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Blockchain-based Fully Peer-to-Peer Energy Trading Strategies for Residential Energy Systems

Tarek AlSkaif, *Member, IEEE* Jose L. Crespo-Vazquez, Milos Sekuloski, Gijs van Leeuwen, and João P. S. Catalão *Senior Member, IEEE*

***Abstract*—This paper proposes two novel strategies for determining the bilateral trading preferences of households participating in a fully Peer-to-Peer (P2P) local energy market. The first strategy is based on the matching between surplus power supply and demand of participants, while the second is based on the distance between them in the network. The impact of the bilateral trading preferences on the price and amount of energy traded is assessed for the two strategies. A decentralized fully P2P energy trading market is developed to generate the results in a day-ahead setting. Besides, a permissioned blockchain-smart contract platform is used for the implementation of the decentralized P2P trading market on a digital platform. Real data from a residential neighborhood, with different varieties of distributed energy resources, located in the city of Amsterdam, The Netherlands, is used for the simulations. Results show that in the two strategies, the energy procurement cost and grid interaction of all participants in P2P trading are reduced compared to a baseline scenario. The total amount of P2P energy traded is found to be higher when the trading preferences are based on distance, which could also be considered as a proxy to enhance energy efficiency in the network by encouraging P2P trading among nearby households. However, the P2P trading prices in this strategy are found to be lower than the first one. Further, a comparison is made between two scenarios: with and without electric heating in households. Although the electrification of heating reduces the total amount of P2P energy trading, its impact on the trading prices is found to be limited.**

***Index Terms*—Distributed energy resources; peer-to-peer energy trading; bilateral trading preferences; local energy markets; blockchain**

I. Introduction

The increasing penetration rates of residential rooftop Photovoltaics (PV) panels as well as other Distributed Energy Resources (DER), such as Electric Vehicles (EV), Battery Energy Storage Systems (BESS) and Heat Pumps (HP), has led to an increase in the number of prosumers, enhanced end-users flexibility and opened up new market opportunities for different stakeholders in the energy system [1]. Different self-consumption policies have been adopted in different countries to enable prosumers selling their energy back to the grid, such as Feed-in-Tariffs (FiT) and net-metering. Such policies have had a positive effect on the adoption of DER in residential energy systems. However, at high penetration rates of DER, it would be favorable technically and economically to maximize the utilization of locally produced energy at the demand side [2], [3].

T. AlSkaif is with the Information Technology Group, Wageningen University and Research, The Netherlands (e-mail: tarek.alskaif@wur.nl). J. L. Crespo-Vazquez is with the Copernicus Institute, Utrecht University, The Netherlands (e-mail: joseluiscrespo@hotmail.com). M. Sekuloski is with Bloxico Software Solutions, Serbia (e-mail: milos.sekuloski@bloxico.com) G. van Leeuwen is with University of Twente, The Netherlands (e-mail: g.e.vanleeuwen@student.utwente.nl). J. P. S. Catalão is with Faculty of Engineering of University of Porto and INESC TEC, Portugal (e-mail: catalao@fe.up.pt).

Send correspondence to T. AlSkaif, E-mail: tarek.alskaif@wur.nl.

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Novel market designs, enabled by recent advancements in Information and Communication Technologies (ICT), are emerging as alternative solutions for coordinating prosumers locally, where prosumers can directly trade energy with each other. These new market designs are called Local Energy Markets (LEM), which are typically end-users centered to enhance individuals' choices [4]. Different categories of LEM structures can be distinguished in literature depending on their degree of decentralization. The two main categories are fully Peer-to-Peer (P2P) and community-based markets [4], [5].

In P2P markets, energy can be traded between end-users directly following a predefined matching strategy. Using some ICT-based platforms, such as blockchain with smart contracts, there is technically no need for a centralized entity to manage the trades [6]. One iconic study from the Brooklyn microgrid implemented a P2P trading scheme, where supply and demand bids are matched using a conventional merit-order dispatch and the trading price is cleared for all participants [7]. While this mechanism simplifies the management of trades in a community, it is arguable that it does not exploit the full potential of P2P markets. In fully P2P markets, trades are conducted bilaterally and maximum financial independence, privacy and freedom of choice should be guaranteed. Fully P2P market designs have been explored recently in various studies [8], [9]. For instance, in [9], a unified P2P market model has been formulated. This scheme may be operated with both bilateral trades and a centralized pool market. A P2P market that incorporates joint energy trading and uncertainty trading is proposed in [10]. In [11], a bilateral trading mechanism is used for product differentiation between participants, where a multi-bilateral economic dispatch formulation is introduced and solved using consensus optimization.

While interesting, these earlier studies do not provide concrete strategies for building the bilateral trading preferences or an assessment of their impact on the price and amount of energy traded locally. The bilateral trading preferences of participants could reflect, for instance, prosumers' preferred returns for exchanging their surplus locally generated energy or consumers preferred source of energy. Therefore, the strategy according to which bilateral trading preferences are designed is crucial for actual implementation of P2P markets in residential energy systems. There, the choice of preferred trading partners is typically dependant on residents motives (e.g., environmental or economic), personal relationships or their identity in a community [12]. This could potentially enable participants with different motives to have control over their energy exchange.

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This paper presents a decentralized fully P2P energy trading market and proposes two different strategies for determining the bilateral trading preferences of participants in the market, as a new contribution to earlier studies. The first strategy is based on the matching between surplus supply and demand of participants, while the second is based on the distance between them in the network. The first strategy could be considered as an economic and market-based strategy, whereas the distance-based strategy could also be considered as a proxy to enhance energy efficiency in the network when performing P2P energy trading. Further, the impact of the two strategies on the price and amount of energy traded locally is assessed and compared. Since advanced ICT are needed for the actual realization of fully P2P markets, we demonstrate how the decentralized P2P energy trading market could be implemented on blockchain as a digital platform. Indeed, the use of blockchain with smart contracts can enable the implementation of decentralized energy trading mechanisms due to their inherent technical characteristics, such as traceablility, immutability, automation and security.

The applications of blockchain-smart contracts have recently covered different domains, such as digital media [13], agriculture supply chain [14], and IoT devices [15]. Besides, their applications to the area of smart grids have recently received an increased attention, such as for secure and privacy-preserving energy trading [16]–[18], microgrids management [19], crowd-sourced energy system with optimal power flow in distribution network [20], voltage regulation in active distribution networks [21], privacy-preserving payments of EVs in Vehicle-to-Grid (V2G) networks [22], balancing electricity transmission networks using EVs [23]. The applications and challenges of using blockchain as a secure, distributed cyber infrastructure for the future grid are discussed in [24]. A practical implementation of blockchain in microgrids with local energy trading is presented in [6], [7]. However, the formulated LEM does not consider fully P2P energy trading with bilateral preferences. By using the proposed blockchain-based fully P2P energy trading market with different bilateral trading strategies, maximum freedom and autonomy for end-users can be guaranteed, since it enables them to incorporate their preferences in selecting their trading partners and run the network without the need for a centralized energy management entity. The contributions of this work can be summarized as:

- A fully P2P energy trading optimization model for residential energy systems with different varieties of DER is presented. The model is decomposed and solved in a decentralized manner.
- Two novel bilateral trading strategies are proposed for calculating the trading preferences (i.e., coefficients). The first strategy is based on the matching between demand and surplus power supply of participants. The second strategy is aimed to enhance energy efficiency by encouraging P2P trading among nearby participants.
- A comprehensive implementation of the decentralized fully P2P energy trading model on a permissioned blockchain-smart contract platform is presented.
- An electric heating model is incorporated in the optimization model to show the impact of heating electrification on the results.

The rest of the paper is structured as follows. The system design, assumptions and problem setup are presented in Section II. Section III presents the decentralized formulation of the fully P2P energy market. The two strategies for determining the bilateral trading preferences are detailed in Section IV. In Section V, the implementation of the P2P trading market model on a permissioned blockchain platform is presented. Numerical results and discussions are given in Section VI. Finally, the paper is concluded in Section VII with several pointers to future work.

