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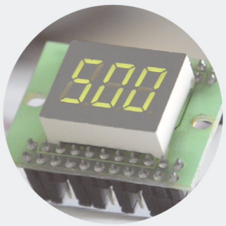


ANALYSIS OF PEER-TO-PEER ELECTRICITY TRADING MODELS IN A GRID-CONNECTED MICROGRID

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Abstract

The thesis proposed an investigation on the implementation of peer-to-peer (P2P) energy transaction platforms in power systems as a possible energy management solution to deal with distributed generation (DG) and renewable energy sources (RES) penetration. Firstly, a state of the art of the current P2P trading technologies development is provided, reviewing and analysing several projects carried out in this field in recent years and doing a comparison of the models, considering their commonalities, strengths and shortcomings, along with.an overview of the main techniques utilized. In the second stage, the focus shifts on the presentation of the structure of the system used in the case study investigated in the project. A multi agent system (MAS) integrated with a micro grid management platform (μGIM) acts in a grid connected microgrid located in an office building, equipped with solar panels (PVs) to operate energy transactions among different agents (prosumers/consumers). Each agent is represented by a tenant of a zone in the building, which owns a part of the total photovoltaic generation. From the starting point of the English auction model, initially used in the trading platform, two new algorithms have been implemented in the system in an attempt to improve the efficiency of the trading process. The algorithms formulation is based on the analysis of the initial model behaviour and results, and is supported by the state of art provided in the first chapter. A specific simulation platform was used to run the model using consumption data recorded from previous week of monitoring, in order to compare different trading algorithms working on the same consumption/generation profile. The developments obtained from this study proves the capabilities of the P2P energy trading to advantage the end users, allowing them to manage their own energy and pursue their personal goals. They also emphasize that this type of models have still a good improvement margin and with further studies they can represent a key element in the future smart grids and decentralized systems.

Keywords

Transactive energy, Peer-to-Peer transactions,migrogrids,energy auctions.

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Abbreviations

μGIM – Micro Grid Intelligent Management

DF – Directory Facilitator

DG – Distributed Generation

DSM – Demand Side Management

FIFO – First In First Out

IoT – Internet of Things

MAPE – Mean Absolute Percentage Error

MAS – Multi Agent System

MG – Micro Grid

MILP – Mixed Integer Linear Programming

OS – Operative System

P2G – Peer-to-Grid

P2P – Peer-to-Peer

PV – Photovoltaic panels

RES – Renewables Energy Sources

SBC – Single Board Computer

SVM – Support Vector Machine

TE – Transactive Energy

V2G – Vehicle-to-Grid

VPN – Virtual Private Network

VTN – Virtual Top Node

1. INTRODUCTION

Technological progress alongside economical, structural and demographic growth of the society is continuously raising the bar in the direction of higher energy consumption. To fulfill this energy need, many paths can be undertaken. However, the set of available options to adopt is significantly reduced if some essentials constraints are taken into account. The most significant of those is the relentlessly growing level of greenhouse gasses in the atmosphere (especially CO2, which has grown massively in the century, because of human's activities such as deforestation and industrialization), which has already brought us to face the first signs of climate-changing. Therefore, an environmentally friendly approach should be adopted when considering how to provide the energy. In recent years, distributed energy resources (DERs) and communication/control techniques at the consumer level have been adopted more consistently, mainly due to their fast development and increasing production. With the contribution of these technologies, the passive consumers have the possibility to actively manage their consumption, generation and storage of energy, becoming proactive consumers (Prosumers) [1] This increased the diffusion of peer to peer energy transactions platforms, used to connect prosumers or end users in order to create a trading internal market that allows the participants to manage the distributed generation (DG) locally through energy exchanges. The diffusion of the trading platforms has also been accelerated by the further growth of the IoT technologies and smart homes, which allows normal households/end users to becomes interactive and take part in energy sharing communities, such as microgrids (MG) and smart grids (SG), former studies shows the advantages of these applications [2]. This paradighm has been introduced to reach higher levels of energy management; and is a promising alternative to be adopted for the pursuit of a possible solution for a decarbonized energy production scenario. The peer-to-peer electricity trading technology has proven to bring effective advantages in decentralized microgrid energy markets, promoting and facilitating the integration of renewable energy sources (RES) in local energy distribution systems [3]. Further development in this direction will help the progressive penetration of renewables, the general decentralization of the electricity market.and the also the progressive diffusion of the electric vehicles (EVs) in the global panorama. However, a direct consequence of the implementation of this kind of systems is the sizable growth in the complexity, either in terms of grid architecture that in the modelling and regulation of the transactive market. Although the relative youth of these kind of systems makes it hard to find a proper evaluation paramiter to measure the real effectiveness of their implementation,some research has been made also in this field [4]. A system using transactive energy can have different aspects and characteristics, which are currently being studied in many projects being carried all over the world.

In this study, a state of art of the peer to peer energy transactions technology is provided, as an additional contribution to the evaluation of his current state of progress and development so far. Secondly, some specific trading algorithms are proposed, with an overview of the obtained results and considerations on the possible future perspective of the analyzed trading techniques.

2. PEER-TO-PEER ENERGY TRADING CONCEPT

In the introduction part, we mentioned the main purposes and the goals of the peer to peer energy transaction. In this section, we are going to dive deep into the concept to make the structure and the mechanisms clear. For a better understanding of the phenomenon, we provide an overview of the different parts (whether they are physical like a measuring system or conceptual like a programming language or an algorithm) that compose a P2P energy trading platform.

2.1. ARCHITECTURE

In a P2P transaction system, there is the need for a highly interconnected grid. This is necessary as, in a hypothetical ideal trading scenario, there are many agents involved, and they have to be able either to buy or to sell energy among each other in any given moment and also because of the substantial distributed generation (DG) that this kind of environment features. Considering this aspect, several studies in this field have been carried in proper microgrids (they can be seen as a group of localized electricity sources, final users, and, in many cases, even storage systems) as they have the desired characteristics to allow this kind of task. Most of them also have the merit of being able to work both connected to the main grid or in islanded mode, if needed. A classic example of an environment in which such a microgrid can be implemented is a building with DG (typically through PVs). This type of MG has been integrated into places like research centers inside universities and small residential centers[5]. Going further in detail into the internal structure of a P2P trading platform, we can identify the typical characters or "players" that take part in the transaction. The heart of the transaction architecture is usually represented by the prosumers. Prosumers are the equivalent for proactive consumers, as they are electricity consumers, but they also generate electricity, which they can use for their consumption and the trading. Although the case study considered in this project will focus on a small building with PVs, in many other cases we can also find ordinary consumers, or independent small generators, mostly represented by RES such as small hydro electrics or wind turbines.

2.2. CONTROL SYSTEM

A grid designed to operate under transactive conditions presents an evident additional complexity, due particularly to the management of the energy flows, which are more consistent and variable (transitory conditions) in comparison with the ones we would have in a "one-way" radial grid or a classical mesh grid. Consequently, an appropriate control system is required, to secure everything runs properly and avoid congestions, overloading, and many other types of issues that can occur in such a system. This may consist of a particular architecture of the grid itself, to ease the controlling task, and more likely in the adoptions of particular equipment voted for the purpose. the control function can have several extensions; can be used for instance to control the voltage, to manage the capacity of DERs or the electricity demand on the consumers side; moreover, in this type of systems, the control function has to be exercised both in the physical energy flow and in the financial flow, as the transactions involved are of both energetic and economic. Peculiar devices used to accomplish this are the soft open points (SOPs) capable of many functions like active power flow control, reactive power compensation and voltage regulation [6]. Also, digital grid controllers (DGCs) and Routers (DGRs) are often adopted. The DGC can communicate with the Digital Grid Platform that provides the transaction function and it contains a set of basic sensors, for instance, temperature and pressure, useful to predict electrical power demand. DGRs execute the control function by enabling the transactions of electricity according to commands coming from external controllers. They play a huge role in mitigating the power fluctuation of the RES and they also allow the system they control to work in island [7]. In a blockchain-based model we can find these two devices working together. they can collect information regarding both power and/or energy amount and price, enable AC-DC-AC conversion to connect the grid to variable sources, interact with other devices such as smart meters and place bids automatically[5].

2.3. DATA MANAGING SYSTEM

In a working TE platform, there is a substantial amount of data at stake. Each player, prosumer or consumer, is executing a specific function, whether this is to produce, store or utilize the energy. Being this energy, or part of it, intended to be exchanged in a transactive environment, a proper system is necessary to measure it in real-time. These data are at first used for the current transactions, but that's not the only purpose they are collected for. They turns out to be required for a certain number of secondary functions, such as the implementation of a forecasting algorithm, which will be used as a base for the future transactions, and also for post-trading analysis, to verify the effectiveness of the running transactive model in terms of efficiency, loss or whatever is the parameter under exam. Such a monitoring function is often accomplished in the P2P paradigm with smart metering tools [8], a practical method to collect data from the electric users/producers and record their consumption/generation profiles. The classical instrument employed today for this task is the smart meter. This tool has been widely used among this type of system thanks to his characteristics and the ease of use. This electronic device can record electric energy generation and consumption data [3] and communicate them to the supplier for monitoring and billing purposes. Besides recording data on an hourly base, smart meters also have a two- way communication path between the meter and the central system. This can happen either with a wired or wireless connection. The second method may be expensive but is undoubtedly more practical as it can be coupled with wi-fi and cellular communication.

2.4. COMMUNICATION SYSTEM

It's clear that in a Peer to Peer energy trading system, that is a considerable amount of information flowing to make the transaction happen. To close the transaction, all the agents, buyers or sellers, need to know a set of basic information without which they can't communicate their will to buy or sell. The typical data involved in this kind of process are the amount of energy available to be sold, the amount of energy that one agent is willing to buy, the price of the seller, the bid of the buyer, the minimum price accepted and so on. All the basic settings to rule the operation. Moreover, whatever is the chosen method to make the transactions happen, A software or a specific program to actuate that set of operations is required. Hence, all of this wouldn't work without a proper communication system that connects all the agents, and, in case the model is carried on a larger scale, the different MGs involved. The implementation of P2P energy trading becomes possible only with the adoption if Smart Grids (SG) technologies, Information and Communication Technologies (ICT), monitoring, and control functions [9] Several communication networks have been adopted in this kind of platform. They allow exchanging data between agents located in different places, either next to each other or in different areas. These communication networks create a net of connections between all the devices involved in the transactive environment. Depending on the typology of the connection and the distance covered, we can divide these networks into three main categories. At first, we have the Local Area Network

(LAN), which is normally used when the distances among the devices that have to communicate are short, like for example a building or a household When the distances start to grow (up to 100 km), the most suitable communication network turns out to be the Metropolitan Area Network (MAN) which has a considerably widest range. In the end, we have the wireless version of the MAN, that have the huge advantage of being able to provide uninterrupted interaction between the grid nodes, even when the transmission lines are affected by external conditions. Besides, this architecture allows us to connect a large number of devices, and it also facilitates the control function [10].

2.5. TRANSACTIVE MODEL

Named the principal aspects that are essential to make the Peer to Peer trading system run properly. The focus can be shifted to the transaction itself. In a system involving a heterogeneous field of agents that can perform different functions, a specific strategy must be adopted to accomplish the trading task. Many projects in this sense, already completed or currently under development, are several; and we are going to briefly introduce and discuss some of them in the next part. It's therefore clear, that such a "strategy" is not uniquely determined but depends on various factors. A possible method that has been adapted many times is to do the decision-making process through a specific algorithm [11];[12]. In this case, many constraints can be included to carry the transaction under the desired circumstances. They could be unlimited cause they depend on the aspect that wants to be studied or highlighted in the case. To name some examples, we can maximize the household savings, minimize the net consumptions, find the optimal charging schedule for an EV or a Battery and so on. Another way to carry the transactions is through an auction process [13];[14]. This technique is often adopted in the field and combined with other methodologies. Being said that also in this case the options are several. The outcome of the auction can be modeled in base on the way the sellers and the buyers are prioritized, the amount that each agent is willing to sell can be subject to changes, the type of auction also is one of the main factors since a lot of them have been used. Fortunately, in the energy trading field, there are few consolidated types of auctions that are considered the main ones; so, we may refer to them in the next parts. Another important aspect is how the auction method deals with the structure of the trading environment, which can be centralized, with the main agent leading and coordinating the transaction, or decentralized, in which every agent is given equal responsibility. Different results have been reached in different cases, which makes hard to compare them. An alternative approach comes also from the Game Theory paradigm [15];[16]. Although this method is similar to an optimization-based one, in the sense that it usually features the main algorithm to model the transactions, the main difference is localized in how the interaction among the different agents is set. This kind of technique leaves space for a vast number of different solutions.

peer-to-peer energy trading concept

2.6. BUSINESS MODEL

The peer to peer energy transaction technology in recent years is aiming to shift the balance of the electricity market; moving from a centralized structure, characterized by few big energy supply companies, to a more competitive and distributed network, with higher DG and RES penetration. The transactions in a P2P trading platform involve either the energy or the money flow. Consequently, we can affirm the economic one is a main aspect in this technology. The transactive environment implies the modeling of a specific Local P2P energy trading market, alternative to the usual grid wholesale market, designed to allow the active interaction between all the participants. In this sense, the soil is fertile for the development of new market platforms capable of adapting to the new decentralized situation, such as [17], which aim to coordinate the trading operation among heterogeneous prosumers. In order to create the conditions suitable for the energy trading among peers, the relationship between the end users and the suppliers (which, in the P2P electricity trading market can be both represented by prosumers) need to be regulated in a proper way, that allows them to have a flexible agreement based on their established conditions. The possible solutions are several. The task can be accomplished by innovative instruments such as smart contracts or bilateral contract networks [18]. The implications in the formulations of a specific business strategy capable to adapt to a typically decentralized context such a P2P trading system, brings out the necessity to consider the business aspect as a separate layer from the other organizational/functional parts of the platform [9]. Therefore, a specific business model to operate the transactions on a local market is required. For business model we mean the platform or the set of tools-organs that makes the transactions related to the energy exchanges in the trading model possible, and the algorithms-formula that regulate the process. [6] provided several considerations on this matter, proposing and analyzing different discussion points.

3. STATE OF ART OF P2P TRADING TECHNOLOGY

With the P2P paradigm being such a wide subject, which involves many different techniques and can be applied in many environments and configurations, we try to frame the problem analyzing an heterogeneous group of models that have been developed in the recent years and investigates a large numbers of trading scenarios. This chapter provides a description of the analyzed models and a comparison based on certain key elements identified in the research.

3.1. ANALIZED MODELS

several projects have been carried on in recent years, with different business models considered. some of the best known have in common the characteristic of exploiting a web portal to interact with the prosumers and the consumers and conduct the transactions. This is the case of

Piclo [19], a P2P electricity trading platform established in the UK, in a collaboration between a technologic company called "Open Utility" and a renewable energy supplier called "Good Energy" In the platform, which offers his clients the possibility to buy energy from local RES, automatically matching demand and offer and providing data metering and all the information required from the customers, the platform is discussed in [20][21][22][23] and [1].

Vandebron in the Netherlands [24], which has a similar concept, giving the costumers the possibility to choose among different local producers, and allowing them to have advantageous bills due to the independence from electricity utilities, discussed in [20];[21];[22];[23] and [1].

