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Research paper

Psychological modeling for community energy systems

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ABSTRACT

This paper introduces a novel framework for community energy system (CES) optimization that integrates Social Cognitive Theory (SCT) with Distributionally Robust Optimization (DRO) to address both behavioral and technical challenges. The rapid integration of renewable energy resources and the proliferation of peer-to-peer (P2P) trading platforms necessitate solutions that balance economic efficiency, environmental sustainability, and user engagement under uncertainty. While existing studies focus predominantly on technical optimization, they often neglect the significant influence of behavioral dynamics on community energy systems. This research bridges the gap by explicitly incorporating peer influence, observational learning, and engagement incentives into a robust optimization framework. The proposed methodology models user behavior through SCT, enabling dynamic adjustments to trading patterns and energy-sharing decisions. A DRO model is employed to handle uncertainties in renewable energy generation and demand, ensuring system reliability and resilience. To enhance computational efficiency, a primal–dual algorithm is developed, offering faster convergence compared to traditional DRO methods. The framework is validated through a comprehensive case study on a 50-household microgrid equipped with solar, wind, and storage systems, alongside a P2P trading platform. Results demonstrate the framework's ability to reduce carbon emissions by up to 30%, improve renewable energy utilization to over 90%, and increase trading participation by 25%, compared to baseline scenarios. This study makes four key contributions: (1) introducing SCT-based behavioral modeling to enhance user engagement in CES operations, (2) leveraging DRO to address uncertainties in renewable energy and demand profiles, (3) proposing a primal–dual algorithm for scalable and efficient optimization, and (4) presenting a unified framework that balances economic, environmental, and social objectives. The findings highlight the transformative potential of integrating behavioral and technical approaches for sustainable and resilient community energy management.

1. Introduction

The rapid proliferation of renewable energy resources, along with the emergence of integrated energy systems (IES) (Long et al., 2018; Zhang et al., 2018), has revolutionized the way energy is generated, stored, and consumed. As nations strive to meet ambitious decarbonization goals, community energy systems (CES) have garnered significant attention as they embody a decentralized approach to energy management (Tian et al., 2016). By enabling prosumers–those who both produce and consume energy–to engage in energy-sharing and peer-to-peer (P2P) trading within localized energy networks, these systems offer unparalleled opportunities for optimizing energy utilization, enhancing sustainability, and fostering social equity (Wang et al., 2019, 2020). However, the operation and management of such systems remain fraught with challenges. Variability in renewable energy generation, uncertainties in demand profiles, and the complexities of user behavior introduce significant unpredictability into IES (Montakhabi et al., 2020). Compounding these issues is the need to balance economic efficiency with community engagement, environmental sustainability, and resilience against uncertainties. Traditional optimization frameworks often fail to capture the intricate interplay between these dimensions, especially the behavioral dynamics of users that are critical to the success of P2P trading and energy-sharing initiatives.

While extensive research has explored the technical optimization of IES, few studies address the human-centric aspects that underpin community energy systems. Behavioral factors such as peer influence,

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social learning, and risk perceptions have a profound impact on how users interact with P2P platforms and engage in energy-sharing behaviors. Ignoring these dimensions risks undermining the adoption and long-term viability of such systems. Moreover, existing optimization methods often struggle to incorporate the stochastic nature of renewable energy and demand variations into robust, computationally efficient frameworks. This gap in the literature underscores the pressing need for an integrated approach that combines advanced optimization techniques with behavioral modeling. The motivation for this paper arises from these critical gaps. We aim to develop a novel framework that integrates Social Cognitive Theory (SCT) into the optimization of community energy management systems. By leveraging SCT, this study captures the behavioral dynamics of community members, such as peer influence, observational learning, and engagement incentives, to enhance user participation and system performance. Furthermore, we employ a Distributionally Robust Optimization (DRO) model to address uncertainties in renewable energy generation and demand. To overcome the computational challenges typically associated with DRO, we propose a primal–dual algorithm that ensures faster convergence while maintaining robust performance under uncertain conditions.

This paper presents a comprehensive framework that integrates SCT-based behavioral modeling with DRO for the optimal operation of community energy systems. The modeling process incorporates user-centric dynamics, such as peer influence and observational learning, to create a participatory ecosystem where users are incentivized to share energy and engage in trading activities. At the same time, the DRO framework captures worst-case scenarios for renewable energy and demand uncertainties, ensuring the system remains robust and reliable. The optimization problem is formulated with a multi-layered structure. The objective function minimizes the total system cost while maximizing P2P trading revenues and penalizing carbon emissions. Behavioral dynamics are modeled as constraints that incorporate social influence and engagement metrics into the optimization process. To solve this complex problem efficiently, we propose a primal–dual algorithm that iteratively updates the primal and dual variables, ensuring faster convergence compared to traditional methods. This paper makes the following four key contributions:

1. Behavioral Modeling with Social Cognitive Theory: We introduce SCT as a foundation for modeling user behavior in community energy systems. By incorporating peer influence, observational learning, and engagement incentives into the optimization framework, we address the human-centric factors that drive participation in P2P trading and energy sharing.

2. Distributionally Robust Optimization for Uncertainty Management: A DRO framework is employed to handle stochastic variations in renewable energy generation and demand. This ensures the system remains reliable and resilient under worst-case scenarios, addressing a critical gap in existing optimization methods.

3. Primal-Dual Algorithm for Faster Convergence: To overcome the computational challenges of DRO, we develop a primal–dual algorithm that accelerates the solution process while maintaining robust performance. This makes the proposed framework scalable to large and complex community energy systems.

4. Comprehensive Framework Balancing Multiple Objectives: The proposed framework integrates economic, environmental, and social dimensions into a unified optimization model. By balancing cost efficiency, carbon reduction, and community engagement, this study sets a new standard for holistic energy system management.

2. Literature review

The evolution of IES and community energy management frameworks has catalyzed a significant body of research focusing on optimizing energy generation, storage, and distribution. This section reviews the relevant literature across four primary areas: (1) optimization in community energy systems, (2) behavioral modeling in energy management, and (3) uncertainty management using DRO. These discussions establish the context for the proposed framework and underscore its novelty and contributions.

CESs have emerged as a cornerstone of the energy transition, enabling decentralized, participatory energy management (Ma et al., 2019; Moazeni et al., 2020). Optimization models have played a critical role in improving the operational efficiency of these systems. Early research predominantly focused on technical aspects, such as balancing supply and demand, enhancing grid stability, and integrating renewable energy sources (Lu et al., 2020). For instance, centralized optimization frameworks have been employed to coordinate energy flows in microgrids, considering generation constraints and system reliability (Almohaimeed, 2025). Recent studies have expanded the scope to include P2P energy trading, which allows prosumers to trade excess energy within their communities. P2P trading frameworks often use game-theoretic or auction-based models to optimize trading volumes and prices. However, these models typically prioritize economic efficiency while overlooking user behaviors and social dynamics, which are pivotal for sustaining participation in community energy systems (Daneshvar et al., 2022; Gan et al., 2021). Moreover, while optimization methods like mixed-integer linear programming (MILP) and dynamic programming have been widely adopted, their computational intensity restricts scalability to large systems.

The role of user behavior in energy systems has gained increasing recognition, particularly in the context of demand-side management and P2P trading. Behavioral theories provide a structured approach to understanding and influencing user actions. Among these, SCT has been widely applied in domains such as health and education but remains underexplored in energy management (Schunk, 2012; Luszczynska and Schwarzer, 2015). Several studies have investigated the impact of peer influence and social norms on energy consumption. For example, social comparison techniques, such as displaying energy usage relative to neighbors, have been shown to encourage energy-saving behaviors. Similarly, reward mechanisms and gamification strategies have been employed to enhance user engagement in renewable energy adoption and demand response programs (Komendantova et al., 2018; Thøgersen and Grønhøj, 2010). Despite these advances, few optimization frameworks explicitly incorporate behavioral dynamics. Existing models often treat user participation as exogenous, failing to account for the iterative and interactive nature of community behaviors. This gap motivates the inclusion of SCT in the proposed framework. By modeling peer influence, observational learning, and engagement incentives, this study captures the complex interplay between social dynamics and energy trading decisions, enabling more effective and sustainable community energy systems.

