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Bi-Level Approach for Flexibility Provision by Prosumers in Distribution Networks

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***Abstract*—The increasing number of Distributed Energy Resources (DERs) provides new opportunities for increased interactions between prosumers and local distribution companies. Aggregating large numbers of prosumers through Home Energy Management Systems (HEMS) allows for easier control and coordination of these interactions. With the contribution of the dedicated end-users in fulfilling the required flexibility during the day, the network operator can easily handle the power mismatches to avoid fluctuations in the load-generation side. The bi-level optimization allows for a more comprehensive and systematic assessment of flexibility procurement strategies. By considering both the network operator's objectives and the preferences and capabilities of end-users, this approach enables a more nuanced and informed decision-making process. Hence, this paper presents a bi-level optimization model to examine the potential for several groups of prosumers to offer flexibility services to distribution companies. The model is applied to the IEEE 33 bus test system and solved through distributed optimization techniques. The model considers various DERs, including Battery Energy Storage Systems (BESS). Results show that the groups of aggregated consumers can provide between ±7 to ±29 kW flexibility in each interval, which is significant. Furthermore, the aggregators' flexibility capacity is closely linked to the demand at each node.**

***Index Terms*—Aggregation, distributed optimization, energy storage systems, flexibility services, home energy management systems, prosumers.**

NOMENCLATURE

Constants

α_i	No-load cost coefficient of unit *i*.
$\eta_s^c,\ \eta_s^d$	Charging and discharging efficiency rates of BESS *s*.
$\xi_{k,i}$	Slope of block *k* of the piecewise linear production cost function of unit *i*.
$\zeta_{m,l}$	Parameter of the *m*-th block used in the linearization of the loss function of line *l* in the pre-contingency state.
π_t	Local marginal price at the point of exchange in period *t*.
B_l	Susceptance of line *l*.
$C_{s,t}^{Deg}$	Degradation cost coefficient of BESS *s* in period *t*.
$C_{s,t}^{Dis}$	Discharge cost coefficient of BESS *s* in period *t*.
$C_{b,t}^{ENS}$	Load shedding coefficient cost at bus *b* in period *t*.
$D_{b,t}$	Load demand of bus *b* in period *t*.
E_S^{Max}, E_S^{Min}	Maximum/minimum limit of stored energy of BESS *s*.
F_l^{Max}	Active power capacity of line *l*.
$Flex_t^{Down}$	Flexibility requirements down in period *t*.
$Flex_t^{Up}$	Flexibility requirements up in period *t*.
G_l	Conductance of line *l*.
$PDTF_{l,b}$	Power transfer distribution factor for line *l* and bus *b*.
L_i	Number of periods unit *i* must be initially offline due to its minimum downtime constraint.
$L_i^{Down,Min}$	Number of periods unit *i* must be initially offline due to its minimum down time constraint.
$L_i^{Up,Min}$	Number of periods unit *i* must be initially online due to its minimum down time constraint.
PC_s^{Max}, PC_s^{Mi}	Maximum and minimum charge limits of BESS *s*.
PD_s^{Max}, PD_s^{M}	Maximum and minimum discharge limits of BESS *s*.
P_i^{Max}, P_i^{Min}	Maximum and minimum production limits of unit *i*.
p_i^{on-off}	Initial commitment state of unit *i* (1 if it is online, 0, otherwise).
p_i^{Down}, p_i^{Up}	Minimum down and up times of unit *i*.
$p_i^{Downinit}$	Number of periods unit *i* has been offline prior to the first period of the time span.
p_i^{Upinit}	Number of periods unit *i* has been online prior to the first period of the time span.
RD_i, RU_i	Ramp-down and ramp-up rate limits of unit *i*.
RSD_i, RSU_i	Ramp limits for the shut-down and start-up of unit *i*.
SDC_i, SUC_i	Shut-down and start-up cost coefficients of unit *i*.

Variables

$\Delta f_{m,l,t}$	Contribution of block *m* to the active power flow on line *l* in period *t*.
$\Delta p_{k,i,t}$	Active power produced in block *k* of the piecewise linear production cost function of unit *i* in period *t*.
$e_{s,t}$	Level of the stored energy of BESS *s* in period *t*.
$ens_{b,t}$	Load shedding at bus *b* in period *t*.
$f_{l,t}$	Active power flow on the line *l* in period *t*.
$f_{l,t}^{+}, f_{l,t}^{-}$	Auxiliary variables used to model the active power flow on the line *l* in period *t*.
$f_{l,t}^{loss}$	Active power loss of line *l* in period *t*.
$NP_{n,t}$	Exchanged power point *n* with network in period *t*.
$p_{i,t}$	Active power generation of unit *i* in period *t*.

$pc_{s,t}, pd_{s,t}$	Level of charge and discharge power of BESS s in period t.
$pv_{b,t}$	Solar power of node b in period t.
$v_{i,t}$	Binary variable equal to 1 if unit i is online in period t and 0, otherwise.
$y_{i,t}$	Binary variable equal to 1 if unit i is started up in period t and 0, otherwise.
$z_{i,t}$	Binary variable equal to 1 if unit i is shut down in period t and 0, otherwise.

Sets

B	Set of bus indexes.
I	Set of generating unit indexes.
K	Set of indexes of blocks of the piecewise linear production costs.
L	Set of indexes of transmission lines in service in the pre-contingency state.
M	Set of indexes of blocks of the piecewise linear approximation of transmission losses.
S	Set of BESS unit indexes.
T	Set of time indexes.

I. Introduction

THE increasing deployment of behind-the-meter distributed energy resources (DERs) has the potential to transform the operation of power systems [1], [2]. These devices allow for more active participation by smaller consumers. This increased participation can create new opportunities and challenges for the optimal operation of the power system.

