Peer-to-Peer Joint Energy and Reserve Market with Product Differentiation: Centralized Versus Decentralized

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Manuscript received 20 August, 2025; revised 28 May, 2026; accepted 31 May, 2026. Paper no. JEMT-2508-1569.

In modern smart grids, prosumers and distributed energy resources increasingly participate in local electricity markets, while higher renewable penetration raises the need for reserve capacity and operational flexibility. This paper proposes a joint peer-to-peer (P2P) market framework for energy and reserve trading with product differentiation, in which agents negotiate bilaterally with neighboring peers and can trade both energy and reserve capacity. The resulting social-cost minimization problem is formulated and solved using a centralized benchmark together with ADMM-based decentralized and distributed clearing mechanisms. In the fully decentralized market, a coordinator-free consensus ADMM is adopted for direct P2P trading, whereas the hybrid framework employs an exchange ADMM to clear intra-community trades prior to decentralized negotiations across communities. Numerical studies quantify the trade-off between centralized and decentralized clearing in terms of objective value, computation time, and communication burden. The results further demonstrate how product-differentiation coefficients influence market prices and traded quantities. Finally, two coefficient-setting strategies are introduced to steer decentralized market outcomes toward centralized-like or hybrid-like operating points, thereby enabling the market operator or platform designer to influence trading behavior under decentralized clearing.

Keywords: *centralized, decentralized, distributed, peer-to-peer, product differentiation.*

http://dx.doi.org/10.22109/jemt.2026.540360.1569

Nomenclature

P2P	Peer-to-peer.
ADMM	Alternating direction method of multipliers.
$C_n^p(P_n)$	Cost and utility quadratic function for power.
$C_n^p(P_n)$	Linear trading cost and utility for power.
$C_n^r(R_n)$	Cost and utility quadratic function for reserve.
$C_n^r(R_n)$	Linear trading cost for reserve.
C_n^{P2P}	P2P design cost function.
C_n^M	The community cost function.
$M(q_{imp}, q_{\exp})$	Model of the community manager.
C_n^{tot}	Community-based design cost function.
n, m	Indices for peers.
p, r	Indices for power and reserve.
Ω	All peers set.
Ω_g	Producers set.
Ω_{lo}	Consumers set.
Ω_r	Renewable producers set.
ω_n	Set of trading partners for peer n.
D	Decision-making variables.
Ω^u	Set for upper level in hybrid design.
Ω^b	Set for bottom level in hybrid design.
Ω_c	Set for communities in hybrid design.
it	Index of iteration.
s, t	Primal and dual residuals.
P_{nm}	Traded power quantity between agent n and m.
R_{nm}	Traded reserve quantity between agent n and m.

P_n	Net energy injection of each agent.
q_n	Energy imported by peer n from the community.
α_n	Energy imported by peer n.
β_n	Energy exported by peer n.
q_{imp}	Total energy imported.
$q_{\exp}$	Total energy exported.
$\lambda_{n,m}$	Energy price.
v_{nm}	Reserve price.
w	weighting factor for aggregation.
a_n^p, b_n^p	Coefficients of the quadratic power cost function.
a_n^r, b_n^r	Coefficients of the quadratic reserve cost function.
$\overline{P}_n, \underline{P}_n$	Boundaries of power.
$\overline{R}_n, \underline{R}_n$	Boundaries of reserves.
c_{nm}^p	Power trading coefficient
c_{nm}^r	Reserve trading coefficient
γ_{com}	penalization coefficient for trading inside the community
γ_{imp}	penalization coefficient for import of energy.
$\gamma_{\exp}$	penalization coefficient for export of energy.
$\kappa^{incr}, \kappa^{decr}$	Increasing and decreasing factors for adaptive penalty factors.
ρ, τ	ADMM algorithm penalty factors.
χ	Stopping criterion.
p_n^r	Reserve payment for peer n.
u_n	Normalized uncertainty for peer n.

1. Introduction

Electricity markets are traditionally based on conventional top-down and hierarchical approaches [1], limiting the active participation of market players. However, the emergence of smart grids has introduced various optimizations in power systems, including energy management, cost minimization, and distribution-side control. Optimization techniques have been widely applied to the demand side of smart grids [2]. With the integration of distributed energy resources (DERs) and advancements in information and communication technologies, the conventional hierarchical structure of power systems has evolved, creating new generation layers at lower levels [3]. The increasing penetration of DERs, demand response programs, and renewable energy sources, along with advancements in energy storage technologies, have transformed producers and consumers into active participants in the energy market. This shift has introduced new challenges in market clearing and system operation due to growing uncertainties. Future smart distribution networks are expected to consist of multiple interconnected microgrids, which will pose operational challenges such as reconfiguration [4] and market clearing. The rise of proactive consumers, known as "prosumers," who possess both generation and storage capabilities, presents modern opportunities and challenges for power system operation and market clearing. Market clearing methods and supply-demand balancing approaches can be categorized into three groups: (1) centralized, (2) decentralized, and (3) distributed. In a centralized market, a central operator collects data from all participants, solves the market clearing problem, and then disseminates control signals to agents. Although this approach is easy to implement, it suffers from privacy concerns and scalability limitations. In contrast, decentralized and distributed methods offer improved privacy and scalability. The key distinction between these methods is that decentralized approaches operate without a central coordinator, whereas distributed methods involve a coordinator to facilitate consensus among agents. Shared data such as market price and voltage serve as communication signals between agents, enabling enhanced privacy preservation. A comparative analysis of these methods is presented in Table 1 [5]. The integration of prosumers with renewable energy resources has given rise to local electricity markets, fundamentally transforming energy systems. A novel tri-level optimization approach has been proposed to facilitate financial interactions between local electricity markets, wholesale markets, and prosumers [6]. To enable prosumer participation in energy trading, two key mechanisms have been developed: feed-in tariffs and peer-to-peer (P2P) trading. While feed-in tariff schemes are not widely adopted in some countries due to their limited profitability for prosumers [7], P2P electricity markets have emerged as a promising alternative. These markets enable prosumers to engage directly in energy and service transactions. In this context, an active agent (or peer) is defined as any entity that owns or operates assets such as storage, generation, or consumption units. Prosumers may also form communities to enhance cooperation. Hybrid P2P markets, which integrate both P2P and community-based trading models, have also been explored. A comprehensive review of P2P market mechanisms is provided in [8]. The structural components of P2P markets, along with conventional pool-based markets, are illustrated in Figure 1. Consumer preferences play a crucial role in electricity market design, influencing factors such as emissions, distance, and renewable energy types. Consumer-centric electricity markets incorporate these preferences, leveraging P2P and community-based structures. Product differentiation allows dynamic valuation of electricity attributes beyond energy itself [14]. To facilitate transactions, features such as service ratings, distance, and emissions can be incorporated into pricing models through appropriate indexing mechanisms. To ensure efficient P2P market operations, distributed and decentralized optimization techniques are required. Various decentralized approaches, including the alternating direction method of multipliers (ADMM) [15], relaxed consensus innovation [14], consensus ADMM [16], and game theory [17], have been proposed. Ref. [18] focuses on consensus ADMM and proximal ADMM for solving DC optimal power flow (OPF) and AC OPF problems. Additionally, Ref. [19] presents a distributed ADMM approach for solving dynamic DC OPF with demand response. One of the key challenges in applying ADMM to nonconvex problems is the lack of guaranteed convergence [20]. To address this, an auxiliary variable-based ADMM has been proposed for AC OPF [20]. Privacy-preserving P2P trading mechanisms that maximize social welfare using ADMM have been explored in [21]. A decentralized framework for competitive P2P energy trading among retailers and sellers is introduced in [22]. ADMM-based and consensus+innovation techniques ensure agent privacy by allowing them to share only essential trading information, such as energy and price, without disclosing sensitive data. In conventional power systems, reserves are typically provided by the system operator. However, with the increasing penetration of renewable energy sources, uncertainty and reserve requirements have risen significantly.

