteristics Type*	Load range (kW)	Consumption (kWh)	Preferences Flexibility (kWh (%))	DSO price (EUR/kWh)	TSO price (EUR/kWh)
1	(1) House	0.18-0.48	4.24	0.85 (20%)	0.12-0.28	0.12-0.28
2	(2) House	0.06-2.50	14.22	1.42 (10%)	0.14-0.26	0.14-0.26
3	(3) House	0.07-0.36	4.23	0.63 (15%)	0.16-0.2	0.16-0.2
4	(4) Building	1.56-4.35	60.52	1.51 (25%)	0.25-0.28	0.25-0.28

The number in parenthesis is used as a numerical representation of the type in the calculation of Q_i

recombination operators (similar to the well-known genetic algorithms). The performance of solutions is measured by a given fitness function, and at each generation, solutions with inferior performance are stochastically removed, whereas new solutions (generated through a specific operator) are introduced into the population. It is expected that by the principles of natural/artificial selection, the population will gradually evolve towards the optimal fitness value [17].

In fact, different EAs (e.g., genetic algorithms, DE, and many of their variants) follow the same cycle of evolution (i.e., mutation, recombination, and selection). Therefore, most of them can be applied easily by defining an encoding of solutions (i.e., a way to represent solutions to the problem typically as vectors or a numerical string) and a fitness function to evaluate such solutions. Therefore, to capture all the information required by the encoding of a solution in our problem, we define a vector:

$$\vec{x} = [\{x_{a1}, ..., x_{aN}\}, \{x_{b1}, ..., x_{bN}\}, \{x_{f1}, ..., x_{fN}\}] \quad (6)$$

where the first and second group of N variables $\{x_{a1}, ..., x_{aN}\}$ and $\{x_{a1}, ..., x_{aN}\} \in \vec{x}$ are used to represent the coalition structures Ω_{DSO} and Ω_{TSO} respectively; while the third group $\{x_{f1}, ..., x_{fN}\} \in \vec{x}$ is used to represent the percentage of flexibility that players put in each level.

The representation of coalition structures follows a simple label-based clustering encoding [18], in which the position of the element indicates the player $n \in N$, while the value in the position represents the coalition that the player belongs to. This particular encoding was designed to operate over integer values. However, since the applied evolutionary algorithm works over real values, we define the bounds of variables in the first and second groups in the range $[1, k+1]$, being k the maximum allowed number of coalitions. Then, for the decoding process, we use the floor function, which maps the real values to integers in the range $[1, k]$.

For the flexibility provided by each player, i.e., the third group of variables $\{x_{f1}, ..., x_{fN}\} \in \vec{x}$, we use a continuous number in the range $[0, 1]$ representing the percentage of flexibility that player i offers to the DSO market; while the complement of that variable represents the percentage of flexibility offered to the TSO aggregator:

$$V_{DSO,i} = V_{total,i} * x_{f,i} \quad \forall i \in N \quad (7)$$

$$V_{TSO,i} = V_{total,i} * (1 - x_{f,i}) \quad \forall i \in N \quad (8)$$

where $V_{total,i}$ is the total flexibility that player i can provide to the aggregators. Fig. 2 shows an example of an encoded solution, the decoding process, and the resulting coalitions and flexibility for clarification. Notice that each solution has a dimension $D = N * 3$, where N corresponds to the number of players.

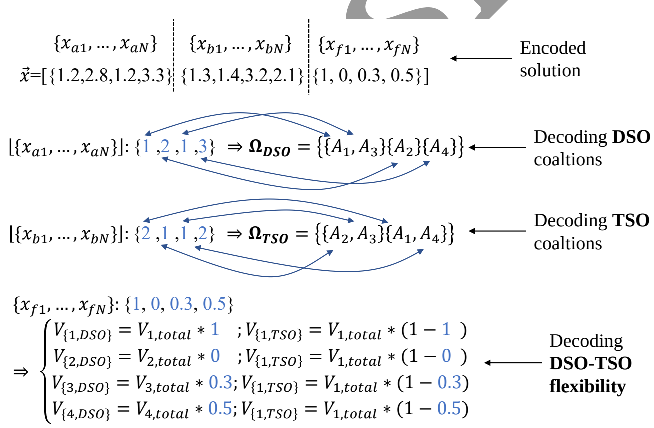

Fig. 2. Individual representation, coding and decoding.

IV. RESULTS AND DISCUSSION

A. Case study and experiments

We assess our approach under two case studies. The first one considers a few number of agents to appreciate the relations and dependencies of the coalitions easily. We also provide a second case study examining a large number of players to analyze the scalability characteristics of our approach.

