IJSOM
International Journal of Supply and Operations Management

A Two-Stage Optimization Model for P2P Market Design Considering Role of Retailer and Demand Response Programs

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Article Info

Article type:
Research Article

Article history:
Received June 20, 2025
Received in revised form October 7, 2025
Accepted December 12, 2025
Available online February 14, 2026

Keywords:
Peer-to-Peer (P2P) energy trading
retailer
demand response
elasticity

ABSTRACT

Objective: With the increasing penetration of distributed energy resources (DERs), peer-to-peer (P2P) energy trading has emerged as a promising mechanism to enhance renewable energy utilization and market efficiency. This study aims to design a P2P electricity market for grid-connected microgrids that coordinates local trading with retail and wholesale markets while accounting for geographical distance and demand response programs.

Methods: A two-stage optimization framework is proposed. In the first stage, a mixed-integer linear programming (MILP) model determines the optimal neighborhood set of prosumers by maximizing renewable energy consumption and minimizing the geographical distance between trading peers. In the second stage, a mixed-integer nonlinear programming (MINLP) model is developed to optimize energy exchanges, battery storage, and pricing decisions, with the objectives of maximizing retailer profit and minimizing prosumer costs. The model incorporates time-based and incentive-based demand response programs and is validated using real residential data from Iran.

Results: The numerical results show that limiting P2P transactions to geographically closer peers improve local renewable energy utilization. Sensitivity analysis on time-based DR programs indicates that the optimal pricing mechanism applies real-time pricing (RTP) to both the retail and P2P markets.

Conclusion: The proposed two-stage P2P optimization framework enhances renewable energy utilization by prioritizing local trading and RTP-based pricing. Results indicate that applying real-time pricing in both retail and P2P markets increases renewable energy share and economic efficiency, while providing actionable insights for sustainable microgrid and P2P market design.

Cite this article: Masoumi, M., & Kheirkhah, A. S. (2026). A Two-Stage Optimization Model for P2P Market Design Considering Role of Retailer and Demand Response Programs. *International Journal of Supply and Operations Management, 13*(1), 109-132. https://doi.org/10.22034/ijsom.2025.110833.3422

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Publisher: Kharazmi University.
DOI: https://doi.org/10.22034/ijsom.2025.110833.3422

1. Introduction

The widespread technical and economic challenges, coupled with the detrimental environmental effects and the privatization of the electricity industry, have propelled various countries towards embracing distributed generation (DGs) and renewable energy sources (Ghorbankhani et al., 2021; US Energy Information Administration, 2019). This concept can offer significant technical and environmental advantages (Ho et al., 2014).

The benefits of Distributed Energy Resources (DERs), coupled with decreasing costs in renewable technologies like Wind Turbines (WTs), Photovoltaic (PV) Panels, and Battery Energy Storage Systems (BESS), have led to their substantial adoption (Zhou et al., 2020). However, the widespread use of DERs introduces challenges (Ghorbankhani et al., 2021; Kaur et al., 2020), such as inverse power flow, bi-directional power flow, intermittency, volatility, and randomness in renewable energy generation, posing obstacles to the control and planning of distribution networks (Zhang et al., 2019(b)).

Peer-to-peer (P2P) energy trading has emerged as a promising solution to address some of these challenges (Zhou et al., 2020), and to enhance the efficiency of distributed energy resources (DERs) (Doan et al., 2022). In P2P energy trading, prosumers equipped with DERs are capable of both generating and consuming electricity. They can directly exchange and share energy with peers, aiming to minimize electricity costs (Guerrero et al., 2021). Nevertheless, achieving this goal is not possible without the presence of smart microgrids (MGs). Smart MGs can be operated in islanded or grid-connected mode.

MGs are primarily operated in grid-connected mode because, without grid connection, consumers may be unable to procure the minimum required energy from distributed generators (DGs) or the P2P market to meet their base load demand, which leads to an imbalance between supply and demand (Doan et al., 2022). However, integrating P2P with grid-connected MG is another challenging issue, as prosumers must deal with both regulated markets, including the main grid, and P2P trading markets (Tushar et al., 2020).

Therefore, most P2P market designs introduce a third-party entity, such as a Distribution System Operator (DSO) or a retailer, to coordinate bilateral transactions and assess P2P market feasibility (Guerrero et al., 2021). In some cases, retailers act as intermediaries between the main grid and end-users, supplying electricity through various sources and facilitating energy sharing within the MG (Aghamohammadloo et al., 2021; Huang et al., 2020). They are responsible for purchasing surplus electricity at feed-in tariffs (FIT), selling it to upstream markets, and satisfying demand by purchasing electricity from the wholesale market during shortages. Additionally, they set FIT, retail electricity prices, and internal P2P market prices. Thus, designing an appropriate pricing mechanism remains a key challenge in P2P market development (Hatami et al., 2009).

Traditional models of electricity pricing incorporate two main charges: (1) a network tariff, which encompasses the expenses related to transmitting electricity from generation to consumption and is commonly regulated, and (2) an electricity price that factors in the costs associated with electricity generation and is frequently established through market mechanisms. Research in the P2P energy trading literature typically focuses on the costs associated with the second type (Sturmberg et al., 2021).

Nomenclature

Indices and sets:

h, h', H	Index and set of households
s, S	Index and set of timeslots in the scheduling horizon
Ch	Set of households with only a PV system installed
Mh	Set of households with a PV system and an energy storage installed
Dh	Set of households without a PV system and an energy storage
N_h	Neighborhood set of household h

Data and parameters:

DS_{hs}	Demand (kWh) of household h for each time slot s
SZ_s	Solar radiation of the PV (kWh/m^2)
O_{hs}	Power produced by PV system of household h in time slot s. (This amount varies for each house based on the number and area of the solar panels used)
$D_{hh'}$	Geographical distance between household h and h' (km)
λ_h	Charging rate (kWh) for household $h \in \{Mh\}$
$BINTI_h$	The initial battery level at time slot 1 for $h \in \{Mh\}$
$Cmin_h$ $Cmax_h$	Minimum and Maximum battery level (kWh) for household $h \in \{Mh\}$
μ_h	levelized cost of energy for the PV system owned by each household $h \in \{Ch \cup Mh\}$ (\$/kWh)
ω_h	levelized cost of storage for the battery owned by each household $h \in \{Mh\}$ (\$/kWh)
C_{LUos}	LUoS charges (\$/kWh)
C_{DUos}	DUoS charges (\$/kWh)
PSE	Wholesale purchase price (\$/kWh)
PRE_s	Wholesale sale price (\$/kWh)
α	Price elasticity of the demand
Bp	Initial energy price (\$/kWh)
rew_s	Incentive payment of DRPs (\$/kWh)
Pen_s	Value of penalty (\$/kWh)
M	A very large number

Variables:

PRS_s	Retail price (\$/kWh) in time slot s.
PRB	Retail feed-in tariff (\$/kWh).
PRH_s	Clearing price for the P2P market in the time slot s
ERH_{hs}	energy purchased from the retailer by household h to use in time s
ERB_{hs}	energy purchased from the retailer to charge the battery of household $h \in \{Mh\}$ in time s
$EHH_{hh's}$	energy purchased from household h' by household h to use in time s
$EHB_{hh's}$	energy purchased from household h' to charge the battery of household $h \in \{Mh\}$ in time s
EER_s	energy purchased from the wholesale market by retailer in time s
ERE_s	energy sold to the wholesale market by retailer in time s
EGH_{hs}	energy generated by household $h \in \{Ch \cup Mh\}$ to use in time s
EGB_{hs}	energy generated by household $h \in \{Ch \cup Mh\}$ to charge its battery in time s
EGR_{hs}	energy generated by household $h \in \{Ch \cup Mh\}$ to sell to the retailer in time s
$EGP_{hh's}$	energy generated by household $h \in \{Ch \cup Mh\}$ to sell to household h' in time s
$EGP'_{hh's}$	Energy sold to household h' by household $h \in \{Ch \cup Mh\}$ in time s in the first stage of model.
BUH_{hs}	energy discharged from the battery of household $h \in \{Mh\}$ to use in time s.
BUR_{hs}	energy discharged from the battery of household $h \in \{Mh\}$ to sell to the retailer in time s.
$BUP_{hh's}$	energy discharged from the battery of household $h \in \{Mh\}$ to sell to the household h' in time s.
BI_{hs}	battery level of the battery of household $h \in \{Mh\}$ at the beginning of time slot s
$Cprofit$	The profit from participating in the P2P market for consumer$h \in \{Dh\}$.
$qp_{hh's}$	P2P purchasing decision of household h' in the time slot s: 1 for purchase energy from household h and 0 otherwise.
$qp'_{hh'}$	If h and h' are neighbours in the first stage of model,1; otherwise, 0
I_{hs}	charging decision of household $h \in \{Mh\}$ in the time slot s: 1 for charging and 0 otherwise
U_{hs}	discharging decision of household $h \in \{Mh\}$ in the time slot s: 1 for discharging and 0 otherwise

However, the costs associated with the first type, including Distribution Use of System (DUoS) and Transmission Use of System (TUoS) charges as components of customer bills, along with the charges related to Local Use of System (LUoS) services, can significantly impact the pricing mechanism of P2P markets.