Table 1. Centralized, distributed and decentralized methods, advantages and disadvantages.

Method	Advantages	Disadvantages
Centralized	Easy to implement; easy to maintain (even under single-point failure)	Difficult to expand; requires high connectivity
Decentralized/ Distributed	Easy to expand; appropriate for large-scale systems; lower computational burden; avoids single-point failure	Requires a two-way communication network; convergence may be affected by communication topology

In [23], an optimal scheduling strategy for energy and reserve in renewable-based microgrids is presented, aiming to minimize environmental emissions while maximizing social welfare. Renewable energy agents can now forecast their uncertainties, and it is argued that they should be responsible for managing the uncertainty they introduce into the system. Relying solely on system operators for reserve provision is not sustainable. From an operational perspective, system operators should determine how to allocate reserves, while renewable agents should bear the cost of reserve procurement. P2P market structures offer a fair mechanism for redistributing reserve costs. Studies in [24] and [25] explore P2P market designs that incorporate reserve considerations. For multi-energy operating reserves in smart energy hubs, a two-stage market framework with a distributed clearing mechanism has been proposed in [26]. The prosumer-based multi-carrier energy system model introduced in [27] includes elements such as heat storage, combined heat and power, battery energy storage, microturbines, and critical loads. Illustrative examples of full P2P and community-based market structures are provided in Figures 2 and 3. This paper investigates centralized, decentralized, and hybrid frameworks for joint peer-to-peer (P2P) energy and reserve trading. The main contributions are summarized as follows:

• Formulate a joint P2P energy and reserve market with product differentiation and bilateral trading mechanisms.

• Provide a unified comparison between centralized clearing and ADMM-based decentralized/distributed clearing approaches, including consensus ADMM for fully decentralized P2P trading and exchange ADMM for intra-community market clearing.

• Quantify the impact of product-differentiation coefficients and ADMM-related parameters on market prices, traded quantities, convergence behavior, objective value, and computational performance.

• Introduce two coefficient-setting strategies that steer decentralized market outcomes toward centralized-like or hybrid-like operating characteristics.

The remainder of this paper is organized as follows. Section 2 presents the market formulations and optimization models. Section 3 reviews the decentralized and distributed optimization techniques adopted for the proposed market structures. Section 4 describes the test system, simulation setup, and numerical results. Finally, Section 5 concludes the paper.

2. Problem formulations

In this section, full P2P, product differentiation, community-based P2P and hybrid P2P mathematical modeling are presented respectively.

To isolate the impact of market structure (centralized versus decentralized versus hybrid) and product differentiation on market outcomes and algorithmic behavior, we adopt a simplified "copper-plate" setting and do not explicitly model power-flow constraints, voltage limits, or line congestion. Consequently, the reported prices correspond to settlement signals under this simplified assumption. Incorporating network constraints is a natural extension: DC power-flow constraints can be added for transmission-level studies, and linearized distribution models (e.g., LinDistFlow) can be used for distribution-level applications. These additional constraints introduce structured coupling that can still be handled within the same ADMM-based decomposition framework. By focusing on the 'copper-plate' model, we establish a fundamental baseline for agent behavior and product preferences. This allows us to disentangle economic incentives from physical congestion rents, which is a necessary step before introducing the additional complexity of network-dependent pricing.

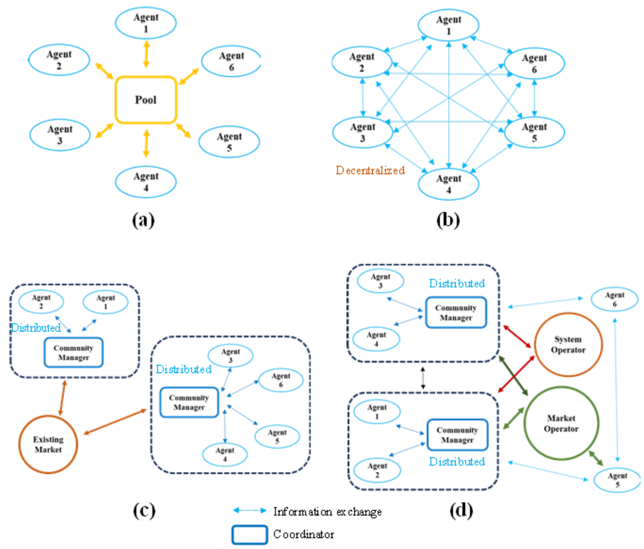

Fig 1. Market structures, Pool-based (a), full P2P (b), community-based P2P (c) and Hybrid P2P (d).

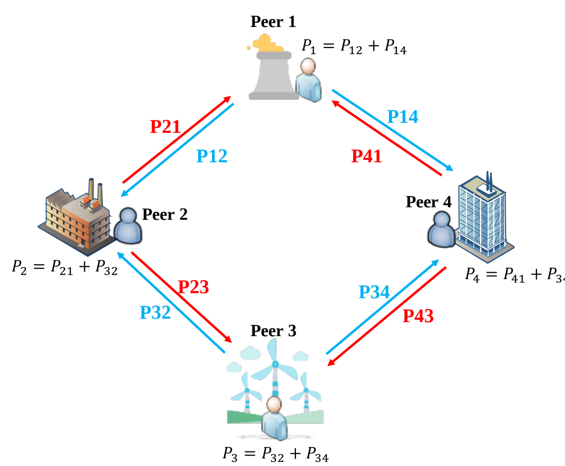

Fig 2. An illustrative example of a full P2P market structure for energy trading.

2.1. Full P2P Trading Modeling

In a peer-to-peer (P2P) market, agents can directly negotiate bilateral transactions for energy and reserve services with neighboring peers, enabling decentralized participation of consumers and producers in local market operations. In this paper, a general mathematical formulation for joint energy and reserve trading is developed. The corresponding P2P market-clearing models for energy and reserve transactions are presented in the following subsections.2.1.1 Full P2P design for energy trading.

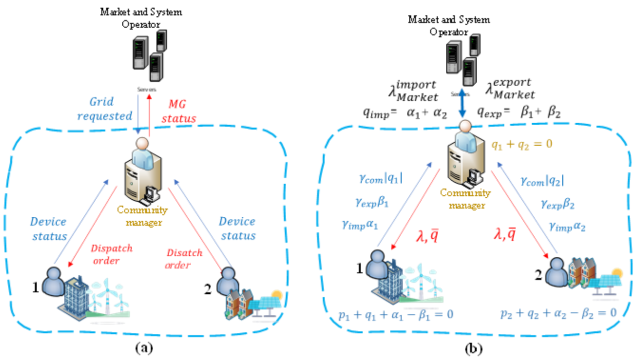

Fig 3. Data (a) and energy (b) exchange in a community-based market structure.

