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Iterative Algorithm For Local Electricity Trading

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***Abstract*—Distribution networks are more active due to demand response programs which causes flexible behavior of end-users. This paper proposes an iterative algorithm to transact electricity based on interplay between aggregators and the Distribution Company (DisCo) considering the amount which the bottom-layer of a distribution system can provide from the aggregated end-users. The performance of the proposed trading algorithm was tested on a 33-bus test system for a distribution network. Similations for different scenarios were made to analyze the impact of different flexibility constraints on sustainability of the system and expected cost on distribution grid's player.**

***Index Terms*—Decentralized energy management, energy flexibility, local energy trading.**

NOMENCLATURE

A. Indices

t	Time periods
j	End-users
k	Aggregators

B. Variables

OF_k^{ag}	Objective function of aggregator k [€].
OF^d	Objective function of the DisCo [€].
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 DisCo and the Real-Time Electricity Market (RTEM) [kWh].
P_{kt}^{A2D}	Energy traded at time t between aggregator k and the DisCo [kWh].
P_{jt}^{D2L}	Energy purchased at time t by end-user j from the DisCo [kWh].
PP_{kt}	An auxiliary variable to reperesent cost of energy trading at time t with the DisCo for aggregator k [€].
PP_{kt}^{dn}	An auxiliary variable to reperesent profit of selling energy at time t to the DisCo for aggregator k [€].
PP_{kt}^{up}	An auxiliary variable to reperesent cost of purchasing energy at time t from the DisCo for aggregator k [€].
z_{kt}	A binary variable which is determined by the DisCo to represent states of electricity price at time t of aggregator k.
λ_{kt}^{A2D}	Electricity price at time t for the aggregator k and the DisCo 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^{D2L}	Price for energy exchanged between the DisCo 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 DisCo 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

Smart grids consist of power systems based on a variety of connected IoT and embedded devices that are able to communicate with each other over the network. As the technology is growing, so does the interest in using the internet to preform daily tasks. Thus, improving the functionality of smart grids, smart homes and their IoT devices, such as energy management and security improvement, have become a major concern of companies throughout the world [1]. In scientific literature, there are many studies on energy management and scheduling of applications in IoT and embedded systems in smart grids at various levels of optimization from the computer and processor level [2] to the network level. According to infrastructure which is provided by smart grids, Demand Response (DR) strategies make the power distribution system more active. Thus, end-users wish to represent flexible behavior in the distribution networks [3]. Therefore, there is a need to develop new market structures to maximize energy flexibility based on decentralized approaches. As such, energy management frameworks for transacting energy in distribution networks are being studied in different recent works.

Ref. [4] proposed the concept of energy transaction nodes, which interface smart buildings with the Local Electricity Market (LEM). Authors of Ref. [5] proposed a price-based method for energy management. In [6], a multi-agent-based market was designed to decentralize decisions for transacting energy. Also, Multi Agent Systems (MAS) have been leveraged in [7] to create a multi-layer market environment based on behavior of electricity market players. In [8], a multi-agent transactive system has been presented where an energy system managed by Micro-Grids (MGs) in a distribution system to solve the complexity of aggregation. In [9], an agent-based model was proposed in which individual agents compute the energy management schedule (based on electricity prices) along with the aggregator locally and afterwards the optimal decision is communicated to a central controller in real-time.

In addition, multiple works have studied the interaction between distributed suppliers and consumers by employing DR strategies. In [10], several suppliers and consumers were considered to develop an adequate DR strategy. Authors in [11] presented a distributed real-time framework based on dual decomposition technique by multi-suppliers to regulate the demand of end-users. In [12], distributed model was developed in order to determine the optimal power flow by considering the regulation of demand in radial networks. In [13], the authors presented centralized energy trading as a bi-level model where the nonconvexity of the problem has been covered by convex relaxation techniques. In [14], a decentralized DR framework has been presented; it takes into account the operational constraints of the system. In [15], a LEM has been proposed in which market agents transact electricity to each other autonomoously. In [16], a contribution-based trading mechanism has been desgined among MGs where MGs act as prosumers. In [17], a hierarchical, real-time, energy trading approach for distribution networks was proposed in which the transactions are between aggregators on one hand and the consumers and DisCo on the other. In [18], energy management among players in the distribution power system was addressed, where an Ising-based model of energy flexbility provided by end-users. In [19], a decentralized approach has been presented based on perspective of end-users taking into account end-users energy flexibility along with the desired reliability level in a distribution network.

