P2P Markets to Support Trading in Smart Grids with Electric Vehicles

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***Abstract*— As energy systems evolve, protecting and empowering consumers is vital, enabling participation in decentralized electricity markets and maximizing benefits from energy resources. The integration of Distributed Energy Resources (DER) and Renewable Energy Sources (RES) fosters new energy communities, shifting from centralized systems to distributed structures. Consumers can sell excess production to neighbors, increasing income, reducing bills, and advancing energy transition goals. This paper proposes a community-based peer-to-peer (P2P) energy market model that reduces costs while respecting network constraints. Using the Alternating Direction Method of Multipliers (ADMM), ensures privacy enhancement, decentralization, and scalability. The Relaxed Branch Flow Model (RBFM) manages constraints, and Electric Vehicles (EVs) reduce imports and costs through strategic discharging. Tested on a 33-bus distribution network, the ADMM-based approach aligns closely with a centralized benchmark, showing minor discrepancies while maintaining system reliability. This model underscores the potential of decentralized markets for consumer-centric, flexible, and efficient energy trading.**

***Index Terms*--Alternating Direction Method of Multipliers; Distributed Energy Resources; Distributed Optimization; Energy Trading; Peer-to-peer Markets**

I. INTRODUCTION

In recent years, the increase of DER, such as Photovoltaic (PV) panels, EVs, and energy storage systems, along with growing awareness of climate change and electrification in sectors like transport, has led to a shift in how electricity is produced, consumed, and traded. RES are decentralizing the power system, creating new market opportunities for distribution network stakeholders and new energy business models like P2P markets [1].

A. Context and Motivation

As decentralized energy production grows, consumers are evolving into prosumers - entities that both produce, store and consume energy- engaging in P2P energy markets to reduce costs [2]. Integrating EVs and PV systems benefits both prosumers and the Distribution System Operator (DSO) by facilitating a Localized Energy Market (LEM) participation and enhancing grid performance through voltage regulation and congestion management [3]. Despite the increasing decentralization, electricity markets remain predominantly top-down, limiting prosumer engagement in resource allocation and pricing [4]. A shift toward bottom-up structures empowers prosumers, fostering more efficient and sustainable energy systems [1,5,6].

B. State of the Art on P2P Markets

The ADMM is widely used in decentralized convex optimization, decomposing global problems into smaller subproblems while ensuring agent privacy, efficient trading, and reduced communication burden [7,8]. Several studies explore decentralized market frameworks. Guerrero et al. [10] applied continuous double auctions with network constraints to optimize costs and balance supply and demand. Blockchain-based P2P trading has been proposed for market decentralization, with [11] leveraging electrical distance and [12] focusing on real-time power loss allocation. Blockchain-ADMM integration, as in [13], improves fairness and grid constraint compliance, though communication delays remain a challenge. Within the ADMM framework, decentralized energy community models achieve performance close to centralized approaches [14,15]. Other works explore asynchronous ADMM for storage optimization [16] and Jacobi-Proximal ADMM for voltage control in P2P trading [17]. ADMM has also been applied to EV management [18] and DSO-coordinated EV charging for system flexibility [19].

II. METHODOLOGY FOR NETWORK-CONSTRAINED P2P MARKETS WITH EVS

A. Centralized P2P Community-Based Mathematical Formulation

A benchmark model was developed, to be used as a reference for the comparison with the results obtained from the distributed network-constrained P2P community-based market. The optimization of the community-based P2P market is designed to maximize the Social Welfare (SW) by minimizing the operational costs associated with electricity generation and

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consumption. This model is non-iterative and consists mainly of two blocks: the P2P market without network constraints, resulting in a network unconstrained market which will then be subjected to the network constraints, in the next block. As an output, the results of the network-constrained market include the intracommunity trades, community consumption, generation, grid imports, and exports, power flow and EV charging and discharging patterns. The market is solved for each period t, which is one hour in the proposed method, and the set of periods, T, corresponds to all hours of a day. It is assumed that peers have complete autonomy over their consumption and DER assets. If local producers cannot meet the demand, consumers have the option to purchase energy at a higher price from external suppliers connected to the transmission network. In this type of market structure, the integration of a Community Manager (CM) can ease the market regulation and establish a better interface with the DSO.