2.1.1. Full P2P design for energy trading

To model the trading process, first sets and then equations corresponding to peers are defined. Ω, Ω_g, Ω_{lo} and ω_n are sets for all peers, producers, consumers and set of trading partners respectively ($\Omega_g, \Omega_{lo} \in \Omega$, $\Omega_g \cap \Omega_{lo} = \phi$). Trading partners is defined as producers or prosumers have trading partners as consumers and consumers have producer and prosumers as trading partners. P_{nm} is traded energy between agent n and m, and P_n is the net energy injection of each agent (equation (1)). Equation (2) is representing energy boundaries and each agent limitation($\underline{P}_n \overline{P}_n \geq 0$). Positive value of P_{nm} corresponds to production or sale (equation (3)) and negative value of P_{nm} corresponds to consumption or purchase (equation (4)). The producer generation cost or consumer utility assumed to be strictly convex function, negative for users and positive for generators [25].

$$P_n = \sum_{m\in\omega_n} P_{nm} \qquad \forall n\in\Omega \tag{1}$$

$$\underline{P}_n \le P_n \le \overline{P}_n \qquad \forall n\in\Omega \tag{2}$$

$$P_{nm} \ge 0 \qquad \forall (n,m)\in(\Omega_g \cup \Omega_r, \omega_n) \tag{3}$$

$$P_{nm} \le 0 \qquad \forall (n,m)\in(\Omega_{lo}, \omega_n) \tag{4}$$

2.1.2. Full P2P design for reserve trading

To model reserve trading, similar to part 2.1.1, R_{nm} is traded reserve between agent n and m, and R_n is the net reserve injection of each agent (equation (5)). Equation (6) is representing reserve boundaries and each agent limitation ($\underline{R}_n \overline{R}_n \geq 0$). Positive value of R_{nm} corresponds to production or sale (equation (7)) and negative value of P_{nm} corresponds to consumption or purchase (equation (8)). The required reserve constraint is represented in (9). The reserve production cost and consumer utility functions are assumed to be strictly convex. Following [25], the utility function coefficients are considered negative for renewable generators and positive for the remaining agents. Reserve is procured jointly with energy within each market-clearing interval considered in this study (e.g., hourly or day-ahead, depending on the considered market horizon). The reserve variables represent committed reserve capacity available for potential activation if needed. However, the real-time activation and deployment of reserve in response to system deviations are not explicitly simulated in this work. Extending the formulation to multi-period settings with explicit reserve-activation dynamics constitutes an important direction for future work.

$$R_n = \sum_{m\in\omega_n} R_{nm} \qquad \forall n\in\Omega \tag{5}$$

$$\underline{R}_n \le R_n \le \overline{R}_n \qquad \forall n\in\Omega \tag{6}$$

$$R_{nm} \ge 0 \qquad \forall (n,m)\in(\Omega_g \cup \Omega_{lo}, \omega_n) \tag{7}$$

$$R_{nm} \le 0 \qquad \forall (n,m)\in(\Omega_{lo}, \omega_n) \tag{8}$$

$$\underline{P}_n \le P_n + R_n \le \overline{P}_n \qquad \forall n\in\Omega_r \tag{9}$$

2.1.3. Market equilibrium

The balance constraints for energy and reserve production and consumption are given in (10) and (11), respectively. The dual variables λ_{nm} and ν_{nm} associated with bilateral energy and reserve trades, represent the corresponding bilateral trading prices for energy and reserve, respectively [25].

$$P_{nm} + P_{mn} = 0 \qquad \forall (n,m)\in(\Omega, \omega_n) \tag{10}$$

$$R_{nm} + R_{mn} = 0 \qquad \forall (n,m)\in(\Omega, \omega_n) \tag{11}$$

2.1.4. Product differentiation

From the perspective of agent (n), the bilateral trade with agent (m) is evaluated according to specific preference or market-design criteria parameterized by positive product-differentiation coefficients for energy and reserve trading. Equations (13) and (14) define the corresponding bilateral trading coefficients for energy and reserve exchanges, respectively. These coefficients may reflect different attributes associated with bilateral transactions, such as emission intensity, electrical distance, network usage charges, renewable-energy labels, or reliability and flexibility characteristics of reserve providers. In this work, the product-differentiation coefficients are treated as exogenous market-design parameters determined by the market operator/DSO or the P2P platform designer. The bilateral trading costs associated with energy and reserve exchanges between agent (n) and its neighboring agent (m) are modeled as linear functions of the exchanged quantities and are formulated in (15) and (16), respectively [25].The product-differentiation coefficients are economically interpreted as preference- or tariff-based adjustment parameters that affect bilateral energy and reserve trades (e.g., reflecting network usage charges, locational congestion-related signals, emissions intensity or renewable-energy labels, and reliability or flexibility attributes of reserve providers). In this work, these coefficients are treated as exogenous market-design parameters determined by the market operator or DSO or the P2P platform designer, rather than by individual agents, in order to guide decentralized trading behavior and support improved system-level efficiency. For example, a product-differentiation coefficient between peers n and m can be defined as a weighted combination of normalized indicators (12). Where d_{nm} represents electrical distance or network usage, e_m denotes emissions intensity, and r_m reflects reserve reliability or flexibility metrics. The bilateral product-differentiation coefficient c_{nm} can itself be constructed as a weighted aggregation of multiple attributes.

$$c_{nm} = w_1 d_{nm} + w_2 e_m + w_3 r_m \tag{12}$$

$$c^p_{nm} = \sum_{i_p\in I_P} c^{i_p}_n \gamma^{i_p}_{nm} \tag{13}$$

$$c^r_{nm} = \sum_{i_r\in I_R} c^{i_r}_n \gamma^{i_r}_{nm} \tag{14}$$

$$C^p_n(P_n) = \sum_{m\in\omega_n} c^p_{nm} P_{nm} \tag{15}$$

$$C^r_n(R_n) = \sum_{m\in\omega_n} c^r_{nm} R_{nm} \tag{16}$$

2.1.5. Production and reserve cost modeling in full P2P market

The utility functions and production costs are modeled using quadratic functions, while renewable agents are treated as must-take producers $\underline{P}_n = \overline{P}_n$ [14]. The quadratic cost functions associated with energy and reserve trading are presented in (17) and (18), respectively [25]. Finally, the total-cost optimization problem is formulated in

(19)– (21) with the corresponding decision variables. The objective function consists of a linear term associated with product differentiation and a quadratic term representing the operational cost of power-generation agent $D = (E_{nm}, E_{nm})$.

$$C_n^p(P_n) = \frac{1}{2} a_n^e P_n^2 + b_n^e P_n \tag{17}$$

$$C_n^r(R_n) = \frac{1}{2} a_n^r R_n^2 + b_n^r R_n \tag{18}$$

$$C_n^{P2P} = C_n^p(P_n) + C_n^{p}(P_n) + C_n^r(R_n) + C_n^{r}(R_n) \tag{19}$$

$$\text{Total P2P Cost} = \sum_{n\in\Omega} C_n^{P2P} \tag{20}$$

$$\min_{D} \sum_{n\in\Omega} C_n^{P2P} \tag{21}$$

s. t. constraints in (1) - (11)