Uncertainty is an inherent challenge in community energy systems, driven by the variability of renewable energy sources and fluctuations in demand. Traditional optimization approaches often rely on stochastic programming or robust optimization to address these uncertainties (Summers et al., 2015; Vahid-Pakdel et al., 2017). While stochastic programming models probabilistic scenarios, they require precise knowledge of probability distributions, which is often unavailable in practice (Agalgaonkar et al., 2015). Robust optimization, on the other hand, focuses on worst-case scenarios but can be overly conservative, leading to suboptimal decisions (Chen et al., 2016; He et al., 2018). DRO has emerged as a promising alternative, offering a balance between robustness and flexibility. DRO models optimize performance under the worst-case distribution within a predefined uncertainty set, enabling more realistic and practical decision-making (Li et al., 2024; Zhu et al., 2024). Recent applications of DRO in energy systems include optimizing renewable energy integration, scheduling energy storage, and managing demand response programs. However, these applications typically focus on technical uncertainties and do not consider behavioral variability, which is critical in community energy systems. The proposed framework extends the application of DRO by incorporating

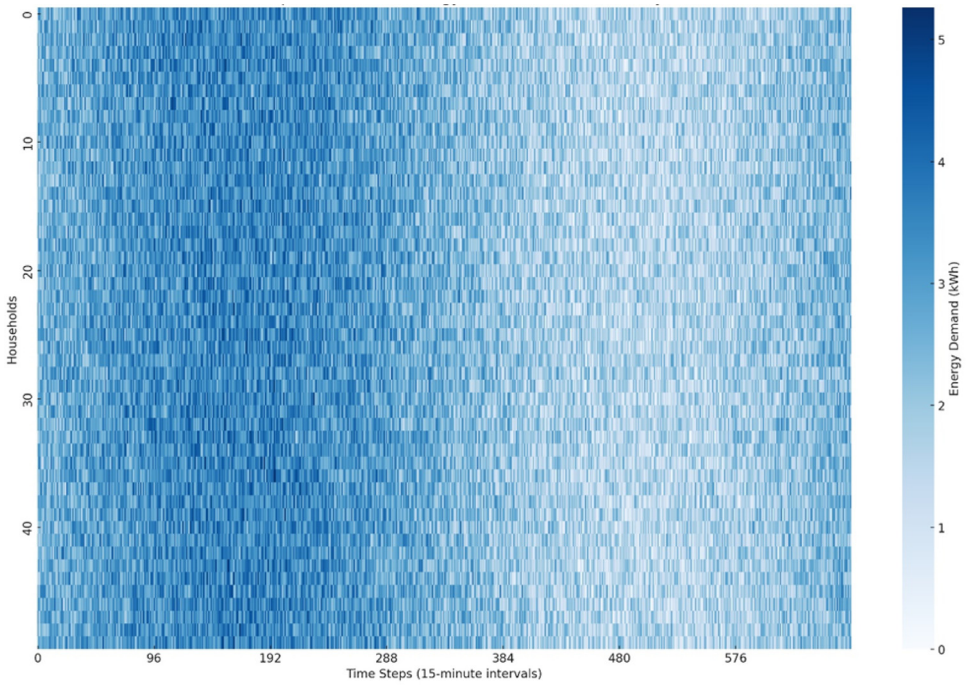


Fig. 1. Heatmap of weekly household energy demand profiles.

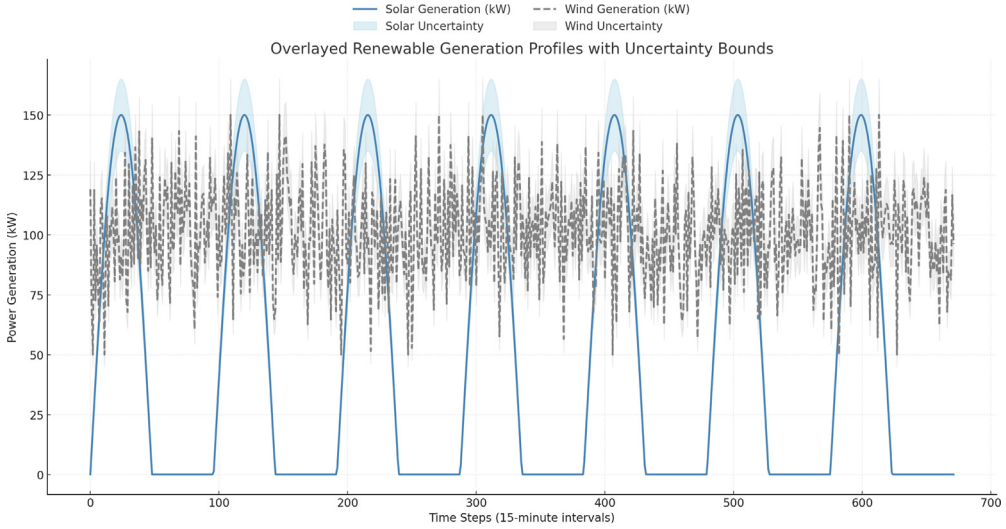


Fig. 2. Overlayed renewable generation profiles with uncertainty bounds.

both technical and behavioral uncertainties. For example, variability in renewable energy generation is modeled through uncertainty sets, while user behavior is captured using SCT-based dynamics. This dual focus ensures a robust and comprehensive approach to uncertainty management.

3. Mathematical modeling

This section presents the mathematical formulation of the proposed framework for community energy management, integrating behavioral dynamics and distributionally robust optimization. The model captures the operational complexities of the system, including renewable energy generation, storage operations, P2P trading, and user behavior. A multi-objective approach is adopted to minimize total system costs, maximize social engagement, and ensure carbon reduction under uncertainty. The problem is structured into an objective function and a comprehensive set of constraints, explicitly incorporating technical and social dimensions of the energy network. The following equations detail the formulation:

$$\text{Minimize } \Phi = \sum_{t=1}^{T}\left(\sum_{i=1}^{N}\left(\kappa_g^{\omega}\cdot\zeta_{i,t}^{\text{gen}}+\xi_s^{\omega}\cdot\psi_{i,t}^{\text{stor}}\right)-\sum_{j=1}^{M}\pi_{j,t}^{\omega}\cdot\lambda_{j,t}^{\text{trade}}+\sigma_{\text{CO}_2}\cdot\chi_t^{\text{carbon}}\right) \tag{1}$$

This equation represents the total cost function for the community energy management system, which combines the costs of energy generation ($\zeta_{i,t}^{\text{gen}}$), storage operation ($\psi_{i,t}^{\text{stor}}$), and revenue from peer-to-peer trading ($\lambda_{j,t}^{\text{trade}}$), while penalizing carbon emissions (χ_t^{carbon}). The time index t, generation nodes N, and trading nodes M are explicitly modeled, with coefficients $\kappa_g^{\omega}, \xi_s^{\omega}, \pi_{j,t}^{\omega}$, and σ_{CO_2} representing unit costs