Even though several previous works have modelled the behavior of market participants in the lower layer of the power system, none have proposed an interplay management model for both energy and flexibility trading between end-users, aggregators and the DisCo. In this study, an iterative algorithm is developed to manage energy trading among aggregators and the DisCo, considering energy flexibility which is provided by end-users. Thus, energy is transacted on the basis of a hierarchical structure among the real-time electricity market and the distribution network's players (e.g. end-users, aggregators, and the DisCo). Besides, flexible behavior of end-users is modeled based on shiftable and self-consumption constraints. As such, a list of the main contributions of this study is defined as follows:

- Developing a management model for trading energy based on Mixed Integer Linear Programming (MILP).
- Proposing an iterative algorithm for exchange energy within a distribution network based on decisions made by aggregators and the DisCo in real-time .
- The evaluation of shiftable and self-consumption flexibilities to be taken into account in the proposed model for energy trading.

This manuscript is organized as follows: Section I (current Section) put forth the motivation for this work, established the state-of-the-art, and outlined the contributions of this study; Section II illustrates the proposed mathematical formulation of the problem; Section III discusses our findings corresponding to the obtained simulation results; Section IV highlights the conclusions of this work.

II. Problem formulation

In this section, the proposed energy management problem to transact energy flexibility locally is presented. First, the energy trading model is described to exchange real-time energy between players (e.g. end-users, aggregators and the DisCo) in the dsitrbution network. Besides, an iterative algorithm is proposed to transact energy between aggregators and the DisCo based on an MILP model of the energy trading problem.

A. Energy trading model

A real-time energy management framework is presented for flexibility trading in a distribution network. Although flexibility is defined as the power system's ability to respond to variations in consumption and generation [20], we focus on energy flexibility [kWh] as a service provided by end-users in this paper. The energy flexbility can be provided by energy storage systems, shiftable and shavable loads of end-users. In this structure, the RTEM can only trade with the DisCo, P_t^{RT}, as shown in Fig.1. In our proposed models, end-users are able to trade energy bi-direcational with their corresponding aggregators and only buy energy from the DisCo to prevent monopolistic energy transaction in corresponding regions of aggregators. End-users provide energy flexibility based on exchanging energy with corresponding aggregator (who bought their scheduled energy), P_{jkt}^{L2A}, and the DisCo, P_{jt}^{D2L}, at prices λ_{kt}^{L2A} and λ^{D2L} (whose amounts are assumed in this paper), respectively. Then, aggregators transact energy, P_{kt}^{A2D}, with the DisCo. It is presumed in this work that the DisCo is both a profitable and a proactive agent with tasks which are disctinct from the Distributed System Operator (DSO) [21].

End-users flexibility is provided based on a real-time increment and decrement of their scheduled loads as represented in (1). Eq. (2) sets a limit for the minimum and maximum values of flexibility. Here, γ_j is defined as flexibility factor which is set between 0 and 1. Also, Eq. (4) presents one-way energy transaction from the DisCo to end-users. Eqs. (5) and (6) represent self-consumption and shiftable limits, respectively, to constrain flexibility.

