Agent-Based Modeling of Peer-to-Peer Energy Trading in a Smart Grid Environment

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Diogo V. Guimarães
FEUP
Porto, Portugal
diogovguimaraes@gmail.com

Matthew B Gough
FEUP and INESC TEC
Porto, Portugal
matthew.gough@inesctec.pt

Sérgio F. Santos
INESC TEC and Portucalense University Infante D. Henrique
Porto, Portugal
sdfsantos@gmail.com

Inês F.G. Reis
INESC Coimbra, Department of Electrical and Computer Engineering
Coimbra, Portugal
inesfreis@deec.uc.pt

Juan M. Home-Ortiz
Department of Electrical Engineering São Paulo State University
Ilha Solteira-SP, Brazil
juan.home@unesp.br

João P. S. Catalão
FEUP and INESC TEC
Porto, Portugal
catalao@fe.up.pt

***Abstract*—The energy system is undergoing a drastic transition towards a system where previously passive consumers will play important roles. These consumers who actively participate in the energy system with a variety of distributed energy resources, such as electric vehicles, solar panels, and battery energy storage systems, become so-called prosumers as they can also generate electricity. This electricity can then be self-consumed, sold to the existing grid, or be sold to other consumers connected to the same electric network through Peer-to-Peer (P2P) trading schemes. This P2P energy trading may offer significant advantages to consumers involved as well as the wider electric system. The use of Agent-Based Modelling (ABM) can help address these problems. ABM models allow to understand complex and dynamic systems by incorporating the behavior of individual agents into the model as the individual behavior of the agents has a direct influence on the outcomes of the systems. In this paper, an ABM model is developed to examine the effects of increased consumer participation within a local energy system. This model utilizes a diverse set of consumers based on real-world data to model and provide insight into the interactions within a P2P energy trading system. The effects of P2P trading on financial outcomes as well as the share of renewable energy utilized within the local energy system is investigated. Results show that ABM models can accurately model P2P energy trading systems and can capture the effects of individual behavior of many active consumers within electrical systems. Also, it is shown that there may be a tradeoff between maximizing P2P energy trades within a community and maximizing the revenues of the prosumers.**

Keywords*—*agent-based modelling, peer-to-peer energy trading, prosumer

I. Introduction

A. Context

The energy system is undergoing a drastic transition towards a system where previously passive consumers will play an important role [1]. These consumers who actively participate in the energy system with a variety of distributed energy resources, such as electric vehicles (EVs), solar panels, and battery energy storage systems, become so-called prosumers as they can simultaneously consume and generate electricity [2].

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The self-generated electricity can then be self-consumed, sold to the existing grid (to retailers or last resort traders) or be sold to other consumers connected to the same electric network through Peer-to-Peer (P2P) trading schemes [3]. P2P energy trading may offer significant advantages to consumers involved (e.g. profit maximization) as well as the wider electric system (e.g. less congestion in higher voltage networks) [1].

It is challenging to use classical, numerical based systems to model and understand the interactions within a P2P system made up of many independent consumers who may have different preferences or abilities to participate in the energy system [4]. The use of Agent-Based Modelling (ABM) can help to address these problems [5]. ABM models allow better understanding of complex and dynamic systems by decomposing them into numerous agents. The incorporation of the behavior of individual agents into the model is key as the agents' behavior has a direct influence on the outcomes of the systems [6]. ABM provides explainable insight into the collective behavior of a diverse set of agents within complex systems. Until recently, the application of ABM to energy systems has been limited but, as the type and number of active agents within energy systems increase, ABM models are becoming more applicable to the energy system.

B. Literature Review

Regarding the specific theme of this paper, it is possible to find other works that address system modeling problems in energy. All the examples discussed in this section use Multi-Agent Systems (MAS) modeling in some way, as does the present paper. MAS are a specific field of ABM in which multiple agents cohabit in the same environment and interact (with each other and with the environment), adjusting their behavior according to external signals received. However, despite also using MAS modeling, it differs from other papers by tackling P2P energy transactions in a smart grid environment. This means its scope is not limited to a microgrid environment but can also be applied to one. Additionally, it is worth to note that the present paper focuses on the economic point of view of the issue - the proof of concept, in comparison to more traditional alternatives - instead of focusing on its technical feasibility, which is more widely discussed.

