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

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Abstract

The thesis proposes an investigation on the implementation of peer-to-peer (P2P) energy trading techniques at a distribution level as a possible energy management solution to deal with distributed generation (DG) and renewable energy sources (RES). Firstly, an overview of the peer-to-peer energy trading concept is provided, reviewing all the hardware, software and components necessary to build a peer-to-peer trading platform. The following chapter propose a state of the art of the current P2P trading technologies development, analysing several projects carried out in this field in recent years and doing a comparison of the models, considering their commonalities, strengths and shortcomings. Another chapter is dedicated to a small bibliographic review of the techniques adopted in the models, taking a closer look to the implemented methods in a conceptual way. Chapter five talks about the main dynamics and scenarios that can occur in the specific case of prosumers interacting in a MG peer-to-peer internal market. 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) is used to create a local decentralized environment composed of five prosumers. The system is placed in a grid connected microgrid, located in an office building. Each one of the agents can rely on a "slice" of energy that comes from a set of PVs installed in the rooftop. this DG allow them to operate energy transactions among each other. Each agent is represented by a tenant of a zone in the building and is considered as an independent entity. 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 and are presented in chapter seven. 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 property of the simulation platform was used to run the model using consumption data recorded from previous weeks 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.

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List of abbreviations

μGIM	–	Micro Grid Intelligent Management
CNLP	–	constrained nonlinear programming
DALI	–	Digital Addressable Lighting Interface
dfDF	–	Directory Facilitator
DG	–	Distributed Generation
DGC	–	Digital Grid Controller
DGR	–	Digital Grid Router
DSM	–	Demand Side Management
DSO	–	Distribution System Operator
EV	–	Electric Vehicle
FIFO	–	First In First Out
ICT	–	Information and Communication Technologies
IoT	–	Internet of Things
LA	–	Local Agent
LAG	–	Local Aggregator
MAPE	–	Mean Absolute Percentage Error
MAS	–	Multi Agent System
MG	–	Micro Grid
MGCC	–	Micro Grid Control Center
MILP	–	Mixed Integer Linear Programming
P2G	–	Peer-to-Grid
P2P	–	Peer-to-Peer
PHEV	–	Plug-in Hybrid Electric Vehicle
PV	–	Photovoltaic panels
RES	–	Renewables Energy Sources
SBC	–	Single Board Computer
SCADA		Supervisory Control and Data Acquisition
SOCP		Second Order Linear Programming
TE	–	Transactive Energy
TSO	–	Trasmission system operator
VPP	–	Virtual Power Plant
WPP	–	Wind Power Plants

Italian version

Il progresso tecnologico insieme alla crescita economica, strutturale e demografica della società alza continuamente il livello nella direzione di un maggiore consumo di energia. Per soddisfare questo crescente fabbisogno di energia, si possono intraprendere molti percorsi. Tuttavia, la serie di scenari disponibili da adottare è notevolmente ridotta se vengono presi in considerazione alcuni vincoli essenziali introdotti nell'ultimo decennio grazie alla sensibilizzazione di diversi paesi sulle tematiche ambientali e la ricerca nel campo dell'efficientamento energetico. Il più significativo di questi è dato dalla necessità di contenere il livello di gas serra nell'atmosfera (in particolare di CO_2, che è cresciuta enormemente nell'ultimo secolo, a causa delle attività umane come la deforestazione e l'industrializzazione), che ci ha già portato ad affrontare i primi segni di cambiamento climatico. Negli ultimi anni, le risorse energetiche distribuite (DER) e le tecniche di comunicazione / controllo a livello di consumatore sono state adottate in modo più consistente, principalmente a causa del loro rapido sviluppo e dell'aumento della produzione. Con il contributo di queste tecnologie, i consumatori finali, che hanno un ruolo tipicamente "passivo" nei sistemi di distribuzione, hanno la possibilità di gestire attivamente il proprio consumo, generazione e stoccaggio di energia, diventando consumatori proattivi (Prosumer) [1] Ciò ha aumentato la diffusione delle piattaforme di transazioni energetiche peer - to - peer, utilizzate per connettere gli utenti finali dotati di sistemi di generazione o accumulo al fine di creare un mercato interno liberalizzato che consenta ai partecipanti di gestire la generazione distribuita (DG) a livello locale attraverso degli scambi di energia. La diffusione delle piattaforme di peer-to-peer (P2P) electricity trading è stata accelerata anche dall'ulteriore crescita delle Internet of Things technologies (IoT) e delle smart homes, abitazioni intelligenti dotate di sistemi di controllo, monitoraggio e comunicazione. Queste tecnologie consentono alle normali famiglie / utenti finali di diventare interattive dal punto di vista energetico, prendendo parte a comunità di condivisione dell'energia all'interno di microgrid (MG) e smart grid (SG). Diversi studi condotti in precedenza evidenziano i vantaggi di queste applicazioni [2]. Questo paradigma è stato introdotto per raggiungere livelli più elevati di gestione energetica; ed è una promettente alternativa da adottare per il perseguimento di una possibile soluzione ad uno scenario di produzione energetica ad emissioni zero. La tecnologia di scambio di elettricità peer-to-peer ha dimostrato di portare vantaggi effettivi nei mercati decentralizzati dell'energia delle microgrid, promuovendo e facilitando l'integrazione delle fonti di energia rinnovabile (RES) nei sistemi di distribuzione di energia locale [3]. Ulteriori sviluppi in questa direzione aiuteranno la progressiva penetrazione delle rinnovabili, il generale decentramento del mercato elettrico e anche la progressiva diffusione dei veicoli elettrici (EV) nel panorama globale. Tuttavia, una conseguenza diretta dell'implementazione di questo tipo di sistemi è la notevole crescita della complessità, sia in termini di architettura di rete che nella modellazione e regolazione del mercato elettrico. Sebbene la relativa giovinezza di questo tipo di sistemi renda difficile trovare un parametro di valutazione adeguato per misurare la reale efficacia della loro implementazione, alcune ricerche sono state fatte anche in questo campo [4]. Un sistema che utilizza energia transattiva può avere diversi aspetti e caratteristiche, attualmente allo studio in molti progetti in corso di realizzazione in tutto il mondo.

La tesi propone un'indagine sull'implementazione di piattaforme di transazione energetica peer-to-peer nei sistemi di distribuzione come possibile soluzione gestione della generazione distribuita (DG) e la penetrazione delle fonti di energia rinnovabile (RES). Il secondo capitolo è interamente dedicato all'inquadramento e la descrizione dei sistemi di P2P electricity trading, in quanto sebbene il concetto alla base sia semplice, i sistemi adottati per questo tipo di applicazione sono molto avanzati ed articolati e rappresentano l'insieme di diverse branche dell'ingegneria come elettrotecnica, elettronica internet e telecomunicazioni informatica.

La fase centrale rappresenta il nucleo di questo lavoro in quanto viene fornito uno stato dell'arte dell'attuale sviluppo delle tecnologie di trading P2P, rivedendo e analizzando diversi progetti realizzati in questo campo negli ultimi anni e facendo un confronto tra modelli, considerando i loro punti in comune, punti di forza e carenze, insieme a. panoramica delle principali tecniche utilizzate soffermandosi sulle tecnologie più promettenti come algoritmi di ottimizzazione, Blockchain, game theory, e le principali tecniche di asta energetica.

Il capitolo cinque si sofferma su alcune caratteristiche principali del mercato elettrico liberalizzato interno che caratterizza questi sistemi di trading, offrendo una panoramica su dinamiche e scenari che possono incorrere nel caso di interazione tra consumatori proattivi (prosumers) all'interno di una microgrid.

Nella seconda parte dell'elaborato, l'attenzione si sposta sulla presentazione della struttura del sistema utilizzato nello specifico caso di studio indagato nel progetto. Un multi agent system (MAS) integrato con una micro grid management platform (μGIM) agisce in una microgrid connessa alla rete situata in un edificio contenente uffici, dotato di pannelli solari (PV) per gestire transazioni energetiche tra diversi agenti (prosumer / consumatori). Ogni agente è rappresentato da un inquilino di una zona dell'edificio, che possiede una parte della generazione fotovoltaica totale. Dal punto di partenza del modello di asta inglese, inizialmente utilizzato nella piattaforma di trading, sono stati implementati nel sistema due nuovi algoritmi nel tentativo di migliorare l'efficienza del processo di trading. La formulazione degli algoritmi si basa sull'analisi del comportamento e dei risultati del modello iniziale, ed è supportata dall' analisi dello stato dell'arte fornito nel primo capitolo. Una specifica funzionalità della piattaforma di simulazione è stata utilizzata per eseguire il modello utilizzando i dati di consumo e generazione registrati dalla settimana precedente di monitoraggio, al fine di confrontare diversi algoritmi di trading che lavorano sullo stesso profilo di consumo / generazione. Gli sviluppi ottenuti da questo studio dimostrano le capacità dei sistemi di scambio energetico P2P di avvantaggiare gli utenti finali, consentendo loro di gestire attivamente la propria energia e perseguire i propri obiettivi personali. Sottolineano inoltre che questo tipo di modelli hanno ancora un buon margine di miglioramento e con ulteriori studi possono rappresentare un elemento chiave nelle future smart grid e sistemi decentralizzati.

Chapter 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 some essentials constraints are taken into account. The most significant of those is the relentlessly growing level of greenhouse gasses in the atmosphere (especially CO_2, 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 paradigm 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 parameter 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 and applied in the case study of a grid - connected MG. with an overview of the obtained results and considerations on the possible future perspective of the analyzed trading techniques.

Chapter 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. As stated before, the main factor that brought to the development of systems for the trading of electricity at a local level is the appearance of the proactive consumer (prosumer). The advent of this new figure in the energy users panorama, generate a consistent group of new dynamics in the energy distribution and energy management fields. Making it necessary to formulate new rules and models for the “adaptation and response” of the electricity market to such a dynamic and aleatory variable. In a future perspective, peer-to-peer energy transactions among prosumers in communities with distributed generation can favor the diffusion of real virtual power plants (VPPs) , plants that integrates several types of RES e.g. wind power plants (WPP) photovoltaics, small hydro turbines as well as storage system. Within the P2P energy trading platforms, different classes of traded energy can be identified and differentiated based on factors like source or destination attributes that are valuable from a prosumer perspective. P2P platforms could be used to facilitate renewable energy trading, accounting for the time and location of energy generation, storage and consumption. the European Consumer Organization has recommended the creation of new transparent mechanisms to track the delivery of renewable energy to end users [1]. Figure 2.1 highlights the concept just expressed, giving a simple and schematic representation of the interactions between different end users at a local distribution network level and the different classes of energy mentioned. The philanthropic prosumer is willing to sell subsidized energy to the low-income household. The green prosumer is able to meet its demand using all-renewable supply by paying a premium for green energy.

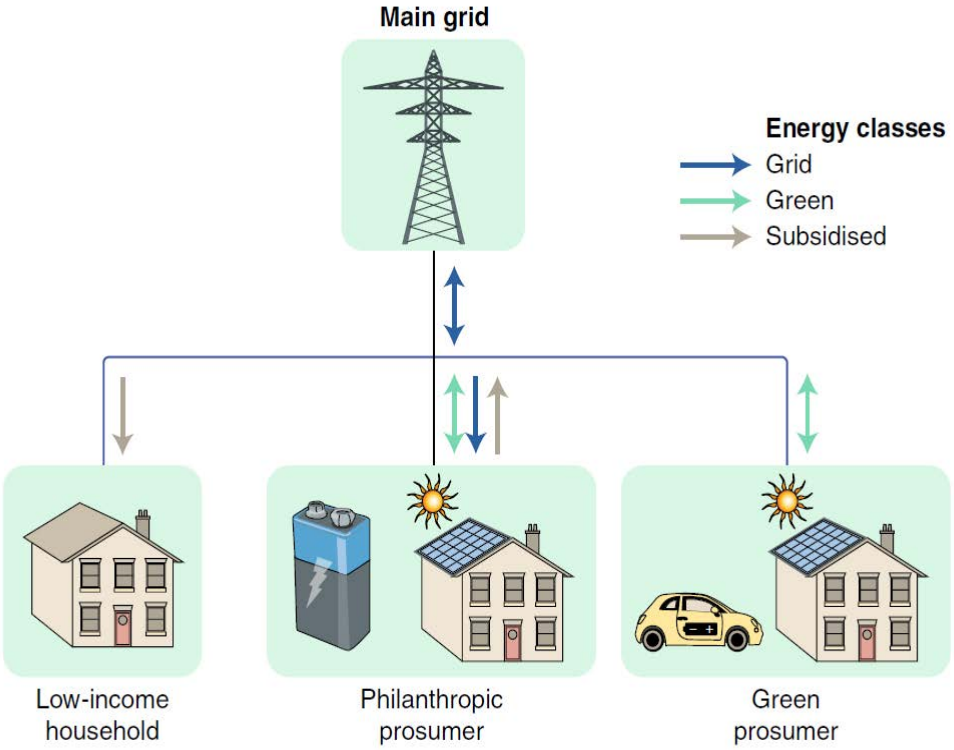


Figure 2.1: prosumers and energy classes representation [1]

Once clarified the role and the importance of the prosumers in the peer-to-peer trading technology, we continue drawing the main elements and concepts that define such platforms:

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. Figure 2.2

shows a schematic example of the network formed by the interconnections between end users necessary to create an efficient and effective trading system.

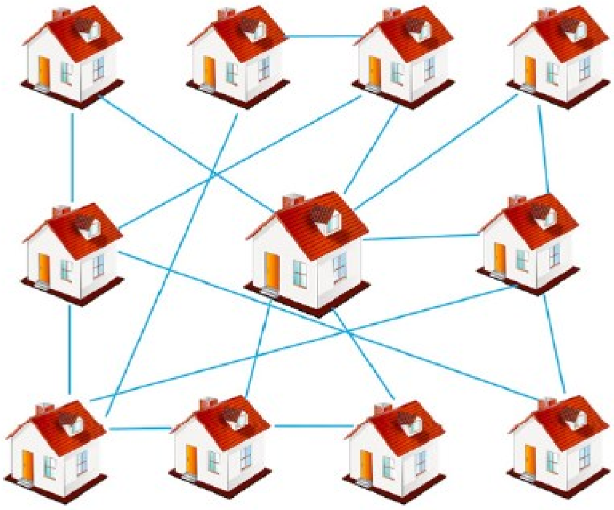


Figure 2.2: Basic P2P network interconnections [21]

2.2 Control system

A grid designed to operate under local transactive conditions presents an evident additional complexity, due particularly to the management of the energy flows, which are more consistent and variable, that can be due to the more extended transitory conditions brought by the large use of RES, 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]. In a P2P energy trading system the resources the network environment are shared among all the participants. Without a central service/provider. each prosumer (or peer) acts as a provider for other peers. In peer to peer architecture, all the autonomous and distributed system is formed by the aggregation of several different nodes called peers collaborating in order to reach some advantages and objectives . In P2P architecture, every peer is given equal responsibilities. Being considered as both an end user and an active player in the grid, a peer can assume three different roles in a P2P energy trading environment [10]:

- **Source**: The source peer can store the whole or a part of the content and intended to share with other peers.