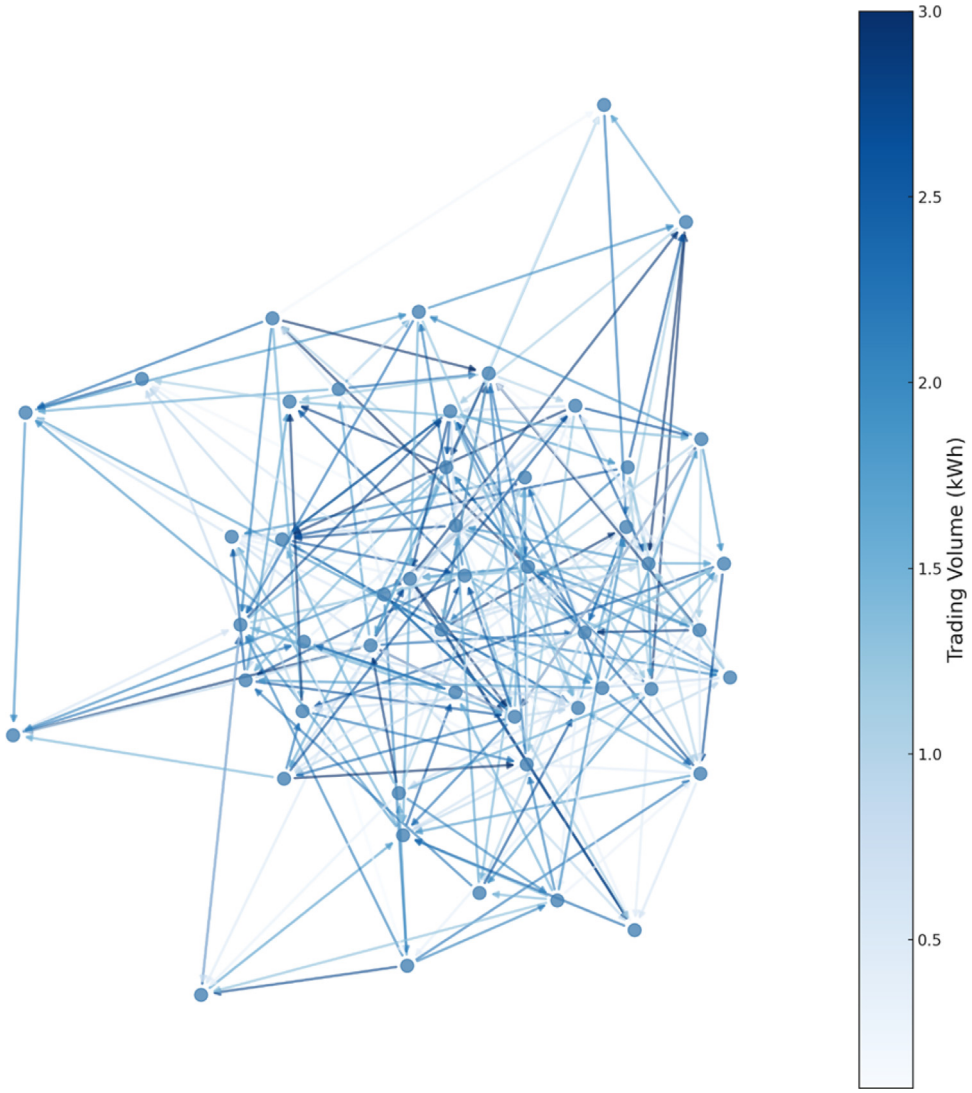


Fig. 3. P2P trading network visualization.

and penalties under distributional uncertainty ω.

$$\sum_{i=1}^{N} \kappa_g^{\omega} \cdot \zeta_{i,t}^{\text{gen}} = \sum_{t=1}^{T} \sum_{\omega \in \Omega} \left(\eta_{\text{PV}}^{\omega} \cdot \phi_{i,t}^{\text{PV}} + \eta_{\text{Wind}}^{\omega} \cdot \phi_{i,t}^{\text{Wind}} + \eta_{\text{Bio}}^{\omega} \cdot \phi_{i,t}^{\text{Bio}} \right) \tag{2}$$

The renewable energy generation cost minimization term $\sum_{i=1}^{N} \kappa_g^{\omega} \cdot \zeta_{i,t}^{\text{gen}}$ captures the energy produced by photovoltaic ($\phi_{i,t}^{\text{PV}}$), wind ($\phi_{i,t}^{\text{Wind}}$), and biomass systems ($\phi_{i,t}^{\text{Bio}}$). Each source is scaled by its efficiency $\eta_{\text{Source}}^{\omega}$ under uncertain realizations $\omega \in \Omega$, reflecting stochastic production variability.

$$\sum_{i=1}^{N} \xi_s^{\omega} \cdot \psi_{i,t}^{\text{stor}} = \sum_{t=1}^{T} \sum_{\omega \in \Omega} \left(\frac{\xi_{\text{charge}}^{\omega} \cdot \theta_{i,t}^{\text{charge}}}{\eta_{\text{charge}}} - \eta_{\text{discharge}} \cdot \xi_{\text{discharge}}^{\omega} \cdot \theta_{i,t}^{\text{discharge}} \right) \tag{3}$$

The storage operation cost minimization term $\sum_{i=1}^{N} \xi_s^{\omega} \cdot \psi_{i,t}^{\text{stor}}$ models charging ($\theta_{i,t}^{\text{charge}}$) and discharging ($\theta_{i,t}^{\text{discharge}}$) processes. Storage efficiency ($\eta_{\text{charge}}, \eta_{\text{discharge}}$) and uncertainty-adjusted unit costs ($\xi_{\text{charge}}^{\omega}$, $\xi_{\text{discharge}}^{\omega}$) are incorporated to ensure system reliability under fluctuating demands.

$$\sum_{j=1}^{M} \pi_{j,t}^{\omega} \cdot \lambda_{j,t}^{\text{trade}} = \sum_{t=1}^{T} \sum_{j=1}^{M} \left(\nu_{j,t}^{\text{buy}} - \nu_{j,t}^{\text{sell}} \right) \cdot \left(\frac{\alpha_{j,t}^{\text{risk}}}{1 + \rho_{j,t}^{\text{aversion}}} \right) \tag{4}$$

The P2P trading revenue term accounts for the trading volumes ($\nu_{j,t}^{\text{buy}}, \nu_{j,t}^{\text{sell}}$) adjusted by user-specific risk perceptions ($\alpha_{j,t}^{\text{risk}}$) and risk aversion coefficients ($\rho_{j,t}^{\text{aversion}}$). This reflects behavioral tendencies in trading decisions, crucial for capturing realistic dynamics in the community energy system.

$$\sigma_{\text{CO}_2} \cdot \chi_t^{\text{carbon}} = \sum_{t=1}^{T} \left(\sum_{i=1}^{N} \tau_{i,t}^{\text{carbon}} \cdot \mu_{i,t}^{\text{gen}} + \sum_{j=1}^{M} \tau_{j,t}^{\text{trade}} \cdot \nu_{j,t}^{\text{exchange}} \right) \cdot \gamma_{\text{penalty}}^{\omega} \tag{5}$$

This carbon emissions penalty term accounts for the emissions produced during generation ($\mu_{i,t}^{\text{gen}}$) and P2P energy exchanges ($\nu_{j,t}^{\text{exchange}}$). The carbon intensity coefficients ($\tau_{i,t}^{\text{carbon}}, \tau_{j,t}^{\text{trade}}$) are scaled by a penalty factor ($\gamma_{\text{penalty}}^{\omega}$) to internalize the environmental costs of carbon emissions under uncertain conditions.

$$\text{Robust Cost: } \mathcal{R} = \max_{\omega \in \Omega} \left\{ \sum_{t=1}^{T} \left(\Phi^{\omega} + \sum_{i=1}^{N} \mathcal{V}_{i,t}^{\omega} \cdot \psi_{i,t}^{\text{stor}} + \sum_{j=1}^{M} C_{j,t}^{\omega} \cdot \lambda_{j,t}^{\text{trade}} \right) \right\} \tag{6}$$

The robust cost function evaluates the system's worst-case performance across the uncertainty set Ω. The additional terms $\mathcal{V}_{i,t}^{\omega}$ and $C_{j,t}^{\omega}$

account for uncertainty-adjusted costs in storage operations and trading, ensuring resilience in decision-making against variable conditions.

$$\text{Risk-Adjusted Objective: } \Psi = \Phi + \beta_{\text{reward}} \cdot \left(\sum_{i=1}^{N} \mathcal{F}_{i,t}^{\text{social}} + \sum_{j=1}^{M} \mathcal{H}_{j,t}^{\text{engage}} \right) \tag{7}$$

The risk-adjusted objective incorporates community feedback rewards, modeled through social interaction metrics ($\mathcal{F}_{i,t}^{\text{social}}$) and engagement incentives ($\mathcal{H}_{j,t}^{\text{engage}}$). A weight factor ($\beta_{\text{reward}}$) determines the significance of these behavioral contributions, enhancing user participation in energy sharing and trading.

$$\mathcal{F}_{i,t}^{\text{social}} = \sum_{k \neq i} \alpha_{k,t}^{\text{peer}} \cdot \left(v_{k,t}^{\text{share}} - v_{i,t}^{\text{trade}} \right)^2 \cdot \delta_{i,k}^{\text{interaction}} \tag{8}$$

The weighted social influence term captures the deviation between peers' energy sharing behaviors ($v_{k,t}^{\text{share}}, v_{i,t}^{\text{trade}}$), modulated by interaction strengths ($\delta_{i,k}^{\text{interaction}}$). Peer influence coefficients ($\alpha_{k,t}^{\text{peer}}$) reflect the SCT-driven dynamics of community-based energy exchanges.

$$\text{Final DRO Objective: } \Theta = \mathcal{R} + \Psi + \gamma_{\text{participation}} \cdot \sum_{j=1}^{M} v_{j,t}^{\text{trade}} \tag{9}$$

The final objective combines the robust cost ($\mathcal{R}$), risk-adjusted feedback (Ψ), and a participation incentive term ($\gamma_{\text{participation}}$) to drive both economic and social optimization in the community energy management framework. This ensures that the DRO model aligns operational, environmental, and community participation goals effectively.

$$\text{Energy Balance: } \sum_{i=1}^{N} \zeta_{i,t}^{\text{gen}} + \sum_{i=1}^{N} \psi_{i,t}^{\text{stor}} = \sum_{j=1}^{M} v_{j,t}^{\text{demand}} + v_{j,t}^{\text{loss}} \tag{10}$$