LUoS charges have arisen with the emergence of P2P electricity trading. Recently, Sturmberg et al. (2021) have adopted a refined distinction between the transmission and distribution systems through a third tier of network pricing for localized regions of the distribution network. While such a proposal is effective in reducing customer costs, it may have other impacts. The implementation of Demand Response Programs (DRPs) with various objectives and constraints can be instrumental in mitigating these effects (Niaei et al., 2022). Therefore, the third challenge involves designing suitable pricing mechanisms based on DRPs to integrate local, retail, and wholesale markets.

Another challenging aspect discussed in the literature is that optimal P2P energy trading needs to consider distances between different participants in the market, as longer distances can result in line losses, reduce the effectiveness of local trading and increase power losses (Islam & Sivadas, 2022; Aalami et al., 2010). These losses are dependent on distance (Lee et al., 2023; Iqbal et al., 2021), so users should be prioritized based on distance parameters, allowing users within a neighborhood to be involved in energy exchange with each other (Malik et al., 2022)

Given the challenges outlined above, this research aims to develop a two-stage optimization model that integrate P2P energy markets with retail and wholesale markets, incorporating demand-side management programs while considering the impact of physical distance between peers on energy loss and efficiency. Additionally, the research will explore the active role of retailers in facilitating energy exchanges and managing flows within the grid, contributing to a more sustainable and efficient P2P electricity market.

The rest of this paper is organized as follows: relevant literature has been reviewed in Section 2. Section 3 introduces the pertinent concepts of the proposed P2P market design and outlines the pricing mechanism. The mathematical formulation of the problem is proposed in Section 4. Section 5 represents the basic data and computational results, and lastly, some relevant conclusions are drawn in Section 6.

2. Literature review

Optimization studies for advanced P2P markets can be categorized into two groups: full P2P markets and community-based markets (US Energy Information Administration, 2019). In full P2P markets, prosumers and consumers directly trade electricity. However, these markets face challenges, particularly with scalability, peers' negotiation, and local energy balance. In the present article, this category of studies is not addressed.

Compared with full P2P markets, community-based markets address these challenges by adding a community coordinator who manages P2P trading activities and facilitates interaction with wholesale energy markets (Zhang et al., 2019(b)). For instance, in the proposed P2P electricity markets in references (Moret & Pinson, 2019; Heo et al., 2021; and Shamsini Ghiasvand et al., 2022), a coordinator is considered as part of community management. Nguyen et al. (2018) have considered a P2P trader in their optimization problem for management, transaction protection, and network usage cost considerations.

In (Long et al., 2018), a Constrained Nonlinear Programming (CNLP) model is formulated for optimizing community-based P2P energy trading. This model allows users to track their orders through the coordinator. In the proposed framework by Huang et al. (2020), the MG operator, acting as a coordinator, validates orders based on how to achieve the minimum total energy consumption in the MG. It also determines the transaction prices and real-time for buying and selling energy. Khodoomi and Sahebi (2023) proposed an optimization model for P2P energy trading, incorporating battery storage for both peers and the local grid, aiming to reduce load shedding and improve overall system performance, while also promoting the use of renewable energy through optimized pricing mechanisms. Zhou et al. (2024) proposed a P2P trading model for urban virtual power plants, integrating prosumer preferences and power demand variation. Their study emphasizes the importance of considering diverse prosumer needs—such as financial returns, green energy preferences, and risk avoidance—to optimize P2P trading and match supply and demand more efficiently. The results showed that the model reduced electricity costs by 48.32% and increased green electricity trading by 49.92%.

Most studies assume that peers first exchange energy among themselves and then balance supply and demand by trading individually or with wholesale/retail markets. In other words, traditional markets act as the 'residual balancer' in P2P trading (Zhou et al., 2020).

There are also various optimization models for P2P trading markets that include not only prosumers but also producers or retailers (Sousa et al., 2019). Grimm et al. (2021) proposed bi-level models to determine the optimal interplay between the retailer’s tariff design and the prosumer’s decisions regarding the use of energy storage, consumption, and purchasing and selling electricity from and to the grid. Aghamohammadloo et al. (2021) presented a retail energy market that includes retailers and prosumers equipped with an energy hub. In their paper, the aim of the optimization model is to maximize the profits of retailers and minimize the costs of prosumers. Cui et al. (2019) proposed a bi-level MILP model where the retailer holds the upper level deciding the internal energy sharing prices to maximize its profits, and prosumers hold the lower level deciding their energy sharing profiles in response to the internal prices. Zhang et al. (2019(a)) introduced a P2P trading framework with consideration of the dynamic retail electricity price.

In literature, DRPs are implemented in distribution systems as a control tool for electricity demand management with specific objectives (Niaei et al., 2022). This technique is predominantly used for optimizing the revenue of energy producers, reducing peak demand, minimizing consumer costs, and maximizing the consumption of clean energy. Most optimization models apply DRP to optimize a set of these objectives. For example, Zhang et al. (2019(a)) proposed an LP optimization model for the P2P energy trading framework, considering dynamic retail prices based on RTP tariffs, for the first time. Kanakadhurga and Prabaharan (2021) studied the impact of DR-based P2P energy trading among prosumers and consumers. Srilakshmi and Singh (2022) have utilized an aggregator for coordinating energy transactions among consumers, and the authors have employed an incentive-based pricing program. Consequently, other pricing programs such as TOU and RTP have not been considered in this model. Ferrara et al. (2021) in their study proposed a two-stage MILP model for the aggregator of prosumers and determined TOU pricing tariffs for consumers in the medium term. However, references (Zhang et al., 2019(a); Kanakadhurga and Prabaharan, 2021; Srilakshmi and Singh, 2022; Ferrara et al., 2021) did not discuss the impact of different pricing programs on the profits or costs of prosumers. Sheidaei and Ahmarinejad (2020) utilized DRPs and electric vehicles to address fluctuations. The simulation results indicated that the profit of the VPP is higher in the case with the TOU tariff compared to the cases with the RTP and CPP mechanisms. The research by Aghamohammadloo et al. (2021) aimed to formulate competition in a retail energy market in the presence of an integrated DRP to reduce prosumer costs and increase retailer profits. Their results suggested that the IDR had an impact on reducing prosumer costs and increasing retailer profits. Kanakadhurga and Prabaharan (2024) explored the impact of price-based demand response with peer-to-peer energy trading in residential smart homes. Their study considers electric vehicles (EVs) and renewable energy-based distributed generation (DG) sources, such as solar PV and wind. They demonstrated that using an optimal Real-Time Pricing (RTP) tariff, combined with an enhanced P2P trading strategy, significantly reduced grid dependency and electricity costs.

The proposed enhanced bidding strategy, involving a double auction mechanism, proved effective in reducing costs for both consumers and prosumers. Gharibi et al. (2025) demonstrated that integrating a demand response program (DRP) with P2P energy trading can significantly enhance microgrid resilience and reduce residential energy expenses.

Their results highlighted the effectiveness of DRP in reshaping energy consumption patterns, improving load management, and fostering energy autonomy in green homes equipped with renewable energy sources.

On the other hand, the success of demand response programs is closely related to the concept of price elasticity of electricity demand. An increase in elasticity improves the outcomes of demand response programs and leads to better control of market prices and energy consumption (Monsef & Khajavi, 2012). However, none of the above studies have addressed this issue. Niaei et al. (2022) proposed a two-stage MINLP using a smart DRP integrated with a machine learning approach for P2P energy trading. The authors considered an incentive-penalty-based DRP, taking into account the stochastic behavior of participants and their variable elasticities. Masoumi and Kheirkhah (2024) proposed a bi-objective MINLP model for designing a P2P electricity market focused on price-based energy management, incorporating incentives and time-based DRPs. Their investigation into the impacts of DRPs showed that the proposed pricing mechanism, along with price elasticity of demand, increased retail profit and overall MG profit by up to 10.3% and 39.98%, respectively.

