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Peer-to-Peer Energy Trading: A Case Study Considering Network Constraints

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Abstract

The large deployment of *distributed energy resources* (DERs) in low voltage networks has introduced new scenarios and opportunities for all users. We present a case study of peer-to-peer (P2P) energy trading under network constraints in a low-voltage network. Decentralised P2P energy trading is one of the future scenarios in the energy sector due to the transition from centralised structures to more flexible schemes, in which the active participation of end-users is a fundamental component. Nevertheless, many challenges arise with the implementation of a P2P market. Customers who participate in a P2P market have physical limits imposed by the technical constraints of the network, which they are connected. The absent of control and management process in the P2P trading may lead to network issues such as overvoltage. In this paper, we present a case study to illustrate the importance of considering the network constraints in the trading models, and we evaluate a P2P market under network constraints by simulating it on a distribution network with 12 self-interested users. The results show the economic benefits that users can take from the market without compromise the operation of the network within its the technical limits.

1. Introduction

The increasing penetration of *distributed energy resources* (DERs) in low-voltage networks plays an important role in the transition of the energy sector. Traditionally, power systems operate under a centralised architecture, in which large power stations dominate electricity generation. However, the rapid deployment of DERs, such as rooftop solar photovoltaic (PV) systems and battery storage, enhances the active participation of small-scale residential users. Indeed, passive consumers are becoming active users (prosumers), who can actively manage and control their consumption of energy. In this way, there are new opportunities and challenges for power systems.

Given this new picture of the system, one of the developing and promoted scenarios is the settlement of community energy markets in distribution networks. The operation of these new local markets is not based on the traditional centralised scheme. Instead, decentralised *peer-to-peer* (P2P) energy trading models may be applied to facilitate the direct participation of all end-users. Consequently, residential users may buy and sell grid-services considering individual strategies and preferences. For instance, households with an energy surplus in their battery storage or with an excess of solar generation could trade energy with other peers. Furthermore, the direct interaction among users without the intervention of a third-party agent it is possible due to the new advances in information and communication technology such as *blockchain* and other *distributed ledger technologies* (DLTs), which employ smart contracts to guarantee transparent peer-to-peer negotiation, as well as to provide high levels of users' information privacy.

In this context, researchers and commercial entities have assessed the implementation of P2P energy trading platforms. In [1], a summary of the most relevant DLTs usable for P2P energy trading in microgrids is presented. It compares the different features (consensus, speed, etc.) of DLTs, and evaluates the implementation of blockchain-based transactions for energy trading. Similarly, the work in [2] proposes the concept of P2P transactions to incentivise the participation of prosumers and coordinate the operation of DERs in *virtual power plants* (VPP). On the commercial side, companies have developed trial projects of decentralised energy services using DLTs in the last years [3]. Using DLTs, users can monetize their energy stored or energy production to trade in the energy market platforms[1].

[1]Examples of DLTs in decentralised P2P energy trading include PowerLedger (https://powerledger.io), Enosi (https://enosi.io), and LO3 Energy (https://lo3energy.com).

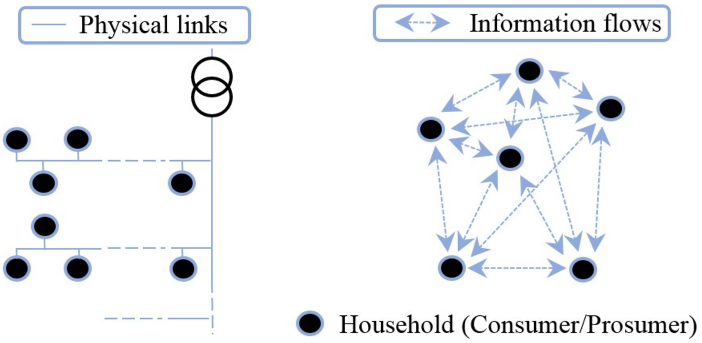


Figure 1: Physical links and information flows between households in a P2P-based energy market

However, trading electricity is different from the exchange of other goods. Despite the importance of *network constraints* for power systems, far too little attention has been paid to them in P2P energy markets projects. Although the agents' information can flow bilateral between users, all agents of the market (consumers and prosumers) are physically connected to a distribution network (as shown in Figure 1). Physical links represent technical limits that must be respected, which presents a major challenge to P2P markets on distribution networks. If technical constraints are not considered, voltage and capacity issues can appear and affect the operation of the system. For example, the high penetration of PV generation leads to overvoltage problems in distribution networks [4]. Moreover, there are externalities associated with power flows, which influence market efficiency. Indeed, real power losses, congestion and voltage limits represent external cost which should be internalised in the trading process. That is, network constraints should be taken into consideration when calculating the financial and power flows.