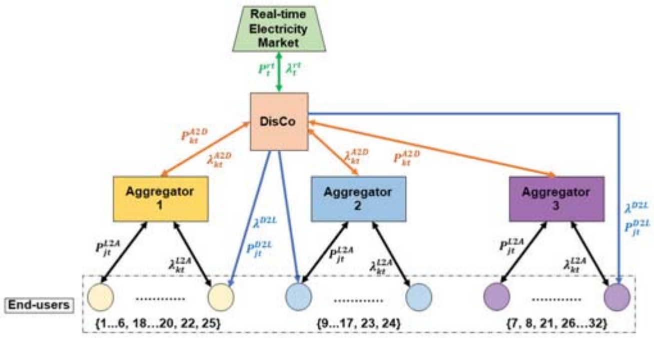

Fig. 1. Energy transaction framework in real-time showing the market players within the distribution network [17], [18].

$$L_{jt} = L_{jt}^{c} - L_{jt}^{f}, \ \forall j, t \tag{1}$$
$$-\gamma_j L_{jt}^{c} \le L_{jt}^{f} \le \gamma_j L_{jt}^{c} \ ,\forall j, t \tag{2}$$
$$L_{jt}^{f} = P_{jkt}^{L2A} - P_{jt}^{D2L}, \ \forall j \in A_k, t \tag{3}$$
$$P_{jt}^{D2L} \ge 0, \forall j, t \tag{4}$$
$$\sum_{j\in A_k} L_{jt}^{f} = 0 \ ,\forall t \tag{5}$$
$$\sum_{t} L_{jt}^{f} = 0 \ ,\forall j \tag{6}$$

Hierarchical bottom-up energy trading from end-users to aggregators, and from aggregators to DisCo is represented in (7). The maximum and minimum constraints of traded energy price between aggregators and the DisCo, λ_{kt}^{A2D}, are represented in (8). (9) provides a balance for energy traded between the DisCo and the RTEM (in the DisCo layer).

$$P_{kt}^{A2D} = \sum_{j\in A_k} P_{jkt}^{L2A}, \forall k, t \tag{7}$$
$$\delta_{kt}\lambda_{kt}^{L2A} \le \lambda_{kt}^{A2D} \le \lambda_t^{rt}, \forall t, k \tag{8}$$
$$P_t^{rt} = \sum_j P_{jt}^{D2L} - \sum_k P_{kt}^{A2D}, \forall t \tag{9}$$

B. Proposed Iterative Algorithm

In this section, an iterative algorithm is proposed to model energy trading based on interaction between aggregators and the DisCo. According to this algorithm, aggregators are in charge of determining the quantity of trades between the aggregators and the DisCo, P_{kt}^{A2D}. Meanwhile, the DisCo sets the price for the transaction, λ_{kt}^{A2D} in the distribution network. Noted that λ_{kt}^{A2D} is different with the real-time electricity price, λ_t^{rt}, which is determined in the RTEM. The proposed algorithm is shown in Fig. 2. As it is seen in (8), λ_{kt}^{A2D} is limited to maximum and minimum bands to be profitable for aggregators. Thus, if the energy exchange between aggregators and the DisCo is positive, $P_{kt}^{A2D} \ge 0$, then the DisCo sets the minimum band of price's limitations. However, the DisCo determines the maximum band of price's limitation where traded energy between aggregators and the DisCo is negative, $P_{kt}^{A2D} < 0$. Hence, we have:

IF $P_{kt}^{A2D} \ge 0 \rightarrow$
$$\lambda_{kt}^{A2D} = Min.\{\delta_{kt}\lambda_{kt}^{L2A}, \lambda_t^{rt}\} \rightarrow z_{kt} = 0.$$
ELSE $P_{kt}^{A2D} < 0 \rightarrow$
$$\lambda_{kt}^{A2D} = Max.\{\delta_{kt}\lambda_{kt}^{L2A}, \lambda_t^{rt}\} \rightarrow z_{kt} = 1.$$

Here, z_{kt} is defined as a binary variable which is determined by the DisCo to represent states of electricity price. In the following, the nonlinear term, $\lambda_{kt}^{A2D} P_{kt}^{A2D}$, which is profit (cost) for the DisCo and aggregator based on their transaction is restated as seen in (10)-(13).

