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Socially Intelligent Energy Management: A Game-Theoretic Approach to Cooperative Residential Microgrids

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Abstract

Microgrids provide an effective strategy for delivering energy while keeping expenses to a minimum. Within residential microgrids, individuals with diverse personality traits can collaborate in multiple ways. Additionally, the distinct decision styles arising from these personality differences can have a substantial impact on the success of their joint activities. The present study explores patterns of collaboration among neighbors with a range of personality traits within residential microgrids that form part of a smart-city ecosystem, thereby supporting energy exchange and reducing the total cost of energy provision. The methodology introduced in this work accounts for uncertainties arising from social conduct and organizes joint action through a game-theoretic structure. That structure works toward achieving an efficient and fair division of energy across participating neighbors, simultaneously driving down expenditures, encouraging cooperative behavior, and applying disincentives for non-cooperative conduct in line with each person's behavioral profile. The suggested technique was tested on a residential benchmark microgrid using the GAMS CPLEX optimizer; two contrasting cases were examined to evaluate how energy storage affects trading decisions. By establishing mean values for discount and penalty rates, the method becomes better suited to diverse microgrid topologies. The analysis further addresses the tension between the utility company's prices and the most advantageous rates from the neighbors' perspective. Simulation results indicate that collaborative behavior enables neighbors to meet surplus requirements and can reduce the microgrid's aggregate operating costs by up to 80%.

Keywords Energy management, Game-theoretic approach, Microgrids, Smart-city ecosystem

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Introduction

Smart cities are generally understood as evolving urban environments whose core aim is to build collaborative networks that stimulate innovation and create new social and economic benefits, while simultaneously narrowing the gap between physical infrastructure, human communities, and digital systems [1]. **Figure 1** organizes the fundamental building blocks of a smart city into eight distinct classes. The eight classes cover humanist aspects, sustainability, smart economy, smart living, citizen and societal involvement, resource optimization, smart administration, and mobility systems [2-4]. Research aligned with this framework has addressed multiple facets, among them the role of people within smart-city settings [5], environmental sustainability [6], intelligent economic structures [7], enhanced quality of everyday life [8], societal features [9], efficient handling of resources [10], modern governance mechanisms [11], and advanced mobility solutions [12]. Broadly speaking, smart energy describes the integration of cutting-edge technologies, networked digital platforms, and adaptive control systems that enable energy to be generated, transmitted, stored, and utilized with high efficiency [13]. As a critical element within the smart-city paradigm, smart energy infrastructure is indispensable for achieving greater

ecological balance, stronger financial outcomes, and higher living standards in cities [4]. In that context, smart energy infrastructure reinforces the broader smart-city agenda by linking smart-economy principles, resource stewardship, mobility networks, and improvements in daily living conditions. Operating as a localized, independent component of a smart energy infrastructure, a residential microgrid can make a major contribution toward more effective resource allocation and lower financial burdens through the active involvement and teamwork of its residents. Modern grid designs facilitate direct energy transactions between property owners, thereby cutting electricity bills [14]. When households join forces in energy-related activities, they strengthen their own energy arrangements, reduce dependence on external suppliers, and open up valuable opportunities for advanced demand-side management (DSM) [15]. Teamwork among nearby residents reduces individual energy bills, enhances system resilience, and helps curb greenhouse gas (GHG) emissions [16, 17].

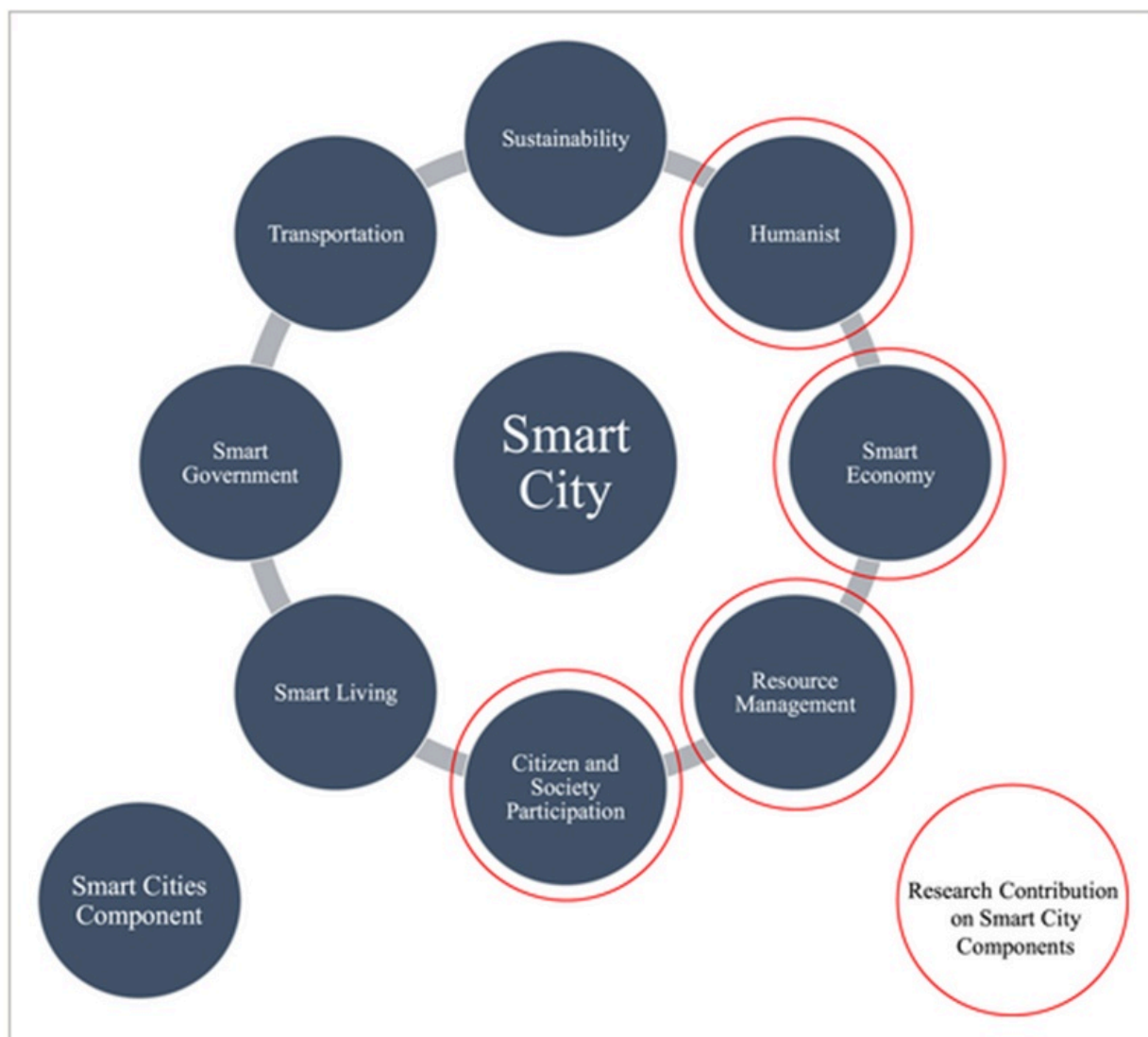


Figure 1. The main components of a smart city [1-3].

Frameworks that coordinate demand-side flexibility within residential districts typically fall into one of four structural types: fully centralized, fully decentralized, hierarchical, or non-hierarchical distributed. Under a non-hierarchical distributed scheme, the home energy management systems (HEMSs) belonging to different households maintain direct connections with one another and freely share relevant data [18]. A HEMS enables the occupant to observe, regulate, and oversee the operation of intelligent household devices [19-21]. These functions become considerably more powerful when neighbors

adopt joint energy-trading practices enabled by the combined use of home energy management systems (HEMSs) and distributed energy resource management systems (DERMSs). Driven by the growing priority of eco-friendly lifestyles, these efforts aim to achieve greater energy efficiency, lower household spending, and stronger ecological outcomes at the neighborhood scale. While HEMS equips each resident with precise oversight and control over personal consumption patterns, DERMS ensures the smooth integration of locally available renewable generation. The resulting cooperative arrangement fosters mutual participation and shared accountability, paving the way for a more durable and greener long-term energy supply. Practical illustrations of neighbor-level energy cooperation supported by HEMS and DERMS include strategies for shifting peak demand, preparing for power disruptions, and achieving financial benefits. As the smart-city model continues to mature, deploying HEMS alongside DERMS to enable shared energy practices among residents stands out as a forward-looking tactic with substantial promise for fundamentally reshaping energy use in urban areas. In the wider effort to promote environmentally responsible city living and advance the smart-city vision, neighbor-to-neighbor energy exchange facilitated by HEMS and DERMS represents a meaningful step forward. Neighbor-based energy exchange of this kind is commonly referred to as peer-to-peer energy sharing. Furthermore, peer-to-peer (P2P) energy sharing can be structured in three principal market configurations: pure P2P, prosumer-to-grid, and hybrid arrangements. Within the pure P2P model, any excess energy produced can be traded directly between participants inside the microgrid [22, 23].

Related works

In a residential neighborhood, many people live in proximity to one another. These residents exhibit a wide range of personality characteristics. Within the context of a residential microgrid, individuals respond differently to requests for collaboration depending on their specific personality traits. The varied responses from neighbors lead to distinct outcomes. When one person seeks assistance, the other residents in the same area are regarded as their 'neighbors'. Each of these neighbors functions as an independent participant in an emerging local electricity market shaped by the conditions within the neighborhood. Beyond the purely technical aspects of the system, the actions of each participant—referred to as a neighbor—are also shaped by their particular social personality type. To properly assess how neighbors behave in energy management scenarios, it is essential to examine the elements that shape their choices. These elements fall into nine broad groups: social motivations, gender, payoff structure, uncertainty, power and position, group size, communication, causes, and frameworks [24]. In addition, when individuals engage in repeated interactions, their conduct is further shaped by distinctive traits such as tolerance, forgiveness, loyalty, leadership, and followership [25]. Declerck *et al.* [26] show that people cooperate to secure both personal gains and collective benefits. Moreover, Breitmoser [27] and Dal Bó and Fréchette [28] classify the prevailing strategies adopted by individuals in neighborhood settings into five main categories. Building on the qualitative strategies outlined in Breitmoser [27], Dal Bó and Fréchette [28], and Nowak and Sigmund [29], Nowak and Sigmund [29] explore patterns of human cooperation. Dal Bó and Fréchette [28] analyze cooperation among people by incorporating dominant strategies and the likelihood of continued interaction. To examine cooperation in repeated games, Duffy and Ochs [30] used a fixed discount factor for all participants. In contrast, the work in Baye and Jansen [31] explores people's willingness to cooperate by introducing stochastic discount factors.

Song *et al.* [32] apply repeated games to demand-side management (DSM) to reduce consumer expenses while accounting for users' discomfort costs. Sofana Reka and Ramesh [33] examine cooperation between consumers and the utility through a tit-for-tat strategy in demand response (DR) programs, aiming to reduce both peak demand and overall costs. In Chang *et al.* [34], home energy management (HEM) units collaborate to minimize costs for the aggregator or retailer within a real-time balancing market. The approach in Mondal *et al.* [35] relies on cooperative game theory for energy management, leading to lower consumer costs; in that framework, neighbors within a microgrid engage in cooperative play, while each microgrid leader participates in non-cooperative games to maximize microgrid profits. Yang *et al.* [36] describe how consumers repeatedly cooperate to address demand response challenges and achieve cost savings, with the utility employing a cartel-like mechanism to impose penalties on non-cooperative participants. In Khorramdel *et al.* [37], personality assessments are employed to forecast how individuals will adhere to energy pricing schemes under demand response initiatives; the findings from Khorramdel *et al.* [37] reveal compliance patterns among

consumers and enable corresponding reductions in their energy expenses. Hanumantha Rao *et al.* [38] adopt a multi-agent system to facilitate peer-to-peer power trading in a local electricity market involving self-interested smart residential prosumers. Within this local market, prosumers can sell surplus generation or purchase needed supply at more favorable rates than those offered by the utility. Game theory is used to model the interactions between participants and the local market, and simulation outcomes confirm that peer-to-peer energy sharing lowers overall energy costs. Perger *et al.* [39] develop a linear optimization model for peer-to-peer energy trading among members of a local energy community equipped with photovoltaic (PV) systems and battery energy storage systems (BESSs). By also accounting for consumers' desire to lower greenhouse gas emissions, the model promotes greater use of renewable resources within the community, thereby decreasing grid purchases, total generation, and associated emissions.

In Nowak and Sigmund [29], cooperation among individuals is examined using qualitative methods and dominant strategies, yet the model omits the probability that the game will continue for each participant. By comparison, a key strength of Dal Bó and Fréchette [28] over Nowak and Sigmund [29] lies in its inclusion of a fixed probability for sustained cooperation. Nevertheless, the comprehensive review of repeated games in Salazar *et al.* [40] highlights mechanisms that reward cooperative behavior and penalize defection. However, both [28] and [29] overlook the use of explicit discount and penalty coefficients to incentivize or deter actions.

The method proposed in Duffy and Ochs [30] applies the same discount factor to every individual. Yet differences in strategy among people may justify the use of varied factors, as suggested by Breitmoser [27] and Dal Bó and Fréchette [28]. To overcome the limitations of a uniform approach, stochastic discount factors were introduced in Baye and Jansen [31] and Chorvat [41]. Still, given the diversity of strategies identified in Breitmoser [27], discount factors should align with each person's specific strategy and readiness to cooperate. Furthermore, as noted in Declerck *et al.* [26], each neighbor's decision to cooperate hinges on the balance of personal and social benefits gained, with the continuation probability varying from one neighbor to another. In that light, Realpe-Gómez *et al.* [42] and Realpe-Gómez *et al.* [43] explore individual cooperation by focusing on the social and personal gains achieved. However, those studies do not incorporate discount and punishment factors for game continuation, nor do they address the potential evolution of people's strategies over time. The present work, therefore, examines cooperation in repeated games by assigning discount and punishment coefficients that reflect participants' qualitative strategies. It also accounts for the likelihood of continued cooperation based on social and individual benefits, as well as the possibility that neighbors' strategies may shift over time.

Song *et al.* [32], Sofana Reka and Ramesh [33], Mondal *et al.* [35], Yang *et al.* [36], and Chang *et al.* [34] employ game-theoretic methods to study neighbor cooperation, with the primary objective of reducing costs for consumers or suppliers. Nevertheless, these works largely ignore the influence of neighbors' behavioral traits, which play a crucial role in shaping cooperation. Additionally, energy sharing among neighbors is absent in Song *et al.* [32], Sofana Reka and Ramesh [33], Mondal *et al.* [35], Yang *et al.* [36], and Chang *et al.* [34]; instead, the upstream grid meets any excess demand. In contrast, Perger *et al.* [39] and Cui and Xiao [44] investigate energy sharing among individuals. Yet those studies fail to consider neighbors' behavioral characteristics, and past cooperation records do not influence future outcomes. In the approach proposed here, consumer behavior is explicitly modeled within repeated games: participants meet excess demand through neighbor cooperation, for instance, by rescheduling deferrable loads, thereby reducing reliance on external purchases and lowering peak demand in residential microgrids. **Figure 2** provides a visual summary of how the proposed model compares with earlier approaches. A comprehensive side-by-side comparison of prior studies and the current proposal is presented in **Table 1**.