These challenges may include the increased communication requirements to allow for a seamless flow of information between a vast number of devices, increased concerns regarding the data privacy of this information, and the ability to coordinate and control a fleet of diverse DERs as a single entity to participate in energy markets predictably and with significant capacity to be financially viable [3], [4].

These challenges can be addressed by aggregating DERs to act as a single entity in energy markets. This can be done using an energy aggregator who coordinates and controls a diverse group of devices [4]. In addition, aggregators can group smaller DERs and act as a single entity. This can help reduce the uncertainty around electricity demand or consumption and meet minimum bid size requirements that the energy market may have [5].

A. Comprehensive Overview and Related Work

It is well known that flexibility in terms of load and generation will be an important asset in energy systems dominated by a large amount of variable renewable energy sources. Flexibility is defined as the ability of an asset to adjust its load or generation in response to an external incentive, most commonly a financial incentive [6]. DERs, through aggregators, can provide this flexibility to the system [4]. However, the optimization framework for aggregators and the communication protocols between the consumers and the aggregator, as well as between the aggregator and the Transmission System Operator (TSO) or the Distribution System Operator (DSO) are not well established [7]. This is the main motivation for this work.

Using aggregators to bundle numerous prosumers (through HEMS) to bid into energy or reserve markets has recently received some research attention. For instance, a model which considers both day-ahead energy markets and local flexibility markets was proposed by [8], which considered a mixed integer linear programming (MILP) approach to managing a set of uncertainty resources, minimizing the aggregator's operating costs. In addition, the model used a centralized approach where the aggregator determines the flexibility profile, which reduces the ability of the HEMS to schedule flexibility services following the prosumer's load and preferences.

In [9], a co-optimized distribution system management system has been presented that considers the high integration of prosumer microgrids registered in the transactive market to analyze the influence of the flow of electricity considering the operation, flexibility, and reliability of the system under study. The study was conducted considering different levels of operation and scheduling scenarios and the uncertainty from renewables. The model was formulated by a bi-level stochastic programming and reformulated as a single mixed-integer model.

The problem of short-term distribution problem was analyzed in [10] considering the tariff design and the flexibility of the distributed energy resources, with the goal to increase the economic operation efficiency of the distribution network. The problem addressed in a bilevel approach is integrating prosumers and power flow constraints by considering a clustering process to design and adapt the tariffs. In [11], a bilevel approach was presented, considering a set of multi-energy players trading with multiple carriers, maximizing profits, and reducing operational risks. The structure is based on the energy market, multi-energy players and demands, and the wholesale electricity market, all together maximizing their profit. The concept was also presented by a decision-making process by a bilevel approach between aggregators and multi-energy players. The authors in [12] presented a systematic review of prosumers' importance in the necessary flexibility shift in power systems, considering the aggregation of prosumers as renewable generation or microgrids communities and the profitability of reduced-carbon applications.

Recently, in [13], a new method for the active participation of prosumers in the local day-ahead flexibility market has been addressed, which considers a collaborative framework for prosumers to use and trade the needed flexibility bids under a competitive and regulated market framework, satisfying the requirements of the distributions system operator. Also, in [14], a bilevel approach has been developed to investigate the improvement of the distribution network and congestion management with the help of procuring flexibility. To this end, a demand-side flexibility strategy is addressed and divided into several levels where prosumers are included to provide the necessary flexibility to the transmission system.

Moreover, a local electricity market designed to increase flexibility was developed [15]. The authors considered a collection of industrial consumers and used peer-to-peer electricity trading and battery energy storage to maximize the usage of DERs. The authors created a MILP model to show that the model can contribute to energy savings for industrial consumers. The authors used data from an actual group of industrial consumers but did not consider any uncertainties.

Hence, a mixture of residential and commercial consumers was considered in [16]. The work included building-level agents coordinating and scheduling various appliances to provide demand response potential and lower building costs. The model was based on decentralized decision-making to help ensure the solution's scalability.

In contrast to the previous contributions, uncertainty was considered in [17], assessing the forecast uncertainty when the scheduling flexibility from prosumers in a decentralized manner is needed. Also, a privacy-preserving collective learning algorithm to reduce the collective peak load of a group of prosumers was developed. The results show that energy imbalances are reduced due to the group-wide optimal scheduling of prosumers' flexibility. The ability of prosumers to provide flexibility services to a DSO using a transactive energy model was developed by [18], considering both a real-time and day-ahead market. Results showed that the greatest share of flexibility was traded in the day-ahead market, with only a small percentage traded in the real-time market.

While it does not consider uncertainties, a model for residential trading flexibility in a nested transactive energy market was developed by [19], formulated as a Mixed Integer Programming (MIP) model, which traded prosumer's flexibilities in two markets: a local flexibility market to reduce peak loads, and a wholesale market to trade energy when the wholesale market price exceeded a certain threshold. Results showed significant improvement in profits for prosumers.

In opposition to previous contributions, a model formulated by [20] is a bottom-up model for scheduling prosumer's flexibility in both day-ahead and intra-day markets. The bottom-up nature of the model relies on a distributed clearing mechanism that preserves the privacy of the prosumer's information. The joint scheduling framework showed prosumers could reduce energy costs while assisting the system operator in maintaining grid constraints; however, it does not consider network congestion.

A contribution that does consider network congestion is presented by [21]. The authors used a virtual battery representation of an electric vehicle (EV) to help contribute to day-ahead flexibility scheduling and ensure adequate spinning reserve for the power system. In addition, the uncertainty of EV driving behavior is considered. This centralized model shows that EVs can contribute to reducing network congestion.