Regarding the technical aspect, it is common to see a focus on voltage restoration and control, having self-sustainability as a key objective.

It should not come as a surprise, considering that in most cases a microgrid environment is considered. Naturally, a lot of them also discuss the incorporation of renewable energy sources (RES) and energy storage systems (ESS) to help flatten the demand curve. Differences between these works mostly lie on how they approach the modeling. For instance, [7] highlights the use of distributed controllers instead of a central controller; [8] suggests a two-layered approach to multi-microgrids, by optimizing the management of a single microgrid, and then the optimization of the cluster, maximizing the use of ESS; [9] deals with microgrid clusters, and suggests dividing them into smaller "sub-microgrids" and optimizing each of those more simple systems in order to improve dynamic performance.

An economic point of view should see its focus turn towards the end user experience - financial operation and modeling depending on end-user behavior and preferences. As [10] puts it: "our focus is on the improvement of community energy status, while traditionally research focused on reducing losses due to transmission and storage, or achieving economic gains". The goal of [10] is to achieve a zero energy community, in which (by definition) a neighborhood achieves null net balance of energy use and RES-based generation; although sharing demand and capacity information should prove necessary in order to balance any system. In turn, [11] exposes the concerns of creating a susceptible environment without privacy in the presence of P2P energy arbitrage; [12] explores how the interdependence between an electric storage unit and an electric power generator varies depending on the degree of their exposure to the environment, using a combination of MAS and distributed Reinforcement Learning; whereas [13] revolves around a demand-side management strategy that takes advantage of different consumption and production profiles in a neighborhood to shift peak loads and minimize electricity costs.

It is possible to see that, regarding this theme, research is mostly dedicated towards a specific need or concern, while leaving the broader subject of P2P energy trading to any adequate means of simulation. With this paper, a broader view is proposed, setting out to prove this concept in any smart grid environment, without such limitations as the high costs of these technologies, the heavy presence of ESS (an early-stage technology), the variable policies regarding EVs and scalability issues using MAS modeling. With this, the intention is that this paper will serve a purpose as indication that even without very radical transformation in our present reality, it is possible to welcome this concept and to put it into motion, not being exclusive to microgrids or new grids or neighborhoods with extremely high financial possibilities. [4] makes a very similar approach, exploiting "generation/demand flexibility from an energy community perspective", and using ABM modeling to simulate social interactions and end-user behavior - arguably the most defining trait of this subject. Going one step further, [14] introduces non-residential members in a community environment similar to that of [4], with a similar objective. Also worth mentioning is [15], that not only evaluates its results based on demand-side flexibility and its impact on electricity costs but also end-user' comfort - a relevant part of the practical popularization of this concept in the future.

C. *Contributions and Paper Organization*

The literature review has shown that while the use of ABM has grown and the benefits of this modelling technique have been demonstrated, there are not many examples of this technique being applied to P2P energy trading systems. This paper addresses this research gap through the development of an ABM model for a P2P energy trading system.

The contributions of this paper are two-fold:

- The development of an ABM model for simulating P2P energy trading between prosumers within a smart grid environment.
- The analysis of the effects of agents with different roles in the model and market structures on the outcomes of the P2P market to identify critical areas for future research.

The rest of the paper is structured in the following manner: Section II introduces the details of both the developed model and the case study considered; Section III presents the results derived from the case study; lastly, the conclusions are discussed in Section IV.

II. System Development

A. *The ABM platform*

The AnyLogic simulation software was used to implement the ABM model. The software provides an integrated development environment (IDE) supporting agent-based, discrete event, and system dynamics modelling as well as a combination of the three [16]. It has been used in diverse settings, including in the energy system [4]. The software is based in the Java programming language and allows users to extend models using Java. AnyLogic has a high degree of flexibility which allows users to fully capture the complexity of the agents' interactions at various levels of detail [17]. Importantly, the software allows for communication between agents which is key as they can transmit information regarding their status and preferences [16].