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Sonnencommunity in Germany [25], where the prosumers can take advantage of an energy management service using the company's batteries to store the electricity they produce from PVs. Discussed in [20];[21];[23] and [1].

Yeloha in the US [26], focused on solar energy, sharing the use of PVs with the consumers which don't own them. Discussed in [20];[21] and [23]

The Brooklyn microgrid project [21];[1] and[3] currently known under different names such as Transactive grid or micro grid sandbox, which consists in an innovative community energy market formed by a group of prosumers with renewable energy suppliers.
The platform design allows the members to interact with each other, buying and selling energy automatically.

Peer Energy Cloud and **Smart Watts** [20];[23], both developed in Germany. The first features a trading platform that exploit Cloud-based technologies, which also investigate on forecasting and recording procedures for electricity consumption.
The second, works on modern information and communication technologies (ICT), aiming to achieve an energy supply optimization.

Lichtblick Swarm Energy [20] also from Germany, which uses a unique IT platform for energy markets and costumers to deal with local power plants and storage energy management.
Electron located in the UK. A project still under development, attempting to create an innovative open source platform which provides metering, billing and switching services for the traders.

The four-layer architecture model [9][16] has a specific trading architecture for prosumers interactions in a grid connected MG. the main novelty is the introduction of a new platform called Elec bay, which allows energy users to sign contracts and make payments with each other.

Despite having similar results in terms of promoting the transactions, all these online platforms utilize different techniques to achieve them.

The Brooklyn MG, as well as the **Electron** platform, uses the blockchain technology to minimize the role of intermediate intervention.
Blockchain is a distributed ledger through which transactions can be carried out without the need of a third party.is a combination of several technologies as consensus mechanisms, cryptography and game theory. Is often coupled with the smart contracts: which can been described as programs or sets of pre-specified rules able too automatically move digital assets. They allow automated buying, selling, and scheduling of transactions.

Other models with the blockchain are:

The DGC based P2P Blockchain network [5], based on an Ethereum blockchain and Proof-of-Authority (PoA) as a consensus mechanism. The model is applied on a small DGC-based network with PVs and batteries.

The P2PEBT system [12], which also features smart contracts and Ethereum platform, but a different consensus Protocol, called Proof-of-Benefit (PoB),

PETCON [14], a trading system based on consortium Blockchain coupled with an iterative double auction mechanism. This system has also achieved to improve transaction security and privacy protection.

P2PEBT and PETCON also offers interesting insights as they work on EVs and they study a way to ease the transaction among them and how to deal with the charging/discharging process, which is one on the main challenges of the P2P technology for the next decades.
Blockchain platforms can potentially reduce transaction costs and support P2P trading on many levels.
Interesting developments have been seen also using game theory, a method to regulate the interactions among agents using mathematical models.
This technique can have various forms as is based on math algorithms, the variable and the formulation can change based on the case and on the strategy intended to be adopted in a particular scenario. This technology is applied in:

The **Game theory shapley value model** [15], where the game theoretic approach is combined with Shapley value to model the trading mechanism and the decision making process of prosumers, and in the **Bayesian Equilibrium model** [13], which features a Bayesian game theory to incorporate the power losses in the bidding strategy.

Other scenarios are presented in the **cooperative microgrids model** [27], which analyses a trading configuration among different MGs cooperating with each other.

μGIMcmodel [28], which presents a framework to carry energy transactions multi agent system (MAS) microgrid using an auction method.

Micro/mini grids model [10], which proposed a trading model for a specific case study micro/mini grids in rural Nepal, analyzing the problem on many levels;

And the **MILP model** [11], an algorithm-based trading model for a mixed community of prosumers and consumers with PVs and batteries, with the goal to find the optimal trading decision and as well as charging/discharging schedule.

In **figure 1** an overview of the group of models is presented:

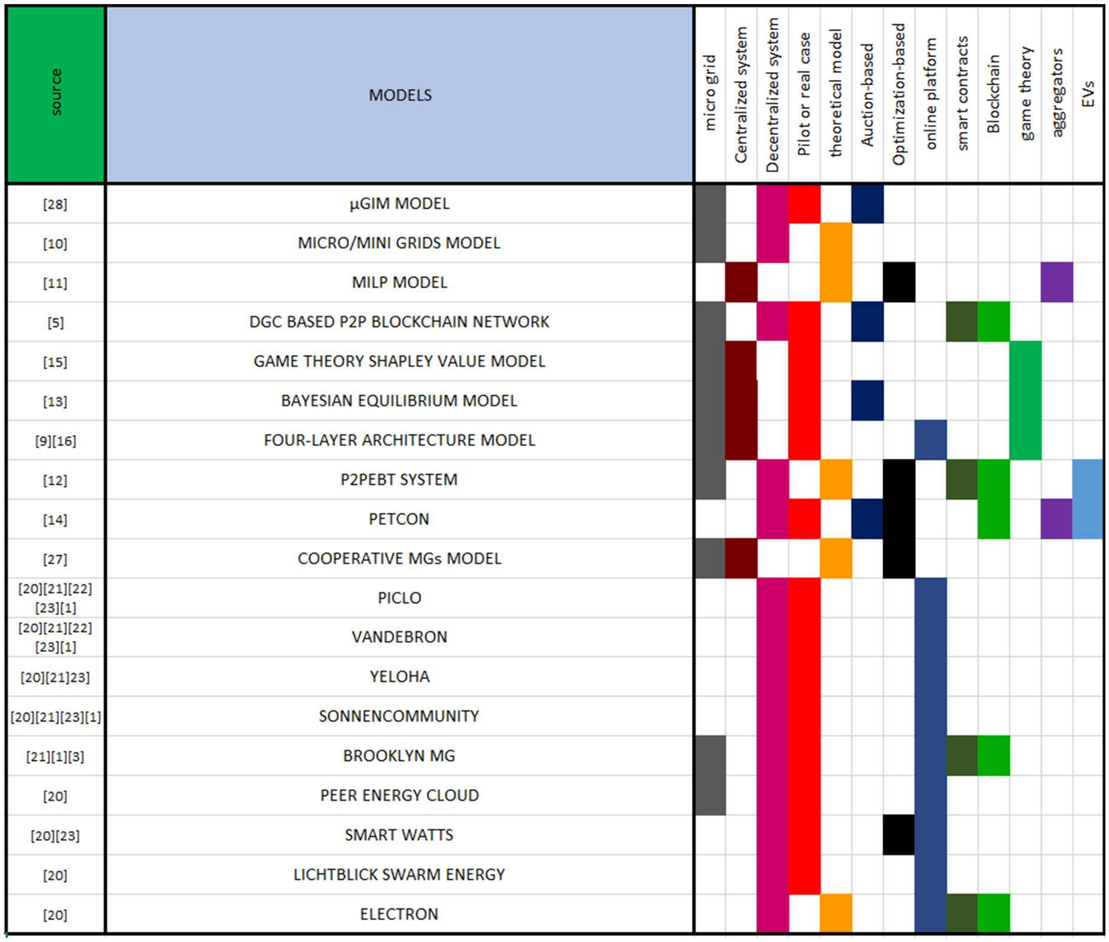


Figure 1: model comparison overview

The models were collected and studied in order to find the commonalities, the short comings and the peculiarities and exploit these information for the development of new trading algorithms to be implemented in the available µGIM - MAS peer-to-peer trading platform [28] wich will be briefly introduced in chapter 5. The table is organized categorizing the model with the following criteria:

Microgrid: The first parameter taken into account, represented by the grey marks, is if the particular case study in which the considered models were applied was characterized by a microgrid (MG). such an "environment" is of specific interest this study because the because is the same in which the system exploited to make P2P trading, in which the transaction models will be implemented, is operating. The smart grids do not fit in this specific category because they have a wider concept and would not be acceptable to identify them as microgrids

Centralized system: To explain this parameter, which is represented by the dark brown marks, some kind of "boundaries" needs to be defined, since is not deriving from a single and well defined feature of the system (that supports the trading model). With this definition the main purpose was differentiate from the other the models which had any kind of central/centralized element. This could be represented by the physical architecture of the system, for instance a case in which the trading involves many prosumers but there is a central element that provides all/most of the energy. Or could be represented by the formulation of the trading process, that may be made to pursue some kind of "centralized optimization" of the transactions, considering the consumers/prosumers involved in the operation like a homogeneous set of agents acting to achieve a common goal. As specified, defined in this way, this characteristic is not straightforward to catch in a model. For instance, is not included in this category if the model utilize a main central organ/tool/device to coordinate/ execute the trading process or for monitoring/ control purposes (which is the case of many of the considered models). In that case the model can still not have a defined centralized behavior or architecture.

Decentralized system: The system is considered decentralized (in contrast with the previous definition of centralized system) if his key elements are distributed or separated from each other. The prosumers/consumers acting in a decentralized environment represent single independent entities, participating in the P2P transactions for themselves in order to reach benefits or personal savings (e.g. residential households with photovoltaic generation). Therefore, this type of models doesn't feature central elements in the trading configuration, and they don't pursue community goals with the trading. They can still have some central device/element to coordinate the transactions and fit in this category. This parameter is represented by the light violet marks.

Pilot or real case: Another important element in this comparison is whether the model was implemented in a real case (real trading system) or in a Pilot (a small-scale, preliminary study which uses real data). In this category, represented by the red marks, have been placed the models wich have been implemented and present results deriving from these kind of "environment".

Theoretical model: This parameter, represented by the yellow marks, indicates that the presented/considered model is not applied on a real scenario or a pilot case sudy, it was only formulated but wasn't realized or was still under developement at the time of the analysis.

Auction based: This is another category that needs particular explainations: the models that features this characteristic are the one who are specifically focused on the Auction Method and his modality and main aspects. So thi category doesn't necessarily includes all the models that uses an auction process to make peer-to-peer transactions, which can also have another techniques/metods implemented. These parameter is represented by the dark blue marks.

Optimization based: The same reasoning of the auction based models hods for this cathegory, represented by the black marks, that indicates the projects that implemented/focused on a specific algorithm in order to optimize the transaction as a function of certain paramethers of the system.

Online platform: The blue marks indicates all the models which exploit an online platform to interface with the custumers and make peer to peer transactions

Smart contracts: To investigate the main techniques that allow the automatization of the P2P transactions, we cathegorized with a dark green box the models that uses this tipe of contract, which are exploited to regulate the "commercial agreement" among the actors in the trading scenario on the base of pre-established agreed rules/conditions.

Blockchain: The light green marks represent the model that features the blockchhain technology. This method, often coupled with the smart contracts, is one of the main techniques studied in the P2P electricity trading fieldin recent years and we take it in to consideration to investigate ways to facilitate and ease the transactions.

Game theory: The green water marks represents the model that features the blockchain technology. This technique is of particular interest because offers a wide range of alternatives in the modelling of the P2P trading platforms and is suitable to be coupled with many of the available technologies.

Aggregators: The purple marks represent the presence of aggregators in the trading scenario. This parameter was included to investigate the role and the contribution in the trading of such a systems, usually integrated non-conventional case studies.

EVs: The light blue marks were used to signal the presence of EVs in the case studies investigated in the models. This aspect is worth to considerate due to study the approaches adopted in the systems/models in order to deal with this particular "devices" and their interaction with the power grid.

Other sensible parameters are considered to analyze the models such as the structure of the system, which can be centralized with a main agent selling the energy to the others, or decentralized, when many agents transact energy among them.
We also consider the present of entities such as the aggregators, to verify their impact on this matter. In the following sections, some of the main adopted methodologies are further explained.

3.2. BLOCKCHAIN

The blockchain technology is a promising technique implemented in the energy transaction field. Blockchain can be defined as a peer-to-peer distributed ledger technology, capable to enable electricity trading to be executed in decentralized, transparent, and secure market environments [14]. This decentralized distributed ledger is digital, and it uses a system composed of “blocks” used to record the transactions, involving a series of computational devices in the process to form a “chain” which identifies uniquely a particular set of transactions. The solidity of this method derives from his internal security. The structure of the chains is impossible to change without the permission of every single block contained in them because such an operation would alter all the involved blocks. The integrity of the chain is guaranteed using consensus mechanism (a mechanism that allows the different players involved in the system to agree on a determined protocol or set of rules) to form new blocks automatically, and cryptography, a mathematical function that “ties” every block to the previous one using a specific identification code/algorithm. Blockchain is designed to carry the transactions among the players automatically, without a third party, and regulate them with pre-established rules. Another main characteristic of the blockchain paradigm is that many of the consensus mechanisms work with a digital currency in the trading market (e.g. bitcoin). This technology is often combined with smart contracts, to make the trading process automatic. There are several types of blockchain platforms, using different currencies, consensus mechanisms (Proof of Work, Proof of Stake, Proof of Authority), platforms (e.g. Ethereum, Consortium) many of which are covered in the proposed state of the art, being implemented in recent projects. Therefore, blockchain is an innovative highly technological solution to develop the P2P energy trading platform and favor the decentralization of the energy market. In the future, blockchain technology may facilitate transparent, disintermediated, and distributed platforms for the energy internet and has the potential to support P2P microgrid operations with prosumers [5].

3.3. GAME THEORY

Another innovative method used to formulate peer to peer trading models in recent years is represented by the game theory paradigm. This method has proved to be particularly suitable for this kind of application, due to his capacity to be able to represent different scenarios. This versatility is due to the structure of the method. The game theory can be described as the study of the mathematical models which regulate the interactions among decision-makers. Therefore, is a method with a very wide field of applications. In a peer-to-peer transactive context, The method can be applied mainly to formulate cooperative or non-cooperative games: In the first case, the players involved in the transactions are designed in order to pursue a common goal or improve a general aspect of the trading model. Game theory allows to create a coalition of the group of prosumers/consumers and study-regulate their overall behavior and their adopted strategies to achieve certain objectives. This type of Formulation is very useful in the studies which propose some form of centralized optimization of the trading process. Another option possible with a game theory methodology, as cited above, is to formulate a non-cooperative environment among the players. This is an interesting aspect, especially to study the trading platforms in a decentralized system. In this kind of formulation, the focus is centered on the interactions between individual players, in which each one is trying to pursue his personal goal. The method allows us to study various options and to analyze all the possibilities in this type of player's interactions, to establish the main paths/strategies to follow for individual players, considering the ones adopted by the others, to achieve the best possible result in the transactions. Different models with applications of game theory are considered in the proposed state of the art and will provide a sensible contribution to the research of model improvements made in the second part of the work.

3.4. ENERGY AUCTIONS

As shown in the proposed models' comparison overview, the energy auctions are the "core" of the trading system in many of the presented models. They represent the most classical way to carry a transaction in an environment with several players interacting. The auctions provide a simple method to carry the transactions, establishing a simple process to rule the competition among the consumers and prosumers involved in the market and establish the "winners" of the transaction. The auction methods can have several types of formulations and are often combined with other techniques. In many models, specific algorithms/ mechanisms are adopted to optimize the bidding process and different methods (e.g. game-theoretic approaches [29]) are used to set the initial conditions or model the behavior of the agents in the transactive market, but the final stage of the trading process is ruled with an energy auction. The main actors in the auction process are the bidders or buyers (which submit their offer in the P2P market) and the sellers (which communicate the price they are willing to apply to their energy). There are in addiction some ways to refer to an amount of energy, based on how it is divided. In an auction description, the term "lot" and "items" will be used concerning a certain amount of energy and the group of smaller amounts that compose it. In the trading panorama, many types of auctions are used. The differences between them can be really slight; they can have features or rules deriving from another type or from a mix of other type of auctions. To give a general example, four main types of energy auctions (English, Dutch, Blind and Vickrey) identified and discussed in [28] are reported here below:

In the **English** auction, the agents participating have to bid over the price of the lot. The price also grows as the auction progresses, overpassing the bids. When the auctioneer stops receiving bids, the auction ends, and the energy goes to the bidder with the higher bid.

