Monopolistic and Game-based Approaches to Transact Energy Flexibility

Amin Shokri Gazafroudi, *Student Member, IEEE,* Miadreza Shafie-khah, *Senior Member, IEEE,* Francisco Prieto-Castrillo, Juan Manuel Corchado, *Member, IEEE,* and João P. S. Catalão, *Senior Member, IEEE*

Abstract—The appearance of the flexible behavior of end-users based on demand response programs makes the power distribution grids more active. Thus, electricity market participants in the bottom layer of the power system, wish to be involved in the decision-making process related to local energy management problems, increasing the efficiency of the energy trade in distribution networks. This paper proposes monopolistic and game-based approaches for the management of energy flexibility through end-users, aggregators, and the Distribution System Operator (DSO) which are defined as agents in the power distribution system. Besides, a 33-bus distribution network is considered to evaluate the performance of our proposed approaches for energy flexibility management model based on impact of flexibility behaviors of end-users and aggregators in the distribution network. According to the simulation results, it is concluded that although the monopolistic approach could be profitable for all agents in the distribution network, the game-based approach is not profitable for end-users.

Index Terms—Decentralized energy management, energy flexibility, game-based energy management, local energy trading.

NOMENCLATURE

A. Indices

t	Time periods [h].
j	End-users.
k	Aggregators.
i	Iterations.

B. Variables

OF_k^{ag}	Objective function of aggregator k [€].
OF^{dso}	Objective function of the DSO [€].
OF_j^{eu}	Objective function of end-user j [€].
L_{jt}	Real-time load at time t of end-user j [kWh].

L_{jt}^f	Energy flexibility at time t for an end-user j [kWh].
P_{jkt}^{L2A}	Energy traded at time t between an end-user j and an aggregator k [kWh].
P_t^{rt}	Real-time energy exchanged at time t between the DSO and the Real-Time Electricity Market (RTEM) [kWh].
P_{kt}^{A2DSO}	Energy traded at time t between aggregator k and the DSO [kWh].
P_{jt}^{DSO2L}	Energy purchased at time t by end-user j from the DSO [kWh].
PP_{kt}	An auxiliary variable representing the cost of energy traded at time t with the DSO for aggregator k [€].
PP_{kt}^{dn}	An auxiliary variable representing the profit obtained from the energy sold at time t to the DSO for aggregator k [€].
PP_{kt}^{up}	An auxiliary variable representing the cost of the energy purchased at time t from the DSO for aggregator k [€].
z_{kt}	A binary variable which is determined by the DSO to represent states of electricity price at time t of aggregator k.
λ_{kt}^{A2DSO}	Electricity price at time t for the aggregator k and the DSO exchanges [€/kWh].

C. Parameters

L_{jt}^c	Scheduled load at time t for end-user j [kWh].
M	Large number.
ϵ	Small number as the stopping criteria for the iterative loop.
λ^{DSO2L}	Price for energy exchanged between the DSO and end-users [€/kWh].
λ_{kt}^{L2A}	Price for electricity exchanged at time t between the aggregator k and the aggregated end-users [€/kWh].
λ_t^{rt}	Price for electricity exchanged at time t between the DSO and the RTEM [€/kWh].
δ_{kt}	Profit guarantee factor at time t for aggregator k ($\delta_{kt} > 1$).
γ_j	Flexibility factor for end-user j ($0 \leq \gamma_j \leq 1$).

I. INTRODUCTION

POWER distribution systems are more active than their conventional structures due to Demand Response (DR) strategies and increment of distributed energy resources power

generation. Thus, centralized electricity markets cannot follow the flexible behavior of end-users in the bottom layer of the distribution systems [1]. Therefore, new decentralized market structures are required to provide energy flexibility. There are different works in this area which presented energy management mechanisms for energy transaction in power distribution networks.

Several works presented models for the local electricity markets, transactive energy and multi agent-based energy management systems in distribution network. For instance, Ref. [2] presented the transactive energy nodes that connect buildings and the Local Electricity Market (LEM). In this way, the energy management problems of both buildings and the local market are optimized simultaneously. In [3], a price-based method has been proposed for energy management. Authors in [3] presented a distributed approach to decompose the central energy management system into several local and independent systems. In [4], authors designed a multi agent-based transactive energy market for decentralize decision-making. In [4], the Distribution System Operator (DSO) is responsible for determining locational marginal price, the balance between generation and consumption, and guarantees the resiliency and reliability in the distribution network. In [5], a multi-layer market environment based on Multi Agent Systems (MASs) is presented to model the behavior of electricity market players. By using an incomplete information game theoretic model, each customer selects its supplying agent, so the agents must compete with each other to keep their customers. In [6], authors presented a real-time price-based method to control the frequency. In this way, agents and the aggregator solve their own energy management problems locally and send their optimum decisions to the central price controller. Then, the central controller modifies the price and sends it back to local agents.

In addition, a part of the literature addresses the interaction between multi-suppliers and multi-consumers through DR strategies or demand regulation. In [7], the DR strategy is performed in systems with several suppliers and a number of domestic consumers. In [8], a distributed real-time framework has been presented by multi-suppliers to regulate customer demand. On this basis, a dual decomposition technique has been employed for energy allocation. In [9], a distributed model has been introduced to find optimal power flow in radial networks considering the regulation of demand. In [10], demand control strategies have been modeled by the Stackelberg game between suppliers and consumers. In [11], a framework has been presented to find the optimal consumers demand and their bill payments by using an adaptive consumption level pricing. In [12], the centralized energy trading has been formulated as a bi-level model, and the nonconvexity of the problem is covered by convex relaxation techniques. Then, the privacy issue has been addressed by employing a decentralized energy trading framework. In [13], a decentralized DR framework has been presented which considers the operational constraints of the system into account. To this end, the individual entities respond to the control signals in order to update their demand/generation profiles.

In addition, energy trading models based on game theory are another line of research that has been presented in several works. Ref. [14] presented a distributed mechanism to exchange energy between Micro-Grids (MGs) in a competitive market. Moreover, a hierarchical decision-making mechanism is proposed in the Stackelberg game. In [15], a LEM has been proposed in which market agents transact electricity with each other independently. Therefore, consumers can purchase their demand from producers directly at the market-clearing price that is set by the local market operator. Also, each agent only shares its energy price and quantity with the market in each decision-making time period. In [16], an adaptive learning algorithm has been presented to find the Nash equilibrium with incomplete information. In the presented game, players use a learning automation structure to provide their action probability distributions according to their private information. Ref. [17] designed a contribution-based trading mechanism among MGs. The MGs are either providers or consumers depending on the status of their electricity production and the local demand. The authors went one step further and presented an event-driven electricity trading system among MGs in which the trading happens when one consumer demands electricity [18]. In the game theoretic model, a consumer-side reward concept has been also presented to motivate the trading system. In [19], a multi-agent transactive system has been presented where an energy management system prompted by MGs in a distribution system to solve the complexity of aggregation. Hierarchical structure is one of the proposed approaches for local energy trade in the distribution network. In [20], a hierarchical framework has been presented for the real-time trading in the power distribution grids. Thus, aggregators transact with electrical consumers and the distribution company. Authors in [21] couple the energy management problem with and Ising-based model to study the interaction through them in the power distribution system. In this way, the energy flexibility of the consumers has been modeled through the Ising spin-based model.