2.2. Community-based P2P mechanism

In future smart-grid architectures, microgrid (MG)-based community structures are expected to play an important role in local electricity markets [25]. Community-based distributed frameworks provide an appropriate environment for implementing hybrid and hierarchical P2P market mechanisms. In this market structure, peers and community managers are the main participants. The community cost, community-manager cost, and total community cost formulations are presented in (22)– (24), respectively. Equations (24) to (29) presents related constraints. Let us consider n peers each of them with production p_n and total cost C_n^M . In presented equations $D = (p_n, q_n, \alpha_n, \beta_n)$ are decision variables. M is community manager cost function and q_{imp} , q_{exp} are continuous variables for import and exported energies with main grid peers which are related to the community manager. Equation (25) presents power balance constraint. Equation (26) illustrates traded energy within community and equation (27) and (28) presents traded energy with main grid peers. Equations (31) and (32) presents optimization problem form to model community-based P2P market structure.

$$C_n^M(p_n, q_n, \alpha_n, \beta_n) = a_n^e p_n^2 + b_n^e p_n + \gamma_{com}\left|q_n\right| + \gamma_{imp}\alpha_n + \gamma_{exp}\beta_n \tag{22}$$

$$M(q_{imp}, q_{exp}) = \gamma_{imp} q_{imp} + \gamma_{exp} q_{\exp} \tag{23}$$

$$C_n^{tot} = C_n^M(p_n, q_n, \alpha_n, \beta_n) + M(q_{imp}, q_{exp}) \tag{24}$$

$$p_n + q_n + \alpha_n - \beta_n = 0 \qquad \forall n \in \Omega \tag{25}$$

$$\sum_{n\in\Omega} q_n = 0 \tag{26}$$

$$\sum_{n\in\Omega} \alpha_n = q_{imp} \tag{27}$$

$$\sum_{n\in\Omega} \beta_n = q_{\exp} \tag{28}$$

$$\alpha_n, \beta_n \ge 0 \qquad \forall n \in \Omega \tag{29}$$

$$\underline{p}_n \le p_n \le \overline{p}_n \qquad \forall n \in \Omega \tag{30}$$

$$\text{Total community-based cost} = \sum_{n\in\Omega} C_n^{tot} \tag{31}$$

$$\min_{D} \sum_{n\in\Omega} C_n^{tot} \tag{32}$$

s. t. constraints in (25)-(30)

2.3. Hybrid P2P mechanism

This market structure combines the full P2P and community-based P2P designs. There is no single generic mathematical formulation for hybrid P2P mechanisms; here we adopt a two-level formulation. The whole-system optimization problem is shown in (33) with decision variables. In (33), the objective function aggregates the full-P2P and community-based costs. The lower-level optimization (community-based design) is solved first to determine each community's energy surplus/deficit (as in (35)); then the upper-level problem clears P2P negotiations among individual peers and community managers using (34), subject to the corresponding constraints. The community manager can then trade with other community managers and individual peers while satisfying (36) [8].

$$\min_{D} \sum_{n\in\Omega^u} C_n^{P2P} + \sum_{n\in\Omega^b} C_n^{tot} \tag{33}$$

s. t. upper level (full p2p):

constraints in (1) – (11) (34)

$$\sum_{m\in\omega_n} p_{nm} = q_{\exp}^n - q_{imp}^n \qquad \forall (n,m) \in (\Omega_{co}, \omega_n) \tag{35}$$

bottom level (community-based design)

Constraints in (25) – (30) $\quad \forall n \in \Omega^b$ (36)

2.4. Modeling assumptions and limitations

The proposed formulations consider a single-period market-clearing problem with deterministic demand and generation profiles. Perfect information is assumed during each market-clearing interval, while temporal coupling effects (e.g., ramping limits and inter-temporal storage constraints) and stochastic uncertainty are not explicitly modeled. These assumptions are adopted to maintain focus on market-design mechanisms and the comparison of centralized, decentralized, and hybrid solution paradigms. Multi-period and stochastic extensions, including explicit reserve activation and uncertainty-aware formulations, constitute important directions for future work.

3. Decentralized and distributed optimization

In this section, the mathematical formulations and the fundamental concepts of the decentralized and distributed optimization techniques adopted for the proposed market structures are presented. The formulations demonstrate that P2P market problems can be solved using both centralized and decentralized approaches. However, decentralized methods are generally more suitable for preserving the autonomy and peer-based characteristics of P2P markets. In community-based market structures, a community manager acts as a coordinator and solves the optimization problem for each community using distributed algorithms. Hybrid P2P market structures combine distributed and decentralized coordination mechanisms to exploit the advantages of both approaches. Optimization problems with decomposable structures are commonly categorized into problems with complicating variables and problems with complicating constraints. As illustrated in Figure. 4, Augmented Lagrangian Relaxation (ALR) is a widely used approach for solving decomposable optimization problems with complicating constraints. Related decomposition techniques include the Auxiliary Problem Principle (APP) and the Alternating Direction Method of Multipliers (ADMM). ADMM decomposes the global optimization problem into smaller local subproblems associated with individual agents while limiting the amount of exchanged information. In this framework, only essential trading information, such as exchanged energy, reserve quantities, and price-related variables, is shared among agents, thereby supporting privacy-preserving coordination. In conventional and exchange ADMM algorithms, a coordinator is responsible for updating the dual and coupling variables, resulting in a distributed optimization structure. In contrast, consensus ADMM eliminates the need for a central coordinator and enables fully decentralized coordination among agents. This property makes consensus ADMM particularly suitable for decentralized market structures where participant autonomy and privacy are important considerations. Although consensus-based methods may require a relatively high number of iterations, conventional and exchange ADMM methods generally exhibit faster convergence behavior but rely on some degree of centralized coordination. In this paper, both consensus ADMM and exchange ADMM are employed to solve the decentralized and distributed optimization problems associated with the proposed market structures.

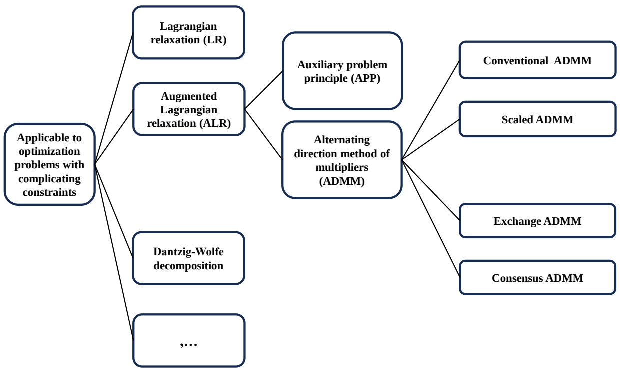

Fig 4. Applicable to optimization problems with complicating constraints.

