A Hierarchical Optimization Framework for Peer-to-Peer Energy Trading in Medium- and Low-Voltage Distribution Networks

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***Abstract*—This paper introduces a new hierarchical optimization framework for coordinating peer-to-peer (P2P) energy trading among users in medium-voltage (MV) and low-voltage (LV) distribution networks. The framework models LV networks as energy communities (ECs) with distributed energy resources (DERs), where community members trade energy internally and with external communities via the MV-LV interface. The MV network, which also integrates DERs, establishes operational strategies for inter-EC energy transactions and efficiently allocates resources to meet the energy demand of the ECs. The optimization models are based on the second-order cone relaxation to consider network restrictions and assume an operation within a day-ahead market structure. Thus, the proposed bilevel optimization model adopts an EC-center approach, with the LV networks acting as multiple leaders at the first level, where the ECs establish the energy requirements, and the second level is represented by the MV network, which adjusts its resource dispatch to ask the energy demand efficiently. The IEEE 33-bus system and a modified version of the IEEE 906-bus systems are used to represent the MV and the LV networks, respectively, and to test the algorithm. Simulation results demonstrate the algorithm's effectiveness in optimizing energy flows, balancing community needs, and complying with network constraints.**

***Index Terms*—Local electricity markets, Distributed energy resources, Energy communities**

I. Introduction

Peer-to-peer (P2P) energy trading has become an innovative framework enabling users with DERs to participate actively in local electricity markets (LEM). This approach allows prosumers (users who produce and consume energy) to exchange surplus energy directly with other prosumers or traditional consumers. By facilitating these transactions, P2P energy trading promotes decentralized energy management, enhances the utilization of DERs, and empowers users to play a more significant role in the energy transition.

In recent years, several optimization models have been presented in the literature to simulate the P2P operation in LV, MV, and transmission networks. For example, in [1], the concept of 'enTrade' is introduced as a way of speeding up the real-time P2P trading between buyers and sellers in a distributed electricity market. It combines players' stochastic behavior analysis with a game theory-based leader-follower model through bilevel optimization. In [2], a Nash bargaining game-theory-based P2P transactions model to maximize the profits of the charging stations is proposed in a distributed manner through the alternating direction method of multipliers (ADMM) to solve a proposed bi-level-parallel coupling structure of the coordination problem. An accelerated asynchronous distributed algorithm based on the ADMM is developed in [3] to solve the proposed bi-level problem to optimize the electricity/heat network managed by an integrated community energy system (ICES) operator on building prosumers' by using a P2P multi-energy trading scheme. In addition, authors in [4] developed a bilevel framework for prosumers that enables the joint optimization of internal energy scheduling and external P2P trading, allowing prosumers to optimize both simultaneously.

On the other hand, in [5], a hierarchical coordination framework at the transmission and distribution level is proposed to optimize the energy trade among electric vehicle charging stations through a P2P mechanism. Power network constraints are considered by the distribution system operator to coordinate and adjust the energy trade. Usually, the P2P framework is employed at the user level due to local interactions, particularly in LV networks, such as in [1], [6]. However, works like [5], [7], and [8] introduce the P2P concept at higher voltage levels for residential users, electric vehicle charging stations, or large-scale DERs by taking into consideration the power network constraints in order to limit the high-risk transactions to maintain the network limits. A more developed strategy that encompasses a network charge policy for P2P trading is introduced in [4], which includes network congestion costs, loss costs, and modernization costs, calculated using distribution locational marginal prices (DLMP) and Thevenin impedance.

Most existing hierarchical approaches for modeling P2P energy trading adopt a single-leader multiple-follower structure, where end-users or LV networks act as passive followers. In such frameworks, LV participants must adapt to the decisions made by the upper-level entity, limiting their active participation in LEMs. Moreover, these models often restrict P2P trading to the follower level, neglecting interactions between the leader and follower stages. In contrast, the main contribution of this paper is developing a hierarchical optimization model that empowers LV networks to act as leaders, actively defining their internal P2P transactions and aggregated energy needs. The MV network operates as a follower, coordinating and responding to the collective requirements of the LV networks. Specifically, the model manages energy exchanges both within individual LV networks (facilitating internal P2P trading) and between different LV networks interconnected through the MV grid. The MV side acts as a mediator, enabling inter-community energy transactions while also supplying additional energy requirements. This hierarchical structure ensures efficient multi-level coordination, optimizes DER utilization, and promotes a more decentralized and user-centric energy system.

