Participation of Prosumer in Local Energy Market based on Preferences

Arun Koomar Nagaraj

Thesis to obtain the Master of Science Degree in

Energy Engineering and Management

Supervisors: Prof. Hugo Gabriel Valente Morais
Dr. Amâncio Lucas de Sousa Pereira

Examination Committee

Chairperson: Prof. Susana Isabel Carvalho Relvas
Supervisor: Prof. Hugo Gabriel Valente Morais
Member of the Committee: Prof. Tiago Manuel Campelo Ferreira Pinto

December 2021

Acknowledgments

I would like to express my deep gratitude to Professor Hugo Morais and Professor Lucas Pereira my dissertation supervisors at Instituto Superior Tecnico, for their insight, support and sharing of knowledge that has made this Thesis possible.

I would like to thank my parents for their friendship, encouragement and caring over all these years, for always being there for me through thick and thin and without whom this project would not be possible.

Last but not least, to all my friends and colleagues that helped me grow as a person and were always there for me during the good and bad times in my life. Thank you.

Abstract

Over the time, many peer-to-peer energy trading mechanisms have been proposed. Nonetheless, they continue to face challenges in terms of infrastructure spending and environmental value creation. The main goal of this thesis is to improve the socioeconomic aspects of the local energy market by designing a simple trading mechanism in which the distance of peers participated in the Local Energy Markets (LEM) from the community centre is used as the preference. The trading decisions are based on the merit order list generated, considering the price and preferences of the market peers. The proposed method is tested on a 14-participant market, and simulation results are compared to those of the existing python library Pymarket, which is a key enabler of ongoing research in the Local Energy Markets (LEM). The findings show that the proposed strategy produces more environmental value and higher profits for market participants than the traditional game theory-based approach.

Keywords

Game Theory, Local Energy Trading,Peer-to-Peer trading, Pymarket, Sustainable Value.

Resumo

Com o tempo, muitos mecanismos de comércio de energia par a par foram propostos. No entanto, eles continuam a enfrentar desafios em termos de gastos com infraestrutura e criação de valor ambiental. O principal objetivo desta tese é melhorar os aspectos socioeconômicos do mercado de energia local, projetando um mecanismo de negociação simples no qual a distância dos pares participantes nos Mercados Locais de Energia (LEM) do centro comunitário é usada como preferência. As decisões de negociação são baseadas na lista de ordens de mérito gerada, considerando o preço e as preferências dos pares de mercado. O método proposto é testado num mercado de 14 participantes, e os resultados da simulação são comparados aos da biblioteca python existente Pymarket, que é uma ferramenta chave para o desenvolvimento de Mercados Locais de Energia (LEM). Os resultados mostram que a estratégia proposta produz mais valor ambiental e maiores lucros para os participantes do mercado do que a abordagem tradicional baseada na teoria dos jogos.

Palavras Chave

Teoria dos Jogos, Comércio Local de Energia, negociação par-a-par, Pymarket, Valor Sustentável.

Contents

List of Figures

List of Tables

List of Algorithms

Listings

Acronyms

LEM	Local Energy Market
IoT	Internet of Things
SMILE	Smart Island Energy System
RAM	Autonomous Region of Madeira
DER	Distributed Energy Resource
DSO	Distributed System Operators
BBS	Battery Based Storage
VPPs	Virtual Power Plants
P2P	Peer to Peer
ML	Machine Learning
EEM	Empresa de Eletricidade da Madeira
DGs	Distributed Generations
PHEVs	Plug-in Hybrid Electric Vehicles
EV	Electric Vehicles
AMI	Advanced Metering Infrastructure
EMS	Energy Management Systems
PV	Photovoltaic

1

Introduction

Contents

Global population and industrialisation have grown significantly over the years, increasing our consumption and demand for energy. The increase in energy demand over recent decades and advancements in technologies have created the need to improve the distribution network [1]. This development in technology enables residents to have their own Distributed Energy Resource (DER) - Rooftop solar, microturbines, battery storage, and electric vehicles are some examples of DER. By integrating these DERs into the distribution network, an active system capable of bidirectional power flow should be created. Furthermore, when compared to the traditional power network, this decentralised energy system has numerous environmental and operational advantages. Technological advancements in smart energy meters, home batteries, and other Internet of Things (IoT) devices enable customers to become prosumers—people who consume and produce energy—which has encouraged DER installation in the local community. Despite this, the increased DER penetration has caused a number of operational and technological problems dependent on their geographic location. People began local energy trading within their communities to solve these geographically based limitations. Local energy trading is gaining traction in the field of distribution networks.

In traditional power system the consumers purchase energy from utilities or retailers. Traditional markets, in some ways, resemble vertically integrated operations as described in figure 1.1. Consumer tariffs in the traditional market are extremely high when compared to their buy-back rates, resulting in a lower number of participants in the energy market [2]. People are getting increasingly interested in the sharing economy notion as a result of the success of business strategies such as Airbnb and Uber. This prompted them to apply these business models to the electricity grid and create a Local Energy Market (LEM), a trading platform where people can sell and buy energy, thereby encouraging more renewable deployment within the community. Participation in LEM, on the other hand, gives consumers greater control over their electricity consumption, price, and system flexibility. Furthermore, local energy trading allows individuals to contribute to their communities by allowing them to use green energy while earning more from distributed generation, with or without storage systems. Simultaneously, through LEM, people who lack the infrastructure to access renewable energy can benefit from local renewable energy installed by neighbors within the community through local energy trading [3]. The following are the objectives of local electricity markets [4]:

- Local demand must be managed to match intermittent supply.
- Congestion and transmission/distribution constraints should be considered.
- Participants' financial management should be supported, taking into account their location and network requirements.
- Replace/postpone grid investments with utilisation of local flexibility.

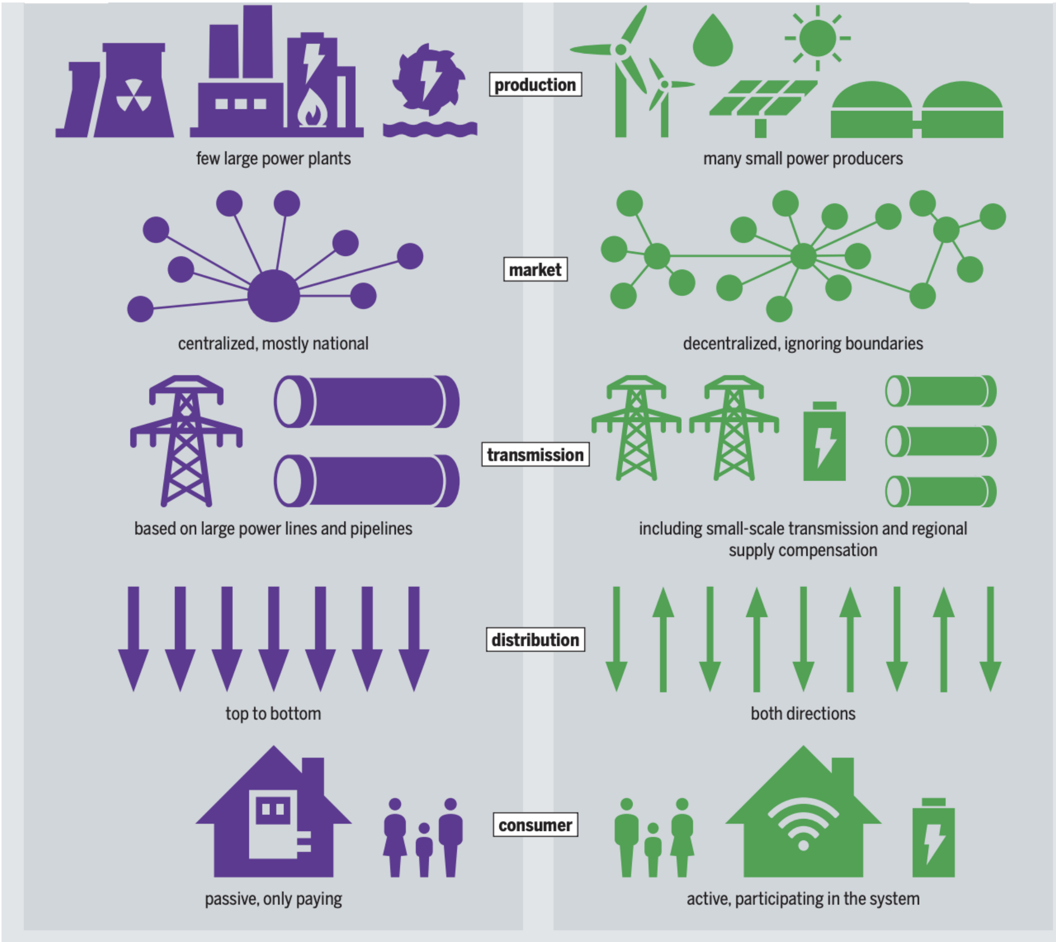


Figure 1.1: Traditional Energy Market vs Decentralised Local Energy Market [5]

The challenges and implementation of local electricity markets differ from those of traditional power markets, which do not necessarily require such close attention to the distribution grid. As a result, the challenges of local electricity markets are closely linked with those of optimal distribution grid operation. These five factors have been identified as the primary sources of difficulties in establishing and operating a local electricity markets [4].

- Optimized use of distributed supply.
- Optimized utilisation of demand response.
- Localized markets must be operated in an efficient and secure manner, as well as technically implemented.
- Existing and emerging legal frameworks.
- Human interaction and socioeconomic aspects

The LEM approach can simplify system operation when there is a high penetration of DERs at interconnected nodes in a network. LEM can also be used to operate intra/inter microgrids and Virtual Power Plants (VPPs), resulting in a scalable, flexible, and dependable power system. Furthermore, LEMs flexibility services are changing distribution companies' approaches. Bilateral energy exchange, market decentralization, and widespread end-user participation are some of the distinguishing features of such a market. Prior implementations, on the other hand, were all aimed at achieving technical and/or economic goals. As a result, the primary goal of this thesis is to enhance the social aspects of the LEM market [6].

1.1 Motivation

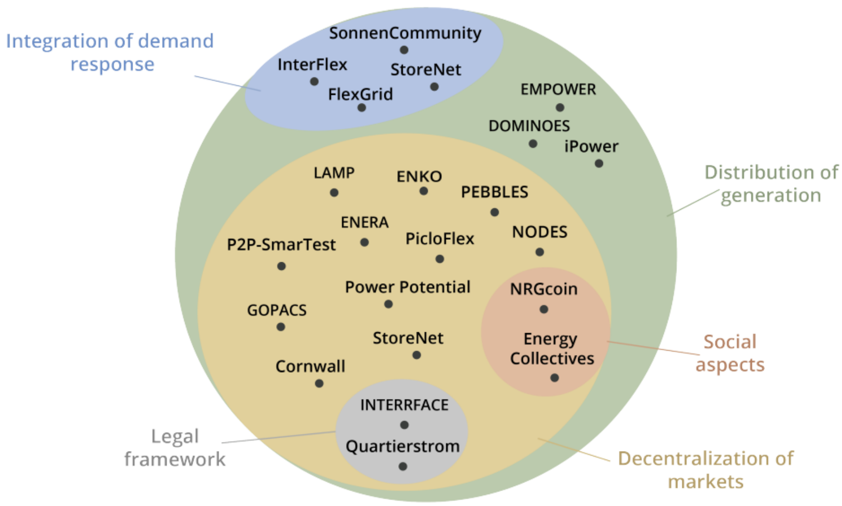


Figure 1.2: LEM challenges addressed by existing projects [4]

From Figure 1.2, it is possible to see that the majority of existing projects aimed to improve factors such as integrated demand response, generation distribution, and market decentralisation. Whereas the fewest projects concentrated on improving social aspects and the legal framework. One of the advantages of the local energy market over traditional markets is the ability to address the various preferences of consumers and prosumers in a more assertive manner. The *NRGcoin*[1] project proposes trading energy between renewable energy producers and local consumers using smart contracts in an LEM. The project's goal is to make it easier for end users to express their preferences for local emission-free energy by lowering volatility [7]. *Energy Collective* uses consensus-based pricing in a local market environment, where user pricing is determined by individual user preferences [8]. The purpose of this thesis is to im-

[1] https://nrgcoin.org/

prove the social aspects of the LEM, by developing a merit order list based on participants transmission distance and bidding price. This merit order list is used to generate trading pairs for energy trading. Furthermore, it covers the transmission loss by penalising market participants based on transmission distance.

1.2 Organization of the Document

This thesis is structured as follows: Chapter 2 describes the current state of the art in the local energy market, including market topologies, market clearing mechanisms, and prior implementation on the local energy market. The mathematical model and Python implementation of the proposed solution are explained in Chapter 3. Chapter 4 describes the Smart Island Energy System (SMILE) project's simulation results based on various scenarios, as well as the one-day simulated market result. The limitations and future scope of the proposed solution are described in Chapter 5.

2

Literature Review

Contents

2.1 Local Energy Market

In traditional power supply, consumers purchase energy from a utility/retailer for fixed or time-of-use tariffs, while prosumers sell their excess energy at buy-back rates. Despite this, consumers' electricity market tariffs are very high when compared to their buy-back rates, and these consumer tariffs do not include the other benefits that renewable generation brings to the power system [3]. In traditional system, the entire market is designed to deliver generated power from a couple of large power generation sites to multiple customers. The decentralized energy market, on the other hand, brings together a large number of small-scale prosumers and DERs [9].

