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Single-unit and multi-unit auction framework for peer-to-peer transactions

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A B S T R A C T

Peer-to-peer transactions appear in smart grids as a way to enable the direct transaction of energy among end-users (i.e., consumers, producers, and prosumers). This concept promotes the efficient use of local renewable energy sources among neighbours. Several studies proposed the application of peer-to-peer models for energy communities, microgrids, and aggregators to decrease energy costs for end-users and to promote the balance between consumption and generation. In this paper, it is proposed a framework to test, and validate, using a real environment, single- and multi-unit peer-to-peer auctions. It is also proposed six lightweight fully distributed peer-to-peer auction models, avoiding the need for a central operator. The lightweight of the proposed models enables their execution in the fog-computing layer using single-board computers deployed in end-users. The proposed framework, together with the proposed day-ahead models, was tested and validated in a real microgrid with five prosumers. The results of two weeks are discussed using a comparative economic analysis. The proposed framework and models were able to reduce energy costs for the end-users, promoting competitive free market behaviours, with multi-unit models outperforming single-unit models in the overall trading efficiency and monetary profits.

1. Introduction

Over recent years, distributed energy resources (DERs) have been massively integrated into the power grid, bringing benefits to the grid [1] and to end-user [2]. Also, the penetration of renewable energy sources (RESs) is rapidly increasing, and some predict that, by 2050, 60% of the world's generation will be provided by RESs [3]. The large growth of DERs has been leading to the decentralization of the power system, and to the shifting of the paradigm towards a distributed smart grid [45]. Microgrids have been used to solve integration issues of RESs by managing local demand and local supply, including the management of DERs [6]. However, the increasing penetration of intermittent energy generation from renewables, such as photovoltaic (PV) panels and wind turbines, has raised concerns about the grid's stability and reliability [7,8].

Transactive energy (TE) is defined, by The GridWise Architecture Council (GWAC), as "*a system of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter*" [9], indicating that the main purpose of TE is the continuous balancing between consumption and generation through economic methodologies. This concept, actively contributes to the stability and reliability of the grid, enabling the massive penetration of distributed energy sources, namely renewable and clean energy sources [10].

Seen as one of the most promising implementations of TE, peer-to-peer (P2P) markets allow producers, consumers, and prosumers to trade energy among each other in a market platform, ensuring their autonomy and decision [11]. Through this concept, a local energy market can be conceived in which end-users engage in bi-directional communication, providing bids and offers to the market autonomously, based on their own local needs and preferences [12]. While this approach puts greater regard to end-user autonomy [13] and reduces their electricity billing, it also may be used to solve network management issues, ensuring greater network stability and energy efficiency [11].

P2P transactions are commonly used for energy sharing among end-users, especially energy communities [14]. In [15], an intercommunity P2P framework is proposed to allow energy transactions among end-users considering real-time uncertainties. A P2P model to promote the community's welfare prioritizing the end-users willingness-to-pay, over

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self-consumption, is proposed in [16]. However, P2P models must be carefully studied, tested, and evaluated before being deployed. An evaluation framework is proposed in [17], allowing the evaluation of bill sharing, mid-market rate, and supply and demand ratio models. In [18], a multi-agent approach is used to test and simulate P2P transactions among end-users, where the proposed framework applies evaluation indexes to evaluate the performance of models. While this type of framework allows the simulation of P2P models, there is still a lack of real deployments where P2P can be tested.

P2P models can also be applied to increase the efficient use of energy storage units in a community [19]. In [20], a model for P2P energy sharing allows the distribution use of energy storage units in a community. A two-stage aggregation model for microgrids is proposed in [21] where local renewable generation is shared among end-users to be consumed and stored.

Over recent years multiple P2P energy trading projects have emerged. In the UK, the Piclo project enables P2P energy trading through auctions held between local renewable energy producers and business customers [22]. In Germany, the sonnenCommunity project allows P2P trading among sonnenBatterie owners [23]. In the US, the Brooklyn Microgrid project connects prosumers and consumers who can trade energy in near-real-time through a platform in their local marketplace [24]. In Bangkok, Thailand, a P2P renewable energy trading solution was implemented in the T77 precinct connecting a shopping centre, a school, an apartment building, and a dental hospital [25,26].

A common approach, to solve P2P transactions, is the use of game theory techniques [27]. The Stackelberg equilibrium is used in [28] together with the application of demand response programs to maximize the profit of the energy-shared provider. In [29], the Stackelberg equilibrium is used to share energy among players in a virtual energy station. The Nash equilibrium is estimated in [30], where a non-cooperative stochastic game is used. Approaches based on game theory promote the equilibrium of prices but bring high complexity that is difficult to scale. Also, the use of low computational hardware to participate in game theory models can be unachievable.

Market-based designs are also a possible approach to address P2P transactions. In recent years, several studies regarding the use of auction-based market-clearing methods to achieve efficient energy allocation and fair electricity prices have been conducted. An auction-based market clearing mechanism is presented in [31], where market performance indexes are used to compare different trading methods. In [32] a double auction mechanism is proposed to maximize the welfare of market subscribers. Another research study has compared the performance of four different bidding strategies across two auction mechanisms using a game theory approach [33].

Most studies concerning P2P energy trading focuses on energy management and on simple economic aspects. Monetary profit alone does not provide a good measure of the market's performance, and a deeper analysis must be made to perceive how an auction model deals with competitiveness and shifts in supply and demand, considering both overall outcome, fairness, and free-market behaviours. Hence, this paper provides an analysis of how a P2P market behaves under an auction framework, and a comparison between different auction models, focusing on economic concepts and competitive-market behaviours.

This paper's main contributions are the proposal of a single-unit and multi-unit energy auction framework for P2P transactions, and the comparative economic analysis of four single-unit and two multi-unit P2P energy trading auction models. These models have been built to be executable in the edge and fog layers using low computation hardware. This means that the proposed P2P models can be placed in real scenarios using a distributed auction approach, without depending on a centralized provider/player or demanding a server or a cloud solution.

The proposed auction models are applied to a real microgrid pilot with five prosumers. The microgrid's prosumers are represented using the μGIM platform that enables the necessary communications among agents, and where each prosumer is represented by an agent [34]. Each prosumer manages a small office and tries to minimize his/her energy cost by participating in the P2P auction market. This paper presents the comparative competitive-market analysis of the developed auction models considering two heterogeneous case studies: a week with a high energy generation profile compared to the consumption profile and allowing more energy to be transacted, and a week with a low generation profile compared to the consumption profile allowing less energy to be transacted.

Following this introductory section, the paper is organised as follows. In Section 2, the P2P auction framework is presented, providing a brief overview of the μGIM platform and introducing concepts used throughout the remaining of the paper. Section 3 and Section 4 present the proposed and implemented single-unit and multi-unit auction models, respectively, describing each one in detail. The considered case studies are explored in Section 5. Section 6 introduces and discusses the results obtained from the P2P transactions of each auction model, considering the case studies. This paper concludes with Section 7, stating the main conclusions that could be taken from the comparative competitive-market analysis of the P2P trading models and the prospects for future work.

2. Peer-to-peer auction framework

The proposed peer-to-peer auction framework was developed in the Microgrid Intelligent Management (μGIM) platform. This multi-agent system allows the representation of end-users, integrating the end-users loads and resources, and providing an energy management solution for the end-users building/home. The μGIM, not only can manage the end-users building/home, but also provides a communication layer to enable communication and negotiation with other end-users and players.

2.1. μGIM

The six auction models were implemented, compared, and validated through the μGIM platform proposed in [34]. This solution provides an agent-based management system that enables the monitoring and control of building resources, as well as energy trading among microgrid end-users. The agents run in low-cost and low-power single-board computers (SBC) and energy analysers and internet of things devices, such as smart plugs, are used to manage energy resources.