$$\lambda_{kt}^{A2D} P_{kt}^{A2D} = \{\delta_{kt}\lambda_{kt}^{L2A}(1 - z_{kt}) + \lambda_t^{rt} z_{kt}\} P_{kt}^{A2D} = PP_{kt}, \forall t, k \tag{10}$$
$$PP_{kt} = PP_{kt}^{dn} + PP_{kt}^{up} \forall t, k \tag{11}$$
$$PP_{kt}^{dn} = \delta_{kt}\lambda_{kt}^{L2A}(1 - z_{kt}) P_{kt}^{A2D}, \forall t, k \tag{12}$$
$$PP_{kt}^{up} = \lambda_t^{rt} z_{kt} P_{kt}^{A2D}, \forall t, k \tag{13}$$

Eqs. (12) and (13) are redefined as mixed integer linear constraints according to Ref. [22]. Hence, Eq. (10) is redefined as presented in (14)-(18).

$$-z_{kt}M \le PP_{kt}^{dn} - \delta_{kt}\lambda_{kt}^{L2A} P_{kt}^{A2D} \le z_{kt}M, \forall t, k \tag{14}$$
$$-\gamma_j \delta_{kt}\lambda_{kt}^{L2A}(1 - z_{kt}) \sum_{j\in A_k} L_{jt}^{c} \le PP_{kt}^{dn} \le \gamma_j \delta_{kt}\lambda_{kt}^{L2A}(1 - z_{kt}) \sum_{j\in A_k} L_{jt}^{c}, \forall t, k \tag{15}$$
$$-(1 - z_{kt})M \le PP_{kt}^{up} - \lambda_t^{rt} P_{kt}^{A2D} \le (1 - z_{kt})M, \forall t, k \tag{16}$$
$$-\gamma_j \lambda_t^{rt} z_{kt} \sum_{j\in A_k} L_{jt}^{c} \le PP_{kt}^{up} \le \gamma_j \lambda_t^{rt} z_{kt} \sum_{j\in A_k} L_{jt}^{c}, \forall t, k \tag{17}$$
$$-\gamma_j z_{kt} \sum_{j\in A_k} L_{jt}^{c} \le PP_{kt}^{A2D} \le \gamma_j (1 - z_{kt}) \sum_{j\in A_k} L_{jt}^{c}, \forall t, k \tag{18}$$

Therefore, the objective functions of aggregators and the DisCo are represented in (19) and (20), respectively. Hence, the respective energy management problems are presented considering (11), and (14)-(18).

$$OF_k^{ag} = \sum_t \sum_{j\in A_k} \lambda_{kt}^{L2A} P_{jkt}^{L2A} - \sum_t PP_{kt}, \forall k \tag{19}$$
$$OF^{d} = \sum_t PP_{kt} + \sum_t \lambda_t^{rt} P_t^{rt} - \lambda^{D2L} \sum_t \sum_j P_{jt}^{D2L} \tag{20}$$

As represented in (19), the objective function consists of two terms: first term, $\sum_t \sum_{j\in A_k} \lambda_{kt}^{L2A} P_{jkt}^{L2A}$, represents the expected trading energy cost between end-users and aggregator k, and the second one, $\sum_t PP_{kt}$, represents the expected energy transaction profit between aggregator k and the DisCo. In (20), OF^d includes three terms consisting of the expected cost of energy transaction with aggregators, $\sum_t PP_{kt}$, the expected cost of energy exchanged with the RTEM, $\sum_t \lambda_t^{rt} P_t^{rt}$, and the expected profit from based on selling energy to end-users, $\lambda^{D2L} \sum_t \sum_j P_{jt}^{D2L}$.

According to the proposed algorithm, aggregators and the DisCo make decisions regarding their own autonomous energy management problem considering interaction signals among aggregators and the DisCo. In the following, the energy management problems of aggregators and the DisCo are presented:

- Aggregators' problem (Problem A):

$Min.\ EC^{ag} = \sum_k OF_k^{ag}$

s.t. (1)-(3), (5)-(7), (11), (14)-(18).