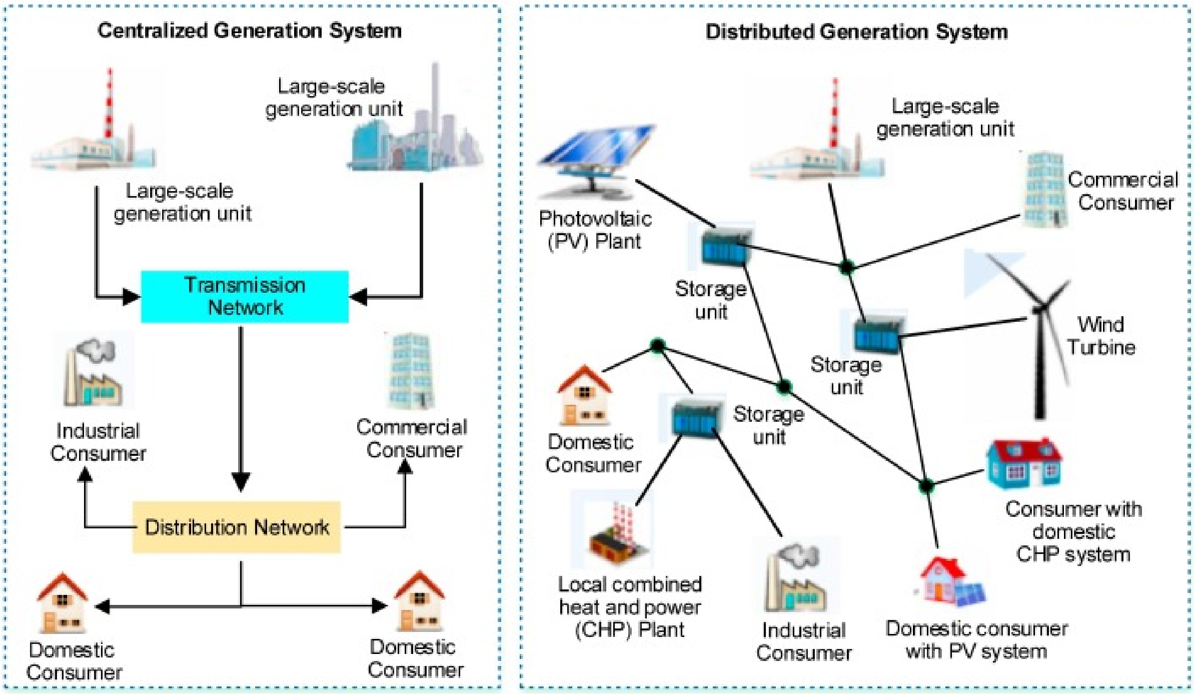


Figure 2.1: Centralised vs Decentralised Energy Market [10]

Local energy trading, in general, refers to the transfer of energy from a prosumer with excess energy to consumer with a deficit. Local energy trading is divided into three groups based on the association of market agents, as described in Figure 2.2 [6].

a) **P2P energy trading:** In the full P2P market, market participants interact directly with one another without the use of middlemen.

b) **Trading of energy through a mediator:** A mediator participates in the market on behalf of sellers and buyers, allocating energy from sellers to buyers, while customers act as price-takers in a passive role.

c) Sellers and buyers can trade energy directly or through a middleman.

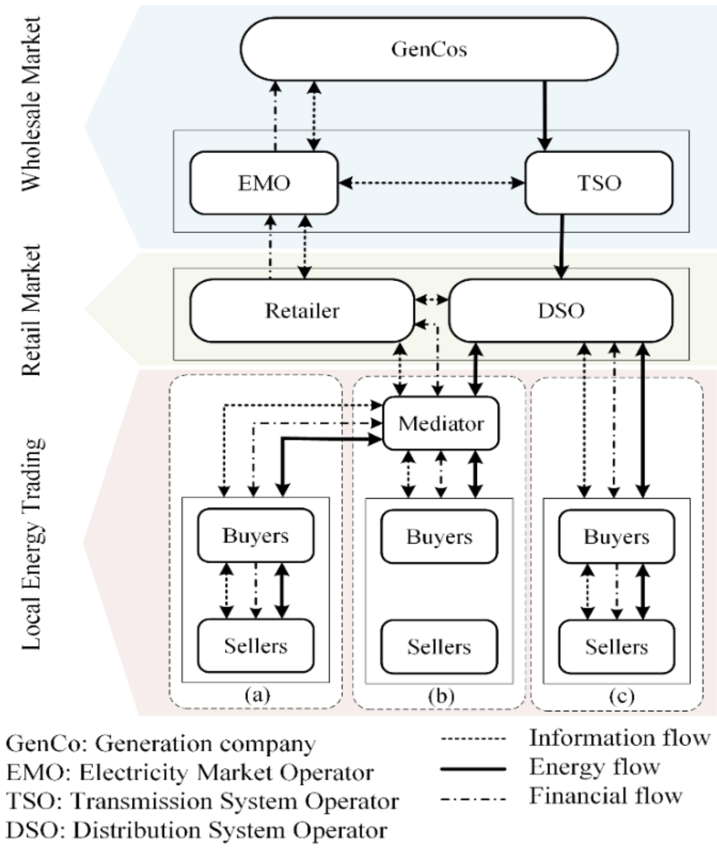


Figure 2.2: Local Energy Market Design [6]

Market Participants

Seller : Participant with the ability to generate or store energy can be a seller in the LEM. Person who owns one or more DER, such as Distributed Generations (DGs), Plug-in Hybrid Electric Vehicles (PHEVs), energy cells, etc. ...

Buyer : Participants who purchase energy from LEM. Energy can be purchased from the market by both consumers and prosumers. In fact, prosumers with excess energy are sellers, and if they require more energy, they will enter the market as buyers.

Mediator : An independent agent who negotiates the purchase of electricity from retailers by combining two or more consumers into a single purchasing unit.

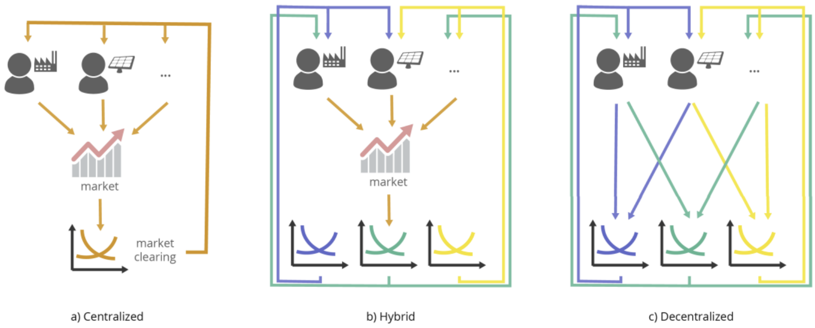


Figure 2.3: Different Local Energy Market Topology [4]

2.2 Market Topologies

a) **Centralized / Pool Market Trading** - The coordinator acts as a communication bridge between market participants in centralized / pool market trading. The coordinator gathers information from market participants and decides on market transactions and energy import/export between market participants.

b) **Hybrid** - A hybrid market is one that combines centralized and decentralized elements. In this market, the coordinator usually indirectly influences market participants by sending pricing signals, rather than directly instructing market participants about market transactions.

c) **Decentralized / Full Peer to Peer (P2P)** - There are no centralized coordinators in decentralized P2P energy trading markets, and market participants can directly trade with one another. Market participants' privacy is well protected in decentralized markets, and information is partially shared among market participants.

Market Topologies	Advantages	Disadvantages
Centralized / Pool Market Trading	High coperation among community members	Low Scalability, Reliability
	Good support for grid operators	High maintenance cost
	High-quality energy services	Not consumer-centric
Hybrid	High Scalability	Integration and handling of extensive data sets
	Smooth integration into existing systems	Multi-market coordination
Decentralized / Full P2P(Bilateral)	High Scalability, Low computational cost	Legal framework
	Customer-centric	Creation of environmental value

Table 2.1: Market topologies advantages and disadvantages P2P:challenge

Considering the size of participants in LEM, Decentralized / Full P2P topology is used in designing LEM.

2.3 Trading Mechanism

Market Clearing Methods	
Distributed Method	Decomposition Method
	Networked Optimization
	Game Theory Based
	Multi - Agent System
Other Methods	Auction Based
	Multi level Optimization

Table 2.2: Types of Local Energy Market Clearing Mechanisms

Table 2.2 explains the various market clearing methods used in local energy markets. These methods are typically not used independently, and a combination of them will be used for market clearing to improve the accuracy and efficiency of system. Selecting market clearing methods is influenced by a variety of factors like [4],

Assumptions

Market structure

Behaviour of market player

Market rules

The distributed optimisation algorithms are divided into four categories: decomposition, networked optimisation, game-theoretic, and agent-based methods. The majority of the local energy market focus on using distributed optimisation methods because they are effective in markets with fewer players, on contrast to auction and multi-level optimisation methods, which are better suited to large markets with many market participants.

The decomposition method is the common approach for distributed optimisation, in which a large-scale complex problem is divided into several small problems depending on the structure and constraints of the objective function. After decomposition, each small problems can be solved independently, but a coordinator is required to ensure that local decisions converge to the global optimum [11].

When a problem needs to be decomposed based on its original structure, networked optimization is used. The interaction of decision markers is based on the communication structure, and decomposition is required to match this structure. The complete distribution network is illustrated by a graph in this method, the graph's vertices represents market participants like buyer/seller/agents. To model a local market in a distribution network, various graphs such as random graphs, directed and undirected graphs, weighted and unweighted graphs, can be used. This method is used in a market where players can only exchange information with their immediate players [12].

Game theory is defined as the study of a statistical model of several decision-making players with potential cooperation and conflicting objectives. A cooperative game is a competition between groups of cooperative players, whereas a non-cooperative game is one in which players make their own decisions. Typically, game theory is used to counteract selfish behavior in LEMs. Game theory can be applied in situations where information exchange is impractical for market participants, and thus agents prefer to optimize their local or private objectives while reacting to limited network information [13].
This method is applicable to large-scale systems involving various types of interactions. Each market player in this method is considered an agent (Buyer/Seller), and this method can be as simple as a single variable or as complex as with infinite actions and decisions. Markets designed based on this model are highly adaptable, scalable, and highly reliable. But this method suits for large market participants [14].

Trading Model	**Advantage**
Centrally controlled Energy Trading between two microgrids	Optimization method adopted to meet demand and response is centrally controlled and reliance on a central entity leads to stability between connected microgrids.
Centrally controlled and incentive driven Connection of multiple users to a same microgrid	The technique adopts two optimization methods (centrally controlled and incentive-driven) which beneficiates in improving accuracy. Also, privacy among the connection is also maintained
Centrally controlled and game theoretic Trading among local consumers and prosumers	The employed game-theoretic model leads to an efficiency of optimization model.
Cooperative Energy Trading between a group of prosumers	Mutual benefit is a key concern for cooperative optimization models that cause model stability.
Game theoretic Energy trading between multiple prosumers and a single consumer	The model addresses the issue of uncertainty of energy trading between microgrids

Table 2.3: Different Trading model and their advantages [13, 15, 16]

The formulation of a decentralised electricity markets explained by authors in [17]. The energy market is designed in such a way that communication links among market stakeholders (Buyer, Seller, and Agent) are the only variables defining the type of market architecture: from community-based to peer-to-peer, pool markets, and any hybrid combination of all of these architectures. As a result, the negotiation process is transformed into a decentralized consensus problem, for which various optimisation techniques such as game theoretical algorithms and distributed control strategies can be used [15].

The authors in [18] identifies that the centralised market has high understanding among the market participants, high flexibility within the communities and high aid in services related to grid. But the author's also addresses the challenges like impartialities in energy sharing and struggle to maintain participants interactions in market balance. These shows the current market lacks in customer centric values.

While [15] and [17] describes the market mechanism and negotiation techniques, it fails to address the uncertainties in performing game theoretical algorithms. The authors in [19] address this uncertainty and heterogeneity in market participants on decentralised electricity markets by defining cost and utility curves. These cost and utility curves are based on risk attitudes, which aids in the recovery of market fairness and efficiency. Human error in including risk attributes and challenges in financial transactions continues to be a significant disadvantage in overall performance.

The advancement of technologies such as IoT, Blockchain, and Machine Learning (ML) has helped in understanding the majority of the obstacles in the LEM. The authors in [20] focuses on a blockchain-enabled predictive energy trading platform built on the combination of machine learning and blockchain model. This advancement in technologies improved the local energy market operation and creates a better control comparing to the previous model.

However, technological advancements have failed to address the issues raised in chapter 1, regarding maintenance costs and transmission loss. The authors in [21] focus on including transmission and maintenance cost through network charges, by including electrical distance between agents in a LEM. Using incentives, they accounted the grid-related costs. This mechanism encourages encourages market participants to sell the energy to the buyers near by avoiding network overload. If network charges are not chosen wisely, it will affect the market participants and this approach may result in inefficient or unfeasible solutions.

Authors in [22] explains various models for consumer-centric markets. Market evolution from pool-based structures at the micro-grid level to full peer-to-peer network described in [23]. The degree of centralisation is important in implementing these peer-to-peer models because it tells us whether the market requires an external agent [23] and [24]. A market framework that allows all agents to express their preferences is critical; because electricity is priced uniformly in forward markets, expressing preferences should have a significant impact on market performance [25]. The implementation of such novel market structures in which user preferences play a critical role in trading decisions is a cornerstone for behavioural change among electricity consumers [26].

According to the literature review, technological advancement focuses on improving overall system modelling while struggling to improve social aspects and participant motivation. Taking this into account, this thesis focuses on improving social aspects by incorporating participant-specific product differentiation in the Local Energy Market. Since the proposed work is centered on small-scale community-based markets, a simple market clearing mechanism based on a merit order list can be used. Unlike the game theory model mentioned in paper [13], distance and price play an important role in creating trading pairs in this work. The result obtained from proposed solution is compared with the market result obtained from Pymarket, which is a significant enabler of ongoing research in the LEM [27].

