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Research Paper

A Two-Stage Multi-Objective Optimal Day-Ahead Peer to Peer Energy Trade and Pricing Considering Electric Vehicles in Microgrid

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Abstract— *Due to recent developments in communications and the increasing penetration rate of distributed generation (DGs), new players in the energy market, known as prosumers, have emerged. Prosumers can both produce and consume power, offering benefits such as on-site power consumption, peak shaving, and postponing the power transmission network investment costs. This paper presents a two-stage day-ahead peer-to-peer pricing and power exchange model among local market participants, including the upstream grid, consumers, prosumers (equipped with rooftop solar panels), and electric vehicles. In the first stage, initial pricing is determined using the mid-market rate pricing method, taking into account each participant's declared demand and the forecasted solar production of prosumers. In the second stage, the random behavior of electric vehicles is modeled through scenario generation, and their dynamic behavior is incorporated into the pricing scheme. The proposed model aims to minimize two objectives: trading costs and electrical power losses due to the exchange of power among participants. This two-objective problem is reformulated as a single objective using the epsilon-constraint method. The resulting MINLP model is solved in GAMS using the DICOPT solver, and the best-compromised solution is identified through the Min-Max method. Simulation results indicate a 6.7% reduction in costs, with all participants benefiting economically. Additionally, on-site interactions led to a decrease in congestion on two lines connecting to the upstream grid by 5.02% and 6.66%, respectively.*

Keywords—Electrical power loss, electric vehicle, peer to peer, pricing strategy, prosumer.

NOMENCLATURE

Abbreviations

DG	Distributed generation
ESS	Energy storage system
EV	Electric vehicle
GAMS	General algebraic modeling system
IoT	Internet of Thing
MG	Microgrid
MINLP	Mixed integer non-linear programing
P2P	Peer to peer
PDF	Probability distribution function
PER	Renewable energy resource
PL	Parking lot
SOC	State of charge
ToU	Time of use

Binary Variables

$U_{av}(e,p,q)$ 1 If the line between bus p and q is in the path of interaction of EV e with the upstream grid, otherwise 0

$U_{av}(i,e,p,q)$ 1 If the line between bus p and q is in the path of interaction prosumer i with EV e, otherwise 0

$U_{av}(i,k,p,q)$ 1 If the line between bus p and q is in the path of interaction prosumer i with consumer k, otherwise 0

$U_{av}(i,p,q)$ 1 If the line between bus p and q is in the path of interaction of the prosumer i with the upstream grid, otherwise 0

$U_{av}(k,e,p,q)$ 1 If the line between bus p and q is in the path of interaction consumer k with EV e, otherwise 0

$U_{av}(k,p,q)$ 1 If the line between bus p and q is in the path of interaction of the consumer k with the upstream grid, otherwise 0

$U_{ch}(e,m,t)$ 1 if EV e in parking lot m at hour t is charged, otherwise 0

$U_{dch}(e,m,t)$ 1 if EV e in parking lot m at hour t is discharged, otherwise 0

Parameters

$t_{detention}(e,m)$ Detention time of EV e in parking lot m (h)

$G^{i}(t)$ Electrical power generation of prosumer i at hour t (kW)

$G_{T}(t)$ Total Electrical power generated by prosumers at hour t (kW)

$M^{i}(t)$ Electrical power consumption of prosumer i at hour t (kW)

$M^{k}(t)$ Electrical power consumption of consumer k at hour t (kW)

$M_{T}(t)$ Total Electrical power consumed by prosumers and consumers at hour t (kW)

P_{ch}^{max} Maximum charging Electrical power of batteries of EVs (kW)

P_{dch}^{max} Maximum discharging Electrical power of batteries of EVs (kW)

Soc_{EV}^{max} Maximum SoC of EVs (kWh)

Soc_{EV}^{min} Minimum SoC of EVs (kWh)

$Soc_{in}(e,m)$ Arrival SoC of EV e in parking lot m (kWh)

$Soc_{out}(e,m)$ Departure SoC of EV e in parking lot m (kWh)

$t_{a}(e,m)$ Arrival time of EV e in parking lot m (h)

$t_{d}(e,m)$ Departure time of EV e in parking lot m (h)

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η_{ch}, η_{dch} Charging and discharging efficiency of batteries of EVs

Set and Indices

e Index of EVs
i, j Indices of prosumers
k Index of consumers
m Index of parking lots
N_c Set of consumers
N_p Set of prosumers
N_{bus} Set of buses
N_{EV} Set of EVs
N_{PL} Set of EV parking lots
p, q Indices of buses
T Set of times
t Index of time

Variables

$C_{buy}(t)$ Price of procurement electrical power from upstream grid at hour t ($)
$C_{ex}(t)$ Price of P2P electrical power trade when local production is greater than demand at hour t ($)
$C_{im}(t)$ Price of P2P electrical power trade when local demand is greater than production at hour t ($)
$C_{new}(t)$ Updated P2P energy trade price considering participation of EVs in P2P market at hour t ($)
$C_{P2P}(t)$ Price of P2P trading electrical power with local market at hour t ($)
$C_{PP}(t)$ Unified market of electrical power price in the P2P market in different conditions at hour t ($)
$C_{sell}(t)$ Price of selling electrical power to upstream grid at hour t ($)
$P_(L_{p,q}))(t)$ Electrical power flow of line connecting bus p and bus q at hour t (kW)
$P_{ch}(e,m,t), P_{dch}(e,m,t)$ Charging and discharging electrical power of EV e in parking lot m at hour t (kW)
$P_{im}^{EV}(e,m,t), P_{ex}^{EV}(e,m,t)$ Imported and exported electrical power EV e in parking lot m traded by upstream grid at hour t (kW)
$P_{im}^{i}(t), P_{ex}^{i}(t)$ Imported and exported electrical power prosumer i traded by upstream grid at hour t (kW)
$P_{im}^{k}(t)$ Electrical power imported to consumer k by upstream grid at hour t (kW)
$R(p,q)$ Resistance of line connecting bus p and bus q (ohm)
$Soc_{EV}(e,m,t)$ State of charge of EV e in parking lot m at hour t (kW)
Z Positive variable
$P^{e\to i}(m,t), P^{i\to e}(m,t)$ Electrical power traded among prosumer i and EV e in parking lot m at hour t (kW)
$P^{e\to k}(t)$ Electrical power sold to consumer k by parking lot e at hour t (kW)
$P^{i\to k}(t)$ Electrical power sold to consumer k by prosumer i at hour t (kW)
$P^{j\to i}(t), P^{i\to j}(t)$ Electrical power traded among prosumer i and j at hour t (kW)

1. INTRODUCTION

Continuous power transmission expansion can increase costs, complexity, and the size of network equipment. Conversely, DG expansion schemes can delay the capital costs for transmission build-up. These units have the potential to meet the demands of consumers locally, resulting in reduced power congestion in power transmission lines. A management system equipped with communication links is required to coordinate numerous DGs. The integration of communication infrastructures, DGs, and some controllable participants like EVs leads to the concept of active distribution networks. Communication and IoT developments have enabled the creation of a peer-to-peer (P2P) local energy market in conjunction with the active distribution network, so the power grid is no longer the only medium of power exchange. Indeed, the P2P energy market comprises two layers: physical and virtual. The physical layer includes DGs and power, while the virtual layer handles communications [1]. The market participants are categorized into three groups: producers, consumers, and prosumers. Prosumers can act as both producers and consumers simultaneously. Examples include a household with rooftop solar panels or an EV. When considering DGs, it is advantageous to take into account each region's natural and geographical capabilities. However, a challenge is the limited space available for DG installation, particularly because some RERs are not feasible on a small household scale. Rooftop solar panels provide a viable solution to this obstacle, as solar energy can be utilized in infrastructures as small as a house [2]. By equipping a building with a rooftop solar panel, the building transforms from a consumer to a prosumer.