B. Goals, Contributions, and Manuscript Organization

To fulfill the required flexibility with the contribution of dedicated end-users during the day, an optimization problem should be solved to minimize the load-generation mismatches. The optimization problem provides a systematic approach to assess and determine the optimal flexibility procurement strategies. By formulating the problem as a bi-level optimization model, it considers both the objectives of the network operator, i.e., maintaining load-generation balance, while the preferences and capabilities of end-users are met. To facilitate such interactions and ensure efficient coordination, an optimization problem is necessary. It allows for better control and management of the power mismatches that may arise from distributed generation and energy consumption.

The research has shed light on the existing gap in bi-level distributed optimization that considers uncertainties and incorporates losses while optimizing prosumers through an aggregator. In response to this gap, this paper introduces a novel bi-level optimization model that examines the potential of multiple prosumers in offering flexibility as a service to distribution companies. The contributions of this study can be outlined as follows:

- Addressing the provision of balancing services to the TSO by aggregating prosumers instead of relying solely on large industrial entities [22]. The proposed framework formulates the problem as a MILP and utilizes distributed optimization techniques to achieve its solution. This approach ensures more efficient and effective utilization of resources while catering to the needs of the TSO.
- Introducing a new bi-level optimization framework where a Home Energy Management System (HEMS) optimizes its daily load profile and determines the provision of flexibility, which is then communicated to the local distribution companies (LDC) [23]. This approach empowers HEMS to actively participate in the optimization process and align its energy consumption with the requirements of the LDC, leading to improved system flexibility and resource utilization.
- Incorporating distribution losses into the problem formulation, enabling accurate assessment of the impact of aggregators on the local distribution companies and facilitating the more precise provision of flexibility services. By considering distribution losses, the model provides valuable insights into the true effects of aggregators on the distribution network, enabling LDCs to make informed decisions regarding flexibility procurement and management.

These contributions are realized through developing and applying a bi-level optimization model that enhances control over HEMS. The model's distributed solution approach improves communication protocols and effectively addresses the research gaps identified during the literature review. By embracing these advancements, the energy sector can enhance its ability to leverage the potential of prosumers and achieve more efficient and sustainable energy management.

This manuscript has the following structure: the mathematical formulation of the developed model is presented in Section II. Section III contains the details of the case studies and the results of applying the model to a test system. Finally, Section IV has the relevant conclusions.

II. Mathematical Formulation

This section contains the mathematical formulation details describing this flexibility framework. The structure of this framework is as follows: the upper-level DSO interacts with middle-level aggregators who, in turn, interact with the prosumers at the lower level to participate in the provision of flexibility requirements imposed by the DSO.

The DSO interacts with the prosumers by coordinating their operations through an iterative negotiation mechanism. Negotiation is carried out using the Distribution Locational

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Marginal Prices (DLMP) obtained by the DSO.

First, the market communicates the LMP to the DSO, which then computes the DLMPs and transmits them to the aggregators, sharing them with each prosumer. In addition, DLMP includes the losses component, which makes each price different. After that, prosumers respond to the aggregators by offering their provision of flexibility bids accordingly, without sacrificing the prosumer's comfort and preferences.

Prosumers voluntarily register to participate in flexibility by receiving monetary compensation if they modify their base demand profile. Finally, the aggregator collects all the flexibility offered by the prosumers and sends them to the DSO, which sends them to the market operator. This procedure is performed iteratively until reaching a point of convergence for both the DSO and aggregators.

Fig. 1 graphically describes the negotiation communication between the market, DSO, aggregators, and prosumers. The objective function to be minimized is expressed in (1) and includes the total operating generation costs, start-up, and shut-down costs, not supplied energy costs, energy exchange costs, and storage charging and discharging costs.

$$Min \sum_{t\in T}\left[\begin{array}{l}\sum_{i\in I}\left(\alpha_i v_{i,t}+\sum_{k\in K}\xi_{k,i}\Delta p_{k,i,t}+SDC_i z_{i,t}+SUC_i y_{i,t}\right)\\ +\sum_{s\in S}\left(C_{s,t}^{Deg}pc_{s,t}+C_{s,t}^{Dis}pd_{s,t}\right)+\sum_{b\in B}C_b^{ENS}ens_{b,t}\\ -\sum_{n\in N}\pi_t NP_{n,t}\end{array}\right] \tag{1}$$

System power balance is imposed in (2), and flexibility requirements are set in (3)-(4). The generator quadratic cost curve is represented by linear sections [24].

$$\begin{array}{l}\sum_{i\in I}p_{i,t}+\sum_{b\in B}pv_{b,t}+\sum_{s\in S}pd_{s,t}+\sum_{b\in B}ens_{b,t}=\\ \sum_{b\in B}\left(Pd_{b,t}^{\inf}+Pd_{b,t}^{flx}\right)+\sum_{s\in S}pc_{s,t}+\sum_{l\in L}f_{l,t}^{loss}+\sum_{n\in N}NP_{n,t}\end{array} \tag{2}$$