The μGIM platform provides a base for peer-to-peer energy trading markets where microgrid's end-users can participate, to buy or sell energy. The auctions are distributed and auctioned by the sellers. However, the μGIM platform only had a pre-existing English model, discussed in [35]. This paper presents five new auction models and their respective bidding strategies that are proposed and tested in the μGIM platform, alongside the pre-existing English model.

In the μGIM platform, agents perform local hour-ahead and fifteen-minute-ahead forecasts to predict what their consumption and generation will be for the next periods. These forecasts are obtained using support vector machine (SVM) algorithms that consider as input the historical data and weather forecasts provided by third-parties. The peer-to-peer auctions are performed each hour and agents use the hour-ahead forecasted consumption and generation to decide on the amount of energy to buy or sell at each auction [35].

The forecasts, available by μGIM platform, enable the end-users to manage their energy usage ahead in time. This allows end-users to participate in auctions for energy trading. Where they can negotiate and bid energy lots among each other. Therefore, an hour-ahead auction-based approach is proposed in this paper to enable energy trading among end-users, promoting the use of local generation, namely volatile renewable energy sources.

2.2. Auctions

A large variety of market schemes fall under the concept of "auction" [36]. Hence, it can be difficult to accurately describe what constitutes an auction. Across all typical market models that are considered as auctions, prevails the use of bids for buyers to report their willingness to pay, and the market's outcome is deduced solely from these reported values [36].

In the proposed framework, an auction is considered to be an hourly event in which an auctioneer gathers energy lots to be sold and performs auctions in which buyers submit bids for the given units to whom they are then sold. The set of lots to be auctioned constitutes an "auction catalogue" and an auction model consists of rules and logic that govern the process by which the lots in the auction catalogue are auctioned. Thus, the nature of the energy lots, the way the lots are auctioned, the bids, and the outcome vary across different auction models.

The considered P2P auction models are executed on an hourly basis and the process consists of two distinct phases: the first consists of the gathering of the energy lots to sell; and the second one focuses on the collection of bids and on calculating the auction's outcome. The first phase is executed at the 30-minute, after which the second phase begins, at the 35-minute mark. Based on their hour-ahead forecasts, the agents attempt to negotiate their next-hour energy surplus or deficit encapsulated as energy lots to sell or as bids to buy lots through P2P energy trading.

An energy lot is represented by the amount of energy (in Wh) that a seller wishes to sell together with the minimum price at which it can be sold, which is presented in EUR/kWh (the same price format is used for biding). An agent determines the amount of energy to sell in an auction as in equation (1)

$$E^s_{a_{ac}} = F_{gen_{h+1}} - F_{cons_{h+1}} \tag{1}$$

where $E^s_{a_{ac}}$ is the amount of energy to be sold by agent a in the auction catalogue ac given the hour-ahead forecasted generation $F_{gen_{h+1}}$ and consumption $F_{cons_{h+1}}$.

The prices of bids and lots are limited by the retailer selling and buying energy prices. These limits define the minimum and maximum values at which an energy lot can be traded. These values correspond to the purchase price of energy from the retailer and the price of selling energy to the retailer. Evaluations that reside outside these boundaries are deemed irrational, as an agent would be better off trading with the conventional grid instead. A seller's minimum price for an auction is designated as $L^{min}_{a_{ac}}$ and is given by equation (2)

$$L^{min}_{a_{ac}} = mP^s_a * M^s_h \tag{2}$$

where $L^{min}_{a_{ac}}$ is the minimum price of agent a' s lots in EUR/kWh, M^s_h is the price of selling 1.0 kWh to the conventional grid and mP^s_a is a parametrized value of agent a that denotes the minimum percentage of M^s_h that the agent is willing to sell for.

In a single-unit auction, an energy lot is sold to only one buyer, considering that the lot cannot be divided among multiple buyers (i.e., it is an indivisible unit). If a seller reports all the energy to be sold as a single lot, e.g. 2.0 kWh, there may be no buyer that wishes to buy that amount. As an alternative, the auctioneer could auction 1 Wh at a time, but this procedure would result in auctions taking too long to conclude, and in cases where the amount to trade is particularly high some of the energy may not be able to be sold, with the auction ending before all units in the auction catalogue are auctioned. The use of a maximum lot size threshold solves this issue by making it so that large energy lots are auctioned as smaller sized lots that buyers may wish to bid for. The number of lots that a seller will submit to auction is given by equation (19).

$$\mathrm{L}^{\mathrm{number}}_{\mathrm{a_{ac}}} = \left\lceil \frac{E^s_{a_{ac}}}{ML^s_a} \right\rceil \tag{3}$$

where $L^{number}_{a_{ac}}$ denotes the number of lots to sell and ML^s_a corresponds to agent a's maximum lot size. The use of the maximum lot size parameter enables the auctioning of a multi-unit commodity, such as energy, as a single-unit commodity and, therefore, the use of single-unit auction models for P2P energy trading. Thus, a seller, instead of reporting a single lot, delivers an array of energy lots to be auctioned, each with a maximum size of ML^s_a. The maximum size will define the size of energy lots that agent a will auction. For instance, if agent a has 110 Wh to sell and $ML^s_a = 50Wh$, then agent a will auction three energy lots: two lots of 50 Wh, and one lot with the remaining 10 Wh.

In a multi-unit auction, an energy lot can be sold to multiple buyers, being seen as a divisible unit, or a set of units. Thus, a seller wishing to sell 2.0 kWh will announce this amount as single energy lot, which can then be sold to one buyer if this one desires the whole lot, or to multiple buyers, partitioning the lot into various smaller lots. The amount of energy to sell in an auction is advertised by each seller as an array with a single element.

The amount of energy that can be traded in an auction, considering the consumption and generation hourly data for each agent is given by equation (4)

$$E^t_{h+1} = min\left(E^s_{h+1}, E^b_{h+1}\right) \tag{4}$$

where E^s_{h+1} consists of the summation of the amount of energy, equation (5), that each agent has to sell in $h+1$, which is given by the difference between forecasted generation and consumption, equation (6). Likewise, E^b_{h+1} is the summation of each agent's amount of energy to buy, equation (7), resulted from the difference between forecasted consumption and forecasted generation, equation (8). For equations (6) and (8), if the difference between consumption and generation, and vice-versa, is negative: zero is considered instead.

$$E^s_{h+1} = \sum_a E^s_{a_{h+1}} \tag{5}$$

$$E^s_{a_{h+1}} = \begin{cases} 0, F_{gen_{h+1}} \le F_{cons_{h+1}} \\ F_{gen_{h+1}} - F_{cons_{h+1}}, F_{gen_{h+1}} > F_{cons_{h+1}} \end{cases} \tag{6}$$

$$E^b_{h+1} = \sum_a E^b_{a_{h+1}} \tag{7}$$

$$E^b_{a_{h+1}} = \begin{cases} F_{cons_{h+1}} - F_{gen_{h+1}}, F_{gen_{h+1}} < F_{cons_{h+1}} \\ 0, F_{gen_{h+1}} \ge F_{cons_{h+1}} \end{cases} \tag{8}$$

where E^t_{h+1} is the amount of energy to be traded, and E^s_{h+1} and E^b_{h+1} are the amounts of energy to sell and to buy in $h+1$, by all agents.

3. Single-unit auctions

A buyer's bidding behaviour varies according to the bidding strategy put in place for the given auction type. A bidding strategy defines rules and constraints that a buyer must follow to determine whether to submit the bid and the value of the bid.