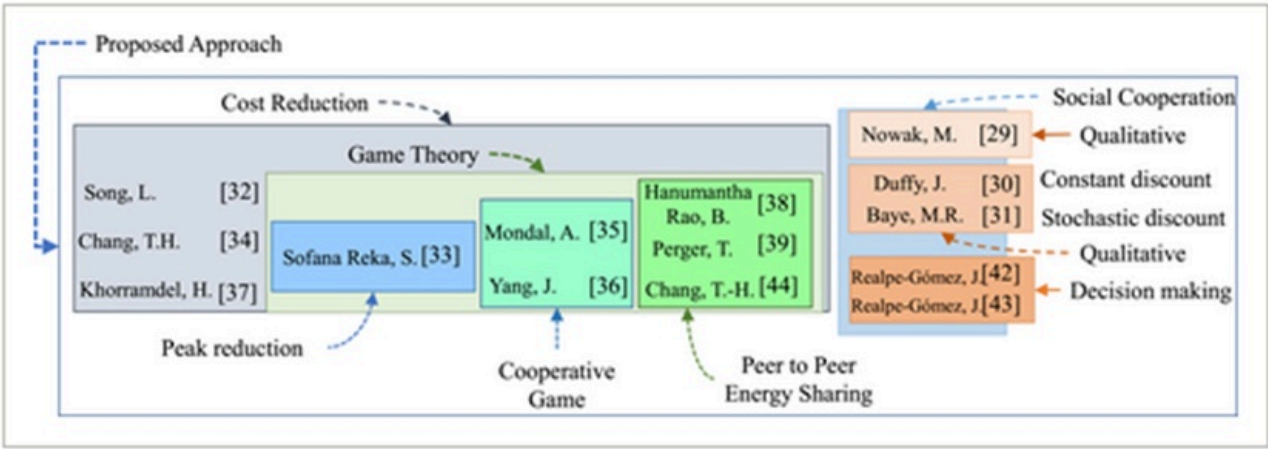


Figure 2. Comparison of the reviewed papers.

Table 1. Detailed comparison of existing works with the proposed study.

Ref.	Social science				Electrical engineer					
	Cooperation		Decision making		Game theory	Peak reduction	Cost reduction	P2P	DG	Cooperative game
	Qualitative	Quantitative	Social benefit	Individual benefit						
Dal Bó and Fréchette [28]	X	—	—	X	—	—	—	—	—	—
Nowak and Sigmund [29]	X	—	—	X	—	—	—	—	—	—
Duffy and Ochs [30]	—	X	X	X	—	—	—	—	—	—
Baye and Jansen [31]	—	X	X	X	—	—	—	—	—	—
Song et al. [32]	—	—	—	—	X	—	X	—	X	—
Sofana Reka and Ramesh [33]	—	—	—	—	X	X	X	—	—	X
Chang et al. [34]	—	—	—	—	X	—	X	—	—	X
Mondal et al. [35]	—	—	—	—	X	—	X	—	X	X
Yang et al. [36]	—	—	—	—	X	—	X	—	—	X

Khorramdel et al. [37]	—	—	—	—	X	—	X	—	X	—
Hanumantha Rao et al. [38]	—	—	—	—	X	—	X	X	X	—
Perger et al. [39]	—	—	—	—	X	X	—	X	X	X
Cui and Xiao [44]	—	—	—	—	X	X	—	X	X	X
Proposed approach	X	X	X	X	X	X	X	X	—	—

To the best of our knowledge, no prior work has comprehensively investigated the role of individual behavioral diversity—including motivational, psychological, and social factors that shape decision-making—in influencing peer-to-peer energy sharing within smart grids. Unlike earlier studies on smart cities and peer-to-peer mechanisms, the current research explores cooperation among individuals in smart-city environments by explicitly accounting for the heterogeneity in people's behaviors and the factors that drive them. The first part of the paper identifies the key determinants of individual behavior and evaluates their impact on decision-making. Building on these behavioral determinants, the next phase applies game-theoretic modeling to assess how such behavioral variations affect participation in peer-to-peer energy-sharing schemes.

In the baseline scenario considered here, individuals forecast their energy needs and procure the required electricity from the utility at day-ahead prices. If a neighbor subsequently experiences excess demand, that additional requirement is met at spot-market rates. By contrast, the approach proposed in this study enables consumers to satisfy surplus demand through neighborly cooperation rather than purchasing from the utility. Specifically, a consumer in need broadcasts a cooperation request to nearby residents; each neighbor then decides whether to assist or withhold support, based on the requesting consumer's prior conduct and their own personality characteristics.

Unlike some works [29–33, 35–39, 41–45], this paper examines the influence of human factors in smart cities not only through demand response programs but also via peer-to-peer energy-sharing arrangements. In conventional distribution networks—and even in many earlier active distribution systems—individual behavior was rarely treated as a decisive element because distributed generation units (DGs) had only marginal effects on the wider network. Today, however, advanced smart grids that form the backbone of smart cities are home to a rapidly expanding population of prosumers (entities that both consume and produce energy). Under these conditions, merely managing technical uncertainties is inadequate; integrating the social and behavioral patterns of city dwellers into modeling and decision frameworks has become indispensable. In essence, the present study incorporates the interactions among neighborhood consumers, their strategic choices, behavioral profiles, and the cumulative history of cooperation when determining future cooperative decisions.

The main contributions of this paper are as follows:

- Translating the factors that govern neighbors' behavioral patterns and strategic choices into quantifiable discount and punishment values, represented via a nonuniform distribution. To incorporate these values, the model first draws on the diverse strategic profiles linked to distinct personality types [27, 28]. It then assigns personalized discount and punishment coefficients to each participant according to their personality traits for use in the repeated-game setting [46–48].

- Leveraging neighbors' behavioral tendencies and mutual interactions to resolve certain technical issues in the system by harnessing social capital. Cooperation depends heavily on the benefits individuals have previously realized. Given the recurrent nature of interactions within a neighborhood, repeated-game analysis becomes essential for evaluating cooperative tendencies. Accordingly, a repeated-game framework that applies discount and punishment coefficients is adopted. As outlined earlier, these coefficients are derived from an analysis of participants' behavioral strategies during their ongoing interactions.
- Deriving average behavioral and strategic profiles across individuals to promote neighborhood-wide cooperation. To enhance the method's generalisability to other communities, the study examines mean discount and punishment factors as indicators of cooperative neighborhoods.

The overall objective of the study is illustrated in **Figure 3**.

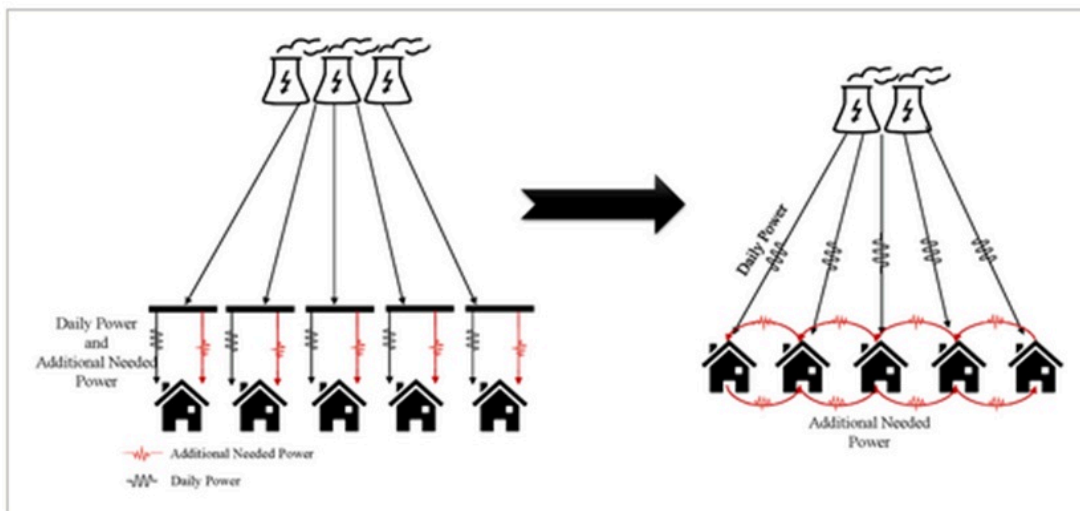


Figure 3. Distributed Power Sharing.

The paper first reviews neighbors' strategic behaviors, drawing on the social science literature, and examines the likelihood of game continuation and strategy adaptation over time. It then introduces discomfort costs along with the utility functions of neighbors. Next, it details the repeated-game-theoretic framework for modeling neighbor interactions, presents the objective function that minimizes neighbors' costs, and describes the residential test microgrid used to demonstrate the proposed method. The simulation setup, case studies, and numerical findings are then presented. Finally, the paper concludes with the main findings and conclusions

Social Behavior Modeling

This section examines the behavioral patterns of neighbors within the microgrid. It outlines the dominant strategies adopted by neighbors and provides a qualitative description of these behaviors, given that neighbors' actions are shaped by numerous influencing factors [24, 25, 49]. It also explores the discount and punishment factors, which are closely tied to neighbors' dominant strategies, and assigns specific values to them based on the identified strategies. Furthermore, cooperative decision-making can be understood as intentional choices that yield economic or social advantages [26]. The decision processes and likelihood of sustained cooperation are analyzed by considering accumulated social and individual payoffs. Finally, the potential for individuals to shift their strategies over time is addressed.

Neighbors' personality traits

The prevailing strategies among neighbors fall into five distinct categories [27, 28], as listed below:

1. Always Cooperate (AC): Neighbors in this category consistently choose to cooperate regardless of the opponent's actions.
2. Always Defect (AD): These neighbors invariably opt to defect in every interaction.
3. Tit-for-Tat: The neighbor mirrors the most recent action taken by the opponent.
4. Win-Stay-Lose-Shift (WSLS): The neighbor begins by cooperating; however, if the opponent defects at any point, the neighbor switches to defection for all subsequent rounds.
5. Suspicious Tit-for-Tat (S-tft): This neighbor starts with defection, but once the opponent cooperates, the neighbor begins to replicate the opponent's previous move.

Discount and penalize coefficients

In repeated games, participants often discount future payoffs to reflect the value they place on continuing participation [47, 48]. Neighbors apply Eq. 1 to adjust their utility using a discount factor ($\delta \in [0, 1)$):

$$Pr_n(\sigma) = (1 - \delta_n) \sum_{r=1}^R \delta_n^{r-1} u_n(\sigma), \quad (1)$$

Where $u_n(\sigma)$ represents the expected utility of the n th neighbor in round r .

Additionally, neighbors impose penalties on defectors [50]. The punishment mechanism is formalized in Eq. 2 [46]:

$$Pr_n(\sigma) = (1 - \lambda_n) \sum_{r=1}^R \lambda_n^{r-1} u_n(\sigma), \quad (2)$$

Where $g_n^r(\sigma)$ stands for the n th neighbor's expected utility in round r , and λ_n is the punishment coefficient of the n th neighbor ($\lambda \in (1, 2]$).

Analyzing neighbors' action and strategy

In the present work, discount and punishment coefficients are modeled as nonuniform distribution functions characterized by a mean value m (Figure 4 [31, 41]). In contrast to Baye and Jansen [31] and Chorvat [41], the mean is determined according to the qualitative strategies exhibited by neighbors. Accordingly, each neighbor is associated with a nonuniform probability distribution featuring distinct mean and standard deviation parameters. The dominant strategy primarily governs the mean, while factors that modulate cooperation influence the standard deviation [25].

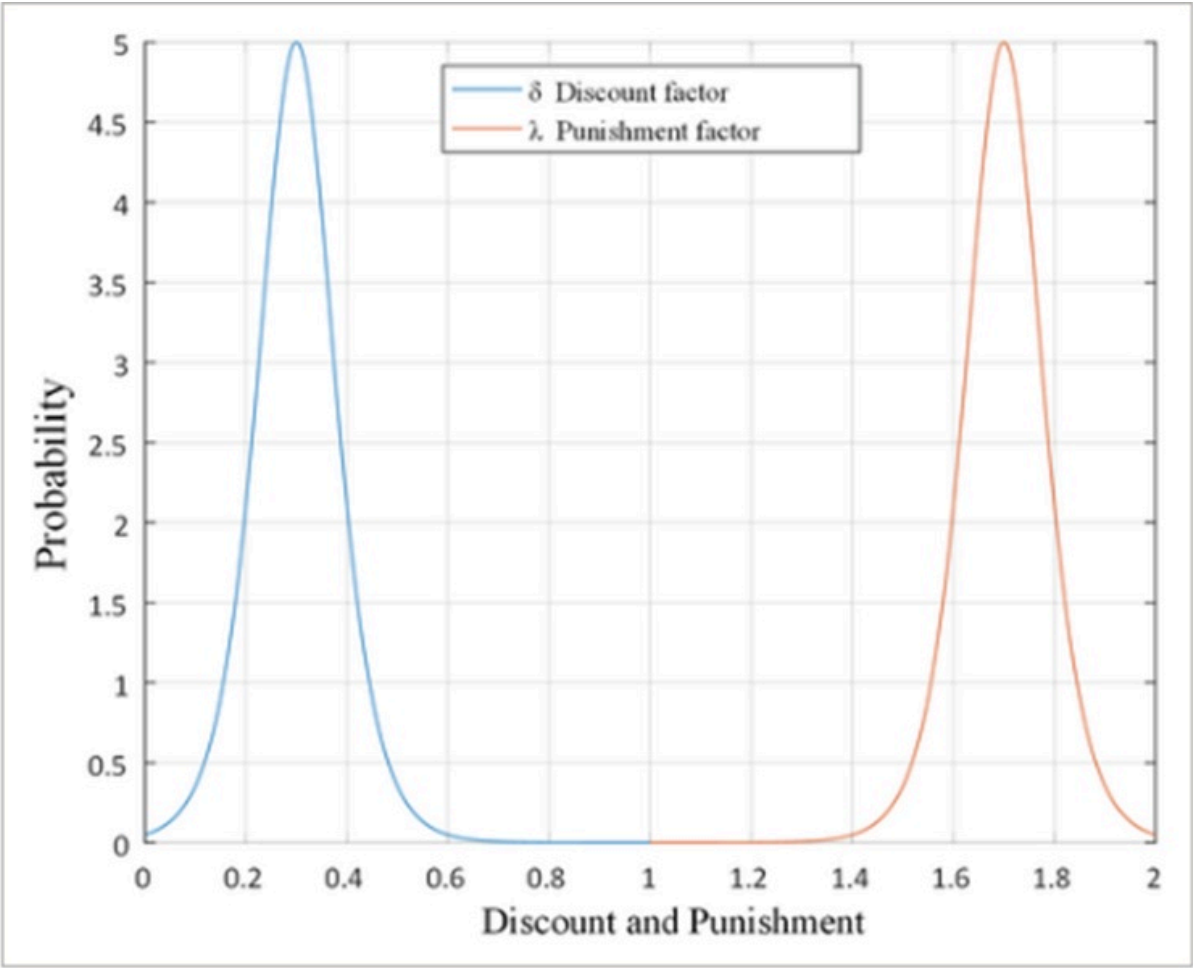


Figure 4. Discount and punishment coefficients.