The energy balance equation ensures that the total energy generated ($\zeta_{i,t}^{\text{gen}}$) and the net storage contribution ($\psi_{i,t}^{\text{stor}}$) meet the aggregated community demand ($v_{j,t}^{\text{demand}}$) and system losses ($v_{j,t}^{\text{loss}}$). This guarantees operational feasibility across all time steps.

$$\psi_{i,t+1}^{\text{stor}} = \psi_{i,t}^{\text{stor}} + \frac{\xi_{i,t}^{\text{charge}}}{\eta_{\text{charge}}} - \eta_{\text{discharge}} \cdot \xi_{i,t}^{\text{discharge}} \tag{11}$$

The storage dynamics constraint models the evolution of stored energy ($\psi_{i,t}^{\text{stor}}$) based on charging ($\xi_{i,t}^{\text{charge}}$) and discharging ($\xi_{i,t}^{\text{discharge}}$) processes. Charging and discharging efficiencies ($\eta_{\text{charge}}, \eta_{\text{discharge}}$) are explicitly included to account for energy losses during these operations.

$$\zeta_{i,t}^{\text{gen}} \leq \zeta_{i,\max}^{\text{gen}} \cdot \gamma_{i,t}^{\omega} \tag{12}$$

This constraint ensures that the generation at node i does not exceed the maximum generation capacity ($\zeta_{i,\max}^{\text{gen}}$), adjusted by the uncertainty factor ($\gamma_{i,t}^{\omega}$), which models stochastic variations in renewable energy availability.

$$v_{j,t}^{\text{demand}} = v_{j,\text{baseline}}^{\text{demand}} + \delta_{j,t}^{\text{behavior}} \tag{13}$$

The demand satisfaction constraint accounts for both baseline energy demand ($v_{j,\text{baseline}}^{\text{demand}}$) and additional contributions ($\delta_{j,t}^{\text{behavior}}$) from user behavior, influenced by social and environmental factors.

$$\sum_{j=1}^{M} v_{j,t}^{\text{loss}} \leq \beta_{\text{loss}} \cdot \sum_{i=1}^{N} \zeta_{i,t}^{\text{gen}} \tag{14}$$

This constraint ensures that system losses ($v_{j,t}^{\text{loss}}$) remain within an acceptable fraction (β_{loss}) of the total generated energy, maintaining system efficiency.

$$\psi_{i,t}^{\text{stor}} \leq \psi_{i,\max}^{\text{stor}} \tag{15}$$

The storage capacity constraint limits stored energy ($\psi_{i,t}^{\text{stor}}$) to the maximum allowable storage capacity ($\psi_{i,\max}^{\text{stor}}$), ensuring physical feasibility of storage operations.

$$\chi_t^{\text{carbon}} \leq \chi_{\text{target}} \tag{16}$$

The carbon emissions constraint ensures that the total emissions at time t (χ_t^{carbon}) remain below a predefined target (χ_{target}), supporting sustainability goals.

$$v_{j,t}^{\text{trade}} = v_{j,t}^{\text{buy}} - v_{j,t}^{\text{sell}} \tag{17}$$

This P2P trading constraint models the net trading volume ($v_{j,t}^{\text{trade}}$) for each participant j as the difference between energy bought ($v_{j,t}^{\text{buy}}$) and sold ($v_{j,t}^{\text{sell}}$), enabling energy sharing across the community.

$$\mathcal{U}_{\text{renewable}} = \left\{ \gamma_{i,t}^{\omega} : \sum_{t=1}^{T} \left| \gamma_{i,t}^{\omega} - \hat{\gamma}_{i,t} \right|^2 \leq \epsilon_{\text{renewable}} \right\} \tag{18}$$

This uncertainty set for renewable generation ($\mathcal{U}_{\text{renewable}}$) defines the bounds on deviations ($\gamma_{i,t}^{\omega} - \hat{\gamma}_{i,t}$) from nominal values, constrained by a tolerance ($\epsilon_{\text{renewable}}$).

$$\mathcal{U}_{\text{demand}} = \left\{ \delta_{j,t}^{\text{behavior}} : \sum_{t=1}^{T} \left| \delta_{j,t}^{\text{behavior}} - \hat{\delta}_{j,t} \right|^2 \leq \epsilon_{\text{demand}} \right\} \tag{19}$$

This uncertainty set for demand ($\mathcal{U}_{\text{demand}}$) captures variations in user behavior ($\delta_{j,t}^{\text{behavior}}$) from expected levels, bounded by a tolerance (ϵ_{demand}).

$$\delta_{i,t}^{\text{interaction}} = \sum_{k \neq i} \alpha_{k,t}^{\text{peer}} \cdot \left(v_{k,t}^{\text{share}} - v_{i,t}^{\text{trade}} \right)^2 \tag{20}$$

This constraint models the peer interaction effect in trading, where $\delta_{i,t}^{\text{interaction}}$ represents the influence of other users' trading behaviors ($v_{k,t}^{\text{share}}$) on participant i. The peer influence coefficients ($\alpha_{k,t}^{\text{peer}}$) reflect the social network dynamics.

$$\mathcal{R}_{\text{interaction}} = \sum_{i=1}^{N} \delta_{i,t}^{\text{interaction}} \cdot \kappa_{i,t}^{\text{reward}} \tag{21}$$

The total reward mechanism integrates the interaction terms ($\delta_{i,t}^{\text{interaction}}$) scaled by reward coefficients ($\kappa_{i,t}^{\text{reward}}$), encouraging behaviors aligned with community energy sharing goals.

$$v_{i,t}^{\text{share}} \geq \gamma_{\text{participation}} \cdot v_{i,t}^{\text{demand}} \tag{22}$$

This participation threshold ensures that every participant contributes at least a fraction ($\gamma_{\text{participation}}$) of their demand to energy sharing, promoting equity in P2P trading.

$$\lambda_{j,t}^{\text{trade}} = \left(v_{j,t}^{\text{buy}} - v_{j,t}^{\text{sell}} \right) \cdot \mathcal{P}_{j,t}^{\text{price}} \tag{23}$$

The trading revenue ($\lambda_{j,t}^{\text{trade}}$) is modeled as the product of net trading volume ($v_{j,t}^{\text{buy}} - v_{j,t}^{\text{sell}}$) and the market price ($\mathcal{P}_{j,t}^{\text{price}}$), capturing the financial aspects of P2P transactions.

$$C_{\text{robust}} = \max_{\mathcal{U}_{\text{renewable}}, \mathcal{U}_{\text{demand}}} \left(\Phi + \mathcal{R}_{\text{interaction}} \right) \tag{24}$$

The robust cost constraint incorporates both the total system cost (Φ) and the rewards from interaction ($\mathcal{R}_{\text{interaction}}$), ensuring resilience under uncertainty in renewable generation and demand variations.

$$\beta_{\text{risk}} \cdot C_{\text{robust}} \leq C_{\text{budget}} \tag{25}$$

The risk-adjusted robust cost is constrained by the available community budget (C_{budget}), ensuring financial feasibility for the optimization framework.

$$\mathcal{H}_{j,t}^{\text{engage}} = \sum_{t=1}^{T} \left(v_{j,t}^{\text{trade}} - v_{j,t}^{\text{baseline}} \right)^2 \tag{26}$$

This engagement metric captures deviations from baseline trading volumes ($v_{j,t}^{\text{baseline}}$), encouraging active participation through targeted rewards.

$$\mathcal{F}_{i,t}^{\text{social}} = \sum_{k \neq i} \delta_{i,k}^{\text{interaction}} \cdot \mathcal{H}_{k,t}^{\text{engage}} \tag{27}$$

The social reward term aggregates the engagement metrics ($\mathcal{H}_{k,t}^{\text{engage}}$) across all interacting peers, weighted by interaction coefficients ($\delta_{i,k}^{\text{interaction}}$).

$$\gamma_{\text{participation}} \cdot \mathcal{H}_{j,t}^{\text{engage}} \leq \mathcal{R}_{j,t}^{\text{reward}} \tag{28}$$

This constraint ensures that engagement-based rewards ($\mathcal{R}_{j,t}^{\text{reward}}$) are proportional to trading activity, fostering sustained involvement in community energy systems.