Peers must share information with their CM in order to solve the minimization problem resulting in market clearing. In the local market, each agent is identified by the CM as a buyer or a seller based on the difference between their generation and demand. Each producer offers a price for electricity and the quantity of electricity he wants to sell to the market. Similarly, each consumer offers his preferred price and the quantity of electricity he wants to purchase from the community.

As the goal of this optimization problem is to minimize the total operating costs of the community, given the network operating constraints, the objective function comes as in (1):

$$\min \sum_{t\in T}\left(\sum_{n\in\Omega_n}\left(P_{t,n}^{g} - P_{t,n}^{c} + P_{t,n,EV}^{dch} - P_{t,n,EV}^{ch}\right)\cdot \pi_{t,n}\right) - \sum_{n\in\Omega_n}\left(\beta_{t,n}\cdot \pi_{t,n}^{FIT}\right) + \sum_{n\in\Omega_n}\left(\alpha_{t,n}\cdot \pi_{t,n}^{SUP}\right) \tag{1}$$

s.t.

$$P_{t,n}^{g} - q_{t,n} - \beta_{t,n} + P_{t,n,EV}^{dch} = 0 \quad \forall(t,n) \in \left(T, \Omega_p\right) \tag{2}$$

$$P_{t,n}^{c} - q_{t,n} - \alpha_{t,n} + P_{t,n,EV}^{ch} = 0 \quad \forall(t,n) \in \left(T, \Omega_c\right) \tag{3}$$

$$\sum_{n\in\Omega_n} q_{t,n} = 0 \quad \forall t \in T \tag{4}$$

$$P_{t,n}^{g} - P_{t,n}^{c} + P_{t,n,EV}^{dch} - P_{t,n,EV}^{ch} = \sum_{j\in N} P_{t,j,n}^{F} - \sum_{j\in N} P_{t,n,j}^{F} - R_{n,j} I_{j,n,t}^{2} \quad \forall(n,t) \in \left(N^E, T\right) \tag{5}$$

$$Q_{t,n}^{g} - Q_{t,n}^{c} = \sum_{j\in N} Q_{t,j,n}^{F} - \sum_{j\in N} Q_{t,n,j}^{F} - X_{n,j} I_{j,n,t}^{2} \quad \forall(n,t) \in \left(N^E, T\right) \tag{6}$$

$$V_{n,t} - V_{j,t} = 2\left(R_{n,j}\cdot P_{t,j,n}^{F} + X_{n,j}\cdot Q_{t,n,j}^{F}\right) - I_{n,j,t}\left(R_{n,j}^{2} + X_{n,j}^{2}\right) \quad \forall(n,j,t) \in \left(N^E, N^E, T\right) \tag{7}$$

$$V_{n,t}^{2}\cdot I_{n,j,t}^{2} \geq \left(P_{n,j,t}^{F}\right)^{2} + \left(Q_{n,j,t}^{F}\right)^{2} \quad \forall(n,j), t \in \left(L^E, T\right) \tag{8}$$

$$0 \leq P_{t,n}^{g}, Q_{t,n}^{g} \leq \overline{P_{t,n}^{g,max}}, \overline{Q_{t,n}^{g,max}} \quad \forall(t,n) \in \left(T, \Omega_p\right) \tag{9}$$

$$\underline{V_{t,n}^{min}} \leq V_{t,n} \leq \overline{V_{t,n}^{max}} \quad \forall(n,t) \in \left(N^E, T\right) \tag{10}$$

$$\underline{E_{bat(ev)}} \leq E_{stored(ev,t)} \leq \overline{E_{bat(ev)}} \quad \forall n \in \Omega_c \tag{11}$$

$$X_{Ch(ev,t)} + X_{Dch(ev,t)} \leq 1 \quad \forall(n,t) \in \left(\Omega_c, T\right) \tag{12}$$

$$P_{Ch(ev,t)} \leq P_{max(ev,t)}\cdot X_{Ch(ev,t)} \quad \forall(n,t) \in \left(\Omega_c, T\right) \tag{13}$$

$$P_{Dch(ev,t)} \leq P_{max(ev,t)}\cdot X_{Dch(ev,t)} \quad \forall(n,t) \in \left(\Omega_c, T\right) \tag{14}$$

$$E_{store(ev,t)} = E_{store(ev,t-1)} - E_{trip(ev,t)} + \Delta t\cdot \eta_{Ch(ev)} P_{Ch(ev,t)} - \Delta t\frac{P_{Dch(ev,t)}}{\eta_{Dch(ev)}} \quad \forall(n,t) \in \left(\Omega_c, T\right) \tag{15}$$

$$\alpha_{n,t}, \beta_{n,t} \geq 0, q_{n,t} \in R \quad \forall(n,t) \in \left(\Omega_n, T\right) \tag{16}$$