II. System Design and Assumptions

The study considers a residential energy community (i.e., or a microgrid) that consists of a set of nodes $\mathcal{N}$, indexed by $i = 0, 1, \ldots, N$. While a node might represent a household, a building or any DER (e.g., a community battery) located in the distribution network, this study focuses on households only[1]. All households have a connection to the main grid and can inject/withdraw power to/from the grid through that connection. Part of their electricity demand is fixed and can be described by a load profile. The baseload demand of household i at timestep $t \in \mathcal{T} = \{t_0, t_0 + \Delta t, t_0 + 2\Delta t, \ldots, T\}$ is denoted $P^{\mathrm{l}}_{i,t}$, which is assumed to be deterministic in this study. The power withdrawn/injected from/to the grid is denoted $p^{\mathrm{g}}_{i,t}$ and has an associated price represented by λ^{buy} for buying energy from the grid, and λ^{sell} for selling energy back to the grid (i.e., at a lower tariff). These price signals are assumed to be different at each t and the same for all households in the community. The cost function for each household i in timestep t can then be formulated as:

$$C^{\mathrm{g}}_{i,t}(p^{\mathrm{g}}_{i,t}) = \lambda^{buy}_t \cdot [p^{\mathrm{g}}_{i,t}]^- - \lambda^{sell}_t \cdot [p^{\mathrm{g}}_{i,t}]^+, \quad \forall\, i \in \mathcal{N}, t \in \mathcal{T}, \quad (1)$$

where

$$[p^{\mathrm{g}}_{i,t}]^+ = max\{p^{\mathrm{g}}_{i,t}, 0\}, \quad \forall\, i \in \mathcal{N}, t \in \mathcal{T}, \quad (2)$$

$$[p^{\mathrm{g}}_{i,t}]^- = max\{-p^{\mathrm{g}}_{i,t}, 0\}, \quad \forall\, i \in \mathcal{N}, t \in \mathcal{T}. \quad (3)$$

A household can own a different variety of DER, such as a PV system, an EV and/or a BESS. The amount of power obtained from the PV system at t in i is denoted $P^{\mathrm{pv}}_{i,t}$, which is assumed to be perfectly known and uncontrollable in this work. The presence of EV and BESS yields additional constraints. An EV is considered to be a flexible load where both the time and quantity of the charging power $p^{\mathrm{ev}}_{i,t}$ can be controlled. The total EV daily charging energy must equal to the EV daily energy requirement E^{ev}_i (see (4)). Furthermore, EV charging rate is constrained within upper and lower charging limits. A binary input parameter $\omega_{i,t}$ is used in (5) to indicate the timeslots at which the EV charging can be scheduled.

$$\sum_{t=0}^{T} p^{\mathrm{ev}}_{i,t}\Delta t = E^{\mathrm{ev}}_i, \qquad \forall\, i \in \mathcal{N}, \quad (4)$$

$$\omega_{i,t}\underline{p}^{\mathrm{ev}} \le p^{\mathrm{ev}}_{i,t} \le \omega_{i,t}\overline{p}^{\mathrm{ev}}, \qquad \forall\, i \in \mathcal{N}, t \in \mathcal{T}. \quad (5)$$

For the BESS, the net battery power $p^{\mathrm{b}}_{i,t}$ is defined as the difference between the discharging power $p^{\mathrm{bd}}_{i,t}$ and the charging power $p^{\mathrm{bc}}_{i,t}$, as:

$$p^{\mathrm{b}}_{i,t} = p^{\mathrm{bd}}_{i,t} - p^{\mathrm{bc}}_{i,t}, \quad \forall\, i \in \mathcal{N}, t \in \mathcal{T}. \quad (6)$$

The State of Charge (SoC) of the battery is represented by $SoC^{\mathrm{b}}_{i,t}$, and the efficiency of charging and discharging are denoted $\eta^{\mathrm{b}}_{\mathrm{c}}$, $\eta^{\mathrm{b}}_{\mathrm{d}}$, respectively. The $SoC^{\mathrm{b}}_{i,t}$ can then be determined as:

$$SoC^{\mathrm{b}}_{i,t} = SoC^{\mathrm{b}}_{i,t-1} + (\eta^{\mathrm{b}}_{\mathrm{c}} p^{\mathrm{bc}}_{i,t} - \frac{p^{\mathrm{bd}}_{i,t}}{\eta^{\mathrm{b}}_{\mathrm{d}}})\Delta(t), \quad \forall\, i \in \mathcal{N}, t \in \mathcal{T}. \quad (7)$$

[1]In the rest of the manuscript, the terms "household" and "users" will be used to represent a physical node in the network participating in P2P trading.

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$p^{\text{bd}}_{i,t}$, $p^{\text{bc}}_{i,t}$ and $SoC^{\text{b}}_{i,t}$ are all constrained within upper and lower limits.

The impact of full electrification on the price and amount of P2P traded energy will be assessed in this work. Therefore, Space Heating (SH) in households is assumed to be delivered using an HP, which is considered as a flexible load, while ensuring end-users' comfort. The following model is used to predict the Coefficient of Performance (CoP) of the HP:

$$CoP_t = a_0 + a_1\Delta\mathrm{T} + a_2\Delta\mathrm{T}^2, \tag{8}$$

where $\Delta\mathrm{T}$ is the temperature difference between the outside environment and the supply temperature. The parameters a_0, a_1 and a_2 are the HP model coefficients [3], [25].

The SH demand can be scheduled using a decision variable $q^{\text{sh}}_{i,t}$, which is generated by multiplying the thermal heat loss of the building (U^i) with the temperature difference between the inside and outside environment at each t (see (9)). This approach can add flexibility to the HP by setting the boundaries of the SH demand profile flexibly since the maximum and minimum temperature of the inside building environment ($k^{i,t}_{\text{building}}$) are configurable parameters of the problem.

$$q^{\text{sh}}_{i,t} = U^i(k^{\text{building}}_{i,t} - \mathrm{T}^{\text{amb}}_t), \quad \forall i \in \mathcal{N}, t \in \mathcal{T}. \tag{9}$$

The daily flexible electric SH supply should be equal to the daily electric heat demand profile of the household ($\sum_{t=1}^{T} D^{\text{sh}}_{i,t}$) as:

$$\sum_{t=1}^{T} q^{\text{sh}}_{i,t} = \sum_{t=1}^{T} D^{\text{sh}}_{i,t}, \quad \forall i \in \mathcal{N}, t \in \mathcal{T}. \tag{10}$$

However, the above constraints result in an unbounded daily SH demand profile, neglecting the comfort of the residents. Therefore, the following constraint is applied to sustain comfort levels and ensures that the inside temperature is within the range of predefined minimum ($\mathrm{T}^{\text{building,min}}_i$) and maximum ($\mathrm{T}^{\text{building,max}}_i$) inside building temperatures, as:

$$\mathrm{T}^{\text{building,min}}_i \leq k^{\text{building}}_{i,t} \leq \mathrm{T}^{\text{building,max}}_i, \quad \forall i \in \mathcal{N}, t \in \mathcal{T}. \tag{11}$$

The amount of electricity provided by the HP is the SH demand divided by the CoP of the HP at each t .

$$p^{\text{hp}}_{i,t} = \frac{q^{\text{sh}}_{i,t}}{CoP_t}, \quad \forall i \in \mathcal{N}, t \in \mathcal{T}. \tag{12}$$

The following constraint ensures that the total amount of power provided by the HP cannot be higher than its maximum installed power.

$$0 \leq p^{\text{hp}}_{i,t} \leq P^{\text{hp,installed}}_i, \quad \forall i \in \mathcal{N}, t \in \mathcal{T}. \tag{13}$$

For determining the maximum installed power of the HP ($P^{\text{hp,installed}}_i$), the HP is sized to supply the annual peak of the heat demand of i (Q^{peak}_i) divided by the minimum expected CoP (CoP_{min}) to provide sufficient heating during cold days.

The fast ramping rates of the HP are constrained as:

$$|p^{\text{hp}}_{i,t} - p^{\text{hp}}_{t-1,i}| \leq P^{\text{ramp,max}}_i, \quad \forall i \in \mathcal{N}, t \in \mathcal{T}, \tag{14}$$

where $P^i_{\text{ramp,max}}$ is the maximum ramp rate of the HP in i.