In the **Dutch** auction the process is reverse, the price is initially high and decrease as the auction progresses. The bidders, which submit their bids at the beginning of the auction, are prioritized from the highest to the lowest. The highest bid is the winner of the auction, the other bidders get to buy their lots following the priority order.

In the **Blind** auction, diferently from the first two, the auctioneer communicates the lot before the bidding and collect the bids from the agents, which are "sealed" to the amount to the lot. As in the previous situation, the energy goes to the bidder with the highest bid, who pays the amount he offered.

Finally, In the **Vickrey,** the mechanism is almost identical to the Blind type, with the main difference that the winner of the auction gets to pay the offer/bid of the runner up. In

4. TRADING MARKET STRUCTURE

As seen from the bibliographic report presented in the first part of the document, a particularly favorable location to host the necessary condition to deploy a P2P electricity trading model is a microgrid (MG). Has been showed also that most of the trading models utilize an auction process to "solve" the trading and assign the energy to be traded. The trading algorithms that will be implemented in this study are particular types of auction models, with mixed characteristics and the case study in which they are applied features a grid-connected MG with five prosumers. This chapter take a deeper look to the main dynamics that can occur when the different agents present in a microgrid (producers, prosumers, consumers) interact with each other in order to trade energy. When an auction process is operated in a microgrid. The participants are divided in sellers and buyers, and they are both required, independently from the type of auction, to submit their bids, regarding an offer for the buyer and a price for the seller, with them the agents also communicate the quantities to be sold and bought. The auction process creates a sort of microgrid's peer-to-peer internal market, which has different conditions to the ones in the classic main grid electricity market, because the price is "dynamic" Every time an auction process takes place the quantities and the prices change depending on the situations, because are determined by the bids of buyers, sellers and by the Auction itself, which can have different rules, constraints or also change the priority order of the transactions. Once the winners of the energy are established, the responsible of the process coordination "solve" the auction (establish what price will each of them pay, and so on).

4.1. MARKET SCENARIOS

The bidding process prior to the auction execution cannot be totally unregulated. Some constraints have to be taken in consideration to regulate them, the constraints are necessary both for the traders (sellers and buyers) and the microgrid itself. In the first case, they avoid the agents to be penalized by the auction process, bidding over the price of the main grid, secondly they can be used to set the agents personal goals, establishing a threshold that work as the limit price/bid that the single agent are willing to pay/accept. In the case of the system, constraints can be several and dependent on different conditions. Another main aspect of the bidding is determined by their type. The bids can come either from the buyers and from the sellers and the auction coordinator need to be able to recognize them in order to organize the auction process. The capability of the auctioneer to do so depends on how the system is configurate, a classic way to differentiate the bidders is to assign a positive or negative sign depending on whether they are submitting an offer on a price in the market. The same principle can be adopted with the quantities. Once the market opens to the bids and gets past the bidding process, everything is set to proceed with the auction, defining the winners and distributing the lots of energy to the selected bidders. this procedure is called market clearing [30]. To examine the interactions between buyers and sellers in an usual auction market situation, with several amounts put on sale or requested by the buyers, some of the most probable trading scenarios that can occur in the P2P market will be outlined below. In these representations, the bidders are drawn in a price/quantity chart and sorted by increasing price (if sellers) and decreasing offer (if bidder), forming two different curves. These two curves will establish the trend of the market and their intersection will be the natural price and quantity in which the auction would be "solved" following the natural P2P trading market trend. The first two situations scenarios show two of the most common clearing situations. In the first one the clearing price is the one submitted by a specific seller, which in this way becomes a "marginal seller" [30]. All the sellers below that price get to sell their energy at that price, but the marginal seller is able to sell only a part of his energy on sale. In an analogue way in the second scenario there is a "marginal" buyer which establish the clearing price with his submitted bid. All the buyers with a higher bid will be able to purchase their desired energy amount except the marginal buyer which will obtain only a part of it. These scenarios are portrayed in **Figure 2 (a)** and **Figure 2 (b).**

(a) Marginal seller scenario

(b) Marginal buyer scenario

Figure 2: marginal buyer and seller scenarios [30.]

In the next examples are shown other two basic clearing situations, which are slightly different from the two already presented. In the first one the market stabilizes at a definite quantity, but not at a definite price, because the two curves are both in an ascending/descending phase. In this case the clearing price is not defined in a univocal way but rather by a compromise between the clearing quantity seller/buyer. In the second one the situation is almost the same, with the difference that there are two seller bids that intersect with the descending front of the bidder. In this case the clearing price needs to be set below the second seller bid in order to exclude him from the auction winners and preserve the demand-offer equilibrium. If the clearing price is decided with the criterium of the previous case, that seller have a certain chance to win the auction, but there would be no buyer to meet his request. These scenarios are portrayed in **Figure 3 (a)** and **Figure 3 (b)**

(a) Equal clearing quantities scenario

(b) Equal clearing quantities, close next seller bid scenario

Figure 3: Equal clearing quantities scenarios [30.]

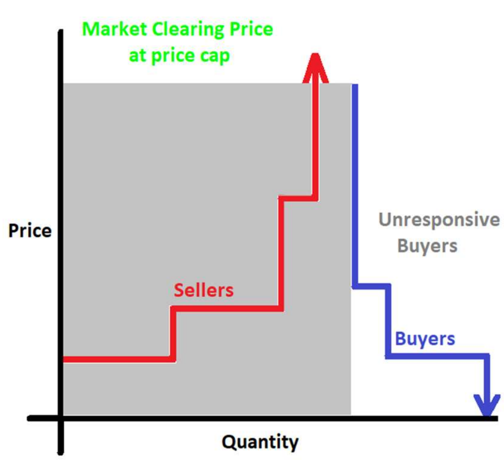
These last two cases complete the main clearing scenarios possible in a P2P auction trading process in a microgrid (MG). In the same way of **figure 3 (b)**, in an equal clearing quantities scenario there can also be a seller with two valid bids. The price is then established with the same mechanism, paying attention to exclude this buyer from the winners. The second scenario is very rare because it features a case in which the intersection between the seller and the buyer have the same price and the same quantity. This is the most ideal clearing situation possible because the market clears naturally at that quantity and price and there are no sellers or buyers with a residual quantity or no price compromise between the marginal agents. These scenarios are portrayed in **Figure 4 (a)** and **Figure 4 (b).**

(a) quantity equal, close next buyer bid

(b) equal clearing quantities and prices

Figure 4: equal clearing quantities scenarios 2 [30.]

To conclude this chapter, in **Figure 5 (a)** and **Figure 5 (b)** are represented two common scenarios of market failure. In the first, the sellers don't have enough energy to meet the minimum request of the buyers, which are defined as "unresponsive buyers" [30] while in the second it is impossible to find an agreement on the price because all the offers are below the minimum price submitted by the buyers. In both of these cases, the market fails to clear and there is no trading on the P2P market.



(a) Failure to clear

(b) null market clea ring

Figure 5: not clearing scenarios[30.]

The presented scenarios are the most common situations and market clearing alternatives that can occur in a classic auction process. They can be exploited in the simulation and formulation phase of new trading algorithms to see the effectiveness of the considered methods. Other “rare” scenarios are possible but will not be treated in this section as it only gives a general overview of the Auction model trading scenarios in a microgrid (MG).

5. USED P2P TRADING SYSTEM

Once outlined the main charachteristics of the peer-to-peer electricity trading concept and how it works, given an exhaustive state of the art of the current developement and advancement of thetechnology so far and explained closely the main market mechanisms in a classical bidders-sellers trading environment. This section is used to introduce the peer-to-peer energy trading system utilized in the project. The whole system has been developed by the GECAD (Grupo de Investigação em Engenharia do Conhecimento e Apoio à Decisão) research group of ISEP (Istituto Superior de Engenharia do Porto, PT) in the last decade. It's the result of several projects implemented in the building to investigate on demand response, energy management and transactive energy. The study has been carried in the GECAD building, which, in the model, is configured as a multi agent system (MAS), with the main agent coordinating the energy transaction among all the actors using an English-type auction; Placing bids and matching demand and offer. The actors are no other than small parts of the building (Office rooms, laboratories, common areas), each one with his own generation, provided by PVs (which are installed on the building rooftop). They are represented by single boards computers (SBC). A monitoring system records all the consumption and production data in real-time and an explicit forecasting algorithm is used to place the bids by the agents. The system runs in a micro grid intelligent management (μGIM) platform with raspibian operating system and java software. The task of this study is to prepare the soil for further developments in this kind of model, considering different paths to achieve the final result and a punctual analysis of the obtained data put into perspective. In the next paragraphs, si shown a detailed descriptions af all the main aspects of the sistem: the architechture of the single agents, the communication channel among them, how the transaction works, the rules followed by the transactions, the constraints of the system, what are the autcomes of the trading and so on. The technologies used in the building were developed in studies prior to this project and are widely explaned in [28];[31] and [32]. The description of the system operated in this chapter touches only the essential points necessary to understand the P2P energy trading's platform and his working mechanism.

5.1. THE MULTI AGENT SYSTEMS

In recent years, due to an intense study and development of smart grid technologies and IoT, the operation of MGs and multi-agent energy management systems in liberalized electricity has been widely discussed. Multi-agent system and smart Microgrids are technologies with a good potential to favor renewable energy resources integration in emerging scenarios and energy system decentralization. Their contribute is oriented to allow final users to participate actively in the system and not only as a passive load.

These systems way of working can be considered as a liberalized market, with bilateral contracts among all the players to establish a mutual trading agreement, auctions or energy pools for the energy assignment process. In past studies, the entities in the markets were all modelled as either generators or consumers. However, in a case such the one in exam, prosumers can both generate and consume electricity. They are therefore an important type of market entities and they need to be modelled opportunely to be able to shift from the function of generator to the one of load. The results of this configuration are a different way of dealing with the energy trading process [16]. MAS are particularly suitable for the microgrid applications and they can accomplish multiple function in order to increase the efficiency of the system. In the Microgrid analyzed in this project, trading operations and management are supported by a MAS (developed and discussed in [28];[31] and [32]), that helped the system to improve supply reliability and stability (using demand side management techniques) and enabled P2P energy trading among the agents. Consumers and prosumers are acting in a grid connected Microgrid, which has proven to be an ideal environment for tests on the TE field. In fact, is able to emphasize the benefits and the gaps in the agents personal achievement or in the entire community, whether they are involved in a trading operation using the internal liberalized market or they are simply interfacing with the external grid using it as a standard supplier or as a tank to inject the surplus of energy produced by the distributed generation. In the microgrid, energy management is performed using local energy demand and renewable energy sources. Depending on the configuration, the microgrid can work either connected to the grid or in islanded mode.

Agents in the MAS can represent a wide range of objects. “The use of MAS allows the individual agent-representation of each microgrid player, enabling the exchange of data and information among them. This allows the build of distributed intelligent communities able to compete and/or cooperate to achieve individual and common goals” [28].

The models analyzed in this project are a decentralized type. Therefore, they have the property to allow the agents to pursue individual goals (i.e. Minimize the energy bill) as well as global goals of the microgrid (i.e. incentivize energy transactions in order to limit the dependence from the main grid). This is enabled by the μGIM-MAS, where each microgrid player is represented by an individual agent running in a single-board computer (SBC). After the model presentation, an overview of the results achieved by the peer-to-peer transactions will be provided. The μGIM system is used to execute the microgrid auctions for peer-to-peer transactions. The office building is divided by four tenants, where each one is a prosumer; the building’s manager/owner is also represented by an agent. The five agents/players can participate in the energy auctions where they can sell and buy energy. The auction model initially running in the system is distributed, open, and without centralized energy management.

5.2. OFFICE BUILDING DEPLOYMENT

As mentioned in the previous chapter, the MAS can have several applications. The µGIM-MAS system [32] that will be used to run the trading models is located in an Intelligent office building. The building has been subject of previous studies in the path to develop the current multi agent system, which is designed to operate the energy trading among the agents. In the building is also installed a specific algorithm for generation - consumption balance [31]. The algorithm follows a prioritization logic among the main loads running in the office and calculate the optimal solution to balance generation and consumption. In this section, the focus will be shifted on the building deployment, as it contains some essential information about the agents configuration, the hardware tools installed and software programs running in the building, necessary to introduce the following trading model. This chapter will also talk about the architecture of a single building's agent. In order to manage the electrical resources of the building, an adequate structure to support and execute the power flow monitoring and control is required. Therefore, the office building features a six-layer architecture, implemented and discussed in [31], with each one of these layers performing a different function complementary to the others. The six interconnected layers, (which recalls the general description of the main lines given in the section 2) are listed below:

Multi-agent layer: This layer, which exploit a JADE framework, is necessary for the agents to communicate and also for registrations and connectivity functions.

Computational Layer: In this layer, SBC serve as computational platforms, allowing the agents to process complex operations, using several computing technologies.

Persistence Layer: The forecasting algorithm is one of the key elements for the functioning of the energy management system. This layer has the function to provide the historical data to the algorithms, that are then used to “predict” the generation or consumption in a next given period.

Energy Management Layer: This layer contains a wide variety of algorithms used in the system and also the business logic of the agents.

Integration Layer: This layer is responsible for the integration, monitoring and control of internet of things (IoT) devices in the system, exploiting several communication protocols.

Graphical user interface layer: The Graphical User Interface is designed for external users. It provides hardware devices (such as screens) to allow them to visualize or interact with the system.

Figure 6 shows a graphic representation of the described layers with the main technologies utilized in the six-layer architecture [31]. In **figure 7** is possible to see the structure of the SBC, which represent the “core” of the system.