Where a radial distribution network with N nodes and L lines was considered. $P_{t,n}^{g}$ is the power generated by the producers, belonging to the subset Ω_p and $P_{t,n}^{c}$ is the power consumed by the consumer nodes belonging to subset Ω_C in the interval t. Variable α refers to the imports from the external grid, subject to the price of the retailer, π_{SUP} and β refers to the exports to the grid, associated with the Feed-in-tariff (FIT), π_{FIT} . Constraints (2) and (3) refer to the energy balance of producers and consumers. $q_{t,n}$ refers to the intracommunity trades in the community performed by every agent in set $\boldsymbol{\Omega}$. The sum of these trades necessarily needs to be equal to zero, which is ensured by (4). Constraints (5) and (6) respectively define the power flow for active and reactive power. It is important to note that the reactive power associated with the EVs is assumed to be null. The power variables related to the EVs are $P_{t,n,EV}^{ch}$ and $P_{t,n,EV}^{dch}$, which respectively represent the charging and discharging power. Variables $P_{t,l}^{F}$ and $Q_{t,l}^{F}$ represent the active and reactive power injected in a given line l in period t. R_l and X_l represent the resistance and reactance of line l in period t. Voltage drop at any line is assured by (7) and (8) ensures that the power transmitted through a branch does not exceed the product of the voltage and current capacities at any node, aligned with the RBFM. Constraint (9) ensures the power generated does not exceed the maximum installed capacity limits, $P_{t_{max}}^{g}$ and $Q_{t_{\max}}^{g}$. Constraint (10) ensures that the voltage at each node remains within the specified minimum and maximum limits, V_{min}^{t} and $V_{\max}^{t}$. Constraint (11) defines the energy storage limits for EV batteries, which was considered as 40 kWh. In (12) it is ensured that the battery cannot charge and discharge simultaneously, by using binary variables X_{Ch} and X_{Dch}. Constraints (13) and (14) limit the charging and discharging power of each EV battery to 11 kW. In (15) the State-of-charge (SOC) of the EVs in the community is defined for each period of time. The charging/discharging efficiencies and power limits of the batteries are defined in (13) and (14).

B. ADMM-based Formulation and Implementation

The network-constrained community-based model, outlined in the centralized model includes several key coupling constraints such as those related to active and reactive power balance and intracommunity energy trades. By using the steps described in Fig. 1 one can distribute the market and decompose the initial problem.

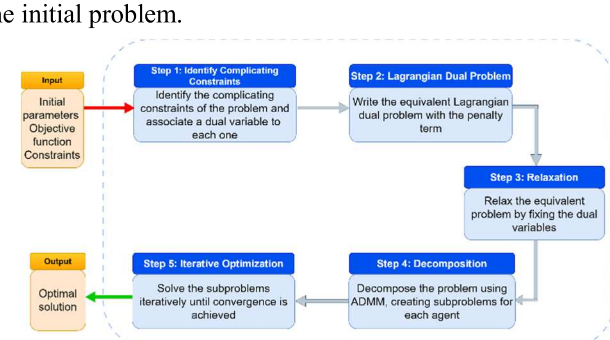

Figure 1. Decomposition technique – ADMM for distributed optimization.