In P2P trading, every household can exchange an amount of net power with other households in the network. The net power exchange in i at t is denoted $p_{i,t}$, whose positive value represents a surplus power (i.e., can be sold), and negative value represents a residual demand (i.e., need to be bought). The net power $p_{i,t}$ is determined using an energy balancing formula as:

$$p_{i,t} = p^{\text{g}}_{i,t} + P^{\text{pv}}_{i,t} + p^{\text{b}}_{i,t} - P^{\text{l}}_{i,t} - p^{\text{ev}}_{i,t} - p^{\text{hp}}_{i,t}, \quad \forall\, i \in \mathcal{N}, t \in \mathcal{T}. \tag{15}$$

III. Decentralized Fully P2P Energy Trading

A. Market Design

A P2P market model, which is a special case of the unified formulation proposed in [9], is used in this study. This model allows the designation of a bilateral trading coefficient to every individual trade. We assume that all households in the network are rational and non-strategic market agents. The objective is to minimize the overall costs in the network for all households N over a time horizon T. This includes the costs (revenues) for withdrawing (injecting) power to the grid as well as the costs (revenues) of trading energy bilaterally with other households in the network. The problem can be formulated as:

$$\text{minimize} \quad \sum_{t=0}^{T}\sum_{i=0}^{\mathcal{N}} \left[C^{\text{g}}_{i,t}(p^{\text{g}}_{i,t}) + \sum_{j=0}^{\mathcal{M}} \gamma_{ij,t}|d_{ij,t}| \right], \tag{16a}$$

$$\text{subject to:} \quad (4)-(7), (9)-(15),$$

$$p_{i,t} = \sum_{j=0}^{\mathcal{M}} d_{ij,t}, \qquad [\mu_{i,t}], \forall\, i \in \mathcal{N}, t \in \mathcal{T}, \tag{16b}$$

$$\boldsymbol{D}_t = -\boldsymbol{D}_t^{\intercal} \qquad [\boldsymbol{\Xi}_t], \forall\, t \in \mathcal{T}, \tag{16c}$$

In this formulation, $\mathcal{M}$ indexed by j represents the set of trading partners of household i. Bilateral trading preferences can be decided by a household owner using the parameter $\gamma_{ij,t}$, which is a bilateral trading coefficient imposed by i on the trade with another household j, and $d_{ij,t}$ is the quantity of energy traded between i and j. The total amount of traded energy between i and all other households at each t must be equal to the net power of i at that t (determined in (15)) as ensured by (16b). The dual variable $\mu_{i,t}$ associated to this constraint represents the perceived energy price by i. The matrix $\boldsymbol{D_t}$ contains the quantities of all bilateral trades in the network at each t and the associated dual variable matrix $\boldsymbol{\Xi_t}$ contains the prices of all trades at that t. The reciprocity of trading quantities as well as of trading prices $\boldsymbol{\Xi}$ are ensured by (16c) at the optimal solution of problem (16).

B. Decentralized Formulation

The general-form consensus optimization of the Alternating Direction Method of Multipliers (ADMM) is chosen in this work to decompose the centralized formulation in (16) into several sub-problems and each household solves its corresponding sub-problem separately and independently. The solution of those sub-problems are then coordinated to come to a solution of the global problem [26].

After solving its sub-problem locally, every household will determine its own optimal local trading quantities schedule $\boldsymbol{D}$, which is treated as a coupling variable that corresponds to the global variable $\boldsymbol{C}$. Following [9], $(\boldsymbol{C}-\boldsymbol{C}^{\intercal})/2 = \boldsymbol{D}$ is defined as the average of the trading quantity proposed by i to j and the one proposed by j to i. Consensus between households happens when those trading values are equal which is guaranteed by ADMM at optimality, since the considered optimization problem formulated in (16) is convex [26]. In this formulation, the local private energy information of each household (e.g., PV generation, power demand, EV charging pattern) are not shared with the network and remain private.

Using this consensus constraint, the fully decentralized augmented Lagrangian for the bilateral trading model at each

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iteration k and for each household i can be formulated as:

$$\left(p_i^{\mathrm{g}}, D_i\right)^{k+1} = \underset{p_i^{\mathrm{g}}, D_i}{\operatorname{argmin}} \sum_{t=0}^{\mathcal{T}} \left[C_{i,t}^{\mathrm{g}}(p_{i,t}^{\mathrm{g}}) + \sum_{j=0}^{\mathcal{M}} \left[\gamma_{ij,t} |d_{ij,t}^{k+1}| + (\rho/2)\Big(\frac{d_{ij,t}^k - d_{ji,t}^k}{2} - d_{ij,t}^{k+1} + \xi_{ij,t}^k/\rho\Big)^2 \right] \right] \quad (17)$$

subject to:

$$(4) - (7), (9) - (15) \text{ and } (16b),$$

where $\rho > 0$ is the penalty parameter and ξ is the dual variable that represents the price of each bilateral trade being updated in each iteration k of the ADMM method, as:

$$\xi_{ij,t}^{k+1} = \xi_{ij,t}^k - \rho(d_{ij,t}^{k+1} + d_{ji,t}^{k+1})/2. \quad (18)$$

The consensus is obtained when the ADMM algorithm converges, which is determined using the following conditions:

$$\left\|r^k\right\|_2 \leq \epsilon_p, \quad \left\|s^k\right\|_2 \leq \epsilon_d, \quad (19)$$

where r and s are the primal and dual residuals, and ϵ_p and ϵ_d are the tolerances in the primal and dual residuals, which are typically assigned a very low value [26].

IV. Bilateral Trading Strategies

A matrix of bilateral trading coefficients $\mathbf{\Gamma}$ is defined, which contains all bilateral trading coefficient values between any household ($i \in \mathcal{N}$) and its peers ($j \in \mathcal{M}$) in the network. This matrix can be used to indicate preferred trading partners and enable product differentiation [11]. According to the formulation in (17), the smaller the value of $\gamma_{ij,t}$, the more favorable the associated trade with household j. In this section, different strategies for setting up the matrix $\mathbf{\Gamma}$ are proposed.

A. Supply-Demand Matching Strategy (ST1)

In this strategy, the bilateral trading coefficients are built based on the matching between power demand and surplus PV power generation of households. In this regard, the willingness of i to trade at t is proportional to the magnitude of its expected deficit demand or surplus PV generation (i.e., $P_{i,t}^l - P_{i,t}^{\mathrm{pv}}$). Following this strategy, it is assumed that households with a surplus power are more likely to trade energy with households with a power deficit, and vice versa. This strategy could be adopted to create a bilateral trading market where an economic mechanism is prioritized. In order to reflect these assumptions in the bilateral trading coefficients, several steps are taken.

First, the expected net budget matrix $\boldsymbol{P}^{\mathrm{net}}$ is determined which contains the net power of all households (i.e., N rows indexed by i) across all timesteps (i.e., T indexed by t). From this matrix, two new matrices $\boldsymbol{P}^{\mathrm{buy}}$ and $\boldsymbol{P}^{\mathrm{sell}}$ are defined, which contain the amount of net power that each household wants to sell or buy, respectively, at every timestep. Then, each row in $\boldsymbol{P}^{\mathrm{buy}}$ and $\boldsymbol{P}^{\mathrm{sell}}$ is normalized according to the maximum deficit and surplus budget in that row, respectively. After that, matrices $\mathbf{\Gamma}^{\mathrm{b,rel}}$ and $\mathbf{\Gamma}^{\mathrm{s,rel}}$ are created, which represent the relative willingness of households to buy or sell energy. Parameter χ represents the maximum baseline value for bilateral trading coefficients. Using $\mathbf{\Gamma}^{\mathrm{b,rel}}$ and $\mathbf{\Gamma}^{\mathrm{s,rel}}$, the final 3D matrix of bilateral trading coefficients $\mathbf{\Gamma}$ is then identified.

At the maximum value of $\gamma_{ij,t} = \chi$, households i and j are considered to be very unlikely trading partners. χ is set at a high value, meaning that all bilateral trading coefficients have a value of anywhere between 0 and χ. The procedure in ST1 is detailed in Algorithm 1.