$$\sum_{b\in B}Pd_{b,t}^{flx}\geq Flex_t^{Up} \tag{3}$$

$$\sum_{b\in B}-Pd_{b,t}^{flx}\geq Flex_t^{Down} \quad ;\forall t\in T \tag{4}$$

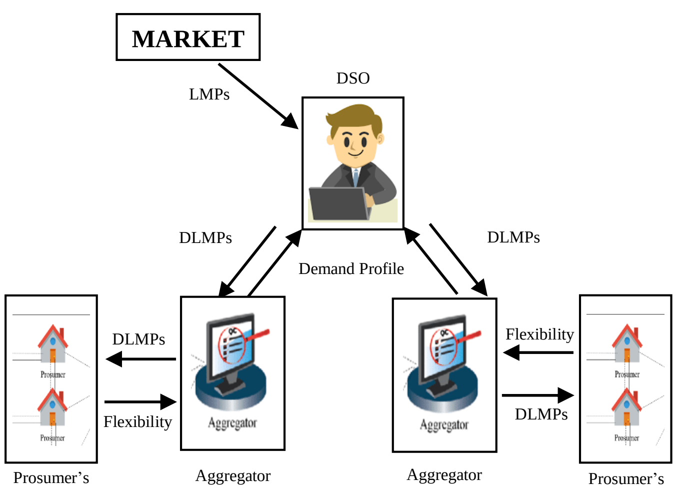

Fig. 1. Market-DSO-Aggregator-Prosumers Communications.

As a result, a linear program is addressed rather than the computationally challenging approach of a linear quadratically-constrained programming problem. Hence, the generation blocks used in the piecewise linear production costs are characterized in (5) and (6).

$$p_{i,t}=\sum_{k\in K}\Delta p_{k,i,t}\ ;\forall i\in I,\forall t\in T \tag{5}$$

$$0\leq \Delta p_{k,i,t}\leq \frac{P_i^{Max}}{|K|}\ ;\forall k\in K,\forall i\in I,\forall t\in T \tag{6}$$

Production limits are set in (7), ramp rates are modeled in (8)-(9), and minimum operating times are expressed in (10)-(12).

$$v_{i,t}P_i^{Min}\leq p_{i,t}\leq v_{i,t}P_i^{Max}\ ;\forall i\in I,\forall t\in T \tag{7}$$

$$-p_{i,t-1}\leq v_{i,t-1}RU_i+y_{i,t}RSU_i\ ;\forall i\in I,\forall t\in T \tag{8}$$

$$-p_{i,t}+p_{i,t-1}\leq v_{i,t}RD_i+z_{i,t}RSD_i\ ;\forall i\in I,\forall t\in T \tag{9}$$

$$v_{i,t}=p_i^{on-off}\ ;\forall i\in I,0\leq t\leq L_i^{Up,Min}+L_i^{Down,Min} \tag{10}$$

$$\sum_{\tau=t-Pg_i^{UP}+1}^{t}y_{i,t}\leq v_{i,t}\ ;\forall i\in I,\forall t\in L_i^{Up,Min} \tag{11}$$

$$\sum_{\tau=t-Pg_i^{Down}+1}^{t}z_{i,t}\leq 1-v_{i,t}\ ;\forall i\in I,\forall t\in L_i^{Down,Min} \tag{12}$$

The logic of operation in (13)-(14), and binary nature of the variables $u_{i,t}, y_{i,t}$, and $z_{i,t}$ are described by (15).

$$y_{i,t}+z_{i,t}\leq 1;\forall i\in I,\forall t\in T \tag{13}$$

$$v_{i,t}=v_{i,t-1}+y_{i,t}-z_{i,t}\ ;\forall i\in I,\forall t\in T \tag{14}$$

$$v_{i,t},y_{i,t},z_{i,t}\in\{0,1\}\ ;\forall i\in I,\forall t\in T \tag{15}$$

A generic ESS model is selected as the reference formulation. In detail, the constraints described by (16)-(17) represent ESS's charging/ discharging operational bounds.

$$PD_s^{Min}\leq pd_{s,t}\leq PD_s^{Max}\ ;\forall s\in S,\forall t\in T \tag{16}$$

$$PC_s^{Min}\leq pc_{s,t}\leq PC_s^{Max}\ ;\forall s\in S,\forall t\in T \tag{17}$$

Eq. (18) is a constraint that indicates the actual state of charge of the storage unit. Eq. (19) is a constraint that limits the value of the storage unit's maximum and minimum state of charge. Finally, Eq. (20) is a constraint that indicates that the state of charge at the end of the scheduling period would be the same as at the beginning.

$$e_{s,t}=e_{s,t-1}+\eta_s^c pc_{s,t}-\frac{pd_{s,t}}{\eta_s^d}\ ;\forall s\in S,\forall t\in T \tag{18}$$

$$E_s^{Min}\leq e_{s,t}\leq E_s^{Max};\forall s\in S,\forall t\in T \tag{19}$$

$$e_{s,1}=e_{s,T}\ ;\forall s\in S \tag{20}$$

The distribution network is characterized by using a linear DC power flow model. Eq. (21) is a constraint that represents the power flows, and (22)-(23) are the constraints that enforce the corresponding line flow capacity limit, including distribution losses. Notice that only power flows are checked in one direction, given that power flows are always positive due to transmission loss modeling.

$$f_{l,t}=\sum_{b\in B} PDTF_{l,b}\left(\sum_{i\in I_b} p_{i,t}-D_{b,t}+ens_{b,t}+pv_{b,t}+\sum_{s\in S}\left(pd_{s,t}+pc_{s,t}\right)\right);\forall l\in L,\forall t\in T \quad (21)$$

$$f_{l,t}+0.5\,f_{l,t}^{loss}\le F_l^{Max};\forall l\in L,\forall t\in T \quad (22)$$

$$-f_{l,t}+0.5\,f_{l,t}^{loss}\le F_l^{Max};\forall l\in L,\forall t\in T \quad (23)$$

The distribution losses allow the DSO to obtain a more realistic operational solution, so the DMLP differs for each node. The piecewise linear transmission losses modeling, reported in [24], is applied to convert the active power loss quadratic function to a linear programming formulation.