Given this context, this paper presents a case study of a local energy market and explores the decentralised P2P market approach. In particular, this study shows simulation results of P2P energy trading under network constraints and describes the importance of taking into account the underlying technical constraints in P2P energy markets. The rest of the paper is structured as follows. Section 2 introduces preliminaries concepts of P2P energy markets. In Section 3, the description of the methodology used in this study is presented. Section 4 summarizes the trading mechanism scheme that the case study of this paper builds on. Section 5 presents the case study and simulation results.We conclude this paper in Section 6.

2. Preliminaries

The P2P scheme adopted is illustrated in Figure 1. The information flows between peers in a decentralised manner. As such, every peer can interact through financial flows with the others. It should be noted that the interaction channels (e.g. DLTs) are separate from the physical links. The P2P scheme is composed of H households agents, which are interacting among themselves over a decision horizon $\mathcal{T} := \{\tau, \tau + \Delta\tau, \ldots, \tau + T - \Delta\tau\}$ (typically one day) consisting of T time-slots. Specifically, the network comprises a set of nodes $\mathcal{N} := \{0, 1, 2, \ldots, N\}$. We index the nodes in $\mathcal{N}$ by $i = 0, 1, \ldots, N$.

2.1. Problem Description

We consider a smart grid system for a P2P energy trading in a low-voltage (LV) network under a decentralised scheme. This a realistic assumption since currently there are pilot projects based on this concept, and it does not interfere with existing institutional arrangements (retail)[2].

[2]Examples of pilot projects include Decentralised Energy Exchange (deX) Project, available at https://arena.gov.au/projects/decentralised-energy-exchange-dex/; and White Gum Valley energy sharing trial, available at https://westernpower.com.au/energy-solutions/projects-and-trials/white-gum-valley-energy-sharing-trial/.

Traditionally, centralised schemes have been considered for local markets or energy trading on low-voltage networks [5–8]. In this way, a central entity (e.g. *distribution system operator* (DSO), aggregator, etc.) receives information from all users to optimise the dispatch of DERs. Thus, households are willing to change their consumption patterns and to share their energy in order to optimise the social welfare. To solve the optimisation problem, the central entity might require the control of assets and resources of the users. Unlike traditional and centralised schemes, we consider that in a P2P market users are self-interested and have complete control of their energy used.

Let $\mathcal{H} = \{1, 2, \dots, H\}$ be the set of all *households* in the local grid, which is composed of the union of two sets: consumers $\mathcal{P}$ and prosumers C (i.e. $\mathcal{H} = \mathcal{P} \cup C$). We assume that all households are capable of predicting their levels of demand and generation for electrical energy for a particular time slot t. Specifically, we assume consumers bid in the market based on their demand profiles. As such, a demand profile is not divided into tasks or device utilization patterns, so that is the demand levels represent the total energy consumption over time. In particular, prosumers have PV systems, battery storage and *home energy management systems* (HEMS).

2.2. Household Agent Model

A household $h \in \mathcal{H}$ uses d_t^h units of electrical energy in slot t. Likewise, a household $h \in \mathcal{H}$ has w_t^h units of energy surplus in slot t. The total quantity of electrical energy purchased in a slot t is given by x_t^+, and its price is denoted by s_t^+. The total energy consumption x_t^+ includes the amount of electrical energy purchased from the grid and from the local market. Similarly, the quantity of electrical energy sold in a slot t is given by x_t^-, and its price is denoted by s_t^-. Each prosumer in $\mathcal{P}$ uses its HEMS to optimise its self-consumption, considering their demand and energy surplus by solving the following mixed-integer linear programming (MILP) problem [9]:

$$
\begin{aligned}
\underset{x \in \mathcal{X}}{\text{minimise}} \quad & \sum_{t \in \mathcal{T}} (s_t^+ x_t^+ - s_t^- x_t^-) \\
\text{s.t.} \quad & \text{device operation constraints,} \\
& \text{energy balance constraints, } \forall t \in \mathcal{T},
\end{aligned}
\tag{1}
$$

where $\mathcal{X}$ is the set of decision variables $\left\{x_t^+, x_t^-\right\}$. State variables in the model are s_k^+ and s_t^-. The former is associated with the price of energy in time slot t, and the latter with the incentive received for the contribution to the grid. In other words, s_t^+ and s_t^- are related to import tariffs (e.g. flat, time-of-use) or export tariffs (e.g. feed-in-tariff). The outcome of this process provides *net load profiles* for users with HEMS. After this, prosumers sell their energy surplus on the local P2P market to consumers who participate in the P2P energy trading process.