Algorithm 1: ST1: Supply-demand matching strategy.

foreach *household* $i \in \mathcal{N}$ **do**
- $P_i^l \leftarrow$ power demand profile
- $P_i^{\mathrm{pv}} \leftarrow$ PV generation profile

Build the net budget matrix $\boldsymbol{P}^{\mathrm{net}}$ (N x T):
$$\boldsymbol{P}^{\mathrm{net}} = \boldsymbol{P}^{\mathrm{pv}} - \boldsymbol{P}^{\mathrm{l}}$$

Split $\boldsymbol{P}^{\mathrm{net}}$ in two matrices $\boldsymbol{P}^{\mathrm{buy}}$ and $\boldsymbol{P}^{\mathrm{sell}}$, where each element in these matrices is defined as:
$$p_{i,t}^{\mathrm{buy}} = \begin{cases} 0 & \text{if } p_{i,t}^{\mathrm{net}} \geq 0 \\ p_{i,t}^{\mathrm{net}} & \text{if } p_{i,t}^{\mathrm{net}} < 0 \end{cases} \quad (20)$$
$$p_{i,t}^{\mathrm{sell}} = \begin{cases} p_{i,t}^{\mathrm{net}} & \text{if } p_{i,t}^{\mathrm{net}} > 0 \\ 0 & \text{if } p_{i,t}^{\mathrm{net}} \leq 0 \end{cases} \quad (21)$$

Set the maximum coefficients baseline value (χ)

Normalize each row in $\boldsymbol{P}^{\mathrm{buy}}$ and $\boldsymbol{P}^{\mathrm{sell}}$ using $\overline{P}_{\mathrm{max}}^{\mathrm{buy}}$ and $\overline{P}_{\mathrm{max}}^{\mathrm{sell}}$, as:
$$\mathbf{\Gamma}^{\mathrm{b,rel}} = \frac{\chi}{2} \frac{\boldsymbol{P}^{\mathrm{buy}}}{\overline{P}_{\mathrm{max}}^{\mathrm{buy}}} \quad (22)$$
$$\mathbf{\Gamma}^{\mathrm{s,rel}} = \frac{\chi}{2} \frac{\boldsymbol{P}^{\mathrm{sell}}}{\overline{P}_{\mathrm{max}}^{\mathrm{sell}}} \quad (23)$$

Build the 3D matrix of bilateral trading coefficients $\mathbf{\Gamma}$ based on $\mathbf{\Gamma}^{\mathrm{b,rel}}$ and $\mathbf{\Gamma}^{\mathrm{s,rel}}$, as:
$$\gamma_{ij,t} = \begin{cases} \chi & \text{if } \gamma_{i,t}^{\mathrm{s,rel}}, \gamma_{j,t}^{\mathrm{s,rel}} > 0 \\ \chi & \text{if } \gamma_{i,t}^{\mathrm{b,rel}}, \gamma_{j,t}^{\mathrm{b,rel}} > 0 \\ \chi - (\gamma_{i,t}^{\mathrm{b,rel}} + \gamma_{j,t}^{\mathrm{b,rel}} + \gamma_{i,t}^{\mathrm{s,rel}} + \gamma_{j,t}^{\mathrm{s,rel}}) & \text{otherwise} \end{cases} \quad (24)$$

B. Distance-based Matching Strategy (ST2)

The other proposed strategy for matching between households is based on their distance to each other in the network. The distance here represents the number of connections between households. For instance, a directly connected households have distance of unit 1. Clearly, the distance between households depends on the topology of the network, which is assumed to be known in this strategy. Generally, households are connected to distribution networks, which typically have a radial topology. Hence, the network can be represented as a multi-way tree (i.e., a decision tree that can have more than two children). This strategy is more focused on reducing long-distance electricity flows through the lines, potentially enhancing energy efficiency in the network by encouraging P2P trading among nearby households.

The first step in this strategy is to build the N x N child and parent matrices based on the network topology. The neighbours of a particular household i can be regarded as the parent and children of that household. A household j that is closer to the root in the tree is called the parent of i, while i is called the child of j. After that, two separate vectors are created, $\mathbf{vp}$ and $\mathbf{vc}$, each of which contains the list of all parents and children in the network, respectively. Finally, the distance between each two households $i \in N$ and $j \in N$ in the network (d_{ij}) is calculated using a recursive function $findDist(i, j)$. Descriptions of the ST2 algorithm and the $findDist(i, j)$ function are provided in Algorithm 2.

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Algorithm 2: ST2: Distance-based matching strategy.

Receive the network topology
Build the N x N child and parent matrices based on the network topology
Identify the children and parents IDs of each household and store them in two separate vectors (**vp** and **vc**)
Find and store the distance d_{ij} between each two households ($i \in N$ and $j \in N$) in the network using the $findDist(i,j)$ function
Function $findDist\,(i,j)$ **:**
    $d_{ij} \leftarrow 0$ (initial value of the distance);
    if $i == j$ **then**
        return d_{ij} (a household's distance to itself is zero);
    else if $vp_i == j \,||\, vp_j == i$ **then**
        return d_{ij}+1 (one household is a parent of the other);
    else if $vp_i == vp_j$ **then**
        return d_{ij}+2 (households are children of the same parent);
    else
        $n \leftarrow max(vp_i, vp_j)$
        $m \leftarrow min(i,j)$
        if $vp_n == m$ **then**
            return $findDist(vp_n, m)$ (m is a grandparent of n);
        else if $vp_m == n$ **then**
            return $findDist(vp_m, n)$ (n is a grandparent of m);
        else
            return $findDist(n,m) + 1$ (other cases);
End Function
Set the trading coefficients based on distance:
foreach $i \in N$ **do**
    foreach $j \in N$ **do**
        $\gamma_{ij} \leftarrow d_{ij} = findDist(i,j)$
Return the final bilateral trading coefficients matrix $\mathbf{\Gamma}$

V. Implementation of P2P Energy Trading Market on Blockchain

A. Blockchain Platform Selection

By adopting blockchain and smart contracts technologies, the decentralized P2P energy trading formulation, presented in Section III-B, can be implemented in a secure, verifiable and automated manner. The IBM Hyperledger Fabric (HLF) [27] is chosen in this study as a permissioned blockchain platform. Multiple blockchain platforms were analyzed based on literature and experts' opinions and experience, such as EnergyCoin [28], Ethereum [29], [30] and HLF [31]. The HLF ended up as the most suitable solution for the decentralized fully P2P market due to its ability to support smart contracts while at the same time offering a better performance compared to other platforms due to its unique consensus protocol. One of its main characteristics is that it is a permissioned blockchain which, for P2P energy trading applications, appears as an advantage since it is necessary to know the identify of the households participating in energy trading. Besides, the HLF brings a lot of customization options, one of which is that it allows changing the block creation configuration in the runtime, therefore adapting the speed of transactions depending on the situation within the system. The HLF provides smart contract support in the form of Chaincode that can be written using the most popular programming languages (i.e., Go, Java or NodeJS) [27], [31].

B. Components of the Considered HLF Organization

The P2P HLF organization considered in this study is made of the following components: Peers[2] (i.e., each has a state database and a blockchain database), a Certificate Authority (CA), a CA Database, a Chaincode container on top of each Peer and an Orderer. The considered HLF organization is depicted in Fig. 1.

Peers are components that host ledgers (i.e., a blockchain database and a state database) and a smart contract (i.e., Chaincode). Each Peer within the organization is mutually synchronized (i.e., containing the same data). The CA is a component responsible for validating the identity of permissioned users (i.e., households) which join the blockchain network by issuing and revoking digital certificates that will be used as identifiers for households when communicating with the HLF. The P2P trading Chaincode algorithm is a program that runs on each HLF Peer and represents a logical interface between a household and the HLF. The Orderer (i.e., the Ordering Service) is a component responsible for creating blockchain blocks and ensuring that once a Peer receives a block, it is guaranteed to be final and correct.

The P2P trading service represents a household's energy management system that runs the ADMM local optimization problem (i.e., formulated in Section III-B). A Hyperledger SDK is used in order to communicate with the HLF organization. The Hyperledger SDK is called by the P2P trading service in order to register and retrieve a certificate from the CA, as well as to create and send a transaction proposal that will be processed within the HLF organization.

C. Chaincode Information and Consensus Protocol

Each HLF Peer has the same version of P2P trading Chaincode algorithm which, besides being an interface between a user and the Hyperledger, plays a vital role in the consensus mechanism. In each iteration of the ADMM algorithm, the role of the P2P trading Chaincode in this work is to store the trading quantity pairs for each household and construct the bilateral trading quantities matrix (i.e., the matrix $\boldsymbol{D}$ described in Section III), which will be retrieved back by each corresponding household. For both storing and fetching, in order to invoke the Chaincode, each user has to include a valid certificate that was already issued by the CA. The P2P trading Chaincode is benchmarked according to the number of P2P trading users (i.e., execution time required for constructing the bilateral trading quantities matrix). The outcome is presented in Table I, which shows a reasonable execution time by the Chaincode for the considered P2P trading application.

The HLF consensus protocol is divided into three phases: i) Endorsement phase, ii) Ordering phase, and iii) Validation phase. In the Endorsement phase, a user's transaction proposal is being

[2]The term "Peer" here refers to a component of the HLF. It is important to distinguish this term from the "peer" used in P2P trading to represent a household or user in the network.