1.1. Motivation

The P2P energy market provides an online platform that enables market players to trade energy directly at an agreed price. Those without any production capacity could benefit from local electricity produced by other participants. One of the most important issues is setting a win-win price between ToU prices and feed-in tariffs. In this manner, buyers would save on their costs, and sellers could earn more profit. This could drive the market, attract more participants, and increase the tendency for DG expansion [3]. Also, EV owners could benefit from such a fair market because, considering their battery capacity, they could interact bidirectionally with the market and gain from both buying and selling power to other peers [4]. In a P2P market consisting of various DGs, prosumers, and specially EVs, Pricing is a challenging issue. The differences between EVs and other sources create energy management and pricing challenges. For example, the installed capacity of a rooftop solar panel is determined. With the available forecasting facilities for solar radiation, approximate day-ahead information about power generation output would be possible. In this way, pricing is determined with acceptable accuracy based on production and consumption forecasts. However, the number of available EVs and their preferences are more diverse. Regarding the existing challenges, researchers paid less attention to pricing mechanisms in the P2P market with the penetration of EVs [5, 6]. Authors in Ref. [7] Considered P2P only amongst EV charging stations. There are no more market players, and there is no longer any pricing scheme. Indeed, the authors aimed to use the battery capacity of EVs for ancillary services and reduce the charging cost of EVs, which is desirable for owners. Thanks to IGDT, they controlled the robustness parameter of uncertainty modeling of EVs. Ref. [8] analyzes an industrial hub in conjunction with electric vehicles and considers both heat and power peer to peer transactions. Pricing remains static, and the dynamic behavior of participants, particularly electric vehicles, is not taken into account. Ref. [9] has set prices without considering EVs and ESSs and using the concept of levelized cost of electricity (LCOE) and other constraints to satisfy consumers and prosumers Ref. [10] focuses on developing a smart contrast-based electronic wallet for automatic charging payment of electric vehicles to foster a trust-based relationship and a user-friendly application for EV owners. Ref. [11] investigates the effect of EVs and shiftable loads on P2P energy trading. Machine washings and dishwashings are considered flexible loads. Also, the degradation cost of EV batteries is modeled. However, the authors set a static price between the selling price and the purchase price to promote the local consumption approach. Ref. [12] deals with the issue of local and P2P energy exchange between EVs. Their proposed model achieves demand response by providing incentives to discharge EVs to balance the local electricity demand out of their self-interest. An iterative double auction mechanism is presented for charging and discharging EVs to maximize social welfare. Ref. [13] proposes the transactive energy in the presence of EVs, but the number of EVs and their required power are predetermined. With such an assumption, EVs behave like other ESSs reviewed in previous works.

1.2. Literature review

Energy can be traded on a multi-apartment scale or even between MGs on the P2P architecture. Refs. [14, 15] deal with the energy trade between smart homes and apartments. Ref. [16] focuses on buildings in the P2P market. In this regard, they not only simulate precisely the performance of electric usage and storage but also consider and model the thermal appliances. The result shows that the operational cost of prosumers decreased by around 3%. The P2P energy trade between MGs could be more complex due to the connection between several energy sources and their independent decisions. Refs. [17–19] deal with P2P power exchange between several MGs and related issues. Game theory's capabilities in the P2P market are considered in some references. In Ref. [20], a Cooperative Stackelberg game is formulated in which the centralized power system acts as the leader that needs to decide on a price at the peak demand period to incentivize the prosumers not to seek any energy from it. The prosumers, on the other hand, act as followers and respond to the leader's decision by forming suitable coalitions with neighboring prosumers to participate in P2P energy trading to meet their energy demand. In addition, Ref. [21], employing a motivational game-theoretic approach, proposes how a motivational psychology framework can be used effectively to design P2P energy trading to increase user participation. Ref. [22] makes competition between sellers as well as buyers to select a seller. Ref. [23] models the P2P market using a multi-leader-multi-follower game. They examine three different local communities and find that converting extra electric energy to other forms of energy could be more beneficial than storing it. Ref. [24] investigates the possibility of using retired EV second-life batteries in the P2P market using the double-sided auction method. The result indicates that the capital cost of these retired batteries is lower, but the economic benefits of new ones in the community market are better. The challenges of large loads as well as the ancillary services in the P2P market are considered in references. In Ref. [25], the authors manage the load of a large industrial unit with a water supply plant in the P2P energy market. Case studies on a water supply plant show that optimized load management under this new market structure significantly reduces electricity costs compared to the spot market. Ref. [26] proposes a coupling market framework in which the P2P energy trading market can participate in both energy and ancillary service markets. The P2P energy trading market is modeled as an equivalent federated power plant that provides ancillary services and energy for the other market entities. Their proposed method could encourage DG owners to participate spontaneously in the ancillary service market. DGs would play a vital role in the P2P market, and due to the random behavior of those driven by natural resources, the ESS is considered in many studies to mitigate the inevitable uncertainties [27]. Ref. [28] examines the individual installation of ESS in the place of each prosumer or as an integrated unit. However, No uncertainty is considered for power production or the price. Ref. [29] optimizes the installation of ESSs and P2P energy exchange in various case studies, including different configurations of ESSs in MG. Ref. [30] investigates how residential ESS contributes to local demand side flexibility in an integrated market setting. P2P market consists of two layers; physical and virtual. The virtual layer provides a secure network environment for all the peers to have equal access to the P2P market [31]. As the trend moves towards decentralization, it is essential to debate how to establish trust and privacy in interconnected digital societies [32]. many studies focuses on the virtual layer of P2P market instead of physical layer and consider blockchain in their studies. Block chain technology is an advanced database mechanism that allows transparent information sharing within a business network. A blockchain database stores data in blocks that are linked together in a chain. Blockchain is a well-known network to handle peer to peer interactions. Meanwhile, when it comes to the electricity P2P market, its specific limitations would be a challenge [33]. Ref. [34] tries to reduce transaction costs and enables micro-transactions in a decentralized and democratic energy market. Leverage block chain technology is used in Ref. [35]. Ref. [36] proposes IoT–blockchain architecture utilizes a Chainlink oracle network and a private Ethereum blockchain. Ref. [37] proposes a real-time system that incorporates the concepts of prioritization an cryptocurrency to incentivize EV users to be collectively charged by a renewable energy-friendly schedule. The system implements a ranking scheme by giving charging priority to users with a better renewable energy usage history. With an increasing demand for climate resiliency, water sensitivity, nature inclusiveness and energy efficiency in dense urban environments, the call for layered and multifunctional use of rooftops is rising [38]. In distribution networks, the lack of space would be an obstacle for some kinds of integrated DGs. Capabilities of rooftop solar panels considered in some researches. Also, Decarbonizing the building sector is key to meet the EU climate goals by 2050 [39]. Authors in Ref. [39] uses special techniques to estimate the main spatial and temporal characteristics of the rooftop PV energy production potential. It predicts major improvement could be achieved in the EU's rooftop solar energy production by around 2040. Ref. [40] analyses a rooftop solar panel system on a car parking area in Thailand. Ref. [41] surveys assesses the potential for residential rooftop solar panel installation across Qatar, considering different issues like space availability. As a consequence of skyscrapers and the shade effects of tall buildings, finding the best candidate places, would be crucial. Ref. [42] use data envelopment analysis to evaluate suitable candidates for rooftop solar panel installation. EVs bring both opportunities and challenges to MGs [43, 44]. Studies consider different aspects of EVs. Power quality concerns considered in Ref. [45] and the location and capacity of charging stations obtained to reduce voltage drop and total harmonic distortions. To considering frequency regulation, Ref. [46] presents a new robust load frequency controller for EV aggregators. Some references try to meet the EV requirements by renewable natural resources; in this manner, metaheuristic algorithms like genetic algorithms could be helpful [47].