2.3. Network Model

We consider a radial distribution network $\mathcal{G}(\mathcal{N}, \mathcal{E})$, consisting of a set of nodes $\mathcal{N}$ and a set of distribution lines (edges) $\mathcal{E}$ connecting these nodes. Using the notation of the branch flow model [5], we index the nodes by $i = 0, 1, \dots, N$, where the root of our radial network (Node 0) represents the substation bus, and it is considered as the slack bus. The other nodes in $\mathcal{N}$ represent branch nodes.

Denote a line in $\mathcal{E}$ by the pair (i, j) of nodes it connects, where j is closer to the feeder 0. We call j the parent of i, denote by $\varsigma(i)$, and call i the child of j. Denote the child set of j as $\delta(j) := \{i : (i, j) \in \mathcal{E}\}$. Thus, a link (i, j) can be denoted as $(i, \varsigma(i))$.

For each line $(i, \varsigma(i)) \in \mathcal{E}$, let I_{ij} be the complex current flowing from nodes i to $\varsigma(i)$, let $Z_{ij} = R_{ij} + iX_{ij}$ be the impedance of the edge, and $S_{ij} = P_{ij} + iQ_{ij}$ be the complex power flowing from nodes i to $\varsigma(i)$. On each node $i \in \mathcal{N}$, let V_i be the complex voltage, and $S_i = P_i + iQ_i$ be the net complex power injection. Define $v_i := |V_i|^2$. We assume the complex voltage V_0 at the feeder root node is given and fixed. Let $\mathbf{V} = \left[v^1, \dots, v^N\right]$ be the concatenation of voltage vectors in all nodes in the network.

3. Methodology

In this section, we describe the methodology to implement P2P energy trading under network constraints with self-interested agents. Our methodology is based on a sensitivity analysis to evaluate the impact of energy exchanges in the

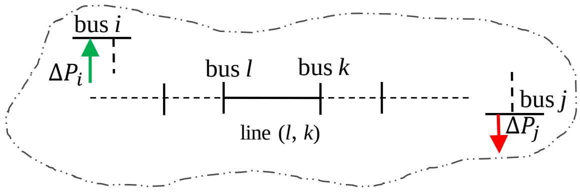


Figure 2: Exchange between two nodes

network. Indeed. this approach is a viable alternative to the *distribution optimal power flow* (DOPF) approach which is traditionally considered for addressing the problem of DER dispatch subject to network constraints. Since the main focus of this paper is present a particular case study rather than explain the methodology, we have only included its main components in this paper. Interested readers can find further information in our previous work presented in [10].

We consider P2P trading a similar situation to the bilateral trading in a power system. Figure 2 illustrates the situation where a user located at Bus j has purchased energy from the prosumer located at Bus i. The exchange process (injection and absorption of power) implies physical changes in the power flows through the lines in the network. Hence, our aim is to estimate the impact of the injection and absorption of that amount of power on the grid.

The methodology implemented in this work embeds analytically derived sensitivity coefficients to guarantee bilateral transactions as well as internalizing the external costs associated with the power flows. Specifically, we incorporate three factors in the market mechanism:

- *Voltage sensitivity coefficients* (VSCs): Through VSCs, we can estimate the variation in the voltages as a function of the power injections in the network;
- *Power transfer distribution factors* (PTDFs): These reflect the changes in active power line flows due to an exchange of active power between two nodes;
- *Loss sensitivity factors* (LSFs): These reflect the portion of system losses due to power injections in the network.

3.1. Voltage Sensitivity Coefficients Formulation

The traditional approach to obtain the VSCs is to use the Jacobian matrix after solving the Newton-Raphson power flow. Calculating the inverse of the Jacobian at a given operating point gives an idea of the voltage changes (ΔV_i) due to changes in power injections (ΔP_i, ΔQ_i) as follows:

$$\Delta V_i = \left(\frac{\partial V_i}{\partial P_i}\right)\Delta P_i + \left(\frac{\partial V_i}{\partial Q_i}\right)\Delta Q_i. \tag{2}$$

where P and Q are the vectors of real and reactive nodal injections, and V is the vector of voltage magnitudes. However, running a full load power flow every time the state of the network changes may not be feasible or tractable. Therefore, in our study, we use the analytical derivation of VSCs proposed in [11]. In doing so, we use the so-called compound admittance matrix. The relation of the power injection and bus voltages is given by[3]:

$$S_i^* = V_i^* \sum_{j \in \mathcal{N}} Y_{ij} V_j \; i \in \mathcal{N}. \tag{3}$$

To obtain VSCs, the partial derivatives of the voltages with respect to the active power P_k of a Bus $k \in \mathcal{N}/0$ are computed. The partial derivatives of the voltage magnitude are expressed as:

[3] For a scalar, vector, or matrix A, A' denotes its transpose and A^* its complex conjugate (e.g. V^*).

$$\Delta |V_i| = \frac{\Delta P_k}{|V_i|} \mathrm{Re}\left(V_i^* \frac{\partial V_i}{\partial P_k} \right). \tag{4}$$

Voltage changes can therefore be calculated based on the power changes in specific buses of the network.