The remainder of this paper is organized as follows. Section II outlines the main assumptions of the optimization model and describes the market framework. Section III details the mathematical formulation and the proposed solution approach. Section IV presents the case study and discusses the computational results. Finally, Section V summarizes the key findings and outlines directions for future research.

II. Market framework and assumptions

This study assumes a day-ahead operational framework for coordinating DERs within LEM, allowing operators to efficiently manage energy across the MV and LV distribution networks and minimize their energy procurement from wholesale electricity markets. To do this, a hierarchical structure is adopted, assigning the LV networks the role of leaders while the MV network operates as the follower. This design emphasizes the centrality of the end-users on the LV side, empowering them to actively participate in LEMs by prioritizing their preferences in the initial optimization stage. Thus, the framework ensures that community-level energy needs are addressed before optimizing the overarching MV-level operations. This hierarchical framework inherently defines a bilevel optimization problem where the upper level (LV side) determines their energy requirements and interactions, focusing on minimizing their dependency on the MV network. At the lower level, the MV grid adjusts its operational strategies to accommodate the aggregated energy needs of the LV side while complying with network constraints. Likewise, the model assumes the existence of the necessary infrastructure for communication, real-time metering, and regulatory mechanisms, ensuring that the system can operate efficiently. While regulation and market incentives are essential to enable and sustain the proposed hierarchical P2P trading scheme, this paper does not focus on designing such regulatory frameworks. Instead, we assume that appropriate policies and incentive mechanisms are already in place to support the participation of distributed agents in LEMs. This allows the study to concentrate exclusively on the operational coordination and energy management aspects across MV and LV networks. A schematic representation of the previous description can be observed in Fig. 1

Mathematically, this structure offers an advantage in terms of scalability and computational feasibility. For instance, extending the model to incorporate stochastic elements only

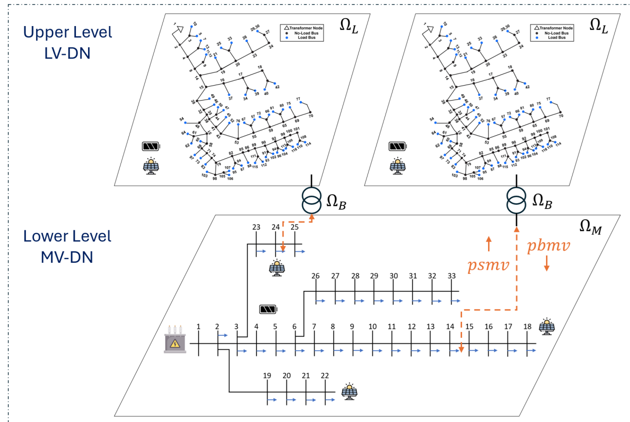

Fig. 1. Hierarchical model scheme

impacts the leader-level problem encapsulating the LV network decisions, which depend on stochastic parameters. Thus, the follower problem only optimizes the MV side response and remains deterministic and insulated from these stochastic variations. Consequently, the computational complexity of solving the entire hierarchical model remains manageable, even with the inclusion of stochastic elements.

III. Optimization Models and Solution Approach

This section introduces the operational and P2P trading market constraints for LV and MV networks, the hierarchical optimization model, and the strategy to solve the bilevel optimization problem.