1.3. Contributions and organization

This paper presents a two-stage multi-objective probabilistic approach for pricing and management of day-ahead electrical power trades in the presence of EVs. In the first stage, regarding the declared demand of each agent and forecasted solar production of prosumers, initial pricing is determined using the mid-market rate pricing method. In the second stage, by modeling the random behavior of EVs, final pricing and electrical power exchanged between participants are identified, considering EVs' stochastic charging and discharging mechanism. The First objective of the proposed model is trading cost, while the second objective is electrical power loss due to the electrical power exchange among participants. The epsilon constraint method solves the proposed model, and the Min-Max method derives the best-compromised solution.

The main contributions of this paper are as follows:

- Presenting a two-stage pricing strategy considering EVs,
- Modeling the uncertainty of EV's behavior using scenario generation,
- Proposing electrical power loss as a supplementary objective function along with trading cost,
- Converting the two-objective proposed method as a single objective using Epsilon constraint method, and
- Presenting an optimal P2P energy market considering various types of participants.

The rest of this paper is organized as follows: Section 2 presents the problem formulation. Section 3 deals with the uncertainty modeling of EVs. Section 4 states the solution algorithm. Section 5 describes the application of the mathematical algorithm to the proposed model. Section 6 explains the case study and simulation results. Finally, Section 7 presents the conclusions.

2. Problem formulation

This section discusses problem formulation, constraints, pricing strategy, and objective functions. Fig. 1 provides an overview of the P2P energy trading in a MG involving four types of agents: the upstream grid, prosumers, EVs, and consumers. A P2P energy market consists of two layers: physical and virtual. The physical layer refers to the actual exchange of energy using standard wires or advanced wireless technologies. The virtual layer is responsible for creating a data and communication network to enable peers to interact with each other and store the history of transactions. The communication and power links between participants are shown in Fig. 1. Moreover, double arrows between two participants showcase their bidirectional power exchangeability compared to those with simple arrows.

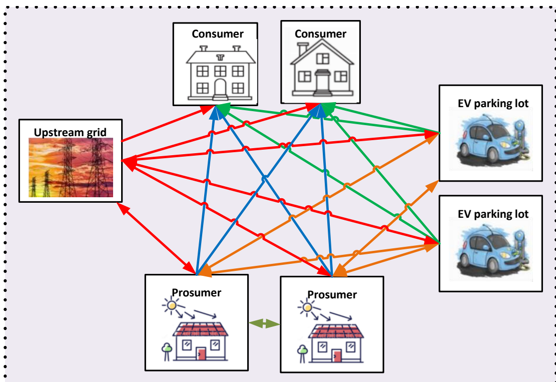

Fig. 1. Overview of P2P energy market.

2.1. Problem constraints

A) Electrical power balance for prosumers

Fig. 1 shows four ways to supply prosumers: utilizing the unit's own generation capacity (solar panels), receiving electrical power from other prosumers via P2P energy market, importing electrical power from the upstream grid, and purchasing electrical power from EV parking lots. The electrical power balance for each prosumer is written as:

$$\begin{aligned} & G^i(t)+\sum\nolimits_{j\in N_p, j\neq i} P^{(j\to i)}(t)+P^i_{im}(t)+ \\ & \sum\nolimits_{m\in N_{PL}}\sum\nolimits_{e\in N_{EV}} P^{(e\to i)}(m,t)= \\ & M^i(t)+\sum\nolimits_{j\in N_p, j\neq i} P^{(i\to j)}(t)+P^i_{ex}(t)+ \\ & \sum\nolimits_{m\in N_{PL}}\sum\nolimits_{e\in N_{EV}} P^{(i\to e)}(m,t)+ \\ & \sum\nolimits_{k\in N_c} P^{(i\to k)}(t) \qquad \forall t\in T,\ \forall i\in N_P \end{aligned} \tag{1}$$

B) Electrical power balance for consumers

Compared to prosumers, consumers do not have the production capacity and must meet their needs through prosumers, the upstream grid, and EV parking lots as follows:

$$\begin{aligned} & \sum\nolimits_{i\in N_p} P^{(i\to k)}(t)+P^k_{im}(t)+ \\ & \sum\nolimits_{m\in N_{PL}}\sum\nolimits_{e\in N_{EV}} P^{(e\to k)}(m,t)= \\ & M^k(t) \qquad \forall t\in T,\ \forall k\in N_c \end{aligned} \tag{2}$$

C) Electrical power balance for EVs

The Electrical power required to charge EVs in parking lots is provided by prosumers in the P2P energy market as well as the upstream grid as follows:

$$\begin{aligned} & \sum_{m\in N_{\mathrm{PL}}}\sum_{e\in N_{\mathrm{EV}}} P_{\mathrm{ch}}(e,m,t)= \\ & \sum_{m\in N_{\mathrm{PL}}}\sum_{e\in N_{\mathrm{EV}}} P^{\mathrm{EV}}_{\mathrm{im}}(e,m,t)+ \\ & \sum_{i\in N_p}\sum_{m\in N_{\mathrm{PL}}}\sum_{e\in N_{\mathrm{EV}}} P^{i\to e}(m,t), \quad \forall t\in T \end{aligned} \tag{3}$$

On the other hand, the total power discharged by the EV parking lots can be transferred directly to the prosumers or consumers via the P2P energy market or sold to the upstream grid as:

$$\begin{aligned} & \sum_{m\in N_{\mathrm{PL}}}\sum_{e\in N_{\mathrm{EV}}} P_{\mathrm{dch}}(e,m,t)= \\ & \sum_{m\in N_{\mathrm{PL}}}\sum_{e\in N_{\mathrm{EV}}} P^{\mathrm{EV}}_{\mathrm{ex}}(e,m,t)+ \\ & \sum_{k\in N_c}\sum_{m\in N_{\mathrm{PL}}}\sum_{e\in N_{\mathrm{EV}}} P^{e\to k}(m,t)+ \\ & \sum_{i\in N_p}\sum_{m\in N_{\mathrm{PL}}}\sum_{e\in N_{\mathrm{EV}}} P^{e\to i}(m,t), \quad \forall t\in T \end{aligned} \tag{4}$$

The amount of charge and discharge of every EV in the parking lot in each period is limited to the maximum charge and dis charge capacity of their battery as follows [48]:

$$\begin{aligned} & 0\leqslant P_{\mathrm{ch}}(e,m,t)\leqslant \frac{P^{\max}_{\mathrm{ch}}\cdot U_{\mathrm{ch}}(e,m,t)}{\eta_{\mathrm{ch}}}, \\ & \forall t\in T, \forall e\in N_{\mathrm{EV}}, \forall m\in N_{\mathrm{PL}} \end{aligned} \tag{5}$$

$$\begin{aligned} & 0\leqslant P_{\mathrm{dch}}(e,m,t)\leqslant P^{\max}_{\mathrm{dch}}\cdot U_{\mathrm{dch}}(e,m,t)\cdot\eta_{\mathrm{dch}}, \\ & \forall t\in T,\ \forall e\in N_{\mathrm{EV}},\ \forall m\in N_{\mathrm{PL}} \end{aligned} \tag{6}$$