As noted by Lehrer and Yariv [47] and Berg and Kärki [48], neighbors with a strong willingness to sustain cooperation tend to have a discount factor δ close to 1. In contrast, those with low willingness tend to have δ approaching 0. Consequently, neighbors following the AC strategy are assigned the highest discount factor and the lowest punishment factor. In contrast, AD neighbors receive the lowest discount factor and the highest punishment factor for subsequent rounds. Neighbors employing tit-for-tat strategies fall in the intermediate range for both δ and λ . For WSLS neighbors, discount factors align closely with those of AC, while punishment factors resemble those of AD. Suspicious tit-for-tat neighbors exhibit discount factors near the midpoint between tit-for-tat and AD, with punishment factors similar to tit-for-tat [51].

According to Eq. 1, the n th neighbor receives a cooperation payoff when the opponent cooperates. Conversely, Eq. 2 assigns a defection payoff when the opponent defects.

Considering the qualitative strategies, the corresponding discount and punishment value ranges are presented in Table 2. The distribution of personality types among neighbors is based on percentages reported in Dal Bó and Fréchette [28].

Table 2. Range of discounts and penalties for each strategy and percentage of each personality.

			S1	Neighbors' number
AC	0.8–1	1–1.2	10	1

AD	0–0.2	1.8–2	20	2–3
Tft	0.4–0.6	1.4–1.6	40	4–7
WSLS	0.6–0.8	1.6–1.8	20	8–9
S-tft	0.3–0.5	1.3–1.5	10	10

Decision-making and cooperation probability

Both personal rewards and adherence to social norms shape decisions to cooperate or defect. To incorporate these influences, Eqs. 3–5 are adopted [42, 43]:

$$x_n(t+1) = \frac{1}{1 + e^{-\beta D_n(t+1)}}, \quad (3)$$

$$D_n(t+1) = (1 - \gamma) D_n(t) + \Delta W_n(t), \quad (4)$$

$$\Delta W_n(t) = \Delta I_n(t) + h \Delta N_n(t), \quad (5)$$

Where $\Delta W_n(t)$ and $D_n(t)$ represent outcomes related to individual and social considerations, $\Delta I_n(t)$ captures individual rewards (intrinsic motivation), $\Delta N_n(t)$ reflects normative motivation to conform to social expectations, and $x_n(t+1)$ denotes the probability of cooperation in the next round.

In this framework, neighbors cooperate whenever the cooperation probability exceeds 60 %; otherwise, they defect [43]. The nonnegative parameter γ accounts for the weight given to past behavior in current decisions. A value of $\gamma = 0$ implies that historical actions dominate decision-making, whereas $\gamma = 1$ means only the present circumstances matter. For the present study, γ is set to 0.8 [30, 31].

The positive parameter β quantifies the level of rationality in neighbors' decision-making. When β equals zero, the neighbor selects cooperation or defection entirely at random, without regard to either individual or social motivations. As the value of β increases, the influence of rationality on choices grows correspondingly. In this work, the β parameter is set to 0.31 [42, 43, 52].

The strength of social normative motivation is determined by the extent to which neighbors conform (or fail to conform) to norms and by the mutual interactions among them. The parameter h modulates the weight that social norms carry in shaping neighbors' decisions. A larger value of h amplifies the role of social norms, potentially leading a neighbor to cooperate even when individual rewards are absent, solely under normative pressure. Here, the h parameter is set to 0.31 [30, 31].

Social norms

Three weighted components determine the relevance of social norms: the individual's own conformity (or nonconformity) to the norm, the conformity (or nonconformity) of other neighbors to the same norm, and the interaction between these two aspects. These are weighted by the positive parameters w_c , w_o , and w_i , respectively. Eq. 6 is employed to incorporate neighbors' social norms.

$$\Delta N = \omega_c(2c^r - 1) + w_o O^r + \omega_i c^r O^r. \quad (6)$$

O^t represents the total number of neighbors who cooperated in the given round. The first and third terms in Eq. 6 are included or excluded depending on whether the individual cooperated ($c^r = 1$) or defected ($c^r = 0$) in round r . The second term remains nonnegative in all cases [43]. The weights assigned to self-conformity (or nonconformity), others' conformity (or nonconformity), and their interaction are 1, 0.33, and 3.2, respectively [42, 43, 52].

Individual norms

Individual norms are modeled using the prisoner's dilemma framework. Each neighbor interacts pairwise with every other neighbor in the social network by playing a two-player game. The payoff structure for the n th neighbor responding to the m th neighbor's action is given as follows [42]. Eq. 7 is used to capture individual norms:

$$\begin{aligned} \Delta I_{nm} &= c^r \Delta I_c + [1 - c^r] \Delta I_D \\ \Delta I_c &= R - T \\ \Delta I_D &= S - P \end{aligned}, \quad (7)$$

Where c^r indicates the strategy chosen by neighbor m in round r ($c^r = 1$ for cooperation, $c^r = 0$ for defection).

Here, R denotes the reward payoff received by the n th neighbor when both players cooperate, P is the punishment payoff when both defect, S is the sucker's payoff when the n th neighbor cooperates while the m th defects, and T is the temptation payoff when the n th neighbor defects while the m th cooperates.

Within a utility-based decision framework, neighbors can either continue cooperating or opt out of the cooperative arrangement. While cooperation enables cost savings, withdrawing from cooperation carries strategic consequences: it may trigger reciprocal defection from others, ultimately raising the cost of meeting excess demand. Accordingly, the individual norms of neighbors—considering the utility associated with cooperation or opting out—are expressed in Eqs. 8–11:

$$\begin{aligned} R &= \{R_{\text{price}}(t) - U_m(P(t)) * (1 - \delta_m)\} \\ &+ \{R_{\text{price}}(t) - U_m(P(t)) * (1 - \delta_m - \delta_m^2)\} \\ &+ \{U_n(P(t)) * (1 - \delta_n) - U_n(P(t))\}, \end{aligned} \quad (8)$$

$$S = \{U_n(P(t)) * (1 - \delta_n) - U_n(P(t)) + (U_n(P(t)) - R_{\text{price}}(t))\}, \quad (9)$$

$$\begin{aligned} T &= \{R_{\text{price}}(t) - U_m(P(t)) * (1 - \delta_m)\} + \{U_n(P(t)) \\ &- R_{\text{price}}(t)\} + \{U_n(P(t)) - U_n(P(t)) * (1 - \delta_n)\} \\ &- \{U_m(P(t)) * (1 - \delta_m) - U_n(P(t))\}, \end{aligned} \quad (10)$$

$$P = \{U_n(P(t)) - R_{\text{price}}(t)\}, \quad (11)$$

Where $R_{\text{price}}(t)$ represents the spot-market price set by the distribution company at time t , and $U_n(P(t))$ denotes the n th neighbor's energy utility.

In [Eq. 8](#), when both neighbors cooperate, the n th neighbor benefits from reduced costs for excess energy thanks to the m th neighbor's cooperation (factoring in the m th neighbor's discount factor). However, continued cooperation into the next round requires the n th neighbor to forgo a utility equivalent to their own discount factor.

[Eq. 9](#) describes the payoff when the n th neighbor cooperates. Still, the m th neighbor opts out: the n th neighbor sacrifices utility according to their discount factor, yet receives no reciprocal benefit since the m th neighbor has withdrawn.

In [Eq. 10](#), if the n th neighbor opts out while the m th neighbor continues to cooperate, the n th neighbor enjoys lower procurement costs for their demand (leveraging the m th neighbor's discount factor).

Finally, [Eq. 11](#) applies when both neighbors choose to opt out: each must procure excess demand directly from the distribution company at full spot-market prices, incurring higher expenses and losing the benefits of cooperation.

Probability of changing strategy

After several rounds of play, neighbors may revise their strategy by comparing their accumulated profits with those of others. Specifically, a neighbor can adopt the strategy of the participant who has achieved the highest profit. The likelihood of such a strategy switch is determined using the Fermi equation [\[53\]](#). [Eq. 12](#) gives the probability ζ that the n th neighbor will change strategy:

$$\zeta = \frac{1}{1 + \exp[-(P_{an} - P_n)/K]}, \quad (12)$$

Where ζ represents the probability of strategy change for the n th neighbor, P_n is the total profit earned by the n th neighbor (in cents), K indicates the degree of randomness or noise in decision-making, and P_{an} denotes the average payoff of the n th neighbor (in cents), calculated as shown in [Eq. 13](#):

$$P_{an} = \sum_{\sigma} \frac{P_{\sigma}}{N}, \quad (13)$$

Where σ identifies the n th neighbor, N is the total number of neighbors, and P_{σ} is the payoff (in cents) obtained by neighbor σ .

In the present study, the parameter K is set to 0.8 [\[53\]](#). Whenever the computed probability ζ exceeds 0.8, the neighbor adopts the strategy currently used by the neighbor who has realized the greatest profit.

MG modeling and Proposed Case Study

The opening section introduces the key performance indices used to evaluate the proposed model. This is followed by a description of the case study used for validation.

Consumer discomfort cost

The willingness of consumers to cooperate depends heavily on the flexibility of their demand profiles. Shifting demand patterns impose a discomfort cost on the individual adjusting [54]. This discomfort cost is borne by the neighbor who initiates the cooperation request. A linear formulation of discomfort cost, originally presented in Song et al. [32], is adopted here and given in Eq. 14:

$$DP_n(t) = k_n^t * dp_n(t), \quad (14)$$

Where $DP_n(t)$ is the discomfort cost incurred by the n th neighbor during time interval t (in cents), k_n^t represents the discomfort coefficient of the n th neighbor (in cents/kW), and $dp_n(t)$ is the amount of power shifted by the n th neighbor from time t to another interval (in kW). The coefficient k_n^t reflects the neighbor's reluctance or willingness to alter demand patterns and is selected based on the values reported in Song et al. [32].

Neighbor's utility

The utility function quantifies the satisfaction a neighbor derives from their total power consumption. Since utility reflects contentment with energy use, zero consumption corresponds to zero utility. Earlier research has demonstrated that consumer behavior in power systems can be effectively represented using utility functions [55, 56]. To ensure the utility function U_n for the n th neighbor is appropriate, it must satisfy the following three conditions, expressed in Eqs. 15–17 [57]:

- The utility function must be strictly increasing with respect to power consumption.
- Consumption levels exceeding the neighbor's maximum acceptable amount should result in saturation of satisfaction (modeled as a bounding constraint).
- Zero power consumption must yield zero utility.

$$\partial U_n(P_n) / \partial P_n \geq 0, \quad (15)$$

$$\partial^2 U_n(P_n) / \partial P_n^2 \leq 0, \quad (16)$$

$$U_n(0) = 0. \quad (17)$$

A differentiable, concave function that equals zero at $P_n = 0$ meets these criteria. A quadratic utility function fulfills this requirement and is therefore adopted, as shown in Eq. 18:

$$U_n(P_n(t)) = \begin{cases} \omega_n P_n(t) - \alpha_n P_n^2(t) & P_n \leq \omega_n / 2\alpha_n \\ \omega_n^2 / 4\alpha_n & P_n \geq \omega_n / 2\alpha_n \end{cases}. \quad (18)$$

The parameters ω_n and α_n vary from neighbor to neighbor. Their specific values for each neighbor are provided in Table 3 [58]. The discount factor δ_n and punishment factor λ_n are taken from Table 2.

Table 3. ω_n , α_n , δ_n , and λ_n for neighbors.

Neighbors' number				
1	154.53	0.0935	0.9592	1.0197
2	146.52	0.0417	0.0524	1.9359
3	165.78	0.1007	0.0671	1.8273
4	63.54	0.0561	0.5442	1.5558
5	97.65	0.0540	0.4214	1.5430
6	170.19	0.1414	0.5308	1.5807
7	168.84	0.0793	0.4988	1.5782
8	141.3	0.1064	0.6668	1.6396
9	128.52	0.0850	0.7397	1.6061
10	91.35	0.0460	0.4488	1.4

Since the proposed method relies on linear optimization, the quadratic utility function in Eq. 18 is linearised, yielding the expression given in Eq. 19 [59, 60].

$$U_n(P_n(t)) = \begin{cases} (\omega_n - 6\alpha_n)P_n(t) + 9\alpha_n & P_n \leq \omega_n/2\alpha_n \\ \omega_n^2/4\alpha_n & P_n \geq \omega_n/2\alpha_n \end{cases}. \quad (19)$$

Repeated game structure

Considering the set of neighbors (N), the collection of individual action sets ($\{A_n\}_{n=1}^N$), and the collection of per-neighbor cost functions ($\{c_n\}_{n=1}^N$).

Within the repeated-game framework, during the r th round, the n th neighbor issues a request for surplus energy to the other neighbors. The complete history of the n th neighbor up to round r is expressed as

$\eta_n^r = \{a_n^0, u_n^0, \dots, a_n^{r-1}, u_n^{r-1}\} \in (A_n \times \rho_n)$, where a_n^r denotes the action taken by the n th neighbor in round r ($a_n^r = 1$ in case of cooperation, a_n^r otherwise). The associated history of utilities for that neighbor is denoted

$\eta_n^r = \{u_n^0, \dots, u_n^{r-1}\} \in (\rho_n)$. The public strategy of the n th neighbor is defined as a function that maps the

observed public history to the action chosen in the current round, represented as $\tau_i = \bigcup_{r=0}^R (\rho_n)^r \rightarrow A_n$ [32, 61].

Furthermore, each neighbor's starting strategy is determined according to their inherent qualitative personality characteristics. The initial cooperation configuration for every neighbor is illustrated in Figure 5.

$$a_n^0 = \begin{matrix} & \begin{matrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \\ 10 \end{matrix} & \left\{ \begin{array}{cccccccccc} 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array} \right\} \end{matrix}$$

Figure 5. Initial states of neighbors.

In the matrix shown in **Figure 5**, the row index corresponds to the neighbor issuing the cooperation request, while the column index indicates the initial cooperation state of the receiving neighbor.

As previously depicted in **Figure 4**, neighbors apply a discount factor to the anticipated payoffs from cooperative partners and impose a punishment factor on defectors. These discount and punishment coefficients vary across neighbors and are directly linked to their specific personality profiles.

The overall repeated energy-sharing game is formally defined as $\{N, \cup_{r=0}^{\infty} (p_n)r, \{C_n(\tau)\}_{Nn=1}\}$, where N represents the set of neighbors, $\cup_{r=0}^{\infty} (p_n)r$ denotes the union of all possible public histories, and $\{C_n(\tau)\}_{Nn=1}$ comprises the cost functions associated with the repeated game for each neighbor.