AnyLogic is well suited for the modelling of dynamic systems characterized by a non-linear behavior, agent memory, non-intuitive interactions between agents and variables, and time and causal dependencies [18]. In addition, these systems generally include many agents and various forms of uncertainty, similarly to what happens in energy systems

AnyLogic has a graphic environment with programmable blocks. In this model, a population type agent ("people") was placed inside the main environment ("main"). The upper level ("main") code influences the entire model and runs before entering the lower-level code ("people"). In the lower level, the code effects each agent individually in a successive manner, although interaction between agents must be coded differently. Each function and event parameter can be individually coded and customized: events can be timed to activate other code blocks; agents, connections and even environments can be customized to set actions and code for individual agents or functions.

The AnyLogic environment used to develop the model is shown in Fig. 1. The various user created functions, the input data files, various variables and options for altering the environment of the model are shown in Fig. 1.

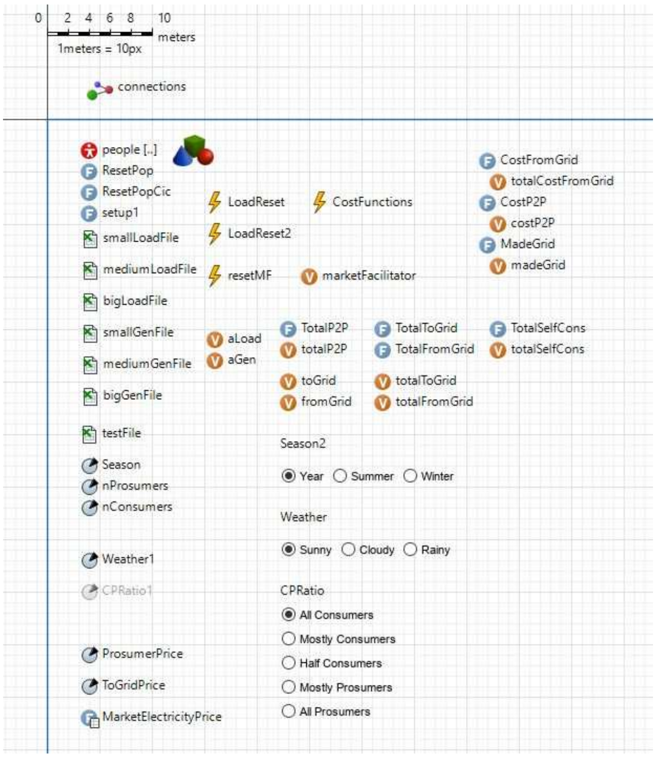

Fig. 1: User created environment in AnyLogic

B. Case Study

The model includes a virtual population of 100 agents. Each agent represents a household with a unique load and generation profile. All agents are randomly placed in a virtual environment and are connected to each other, which enables them to participate in energy transactions with each other. Note that although agents are randomly distributed by the software, they are placed in the same place in every simulation, allowing for consistent analysis.

Each simulation is run for 24 hours. The simulations are run in varying conditions to make a sensitivity and cost analysis. The varying inputs are seasonality and weather conditions, since these factors influence load and generation profiles, and the share of prosumers and consumers in the mix of agents. Considering price signals and messages from other agents, a prosumer agent can decide when to self-consume their self-generated energy, when to buy energy from the grid, when to establish P2P energy trades with other agents or when to sell energy to the grid. In turn, the range of decisions made by consumer agents is more constrained since they only interact to buy energy from the grid or from prosumers in the system.

The individual load profiles were retrieved from [19], a North American database including data from more than 1000 locations for at least 12 years. This ensures data is not influenced by specific events (e.g., financial crisis, microclimates or unique cultures) and is as generic as possible, allowing the model to be replicated in other scenarios. The retrieved profiles provide yearly and seasonal (summer and winter) average demand data, with a discretization of one hour and are adjusted according to the household size.

The self-generated energy is solely provided by photovoltaic (PV) panels installed in each agent's facilities (distributed configuration). No other type of energy production was considered. The PV generation data was retrieved from [20] and represents the yearly averages, aggregated per hour.