3.2. Power Transfer Distribution Factors

Since the exchange of energy involves power flow through physical routes, PTDFs can give an idea of the sensitivity of the active power flow with respect to various variables. Specifically, the injection shift factor (ISF) quantifies the redistribution of power through each branch following a change in generation or load on a particular bus. It reflects the sensitivity of a flow through a branch with respect to changes in generation or load. Once we obtain the ISFs, we can calculate the PTDFs, which capture the variation in the power flows with respect to the injection in Bus i and a withdrawal of the same amount at Bus j [12, 13].

In order to calculate the ISFs, we use the reduced nodal susceptance matrix. The ISF of a branch $(k, l) \in \mathcal{E}$ (assume positive real power flow from Bus k to l measured at Bus k) with respect to Bus $i \in \mathcal{N}$, which we denote by Ψ^i_{kl}, is the linear approximation of the sensitivity of the active power flow in branch (k, l) with respect to the active power injection at Bus i with the location of the slack bus specified and all other quantities constant. Suppose P_i varies by a small amount, ΔP_i, and let ΔP^i_{kl} be the change in the active power flow in branch (k, l) (measured at Bus k) resulting from ΔP_i. Then, it follows that:

$$\Psi^i_{kl} := \frac{\partial P_{kl}}{\partial P_i} \approx \frac{\Delta P^i_{kl}}{\Delta P_i}. \tag{5}$$

To calculate these values, we use an approximation of the network equations. Let $\tilde{B} = \mathrm{diag}\{b_{kl}\}$, which is a diagonal matrix whose entries are b_{kl}, the susceptance of branch (k, l). Also, denote the branch-to-node incidence matrix by $A = [..., a_{kl}, ...]^{'}$, where $a_{kl} \in \mathbb{R}^n$ is a vector in which the k^{th} entry is 1 and the l^{th} entry is -1. Then, by using the DC approximations, we arrive at the expression:

$$\Delta P_{kl} \approx \tilde{B}_{kl} A B^{-1} \Delta P, \tag{6}$$

where $\tilde{B}_{kl}$ is the row in $\tilde{B}$ corresponding to branch (k, l), and $B = A^{'} \tilde{B} A$. Denote $\Psi_{kl} = \left[\Psi^1_{kl}, ..., \Psi^i_{kl}, ..., \Psi^N_{kl}\right]^{'}$, then the model-based linear sensitivity factors for branch (k, l) with respect to active power injections at all buses are given by:

$$\Psi_{kl} = \tilde{B}_{kl} A B^{-1}. \tag{7}$$

Once the ISFs are obtained, we compute PTDFs. A PTDF, Φ^{ij}_{kl}, provides the sensitivity of the active power flow in branch (k, l) with respect to an active power transfer of a given amount of power, ΔP_{ij}, from Bus i to j. The PTDF for a branch (k, l) with respect to an injection at a Bus i that is withdrawn at a Bus j is calculated directly from the ISFs as follows:

$$\Phi^{ij}_{kl} = \Psi^i_{kl} - \Psi^j_{kl}, \tag{8}$$

where Ψ^i_{kl} and Ψ^j_{kl} are the line flow sensitivities in branch (k, l) with respect to injections at Buses i and j, respectively.

3.3. Loss Sensitivity Factors

We derived the LSFs using a similar approach to the use above. The term for the LSF is given by [14]:

$$\frac{\partial P_{\text{loss}}}{\partial P_k} = 2\mathrm{Re}\left[\mathbf{V}^{*T} G \frac{\partial V}{\partial P_k} \right], \tag{9}$$

where the partial derivatives are obtained from VSCs calculation, and G is the conductance matrix. In order to assign losses associated to a changes in the power, we consider the approach to attribute losses to bilateral exchanges. For example, in the bilateral exchange in Figure 2, there is a bilateral exchange from Bus i to j. The terms $\frac{\partial P_{\text{loss}}}{\partial P_i}$ and $\frac{\partial P_{\text{loss}}}{\partial P_j}$ are the loss sensitivities with respect to power injection at bus i and to power out at Bus j respectively. Then the *bilateral exchange coefficient* (BEC) is defined as follows:

$$\mathrm{BEC}^{ij} = \frac{\partial P_{\mathrm{loss}}}{\partial P_i} - \frac{\partial P_{\mathrm{loss}}}{\partial P_j}. \tag{10}$$

The bilateral exchange coefficient (BEC) can be used to associate the losses due to a bilateral transaction [15].