3.1. Consensus ADMM for P2P joint energy and reserve market

Consensus ADMM is one of the augmented-Lagrangian decomposition methods for solving optimization problems with complicating constraints [28]. In this section, the joint P2P energy-and-reserve trading problem is solved using consensus ADMM. In the full P2P formulation, the coupling constraints are (10) and (11), which link pairs of agents. The corresponding dual variables provide the bilateral energy and reserve prices, and the positive penalty factors tune the convergence behavior. For each agent n, the local optimization problem at iteration k is given in (37)– (41).

Remark on convergence: Consensus ADMM enjoys strong convergence guarantees for convex problems. In this work, each agent solves a convex quadratic program with linear constraints; therefore, the local subproblems are convex, and the algorithm exhibited stable convergence behavior under the adopted residual-based stopping criteria. For non-convex extensions (e.g., detailed AC network models), global optimality is not generally guaranteed, and ADMM solutions are typically interpreted as locally stationary (KKT) points. In such cases, penalty tuning and convergence tolerances become critical for robust practical performance. Furthermore, given the convexity of the lower-level problems, the coordinated solution corresponds to the global optimum of the equivalent centralized optimization problem.

$$P_n^{it+1}, R_n^{it+1} = \underset{\{P_n, R_n\}}{\arg\min} \quad C_n^p(P_n) + C_n^p(P_n) + \tag{37}$$

$$+C_n^r(R_n) + C_n^r(R_n) +$$

$$\sum_{m\in\omega_n} \lambda_{nm}^{it}(\bar{P}_{nm} - P_{nm}) + v_{nm}^{it}(\bar{R}_{nm} - R_{nm}) +$$

$$\frac{\rho}{2}(\bar{P}_{nm} - P_{nm})^2 + \frac{\tau}{2}(\bar{R}_{nm} - R_{nm})^2$$

s. t. constraints (1) – (9)

$$\bar{P}_{nm} = \frac{P_{nm}^{it} - P_{mn}^{it}}{2} \tag{38}$$

$$\bar{R}_{nm} = \frac{R_{nm}^{it} - R_{mn}^{it}}{2} \tag{39}$$

$$\lambda_{nm}^{it+1} = [\lambda_{nm}^{it} - \frac{\rho(P_{nm}^{it+1} + P_{mn}^{it+1})}{2}]^+ \tag{40}$$

$$v_{nm}^{it+1} = [v_{nm}^{it} - \frac{\tau(R_{nm}^{it+1} + R_{mn}^{it+1})}{2}]^+ \tag{41}$$

3.1.1. Market converges and algorithm acceleration

In this section, we define four stopping criteria: primal (SP) and dual (TP) residuals for energy, and primal (SR) and dual (TR) residuals for reserve. The market is considered converged when the aggregated local residuals fall below the global tolerances. Equations (46)– (49) provide the definitions of SP, TP, SR, and TR. The number of iterations and the convergence speed depend strongly on the penalty factors. Although ADMM converges for any constant penalty factor in theory (for convex problems), practical performance depends on penalty selection. By adaptively updating the penalty factors according to (42)– (51), convergence can be accelerated; the parameters define decreasing and increasing factors used for this update [25].

$$s_{n,p}^{it+1} \triangleq \sum_{m\in\omega_n} (P_{nm}^{it+1} + P_{mn}^{it+1})^2 \tag{42}$$

$$s_{n,r}^{it+1} \triangleq \sum_{m\in\omega_n} (R_{nm}^{it+1} + R_{mn}^{it+1})^2 \tag{43}$$

$$t_{n,p}^{it+1} \triangleq \sum_{m\in\omega_n} (P_{nm}^{it+1} - P_{nm}^{it})^2 \tag{44}$$

$$t_{n,r}^{it+1} \triangleq \sum_{m\in\omega_n} (R_{nm}^{it+1} - R_{nm}^{it})^2 \tag{45}$$

$$SP^{it+1} \triangleq \sum_{n\in\Omega} t_{n,p}^{it+1} \le \chi_p^s \tag{46}$$

$$SR^{it+1} \triangleq \sum_{n\in\Omega} s_{n,r}^{it+1} \le \chi_r^s \tag{47}$$

$$TP^{it+1} \triangleq \sum_{n\in\Omega} t_{n,p}^{it+1} \le \chi_p^t \tag{48}$$

$$TR^{it+1} \triangleq \sum_{n\in\Omega} t_{n,r}^{it+1} \le \chi_r^t \tag{49}$$

$$\rho^{it+1} = \begin{cases} \kappa^{incr}\rho^{it} & if\ SP^{it} > 10*TP^{it} \\ \rho^{it}/\kappa^{decr} & if\ TP^{it} > 10*SP^{it} \\ \rho^{it} & otherwise \end{cases} \tag{50}$$

$$\tau^{it+1} = \begin{cases} \kappa^{incr}\tau^{it} & if\ SR^{it} > 10*TR^{it} \\ \tau^{it}/\kappa^{decr} & if\ TR^{it} > 10*SR^{it} \\ \tau^{it} & otherwise \end{cases} \tag{51}$$

3.2. Exchange ADMM for communities in hybrid P2P

Exchange ADMM is an augmented-Lagrangian decomposition method for optimization problems with complicating constraints. In this section, the internal energy-trading problem of each community is modeled and solved using exchange ADMM [28]. For a simple community with a producer and a consumer (N=2), the coupling constraint is (26), which links the two peers. The corresponding dual variable yields the traded-energy price, and the positive penalty factor tunes convergence. For each peer n, the local optimization problem at iteration k is given in (52)– (55). A flowchart of the centralized, decentralized, and hybrid mechanisms is shown in Figure 5.

If each community contains one producer peer and one consumer peer ((N = 2)), the coupling (or complicating) constraint is formulated in (26). This constraint links the optimization problems of the two peers through the bilateral energy-trading variable. The corresponding dual variable represents the bilateral traded-energy price, while ρ denotes the positive penalty parameter of the ADMM algorithm. For each peer (n), the local optimization problem at iteration (k) is presented in (52)– (55). The flowcharts corresponding to the centralized, decentralized, and hybrid market-clearing mechanisms are illustrated in Figure. 5.

$$p_n^{it+1} = \underset{p_n}{\arg\min} \; C_n^M(p_n, q_n, \alpha_n, \beta_n) + M(q_{imp}, q_{exp}) + \lambda_n^{it} q_n + \frac{\rho}{2}(q_n^{it} - (q_n^{it-1} - 2\bar{q}^{it-1}))^2 \quad (52)$$

$$\bar{q} = \frac{q_n^{it} - q_m^{it}}{2} \quad (53)$$

$$\lambda^{it+1} = \lambda^{it} - \rho(-q_n^{it} - q_m^{it}) \quad (54)$$

s. t. constraints (24), (26)-(29)

$$\left\| \lambda^{it+1} - \lambda^{it} \right\|_2 \le 0.001 \quad (55)$$

4. Test system and simulation results

4.1. Case study and parameters

For the purpose of discussion and illustration, this paper considers a 3-bus system with 6 agents, as depicted in Figure 6. Each bus contains 2 agents, which represent various production and consumption units. Specifically, Agent 1 is a conventional generator, while Agents 2 and 3 represent renewable producers (Agent 2 is a wind generation unit, and Agent 3 is a photovoltaic generation unit). Agents 4, 5, and 6 are industrial and household consumers, respectively. The characteristics of each agent for energy trading and reserve trading are presented in Tables 2 and 3. To implement a hybrid-P2P market structure, the test network shown in Figure 7 is considered. This network comprises two communities, each with two peers and a manager (coordinator), along with two individual peers in the grid.