The PV installed capacity was defined according to the household size established by the demand profiles as the bigger houses tend to have more PV panels installed.

Also, to simulate price signals, the following assumptions were made: the market energy price (representing the price paid for the energy deficits bought from a retailer) was taken from [4]; the price of selling electricity to the grid was set at 90% of the hourly price of the market, in accordance with [21]; and the price for P2P transactions was set at 45% of the hourly price of the market according to [22].

III. Results

A. Baseline

To establish a basis for comparison, the most common case for a generic neighborhood was selected - a population made of 100% consumers. This, of course, implies 0% prosumers which means that there is no local self-generated energy, users are completely dependent on grid supply and P2P energy transactions are not possible.

In this setting, only the demand profiles were considered and, collectively, the 100 consumer agents demanded a total of 4070 kWh during the 24-hour period. The energy mix of the consumers is shown in Fig. *2*. As expected, the demand was completely satisfied by importing energy from the grid ("From Grid").

As expected, in a scenario with only consumers, there is only the hourly load profile ("Load") that overlaps with the energy bought from the grid ("From Grid"). At every point in time, given that there is no generation, all agents must buy their energy directly from the grid. This is a good opportunity to observe the demand curve, where a very high demand can be seen at the later hours of the day, reflecting typical residential consumption patterns.

B. Altering the penetration of prosumers

This section exploits the incorporation of prosumers in the mix of agents to analyze their contribution to the validation of the model. Different shares of prosumers were tested starting with 25%, then 50%, 75% and 100% of prosumers in the mix of agents. By including increasing numbers of prosumers, local generation is increasingly brought into the system and self-consumption and P2P transactions are enabled.

Following such reasoning, the higher the penetration of locally produced RES, the more self-sustainable and independent the microgrid will be from external energy suppliers. With this model in place, costs should also decrease. Of course, this will only be applicable when there is generation (when solar power is available), so there should be a clear difference when the natural resources allow it to be.

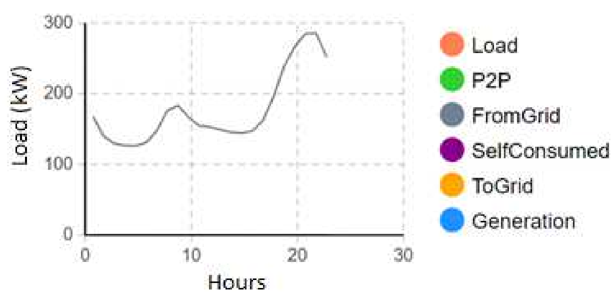

Fig. 2: Energy balance of the baseline with no prosumers

This does mean that we should still witness a considerable amount of energy being purchased from the grid during the periods of no solar availability (e.g., night/dawn).

The amounts of energy coming from the different sources when different shares of prosumers are considered are shown in TABLE *I*. In the baseline case (no prosumers), 100% of the energy is imported from the grid. As more prosumers are introduced into the model, the amount of energy required from the grid decreases and the amounts of energy self-consumed and traded locally increase. The level of self-consumption increases linearly with the penetration of prosumers. Interestingly, the amount of energy traded between peers decreases when all the agents are prosumers. This could be because all the agents are generating power and cannot easily find a buyer for the excess generation.

In Fig. *3*, 4, 5 and 6 the results from the simulations with 25%, 50%, 75% and 100% penetration of prosumers are presented. When 25% of agents are prosumers (Fig.3), although part of the demand can be supplied by self-generation and energy coming from P2P transactions, the system remains heavily dependent on grid power supply, even during the periods of solar availability. With the introduction of more prosumers in the system (Fig.4) the dependence on grid supply is reduced and nullified during peak PV generation periods. Finally, when the number of prosumers is dominant in the system (Fig.5 and 6), much of the demand during periods of PV availability is supplied by self-consumption and energy traded between prosumers, contributing to the temporary self-sufficiency of the system. In these settings, the self-generated energy exceeds the demand ("load") in some periods and surplus energy is exported and sell to the grid which allows to foresee profits for prosumers. When all the agents are prosumers (Fig. 6), an interesting behavior is registered: less energy is traded between peers when compared to the previous cases. This fact happens due to the abundance of self-generated energy and the reduced need to purchase energy from other prosumers during periods of solar availability.