Table I presents the base profiles and characteristics of the considered players. Three different profiles of residential houses and one of a building are considered. The sample power profiles were taken from open datasets available in PES ISS website[1]. We assume that players can set some preferences, e.g., the flexibility they are willing to provide (in the form of load reduction), and the desire price they are expecting to obtain for joining a DSO or TSO coalition. We generate the expected prices for each of the next 24 hours using a randomized value between the ranges presented in the table.

[1]Open data online at http://sites.ieee.org/pes-iss/data-sets/

TABLE II
COALITION STRUCTURES AND UTILITIES FOR FOUR AGENTS CONSIDERING THE BASELINE AND HYDE AS THE EVOLUTIONARY APPROACH.

	Coalitions		**Flex offer**	**Utility**		
	Ω_{DSO}	Ω_{TSO}	x_{fi}	$U_i(\Omega_{DSO})$	$U_i(\Omega_{TSO})$	**USW**
GCo	{1,2,3,4}	{1,2,3,4}	{1,1,1,1}	[78.7, 140.7, 57.8, 2441.9]	[0, 0, 0, 0]	2719.1
	{1,2,3,4}	{1,2,3,4}	{0,0,0,0}	[0, 0, 0, 0]	[77.8, 145.2, 57.3, 2406]	2686.2
	{1,2,3,4}	{1,2,3,4}	{0.5,0.5,0.5,0.5}	[39.4, 70.3, 28.9, 1220.9]	[38.9, 72.6, 28.7, 1203]	2702.7
ICo	{1}{2}{3}{4}	{1}{2}{3}{4}	{1,1,1,1}	[78, 111, 45.8, 1668.9]	[0, 0, 0, 0]	1903.9
	{1}{2}{3}{4}	{1}{2}{3}{4}	{0,0,0,0}	[0, 0, 0, 0]	[68.7, 112.8, 46.8, 1654.2]	1882.5
	{1}{2}{3}{4}	{1}{2}{3}{4}	{0.5,0.5,0.5,0.5}	[39, 55.7, 22.9, 834.4]	[34.4, 56.4, 23.4, 827.1]	1893.2
HyDE-Co	{1,2,3,4}	{1,4}{2,3}	{1,0,0,0}	[128, 0, 0, 0]	[0, 203.6, 79.8, 3308.4]	3719.8

Notice that the ranges of prices for each player were selected equally for the DSO and TSO aggregator. While the impact of such prices is out of the scope of this paper, further studies in this regard are highly encouraged.

For the second case study, we generate agent data using a randomized function with uniform distribution, 20% around the four standard profiles of Table I. We generated 100 players of each type of house, and 60 corresponding to buildings, having a total of 360 players. The goal of the second experiment is to test the scalability of our approach, which is of paramount importance in real-world applications.

B. Results and discussion

The first experiment considers a small case study with four players. As a baseline, we include solutions concerning full cooperation (grand coalition - GCo) and no cooperation (independent coalition - ICo) of players. Since strategic behavior of agents involves the decision of putting flexibility into two markets, we consider three particular cases for each of the coalitions as baseline for comparison purposes, namely, i) players offering all the flexibility to the DSO aggregator (DSO-all), ii) players offering all flexibility to the TSO aggregator (TSO-all), iii) players offering fifty-fifty percent to DSO and TSO respectively (50-50).

Table II summarizes the results of the baseline, and the one obtained with the evolutionary algorithm (labeled as HyDE-Co). The Table includes the coalitions formed, the flexibility offered to the DSO market (the complement is offered to the TSO market), and the utilities and USW for each member. It can be seen that from the baseline solutions, the grand coalition (i.e., full cooperation) gives better pay-offs for their members than going alone to the markets. Nevertheless, HyDE was able to find a partition with a better pay-off for all their members when two coalitions ($\Omega_{DSO} = \{1, 0, 0, 0\}$) are formed to go for the TSO aggregator. Moreover, it turns out more advantageous for player one to put all its flexibility in the DSO market (i.e., V_{DSO} equivalent to $\{1, 0, 0, 0\}$), while players 2,3,4 prefer to put all their flexibility into the TSO market. While HyDE cannot provide guarantees of finding the optimal value, the same solution was achieved after 30 different runs of the algorithm, which provide some empirical evidence of the robustness of the approach.

We repeat the experiment, but this time considering 360 players to test the scalability and convergence properties of HyDE. Table III presents the utilities achieved with the baseline, and the ones got with HyDE (row EA Coalition). Notice that compared to the case of four agents, this time, independent coalitions provide an improvement of around 60% of the utility social welfare compared with a baseline based on the grand coalition (GCo). Moreover, HyDE can find a coalition structure and flexibility provision with 208% of improvements. However, due to the stochastic characteristics of HyDE, it requires 50000 iterations (around 2 hours) to achieve such results.

TABLE III
AGGREGATED UTILITIES, SOCIAL WELFARE, AND PERCENTAGE OF IMPROVEMENT CONSIDERING 360 AGENTS.