It is not possible to charge and discharge batteries of an EV at the same time [48]. Thus:

$$\begin{aligned} & U_{\mathrm{ch}}(e,m,t)+U_{\mathrm{dch}}(e,m,t)\leq 1, \\ & \forall t\in T,\ \forall e\in N_{\mathrm{EV}},\ \forall m\in N_{\mathrm{PL}} \end{aligned} \tag{7}$$

When the EVs enter the parking lot, the battery charge level is equal to its initial charge as Eq. (8), but in the following hours and before leaving the parking lot, the electrical power changes according to Eq. (9). Eq. (10) guarantees that EVs leave the parking lot with maximum stored energy in their batteries [48].

$$\begin{aligned} & \mathrm{Soc}_{\mathrm{EV}}(e,m,t)=\mathrm{Soc}_{\mathrm{in}}(e,m), \\ & t=t_a(e,m),\ \forall e\in N_{\mathrm{EV}},\ \forall m\in N_{\mathrm{PL}} \end{aligned} \tag{8}$$

$$\begin{aligned} & \mathrm{Soc}_{\mathrm{EV}}(e,m,t)=\mathrm{Soc}(e,m,t-1)+ \\ & (P_{\mathrm{ch}}(e,m,t)\times\eta_{\mathrm{ch}})-\left(\frac{P_{\mathrm{dch}}(e,m,t)}{\eta_{\mathrm{dch}}}\right), \\ & \forall t\in T, \forall e\in N_{\mathrm{EV}}, \forall m\in N_{\mathrm{PL}} \end{aligned} \tag{9}$$

$$\begin{aligned} & \mathrm{Soc}_{\mathrm{EV}}(e,m,t)=\mathrm{Soc}_{\mathrm{out}}(e,m), \\ & t=t_d(e,m),\ \forall e\in N_{\mathrm{EV}},\ \forall m\in N_{\mathrm{PL}} \end{aligned} \tag{10}$$

During detention time in the parking lot, the amount of charge or discharge of EVs should be such that the battery capacity does not exceed the minimum and maximum capacity as follows [48]:

$$\begin{aligned} & \mathrm{Soc}^{\min}_{\mathrm{EV}}\leq \mathrm{Soc}_{\mathrm{EV}}(e,m,t)\leq \mathrm{Soc}^{\max}_{\mathrm{EV}}, \\ & \forall t\in T,\ \forall e\in N_{\mathrm{EV}},\ \forall m\in N_{\mathrm{PL}} \end{aligned} \tag{11}$$

2.2. Pricing strategy

This subsection presents the formulation of power exchange pricing in the local P2P market.

A) First stage

In the first stage, pricing is determined using mid-market rate method, concerning the demand of each participant and solar power generation without considering EVs. The mid-market rate method [49] adjusts hourly prices based on the balance of supply and demand. Indeed, at this stage, the dynamic behavior of EVs is not considered, and only the declared demand and solar power generation capacity are factored into pricing. When the demand matches power production, the P2P energy price is assumed to be the average of the purchase and sale prices with the upstream grid as follows [49]:

$$C_{\mathrm{P2P}}(t) = \frac{C_{\mathrm{sell}}(t) + C_{\mathrm{buy}}(t)}{2} \quad \forall t \in T \tag{12}$$

It is assumed that $G_T(t)$ is the total power output of prosumers (solar cells) per hour as [49]:

$$G_T(t) = \sum_{i \in N_p} G^i(t) \quad \forall t \in T \tag{13}$$

and $M_T(t)$ is the total power consumption of consumers and prosumers per hour as [49]:

$$M_T(t) = \sum_{i \in N_p} M^i(t) + \sum_{j \in N_c} M^j(t) \quad \forall t \in T \tag{14}$$

According to the total production of prosumers and the total demand at each time, the purchase or sale price of electrical power in the context of P2P energy trade is determined as [49]:

$$\tau = 1/W, \ W \ is \ the \ motor \ weight \tag{15}$$

B) Second stage

At this stage, by modeling EVs and their uncertainties, the pricing issue is updated in accordance with the behavior of EVs, and then, the energy exchange is done according to the set price. EVs can coordinate their activities according to the hourly price and the amount of supply and demand. With their activity and depending on the process of charging or discharging, they cause a change in the amount of energy consumed or produced. At this stage, it is assumed that the initial price changes in the proportion to the behavior of EVs. Obviously, the initial price should be reduced by increasing the electrical power generation due to EV discharging, and it should be increased by increasing the demand due to the EV charging. Electrical power balance changes due to the process of charging and discharging of EVs are calculated in Eq. (16). Then, the price is updated in proportion to changes in the balance of power consumption and production. Z is a positive variable; therefore, the price changes align with the electrical power change sign.

$$\Delta P(t) = \sum_{m \in N_{PL}} \sum_{e \in N_{EV}} P_{ch}(e,m,t) - \sum_{m \in N_{PL}} \sum_{e \in N_{EV}} P_{dch}(e,m,t) \quad \forall t \in T \tag{16}$$

$$C_{\mathrm{new}}(t) = C_{\mathrm{PP}}(t) \times (1 + Z \times \Delta P(t)) \quad \forall t \in T \tag{17}$$

To maintain financial incentives, the updated price due to the changes in production and consumption should still be lower than the electricity purchase tariff from the upstream grid. In other words, EVs should not increase the demand by concentrating their charge over an hour since this will result in the updated price exceeding the purchase price of electricity from the upstream grid. Hence, the financial incentive to participate in the P2P energy market will disappear. This limitation is formulated as:

$$C_{\mathrm{new}}(t) \le C_{\mathrm{buy}}(t) \quad \forall t \in T \tag{18}$$

2.3. Objective functions

In this subsection, two objective functions are presented to minimize the economic costs of the market as well as the cost of electrical power loss. The purpose of presenting the second objective function is to consider technical issues such as electrical power losses in addition to economic costs for selecting the appropriate partner for electrical power exchange.