Decision-making variables: L_{jt}, L_{jt}^f, P_{jkt}^{L2A}, P_{kt}^{A2D}, PP_{kt}, PP_{kt}^{dn}, PP_{kt}^{up}. *Fixed variables:* P_{jt}^{D2L}, z_{kt}. *Passed variables to problem D:* P_{kt}^{A2D}.

- DisCo's problem (Problem D):

$Min.\ EC^d = OF^d$

s.t. (4), (9), (11), (14)-(18).

Decision-making variables: P_{jt}^{D2L}, P_t^{rt}, PP_{kt}, PP_{kt}^{dn}, PP_{kt}^{up}. *Fixed variables:* P_{kt}^{A2D}. *Passed variables to problem A:* P_{jt}^{D2L}, z_{kt}.

In this way, P_{kt}^{A2D} is determined by aggregators in problem A, and it is a fixed variable in problem D. However, in Problem D, P_{jt}^{D2L} and z_{kt} are determined by the DisCo, and they are fixed varaibles in problem A. In this structure, the energy flexibility of bottom-layer of the system is managed only by aggregators. This model has an advantage of being able to directly manage the quantities energy which are being traded between aggregators and the DisCo, P_{kt}^{A2D}. However, the expected costs of end-users in decision-making is not seen (where end-users are the main agents providing flexibility in the system) which is the lack of this algorithm.

III. Results and Discussions

A. Case Study

In this paper, the 33-bus test system presented in [17]- [19] and [23] is used to assess the proposed algorithm for energy trade management as shown in Fig.3. Three aggregators and the price at which they trade electricity in their corresponding regions are presented in Table I. Moreover, it is assumed that $\lambda^{D2L} = 0.6$ [€/kWh], $\gamma_j = 0.1$, and $\delta_{kt} = 1.1$ according to Refs. [17] and [18]. Also, ϵ is assumed to equal $1e^{-10}$ as the stopping criteria of the iterative loop. Energy flexibility scenarios are presented in Table II. The proposed MILP model was implemented and solved using the General Algebraic Modeling System (GAMS) version 24.0.2 [24].

B. Simulation Results

The impact of the proposed iterative algorithm on the expected costs for aggregators and the DisCo is studied in this

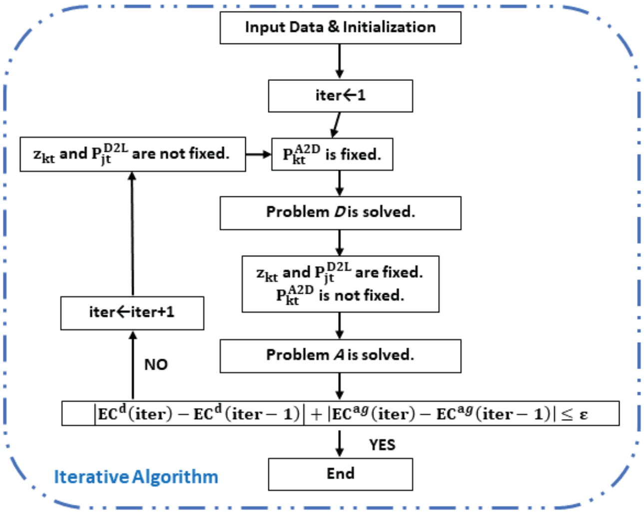

Fig. 2. Proposed iterative algorithm for real-time energy trading between aggregators and the DisCo.

TABLE I
Hourly prices for energy transacted between consumers and aggregators and between the RTEM and the DisCo [17]- [19].

Time (h)	$\lambda_{k=1,t}^{L2A}$ [€/kWh]	$\lambda_{k=2,t}^{L2A}$ [€/kWh]	$\lambda_{k=3,t}^{L2A}$ [€/kWh]	λ_t^{RT} [€/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

TABLE II
Energy flexibility scenarios.