3

Methodology

Contents

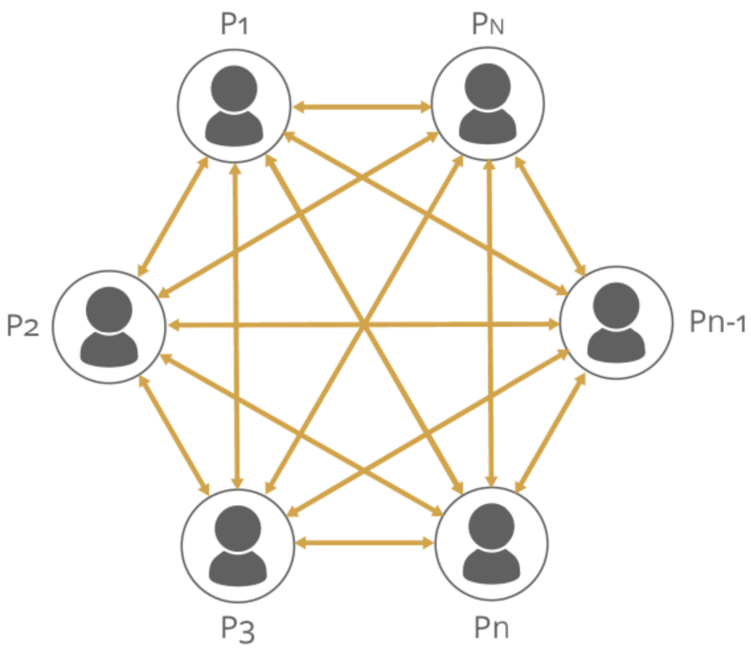


Figure 3.1: Local Energy Market [4]

There are two main types of stakeholders in the proposed LEM mechanism: the buyer and the seller. Each seller has at least one unit of energy for sale, and each buyer has the ability to buy at least one unit of energy. To bid in the market, the user must first register and provide the required information. In the proposed local market, the necessary informations are listed below.

- Quantity - The quantity of electricity in kW that the user wishes to sell or buy in the local energy market.
- Location - The user's distance from the community center in kilometers.
- Price - The price in € at which the user wishes to sell or buy energy in the local energy market .
- Buying - True - if the user chooses to purchase energy from the market; False - if the user chooses to sell energy in the market.

The proposed LEM is designed based on the following mentioned conditions. Conditions 2 and 3 are presented in [13].

1) To exchange energy among neighbours in a community, with interaction based on full peer-to-peer topology.
2) Agents are informed about the value of the traded good in an asymmetrically manner.

3) Once the market is open, no new buyers or sellers are permitted.

4) Sellers and buyers are ranked based on the price and distance.

5) The merit order list is used to create trading pairs.

3.1 Local Energy Market - Mathematical Model

The mathematical model of the proposed LEM structure is adapted from [28] and is formulated as following,

In Equation 1, P_n is the net active power injection by each agent n and is equal to the sum of traded quantities with set of nearby agents in the community $m \in \omega_n$.

$$P_n = \sum_{m \in \omega_n} P_{nm} \tag{1}$$

The power boundaries of each agents n participating in the LEM are defined by the below mention equation 2

$$\underline{P_n} \leq P_n \leq \overline{P_n} \tag{2}$$

Each agent n in theLEM can play the roles of producer, consumer, and prosumer. The agent's market role is determined by the agent's need for energy consumption or available excess energy energy in a specific period t. In the case of the prosumer, where the agent can be either a seller or a buyer, the sign of the decision variable determines the agent's role.

1) The agent n is a producer, when $(P_{nm} \geq 0)$.

2) The agent n is a consumer, when $(P_{nm} \leq 0)$.

3) In Prosumer case, the agent n acts as seller when $(P_{nm}^{+} \geq 0)$, and buyer when $(P_{nm}^{-} \leq 0)$.

The supply-demand equilibrium is represented below by a set of reciprocity constraints involving all agents $n \in \omega$ and $m \in \Omega$

$$P_{nm} + P_{mn} = 0$$

The equation 3 maximize the social welfare of the agents n, participating in the local energy market, under the constraints mention from $(3b\ and\ 3d)$.

1) Time t - The agent participates in the local energy market on an hourly basis.

2) The total cost of the model is denoted by $C_{n,t}$

3) $\tilde{C}_{n,t}$ represents the product differentiation function, which includes additional preferences.

4) $P_{n,t}$ is the net power of n agents at time t, and it is positive for producers but negative for consumers.

5) The sets of producers and consumers are denoted by Ω_p and Ω_c.

$$\min_{D} \sum_{n\in\Omega} C_{n,t}(P_{n,t}) + \tilde{C}_{n,t}(P_{n,t}) \tag{3}$$

$$s.t. P_{n,t} = \sum_{m\in\omega_n} P_{n,m,t}\ n \in \Omega, t \in T \tag{3a}$$

$$\underline{P}_{n,t} \leq P_{n,t} \leq \overline{P}_{n,t}\ n \in \Omega,\ t \in T \tag{3b}$$

$$P_{n,m,t} + P_{m,n,t} = 0\ n \in \Omega, m \in \omega_n, t \in T \tag{3c}$$

Equation 4 describes the overall trading coefficient of the agent n, can include various preferences under criterion g. Distance, energy source, economic status, emissions, and other environmental factors belongs to criteria g. Each agent's criteria are denoted by γ^g_{nm}.

$$c_{nm} = \sum_{g\in\mathcal{G}} c^g_n \gamma^g_{nm} \tag{4}$$

In the proposed solution takes distance as a preference. In this case, γ^g_n would contain the distance between the agents n and m in kilometer. The main goal of the proposed solution is to create a simple trading mechanism. Given this, we will replace equation 4 by generating a merit order list based on the agent's price and preferences. A penalty will be included in the agent's bidding price to cover the transmission losses between agents using equation 5 and 6.

$$Buyer\ price = Bidding\ Price_{buyer} - \frac{Distance_{buyer}}{Quantity_{buyer}} \times 0.1\ euro \tag{5}$$

$$Seller\ price = Bidding\ Price_{seller} + \frac{Distance_{seller}}{Quantity_{seller}} \times 0.1\ euro \tag{6}$$

3.2 Proposed Mechanism - Algorithm

The proposed solution focuses on creating a market without the use of an agent. A Python library is created to simulate the proposed methodology.

3.2.1 Bid Registration

The below-mentioned algorithm is used to register the buyer/seller in the Local Energy Market. Table 3.1 shows the outcome of the user registration algorithm.

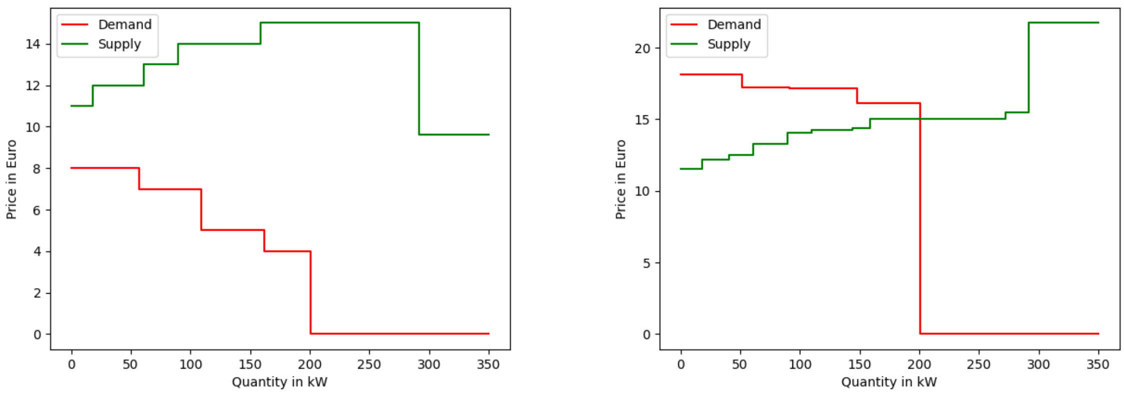
Algorithm 3.1: Local Energy Market - User Registration

Function `Bid Manager`($Quantity$, $Price$, $User$, $Buying$,$Distance$):

```
new bid = (Quantity, Price, User, Buying,Distance)
self.bids.append(new bid)
self.n bids += 1
pd.Dataframe(Quantity,Distance,User ID,Price,Buying)
return bids
```

Quantity in kW	Price in €	User	Buying	Distance in KM	Renewable
34	14	1	FALSE	89	True
52	18	13	TRUE	52	True
53	16	14	FALSE	54	True
39	17	15	TRUE	80	True

Table 3.1: Example of bids registered in the market



(a) Supply vs Demand Example 1

(b) Supply vs Demand Example 2

Figure 3.2: Example of supply vs demand graph obtained from user registered bid.

In Algorithm 3.1, details such as $(Quantity, Distance, UserID, Price, Buying)$ are obtained from users through a registration portal or, in this case, a pre-stored excel file. Line 1 reads the value from the excel file and sends it to the $Python\ Bid\ Module$. Line $2\ and\ 3$, generates the user bid by appending the user information from the excel file. Line 4 converts the user details into a *pandas data frame*, with the output looking more like a data format in an excel sheet. This pandas conversion was implemented to facilitate data handling.

Table 3.1 shows an example of output from the *Python Bid Module*, and Figure 3.2 shows a sample graph generated by the *Python Bid Module* after registering the user's bid. Only when the supply and demand bids intersect the market transaction occurs this is illustrated in Figure 3.2 $b)$. In case of Figure 3.2 $a)$, no market transaction occurs because the supply and demand bids do not intersect. This supply and demand bid intersection was primarily determined by the user's bidding price.

3.2.2 Creation of merit order list and trading pair

Upon creating the bidding list, the price of buyer and seller gets updated as per equations 5 & 6.

Algorithm 3.2: Local Energy Market - Merit Order List and Trading Pairs Formation

```
Function Merit Order List and Trading Pairs Formation (Bids):
1  buying = bids[bids.buying]
2  selling = bids[bids.buying == False]
3  buying['price']= np.round(bids['price']-(bids['Distance']/bids['quantity']*0.1),3)
4  selling['price']= np.round(bids['price']+(bids['Distance']/bids['quantity']*0.1),3)
5  Seller list = selling.sort values(['price','Distance'], ascending=True)
6  Buyer list = buying.sort values(['price','Distance'], ascending=False, True)
7  for UserID ∈ buyerlist do
8      for UserID ∈ sellerlist do
9          Create trading list(user ID from buyer list , user ID from seller list)

   return trading pairs
```

Algorithm 3.2 takes the bids output from Python Bid Module. The main goal of this proposed methodology is to to include social aspects (product differenciation) of LEM. Taking this into account, equation 5 & 6 are used to update the bidding price. This updated price is determined by the user's location - the distance from the community center / market hosting area; this process is described in Lines $3\ and\ 4$. After updating the price, Line $5\ and\ 6$ generates the buyer and seller merit order list by ranking them based on their price and nearest distance. Line $7-9$ generates potential trading pairs by matching the highest ranked buyer with all sellers based on their rank in the merit order list.

The sample raw bid output from the $Python\ bid\ module$ is described in Table 3.2. In Tables 3.3 and 3.4, the price is updated based on the user's distance, and user's are ranked based on their distance and price. The sample merit order list generated by algorithm 3.2 is shown in Tables 3.3 and 3.4. Following the creation of a merit order list, possible trading pairs are generated by mapping users from the buyers' merit order list to users from the sellers' merit order list. For example, the first user in Table 3.3 is **User 12**, will be mapped to the first user in Table 3.4 which is **User 1** and then with next user from Table 3.4, **User 13** and so on. This process is repeated until **User 12** is paired with all of the available sellers in Table 3.4.

Quantity in kW	Price in euro	User ID	Buying	Distance in KM
69	0.74	1	FALSE	1
53	0.81	2	FALSE	9
150	0.76	3	FALSE	2
80	0.95	4	TRUE	3
100	0.99	5	TRUE	7
59	1.01	6	TRUE	2
72	0.79	7	FALSE	0
82	0.85	8	FALSE	2
110	0.97	9	TRUE	6
58	0.74	10	FALSE	7
60	0.82	11	TRUE	4
50	1.06	12	TRUE	2
113	0.74	13	FALSE	9
53	0.76	14	FALSE	3

Table 3.2: Example of Bids from the Python bid module

Quantity in kW	Price in euro	User ID	Buying	Distance in KM
50	1.056	12	TRUE	2
59	1.007	6	TRUE	2
100	0.983	5	TRUE	7
110	0.965	9	TRUE	6
80	0.946	4	TRUE	3
60	0.813	11	TRUE	4

Table 3.3: Buyers' merit order list

Quantity in kW	Price in euro	User ID	Buying	Distance in KM
69	0.741	1	FALSE	1
113	0.748	13	FALSE	9
58	0.752	10	FALSE	7
150	0.761	3	FALSE	2
53	0.766	14	FALSE	3
72	0.79	7	FALSE	0
53	0.827	2	FALSE	9
82	0.852	8	FALSE	2

Table 3.4: Sellers' merit order list

The number of trading rounds in this proposed mechanism is determined by the number of available buyers, The possible trading pairs for each round considering the Tables 3.3 & 3.4 are listed below:

Round 1 $(12, 1), (12, 13), (12, 10), (12, 3), (12, 14), (12, 7), (12, 2), (12, 8)$

Round 2 $(6, 1), (6, 13), (6, 10), (6, 3), (6, 14), (6, 7), (6, 2), (7, 8)$

Round 3 $(5, 1), (5, 13), (5, 10), (5, 3), (5, 14), (5, 7), (5, 2), (5, 8)$

Round 4 $(9, 1), (9, 13), (9, 10), (9, 3), (9, 14), (9, 7), (9, 2), (9, 8)$

Round 5 $(4, 1), (4, 13), (4, 10), (4, 3), (4, 14), (4, 7), (4, 2), (4, 8)$

Round 6 $(11, 1), (11, 13), (11, 10), (11, 3), (11, 14), (11, 7), (11, 2), (11, 8)$

3.2.3 Market Transaction

Section 3.2.2 discusses the working of Line $1-9$ from algorithm 3.3. Line 10 receives the potential trading pairs generated by algorithm 3.2. Considering the sample trading pairs from 3.2.2, in round 1, all potential sellers will try to trade with highest ranked user in buyers merit order list. The buyer and seller will reach an agreement based on the condition mentioned in Line 11, if the trading pair meets the required condition, the buyer and seller will reach an agreement, and the transaction will take place. The quantity traded will be determined by the conditions listed below.

$$Traded\, Quantity \;=\; min(quantities\_buyer,\; quantities\_seller)$$

The trading price will be determined by the buyer's price, which is updated in Line 13. Line $14\; and\; 15$, update the transaction details; this is more like a ledger-based information, where details such as traded quantity, trading price, buyer and seller ID, and whether the buyer/seller is available for the next round are stored. Line $16-17$, deducts the traded quantities from the buyer and seller's total available quantities. The table 3.5 describes the sample output from the algorithm 3.3.