Although various models have been presented in the literature to study the behavior of market participants in the bottom layer of the power system, an interplay model for energy flexibility management through end-users, aggregators and DSO has not been addressed. In distributed and decentralized energy trading approaches, players in the distribution network manage energy to gain maximum profit for themselves without considering the profits of the DSO as an agent who acts as a policy-maker in the distribution network. However, the interplay model presents a manner that players (in different layers of the distribution network) can not also make optimal decisions independently, but are also able to exchange their desired decisions to the DSO. Energy flexibility is defined as the ability to change the behaviour of power system players related to their energy production or demand due to reaction to price or other incentive signals [22].

In this paper, end-users are defined as agents who are in charge of providing energy flexibility in the system. Thus, they are able to modify their demand pattern in the real-time energy transaction. In other words, energy flexibility has been defined as a service that end-users are able to provide due to their flexible behaviour on their scheduled

electrical demand. Thus, flexibility has not been modelled as a contracted capacity. In this paper, we present monopolistic and game-based approaches for energy flexibility management in the power distribution system. In this way, a hierarchical structure is proposed to transact energy among the real-time electricity market and distribution network's agents (end-users, aggregators, and the DSO). Moreover, flexible behaviors of end-users and aggregators are modeled to provide shiftable and sustainable demands in power distribution grid. According to our proposed monopolistic approach, all end-users and aggregators are able to manage their energy flexibility independently through a bottom-up approach. However, our proposed game-based approach is defined to overcome the challenge posed by decisions made by agents in the distribution network. In other words, we model the interactions between agents (the DSO and aggregators, or the DSO and end-users) as an iterative algorithm in the game-based approach. Thus, the contributions of this paper can be summarized as follows:

- Regarding the formulation of the proposed energy flexibility management, a Mixed Integer Linear Programming (MILP) model is proposed to resolve the non-linearity of cost/profit for the energy transacted between players in the problem.
- Regarding energy-trading strategies, monopolistic and game-based approaches are proposed for energy flexibility management through end-users, aggregators and the DSO in the distribution network.
- Regarding analysing the system, different types of flexibility are defined and assessed in the proposed energy management problem.

The rest of this paper is organized as follows. In Section II, the problem formulation is described. Section III introduces our approaches to manage energy flexibility in the distribution network. Then, the simulation results of the 33-bus test system are illustrated in Section IV. Finally, our findings are discussed in Section V.

II. PROBLEM FORMULATION

In this section, we propose a real-time energy management problem for transacting energy flexibility among three types of agents in the power distribution systems, e.g., end-users, aggregators, and the DSO. In this structure, the RTEM can only exchange real-time energy flexibility with the DSO, P_t^{RT}, as shown in Fig.1.

According to our proposed approach, consumers exchange energy flexibility with the corresponding aggregator (who bought their scheduled energy), P_{jt}^{L2A}, and the DSO, P_{jt}^{DSO2L}, at prices λ_{kt}^{L2A} and λ^{DSO2L}, respectively. Here, we consider λ^{DSO2L} as given amount. Then, the aggregator transacts energy flexibility, P_{kt}^{A2DSO}, with the DSO. Despite the real-time flexibility transactions between consumers and aggregators, and aggregators and the DSO are two-way, consumers can only buy real-time energy from the DSO. Next, corresponding equations of each agent are described. Each end-user can decrease or increase its scheduled load in the real-time to provide either upward or downward flexible load, respectively, as represented in (1). Eq. (2) represents minimum and
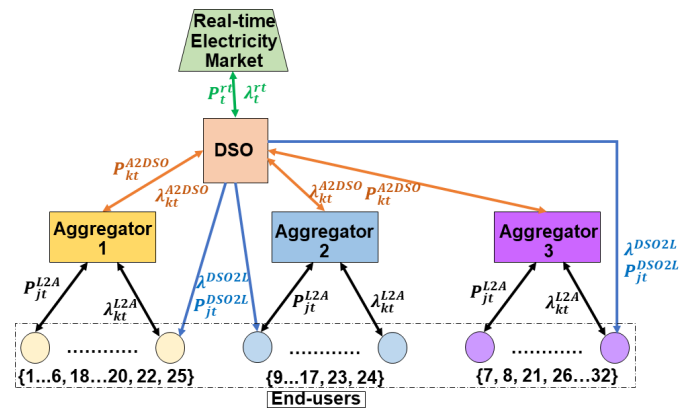

Fig. 1: Agents and real-time energy transaction framework of the distribution network [20], [21].

maximum limitations of the energy flexibility. Here, γ_j is defined as a flexibility factor which can be set between 0 and 1. The flexible energy splits itself into real-time energy exchanged with corresponding aggregator (P_{jt}^{L2A}) and the DSO (P_{jt}^{DSO2L}) as represented in (3). Moreover, Eq. (4) states that the real-time energy transaction between the end-users and the DSO is one-way (from the DSO to end-users). In this paper, end-users are considered to be shiftable loads to provide energy flexibility as represented by (6). Besides, each end-user can be limited over all end-users that are aggregated by the same aggregator in each time step as seen in (5).

$$L_{jt} = L_{jt}^c - L_{jt}^f, \ \forall j, t \tag{1}$$

$$-\gamma_j L_{jt}^c \le L_{jt}^f \le \gamma_j L_{jt}^c, \ \forall j, t \tag{2}$$

$$L_{jt}^f = P_{jt}^{L2A} - P_{jt}^{DSO2L}, \ \forall j, t \tag{3}$$

$$P_{jt}^{DSO2L} \ge 0, \forall j, t \tag{4}$$

$$\sum_{j \in A_k} L_{jt}^f = 0, \ \forall t \tag{5}$$

$$\sum_t L_{jt}^f = 0, \ \forall j \tag{6}$$

According to our hierarchical structure, the total transacted energy flexibility through end-users and aggregators should be exchanged through aggregators and the DSO as represented in (7). Moreover, Eqs. (8) and (9) are defined in the aggregators' layer to provide self-consumption and shiftable traded real-time energy between aggregators and end-users as well as (5) and (6) which have been represented in the bottom layer of the system.