Objective function

The primary goal of this research is to reduce the cost of meeting excess energy demand by promoting neighbor-to-neighbor cooperation. The total cost incurred by a neighbor requiring assistance comprises two components: (i)

discomfort costs resulting from rescheduling the operation of household devices, and (ii) lost utility due to reduced energy availability. Furthermore, if a cooperating neighbor offers a price higher than the distribution company's, the requesting neighbor will opt to purchase directly from the utility [62]. Similarly, if cooperating neighbors cannot supply the full requested amount, the shortfall must be covered by purchasing from the distribution company. To achieve cost minimization, the objective function given in Eq. 20 is minimized:

$$C_n = \sum_1^t \sum_1^n (DP_n(t) + U_n(P_n(t))) + \sum_1^t C_u(t) * P_u(t), \quad (20)$$

Where C_n is the total cost function for the n th neighbor, $DP_n(t)$ represents the discomfort cost incurred by the n th neighbor at time t (in cents), $U_n(P(t))$ denotes the utility value associated with the n th neighbor's energy consumption (in cents), $P_n(t)$ is the power received from cooperating neighbors at time t (kW), $C_u(t)$ indicates the cost of purchasing power from the distribution company (in cents), and $P_u(t)$ is the amount of power procured from the distribution company at time t (in kW).

The power supplied by any cooperating neighbor must not exceed their available capacity, as enforced by the constraint in Eq. 21:

$$P_n(t) \leq MP_n(t), \quad (21)$$

Where $MP_n(t)$ is the maximum power that the n th neighbor can provide at time t .

An additional balance constraint, presented in Eq. 22, ensures that the neighbor's total power requirement is fully satisfied by the combined supply from neighbors and the distribution company:

$$\sum_1^n P_n(t) + P_u(t) = TP(t), \quad (22)$$

Where $TP(t)$ denotes the total power demand of the neighbor at time t (in kW).

Residential microgrid: case study

The residential microgrid under study includes one distribution company and 10 neighboring households (consumers), as depicted in Figure 6. Each household is equipped with a smart meter and a home energy management system (HEMS). Neighbors have full visibility into one another's demand and consumption patterns and can engage in direct energy sharing. Additionally, every neighbor maintains a connection to the distribution company and receives both day-ahead and real-time (spot) market price signals.

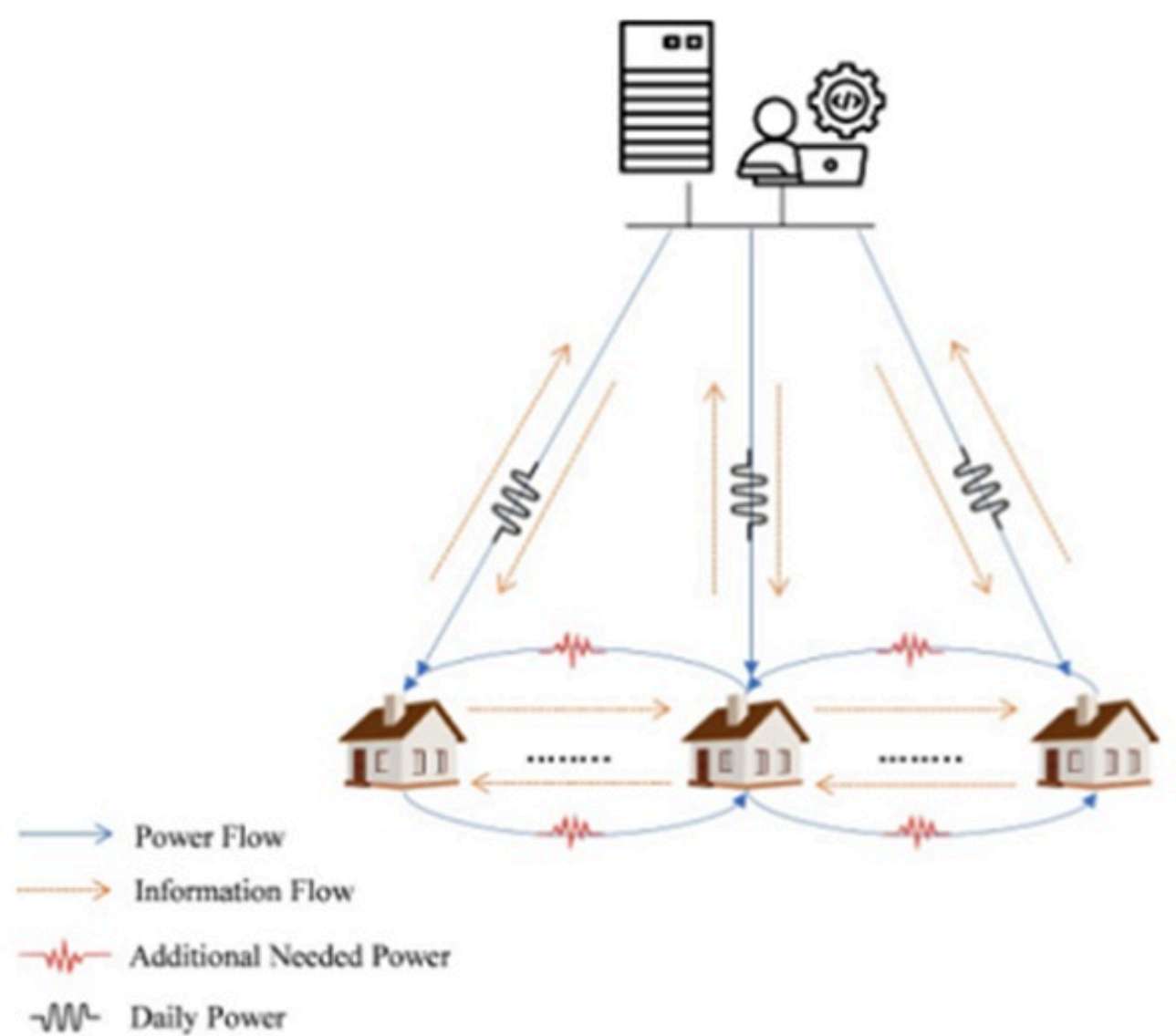


Figure 6. Assumed to show the residential microgrid configuration with 10 neighbors and the distribution company connection.

The set of consumers is denoted by $N = \{1, 2, \dots, 10\}$. Time is discretized into 24 intervals, $t = 1, 2, \dots, 24$. In each simulation run, the game is repeated for 600 rounds. At the beginning of each round, one neighbor is randomly selected to issue a cooperation request. Because simulation outcomes can vary depending on the sequence in which neighbors are chosen, the final reported results represent the average performance across 100 independent game repetitions. This averaging process ensures that the findings remain robust and are not sensitive to the specific order of neighbor selection.

At each round, neighbors utilize the household devices listed in Table 4 [63]. Their consumption profile, along with the predefined energy prices, is illustrated in Figure 7 [64]. As shown in Figure 7, the peak period extends from 13:00 to 20:00. During these hours, spot-market prices rise to roughly seven times the day-ahead market rates. Should neighbors' demand exceed forecast levels, they must cover the additional energy at spot-market prices.

Table 4. Devices and their times of use.

Devices	
Stone	(3 kW, 13, 15)
Air conditioner	(1.5 kW, 16, 18)
Dishwasher	(1.5 kW, 19, 20)

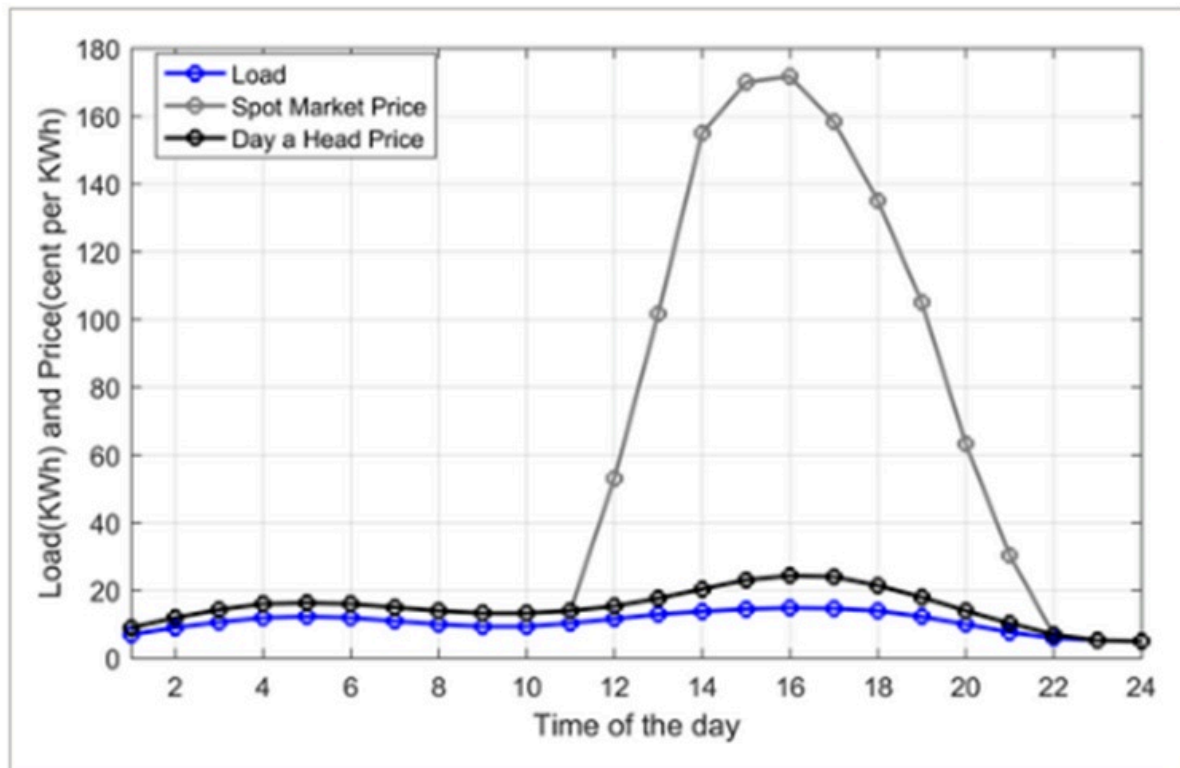


Figure 7. Power and cost diagram.

It should be noted that each neighbor's actual consumption is allowed to vary by $\pm 25\%$ around the nominal values provided. Furthermore, in line with Pavan Kumar and Bhimasingu [65], 5% of each neighbor's total consumption is treated as deferrable load that can be rescheduled.

In the second phase of the analysis, every neighbor is equipped with an individual energy storage system. This enables neighbors to sell any surplus energy stored in their batteries either to other neighbors or directly to the distribution company at predetermined prices. The surplus stored energy available from each neighbor per hour is detailed in [Table 5](#) [66].

Table 5. Surplus stored energy for each hour.

t	17	18	19	20	O.W
P_{bat} (Kw)	2.28	2.16	3.69	1.86	0

Simulation and Results

The cost-minimization problem is formulated and solved using GAMS via linear programming. Data preprocessing and post-processing tasks are performed in MATLAB. The linear optimization model is solved using CPLEX 12.8 on a personal computer with a Ryzen 5 4500U processor running at 2.3 GHz and 8 GB of RAM.

The simulation scenarios are divided into two primary cases. In the first case, neighbors assist one another by shifting deferrable loads. In the second case, neighbors possess energy storage systems and can sell excess stored energy either to the distribution company or to neighboring households. Both sets of simulations focus on evaluating how neighbor-to-neighbor cooperation influences the amount of power transferred and the total cost incurred to satisfy excess demand.

Within each main case, three distinct subcases are examined:

- Subcase 1: Simulations are conducted assuming fixed energy utility values for neighbors and unchanging strategies.
- Subcase 2: Neighbors' cooperation is analyzed with variable energy utility values while strategies remain fixed.
- Subcase 3: Neighbors have heterogeneous energy utilities and are permitted to adapt their strategies over time.

To facilitate the application of the proposed method to other residential neighborhoods, the average price at which surplus stored energy is sold is calculated. Additionally, mean discount and punishment factors are determined to help identify neighborhoods characterized by high levels of cooperation.

The final part of this section validates the simulation outcomes by cross-referencing them with established findings from social science and electrical engineering literature.

To implement the proposed approach, the solution procedure begins by randomly selecting one neighbor to issue a cooperation request. The remaining neighbors then decide whether to cooperate or defect, based on the requester's historical behavior, their own personality traits, and the anticipated profit from cooperation. Subsequently, the requesting neighbor optimizes the procurement cost of their excess demand by comparing offers from cooperating neighbors against the distribution company's price. Following each decision, the requester adjusts the utility value assigned to non-cooperative neighbors upward and to cooperative neighbors downward, in accordance with their personality profile. In every round of the game, each neighbor's discount and punishment factors are updated by taking the average values from [Table 3](#) and applying a 5 % standard deviation within the range specified for their strategy in [Table 2](#).

The simulations employ a complete-information repeated game to ensure equitable distribution of benefits among neighbors. Complete information implies that the neighbor issuing the cooperation request is fully aware of each potential responder's identity, their decision (cooperate or defect), and the exact amount of power they can supply. Consequently, following any cooperation or defection, the requester can immediately adjust future utility values—reducing them for cooperative partners or increasing them (as punishment) for defectors—in subsequent rounds. A flowchart depicting the overall problem-solving algorithm is provided in [Figure 8](#).

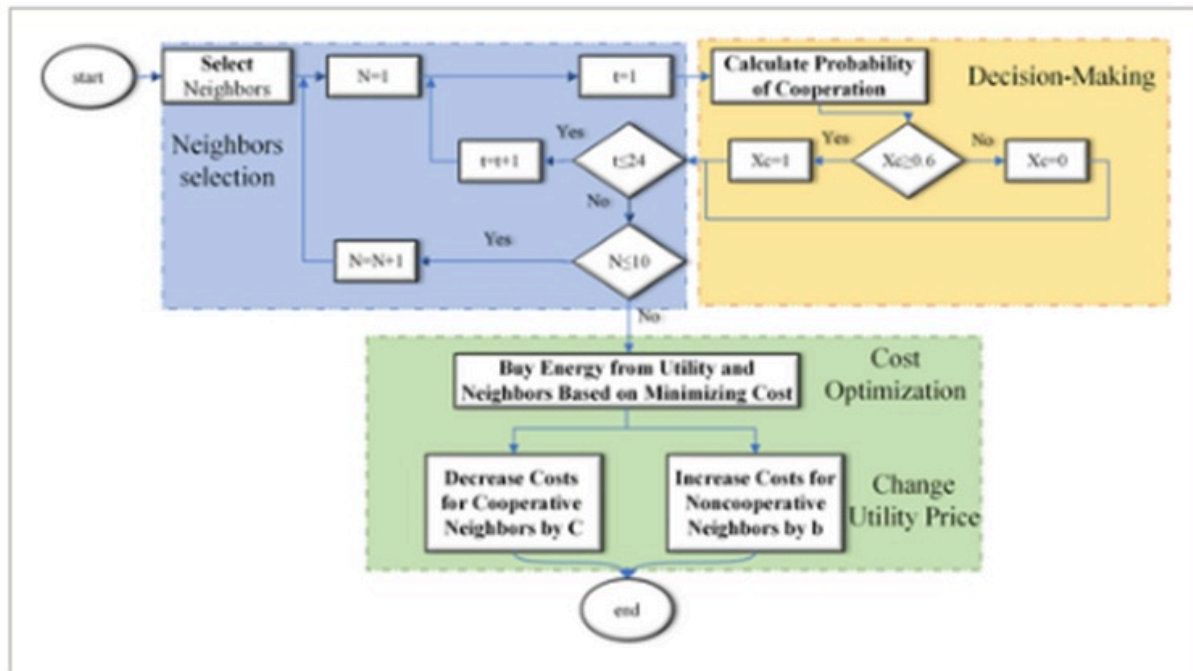


Figure 8. Problem-solving algorithm flowchart.