The line flow is represented by a linear combination of two non-negative variables, as shown in (24)-(26). Each interval's upper and lower limits are set in (27). The loss magnitude on line l is expressed in (28). The exclusivity condition, constraints (29)-(31), requires variables $f_{l,t}^{+}$ and $f_{l,t}^{-}$ cannot be simultaneously different from 0.

$$f_{l,t}=f_{l,t}^{+}-f_{l,t}^{-};\forall l\in L,\forall t\in T \quad (24)$$

$$\sum_{m\in M}\Delta f_{m,l,t}=f_{l,t}^{+}+f_{l,t}^{-};\forall l\in L,\forall t\in T \quad (25)$$

$$f_{l,t}^{+},\,f_{l,t}^{-}\ge 0;\forall l\in L,\forall t\in T \quad (26)$$

$$0\le \Delta f_{m,l,t}\le \frac{F_l^{Max}}{|M|};\forall l\in L,\forall m\in M,\forall t\in T \quad (27)$$

$$f_{l,t}^{loss}=\left(\frac{G_l}{B_l^2}\right)\sum_{m\in M}\zeta_{m,l}\Delta f_{m,l,t};\forall l\in L,\forall t\in T \quad (28)$$

$$0\le f_{l,t}^{+}\le w_{l,t}F_l^{Max},\ \forall l\in L,\ \forall t\in T \quad (29)$$

$$0\le f_{l,t}^{-}\le (1-w_{l,t})F_l^{Max};\forall l\in L,\ \forall t\in T \quad (30)$$

$$w_{l,t}\in\{0,1\};\forall l\in L,\ \forall t\in T \quad (31)$$

where:

$$L_i^{Up,Min}=\max\left(0,\min\left(\left(p_i^{Up}-p_i^{Up,init}\right)p_i^{On-Off}\right)\right);\forall i\in I$$

$$L_i^{Down,Min}=\max\left(\min\left(\left(p_i^{Down}-p_i^{Down,init}\right)\left(1-p_i^{On-Off}\right)\right)\right);\forall i\in I$$

$$\zeta_{m,l}=(2m-1)\left(\frac{F_l^{Max}}{|M|}\right);\forall m\in M,\forall l\in L$$

$$NP^{Min}\le NP_{n,t}\le NP^{Max};\ \forall t\in T \quad (32)$$

Constraint (32) represents the minimum and maximum limits of power exchange, where NP^{Max} and NP^{Min} are the maximum and minimum power exchanges with the grid.

In this model, the first level minimizes the production costs of the distribution system, considering the technical constraints of storage, energy flows, power balance, and technical constraints of the generators. Hence, the upper-level problem contains the binary decision variables determining the optimal on/off unit statuses.

The lower-level problem is the aggregator problem. Aggregators aim to minimize energy procurement costs while meeting the required energy requirements, similar to flexible loads [25]. The second level acts as a follower of the first one. The aggregator uses a flexibility management system to reschedule some appliances and match, as close as possible, the flexibility curve procured by the DSO. Hence, the objective function that maximizes the aggregator profits can be modeled as minimizing the remuneration paid to the households [26]. Specifically, the lower-level problem is formulated as follows for each demand aggregator:

$$Minimize\ \sum_{t\in T}\lambda_t^{SF}\left(\sum_{b\in B}\left|Pd_b^{Base}-Pd_b^{flx}\right|\right)+\lambda_t^{RT}\left(\sum_{b\in B}\left|Pd_b^{Base}-Pd_b^{flx}\right|\right)$$

$$S.\,to\ \ Pd_{,tb}^{flx}=Pd_{b,t}^{u}-\sum_{sf\in SF}A_{sf,t}^{flx}-\sum_{rt\in RT}B_{rt,t}^{flx};\forall t\in T.$$

$$A^{flx\,Min}\le A_{sf,t}^{flx}\le A^{flx\,Max};\forall sf\in SF,\forall t\in T.$$

$$B^{flx\,Min}\le B_{rt}^{flx}\le B^{flx\,Max};\forall rt\in RT,\forall t\in T.$$

where Pd_m^{u} is the underlying prosumer demand of aggregator b, A represents heavier loads such as washing machines, clothes dryers, and dishwashers, and B represents real-time controllable loads such as lighting systems, entertainment systems, and desktops.

III. Numerical Simulation and Discussion

The IEEE 33-bus distribution system, shown in Fig. 2, validates the proposed framework. The complete network data is given in [27]. Two diesel generators are installed in buses 2 and 3, respectively, and six BESS are installed in buses 5, 10, 13, 20, 24, and 31. Table I and Table II show the diesel generator and storage data information [28]. In addition, two 0.5-MW PV units are located at buses 9 and 12, and two 0.6-MW wind farms are located at 14 and 20, respectively.

The optimization problem was implemented in GAMS, and CPLEX was used as the solver. Simulations were performed on a personal computer with an Intel Core i7, 2.5GHz, and 16 GB RAM. In this system, nine buses participate via an aggregator to fulfill DSO flexibility requirements.