4.2. Simulation results

The proposed centralized, decentralized, and distributed optimization models were implemented in Python using the Pyomo optimization framework [29], [30] and solved using the Gurobi optimizer [31]. The simulations were conducted on a PC equipped with an Intel(R) Core(TM) i7-4510U processor operating at 2.00–2.60 GHz, 8 GB RAM, and a 64-bit operating system.

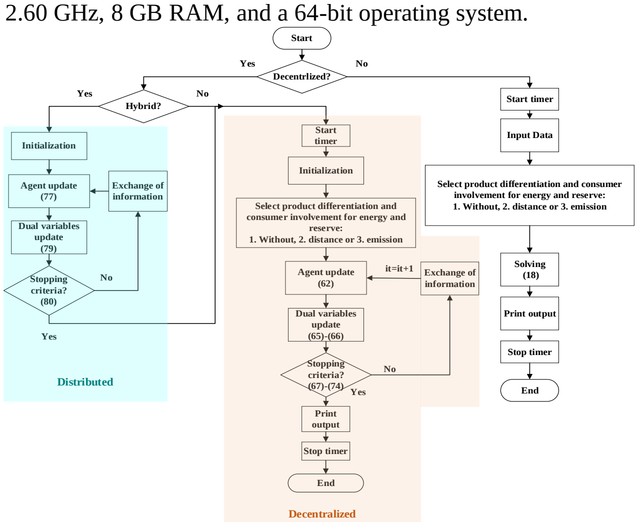

Fig 5. Flowchart of centralized, decentralized and hybrid mechanisms

Table 2. Each agent's data for energy trading.

Agent Number	Agent Type	Bus	a_n^p [\$/MW^2]	b_n^p [\$/MW]	$\bar{P}_n$ [MW]	$\underline{P}_n$ [MW]
1	conventional	1	0.03	18.2	100	0
2	renewable	2	0.013	5.3	15	15
3	renewable	3	0.014	7.3	17	17
4	industrial	1	0.03	13	-10	-30
5	Household	2	0.03	13.8	-15	-25
6	Household	3	0.028	10.5	-12	-20

Table 3. Each agent's data for reserve trading.

Agent Number	Agent Type	Bus	a_n^r [\$/MW^2]	b_n^r [\$/MW]	$\bar{R}_n$ [MW]	$\underline{R}_n$ [MW]
1	conventional	1	0.015	6.1	17	0
2	renewable	2	0	1	-4.8	-4.8
3	renewable	3	0	1	-6.9	-6.9
4	industrial	1	0.015	7.9	10	0
5	Household	2	0.01	6.8	8	0
6	Household	3	0.014	8.8	6	0

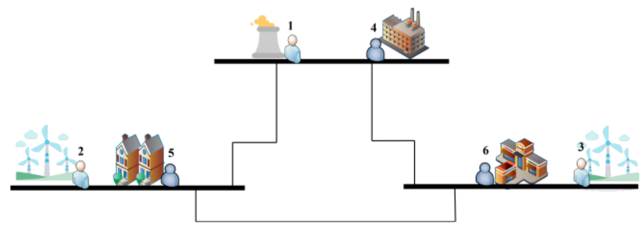

Fig 6. Test system.

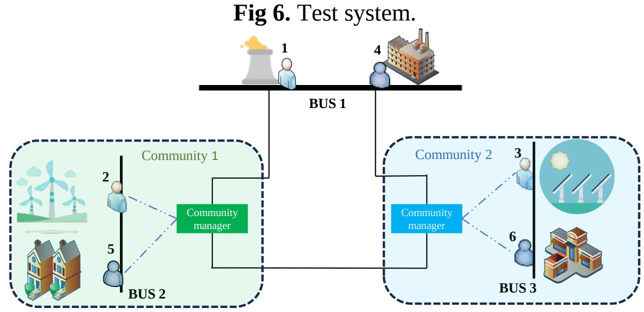

Fig 7. Hybrid P2P-community based test system.

4.2.1. Effect of the Penalty Factor on the Results

The results comparing centralized and decentralized solving methods without product differentiation for energy and reserve trading are presented in Figures 8 and 9. As shown in Figure 8, the system's total cost is lower when the optimization problem is solved centrally. The penalty factor in the consensus ADMM algorithm significantly influences the overall system cost function, particularly when this factor is high. When the penalty factor is low, the objective function in both centralized and decentralized solutions become nearly identical. Figure 9 illustrates the effect of the penalty factor on solving time. As observed, a higher penalty factor reduces the solution time but decreases its accuracy. However, the centralized solution remains substantially faster. The Python time module was used to measure the execution time of the code. From the results, it is evident that increasing the penalty parameter enhances the speed of the optimization problem's solution, although this comes at the cost of greater deviation from the solution obtained through the centralized approach.

4.2.2. Influence of Product Differentiation Mechanisms on Market Clearing Prices

Figures 10(a) and 10(b) illustrate the impact of product differentiation between agents 1 and 5 (with agent 1 as the energy supplier and agent 5 as the energy consumer) on energy prices. As observed, in the centralized solution approach (Figure. 10(a)), an increase in the coefficient affects only the bilateral trading price between agents 1 and 5. However, in the decentralized solution approach (Figure. 10(b)), a slight impact is also observed on the prices of other agents. Similarly, Figures 10(c) and 10(d) depict the impact of product differentiation between agents 1 and 3 (with agent 1 as the reserve supplier and agent 3 as the reserve consumer) on reserve prices. In the centralized solution approach (Figure. 10(c)), an increase in the coefficient affects only the price between agents 1 and 3, whereas in the decentralized solution approach (Figure. 10(d)), a minor influence is also observed on other prices.

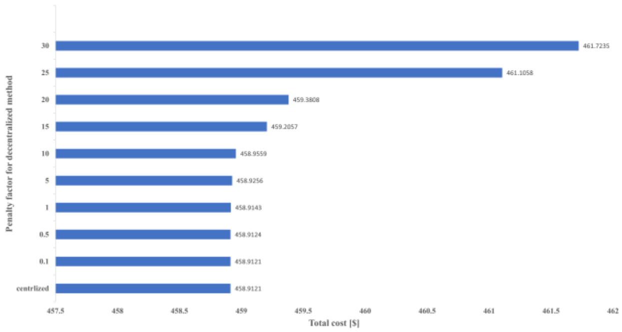

Fig 8. Decentralized algorithm penalty factor impact on system total cost.

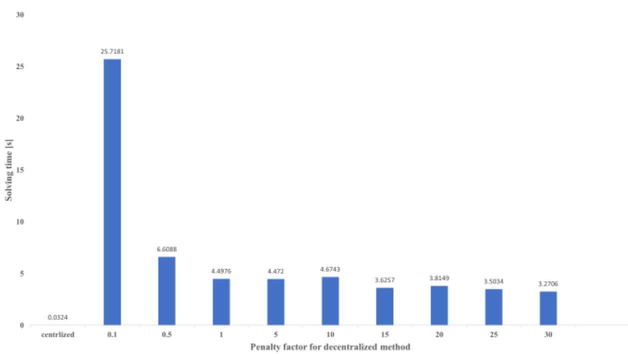

Fig 9. Decentralized algorithm penalty factor impact on solving time.