4. Trading Market Mechanism

The market mechanism for a P2P energy trading developed in this paper builds on our previous work [10, 16]. There are three components to our market mechanism: (i) a *continuous double auction* (CDA), (ii) the agents' bidding strategies, and (iii) the network permission structure, as described below.

4.1. Continuous Double Auction

A CDA matches buyers and sellers in order to allocate a commodity. It is widely used, including in major stock markets like the NYSE and NASDAQ. A CDA is a simple market format that matches parties interested in trading, rather than holding any of the traded commodity itself. This makes it very well suited for P2P exchanges. Bids into a CDA indicate the prices that participants are willing to accept a trade, and reflect their desire to improve their welfare. As such, the CDA tends towards a highly efficient allocation of commodities [17]. In more detail, a CDA comprises:

- A set of *buyers* $\mathcal{B}$, where each $b \in \mathcal{B}$ defines its trading price π_b and the amount of energy to purchase σ_b.
- A set of *sellers* $\mathcal{S}$, where each $s \in \mathcal{S}$ defines its trading price π_s and the amount of energy to sell σ_s.
- An *order book*, with bids $o_b(b, \pi_b, \sigma_b, t)$, made by buyers $\mathcal{B}$, and asks $o_s(s, \pi_s, \sigma_s, t)$, made by sellers $\mathcal{S}$.

Figure 3 illustrates a dynamic example of the state of the order book with asks and bids. Readers who are using the electronic copy of the paper can play the example. At $t = 1$ there are four orders and four asks. The gap between the best bid (35.21) and the best ask (35.31) is called spread. At $t = 2$, a new ask arrives to the order book. This new ask matches with the best bid. Therefore, the orders are match and the transaction is agreed. At $t = 3$, the amount purchased is discounted from the total amount required for that bid. This process is repeated continuously with the arrival of new orders.

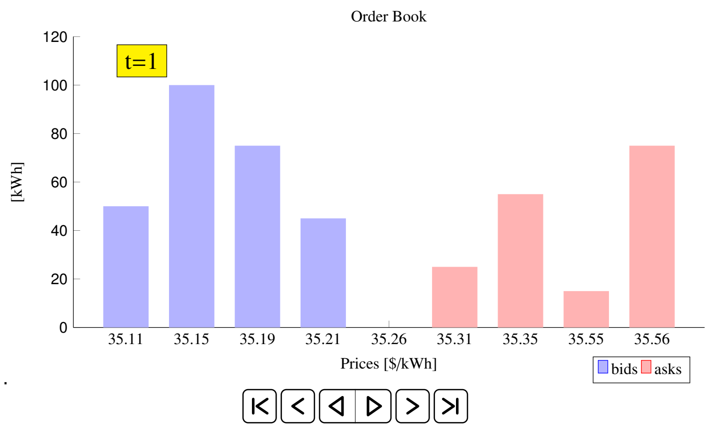


Figure 3: Example of the arrival of a new ask and matching process in the order book.

Specifically, pseudo-code of the matching process in a CDA is given in Algorithm 1. A CDA is run for each time slot separately. Any intertemporal couplings that arise on a customer's side from using batteries or loads with long minimum operating times are not passed up to the market clearing entity. Once the market is open, arriving orders are queued in the *order book* for trades during a fixed interval t_d (lines 2-8), which is limited by the start time t_d^{st} and the trading end time t_d^{end} (i.e. $t_d^{\mathrm{end}} = t_d^{st} + t_d$). During the trading period, orders are submitted for buying or selling

Algorithm 1 Matching process in a CDA with ZIP traders

1: **while** market is open **do**
2: randomly select a new ZIP trader
3: **if** buyer **then**
4: new $o_b(b, \pi_b, \sigma_b, t)$
5: **else**
6: new $o_s(s, \pi_s, \sigma s, t)$
7: **end if**
8: allocate a new order in the *order book*
▷ Evaluate matching process with best bid and ask
9: **if** $\pi^*_b \geq \pi^*_s$ **then**
10: clear orders o^*_b and o^*_s at a price π_t and amount σ_t
11: **end if**
▷ Update values of profit margins
▷ Buyers
12: **if** the last order was matched at price π_t **then**
13: all buyers for which $\pi_b \geq \pi_t$, raise their margins;
14: **if** the last trader was a seller **then**
15: any active buyer for which $\pi_b \leq \pi_t$,
16: lower its margin;
17: **end if**
18: **else**
19: **if** the last trader was a buyer **then**
20: any active buyer for which $\pi_b \leq \pi_t$,
21: lower its margin;
22: **end if**
23: **end if**
▷ Sellers
24: **if** the last order was matched at price π_t **then**
25: all sellers for which $\pi_s \leq \pi_t$, raise their margins;
26: **if** the last trader was a buyer **then**
27: any active seller for which $\pi_s \geq \pi_t$,
28: lower its margin;
29: **end if**
30: **else**
31: **if** the last trader was a seller **then**
32: any active seller for which $\pi_s \geq \pi_t$,
33: lower its margin;
34: **end if**
35: **end if**
36: **end while**