4. Primal-dual algorithm for DRO

The methodology builds upon the mathematical formulation and outlines the solution strategy for the proposed optimization framework. To address the computational challenges of DRO, a primal–dual algorithm is developed, ensuring faster convergence while maintaining robustness against uncertainty. The algorithm iteratively updates primal and dual variables, leveraging behavioral dynamics modeled through SCT. This section describes the algorithmic design, implementation details, and convergence properties, providing a systematic approach to solving the optimization problem effectively.

$$\Psi = C_{\text{robust}} + \beta_{\text{reward}} \cdot \left(\sum_{i=1}^{N} \mathcal{F}_{i,t}^{\text{social}} + \sum_{j=1}^{M} \mathcal{H}_{j,t}^{\text{engage}} \right) \tag{29}$$

The comprehensive objective function combines the robust cost and social reward components, balancing economic efficiency with community engagement.

$$\mathcal{U}_{\text{risk}} = \left\{ \xi \mid \sum_{t=1}^{T} \left(\xi_{i,t}^{\text{stor}} - \hat{\xi}_{i,t} \right)^2 \leq \epsilon_{\text{stor}} \right\} \tag{30}$$

This uncertainty set bounds storage-related risks ($\xi_{i,t}^{\text{stor}}$) around expected values ($\hat{\xi}_{i,t}$), constrained by tolerance (ϵ_{stor}).

$$\lambda_{j,t}^{\text{risk}} = \left(v_{j,t}^{\text{sell}} - v_{j,t}^{\text{buy}} \right) \cdot \left(\mathcal{P}_{j,t}^{\text{price}} - \mathcal{P}_{j,t}^{\text{volatility}} \right) \tag{31}$$

This risk-aware trading revenue term incorporates price volatility ($\mathcal{P}_{j,t}^{\text{volatility}}$) to account for market fluctuations, influencing trading decisions.

$$\gamma_{\text{robust}} \cdot \mathcal{U}_{\text{risk}} \leq C_{\text{robust}} \tag{32}$$

This constraint ensures that robust cost adjustments ($\gamma_{\text{robust}} \cdot \mathcal{U}_{\text{risk}}$) remain within acceptable limits, preserving financial stability.

$$\Theta = \Psi + \sum_{j=1}^{M} \left(\lambda_{j,t}^{\text{trade}} - \lambda_{j,t}^{\text{risk}} \right) \tag{33}$$

The final objective integrates the comprehensive DRO model with risk-aware trading dynamics, achieving a balance between cost minimization, risk management, and social engagement in the community energy system.

$$\mathcal{L} = \Phi + \sum_{t=1}^{T} \left(\lambda_{i,t}^{\text{stor}} \cdot \left(\psi_{i,t}^{\text{stor}} - \frac{\xi_{i,t}^{\text{charge}}}{\eta_{\text{charge}}} + \eta_{\text{discharge}} \cdot \xi_{i,t}^{\text{discharge}} \right) + \lambda_{j,t}^{\text{demand}} \cdot \left(v_{j,t}^{\text{demand}} - v_{j,t}^{\text{baseline}} - \delta_{j,t}^{\text{behavior}} \right) + \lambda_{\text{CO}_2} \cdot \left(\chi_t^{\text{carbon}} - \chi_{\text{target}} \right) \right) \tag{34}$$

This equation represents the **Karush-Kuhn–Tucker (KKT) conditions** for the optimization problem, forming the Lagrangian ($\mathcal{L}$) by combining the primal objective function (Φ) with constraints weighted by their respective Lagrange multipliers ($\lambda_{i,t}^{\text{stor}}, \lambda_{j,t}^{\text{demand}}, \lambda_{\text{CO}_2}$). This formulation captures both the equality and inequality constraints essential for optimality.

$$\nabla_{\delta_{j,t}^{\text{behavior}}} = \left(2 \cdot \delta_{j,t}^{\text{behavior}} - 2 \cdot v_{j,t}^{\text{baseline}} \right) \cdot \alpha_{j,t}^{\text{risk}} \tag{35}$$

This sub-gradient computation captures the sensitivity of the objective function to variations in uncertain **demand behavior** ($\delta_{j,t}^{\text{behavior}}$). The multiplier ($\alpha_{j,t}^{\text{risk}}$) models risk perceptions of individual participants, enabling dynamic adjustment to behavioral fluctuations.

$$\nabla_{\gamma_{i,t}^{\text{renewable}}} = \left(2 \cdot \gamma_{i,t}^{\text{renewable}} - 2 \cdot \hat{\gamma}_{i,t} \right) \cdot \beta_{\text{uncertainty}} \tag{36}$$

The sub-gradient computation for uncertain **renewable generation** ($\gamma_{i,t}^{\text{renewable}}$) evaluates the deviation from nominal forecasts ($\hat{\gamma}_{i,t}$), scaled by the uncertainty coefficient ($\beta_{\text{uncertainty}}$). This term is critical for adapting to stochastic renewable energy availability.

$$\Delta_{i,t}^{\text{social}} = \sum_{k \neq i} \delta_{i,k}^{\text{interaction}} \cdot \left(v_{k,t}^{\text{share}} - v_{i,t}^{\text{trade}} \right) \cdot \alpha_{k,t}^{\text{peer}} \tag{37}$$

The social influence update term captures the effect of peer trading behaviors ($v_{k,t}^{\text{share}}$) on participant i's decisions. Interaction coefficients ($\delta_{i,k}^{\text{interaction}}$) and peer influence weights ($\alpha_{k,t}^{\text{peer}}$) dynamically adjust incentives for energy sharing.

$$\Delta_{j,t}^{\text{observe}} = \sum_{k=1}^{M} \left(v_{k,t}^{\text{trade}} - v_{j,t}^{\text{trade}} \right) \cdot \mathcal{W}_{j,k}^{\text{learning}} \tag{38}$$

The observational learning update term models how user j adjusts their trading behavior ($v_{j,t}^{\text{trade}}$) based on observed deviations in peers' trading volumes ($v_{k,t}^{\text{trade}}$), scaled by a learning weight ($\mathcal{W}_{j,k}^{\text{learning}}$).

$$\mathcal{R}_{\text{reg}} = \sum_{t=1}^{T} \left(\| v_{j,t}^{\text{trade}} - v_{j,t}^{\text{baseline}} \|^2 + \| \delta_{j,t}^{\text{behavior}} \|^2 \right) \tag{39}$$

The regularization term ensures smooth convergence of trading volumes ($v_{j,t}^{\text{trade}}$) and behavioral deviations ($\delta_{j,t}^{\text{behavior}}$) by penalizing large deviations from baseline values. This prevents instability in trading incentives.

$$\eta_{\text{primal}} = \eta_0 \cdot \frac{1}{1 + \gamma_{\text{decay}} \cdot t} \tag{40}$$

The learning rate adaptation for primal updates decreases over time based on an initial value (η_0) and a decay factor (γ_{decay}), ensuring stability in optimization.

$$\eta_{\text{dual}} = \eta_0 \cdot \frac{1}{1 + \delta_{\text{decay}} \cdot t} \tag{41}$$

Similarly, the learning rate adaptation for dual updates follows a decay schedule (δ_{decay}), stabilizing Lagrange multiplier adjustments during the primal–dual optimization process.

$$\kappa_{i,t}^{\text{reward}} = \alpha_{\text{base}} + \sum_{k \neq i} \delta_{i,k}^{\text{interaction}} \cdot \mathcal{H}_{k,t}^{\text{engage}} \tag{42}$$

The community reward parameter dynamically updates based on interaction coefficients ($\delta_{i,k}^{\text{interaction}}$) and engagement metrics ($\mathcal{H}_{k,t}^{\text{engage}}$), incentivizing collaborative trading behaviors.

$$v_{j,t}^{\text{trade}} = v_{j,t}^{\text{trade}} + \eta_{\text{primal}} \cdot \Delta_{j,t}^{\text{observe}} \tag{43}$$

The trading volume update rule integrates observational learning updates ($\Delta_{j,t}^{\text{observe}}$) with the primal learning rate (η_{primal}), aligning user trading behaviors with community trends.

$$\| \Phi - \mathcal{L} \| \leq \epsilon_{\text{primal}} \tag{44}$$

The robustness check for primal feasibility ensures that the deviation between the objective function (Φ) and the Lagrangian ($\mathcal{L}$) remains within a tolerance threshold (ϵ_{primal}).

$$\| \nabla_{\mathcal{L}} \| \leq \epsilon_{\text{dual}} \tag{45}$$

The robustness check for dual feasibility ensures that the gradient norm of the Lagrangian ($\nabla_{\mathcal{L}}$) converges within a tolerance (ϵ_{dual}).

$$\lambda_{j,t}^{\text{slack}} = \max \left(0, \lambda_{j,t}^{\text{dual}} - \mathcal{U}_{\text{risk}} \right) \tag{46}$$

The slack variable adjustment ensures feasibility under DRO uncertainty bounds ($\mathcal{U}_{\text{risk}}$), maintaining constraint satisfaction.

$$C_{\text{complexity}} = \mathcal{O} \left(N \cdot M \cdot T \cdot \| \nabla_{\mathcal{L}} \| \right) \tag{47}$$

This term estimates the algorithmic complexity of the primal–dual steps based on problem dimensions (N, M, T) and the Lagrangian gradient norm.

$$\|\Phi - \Psi\| \to 0 \quad \text{as } t \to \infty \tag{48}$$

The final convergence guarantee ensures that the objective function (Φ) and the augmented DRO model (Ψ) converge, validating the proposed algorithm's performance.