The power flow for the LV networks is modeled using the second-order cone AC-OPF (SOC-ACOPF) [9] to represent the network constraints, ensuring that energy exchanges between peers satisfy physical and operational network limitations, as follows:

$$\sum_{(i,j)\in\mathcal{L}} p_{i,j}^L - \sum_{(j,i)\in\mathcal{L}} (p_{j,i}^L - R_{j,i}^L \ell_{j,i}^L) = \begin{cases} \Delta p_{i,t}^L & \text{if } \forall i \in \Omega_L \\ \Delta B_{i,t}^L & \text{if } \forall i \in \Omega_S \end{cases} \tag{1a}$$

$$\sum_{(i,j)\in\mathcal{L}} q_{i,j,t}^L - \sum_{(j,i)\in\mathcal{L}} (q_{j,i,t}^L - X_{j,i}^L \ell_{j,i,t}^L) = \Delta Q_{i,t}^L \tag{1b}$$

$$\Delta p_{i,t}^L = pg_{i,t}^L - PL_{i,t}^L + ds_{i,t}^L - ch_{i,t}^L \tag{1c}$$

$$\Delta B_{i,t}^L = pbmv_{i,t} - psmv_{i,t} \tag{1d}$$

$$\Delta Q_{i,t}^L = qg_{i,t}^L - QL_{i,t}^L \tag{1e}$$

$$v_{j,t}^L = v_{i,t}^L - 2(R_{i,j}^L p_{i,j,t}^L + X_{i,j}^L q_{i,j,t}^L) + ({R^L}^2_{i,j} + {X^L}^2_{i,j})\ell_{j,i,t}^L \tag{1f}$$

$$(p_{i,j,t}^L)^2 + (q_{i,j,t}^L)^2 \le \ell_{j,i,t}^L v_{i,t}^L \tag{1g}$$

$$Q_{min}^L \le qg_{i,t}^L \le Q_{max}^L \tag{1h}$$

$${V^L}_i^{min} \le v_{i,t}^L \le {V^L}_i^{max} \tag{1i}$$

$$pg_{i,t}^L \le {PG^L}_{i,t}^{max} \tag{1j}$$

$$\ell_{i,j,t}^L \le {I^L}_{i,j}^{max} \tag{1k}$$

The active power balance in Eq. (1a) distinguishes substation buses, where energy is exchanged with the upstream MV network (Ω_S) from the remaining buses representing consumption or generation nodes (Ω_L). Thus, in Eq. (1c), the users are summarized under the variable $\Delta p^L_{i,t}$, which encompasses traditional users and prosumers with PV systems (pg^L), battery energy storage systems (BESS), and uncontrollable loads (PL^L). Similarly, variable $\Delta B^L_{i,t}$ captures the energy exchanged through the substation, where $pbmv$ denotes the energy purchased from the MV network and $psmv$ refers to the energy sold to it. The remaining constraints correspond to the classical SOC-ACOPF formulation.

The BESS formulation considers the following well-known constraints:

$$soc^L_{i,t} = soc^L_{i,t-1} + \left(\varphi^{ch} ch^L_{i,t} - \frac{1}{\varphi^{ds}} ds^L_{i,t}\right)\Delta t \tag{2a}$$

$$\Gamma^{Lbt}_i SOC^{min}_L \leq soc^L_{i,t} \leq \Gamma^{Lbt}_i SOC^{max}_L \tag{2b}$$

$$ch^L_{i,t} \leq PB^{bt}_L(1 - w^L_{i,t}) \tag{2c}$$

$$ds^L_{i,t} \leq PB^{bt}_L w^L_{i,t} \tag{2d}$$

Eqs. (2) define the constraints associated with the battery state-of-charge (soc), a binary variable (w^L) that prevents simultaneous charging (ch) and discharging (ds) processes, and parameters that establish the operational limits of the BESS. These parameters include the minimum and maximum state-of-charge (SOC^{min}_L, SOC^{max}_L), the BESS capacity (Γ^{Lbt}), and the maximum power rate (PB^{bt}_L).