Because the objective function is minimized independently for each neighbor, each with a unique performance history and behavioral profile, no single, universal equilibrium point exists for the game. Rather than seeking one global equilibrium, the model identifies local equilibrium points tailored to each neighbor's specific behavior and personality traits. These individualized balance points collectively ensure stability and equilibrium across the entire system, with game-theoretic principles providing the necessary guarantees for overall performance.

Numerical results

Case 1

In the first main case, neighbors assist one another by shifting their deferrable loads. The analysis proceeds through three subcases. Initially, simulations are conducted under the assumption of fixed energy utility values for all neighbors and unchanging behavioral strategies. In the second subcase, cooperation is examined under variable energy utility values while strategies remain fixed. Finally, in the third subcase, neighbors exhibit heterogeneous energy utilities and can adapt their strategies over time.

The first subcase focuses on cooperation under constant energy utility. The objective here is to evaluate how neighbors' personality traits influence the costs they ultimately pay. In this scenario, strategies are held fixed, and energy, excess demand, and deferrable load volumes remain constant across all neighbors. As depicted in **Figure 9**, the 8th and 9th neighbors—who follow WSLS and tit-for-tat (tft) strategies, respectively—incur substantially lower costs than most others. In contrast, the 2nd and 3rd neighbors, who adopt the Always Defect (AD) strategy, incur significantly higher costs than the rest of the group. Furthermore, neighbors employing WSLS strategies receive the highest amounts of transferred power, whereas those with AD strategies receive the lowest.

Additionally, the 2nd and 3rd neighbors (AD) incur particularly high costs by the final round due to their persistent refusal to cooperate, forcing them to procure most of their excess demand directly from the distribution company. Meanwhile, the 1st neighbor—consistently cooperative in all situations—gradually experiences reduced cooperation from others after several rounds, as neighbors adjust their responses to repeated one-sided assistance. Likewise, the 10th neighbor, who

follows the Suspicious Tit-for-Tat (S-tft) strategy and is initially reluctant to cooperate, pays more than neighbors using standard tit-for-tat.

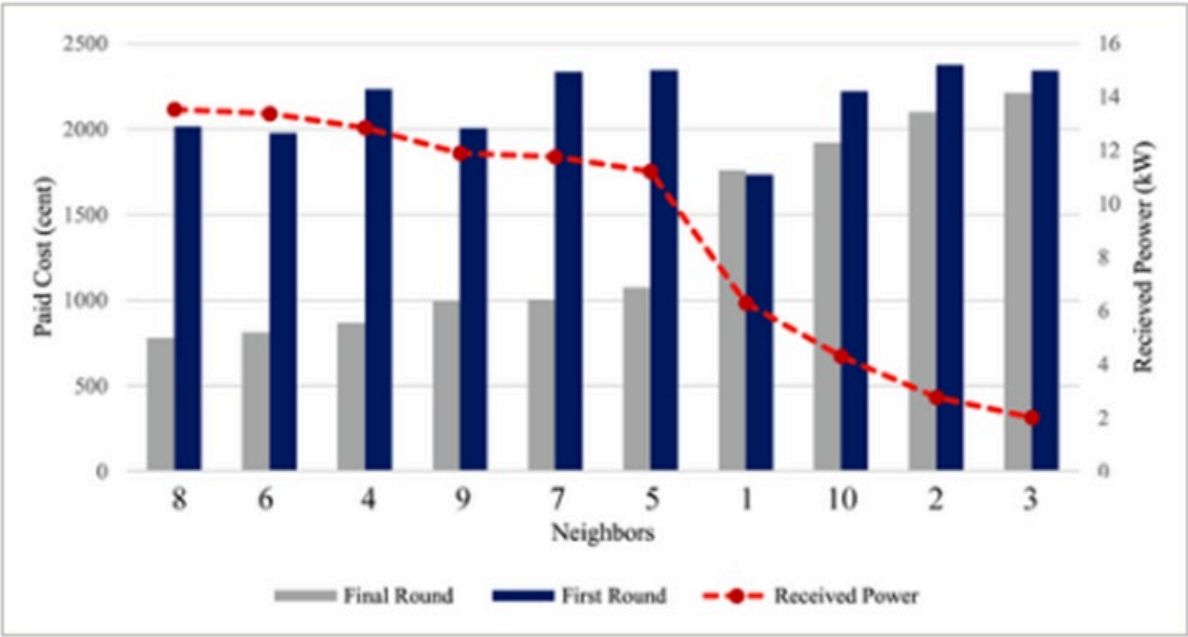


Figure 9. Neighbors received power and paid costs at the first and final rounds under constant-utility and non-changing strategies.

The results shown in [Figure 9](#) indicate that, when strategies are fixed, neighbors employing WSLS and tft strategies achieve the lowest costs. These findings align closely with observations reported in Imhof *et al.* [67] and Bone *et al.* [68].

In the second subcase, cooperation is analyzed under fixed personality traits but with varying energy utility values across neighbors. Here, neighbors can respond to cooperation requests solely by rescheduling deferrable devices. A neighbor who obtains energy through cooperation compensates cooperating neighbors with both discomfort costs and utility-based payments. This subcase aims to assess the impact of unchanging personality traits on overall energy procurement costs. [Figure 10](#) illustrates the power received and costs paid by each neighbor under fixed strategies but variable utility.

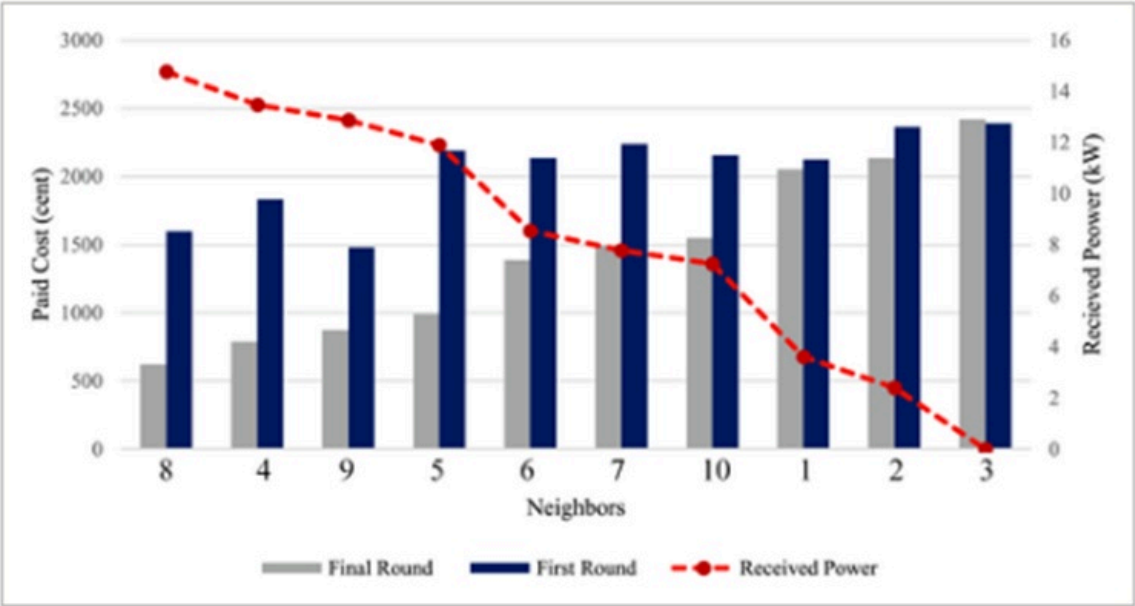


Figure 10. Neighbors’ received power and paid costs at the first and final rounds under constant strategies and variable utility.

By cross-referencing [Figure 10](#) with the parameter values in [Table 3](#), it becomes evident that although the 8th, 6th, and 9th neighbors possess higher energy utility than the 4th and 5th neighbors, they still incur lower total costs. Similarly, the 1st neighbor’s higher utility leads to reduced cooperation from others compared with the 10th neighbor. Consistent with the previous subcase, neighbors following WSLs and tft strategies pay the lowest costs and receive the largest amounts of power from others.

In the third subcase, cooperation is examined under heterogeneous energy utilities and adaptive (changeable) strategies. [Figure 11](#) presents the power received and costs paid by neighbors when strategies are allowed to evolve.

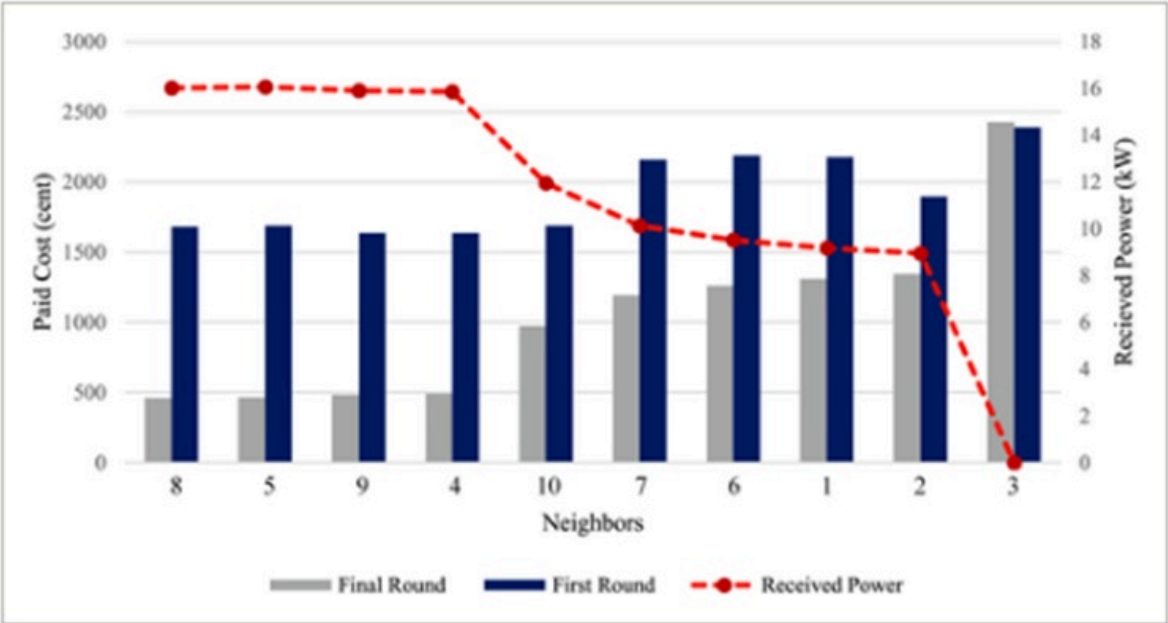


Figure 11. Neighbors received power and paid costs at the first and final rounds under different energy utilities and variable strategies.

A comparison of **Figures 10 and 11** reveals that shifting from fixed to adaptive strategies results in a noticeable increase in the total volume of energy shared among neighbors. Notably, the 2nd and 3rd neighbors (AD strategy) benefit from lower costs early in the game due to their initial non-cooperative history. Conversely, the 8th and 9th neighbors (WSLS) attract more power transfers over time thanks to their consistent cooperative record. Additionally, the 10th neighbor—whose utility is lower than that of the 1st, 6th, and 7th neighbors—experiences a marked increase in cooperation from others once strategy adaptation begins.

As shown in **Figures 10 and 11**, the possibility of neighbors switching strategies toward those that have historically achieved higher payoffs leads to lower overall procurement costs when strategies are changeable, compared with when they are fixed. Neighbors exhibiting cooperative tendencies consistently achieve the lowest costs in both scenarios, whereas non-cooperative neighbors—specifically the 2nd and 3rd—incur the highest expenses across all subcases.

Case 2

This case follows a structure similar to the previous one and includes three distinct subcases: first, neighbors have constant energy utility values and fixed (nonchangeable) strategies; second, each neighbor is assigned a different energy utility value while strategies remain fixed; and third, neighbors possess heterogeneous energy utilities and are permitted to adapt their strategies to maximize their individual payoffs. In the present case, at each round, neighbors decide whether to sell any surplus energy stored in their batteries to the distribution company or to supply it directly to other neighbors. The selling price for excess energy from storage is set at 1.5 times the day-ahead market purchase price. The costs incurred in the first round, the costs in the final round, and the quantities of energy exchanged among neighbors under constant-utility and fixed-strategy scenarios are presented in **Figure 12**.

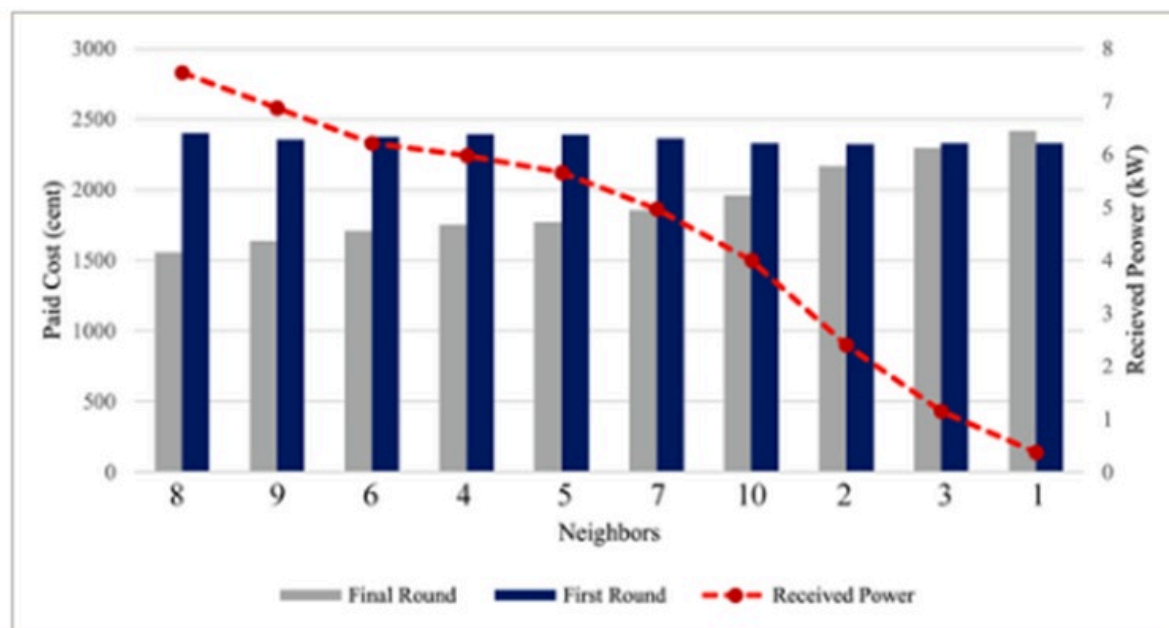


Figure 12. Neighbors received power and their costs at the first and final rounds in constant-utility and non-changeable strategies, considering energy storage.