Some Limited studies in the literature review have examined the impact of distance between peers in peer-to-peer trading. For example, Doan et al. (2022) examined the effects of the distance between prosumers and consumers on their decision-making through an LP mathematical model. They considered trading cost for per unit of geographical distance (based on Euclidean distance) between peers as a transaction price, aiming to incentivize prosumers to trade with their neighbors. Sheidaei and Ahmarinejad (2020) presented a two-stage MILP model where in the first stage, the service area of each prosumer was determined, taking into account certain technical constraints of the network. A quadratic programming (QP) model based on priorities for P2P energy trading considered in (Sebastian et al., 2019). However, it considered different levels of energy purchase as priority thresholds and does not account for the distance between sellers/buyers. In (Nguyen et al., 2018) the authors modeled a MG system with DERs and P2P sharing using a nonlinear programming (NLP) model. They adopted an approach to reduce system losses based on distance optimization. Talebi et al. (2025) proposed a robust P2P energy trading framework, considering the electrical distance between market players and transmission costs. They introduced a decentralized trading platform that utilizes the Power Transfer Distribution Factor (PTDF) method to allocate power loss and network utilization fees fairly, based on the network's physical topology and the electrical distance between peers. Their findings indicate that accounting for transmission costs, including power loss, can significantly affect the overall market efficiency and social welfare, highlighting the importance of the electrical distance between peers in P2P energy trading.

The integration of P2P markets with retail markets, pricing mechanisms, and the consideration of service areas for prosumers based on the distance between participants are factors that significantly impact the successful implementation of peer-to-peer (P2P) electricity trading in smart MGs. However, most optimization models proposed in the referenced literature have individually addressed these factors (Table 1). In most studies, energy could be exchanged between all houses, greatly increasing the model's complexity, with only transaction costs influencing exchanges. This study addresses this challenge by allowing only houses identified as neighbors in the first stage to exchange energy, thus reducing the model's complexity.

Table 1. Literature related to energy market.

Authors	Year	Market Type			Method	Pricing Mechanism				Consideration of Distance Between Peers	Case study
						DRP					
		Wholesale	Retail	P2P		Time-based	Incentive-based	Price elasticity of demand	LUOS+DUOS		
Long et al.	2018			*	CNLP	*					–
Nguyen et al.	2018			*	NLP	*			*		Australia
Sebastian et al.	2019			*	QP					*	Australia
Moret & Pinson	2019			*	ADMM					*	Australia
Cui et al.	2019		*	*	MILP	*					–
Zhang et al.(a)	2019		*	*	MILP	*					–
Huang et al.	2020		*	*	MILP	*					–
Sheidaei and Ahmarinejad	2020			*	MILP	*					–
Kanakadhurga and Prabaharan	2021			*	MILP	*					India
Heo et al.	2021			*	LR	*				*	South Korea
Grimm et al.	2021		*		MILP	*					–
Ferrara et al.	2021		*	*	MILP	*					–
Aghamohammadloo et al.	2021		*		MILP		*				–
Doan et al.	2022			*	LP/ ADMM	*				*	–
Shamsini Ghiasvand et al.	2022		*	*	MILP	*					–
Niaei et al.	2022			*	MINLP		*	*			–
Khodoomi and Sahebi	2023			*	ADMM						–
Zhou et al.	2024			*	ADMM	*				*	Australia
Kanakadhurga and Prabaharan	2024			*	MILP	*					–
Masoumi and Kheirkhah	2024		*	*	MINLP	*	*	*	*		Iran
Gharibi et al.	2025			*	SLGP[a]	*					Canada
Talebi et al.	2025		*	*	ADMM					*	–
Current paper			*	*	MILP/ MINLP	*	*	*	*	*	Iran

[a] Sequential Linear Goal Programming (SLGP)

3. Problem definition

Figure 1 illustrates the conceptual model used in this study for peer-to-peer (P2P) electricity trading in a smart microgrid (MG). The key market entities are as follows: Prosumers: Users with photovoltaic (PV) systems, divided into two categories—prosumers with battery energy storage systems (BESSs), represented by *Mh*, and prosumers without BESSs, represented by *Ch*. Consumers: Users without PV systems who can reduce their electricity costs by participating in the P2P market and purchasing electricity at lower prices, set as *Dh*. Retailer: A third-party entity that purchases electricity from wholesale markets and prosumers, and sells it to consumers. The retailer, acting as a rational participant, also assumes the role of the MG Control System (MCS) operator. This includes implementing the P2P energy system, organizing, coordinating, and settling P2P transactions and exchanges.

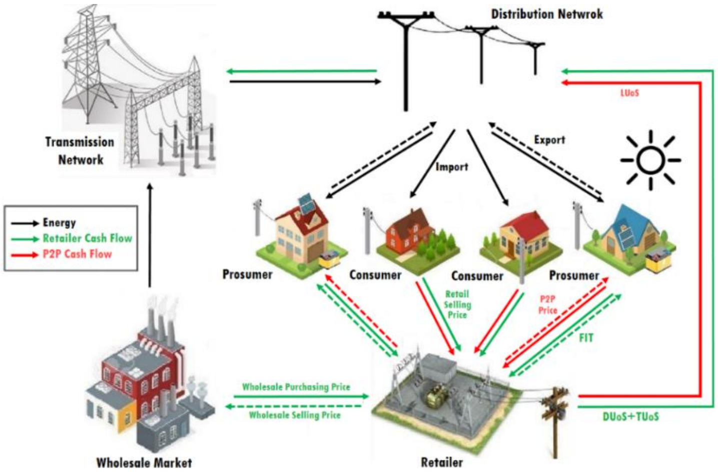


Figure 1. Structure of the smart MG with P2P electricity trading (Adopted from Nguyen et al. (2018))

The community is a set of consumer and prosumer households that differ from each other in their energy consumption patterns and electricity generation levels. Each household can only exchange energy with those in its neighborhood set (*Nh*). However, all of them can exchange energy with the retailer. It is assumed that smart metering infrastructure exists for energy and information exchange between the retailer and community members. In this problem, households can meet their energy needs for consumption and battery charging from both the retailer and the P2P market. Similarly, prosumers can supply their surplus energy to both the retailer and the P2P market. The type of PV and BESS is similar for all prosumers, and decisions related to the selection of energy system types are not considered. By setting retail and P2P market prices, the retailer clears the market, aiming to maximize its total profit while minimizing costs for prosumers. The primary objective is to ensure the fulfillment of all demand and the efficient utilization of DERs, with a simultaneous focus on increasing the consumption of renewable and clean energy. The proposed P2P market is specifically designed for energy trading among geographically closer peers, considering the fact that buyers/sellers with smaller distances will cause fewer losses in the transmission, leading to the higher effectiveness of the P2P trading mechanism. In this regard, the proposed two-stage optimization model, in the first stage, determines the service area for each prosumer through a mathematical model and introduces an optimal neighbourhood set for each prosumer. This enables negligible energy losses and increasing the utilization of renewable energy sources. It is worth mentioning that the topology and member locations in the MG are static parameters that remain same during the trading periods.Then, in the second stage, optimal management of energy exchanges, energy storage, DRPs, and pricing is addressed.

3.1 Pricing mechanism and DRP

The pricing mechanism of the system operates in such a way that the electricity surplus from prosumers is purchased by the retailer at Feed-In Tariffs, and then it is sold to community members at real-time tariffs (RTP). Additionally, if there is an overall surplus of energy in the MG, this surplus electricity can be sold to the wholesale market at fixed tariffs. It is noteworthy that none of the prosumers have direct access to the wholesale energy market and can only buy or sell their energy through the retailer. Therefore, community members purchase electricity from the retailer during off-peak periods when the electricity prices are low to meet their consumption and charge batteries. During peak periods with high electricity prices, they can satisfy their demand using DERs or the P2P market. On the other hand, by incorporating a time-based and incentive-based DRP into the pricing mechanism and simultaneously implementing

RTP and I/C programs—while considering the self-elasticity of demand—the retailer encourages consumers to use renewable energy and participate in P2P transactions during periods of high wholesale prices. Moreover, in this configuration, energy flows within a specific local region incur a LUOS charge instead of the traditional DUOS charge, which remains applicable to flows through the upstream sections of the distribution network. The boundary between DUOS and LUOS regions is defined as a medium voltage to low voltage transformer, managed by retailers acting as DSOs. These charges apply equally to both imports and exports and are calculated as a percentage of the base electricity prices. Consequently, electricity flow between the retailer and community members incurs DUOS charges, while energy exchanges among community members are subject to LUOS charges. All these costs are borne by the retailer, with wholesale market prices predetermined for them.

4. Mathematical model

In this section, we formulate the mathematical model of problem.