The energy trading among peers within the LV network is modeled using the constraints presented in [10], as follows:

$$\Delta p^L_{i,t} = \Delta p^{L+}_{i,t} - \Delta p^{L-}_{i,t} \tag{3a}$$

$$\Delta p^{L+}_{i,t} = p^{Lsg}_{i,t} + p^{Lsm}_{i,t} \tag{3b}$$

$$\Delta p^{L-}_{i,t} = p^{Lbg}_{i,t} + p^{Lbm}_{i,t} \tag{3c}$$

$$\Delta p^{L+}_{i,t} \leq M(y^L_{i,t}) \tag{3d}$$

$$\Delta p^{L-}_{i,t} \leq M(1 - y^L_{i,t}) \tag{3e}$$

$$\sum_{i\in\mathcal{A}} p^{Lsm}_{i,t} = \sum_{i\in\mathcal{A}} p^{Lbm}_{i,t} \tag{3f}$$

$$\sum_{i\in\mathcal{A}} p^{Lsg}_{i,t} = psmv_t \tag{3g}$$

$$\sum_{i\in\mathcal{A}} p^{Lbg}_{i,t} = pbmv_t \tag{3h}$$

Eqs. (3) include a binary variable (y^L) to prevent users from simultaneously buying and selling energy. If Δp^L is positive (Δp^{L+}), it indicates that the user has an energy surplus and can sell it either in the local market (p^{Lsm}) or to the MV network. In contrast, if Δp^L is negative (Δp^{L-}), the user can purchase energy either from other users (p^{Lbm}) or from the MV network (p^{Lbg}). Similarly, Eq. (3f) ensures that all energy sold in the internal local P2P market is fully purchased. Additionally, Eqs. (3g) and (3h) guarantee that the energy sold to or purchased from the MV network matches the energy exchanged at the substation.

Given that the primary objective of this paper is to model a hierarchical problem where the LV networks act as multiple leaders and the MV grid serves as the follower, certain assumptions are necessary to ensure the tractability of the problem. These assumptions simplify the complexity inherent in the two-voltage-level structure, enabling a more practical formulation and solution. By carefully selecting these assumptions, the model retains its ability to capture key interactions between the two distribution network voltage levels while balancing computational feasibility and real-world applicability. Thus, this paper uses a linear version [11] of the SOC-ACOPF to represent MV limitations, which assumes that the line losses are despicable by modifying Eqs. (1a), (1b), and (1f), as follows:

$$\sum_{(i,j)\in\mathcal{L}} p^M_{i,j} - \sum_{(j,i)\in\mathcal{L}} (p^M_{j,i}) = \begin{cases} \Delta C_{i,t} & \text{if } \forall i \in \Omega_M \\ \Delta B_{i,t} & \text{if } \forall i \in \Omega_B \\ \Delta S_{i,t} & \text{if } \forall i \in \Omega_S \end{cases} \tag{4a}$$

$$\sum_{(i,j)\in\mathcal{L}} q^M_{i,j,t} - \sum_{(j,i)\in\mathcal{L}} (q^M_{j,i,t}) = \Delta Q_{i,t} \tag{4b}$$

$$v^M_{j,t} = v^D_{i,t} - 2(R^M_{i,j} p^M_{i,j,t} + X^M_{i,j} q^M_{i,j,t}) \tag{4c}$$

Note that Eq. (4a) includes the terms $\Delta B_{i,t}$ corresponding to the energy coming from the LV network and the term $\Delta S_{i,t}$, which corresponds to the energy exchanged with the main grid:

$$\Delta B_{i,t} = pblv_{i,t} - pslv_{i,t} \tag{5}$$

$$\Delta S_{i,t} = p\kappa^{bg}_{i,t} - p\kappa^{sg}_{i,t} \tag{6}$$

Similarly, new operational constraints must be incorporated into the MV side, including the maximum power PV generation can inject (pg^M), the maximum power exchanged with the external grid ($p\kappa^{bg}$, $p\kappa^{sg}$), and voltage limits.

$$pg^M_{i,t} \leq PG^{max}_i \tag{7a}$$

$$p\kappa^{bg}_{i,t} \leq PSub^{max}_i \tag{7b}$$

$$p\kappa^{sg}_{i,t} \leq PSub^{max}_i \tag{7c}$$

$$V^{M}{}^{min}_i \leq v^M_{i,t} \leq V^{M}{}^{max}_i \tag{7d}$$

The BESS operation in the MV network assumes 100% efficiency, eliminating the need for a binary variable and enabling the use of a linear model as follows:

$$soc^M_{i,t} = soc^M_{i,t-1} + ds^M_{i,t}\Delta t \tag{8a}$$

$$-PB^{bt}_M \leq ds^M_{i,t} \leq PB^{bt}_M \tag{8b}$$

$$\Gamma^{Mbt}_i SOC^{min}_M \leq soc^M_{i,t} \leq \Gamma^{Mbt}_i SOC^{max}_M \tag{8c}$$

where $ds^M \in \mathbb{R}$ states that negative values indicate discharging and positive values indicate charging.