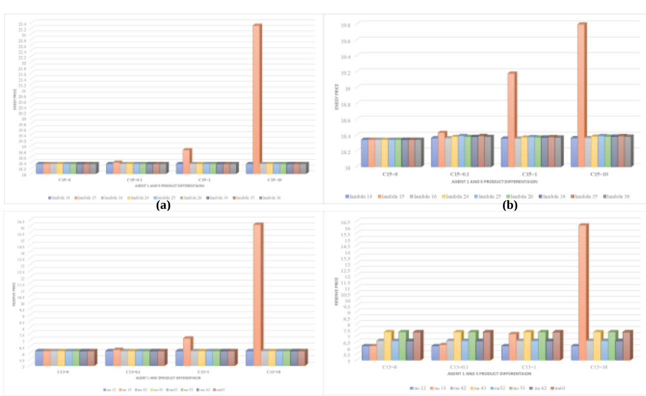

Fig 10. Effect of product differentiation on energy price (a) in centralized (b) in decentralized optimization, effect of product differentiation on reserve price (c) in centralized (d) in decentralized optimization, effect of product.

4.2.3. Product differentiation based on economic cost

In the hybrid system where both communities and independent agents coexist, each community operator determines the internal energy trading price together with the corresponding import and export prices based on the selected market parameters. Table 4 presents the results associated with the two communities solved using the distributed framework. In this section, the hybrid market mechanism together with product differentiation is used to regulate the amount of energy exchanged between communities according to their export prices. According to the simulation results, community 1 acts as an energy exporter because its production exceeds its consumption, whereas community 2 operates as an importer due to its higher demand. The simulations further show that different product-differentiation coefficients can influence not only the exchanged energy between communities and peers, but also the objective values of individual agents. This behavior results from the decentralized coordination structure of the hybrid market mechanism. Table 5 illustrates the effects of varying product-differentiation coefficients on the exchanged energy and the objective value of Agent 1. As observed, the product-differentiation coefficients enable the system operator to reduce the operational cost of Agent 1, which corresponds to the conventional generation unit.

4.2.4. Transformations in Decentralized Market Behavior

From another perspective, the proposed coefficients can be used to modify decentralized market outcomes. As illustrated in Table 6, two groups of coefficients are introduced: one group steers the decentralized market toward centralized-like behavior, while the other drives the market toward hybrid-P2P operating characteristics. By applying the first group of coefficients, the decentralized market outcome becomes similar to that of a centralized market. In contrast, the second group of coefficients induces market behavior consistent with the hybrid-P2P structure. Consequently, modifying the coefficients can alter the effective market behavior and cause the resulting trading patterns to resemble those of alternative market structures. As shown in Figure 11, the application of the centralization-oriented coefficients causes the exchanged power profiles to closely match those obtained under the centralized market framework, resulting in nearly overlapping curves. Similarly, Figure 12 demonstrates that the coefficients associated with hybrid-P2P behavior produce exchanged-power profiles consistent with those of the hybrid market structure. These coefficients also affect market prices. As presented in Table 7, the introduction of the proposed coefficients increases both the overall price levels and the price variations among peers. In particular, the coefficients associated with hybrid-P2P behavior exhibit a stronger influence on market prices and lead to a more pronounced price increase.

Table 4. Data and simulation results for community 1 & community 2

Community	γ_{com}	γ_{imp}	γ_{exp}	Generation	Consumption	Import/export	Community price
1	0.001	19	20	6.75	1.75	5 (export)	19.9
2	0.5	18	19	4.9	9.9	5 (import)	17.5

Table 5. The effects of varying product differentiation coefficients on the exchanged energy and the objective function of Agent 1.

Product differentiation	0	0.1	0.2	0.5	10	20	30	40
Peer 1 to peer 4	6.214	6.20	6.199	6.198	6.635	6.965	6.402	6.011
Peer 1 to community 2	3.876	3.916	3.915	3.914	3.406	3.114	3.704	4.064
Peer 1 objective function [$]	199.78	196.59	196.57	196.51	195.60	195.04	193.45	192.29

Table 6. Coefficients to change the decentralized P2P market structure

Changing to Centralized behaving	Changing to Hybrid behaving
c14=0	c14=0
c15=0.09	c15=0.6
c16=0.08	c16=0.65
c24=0.008	c24=0.5
c25=0.018	c25=0
c26=0	c26=0.07
c34=0.1	c34=0.8
c35=0	c35=0.5
c36=0.07	c36=0

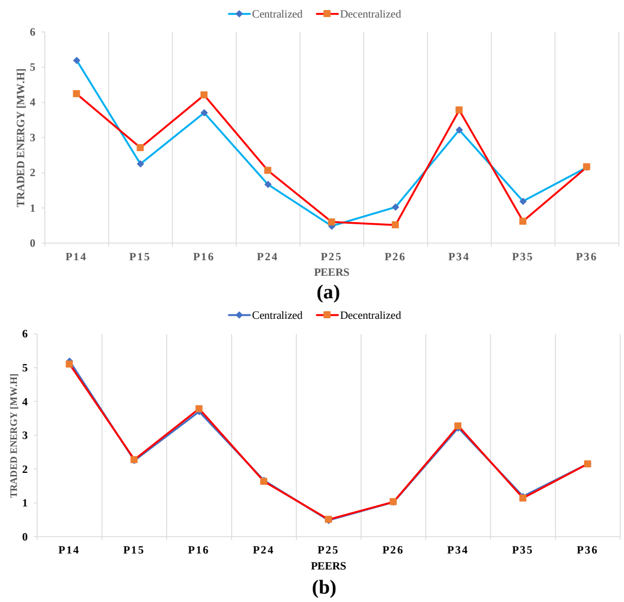

Fig 11. Transition in market participants' behavior from a decentralized to a centralized structure: (a) without coefficients, (b) with coefficients.

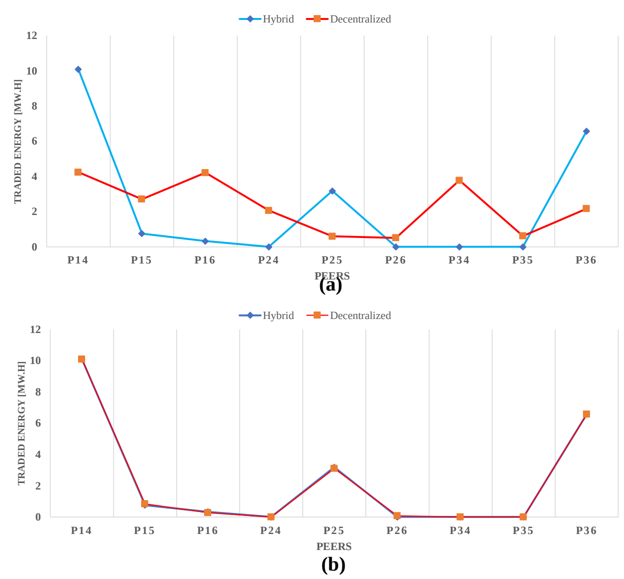

Fig 12. Market participants' behavior transitioning from decentralized P2P to hybrid P2P: (a) without coefficients, (b) with coefficients.