A) Economic cost of the market

In this objective function, the goal is to minimize the total cost of all participations in P2P energy market. Pricing and selection of suitable pairs for P2P power exchange and also, the time and amount of electrical power exchange with the upstream grid are done in such a way that the cost of power supply for all participants is minimized.

$$\begin{aligned} F_1 = & \\ & \sum_{t \in T} \Bigg\{ \Bigg(\sum_{i \in N_p} \sum_{j \in N_p, j \neq i} P^{(i \to j)}(t) + \sum_{i \in N_p} \sum_{k \in N_c} P^{(i \to k)}(t) + \sum_{i \in N_p} \sum_{m \in N_{PL}} \sum_{e \in N_{EV}} P^{(i \to e)}(m,t) \Bigg) \cdot \\ & C_{\mathrm{new}}(t) - \Bigg(\sum_{j \in N_p} \sum_{i \in N_p, j \neq i} P^{(j \to i)}(t) + \sum_{m \in N_{PL}} \sum_{e \in N_{EV}} \sum_{i \in N_p} P^{(e \to i)}(m,t) \Bigg) \cdot \\ & C_{\mathrm{new}}(t) + \Bigg(\sum_{i \in N_p} P^i_{im}(t) + \sum_{k \in N_c} P^k_{im}(t) + \sum_{m \in N_{PL}} \sum_{e \in N_{EV}} P^{EV}_{im}(e,m,t) \Bigg) \cdot \\ & C_{\mathrm{buy}}(t) - \Bigg(\sum_{i \in N_p} P^i_{ex}(t) + \sum_{m \in N_{PL}} \sum_{e \in N_{EV}} P^{EV}_{ex}(e,m,t) \Bigg) \cdot C_{\mathrm{sell}}(t) \end{aligned} \tag{19}$$

B) Electrical power loss

In order to consider the electrical power losses in the agent's decision to select the corresponding partner for the P2P trade, an objective function is defined in proportion to the resistance of the lines, which connect agents to each other. For this purpose, the total electrical power of every line between buses is calculated and multiplied by the resistance of that line as:

$$\begin{aligned} & P_{L_{(p,q)}}(t) = \\ & \sum_{i \in N_p} \left[(P^i_{im}(t) + P^i_{ex}(t)) \cdot U_{\mathrm{av}}(i,p,q) \right] + \\ & \sum_{k \in N_c} \left[P^k_{im}(t) \cdot U_{\mathrm{av}}(k,p,q) \right] + \\ & \Bigg(\sum_{m \in N_{PL}} \sum_{e \in N_{EV}} P^{EV}_{im}(e,m,t) + \sum_{m \in N_{PL}} \sum_{e \in N_{EV}} P^{EV}_{ex}(e,m,t) \Bigg) \cdot \\ & U_{\mathrm{av}}(e,p,q) + \sum_{j \in N_p, j \neq i} \sum_{j \in N_p} \left[P^{(i \to j)}(t) \cdot U_{\mathrm{av}}(i,j,p,q) \right] + \\ & \sum_{i \in N_p} \sum_{k \in N_c} \left[P^{(i \to k)}(t) \cdot U_{\mathrm{av}}(i,k,p,q) \right] + \\ & \sum_{m \in N_{PL}} \sum_{e \in N_{PL}} \sum_{i \in N_p} \left[P^{(e \to i)}(m,t) \cdot U_{\mathrm{av}}(e,i,p,q) \right] + \\ & \sum_{m \in N_{PL}} \sum_{e \in N_{PL}} \sum_{k \in N_c} \left[P^{(e \to k)}(m,t) \cdot U_{\mathrm{av}}(e,k,p,q) \right] \quad \forall t \in T \end{aligned} \tag{20}$$

$$F_2 = \sum_{t \in T} \sum_{p \in N_{\mathrm{bus}}, \mathrm{p} \neq q} \sum_{q \in N_{\mathrm{bus}}} \left[P_{L_{(p,q)}}(t) \times R(p,q) \right] \tag{21}$$

3. Uncertainty Modelling of EVs

The arriving time of EVs in the parking lot is shown by Fig. 2 [43]. The departure time of EVs is obtained by adding the detention time of EVs in the parking lot to their arrival time. Detention time of EVs is modeled using normal PDF with mean time of 10 hours and standard deviation of 0.924 as shown by Fig. 3 [43].

$$t_d(e,m) = t_a(e,m) + t_{\text{detention}}(e,m), \quad \forall e \in N_{\text{EV}}, \forall m \in N_{\text{PL}} \tag{22}$$

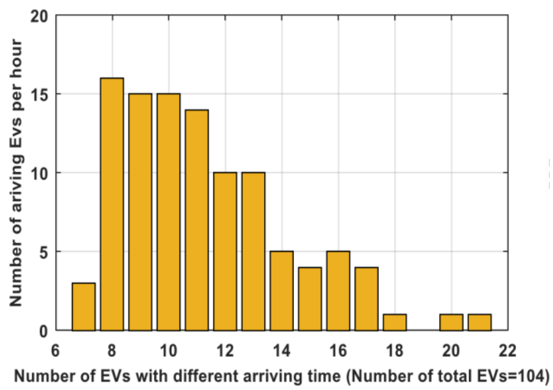

Fig. 2. Number of EVs with arriving time.

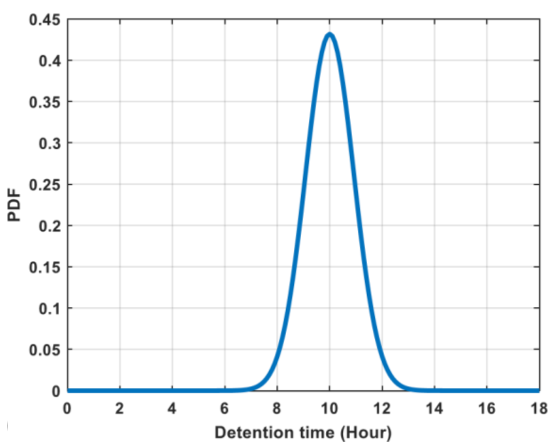

Fig. 3. Detention time of EVs in parking lot.

The SoC of EVs entering the parking lot is modeled using normal PDF with mean and variance of 45 and 15, respectively as illustrated in Fig. 4.

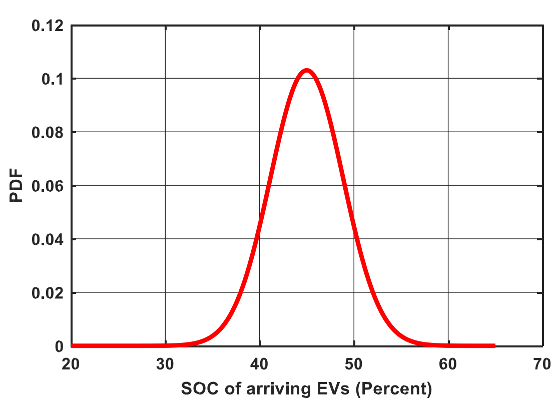

Fig. 4. Initial SoC of EVs.

4. Solution Algorithm

4.1. Epsilon constraint method

In multi-objective optimization, several objective functions must be optimized simultaneously. The general form of a multi-objective optimization problem is as follows [44]:

$$\text{Min}(x) = f_1(x), \ldots, f_N(x) \tag{23}$$

$$\text{s.t.} g(x) \le 0, \; h(x) = 0, \; x \in R^n \tag{24}$$

Here $g(x)$ and $h(x)$ are the set of inequality and inequality constraints, respectively. In these problems, due to the existence of a set of functions with conflicting goals, instead of a specific solution, a set of solutions is obtained called Pareto front solutions. Pareto optimal solution is the optimal solution that cannot be improved in one of the objective functions unless the performance of the solution in at least one of the rest objective functions is deteriorated. The Epsilon constraint method is based on converting a multi-objective optimization problem into a single-objective optimization problem in such a way that except for one of the objective functions, the rest become constraints and the new constrained optimization problem is optimized [44].

$$\min F(x) = f_i^x \tag{25}$$

$$\text{s.t. } f_j(x) \le \epsilon_j, \quad j = 1, \ldots, n, \; j \ne i \tag{26}$$

$$(x) \le 0, \; h(x) = 0, \; x \in R^n \tag{27}$$

$$f_j^{\min} \le \varepsilon_j \le f_j^{\max} \tag{28}$$

4.2. Min-max method

In this paper, the Min-Max method is employed to find the best compromised solution from the set of Pareto set solutions. Assuming the existence of n objective functions and m Pareto points, the optimal Pareto point is obtained as follows [44]:

$$\text{norm}_j^k = \frac{f_j^k - f_j^{\min}}{f_j^{\max} - f_j^{\min}}, \quad j = 1, \ldots, n, \; k = 1, \ldots, m \tag{29}$$

$$\text{norm}^k = \min(\text{norm}_j^k), \quad k = 1, \ldots, m \tag{30}$$

$$\text{opt} = \left\{ o \left(o \mid \text{norm}^o = \max(\text{norm}^k) \right) \right\}, \; o \in k \tag{31}$$

$norm^k$ displays the minimum value between the n objective functions at m Pareto Front points. After calculating this vector, its maximum value is calculated and the o-point of the Pareto leads to the maximum $norm^k$ to be selected as the optimal point.