4.1 First stage: Determining the prosumer service area

The formulation of the proposed bi-objective optimization model for determining the prosumers' service areas can be stated as follows:

$$Max\ F1 = \sum_{s \in S} \sum_{h \in Ch \cup Mh} \sum_{h' \in H} EGP'_{hh's} \tag{1}$$

$$Min\ F2 = \sum_{s \in S} \sum_{h \in Ch \cup Mh} \sum_{h' \in H} D_{hh'}.qp'_{hh'} \tag{2}$$

s.t.

$$\sum_{h' \in H} EGP'_{hh's} \leq O_{hs}.SZ_{hs} \qquad \forall s, h \in (Ch \cup Mh) \tag{3}$$

$$\sum_{h' \in H} EGP'_{hh's} \leq \sum_{h' \in H} Ds_{h's} \qquad \forall s, h \in (Ch \cup Mh) \tag{4}$$

$$\sum_{h \in Mh, h \neq h'} qp'_{hh'} \geq 1 \qquad \forall h' \in H \tag{5}$$

$$EGP'_{hh's} \leq M.qp'_{hh'} \qquad \forall h, h' \in H \tag{6}$$

$$EGP'_{hh's} \geq 0, \quad qp'_{hh'} \in \{0,1\} \tag{7}$$

The objective function relating to determining the service area of each prosumer is stated as maximizing the utilization of renewable resources as (1). The second objective function is formulated to minimize the total distances between prosumers and the served households as (2), to reduce transmission costs and losses. Constraints (3) and (4) ensure that the total energy sold by a prosumer to other households will not exceed the prosumer's output and the total demand of the other households, respectively. It is also considered that each household must be served by at least one prosumer; this constraint is expressed by (5). Constraint (6) is a conditional constraint that states if peers are not in the same neighborhood set, no energy exchange will occur between them. In addition, the decision variables need to satisfy constraints (7).

4.2 Second stage: Pricing and Energy management

The second stage of the present optimization model is a development of our previously proposed model (Masoumi and Kheirkhah, 2024). However, distance-based transaction costs have been removed, as the first stage of the current two-stage model determines the set of permissible neighboring exchanges. Therefore, these costs, along with energy losses, have been disregarded. Moreover, in the previous model, a constraint was imposed on the retailer's allowable purchase from the upstream market. In this model, this constraint has been removed to better analyze the effects of price limitations and demand response programs on the retailer's electricity purchase from the wholesale market.

The objective functions of the second stage can be mathematically stated as follows:

$$\begin{aligned} Max\ F2 = \sum_{s\in S}\Bigg\{ & PSE.ERE_s + \left(\sum_{h\in H} PRS_s.ERH_{hs} + \sum_{h\in Mh} PRS_s.ERB_{hs}\right) - PRE_s.EER_s \\ & - \left(\sum_{h\in Ch\cup Mh} PRB.EGR_{hs} + \sum_{h\in Mh} PRB.BUR_{hs}\right) \\ & - C_{DUos}.\left(\sum_{h\in H} ERH_{hs} + \sum_{h\in Mh} ERB_{hs} + \sum_{h\in Ch\cup Mh} EGR_{hs} + \sum_{h\in Mh} BUR_{hs}\right) \\ & - C_{LUos}.\left(\sum_{h\in Ch\cup Mh}\sum_{h'\in N_h} EGP_{hh's} + \sum_{h\in Mh}\sum_{h'\in (Ch\cup Mh)\cap N_h} EHB_{hh's}\right)\Bigg\} \end{aligned} \tag{8}$$

$$\begin{aligned} Min\ F3 = & \\ \sum_{s\in S}\Bigg\{ & \left(\sum_{h\in Ch\cup Mh} PRS_s.ERH_{hs} + \sum_{h\in Mh} PRS_s.ERB_{hs}\right) + \mu_h.\left(\sum_{h\in Ch\cup Mh}\left(EGH_{hs} + EGB_{hs} + EGR_{hs} + \sum_{h'\in N_h} EGP_{hh's}\right)\right) + \\ & \sum_{h\in Mh} \omega_h\,.\left(BUH_{hs} + BUR_{hs} + \sum_{h'\in N_h} BUP_{hh's} + \sum_{h'\in (Ch\cup Mh)\cap N_h} EHB_{hh's} + ERB_{hs} + EGB_{hs}\right) - \\ & PRH_s.\left(\sum_{h\in Ch\cup Mh}\sum_{h'\in N_h\cap Dh} EGP_{hh's} + \sum_{s\in S}\sum_{h\in Mh}\sum_{h'\in N_h\cap Dh} BUP_{hh's}\right) - PRB.\left(\sum_{h\in Ch\cup Mh} EGR_{hs} + \sum_{h\in Mh} BUR_{hs}\right)\Bigg\} \end{aligned} \tag{9}$$

The first objective function (8) represents the net energy profit of the retailer within the planning horizon. This objective function considers the revenues earned from selling energy to the wholesale market and households, the cost of purchasing energy from the wholesale market and prosumers, as well as the costs of DUoS and LUoS.

The second objective function of the proposed mathematical model in (9) is associated with the net costs incurred by the prosumers, including the costs of purchasing electricity from the retailer, the cost of using PV and BESS, revenues from selling electricity to households without energy resources, and the retailer. It is noteworthy that in the proposed centralized model, all prosumers function as equal agents. Since the amount paid by one member is received by another, these conditions are eliminated from the optimization objective function. The above-mentioned objective functions are subjected to the following constraints:

4.2.1 Demand constraints

$$DS_{hs} = ERH_{hr} + \sum_{h' \in (Ch \cup Mh) \cap N_h} EHH_{hh's} \qquad \forall h \in Dh, s \tag{10}$$

$$DS_{hs} = ERH_{hs} + \sum_{h' \in (Ch \cup Mh) \cap N_h} EHH_{hh's} + EGH_{hs} \qquad \forall h \in Ch, s \tag{11}$$

$$DS_{hs} = ERH_{hs} + \sum_{h' \in (Ch \cup Mh) \cap N_h} EHH_{hh's} + EGH_{hs} + BUH_{hs} \quad \forall h \in Mh, s \tag{12}$$

Constraints (10)– (12) ensure that the demands of households in various sets will be satisfied. Several household DG portfolios are considered in our model. Therefore, supply for demand can be met by several resources. Households belonging to *Dh* can only purchase energy from retailer or the P2P market to satisfy the demand. In addition, the energy from solar PV systems (*Ch* and *Mh*) and the BESS (*Mh*) are applied.

4.2.2 PV output constraints

$$EGR_{hs} + \sum_{h' \in N_h} EGP_{hh's} + EGH_{hs} \ \leq O_{hs}.SZ_{hs} \qquad \forall h \in Ch, s \tag{13}$$

$$EGR_{hs} + \sum_{h' \in N_h} EGP_{hh's} + EGH_{hs} + EGB_{hs} \ \leq O_{hs}.SZ_{hs} \qquad \forall h \in Mh, s \tag{14}$$

Constraints (13)– (14) guarantee that the utilization of energy generated by the solar PV systems will not exceed their outputs. In our model, solar energy can be allocated for household loads, battery charging, selling to retailer, or the P2P market.

4.2.3 BESS constraints

$$BI_{h(s+1)} = BI_{hs} + ERB_{hs} + \sum_{h' \in (Ch \cup Mh) \cap N_h} EHB_{hh's} + EGB_{hs} - \left(BUH_{hs} + BUR_{hs} + \sum_{h' \in N_h} BUP_{hh's}\right) \quad \forall h \in Mh, s \tag{15}$$

$$BI_{h1} = BINTI_h \qquad \forall h \in Mh \tag{16}$$

$$Cmin_h \leq BI_{hs} \leq Cmax_h \qquad \forall h \in Mh, s \tag{17}$$

$$ERB_{hs} + \sum_{h' \in (Ch \cup Mh) \cap N_h} EHB_{hh's} + EGB_{hs} \leq \lambda_{hs}.I_{hs} \qquad \forall h \in Mh, s \tag{18}$$

$$BUH_{hs} + BUR_{hs} + \sum_{h' \in N_h} BUP_{hh's} \leq \lambda_{hs}.U_{hs} \qquad \forall h \in Mh, s, t \tag{19}$$

$$I_{hs} + U_{hs} \leq 1 \qquad \forall h \in Mh, s \tag{20}$$

Constraints (15)– (20) are applied to capture the dynamics in battery levels through different time slots. Depending on the decisions related to charging or discharging made in each time slot, the battery level will either increase, decrease, or stand still. These constraints represent the states of the battery and technological constraints concerning battery capacity and charging/discharging operations. Constraint (20) ensure that in every time slot, the battery can only charge or discharge (not both).