- **Intermediate**: Intermediate peer plays the role of a transport node to facilitate the streaming mechanism. It receives the given content and transmits it to the next intermediate.

- **Destination**: It is the client peer who requests for the content. It can obtain content from one or more sender peer depending on the architecture.

Figure 2.3 gives an overview of a P2P control architecture in a community MG, showing the main devices that compose each local agent (LA) solar panel or a wind turbine, inverter, grid controller and so on. The micro grid control center (MGCC) is connected to each LA and is responsible for the monitoring of the power flow In this type of configuration the quality and performance of the controllers is fundamental as they allow the correct functioning of the energy exchanges. Thus, any problem in the server could interrupt any kind of energy transfer from one node to another within or out of the network. The system has interconnections among all the LA either in term of electrical grid connection that communication channel

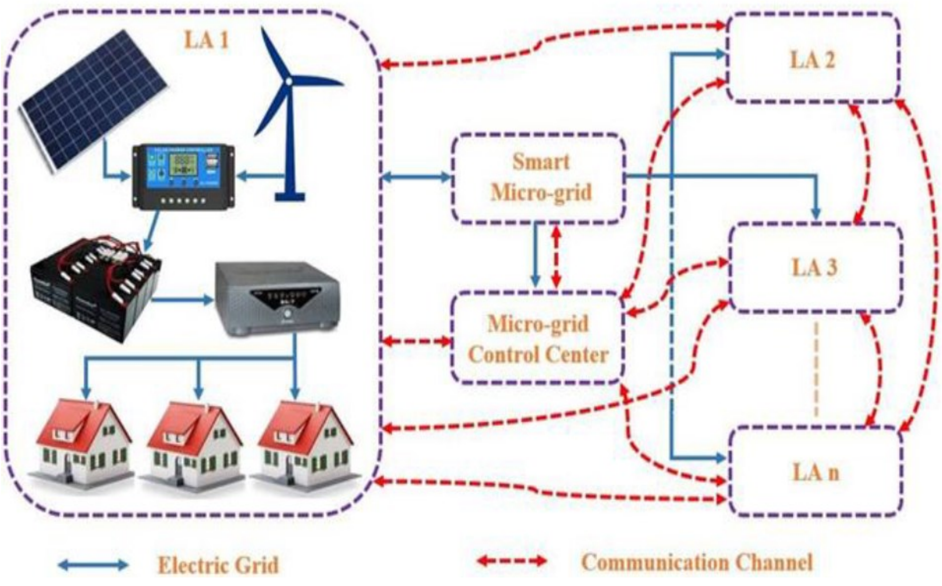


Figure 2.3: P2P control architecture in a MG [10]

2.3 Data management 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. 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. The study proposed in [8], put in evidence the suitability of such device to track representative demand profiles. Figure 2.4 shows a representation of weekly consumption data collected from a case study that includes four customers.

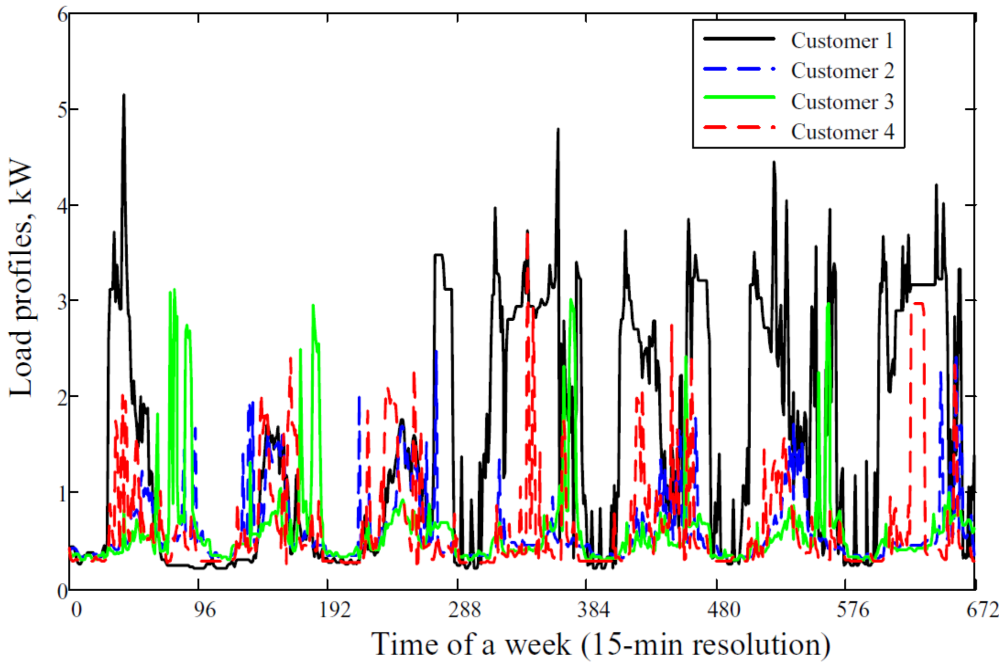


Figure 2.4: Representation of demand profiles from smart metering [4]

This tool has been widely used among this type of system thanks to his characteristics that allows it to 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

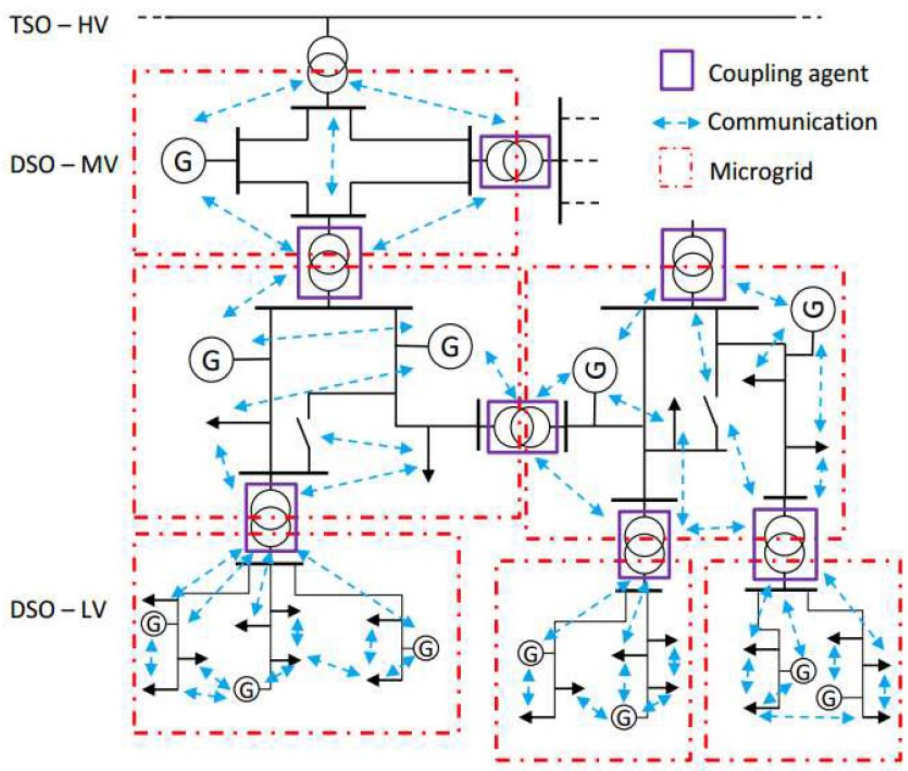


Figure 2.5: Communication channels in a multilevel P2P control architecture [6].

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] the capability of such systems to enable the local trading market operations is discussed in several works. In figure is possible to see the representation of another P2P control architecture, that involves several MG at different voltage levels. This type of energy trading models make necessary the introductions of new business entities as the Distribution System Operator (DSO) or Transmission System Operator (TSO). They will be further explained in the business model section. Figure 2.5 shows all the communication channels necessary in the MG for all the players to interact with each other and with the third parties in order to make the transactions. This particular architecture was developed in [6].

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 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 adaptation to the new decentralized situation. An example can be seen in [17], which proposes a P2P market platform which aim to coordinate the trading operation among heterogeneous prosumers. Figure 2.6 shows a block diagram of the platform, which is designed to allow the prosumers to trade energy with each other, and with the main grid, interfacing also with the wholesale electricity market.

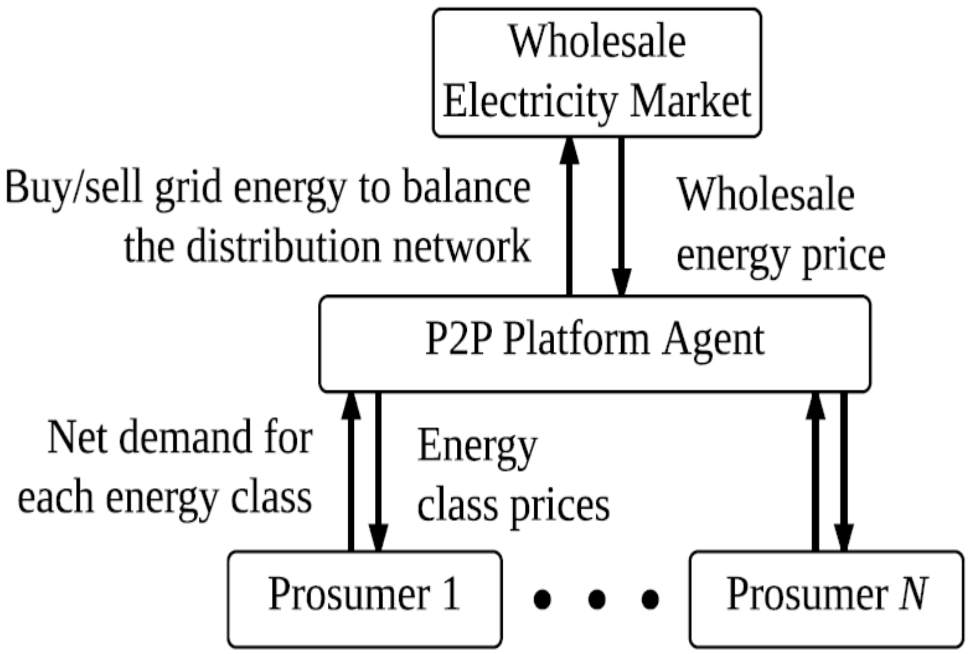


Figure 2.6: block diagram of the P2P market platform [17]

The platform is formulated to obtain some objectives like maximizing power flows between the prosumers, satisfy power network constraints and prosumer energy resource constraints, maintaining the distribution network power balance dealing with each prosumer renewable generation, energy storage and load constraints. And also satisfy informational constraints for scalability and data privacy. In this system, only the P2P platform has access to the wholesale electricity market and each prosumers' energy resource capacities, preferences and renewable generation and load predictions are private information. The solution needs to account for the prosumers' heterogeneous energy supply/demand preferences, battery depreciation costs and the cost of buying energy from the wholesale electricity market It is assumed the prosumers have individual energy preferences. For example:

1. Prosumers may prefer to obtain the best financial return, regardless of the source/destination of their energy.

2. Prosumers may prefer to obtain energy from local sources or particular generation technologies.

3. Prosumers may prefer to trade energy with particular subscribers (e.g, low-income residents, community organizations).

To account for the prosumers' heterogeneous preferences, each unit of energy in the distribution network is assigned an 'energy class' (like the ones introduced in the beginning of the chapter) relating to relevant attributes of its source [17].

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. Such architecture can be seen in figure 2.7 (from the study proposed in [9]) Business layer has the task to determine how electricity is exchanged among peers and with the third parties. Therefore, it contains all the main subjects that are involved in the process and which financial relationship need to be regulated. Subjects as peers, suppliers, distribution system operators (DSOs) and energy market regulators [9]. Various kinds of business models could be developed in this layer to implement different forms of P2P energy trading.

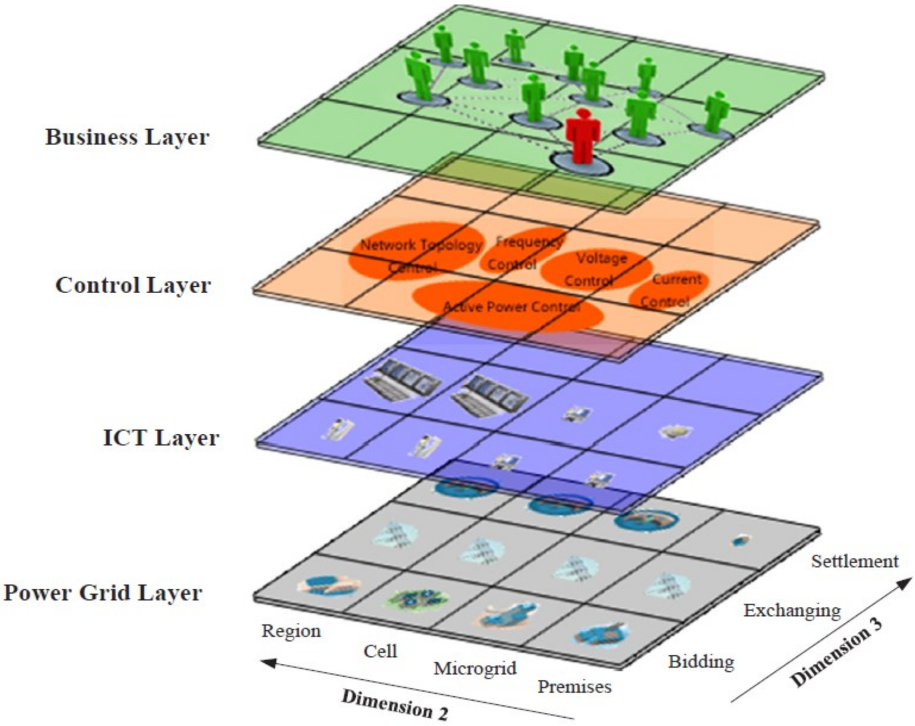


Figure 2.7: four-layers P2P trading system [9]

Therefore, a specific business model to operate the transactions on a local market is required. For business [6] provided several considerations on this matter, proposing and analyzing different discussion points.

2.6 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. The 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.

Chapter 3

State of art of P2P energy trading

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 represents the core of the research conducted in this study. In the first section provides a synthetic description of the analyzed models, trying to frame the typology of the adopted techniques. The approach adopted in the analysis is explained in the following section, with a comparison between the considered models and the description of the key elements identified in the research. The last two sections are dedicated to the further and more detailed explanation of the main strategies adopted in the models and the conclusions of the analysis in relation to the case study considered in this project.

3.1 Models analyzed

Here below are briefly presented all the trading models, busyness models, architectures and platforms considered in the analysis, the µGIM platform represents the trading platform utilized in this project, in which is running an English auction model. The system is inserted in the analysis for comparison matters.