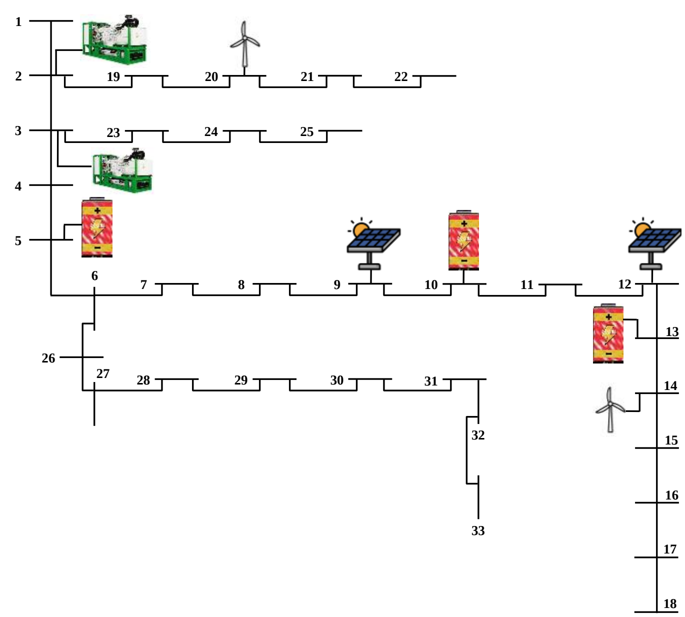

Fig. 2. IEEE 33-bus system.

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TABLE I. DIESEL GENERATOR PARAMETERS

DG	Bus	Pg_i^{Min}	Pg_i^{Max}	RSD_i	RSU_i	RU_i	RD_i	Cost
1	2	0.8	2	1	1	1	1	61.3
2	3	0.8	2	1	1	1	1	65.6

TABLE II. BESS PARAMETERS

BESS	Bus	E_i^{Min}	E_i^{Max}	η_s^c	η_s^d	Degradation ($)	Discharge ($)
1	5	0.05	0.25	0.90	0.90	0.3	0.2
2	10	0.05	0.3	0.90	0.90	0.3	0.2
6	13	0.05	0.25	0.85	0.85	0.3	0.2

TABLE III. AGGREGATOR PARAMETERS

Aggregator	Bus	kW
1	4	±6
2	7	±12
3	8	±8
4	24	±29.4
5	25	±29.4
6	29	±7.2
7	30	±6
8	31	±7.5
9	32	±8.4

A. A weekday flexibility procurement analysis

Table III shows the flexibility capacity of each aggregator. Aggregators can provide between ±7 to ±29 kW flexibility in each period interval. Furthermore, aggregators' flexibility capacity is closely linked to the demand at each node. Hence, nodes with a high load provide greater flexibility capacity, while nodes with a lower load provide lower flexibility capacity. Fig. 3 displays a typical weekday demand pattern, which discretizes the continuous demand in 15-minute periods. Demand reaches its peak value in hour 20, 3715 kW, while minimum demand, 1486 kW, occurs in hour 3. The wind generation pattern is the same in both generators, similarly for the PV systems.

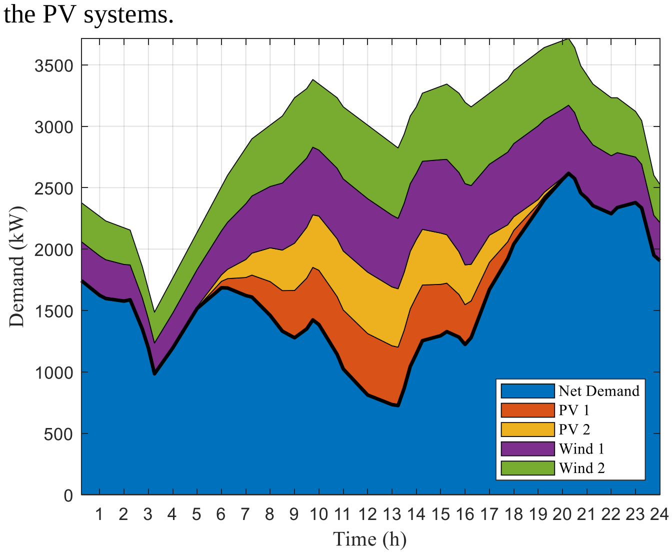

Fig. 3. Forecasted total demand, photovoltaic generation, wind generation, and net demand.

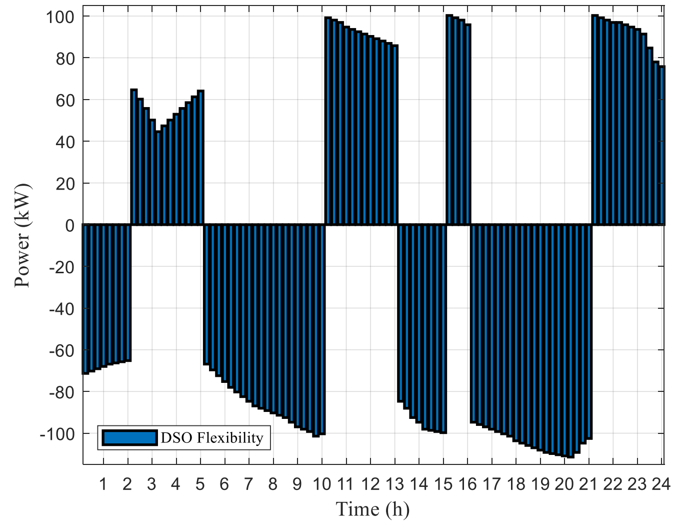

Fig. 4. DSO flexibility requirements.