4.2.4 Trading constraints

$$EHH_{hh's} \leq DS_{hs}.qp_{h'hs} \qquad \forall h' \in (N_h \cap (Ch \cup Mh)), h \in H - Mh, s \tag{21}$$

$$EGP_{hh's} \leq (O_{hs}.SZ_{hs}).qp_{hh's} \qquad \forall h \in C_h, h' \in N_h, s \tag{22}$$

$$EHH_{hh's} + EHB_{hh's} \leq DS_{hs}.qp_{h'hs} \qquad \forall h \in (Mh \cap Nh'), h' \in (Ch \cup Mh), s \tag{23}$$

$$EGP_{hh's} + BUP_{hh's} \leq \left(Cmax_h + (O_{hs}.SZ_{hs})\right).qp_{hh's} \qquad \forall h \in Mh, h' \in N_h, s \tag{24}$$

$$qp_{hh's} + qp_{h'hs} \leq 1 \qquad \forall h, s \tag{25}$$

Constraints (21)– (24) indicate which resources are utilized to export energy to the P2P market and how the energy purchased from the P2P market is allocated. Additionally, Constraint (25) ensures that energy trading within a specific time slot between two households cannot be bidirectional.

4.2.5 Balance constraints

$$\sum_{h'\in(C_h\cup M_h)} \sum_{h\in N_{h'}} EHH_{hh's} + \sum_{h'\in(C_h\cup M_h)} \sum_{h\in(N_{h'}\cap M_h)} EHB_{hh's} = \sum_{h\in C_h} \sum_{h'\in N_h} EGP_{hh's} + \sum_{h\in M_h} \sum_{h'\in N_h} BUP_{hh's} \qquad \forall s \tag{26}$$

$$EGP_{h,h',s} = EHH_{h',h,s} \qquad \forall h \in \{Ch \cap N_{h'}\}, h' \in \{H - Mh\}, s \tag{27}$$

$$EGP_{h,h',s} + BUP_{h,h',s} = EHH_{h',h,s} \qquad \forall h \in \{Mh \cap N_{h'}\}, h' \in \{H - Mh\}, s \tag{28}$$

$$EGP_{h,h',s} = EHH_{h',h,s} + EHB_{h',h,s} \qquad \forall h \in \{Ch \cap N_{h'}\}, h' \in Mh, s \tag{29}$$

$$EGP_{h,h',s} + BUP_{h,h',s} = EHH_{h',h,s} + EHB_{h',h,s} \qquad \forall h \in \{Mh \cap N_{h'}\}, h' \in Mh, s \tag{30}$$

$$\sum_{h\in(C_h\cup M_h)} EGR_{hs} + \sum_{h\in M_h} BUR_{hs} + EER_s = \sum_{h\in H} ERH_{hs} + \sum_{h\in M_h} ERB_{hs} + ERE_s \qquad \forall s \tag{31}$$

$$ERE_s \leq \textstyle\sum_{h\in M_h} BUR_{hs} + \sum_{h\in(C_h\cup M_h)} EGR_{hs} \qquad \forall s \tag{32}$$

Constraints (26)– (30) ensure that the trading amount in the P2P market is balanced. Constraint (31) ensures the equilibrium of the amount of buying and selling in the retail market within each time slot. Constraint (32) specifies that only energy from DGs is used for selling electricity to the wholesale market.

4.2.6 Pricing constraints

$$ERH_{hs} \leq Ds_{hs}.\left(1+\alpha.\frac{PRS_s - Bp + rew_s + pen_s}{Bp}\right) \qquad \forall h \in \{H - Mh\}, s \tag{33}$$

$$ERH_{hs} + ERB_{hs} \leq Ds_{hs}.\left(1+\alpha.\frac{PRS_s - Bp + rew_s + pen_s}{Bp}\right) \qquad \forall h \in Mh, s \tag{34}$$

$$PRE_s \ \leq PRS_s \leq PRS_{max} \qquad \forall s \tag{35}$$

$$PRB \leq PRH_s \leq PRS_s \qquad \forall s \tag{36}$$

$$\sum_{s\in S} DS_{hs}.PRS_s - \sum_{s\in S} ERH_{hs}.PRS_s - \sum_{s\in S}\ \sum_{h\prime\in(Ch\cup Mh)\cap N_h} EHH_{hh\prime s}.PRH_s = Cprofit \qquad \forall s, h \in Dh \tag{37}$$

Constraints (33) and (34) impose the DRP on the amount of electricity consumed from the retailer. Constraint (35) establishes the minimum and maximum allowable rates for retailer price based on the lower and upper bounds derived from wholesale market prices. For each retailer, these prices can be at least equal to the wholesale market price and at most several times higher than it. Constraint (36) ensures that P2P tariffs are lower than the retail electricity selling price and higher than FIT, encouraging community members to initially participate in the P2P and then retail market. Constraint (37) calculates the profit for households without DGs participating in the P2P market as a positive variable. This is done so that P2P market prices are determined in a way that these households do not incur losses by involving in the P2P market.

In addition, all decision variables need to satisfy constraints (38):

$$qp_{hh\prime s}, I_{hs}, U_{hs} \in \{0,1\}$$

$$PRR_r, PRH_s, ERH_{hst}, ERB_{hst}, EHH_{hh'st}, BUP_{hst}, BI_{hst}, EHB_{hh'st}, EGH_{hst}, EGB_{hst},$$

$$EGR_{hst},, EGP_{hh\prime st}, BUH_{hst}, BUR_{hst}, Cprofit \geq 0 \tag{38}$$

5. Result

5.1 Basic Data

Iran stands as one of the prominent energy productions in the Middle East, has a huge potential for using renewable energies (Hoseinzadeh et al., 2020). Iran benefits from around 2900 hours of sunlight annually, exceeding 3200 hours in specific locations, and an average yearly receipt of 1800–2200 kwh of solar energy per square meter, surpassing the global average. Tehran, as the economic and cultural hub of Iran, has undergone significant urban development, resulting in a surge in electricity demand (Banirazi Motlagh et al., 2023). With a population of 9 million people, all with access to the electrical grid, the city is characterized by limited and valuable land. Thus, the adoption of rooftop PV systems in Iran, particularly in Tehran, is not only justified but also recommended over other renewable energy sources (Hoseinzadeh et al., 2020).

On the other side, Iran, as a developing country, grapples with challenges in power production, transmission, and distribution including insufficient power production, are prevalent. Acknowledging these challenges, Iran's grid management company (IGMC) took a proactive step in 2010 by designing a time-of-use DRP intended for nationwide implementation (Monsef & Khajavi, 2012). Therefore, this study applies the proposed two-stage optimization model to a hypothetical residential MG based on real data from Tehran, Iran.

We simulated different household load profiles using data from (shakouri & Kazemi, 2017). This data pertains to the electricity consumption of four households in Tehran, Iran, on a selected day in September. Each household used a variety of appliances, as depicted in Figure. 2. To enhance the diversity of consumer load profiles, we randomly distributed load shapes for additional households based on the average electricity usage of the aforementioned four households. The solar profile, representing the amount of solar radiation captured by PV panels (in kilowatts per square meter), was derived from information obtained from source (Iran's Meteorological Organization, 2023) (Figure 3). The electricity price data are obtained from Masoumi and Kheirkhah (2024). The official currency of Iran is the Rial (IRR). However, due to inflation and fluctuations in the exchange rate under international sanctions, all prices in this study are converted to U.S. cents based on the average exchange rate in September 2023. According to the Central Bank of Iran, 1 U.S. cent ≈ 4,947 IRR during this period. The initial (base) electricity price in Iran varies throughout the year depending on sectors, cities, months, and the monthly consumption level of consumers.

In this study, the adopted base electricity tariff is 0.667 ¢/kWh, while the wholesale purchase price was considered 5.465 ¢/kWh, based on the average rate of the Green Power Board. The incentive and penalty rates used in the demand response program are based on Tavanir data. During off-peak (00:00–07:00) and mid-peak periods (08:00–11:00 and 18:00–19:00), consumers receive rewards of 0.119 ¢/kWh and 0.0475 ¢/kWh, respectively. During peak periods (12:00–17:00 and 20:00–23:00), a penalty of 0.238 ¢/kWh is applied. Wholesale electricity price data (per kWh) were collected from the Iran Electricity Market website (IRMA), based on real-time pricing (RTP) tariffs on the selected day.