The objective functions for both levels minimize the energy purchased from their respective upstream levels. Thus, the following expression for the LV side minimizes the energy purchased from the MV network, as follows:

$$\min Z = \sum_{k\in\Omega_B} \sum_{i\in\Omega_{S_k}} \sum_{t\in\mathcal{T}} pbmv_{i,t} - psmv_{i,t} \tag{9}$$

Note that the objective function in (9) minimizes the net energy cost for each bus $i \in \Omega_{S_k}$ where $k \in \Omega_B$. This indicates that for each boundary bus k in the MV side, there is a corresponding substation Ω_{S_k} in the LV side, which connects to a bus i serving as the interconnection point between the MV and LV distribution networks.

Similar to the LV network, the objective function of the MV grid is expressed as follows:

$$\min z = \sum_{i \in \Omega_S} \sum_{t \in \mathcal{T}} \lambda_M^{bg} p\kappa_{i,t}^{bg} - \lambda_M^{sg} p\kappa_{i,t}^{sg} + \sum_{i \in \Omega_M} \sum_{t \in \mathcal{T}} C_i^{PV} pg_{i,t}^M \tag{10}$$

The objective function in (10) considers the energy prices for selling (λ_M^{sg}) or buying (λ_M^{bg}) to/from the primary grid in addition to the energy injected from the PV systems. Note that, in this formulation, there is no cost for operating the BESS connected in the MV network, and the PV operational cost is assumed $C^{PV} < \lambda^{sg}, \lambda^{bg}$. This assumption implies that the energy supplied by DERs to meet the LV network requirements is limited. As each LV grid aims to minimize its energy procurement from the MV side, the decisions made by one LV network affect the others. This is because the available DER resources are finite, meaning that when one LV grid optimizes its energy consumption, it can impact the energy available for other LV grids, influencing their objective of minimizing reliance on the MV network. This interdependence is a key feature of the bilevel optimization problem, where multiple LV networks act as leaders, and the MV grid serves as the single follower.

To tackle the bilevel optimization problem, the proposed problem is decomposed into a master problem (MP) and a subproblem (SP). This decomposition approach allows for addressing the interdependence between the decisions of the LV networks (leaders) and the MV network (follower) efficiently. By applying Benders decomposition, it can iteratively solve the master and the subproblem, where the MP handles the decisions of the LV side, while the SP focuses on the response of the MV network. Thus, the MP can be expressed as follows:

$$\begin{aligned} &\min Z = \alpha \\ &\text{Subject to: } (1), (2), \text{and } (3) \end{aligned} \tag{11}$$

Note that the expression in (9) has been modified using α, which is a continuous variable in the objective function of the MP for decomposing the bilevel formulation. α serves as a surrogate for the objective value of the leader's (first-level) optimization problem. This transformation is key for decoupling the leader's decisions from the follower's (second-level) response. By including α in the MP objective function, it approximates the leader's problem while ensuring that the solution space remains feasible through the Benders cuts. The Benders cuts, generated from the SP, then provide a series of constraints that iteratively refine the value of α, ensuring that it is at least as large as the optimal objective value of the SP. Thus, the SP is defined as follows:

$$\begin{aligned} &\min z = \sum_{i \in \Omega_S} \sum_{t \in \mathcal{T}} \lambda_M^{bg} p\kappa_{i,t}^{bg} - \lambda_M^{sg} p\kappa_{i,t}^{sg} + \sum_{i \in \Omega_M} \sum_{t \in \mathcal{T}} C_i^{PV} pg_{i,t}^M \\ &\text{Subject to: } (4), (7), (8) \end{aligned} \tag{12}$$

However, the energy exchanged between the MV and LV networks, determined in the MP (11), must be incorporated into the SP (12) as parameters via the following constraints:

$$pslv_{i,t} = \widehat{pbmv}_{i,t} \tag{13a}$$

$$pblv_{i,t} = \widehat{psmv}_{i,t} \tag{13b}$$

The dual variables associated with Eqs. (13) are utilized in the decomposition algorithm to generate the Benders cuts as summarized in 1.