These results allow to infer that the highest percentage of P2P energy traded in these conditions would likely be somewhere between 50 to 75% of prosumers in the agents mix.

TABLE I: IMPACT OF CHANGING PENETRATION OF PROSUMERS (%)

	From Grid	Self-Consumption	P2P trades	To Grid
Baseline	100	0.0	0.0	0.0
25%	87.4	5.2	7.4	0.0
50%	74.2	10.4	15.4	1.0
75%	68.7	15.3	16.0	7.2
100%	65.8	20.8	13.35	18.2

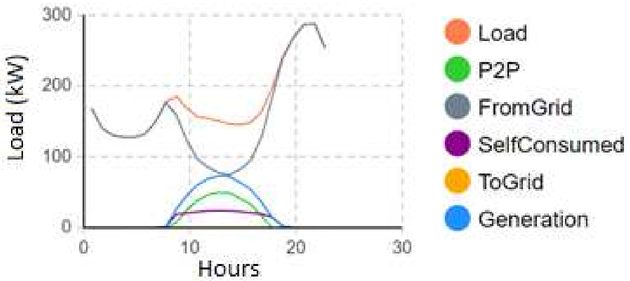

Fig. 3: Energy balance with 25% penetration of prosumers

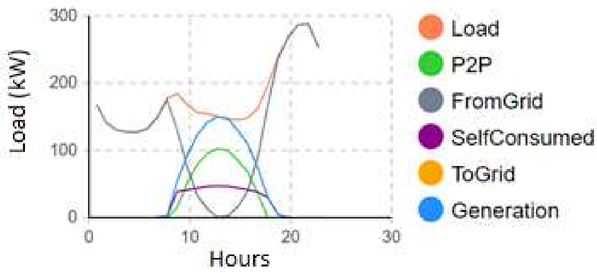

Fig. 4: Energy balance with 50% penetration of prosumers

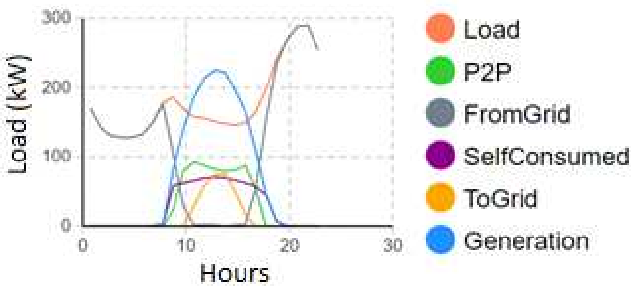

Fig. 5: Energy balance with 75% penetration of prosumers

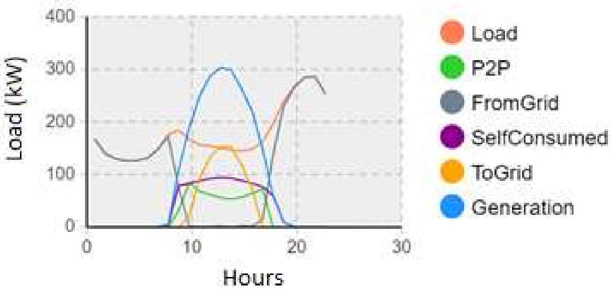

Fig. 6: Energy balance with 100% penetration of prosumers

That balance is where the model would reach most success. Nevertheless, a 25% prosumer presence already had considerable impact and could be a reasonable starting point. The 75% prosumer presence setting was the one performing better. After this point we saw a drop in the model efficiency, providing relevant clues. These results reinforce the need to adjust the installed generation capacity according to the demand needs as best as possible. The oversizing of systems and the production of surpluses may not be advantageous, especially if local exchanges are not possible and if the surpluses remuneration is not economically attractive. Also, the results reveal that the scalability of this model should not be a problem. It should work in any neighborhood scale if the relative geographical distribution of the agents is not highly unfavorable, in which case transmission losses could come into discussion.