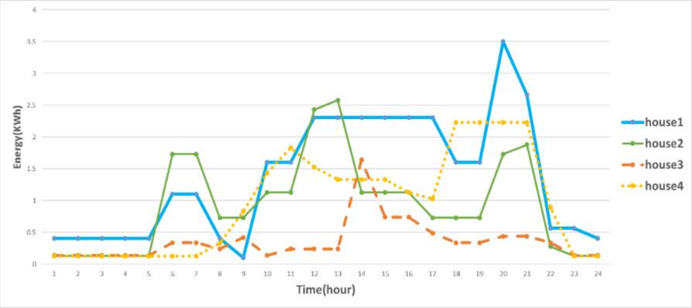


Figure 2. The energy consumption pattern of houses.

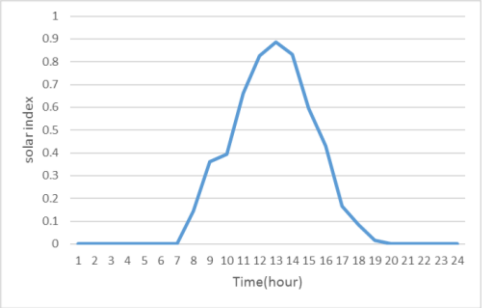


Figure 3. solar radiation in selective area

The DUoS and LUoS charges were considered to be 8% and 1% of the initial energy price, respectively. The PV systems used in the simulation were selected based on commercially available models in the Iranian market. Their technical and economic specifications, along with those of the BESS, are summarized in Table 1.

Table 1. Specifications of the PV Systems and BESS Used in This Study

Specification	PV System	BESS
Manufacturer	TABAN	Euronet
LCOE (¢/kWh)	1.9	3.34
Quantity	16–24 units	8–10 units
Capacity (kWh)	0.32 kWh per module	1.2 kWh per unit
Type	TBM72-320 Polycrystalline	Deep-cycle Gel Battery
Efficiency (%)	16.5%	> 90%

The total area of the PV panels for each household ranges from 32 to 40 m². As described in Section 3, this study considers three categories of households based on their adopted technologies. In our simulation, we construct a theoretical scenario in which 20% of the households own PV systems, 20% own energy storage systems, and the remaining 60% do not have distributed generation units.

5.2 Numerical result

In this section, we present the computational results of the peer-to-peer electricity market design problem. To solve the proposed two-stage model, we utilized GAMS software version 25.1.5, employing commercial MILP and MINLP solvers. Also, the LP-metric method is used to transform the bi-objective optimization model into a single-objective model in both stages of our model. By solving the first-stage of the mathematical model, involving 145 households and 58 prosumers, the service areas for each prosumer are determined (Figure 4). As depicted in Figure 4 prosumers can serve multiple consumers, depending on the amount of generation. Figure 5 illustrates the aggregate energy consumption patterns for all households in community.

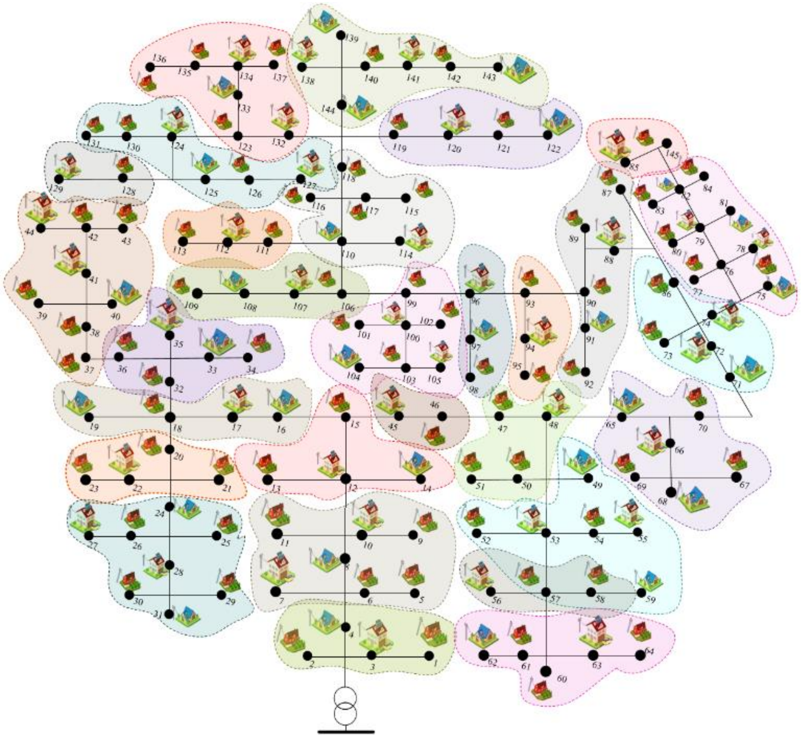


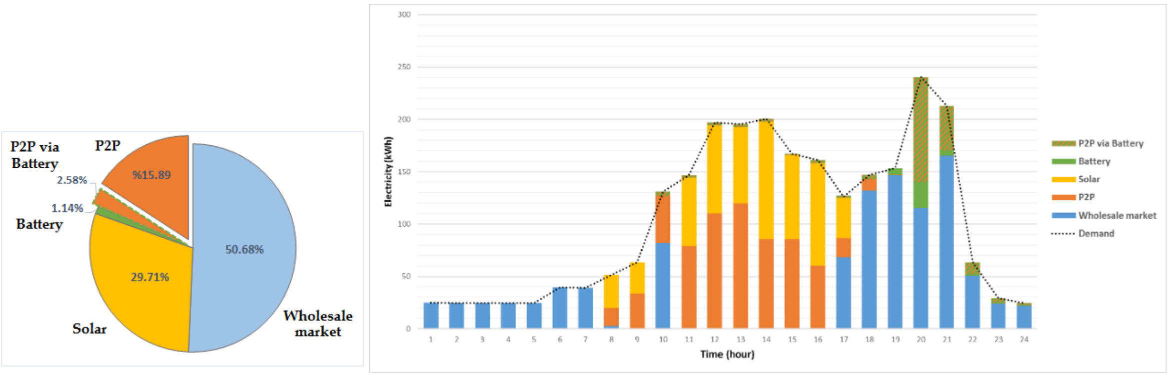
Figure 4. The service areas of prosumers

The pie chart in Figure 5 (a) shows the energy sources consumed by households on the corresponding day. As only 40% of the households in our simulation possess PV and BESS systems, it is not surprising that more than half of the energy is from the wholesale market (50.68% of the total energy).

In this study, all households initially utilize the energy generated by PV systems for personal consumption and then sell the surplus. Therefore, the second largest source of energy is from PV systems (to use) (29.71% of the total energy). 18.47% of the total energy is supplied through energy exchanges between peers (via PV systems (15.89%) and BESS (2.58%)) by the P2P market. Finally, batteries do not play a critical role in energy supply since the operational cost is still quite high, and the capacity and maximum charge/discharge rate are limited. Batteries contribute a modest 1.14%

to the total energy supply for personal consumption in each household. Nevertheless, the contribution of batteries in total energy is 3.72%. The energy sources are broken down for each hour in Figure 5(b). As observed, the household consumption during the early morning hours (1 to 7 AM) is solely supplied by the upstream market since the prices are very low, and even retailers have considered incentive tariffs for its prices. In the day, around 8 AM, PV systems start to generate electricity to use and export to the grid (i.e., back to the retailer) or the P2P market. From 8:00 to 17:00, the PV outputs can satisfy roughly 85% of the electricity demand in the simulated community. Around noon, when the PV outputs exceed the demand of the prosumers, the surplus electricity is traded in the P2P market, followed by charging the battery and selling it back to the retailer.

Details about the battery operations and P2P trading activities are shown in Figure 6 and 7, respectively. More specifically, Figure 6 illustrates how households (*Mh*) charge and discharge their batteries. These batteries are charged from PV systems during the day.



(a)

(b)

Figure 5. Electricity consumption patterns. (a) Sources of Energy to satisfy Demand (overall). (b) Sources of Energy to satisfy Demand (hourly).