5. The Application of Solution Algorithm on Mathematical Model

The proposed model includes binary and continuous variables. The Charging/ discharging mode of EVs needs to be binary variables while the output/input electrical power of prosumers, input electrical power of consumers, traded electrical power with the grid, output/input electrical power of parking lots, electricity price of local market, and electricity price for trading with the upstream grid at every hour are all continues variables. Decision variables are as follows:

$$Y(t) = \begin{bmatrix} P^{i\to j}(t), & P^{j\to i}(t), & P^{i\to k}(t), & P^{i\to e}(m,t), & P^{e\to i}(m,t), & P^{i}_{\text{im}}(t), \\ & P^{k}_{\text{im}}(t), & P^{\text{EV}}_{\text{im}}(e,m,t), & P^{i}_{\text{ex}}(t), & P^{\text{EV}}_{\text{ex}}(e,m,t), & \\ & & C_{\text{new}}(t), & C_{\text{buy}}(t), & C_{\text{sell}}(t) & \end{bmatrix}$$

$$\forall t \in T, \forall e \in N_{\text{EV}}, \forall m \in N_{\text{PL}}, \forall k \in N_{\text{c}}, \forall i,j \in N_{\text{p}} \tag{32}$$

The solver of the proposed model is DICOPT solver, which has a worthy ability to elucidate MINLP problems [45]. The DI-COPT has been founded on the Simplex mathematical technique and it is a tool of the GAMS software. A PC with suitable features including Intel Core i7, 2.5GHz CPU with 12 GB of RAM is employed for performing simulations. Fig. 5 exemplifies the execution flowchart of the proposed model.

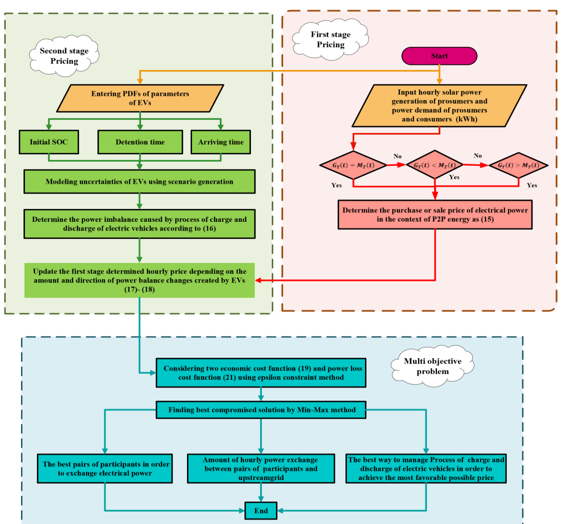

Fig. 5. Flowchart for executing the proposed model.

6. Simulation Results

6.1. Under study system data

In order to investigate the objective functions as well as the advantages of power trade in the context of P2P market, the study was conducted in a 6-bus test system. The 6-bus test system and its information is taken from [45] as Table 1. Three prosumers, a consumer and a EVs parking lot are located in the network buses as shown in Fig. 6. The parking lot has a capacity of 104 EVs during the day, and the cars entry and exit details and other information were stated in Section 3. It is assumed that solar radiation is the same for each prosumer and the difference in solar generation is due to the difference in installed capacities. Information related to charging and discharging EVs is taken from [46].

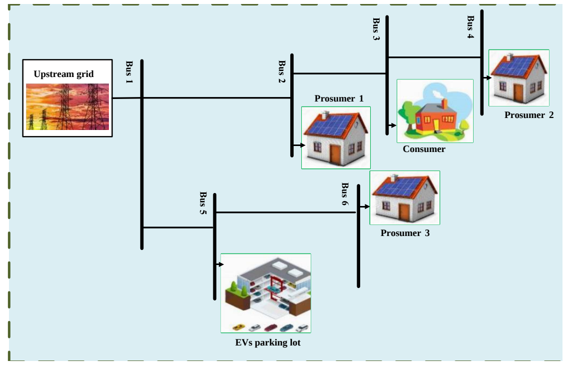

Fig. 6. 6-bus test system.

6.2. Case studies

To evaluate the efficacy of the proposed model, two case studies are considered as follows:

- **Case A:** Only considering economic cost of the market and formulating the proposed model as a single objective problem.
- **Case B:** Simultaneously considering economic cost of the market and electrical power loss and formulating the proposed model as a multi-objective problem.

A) Case A

Fig. 7 shows the cost of power exchange in a P2P market in both the presence and absence of EVs and charge and discharge of EVs. It is clear that the prices set in both cases are lower than the purchase price of electricity from the upstream grid, and on the other hand, the selling price of electrical power in P2P energy market is higher than that of the upstream grid. In this way, the producers will be able to sell their products at a higher price, and on the other hand, buyers will be able to supply their energy at a lower price. This benefits both the buyers and sellers of electrical power, creating a win-win situation. It is noticeable that most of the power needed to charge electric vehicles is supplied during the hours of 7-11 and 15-18, when the cost of electricity is at its lowest and solar energy is available. Consequently, during these hours, the initial demand increases with the updated price, according to Eq. (15), yet it remains lower than the cost of purchasing electricity from the grid. On the other hand, during peak electricity pricing hours from 12-14 and 19-22, EV batteries supply more electrical power, decreasing prices. However, the price remains higher than the selling price back to the grid, especially during the evening hours when the power price is at its peak and solar power production is at zero.

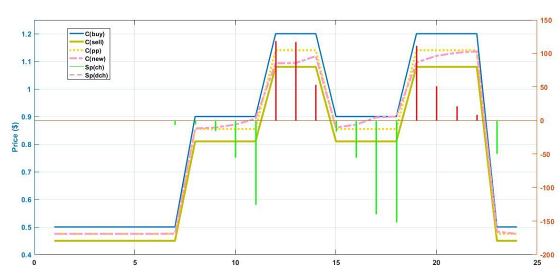

Fig. 7. Purchase and selling price of conventional market and P2P market.

It can be noted that the cost function for this case study is $21.99315, while the figures for the system with the same specifications but without the ability to P2P power trade stood at $23.46825, which shows an increase of 6.7%. Taking the economic cost of the market into account as an objective function reduces the overall cost of participation. However, it is essential to assess all participants' profit or loss status compared to the current power trading system with the upstream network. This is because,

Table 1. Dataset of EVs in P2P energy market.