C. *Effect of weather*

The impact of seasonality and weather in the results was also examined. The configuration mix of 50% prosumers and 50% consumers was considered. Simulations were performed by using demand hourly average data of summer months. While the comparison in this section is between a sunny summer day and a cloudy winter day, the demand profiles of the summer day were used for both scenarios to allow for the comparison between the scenarios. This was done to show how the weather conditions affect generation and thus the number of P2P transactions.

The demand to be supplied in summer is much lower than the yearly average, but the generation values stayed the same.

To further test the impact of the weather on the results, two scenarios were analyzed: the "sunny" summer day and the "cloudy" winter day. The simulation of a "sunny" summer day is shown in Fig. *7* while Fig. *8* displays the simulation results of a "cloudy" winter day. By comparing both figures, the influence of the weather variability on the model self-consumption, local trading and dependence on external energy suppliers is clearly revealed.

In the "sunny" summer day, considerable generation surplus amounts are made available at peak generation hours. This shows that agents can be, at some extent, self-sufficient from external suppliers during some periods. In this scenario, up to 17% of the demand may be supplied by P2P transactions while a 70% dependency from the grid is kept. In turn, in the "cloudy" winter day, the dependency from the grid increased by 7% as the demand supplied by both P2P transactions and self-consumption decrease. This worsening of the results is expected due to the decrease of PV availability. In this scenario, there is no generation surplus, and no energy being sold to the grid. Thus, at no point in time, agents can be completely self-sufficient from external energy providers. This shows that weather has indeed a great influence on systems' autonomy and P2P transactions since they are dependent on generation surpluses at a given time.

D. Financial Analysis

Finally, the financial results were calculated to compare all cases. Costs associated with self-consumption were not calculated as operational and the maintenance costs of PV panels were not considered. Keeping in mind that these results aim to benefit the population of agents, the costs related to P2P transactions will be noted but not accounted as positive nor negative since while one agent is paying this value, another one is gaining the same - as such, no financial gains nor losses from the transactions are considered. In the situations where there was no surplus, no energy was sold to the grid and no currency was made.

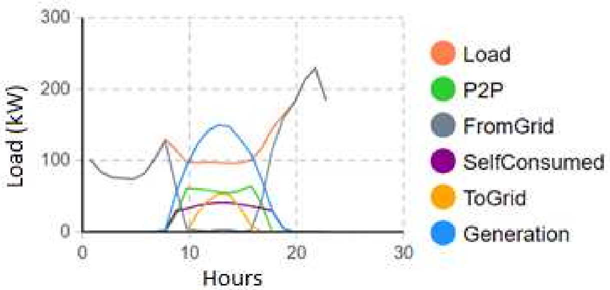

Fig. 7: Energy mix for a "sunny" summer day

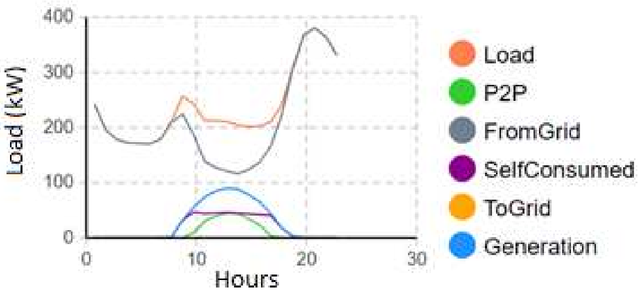

Fig. 8: Energy mix for a "cloudy" winter day

The same goes for the situation where no P2P transactions happened - there were no costs nor gains.

The "winter" scenarios registered worse financial outcomes compared to the normal cases with the same number of prosumers, with 19% and 29% higher costs from the grid due to the increase in demand and decrease in self-generation which means more energy has to be bought from the grid. The simulations in which least money was spent by buying energy from the grid were the two "summer" scenarios, in which the costs were reduced by nearly half (49% and 54%) when compared with the baseline case. When considering the energy sold to the grid, the scenarios with a higher presence of prosumers are the ones performing better. When all the agents are prosumers, the energy sold to the grid accounts for almost 17% of all costs, meaning that the costs from the grid would be halved compared to the baseline case.