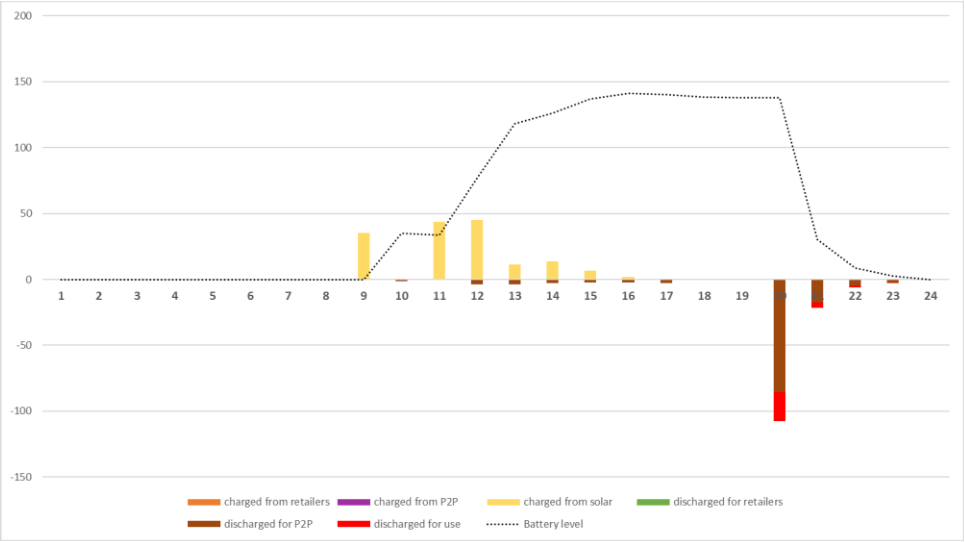


Figure 6. Total battery charge and discharge operations for all households in the *Mh* set.

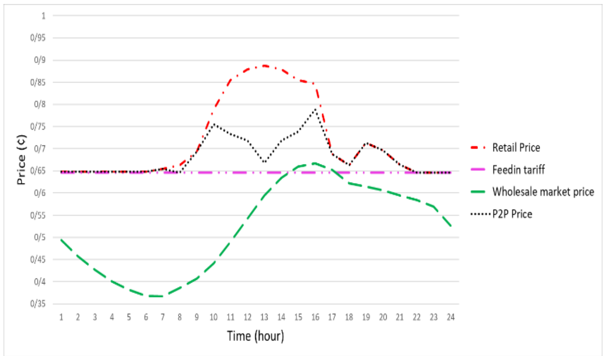


Figure 7. Daily price of P2P market, FIT, and retailer prices based on DRP.

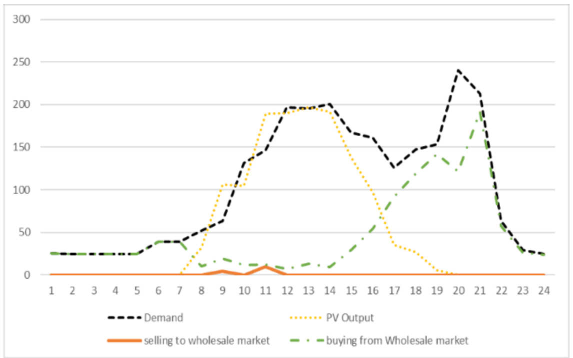


Figure 8. Microgrid imports and exports to/from the main grid.

On the other hand, batteries discharge during peak hours or when electricity generation by solar panels reaches its minimum to meet the energy needs of households, either for personal consumption or for the P2P market. Figure 7 displays the clearing price for P2P trading, as well as the FIT and purchasing price from the retailer throughout the day. As mentioned earlier, these prices are determined considering the RTP for both P2P and the retail market, with the retailer applying an I/C based tariff to its prices. As is evident, P2P market prices decrease during periods when the outputs of the PV system reach their highest level. Conversely, retail prices during these hours increase to encourage households to consume renewable energy. Figure 8 illustrates the MG's import/export to/from the upstream grid. It is easy to see that the majority of the energy generated by PV systems is consumed within the MG.

5.3 Sensitivity analyses

In our previous study (Masoumi and Kheirkhah, 2024), we examined the impacts of DRPs and the price elasticity of electricity consumption from the retailer on optimal solutions, renewable energy consumption, and prices across various scenarios. The results showed that by incorporating incentive-based and time-based DRPs, along with demand-price elasticity, retail profit increased, prosumers' costs decreased, and renewable energy consumption rose by 24.6%. In this sub-section, we further investigate the sensitivity of different time-based tariffs, including Fixed Price (FP), Time of Use (TOU), and Real-Time Pricing (RTP), with respect to their impact on optimal solutions in nine scenarios, as outlined in Table 2.

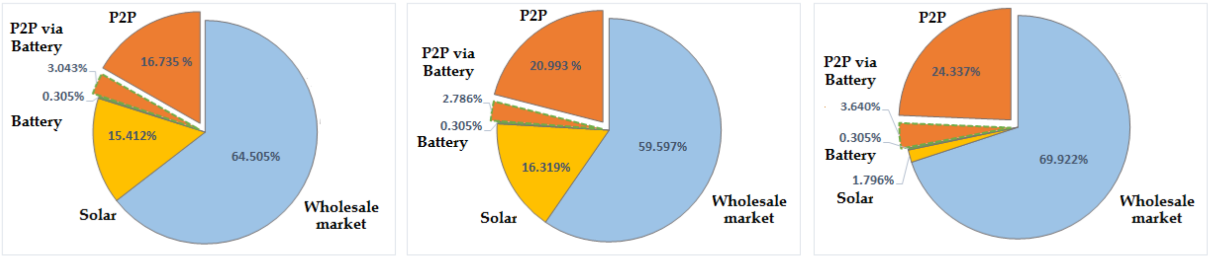
Table 2. The impact of Time-based DRPs on Total Retailer Profit and Total Prosumer Costs.

NO.	Scenario	Retailer Profit(F_3)(¢)	Prosumers Cost (F_4)(¢)
1	FP for both P2P and retail market	3105.44	2968.90
2	FP for retailer and TOU for P2P market	3015.98	2635.41
3	FP for retailer and RTP for P2P market	3363.22	2883.14
4	TOU for retailer and FP for P2P market	3923.01	2877.41
5	TOU for both P2P and retail market	4067.98	2587.57
6	TOU for retailer and RTP for P2P market	4173.45	2313.71
7	RTP for retailer and FP for P2P market	3400.64	2898.47
8	RTP for retailer and TOU for P2P market	4058.15	2265.64
9	RTP for both P2P and retail market	3413.93	2467.33

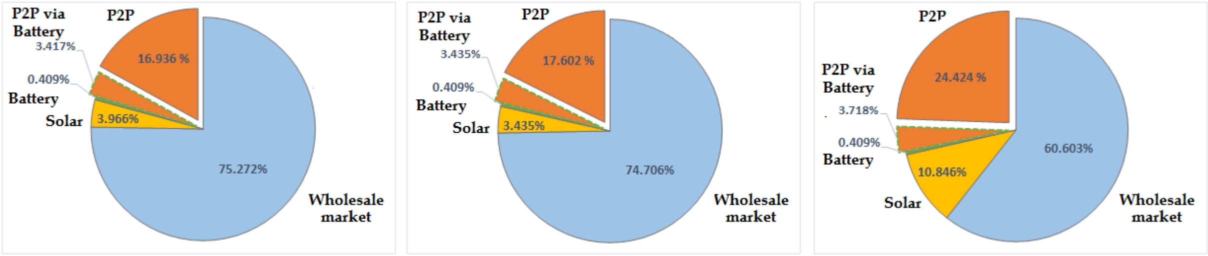
According to Table 1, the highest and lowest retail profits are observed in Scenarios 6 and 2, respectively. The reduction in retail profit in FP tariffs can be attributed to retailers being required to purchase electricity from the upstream grid at higher prices during peak hours to satisfy demand while selling it to consumers at a fixed price.

In Scenario 6, the retailer supplies a significant portion of energy by purchasing it from prosumers at a low FIT during peak hours when wholesale electricity prices are high. Moreover, in this scenario, the retailer sells electricity to consumers during off-peak and low-load hours at higher prices than wholesale prices, leading to a substantial increase in its profit.