Regarding the single-unit auction models, for all the bidding strategies the buyer will submit a bid if and only if (9) holds true

$$L^{size}_{i_{ac}} \le E^b_{a_{ac}} - E^{bp}_{a_{ac}} \tag{9}$$

where $L^{size}_{i_{ac}}$ is the size of lot i from the auction catalogue ac, $E^b_{a_{ac}}$ is the amount of energy that agent a wishes to buy and $E^{bp}_{a_{ac}}$ corresponds to the energy that has been previously bought in the auction. This means that no buyer will bid energy lots with more energy than it is needed. This constraint is used due to the indivisible nature of the single-unit lots, which implies that a buyer must acquire the entire lot. This way, the buyer only bids for lots that can be entirely consumed.

3.1. English auction

The English auction is an open ascending-price single-unit auction in which participants must bid a value higher than that of the latest bid. The auctioneer stops the auction when no new bids are received in a certain amount of time, and the lot is sold to the highest bidder. A buyer can only then submit a bid that is higher than the last submitted bid, such that the bidding price ascends as more bids are submitted. The corresponding bidding strategy follows the one described in [34].

$$SO_{a_{iac}} = SP_a * M_h^b \tag{10}$$

$$IO_{a_{iac}} = L_{iac}^{hb} * IP_a \tag{11}$$

$$MO_{a_{iac}} = MP_a * M_h^b \tag{12}$$

where $SO_{a_{iac}}$ corresponds to the *starting offer* for the lot *i*, from the auction catalogue *ac*, and SP_a is a parameterized percentage value to be multiplied by the purchase market price, M_h^b. The $IO_{a_{iac}}$ is the *incremented offer*, calculated by the product of L_{iac}^{hb}, the current highest bid for lot *i*, and the increment percentage IP_a. The *maximum offer* $MO_{a_{iac}}$ is the product of the maximum price percentage value MP_a and M_h^b. At the start of each auction the L_{iac}^{hb} is set to be equal to L_{iac}^{min}, ascending according to the submitted bids.

The constraint in equation (13) validates if the *maximum offer* parameter is higher than the current auction price. If held true, agent *a* will submit an offer ($O_{a_{iac}}$) for lot *i* according to equation (14), otherwise, no bid will be submitted.

$$L_{iac}^{hb} < MO_{a_{iac}} \tag{13}$$

$$O_{a_{iac}} = \begin{cases} SO_{a_{iac}}, L_{iac}^{hb} < SO_{a_{iac}} \\ IO_{a_{iac}}, L_{iac}^{hb} \geq SO_{a_{iac}} and IO_{a_{iac}} \leq MO_{a_{iac}} \\ MO_{a_{iac}}, L_{iac}^{hb} \geq SO_{a_{iac}} and IO_{a_{iac}} > MO_{a_{iac}} \end{cases} \tag{14}$$

Hence, bids are received in ascending order, and after each bid, the auction will wait and listen for a higher bid, before closing. If a higher bid is received, the closing time is reset, and the auction will attempt to wait again. The amount of time that the auction will wait for is given by the "closing time", a set parametrized value. When the closing time expires, the auction for the given lot closes, and if bids have been received: the winning buyer acquires lot *i* from the seller at $O_{a_{iac}}$, which corresponds to L_{iac}^{hb}.

3.2. Dutch auction

This model is based on the Dutch auction, which is an open descending-price single-unit auction where the auctioneer sets a high enough price so that, presumably, no buyer would want to buy at such price, and decrements the price at a given rate. The buyers can choose to bid at the current price set by the auctioneer or wait until the price is further lowered. The auctioneer then sells the item to the buyer that first submits a bid.

In a Dutch auction, the auctioneer is responsible for calling out a current auction price at which each buyer may choose whether to bid. The current auction price is first set by the auctioneer to the purchase market price (M_h^b), which corresponds to the highest value at which a lot can be rationally sold. This value is advertised to the buyers and if no bid is submitted the current auction price is decremented for the following iteration as in equation (15).

$$CP_{i_{ac}} = CP_{i_{ac}} * (1 - DP) \tag{15}$$

where $CP_{i_{ac}}$ corresponds to the current auction price for lot *i* of auction catalogue *ac*, and DP refers to a decrement percentage, which is multiplied by the current price, thus decrementing it. The current price is decremented, advertised, and decremented again until reaching the lot's minimum price (L_{iac}^{min}), after which the lot cannot be sold. A lower decrement percentage (DP) leads to longer auctions, which take a longer time to reach the lot's minimum price, and a higher decrement percentage (DP) results in fewer iterations. A decrement percentage (DP) of 0.10 was considered and deemed appropriate, as it provides a balance between both extremes.

The winning buyer is the first buyer to submit a bid, accepting the current price ($CP_{i_{ac}}$) advertised by the auctioneer. Each buyer calculates a bid $O_{a_{iac}}$ as in equation (16).

$$O_{a_{iac}} \in U\left(L_{iac}^{min}, MO_{a_{iac}}\right) \tag{16}$$

where $O_{a_{iac}}$ is a possible bid from agent *a* for lot *i* in auction catalogue *ac*, randomly drawn from the uniform distribution $U\left(L_{iac}^{min}, MO_{a_{iac}}\right)$. The random draw from the given distribution means that a value is chosen at random from the range of L_{iac}^{min} to $MO_{a_{iac}}$.

If the condition (17) is held true, the buyer submits the bid, otherwise, the buyer will wait for the price to lower further before bidding, increasing the possible profit gained from the trade while risking that another buyer will bid first and acquire the energy lot.

$$O_{a_{iac}} \geq CP_{i_{ac}} \tag{17}$$

3.3. First-Price auction

The first-price sealed-bid auction, also known as the "blind" auction, is a single-unit auction in which each buyer submits a bid in a sealed-envelope fashion such that the information regarding their bid remains private throughout the auction process. The auctioneer unseals the bids and sells the item to the highest bidder. Contrary to the open auctions, in the sealed-bid auctions, the bids for a lot are all submitted in one iteration.

In the first-price sealed-bid auctions, each buyer submits at most one bid for each auctioned lot. The bid calculation and submission are preceded by the constraint (18), which validates that the maximum price that the buyer is willing to pay surpasses the minimum price at which the lot can be sold. If the constraint is not held true, the buyer will not submit a bid for the given lot.

$$L_{iac}^{min} < MO_{a_{iac}} \tag{18}$$

Following constraint (18), each buyer calculates a bid by randomly drawing a value from a uniform distribution as in equation (16), then submitting it to the auctioneer. The auctioneer waits for a certain period for all buyers to finish bidding (closing time value), after which the sealed bids are opened, and the winning buyer is chosen based on the highest bid. The winning buyer proceeds to pay its' respective bid.

3.4. Second-price auction

The second-price auction proposed by William Vickrey in [37], is a sealed-bid single-unit auction in which the winning buyer pays the second-highest bid, instead of its own. As in the first-price auction, buyers submit sealed bids and the auctioneer opens the sealed bids and sells the item to the highest bidder.

If only one bid has been submitted, the price paid in the Vickrey auction corresponds to the minimum price for the lot, L_{iac}^{min}. Hence, in the Vickrey auction, the winning buyer always pays a lower value independent from his own bid.

Although rare, two bids can present the same value, thus consisting in a tie. As a tiebreaker mechanism, the bid's age is considered, thus choosing the oldest bid over the latest, for both the Vickrey and Blind models.

4. Multi-unit auctions

In the two multi-unit auction models, proposed in this paper, lots are sold in a sequential manner, similar to the single-unit auctions, contrary to popular implementation wherein all the energy lots are auctioned in one go, simultaneously.

Through the simultaneous approach, buyers and sellers announce their energy deficit and surplus as bids and lots, respectively. The auctioneer proceeds to order bids in descending prices and lots in ascending order. After the initial ordering process, the auctioneer matches bids and lots, thus deciding the auction's outcome. Through this approach, buyers do not know that lot they are bidding for, for it is decided for them by a central entity (the auctioneer). The matching of bids and lots by a central entity is contradictory to peer-to-peer trading, in which decision making is distributed across autonomous entities.