Traded Quantity in kW	Traded Price in €	Buyer	Seller	Remaining Energy Seller in kW	Remaining Energy Buyer in kW
18	18.1	13	5	0	34
23	18.1	13	4	0	11
19	17.133	12	2	0	38
34	17.133	12	1	0	4
4	17.133	12	3	11	0
11	16.102	14	3	0	42
42	16.102	14	7	71	0

Table 3.5: Sample transaction module output

Algorithm 3.3: Local Energy Market - Market Transaction

Function `Market Transaction`($Bids$):

buying = bids[bids.buying]

selling = bids[bids.buying == False]

buying['price']= np.round(bids['price']-(bids['Distance']/bids['quantity']*0.1),3)

selling['price']= np.round(bids['price']+(bids['Distance']/bids['quantity']*0.1),3)

Seller list = selling.sort values(['price','Distance'], ascending=True)

Buyer list = buying.sort values(['price','Distance'], ascending=False, True)

for $UserID \in buyerlist$ **do**

  for $UserID \in sellerlist$ **do**

    `Create trading list(user ID from buyer list , user ID from seller list)`

for $UserID \in Trading\ Pair\ List$ **do**

  if $Price_{Buyer} \geq Price_{Buyer}$ & $Quantity_{Buyer/Seller} > 0$ **then**

    Traded Quantity $=$ min(quantities[buyer] ,quantities[seller])

    Traded Price $=$ price[buyer]

    trans buyer $=$ (b, q, round(p,4), s, (quantities[b] - q) $<$ 0)

    trans seller $=$ (s, q, round(p,4), b, (quantities[s] - q) $>$ 0)

    quantities[b] $-=$ q

    quantities[s] $-=$ q

    `trans.add transaction(trans buyer)`

    `trans.add transaction(trans seller)`

return transactions

3.2.4 Market Profit

Algorithm 3.4: Local Energy Market - Profit

```
  Function Profit(Bids, Transactions):
1     tmp = bids.reset index().rename(columns='index': 'bid').copy()
2     tmp = tmp[['bid', 'price', 'buying', 'User']]
3     merged = transactions.get df().merge(tmp, on='bid').copy()
4     merged['gain'] = merged.apply(lambda x : get gain(x), axis=1)
5     profit player = merged.groupby('User')['gain'].sum()
      Function Gain(x):
6         gap = row.price y - row.price x
7         if not row.buying then
8             gap = - gap
          return gap
      return profit
```

Algorithm 3.4, computes the profit made by each user who participates in the market. The output of Algorithm 3.3 and 3.1 are used to calculate the user profit. Line 3 merges the transaction details based on the bid details and generates two price lists: row.price x - the price at which the user agreed for the transaction and row.price y - the price the user provided when registering. Line 4 computes the gain,

$$gain = Price\ the\ user\ provided\ while\ registration - Price\ at\ which\ user\ agreed\ for\ transaction$$

$$Profit = gain * traded\ quantity$$

4

Case Study & Result

Contents

Several Local Energy Markets (LEMs) have been proposed in order to align energy consumption with excess supply of renewable generation. This is implemented in the python library $Pymarket$ [27], which is an essential element of ongoing research in LEMs [27] [29]. To validate the proposed trading mechanism, we will compare the market results with those from the $Pymarket$ [27]. Different scenarios will be simulated and results will be compared. The bids serves as an input for the proposed mechanism designed in python as well as for the $Pymarket$ [27]. The result obtained from proposed mechanism and $Pymarket$ [27] will be compared. These results will help us to understand the impact of distance and price in Local Energy Market. The $Pymarket$ [27] was designed considering the following conditions,

- Agents are asymmetrically informed about the value of the traded good.
- No new entrants are allowed once the market is open.
- Trading pair generation is based on game theory [13].

4.1 SMILE

The Autonomous Region of Madeira (RAM) aims to incorporate 50 percent renewable energy by 2020/2021. In this regard, the local Distributed System Operators (DSO) / (Empresa de Eletricidade da Madeira (EEM)) and governmental entities are working together on the new project SMILE (Smart Island Energy System), which is co-funded by the European Commission under the Horizon 2020 program. SMILE is made up of three large-scale pilot projects on three European islands (Madeira in Portugal, Sams in Denmark, and Orkneys in the United Kingdom) with similar geography but different policies, energy markets, and restrictions. The SMILE project seeks to demonstrate both technological and non-technological solutions suited to local conditions, with a focus on distribution system to facilitate demand response schemes, smart grid functionalities, storage, and energy system integration, with the true objective of laying the foundations for the market introduction of the tested innovation in coming years.

The Madeira involves 5 pilots addressing three main problems/issues:

- Optimization of self-consumption in domestic and commercial installations in only regime with the help of Battery Based Storage (BBS) (pilots 1 and 2).
- Electric Vehicles (EV) smart charging (pilots 3 and 4).
- Voltage control with battery storage at the substation level (pilot 5).

ID	TYPE	CONSUMPTION INSTALLATION			SOLAR PV INSTALLATION	
		PPC(kVA)	***Phases***	***Tariff***	***NP (kWp)***	***Phases***
UPAC 1	RESIDENTIAL	6.9	SF	2 TOU	0.39	SF
UPAC 2	RESIDENTIAL	6.9	SF	SR	1.5	SF
UPAC 3	RESIDENTIAL	5.75	SF	2 TOU	1	SF
UPAC 4	RESIDENTIAL	6.9	SF	SR	0.5	SF
UPAC 5	RESIDENTIAL	6.9	SF	SR	1.25	SF
UPAC 6	COMMERCIAL	10.35	3P	2 TOU	2.7	3P
UPAC 7	COMMERCIAL	20.7	3P	2 TOU	3.92	3P
UPAC 8	RESIDENTIAL	6.9	SF	SR	4.5	SF
UPAC 9	RESIDENTIAL	6.9	SF	SR	1.5	SF
UPAC 10	RESIDENTIAL	6.9	SF	2 TOU	1.5	SF
UPAC 11	RESIDENTIAL	6.9	SF	2 TOU	3	SF
UPAC 12	RESIDENTIAL	6.9	SF	SR	1.5	SF
UPAC 13	COMMERCIAL	10.35	3P	SR	0.75	3P
UPAC 14	COMMERCIAL	10.35	3P	2 TOU	1.5	3P

Table 4.1: Technical details of the installed UPACs (PPC: Peak Power Contract, IPV: Installed PV, TOU: Time of Use, SR: Single-rate, SP: Single Phase, 3P: Three Phases)

As part of the SMILE program, selected UPACs [2] (A self-consumption production unit) on Madeira Island are retrofitted with Advanced Metering Infrastructure (AMI) and Energy Management Systems (EMS). This thesis simulates the LEM using data from these selected UPACs. The user/peer is a mix of residential and commercial customers who have their own Photovoltaic (PV) installation and thus qualify as a prosumer. The below mentioned 4.1 gives the overview about UPAC details and other technical informations [30].

The data used in this thesis is obtained from SMILE project. The installed capacity details of selected UPACs can be found in Table 4.1. Figure 4.1, shows that even though the UPAC 7 has one of the highest DER installations, the excess energy considered every hour from UPAC 7 is very low. Given this, UPAC's total monthly excess energy obtained from EMS is used to simulate and verify the proposed local energy market.

4.2 Proposed Solution - Verification

This section uses one of UPAC's total monthly available excess energy obtained from energy management system as the input data. Distance of buyer / seller from community centre / market hosted area is assumed to be within 10 Km radius. The prices in euros used in the simulation are the average market prices obtained from existing peer-to-peer markets [31]. This information is used to validate the trading mechanism mentioned in chapter 3. The buyers and sellers are ranked upon their price and distance. The trading pair is obtained by pairing each available buyer to available seller, depending on their merit

[2]"A self-consumption production unit (UPAC) allows you to produce and consume your own energy through renewable means, saving on your electricity bill, and contributing to the improvement of the environment and avoiding CO2 emissions".

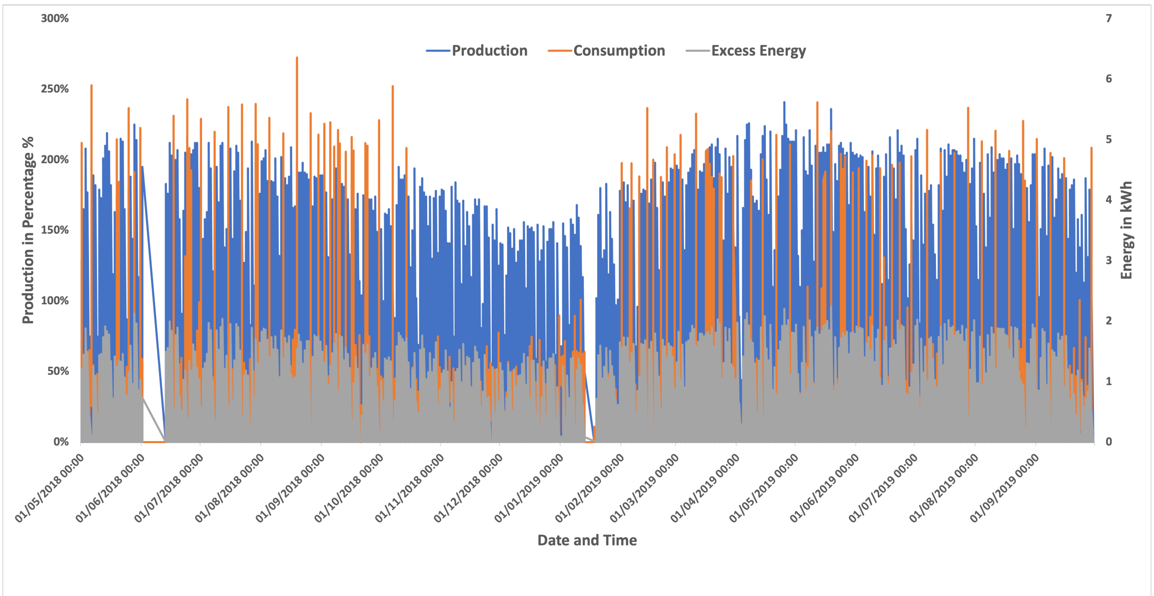


Figure 4.1: UPAC 7 consumption vs excess energy.

Quantity in kW	Bidding Price in €	User ID	Buying	Distance in KM	Price in € based on equation 5 and 6
69	0.74	1	FALSE	1	0.741
53	0.81	2	FALSE	9	0.827
150	0.76	3	FALSE	2	0.761
80	0.95	4	TRUE	3	0.946
100	0.99	5	TRUE	7	0.983
59	1.01	6	TRUE	2	1.007
72	0.79	7	FALSE	0	0.79
82	0.85	8	FALSE	2	0.852
110	0.97	9	TRUE	6	0.965
58	0.74	10	FALSE	7	0.752
60	0.82	11	TRUE	4	0.813
50	1.06	12	TRUE	2	1.056
113	0.74	13	FALSE	9	0.748
53	0.76	14	FALSE	3	0.766

Table 4.2: Bids used to verify the proposed mechanism

order list.