By doing so, an individual multi-variable, multiperiod optimization subproblem is created for each agent:

$$
\begin{aligned}
&\min \sum_{t}^{T} \pi_{n,t} \left(P^{g_{t,n}^{(k)}} - P^{c_{t,n}^{(k)}} + P^{dch_{t,n,EV}^{(k)}} - P^{ch_{t,n,EV}^{(k)}} \right) - \pi_{n,t}^{FiT} \left(\beta_{n,t}^{(k)} + \sum_{j \neq n}^{\Omega_n} \widehat{\beta_j^{(k-1)}} \right) \\
&+ \pi_{n,t}^{SUP} \left(\alpha_{n,t}^{(k)} + \sum_{j \neq n}^{\Omega_n} \widehat{\alpha_j^{(k-1)}} \right) + \widehat{\theta_{n,t}^{(k-1)}} q_{n,t}^{(k)} + \frac{\rho}{2} | q_{n,t}^{(k)} - \left(\widehat{q_{n,t}^{(k-1)}} - \frac{1}{\Omega_n} \sum_{n}^{\Omega_n} \widehat{q_{n,t}^{(k-1)}} \right) |^2 \\
&+ \sum_{j \in C_n} \left(\widehat{\lambda_{j,t}^{(k-1)}} \left(P^{F_{(k)}^{j,t}} - \widehat{P^{F_{(k-1)}^{j,t}}} \right) + \frac{\rho}{2} | P^{F_{(k)}^{j,t}} - \widehat{P^{F_{(k-1)}^{j,t}}} |^2 \right) \\
&+ \sum_{j \in C_n} \left(\widehat{\delta_{j,t}^{(k-1)}} \left(Q^{F_{(k)}^{j,t}} - \widehat{Q^{F_{(k-1)}^{j,t}}} \right) + \frac{\rho}{2} | Q^{F_{(k)}^{j,t}} - \widehat{Q^{F_{(k-1)}^{j,t}}} |^2 \right) \qquad \forall n \in \Omega_n
\end{aligned} \tag{17}
$$

In the formulation presented, the more complex problem can be divided into two parts: the primal problem encompasses the first three terms, which are directly related to the energy transaction costs incurred and the rest of the terms give respect to the dual problem. A notable distinction compared with the respective equivalent in the centralized model is the fact that each agent receives the total amount of imports and exports done by the rest of the community in the previous iteration by communicating with their adjacent neighbors and the ADMM coordinator. Unlike the centralized model, where the CM collects and processes data, in this decentralized approach, each agent independently receives the total amount of imports and exports executed by the rest of the community in the previous iteration of the ADMM algorithm. This mechanism ensures that individual agents remain aligned with the collective goals of the community whose distributed architecture is depicted in Fig. 2.

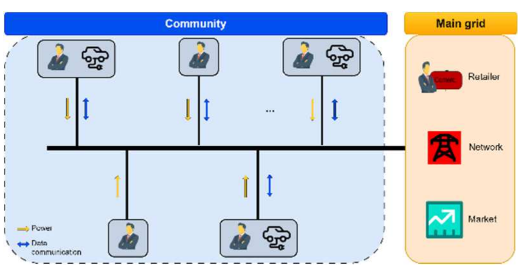

Figure 2. Energy community's distributed architecture.

The penalty term, ρ, is a term that is added to the objective function combined with the coupling constraint and the square of the norm of the constraint in order to make the model adhere to the imposed constraints by adding a quadratic term to the objective function but not changing the optimal solution. As a result, the algorithm is encouraged to find a solution that satisfies the constraints of the problem. Variable θ represents the dual of (4) and represents the price established for the intra-community trades, which was modelled to vary between the export price and import price, according to:

$$\pi^{FIT} \leq \theta^{LEM} \leq \pi^{imp} \tag{18}$$

It is noteworthy that, while the selling price is typically lower than the buying price, this is not always the case. Variables λ and δ are the dual variables associated with active power flow balance and reactive power flow balance, respectively, that are updated at each iteration of the algorithm. In the case of convex problems, dual variables will converge to the dual values associated with the constraints of the centralized approach [7]. The dual variables will be updated throughout the iteration, indexed by k, as shown in (20)-(22):

$$\theta_{n,t}^{(k)} = \theta_{n,t}^{(k-1)} + \rho \left(\frac{1}{\Omega_{n,t}} \cdot \sum_{n,t \in \Omega_{n,t}} \widehat{q_{n,t}^{(k)}} \right) \tag{19}$$

$$\lambda_{n,j,t}^{(k)} = \lambda_{n,j,t}^{(k-1)} + \rho \left(P_{n,j,t}^{F^{(k)}} - \widehat{P_{n,j,t}^{F^{(k-1)}}} \right) \tag{20}$$