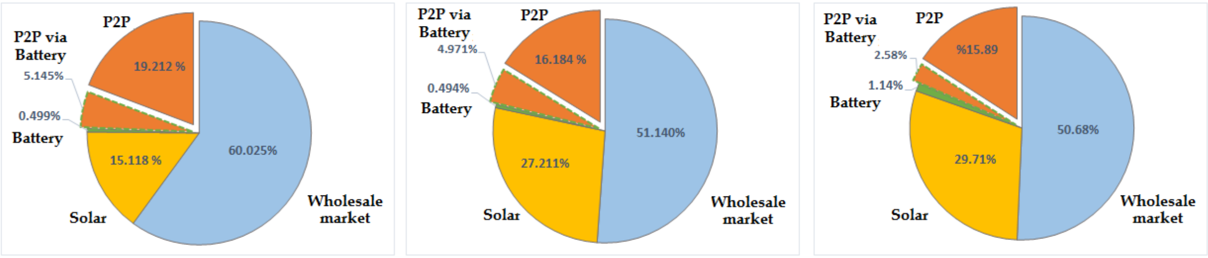
Based on Figure 9, it can be observed that RTP tariffs for the retailer can influence its purchasing decisions from the wholesale market and increase the share of renewable energy within MG. The highest and lowest prosumer costs occur in Scenarios 1 and 8, respectively. In Scenarios 1 and 3, despite the P2P market having a larger contribution to satisfy demand (Figure 9(a) and 9(c)), prosumers earned lower profits. This is because, to encourage households to participate in the P2P market, prices are generally lower than in Scenario 8.



a. scenario1 **b. scenario2** **c. scenario3**



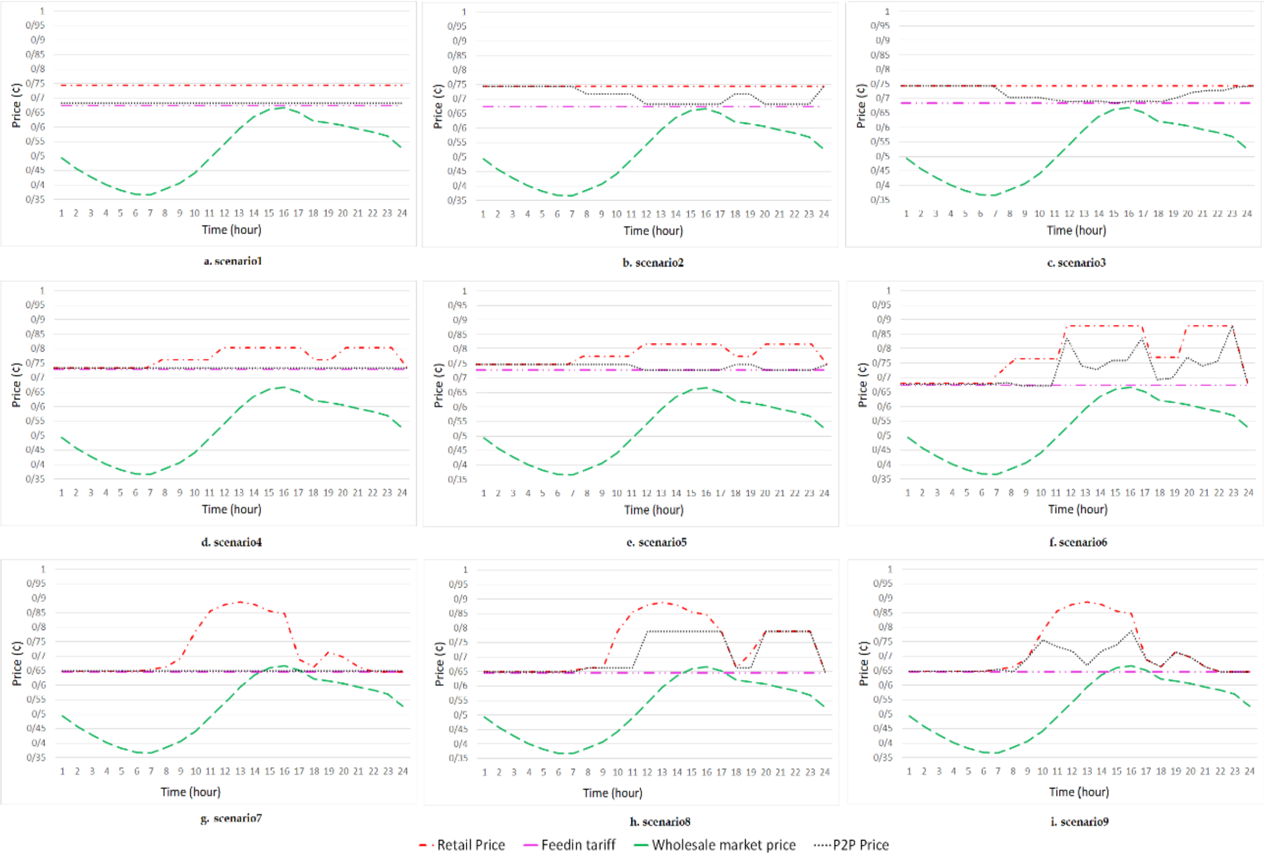
d. scenario4 **e. scenario5** **f. scenario6**



g. scenario7 **h. scenario8** **i. scenario9**

Figure 9. The impact of Time-based DRPs on Sources of Energy to satisfy Demand (overall) for 9 scenarios.

According to Figure 10, in Scenario 4, the FIT offered by the retailer is the highest compared to other scenarios. Simultaneously, fixed prices in the P2P market are relatively low. Consequently, prosumers minimize their costs by selling a substantial portion of their generated electricity first to the retailer and then to the P2P market. This results in a minimal contribution of solar energy for self-consumption (3.966%). As a result, households source 75.272% of their energy needs from the upstream market. However, in Scenario 9, while the retail selling prices of electricity are higher compared to other scenarios. Consequently, prosumers prefer to allocate a larger portion of the electricity generated by PV systems for personal consumption. As a result, the contribution of solar energy for self-consumption reaches its highest level in all scenarios (29.71%), and overall, the amount of purchased electricity from the upstream market reaches its lowest level (50.68%).



a. scenario1

b. scenario2

c. scenario3

d. scenario4

e. scenario5

f. scenario6

g. scenario7

h. scenario8

i. scenario9

Figure 10. The impact of Time-based DRPs on clearing price of P2P market, FIT and purchasing price of retailer, for 9 scenarios.

6. Conclusions and future research

In this paper, we proposed a two-stage optimization model for P2P energy trading, focusing on maximizing renewable energy consumption and minimizing the geographical distance between peers in the first stage. The second stage aims to optimize energy exchange and storage management to maximize retailer profits and minimize prosumer costs within a grid-connected microgrid. The results show that no single scenario optimizes all objectives; however, adopting RTP tariffs in both retail and P2P markets lead to a higher share of renewable energy in the microgrid supply.

This study provides several key managerial insights for policymakers and energy market participants. Developing renewable energy resources requires substantial investments. Encouraging private sector participation and delegating responsibilities to electricity retailers can reduce costs, accelerate deployment, and enhance long-term energy security. Limited adoption of PV panels and renewable energy by end-users is a major challenge due to high initial costs.

Providing appropriate infrastructure for P2P energy trading can incentivize consumer engagement and expand renewable energy utilization. Implementing smart grids and demand response programs can optimize consumption, reduce costs, and manage peak loads effectively. Equipping around 40% of households with rooftop PV panels can reduce fossil fuel consumption by over 50% and CO_2 emissions, alleviating network stress and lowering social costs related to power outages. Time-of-use tariffs and reward-based mechanisms can further optimize electricity consumption by motivating consumers to shift demand toward renewable sources, reducing peak load and enhancing overall grid efficiency.

Despite these managerial insights, the model has several limitations that should be considered. One key limitation is the assumption of widespread availability of renewable energy, particularly through PV systems, which may not always be realistic in regions like Iran, where the adoption of such technologies is still limited. Additionally, the current model does not consider the impact of regulatory and policy constraints that could affect the feasibility and scalability of P2P energy markets. Moreover, the role of battery storage in stabilizing energy markets and improving the overall efficiency of P2P systems requires further exploration, particularly in contexts with intermittent renewable generation. Although this study is based on real data from Iran, it is important to note that the model operates within a hypothetical scenario, as such network configurations do not yet exist in practice. This may influence the results and their applicability to real-world situations. Assumptions regarding the availability of renewable energy and the structure of P2P energy trading markets may not fully reflect the complexities of actual grid operations and market conditions.

Future studies could build on this model by integrating multiple retailers within a multi-microgrid environment, offering a more comprehensive analysis of competitive dynamics and their effects on market efficiency. A deeper investigation into the techno-economic impacts of PV systems and battery storage on P2P energy trading would also be valuable, particularly in residential settings with decentralized renewable energy generation. Additionally, addressing the modelling of uncertainty in renewable energy output and demand is crucial. In real-world conditions, both renewable energy generation and demand are subject to uncertainty. Modelling these uncertainties will help design systems with greater resilience to fluctuations, thus improving reliability. Furthermore, in countries like Iran, where load shedding is implemented during certain seasons by distribution companies, incorporating the potential for outages into the model could bring the system closer to real-world conditions. This would help better understand the impacts of outages and design more robust strategies to handle such challenges. Lastly, research into developing equitable and efficient profit-sharing mechanisms for P2P markets is essential to ensure fair participation and enhance the economic sustainability of such systems.

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