$$P_{kt}^{A2DSO} = \sum_{j \in A_k} P_{jt}^{L2A}, \forall k, t \tag{7}$$

$$\sum_{j \in A_k} P_{jt}^{L2A} = 0, \ \forall t \tag{8}$$

$$\sum_t P_{jt}^{L2A} = 0, \ \forall j \tag{9}$$

The maximum and minimum constraints of the price of energy traded between aggregators and the DSO, λ_{kt}^{A2DSO}, are represented in (10). Besides, the balancing equation in the

layer of the DSO to trade real-time energy flexibility through the DSO and the RTEM, and the rest of the agents presented in (11).

$$\delta_{kt}\lambda_{kt}^{L2A} \leq \lambda_{kt}^{A2DSO} \leq \lambda_t^{rt}, \forall t, k \qquad (10)$$

$$P_t^{rt} = \sum_j P_{jt}^{DSO2L} - \sum_k P_{kt}^{A2DSO}, \forall t \qquad (11)$$

In this way, the objective functions of end-users, aggregators, and the DSO are represented in (12), (13), and (14), respectively. In (12), the objective function of each end-user is expressed which should be minimized. The objective function of end-user j consists of two terms. First term represents the objective function due to buy real-time energy from the DSO, and the second term states the profit due to sell energy flexibility to the aggregator. As represented in (13), the objective function consists of two terms which consists of the cost due to trading energy flexibility with the end-users, and the profit due to energy transaction with the DSO, (however, $\lambda_{kt}^{A2DSO} P_{kt}^{A2DSO}$ makes the problem non-linear). In (14), OF^{dso} includes three terms consisting of the objective function of energy transaction with aggregators, the cost of exchanged energy with the RTEM, and the profit due to sell energy to end-users.

$$OF_{j \in A_k}^{eu} = \lambda^{DSO2L} \sum_t P_{jt}^{DSO2L} - \sum_t \lambda_{kt}^{L2A} P_{jt}^{L2A} \qquad (12)$$

$$OF_k^{ag} = \sum_t \sum_{j \in A_k} \lambda_{kt}^{L2A} P_{jt}^{L2A} \qquad (13)$$
$$- \sum_t \lambda_{kt}^{A2DSO} P_{kt}^{A2DSO} \forall k$$

$$OF^{dso} = \sum_t \lambda_{kt}^{A2DSO} P_{kt}^{A2DSO} + \sum_t \lambda_t^{rt} P_t^{rt} \qquad (14)$$
$$- \lambda^{DSO2L} \sum_t \sum_j P_{jt}^{DSO2L}$$

III. Energy Flexibility Management Approaches

In this section, we define two approaches, monopolistic and game-based, to manage energy flexibility in the power distribution system. In the monopolistic approach, all end-users and aggregators are able to manage their energy flexibility autonomously. However, we define interactions between the DSO and aggregators, or the DSO and end-users in the game-based approach for the energy flexibility management problem. In addition, an MILP model of our proposed energy flexibility management problem is presented in the following.

A. MILP model

As mentioned in Section II, $\lambda_{kt}^{A2DSO} P_{kt}^{A2DSO}$ makes the objective functions of the aggregators and the DSO as represented in (13), and (14). In this paper, we propose a model in which the DSO is in charge of determining the price of energy traded between the aggregators and the DSO, λ_{kt}^{A2DSO}, with the aim of minimizing its objective function, OF^{dso}. Also, λ_{kt}^{A2DSO} is limited to maximum and minimum bands according to (10). In this way, if energy exchanged between

aggregators and the DSO is positive, $P_{kt}^{A2DSO} \geq 0$, then the DSO sets the minimum price limitations bands. However, the DSO determines the maximum band of price's limitation where energy traded between aggregators and the DSO is negative, $P_{kt}^{A2DSO} < 0$. Hence, we have:

IF $P_{kt}^{A2DSO} \geq 0 \rightarrow$
$$\lambda_{kt}^{A2DSO} = Min.\{\delta_{kt}\lambda_{kt}^{L2A}, \lambda_t^{rt}\} \rightarrow z_{kt} = 0.$$
ELSE $P_{kt}^{A2DSO} < 0 \rightarrow$
$$\lambda_{kt}^{A2DSO} = Max.\{\delta_{kt}\lambda_{kt}^{L2A}, \lambda_t^{rt}\} \rightarrow z_{kt} = 1.$$

Here, z_{kt} is defined as a binary variable which is determined by the DSO to represent states of electricity price which are set by the DSO. Thus, the nonlinear term is restated as seen in (15).

$$\lambda_{kt}^{A2DSO} P_{kt}^{A2DSO} = \{\delta_{kt}\lambda_{kt}^{L2A}(1 - z_{kt}) \qquad (15)$$
$$+ \lambda_t^{rt} z_{kt}\} P_{kt}^{A2DSO} = PP_{kt} \forall t, k$$

$$PP_{kt} = PP_{kt}^{dn} + PP_{kt}^{up} \forall t, k \qquad (16)$$

$$PP_{kt}^{dn} = \delta_{kt}\lambda_{kt}^{L2A}(1 - z_{kt}) P_{kt}^{A2DSO} \forall t, k \qquad (17)$$

$$PP_{kt}^{up} = \lambda_t^{rt} z_{kt} P_{kt}^{A2DSO} \forall t, k \qquad (18)$$

As represented in (16), PP_{kt} is split into PP_{kt}^{dn} and PP_{kt}^{up}. In this way, each of these nonlinear constraints, (17) and (18), can be redefined as mixed integer linear constraints according to Ref. [23]. Hence, Eq. (15) is redefined as presented in (19)-(23).

$$-z_{kt}M \leq PP_{kt}^{dn} - \delta_{kt}\lambda_{kt}^{L2A} P_{kt}^{A2DSO} \leq z_{kt}M \forall t, k \quad (19)$$

$$-\gamma_j \delta_{kt}\lambda_{kt}^{L2A}(1 - z_{kt}) \sum_{j \in A_k} L_{jt}^c \leq PP_{kt}^{dn} \qquad (20)$$
$$\leq \gamma_j \delta_{kt}\lambda_{kt}^{L2A}(1 - z_{kt}) \sum_{j \in A_k} L_{jt}^c \forall t, k$$

$$-(1 - z_{kt})M \leq PP_{kt}^{up} - \lambda_t^{rt} P_{kt}^{A2DSO} \qquad (21)$$
$$\leq (1 - z_{kt})M \forall t, k$$

$$-\gamma_j \lambda_t^{rt} z_{kt} \sum_{j \in A_k} L_{jt}^c \leq PP_{kt}^{up} \qquad (22)$$
$$\leq \gamma_j \lambda_t^{rt} z_{kt} \sum_{j \in A_k} L_{jt}^c \forall t, k$$

$$-\gamma_j z_{kt} \sum_{j \in A_k} L_{jt}^c \leq PP_{kt}^{A2DSO} \qquad (23)$$
$$\leq \gamma_j (1 - z_{kt}) \sum_{j \in A_k} L_{jt}^c \forall t, k$$