On the other hand, the sequential approach consists of auctioning one lot a time, sequentially, thus allowing buyers to have knowledge about what they are bidding for, and to bid accordingly. The sequential approach offers a higher degree of independence and autonomy with distributed decision making, which in turn is consistent with peer-to-peer trading.

4.1. Uniform-price auction

The uniform-price auction (UPA) consists of a sequential multi-unit auction in which each lot of the auction's catalogue is sequentially sold at a given market-clearing price. The market-clearing price is a value at which a lot's energy will be traded at. In this auction, this price can refer to the value of the highest losing bid or the lowest winning bid [36,38]. In this paper, the highest losing bid market-clearing price is considered.

In multi-unit auctions, the buyers submit multiple bids based on declining marginal prices (i.e., curving bid). This concept dictates that the value of obtaining an additional unit decreases as more units of a given commodity are acquired.

The marginal price can decrease in multiple different ways, varying based on individual preferences, commodity, and external environmental factors. In this paper, a simple linear decrease behaviour is considered, as depicted in equation (19).

$$P = \left(-\frac{E^{bp}_{a_{ac}}}{E^{b}_{a_{ac}}} + 1 \right) * \left(O_{a_{i_{ac}}} - L^{min}_{i_{ac}} \right) + L^{min}_{i_{ac}} \tag{19}$$

where P corresponds to the marginal price to be paid given the amount of energy already bought ($E^{bp}_{a_{ac}}$).

The price paid for the first unit to be obtained corresponds to the maximum value $O_{a_{i_{ac}}}$, and it decreases linearly, with the last unit price being close to the minimum value $L^{min}_{i_{ac}}$. The maximum value is randomly drawn from a uniform distribution, as in equation (16).

A buyer partitions his desired energy volume into multiple bids and calculates their values in accordance with the decreasing marginal price concept, following equation (19). The energy allocation through several bids is analogous to the way that a seller submits multiple energy lots to be sold in a single-unit auction, meaning that the energy is segmented into multiple bids based on a maximum bid size threshold. The number of bids to be submitted is given by equation (20).

$$O^{number}_{a_{i_{ac}}} = \left\lceil \frac{E^{b}_{a_{ac}}}{ML^{s}_{a}} \right\rceil \tag{20}$$

in which $O^{number}_{a_{i_{ac}}}$ corresponds to the number of bids of agent a for a lot i of the auction catalogue ac, obtained by all the energy to be bought, $E^{b}_{a_{ac}}$, divided by the maximum size threshold, ML^{s}_{a}. As in the single-unit lot scenario, in this paper, the maximum size threshold is globally set to 100 Wh.

4.2. Discriminatory-price auction

The Discriminatory-Price auction (DPA) is a "pay-as-bid" sequential multi-unit auction. In this auction, buyers submit a single curve bid in a sealed-bid format, and the auctioneer orders the bids in descending order, allocating energy from the highest to the lowest bid until all energy is allocated or the bids fall below the lot's minimum value, as in the UPA.

Contrary to the UPA, in the DPA there is no market-clearing price, given that each buyer pays its' respective bid value. This leads to scenarios in which two or more buyers split the same lot but pay potentially different prices.

5. Case studies

This study considers a microgrid with five prosumers represented by five μGIM agents: agent Z.0, agent L.1, agent L.2, agent L.3, and agent R.2. Each agent is responsible for the energy management of a physical segment of a building. Five SBCs were used, one for each agent: two NanoPi M1 Plus (with 1.2 GHz quad-core CPUs and 1 GB of RAM running the Ubuntu 16.04.6 LTS operating system), and three Raspberry Pi Model B+ (with 1.4 GHz 64-bit quad-core CPUs and GB of RAM running the Raspberry Pi OS operating system).

Each agent was responsible to store its own data, using PostgreSQL 9.5.19 local databases running locally in their SBC. The resulted data is analysed in this paper and can be seen in full in [39].

The building's total generation is derived from an array of PV panels with 10.0 kW peak generation and was distributed among the five agents, with Z.0 receiving 60% of total generation (i.e., 6.0 kW peak generation) and the remaining agents receiving 10% each (i.e., 1.0 kW each).

In this paper, a ML^{s}_{a} (i.e., maximum lot size) of 100 Wh was considered for every agent. Also, every agent is configured with an mP^{s}_{a} of 110%. Regarding the English auction, the "closing time" was defined as a subsecond value of 900–650 ms. This value is considered as more than sufficient due to the fast communication speed verified in the agent-based μGIM platform.

The results presented in this paper were gathered from the P2P energy trading framework considering the four single-unit and the two multi-unit P2P models, proposed and described in this paper. The trading was done between the five microgrid's agents, using consumption and generation data from May 13th to May 18th, 2019, and September 30th to October 6th, 2019, full weeks from Monday to Sunday. In total, 2.016 periods were executed where agents could freely participate in P2P auctions and a total of 5280 energy lots were transacted among end-users.

The energy data portrait the real consumption and generation of an office building in which the research has been conducted. The building is occupied on workdays (Monday to Friday), from 08:00 to 20:00. The building's activity begins at 08:00 when the first building's occupants begin to arrive; most occupants arrive until 11:00. The lunchbreak is flexible but generally occurs between 13:00 and 14:00. At the end of the day, the first occupants begin to leave the building at 17:00, and at 20:00 the building is typically left unoccupied. During the night-time (20:00–08:00), and on Saturdays and Sundays, the building has no occupants.

The agents are free to participate in the P2P distributed auctions to buy and sell energy from their neighbours. However, all of them are connected to an energy retailer where they can also buy and sell energy at less attractive prices. The market prices considered in this case study were 0.10 EUR/kWh, for the selling market price, and 0.20 EUR/kWh, for the purchasing market price.

The consumption and generation during the considered week of May is representative of a high energy generation profile, while the values pertaining to the week of September/October correspond to a relatively low energy generation profile. Both weeks were chosen to analyse energy trading where there is a high generation profile, in this case with a surplus (more energy generated than consumed) on some days, and a low generation profile, providing a heterogeneous range of profiles in which to compare the P2P models.

Fig. 1 and Fig. 2 refer to energy consumption, generation, and the amount of energy available for trading in the microgrid for the two considered case studies.

On the high generation energy profile (Fig. 1), the stationary consumption revolved around 3–4 kWh, occurring during the night and on weekends, i.e., in periods in which the building is not being used. During the week, at daytime the consumption began to significantly increase in the period from 10:00 to 11:00 and still increasing until 13:00. After 13:00, the increase in consumption either slowed down – on the 13th and 14th of May – or slightly decreased – on the 15th, 16th, and 17th of May – due to lower usage of the building premises during lunch.

Work resumes at 14:00, and the consumption increases until around 16:00–18:00, when it peaked at 8.5–9.3 kWh, on the 13th, 14th, and 15th of May, and at around 7–7.5 kWh, on the 16th and 17th of May. After 18:00 the consumption drops, hitting the stationary consumption level around 20:00. Generation throughout the week began at 07:00 and lasted until 21:00. During the weekdays, it peaked at 13:00–14:00, with values revolving around 6–7 kWh. On the weekend, generation increased and hit peaks of 7–7.3 kWh, and surpassed consumption, meaning that some of the generated energy could not be traded within the microgrid, having to be sold to the grid at the market selling price.

On the low generation energy profile (Fig. 2), stationary consumption revolved again around 3–4 kWh, during night-time and on the weekend. On weekdays, the consumption increased from 10:00 to 13:00, decreasing or slowing down at around 13:00–14:00 h, and increasing until peaking at 16:00–17:00. Afterward, consumption decreased until 20:00. The consumption peaked at values revolving around 8.3–8.8 kWh, with an exceptionally high peak on September 30th, at 10 kWh. The generation began at 08:00, lasting until 20:00, and peaking around 13:00–14:00. The daily peaks were registered in the range of 3.3–4.5 kWh. From Monday to Friday, the amount of energy that could be traded was very low, not more than 1.0 kWh, and on some days even below 100 Wh. On the weekend, the decrease in consumption led to an increase in the energy that could be traded, which went up to around 2.0 kWh at the highest peak.