Scenario	*Min.*	*s.t.*
$A1$	EC^{ag}	(1)-(4), (7), (9), (11), and (14)-(18).
$A2$	EC^{ag}	(1)-(4), (6)-(7), (9), (11), and (14)-(18).
$A3$	EC^{ag}	(1)-(5), (7), (9), (11), and (14)-(18).

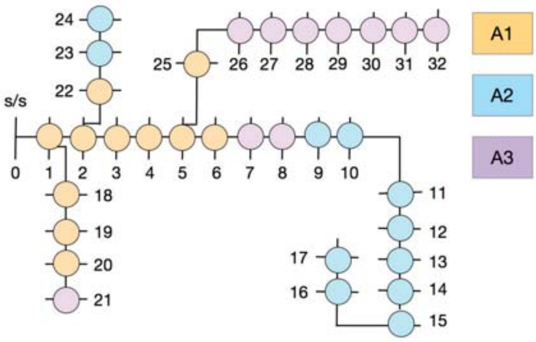

Fig. 3. The 33-bus test system and aggregators [17]- [19] and [23].

TABLE III
TOTAL EXPECTED COSTS OF AGGREGATORS AND THE DISCO BASED ON THE ITERATIVE ALGORITHM.

	EC^{ag} [€]	EC^{d} [€]
$A1$	-239.444	-3339.466
$A2$	-143.924	-2413.909
$A3$	-72.618	-1753.407

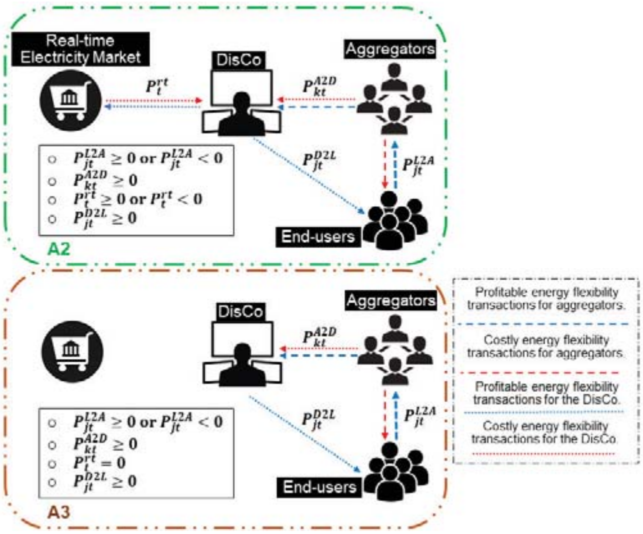

Fig. 4. Impact of flexibility scenarios on real-time energy transaction flows through end-users, aggregators, the DisCo, and the RTEM based on iterative algorithm.

Section. The three flexibiity scenarios defined in Table II ($A1$-$A3$) were used to assess the proposed system's performance under different conditions. In Scenario $A1$, the end-users were modelled as interruptible loads. Shiftable loads were included in Scenario $A2$. Finally, in Scenario $A3$, the self-consumption constraint was incorporated to model aggregation of end-users. Table III shows total expected costs of aggregators and the DisCo based on the proposed energy trading algorithm. As the amount of EC^{d} is much higher than EC^{ag}, decisions which are made by the DisCo are more effective on convergence of our proposed iterative algorithm

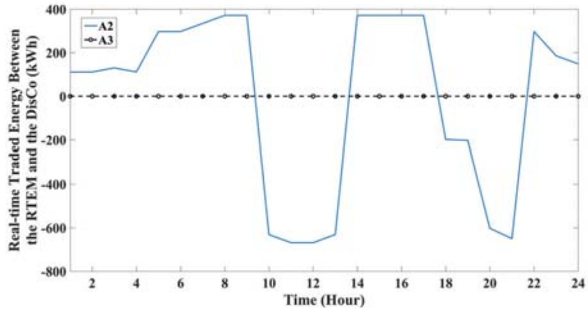

Fig. 5. Energy exchanged between the DisCo and the RTEM in real-time for scenarios $A2$ and $A3$.