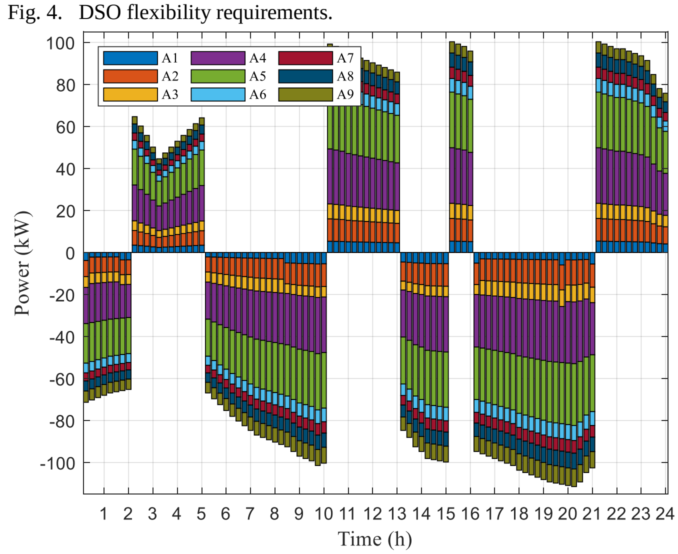

Fig. 5. Flexibility contributions from aggregators (A1-A9).

The flexibility profile requirement demanded by the DSO during a day using 15-minute intervals is depicted in Fig. 4. As can be seen, the DSO requests upward or downward flexibility throughout the day. The maximum and minimum upward flexibility requirements occur during the 15:15 period (100.3 kW) and the 3:15 period (44.58 kW). On the other hand, the maximum and minimum downward flexibility requirement occurs during the 20:15 (111.5 kW) and 2:00 periods (65.2 kW), respectively.

Fig. 5 shows the sum of the contributions of aggregators during the 24 hours. It can be seen how these nodes' flexibility contributions cover the DSO's flexibility requirements. The nodes with a higher percentage of demand response provide the greatest amount of flexibility to cover the flexibility requirements of the DSO.

Fig. 6 shows the flexibility contributions by the aggregator from 8:45 to 9:00 periods. This time interval was taken arbitrarily.

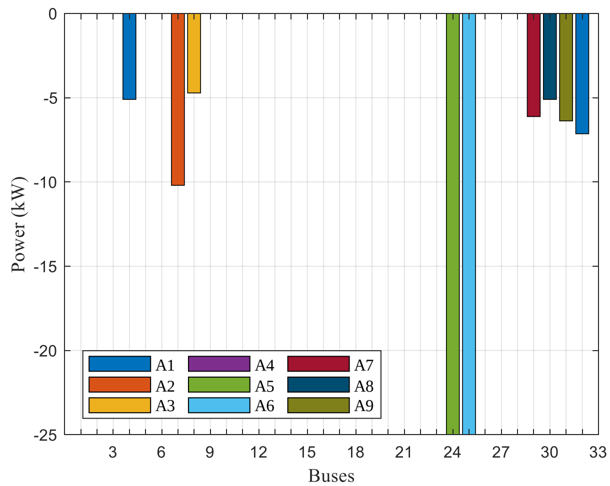

Fig. 6. Contributions from aggregators at 8:45 period.

As shown in Fig. 5, the greatest flexibility contribution comes from aggregators 4 and 5, contributing 24.99 kW each. The rest of the aggregators fulfill the DSO requirements, contributing from 4.718 kW to 10.2 kW. Fig. 7 shows the diesel generator, storage outputs, the original and final net demand, and distribution losses. The model without losses meets the same flexibility requirements, obtaining an optimal solution costing $ 9409.38. In contrast, the loss model has an optimal solution with a total cost of $ 10656.79.

Flexibility requirements modify the original net demand resulting in the final net demand. For example, when downward flexibility is required, the final net demand decreases, as seen in the hours ranging from 5:00 to 10:00. Conversely, when upward flexibility is needed, the final net demand rises. A clear example is the period covering 20:00 to 24:00. Regarding generation, diesel unit 1 remains connected during all periods, while diesel unit 2 is only turned on from hour 17 to hour 24. Storage makes a small contribution, mainly during peak hours. However, in the loss model, diesel generators are forced to increase their generation output, which causes an increase in total cost.

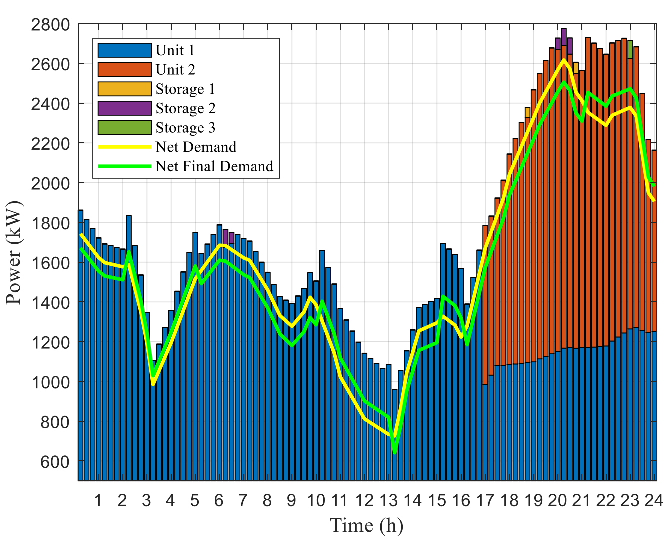

Fig. 7. Generation and demand throughout the 24 hours.

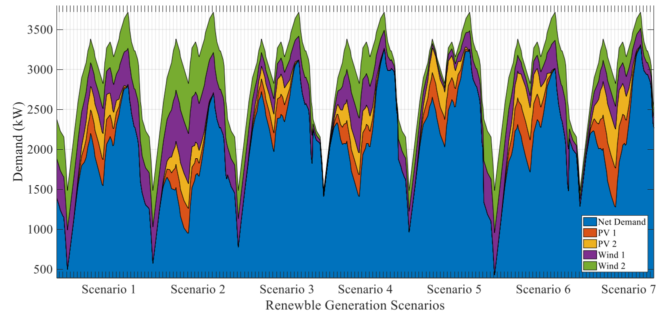

Fig. 8. Power generation contribution for fixed load scenarios

The case with no flexibility requirements imposed by the DSO results in an optimal solution with a total cost of $10828.67, being around 2% more expensive than the case with flexibility requirements. The cost difference is passed to prosumers as remuneration.