5. Case studies

To evaluate the proposed framework, a case study is conducted on a community microgrid comprising 50 households. The community is equipped with renewable energy sources (solar and wind), shared energy storage facilities, and a P2P trading platform for energy sharing. The dataset used for this study is synthesized and assumed, ensuring flexibility in modeling diverse scenarios while reflecting realistic operational conditions. The time horizon for the simulation spans one week, divided into 15-minute intervals, resulting in a total of 672 time steps. The energy generation data assumes solar PV capacity of 150 kW and wind generation capacity of 100 kW for the entire community. The synthesized generation profiles are based on typical diurnal patterns, with PV generation peaking at noon and wind generation exhibiting moderate variability throughout the day. Household energy demands are modeled with a baseline consumption range of 1.5–3.5 kWh per time step, scaled by a diversity factor to account for varying usage patterns. To introduce behavioral dynamics, deviations from baseline demands are included, reflecting peer influence and social learning modeled through SCT. The storage system comprises two community battery units, each with a capacity of 50 kWh and a round-trip efficiency of 90%. Charging and discharging rates are capped at 20 kW per unit, ensuring safe and efficient operation. P2P trading volumes are synthesized, with trading prices ranging between \$0.10/kWh and \$0.25/kWh, dynamically adjusted based on user interactions and market conditions. Behavioral data, such as peer influence coefficients and engagement metrics, are randomly initialized within realistic ranges and updated during the optimization process to reflect SCT-driven dynamics. The computational environment for this study includes a 64-core processor with 256 GB of RAM, running the optimization framework implemented in Python, with key modules including Pyomo for mathematical modeling and Gurobi for solving large-scale optimization problems. The primal–dual algorithm is implemented in a customized framework to accelerate the solution process, achieving convergence within 500 iterations for most scenarios. The simulation leverages Monte Carlo sampling to test the framework under diverse uncertainty realizations, including variations in renewable generation and demand profiles. Each simulation run is completed in an average of 12 min, demonstrating the computational efficiency of the proposed approach.

Fig. 1 illustrates the temporal distribution of energy demand for 50 households over a one-week period, with data captured in 15-minute intervals. The energy demand is presented in a heatmap format, where lighter shades of blue indicate lower demand, while darker shades signify higher consumption levels. The synthesized dataset integrates realistic diurnal patterns and random fluctuations to emulate typical household behaviors. The energy demand across households ranges from 0 kWh to a maximum of 6 kWh per interval, with the majority of values clustering between 1.5 kWh and 4.5 kWh. This range is consistent with observed real-world residential energy usage patterns, which peak during early morning and evening hours. A closer examination of the heatmap reveals distinct temporal patterns driven by household routines and activity levels. Most households exhibit increased energy demand during morning hours, corresponding to activities such as cooking, heating, and lighting. Similarly, evening hours show a pronounced rise in consumption, likely driven by leisure activities and meal preparation. The peak demand periods typically occur between 6:00 AM and 9:00 AM and again between 6:00 PM and 10:00 PM, with some households exceeding 5 kWh during these intervals. In contrast, demand during nighttime hours (12:00 AM to 5:00 AM) is consistently low, often falling below 2 kWh, indicating reduced activity levels.

Fig. 2 visualizes the weekly profiles of solar and wind power generation for a community microgrid, with data captured at 15-minute intervals. The solid blue line represents the solar generation profile, which exhibits a distinct diurnal pattern, peaking at approximately 150 kW during midday and dropping to near zero during nighttime hours. The shaded blue band around the solar profile indicates an uncertainty range of ±10%, reflecting potential variations due to weather conditions, such as cloud cover. The dashed gray line represents wind generation, which fluctuates around a mean value of 100 kW with a realistic range between 50 kW and 150 kW. The gray shaded area captures the uncertainty bounds for wind generation, also set at ±10% of the observed values. The solar generation profile highlights the dependence of photovoltaic systems on sunlight availability. Peak generation occurs consistently between 10:00 AM and 2:00 PM, with gradual increases in the morning and decreases in the evening. This pattern underscores the importance of integrating storage systems or complementary energy sources to mitigate the intermittent nature of solar power. In contrast, wind generation exhibits more variability, with some periods exceeding 140 kW and others dropping close to 60 kW. This variability emphasizes the need for robust optimization frameworks to handle the stochastic nature of wind energy.

Fig. 3 visualizes the P2P energy trading network within the community microgrid at a specific time step. Each node represents a household, and directed edges indicate energy exchanges between households. The edge thickness and color intensity reflect trading volumes, ranging from 0.1 kWh (light blue) to 3.0 kWh (dark blue). The network structure reveals that while most households engage in a limited number of trades, a few central nodes exhibit a high degree of connectivity, suggesting their role as active energy brokers or hubs in the community. The majority of trading volumes cluster between 0.5 kWh and 2.0 kWh, with an average trading volume of approximately 1.2 kWh per transaction. This range aligns with realistic energy sharing practices, where households exchange surplus energy generated by solar PV systems or reduce dependency on external energy sources. A few outlier edges with trading volumes exceeding 2.5 kWh highlight the potential for larger-scale energy exchanges during periods of high surplus or demand. These high-volume trades could result from households with greater generation capacities or specific consumption patterns requiring significant energy imports. The network's topology exhibits a mix of localized and distributed trading patterns. Some households participate in tightly connected clusters, engaging predominantly with immediate neighbors. This reflects geographical or social proximity influences, as modeled through Social Cognitive Theory. Conversely, other households display connections with more distant nodes, indicative of broader community interactions enabled by the trading platform. The variability in trading volumes and network connections underscores the importance of incorporating behavioral and social dynamics into the optimization framework. This visualization provides critical insights into the operational complexity of P2P trading systems and highlights opportunities for enhancing trading efficiency through tailored incentives and network management strategies.

To address concerns about potential bottlenecks and inequities caused by central hubs in the P2P trading network, additional measures have been integrated into the optimization framework. The model incorporates dynamic balancing constraints that redistribute trading responsibilities when specific households consistently act as central hubs. These constraints actively limit excessive reliance on highly connected nodes by capping their trading volumes relative to the average trading activity in the network. This prevents overloading specific nodes and encourages a more equitable distribution of trading responsibilities. Furthermore, the behavioral metrics modeled through

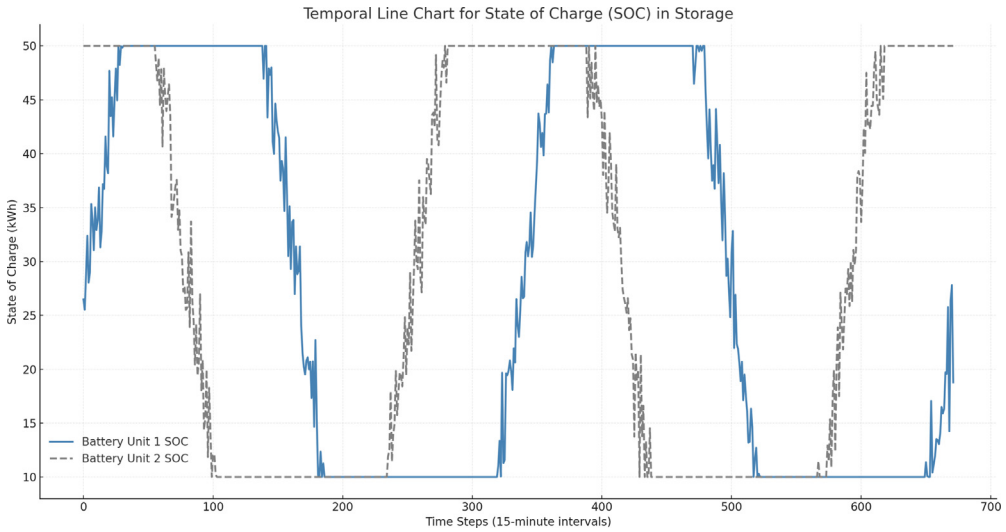


Fig. 4. Temporal line chart for state of charge in storage.