On the high generation week, the generation period is longer than that of the low generation week, with the generation of energy beginning earlier and ending later in the day. The same effect was verified in the amount of energy to be traded, in which trade occurred during longer periods through the week as compared with the low generation week. This resulted in more energy to be traded, despite peaks of energy to trade on the low generation week matching the high generation week, at around 2.0 kWh.

6. Discussion

Fig. 3 and Fig. 4 show the daily trading volume for each of the framework's models, regarding the two considered weeks, disregarding retailer transactions. Fig. 4 shows energy efficiency (percentage of energy traded) throughout the case studies the results shown in Fig. 3 show that all the models performed well, having close volumes of transacted energy. The differences between the models can be seen in Fig. 4, which presents the volumes in a percentage format, based on the maximum volume of energy that could have been traded. The multi-unit models (UPA and DPA) both achieved 100% of energy efficiency throughout the case studies. The single-unit models showed a worse performance, and no individual model consistently surpassed the other three single-unit models, with the four models showing close results throughout the case studies. However, the Dutch auction was the worst auction model on most occasions. Despite the differences between the six models, the lowest daily percentage was that of the Dutch and English models, on May 17th, sitting at 96.6%, which proves that all of the models performed very well throughout the case studies, with daily values above the 95.0% threshold.

The percentage of energy trading of the single-unit auctions decreased as the volume of energy to be traded increased. This can be explained by the choice of which lot to auction being based on a FIFO (first-in-first-out) method. Consider two buyers – buyer A and buyer B – with demands of 60 Wh (buyer A), and 50 Wh (buyer B), and a single-unit auction with an auction catalogue with two lots of 50 Wh and 60 Wh each. If buyer A, with 60 Wh demand, acquires the 50 Wh lot, then the 60 Wh lot will not be sold, due to buyer B needing only 50 Wh. In this scenario, buyer B does not acquire its desired energy, and buyer A acquires a suboptimal amount.

Fig. 5 depicts the relationship between energy efficiency, registered every hour throughout the case studies, and the volume of energy to trade in the respective hour. Initially, the efficiency remains at 100%, decreasing slightly as the trading volume increases, but begins again to increase, reaching the 100% mark towards the end. It seems to be that with further increases in trading volume, the efficiency will tend to increase towards the 100% mark.

Although further studies are required to ascertain these beliefs. The results show that the lot size impacts the amount of energy being transacted in each auction. Therefore, energy lots smaller will have the ability to increase energy efficiency while increasing the number of lots in the auction catalogue. An alternative would be the set of energy lots according to a distribution function or a new strategy of lots creation, enabling the agent to provide several lot sizes in the same auction, contemplating the existence of small, medium, and large lot sizes.

Regarding pricing in P2P energy transactions, Fig. 6 shows the daily average for each model, as well as the volume of energy to buy, to sell, and to be traded in the microgrid during the two weeks. The figure can be divided into four scenarios: (I) May 13th to 17th, with moderate-

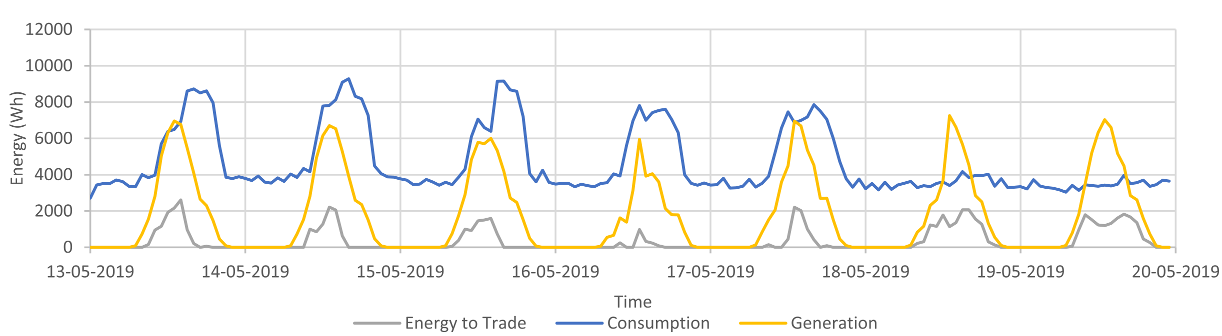

Fig. 1. Energy profile for high generation week (May 13th to 19th, 2019).

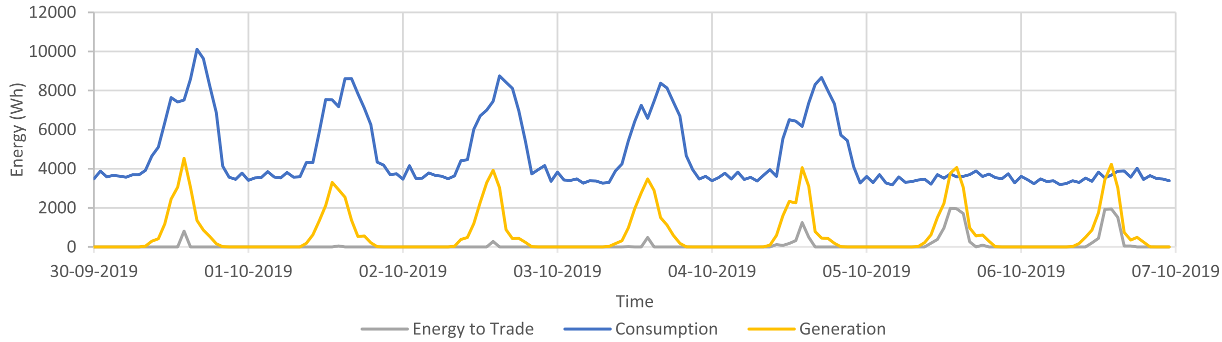

Fig. 2. Energy profile for low generation week (September 30th to October 6th, 2019).

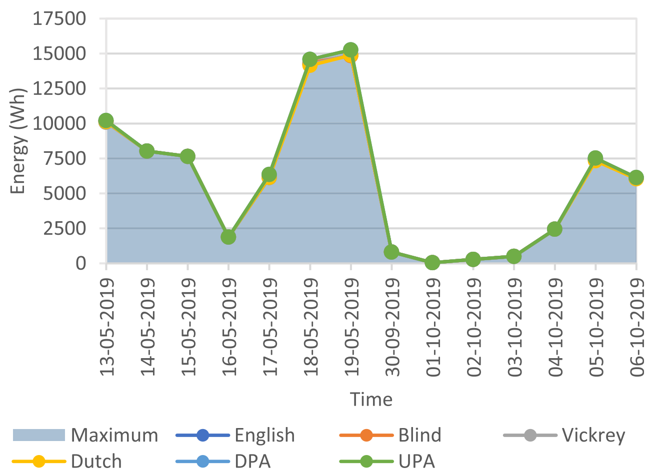

Fig. 3. Amount of daily energy traded for each model, during both high and low generation weeks.

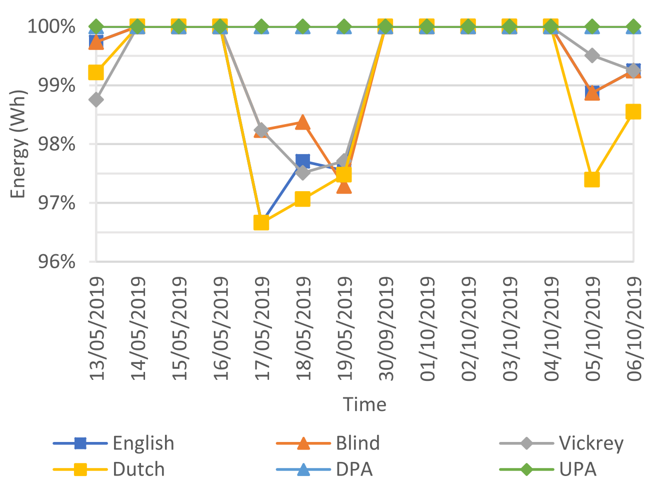

Fig. 4. Percentage of daily energy trading efficiency for each model during both high and low generation weeks.