$$\delta_{n,j,t}^{(k)} = \delta_{n,j,t}^{(k-1)} + \rho \left(Q_{n,j,t}^{F^{(k)}} - \widehat{Q_{n,j,t}^{F^{(k-1)}}} \right) \tag{21}$$

$$\widehat{V_{n,t}} = V_{n,t}^{(k-1)} \tag{22}$$

The main advantage of using the ADMM method is its ability to distribute the market while protecting the agents' data privacy. Firstly, ADMM enables the decomposition of a complex problem into a series of smaller subproblems that can be independently solved by each agent. The optimization can be achieved with minimal communication regarding the dual variables, reducing the need for extensive data exchange and thus preserving the privacy and confidentiality of the agents' information. This approach facilitates efficient problem-solving and ensures the integrity and security of the agents' data throughout the distributed optimization process.

The main disadvantage of the ADMM framework might be its convergence rate. The algorithm will run until convergence is reached, which will be checked by the following equations:

$$
\begin{aligned}
&\sum_{t \in T} \sum_{n \in \Omega_n} \left(\pi_{n,t} \cdot q_{n,t}^{(k)} - \pi_{n,t}^{FiT} \cdot \beta_{n,t}^{(k)} + \pi_{n,t}^{SUP} \cdot \alpha_{n,t}^{(k)} \right) \\
&- \left(\pi_{n,t} \cdot q_{n,t}^{(k-1)} - \pi_{n,t}^{FiT} \cdot \beta_{n,t}^{(k-1)} + \pi_{n,t}^{SUP} \cdot \alpha_{n,t}^{(k-1)} \right) \leq \epsilon_1, \quad \forall n \in N
\end{aligned} \tag{23}
$$

$$P_{n,j,t}^{F^{(k)}} - P_{j,n,t}^{F^{(k)}} \leq \epsilon_3 \tag{24}$$

$$Q_{n,j,t}^{F^{(k)}} - Q_{j,n,t}^{F^{(k)}} \leq \epsilon_4 \tag{25}$$

Where the allowed tolerances are defined as low as 1×10^{-4}. In the occasion that convergence is not achieved, the ADMM algorithm has a maximum number of iterations set as 20000.

III. Case Study

A. 33-Bus Test Case

This section presents the 33-bus test case employed to evaluate the proposed methodology within a MV radial distribution network. The main goal is to demonstrate that the proposed distributed model allows trading between peers and market clearing while adhering to the network constraints achieving comparable results to the centralized approach while preserving the agents' privacy. In parallel, the integration of EVs can play an interesting role by reducing import requirements, thereby lowering costs and mitigating potential voltage issues.

B. Network and Data Description

A 33-bus MV radial distribution network with a nominal bus voltage of 12.66 kV is used. Real prices from the MIBEL were considered for community imports, with bids set at 85% of the import price. Import prices are from September 19, 2024, where the prices remain relatively stable throughout the day, with no periods of near-zero prices. The composition of the community includes a total of 11 PV systems installed at nodes 2, 6, 9, 14, 17, 18, 19, 20, 23, 26, and 32. These distributed PV systems provide renewable energy to the community, which is complemented by 21 EV owned by the community consumers. The integration of these resources allows for a decentralized energy supply, contributing to the balance between local production and consumption.

C. *Distributed Model Results*

The distributed model results presented in Table 1 reveal that supply always matches the community's power demand, ensuring the system remains balanced throughout the simulation. This balance is crucial for the overall stability of the market, as it guarantees that consumption is fully met. This is achieved primarily through a combination of external energy imports and local PV production. However, the reliance on external sources becomes particularly pronounced during periods when local PV generation is insufficient, and consumption is at its peak, such as in periods 18 to 21. In these critical periods the integration of EVs could play a more substantial role in balancing the energy supply.