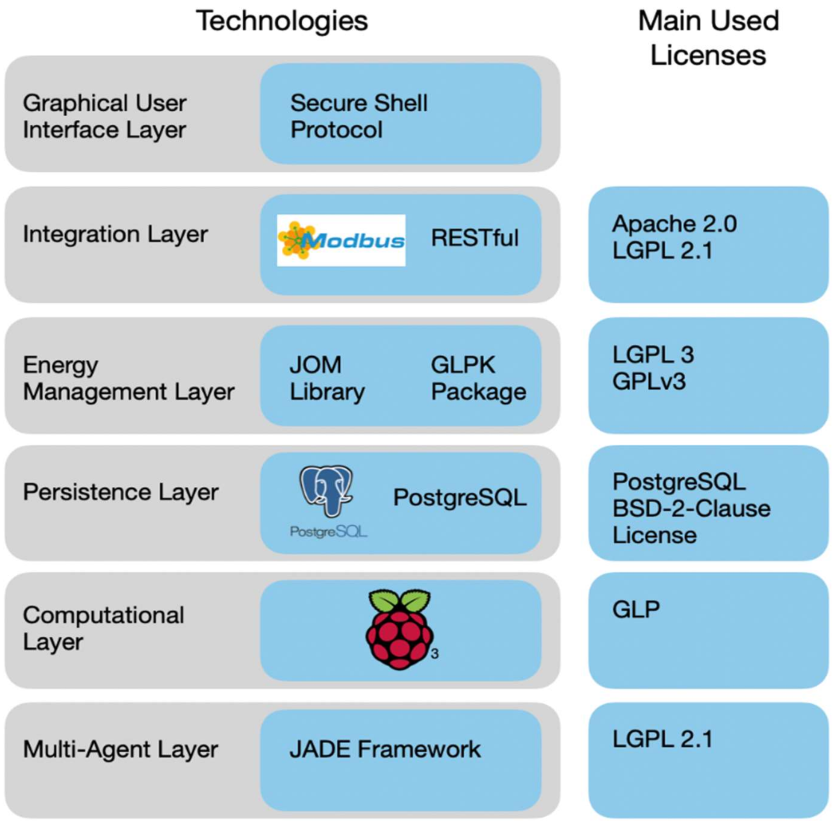


Figure 6: Agents architecture Layers representation [31.]

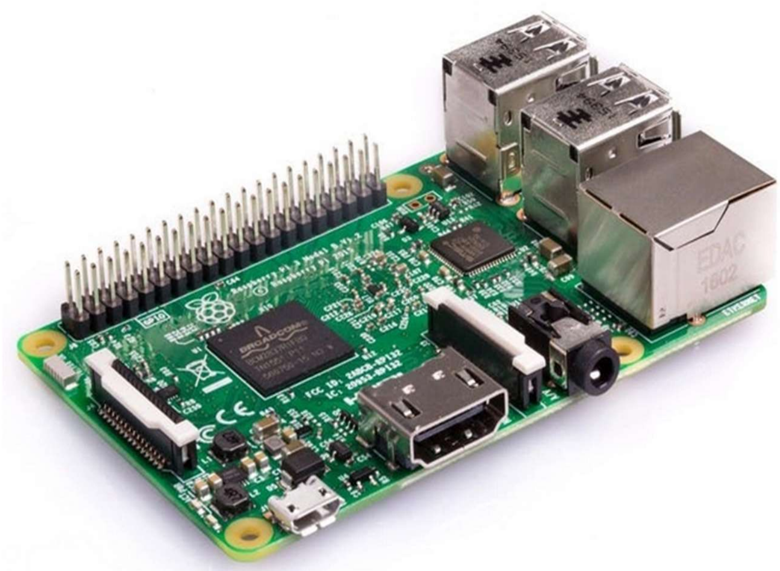


Figure 7: design of a raspberry Pi 3 Model B Single Board Computer

The office building is equipped with PVs, installed all along the rooftop in the south oriented side. That is the optimal position to catch as much direct radiation as possible, because they are steady, so they are not equipped with any support that allows them to follow the movement of the sun in order to always have an optimal angle of incidence with the radiation. The agents deployed in the office building act as different and independent end-users in the trading market, managing their own energy and operating transactions to achieve their own goals. As different entities, they also have their own energy contract.
This modelling is structured on purpose to investigate on decentralized scenarios, the agents actions in the transaction market can be compared, for instance, to a hypothetical residential center case study, in which every household has his own generation with PV's and his own energy provider contract. In that trading scenario each different prosumer (represented by the houses with photovoltaic generation) will try to reach his personal goal in the peer to peer market, adapting his bidding strategy consequently. Therefore, the agents are programmed to act in a competitive way. In **Figure 8** shows a graphical representation of the building, with the different agent's zones identified with different colors [28].

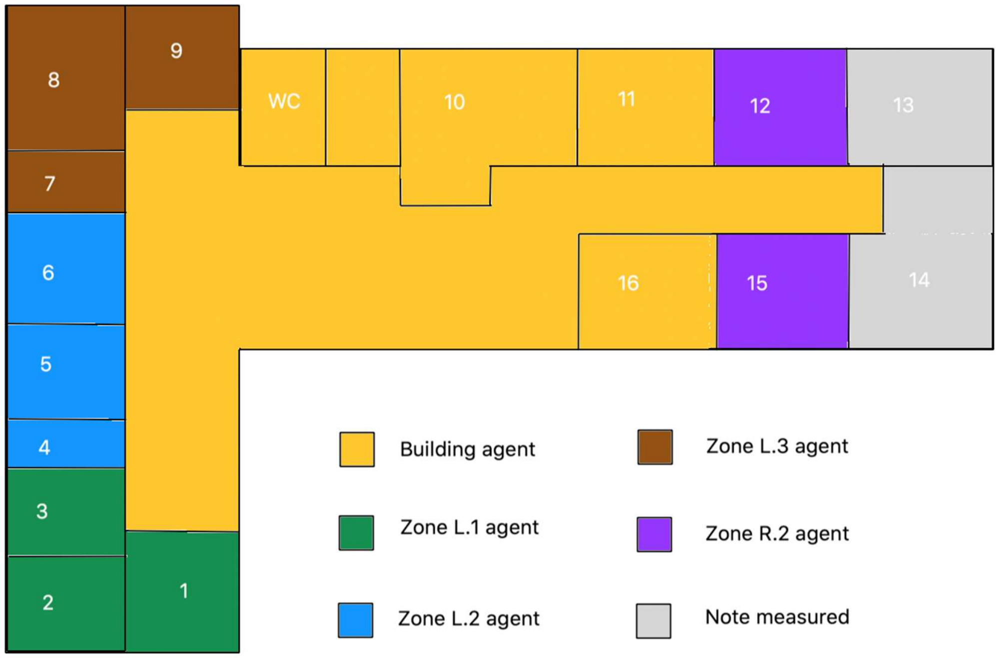


Figure 8: Agent's zones partition [28]

That being said, lets briefly outline the operation area of each agent (as specified in [28]). The common areas, plus some office rooms, are managed by agent Z0 (which has also the role of building agent-Auctioneer). Zones L.1 and L.3 are composed by normal offices, as L.2, with the only exception made by the server room (the smaller one). R2, is renting rooms 12 and 15, which are another office and a laboratory with several equipment installed. Rooms 13 and 14 are not considered or measured, although room 14 contains all the SBCs installation exploited in this system, for two main reasons: Firstly, is taken into account that the consumption of this area is negligible in comparison to the one of the other zones (room 13 acts only as a warehouse for building's electrical/electronic equipment). And secondly, for the purpose of the study is worth to monitor the consumption, generation and energy flow of the mere agents operating trades in the market and not of the trading system itself. The total generation of the PVs installed in the building is 10 kW, distributed among the agents in equal way (1 kW each) except for Z0 that is responsible for 6 kW.
As specified previously, in the six-layer representation of the agent's architecture, each agent is represented by a Raspberry Pi board (the SBCs introduced in the first part of the chapter) The building agents has the main task to coordinate and synchronize the transactive energy auction process, but it also takes part on the auctions. Moreover, His SBC runs both the µGIM agent, and JADE directory facilitator (DF) agent. **figure 9** shows the connections among the agents [28]. PostgreSQL is a remote server used to amplify the storage capacity of the system in order to store "old data" from the SBC.

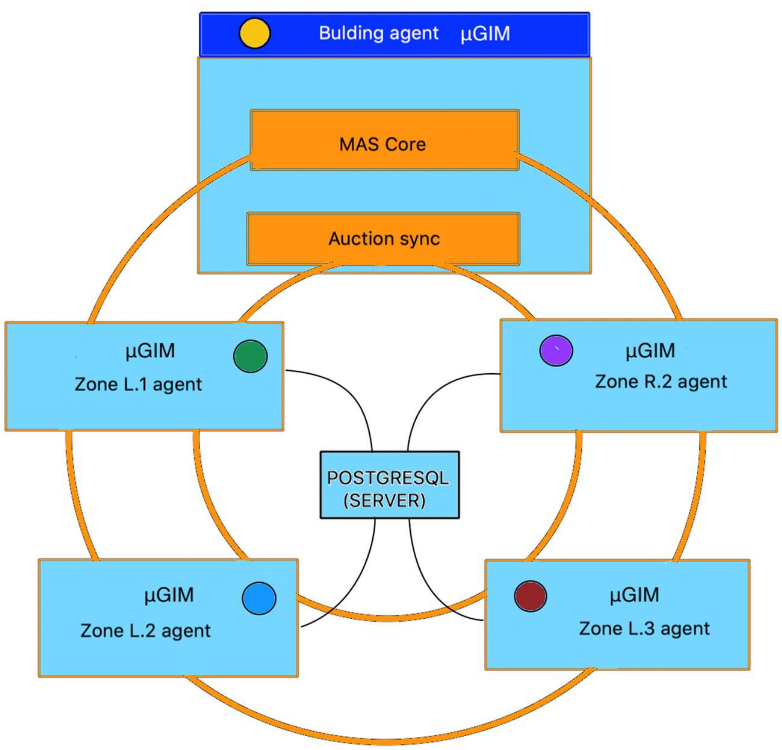


Figure 9: representation of agent's connections [28]

The monitoring and control function in the entire building, exploit an assembly of sensors, energy analyzers and smart plugs [31]. The system, with all the agents SBC, is situated in room 14 of the building (always referring to the zones division showed in **Figure 8**). Despite only one type of auction configured in the system, µGIM platform is able to perform four available auction types (that have been previously discussed in section 3.3). Thanks to the monitoring system and his metering function presented in [32], it's possible to draw a profile of the consumption of the agents. Considering the activity schedule in the research group and the installed devices load profile, is fair to say that the consumption of the building has a profile that repeat himself "ciclically" every week. That's one of the reasons why the simulations conducted cover a period of one week. More specifically, the simulations will be done using the consumption data of a winter week and a spring week, to see the behavior of the agents and of the entire trading model in these two different cases. In fact, the consumption profile varies mainly depending on the external temperature, therefore according to the seasons. In winter there would be an additional "slice" of energy consumption due to the heather, while in summer, due to the air conditioning system. In this second case, there is a specific consumption increment in the zone L2, due to the cooling system in the server room, which needs to be kept under a certain temperature. The agent's building and the agent L.2 usually have the two biggest consumptions. An example of a week of consumption data, regarding the building's agent (Z0), referred to the measurement collected in the week from 10 to 16 April 2019, and reported in [33], can be seen in **figure 10.**

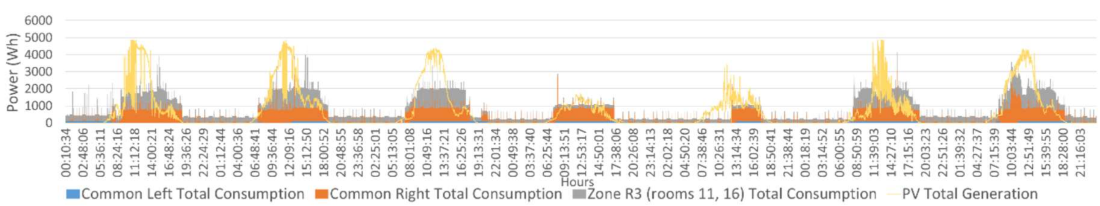


Figure 10: agent Z0 weekly consumption metering profile [33.]

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5.3. TRADING PLATFORM

In this section, the focus is shifted on the Microgrid Intelligent Management (µGIM) platform for peer-to-peer transactions among microgrid agents. This agent-based platform is used to perform the energy management of the building's load and resources and to execute and coordinate an energy transaction among the players. As Explained in the building deployment section, all the players that compose the µGIM platform run in a Single Board Computer (SBC). Despite not having the conditions to work in island (the only supply of the building when the MG is detached from the main grid is represented by the solar panels) the aim of the agent's community is to maximize the internal trading, optimizing the available production. A schematic representation of the architecture of the platform, with all the elements briefly cited in the chapter introduction, is shown in **figure 11**, with the operative system, software and programming language utilized. The system implementation, prior to this study, is presented in [32].

Figure 11: µGIM overall architecture [32]

Given the impossibility for the agents or "peers" to both buy and sell simultaneously, the amount to be traded need to be known in advance. This is done through the use of forecasting algorithms. This happens for electrical reasons, the energy that an agent will need to sell/buy have to be known in advance because the transaction has to happen before the moment in which the agents need to sell/buy the energy, so he can dispose of that energy in the exact moment he needs it. These forecasting algorithms are used both for generation and consumption. The forecasting algorithms used in the model are object of studies and experimentation. In fact, they represent a susceptible point in the operation of the model. With their action they decide the amount of energy to be traded, and this determines the outcome of the transaction. Therefore, an eventual error in the forecast can unavoidably lead to a wrong trading. For these reasons, several algorithms have been tested with the current model, as it has been changed periodically, more precisely, cyclically.
As an example, equation (5.1) reports the formulation of one of the first algorithms implemented.

$$f\,C_{h+1} = 0.5 \times C_{h-1} + 0.3 \times C_{h-2} + 0.2 \times C_{h-3} \tag{5.1}$$

Where h represents the hour, an C_i represents the consumption, in Wh, for the hour i. As can be seen, this historic-based algorithm (historic because uses past generation- consumption data) is a weighted arithmetic mean of the last three hours, prioritized from the closest to the forecasted hour, to the further. In the transactions, the error of the forecasting algorithm is represented as mean absolute percentage error (MAPE) of the previous week.
Several forecasting actions runs in the system periodically. There is a forecasting action that "predicts" the consumption and generation for 15 minutes ahead, and runs in the system four times per hour, a "one hour ahead" forecasting action (running one per hour, at the 18th minute), which is the one actually used for the trading and two more actions, executed only by the building agent (which has the task to coordinate the auctions) and used for the request of the available sellers and their synchronization.
They agents are able to adopt their own strategies, which are not related to the ones of the other agents, in order to "squeeze" the maximum advantage from the trading operation. In this competitive scenario, players manage to react to other's agents' strategies using the pro-activeness and reactivity capabilities, described in [28]
In the µGIM system can execute four types of auctions, (see section 3.3 for further details) for peer-to-peer trading. Anyway, only the English auction type is configurated to be used in the trading. For a better understanding of the mechanism, is better clear out some differences in the auction terminology. The term auction will be used only when referring to the sale/purchase of a single energy amount, while the entire trading process, which takes place in an entire hour and involve all the participant buyer/ sellers, will is called auction catalogue.
A simple diagram representing of how the English auction process works in the system and the interactions between the different agents and the auction coordinator (represented by the building agent) is showed in **Figure 12.**