The trading pairs are

{(11, 9), (11, 12), (11, 0), (11, 13), (11, 2), (11, 6), (11, 1), (11, 7), (5, 9), (5, 12), (5, 0), (5, 13), (5, 2), (5, 6), (5, 1), (5, 7), (4, 9), (4, 12), (4, 0), (4, 13), (4, 2), (4, 6), (4, 1), (4, 7), (8, 9), (8, 12), (8, 0), (8, 13), (8, 2), (8, 6), (8, 1), (8, 7), (3, 9), (3, 12), (3, 0), (3, 13), (3, 2), (3, 6), (3, 1), (3, 7), (10, 9), (10, 12), (10, 0), (10, 13), (10, 2), (10, 6), (10, 1), (10, 7)}

These are the list of all possible pairs, the transaction takes place depend on the market condition

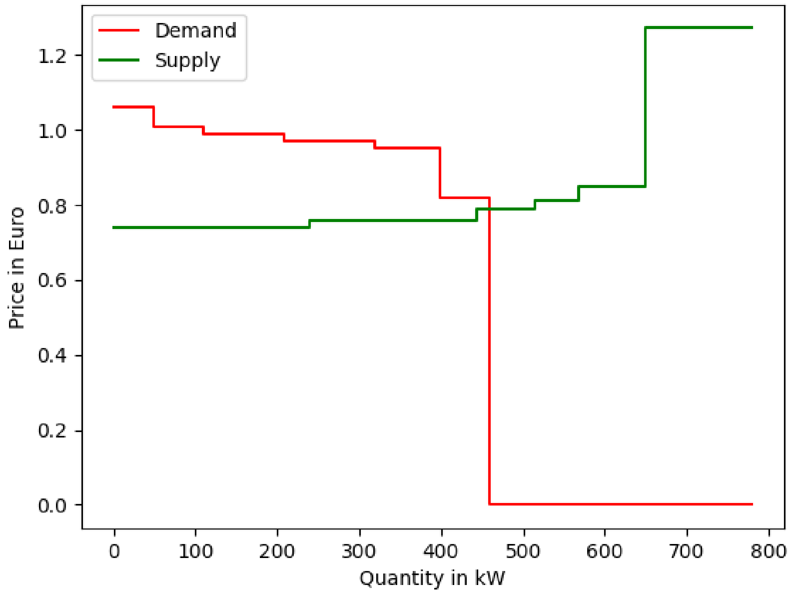


Figure 4.2: Supply vs Demand.

mentioned in chapter 3.

The trading pairs in each round and their outcomes are mentioned in Table 4.3 and Figure 4.4 describes the trading between the market participants.

- Round 1 : Trades until quantity of $buyer/seller = 0$
  1. 50 kW traded between user 12 and 1 at €1.056, user 12 traded as much as required, user 12 will exit the market in this round.
- Round 2: Trades until quantity of $buyer/seller = 0$
  1. 19 kW traded between user 6 and 1 at €1.007, still user 6 needs 40 kW but user 1 has sold all the energy as a result the next seller in the trading list will start trading
  2. 40 kW traded between user 6 and 13 at €1.007, user 6 traded as much as required, user 6 will exit the market in this round.
- Round 3: Trades until quantity of $buyer/seller = 0$
  1. 73 kW traded between user 5 and 13 at €0.983
  2. 27 kW traded between user 5 and 1 at €0.983
- Round 4 : Trades until quantity of $buyer/seller = 0$

1. 31 kW traded between user 9 and 10 at €0.965
2. 79 kW traded between user 9 and 3 at €0.965

- Round 5 : Trades until quantity of $buyer/seller = 0$

1. 71 kW traded between user 4 and 3 at €0.946
2. 9 kW traded between user 4 and 14 at €0.946

- Round 6 : Trades until quantity of $buyer/seller = 0$

1. 44 kW traded between user 11 and 14 at €0.813
2. 16 kW traded between user 11 and 7 at €0.813

The result from the table 4.3 verifies the proposed solution, where the distance of user is considered in making trading decision. The table 4.3 explains the complete trading process.

Traded Quantity in kW	**Traded Price in €**	**Buyer**	**Seller**	**Remaining Energy Seller in kW**	**Remaining Energy Buyer in kW**
50	1.056	12	1	19	0
19	1.007	6	1	0	40
40	1.007	6	13	73	0
73	0.983	5	13	0	27
27	0.983	5	10	31	0
31	0.965	9	10	0	79
79	0.965	9	3	71	0
71	0.946	4	3	0	9
9	0.946	4	14	44	0
44	0.813	11	14	0	16
16	0.813	11	7	56	0

Table 4.3: Result of market transaction

4.3 Case Study

Three different scenarios are used in the case study. Scenarios 1 and 2 each have three cases. Scenario 3 is a one-day simulation based on SMILE project UPAC data. Scenarios 1 and 2 are more related to a sensitivity analysis to determine the effect of market price and distance on market participant's profit.

- Scenario 1 - Quantity and distance of market participant's are fixed, three distinct sets of bidding prices will be used.
- Scenario 2 - Quantity and price of market participant's are fixed, three distinct sets of distance will be used.

The following are the assumptions that were used in this simulation:

1) Market Participants

    1. **Buyer** - Consumption $>$ Production.
    2. **Seller** - Consumption $<$ Production.

2) The buyer's or seller's distance from the community center / market hosted area is assumed to be within a 10 km radius..

3) In the simulation, the prices in € used are the average market prices obtained from existing peer-to-peer markets. [31].

4) There is no involvement of an outside agent.

4.4 Scenario 1

4.4.1 Case 1

Quantity in kW	Price in €	User	Buying	Distance in Km
69	0.74	1	FALSE	1
53	0.81	2	FALSE	9
150	0.76	3	FALSE	2
80	0.95	4	TRUE	3
100	0.99	5	TRUE	7
59	1.01	6	TRUE	2
72	0.79	7	FALSE	0
82	0.85	8	FALSE	2
110	0.97	9	TRUE	6
58	0.74	10	FALSE	7
60	0.82	11	TRUE	4
50	1.06	12	TRUE	2
113	0.74	13	FALSE	9
53	0.76	14	FALSE	3

Table 4.4: Case 1 - Bids

User ID	Distance in Km	Bidding Price in €	Market Result - Profit in €	
			Pymarket	Proposed Method
1	1	0.74	6.42	20.87
2	9	0.81	0.32	0
3	2	0.76	33.5	29.4
4	3	0.95	0	0
5	7	0.99	0	0
6	2	1.01	0	0
7	0	0.79	13.5	0.37
8	2	0.85	0	0
9	6	0.97	0	0
10	7	0.74	13.34	13.54
11	4	0.82	0	0
12	2	1.06	0	0
13	9	0.74	16.8	28.42
14	3	0.76	13.25	4.01

Table 4.5: Case 1 Market Comparision

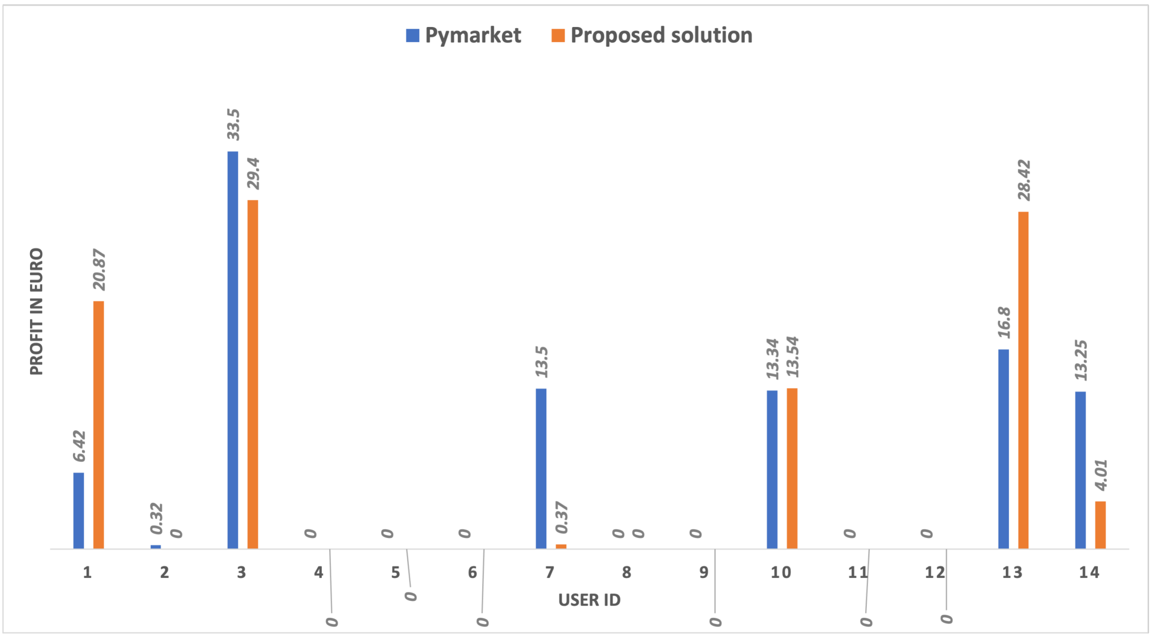


Figure 4.3: Case 1 result on comparing Pymarket with proposed solution

In Case 1, the bidding prices are priced in a narrow range, whereas the distances of the users are spread across a 10 kilometer radius. This is a typical real-life scenario where bidding and distance have a narrow margin. The bids generated during user registration are sent to Pymarket and to the proposed solution. The difference between these two methods is about how the trading pair is formed. Because the primary goal of this thesis is to increase the LEM's socio-aspects by motivating more users participation, the trading pairs are formed based on user price and distance, as opposed to the pymarket, where trading pairs are formed based on a game theory model. According to table 4.5, user 1 has 1 km transmission distance and a bidding price of 0.74 €, which is the lowest bidding price when compared to other users. User 1 made a profit of 6.42 € in Pymarket, while the same user made a profit of 20.87 € using the proposed solution. user 2 has 9 km highest transmission distance and a bidding price of 0.81 €, which is a higher bidding price when compared to most of market participants. User 2 made a profit of 0.32 € in Pymarket, while the same user made a profit of 0 € in the proposed solution. When the user profit between proposed solution and pymarket is compared, 80 percent of participants in proposed solution have higher profit than participants in pymarket. The only cases in which they make less profit are with users 7 and 14. In this case, both users have very short transmission distances, but their bidding price is higher, so the proposed system prefers other users over them.

4.4.2 Case 2

Quantity in kW	Price in €	User	Buying	Distance in Km
69	2.74	1	FALSE	1
53	0	2	FALSE	9
150	0.76	3	FALSE	2
80	0.95	4	TRUE	3
100	0.99	5	TRUE	7
59	1.01	6	TRUE	2
72	0	7	FALSE	0
82	0.85	8	FALSE	2
110	0.97	9	TRUE	6
58	0	10	FALSE	7
60	0.82	11	TRUE	4
50	1.06	12	TRUE	2
113	0.74	13	FALSE	9
53	0.76	14	FALSE	3

Table 4.6: Case 2 - Bids

In Case 2, From table 4.7, user 1 has the highest bidding price compared to the other market participants, and the user is also a seller; however, due to market conditions, this user will not trade any energy with other market participants, so the user earns 0 € in both the pymarket and the proposed solution. User 2 , User 10 are priced at 0 €, and despite showing the highest transmission distance, due to their low bidding price, they will be given preference over the other participants. This is a typical example , when the market has a very low bidding price of 0 €, both pymarket and the proposed solution provide very similar user profit. User 7 makes the most money, this is primarily due to the fact that user 7 has the lowest bidding price and the shortest transmission distance.

User ID	Distance in Km	Bidding Price in €	Market Result - Profit in €	
			Pymarket	Proposed Method
1	1	2.74	0	0
2	9	0	51.41	52.1
3	2	0.76	38	22.09
4	3	0.95	0	0
5	7	0.99	0	0
6	2	1.01	0	0
7	0	0	25.65	74.95
8	2	0.85	6.84	0
9	6	0.97	0	0
10	7	0	47.56	57.9
11	4	0.82	0	0
12	2	1.06	0	0
13	9	0.74	16.09	25.89
14	3	0.76	10.07	0.69

Table 4.7: Case 2 Market Comparison

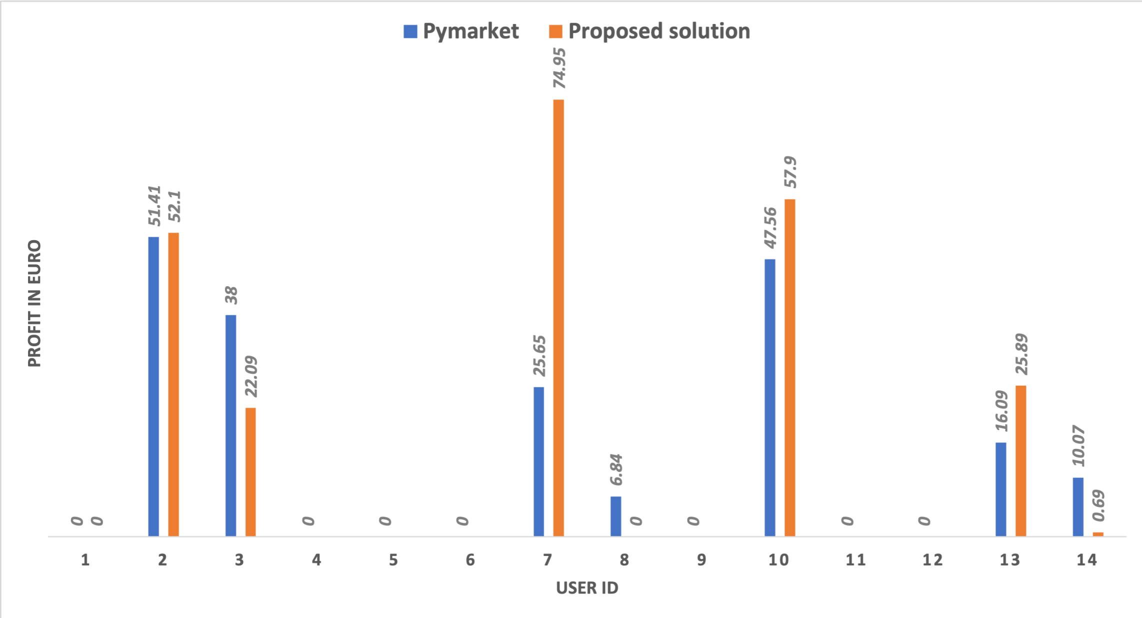


Figure 4.4: Case 2 result on comparing Pymarket with proposed solution

4.4.3 Case 3

Quantity in kW	Price in €	User	Buying	Distance in Km
69	2.74	1	FALSE	1
53	0	2	FALSE	9
150	1.76	3	FALSE	2
80	0.95	4	TRUE	3
100	0.99	5	TRUE	7
59	1.01	6	TRUE	2
72	0	7	FALSE	0
82	2.85	8	FALSE	2
110	0.97	9	TRUE	6
58	0	10	FALSE	7
60	0.82	11	TRUE	4
50	1.06	12	TRUE	2
113	0.74	13	FALSE	9
53	2.76	14	FALSE	3