As illustrated in **Figure 12**, the initial costs across neighbors are relatively similar. However, as the game progresses, neighbors employing WSLS and tit-for-tat (tft) strategies consistently achieve lower total costs than the rest of the group. These same neighbors also receive the largest amounts of power from others. In contrast, neighbors following the Always

Cooperate (AC) and Always Defect (AD) strategies incur higher costs than those following the other strategies. When **Figures 9 and 12** are compared, it becomes apparent that, because neighbors in this scenario can sell surplus battery energy to the distribution company, their overall paid costs are higher than in the case without storage. Additionally, the volume of power received through neighbor-to-neighbor transfers is noticeably lower when energy storage systems are available.

In the second subcase, neighbors are assigned distinct energy utility values while their strategies remain unchanged. The outcomes of this subcase are displayed in **Figure 13**. As shown in **Figure 13**, neighbors with WSLS and tft strategies obtain more power from others than the remaining participants. Moreover, higher volumes of received power from neighbors correlate with reduced total paid costs. Furthermore, the 2nd and 3rd neighbors—due to their reluctance to cooperate—incur substantially higher costs to meet excess demand than the rest of the group, and they receive the smallest amounts of transferred power. In addition, the 10th neighbor, whose energy utility is lower than that of the 1st, 5th, 6th, and 7th neighbors, experiences increased cooperation from others, resulting in a lower total paid cost than those four neighbors. It should be noted that the first-round costs for all neighbors are influenced by the random selection of the neighbor issuing the cooperation request, their initial behavioral tendencies, and their prior cooperation history.

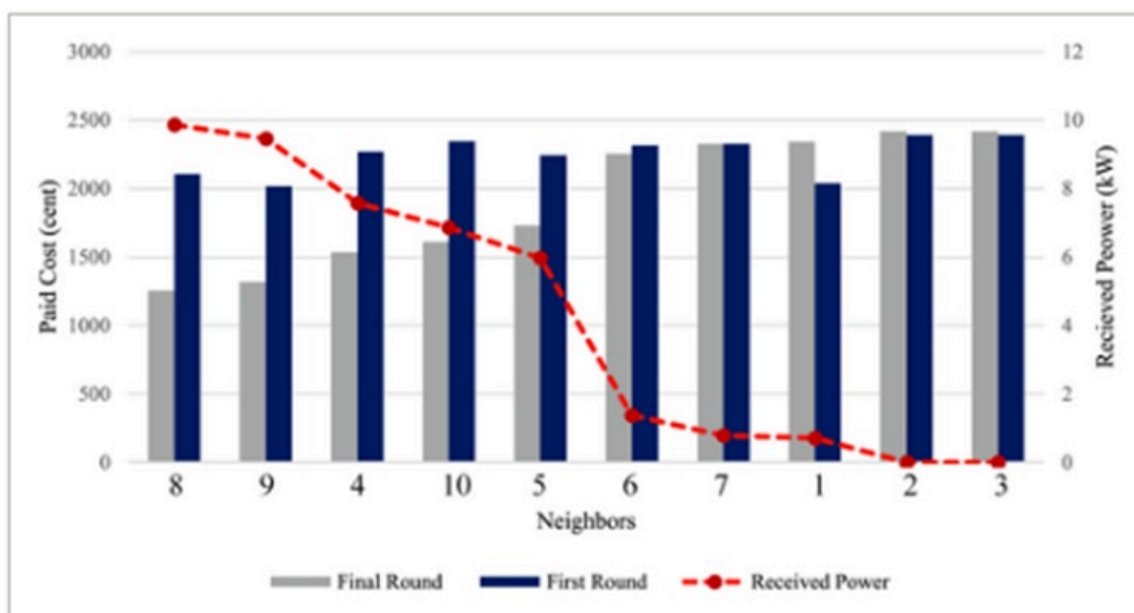


Figure 13. Neighbors received power and their costs were paid at the first and final rounds under different energy utilities and non-changeable strategies, with energy storage considered.

Figures 12 and 13 together demonstrate that variations in neighbors' energy utility levels directly affect the amount of power they receive from others and, consequently, the total costs they ultimately pay.

A comparison between **Figures 10 and 13** reveals that the option to sell surplus stored energy to the distribution company reduces overall cooperation among neighbors. As power transfers from neighbors decline, participants' total procurement costs increase.

The third subcase examines how the ability to change strategies influences cooperation patterns. In this scenario, neighbors continue to have different energy utility values. The results for this subcase are presented in **Figure 14**.

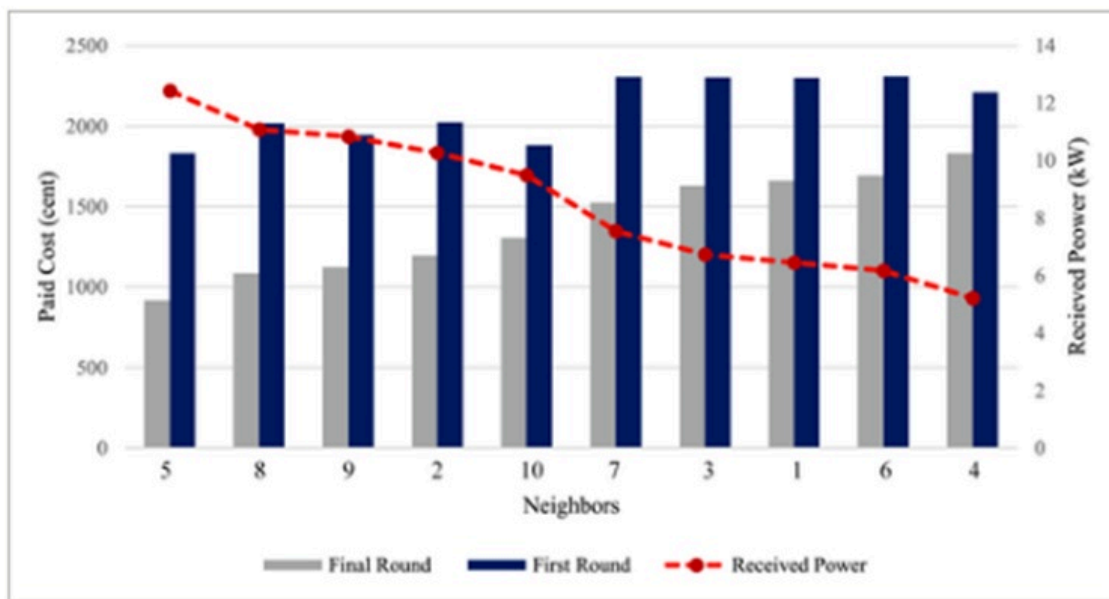


Figure 14. Description of neighbors receiving power and paying costs at the first and final rounds under different energy utilities and changeable strategies, considering energy storage.

Figure 14 highlights that enabling neighbors to revise their strategies leads to a clear rise in the volume of power exchanged directly among them. This shift results in a meaningful reduction in the cumulative costs each neighbor ultimately bears. Even when participants gravitate toward lower-cost behavioral patterns through adaptation—as seen in prior subcases—those consistently applying WSLs still register the most favorable expense levels.

When **Figures 13 and 14** are placed side by side, it is evident that permitting strategy adaptation boosts inter-neighbor power transfers and, as a direct consequence, trims the final procurement expenditures.

Figures 11 and 14 together show that, in setups lacking storage capacity (where excess energy cannot be offloaded to the utility), neighbors face noticeably lower overall expenses.

Comparison across case studies

The present subsection compares the outcomes across the different simulation scenarios. Aggregate power transferred to each neighbor from others, total expenditures incurred, and mean cost per behavioral strategy are summarised in **Figures 15–17**, respectively. **Figure 15** makes clear that the introduction of battery storage substantially lowers the cumulative energy traded peer-to-peer, mainly because neighbors gain the economically attractive option of selling surplus stored energy back to the distribution company.

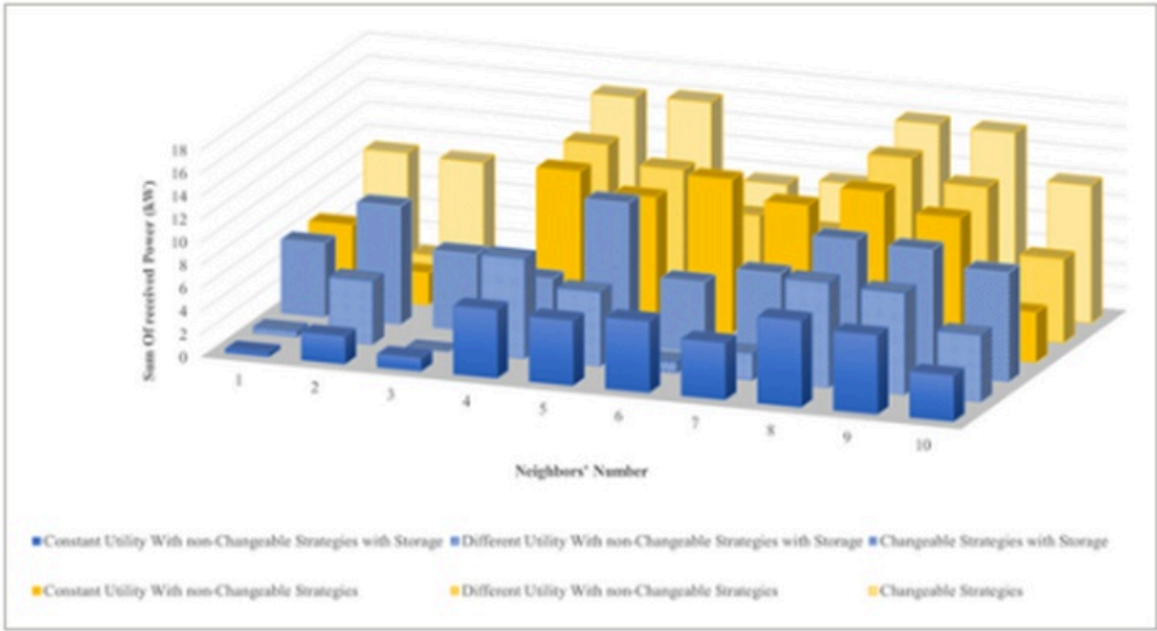


Figure 15. Aggregate power received from neighbors across the various simulation scenarios (kW).

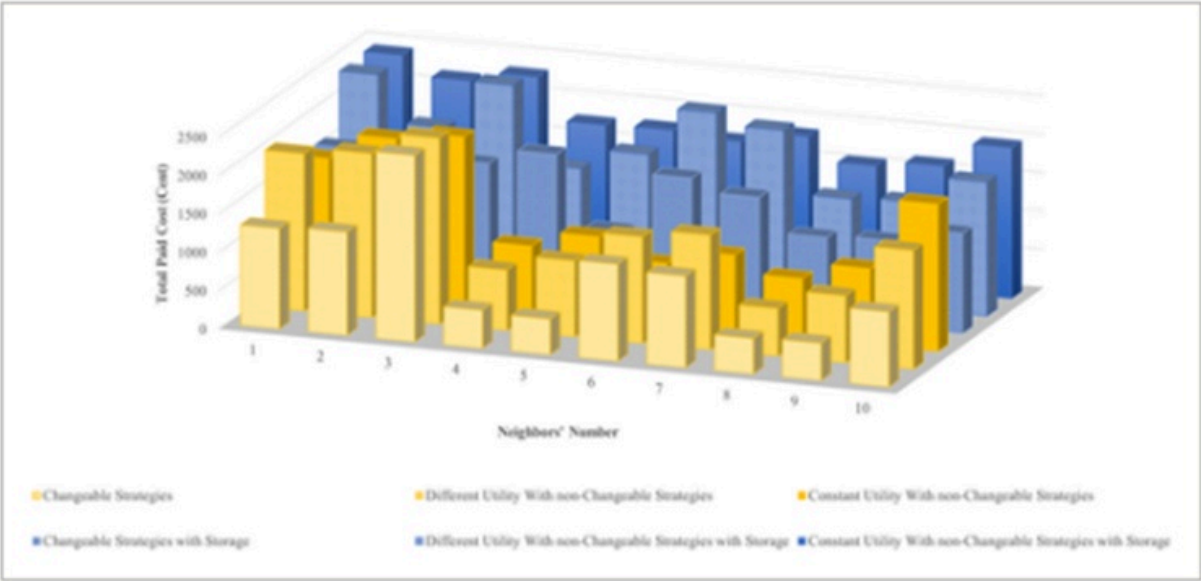


Figure 16. Total paid costs of neighbors in the different simulation scenarios (cents).

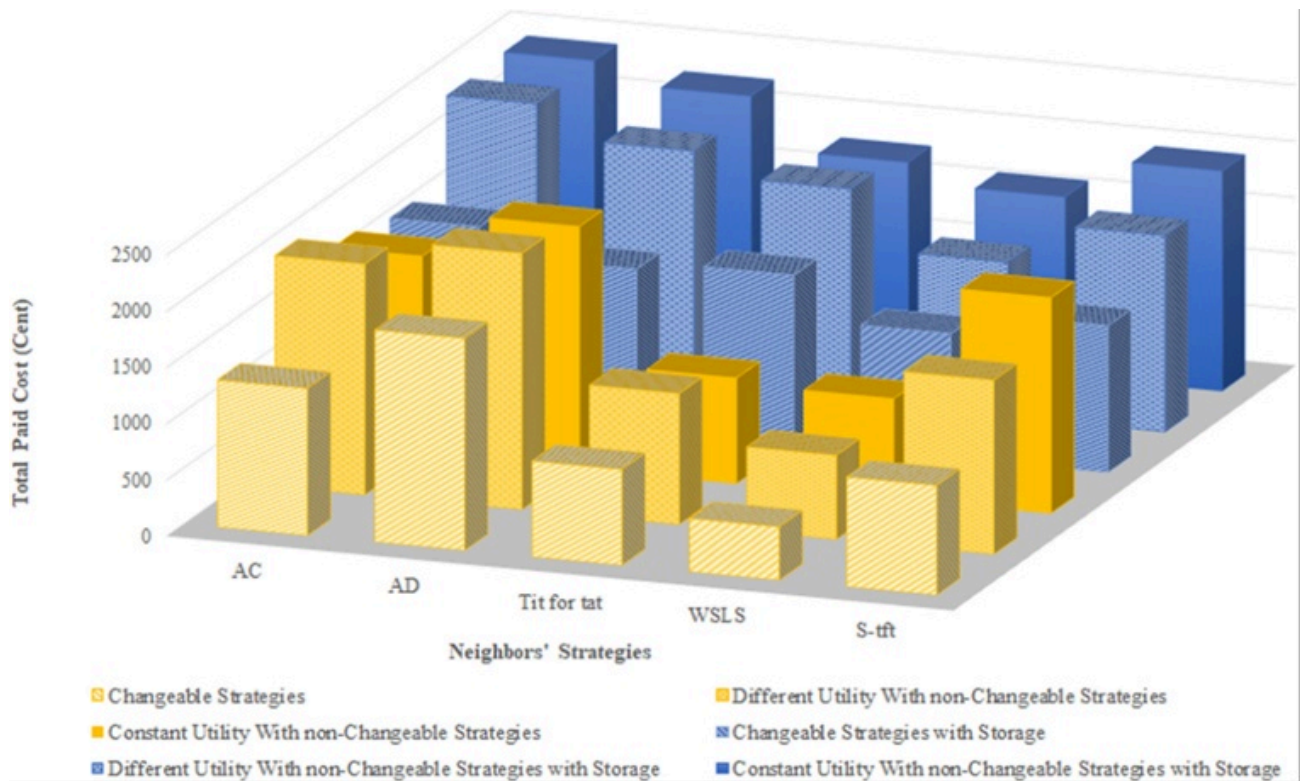


Figure 17. Mean final paid cost broken down by strategy type across the simulation scenarios (cents).