Thus, Eqs. (19) and (20) represent (17). On the other hand, Eqs. (21) and (22) express (18). Moreover, the relationship between the energy transacted through aggregators and the DSO, PP_{kt}^{A2DSO}, and its corresponding electricity price, λ_{kt}^{A2DSO}, is represented in (23). According to (23), z_{kt} equals 0 when PP_{kt}^{A2DSO} is positive. On the other hand, z_{kt} as binary variable is equal to 1 when PP_{kt}^{A2DSO} is negative. Therefore, the objective functions of aggregators and the DSO should be redefined as they are represented in (24) and (25), respectively. Hence, the respective energy management problems should be presented considering (16), and (19)-(23).

$$OF_k^{ag'} = \sum_t \sum_{j \in A_k} \lambda_{kt}^{L2A} P_{jt}^{L2A} - \sum_t PP_{kt} \forall k \quad (24)$$

$$OF^{dso'} = \sum_t PP_{kt} + \sum_t \lambda_t^{rt} P_t^{rt} \quad (25)$$
$$- \lambda^{DSO2L} \sum_t \sum_j P_{jt}^{DSO2L}$$

B. Monopolistic Approach

1) Aggregators-based: Here, the decentralized energy management problem is modeled from the aggregators' perspective as seen in the following (Problem $M1$):

Min. $OF^{ag'} = \sum_k OF_k^{ag'}$
s.t. (1)-(9), (11) and (16), and (19)-(23).

Each aggregator transacts energy flexibility with the consumers which are in its region, and the DSO. However, aggregators are not able to exchange energy with other aggregators and their corresponding end-users. Moreover, all four types of flexibility definition can be considered in this approach.

2) Consumers-based: In this section, a decentralized energy flexibility management problem is modeled by consumers. Thus, end-users manage their energy flexibility autonomously. Also, consumers can only provide shiftable loads and energy transaction with the aggregator, Eq. (6) and (9), respectively. Hence, Eqs. (5) and (8) are not provided in this approach as it needs coalition of the consumers in the aggregators' layer. Each end-user transacts energy flexibility with its corresponding aggregator. Besides, end-users are able to buy real-time energy from the DSO. Therefore, the consumer-based decentralized energy flexibility management problem is modeled in the following (Problem $M2$):

Min. $OF^{eu} = \sum_j OF_j^{eu}$
s.t. (1)-(4), (6)-(7), (9), (11), (16), and (19)-(23).

Hence, this problem can be decomposed to j independent problems in which each end-user manages its own energy flexibility without coalition with other end-users. In this way, end-users are able to provide only shiftable loads, because Eqs. (5) and (8) are not considered in this approach which requires end-users to cooperate with each other in order to improve the sustainability of the power distribution grid.

C. Game-based Approach

1) Interaction between Aggregators and the DSO: In this section, the transaction of energy flexibility is modeled in terms of interaction between the aggregators and the DSO. In our proposed game-based algorithm, aggregators are in charge of determining the quantity of energy flexibility traded between the aggregators and the DSO, P_{kt}^{A2DSO}. However, the DSO determines the electricity price of energy transaction between the aggregators and the DSO, λ_{kt}^{A2DSO}. Thus, the DSO sets z_{kt} to represent states of electricity price in the MILP model of the energy management problem. Algorithm 1 represents our proposed game-based algorithm for energy flexibility trade through the aggregators and the DSO as seen in Fig. 2(a). According to Algorithm 1, each aggregator k and the DSO make decisions regarding their own autonomous
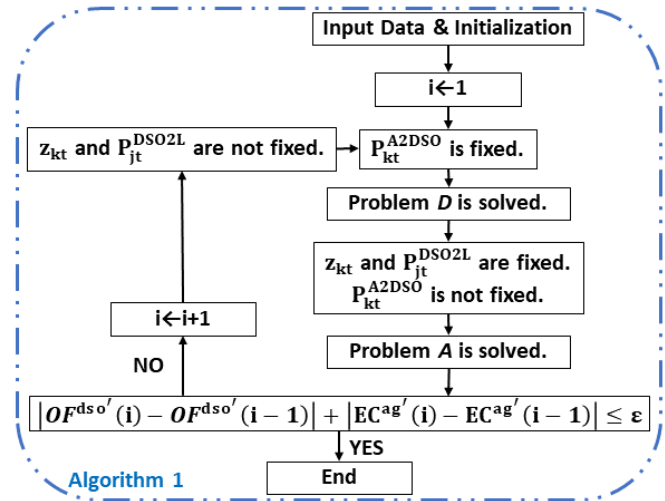
(a) Algorithm 1.
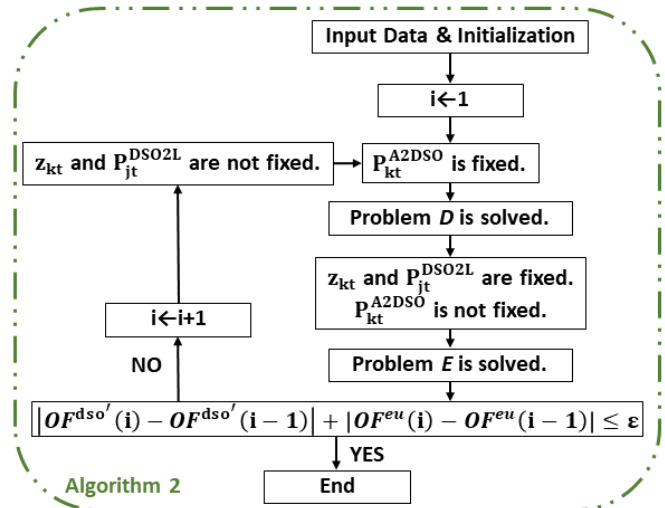
(b) Algorithm 2.

Fig. 2: Game-based interaction to transact energy between aggregators and the DSO (a), end-users and the DSO (b).

energy management problem considering interaction signals among aggregators and the DSO. Below, the energy management problems of aggregators and the DSO are presented:

- Aggregators' problem (Problem A):
  Min. $OF^{ag'} = \sum_k OF_k^{ag'}$
  s.t. (1)-(3), (5)-(9), (16), (19)-(23).
- DSO's problem (Problem D):
  Min. $OF^{dso'}$
  s.t. (4), (11), (16), (19)-(23).