Table 1. Community Output Data

Period (h)	Total PV Generation (MW)	Total EV Discharges (MW)	Total Imports (MW)	Total Supply (MW)	Total Consumption (MW)	Total EV Charge (MW)	Total Demand (MW)
1	0.000	0.000	0.924	0.924	0.821	0.104	0.925
2	0.000	0.000	0.568	0.568	0.525	0.044	0.569
3	0.000	0.000	0.456	0.456	0.401	0.056	0.457
4	0.000	0.022	0.357	0.379	0.294	0.086	0.380
5	0.000	0.031	0.385	0.416	0.342	0.075	0.417
6	0.000	0.021	0.365	0.386	0.300	0.087	0.387
7	0.017	0.000	0.446	0.463	0.406	0.057	0.463
8	0.093	0.007	0.406	0.506	0.466	0.040	0.506
9	0.228	0.000	0.511	0.740	0.739	0.000	0.739
10	0.292	0.000	0.776	1.068	1.068	0.000	1.068
11	0.695	0.020	1.003	1.718	1.673	0.044	1.717
12	0.957	0.056	0.935	1.949	1.904	0.044	1.948
13	1.262	0.007	0.485	1.754	1.725	0.028	1.753
14	2.030	0.043	0.012	2.084	1.995	0.088	2.083
15	1.818	0.033	0.238	2.088	2.064	0.023	2.087
16	1.262	0.000	0.960	2.221	2.195	0.025	2.220
17	1.047	0.000	1.177	2.224	2.223	0.000	2.223
18	0.963	0.000	1.602	2.566	2.565	0.000	2.565
19	0.600	0.016	2.072	2.688	2.633	0.055	2.688
20	0.217	0.098	2.514	2.831	2.787	0.044	2.831
21	0.043	0.099	2.543	2.685	2.641	0.044	2.685
22	0.000	0.016	2.138	2.154	2.136	0.019	2.155
23	0.000	0.000	1.956	1.956	1.957	0.000	1.957
24	0.000	0.000	1.542	1.542	1.543	0.000	1.543

While the primary role of the EV is providing transportation for their owners, they also offer an additional benefit in the community's energy strategy. Even though the observed data shows that EV discharges are generally low, there are specific periods such as 12, 14, 15, 19, 20, and 21 where energy is drawn from the EVs to support the grid, particularly during times of peak consumption, as seen in Fig. 3.

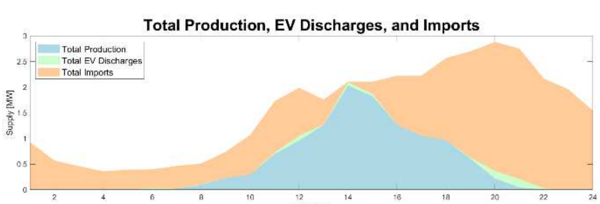

Figure 3. Community's total supply mix.

To quantify this contribution, it is useful to focus on the period with the highest aggregated EV discharges. In period 21, the energy discharged from the EVs was 99 kWh, accounting for approximately 3.75% of the total consumption of 2.641 MWh during this period. Although this percentage may seem modest, it demonstrates the role that EVs can play in supporting the grid during peak demand, particularly when PV production is low.

The inverse relationship between PV generation and imports highlights the community's commitment to self-sufficiency, optimizing the use of DERs. This strategy effectively reduces energy costs by prioritizing self-consumption and intra-community trading before engaging in imports from the external grid. For instance, during periods of high PV production, such as the 14th period, imports are minimized (0.012 MWh), ensuring that locally generated energy meets the community's demand. Conversely, when PV generation is low or absent, imports increase, as observed in the 21st period with an import peak of nearly 2.5 MWh. This approach demonstrates how the community strategically leverages locally generated power to meet its needs first, resorting to external imports only when necessary. By doing so, the community not only minimizes its reliance on external sources but also capitalizes on the economic benefits of prioritizing local energy resources. Consumers can purchase energy within the community to meet their power demand at a cheaper price than the import price set by external retailers, while producers within the community can sell their surplus energy at a higher price than the FIT, maximizing their revenue. Furthermore, this strategy can offer resilience against market price volatility. By relying less on external energy markets, the community is less exposed to sudden spikes in energy prices.