units of electrical energy in time-slot t. At the end of the trading period, the market closes, thereby no more offers are received." We assume the orders arrive according to a Poisson process with mean arrival rate λ. The current best bid (ask) is the earliest bid (ask) with the highest (lowest) price. A bid and an ask are matched when the price of a new bid (ask) is higher than or equal to the price of the best ask $o^*_s(s^*, \pi^*_s, \sigma^*_s, t^*)$ (the best bid $o^*_b(b^*, \pi^*_b, \sigma^*_b, t^*)$) in the order book (line 9). However, if a new bid (ask) is not matched, then it is added to the order book, recording its arrival time and price. Note that after matching, an order may be only partially covered. If this is the case, it will remain at the top of the order book waiting for a new order. This process is executed continually during the trading period as new asks and bids arrive.

4.2. Bidding Strategies

Conventionally, market participants (buyers and sellers) define their asks and bids based on their preferences and the associated costs. The HEMS act as agents for the customers, and are continually responding to new stochastic information. As such, they appear very unpredictable from the outside. Moreover, because the market is thin, this can produce large swings in available energy and prices. In this context, constructing an optimal bidding strategy is futile, but simple bidding heuristics are still valuable. In particular, in our study the agents are *zero intelligence plus* (ZIP) traders [16, 18]. ZIP traders use an adaptive mechanism which can give performance very similar to that of human traders in stock markets. Agents have a profit margin which determines the difference between their limit prices and

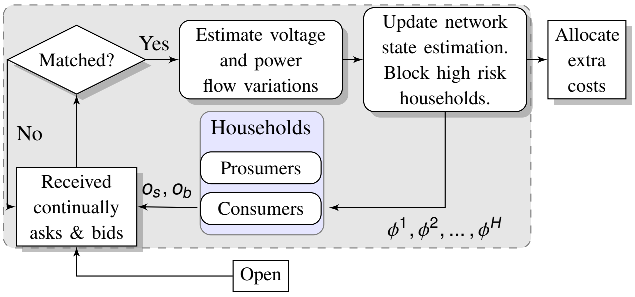


Figure 4: Schematic of the P2P trading under network constraints.

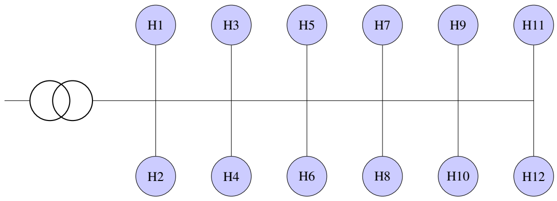


Figure 5: Test case network

their asks or bids. Under this strategy, traders adapt and update their margins based on the matching of previous orders (lines 12-23 for buyers and lines 24-35 for sellers). Indeed, the participation of ZIP traders in a CDA allows us to assess the economic benefits of the market separate from that of a particular bidding strategy. Specifically, ZIP traders are subject to a budget constraint ($L_{\max}$ and $L_{\min}$ are the maximum and minimum price respectively) which forbids the trader to buy or sell at a loss. Then, buyers and sellers select their bids or asks uniformly at random between these limits.

4.3. Network Permission Structure

The outline of the mechanism is presented in Figure 4. A third party entity (e.g. DSO) validates the transactions using a network permission structure based on the network's features and sensitivity coefficients. Every time one ask and one bid are matched, voltage variation and line congestion are evaluated. All households receive a signal (ϕ^h) which informs them if they can still participate in the market without causing problems in the network. As such, power curtailment is implicitly incorporated in the trading as users who do not match their orders, cannot export electricity to the network.