In this structure, the energy flexibility in the bottom-layer of the system is managed only by aggregators. This model has an advantage to manage directly quantity of energy traded between the aggregators and the DSO, P_{kt}^{A2DSO}. However, the weakness of this approach is to not see the profits and costs of end-users in decision-making where end-users are the main agents to provide energy flexibility to the system. Moreover, convergence is a challenge in the proposed iterative algorithm. Thus, Eq. (26) is defined as a convergence condition

for Algorithm 1 to trade real-time energy between aggregators and the DSO.

$$|OF_i^{dso'} - OF_{i-1}^{dso'}| + |OF_i^{ag'} - OF_{i-1}^{ag'}| < \epsilon \qquad (26)$$

2) Interaction between End-users and the DSO: In this approach, end-users and the DSO are the agents who manage energy flexibility, and aggregators are considered to be non-profitable players in the power distribution network. Here, the energy management problem of the DSO is identical to respective one in game-based interaction between the aggregators and the DSO (Problem D). Thus, the energy management problem of end-users is:
- End-users' problem (Problem E):
    Min. OF^{eu}
        s.t. (1)-(4), (6)-(7), (9), (16), and (19)-(23).

In this way, the convergence condition for Algorithm 2 is defined according to (27).

$$|OF_i^{dso'} - OF_{i-1}^{dso'}| + |OF_i^{eu'} - OF_{i-1}^{eu'}| < \epsilon \qquad (27)$$

In Problem E, end-users manage their own energy flexibility independently and control the energy traded through the aggregators and the DSO. On the other hand, the DSO sets the electricity price for the transaction of energy between the aggregators and the DSO based on Algorithm 2 which has been presented in Fig. 2(b).

IV. MATHEMATICAL DISCUSSION

This section analyses monopolistic and game-based approaches to trade energy flexibility in the distribution network. In this way, for the consumers-based (Problem $M2$), three scenarios are defined to study the impact of flexibility constraints on the energy management problem. Additionally, for the aggregators-based (Problem $M1$), the impact of energy flexibility is assessed in five scenarios. These scenarios are presented in Table I. In $C1$ and $A1$, end-users play as interruptible loads that provide energy flexibility. End-users provide shiftable load in scenarios $C2$ and $A2$. In $C3$ and $A4$, the shiftable energy flexibility service is provided by end-users. The community of end-users acts as a self-consumption and sustainable energy system in scenario $A3$. However, scenario $A5$ represents the impact of self-consumption energy flexibility service provided by a community of end-users to the sustainable distribution network.

A. Monopolistic Approach

1) Aggregators-based: In the monopolistic approach from the perspective of aggregators, $OF_k^{ag'} (= OF_k^{ag})$ should be minimized by aggregators. According to (7), P_{kt}^{A2DSO} equals $\sum_{j \in A_k} P_{jt}^{L2A}$. In this way, OF_k^{ag} is represented in (28). Moreover, according to (10), λ_{kt}^{A2DSO} is greater than λ_{kt}^{L2A} if $\delta_{kt} > 1$. In other words, if $\delta_{kt} > 1$, we have:

$$OF_k^{ag} = \sum_t \sum_{j \in A_k} (\lambda_{kt}^{L2A} - \lambda_{kt}^{A2DSO}) P_{jt}^{L2A}, \forall k \qquad (28)$$

$$\lambda_{kt}^{L2A} - \lambda_{kt}^{A2DSO} < 0, \forall t, k \qquad (29)$$

TABLE I: Energy flexibility's scenarios.

Scenario	Min.	s.t.
$C1$	OF^{eu}	(1)-(4), (7), (11), (16), and (19)-(23).
$C2$	OF^{eu}	(1)-(4), (6)-(7), (11), (16), and (19)-(23).
$C3$	OF^{eu}	(1)-(4), (7), (9), (11), (16), and (19)-(23).
$A1$	$OF^{ag'}$	(1)-(4), (7), (11), (16), and (19)-(23).
$A2$	$OF^{ag'}$	(1)-(4), (6)-(7), (11), (16), and (19)-(23).
$A3$	$OF^{ag'}$	(1)-(5), (7), (11), (16), and (19)-(23).
$A4$	$OF^{ag'}$	(1)-(4), (7), (9), (11), (16), and (19)-(23).
$A5$	$OF^{ag'}$	(1)-(4), (7)-(8), (11), (16), and (19)-(23).

According to (28) and (29), aggregators are willing to maximize P_{jt}^{L2A}. Thus, we obtain $P_{jt}^{L2A} > 0$ as it is shown in Fig. 3 (a). However, Eqs. (5) and (6) constrain L_{jt}^f. Hence, P_{jt}^{L2A} is positive in $A1$-$A3$ considering these constraints and push end-users to buy energy from the DSO. However, P_{jt}^{L2A} should be positive and negative in different time intervals based on (8) and (9) in $A4$ and $A5$.

2) Consumers-based: End-users minimize their corresponding objective function, $OF_{j \in A_k}^{eu}$. As it is seen in (12), $OF_{j \in A_k}^{eu}$ consists of two terms. End-users minimize the first term ($\lambda^{DSO2L} \sum_t P_{jt}^{DSO2L}$) and maximize the second term ($\sum_t \lambda_{kt}^{L2A} P_{jt}^{L2A}$). According to (4), P_{jt}^{DSO2L} is greater than and equal to zero. Hence, P_{jt}^{DSO2L} must be equal to zero in order to minimize the first term of $OF_{j \in A_k}^{eu}$. In this way, end-users only transact energy flexibility with the aggregators in the monopolistic approach from the perspective of end-users as seen in Fig. 3 (b).
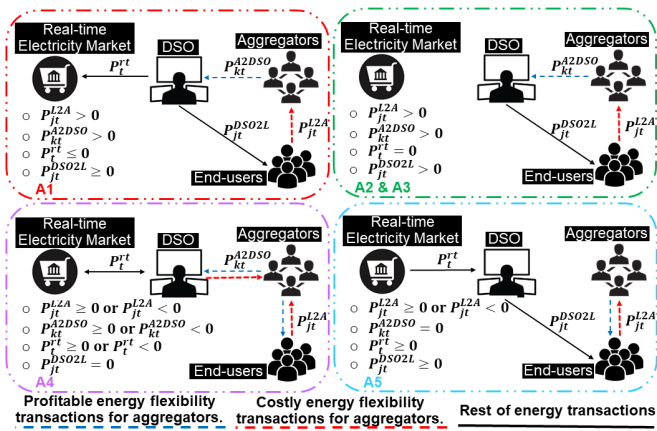
B. Game-based Approach