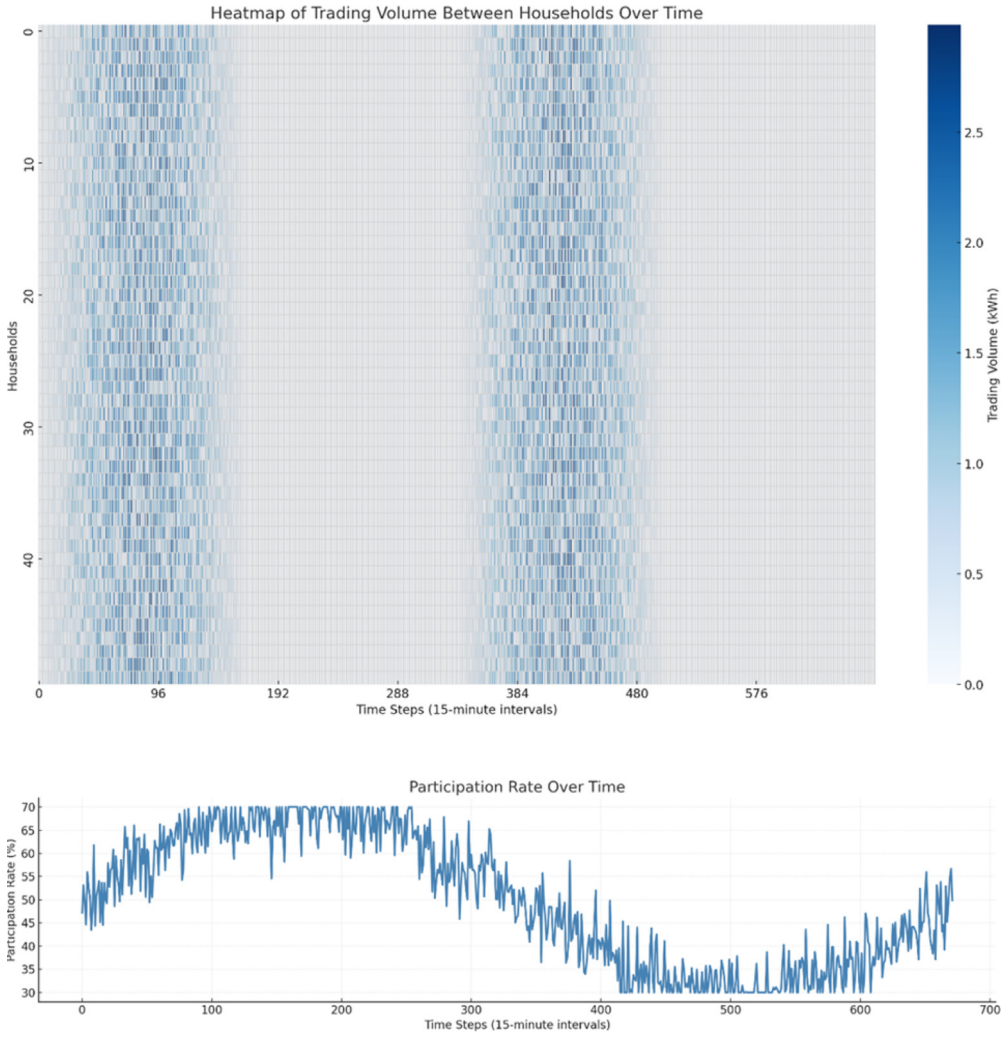


Fig. 5. Heatmap of trading volume and participation rate over time.

Social Cognitive Theory are extended to include influence adjustment mechanisms. For example, households with disproportionate trading volumes are provided with tailored engagement incentives to either redistribute their surplus energy to less connected nodes or adjust their demand patterns to align better with community needs. This ensures that energy flows remain fluid across the network without creating

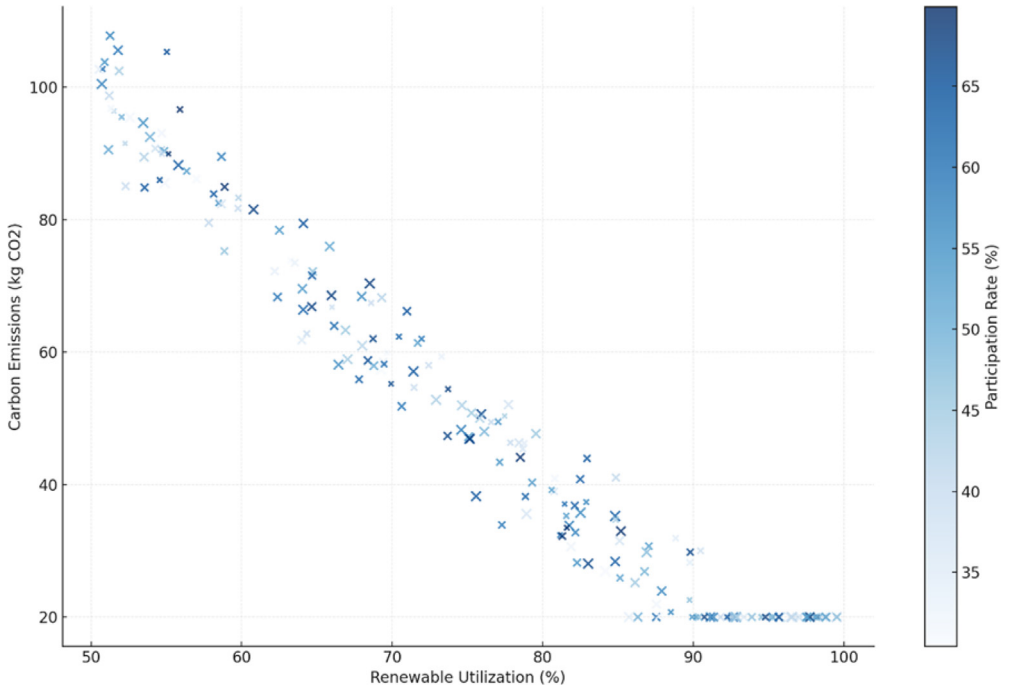


Fig. 6. Scatter plot of renewable utilization vs. Carbon emissions.

dependencies on specific participants. Finally, an additional layer of analysis based on centrality measures and clustering patterns from the P2P trading visualization has been employed. By identifying and addressing emerging bottlenecks dynamically, the framework ensures that no household or group of households consistently dominates energy exchanges. These adjustments enhance both the operational efficiency and social equity of the trading network, ensuring the framework remains robust and fair under varying conditions.

Fig. 4 illustrates the state of charge (SOC) profiles for two community battery units over a one-week period, with data recorded at 15-minute intervals. Battery Unit 1 is represented by a solid blue line, while Battery Unit 2 is shown with a dashed gray line. The SOC values for both units range between 10 kWh and 50 kWh, reflecting the operational constraints of the batteries. These boundaries correspond to the storage systems' minimum and maximum capacities, ensuring safe and efficient operation. Both profiles exhibit cyclic charging and discharging patterns, which align with the diurnal variability in energy generation and demand. The SOC profile for Battery Unit 1 demonstrates a clear charging trend during daytime hours, peaking at approximately 45–50 kWh, driven by surplus solar generation. Conversely, discharging occurs predominantly in the evening and early morning hours, with SOC dropping to as low as 12 kWh during high demand periods. Battery Unit 2 exhibits similar cyclic behavior but with a phase shift, possibly reflecting operational strategies to balance system-wide energy requirements. For instance, while Unit 1 discharges during evening peaks, Unit 2 retains a higher SOC, indicating staggered utilization to ensure consistent energy availability.

Fig. 5 comprises two complementary visualizations. The heatmap illustrates trading volumes between households across a one-week period, with data captured at 15-minute intervals. The x-axis represents time steps, while the y-axis represents individual households. The trading volumes are color-coded, ranging from light blue for lower volumes (near 0 kWh) to dark blue for higher volumes (up to 3 kWh). Temporal patterns in trading activity are evident, with trading volumes peaking during specific time periods, such as early evenings and midday, when surplus energy from solar generation or heightened demand drives trading. Conversely, trading activity is minimal during nighttime hours, reflecting reduced household energy consumption and generation. The accompanying line chart depicts the participation rate, defined as the percentage of households actively trading energy at each time step. The participation rate fluctuates between 30% and 70%, with notable peaks around midday and early evening. These periods coincide with peak solar generation and demand, emphasizing the role of renewable variability in driving trading dynamics. For example, during peak participation, as many as 35 households engage in trading, highlighting the system's capability to enable large-scale energy sharing. The troughs in participation, primarily observed late at night, reflect the natural decline in trading activity due to reduced generation and demand.