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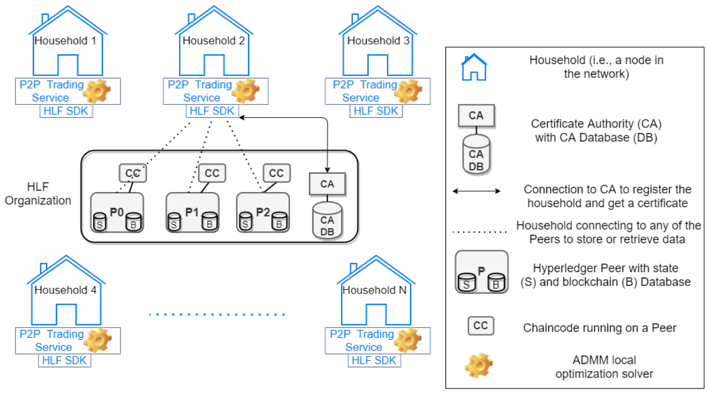
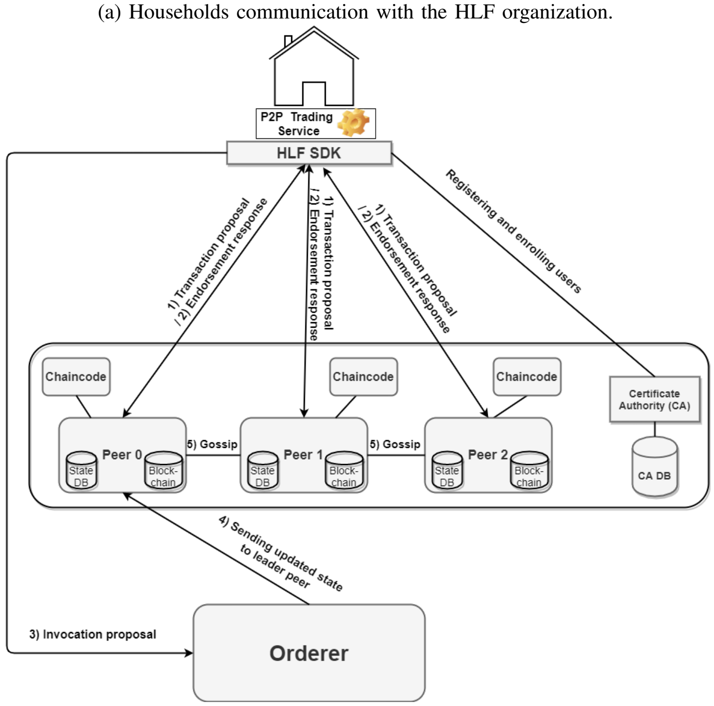


(a) Households communication with the HLF organization.



(b) Consensus protocol for each household within the considered HLF organization.

Fig. 1. The HLF-based P2P energy trading network architecture.

sent to one or more endorsing Peers. Since each Peer contains a P2P trading Chaincode algorithm, endorsing Peers verify the user's certificate issued by the CA and transaction proposal inputs and return an endorsement response which consists of endorsing peers signatures and a read/write set that is created from the Chaincode execution on the current version of the ledger. In the Ordering phase, endorsement responses are being passed to the Ordering Service, which then creates a blockchain transaction. This transaction is stored within a blockchain block which is eventually sent to the Leader Peer (i.e., Peer 0 in Fig. 1). The Leader Peer further propagates the block to the other Peers in the organization via the Gossip protocol. In the Validation phase, all Peers validate the transaction based on the endorsement policies, and check if there were any changes on the ledger related to the read/write set since it was generated. If valid, a transaction is committed and this will finally create a mutually synchronized and updated state databases between all Peers in the organization [27], [31].

When having an Ordering Service composed of multiple HLF organizations, there is an option for a distributed Ordering Service implementation (e.g., with the Raft Crash Fault Tolerant

TABLE I
CHAINCODE EXECUTION TIME FOR CONSTRUCTING THE BILATERAL TRADING QUANTITIES MATRIX ($\boldsymbol{D}$).

Number of users N	10	30	50	70	100	150
Chaincode execution time (sec)	0.114	0.161	0.245	0.457	0.879	1.787

(CFT) mechanism) [32]. This is required when users from different HLF organizations perform P2P trading between each other. However, in our study, we assume that all users in the permissioned P2P energy trading network belong to the same HLF organization.

D. Implementation

The first step of the implementation is to initialize the HLF network. Once the network is up and running, the simulation of P2P trading can start. For each household participating in P2P trading, a user related to that household is created and registered. Its certificate is then retrieved from the CA. The implementation procedure following the consensus protocol is illustrated in Fig. 1 (b) and described below in more details.

1) A user sends a transaction proposal, via its HLF SDK, to a random endorsing Peer that contains the following: (i.e., beginning of the Endorsement phase):
   a) A Chaincode method information used for sending trading quantities.
   b) The user trading quantities data: its ID and a matrix (N^xT) of all users in the network for each timestep.
   c) A certificate related to that user.
2) The endorsing Peer checks whether the transaction proposal is valid (i.e., contains the information mentioned in the first step), and simulates the P2P trading Chaincode algorithm. It returns an endorsement response back to the HLF SDK of the user.
3) An invocation proposal, which contains the transaction and the endorsement response, is sent to the Orderer to generate a blockchain block with the trading quantities transaction (i.e., beginning of the Ordering phase).
4) The Orderer sends a new blockchain block to the Leader Peer (e.g., Peer 0 in Fig. 1).
5) Using the Gossip protocol, the block is propagated to the other Peers, which validate the transaction signatures based on the endorsement policies (i.e., beginning of the Validation phase).
6) If valid, a transaction is committed and each Peer performs the following:
   a) Appends a new block within the blockchain database.
   b) Updates the state database with a set of trading quantity pairs (State DB in Fig. 1). After the update, there will be multiple trading quantity pairs related to a user (i.e., one for each participating user in the network). For example, if there are 21 households, there will be 21 pairs related to the sending user. A sending user paired with itself with a zero trading quantity.

The information related to the simulation of the optimization algorithm on the HLF organization (e.g., trading coefficients, max number of iterations for ADMM, trading quantity pairs, etc) can be found in the state DB and the blockchain DB within each Peer. However, the local private energy information of each household (e.g., PV generation, power demand, EV charging pattern) are not shared with the organization and remain

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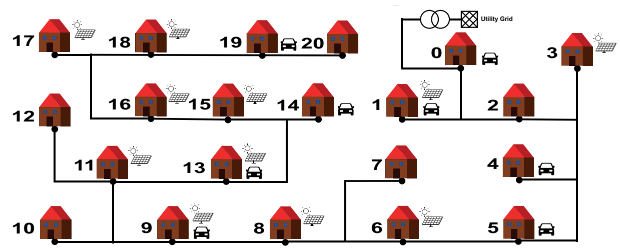

Fig. 2. Topology and distribution of households and DER in the considered residential network.

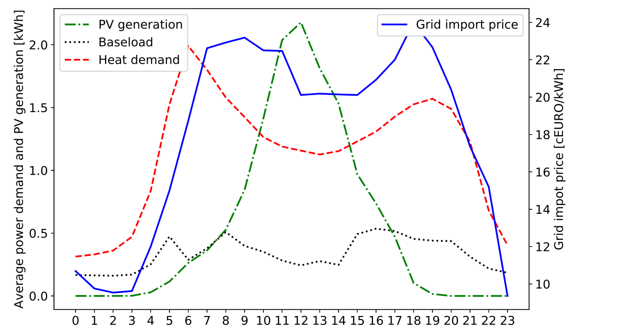

Fig. 3. Grid price, average PV generation and power demand of the N=21 households in the selected day.

private. After the simulation finishes, all the optimization results (e.g., number of iterations required, optimal trading quantities, optimal trading prices, optimal power schedules of flexible load, total trading cost and grid cost as well as the total time until convergence) can be stored in an output folder in a .csv format, which are then used to present the results in the next section.

VI. Numerical Evaluation and Discussions

A. Case Study and Simulation Setup

A realistic case study is considered to evaluate the proposed blockchain-based P2P energy trading market model and compare the different proposed strategies. The simulation uses actual hourly baseload and PV output power generation data of N=21 households who participated in an energy community pilot in the city of Amsterdam, The Netherlands. Only two households in this community own an HP for electric heating. Hence, the hourly electric heating demand and hourly ambient temperature of those two households are used to generate that data for the rest of the households in the community (i.e., for simulation scenarios with electric heating).