1) Interaction between aggregators and the DSO: As highlighted before, aggregators determine the energy transacted between the DSO and aggregators in this approach. However, the DSO is in charge of setting the price of the energy traded between the DSO and the aggregators. Moreover, the DSO determines the energy sold to the end-users, P_{jt}^{DSO2L}. The DSO minimizes its objective function. As seen in (14) and (25), $OF^{dso}(= OF^{dso'})$ contains three terms. The DSO minimizes first and second terms, and it maximizes the third one ($\sum_t \sum_j \lambda^{DSO2L} P_{jt}^{DSO2L}$). Thus, P_{jt}^{DSO2L} is positive in all cases in the game-based approach as it is illustrated in Fig. 4. According to (3), as P_{jt}^{DSO2L} is positive in the game-based approach, P_{jt}^{L2A} is greater than L_{jt}^f as represented in (30). In this way, if Eq. (6) is considered ($\sum_t L_{jt}^f = 0$), it is given that:

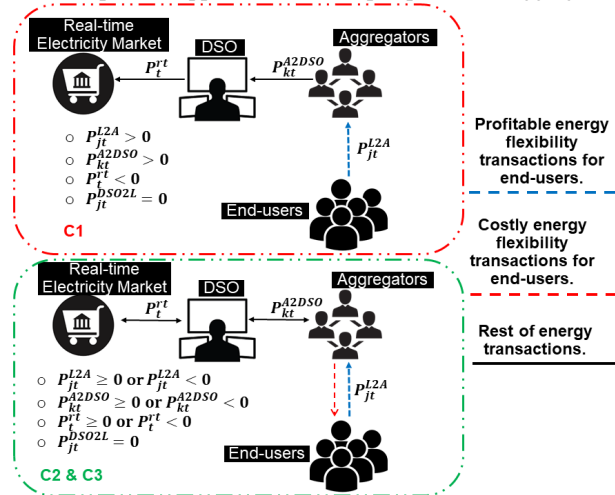$$P_{jt}^{L2A} > L_{jt}^f, \forall t, j \qquad (30)$$

$$\sum_t P_{jt}^{L2A} > 0, \forall j \qquad (31)$$

$$\sum_{j \in A_k} P_{jt}^{L2A} > 0, \forall j \qquad (32)$$

As seen in (31), constraint (9) is not feasible in this case. In other worlds, it is not feasible to consider constraints (6) and (9) simultaneously in the game-based approach from the perspective of the aggregators. Moreover, if Eq. (5) is

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(a) Monopolistic approach from the perspective of aggregators.

(b) Monopolistic approach from the perspective of end-users.

Fig. 3: Real-time traded energy flows through agents in the monopolistic approach.

(a) Game-based interaction between aggregators and the DSO.

(b) Game-based interaction between end-users and the DSO.
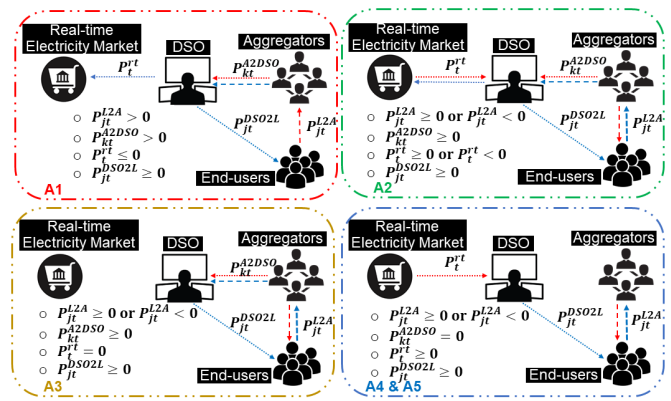
Fig. 4: Real-time traded energy flows through agents in the game-based approach.

considered ($\sum_{j \in A_k} L_{jt}^f = 0$), Eq. (32) is obtained. Thus, according to (7) and (32), we have $P_{kt}^{A2DSO} > 0$. In this way, λ_{kt}^{A2DSO} equals $\delta_{kt}\lambda_{kt}^{L2A}$, if $\delta_{kt}\lambda_{kt}^{L2A}$ is less than λ_t^{rt}.
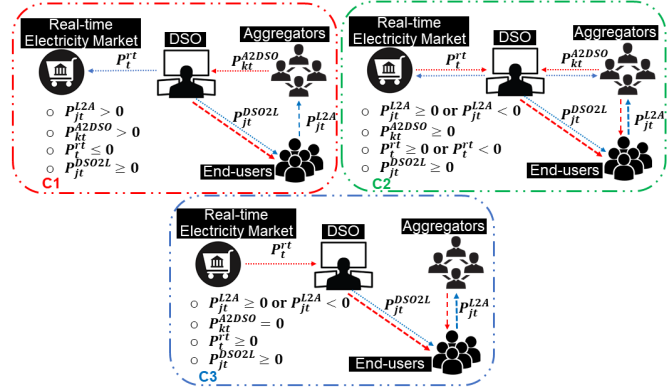
2) Interaction between End-users and the DSO: In this approach, P_{jt}^{DSO2L} is determined by the DSO. On the one hand, end-users do not have any direct control on P_{jt}^{DSO2L}. For this reason, end-users buy the real-time energy from the DSO in the game-based approach. On the other hand, the DSO minimizes its objective function in this approach. Here, we replace P_{jt}^{DSO2L} with L_{jt}^f and P_{jt}^{L2A} according to (3). Therefore, $OF_{j \in A_k}^{eu}$ is represented in (33). In this way, if constraint (6) is considered ($\sum_t L_{jt}^f = 0$), Eq. (34) is obtained:

$$OF_{j \in A_k}^{eu} = \lambda^{DSO2L} \sum_t (P_{jt}^{L2A} - L_{jt}^f)$$
$$- \sum_t \lambda_{kt}^{L2A} P_{jt}^{L2A}, \forall j$$
$$= \sum_t [(\lambda^{DSO2L} - \lambda_{kt}^{L2A})P_{jt}^{L2A} - \lambda^{DSO2L} L_{jt}^f], \forall j \quad (33)$$

$$OF_{j \in A_k}^{eu} = \sum_t [(\lambda^{DSO2L} - \lambda_{kt}^{L2A})P_{jt}^{L2A}, \forall j \quad (34)$$

Thus, end-users minimize P_{jt}^{L2A}, if $\lambda^{DSO2L} > \lambda_{kt}^{L2A}$. Furthermore, $\sum_t P_{jt}^{L2A}$ is greater than zero, and P_{jt}^{L2A} could be positive or negative in different time intervals as it is shown in Fig. 4 (b). If constraint (9) is considered, Eq. (35) is given. Thus, $\sum_t L_{jt}^f$ is negative because the energy traded between the end-users and the DSO is positive in the game-based approach.