B. Scalability of the proposed method

In this section, the flexibility procurement analysis has been performed to provide more features of the proposed method in terms of the scalability of the method presented in this paper. Hence, two different case studies have been settled to deal with the performance of the flexibility that can be provided for other chronological loads and generation variations.

In the first scenario, the daily demand profile is supposed to be fixed, and the renewable power generation profiles are different. The amount of flexibility that should be provided is supposed to be constant according to the needs of DSO.

Fig. 8 shows how renewable generation varies; conventional generation is adapted to fulfill the demand. Conventional generation is reduced in scenarios with higher renewable energy penetration; a clear example is observed in Scenario 2. On the other hand, conventional generation increases in scenarios with lower renewable energy penetration, as observed in Scenario 5.

Fig. 9 depicts the flexibility service provided by aggregators. As it is stated, the flexibility requirements remain fixed during the different scenarios. However, there is a difference between scenarios due to renewable generation varies, so the flexibility contributions at each node are different. Hence, aggregators contribute with different flexibility levels to the system to meet the requirements imposed by the DSO. This paper has studied the chronological load profile for a given week to address different load-generation profiles. The demand and renewable energy penetration varied over a week for the given week, as shown in Fig. 10.

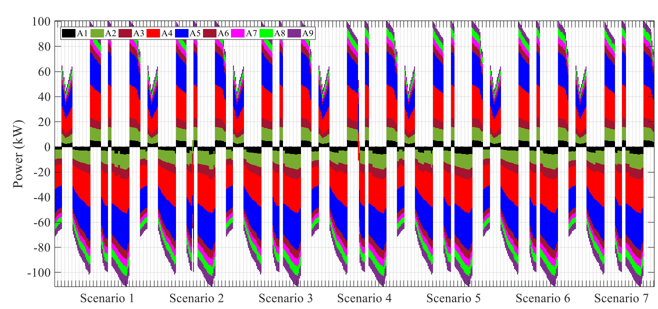

Fig. 9. Flexibility provided by different aggregators in fixed load scenarios.

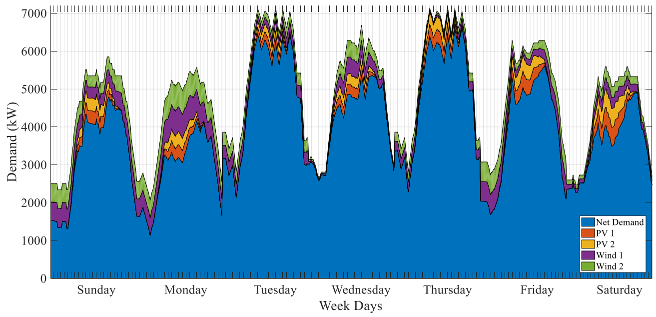

Fig. 10. Load serving profile for the given week.

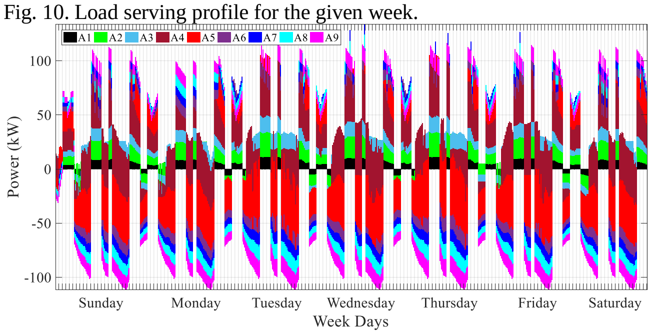

Fig. 11. Flexibility provided by different aggregators for the studied week.

As can be seen, Monday presents high renewable penetration, while the lowest renewable penetration occurs on Tuesday. Fig. 11 illustrates the DSO requirements for this case. The sum of the flexibility contributions of all aggregators fulfills the DSO flexibility requirements.

IV. Conclusion

This paper presents a bi-level approach to procure the flexibility that can be provided by active prosumers in distribution networks. The aggregators are the entity responsible for procuring the flexibility required for the DSO. The scale of the flexibility supplied at the aggregator level can be sold to the DSO. The model comprises the market signal and flexibility terms to activate the participation factors by the prosumers, considering the distribution network constraints as well, and a distributed optimization technique is adopted to solve this problem. Results show aggregated consumer groups can provide between ±7 to ±29 kW flexibility in each interval. Furthermore, the aggregators' flexibility capacity is closely linked to the demand at each node. Hence, nodes with a higher load provide greater flexibility capacity, while nodes with a lower load provide lower flexibility capacity. Indeed, the proposed strategy provides more insights to the DSO and Aggregators while they are deciding to trade the flexibility requirements in the realistic operation of the distribution networks. In this paper, the model is investigated to deal with the load-generation fluctuations at the prosumer level and the hourly unbalance at the load-serving capability of the DSO. Hence, the contribution of the aggregators to provide flexibility to the DSO is essential. On the other hand, some dedicated prosumers are eager to contribute to such activities to benefit from the incentives or direct payments. The proposed bi-level model effectively matches the flexibility needs and how to provide it for a given day. The model is tested and verified for different operating days for a given week to show the effectiveness of the proposed strategy. The resilience analysis of prosumers by increasing renewable generation and the impact of appliance efficiencies could be the future trend of the current research.

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