Table 4.8: Case 3 - Bids

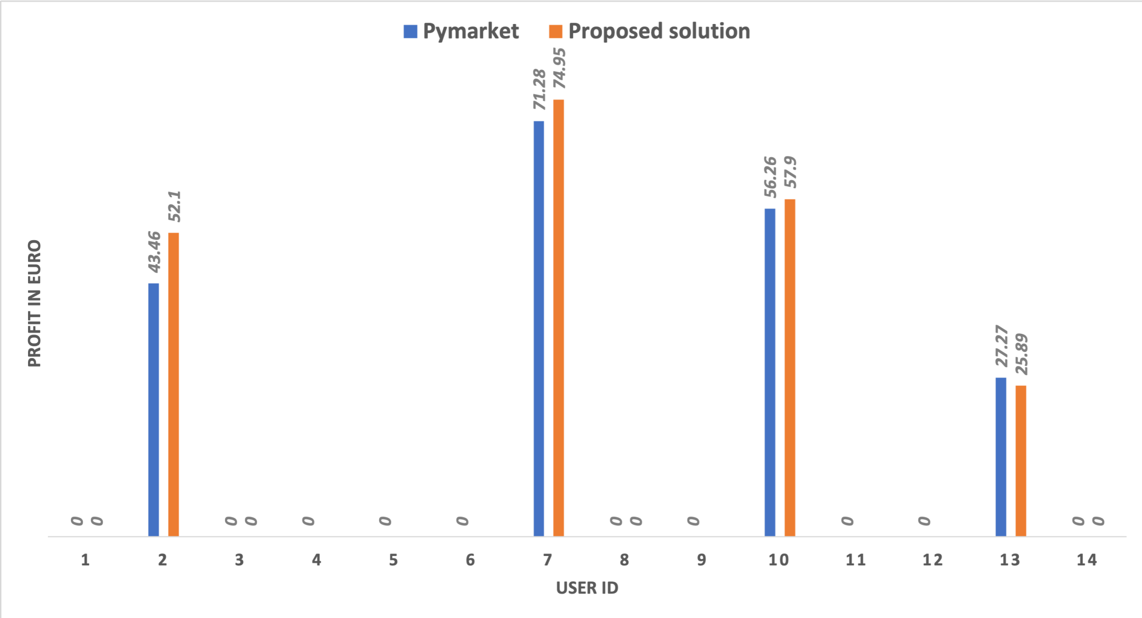


Figure 4.5: Case 3 result on comparing Pymarket with proposed solution

User ID	Distance in Km	Bidding Price in €	Market Result - Profit in €	
			Pymarket	Proposed Method
1	1	2.74	0	0
2	9	0	43.46	52.1
3	2	1.76	0	0
4	3	0.95	0	0
5	7	0.99	0	0
6	2	1.01	0	0
7	0	0	71.28	74.95
8	2	2.85	0	0
9	6	0.97	0	0
10	7	0	56.26	57.9
11	4	0.82	0	0
12	2	1.06	0	0
13	9	0.74	27.27	25.89
14	3	2.76	0	0

Table 4.9: Case 3 Market Comparison

In Case 3 from Table 4.9, multiple sellers were priced at very high bidding prices, but due to market conditions, they never participated in trading. When comparing pymarket and the proposed solution, users 2, 7, 10 and 13 have similar results. This is primarily due to the bidding price, as these users were priced at the lowest and second lowest bidding price, respectively.

4.5 Scenario 2

4.5.1 Case 4

Quantity in kW	Price in €	User	Buying	Distance in Km
69	0.74	1	FALSE	6
53	0.81	2	FALSE	3
150	0.76	3	FALSE	10
80	0.95	4	TRUE	2
100	0.99	5	TRUE	5
59	1.01	6	TRUE	4
72	0.79	7	FALSE	10
82	0.85	8	FALSE	2
110	0.97	9	TRUE	8
58	0.74	10	FALSE	5
60	0.82	11	TRUE	10
50	1.06	12	TRUE	9
113	0.74	13	FALSE	10
53	0.76	14	FALSE	6

Table 4.10: Case 4 - Bids

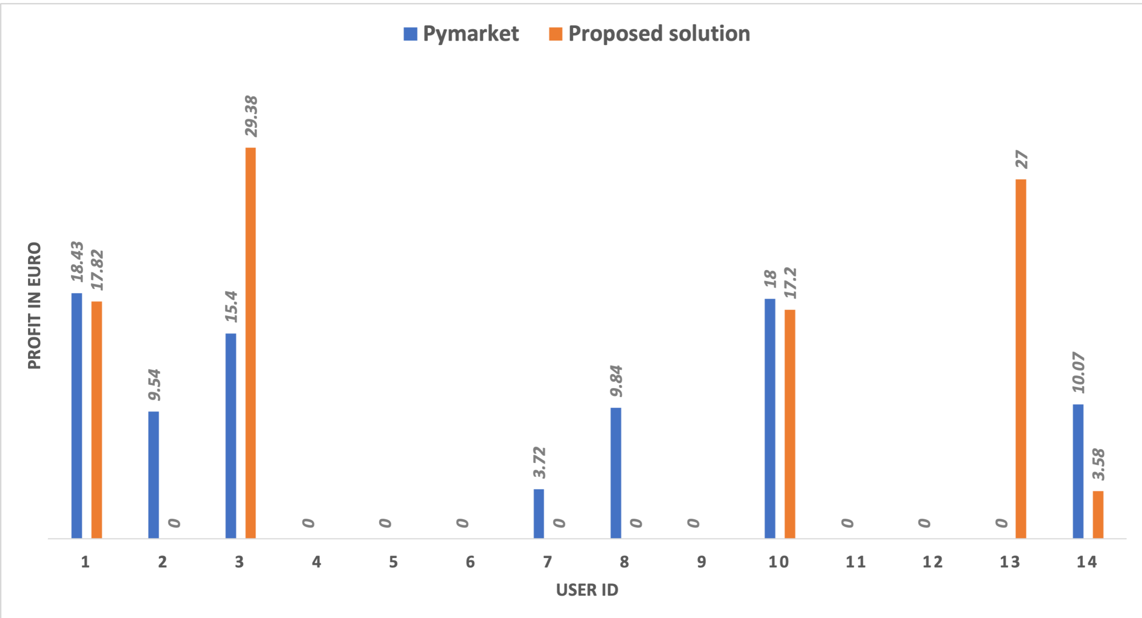


Figure 4.6: Case 4 result on comparing Pymarket with proposed solution

The bidding prices and distance in Case 4 are in a narrow range , Table 4.11. User 2 has one of the shortest transmission distances, but the user's bidding price is high in comparison to the majority of market participants, so this user has 0 € profit in the proposed solution. User 3, on the other hand, has the longest distance and the second lowest bidding price; in pymarket, the user made 15.4 €and in the proposed solution, the user made 29.38 €. User 1,3,10,13, and 14 have a close bidding price range, and they also have the lowest bidding price when compared to other participants; when the profit is compared, these users have a similar profit comparing the pymarket. Despite having the longest transmission distance, users 3 and 13 made more profit in the proposed solution due to the user's lowest bidding price.

User ID	Distance in Km	Bidding Price in €	Market Result - Profit in €	
			Pymarket	Proposed Method
1	6	0.74	18.43	17.82
2	3	0.81	9.54	0
3	10	0.76	15.4	29.38
4	2	0.95	0	0
5	5	0.99	0	0
6	4	1.01	0	0
7	10	0.79	3.72	0
8	2	0.85	9.84	0
9	8	0.97	0	0
10	5	0.74	18	17.2
11	10	0.82	0	0
12	9	1.06	0	0
13	10	0.74	0	27
14	6	0.76	10.07	3.58

Table 4.11: Case 4 Market Comparison

4.5.2 Case 5

Quantity in kW	Price in €	User	Buying	Distance in Km
69	0.74	1	FALSE	2
53	0.81	2	FALSE	3
150	0.76	3	FALSE	1
80	0.95	4	TRUE	2
100	0.99	5	TRUE	0
59	1.01	6	TRUE	2
72	0.79	7	FALSE	1
82	0.85	8	FALSE	0
110	0.97	9	TRUE	3
58	0.74	10	FALSE	1
60	0.82	11	TRUE	0
50	1.06	12	TRUE	2
113	0.74	13	FALSE	1
53	0.76	14	FALSE	1

Table 4.12: Case 5 - Bids

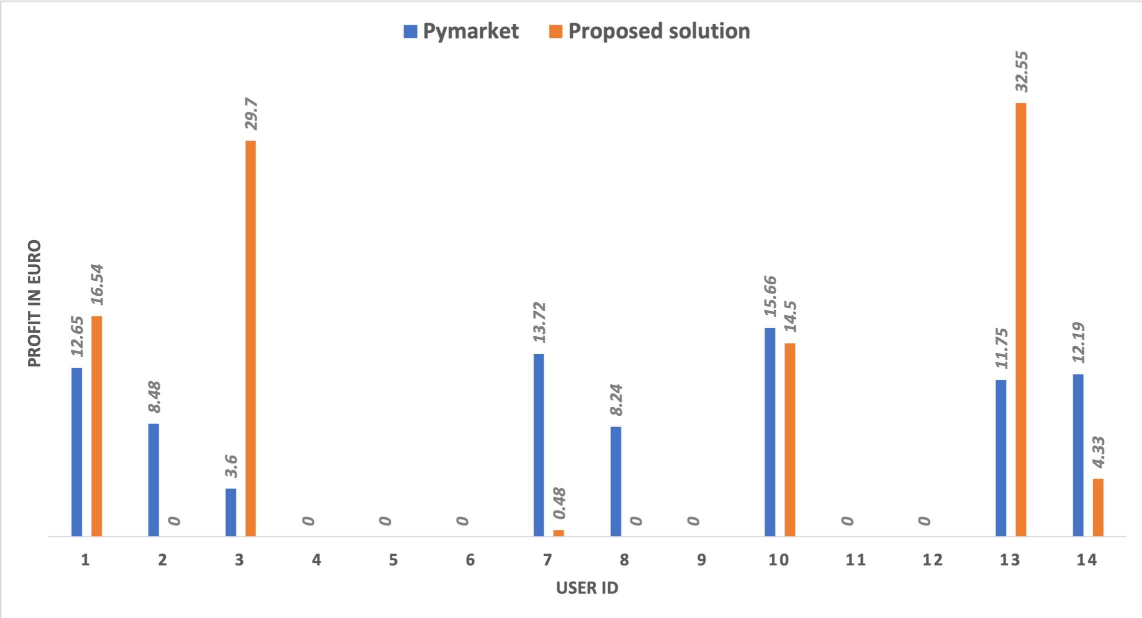


Figure 4.7: Case 5 result on comparing Pymarket with proposed solution

In case 5, table 4.13 all the market participants are placed under a 3 KM radius , with a bidding price in a narrow range. In this case, the proposed solution generates a reasonable profit when compared to the profit generated by pymarket. This is primarily due to the fact that , proposed solution's weights price and distance equally when making trading decisions. The only case in which the proposed solution has a lower profit is with user 2, user 7 and user 8. Despite the fact that the user's has the shortest transmission distance, the user's bidding price was high, and thus the proposed solution preferred other players over this user's.