$$\sum_t L_{jt}^f = - \sum_t P_{jt}^{DSO2L}, \forall j \quad (35)$$

V. SIMULATION RESULTS

A. Case Study

In this paper, a 33-bus test system is used from [20], [21], [24] to assess our proposed approaches to manage energy flexibility as shown in Fig.5. Three regions have been considered which are managed by their corresponding aggregators. The energy price which is traded in each of this region is different as shown in Table II. Also, we assume that $\lambda^{DSO2L} = 0.6$ [€/kWh], $\gamma_j = 0.1$, and $\delta_{kt} = 1.1$ according to Refs. [20] and [21]. Our proposed energy management models are studied in both, monopolistic and game-based approaches. Also, our proposed MILP models are solved in Generalised Algebraic Modelling system (GAMS) [25].
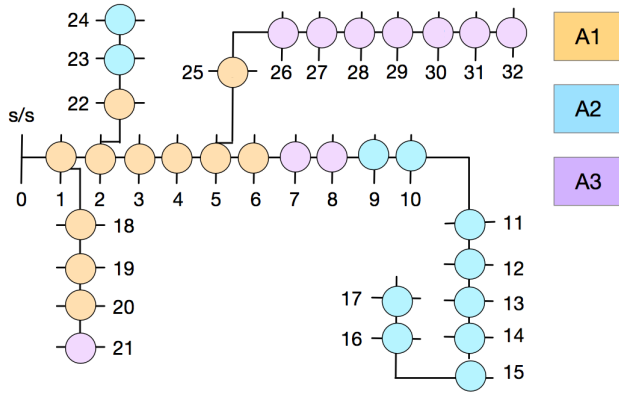
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Fig. 5: 33-bus test system and aggregators [20], [21], [24].

TABLE II: Prices of traded energy between consumers and aggregators [20], [21].

Time (h)	$\lambda^{L2A}_{k=1,t}$ [€/kWh]	$\lambda^{L2A}_{k=2,t}$ [€/kWh]	$\lambda^{L2A}_{k=3,t}$ [€/kWh]	λ^{RT}_t [€/kWh]
1	0.05	0.08	0.06	0.13
2	0.05	0.08	0.07	0.12
3	0.05	0.09	0.07	0.15
4	0.04	0.07	0.05	0.11
5	0.11	0.18	0.15	0.30
6	0.12	0.20	0.16	0.32
7	0.13	0.22	0.17	0.35
8	0.15	0.24	0.19	0.40
9	0.16	0.25	0.20	0.42
10	0.24	0.41	0.33	0.66
11	0.26	0.42	0.36	0.71
12	0.28	0.43	0.37	0.74
13	0.25	0.40	0.32	0.69
14	0.18	0.26	0.21	0.50
15	0.15	0.24	0.20	0.41
16	0.14	0.22	0.18	0.40
17	0.15	0.25	0.19	0.42
18	0.20	0.36	0.30	0.60
19	0.21	0.36	0.29	0.65
20	0.22	0.41	0.30	0.67
21	0.24	0.42	0.33	0.70
22	0.12	0.22	0.16	0.35
23	0.11	0.19	0.15	0.28
24	0.06	0.09	0.07	0.15

B. Evaluation of Monopolistic Approach

In this section, the energy flexibility management problem in the power distribution system is studied according to the monopolistic approach. As it has been explained in Section III. B, the proposed energy management problem is modeled on the basis of only one group of agents- e.g. consumers or aggregators.

Table III shows the impact of energy flexibility on total objective functions of end-users, aggregators, and the DSO in the monopolistic approach. As presented in Table III, OF^{eu}, $OF^{ag'}$, and $OF^{dso'}$ are negative in $C1$. In other words, energy flexibility transaction is profitable for all end-users, aggregators and the DSO. It is because of the bottom-up

TABLE III: Total costs of end-users, aggregators, and the DSO in the monopolistic approach.

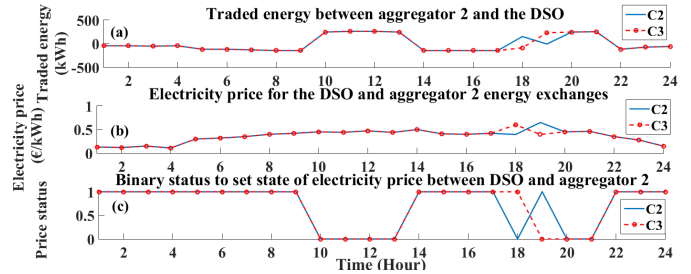|	$C1$	$C2$	$C3$	
OF^{eu} [€]	-2394.438	-714.291	-714.291	
$OF^{ag'}$ [€]	-239.444	733.548	749.681	
$OF^{dso'}$ [€]	-2273.819	-1461.078	-1489.181	
	$A1$	$A2$ & $A3$	$A4$	$A5$
OF^{eu} [€]	870.642	3178.062	-30.991	1917.450
$OF^{ag'}$ [€]	-239.444	-239.444	-0.262	0
$OF^{dso'}$ [€]	-2869.32	-2938.618	-23.309	-30.217

Fig. 6: Traded energy (a) electricity price (b), and z_{kt} (c) between aggregator 2 and the DSO in $C2$ and $C3$ in the monopolistic approach.

energy flexibility flow from end-users to aggregators, from aggregators to the DSO, and from the DSO to the RTEM. In $C2$ and $C3$, the total costs of the aggregators are positive. In these scenarios, there are bidirectional energy transactions between end-users and aggregators, aggregators and the DSO, and the DSO and the RTEM as seen in Fig. 3(a). Also, end-users do not wish to buy real-time energy from the DSO. Fig. 6 shows the energy traded between aggregator 2 and the DSO, their corresponding electricity price, and $z_{(k=2)t}$. As seen in Fig.6(c), $z_{(k=2)t}$ is equal to 1 when $P^{A2DSO}_{(k=2)t}$ is negative. On the other hand, $z_{(k=2)t}$ equals 0 when $P^{A2DSO}_{(k=2)t} \geq 0$. In this way, optimal scenarios (instead of $C1$) for aggregators and the DSO are $C2$ and $C3$, respectively. Thus, the DSO allows end-users to manage their own energy flexibility in a decentralized manner because this approach is profitable for them in all scenarios. However, if aggregators are players who are in charge of making laws for their corresponding consumers, $C2$ and $C3$ are not profitable for aggregators. In this way, aggregators do not allow end-users to manage energy flexibility in a decentralized manner. Moreover, Table III indicates that $OF^{ag'}$ equals zero, and there is no exchanged energy between aggregators and the DSO in $A5$. Therefore, $A5$ cannot encourage aggregators as decision-makers in Problem 2. On the one hand, in $A4$, the total objective functions of all agents are negative. In other words, $A4$ is profitable for all agents. On the other hand, the power distribution network is more sustainable and does not depend on the upstream grid in $A2$ and $A3$ as shown in Fig. 3(b). However, the DSO bought real-time energy from the RTEM in $A5$. Thus, $A5$ is the worst scenario for the monopolistic approach from the perspective of aggregators.
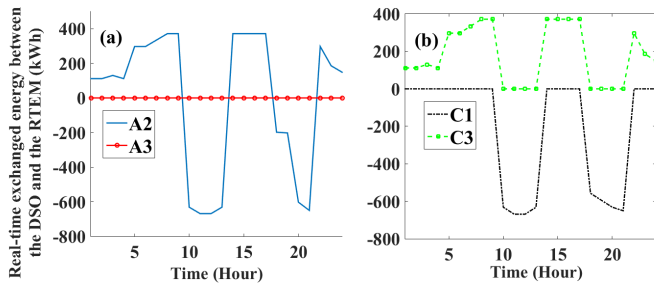
Fig. 7: Real-time exchanged energy between the DSO and the RTEM in $A2$ and $A3$ (a), in $C1$ and $C3$ (b) in game-based approach.