- **µGIM platform**

  This model has been developed by the GECAD research group of ISEP (PT) to investigate on P2P energy trading among prosumers. The study has been carried on in the research center building, which, in the model, is configured as a decentralized system, with the main agent coordinating the energy transaction among all the actors with an English-type auction. Placing bids and matching demand and offer. The actors are nonother than small parts of the building, each one with is own generation, as the building has PVs. 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 µGIM platform with a raspibian operating system and java software.

- **Piclo [19]**

Piclo is a P2P electricity trading platform developed in the UK in a collaboration between a technologic company called “Open Utility” and a renewable energy supplier called “Good Energy” The platform is designed to allow consumers to buy electricity directly from local renewables sources. The platform exploits a combination of meter data, power generation cost and consumer preference information in order to match electricity demand and supply. The matching process runs every 30 minutes. Piclo’s costumers have also the possibility to select and prioritize which generators to buy electricity from (e.g. hydro, wind). Piclo take preferences into account in the matching phase. Electricity suppliers and consumers use Piclo's online services (like data visualizations and analytics) on their portable devices. The platform is further discussed in ([20][21][22] and [23]).

- **Vandebron [24]**

Vandebron is another online platform, born in Netherland, where energy consumers can buy electricity directly from independent producers. In exchange for a monthly subscription for both sides (generators and consumers) Vandebron provides to the customers all the necessary services connecting consumers to local suppliers and allowing them to exchange energy, and balances the market. The platform give the opportunity to the clients to purchase electricity without the intermediation of utility companies. Both consumers and producers obtain benefits (in terms of earnings or savings) with P2P electricity trading. The platform is further discussed in ([20][21][22] and [23]).

- **Yeloha [26]**

Yeloha is another trading platform, born in the US, that allows consumers to buy energy from RES. The principle behind this platform is slightly different from the others in the sense that is exclusively focused on solar power plants. Yeloha gives the possibility to users which do not own a solar system to purchase photovoltaic energy generated by other customers with solar systems. The subscribers have the opportunity to get a reduction in their utility bills through P2P electricity trading. The owners of the solar panel installation site participates as a provider, creating a local “green” market. The platform is discussed in [20];[21] and [23]

- **Sonnencommunity [25]**

SonnenCommunity is a community of consumers which share and exploit battery storage systems for energy management. The concept was created by sonnenBatterie, a storage manufacturer in Germany. Thanks to the storage capability of the community, the installers of the renewable energy facilities can store the electricity from the renewables in their batteries and also manage the electricity stored in them, utilizing or selling it. The platform shows a great potential to expand the supply of renewables. A central software is used to connect and monitor all community members and balance energy supply and demand. The system combines distributed generation with battery technology and digital networking. Discussed in [20];[21];[23] and [1].

- **Peer Energy Cloud [20]**

PeerEnergyCloud has been a project carried out in Germany. The innovative element introduced was the study and development of cloud-based technologies. The system was applied and tested in a local Peer to peer electricity trading platform. The main purpose of the project was to evaluate the capacity of P2P trading to deal with excessive local production, DG and energy management. The research also touched other topics such as the investigation of innovative recording and forecasting techniques to manage the consumption and generation data and new business models for the P2P electricity trading market.

- **Smart Watts [23]**

Smart Watts was a German project. The objective pursued was to investigate and support P2P energy trading programs trough the use of modern information and communication technologies (ICT), New techniques were developed and tested in order to optimize the energy supply profiles in a decentralized community with RES and prosumers. The project emphasize ICT optimization potential and capabilities in dealing with supply security.

- **Lichtblick Swarm Energy [20]**

This project consist in the development a unique and innovative IT platform, called swarm conductor, in order to create a P2P trading system. The platform is part of a wider package of services called swarm energy, provided by the energy supply company Lichtblick.

The platform has a offers a full variety of services and products for local and residential electric consumers and stakeholders. The electricity trading is promoted trough energy management and optimization of the consumers DG and storage devices.

- **Electron [20]**

Electron is a new open-source platform (still under development) that includes metering and billing systems. Like swarm conductor, it offers several consumer energy services both for for gas and electricity. The blockchain technology combined with the smart contracts, utilized in the platform, to make possible and automatic the transactions. The platform is programmed to be fully decentralized and open to the end users.

- **Brooklin MG [3]**

is a microgrid project running in Brooklyn (New York), known under different names such as Transactive grid or micro grid sandbox, which consists in an innovative community MG 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. Likewise many of the other platforms just mentioned, consumers can choose where to buy energy between several local energy producers with RES. The trading improves the MG efficiency by better usage of the local resources.

- **Micro/Mini grids model [10]**

The proposed model is the result of a study conducted at the Kathmandu University (Nepal) with the purpose of solving major issues in the rural Nepal's energy system. The main problems treated by the study were the distribution of the revenues, transparency, and sharing of operating and maintenance cost of mini-grid. The case study of the proposed model consists of multiple local systems which operate under different functional groups. All of the individual plants, which are responsible to produce electricity for the connected community, are connected to the grid system through a net energy meter responsible for the monitoring and recording function of the end users and prosumers involved. The core of the trading system in the architecture is represented by a commutation system, which connects all the different individual plants in order to allow them the communication and energy trading operation. The local system are also monitored by a central body that have the specific function of carrying the transactions trough his connection with a local banking system. The communication network adopted is the Wireless MAN (WMAN), whose architecture is approved by the IEEE 802.16 committee for standardization

- **MILP model [11]**

This research was carried out in Australia with the support of different entities. The main goal of the study to validate the effectiveness of the combined use of DG technologies such as photovoltaic panels and the capability of the peer- to -peer trading technology to manage the local generation and bring benefits to the prosumers community. The transactive model was developed using a mathematical optimization and applied in a simulation framework. The case study in which the algorithm is applied features a local community of 500 households. The optimization is done trough a mixed-integer linear programming (MILP) algorithm, which utilizes a wide number of constrains (parameters of the system) in order to calculate the optimal charge/discharge schedule of the batteries that maximize the income of the players in the P2P trading market. The model is also designed to allow the consumers exchange energy both peer-to-peer and with the retailer. Figure 3.1 shows a graphic representation of the trading scenario proposed in the study.

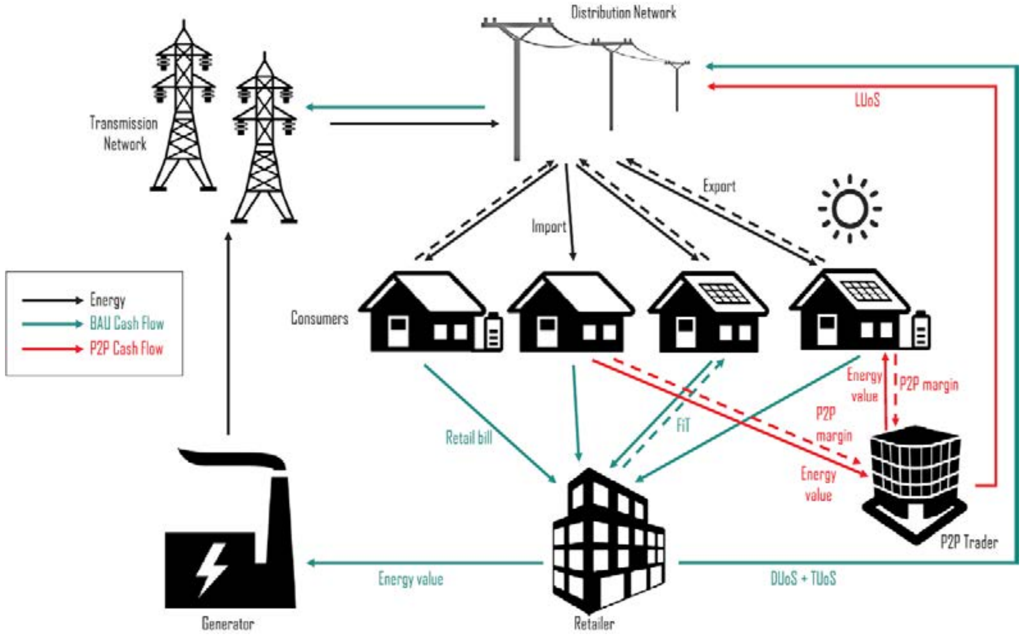


Figure 3.1: MILP model's P2P trading market conceptual representation [11]

- **Game Theory Shapley Value Model [15]**

This work, conducted in Cardiff university, proposes a P2P trading mechanism for a small residential MG with 10 (five prosumers with PV's and batteries and five consumers). The game theory paradigm was used to create a cooperative environment among the peers and find the optimal trading solution from a collective perspective. To model the coalition's decision-making process with the game-theoretic approach, a constrained nonlinear programming (CNLP) optimization was executed. The method allow to insert the individual batteries control as a decision variable in the process variable. In addiction to the above mentioned, another mathematical method was adopted to ensure fairness and optimality in the trading., such as shapley value, a precise pricing technique to calculate the bill or the income of the players. With this combination of mathematical approaches, the platform managed to achieve an optimal P2P energy trading result and a fair distribution of bills among the prosumers involved.

- **Bayesian equilibrium model [13]**

This study, carried out by the university of bath (UK) proposes a new energy auction type (VCG auction) and establishes a market platform with a specific mechanism that ensure fair and efficient bidding. It also has the goal to contain the power losses in the system within an acceptable value. Bayesian Game Theory strategy has been adopted to find an appropriate bidding formulation. In the proposed P2P energy trading model was used the IEEE 33-bus distribution system, which includes prosumers and consumers. The above-mentioned system had a centralized layout, with one seller and multi-buyers. The method has proven to be able to maximize the utility for prosumer on a typical distribution network.

- **Four-Layer architecture model [9]**

Another architecture was developed in a collaboration between Cardiff University (UK) and Tianjin University (China) is proposed [9]. The main focus of the study was on presenting a specific multilevel trading model that proves the feasibility of peer-to-peer trading on different scales and also separate the main aspects/phases of the trading in different operational layer, showing their interoperability. Moreover, a business model for customers P2P trading was applied in a benchmark LV grid-connected microgrid network. The core of the bidding system is the Elecbay platform, which was also proposed and simulated using a game theory approach. Non cooperative game theory was used to find the most possible bidding configuration trough the use of Nash Equilibrium, The results obtained by this method show the capability of P2P energy trading to manage DG and match demand and offer at a local level optimizing the local resources.

- **DGC based P2P Blockchain network [5]**

This case pilot project takes place in Urawa Misono, Japan, and was developed in the contest of a study aiming to explore concrete challenges of blockchain in the energy sector and to discuss opportunities to overcome them. The case includes ten consumers, five prosumers, and a shopping mall. Prosumers are connected to sub-power lines for P2P-trading and also with a distribution line to the other “actors” and the grid. Prosumers’ equipment consists of a solar PV system, battery, smart meter, DGC, and DGR. This devices are capable to act in a coordinated way in order to accomplish a set of functions (such as monitoring and recording data, AC-DC conversion and internal communication between the nodes) that allow the peer to peer electricity within the considered Microgrid. The system places bids for power purchases and sales in a Ethereum blockchain-based P2P network, which utilizes a Proof of authority (PoA) consensus mechanism to validate the transactions. The power transactions are finalized by the DGR itself, while DGC is directly involved in the process as it records the transactions on the blockchain. The model also features smart contracts, which provide an efficient method to make the trading process automatic. The trading modality is based on an auction-type process called Zaraba method,

- **PETCON [14]**

This project was developed under the support of the Guangdong province. It presents a P2P electricity trading model properly designed for trading among plug-in Hybrid Electric Vehicles (PHEVs). The goal is to promote P2P trading incentivizing the PHEVs to inject energy in the grid. The model is applied in a Smart Grid with several charging stations. To achieve the proposed goal, a consortium-type blockchain technology was adopted in order to make automatic transactions without a third party and validate them using a proof-of-work consensus protocol. In order to actuate the consensus mechanism the model rely on local aggregators (LAGs) The trading process among PHEVs was carried using an iterative double auction mechanism. The platform achieve an efficient, secure and fair energy trading and shows the capability of the PHEVs to effectively balance the local demand. The main steps of the Blockchain trading protocol are represented in figure 3.2.

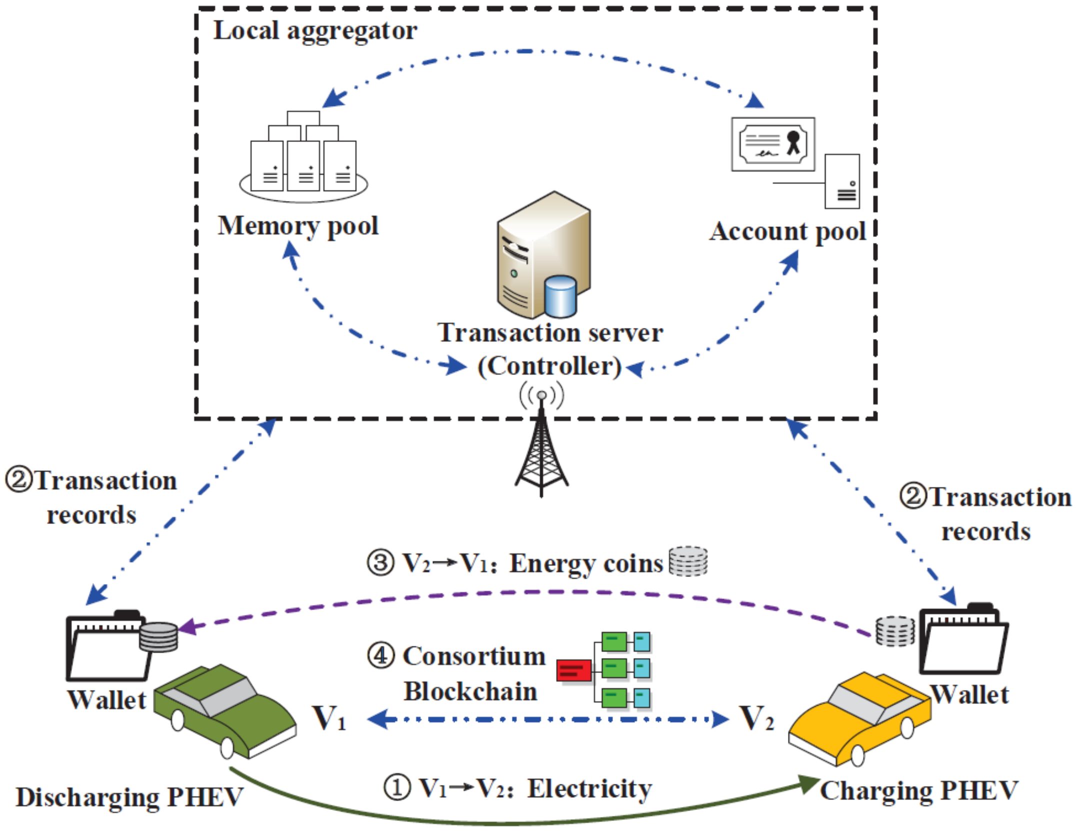


Figure 3.2: Localized P2P energy trading among PHEVs using energy coins [14]

- **P2PEBT system [12]**

This project, propose a Peer-to-Peer Electricity Blockchain Trading (P2PEBT) system based on the current charging and discharging schemes for electric vehicles (EV) in a smart grid. The Ethereum-type Blockchain implemented in the system utilize a proof-of-Benefit (PoB) consensus algorithm, combined with smart contracts in order to incentivize the EVs participation in the P2P market. The process formulation achieve the maximal benefit scenario and manage to balance local demand.. It also provides safety in the transactions and lower power fluctuation. A block diagram of the trading process adopted in the system is portrayed in figure 3.3.