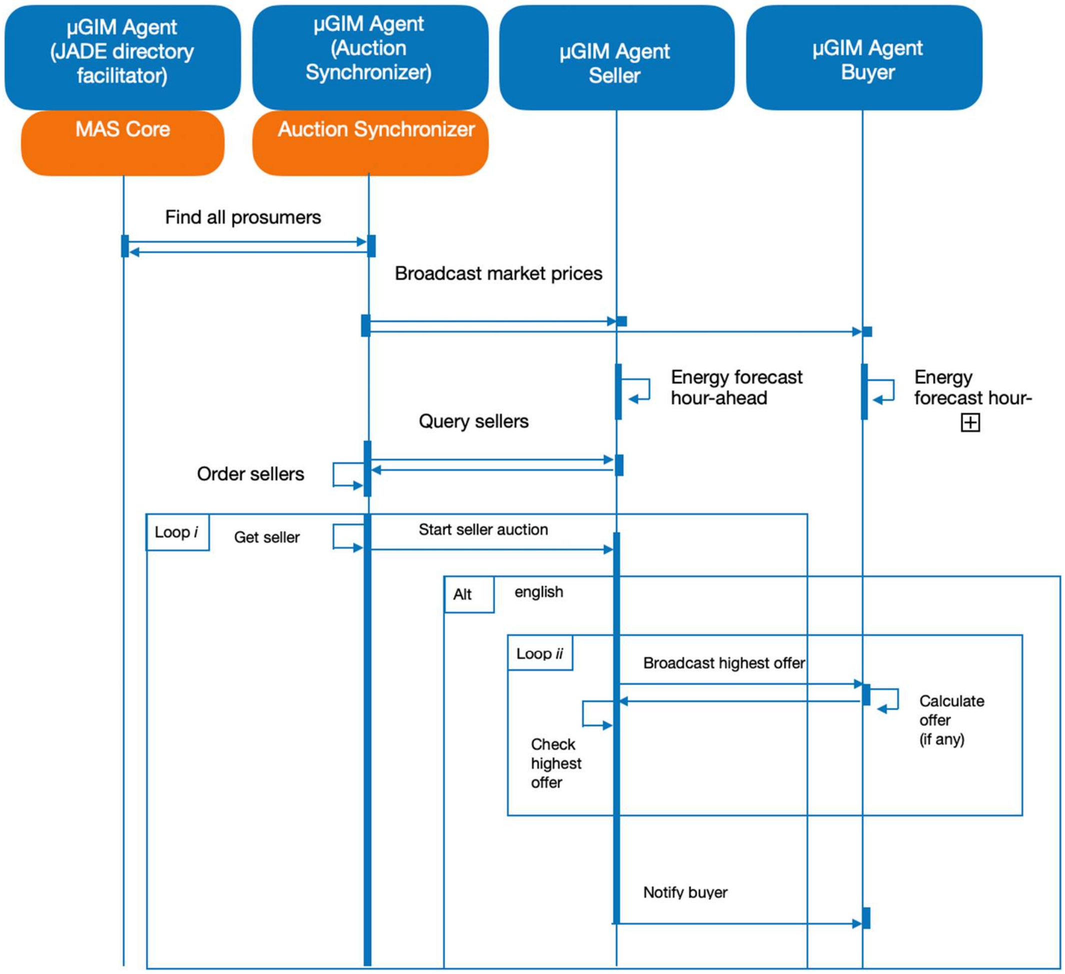

Figure 12: transactive energy process diagram [28]

The agents have a file in that contains all the main information of their configuration [28]. This information are used to regulate the terms of the transaction. The file contains details about the amount of energy to put on sale or to buy, indicated with different notation depending on the chosen strategy. For instance, if the agent wants to sell all the energy he produces, only the difference between generation and consumption, only a percentage of it. (Same thing from the buyer perspective). Details about the bidding process, as the minimum or maximum price that the agents are willing to offer/accept for a certain amount, expressed in a percentage value that is referred to the unit (EUR/kWh) price of the market.
Figure 13 shows a representation of the configuration file of an agent; the terminology adopted in the notation is explained in [28].

```
"transactive energy" : {
        "peer-to-peer_market" : {
            "calculations" : {
                "at": "21 * * * *"
            },
            "buy" : {
                "baseline"          : "deficit",
                "energy"            : 80,
                "max_price"         : 90,
                "starting_price"    : 30,
                "increment"         : 10
            },
            "sell" : {
                "baseline"          : "surplus",
                "energy"            : 80,
                "min_price"         : 110,
                "max_lot_size_wh"   : 100
            },
            "store" : true
        }
    }
```

Figure 13: energy configuration display of the agents[28]

5.4. ENGLISH AUCTION TRADING RESULTS

Given a brief introduction of the system to operate the transactions among peers, This section is dedicated to show an overview of the results obtained by the English auction model [28]. These results will be used as a comparison term in section 6, were the results of the Basic prioritization and iterative auction trading algorithms, implemented in this project, will be presented. This comparison will be a useful contribution to measure the real advantages and improvements introduced by the new methods.
The considered week goes from 3 to 9 March 2020 (Monday-Sunday) energy transactions. The results shows all the useful information and parameters to evaluate the correct functioning of the model: the information regarding the forecast algorithm and his error express in relative value, the real consumption and generation data for each agent, the amount of wrong trading among the agents due to the forecast errors (kWh) number of transaction operated, medium energy cost of the entire week and average energy price with and without transactions. As specified in section 4, the internal P2P market has a dynamic-variable pricing. For this reason, the price variation reached in that specific week with the English auction model operating the transactions is related only to that period and to that specific consumption, generation profiles.
The results, with the specified parameters, are presented in figure 3, (reported from [28])

Table 1: microgrid's overall weekly results [28]

		Z.0	L.1	L.2	L.3	R.2	Microgrid
Energy	Consumption (kWh)	147.311	109.298	171.986	91.891	41.860	562.347
	Generation (kWh)	169.429	28.775	28.775	28.775	28.775	284.531
Errors	Forecast MAPE Cons.	10.27 %	10.04 %	9.54 %	9.61 %	9.95 %	9.88 %
	Forecast MAPE Gen.	6.26 %	6.57 %	6.52 %	6.50 %	6.75 %	7.16 %
P2P analyses	Bought (kWh)	0.000	5.427	13.225	6.237	2.215	27.104
	Sold (kWh)	22.705	0.032	0.000	1.917	2.450	27.104
	Best choice periods	35	39	51	38	32	195
	Wrong sale periods	4	1	0	1	3	9
	Sold too much periods	15	1	0	2	8	26
	Wrong purchase periods	0	0	0	0	1	1
	Bought too much periods	0	2	1	1	0	4
	Wrong trading (kWh)	4.320	0.094	0.003	0.069	0.250	4.736
	Total number of transactions	54	43	52	42	44	235
	% of best choices	64.81 %	90.70 %	98.08 %	90.48 %	72.73 %	82.98 %
Energy costs	Week cost	1.4065 €	15.5273 €	27.9279 €	13.1305 €	3.3261 €	61.318 €
	Week Cost (w/o P2P)	2.3756 €	16.2455 €	28.6661 €	13.3470 €	3.4803 €	64.115 €
	Price per kWh (EUR/kWh)	0.0095 €	0.1421 €	0.1624 €	0.1429 €	0.0795 €	0.1090 €
	Price per kWh (EUR/kWh) (w/o P2P)	0.0161 €	0.1486 €	0.1667 €	0.1452 €	0.0831 €	0.1140 €
P2P energy	Price variation (w/ and w/o P2P)	40.79 %	4.42 %	2.58 %	1.62 %	4.43 %	4.36 %
	Trading in consumption	0.00 %	4.97 %	7.69 %	6.79 %	5.29 %	4.82 %
	Trading in generation	13.40 %	0.11 %	0.00 %	6.66 %	8.51 %	9.53 %

6. ALGORITHMS TEST

Given the initial transactive configuration (already implemented in the building) as a starting point, an accurate data analysis has been made in order to catch the real short comings of the current model and find an alternative path to operate the transactions in a more efficient and effective way. Therefore, this section is based specifically on the transactive model and his behavior when subject to substantial and non-substantial changes. The model features a classical tipe of auction in wich there is an upside play among all the bidders over the price of the desired lots (they bit until there is no higher offer submission). Such a tipe of auction has proven to be effective to demonstrate the positive aspects (from a microgrid perspective) of the implementation of an internal trading between agents in the peer-to-peer market, rather than adopting a pure peer-to-grid (P2G) interactions with the main grid. In the classicle grid-consumer interaction, the agents are forced to buy or sell at the grid conditions, without having any sort of contractual power. They don't have the possibility to manage the energy they produce in "surplus" with the PVs and to try to maximize their earnings or have a cheaper bill. Therefore, despite achieving some tangible results, inducing the agents to operate transactions, the English auction model adopted can still be cosidered a basic one, that still leaves room for an optimization, or a general improovement of the data. Where to seek such an improovement is not a straightforward answer. What emerges from the data analysis is the absence of a clear path to get an improovement in the model. The root of the problem is the configuration of the agents. The actual setup open to a vast variety of alternatives. That's a normal consequence of the nature of the problem, in the P2P trading panorama, as exposed in the research of chapter 2, many techniques can be utilized to create an operative transaction environment. These techniques implementation is often dependent on the case study in examined and the adopted/available technologies. Therefore, they cannott all be easily implemented in our system, althought the μGIM-MAS system adopted in this study has proven to be quite versatile (as it is also used for other energy- management purposes in the research center). In the examined project, several different goals were pursued. Some projects had "general/community" goals, as: achieving security of the transactive system, fairness among the prosumers involved in the trading, simplification and automatization of the transactions and propose innovative business platforms or websites for the trading. Other projects had efficiency/technical goals as: maximization of the income of the prosumers, minimizations of the players energy bill, maximization, increase the trading, find the optimal bidding strategy to optimize a certain parameter of the system (e.g. the charging/discharging of households batteries or to EVs) and so on. For the above-cited reasons, the first step in this phase of the study was to identify where to act in the current trading configuration, or, in other words, establish the characteristics most likely to be improved. In addition, the proposed state of art is exploited as a base to extrapolate operative effective changes in the model. Therefore, the next section provides a discussion on the current model performance and his issues - short comings and what brought to the development of the proposed algorithms.

6.1. CONSIDERATIONS

Made the due considerations on the first model results, the initial approach has necessarily been to look for the more visible defects in the auction process and in the bidding strategies of the agents. The main thing to be taken into account is that the model is formulated to create a competitive scenario. Therefore, the agents act without seeking any kind of collaboration among each other and minding only about their goals. From the analysis of the selected week of trading, some sensible parameters regarding the transaction have been picked up. The first objective is to improve any of these values operating slight changes on the formulation of the transactive auction model. These changes have to be operated without altering the competitive scenario already existing and have to be validated bringing either advantages distributed between all the players or community improvement in term of efficiency of the transactions, amount of energy traded, minimization of the wrong trading or optimized number of transaction. Agent uses energy strategies to participate in transactive energy (e.g. sell everything, sell nothing, do aggressive bids, buy at any cost). The following discussion points emerged from the English auction P2P electricity trading model:

Amounts to be traded: The English auction tipe focus the transaction on the amounts sold by the auctioner (like in the most classic of the items' auctions). Therefore, all the action happens aruond the sellers. Anyway,this reduces the possibilities of the buyers, wich have to "fight"for the available amounts. Even though some constraints prevents the bidder to make offers for a lot of with a bigger amount of energy that the amount he needs, nothing prevents the buyer from bidding over small amounts, specialy not knowing what comes after.

Trading order: In this model, the sellers execute they auctions in a precise order(as explained in chapter 3), which respect the FIFO rule (First In First Out). They sell in the same order in which they were presented to the auctioneer (represented by the building's agent). However, that order doesn't respond to any particular criteria and is most likely casual. As it depends only on the system settings, configuration and also because the trading scenario changes every time. Once again, this can penalize the optimal distribution of the amounts among the seller, because the agent's that are willing to buy only knows the lots one at the time,so they cannot come up with an optimal strategy, not knowing if bidding for the current lot be convenient for them or they will have other occasions.

Assignment modality: as specified, the winner in this tipe of auction is the one that submit the highest bid. However, in order to maximize the benerfit obtained from the trading, this method can be counterproductive. This because the agents have to buy the lot at their submitted bid, so if they adopt an "aggressive strategy to maximize the chance to get a lot they will unavoidably raise the price and reduce the advantage that they get from not buying from the grid.

Therefore, in the formulation of a new algorithm for the trading, the goal is to increase the trading efficiency trough the change of the named aspects. In order to do this, the bidding process and the modality of associatng the bids to the sellers must be changed. Regarding these changes, several questions arise. A first one is whether to give a specific prioritization to buyers and sellers (to establish in which order they should buy/sell). This would be useful to add some form of control in the process by establishing the order in which the lots are auctioned. To do such an operation, a specific parameter must be picked to base the prioritization on. The main possibilities are to order the agents partecipating in the transaction by their bids or by the amounts. Giving the priority to the sellers and the bidders with higher amount, could be an effective move to maximize the trading, selling the bigger lots first. However, it can easily turn out to be an umbalanced adjustment. For instance,if an agent have a bigger average production, he will always have the priority in the auctions (like the a Z0 agent in our case study, wich has a peak production power of 6 kW, against the single kW of each of the other four agents). So the scenario would become a sort of centralized trading in which the major producer becomes the main supplier, and the other prosumers risk to see their trading benefits almost totally cancelled. The option of giving the priority based on the bid price seem to be more fitting in this particular scenario. In that case, which agent wins the lots is totally up to the strategy adopted by the bidders, which is subjective. So it doesn't seem to introduce umbalancing factors in the process. Another question regards the amount to be transacted; in a scenario in wich both sellers and buyers are interacting (let's say the bidder bid above the seller price like in the english auction and they agreed for him to pay his bid) and they have both submitted a certain bid/price for a certain amount in the first stage of the process. If the buyer needs a certain quantity X and the seller puts on sale the quantity Y, the doubts in the formulation of the transaction rules is about focusing the process on the buyer or the sellers. There is no rational justification in picking a side and not the other. It's a choice of the developer and of the goal that he want's to achieve. Assuming that the process would be centered on the sellers and on their price/amount, like the initial model, the buyer would have to buy more energy that the amount he needs. In the opposite case, with the process centered on the buyers, it would be no longer mandatory to close the bids. In other words, the seller would get the lot by submitting the best offer but then he will only buy the energy he needs. Leaving the buyer with some "not-traded energy" which would cause him to partecipate in another auction which could overcomplicate the process or iven not be possible anymore, depending on the formulation of the model. Either of these scenarios is unfair or penalize a side of the players partecipating on the P2P transactive market. These are some of the main unknowns regarding the actual process. According to the chosen model, other questions can be raised.