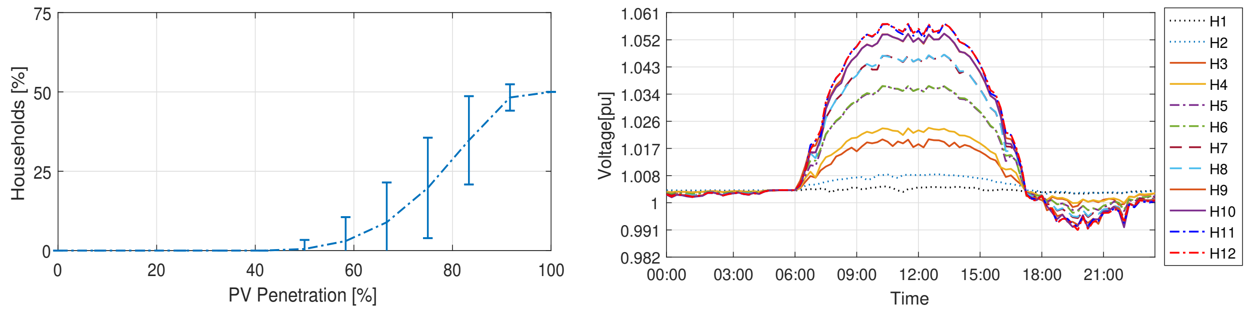
5. System Model - Case Study and Results

Our study is focused on a LV network with a high DERs penetration. The group of households is constituted by consumers and prosumers defined in Section 2. There are three components to our model: the local power *network*, the *customers* and the *market* for trading energy, as defined above.

5.1. Implementation: Test Network

We consider a smart grid system for energy trading at a local level. The methodology is applied to the network shown in Figure 5, which is a modified version from the network presented in [19]. It is comprising one feeder and 12 single phase households. The simulations are carried out with $T = 24$ hours, $\Delta\tau = 15$ minutes and up to 12 agents.

The simulation results are divided in two parts. First, we simulate the case of high PV penetration in the network to illustrate the importance of incorporate the network model into P2P energy trading models. Second, we evaluate a P2P energy trading scenario using the methodology explained above.



(a) **(b)**

Figure 6: (a) Percentage of households with voltage problems. (b) Voltage profiles of all users in the network throughout the day.

5.1.1. High PV penetration

Many studies and projects in local or community energy trading have avoided the conversation about the network constraints [3, 16]. Nonetheless, residential users are physically connected to LV distribution systems. Hence, it is necessary to evaluate the impact of the active participation of end-users in the network.

Specifically, let us assume that users in the network have PV systems with installed capacity of 7.0 kWp, and export their excess of electricity to the network without considering technical restrictions such us voltage limits. This could be the case of P2P trading without considering network constraints, and the energy traded is supplied by non-dispatchable generation such as PV systems. Figure 6a shows the percentage of households with overvoltage issues at different levels of PV penetration in the network. For this feeder, voltage problems start at a penetration of 50%. In the worst case, half of the customers may have voltage issues when the PV generation reaches it maximum values in all users. Figure 6b illustrates the voltage profiles throughout the day. In particular, the highest levels of voltage happens around midday when the peak of PV generation occurs. This situation could be worst in feeders with greater PV systems, as well as in systems with higher resistance values of conductors in the network [4, 10]. Hence, the active participation of users without the consideration of the network constraints may be led to network issues.

5.1.2. P2P energy trading

Our study considers 2 consumers and 10 prosumers which have PV system, battery and HEMS. Each household has a stochastic load consumption profile, with load profiles using the tool presented in [20]. Similarly, PV profiles are generated considering sun irradiance data, capturing the sunniest days in order to evaluate the method on the most challenging yet realistic scenarios. We assume that all prosumers have a PV system with installed capacity of 7.0 kWp and a battery of 10 kWh.

We define the price constraints $L_{\max}$ and $L_{\min}$ based on the values of import and export electricity tariffs through the day. $L_{\max}$ depends on the time-of-use tariff (ToU) and $L_{\min}$ on the feed-in-tariff (FiT). These definitions are consistent in the sense that no buyer would pay more than the tariff of a retailer (ToU), and no seller would sell their units cheaper than the export tariff (FiT). In summary, the process of our model is:

1. The HEMS minimises a prosumer's costs by solving problem (1), using a mixed-integer linear program.
2. Prosumers state the time-slots when they have extra energy to trade.
3. The bidding strategies for the market participants are initialised, using their load and generation profiles and tariffs, and the market is opened.
4. Every time an ask and a bid are matched, the network conditions are evaluated. The market remains open as long as the network constraints are respected.
5. Agents accept the number of units to be exchanged and their prices.