Algorithm 1: Algorithm

Initialize $LB \leftarrow -\infty, UB \leftarrow +\infty, r \leftarrow 0$
while *no stopping criterion is satisfied* **do**
  Solve the MP (11).
  Collect master solutions $pbmv_{k,i,t}, psmv_{k,i,t}$
  Update the lower bound: $LB = \alpha$
  Solve SP (12,13), fixing the corresponding master solution; $\forall k \in \Omega_B$ $(\widehat{pbmv}_{i,t}, \widehat{psmv}_{i,t})$.
  Assign $\eta^r = \sum_{i \in \Omega_S} \sum_{t \in \mathcal{T}} \lambda_M^{bg} p\kappa_{i,t}^{bg} - \lambda_M^{sg} p\kappa_{i,t}^{sg} + \sum_{i \in \Omega_M} \sum_{t \in \mathcal{T}} C_i^{PV} pg_{i,t}^M$
  Collect the dual values of Constraints (13) $(\pi_{k,t}^{psmv,r}, \pi_{k,t}^{pbmv,r})$.
  Update the upper bound: $UB = \min(UB, LB - \alpha^r + \eta^r)$
  Add the Benders' cuts to the master problem. $\alpha^r \geq \eta^r - \phi^r - \varphi^r$
  $\phi^r = \sum_{k \in \Omega_B} \sum_{i \in \Omega_{S_k}} \sum_{t \in \mathcal{T}} \pi_{k,t}^{psmv,r} (\widehat{psmv}_{k,t} - psmv_{k,i,t})$
  $\varphi^r = \sum_{k \in \Omega_B} \sum_{i \in \Omega_{S_k}} \sum_{t \in \mathcal{T}} \pi_{k,t}^{pbmv,r} (\widehat{pbmv}_{k,t} - pbmv_{k,i,t})$
  $r \leftarrow r + 1$.
end

IV. Case Study and Computational Results

The hierarchical optimization model and the algorithm's performance were evaluated using a modified version of the IEEE European test system [12] to represent the LV networks, and the IEEE 33-bus system [13] for the MV side. Fig. 1 illustrates a schematic representation of the test system, where two LV networks are connected to the MV side at buses 14 and 24. The remaining buses in the MV network are modeled as uncontrollable loads, while both levels consider the presence of PV systems and BESS. Specifically, the consumption patterns on the LV side include traditional profiles

TABLE I
DIFFERENCES BETWEEN THE LV NETWORKS

Item	**LV Bus 14**	**LV Bus 24**
Peak Load [kW]	3.4	3.4
Consumption points	17	55
Aggregated Peak Load [kW]	57.8	187
Nº of PV systems	31	31
PV Installed capacity [kW]	195	195
Nº of BESS	31	16
BESS Installed capacity [kWh]	195	108

TABLE II
COMPARATIVE RESULTS WHEN THE DERS IN THE MV ARE LIMITED

Case	Limited MV DER		Unlimited MV DER	
Variables	LV Bus 14	LV Bus 24	LV Bus 14	LV Bus 24
$pbmv$	0,47	1,04	0,25	1,00
$psmv$	1,47	0,75	1,28	0,72
OF	-1,01	0,29	-1,03	0,28

and profiles with users already equipped with PV systems. Table I highlights the differences between the two LV grids.

Table II compares the LV networks' objective functions (OF) under two scenarios: when the MV network has limited or unlimited DER capacity. In the limited DER scenario, the available generation reflects typical PV system output, which is constrained by physical and operational limits. Conversely, the unlimited DER scenario represents a hypothetical situation where generation resources are assumed to be infinite. This eliminates competition among LV networks for shared resources.