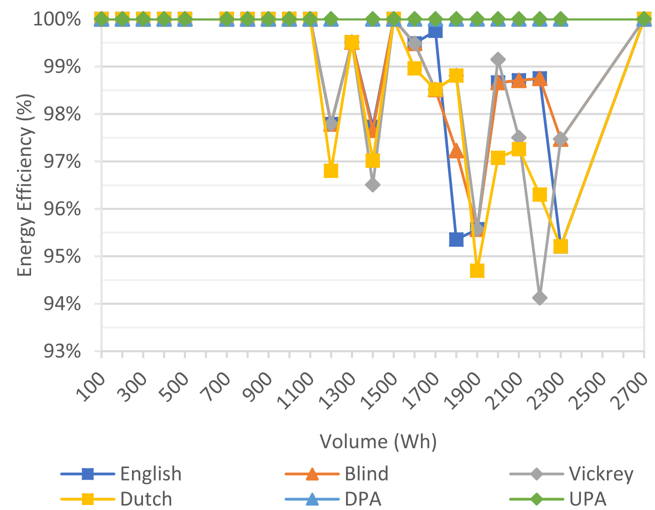

Fig. 5. Energy efficiency percentage by hourly volume of energy traded, gathered from both weeks.

demand and moderate-supply; (II) May 18th to May 19th, with low-demand and high-supply; (III) September 30th to October 4th, with high-demand and low-supply; (IV) October 5th to 6th, with moderate-demand and moderate-supply.

In the scenario I, prices remain consistently moderate. In the second scenario (scenario II) the prices decrease due to the decrease in demand and the increase in supply. The prices in scenario III increase compared to the scenario I and II, with the increase in demand and the decrease in supply. Scenario IV is similar to the scenario I, with moderate-demand, moderate-supply, and hence, moderate price ranges. The price fluctuations according to changes in demand and supply are consistent with the economic law of supply and demand, which states that: if demand increases and supply remains the same, the price increases, and if supply increases while demand remains the same, the price decreases [40].

The way an auction model's prices react to changes in the environment (i.e., supply and demand) varies based on the degree of *price stickiness*, which refers to how much price increases or decreases as a result of supply and demand changes. For example, in a scenario in which demand increases by 2 kWh a model may increase its price by 0.04 EUR/kWh, while another model may increase only by 0.01 EUR/kWh. In the given example, the latter model has a "stickier" price than the first.

The standard deviation of the models' daily average prices experienced throughout the two case studies provides the means to compare the degree of *price stickiness*, given that a high standard deviation (SD) corresponds to a low *price stickiness* degree, and vice-versa. Following this notion, the six models can be divided into three groups, as follows: (I) Vickrey ($SD = 0.014$), UPA ($SD = 0.014$) and DPA ($SD = 0.012$); (II) Dutch ($SD = 0.005$) and Blind ($SD = 0.006$); (III) English ($SD = 0.019$). The first group has a standard deviation of 0.012–0.014, representing a moderate degree of *price stickiness*. The second group presents a standard deviation of 0.005–0.006, half of that of the first group, which in turn indicates to a higher degree of *price stickiness* and less price reactivity to market changes. The third group experiences the lowest degree of *price stickiness* with a standard deviation of 0.019, which can be further analysed by the way in which the daily average price of the English model varies across the case studies and the different market scenarios.

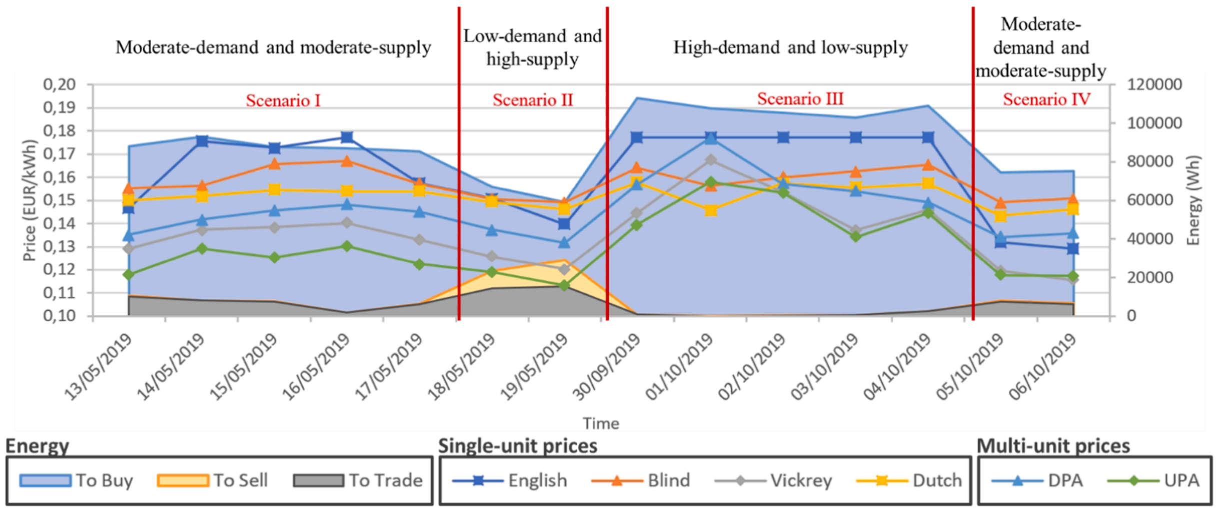

Fig. 6. Daily average prices and consumption/generation energy volume.

Fig. 7 further illustrates how each model's price reacts to supply and demand fluctuations. This figure consists of the model's average hourly prices ordered based on a competitiveness index and grouped into 11 categories, consisting of ranges of 1.0 kWh. The competitiveness index consists of the difference between the amount of energy to buy and the amount of energy to sell in the respective hour. The Vickrey, UPA, and DPA models increase in a linear fashion, as do the Blind and Dutch models, although these two introduce a curve with a much lower inclination than the one followed by the first three models. The English model is the one with the highest price adaptability, increasing at a fast pace, stagnating upon reaching the 2.0–3.0 kWh range.

Fig. 8 and Fig. 9 show the average price and traded energy volume for each model, considering the two case studies, on a per prosumer/agent basis. Regarding the amount of energy traded, there are agents who sold energy, who bought energy, and those who performed both throughout the case studies. Agent Z.0 bought an insignificant amount of energy, and sold around 70 kWh, being the largest seller among the five agents. Besides agent Z.0, the only agents who sold energy were agents L.3 and R.2. These two agents bought and sold energy, although each sold around 5 kWh, and bought an approximate amount. On the other hand, agents L.1 and L.2 acted as unique buyers, not selling any of their generated energy. Agent L.2 was the largest buyer, averaging 51.4 kWh, followed by agent L.1, who bought an average of 21.4 kWh.