The financial impacts of differing levels of prosumers are shown in TABLE *II*. Due to the lower levels of P2P trading taking place in the 100% prosumer setting, the P2P costs are lower than those of the 75% prosumers presence case. However, the revenues generated by the prosumers in the 100% case by selling surplus energy to the grid far exceeds the 75% case. This shows that there may be a tradeoff between maximizing P2P energy trades within a community and maximizing the revenues of the prosumers.

IV. DISCUSSION OF MODEL ASPECTS

Despite the relevant results for the design of more efficient P2P schemes, some limitations of this approach must be further discussed as they influence the results. First, we must discuss the quality of the input data. Average generation and demand data discretized in hourly time frames was considered, bringing a degree of uncertainty to the results. Energy must be delivered when requested, and non-immediate availability is a major fault. In light of this, in a scope of a 24 hours planning period, a 1 hour time frame can hide a lot of issues, such as the time that it takes for the communication between the agents and the market and to check for the availability of energy before going to the next alternative.

Secondly, the model calibration and validation would only be possible by collecting data from a real energy system with similar characteristics. The current lack of such systems does not allow to know how accurate the model is or how far away is it from reality. Thus, although the model's assumptions were made to reproduce a real system as best as possible, the modeling would benefit from the access to real consumption and generation data and preferably with smaller temporal discretization.

Third, the results are affected by the price assumptions. As the current legislation stands in most countries, as Portugal, prosumers would always make more money selling generation surpluses to the grid than to a fellow consumer. The price of selling surplus energy to the grid was set as 90% of the hourly electricity market price, while the P2P transaction price was set as 45% of the market price.

TABLE II: FINANCIAL IMPACTS ON THE AGENTS (€)

	P2P Costs	Import Costs	Export Revenues	Total
Baseline	0.0	1001.45	0.0	1001.45
25%	33.62	882.79	0.0	916.41
50%	69.71	751.94	0.22	821.43
75%	72.38	704.84	67.2	710.05
100%	58.9	669.755	166.56	562.1

This could be managed by a new mechanism like the government subsidizing the other part of the price. It would decrease dependency on the grid and favor RES-based energy (which favors the government) but that would mean to keep relying on subsides.

Lastly, when generation surplus is sold to the grid, especially if the amounts are significant, storage devices and demand-side management approaches must be exploited as it would have a great impact on the results. In a configuration with 50% prosumer presence: in the first time there is enough surplus to have energy sold to the grid, if storage was available, this energy could have been passed on to the next hour, increasing savings and decreasing grid dependency. As another example, in a setting in which all agents are prosumers: energy is not bought from the grid between 10am and 6pm (period of PV availability). However, as the highest peak of the demand curve comes at periods of no generation, there is always a big dependency on the grid. The only way to change this would be to shift part of the demand or store surplus energy during PV availability periods and consume it to flatten the demand peak.

V. CONCLUSIONS

In this work, an ABM model was presented to examine the effects of increased prosumer participation within a local energy system (e.g., neighborhood, local energy community, etc.). This model utilizes a diverse set of agents representing residential consumers and prosumers and is supported by real-world data to model and provide insight into the interactions within a P2P energy trading system. The effects of P2P trading on the agents' financial outcomes as well as the share of renewable energy utilized within the local energy system was investigated.

Even without considering supportive (but expensive) systems, such as storage, the model proved to be feasible by reaching up to 50% energy savings and decreasing grid dependency. Also, the results revealed that to maximize local P2P energy trading, between 50% and 75% of the members of the system must be prosumers. That balance is where the model would reach most success and future approaches will focus on the optimal composition of the system to maximize the energy traded between peers. Still, the results also show that even a small prosumers participation (25%) already has considerable impact on the system performance.

The sensitivity analysis also proved that the model is viable in both seasons but performs better during the summer months even facing intermittent conditions. The model proved to be highly influenced both by climatic conditions (seasonality and intermittence) and by fluctuating consumption patterns: months with higher-than-average demand curves and lower than average generation profiles could render the results near redundant.

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