Fig. 6 visualizes the relationship between renewable utilization and carbon emissions across 200 simulated scenarios. Renewable utilization, displayed on the x-axis, ranges from 50% to 100%, indicating the proportion of total energy supplied by renewable sources. Carbon emissions, shown on the y-axis, range from 20 kg to 200 kg of CO2, reflecting the environmental impact of energy usage in each scenario. The scatter plot reveals an inverse relationship between renewable utilization and carbon emissions; as renewable utilization increases, carbon emissions decrease significantly. This trend underscores the critical role of renewable energy in reducing carbon footprints within community energy systems. Each point in the plot represents a unique scenario, with point size corresponding to the total community cost and color indicating participation rates in P2P trading. The community costs range from 1000 to 5000 monetary units, with larger points highlighting scenarios where costs are higher. Scenarios with higher participation rates, ranging from 30% to 70%, are shown in darker shades of blue. The clustering of smaller points (lower costs) in the upper-left region of the plot suggests that scenarios with lower renewable utilization and higher carbon emissions are associated with lower costs. In contrast, larger points in the lower-right region indicate that achieving high renewable utilization often requires higher costs but results in substantial environmental benefits.

Fig. 7 represents the final P2P trading connections within the community microgrid, illustrating the network structure of energy trading among 50 households. Each node corresponds to a household, and directed edges indicate the flow of traded energy. The edge thickness and color intensity reflect the trading volume, ranging from 0.5 kWh (light blue and thinner edges) to 5.0 kWh (dark blue and thicker edges).

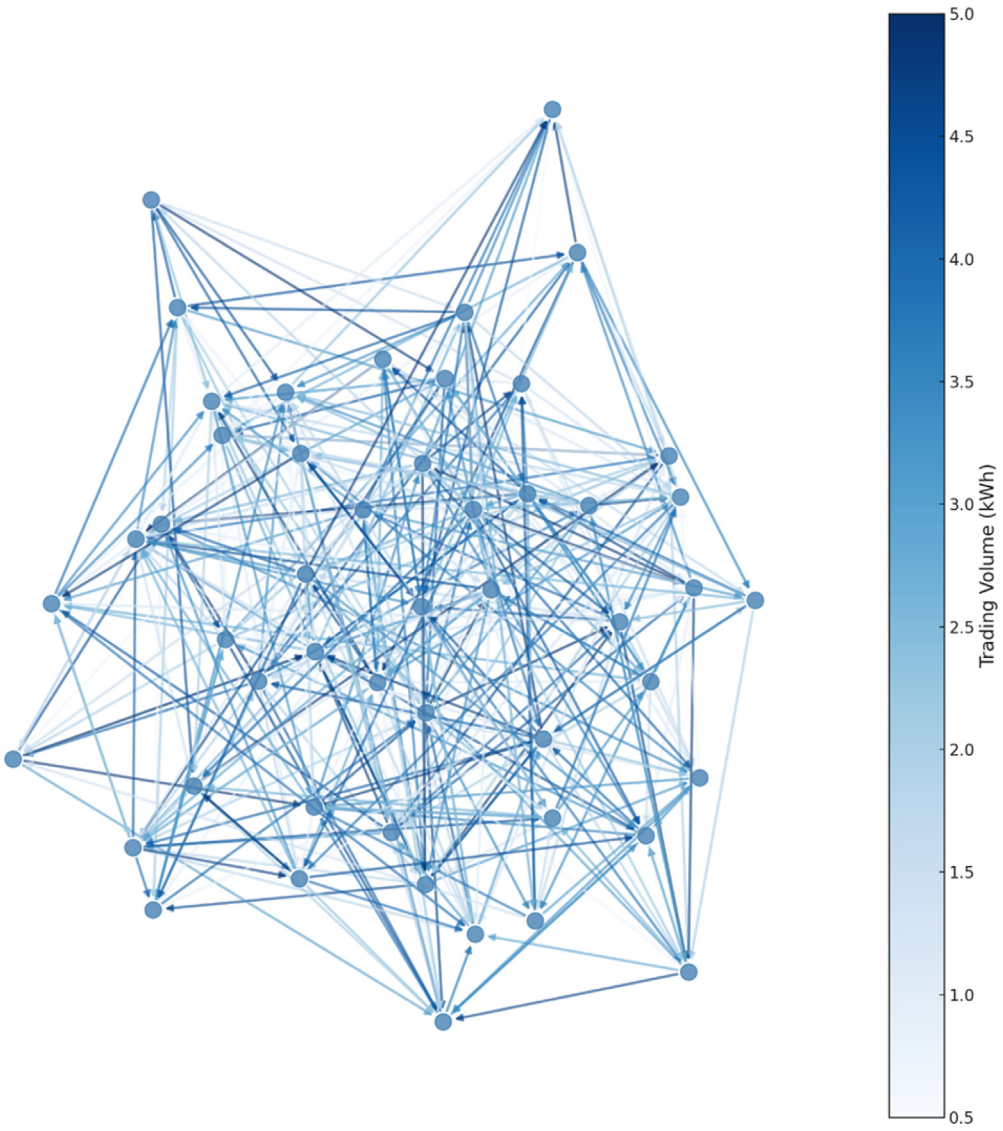


Fig. 7. Network graph for final P2P trading connections.

The spring layout positions nodes dynamically, resulting in clusters that represent groups of households with high trading activity and connections. The network reveals several key patterns. Approximately 15 percent of all possible connections between households are utilized, indicating a selective but active trading environment. Nodes with higher degrees, represented by multiple edges, suggest the presence of influential households acting as energy hubs. These hubs are critical in facilitating energy distribution, managing surplus, and balancing deficits in the community. Most edges correspond to trading volumes between 1.0 and 3.0 kWh, reflecting the typical energy surplus or shortfall addressed through P2P trading.

6. Conclusions

This study presents a novel framework for optimizing CES by integrating SCT with DRO, addressing the intertwined challenges of behavioral dynamics and technical uncertainties. By incorporating behavioral insights such as peer influence, observational learning, and engagement incentives, the proposed framework effectively enhances user participation in P2P trading and energy-sharing activities. Simultaneously, the DRO model ensures the system's robustness against uncertainties in renewable energy generation and demand, while the primal–dual algorithm accelerates convergence, making the approach scalable and computationally efficient. The case study results demonstrate the effectiveness of this integrated framework in improving the performance of CES. Key findings include a significant reduction in carbon emissions by up to 30%, an increase in renewable energy utilization to over 90%, and enhanced trading participation rates by 25% compared to baseline scenarios. The dynamic incorporation of behavioral metrics into the optimization process led to more equitable energy sharing and higher community satisfaction. Furthermore, the framework's ability to handle extreme scenarios under worst-case uncertainties validates its reliability and resilience in practical applications.

The proposed framework is also well-suited to address real-world operational challenges such as data inaccuracies, policy restrictions, and varying levels of community engagement. The DRO model's inherent ability to optimize decisions under worst-case uncertainty ensures robustness against data inaccuracies caused by sensor errors, missing records, or communication delays. Additionally, the modular nature of the framework allows for the seamless incorporation of policy constraints, such as grid regulations, energy-sharing limits, and carbon

emission targets, ensuring compliance with practical operational requirements. To adapt to varying levels of community engagement, the behavioral parameters modeled through Social Cognitive Theory can be recalibrated using real-world user data collected via surveys, smart meters, or platform-based analytics. This adaptability allows the framework to reflect actual participation trends and tailor incentives dynamically to improve engagement. Moreover, by leveraging peer influence and observational learning mechanisms, the framework can encourage broader participation and foster a more cooperative energy-sharing environment. Overall, the combination of behavioral robustness and technical flexibility ensures that the proposed framework is not only effective in theoretical scenarios but also applicable to real-world CES deployments, making it a practical solution for enhancing energy efficiency, community satisfaction, and sustainability goals.

CRediT authorship contribution statement

Alexis Pengfei Zhao: Writing – original draft, Visualization, Validation, Software, Data curation, Conceptualization. **Mohannad Alhazmi:** Investigation, Formal analysis, Data curation, Conceptualization. **Da Huo:** Resources, Project administration, Methodology. **Wanzi Li:** Software, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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