The topology of the network used to calculate the distance between households in ST2 is presented in Figure 2, which also shows the number of prosumers (i.e., 11 households) and the number of households with EV (i.e., 8 households). Those prosumers have a PV capacity between 2-5 kWp. A time-of-use price signal is used from the day-ahead market clearing prices of the European Power Exchange (EPEX), The Netherlands [33]. In all scenarios, the FiT for prosumers is assumed to be 50% of the electricity price at that time (i.e., $\lambda^{sell} = 0.5\lambda^{buy}$). The average EV daily charging requirement (E_{ev}) is set at 7.06 kWh, which is based on the average daily distance travelled by passenger cars in The Netherlands [34]. The EV charging limits are set at $\overline{p}^{\mathrm{ev}}$ = 1.7 [kW] and $\underline{p}^{\mathrm{ev}}$= 0 [kW] and their charging hours (ω_i) are randomly pre-defined, with some households preferring to charge during the day and others during the night. The ownership of BESS is assumed to be by prosumers. The parameters of the BESS in the simulations are assumed to be as follows: $SoC^{\mathrm{b}}_{\mathrm{min}}$= 20%, $SoC^{\mathrm{b}}_{\mathrm{max}}$=80% and $\eta^{\mathrm{b}}_{\mathrm{c}}$=$\eta^{\mathrm{b}}_{\mathrm{d}}$=0.943.

Regarding the parameters values of the electric heating model, the HP model coefficients in Eq. 8, a_0, a_1 and a_2, are specified on 5.06, -0.05 and 0.00006, respectively [25]. The building thermal heat loss is calculated based on the characteristics of an average insulated Dutch house and set as U= 0.1 [W m^{-2} K^{-1}]. The minimum and maximum building temperatures are specified as $T^i_{\mathrm{building,min}}$= 18 °C and $T^i_{\mathrm{building,max}}$=21 °C. The ramp rate power of the HP is set as $P^i_{\mathrm{ramprate,max}}$= 2 [kW].

The IBM HLF blockchain network v1.4.3 is implemented on a local machine with Mac OS and is used to run the decentralized P2P energy trading model for the N=21 households. Python 3 and CVXPY are used to model the optimization problems, while SCS is used for solving them [35]. The stopping criteria (i.e., residuals) in the ADMM algorithm are set at 0.002.

B. Results Discussion

The objective of this study is to assess the impact of trading coefficients on the performance of the P2P energy trading between households and to compare that with a baseline scenario. This performance is assessed with regard to economic indicators and the scheduling of power flows. Another objective is to show how that performance changes when households use electricity for heating. The assessment is performed for a selected spring day using the data described in Section VI-A and visualized in Fig. 3.

Fig. 4 depicts the values of the bilateral trading coefficients calculated according to the two strategies defined and discussed in Section IV. These values are calculated for the selected day and network and will be used in the numerical evaluation. The higher the coefficient value between two households, the less likely a P2P trading will happen between them. The differences between the two figures are apparent in terms of the magnitude and distribution of trading coefficient values. In Fig. 4 (a), the coefficient value between any two households at a given timeslot depends on the matching between their surplus PV generation and demand, as described in Algorithm 1. Therefore, it is clear to notice the differences between values in this strategy. Algorithm 1 sets coefficient value between any household and itself at maximum (i.e., see the counterdiagonal values in Fig. 4 (a)), as no trading can take place between a household and itself. The coefficient values in ST1 are averaged over the day in Fig. 4 (a) for the sake of visualization in one day. Differently, in ST2 the coefficient values are time independent and are solely based on the distance between households in the network. In Algorithm 2, the distance between any household and itself is set at zero (i.e., see the counterdiagonal values in Fig. 4 (b)), which will also prevent trading between any household and itself in ST2.

The economic performance parameters assessed in this study are the P2P trading prices and financial costs for households when buying/selling energy either from/to the main grid or from/to other households. For instance, Fig. 5 compares the P2P clearing price in the two strategies. For the two strategies, further comparison is made in this figure between scenarios with and without electric heating in households. The prices shown are

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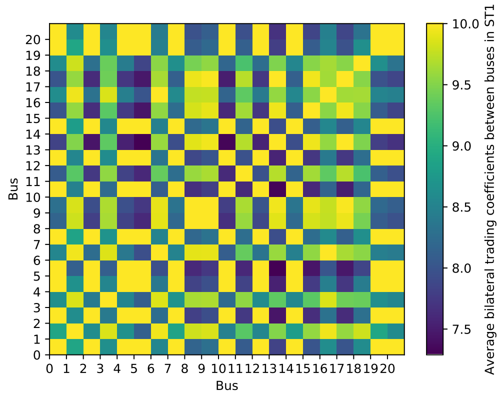
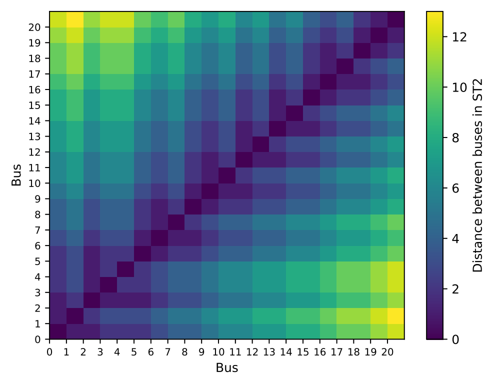
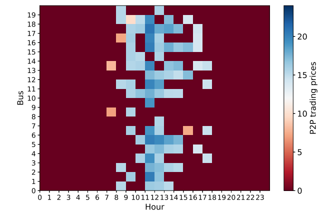


(a) Bilateral trading coefficients in ST1 (surplus-demand matching).

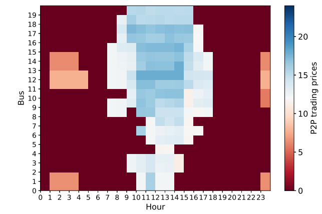


(b) Bilateral trading coefficients in ST2 (distance-based matching).

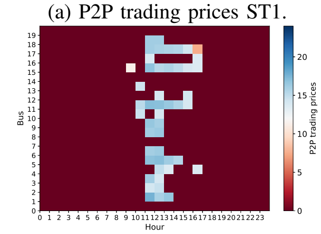
Fig. 4. Bilateral trading coefficient values in ST1 (i.e., averaged in a day) and ST2 (i.e., fixed based on bus location).



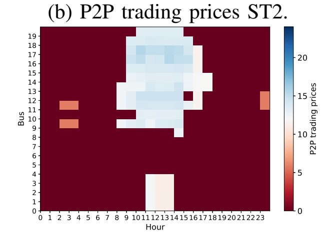
(a) P2P trading prices ST1.



(b) P2P trading prices ST2.



(c) P2P trading prices ST1 (with electric heating).



(d) P2P trading prices ST2 (with electric heating).

Fig. 5. Weighted average P2P energy trading prices between all households in the selected day: Following ST1 (a)/(c) and ST2 (b)/(d), without/with electric heating.

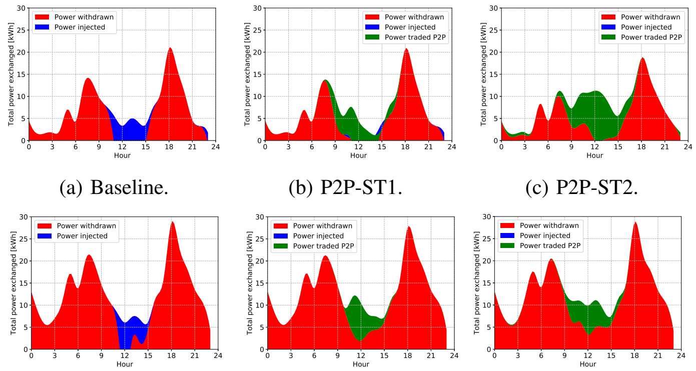
weighted with the trading quantity for each household at each time slot.

Fig. 5 shows that during daytime hours, when trading is most likely to take place, the average internal trading price is always lower than the grid import price, yet higher than the grid FiT. Compared to ST1, energy trading in ST2 is distributed over more hours of the day and more households are participating in P2P trading. In ST1, some households' preferred trading partners could be infeasible due to the technical constraints in the model. On the other hand, the P2P trading price in ST2 is lower than ST1. This can be explained by the strategy used to build the trading coefficients. In ST1, the coefficients in some hours could take a high value if there is no good matching between the surplus and demand values of some pairs of households, and hence no energy trading will happen at that hours. In ST2, the coefficients for neighboring households always take a low value whether or not they have a good matching between their surplus and demand values. This might drive neighboring households to trade more energy and at a lower price even though there might be a better match with a further household in the network. ST2 in this case can represent a scenario in which there is a social connection between households in a network, or could also be considered as proxy to enhance energy efficiency.