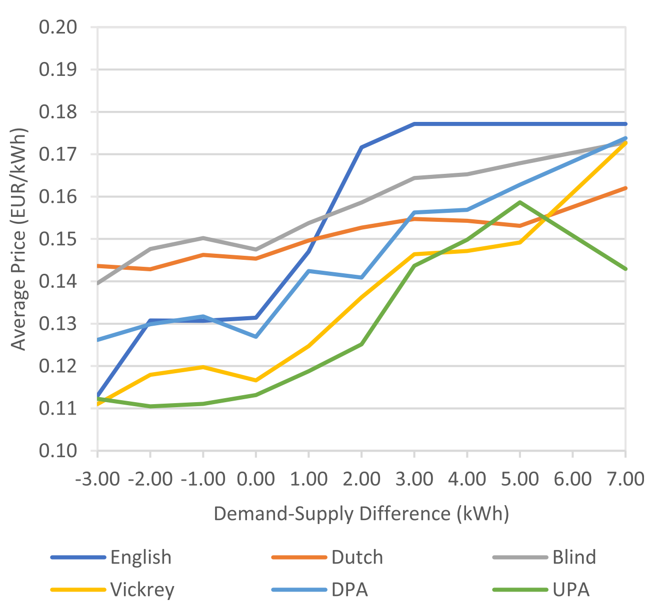

Fig. 7. Average pricing vs the difference between demand and supply (competitiveness).

The average pricing experienced by these agents differs. Agent L.2, the largest buyer, experienced the lowest buying prices on all models. Agent L.1 had lower buying prices than agents L.3 and R.2, despite the differences being negligible on some of the models, such as on the English and Dutch. These results show an inverse relationship between the amount of energy an agent buys and the prices he pays. This relationship is expected and comes in accordance with the economic law of demand, wherein the quantity of demand and price are inversely correlated, meaning that the increase of one of the two values results in the decrease of the other [41].

Regarding the average selling price, agent Z.0 shows a higher selling price than that of agents L.3 and R.2 on the Dutch, Blind, and Vickrey models, and an equivalent or lower price on the English, UPA, and DPA models. According to the law of supply, it is expected that agent Z.0 would experience higher values than those of agents L.3 and R.2. However, on some models, this does not occur. The inconsistency in these results comes from the use of a simplistic strategy for lot minimum price calculation, which is always set to 0.110 EUR/kWh.

The use of a static price makes the sellers behave as *price-takers*, not influencing pricing schemes in the auction models. Therefore, sellers accept the prices set by the buyers who, in turn, influence the market prices through more dynamic bidding strategies, hence acting as *price-makers*. Furthermore, agent Z.0 vastly surpasses agents L.3 and R.2 in terms of volume sold, which could result in agent Z.0 acting in a monopolistic manner with better strategies.

Despite differences between the various models and pricing schemes, all models resulted in profits for every microgrid end-user, as seen in Table 1. The UPA and DPA models showed the highest percentage of monetary savings for the two considered case studies, both with 6.11% and 1.31% for the high and low generation weeks, respectively. The Vickrey, Blind, and English models followed, with 6.02–6.03% and 1.30% for the two case studies. The Dutch model emerged as the worst model, with 6.00% and 1.29%, consistent with the notion that the Dutch was the worst model from an energy trading efficiency perspective.

Agent Z.0, the largest seller, experienced the highest benefit with the Blind model (99.39%, and 5.46% for high generation and low generation weeks, respectively), and the lowest with the Vickrey (52.32%, and 2.49%) and the UPA (46.39%, and 3.13%) models. Agents L.1 and L.2, the largest buyers, had the highest profits with the Vickrey (4.50%, and 0.78% for L.1)(4.91%, and 1.42% for L.2) and the UPA (4.16%, and 0.87%)(5.52%, and 1.23%) models. The Vickrey and the UPA models

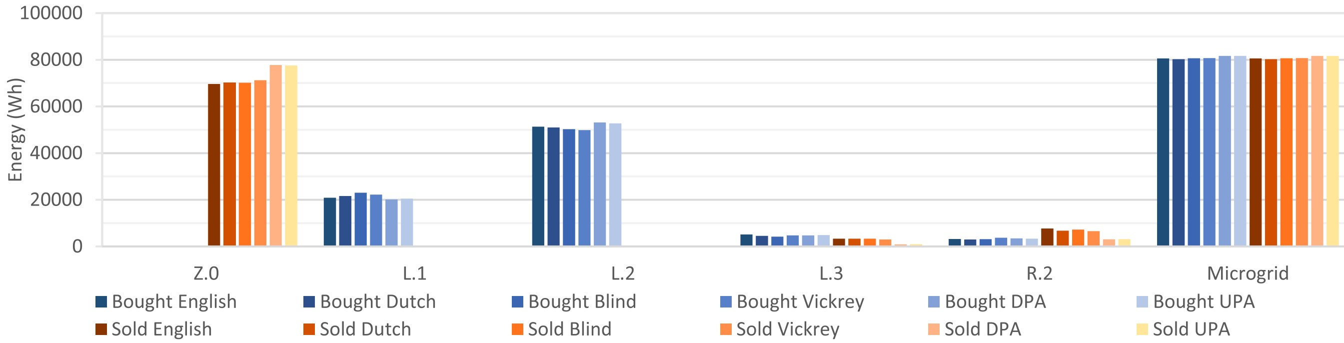

Fig. 8. Individual volume of energy sold and bought in each model.

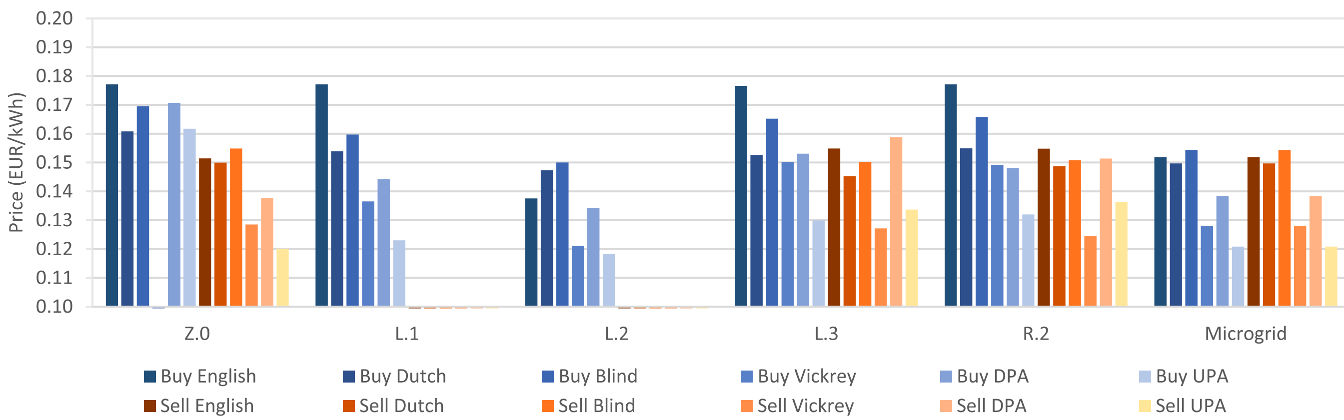

Fig. 9. Individual average prices for each model.

Table 1
Weekly monetary energy expenses, and profit percentage, per agent.