User ID	Distance in Km	Bidding Price in €	Market Result - Profit in euro	
			Pymarket	Proposed Method
1	2	0.74	12.65	16.54
2	3	0.81	8.48	0
3	1	0.76	3.6	29.7
4	2	0.95	0	0
5	0	0.99	0	0
6	2	1.01	0	0
7	1	0.79	13.72	0.48
8	0	0.85	8.24	0
9	3	0.97	0	0
10	1	0.74	15.66	14.5
11	0	0.82	0	0
12	2	1.06	0	0
13	1	0.74	11.75	32.55
14	1	0.76	12.19	4.33

Table 4.13: Case 5 Market Comparison

4.5.3 Case 6

Quantity in kW	Price in euro	User	Buying	Distance in Km
69	0.74	1	FALSE	10
53	0.81	2	FALSE	9
150	0.76	3	FALSE	8
80	0.95	4	TRUE	10
100	0.99	5	TRUE	7
59	1.01	6	TRUE	9
72	0.79	7	FALSE	8
82	0.85	8	FALSE	0
110	0.97	9	TRUE	9
58	0.74	10	FALSE	6
60	0.82	11	TRUE	8
50	1.06	12	TRUE	7
113	0.74	13	FALSE	9
53	0.76	14	FALSE	8

Table 4.14: Case 5 - Bids

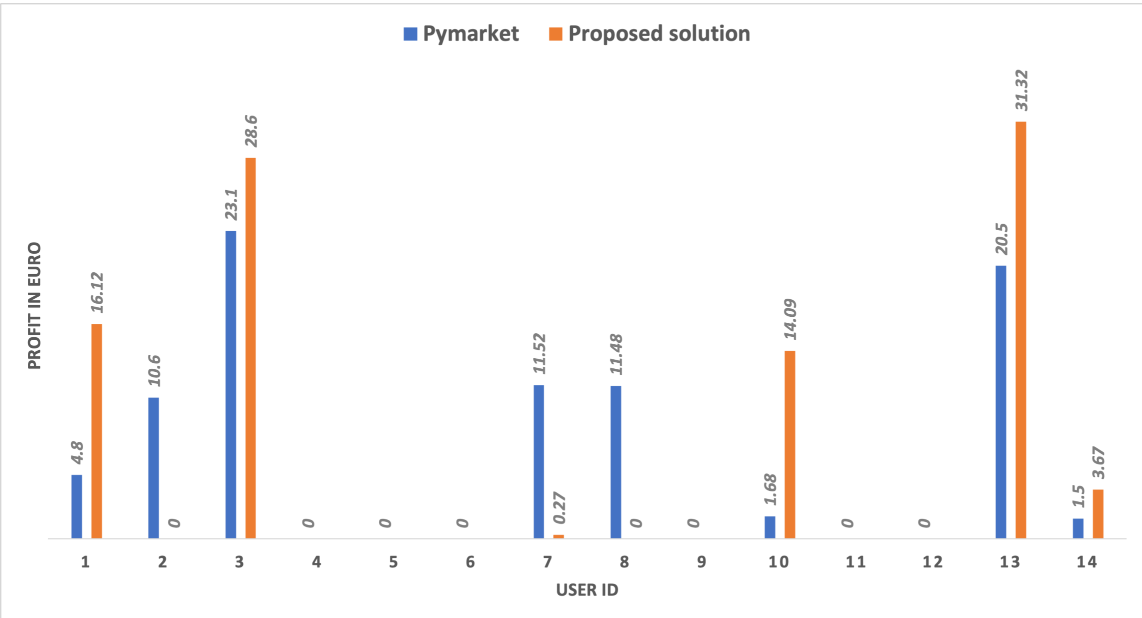


Figure 4.8: Case 6 result on comparing Pymarket with proposed solution

In Case 6, all the participants are placed placed within 7 - 10 Km distance range, with a narrow range of bidding prices. This case is selected to see the the impact of distance when user has a long transmission distance range. In this case, the distance range is (6,7,8,9, & 10 Km), with 6 and 7 being the closest distances. User 12, 10, and 5 are the users in this range. User 10 is a seller who earned a profit of 1.68 € on pymarket and 14.09 €on the proposed solution. User 3 and 7 both have an 8-kilometer transmission range, but User 3 bidding price is less comparing to User 7. Hence, User 3 has given more

User	Distance in KM	Bidding Price in €	Market Result - Profit in €	
			Pymarket	Proposed Method
1	10	0.74	4.8	16.12
2	9	0.81	10.6	0
3	8	0.76	23.1	28.6
4	10	0.95	0	0
5	7	0.99	0	0
6	9	1.01	0	0
7	8	0.79	11.52	0.27
8	0	0.85	11.48	0
9	9	0.97	0	0
10	6	0.74	1.68	14.09
11	8	0.82	0	0
12	7	1.06	0	0
13	9	0.74	20.5	31.32
14	8	0.76	1.5	3.67

Table 4.15: Case 6 Market Comparison

preference comparing to the user 7. As a result, User 3 has given more preference than User 7. In this case, mentioned in table 4.15, the user's with the price range of 0.74 - 0.79 € resulted in a good profit under the proposed solution. Other users, regardless of their location, have never profited. Users in pymarket, on the other hand, have made a reasonable profit regardless of distance or price.

4.6 Scenario 3

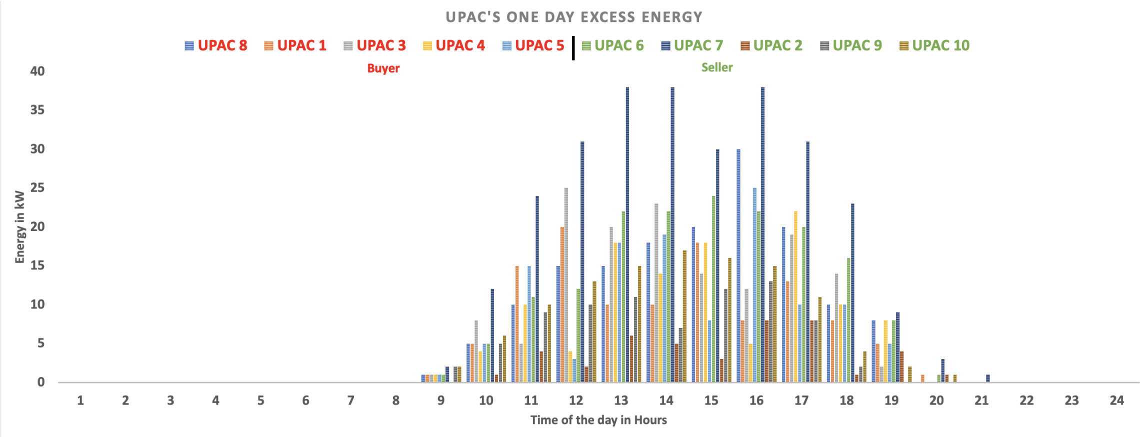


Figure 4.9: UPAC One Day Excess Energy

This section makes use of a full day's worth of UPAC data from the SMILE project. Since the installed capacity of the UPACs is low, the excess energy of each UPAC is scaled to maintain the market equilibrium. In this simulation, ten UPAC from the SMILE project act as market participants. They are classified as buyers or sellers based on the balance between their production and concumption. The following are the assumptions that were used in this simulation: The following are the assumptions that were used in this simulation:

1) Market Participants

   1. **Buyer** - Consumption $>$ Production.

   2. **Seller** - Consumption $<$ Production.

2) The buyer's or seller's distance from the community center / market hosted area is assumed to be within a 10 km radius..

3) In the simulation, the prices in € used are the average market prices obtained from existing peer-to-peer markets. [31].

4) There is no involvement of an outside agent.

The buying and selling prices and distance of the UPACs are fixed in this simulation, and the bidding quantity varies based on UPAC consumption and production. The Table 4.16 describes UPAC's market role, distance, and bidding price.

The obtained result from the proposed solution is validated by comparing market results to $Pymarket$ [27].

User	Distance in Km	Price in €	Role
UPAC 1	0	0.81	BUYER
UPAC 2	7	0.74	SELLER
UPAC 3	4	0.83	BUYER
UPAC 4	10	0.91	BUYER
UPAC 5	3	0.89	BUYER
UPAC 6	5	0.76	SELLER
UPAC 7	2	0.79	SELLER
UPAC 8	1	0.85	BUYER
UPAC 9	9	0.76	SELLER
UPAC 10	6	0.74	SELLER

Table 4.16: UPAC details for market simulation

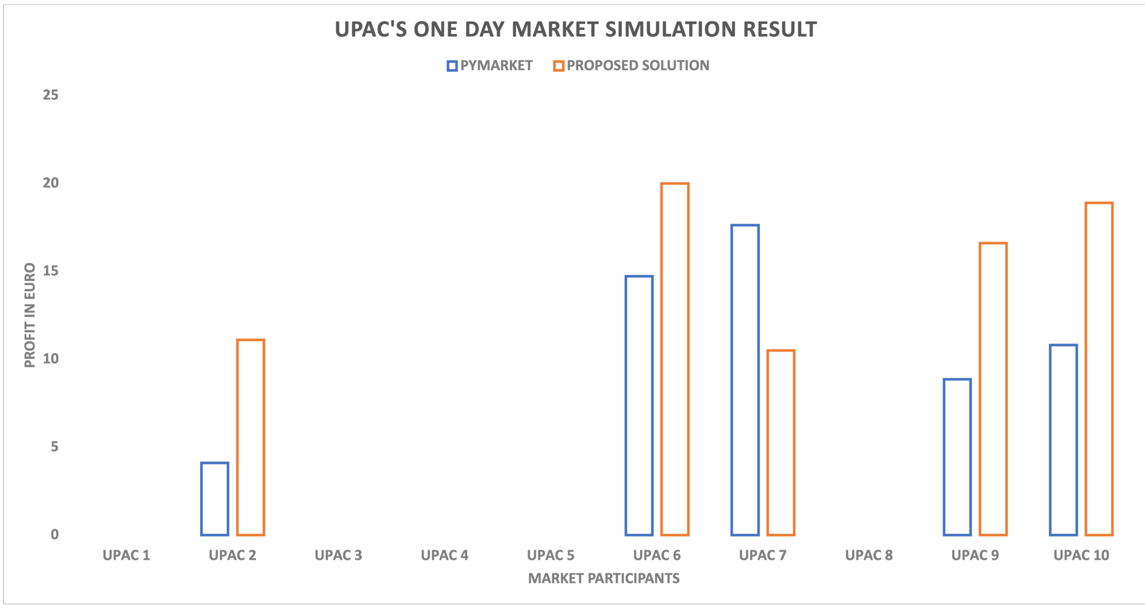


Figure 4.10: UPAC one day market simulation result

Figure 4.10, represents UPACs one-day profit from participating in the proposed local energy market and PYmarket. The results show that all the UPAC has a higher profit in proposed solution than the pymarket, with the exception of UPAC 7. This is primarily due to the fact that UPAC 7 has the highest bidding price when compared to the other UPACs. Because the proposed solution generates a merit order list based on price and distance, other UPACs are preferred over UPAC 7.

The same is true for UPAC 2 and UPAC 6. UPAC 2 has a distance of 7 kilometers and the lowest bidding price compared to the other UPACs, but he receives less profit than UPAC 6, who has a higher bidding price than UPAC 2. This is due to the proposed solution favouring users with the shortest transmission distance.

The below mention Figure 4.11 and 4.12 describes the UPAC profit in hourly basis.

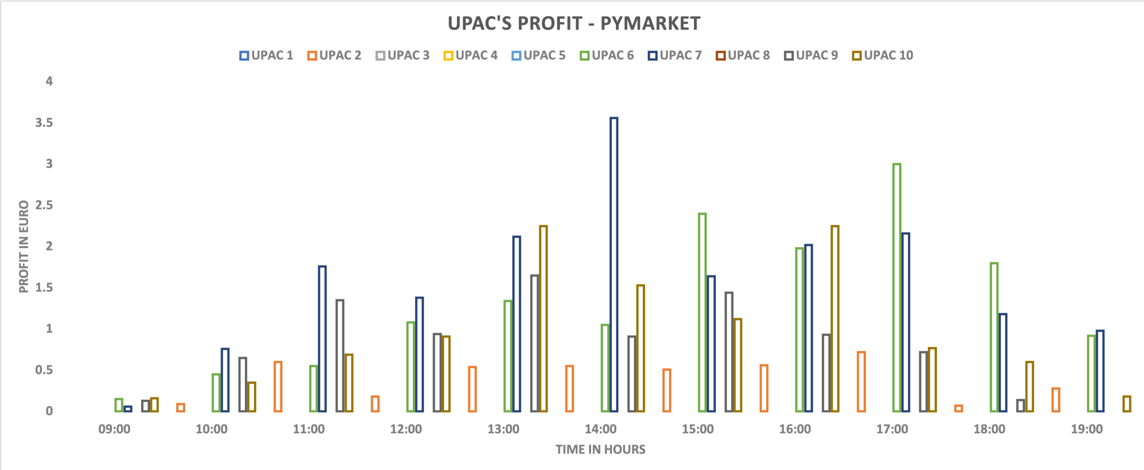


Figure 4.11: UPAC Result PYmarket

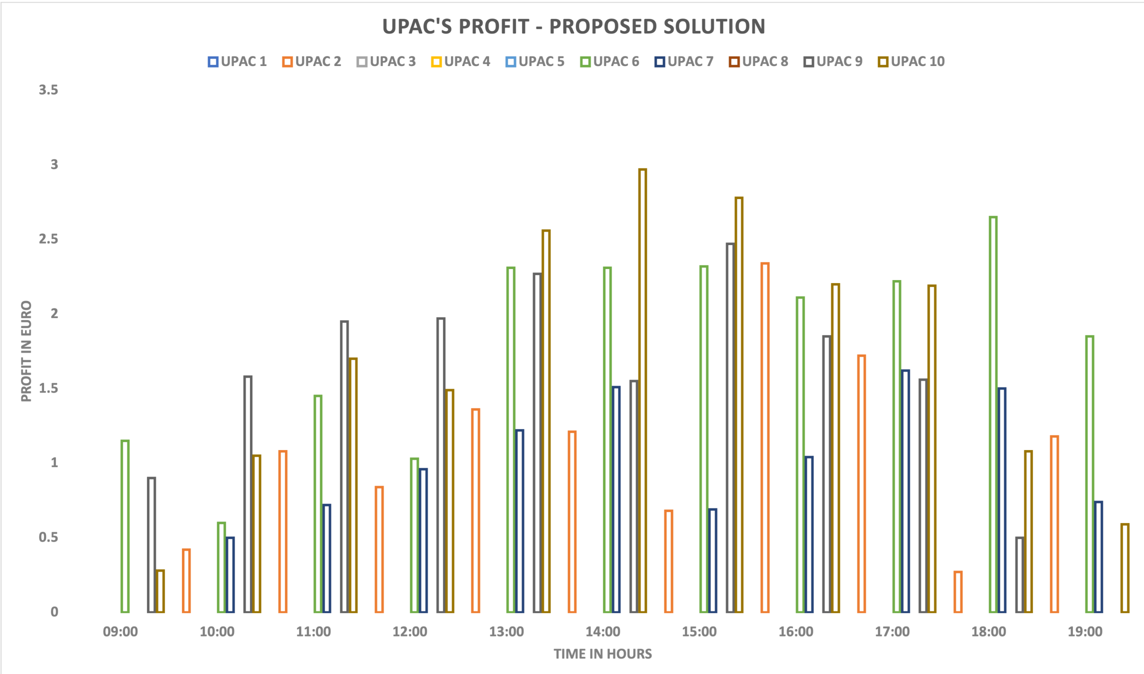


Figure 4.12: UPAC Result Proposed Solution

4.7 Major Findings

- A simple merit order based decentralised bilateral trading scheme is proposed for players in LEM
- Distance from community centre is included as the product differentiation / preference this helps in making trading decision by including the environmental factor, Unlike the game theory where trading decision is randomized.