6.2. BASIC PRIORITIZATION ALGORITHM

As can be seen in the previous section, the initial model had a wide number of aspects to work on in order to pursue a model improvement. For this reason, the algorithm proposed in this section focuses on the mere auction models, without considering the introduction of external elements. The following changes had been applied in attempt to solve the main nodes listed previously. The main lines of the new proposed P2P transactive algorithm are shown here below:

- first price sealed bids, agents don’t see each other bid
- bid linked to the amounts
- minimum price / maximum bid criteria
- if equal bids on equal amounts, amount split between the agents

```
process schedule:

<auction starts>

<auctioner query selllers>
<order sellers by growing prices>

<auctioneer ask bidders>
<order bidders by descending bids>

<calculate the bid average>
<distribute the energy among buyers>
<anounce  prices  and  amounts  to  buyers  and
sellers>

<end>
```

This model, differently from the English auction type, allow the agents to have an aggressive bidding strategy, to try to get the priority on a certain on sale quantity of energy, without having to pay that exact price. Moreover, the concept of “lot” does not exist anymore in this type of process (which is still an auction process). In the previous method, the seller had to

split his own amount in lots for it to be traded. This was necessary in order to try to sell all the energy available, because the buyers tent to lower the offer as the quantity increase and also because they are not incentivized to buy extra energy in that they would have to sell it back to the main grid. The algorithm proposed, establish a simple priority order among both the sellers and the buyers, assigning the energy automatically from the higher ranked sellers to the higher ranked buyers and following the priority chart. The bids are “linked” on the amounts. This means that, explaining from the buyer perspective, the buyer submit to the auctioneer the designed bid (express in Eur/kWh) and the amount the he desire to buy, and he is not willing to buy a different quantity of energy for that price. This way the bid is considered “linked” to that specific quantity of energy. In this case the difference is that there is one single bidding process and the auction doesn’t actually stop because there are no more submitted bids or energy to be sold. It ends because in the bidding scenario that has emerged, the respective buyers bidding curve and seller pricing curve, converges on an appointed price and quantity, which would be the ones who “clear” the market. So, the transactions will happen only as long as there are bids above or prices below the “clearing price”. Clearly, the clearing quantity can be such that a seller doesn’t have the opportunity to sell all his energy due to no more bids available above the clearing price. However, this model allows the players to have no issue with that. In fact, with this configuration, the buyers are not forced to “close a bid” and buy all the amount from a seller. That’s because in this kind of process, the transactions only follow the priority order. Therefore, everything is already set and done and there can be, for example, different buyers buying from the same seller or even a buyer buying from more sellers having submitted only one bid. This model finds and intermediate trading solution that allows seller and buyers to “meet halfway” and trade the desired quantity at an intermediate price. In fact, after the initial bidding and pricing submission, the auctioneer calculates the bid average. This bid average represents the “clearing price” of the auction. Therefore, in the last phase, where the auctioneer will communicate to the winners of the auction the clearing price, because that’s the price at which the energy will be sold/ bought. Moreover, the clearing quantity is the quantity sold/ bought in the auction where all the buyers with bids above the clearing price purchased their energy and/or the sellers with prices below the clearing price sold their energy (the two quantities do not correspond as there can be still sellers below the clearing price with a quantity that no seller requests or the other way around).
A generic seller puts the energy on sale if the resulting value of **equation 6.1** is higher than zero.

$$E^{s}_{a_{ac}} = \begin{cases} 0 & if\ baseline = none \\ F_{gen_{t+1}} - F_{cons_{t+1}} & if\ baseline = surplus \\ F_{gen_{t+1}} & if\ baseline = all \end{cases} \qquad \textbf{(6.1)}$$

This ensure that the agent does not put on sale energy that he needs or that is not willing to sell (considering the strategy adopted).
$E^{s}_{a_{ac}}$ is the amount that the seller is willing to trade in the auction catalogue. with $\boldsymbol{F_{gen_{t+1}}}$ representing the generation data forecasted for the following hour at hour t, and $F_{cons_{t+1}}$ representing the consumption forecast for the following hour also at hour t. The terms

baseline, surplus, none and all are referred to the ones used in the configuration file showed in **Figure 14**.

To preserve the equity in the trading process, if two or more agents submits equal bids on equal amounts, the quantity is divided among them (if the market cannot satisfy all of them). To validate the results, the proposed algorithm has been simulated in the same week as the previous English auction model showed results, from March 3rd to March 9th, 2020. This has been possible because the µGIM platform is equipped with a specific offline simulation option, which can run the trading model with past consumption/generation data taken from the database cited in section 5.2. In absence of this option, the same function can be implemented using a python code. **Table 4** provides an overview of the results from the algorithm simulation.

Table 2: basic prioritization algorithm weekly results 17-23/02/2020.

		Z.0	L.1	L.2	L.3	R.2	Community
Energy	Consumption (kWh)	147,311	109,298	171,986	91,891	41,860	562,347
	Generation (kWh)	169,429	28,775	28,775	28,775	28,775	284,531
Forecast	Forecast MAPE Cons	9,98%	9,85%	10,88%	10,04%	10,12%	10,17%
	Forecast MAPE Gen	6,62%	6,33%	6,77%	6,60%	5,99%	7,29%
P2P	Bought	0,000	2,043	12,733	10,455	3,363	28,594
	Sold	21,065	0,000	0,000	2,312	5,217	28,594
	Best choice periods	31	9	35	42	45	162
	Wrong sale periods	4	0	0	2	4	10
	Sold too much periods	10	0	0	3	6	19
	Wrong purchase periods	0	1	1	0	1	3
	Bought too much periods	0	6	3	1	6	16
	Wrong trading (kWh)	2,491	0,325	0,496	0,057	0,815	4,183
	Total number of transactions	45	16	39	48	62	210
	% of best choices	68,89%	56,25%	89,74%	87,50%	72,58%	77,14%
Energy costs	Week cost [EUR]	1,6181	15,5995	27,9629	12,7293	3,1756	61,085
	Week Cost [EUR] (w/o P2P)	2,3756	16,2455	28,6661	13,3470	3,4803	64,115
	Price per kWh (EUR/kWh)	0,0110	0,1427	0,1626	0,1385	0,0759	0,1086
	Price per kWh (EUR/kWh) (w/o P2P)	0,0161	0,1486	0,1667	0,1452	0,0831	0,1140
P2P energy	Price variation (with and w/o P2P)	31,89%	3,98%	2,45%	4,63%	8,75%	4,72%
	P2P energy trading in consumption	0,00%	1,87%	7,40%	11,38%	8,03%	5,08%
	P2P energy trading in generation	12,43%	0,00%	0,00%	8,03%	18,13%	10,05%

From the current panorama, the introduced changes can be considered effective. The transacted energy of the community kept a good level, with over 28 kWh of peer-to-peer trading. The best choices periods are still in preponderant number (160) over the total number of trading errors (48). The trading errors are direct consequences of the forecasting algorithm Mean Absolute Percentage Error (MAPE) and are represented by four main type of errors (wrong sale, wrong purchase, sold too much, bought too much). The trading algorithm can influence the number of errors optimizing the trading process, trying to make it more effective, with a lower number of transactions. Less transactions would mean less errors but not necessarily less energy traded. The key is to find the right balance. In this phase, only the effectiveness of the proposed model is discussed, the possible improvements are discussed in the result comparison section. The model manages also to keep the wrong trading under the threshold of 5 kW, despite increasing the transacted energy. Speaking of concrete advantages for the microgrid agents, the model manages to achieve a total average community price variation of 4.7 %, with the agent Z0 reaching the value of 31,89% of savings. As specified in the previous chapter, the agent Z0 owns a generation six time bigger than the other players, so it is normal for this case study to have him obtaining a bigger advantage compared to the other players. Always for comparison purposes and to provide a more complete analysis, another week is simulated (using the same option) and shown in **Table 5** This week covers the period from the 10th to the 16th of April 2019 and can be useful to see the behavior of the model in under different consumption and generation profiles due to warmer climatic conditions.

Table 3: basic prioritization algorithm weekly results 10-16/04/2019.

		Z.0	L.1	L.2	L.3	R.2	Community
Energy	Consumption (kWh)	153,696	127,982	295,688	66,364	45,916	689,645
	Generation (kWh)	120,477	20,080	20,080	20,079	20,079	200,795
Forecast	Forecast MAPE Cons	9,59%	9,51%	10,45%	9,55%	9,50%	9,72%
	Forecast MAPE Gen	5,65%	5,51%	6,09%	5,42%	5,14%	6,43%
P2P	Bought	0,000	0,498	19,245	1,815	2,706	24,264
	Sold	21,060	0,078	0,000	1,746	1,380	24,264
	Best choice periods	14	3	26	22	15	80
	Wrong sale periods	10	1	0	6	6	23
	Sold too much periods	11	1	0	2	5	19
	Wrong purchase periods	0	0	0	2	7	9
	Bought too much periods	0	0	0	3	7	10
	Wrong trading (kWh)	3,891	0,050	0,000	0,827	1,242	6,010
	Total number of transactions	35	5	26	35	40	141
	% of best choices	40,00%	60,00%	100,00%	62,86%	37,50%	56,74%
Energy costs	Week cost [EUR]	8,8222	21,5511	54,1692	9,3170	5,1683	99,028
	Week Cost [EUR] (w/o P2P)	9,6122	21,5831	55,1217	9,4787	5,2994	101,095
	Price per kWh (EUR/kWh)	0,0574	0,1684	0,1832	0,1404	0,1126	0,1436
	Price per kWh (EUR/kWh) (w/o P2P)	0,0625	0,1686	0,1864	0,1428	0,1154	0,1466
P2P energy	Price variation (with and w/o P2P)	8,22%	0,15%	1,73%	1,71%	2,47%	2,04%
	P2P energy trading in consumption	0,00%	0,39%	6,51%	2,73%	5,89%	3,52%
	P2P energy trading in generation	17,48%	0,39%	0,00%	8,70%	6,87%	12,08%

In this case the scenario changes completely. The consumption and the generation profiles are significantly different, with the MG total consumption increasing and the generation decreasing. With these profiles, the possibilities of operating transactions decrease in a decisive way, especially because with such a high consumption, the agents are brought to self – consume the energy way more that in the previous week examined. That being said, the model manages to achieve some results even in this situation. The agents trade over 24 kW of energy between each other with agent's L2 buys over 19 of them and Z0 selling over 21. Due to a significantly lower number of transactions, the ratio between the best choice periods and forecast errors drops at 80 over 61. The main aspect that highlights the worst response of the model in this week in comparison with the one seen previously is the fact that the amount of wrong trading goes up to 6 kW even if the total transacted energy is less. Despite these details, the microgrid reach a combined price variation of 2,04%, proving the model effective also in these situations. The response of the model can be considered positive in this scenario not favorable for the transactions. In **figure**s 14 and 15 the weekly consumption and cost variation profiles (with and without P2P) can be seen, respectively for the March week and for the April week.

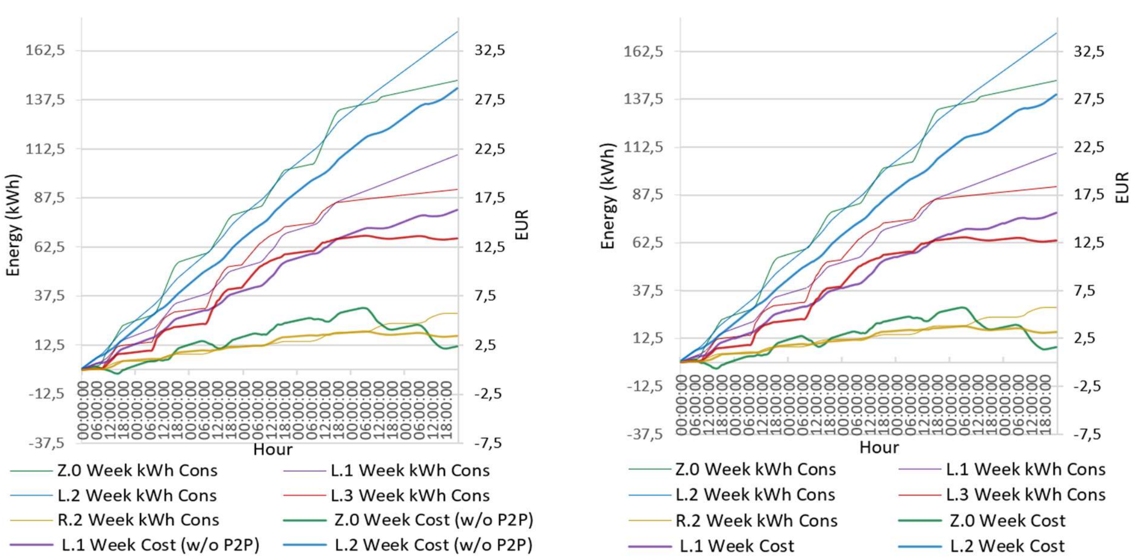

Figure 14: agents weekly consumptions and energy costs 3-9 March 2020

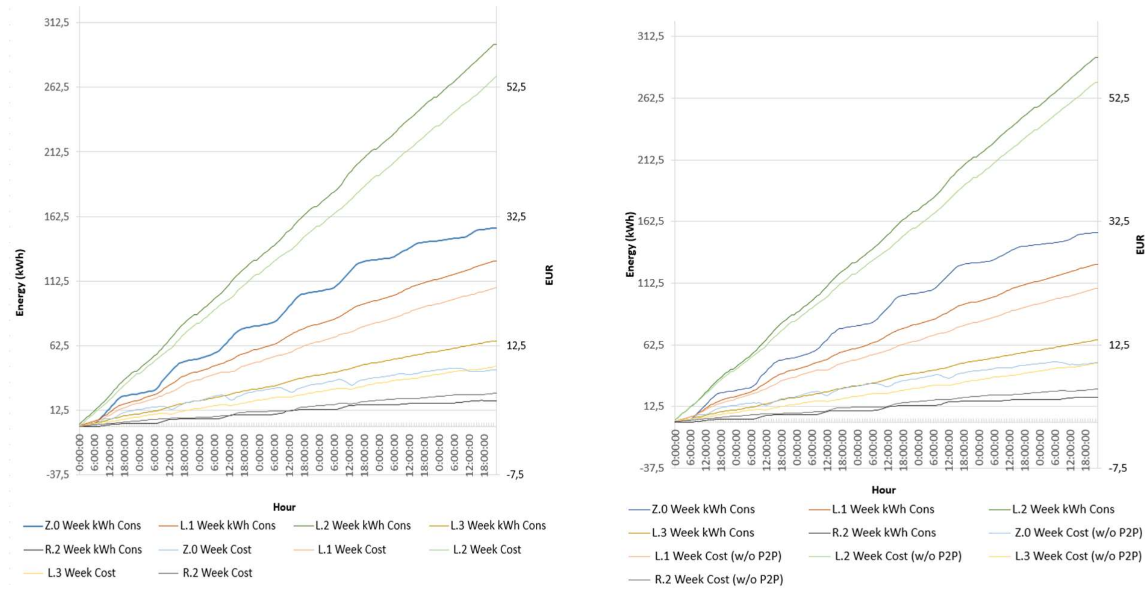

Figure 15: agents weekly consumptions and energy costs 10-16 April 2019

Being the major contributor to the trading, a tangible variation in the hourly week cost profile can be observed comparing the line correspondent to agent Z0. In **figure** 24 and 25 the major consumption of agent L2 can be clearly seen. This is to be attributed to the server room contained in the agent's L2 zones, which increase massively his consumption when the temperatue raise due to the increasing power requested by the cooling system.