4.2.5. Analysis of the Convergence Process

As illustrated in the decentralized section of the flowchart, convergence is assessed using predefined stopping criteria. All stopping tolerances are set to 0.001 and include the primal (SP) and dual (TP) residuals associated with energy trading, as well as the primal (SR) and dual (TR) residuals associated with reserve trading. The corresponding formulations are given in (71)– (74). The evolution and convergence behavior of these residuals are illustrated in Fig. 13.

Table 7. Impact of market changes on trading prices.

price	Decentralized without coefficient	Changing to Centralized behaving	Changing to Hybrid behaving
lambda 14	18.562	18.582	18.536
lambda 15	18.562	18.642	19.12
lambda 16	18.562	18.635	19.172
lambda 24	18.596	18.595	19.125
lambda 25	18.596	18.602	19.096
lambda 26	18.596	18.59	19.158
lambda 34	18.596	18.435	19.118
lambda 35	18.596	18.369	19.241
lambda 36	18.596	18.415	19.156

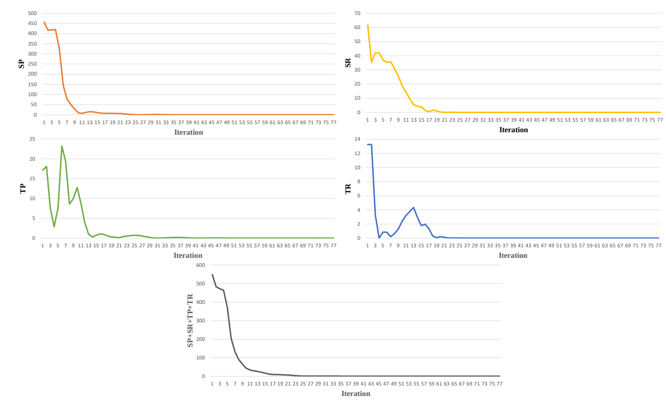

Fig 13. Convergence process of primal and dual energy and reserve residuals.

4.2.6. Scalability and computational burden

Although the case study is intentionally small to provide clear insight into market-structure effects, the proposed implementations are structured to support larger P2P settings. From a computational standpoint, both consensus ADMM (decentralized) and exchange ADMM (distributed) decompose the global optimization problem into local subproblems solved independently by individual agents or communities. From a communication standpoint, each ADMM iteration requires exchanging updated coupling variables over active trading links. Therefore, the communication burden grows approximately linearly with the number of active links |E| and, for sparse trading graphs, approximately linearly with the number of agents. If one communication step is defined as sending one scalar over one link in one direction, then the number of exchanged scalars per ADMM iteration is on the order of 4|E| for sharing the bilateral energy and reserve variables (p_{nm}, r_{nm}) in both directions, and 8|E| if the associated dual variables are also exchanged. In the proposed hybrid design, scalability is further improved by solving intra-community trades locally while reducing the dimensionality of inter-community negotiations. Nevertheless, a full feeder-scale validation and a systematic runtime and iteration benchmark for systems with hundreds of agents remain important directions for future work. Table 8 presents the scalability benchmark of the decentralized consensus-ADMM clearing in terms of runtime, ADMM iteration count, and communication overhead as the number of agents increases.

4.2.7. Sensitivity to Renewable Penetration and Agent Diversity

The proposed framework is also sensitive to the composition of market participants and the penetration level of renewable energy resources through the agents' technical and economic parameters. In general, higher renewable penetration increases local energy availability and may reduce average energy prices, while simultaneously increasing reserve requirements due to renewable variability and uncertainty. Similarly, changes in the diversity of participating agents, such as increasing the share of residential consumers relative to industrial consumers, modify the market equilibrium and trading patterns because of different consumption profiles, flexibility levels, and cost characteristics. Nevertheless, the qualitative behavior of the proposed centralized, decentralized, and hybrid clearing mechanisms, as well as the observed impact of product differentiation coefficients, remains consistent under different agent compositions. A systematic sensitivity analysis with larger and more diverse agent populations is considered an important direction for future work.

Table 8. Scalability benchmark of the decentralized consensus-ADMM clearing.

Agents	ADMM iterations	Runtime [s]	Communication (scalars)
6	66	51.0983919	2244
12	105	220.826003	14280
18	140	331.9304671	42840
24	185	539.2457151	100640

4.2.8. Practical implementation considerations

In practical applications, the proposed hybrid P2P framework can be implemented incrementally as an overlay market layer coordinated by a distribution system operator (DSO), local market operator, or dedicated P2P platform provider. Communities may be organized based on feeder topology, geographical proximity, contractual relationships, or shared operational objectives. Within each community, a local coordinator or community manager can facilitate internal market clearing and settlement, while inter-community transactions are negotiated through decentralized trading mechanisms subject to network usage tariffs and market regulations. The proposed structure is also consistent with emerging regulatory concepts such as local energy communities, transactive energy frameworks, and local flexibility markets. In this context, transparent settlement procedures, communication standards, and privacy-preserving information exchange become important practical considerations for real-world deployment.

4.2.9. Multi-Energy and Ancillary-Service Extensions

The proposed framework is inherently modular and can be extended to incorporate additional energy carriers and ancillary services. In multi-energy settings, the agent models can be augmented with carrier-balance equations, energy-conversion constraints (e.g., power-to-heat or electricity-gas coupling), and carrier-specific operational cost functions. Similarly, ancillary services beyond reserve trading, such as frequency response, voltage support, and local flexibility products, can be integrated by introducing additional service variables and performance constraints within the existing market-clearing structure. These extensions would enable the proposed centralized, decentralized, and hybrid P2P mechanisms to support integrated multi-energy community markets and broader flexibility-management applications.

5. Conclusions

The increasing integration of distributed energy resources (DERs), renewable generation, and demand response programs requires more flexible and decentralized market mechanisms for future power systems. In this paper, a joint peer-to-peer (P2P) market framework for energy and reserve trading with product differentiation was developed and analyzed under centralized, decentralized, and hybrid market-clearing structures. The proposed formulations were solved using centralized optimization as well as ADMM-based decentralized and distributed approaches. The results demonstrated the trade-off between centralized coordination and decentralized market clearing in terms of objective value, computation time, convergence behavior, and communication burden. In particular, the analysis showed that product-differentiation coefficients significantly influence market prices, traded quantities, and agent-level economic outcomes. The numerical results further revealed that, in the decentralized framework, price variations propagate through neighboring trading interactions and lead to broader market-wide adjustments, whereas in the centralized framework, price changes remain more localized to directly affected participants. In addition, the proposed coefficient-setting strategies enable decentralized market behavior to be steered toward centralized-like or hybrid operating characteristics. Finally, the convergence properties of the proposed ADMM-based clearing mechanisms were evaluated through primal and dual residual analysis for both energy and reserve trading. Future work will focus on multi-period and stochastic formulations, explicit reserve activation dynamics, network-constrained market clearing, and extensions to larger-scale and multi-energy P2P systems.

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