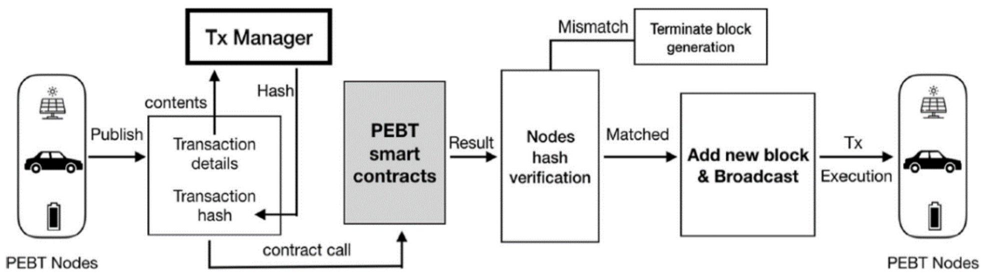


Figure 3.3: P2PEBT transaction process [12]

- **Cooperative MGs Model [27]**

This project proposes an innovative model for peer to peer sharing among different MGs. The method is applied to a radial distribution network testbed. the goal is to show the benefits of peer-to-peer trading among MGs in terms of DG management and energy costs. In the model, the problem is faced in a innovative way, considering the physical and practical constraints of the system in order to execute a mathematical optimization technique. The results shows the ability of the neighboring MGs cooperate in order to find an optimal trading strategy.

3.2 criteria of the Analysis

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] which will be briefly introduced in chapter 5. The table is organized categorizing the model with the following criteria:

1. **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 in this study 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 for the purpose of this analysis to identify them as microgrids

2. **Centralized system:** To explain this parameter, which is represented by the dark brown marks, some kind of "boundaries" needs to be clarified, 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 to 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.

3. **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.

4. **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 which have been implemented and present results deriving from these kind of "environment".

5. **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 study, it was only formulated but wasn't realized or was still under development at the time of the analysis.

6. **Auction based:** This is another category that needs particular explanations: the models that features this characteristic are the one who are specifically focused on the Auction Method and his modality and main aspects. So, this 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/methods implemented. These parameter is represented by the dark blue marks.

7. **Optimization based:** The same reasoning of the auction based models holds for this category, 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 parameters of the system.

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

9. **Smart contracts:** To investigate the main techniques that allow the automatization of the P2P transactions, we categorized with a dark green box the models that uses this type 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.

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

11. **Game theory:** The green water marks represents the model that features the game theory paradigm. 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.

12. **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.

13. **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.

The role of the comparison in this analysis has a double goal:

- **statistic approach:** the collected models are compared to see the main patterns followed in the technology so far.

- **overview:** the comparison also shows a detailed panorama of the different techniques adopted to model the transaction problems.

Moreover, the individual study of each model has the objective to find the strengths and shortcomings of each to seek any improvement paths.

In table 3.1 an overview of the group of models is presented:

Table 3.1: model comparison overview

source	MODELS	micro grid	Centralized system	Decentralized system	Pilot or real case	theoretical model	Auction-based	Optimization-based	online platform	smart contracts	Blockchain	game theory	aggregators	EVs
[28]	µGIM MODEL	■		■	■		■							
[10]	MICRO/MINI GRIDS MODEL	■		■		■								
[11]	MILP MODEL		■			■		■					■	
[5]	DGC BASED P2P BLOCKCHAIN NETWORK	■		■	■		■			■	■			
[15]	GAME THEORY SHAPLEY VALUE MODEL	■	■		■							■		
[13]	BAYESIAN EQUILIBRIUM MODEL	■	■		■		■					■		
[9][16]	FOUR-LAYER ARCHITECTURE MODEL	■	■		■				■			■		
[12]	P2PEBT SYSTEM	■		■		■		■		■	■			■
[14]	PETCON			■	■		■	■			■		■	■
[27]	COOPERATIVE MGs MODEL	■	■			■		■						
[20][21][22] [23][1]	PICLO			■	■				■					
[20][21][22] [23][1]	VANDEBRON			■	■				■					
[20][21]23]	YELOHA			■	■				■					
[20][21][23][1]	SONNENCOMMUNITY			■	■				■					
[21][1][3]	BROOKLYN MG	■		■	■				■	■	■			
[20]	PEER ENERGY CLOUD	■		■	■				■					
[20][23]	SMART WATTS			■	■			■	■					
[20]	LICHTBLICK SWARM ENERGY			■	■				■					
[20]	ELECTRON			■		■			■	■	■			

3.3 Main findings

In this section we are going to provide a brief discussion on the group of models from a collective point of view. We are then going to outline few characteristics and key points to be considered in relation to the application of some of the methodologies in our case study.

Many of the analyzed platforms 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 ,Vandebron , Sonnencommunity ,Yeloha ,Peer Energy Cloud, Smart Watts, Lichtblick Swarm Energy and the Brooklyn microgrid. Even though they are worth to be included in the analysis, as they represent some of most successful pioneering project in the peer-to-peer energy transaction field. They play a side role in the experimental phase of this project as they only present business models. Some of them offer services to the customers (prosumers or consumers) that allow them to participate in trading programs and be supplied by renewables local sources or participate in local market to manage their DG, offering all the required information and technologies to match demand and offer; some of them focus on the design of the electricity market at a local-microgrid level, experimenting on ICT or cloud based technologies to improve monitoring, connectivity and communications in the platform. However, none of these platforms focus on a specific transactive model (as defined in 1.6) that provide strategies for the decision making or the bidding process of the agents involved in the energy transaction. The Brooklyn MG, as well as the Electron platform, uses the blockchain technology to minimize the role of intermediate intervention. 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, 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. 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 Elecbay, which allows energy users to sign contracts and make payments with each other, the simulation of the bidding in elecbay is modelled trough a non-cooperative game using Nash equilibrium. Despite having similar results in terms of promoting the transactions, all these online platforms utilize different techniques to achieve them. Other scenarios are presented in the cooperative microgrids model [27], which analyses a trading configuration among different MGs cooperating with each other, optimizing the energy management strategy trough a SOCP problem. The 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.

This study aim to improve the performance of the μGIM model. The trading platform that allows the model applications is presented in chapter 5. As we can see from the model comparison table, the model feature a basic auction based technique. Just from a mere visual comparison we can notice that many of the analyzed models provide effective trading by combining the energy auction approach with other methods. So the first point of the discussion is whether to implement a new method or try to integrate the existent one with other. The optimization-based models as well as the game theoretic approach model provides a wide range of mathematical approaches worth to implement. In the formulation of the trading algorithms these basic concepts have been taken into account in the new techniques implementation:

[1] **Compatibility**: many of the mathematical models and algorithms implemented in the considered models are specifically conceived and formulated to shape the bidding/decision making process of the transaction as a function of a specific controllable or programmable parameter (e.g. charging/discharging schedule of a battery or of a EV). In our case study we have only agents with PV's, which behavior is totally aleatory and not suitable for the application of such method.

[2] **Main goal**: the application of a specific method utilized in a model wouldn't achieve the main goal of this analysis, which is to combine the positive aspects of the main projects made in this field so far.

[3] **Technological limit:** Another factor to be taken into account is the nature of the MAS utilized in this project. The system was created to prove that the peer to peer technology can be implemented with relatively low cost. For this reason, each agent is represented by a SBC. Such a devise has a small computational capability and does not allow the implementation of all the techniques examined.

Chapter 4

Main technologies

4.1 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]. Considering the future perspective of the Blockchain application, the topology and communication are two main factors that would have an impact on all the main aspects of the trading platforms. Therefore, the topology choice becomes really important for the effectiveness of the methodology in a transactive environment. Four potential topologies of blockchain are portrayed in figure 4.1. Private, semi-private, and consortium blockchains usually have lower energy consumption levels than public topologies as consensus mechanisms acts on a smaller number of nodes (being the private networks sensibly smaller). Semi-private structures are an hybrid type of topology in which the blockchain is managed by a single authority node. Finally, In consortium blockchains, pre-selected authority nodes control access and consensus in a bigger network [5].

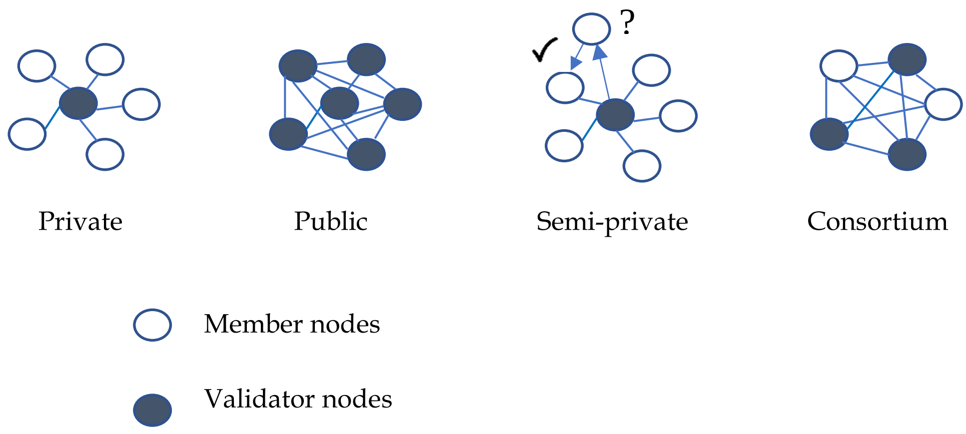


Figure 4.1: blockchain topologies [5]

Two types of node stand out in the figure, the white ones are the member nodes, which have the common task of reading the blockchain and receiving/sending the transaction. The blue nodes are Validator nodes. They are given additional responsibility as they have all the functions of a simple member node, plus they can validate the transactions using consensus mechanism.

4.1.1 Consensus types

A consensus process is an algorithm-type process utilized in distributed systems. The function of such algorithm is to provide an automatic method of agreement among the different actors involved. the agreement is defined on single data values. There are several types of consensus mechanosms developed or tested in former models. The main ones used in the analized models will be briefly presented in this section as an example:

Proof-of-work: This consensus mechanism was presented in [14] In the system, a consortium-type Blockchain was utilized to model the market. As specified before, in this type of blockchain only certain nodes of the distributed system are authorized to validate the transactions. In this case those nodes are represented by LAGs. (but this type of mechanism is usually designed for bitcoin). The core of the process consists on the generation on a specific hash value (encrypted value generated by a hash function) and uses it to connect the new blocks with the previous existent transaction chain. The hash function is designed to give a value with a growing complexity for each level of the blocks. The process involves a reward for the most efficient LAG in the consortium blockchain. The first node to provide a valid proof of- work gets a prize that consist of a certain amount of energy coins. In the final part of the process, once the transaction is validated, a new block is created by the LAG himself and will be used to validate the next transactions.

Proof-of-benefit: this specific consensus algorithm was presented in [12]. The structure of the blockchain is different as in this case all peers-nodes are authorized to validate the transactions.

In the process, some specific functions(PoBRound and PoBMine) are utilized to prepare the creation of a new block generated with the consensus. These functions verify the connections of the last blocks of the chain and extrapolate the necessary information to the new block creation. After this initial procedure, a unique value is generated by an objective function (in a similar way to the hash function in the above mentioned proof-of-work)

In order to determine the block which will execute the following transaction. This value is designed in order to be proportional to the impact of the charging and discharging schedule in the specific peer-to-peer study. So the higher value would be the one accepted and will determine which block will “win” the process. a second algorithm is used to finalize the process executing the transaction determined by the previous one. In Table 4.1, a representation of the first consensus mechanism algorithm is provided.

Table 4.1: proof of benefit consensus algorithm [12]

Algorithm 1 Proof of benefit primitive

```
counter ← MonotonicCounter()
roundBlock ← null
roundTime ← null

function PoBRound(block)
    roundBlock ← block
    roundTime ← GetLocalTime()
end function

function PoBMine(header, previousBlock)
    assert header.parent = Hash(previousBlock)
    assert previousBlock.Parent = roundBlock.parent
    assert Time.now ≥ roundTime + ROUNDTIME

    λ ← GetBenefit()

    //Restart the next mining cycle
    assert counter = MonotonicCounter()
    return(λ, null)
end function
```

4.2 Game theory

Another innovative method usedryj6 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.

4.2.1 Cooperative game

As mentioned, a cooperative game theory algorithm exploit the capacity of a group of players to cooperate in order to achieve common goals and form a coalition. The main focus of this type of mathematical modeling is the prediction of the different options in terms of composition of the coalition group. This evaluation brings to a punctual analysis of all the possible actions/strategy that the community can actuate and allow to adopt the most effective in relation to the goal to achieve. Cooperative game theory is centered on the study of the conformation of the coalitions and the strategies to be adopted to maximize the outcome of the entire community, therefore, can be considered a high-quality approach to the problem's optimality. Another positive aspect of the technique is related to his simplification capability. This could be often the method to be adopted in case the "single elements" behavior in the case study considered result too complicate to model and recreate in a concrete formula or, in alternative, the system doesn't provide sufficient elements to effectively represent it. Thus, adopting this technique, is possible to overcome some limits of the non-cooperative approach, studying the system from a collective point of view. A concrete example of a cooperative game theory application is provided [15]. The method is applied in a case study that includes a community of prosumers with batteries and PVs. The process adopted in this case study consists in the calculation of a common value called energy coalition trough the evaluation of all the possible groups that can take shape among the prosumers. The evaluation of the best solution is done using two main parameters as input variables:

- The net load of the prosumers
- The energy prices of the supplier

In practice, the coalition value is expressed trough a specific function that sum the single load values of the peers involved and multiply the resulting value by the energy price of the supplier that is a function of the coalition's net load itself as depends on whether the grid is required to buy or to sell energy. The solution coming from the coalition calculation is then utilized in a combination with other mathematical methods in order to establish the single players decision making process.

4.2.2 Non cooperative game

A non-cooperative game involves a mechanism totally opposed to the one of the cooperative one. This kind of approach not only does not involve or consider any collaboration among the players, it also formulate a competitive environment in which every peer participate and take decisions in function of his personal benefit. So, being centered on the single player in the P2P market, the non-cooperative game theory technique consist in the study and development of individual strategies in decentralized environment such as the prosumers MGs or the distribution system. The individual strategies development have a considerable complexity if we take into account that their effectiveness is directly influenced by all the other players strategies. Therefore, the variables to consider in the process are several. A consolidated method for the study evaluation of single players strategies in a non-cooperative game is the Nash Equilibrium. From an external perspective, we can define this kind of strategy as lower quality approach in comparison with the cooperative game. His main characteristic makes it less specific and general and can lead to inaccurate solutions (considering the total efficiency of the trading system). A concrete example of non-cooperative game application is provided in [9] where is applied in a case study that involves players within a MG which have the possibility to have a flexible demand profile. The Nash equilibrium is formulated utilizing a function that express the report between the value of energy output of every single player and the one of the whole MG. the function is calculated for every potential strategy to be adopted in the trading. The outcome of the function gives the information necessary to determine the optimal trading strategy combination of the players. This decision is made trough some key performance parameters defined in the study.