To close this section, some considerations on the forecasting algorithm impact can be discussed. A graphical representation of the entity of the forecast error and the resulting trading errors is provided in figure 16 and 17

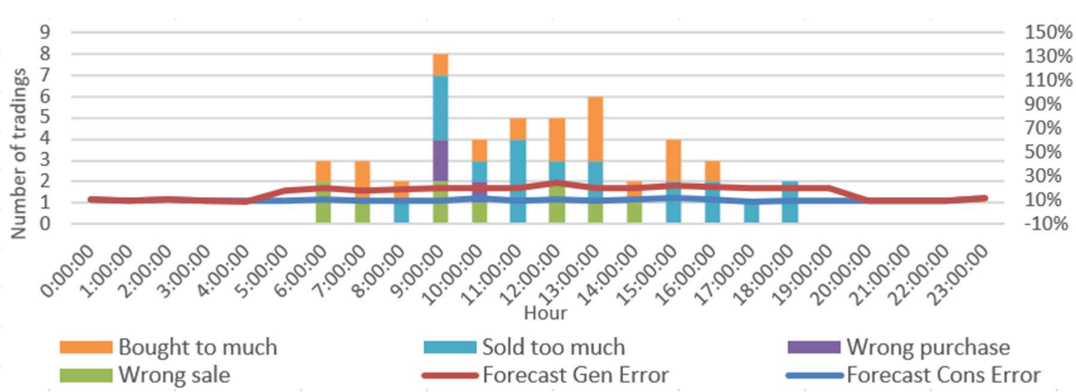

Figure 16: wrong trading periods and forecast errors

algorithms test

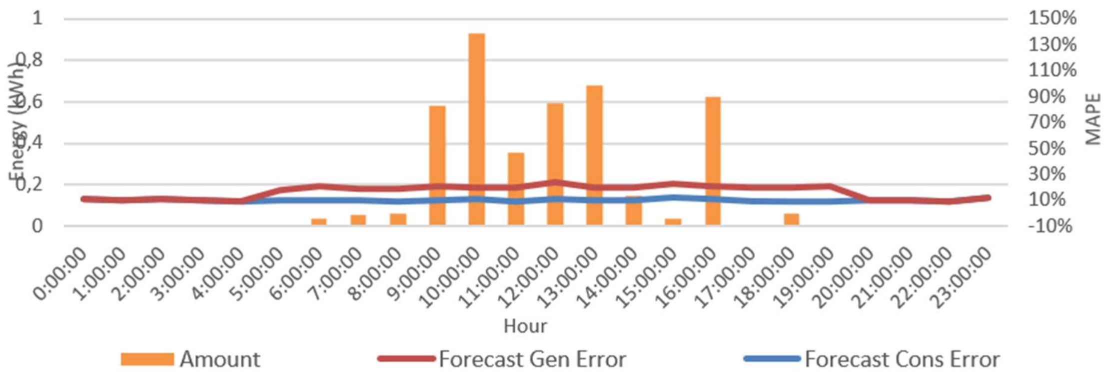

Figure 17: wrong trading amounts and forecast errors

As we can see, the MAPE maintain a constant level throughout all the hours of the day.
The implementation of some changes or some settings to limit the wrong trading due to the forecast algorithms has been considered. The main way to do such an operation would be to act on the configuration of the agents, imposing a correction value to the percentage of value they put on sale or they desire to buy. These are average data, so, with a deeper analysis of the forecast errors' distribution, is clear that this kind of solution cannot be effective. A change in the transacted quantity (either way) will end up only shifting the error in a direction or another, keeping the same average. The forecasting error can be considered a technological limit. Therefore, the solution is to be pursued in the release of a better forecasting algorithms to limit the errors. However, the model can impact the wrong trading with a more efficient trading process. The impact of the proposed algorithms on this parameter will be discussed in the results comparison section.

algorithms test

6.3. ITERATIVE AUCTION ALGORITHM

The basic algorithm implementation presented in the previous section demonstrated how a simple prioritization can increase the trading and affect the bidding strategy of the single agents. Consequently, the distribution of the transactions among the eagents is also impacted. Having showed a tangible improovement in the data, the next logicle step is to push in this direction and try to maximize the benefit, to validate the proposed method. A first approach, deriving from different optimization models analysed in section 2, would be to pick a specific aspect and try to optimize it. The first step taken in this direction has been an attempt to minimize the energy price for the players involved in the transactions, reducing their energy bills and maximizing the benefit they get from the trading, encouraging them to partecipate further in the P2P trading market. The model formulated to do such a change was a "composed auction model" (bid average + pay per bid) with the first transations phase operated in the same fashion of the Basic Prioritization Algorithm proposed in the previous model, with the same prioritization of the buyers/sellers. The main difference/novelty of the model was that after the first "clearing phase" in which the players who won the transaction exchange energy at an intermidiate price, follows a second phase, in which the remainning buyers can buy their desired energy (if available) at their submitted bid. The idea behind this model was to maximize the transacted energy by selling also to the agents that in the previous scenario would have been cut off the auction because of their invalid bid. From a first perspective this model seem to penalize excessively the sellers, because they are forced to accept bids way higher that their submitted price. However, the imposed condition doesn't result unfair because in the previous trading scenario, they would have been forced to sell that energy to the net, being subject to more stringent conditions. The model was supposed to preserve the equilibrium in the bidding strategies of the agents. This because the advantage of bidding lower to get an advantage on the price, was theoretically compensated by the fact that the agent loose the priority in the transactions and is not sure to get the desire energy. However, the better strategy for the agent's in this case was to bid at the minimum pricde possible, to lower the average bid and get the maximum advantage from the transactions. The model have proven to favor only the buyers and penalize the sellers. This case demonstrate that the operation of the maximization of a certain parameter is delicate and an inacurate formulation can lead to a totally unefficient model and affect the agents bidding strategy. Another idea have been to try to operate a sort of centralized optimization, but the road to a complete structural change of the model has proven to be a long theoretical struggle. Moreover, whould have required to change complitely the configuration of the agents in order to creative a cooperative environment, loosing this way the improvements achieved with the previous algorithm. Therefore, for the next formulation of the model has been decided to keep a competitive scenario among the agents. The following proposed algorithhm have been formulated following consideration made on the several bidding strategies adopted on some of the models presented in the proposed state of the art. In particular, the models adopting a game theoretical strategies, (like the ones presented in [15][13][9] and [21]) have been the more approachable to pursue valuable improvements in that they present the most similarities to the P2P trading model's structure adopted in this study. Have been observed that some models adopts iterative processes in order to find the optimal bidding configuration. Therefore, having found the simple auction type model particularly suitable for the implementation of this kind of technique. Has been decided to combine the auction process with an iterative process. The previous proposed algorithm is used as a base for the integration of this method, in order to combine the benefits already obtained with the ones deriving from the new formulation. The proposed iterative auction algorithm is formulated as follows.

Overall rules:

- establish min price for sellers
- establish max bid for bidders
- 1st price sealed bids, bid linked to the amount
- Establish price and bids “steps”

```
Process schedule:
1st iteration:

<query sellers>
<order sellers by growing price>
<query buyers>
<order buyers by descending bid>
<calculate the average weighted price>
<distribute energy amongh buyers and sellers>

2nd iteration

Remaining sellers:
If sold none: lower price by 10%
If sold some: submit new price
Remaining buyers:
If bought none:raise the bid by 10%
If bought some: submit new bid

<query sellers>
<order sellers by growing price>
<query buyers>
<order buyers by descending bid>
<calculate the average weighted price>
<distribute energy amongh buyers and sellers>

Repeat the last iteration until there are the
conditions
```

The first aspect deriving from the adoption of the previous algorithm main lines is found in the fact that this formulation keeps the same prioritization mechanism and average pice logic. The main difference in this aspect is the introduction of the average weighted price, formulated as in **equation 6.2**

$$\frac{\sum(\boldsymbol{bids/prices}) * \boldsymbol{amounts}}{\sum \boldsymbol{amounts}} \quad \textbf{(6.2)}$$

This derive from an observation of the market mechanisms of chapter 4. In the previous algorithm, the average bid is establish in a mathematical way, calculating the average value between all the bids/prices submitted by the players in the auction in order to simulate a classicle clearing scenario. However, the clearing price in such a market scenario is usually established in a graphical way, and it's represented by the intersection point of the sellers price curve and the buyers bid curve. These step-curves (as seen in chapter 4) are built considering both the amount and the bid/price of the agents. The amount plays a crucial role on the clearing price determination. For this reason, the average weighted price has been formuated in order simulate the effect of the amounts associated to de prices on the final clearing price. As in the graphical representation, in this equation a big amount will shift the value of the clearing price in the direction of his associated bid. The purpose of this change is to encourage more "responsible" bidding, avoiding the submission of excessively high bids to get the priority in the auction exploiting the factor that the other agent's bid would lower the clearing price. The main difference from the previous model is the characteristic of the iterative process; after clearing the market with the first auction catalogue, the remaining bidders and sellers may either have residual quantities or the total quantity they had to sell/buy. In the first option, the agent submit a new bid/price for the new amount and partecipate in the second auction (operated with a new iteration) with that new setup. In the second, the seller/buyer proceed to increase the bid/decrease the price, in order to have more favorable conditions in the new iteration and increase the probability to sell/buy.
These price/bid changes have been established as fixed steps of 10% of the previous submitted value. This can be considered a multiple bidding process.
As specified previously. The trading process works hourly, with the amounts that compose the auction catalogue being calculated on the values of hour consumptions.
In a single auction catalogue, the total amount of energy (Wh) put in the P2P market for the trading process is calculated with **equation 6.3.**

$$\boldsymbol{ME_a = min\left(\sum_{a=1}^{m} E^{s}_{a_{ac}}, \sum_{a=1}^{m} E^{b}_{a_{ac}}\right)} \quad \textbf{(6.3)}$$

with m indicating the number of the sellers/buyers participating in the peer-to-peer transaction auctions, $\boldsymbol{E^{s}_{a_{ac}}}$ indicating the amount of energy that an agent is willing to sell and ac indicating the auction catalogue. $\boldsymbol{E^{b}_{a_{ac}}}$ indicating the amount of energy that the same agent wants to buy in the same auctions catalogue.

The minimal price accepted by an agent ($\boldsymbol{L_{a_{ac}}^{min}}$) in an auction catalogue is a fixed value and remains constant during all the auction processes. Such a price is calculated for every agent in the system following the **equation 6.4.**

$$\boldsymbol{L_{a_{ac}}^{min} = mP_a \times M_t^s} \qquad \textbf{(6.4)}$$

where $\boldsymbol{mP_a}$ is the minimum price reported in the sell configuration of the agent and $\boldsymbol{M_h^s}$ represents the market price for energy sold to the grid in hour t, the same hour of auctions catalogue.
In a similar way, the maximum offer that a bidder is willing to submit in an auction catalogue **($\boldsymbol{MO_{ai_{ac}}}$)** is calculated following **equation 6.5.**

$$\boldsymbol{MO_{ai_{ac}} = MP_a \times M_h^b} \qquad \textbf{(6.5)}$$

With the maximum price, $\boldsymbol{MP_a}$ indicated in the configuration file of the agent, and the market price for energy bought $\boldsymbol{M_h^b}$.

These constraints are kept from the original model [28]. The minimum accepted price (for the sellers) and maximum bid for the bidders, are adopted to preserve the agents strategies. In fact, the process stops when there is no more energy to be sold/purchased or the players overcome those constraints

Once again, using the offline option of the platform, the same weeks have been simulated. The complete overview of the obtained results can be seen in **table 6** (for the March week) and **table 7** for the (April week).

Table 4: iterative auction algorithm weekly results 17-23/02/2020.

		Z.0	L.1	L.2	L.3	R.2	Community
Energy	Consumption (kWh)	147,311	109,298	171,986	91,891	41,860	562,347
	Generation (kWh)	169,429	28,775	28,775	28,775	28,775	284,531
Forecast	Forecast MAPE Cons	9,98%	9,85%	10,88%	10,04%	10,12%	10,17%
	Forecast MAPE Gen	6,62%	6,33%	6,77%	6,60%	5,99%	7,29%
P2P	Bought	0,000	3,185	14,262	10,353	0,708	28,508
	Sold	22,958	0,220	0,000	3,277	2,053	28,508
	Best choice periods	37	15	42	37	20	151
	Wrong sale periods	4	1	0	2	4	11
	Sold too much periods	10	1	0	4	4	19
	Wrong purchase periods	0	1	1	0	1	3
	Bought too much periods	0	6	3	1	1	11
	Wrong trading (kWh)	2,491	0,477	0,496	0,059	0,468	3,990
	Total number of transactions	51	24	46	44	30	195
	% of best choices	72,55%	62,50%	91,30%	84,09%	66,67%	77,44%
Energy costs	Week cost [EUR]	1,5380	15,5373	27,9161	12,7035	3,3798	61,075
	Week Cost [EUR] (w/o P2P)	2,3756	16,2455	28,6661	13,3470	3,4803	64,115
	Price per kWh (EUR/kWh)	0,0104	0,1422	0,1623	0,1382	0,0807	0,1086
	Price per kWh (EUR/kWh) (w/o P2P)	0,0161	0,1486	0,1667	0,1452	0,0831	0,1140
P2P energy	Price variation (with and w/o P2P)	35,26%	4,36%	2,62%	4,82%	2,89%	4,74%
	P2P energy trading in consumption	0,00%	2,91%	8,29%	11,27%	1,69%	5,07%
	P2P energy trading in generation	13,55%	0,76%	0,00%	11,39%	7,13%	10,02%

A slight change in the original formulation has been made during the "physical" implementation of the model in the system. The "new price/bid" submission between two iterations due to the change of the seller's/buyers' amount could't be implemented because the system didn't have the possibility to track the actions of the agents after the iterations. This factor can have slightly changed the results obtained. As can be seen from the table, the proposed algorithm implementation managed to keep the transacted quantity on a similar level to the previous algorithm. The number of best choices periods is still way higher than the summ of the forecast error periods (151 over 44), which is a good indicator of the model performance. The wrong trading is still kept under the trashold of 5kW, with a consistent number of transactions operated. Moreover, a price variation of 4.7% have been achieved, which is similar to the previous model results, but the difference can be noticed in the distribution of the price variations amongh the agents, which is more balanced, with all the minor agents gravitating between 2.6% and 4.8% , sign of the optimality of the process adopted.

Table 5: iterative auction algorithm weekly results 10-16/04/2019.