- This proposed methodology shows the effectiveness of considering environmental factors in making trading decision.
- When the market price are high both Pymarket and proposed solution tends to behave symmetrically.
- Majority of cases user who has lowest bidding price and from the shortest distance has higher profit comparing to the user from with longest distance, This shows that the proposed solution have improved the projects sustainable factor.

5

Conclusions

Contents

5.1 Conclusions

This thesis proposes a simple and direct trading mechanism for people who participate in a community-based LEM. The proposed method bases its trading decision on a simple merit order list generated by the market after taking into account the price at which the buyer/seller bids in the market as well as the transmission distance based on the location from which the buyer/seller participates. In contrast to the other methods mentioned in the literature, this solution is extremely simple to implement. Most market clearing mechanisms are designed for large or medium-sized market participants. However, this method can be used for small communities with fewer than ten participants.

The results of the six different cases show that the participants in the proposed solution make more profit than the participants in the LEM, which is based on a non-cooperative game theory model. To maintain trading fairness in a non-cooperative game theory model, trading pairs are formed by random pairing, but the proposed solution involves environmental factors such as transmission distance in determining trading pairs. As a result, the user who participates in the market from the shortest distance earns a higher profit than the user who participates from a longer distance. This encourages user participation in the local energy market. However, the impact of this mechanism in a sustainable community must be thoroughly validated.

5.2 Future Studies

Considering the result the future research directions are suggested as follows

- Considering the distance and traded amount for evaluation would have a better result comparision.
- Including the distance between the peers rather than a fixed point distance would add significant value in market result.
- Comparing the results with network optimization / decomposition method would remove the randomness created by game theory.
- This thesis focuses on distance as an environmental factor, and the merit order list is formed by taking into account the market participants' bidding price and transmission distance. Taking into account more environmental factors such as energy source (renewable/non-renewable), income, type of organisation (private, government, non-profit), and so on, and developing a decision-making mechanism that assesses user weights based on more environmental factors will add further value to the market.

5.3 Recommendation

The proposed mechanism has some limitations and assumptions; the recommendations for a sustainable community-based LEM are listed below,

- The proposed mechanism includes a penalty of 0.1 € for transmission losses; this value must be validated in light of various economic factors and government regulations.
- The proposed system includes a penalty-based mechanism to address transmission loss, which may result in a reduced profit for the seller. To address this, a different type of incentive-based system could be proposed, or user participation in the market may suffer.

Bibliography

[1] *Energy Production and Consumption*, https://ourworldindata.org/energy-production-consumption.

[2] M. Ansarin, Y. Ghiassi-Farrokhfal, W. Ketter, and J. Collins, “The economic consequences of electricity tariff design in a renewable energy era,” *Applied Energy*, vol. 275, p. 115317, 2020.

[3] IRENA, *Innovation landscape brief: Peer-to-Peer electricity trading*. International Renewable Energy Agency, Abu Dhabi, 2020, iSBN:978-92-9260-174-4.

[4] S. Bjarghov, M. Löschenbrand, and I. Saif, “Developments and challenges in local electricity markets: A comprehensive review,” *IEEE Access*, vol. 9, 2021.

[5] *Energy Atlas 2018 - Facts and Figures about Renewables in Europe*, Green European Foundation, https://gef.eu/publication/energy-atlas-2018/.

[6] M. Khorasany, “Market design for peer-to-peer energy trading in a distribution network with high penetration of distributed energy resource,” Ph.D. dissertation, Queensland University of Technology, 2020.

[7] *NRG Coin*, https://nrgcoin.org/.

[8] *Energy Collective*, https://www.comunidadesenergia.pt.

[9] A. Ehsan and Q. Yang, “Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques,” *Applied Energy*, vol. 210, no. 4, pp. 44–59, Feb 2018, https://www.sciencedirect.com/science/article/pii/S0306261917315519.

[10] S. Abapour, K. Zare, and B. Mohammadi-Ivatloo, “Dynamic planning of distributed generation units in active distribution network,” *IET Generation, Transmission & Distribution*, vol. 9, 2015.

[11] F.-Y. Wang and D. Liu, “Networked control systems: Theory and applications,” in *Networked Control Systems*, 2008.

[12] J. Koshal, A. Nedić, and U. V. Shanbhag, “Distributed multiuser optimization: Algorithms and error analysis,” in *Proceedings of the 48h IEEE Conference on Decision and Control (CDC) held jointly with 2009 28th Chinese Control Conference*, 2009.

[13] M. R. Blouin and R. Serrano, “A decentralized market with common values uncertainty non steady states,” *The Review of Economic Studies*, vol. 68, no. 2, pp. 323–346, Apr. 2001.

[14] A. B. Shiflet and G. W. Shiflet, “An Introduction to Agent-based Modeling for Undergraduates,” *Procedia Computer Science*, vol. 29, pp. 1392–1402, 2014.

[15] B. Johansson, A. Speranzon, M. Johansson, and K. H. Johansson, “On decentralized negotiation of optimal consensus,” *Automaticay*, vol. 44, no. 4, pp. 1175–1179, Apr. 2008.

[16] L. Mazzola, A. Denzler, and R. Christen, “Towards a peer-to-peer energy market: an overview,” Mar. 2020.

[17] T. Baroche, F. Moret, and P. Pinson, “Prosumer markets: A unified formulation,” in *2019 IEEE Milan PowerTech*, 2019, pp. 1–6.

[18] T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, and E. Sorin, “Peer-to-peer and community-based markets: A comprehensive review,” *Renewable and Sustainable Energy Reviews*, vol. 104, no. 5, pp. 364–378, Feb 2019, https://www.sciencedirect.com/science/article/pii/S1364032119300462.

[19] P. P. Moret, Fabio and A. Papakonstantinou, “Heterogeneous risk preferences in community-based electricity markets,” *European Journal of Operational Research*, vol. 287, no. 1, p. 36–48, Apr. 2020.

[20] F. Jamil, N. Iqbal, I. Ran, S. Ahmad, and D. Kim, “Peer-to-peer energy trading mechanism based on blockchain and machine learning for sustainable electrical power supply in smart grid,” *IEEE Access*, vol. PP, pp. 1–1, Feb. 2021.

[21] T. Baroche, P. Pinson, R. L. G. Latimier, and H. B. Ahmed, “Exogenous cost allocation in peer-to-peer electricity markets,” *IEEE Transactions on Power Systems*, vol. 34, no. 4, pp. 2553–2564, 2019, doi:10.1109/TPWRS.2019.2896654.

[22] B. S. Y. Parag, “Electricity market design for the prosumer era.” *Nat Energy*, vol. 1, no. 4, pp. 1–6, Mar. 2016.

[23] G. Hug, S. Kar, and C. Wu, “Consensus + innovations approach for distributed multiagent coordination in a microgrid,” *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1893–1903, 2015, 10.1109/TSG.2015.2409053.

[24] F. Moret and P. Pinson, “Energy collectives: A community and fairness based approach to future electricity markets,” *IEEE Transactions on Power Systems*, vol. PP, pp. 1–1, Feb. 2018.

[25] C. Woo, P. Sreedharan, J. Hargreaves, F. Kahrl, J. Wang, and I. Horowitz, “A review of electricity product differentiation,” *Applied Energy*, vol. 114, p. 262–272, Feb. 2014.

[26] E. Heiskanen, M. Johnson, S. Robinson, E. Vadovics, and M. Saastamoinen, “Low-carbon communities as a context for individual behavioural change,” *Energy Policy*, vol. 38, no. 12, pp. 7586–7595, 2010.

[27] D. K. Kiedanski, Diego and J. Horta., “Pymarket a simple library for simulating markets in python.” *Journal of Open Source Software 5*, vol. 1596, no. 46, p. 1, Feb. 2020.

[28] E. Sorin, L. Bobo, and P. Pinson, “Consensus-based approach to peer-to-peer electricity markets with product differentiation,” *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 994–1004, 2019, 10.1109/TPWRS.2018.2872880.

[29] E. Mengelkamp, P. Staudt, J. Garttner, and C. Weinhardt, “Trading on local energy markets: A comparison of market designs and bidding strategies,” in *2017 14th International Conference on the European Energy Market*, 2017, pp. 1–6.

[30] *SMILE*, https://www.fabiodisconzi.com/open-h2020/projects/210038/results.html.

[31] *omie*, https://www.omie.es/.

A

Code of Project

Listing A.1: PYTHON Code - Bid Module

```
from module import *
class BidManager(object):
    col_names = [
        'quantity',
        'price',
        'User',
        'buying',
         'Distance',
        'Renewable',
        'Use',

    ]

```

```
    def __init__(self):
        self.n_bids = 1
        self.bids = []

    def add_bid(
            self,
            quantity,
            price,
            User,
            buying=True,
            Distance=0,
            Renewable=True,
            Use=0,
    ):
        new_bid = (quantity, price, User, buying,Distance,Renewable,Use)
        self.bids.append(new_bid)
        self.n_bids += 1

        return self.n_bids - 1

    def get_df(self):
        df = pd.DataFrame(self.bids, columns=self.col_names)
        return df
```

Listing A.2: PYTHON Code - Market Mechanism

```
from module import *
def p2p_random(bids, p_coef=0.5):
    buying = bids[bids.buying]
    selling = bids[bids.buying == False]
    buying['price'] = np.round(buying['price'] + (buying['Distance'] / buying
        ['quantity'] * 0.1), 3)
    selling['price'] = np.round(selling['price'] - (selling['Distance'] /
        selling['quantity'] * 0.1), 3)
    sd = buying.append(selling)
    bids=sd.sort_values('User',ascending=True)
    quantities = bids.quantity.values.copy()
    prices = bids.price.values.copy()
```

```
    ordered = bids.User.values.copy()
    sorted= bids
    buyy=sorted[sorted.buying]
    buyy=buyy.sort_values(['price','Distance'], ascending=[False, True])
    print( "Buyer /n")
    print(buyy,"/n")
    selll=sorted[sorted.buying==False].sort_values(['price','Distance'],
        ascending=True)
    buy_index=buyy.index.values.copy()
    sell_index = selll.index.values.copy()
    prices1=prices.copy()
    quantities1=quantities.copy()
    list=[]
    for b in buy_index:
        for s in sell_index:
            list.append((b,s))
    trans = P2P_Transaction.TransactionManager()
    for (b, s) in tqdm(list,desc="P2P MARKET---> Trading With Preference
        ......................"):
        if prices[b] >= prices[s]  and quantities[s] > 0 and quantities[b] >
            0 :
            q = min(quantities[b], quantities[s])
            p = prices[b]
            trans_b = (b, q, round(p,4), s, (quantities[b] - q) > 0)
            trans_s = (s, q, round(p,4), b, (quantities[s] - q) > 0)
            trans_h = ( q, round(p, 4),orde[b], orde[s], (quantities[s] - q)
                ,(quantities[b] - q))
            quantities[b] -= q
            quantities[s] -= q
            trans.add_transaction(*trans_b)
            trans.add_transaction(*trans_s)
        time.sleep(0.1)
    return trans,hu
```

Listing A.3: PYTHON Code - Market Profit

```python

from module import *
from tqdm import tqdm
import time
def calculate_profits(
        bids,
        transactions,
        reservation_prices=None,
        fees=None,
        **kwargs):

    users = sorted(bids.User.unique())
    buyers = bids.loc[bids['buying']].index.values
    sellers = bids.loc[~bids['buying']].index.values
    # 101
    if reservation_prices is None:
        reservation_prices = {}
    for i, x in bids.iterrows():
        if i not in reservation_prices:
            reservation_prices[i] = x.price

    if fees is None:
        fees = np.zeros(bids.User.unique().shape[0])

    profit = {}
    for case in tqdm(['bid', 'reservation'],desc="P2P MARKET---> Recording
       Transactions.....................") :
        tmp = bids.reset_index().rename(columns={'index': 'bid'}).copy()
        tmp = tmp[['bid', 'price', 'buying', 'User']]
        time.sleep(0.1)
        if case == 'reservation':
            tmp.price = tmp.apply(lambda x: reservation_prices.get(x.bid, x.
                price), axis=1)
        #doing something
        merged =transactions.get_df().merge(tmp,on='bid').copy()
        merged['gain'] = merged.apply(lambda x: get_gain(x), axis=1)
        profit_player = merged.groupby('User')['gain'].sum()
```

```
        # print(profit_player)
        profit_player = np.array([profit_player.get(x, 0) for x in users])
        profit[f'player_{case}'] = profit_player

        if case == 'bid':
            # print(merged)
            mb = merged.loc[merged['buying']]
            ms = merged.loc[~merged['buying']]
            # print(ms)
            # print(ms.quantity.sum(), mb.quantity.sum())
            # print(ms.price_x * ms.quantity)
            profit_market = (mb.price_x * mb.quantity).values.sum()
            profit_market -= (ms.price_x * ms.quantity).values.sum()
            profit_market += fees.sum()
            profit['market'] = profit_market

    return profit
def get_gain(row):
    """Finds the gain of the row
    Parameters
    ----------
    row : pandas row
       Row obtained by merging a transaction with a
       bid dataframe
    Returns
    -------
    gain
        The gain obtained by the row
    """
    global row1
    row1=row
    gap = row.price_y - row.price_x
    if not row.buying:
        gap = - gap
    return gap * row.quantity
```