4.3 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, differently 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.

Apart from those, other Known auction types used to determine the contract price are the Zaraba Method [5] which matches the orders following price and time priority rules at a price where the lowest offer and the highest bid are matched,

The VCG auction [13], which is a variant of the Vickrey type with sealed bids and the Iterative double auction presented in [14]

4.4 optimization algorithms

Most of the examined methods pursue some type of optimization in the process. carrying the process with the goal to maximizing a selected parameter. In this sections, we briefly present some of the mathematical optimization algorithms used in the P2P trading to find the best available trading solutions:

- **Mixed Integer linear Programming (MILP)**[11]:

  Applicated in a case study with heterogeneous peers (simple end users, households with PVs, storage system or both) this optimization problem uses a wide field of input parameters in order to try consider all the aspects and variables of the case study (e.g. number of prosumers with and without PVs/storage, PV output at the time t, maximum battery charge level and so on). Combined with a set of decision variables represented by the different energies at stake (e.g. energy purchased from the market, purchased from the retailer P2P market, charged/discharged from the battery) to form a function that aims to minimize the net total cost. Several constraints are utilized to keep the desired parameters under control. The constrains can serve for different purposes, in the study they are divided in demand, PV output and battery constraints.

- **Constrained non linear programming (CNLP)**[15];

  This optimization method is applied in a residential community with PVs and battery system with the objective to minimize the energy bill or maximize the earnings of the individual prosumers. The objective function to obtain an energy cost minimization is formulated using the total net load of the energy coalition of the prosumers (calculated with a cooperative game theoretic approach) with the different parameters of the storage system (state of charge, charge/ discharge power and so on) in order to find the optimal charging-dicharging schedule and decision making process in the P2P market to fulfill the main goal.

- **Second order cone programming (SOCP)** [27].

  This optimization problem is applied in a wider case study that involves a distribution network constituted of several connected MGs connected among each other and exchanging energy trough P2P technology. The goal is to minimize the total cost of the P2P network taking in consideration the main contributive factors like the operational costs of the batteries and the power losses in the distribution system. In a similar way to the other optimization techniques, the optimization problem is formulated introducing the constraints with the main parameters of the platform, like system and operational constraints.

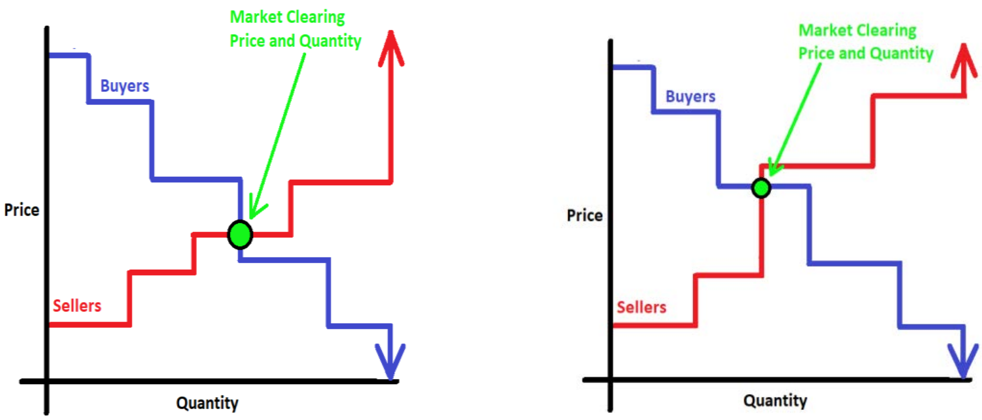
Chapter 5

MG trading market

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).

5.1 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 5.1.



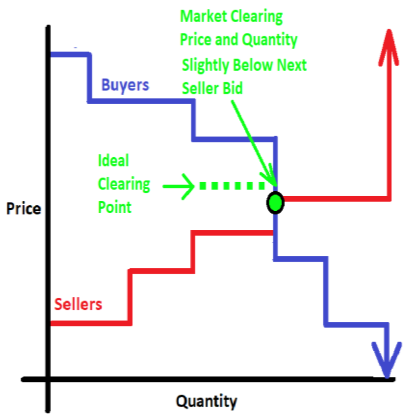
a: Marginal seller scenario

b: Marginal buyer scenario

Figure 5.1: 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 5.2.

a: Equal clearing quantities scenario



b: Equal clearing quantities, close next seller bid scenario

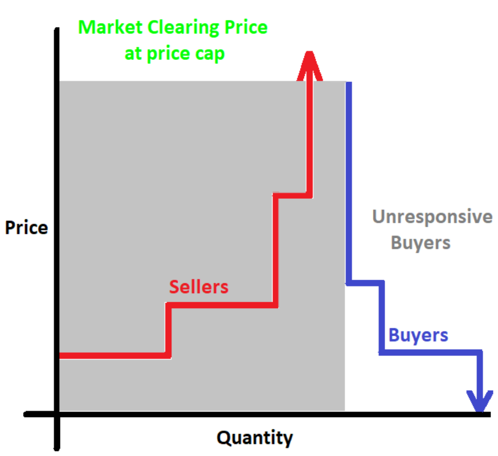
Figure 5.2: Equal clearing quantities scenarios [30]

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 5.2 (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 5.3.

a: quantity equal, close next buyer bid

b: equal clearing quantities and prices

Figure 5.3: Equal clearing quantities scenarios 2 [30]



a: Failure to clear

b: null market clearing

Figure 5.4: Not clearing scenarios [30]

To conclude this chapter, in Figure 5,4 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.

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).

Chapter 6

P2P trading system used

Once outlined the main characteristics of the peer-to-peer electricity trading concept and how it works, given an exhaustive state of the art of the current development and advancement of the technology 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 of all the main aspects of the system: the architecture 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 outcomes of the trading and so on. The technologies used in the building were developed in studies prior to this project and are widely explained 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.

6.1 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.

6.2 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 6.1 shows a graphic representation of the described layers with the main technologies utilized in the six-layer architecture [31]. In figure 6.2 is possible to see the structure of the SBC, which represent the "core" of the system.

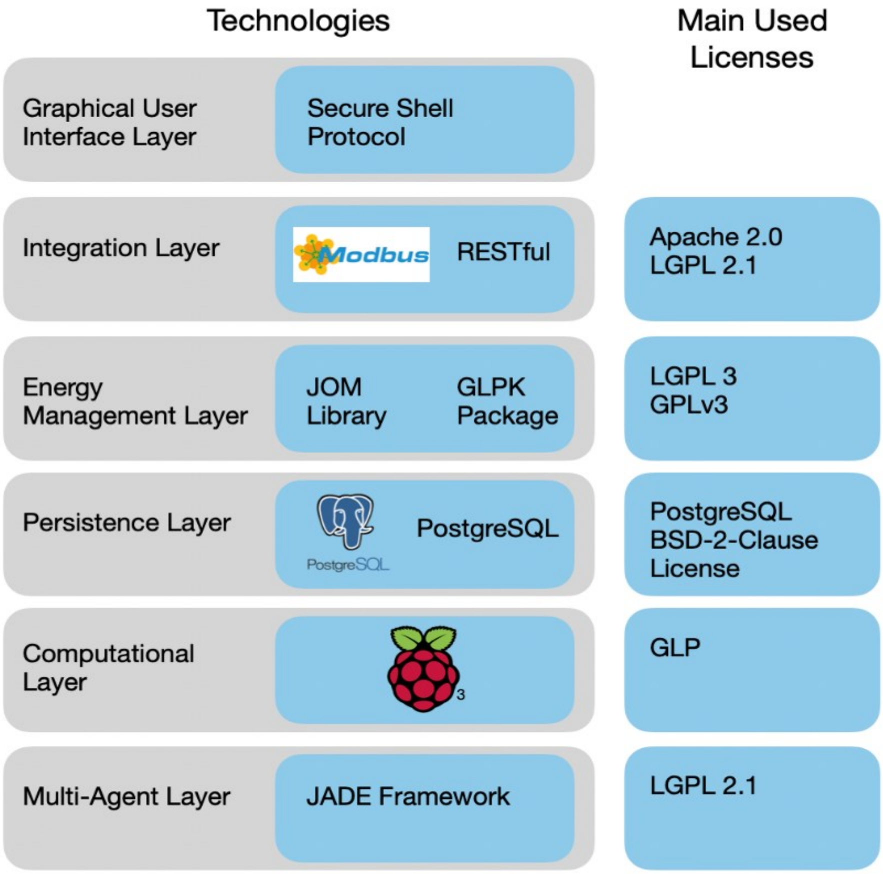


Figure 6.1: agents architecture layers representation [31]

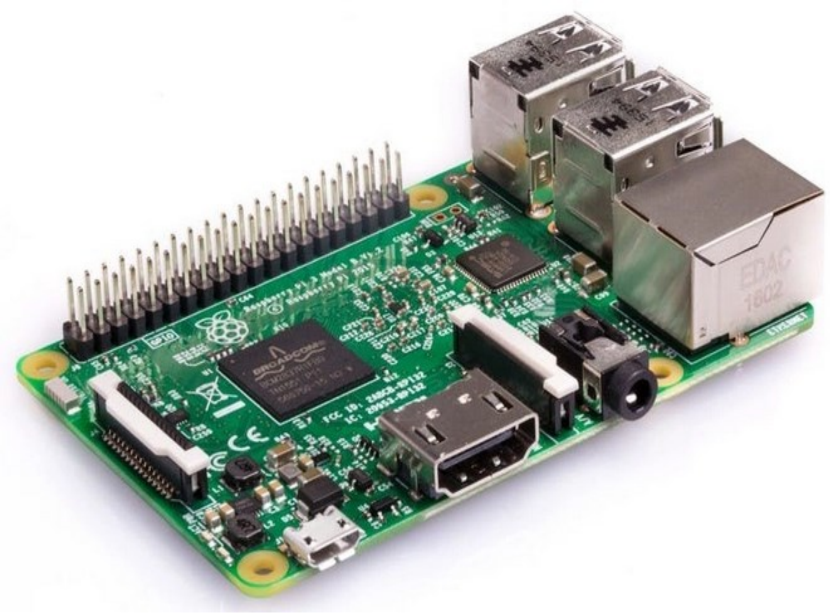


Figure 6.2: Design of a raspberry Pi 3 model B Single Board Computer

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 6.3 shows a graphical representation of the building, with the different agent's zones identified with different colors [28].

Figure 6.3: Agents' zones partition [28]

That being said, lets briefly outline the operational 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 6.4 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.

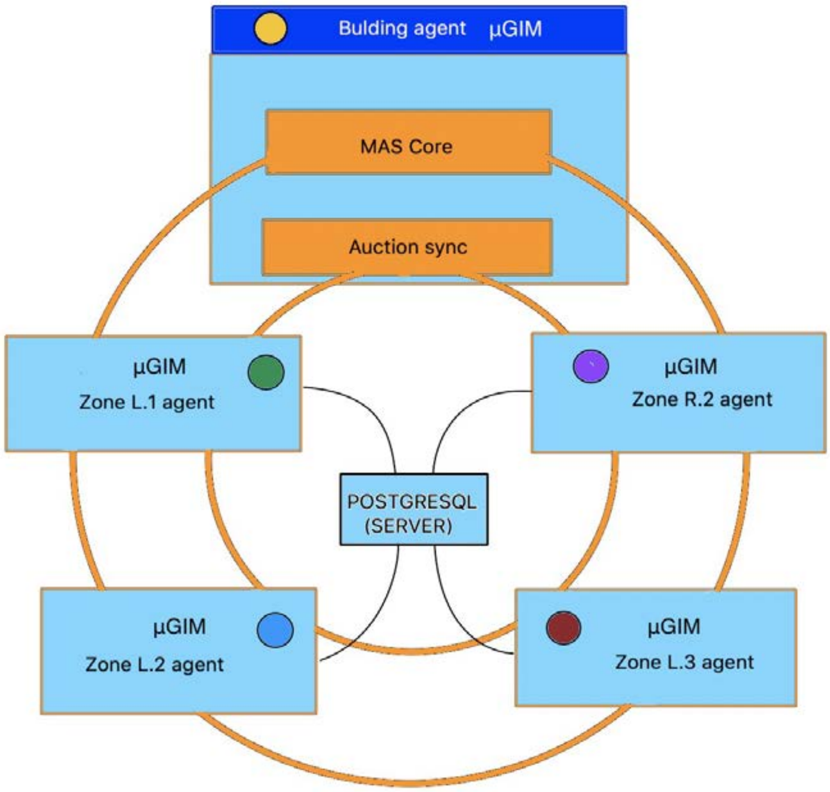


Figure 6.4: Representation of agents' connections [28]

To summarize, The office building has sixteen offices that can be rented. On the rooftop, a total of forty photovoltaic panels are installed, with and individual peak of 250 W. Therefore, the total peak generation of the office is 10 kW. Each agent can have access to 1 kW of peak generation. This is because the offices can only be rented in pairs or triplets due to electrical restrictions (the agents are considered renters of their administrated zones). So each renter has access/control to four photovoltaic panels. The remaining photovoltaic panels are administrated by the building's agent. Differently from the other agents, he is not considered a renter. The building agent or manager is noted as Z.0 and he manages common areas and toilets, as well as the kitchen (room 10) and rooms 11 and 16, which are not rented. The four renters are noted as L.1, L.2, L.3, and R.2.

The supervisory Control and Data Acquisition (SCADA) system, which is integrated with the platform, is composed of several energy analyzers, Programmable Logic Controllers (PLCs), dimmable lamps using Digital Addressable Lighting Interface (DALI) protocol and one grid-connected photovoltaic inverter The hardware deployment for monitoring and control of every agent is shown in figure 6.5.