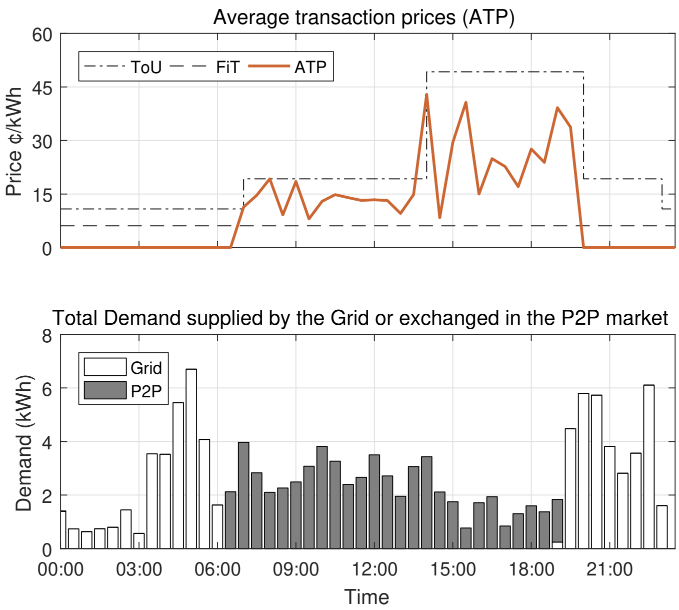


Figure 7: (top) Average transaction prices, and (bottom) demand and generation levels from the P2P market.

To further show the outcomes of the P2P trading, users actively participate in a CDA. The matching process between asks and bids in the P2P market promotes the local balance of demand and generation of end-users. In this case, a market rule allows the prosumers to supply their energy surplus until the total demand is covered.

Figure 7 shows the average transaction price (ATP) and the amount of energy purchased from the grid or in the P2P market during one day. The transaction prices remain in the range of ToU and FiT rates because of the ZIP limits $L_{\max}$ and $L_{\min}$. Hence, both prosumers and consumers obtain monetary benefits by participating in P2P trading. Most of the energy is traded during 7:00 and 14:00. During that time, there is an excess of energy due to PV generation. There are levels of energy traded after 18:00 due to the prosumers who kept some energy in the battery. Once the peak time ends (20:00), the ZIP maximum limit ($L_{\max}$) is low. As a consequence, no prosumers submit any new asks to trade in the market. Moreover, in this case, when the total energy surplus from prosumers is greater than the total demand of consumers (e.g. around midday), some prosumers (those who do not match their asks with consumers' bids) have to curtail their power generation.

Figure 8 presents the voltages profiles at all users' nodes during one day of simulation. There are no cases of over-voltage. The voltages varied between 0.985 pu and 1.015 pu. The most sensible nodes are those that are farther along the feeder, which present the major voltage variations. Due to the network permission structure is incorporated, the network constraints were not breached. Hence, all exchanges respect the network constraints, and the external costs were attributed among the households involved in each transaction.

Finally, we can compare the expenses of users when they have to paid the tariff prices with the case where they trade in the P2P market. That is, without the P2P trading, end-users buy energy at the ToU rate and sell it at the FiT value. In contrast, with P2P, the transaction prices are discovered through the market mechanism. As such, the consumers' expenses in one day decrease, achieving a market benefit of \$1.75. Prosumers have an extra income of \$1.99 in comparison with the revenues that they might receive if they were paid at the FiT value. Hence, the total market benefit is \$3.74.

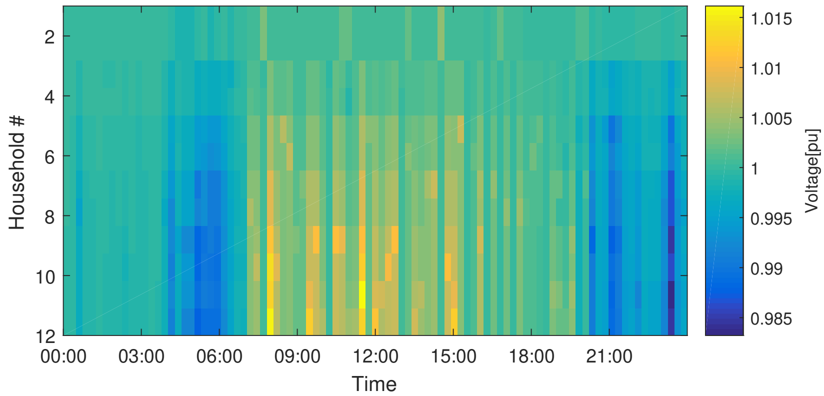


Figure 8: Voltage levels at users'nodes.

6. Conclusions

This paper has presented a case study of P2P energy trading considering network constraints. The impact of the energy transactions in the network has been evaluated through a sensitivity analysis using the VSCs, FTPD, and LPs factors. The simulation results illustrate the importance to consider network constraints in energy trading models. In particular the simulation results show how the market under this approach can be one viable options for the upcoming scenarios of P2P trading. As such, users received economical benefits due to the reduction in the energy cost, the technical constraints are respected and the local balance between generation and demand is achieved.

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