	Utilities			
	$\sum U_i(\Omega_{DSO})$	$\sum U_i(\Omega_{TSO})$	**USW**	**Imp**
GCo DSO all	23111.2	0.0	23111.2	0%
GCo TSO all	0.0	23152.7	23152.7	0.2%
GCo 50-50	11555.6	11576.4	23132.0	0.1%
ICo DSO all	37484.4	0.0	37484.4	62.2%
ICo TSO all	0.0	37623.2	37623.2	62.8%
ICo 50-50	18742.2	18811.6	37553.8	62.5%
HyDE-Co	35120.6	36190.5	71311.1	208.6%

To appreciate the robustness of the coalition structures and flexibility provision found by HyDE, Fig. 3 presents the convergence of the approach after 30 runs. The figure also shows the 95% confidence interval of the 30 runs, which is narrow enough to state good convergence capabilities. We have stopped the algorithm after 50000 (around 2 hours) for practical concerns, but the tendency of the algorithm is still of improvement.

Finally, we have recorded the average variation on the number of coalitions formed during the iteration procedure. Figure 4 shows the average number of DSO and TSO coalitions formed, on average, every 1e4 iterations. It can be seen that a balance is achieved by the algorithm, reducing the number of DSO and TSO to around 190 each. Also, notice that while the number of coalitions remains similar (approximately 400 in total), the USW is improved by the fact that despite the formation of those coalitions, players still have different options to distribute their flexibility, enhancing their utility in the long-term.

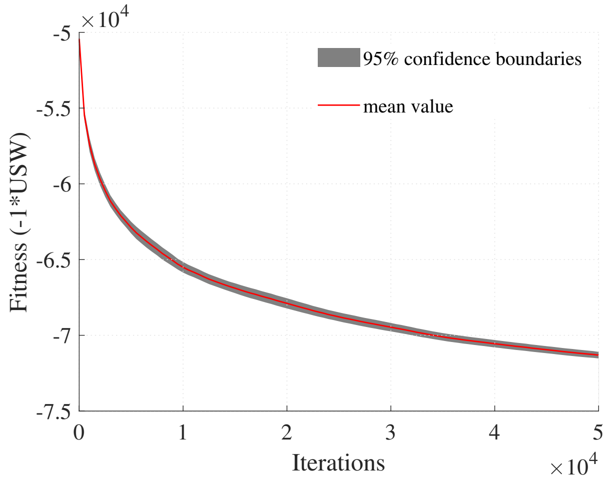

Fig. 3. Convergence and interval confidence boundaries of 30 runs of HyDE.

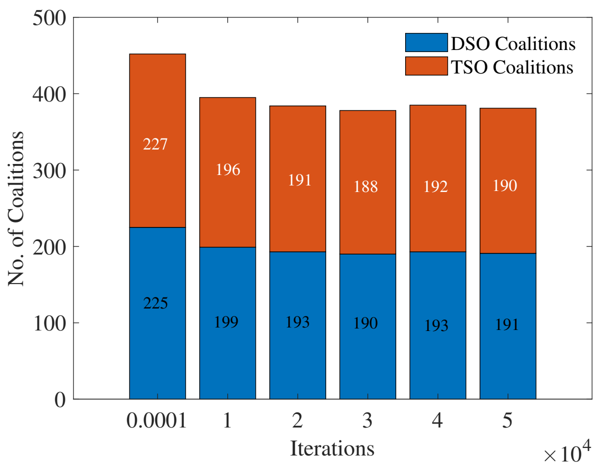

Fig. 4. Number of DSO and TSO coalition variation in function of the iteration process.

V. Conclusion

In this paper, a coalitional game considering DSO-TSO upper level entities procuring flexibility from end-users at the distribution level was proposed. Optimal coalition structure search is an NP-complete problem that requires a large amount of computational resources and time to find optimal solutions using deterministic approaches. For instance, [5] requires 500 minutes to find the optimal solution considering only 14 agents. In this paper, an evolutionary algorithm (HyDE) was proposed to find efficient solutions at acceptable times. It was shown that HyDE can be applied to a case study considering 360 agents, and improving solutions up to 200% with regards to a baseline considering the grand coalition and independent coalitions. While HyDE cannot guarantee optimality, its solutions (30 runs in this work) remains within a narrow 95% confidence interval, taking 2 hours on average to complete the task. Dynamic coalitions is an interesting topic with different lines of research that can be followed as a product of this research. For instance, multi-period decisions considering switching of coalitions in different horizons of time (e.g., depending on the context of dynamic tariff) can give place to very dynamic environments in which faster algorithms are needed. Also, guarantees about optimal bounds of the formed coalitions, either by rigorous or empirical results, is another interesting contribution to follow up this work. Finally, the consideration of network constraints is another addition that is commonly neglected but should be done when local market structures are analyzed.

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