Figure 16 reveals that incorporating variable utility values, along with the possibility of selling stored energy, results in noticeably lower expenses for neighbors who adopt WSLS or tit-for-tat (tft) behaviors compared with the rest of the group. At the same time, the reduced peer-to-peer power sharing that accompanies storage availability pushes total costs upward for the community as a whole.

As further evidenced in **Figure 16**, the 2nd, 3rd, and 10th neighbors—owing to their sustained reluctance to engage in cooperation—and the 1st neighbor—due to persistent one-sided assistance despite others' defection—shoulder markedly higher expenses than most participants. Conversely, neighbors following WSLS and tft profiles, which combine readiness to assist with appropriate reciprocal responses to defection, incur lower costs in the vast majority of situations.

Figure 17 presents the average final paid costs at the strategy level. In every simulated scenario, WSLS and tft participants record the lowest mean expenses. By contrast, those adhering to AD, S-tft, or AC patterns incur consistently higher average outlays than the rest.

If all excess demand were satisfied exclusively through purchases from the distribution company, the system would need to supply 16.5 kW per round, totaling 165 kW across the full set of neighbors. Yet, according to **Figure 15**, the proposed cooperation-based mechanism covers up to 90 % of the total excess energy requirement internally. By addressing peak-period demand through local sharing rather than utility supply, the approach achieves a substantial reduction in external peak load. Moreover, meeting the entire excess demand through the distribution company would cost 25,830 cents. In comparison, the cooperative framework depicted in **Figure 17** reduces the cost of satisfying excess demand by up to 80%.

Average of discount and punishment factor

To facilitate the application of the proposed framework to other residential communities, it is essential to examine the average discount and punishment factors as indicators for recognizing highly cooperative neighborhoods. Specifically,

progressively reducing the considered discount factor while simultaneously increasing the punishment factor enables evaluation of how these parameters influence cooperation among neighbors.

In the adopted approach, the average discount and punishment factors are incrementally adjusted in steps of 0.05 to assess their impact on cooperative behavior systematically. **Figures 18 and 19** depict the average discount and punishment factors across neighbors, for scenarios without and with energy storage, respectively.

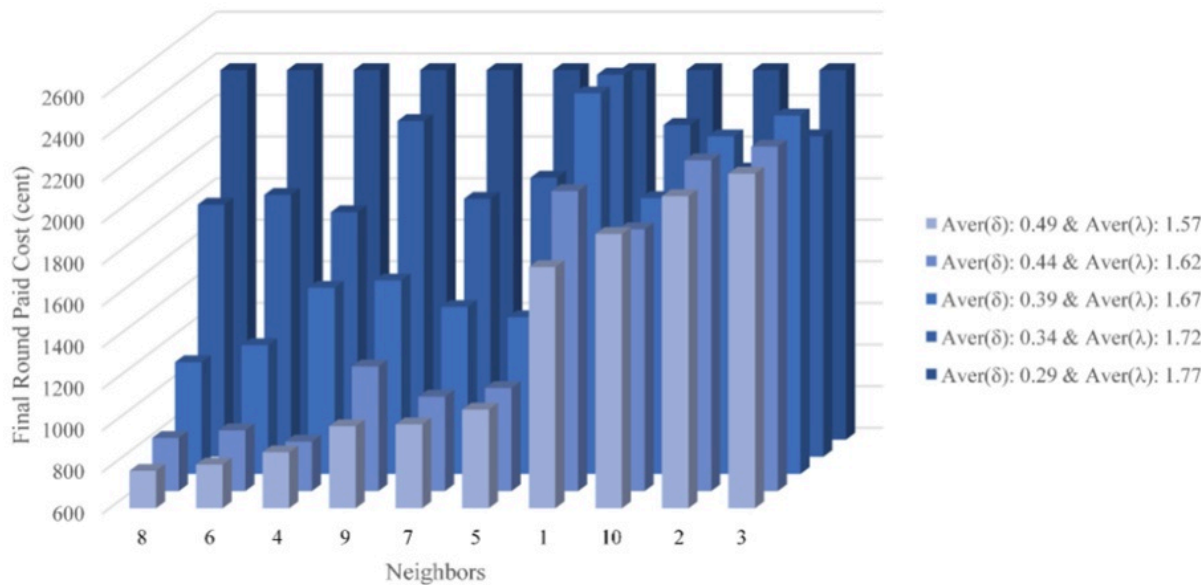


Figure 18. Influence of the average discount and punishment factors on the final paid cost of neighboring participants under constant-utility and fixed-strategy conditions, excluding energy storage.

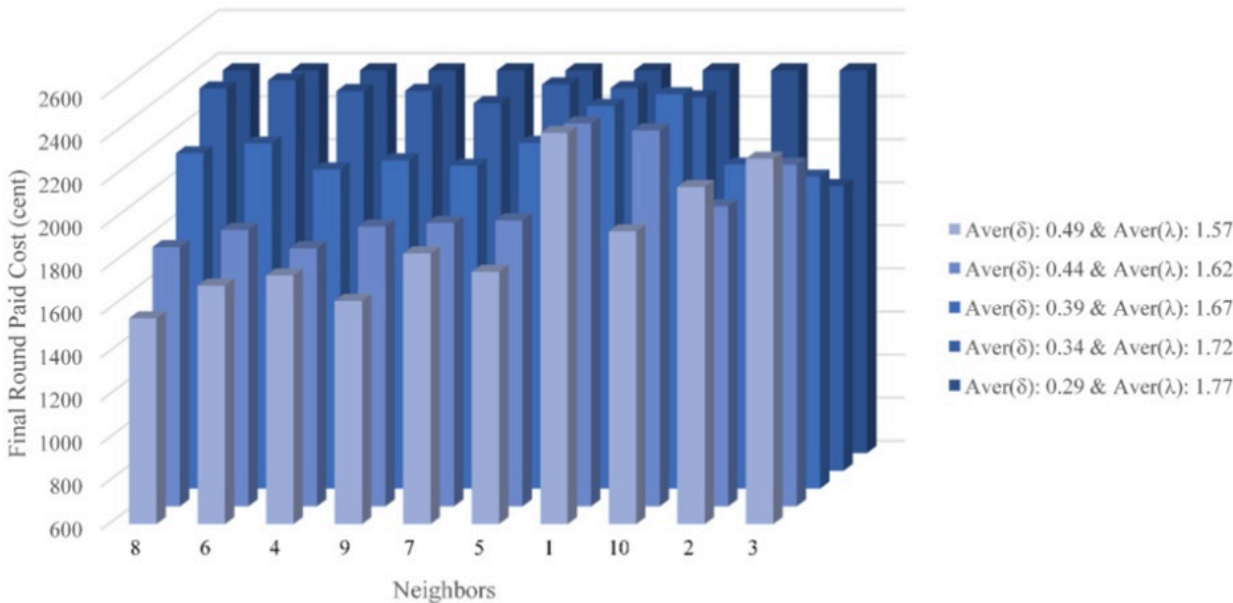


Figure 19. Influence of the average discount and punishment factors on the final paid cost of neighboring participants under constant-utility and fixed-strategy scenarios, including energy storage.

As shown in **Figures 18 and 19**, when the neighborhood-wide average discount factor lies within the interval $\delta \in [0.44, 1)$ and the average punishment factor falls in the range $\lambda \in [1, 1.62]$, a reliable expectation of cooperative behavior from the neighbors can be formed.

Figures 18 and 19 further indicate that, across all simulation rounds and for every tested combination of average discount and punishment values, neighbors adopting WSLS and tit-for-tat (tft) strategies consistently incur lower costs than those following other behavioral profiles. These observations align closely with previous findings by Imhof et al. [67] and Bone et al. [68].

Energy storage purchasing cost

This subsection analyses how progressively increasing the selling price of stored energy affects both the degree of cooperation among neighbors and their ultimate procurement expenses. In the simulations, the price at which stored energy is offered rises after each round of the game. **Figure 20** illustrates that higher stored-energy prices lead to a steady decline in the volume of power exchanged directly between neighbors. As previously observed in **Figures 15 and 16**, this reduction in peer-to-peer transfers forces neighbors to satisfy a larger share of their excess demand by purchasing from the distribution company at spot-market rates, thereby leading to a marked increase in total paid costs.

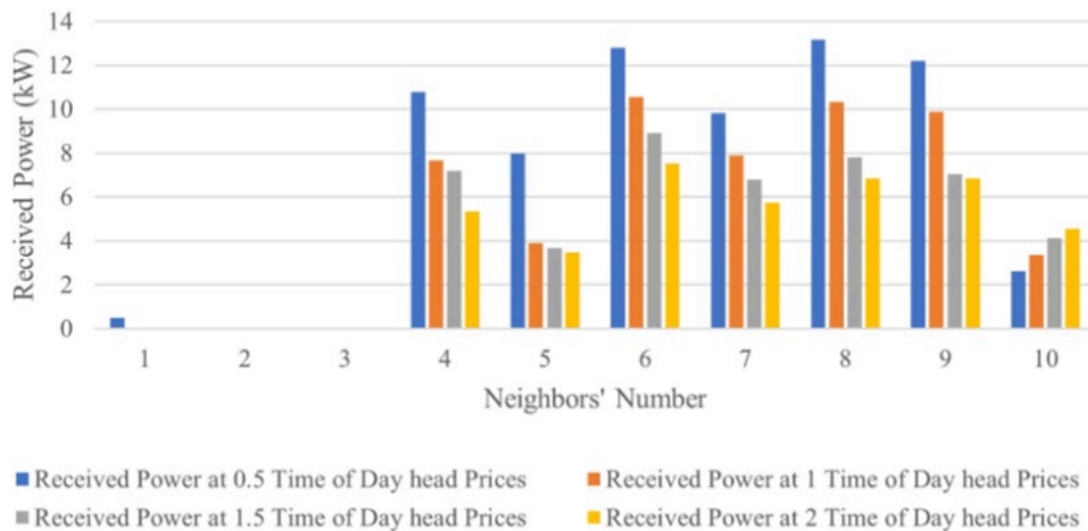


Figure 20. Changes in the power received by neighbors across varying stored-energy selling prices, under constant utility and unchanging strategies.

Furthermore, **Figure 21** demonstrates that even as stored-energy prices increase round by round, neighbors employing WSLS strategies continue to achieve lower final costs than participants using other behavioral approaches.

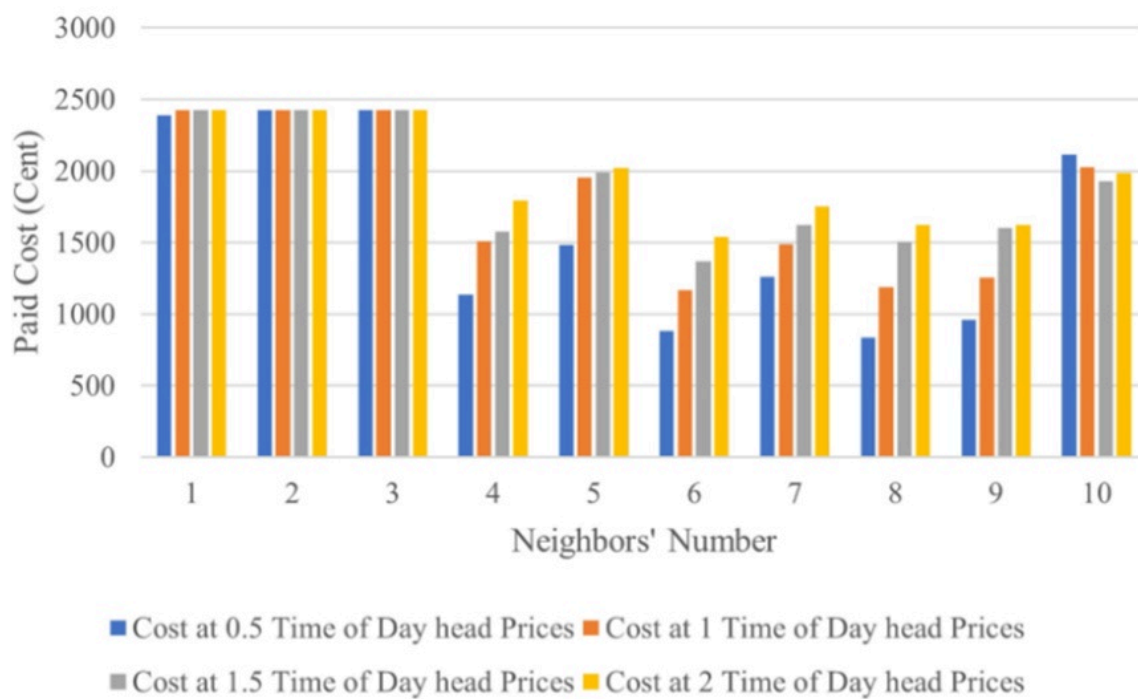


Figure 21. Changes in the final paid costs of neighbors across varying stored-energy selling prices, under constant utility and unchanging strategies.

Results verification

The framework developed in this paper integrates well-established models from social sciences with technical-economic approaches commonly applied to peer-to-peer energy sharing in power systems. Consequently, validation of the proposed method requires a dual perspective that encompasses both social-behavioral and energy-system engineering dimensions. To that end, the behavioral and social characteristics of the problem are compared against relevant studies in the social sciences literature [67, 68]. At the same time, the technical and operational aspects of energy management are cross-checked against findings reported in pertinent publications in the electrical engineering domain [55].

Given that the core focus of the present work is managing energy transactions through the lens of human behavioral patterns, conducting a parallel assessment of these two domains is one of the most robust strategies for confirming the reliability of the results. The key elements of this verification process are outlined in the following paragraphs.

Drawing on social science investigations documented in Imhof *et al.* [67] and Bone *et al.* [68], it is clear that individuals who adopt Always Defect (AD) and Win-Stay-Lose-Shift (WSLS) strategies obtain the lowest and highest net benefits from cooperative interactions, respectively. This implies that, in a neighborhood where every participant follows the AD strategy, cooperation will not emerge. Under such conditions, any neighbor requiring additional power must procure it entirely from the spot market. Conversely, when all neighbors adhere to the WSLS strategy, full cooperation prevails, enabling them to satisfy excess demand through internal sharing collectively. As a direct result, WSLS neighbors incur substantially lower surplus power expenses than their AD counterparts and therefore realize greater overall gains. These behavioral outcomes are in strong agreement with established conclusions drawn from social science research [22, 23].

Figure 22 displays the simulation results for the test residential microgrid, where every neighbor employs the AD strategy, and no energy storage is present. As depicted in **Figure 22**, when all neighbors adopt AD behavior, zero cooperation occurs, forcing each participant to obtain their excess energy exclusively from the distribution company.