Analyzing these scenarios is crucial because the interaction between LV and MV networks significantly influences the problem structure. If the decisions of individual LV networks do not impact the decisions of others in the system, the problem reduces to a two-step optimization framework. In this case, LV networks optimize independently in the first step, followed by a centralized decision-making process at the MV level. However, when resource constraints introduce interdependencies between LV networks, the problem becomes inherently bilevel, requiring coordinated optimization between the LV and MV networks to account for these interactions. Thus, the results in Table II demonstrate that when resources in the MV network are limited, the LV networks compete to access these resources, impacting their OF. For instance, in the case of the LV network at bus 14, the competition causes its OF value to increase from -1.03 to -1.01, indicating a slight performance deterioration. Similarly, for the LV network at bus 24, the OF shifts from 0.28 to 0.29, reflecting a comparable effect of competition on its operational outcome.

Fig. 2 illustrates the energy exchanges within and between the LV networks and their interactions with the MV network. The first plot depicts the power exchanged at the boundary buses, where positive values indicate that the MV network is buying energy from the LV grid. The second plot focuses on P2P energy trading within the ECs associated with each LV network. Here, the energy trading occurs mainly in hours with high PV generation. However, the network at bus 14 has a high

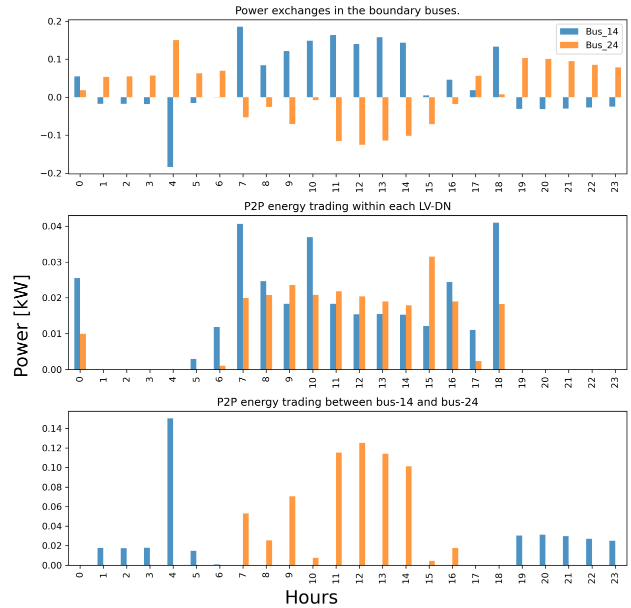

Fig. 2. Energy traded within the LV network and between them through the MV side

BESS capacity installed, so they can trade more energy than the EC connected at bus 24. Finally, the third plot indicates the trading between the EC through the MV network, where the blue bar indicates that the EC at bus 14 buys energy from the EC at bus 24, and the orange bar is the opposite.

V. CONCLUSIONS

This paper presented a hierarchical optimization model for coordinating P2P energy trading within LV networks and between them, using the MV network as a mediator to enable energy exchanges among LV users while meeting their additional energy needs. The model adopts a bilevel approach: in the first stage, ECs within the LV networks act as leaders, defining their dispatch schedules to minimize upstream energy demands, while in the second stage, the MV network, acting as a follower, optimizes its dispatch to meet the aggregated requirements of the LV networks. The results highlight the importance of effective coordination in obtaining a balanced competition among LV networks for renewable resources in the MV network. Such coordination will be essential in future distribution networks with high penetration of DERs and more empowered prosumers actively participating in local energy markets.

Future work could further support the proposed multi-leader single-follower framework by incorporating quantitative comparisons with existing coordination models, particularly those based on single-leader approaches. Such comparisons would provide additional evidence on the benefits of enabling more active participation from LV networks. Moreover, computational scalability could be explored by testing alternative solution algorithms, aiming to enhance the tractability of the proposed model when applied to larger and more complex distribution systems.

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