	Scenario A2				Scenario A3		
	j3	j15	j29		j3	j15	j29
t1	-1.8	-1.8	-4.5	t1	0	0	0
t2	-1.8	-1.8	-4.5	t2	0	0	0
t3	-2.1	-2.1	-5.25	t3	0	0	0
t4	-1.8	-1.8	-4.5	t4	0	0	0
t5	-4.8	-4.8	-12	t5	0	0	0
t6	-4.8	-4.8	-12	t6	0	0	0
t7	-5.4	-5.4	-13.5	t7	0	0	0
t8	-6	-6	-15	t8	0	0	0
t9	-6	-6	-15	t9	0	0	0
t10	10.2	10.2	25.5	t10	10.2	-10.2	-25.5
t11	10.8	10.8	27	t11	10.8	-10.8	-27
t12	10.8	10.8	27	t12	10.8	-10.8	-27
t13	10.2	10.2	25.5	t13	10.2	-10.2	-25.5
t14	-6	-6	-15	t14	0	0	0
t15	-6	-6	-15	t15	0	0	0
t16	-6	-6	-15	t16	0	0	0
t17	-6	-6	-15	t17	0	0	0
t18	9	-3.6	-9	t18	9	-9	-22.5
t19	-3	9.6	24	t19	9.6	-9.6	-24
t20	10.2	10.2	25.5	t20	10.2	-10.2	-25.5
t21	10.5	10.5	26.25	t21	10.5	-10.5	-26.25
t22	-4.8	-4.8	-12	t22	0	0	0
t23	-3	-3	-7.5	t23	0	0	0
t24	-2.4	-2.4	-6	t24	0	0	0

Fig. 6. Quantity of energy flexibility of the end-users at: (1) $j3$ (in region of aggregator 1), (2) $j15$ (in region of aggregator 2), and (3) $j29$ (in region of aggregator 3) in $A2$ and $A3$. Red and green colours represent negative and positive flexibilities, respectively. All values are in kWh.

Instead of $A1$ which is an optimal scenario of the system in which all end-users play as interruptible loads, total expected costs of aggregators and the DisCo are less in $A2$ in comparison with $A3$. On one hand, $A2$ is a more profitable scenario for all players in the power distribution system in comparison with $A3$. However, the distribution network acts more sustainable in $A3$, because end-users, aggregators, and the DisCo make a closed-lope energy trading system as shown in Fig. 4. Meanwhile, the distribution power network is more sustainable and does not depend on the upstream grid in $A3$, as shown in Figs. 4 and 5. Moreover, Fig. 6 shows flexible behavior of end-users $j3$, $j15$ and $j29$ as samples of end-users in regions of aggregators 1 to 3, respectively. As illustrated in Fig. 6, the behavior of sample end-users in $A2$ is more dynamic and flexible than $A3$ that their dynamic behavior increases the profit of end-users. Here, the dynamic behavior of end-users is defined as a variation of up-ward and downward energy flexibility which they can provide in Scenarios $A2$ and $A3$, as shown in Fig. 6.

IV. Conclusion

In this paper, an iterative algorithm has been presented for energy transaction management between distribution network's players. The proposed algorithm has been evaluated based on impacts of end-users flexibility scenarios. By analyzing the results of the simulations for all three scenarios, several conclusions can be made as listed below:

- The self-consumption constraint results in the distribution network becoming a sustainable energy system, in the sense that it has no dependence on the real-time electricity market.
- Higher profits for the aggregators and the DisCo were achieved by shiftable end-users than by self-consumption end-users.
- Flexible behavior of end-users was found to be more dynamic for the shiftable end-users compared to the self-consumption end-users in the proposed energy trading model.

Future work building on this study should develop a model to decentralize the uncertainty modeling of distributed energy resources. In addition, the modelling of a distributed energy management system which takes into consideration peer-to-peer energy trading among end-users and aggregators should be investigated.

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