		Z.0	L.1	L.2	L.3	R.2	Community
Energy	Consumption (kWh)	153,696	127,982	295,688	66,364	45,916	689,645
	Generation (kWh)	120,477	20,080	20,080	20,079	20,079	200,795
Forecast	Forecast MAPE Cons	9,59%	9,51%	10,45%	9,55%	9,50%	9,72%
	Forecast MAPE Gen	5,65%	5,51%	6,09%	5,42%	5,14%	6,43%
P2P	Bought	0,000	2,628	19,298	1,461	0,775	24,162
	Sold	21,687	0,078	0,000	1,377	1,020	24,162
	Best choice periods	14	11	27	12	8	72
	Wrong sale periods	10	1	0	6	5	22
	Sold too much periods	11	1	0	2	4	18
	Wrong purchase periods	0	0	0	1	0	1
	Bought too much periods	0	1	0	5	4	10
	Wrong trading (kWh)	3,891	0,123	0,000	0,040	0,380	4,434
	Total number of transactions	35	14	27	26	21	123
	% of best choices	40,00%	78,57%	100,00%	46,15%	38,10%	58,54%
Energy costs	Week cost [EUR]	8,7619	21,4416	54,1884	9,3818	5,2430	99,017
	Week Cost [EUR] (w/o P2P)	9,6122	21,5831	55,1217	9,4787	5,2994	101,095
	Price per kWh (EUR/kWh)	0,0570	0,1675	0,1833	0,1414	0,1142	0,1436
	Price per kWh (EUR/kWh) (w/o P2P)	0,0625	0,1686	0,1864	0,1428	0,1154	0,1466
P2P energy	Price variation (with and w/o P2P)	8,85%	0,66%	1,69%	1,02%	1,07%	2,06%
	P2P energy trading in consumption	0,00%	2,05%	6,53%	2,20%	1,69%	3,50%
	P2P energy trading in generation	18,00%	0,39%	0,00%	6,86%	5,08%	12,03%

The same positives can be seen from the results of the week represented in **table 7,** with the model that have proved to be effective even in this more "ostile" scenario. The trading has been kept on the same level of the previous model, without increasing the amount of wrong trading. Once again, the trading achieved a microgrid community price variation of 2%. That results to be almost equally distributed amongh the agents. In this case the achievement turns out to be impressive, due to the fact that the agent L2 almost doubled his consumption, introducing a bid "unbalancing factor" in the trading market. Finally, it's worth to notice that the trading reach a consistent 12% of trading in generation, despite having less generation in comparison to the previous considered week. These factors emphasizes the optimizing behaviour of the proposed model. For a more complete view, in **figures 18 and 19** is shown respectively the weekly consumption and energy cost profile of the agents in both the simulated weeks, before and after the application of the transactive model**.**

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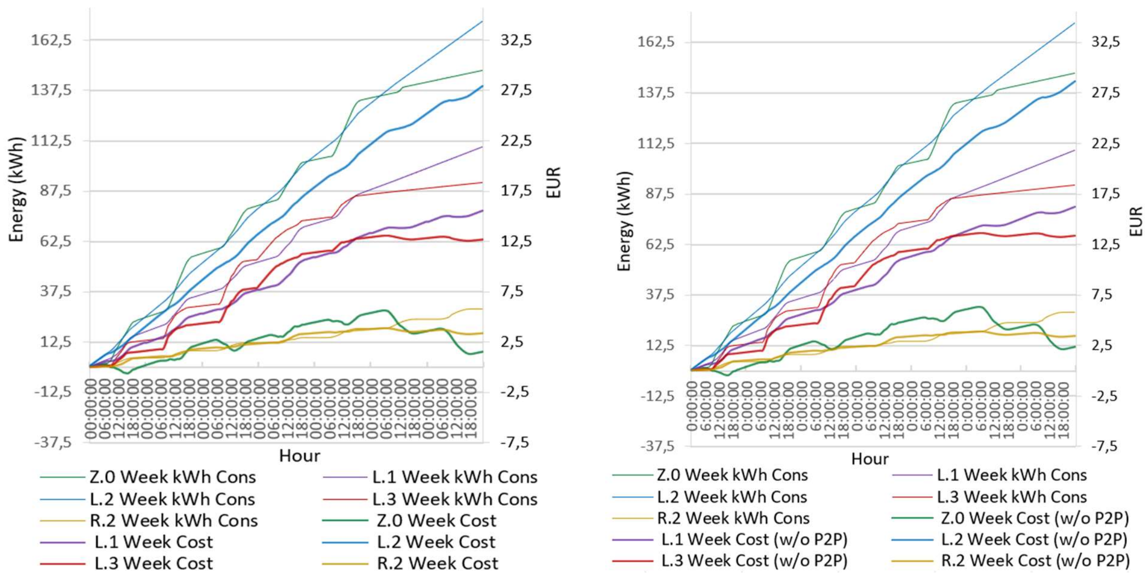

Figure 18: agents weekly consumptions and energy costs 3-9 March 2020

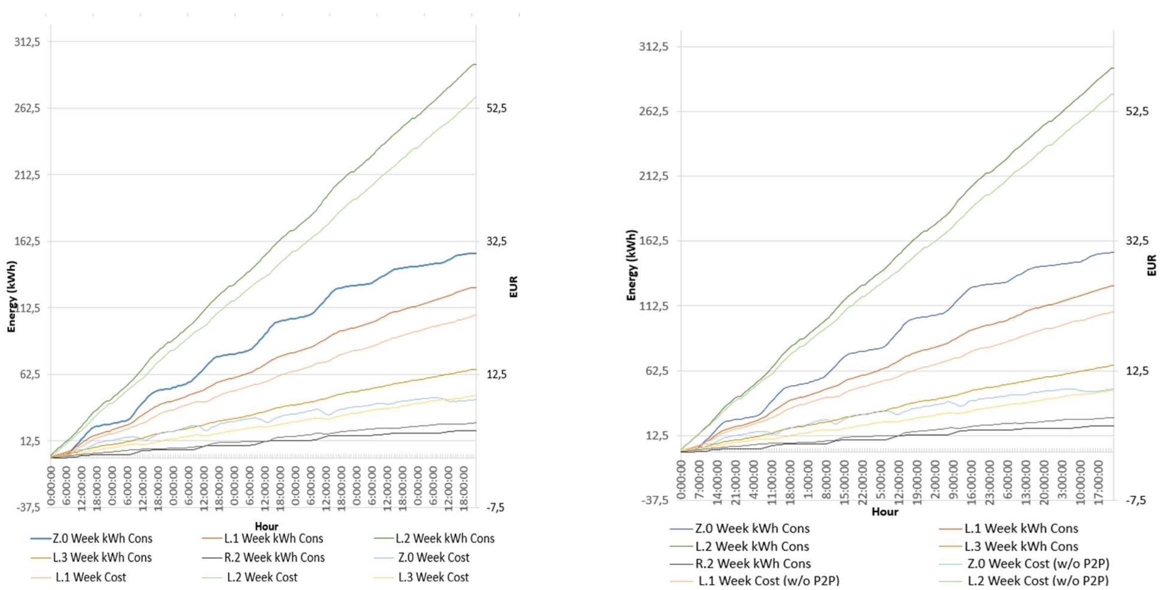

Figure 19: agents weekly consumptions and energy costs 10-16 April 2019

6.4. RESULTS COMPARISON

Now that the proposed algorithms have been widely introduced, their formulations have been explained and the results have been presented, it’s time too evaluate the models performance in therms of effectiveness of the measures implemented and their value in hypotetical future applications of this type of models. Therefore, this last section of the chapter will be dedicated to the comparison to the proposed algorithms with the initial auction model, to see the improvements or/and the difects in the process. **Table** summarizes the key performance values obtained by the three models. In order to make a valid comparison, the table reports the most meaningful results obtained by the three models in the week between 3 and 9 March 2020. As specified before, the week has been simulated with the proposed algorithms using the offline simulation option of the platform, using the past consumption data found in the remote storage database.

Table 6: models result comparison

Parameter	Model 1	Model 2	Model 3
Forecast MAPE consumption [%]	9,88	10,17	10,17
Forecast MAPE generation [%]	7,16	7,29	7,29
Energy bought/sold [kWh]	27.104	28,594	28,508
Best choice periods	195	162	151
Wrong sale periods	9	10	11
Sold too much periods	26	19	19
Wrong purchase periods	1	3	3
Bought too much periods	4	16	11
Wrong trading [kwh]	4,736	4,183	3,990
Number of transactions	235	210	195
Best choices percentage	82,98	77,14	77,44
Week cost (with transactions) [Eur]	61,318	61,085	61,075
Price per kWh	0,1090	0,1086	0,1086
Price variation [%]	4,36	4,72	4,74
Energy trading in consumption [%]	4,82	5,08	5,07
energy trading in generation [%]	9,53	10,05	10,02

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For practical reasons, The table refers to the algorithms using this notation,in the order they were realized/implemented: model 1 = English auction model [28], model 2 = Basic Prioritization Algorithm and model 3 = Iterative Auction Algorithm. the reported data are all referring to the whole microgrid, so to the entire community of agents. The first thing worth to notice is that the new models manage to achieve the initial goal of maximizing the trading. moving from model 1 to model 2, the transacted energy increase by 5.51%. If model 1 is compared with model 3, we register a growth of 5,18 % , equally effective. In fact, when conpared with each other, model 2 and 3 see a difference in the trading of a mere 0,3% in favor of model 2, which can be considered negligible. Looking at the errors, both model 2 and 3 have a higher number of combined errors periods (the sum of the four main errors) with 48 for model 2 and 44 of model 3, but they are distributed differently from the first model. despite having 40 combined errors, model 1 have 26 error periods all in the sold too much section. Sign that model 2 and 3 provide a more balanced trading process (point emphasized also in the previous section when noticed that algorithm 3 achieved similar price variations for all the 4 minor agents). Models 2 and 3 also record a progressively decreasing number of best choice periods compared to model 1: 195, 162 and 151. This can be justified by observing the total number of transactions operated in the trading market by the community, which have a totally similar trend: 235, 210 e 195. Another sensible data to evaluate the efficiency of the transaction process is the amount of wrongly traded energy or wrong trading. is possible to see that the amount of wrong trading consistently decreased from model 1 to model 3. Model 2 achieve a significant wrong trading reduction of 11,67% when compared with model 1, model 3 then gets a further decrease of 4,6%, which goes up to an consistent 15,75% if compared directly with model 1. This wrong trading data becomes even more impressive if combined with the fact that model 3 have more transactive energy in a lower number of transactions. Is fair to say that model 3 improve the quality of the transaction process. This results gain even more meaning if is taken into account the fact that they were achieved using a different forecasting algorithm in model 2 and 3, which had a bigger forecasting error (2,9% more in consumption, 1,8% more in generation). This aspect can also justify the higher number of combined errors found in the 2 algorithms). Looking at the price we notice also that both model 2 and 3 achieve a bigger price variation in comparison to model 1: model 2 and 3 all around 4.7 against the 4,36 of model 1, same thing holds for the price variation: 0,1086 of the new algorithms against the 0,1090 of model 1, and for the week cost: 61,085/075 against the 61,318 of model 1. This last data shows that the new models succeed in both improving the overall efficiency of the P2P trading process and providing and advantage for the single agents, achieving cheaper energy bills The results also shows that a more accurate bidding process can maintain the trading on high levels, despite decreasing the number of the transactions. This would minimize the wrong trading, emphasizing the advantage for the players, being not forced to interact with the grid in order to get rid of the extra energy bought or to buy the energy that they miss because of the wrong forecasted consumption/generation. As a conclusion, **figures 20, 21** Shows the profiles of the main energy flows without trading and using the English auction model [28] and **Figure 22 and 23** Shows the same profiles considering the two trading algorithm proposed in the simulated week.

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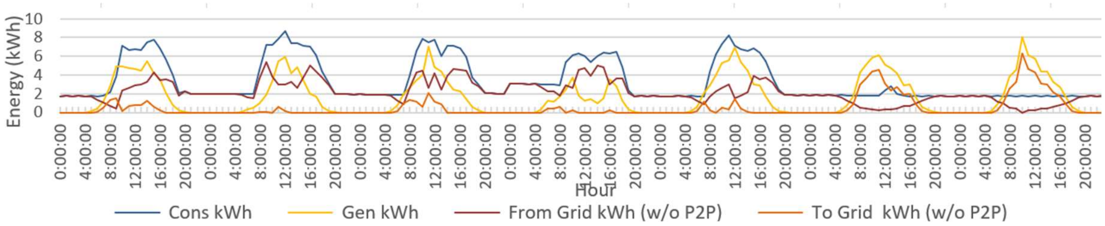

Figure 20: Microgrid's weekly energy profile (without P2P transactions) [28]

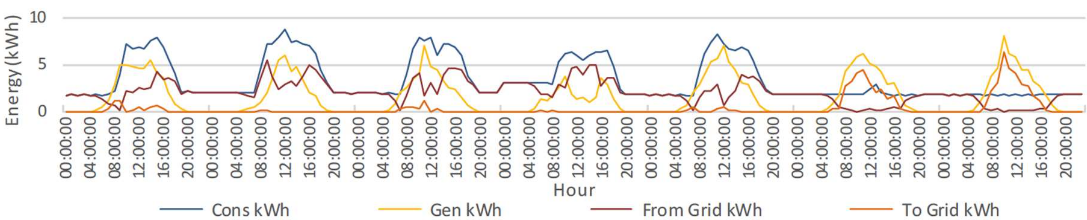

Figure 21: Microgrid's weekly energy profile (with P2P transactions, model 1) [28]

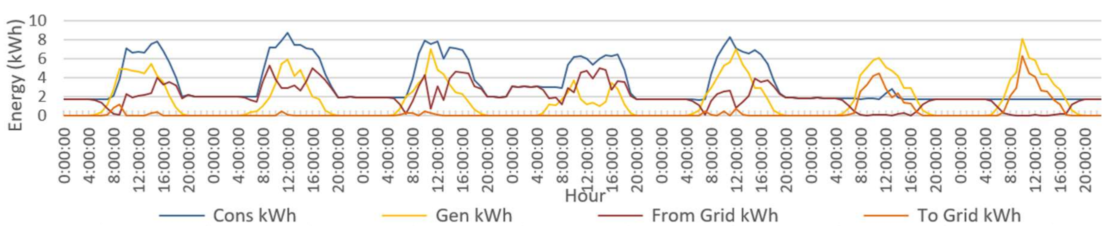

Figure 22: Microgrid's weekly energy profile (with P2P transactions, model 2)

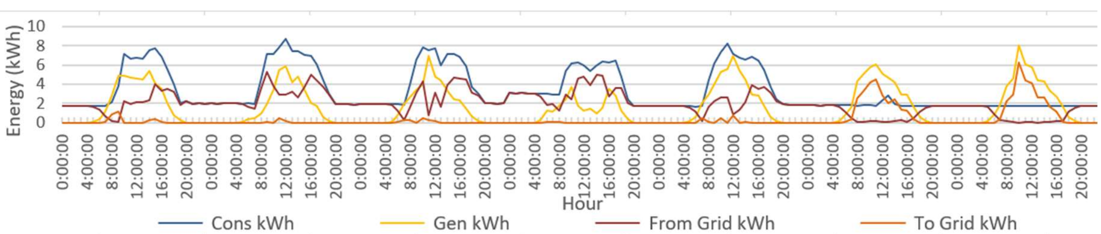

Figure 23: Microgrid's weekly energy profile (with P2P transactions, modell 3)

7. CONCLUSIONS

A natural conclusion that can be drawn from this work is the achnowlegment of the potential of this technology. Nowadays, intelligent systems and smart grids are object of several studies and their number is rapidly growing. The peer - to - peer electricity trading technology represents a big opportunuty for end users with small, independent generation, giving them the possibility to have an active role in the community and partecipate in the energy local market as an active player. The advancement of the technologies in this field and the increasing penetration of RES is offering a major variety of research possibilities and solutions for the developement of the trading environments. This project provided an investigation on P2P energy trading techniques implementation in the specific case study of a microgrid with a multi agent system integrated in an office building, A μGIM platform was used to simulate the transactive models and to configurate the players behaviour in order to create a competitive trading scenario. The analysis was centered on the auction type model and different trading configurations were discussed. The presented results show a noticeable improvement in the efficiency of the transactive process, achieving advantages both for the community and for the single players. The results were obtained trough the application of slight changes to the initial model, supported by the proposed comparison and state of art. This scenario emphasizes the fact that this kind of models are still in the first stage of their developement, with a high margin of improvement. Adopting a similar approach, will be possible to achieve further improovements and developements in the future.

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