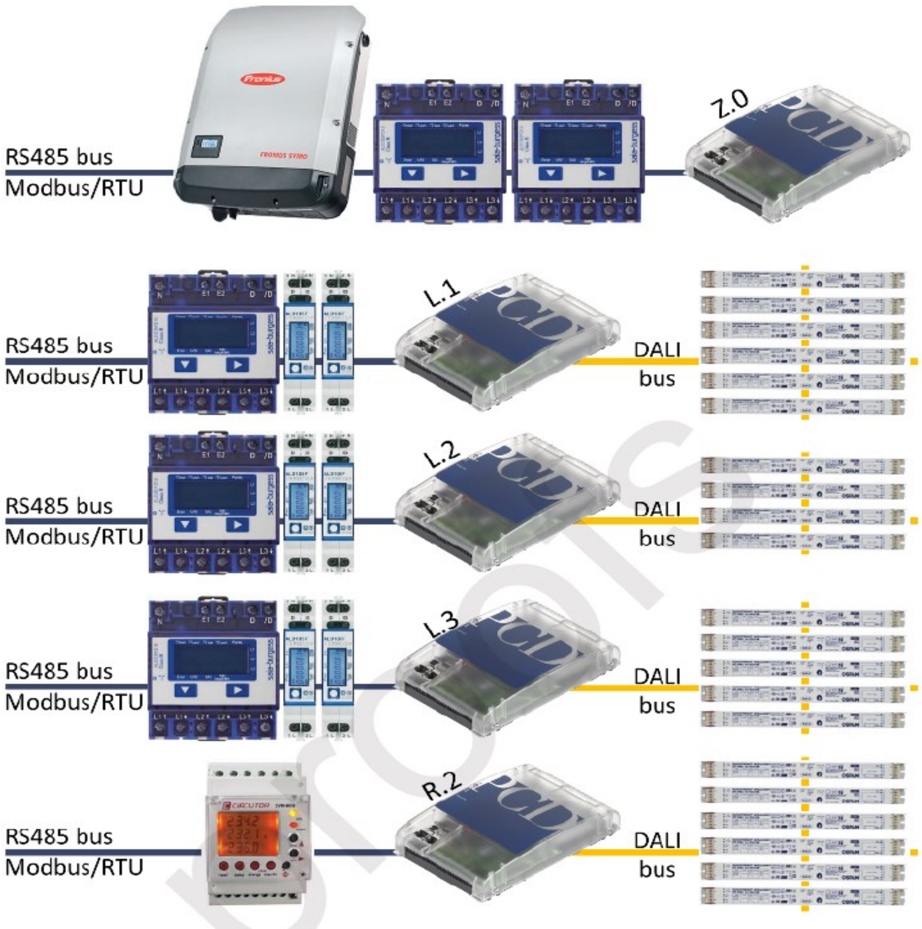
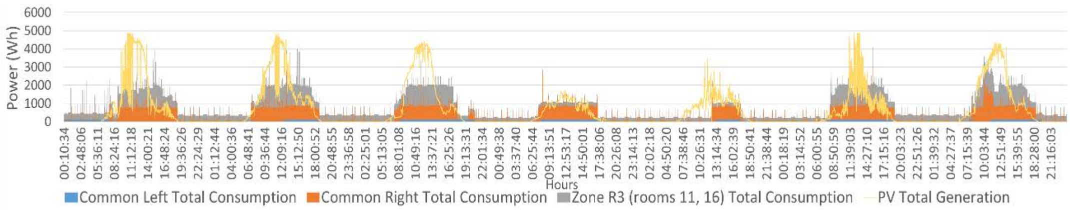
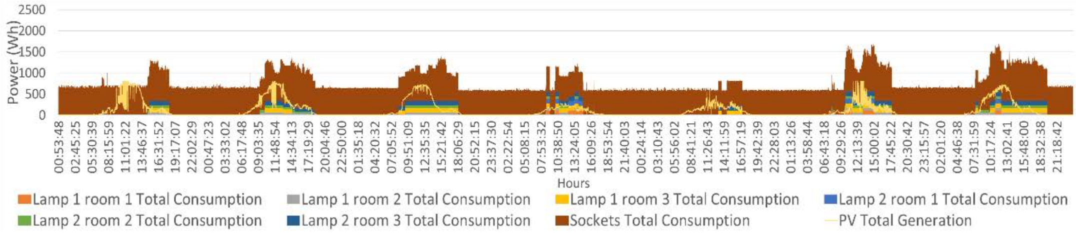


Figure 6.5: Hardware deployment for monitoring and control [32]

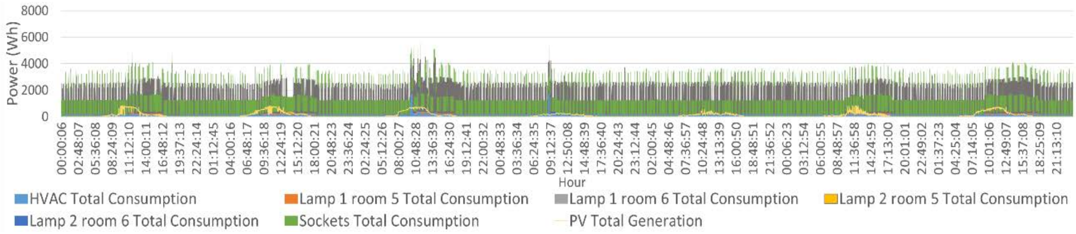
The monitoring and control function exploit an assembly of sensors, energy analyzers and smart plugs [31] in order to make the entire building interactive, allowing the devices to communicate with the central system. The system, with all the agents SBC, is situated in room 14 of the building (always referring to the zones division showed in Figure 6.3). 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 4.3). Thanks to the monitoring system and his metering function [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 "cyclically" 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 agents and referred to the measurement collected in the week from 10 to 16 April 2019, and reported in [33], can be seen in figure 6.6**.**



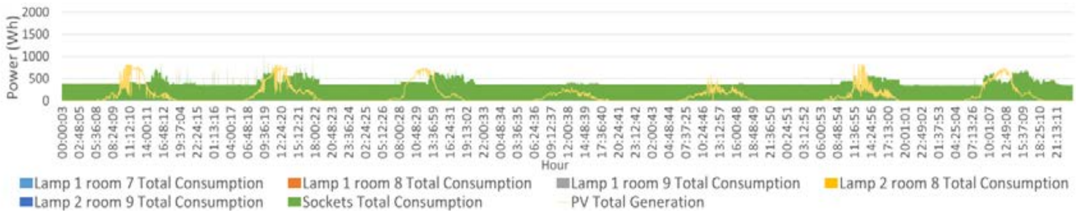
a: Z.0 agent week metering



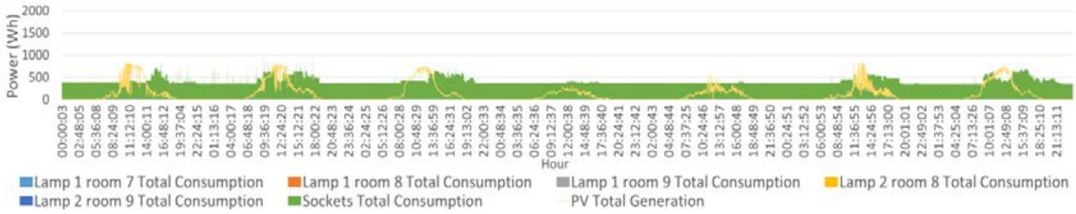
b: L.1 agent week metering



c: L.2 agent week metering



d: L.3 agent week metering



e: R.2 agent week metering

Figure 6.6: agents’ weekly consumption metering profiles [33]

6.3 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 6.7, with the operative system, software and programming language utilized. The system implementation (prior to this study) is presented in [32].

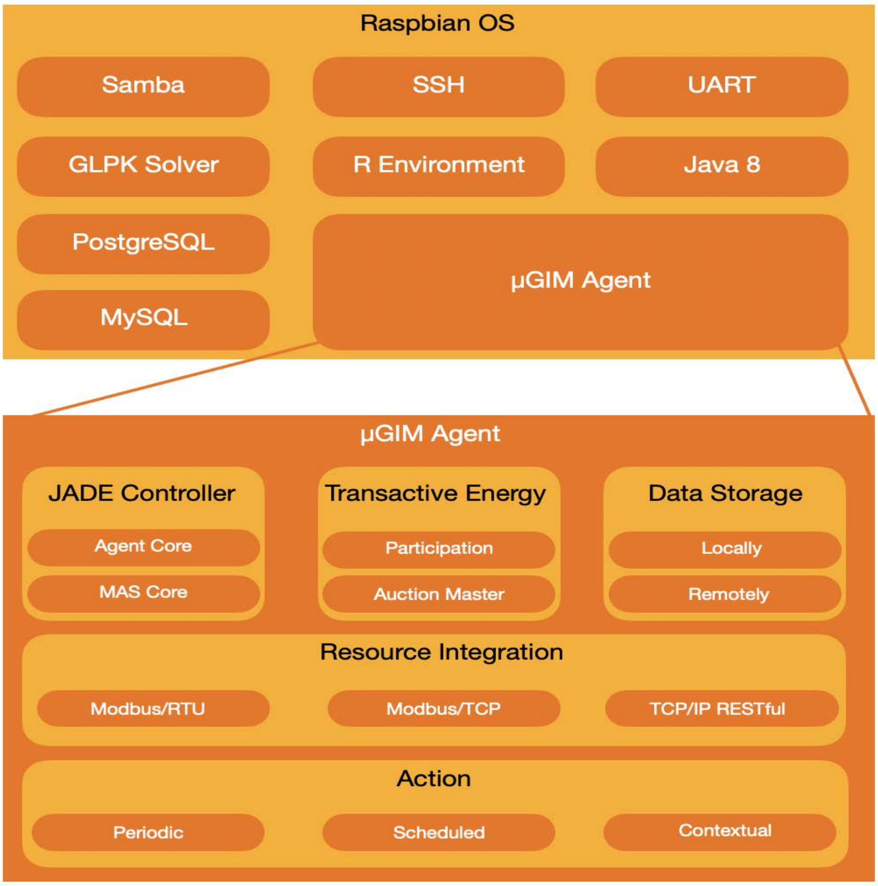


Figure 6.7: µGIM overall architiecture [32]

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.

$$\boldsymbol{f\, C_{h+1} = 0.5 \times C_{h-1} + 0.3 \times C_{h-2} + 0.2 \times C_{h-3}} \qquad \textbf{(5.1)}$$

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 shown in figure 6.8.

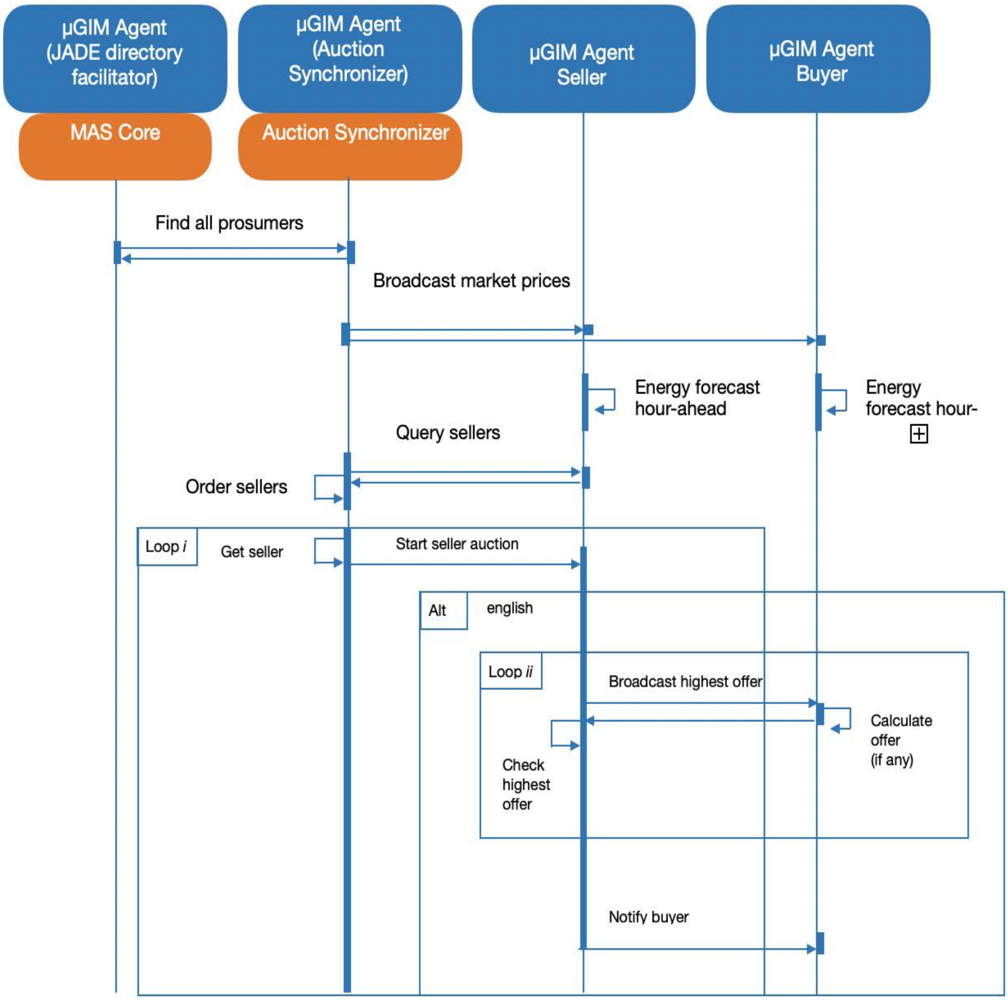


Figure 6.8: transactive energy process diagram [28]

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 6.9 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 6.9: energy configuration file of the μGIM agents [28]

6.4 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 table 6.1, (reported from [28])

Table 6.1: 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 %

Chapter 7

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 type of auction in which 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 classical 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 considered a basic one, that still leaves room for an optimization, or a general improvement of the data. Where to seek such an improvement is not a straightforward answer. What emerges from the data analysis is the absence of a clear path to get an improvement 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 cant all be easily implemented in our system, although 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.

7.1 Former model issues

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 type focus the transaction on the amounts sold by the auctioneer (like in the most classic of the items' auctions). Therefore, all the action happens around the sellers. Anyway, this reduces the possibilities of the buyers, which 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, specially not knowing what comes after.

- **Trading order:** In this model, the sellers execute they auctions in a precise order(as explained in chapter 4.3), 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 type of auction is the one that submit the highest bid. However, in order to maximize the benefit 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 associating 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 participating 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 unbalanced 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, which 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 unbalancing factors in the process. Another question regards the amount to be transacted; in a scenario in which 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 participate in another auction which could overcomplicate the process or even not be possible anymore, depending on the formulation of the model. Either of these scenarios is unfair or penalize a side of the players participating 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.

7.2 Forecasting algorithm impact

Before the presentation of the trading algorithms, is worth to mention some considerations on the forecasting algorithm impact that were discussed during the formulation phase. As specified in chapter five, the system has the possibility to run different forecasting actions. The one specifically utilized for the trading process runs every hour for each agent. During the application of different trading paths, a statistical approach have been utilized to evaluate the influence of the algorithm on the trading efficiency. The implementation of some changes or some settings to limit the wrong trading due to the wrong forecasted energy 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 capability of the proposed algorithms to reduce this parameter will be discussed in the results comparison section. A graphical representation of the entity of the forecast error and the different resulting trading errors is provided in **f**igure 7.1 and 7.2.