Same pattern appears in the scenario with electric heating (i.e., Fig. 5 (c) and (d)). However, the amount of trading in those scenarios is less due to the increased local demand resulted from flexible electric heating and, hence, the less amount of surplus energy available for P2P trading. It is observed that some households in this scenario, in the two strategies, do not trade energy at all (e.g., households 0, 19, 14 and 7 in ST1). Those households are identified to be prosumers and their surplus PV power is used entirely for their flexible electric heating demand. Further, Fig. 5 shows that the impact of electric heating on the trading price magnitude is rather limited.

Fig. 6 shows the distribution of the total power exchange of all households over the day in all strategies and scenarios. A comparison is made with a baseline scenario in which only grid interaction takes place (i.e., without P2P trading). The figure shows that in all P2P trading scenarios, almost all surplus PV energy is exchanged locally, due to the higher P2P selling price than the FiT. Fig. 6 confirms that in ST2 the total power traded between households is higher than ST1. As noted before, the model is driven by the trading coefficient values in this strategy (i.e., low between neighboring households) which affect the P2P trading results. Only a little amount of energy (e.g., 12.96 kWh) is injected to the grid in ST1 (i.e., without electric heating scenario). More numerical details can be read in Table II, which summarizes the results for total power imported from and injected to the grid and total P2P energy exchange between households. Further, it compares the costs for consumers only in all scenarios and shows how the P2P trading can have the potential in reducing the energy procurement costs for consumers in the network. In scenarios with electric heating, a higher power demand can be observed. However, other than the reduced amount of surplus energy available for trading, it can be concluded, based on Fig. 6 and Table II, that the inclusion of electric heating does not largely affect the pattern of P2P energy trading between households.

The results in Fig. 6 and Table II show that P2P trading of locally produced renewable energy can help in reducing the interaction with the main grid, resulting in a more efficient and sustainable use of energy. Besides the economic and technical benefits of P2P trading, the proposed market model with different bilateral trading strategies is important for real-world implementation since it enables participants to incorporate their preferences in selecting their trading partners (e.g., social or environmental), guaranteeing maximum independence and



(a) Baseline. (b) P2P-ST1. (c) P2P-ST2.

(d) Baseline (e-heating). (e) P2P-ST1 (e-heating). (f) P2P-ST2 (e-heating).

Fig. 6. Total power exchange of all households without P2P trading (a)/(d), P2P trading ST1 (b)/(e), P2P trading ST2 (c)/(f), without/with electric heating.

freedom of choice.

Based on the results, ST2 provides both economic and technical efficiency benefits. This strategy enables more households to participate in P2P energy trading during more hours of the day, as shown in Fig. 5, while at the same time considering the technical efficiency in the network (i.e., avoiding long-distance electricity flows through the lines). Besides, it resulted in a better utilization of locally produced PV energy within the community, as observed in Fig. 6 and Table II. In addition, ST2 needs to be calculated only once, as long as the participating households in P2P trading are the same in the network, giving it a further computational benefit over ST1. For instance, the time needed to calculate the coefficient matrix ($\mathbf{\Gamma}$) in ST2 on a local machine was 0.031 sec for N=21 users and 13.22 sec for a random sample of N=200 users.

Regarding the blockchain implementation, we have used the HLF as a permissioned blockchain solution. The P2P trading service in each household, which contains an ADMM local optimization solver, communicates with the HLF organization without sharing the local private energy information of each household. The HLF offers the most suitable blockchain configurations for the considered case study of P2P energy trading within a single energy community or neighborhood, where a single-organization light consensus protocol is sufficient for running the network [32]. However, for larger networks with P2P energy trading between households belonging to multiple blockchain organizations, the blockchain implementation needs to be tested for efficiency of communication and execution speed. In such bigger networks of multiple organizations, the security and smart contract vulnerabilities also become very important to consider. For instance, a malicious organization running the ordering service might be able to impact the order in which the transactions are ordered in a block, which can favor transactions from one organization over those from others or deny service to some organizations. However, the potential impact is limited because controlling the Ordering Service in HLF is not sufficient to get an invalid transaction added to the ledger [32]. A security analysis and the potential threats and attacks in blockchain-based authentication scheme have been recently discussed in [15], [36], and a similar analysis could also be considered in blockchain-based P2P energy trading markets in the future.

Another important challenge in P2P energy markets is to guarantee fairness between energy trading partners. In literature,

TABLE II
NUMERICAL RESULTS FOR ENERGY EXCHANGE AND PROCUREMENT COSTS. THE VALUES ARE SUMMED FOR ALL THE HOUSEHOLDS.

	Without electric heating			All electric		
Scenario	Baseline	ST1	ST2	Baseline	ST1	ST2
All households grid import costs (€)	28.8	25.45	25.01	55.49	54.0	53.56
Consumers only grid import costs (€)	23.12	16.34	14.22	36.83	32.97	32.27
Consumers only P2P trading costs (€)	-	5.97	6.37	-	4.19	2.94
Consumers only total costs (€)	23.12	22.31	20.59	36.83	37.16	35.21
Total P2P energy exchange (kWh)	-	37.48	61.81	-	26.64	31.45
Total grid imports (kWh)	165.04	131.2	123.4	302.17	282.43	281.15
Total grid injection (kWh)	-51.92	-12.96	0.0	-26.93	-0.07	-0.13

there exist different definitions for preserving fairness in P2P energy trading. For instance, game theory has been used to analyze fairness in energy pricing or profit allocation among heterogeneous trading partners [37]–[39]. In [40], fairness is considered in a way that P2P participants reserve market payments are set to be proportional to the uncertainty in their renewable energy generation. On the other hand, P2P energy trading systems could be prone to unfair or malicious behavior from energy buyers or sellers and should be protected against that (i.e., to guarantee that an energy buyer will receive the right amount of energy after paying energy fees to an energy seller, or to verify that the energy buyer is honest about its claims). Such behavior can lead to significant consequences and discourage the participation in P2P energy markets. A blockchain-based timed commitments fairness mechanism has been recently proposed in [41] to solve this issue and enable energy traders, who do not trust each other, to assure fair purchases in a P2P environment. The proposed mechanism implies having a smart contract that is responsible for distributing a valid token-based payment from an energy purchaser to an energy seller once the timed commitment expires. This mechanism provides energy trading systems with the ability to detect fraud and provide fairness to trading participants. Another possible solution for this challenge is to have a financial settlement mechanism a posteriori on the blockchain, in a similar fashion to the financial settlement mechanism proposed for community-based markets in [5]. The smart contract can also be used here to preserve that and assign penalties on incomplete trades and guarantee fairness a posteriori. However, this also implies granting the smart contract access to meter-readings of participants in P2P markets to detect how much energy each participant has sent or received in each bilateral trade. The deviation from the commitment is not restricted to malicious behavior and could also be related to the uncertainty in renewable energy generation.

VII. Conclusions and Future Work

In this paper, two strategies for implementing bilateral trading coefficients on a blockchain-based P2P energy market are proposed. Besides providing benefits, such as the indication of preferred trading partners and product differentiation, it is shown that the proposed platform can provide reduced costs for households as well as reduced overall energy imports from the main grid, increasing efficiency and potentially reducing strain on the grid. The results showed that both ST1 and ST2 strategies provide these benefits. However, the paper recommends ST2 since it enables more households to participate in P2P energy trading during more hours of the day, while at the same time considering the technical efficiency in the network. This strategy resulted in a better utilization of locally produced PV energy within the community. In addition, ST2 needs to be calculated only once, giving it a further computational benefit over ST1.

Furthermore, an outline is provided for integrating the trading platform with a Hyperledger blockchain organization, which is especially useful for its customizability and reliability. By using the proposed P2P trading platform that can accommodate different bilateral trading strategies and functions on blockchain, maximum freedom and autonomy for end-users can be guaranteed.

For future research, the performance of ST1 and ST2 need to be further assessed for different network configurations in terms of topology, consumption patterns and scale. Besides, the Hyperledger blockchain implementation needs to be tested for multiple-organization settings to assess efficiency, scalability and security aspects. In addition, the proposed day-ahead P2P energy trading market needs to be extended for real-time market operation, where a verifiable fairness mechanism on the blockchain or a fair a posterior financial settlement mechanism needs to be defined. This is important in order to make sure that all agreed P2P energy trading transactions between households in the day-ahead phase are delivered in the next day for the agreed price. Addressing the stochastic nature in PV generation, grid price and power demand in a real-time operation is also among the important challenges that we aim to address in a future work. In such a future study, the need for a higher resolution input data is apparent.

References

[1] K. Alshehri, M. Ndrio, S. Bose, and T. Basar, "Quantifying market efficiency impacts of aggregated distributed energy resources," *IEEE Transactions on Power Systems*, 2020.