Participant No.	Type	Bus	Line parameters		Production (kWh)		Consumption (kWh)	
			Connecting buses	Resistance (pu)	Peak	Daily	Peak	Daily
1	Prosumer	2	1-2	0.05	42.77	316.386	52.5	568.17
2	Prosumer	4	1-5	0.1	12.2202	90.3960	2.4	19.88
3	Prosumer	6	2-3	0.05	9.1652	67.797	0.92	9.03
4	Consumer	3	3-4	0.01	-	0.01	0.96	10.4
5	EVs parking lot	5	5-6	0.01	0.94	η_{dch}	0.94	η_{ch}
					2	P_{dch}^{max}	2	P_{ch}^{max}
					2	SOC_{min}	6.68	SOC_{max}

due to the profit of one member who controls a significant part of production or consumption in the group of participants, the total cost decreases while the cost of others increases. In this case, units with increased costs lose motivation to participate in the P2P market. For this purpose, Participation willingness index introduced in [47] is used.

$$\text{PWI} = \frac{P_{\text{lower cost}}}{P} \tag{33}$$

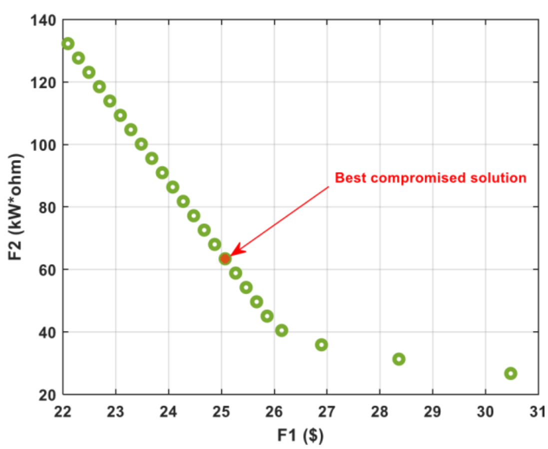

Fig. 8. Pareto solutions and the best compromised solution.

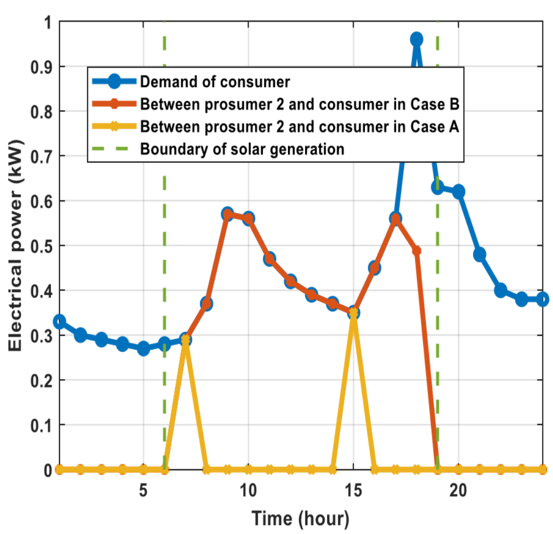

Fig. 9. Electrical power flow between prosumer 2 and consumer.

Where $P_{lower\ cost}$ represents the number of participations whose costs are reduced by taking part in the P2P market, and P is the total number of prosumers and consumers participating

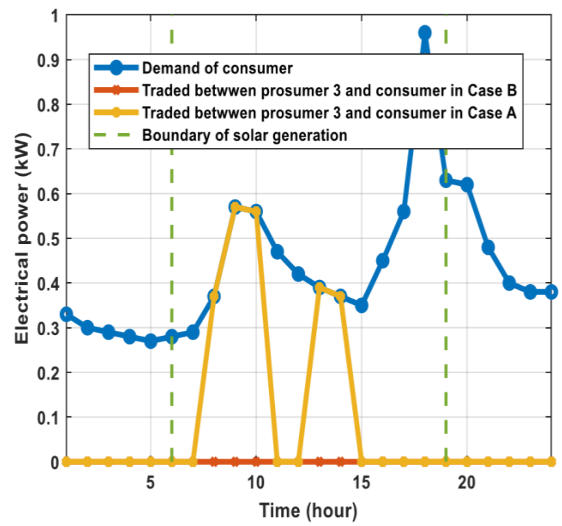

Fig. 10. Electrical power flow between prosumer 3 and consumer.

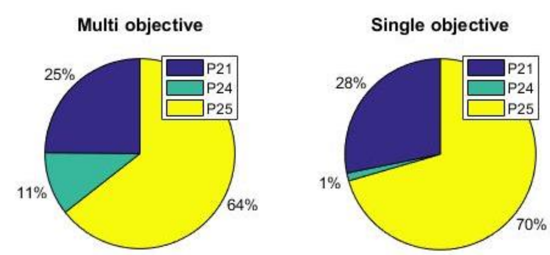

Fig. 11. P2P energy trade among prosumer 2 and other participations.

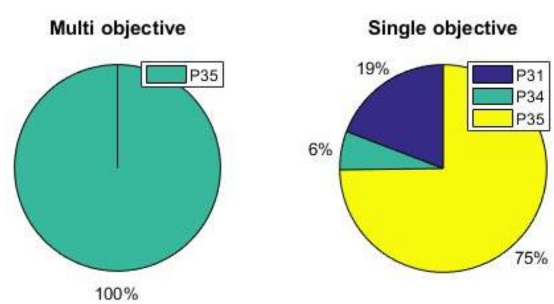

Fig. 12. P2P energy trade among prosumer 3 and other participations.

in the P2P market. By comparing the cost of each participant, the percentage of their cost reduction is 0.48, 5.3, 4.42, 3.96 and 16.697%, respectively. Thus, the value of index PWI is calculated equal to 1. In addition, the power flow of lines 1-2 and 1-5, which are the lines connected to the upstream grid, in P2P energy market shows a decrease of 6.66% in line 1-2 and a decrease of 5.02% in

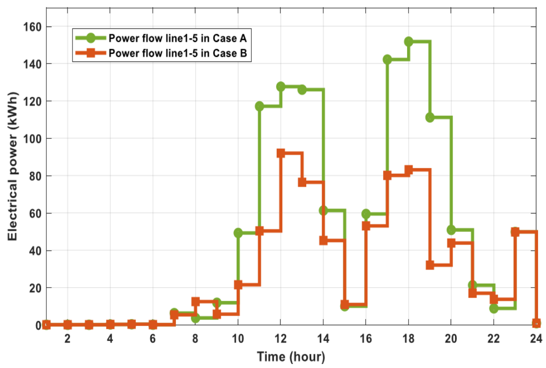

Fig. 13. Power flow line 1-5 as the line with the highest resistance.

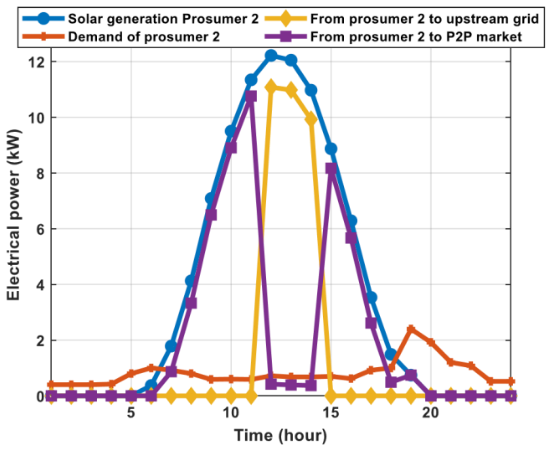

Fig. 14. Electrical power trading of prosumer 2.