			Z.0	L.1	L.2	L.3	R.2	Microgrid
High Generation Week (May 13th to 19th)	**Weekly Expenses (EUR)**	Without P2P	3.069 €	27.575 €	59.921 €	9.538 €	4.611 €	104.714 €
		English	0.123 €	27.174 €	57.611 €	9.281 €	4.225 €	98.414 €
		Dutch	0.327 €	26.749 €	57.903 €	9.232 €	4.219 €	98.430 €
		Blind	0.019 €	26.795 €	58.065 €	9.272 €	4.248 €	98.398 €
		Vickrey	1.463 €	26.335 €	56.978 €	9.295 €	4.343 €	98.414 €
		Discriminatory	0.429 €	26.644 €	57.500 €	9.345 €	4.400 €	98.319 €
		Uniform	1.645 €	26.427 €	56.611 €	9.233 €	4.402 €	98.319 €
	Savings (%)	English	96.01%	1.45%	3.85%	2.70%	8.36%	6.02%
		Dutch	89.35%	3.00%	3.37%	3.21%	8.49%	6.00%
		Blind	99.39%	2.83%	3.10%	2.79%	7.87%	6.03%
		Vickrey	52.32%	4.50%	4.91%	2.55%	5.80%	6.02%
		Discriminatory	86.03%	3.37%	4.04%	2.02%	4.56%	6.11%
		Uniform	46.39%	4.16%	5.52%	3.19%	4.52%	6.11%
Low Generation Week (September 30th to October 6th)	**Weekly Expenses (EUR)**	Without P2P	15.785 €	28.294 €	72.202 €	11.949 €	7.451 €	135.681 €
		English	15.153 €	28.218 €	71.304 €	11.904 €	7.341 €	133.921 €
		Dutch	15.014 €	28.125 €	71.530 €	11.892 €	7.377 €	133.936 €
		Blind	14.923 €	28.178 €	71.565 €	11.899 €	7.355 €	133.921 €
		Vickrey	15.392 €	28.073 €	71.177 €	11.893 €	7.382 €	133.916 €
		Discriminatory	15.154 €	28.157 €	71.350 €	11.892 €	7.355 €	133.908 €
		Uniform	15.292 €	28.049 €	71.315 €	11.882 €	7.370 €	133.908 €
	Savings (%)	English	4.00%	0.27%	1.24%	0.37%	1.47%	1.30%
		Dutch	4.89%	0.60%	0.93%	0.48%	0.99%	1.29%
		Blind	5.46%	0.41%	0.88%	0.41%	1.29%	1.30%
		Vickrey	2.49%	0.78%	1.42%	0.47%	0.92%	1.30%
		Discriminatory	4.00%	0.49%	1.18%	0.47%	1.28%	1.31%
		Uniform	3.13%	0.87%	1.23%	0.55%	1.08%	1.31%

are the ones with the lowest average price. Therefore, they primarily benefit buyers, while the Blind model, due to its higher price, benefits the sellers.

Given the Vickrey and the Blind models as two extremes, it could be assumed that the English model would provide a ground between the two models in which both the buyers and sellers are equally benefited. However, for agent L.1 the English auction is associated with the worst result. An alternative would a sealed-bid single-unit auction model in which first-price and the second-price rules, employed by the Blind and the Vickrey models, are used with 50% probability. This way, both the sellers and the buyers could be equally benefited. This alternative requires further analysis to ensure the hypothesis of equal benefit for sellers and buyers holds true.

Similarly, a case can be made towards the conception of a model balancing the UPA and the DPA, given that the UPA benefits the buyers whilst the DPA benefits the sellers, though to a lesser degree in this study than the Blind model.

Theoretically, the Dutch and the Blind models are strategically equivalent, as well as the English and Vickrey models [36,37], and as such should yield close theoretical revenue. However, results show that in both equivalencies there is a significant difference in average pricing. This discrepancy between theory and the actual results is due to the different bidding strategies being used across the four models, in which the Blind and Vickrey employ similar strategies but different from the ones used by the English and Dutch, due to their open auction nature. The determination of a single price for each lot, to be used in every bid request corresponding to that lot is expected to close the gap between the equivalent single-unit models. Furthermore, the English model does not use randomly drawn values in its bidding strategy, which may also contribute to distinct revenues.

The participation in P2P auctions allows end-users to buy and sell their energy demand and surplus. However, this is based on forecasting algorithms that enable the hour-ahead P2P transactions. The errors associated with the forecasting algorithms will affect the efficient hour-ahead planning of the end-user and during the period it can be forced to sell or buy more energy than the amount transacted in the P2P auctions. In this case, the end-user can have two approaches to balance energy demand and supply, (i) sell or buy the remaining energy at less attractive prices to/from the retailer, and (ii) use the flexibility of local energy resources to balance the consumption and the generation (i.e., local generation available plus the energy bought in P2P auctions). The μGIM solution enables agents to have those two approaches. The negotiation with its neighbours (using P2P) and with the retailer can be seen in [35]. And the real-time balance between consumption and generation, considering user preferences, can be seen in [2].

7. Conclusion

This paper explores the concept of transactive energy through peer-to-peer energy trading within a microgrid, using the μGIM agent-based management system. A single-unit and multi-unit auction framework was proposed, considering six P2P models based on the English, Dutch, Vickrey, and Blind single-unit auctions, and on the discriminatory-price and uniform-price multi-unit auctions. The peer-to-peer models were tested in a real microgrid with five prosumers. The results are shown for a high generation week (May 13th – 19th, 2019), and a low generation week (September 30th – October 6th, 2019). Each model was implemented using simple bidding strategies, most of which based on random draws from uniform distributions, as well as the concept of a lot with a size threshold allowing the use of single-unit auctions for trading multi-unit commodities, such as energy, and the notion of diminishing marginal price, applied to the multi-unit auctions' bidding strategy.

The six hour-ahead proposed models were implemented in the multi-agent system of the microgrid and executed simultaneously every hour. The execution of such models in single-board computers proved the possibility of having low computational hardware deployed in the end-users (fog-computing) to enable peer-to-peer transactions without the need of a centralized operator.

The proposed auction framework for energy trading, through the six peer-to-peer models, has shown compliance with the economic law of supply and demand. Thus, supporting the usage of transactive energy peer-to-peer trading, and the framework in specific, for energy demand and supply balancing, ensuring greater grid reliability and stability. The adoption of more sophisticated strategies for both sellers and buyers would enable a deeper analysis considering both the seller's and the buyer's perspectives. Different strategies might improve the proposed framework and provide the means to compare peer-to-peer auction models based on behaviours closer to those that may be experienced in real-world auction scenarios. Moreover, better strategies for the sellers may enable the analysis of compliance with the economic law of supply and the use of case studies in which the volume of energy to sell is better disperse, avoiding the occurrence of monopolistic behaviours.

The use of flexibility was introduced in this paper as part of a balancing algorithm to be used after peer-to-peer transactions, reducing grid transactions in real-time. However, bid strategies accounting end-user flexibility can be applied to increase the end-user profit in the peer-to-peer auction-based transactions.

The Blind auction model proved to be the best from the sellers' perspective, while the Vickrey and the uniform-price were the models with better results for the buyers. The found results support the creation of a new mixed model based on first- and second-price auction types, to equally benefit buyers and sellers. Likewise, the new model should also take into account the balancing of uniform- and discriminatory-price models.

Despite the differences in seller-buyer benefit ratio, the multi-unit auctions outperformed the single-unit auctions, with a 100% energy trading efficiency and greater monetary savings, registering values of 6.11% on the week with a high generation profile, and 1.31% on the week with a low generation profile, in comparison to the values of 6.00–6.03% and 1.29–1.30% of the single-unit auctions. Therefore, it can be stated that the multi-unit auctions are superior to the single-unit auctions regarding the case studies highlighted in this paper. Although further research is required into the comparison of multi-unit and single-unit auctions, this paper supports the future implementation of multi-unit over single-unit auctions for peer-to-peer energy trading among microgrid end-users.

The proposed framework has proven to be able to test multiple peer-to-peer auction models simultaneously in a real uncontrollable environment, such as the used microgrid. Overall, the four single-unit and the two multi-unit models implemented in the proposed framework enabled approximately 6.00% decrease in energy expenditure on the high generation week and a 1.30% decrease on the low generation weeks. Every end-user in the microgrid benefited from peer-to-peer energy trading through every model, in comparison to peer-to-grid trading. This proves the potential of a transactive energy approach using peer-to-peer auctions for the end-users' economic benefit.

CRediT authorship contribution statement

Daniel Teixeira: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Luís Gomes:** Conceptualization, Methodology, Validation, Investigation, Resources, Writing - review & editing, Visualization, Supervision. **Zita Vale:** Conceptualization, Methodology, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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