TABLE IV: Total costs of end-users, aggregators, and the DSO in the game-based approach.

	OF^{eu} [€]	$OF^{ag'}$ [€]	$OF^{dso'}$ [€]
$A1$	157.767	-239.444	-3339.466
$A2$	1112.969	-143.909	-2413.909
$A3$	1826.025	-72.618	-1753.407
$A4$	2552.205	0	-1065.648
$A5$	2552.205	0	-1065.648
$C1$	159.767	-239.444	-8607.231
$C2$	1111.734	-100.082	-5612.034
$C3$	2552.205	0	-1065.648

C. Evaluation of Game-based Approach

In this section, the proposed energy flexibility management problem is evaluated in terms of a game between end-users and the DSO, and a game between aggregators and the DSO. Thus, iterative game-based algorithms are defined for energy flexibility transaction in the power distribution networks as represented in Algorithms 1 and 2.

In Algorithm 1, it is defined that there is a game-based interaction between the aggregators and the DSO. Here, $A1$-$A5$ are considered to assess the performance of the energy management system. As seen in Table IV, OF^{eu} is positive in all scenarios which means that game-based interaction between aggregators and the DSO is not profitable for end-users. Moreover, $OF^{ag'}$ equals zero in $A4$ and $A5$ because there is no energy transaction from aggregators to the DSO as shown in Fig. 4(a). Thus, $A4$ and $A5$ cannot motivate aggregators to real-time energy flexibility trade with the DSO. Instead of $A1$ which is an optimal scenario of the system in which all end-users play as interruptible loads, the total objective functions of all agents are lower in $A2$ in comparison with $A3$. In other words, $A2$ is a more profitable scenario for all agents in the power distribution system in comparison to $A3$. However, the distribution network acts as the sustainable energy system in $A3$, because end-users, aggregators and the DSO make a closed loop for energy exchange in the distribution network, and the DSO does not exchange energy with the real-time electricity market as seen in Fig. 7(a).

On the other hand, Algorithm 2 defines a game-based energy flexibility transaction between end-users and the DSO. Hence, aggregators are not decision-makers for energy exchange in Algorithm 2. The interaction between end-users and the DSO is studied in three scenarios, $C1$-$C3$. As presented in Table IV, $C1$ is an optimal scenario for all agents in this game. However,

TABLE V: Optimization statistics of the proposed energy management model.

	Execution time [sec]	Absolute/Relative gap	No. Iter.	No. Var.	No. Eq.
$C1$	0.031	0	72	3,398	6,973
$A1$	0.033	0	1450	3,398	6,973

$C3$ is the worst scenario in which OF^{eu} is maximum, and the profit of the DSO is minimum. Also, $OF^{ag'}$ is equal to zero. In addition, in $C3$, the energy transaction between the DSO and the RTEM is one-way (from the RTEM to the DSO) which is not sufficient for the power distribution network as seen in Figs. 4(b) and 7(b). In addition, the MILP problem in the game-based approach was solved by CPLEX 12.0 and the implementation was performed on a laptop with 16 GB RAM, Intel Core i7 2.9 GHz. The computation coss of scenarios $C1$ and $A1$ which are most profitable scenarios for all agents are presented in Table V.

VI. Conclusion

In this paper, we have presented monopolistic and game-based approaches to manage energy flexibility among the agent of the distribution network. The performance of the proposed approaches to manage energy flexibility has been assessed in terms of the impacts of the flexible behaviors of the end-users and aggregators. According to the simulation results, it is found that:

- The monopolistic approach is profitable for all agents in the distribution network, if all end-users participate as interruptible loads.
- Aggregators do not want to participate in DR programs as their profits for the flexibility in energy exchange are equal to zero.
- The game-based approach is costly for all end-users because the DSO is in charge of determining the energy transacted between the DSO and end-users in our proposed approach.
- In the game-based interaction between aggregators and the DSO, the scenario considering the shiftable demand constraint is more profitable than the scenario considering the self-consumption limitation.
- The distribution network acts as a sustainable energy system considering the sustainable demand constraint in the game-based interaction among aggregators and the DSO.

Finally, it should be mentioned that all agents have not been considered as decision-makers in our proposed energy trading strategies. In our future works, an interplay model is presented based on direct interactions among end-users, aggregators and the DSO. Furthermore, we will discuss how the distributed energy management system could be modeled considering peer-to-peer energy trade in distribution networks.

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Amin Shokri Gazafroudi (S'15) received the Ph.D. degree in computer engineering (2019) from the University of Salamanca, Spain. His research interests include electricity markets, decision-making in power systems and demand response.

Miadreza Shafie-khah (M'13-SM'17) is an Assistant Professor at the University of Vaasa, Finland. His research interests include power market, power system optimization, demand response and electric vehicles.

Francisco Prieto-Castrillo is an Assistant Professor of Physics at the Universidad Politécnica de Madrid. With a background in theoretical physics, he has worked in many distant fields; statistical physics, artificial intelligence, smart energy networks and complex Systems.

Juan Manuel Corchado (M'10) is a Full Professor with the Chair at the University of Salamanca. He is also the Director of the BISITE Research Group. His research interests include case-based reasoning, blockchain technology, multi-agent systems, smart cities and IoT.

João P. S. Catalão (M'04-SM'12) is a Professor at the Faculty of Engineering of the University of Porto (FEUP), Porto, Portugal, and Research Coordinator at INESC TEC. His research interests include power system operations and planning, distributed renewable generation, demand response and smart grids.