An important factor that enables the EV to contribute during high-demand periods is their charging profile throughout the day. Fig. 4 illustrates the community's aggregated EV charging profile, showing distinct charging patterns. A noticeable spike in charging activity occurs during the first hour, where EV charge heavily after being plugged in. Following this spike, charging becomes more evenly distributed across the subsequent hours, charging a total of 57% of the total aggregated EV charge until morning usage. Between hours 11 and 16, after the morning usage and before the afternoon usage, an additional 26% of total charging takes place, allowing for partial recharging. This intermediate charging ensures that the EV are prepared for further transportation or potential discharges to support the grid during peak demand. The remaining 17% of charging occurs after the second trip, in the evening, when most EVs are discharging contributing to the grid during high-demand periods. This limited charging strategically prepares some EVs for potential discharges, aligning with community needs while maintaining their SOC above the critical 20% threshold. The lower charging level compared to other periods reflects the dual role of EVs, as they prioritize discharging to stabilize the grid before recharging in preparation for the next day's transportation needs.

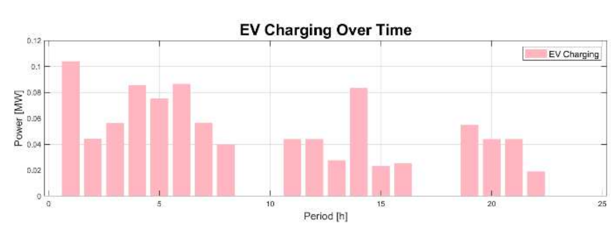

Figure 4. Community's EV charging profile over simulation time.

As seen in Fig. 5 the EV's SOC reaches around 100% before the 8 AM planned trip departure, reflecting a consistent overnight charging strategy. In this case, a charging session during the afternoon ensures the battery has sufficient charge for the 4 PM trip, maintaining reliability for all planned activities. Throughout the day, the SOC remains above the 20% safety margin, demonstrating effective battery management.

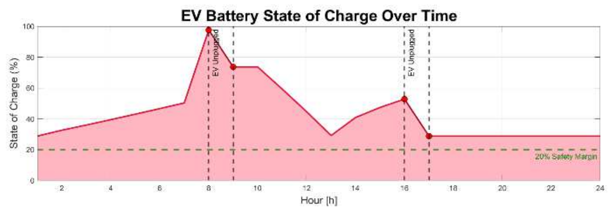

Figure 5. EV battery state-of-charge evolution over simulation time.

Analyzing the distributed model algorithm's performance for the 33-bus network simulation using the ADMM model, the process required 1,169 iterations to converge, resulting in an elapsed time of approximately 3927 seconds. The penalty parameter was set at 100, and the tolerance for convergence was fixed at 1×10^{-4}. An important factor that enables the algorithm convergence is the residual balance technique implemented which is designed to accelerate the convergence of the ADMM algorithm by ensuring that the primal and dual residuals are balanced. Without applying it, it was not always guaranteed that the ADMM algorithm would converge before reaching the 20,000-iteration limit [20].

IV. Conclusions and Future Work

A distributed P2P market clearing algorithm using the ADMM method was developed to address network constraints in a 33-node community with PV systems and EVs. The algorithm demonstrated scalability, reduced communication overhead, and preserved participant privacy compared to the developed centralized model. Both models were tested on a 33-bus network, with the ADMM model closely matching the centralized benchmark results. Importantly, the optimal points between the models remained close, with the ADMM model showing a 9.12% relative error, and both models maintaining stable voltage profiles. These minor discrepancies show that the decentralized ADMM approach provides results closely comparable to the centralized model for this context. EVs played an interesting role in reducing community imports by discharging during peak periods, such as high-demand hours with no PV generation, effectively lowering costs beyond their primary function of transportation. This contribution helped minimize imports and reduced overall energy costs for the community. The ADMM approach offers several advantages over the centralized model, including scalability, reduced reliance on a central entity, and enhanced privacy for participants. By breaking the global optimization problem into smaller subproblems, it minimizes communication while maintaining computational efficiency. The ADMM method effectively balances local generation and demand, reducing energy costs for consumers through energy trading at lower prices compared to imports, while allowing producers to sell at higher prices than traditional FiT models, while adhering to network constraints. Future research could explore transitioning to a consensus-based ADMM approach to reduce computational time, incorporating prosumers into the network, as the agents were previously modelled only as either producers or consumers and improving the ADMM algorithm's convergence rate, exploring techniques like the adaptative penalty parameter.

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