[2] M. S. H. Nizami, M. Hossain, and E. Fernandez, "Multiagent-based transactive energy management systems for residential buildings with distributed energy resources," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 3, pp. 1836–1847, 2019.

[3] T. Terlouw, T. AlSkaif, C. Bauer, and W. van Sark, "Optimal energy management in all-electric residential energy systems with heat and electricity storage," *Applied Energy*, vol. 254, p. 113580, 2019.

[4] Y. Parag and B. K. Sovacool, "Electricity market design for the prosumer era," *Nature energy*, vol. 1, no. 4, pp. 1–6, 2016.

[5] J. L. Crespo-Vazquez, T. Al Skaif, Á. M. González-Rueda, and M. Gibescu, "A community-based energy market design using decentralized decision-making under uncertainty," *IEEE Transactions on Smart Grid*, 2020.

[6] G. van Leeuwen, T. AlSkaif, M. Gibescu, and W. van Sark, "An integrated blockchain-based energy management platform with bilateral trading for microgrid communities," *Applied Energy*, vol. 263, p. 114613, 2020.

[7] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn Microgrid," *Applied Energy*, vol. 210, pp. 870–880, 2018.

[8] T. Morstyn, A. Teytelboym, and M. D. McCulloch, "Bilateral contract networks for peer-to-peer energy trading," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 2026–2035, 2019.

[9] T. Baroche, F. Moret, and P. Pinson, "Prosumer Markets: A Unified Formulation," in *IEEE PowerTech Conference*, 2019, pp. 1–6.

[10] Z. Zhang, R. Li, and F. Li, "A novel peer-to-peer local electricity market for joint trading of energy and uncertainty," *IEEE Transactions on Smart Grid*, 2019.

[11] E. Sorin, L. Bobo, and P. Pinson, "Consensus-Based Approach to Peer-to-Peer Electricity Markets with Product Differentiation," *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 994–1004, 2019.

[12] A. Hackbarth and S. Löbbe, "Attitudes, preferences, and intentions of german households concerning participation in peer-to-peer electricity trading," *Energy Policy*, vol. 138, p. 111238, 2020.

[13] H. R. Hasan and K. Salah, "Proof of delivery of digital assets using blockchain and smart contracts," *IEEE Access*, vol. 6, pp. 65 439–65 448, 2018.

[14] K. Salah, N. Nizamuddin, R. Jayaraman, and M. Omar, "Blockchain-based soybean traceability in agricultural supply chain," *IEEE Access*, vol. 7, pp. 73 295–73 305, 2019.

[15] R. Almadhoun, M. Kadadha, M. Alhemeiri, M. Alshehhi, and K. Salah, "A user authentication scheme of iot devices using blockchain-enabled fog nodes," in *2018 IEEE/ACS 15th international conference on computer systems and applications (AICCSA)*. IEEE, 2018, pp. 1–8.

[16] K. Gai, Y. Wu, L. Zhu, M. Qiu, and M. Shen, "Privacy-preserving energy trading using consortium blockchain in smart grid," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 6, pp. 3548–3558, 2019.

[17] M. Li, D. Hu, C. Lal, M. Conti, and Z. Zhang, "Blockchain-enabled secure energy trading with verifiable fairness in industrial internet of things," *IEEE Transactions on Industrial Informatics*, pp. 1–1, 2020.

[18] M. Khorasany, A. Dorri, R. Razzaghi, and R. Jurdak, "Lightweight blockchain framework for location-aware peer-to-peer energy trading," *International Journal of Electrical Power & Energy Systems*, vol. 127, p. 106610, 2020.

[19] M. L. Di Silvestre, P. Gallo, M. G. Ippolito, E. R. Sanseverino, and G. Zizzo, "A technical approach to the energy blockchain in microgrids," *IEEE Transactions on Industrial Informatics*, vol. 14, 2018.

[20] S. Wang, A. F. Taha, J. Wang, K. Kvaternik, and A. Hahn, "Energy crowdsourcing and peer-to-peer energy trading in blockchain-enabled smart grids," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 8, pp. 1612–1623, 2019.

[21] S. Saxena, H. E. Farag, H. Turesson, and H. Kim, "Blockchain based transactive energy systems for voltage regulation in active distribution networks," *IET Smart Grid*, 2020.

[22] F. Gao, L. Zhu, M. Shen, K. Sharif, Z. Wan, and K. Ren, "A blockchain-based privacy-preserving payment mechanism for vehicle-to-grid networks," *IEEE network*, vol. 32, no. 6, pp. 184–192, 2018.

[23] T. AlSkaif, B. Holthuizen, W. Schram, I. Lampropoulos, and W. van Sark, "A blockchain-based configuration for balancing the electricity grid with distributed assets," *World Electric Vehicle Journal*, vol. 11, 2020.

[24] Z. Dong, F. Luo, and G. Liang, "Blockchain: a secure, decentralized, trusted cyber infrastructure solution for future energy systems," *Journal of Modern Power Systems and Clean Energy*, vol. 6, no. 5, pp. 958–967, 2018.

[25] D. Fischer, T. Wolf, J. Wapler, R. Hollinger, and H. Madani, "Model-based flexibility assessment of a residential heat pump pool," *Energy*, vol. 118, pp. 853–864, 2017.

[26] S. Boyd, "Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers," *Foundations and Trends® in Machine Learning*, vol. 3, no. 1, pp. 1–122, 2011.

[27] E. Androulaki, A. Barger, V. Bortnikov, C. Cachin, K. Christidis, A. De Caro, D. Enyeart, C. Ferris, G. Laventman, Y. Manevich *et al.*, "Hyperledger fabric: a distributed operating system for permissioned blockchains," in *Proceedings of the Thirteenth EuroSys Conference*, 2018, pp. 1–15.

[28] EnergyCoin, "The energycoin," 2019. [Online]. Available: https://www.energycoinfoundation.org/en/

[29] G. Wood, "Ethereum: a secure decentralised generalised transaction ledger," *Ethereum Project Yellow Paper*, 2014. [Online]. Available: https://ethereum.github.io/yellowpaper/paper.pdf

[30] M. Di Angelo and G. Salzer, "A survey of tools for analyzing ethereum smart contracts," in *2019 IEEE International Conference on Decentralized Applications and Infrastructures (DAPPCON)*. IEEE, 2019, pp. 69–78.

[31] IBM, "The hyperledger fabric," 2020. [Online]. Available: https://www.hyperledger.org/

[32] ——, "The ibm hyperledger fabric ordering service," 2020. [Online]. Available: https://developer.ibm.com/articles/blockchain-hyperledger-fabric-ordering-decentralization/

[33] E. P. E. Netherlands, "Day-ahead auction," 2019. [Online]. Available: http://www.apxgroup.com/trading-clearing/day-ahead-auction/

[34] CBS, "CBS StatLine - Verkeersprestaties personenauto's; kilometers, brandstofsoort, grondgebied," 2018. [Online]. Available: https://bit.ly/2OJtaCy

[35] S. Diamond and S. Boyd, "CVXPY: A python-embedded modeling language for convex optimization," *The Journal of Machine Learning Research*, vol. 17, no. 1, pp. 2909–2913, 2016.

[36] H. R. Hasan and K. Salah, "Blockchain-based solution for proof of delivery of physical assets," in *International Conference on Blockchain*. Springer, 2018, pp. 139–152.

[37] W. Lee, L. Xiang, R. Schober, and V. W. Wong, "Direct electricity trading in smart grid: A coalitional game analysis," *IEEE Journal on Selected Areas in Communications*, vol. 32, 2014.

[38] R. Jing, M. N. Xie, F. X. Wang, and L. X. Chen, "Fair p2p energy trading between residential and commercial multi-energy systems enabling integrated demand-side management," *Applied Energy*, vol. 262, 2020.

[39] W. Zhong, S. Xie, K. Xie, Q. Yang, and L. Xie, "Cooperative p2p energy trading in active distribution networks: An milp-based nash bargaining solution," *IEEE Transactions on Smart Grid*, 2020.

[40] Z. Guo, P. Pinson, S. Chen, Q. Yang, and Z. Yang, "Chance-constrained peer-to-peer joint energy and reserve market considering renewable generation uncertainty," *IEEE Transactions on Smart Grid*, vol. 12, 2020.

[41] M. Li, D. Hu, C. Lal, M. Conti, and Z. Zhang, "Blockchain-enabled secure energy trading with verifiable fairness in industrial internet of things," *IEEE Transactions on Industrial Informatics*, vol. 16, 2020.