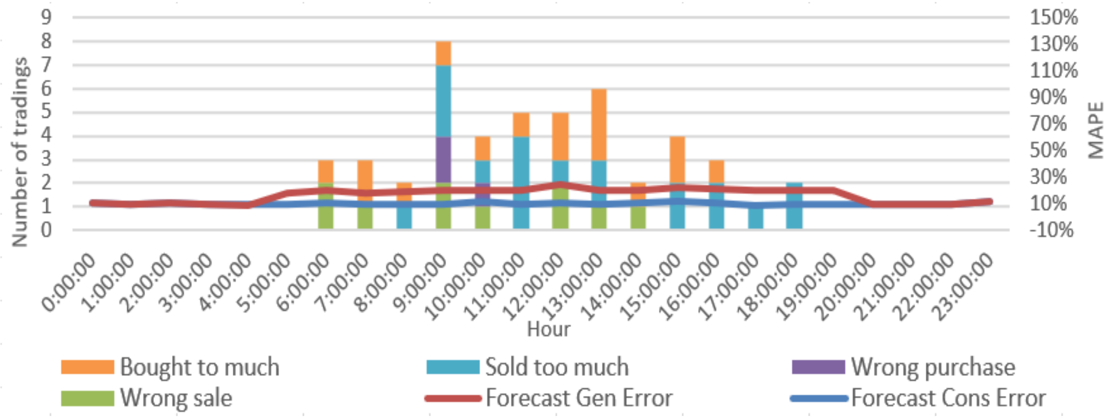


Figure 7.1: Wrong trading periods and forecast errors

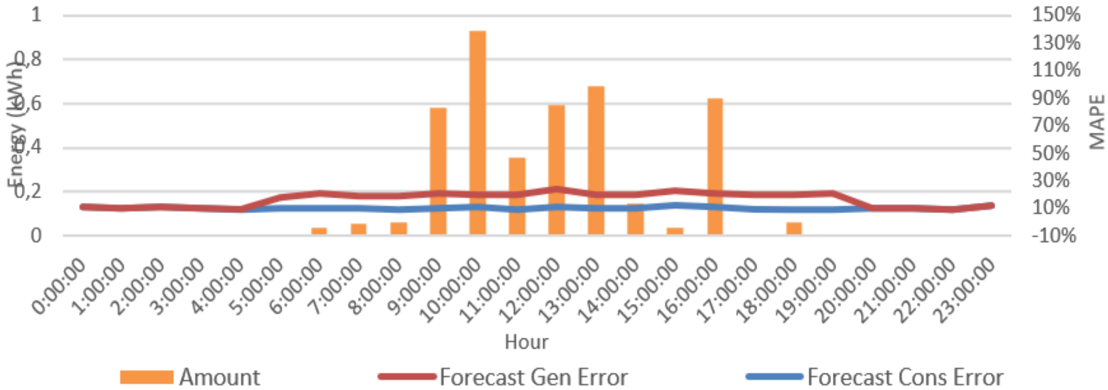


Figure 7.2: wrong trading amounts and forecast errors

As we can see, the MAPE maintain a constant level throughout all the hours of the day both for generation and for consumption and also the two errors have a very similar dimension.

7.3 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 points 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 (every agent submit a single "punctual" bid, and is not aware of the other player's offers)
- bid linked to the amounts (the bids are not a reaction to a price, they are submitted before the process and they are strictly related to the amount the agent is willing to trade)
- minimum price / maximum offer (the bid and price are submitted by the agents only if they respect the constraints of equations 6.7 and 6.8)

The process schedule is reported in table 7.1

Table 7.1: : basic prioritization algorithm schedule

Basic Prioritization Algorithm
1: *auctioneer query sellers*
2: *If* $E^{s}_{a_{ac}}$ *> 0 seller broadcasts energy and price*
3: *order sellers by growing prices*
4: *auctioneer query buyers*
4: *If* $E^{b}_{a_{ac}}$ *> 0; buyer broadcasts energy and bid*
5: *order buyers by descending bids*
6: *calculate the bid average*
7: *distribute the energy among buyers* *If equal bids on equal amounts, split energy among bidders*
8: *announce prices and amounts to buyers and sellers*
9: *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.

$$E_{a_{ac}}^{s} = \begin{cases} 0 & if\ baseline = none \\ F_{gen_{t+1}} - F_{cons_{t+1}} & if\ baseline = surplus \\ F_{gen_{t+1}} & if\ baseline = all \end{cases} \tag{6.1}$$

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).

$E_{a_{ac}}^{s}$ 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 6.9.

In the same way, a buyer will submit the request of energy if equation 6.2 is higher than zero:

$$E^b_{a_{ac}} = \begin{cases} 0 & if\ baseline = none \\ F_{cons_{t+1}} - F_{gen_{t+1}} & if\ baseline = surplus \\ F_{cons_{t+1}} & if\ baseline = all \end{cases} \tag{6.2}$$

$E^b_{a_{ac}}$ is the amount that the buyer is willing to purchase in the auction catalogue.
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).

7.3.1 Application and results

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 7.2 provides an overview of the results from the algorithm simulation.

Table 7.2: basic prioritization algorithm weekly results 3-9/03/2020.

		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 7.3 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 7.3: 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 7.3, 7.4, 7.5 and 7.6 the weekly consumption and cost variation profiles (with and without P2P) can be seen, respectively for the March week and for the April week.

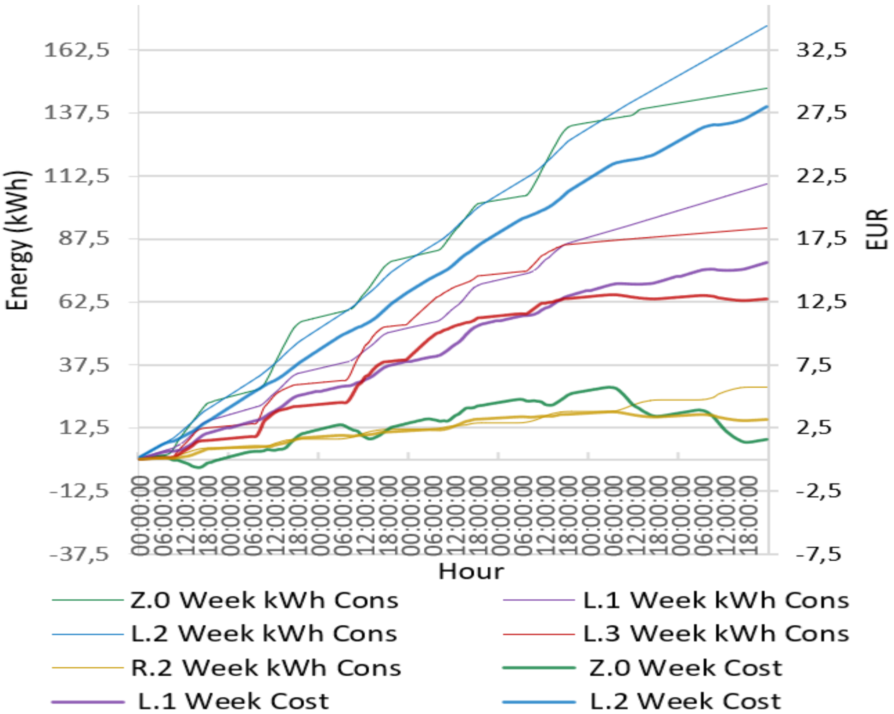


Figure 7.3: Agents' weekly consumption and energy cost with basic prioritization algoritm 3-9 march 2020

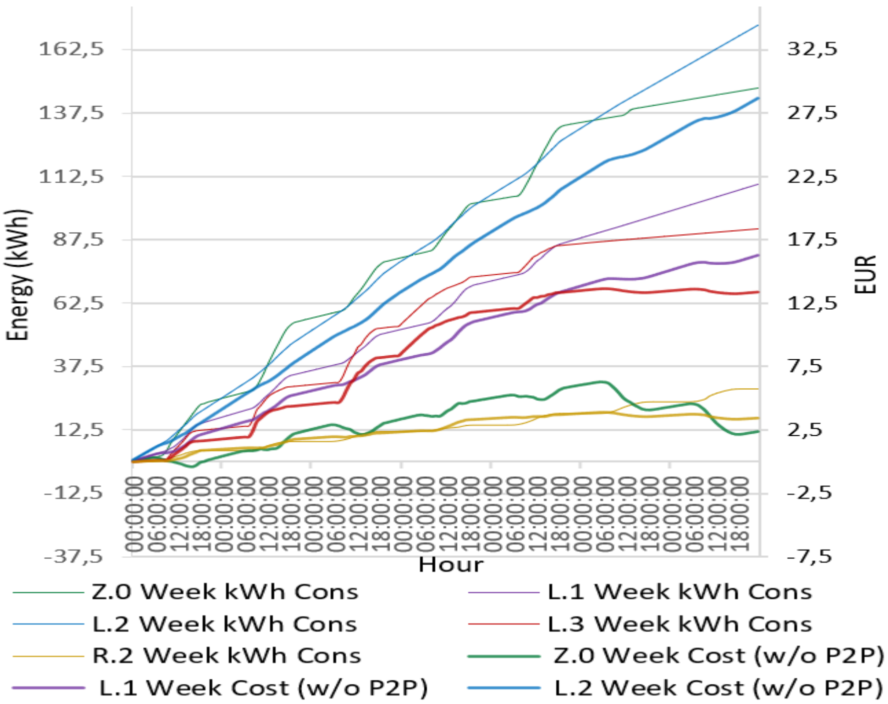


Figure 7.4: Agents' weekly consumption and energy cost without P2P trading 3-9 march 2020

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 7.5 and 7.6. 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 temperature raise, due to the increasing power requested by the cooling system.

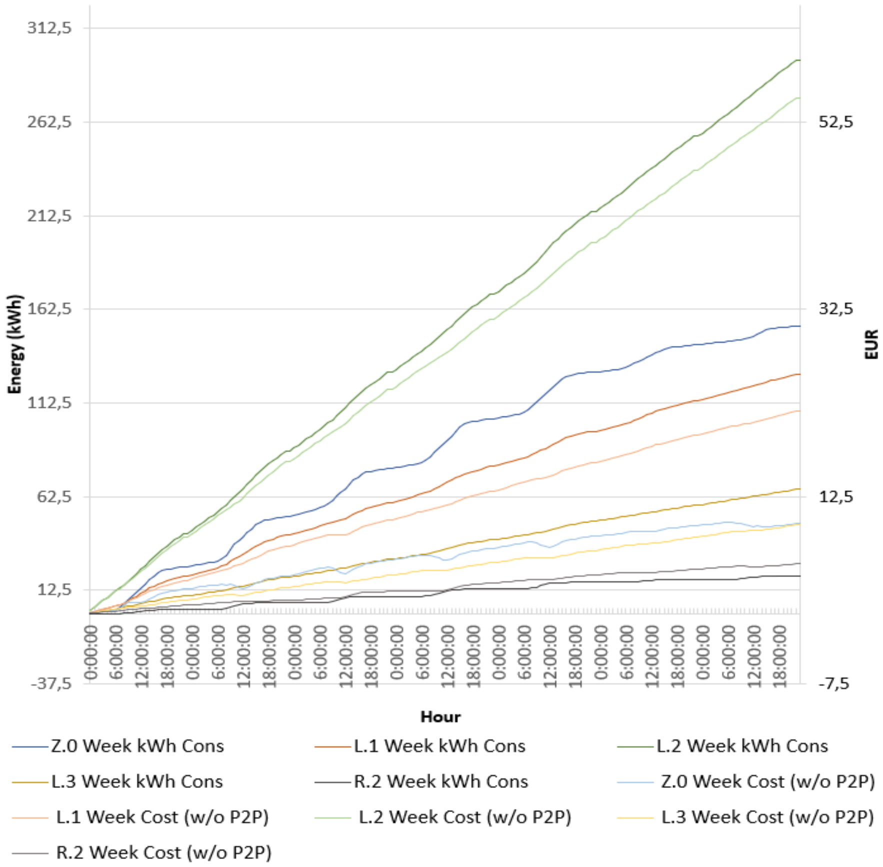


Figure 7.5: Agents' weekly consumption and energy cost without P2P trading 10-16 april 2019

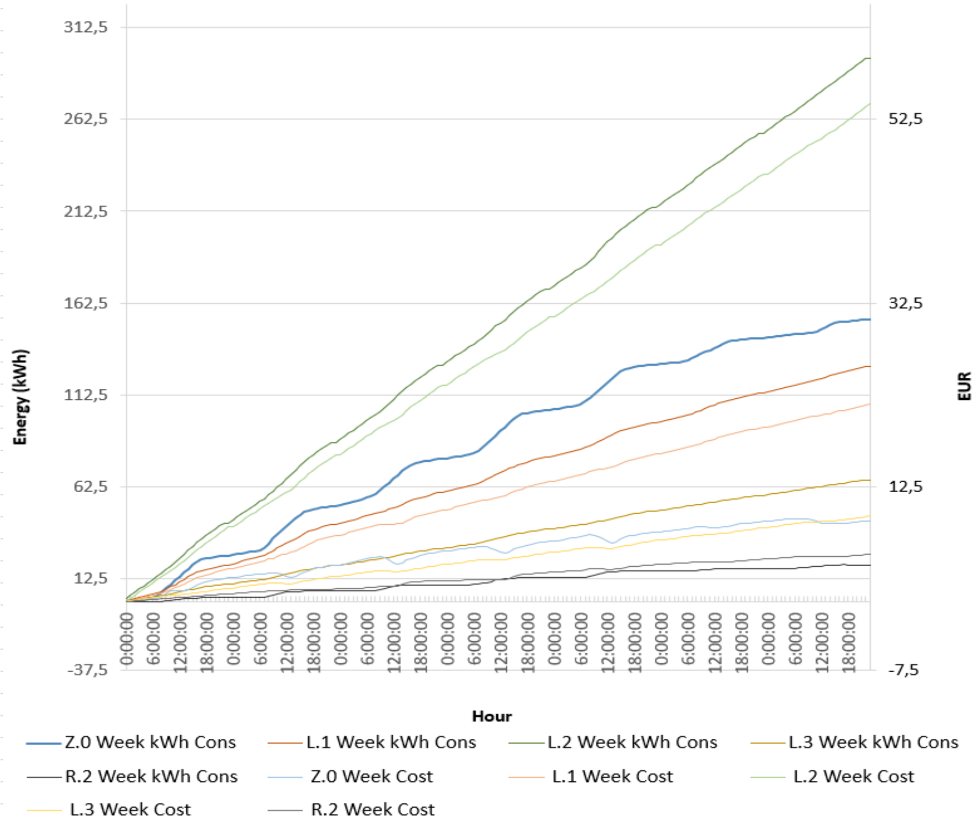


Figure 7.6: Agents' weekly consumption and energy cost with basic prioritization algorith 10-16 april 2019

7.4 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 agents is also impacted. Having showed a tangible improvement in the data, the next logical 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 analyzed 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 participate 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 transactions 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 intermediate price, follows a second phase, in which the remaining 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 price 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 inaccurate formulation can lead to a totally not-efficient 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, would have required to change completely 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 algorithm 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. An overview of the proposed iterative auction algorithm is showed in table.7.4:

Table 7.4: Iterative auction algorithm schedule

Iterative Auction Algorithm
1st *iteration (i=0)*
***1:** auctioneer query sellers*
***2:** If $E^{s}_{a_{ac}}$ > 0 seller broadcasts energy and price (Spa)*
***3:** order sellers by growing prices*
***4:** auctioneer query buyers*
***4:** If $E^{b}_{a_{ac}}$ > 0; buyer broadcasts energy and bid (Sba)*
***5:** order buyers by descending bids*
***6:** calculate the average weighted price*
***7:** distribute the energy among buyers* *If equal bids on equal amounts, split energy among bidders*
2nd *iteration (i = i+1)*
***1:** auctioneer query sellers*
***2:** If sold none: update price (Pi)* *If sold some: submit new price*
***3:** order sellers by growing prices*
***4:** auctioneer query buyers*
***5:** If bought none: update bid (Bi)* *If sold some: submit new bid*
***6:** order buyers by descending bids*
***7:** calculate the average weighted price*
***8:** distribute the energy among buyers*
*Repeat **last iteration** until i = 10 if there are the conditions*
announce prices and amounts to buyers and sellers
End

In which:

- $E^{s}_{a_{ac}}$ and and $E^{s}_{a_{ac}}$are defined as above
- i represents the iteration number
- *Spa* represents the starting price, broadcasted by the seller a in the first iteration [Eur/kWh]
- *Sba* represents the starting offer, broadcasted by the seller a in the first iteration [Eur/kWh]
- Updated price P_i and bid B_i are described in equation 6.3 and 6.4.

$$P_i = s_{pa}\left(1 - \frac{1}{10}i\right) \tag{6.3}$$

$$B_i = s_{ba}\left(1 + \frac{1}{10}i\right) \tag{6.4}$$

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 price logic. The main difference in this aspect is the introduction of the average weighted price, formulated as in equation 6.5

$$\frac{\sum \text{bids}*\text{amounts}+\sum \text{prices}*\text{amounts}}{\sum \text{amounts}} \tag{6.5}$$

This derive from an observation of the market mechanisms of chapter 5. 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 classical 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 formulated 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 participate 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 6.6**.**

$$ME_a = min\left(\sum_{a=1}^{m} E^s_{a_{ac}}, \sum_{a=1}^{m} E^b_{a_{ac}}\right) \tag{6.6}$$

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

The minimal price accepted by an agent ($L^{min}_{a_{ac}}$) 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 6.7.

$$L^{min}_{a_{ac}} = mP_a \times M^s_t \tag{6.7}$$

where mP_a is the minimum price reported in the sell configuration of the agent and M^s_h 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 ($MO_{ai_{ac}}$) is calculated following equation 6.8.

$$MO_{ai_{ac}} = MP_a \times M^b_h \tag{6.8}$$

With the maximum price, MP_a indicated in the configuration file of the agent, and the market price for energy bought M^b_h.

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

7.4.1 Application and results

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 7.5 (for the March week) and table 7.6 for the (April week).

Table 7.5: iterative auction algorithm weekly results 3-9/03/2020.

		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 couldn'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 sum 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 among 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 7.6: 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 7.6, 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 among 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 behavior of the proposed model. For a more complete view, in figure 7.7 and 7.8 are shown the weekly consumption and energy cost profiles of the agents in both the simulated weeks, before and after the application of the transactive model**.**

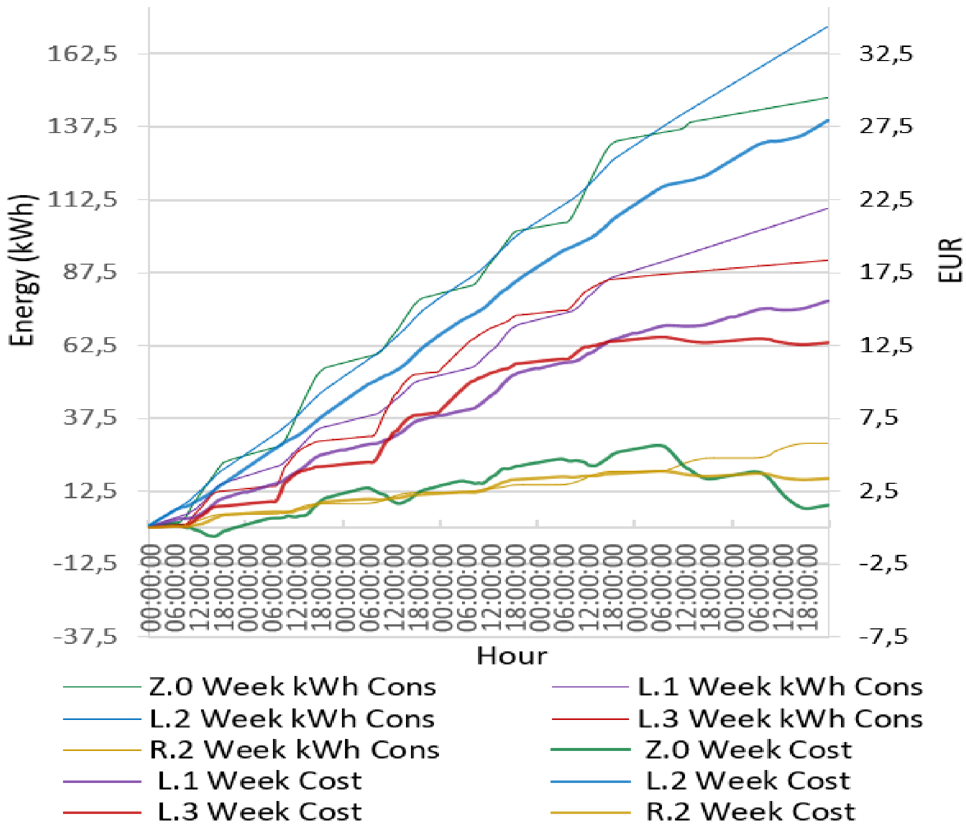


Figure 7.7: Agents' weekly consumption and energy cost with iterative auction algorithm 3-9 march 2020

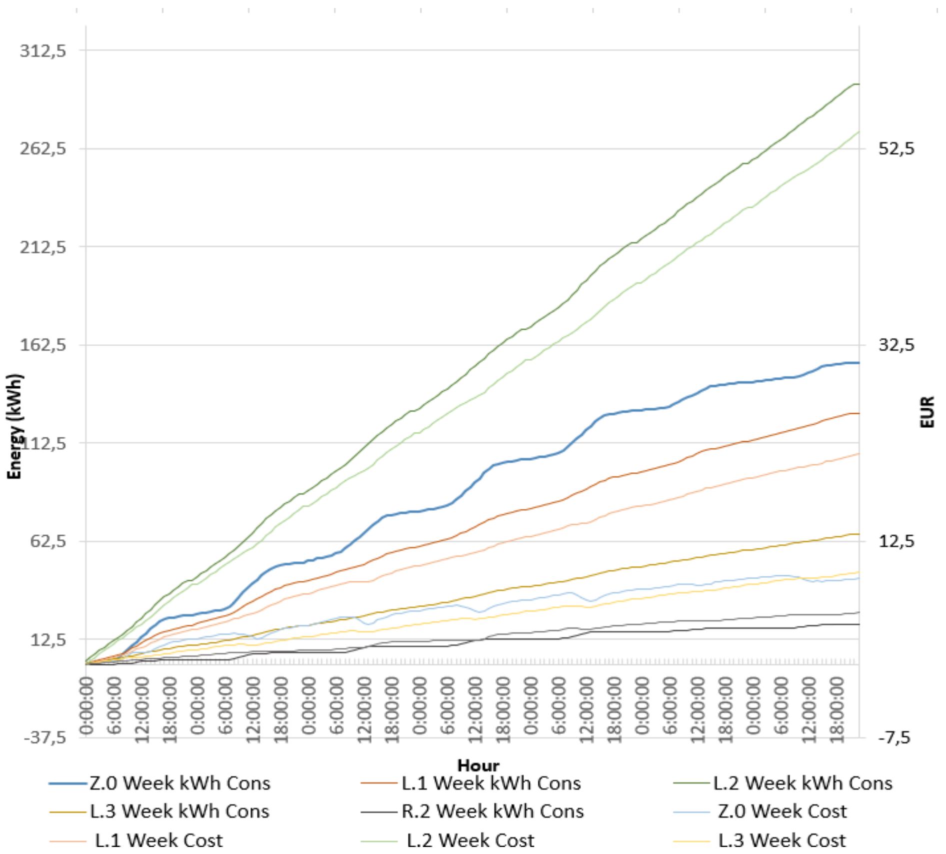


Figure 7.8: Agents' weekly consumption and energy cost with iterative auction algorithm 10-16 april 2019

7.5 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 terms of effectiveness of the measures implemented and their value in hypothetical 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 defects in the process. table 7.7 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 7.7: models MG 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 [Eur/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

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 compared 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 7.9 and 7.10 Shows the profiles of the main energy flows without trading and using the English auction model [28] and figure 7.11 and 7.12 Shows the same profiles considering the two trading algorithm proposed in the simulated week.

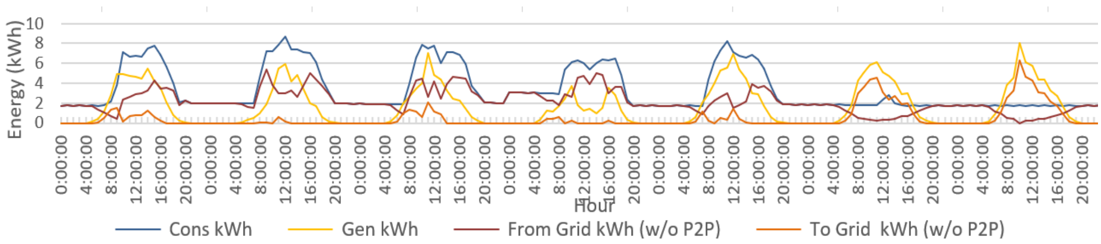


Figure 7.9: microgrid's weekly energy profile (without P2P transactions) [28]

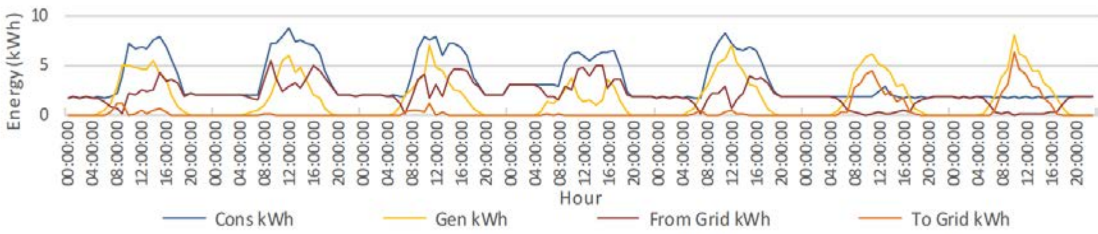


Figure 7.10: microgrid's weekly energy profile (with P2P transactions, model 1) [28]

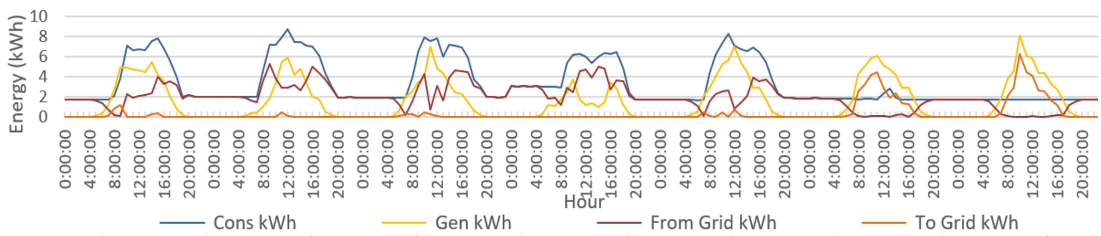


Figure 7.11: microgrid's weekly energy profile (with P2P transactions, model 2)

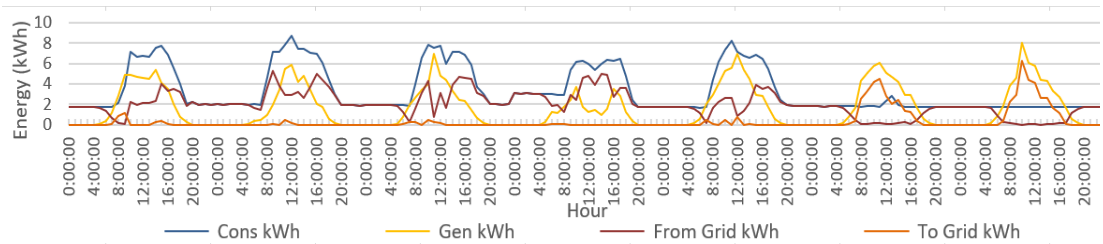


Figure 7.12: microgrid's weekly energy profile (with P2P transactions, model 3)

Chapter 8

Conclusions

A natural conclusion that can be drawn from this work is the acknowledgment of the potential of this technology. Nowadays, intelligent systems and smart grids are object of several studies and their potential is rapidly growing. The peer-to-peer electricity trading technology represents a big opportunity for end users with small, independent generation, giving them the possibility to have an active role in the community and participate 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 development of the trading environments. The concreteness of the trading platforms potential is strongly demonstrated in this study trough the review of many successful process developed and implemented in recent years. The group of models analyzed manages to achieve many goals (price minimization, fairness among the peers, local demand balancing with DG and so on) trough the use of several different techniques and mathematical approaches. In the experimental phase, 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 behavior in order to create a competitive trading scenario. The analysis was centered on the auction type model and different trading configurations were discussed. The main contribution of the thesis on this matter can be summarized in some key points:

- Effectiveness of the trading system: the capability of the MAS to achieve advantages in terms both of maximization of the energy exchange within the MG and cost minimization of the entire community was proved with all the trading configuration tested

- Alternative approach: the thesis provides a new way of approaching the trading problem, analyzing the trading models from an external perspective. This approach has been possible thanks to the current state of development of the technology, which can count on a wide variety of former models.

- Improvement margin: In this project, the results were obtained trough the application of slight changes to the initial model, supported by the proposed comparison ant state of art. Therefore, this work emphasizes the fact that this kind of models are still in the first stage of their development, with a high margin of improvement.

The presented results show a noticeable growth in the efficiency of the transactive process, achieving advantages both for the community and for the single players. Adopting a similar approach to the one showed, further improvements and developments can be achieved in the future. The system utilized in the project, has a good potential as it allows the implementation of various techniques, exploiting the properties and the design of the different agents in the MAS. Speaking of future perspective and progress. The research put in evidence two paths that can be follow to pursue further developments in the system capability. Firstly, one possible scenario is undoubtedly characterized by the implementation of new bidding strategies for the players and game theoretic approaches. In particular, a cooperative game can be modeled in order to evaluate the differences and/or advantages in the system behavior when the different peers cooperate. The other possible scenario features the implementation of new elements in the case study. In particular, in the research center was developed a software capable of simulating the behavior of a EV connected to the grid. The integration of such tool in the trading platform would open to new possibilities like optimization algorithms implementation which consider constraints of the system. .

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