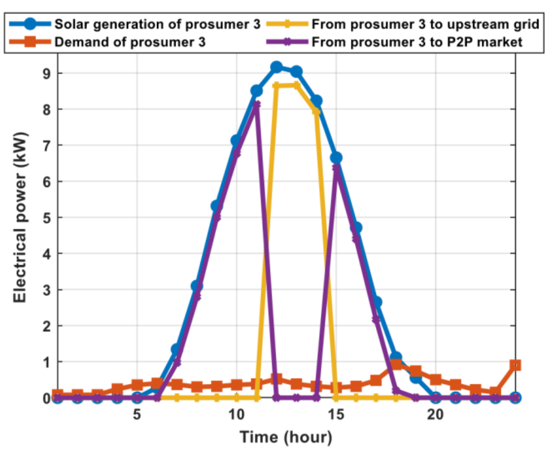

Fig. 15. Electrical power trading of prosumer 3.

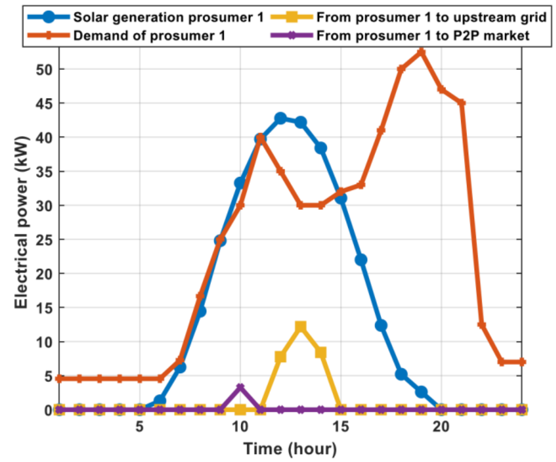

Fig. 16. Electrical power trading of prosumer 1.

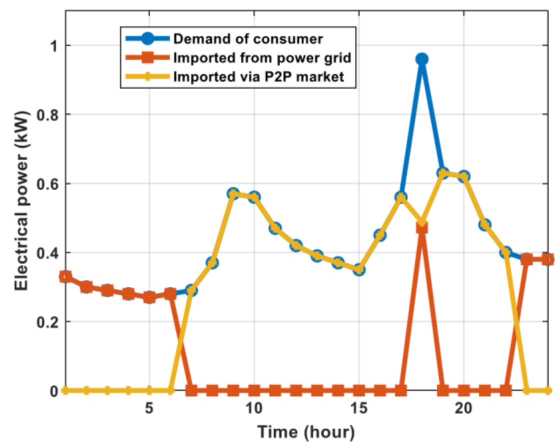

Fig. 17. Electrical power trading of prosumer.

line 1-5 during 24 hours.

B) Case B

In the previous case study, the economic cost was the main factor in decision-making for power exchange between agents. The primary objective of selecting and exchanging power was to minimize the overall costs of the entire system, which includes all agents. However, in power system issues, cost is not the only decision-making factor; technical issues are also involved, and one of the most important factors is minimizing electrical power loss. This study introduces an objective function that includes power transmission losses directly linked to the resistance of the lines between the agents. The objective is to minimize this function to reduce power loss in the decision-making process for power exchange. By considering these two objective functions and using the Epsilon constraint method, Fig. 8 presents the Pareto solutions.

Considering the two objective functions in Case B, the economic cost of the market increases by 13.98% compared to that in Case A. In order to assess how the loss of electrical power affects the distribution and transfer of power between participants, the supply of electrical power to the consumer (Bus 3) through prosumer 1 (Bus 2) and prosumer 3 (Bus 6) is depicted in Figs. 9 and 10. Fig. 9 shows that prosumers 1 and 3 have zero generation capacity during hours 1-6 and 19-24 due to the lack of sunlight. Between these hours, prosumer 2 (Bus 4) contributes more to meeting consumer demand (Bus 3) in Case B compared to Case A. On the opposite side, Fig. 10 shows that in Case B and the interval of 7-18, when there is sunlight, the electrical power transferred from prosumer 2 (Bus 4) to consumer (Bus 3) reaches zero.

Recalling that the electrical power consumption of prosumer 1 is more than its generation capacity, the transferred power from prosumers 2 and 3 to other participants is shown in Figs. 11 and 12, respectively. In Case B, the electrical power transferred from prosumer 2 to the consumer, which has the lowest line resistance among other alternatives, increased; on the other hand, the electrical power exchange with consumer 1 and EVs decreased. Similarly, the electrical power transferred from prosumer 3 to EVs increased, and the transfer power to other participants reached zero. It seems that the high resistance of the line between bus no.1 and bus no.5, which is in the path of power transfer from prosumer 3 to prosumer 1, prosumer 2, and consumer, is effective in this regard.

The line connecting bus no.1 to bus no.5 has the highest resistance among all network lines. Fig. 13 compares the power flow of this line in case B and case A. The result shows that the power flow of this line is lower in case B than in case A.

P2P energy trade allows both consumers and prosumers to take advantage of local renewable energy capacities. P2P electricity trading can also reduce the need for investment in generation capacity and transmission infrastructure to meet peak demand. Fig. 14 illustrates that the major part of Prosumer 2's production is consumed to meet its consumption and local demands via the P2P energy market. Only during hours 12-14 is some of the generation capacity sold to the upstream grid since the solar generation in the prosumers peaks during these hours, and the amount of local generation exceeds the amount of local demand. Prosumer 3 shows a similar pattern, and, as illustrated in Fig. 15, most of the generation is consumed locally by itself or by other prosumers. In Prosumer 1, as shown in Fig. 16, most of the electricity produced is used by the prosumer itself. Excess electricity is only available during hours 10, 12, 13, and 14. During the hours between 12 and 14, the surplus power is sold to the grid because other prosumers do not require it at those times.

On the other hand, as shown in Fig. 17, it can be observed that the electrical power required by consumer during the hours when it is possible to generate electrical power by prosumers and EVs, is locally provided through the P2P market.

By Summarizing Figs. 14-16, just 18% of solar energy produced is sold to the upstream grid during hours 12-14 when solar energy generation exceeds the local demands. This achievement is in line with some of the main benefits of the P2P market, like increasing the use of local products, helping peak shaving, and reducing the upstream grid dependency.

7. Conclusion

Proper pricing is crucial as it can effectively incentivize participation in the P2P energy market. However, electric vehicles (EVs) face pricing challenges due to their owners' unpredictable behavior and the discrepancies with other market participants. This paper proposes an approach for pricing and energy management within a P2P market consisting of various participants, and models a two-stage scheme based on predicted data and the dynamic behavior of EVs across two case studies: Case A and Case B.

In Case A, where the focus was solely on the economic costs of the market as the objective function, the overall cost in the P2P energy market decreased by 6.7% compared to the power exchange in the common market. The success of a P2P market depends on benefiting all participants. Otherwise, participants might lose motivation to engage in such markets. Therefore, the participation willingness index was examined to assess whether all players gain from the market. This metric evaluates the overall value of participating in the P2P energy market, demonstrating that the cost for each participant decreased compared to the traditional method of exchanging power with the upstream grid. Additionally, the congestion on two lines linked with the upstream grid was reduced by 6.66% and 5.02%, respectively, compared to the system without the P2P market. Case B included electrical power loss as part of the decision-making process alongside economic concerns to find an appropriate partner for power exchange. One goal of the P2P market is to increase the amount of on-site power production. Simulation results highlighted the superiority of the P2P market. In this scenario, only 18% of solar power generation was sold to the upstream grid when local demand was less than the total local power supply. Moreover, compared to Case A, the pattern of electrical power exchange among participants was adjusted so that the power transferred through lines with high resistance was reduced.

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