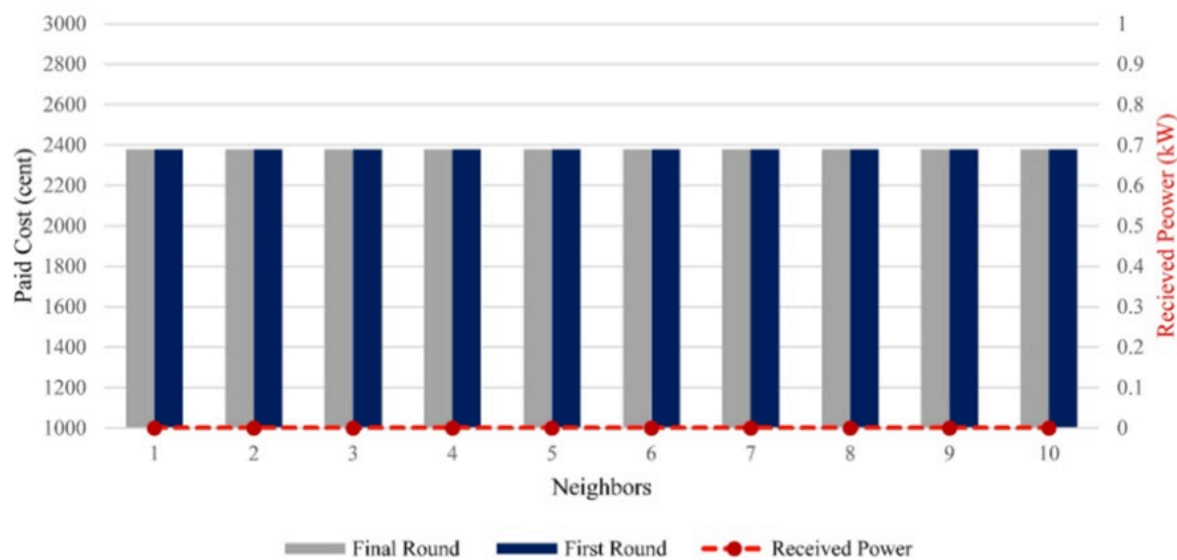


Figure 22. Neighbors' power and paid costs at the first and final rounds with the AD strategy.

The corresponding results for a neighborhood in which all neighbors follow the WSLS strategy are presented in [Figure 23](#). [Figure 23](#) demonstrates that universal adoption of WSLS leads to complete cooperation: all excess demand is met internally through mutual assistance, resulting in markedly reduced energy procurement costs.

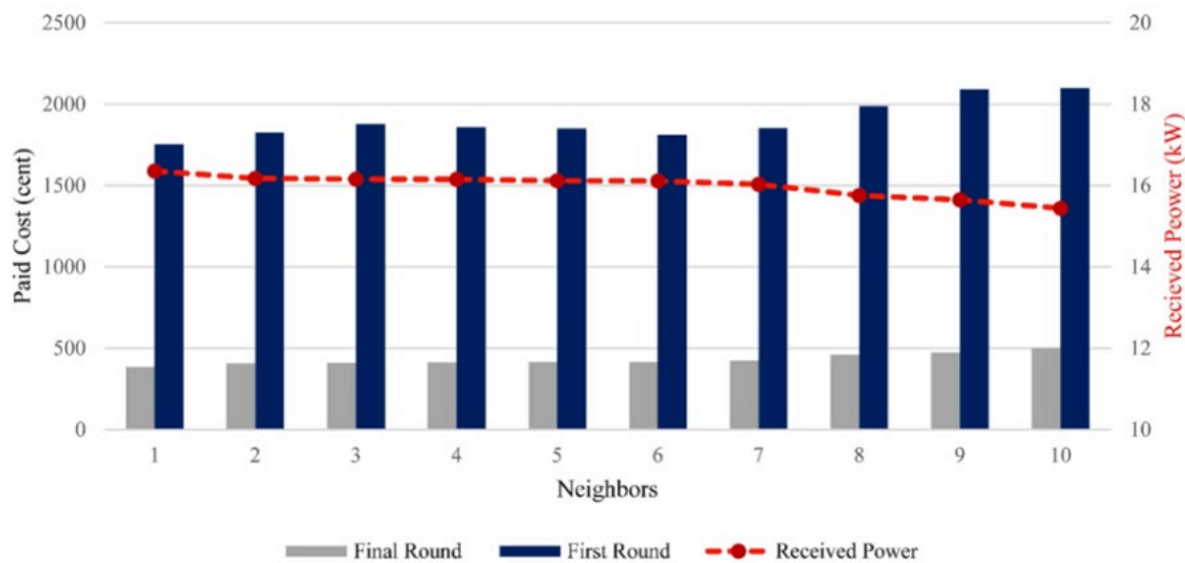


Figure 23. Neighbors received power, and their costs were paid in the first and final rounds under the WSLS strategy.

A side-by-side comparison of [Figures 22 and 23](#) confirms that WSLS participants can meet their entire surplus power requirement through neighbor-to-neighbor collaboration, thereby achieving significantly lower costs than under the AD strategy.

[Figure 24](#) illustrates the power received from neighbors and the associated costs when the AD strategy is applied with energy storage systems. Consistent with the pattern in [Figure 22](#), [Figure 24](#) shows that persistent AD behavior prevents cooperation, compelling neighbors to meet excess demand by purchasing from the distribution company.

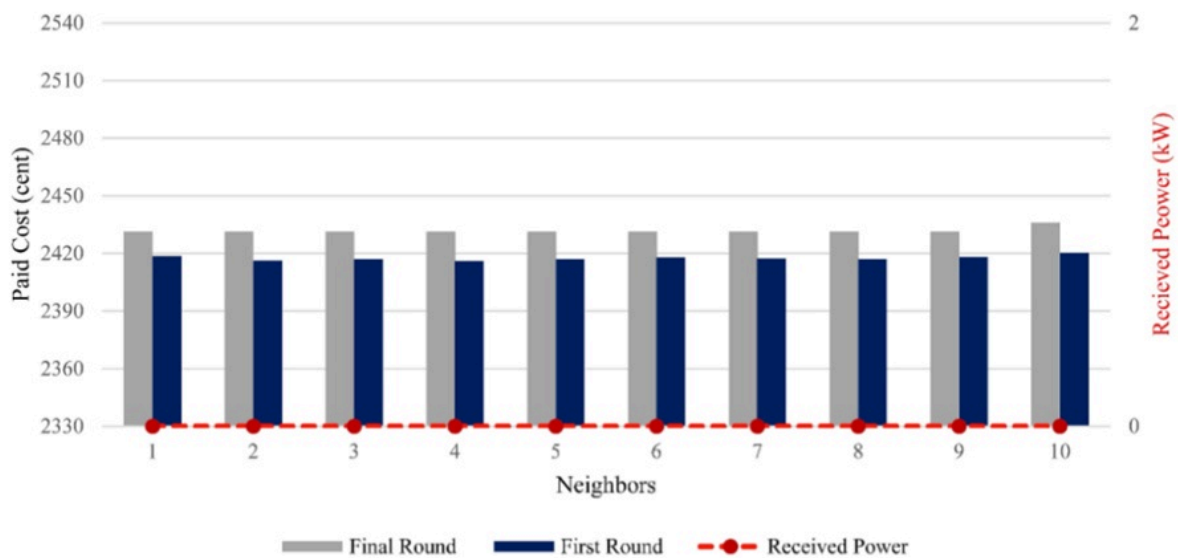


Figure 24. Neighbors received power, and their costs were paid at the first and final rounds with the AD strategy, considering energy storage.

The simulation outcomes for WSLs behavior in the presence of storage are shown in [Figure 25](#). As in [Figure 23](#), [Figure 25](#) indicates that when all neighbors employ WSLs, full cooperation occurs, enabling them to satisfy all excess demand locally and thereby minimize their total expenditures.

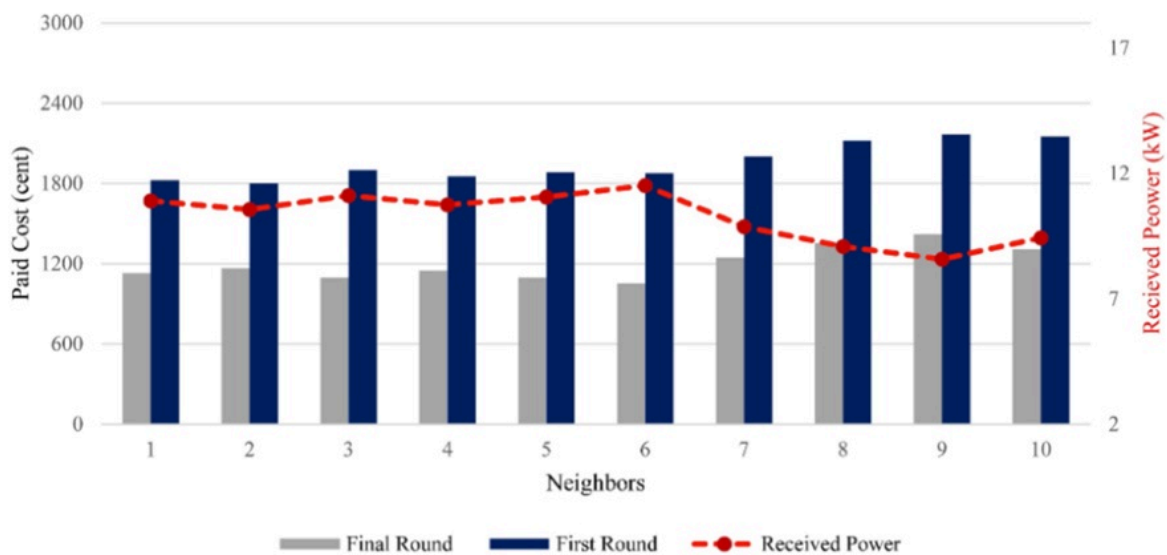


Figure 25. Neighbors received power and paid costs at both the first and final rounds under the WSLS strategy, including energy storage.

Taken together, the results presented in [Figures 22–25](#) reveal that neighborhoods composed entirely of AD participants rely completely on the distribution company for excess power. In contrast, those composed entirely of WSLs participants fulfill their needs entirely through internal cooperation. In realistic settings where neighbors employ a mix of strategies, the amount of power received from others is expected to fall between these two extremes. [Figures 9–17](#) confirm that, across the performed simulations, heterogeneous strategy distributions produce varying levels of received power—yet these

levels consistently lie between the bounds established by pure AD and pure WSLS populations. Given the inverse relationship between received power and procurement cost, the same principle applies to final expenditures: **Figures 9–17** (and related cost plots) show that mixed-strategy scenarios yield intermediate cost outcomes positioned between the high costs of AD-dominated groups and the low costs of WSLS-dominated groups.

In addition, the utility function used to model neighbors' satisfaction with energy consumption is directly adopted from Samadi et al. [55]. In that reference, a rigorous mathematical derivation is provided to justify the selected functional form for capturing individual utility in energy contexts.

Conclusion

As distribution networks evolve into smart grids and more users shift from passive consumers to active prosumers, a deeper examination of how social and behavioral characteristics shape individual decision-making and participation in energy generation and use has become essential. Against this background, the present work investigates cooperation among neighbors in meeting surplus energy requirements, with explicit consideration of each participant's distinct personality traits. These personality traits are represented through corresponding quantitative strategies, along with associated discount and punishment coefficients. The specific values of these coefficients are derived directly from the quantitative strategy each neighbor follows. Moreover, given the wide range of non-technical influences on decision-making, the discount and punishment levels are modeled as nonuniform distributions. This modeling choice enables a systematic assessment of how various non-technical elements impact neighbors' behavioral responses.

The core analysis in this study centers on how neighbors cooperate to cover excess demand, guided by their personality profiles, discount factors, and punishment factors. The simulation outcomes demonstrate that neighbor-to-neighbor cooperation represents a viable and effective means of addressing surplus energy needs, and compared with conventional procurement methods, satisfying excess demand through such cooperation yields substantially lower costs. When benchmarked against spot-market and day-ahead prices, the proposed mechanism achieves reductions of up to 80% in the cost of acquiring excess energy. Simultaneously, it reduces the utility company's required capacity contribution by up to 90% (kW).

The investigations reveal that several key variables—including neighbors' adopted strategies, their individual utility derived from energy consumption, and the neighborhood-wide averages of discount and punishment factors—play significant roles in shaping cooperative outcomes. Importantly, the simulation results generated by the presented methodology closely align with established findings from the social science literature. Across the tested scenarios, participants employing WSLS strategies consistently incur the lowest costs relative to those following other behavioral profiles.

For future investigations, it would be worthwhile to extend the analysis to cooperation in thermal energy sharing. Further valuable directions include assessing the effects of neighbor-level cooperation on critical network performance indicators such as power losses. Additionally, applying a cooperative game-theoretic framework to model neighbor interactions could yield richer insights and support the development of more sophisticated and efficient coordination strategies.

Nomenclature

$Pr_n(\sigma)$: n th neighbor utility

δ_n : n th neighbor discount factor

$u_n(\sigma)$: the expected utility of the n th neighbor

r : the number of rounds

n : neighbor number

λ_n : n th neighbor punishment factor

$x_n(t)$: probability of cooperation at time t

P_σ : payoff (cent) obtained by the neighbor

N : number of neighbors'

$DP_n(t)$: n th neighbor discomfort cost

kt_n : n th neighbor discomfort rate at time t

$dp_n(t)$: neighbor n th transferred power from time t to another time interval

ω_n : demand parameter

α_n : demand parameter

$\{c_n\}_{n=1}^N$: n th neighbors' cost functions

ηr_n : history of n th neighbor up to r th

a_{r_n-1} : the actions of the n th neighbor in the r th round

A_n : sets of neighbors' actions

ρ_n : public history

$C_u(t)$: cost of buying power from the distribution company

$P_u(t)$: power obtained from neighbors n th at time t

$MP_n(t)$: the n th neighbors can supply maximum power at time t

$TP(t)$: total needed power at time t

β : rationality of neighbors' actions

$D_n(t)$: individual and social norms

$\Delta W_n(t)$: individual and social norms

γ : percentage of neighbors' past behavior consideration

$\Delta I_n(t)$: individual rewards

h : social normative motivation

$\Delta N_n(r)$: motivation to follow social norms

ω_c : conformity (nonconformity) of the self with a norm

w_o : conformity (nonconformity) of neighbors with the same norm

ω_i : interaction between ω_c and w_o

c_r : binary variable to express the neighbor cooperation status at round r , if the neighbor cooperated, $c^r = 1$; otherwise, $c^r = 0$

O_r : total cooperative neighbors at round r

Δl_{nm} : n th neighbor individual norms in response to the m th neighbor cooperation

Δl_c : individual norms from cooperation

Δl_D : individual norms from defect

R : n th neighbor reward's payoff when both agents cooperate

T : n th neighbor temptation's payoff when n defects and m cooperates

S : Sucker's payoff when n cooperates and m defects

P : n th neighbor punishment's payoff when both agents defect

$R_{price}(t)$: distribution company spot market prices

$U_m(P(t))$: m th neighbors' energy utility from power P at time t .

ζ : probability of changing the neighbor's strategy

P_{an} : average payoff obtained by the n th neighbor

P_n : the total profit obtained by the n th neighbor

K : level of the disorder

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