Highlights

Modeling the energy community members' willingness to change their behaviour with multi-agent systems: a stochastic approach

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- A multi-agent simulation framework is proposed to model an energy community
- Consumer willingness to change consumption is modeled using a stochastic approach
- Personalized recommendations are computed by optimization to minimize the NEEG
- Community members are distributed into clusters
- Recommendations are developed to coach members to develop a more flexible behavior

Modeling the energy community members' willingness to change their behaviour with multi-agent systems: a stochastic approach

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ABSTRACT

Collective actions in the context provided by energy communities and more sobriety from energy users could both represent a potential solution for significantly reducing carbon emissions in residential areas. However, research are needed to properly understand, model and simulate the collective behaviour of communities owning a PV plant with energy sharing mechanisms suggested by an European directive. In this context, we propose a multi-agent modeling framework for simulating energy communities that is built upon a stochastic interpretation of the willingness of energy users to modify their consumption. The proposed concept includes an intelligent decision support system that assists community members during their daily activities and provides optimal recommendations to minimise the collective net-energy-exchanged-with-the-grid. The paper includes a case study where we present the impact of different community configurations. We emphasize that a community with just 25% of enthusiastic members provides a significant decrease in net-energy-exchanged-with-the-grid comparing to the reference scenario.

Keywords: energy community; multi-agent simulation; recommendation system; systems with humans; net energy exchanged with the grid; behaviour model

1. Introduction

The number of electrical appliances and incentive to promote self-consumption of PV electricity in residential homes has recently placed users in a position in which the conscious behaviour towards energy consumption plays a significant role. This behaviour must be developed in a complementary way to a collective approach towards energy efficiency and sustainability, thus envisioning a way for reaching net zero emissions by 2050.

To this matter, European governing institutions provide a possible approach through the concept of energy communities. More specifically, we may have two types of communities: a renewable energy community and a citizen energy community. Both communities represent legal autonomous entities that are based on open and voluntary participation, are composed from natural persons, local authorities or small-to-medium size businesses and have the primary objective to provide environmental, social and economical benefits to the members (Frieden et al., 2019). Moreover, major decisions regarding a community are subject to a democratic process involving exclusively its members. Both community types have specific characteristics as well: renewable energy communities must be limited to a certain proximity and must be open to all sources of renewable energy (European Parliament and Council of the European Union, 2018), while citizen energy communities have no geographic limitation and are focused solely on electricity (European Parliament and Council of the European Union, 2019). Given these approaches, it would be interesting to investigate and to propose a modeling and simulation framework to properly understand the impact of member reactions to signals in such a community. However, several challenges arise, given the collective nature of a community. First and foremost, the complex behaviour of residential consumers is already posing a certain difficulty in terms of analytic representations (Hong et al., 2016). Consequently, we can anticipate that modeling a community member as an autonomous, consumption oriented entity is a challenge. Furthermore, the organisational form that allows open participation focusing on providing benefits to its members also poses a certain challenge. In this case, a coordination level must be developed based on an intelligent recommendation system (IRS) that supports the members of the community in their daily activities and provides advice to either increase or decrease consumption, according to the benefit of the whole community. An interesting study (Bonino et al., 2012) emphasizes that psychological *goal setting* strategies may represent a possible way to improve the awareness of users towards energy consumption.

There are many activities that can be developed in an energy community: energy sharing between members, peer-to-peer trading or renewable energy production Gjorgievski et al. (2021).In recent works, peer-to-peer trading of energy and non-cooperative games as in Tomin et al. (2022) are being researched especially to investigate individual profit. However, we propose a method that is evaluated at collective level, according to metrics such as the net-energy-exchanged-with-the-grid (NEEG) which represents

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Table 1
Terminology

Abbreviation	Description
PV	Photovoltaic
NEEG	net energy exchanged with the grid
SC	self consumption
SS	self sufficiency
Δt	sampling time [h]
H	variable to define a house
α_{H_j}	action recommended to house j
$\mathcal{A}$	set of recommended actions in a day
$p^{expected}_{Load,H_j}$	expected load of house j [W]
$p^{estimated}_{Load,H_j}$	estimated load of house j [W]
$p^{expected}_{PV}$	expected PV production of the community [W]
$p^{expected}_{Grid}$	expected PV power from the grid [W]
$p^{simulated}_{Load,H_j}$	simulated load of house j [W]
$p^{simulated}_{Load}$	simulated load of the community [W]
$p^{expected}_{Load}$	expected load of the community [W]
n	number of PV modules
p_{module}	rated power of a module [W]
f	pv power scaling factor [%]
G	Incident solar radiation $[W/m^2]$
G_{STC}	Incident solar radiation at standard temperature conditions $[1kW/m^2]$
Δp	change in consumption [%]
Δp_{strong}	strong change in consumption [%]
Δp_{mod}	moderate change in consumption [%]
m	type of agent
N	number of hours in a period
Θ_m	agent set of type m
$P_{\Theta_m}(Y)$	probability for agent in set Θ_m to follow recommendation
$P_{\Theta_m}(N)$	probability for agent in set Θ_m to not follow recommendation
$\tau^{PV}_{lim\_sup}$	superior limit for PV production period
$\tau^{PV}_{lim\_inf}$	inferior limit for PV production period
$\tau^{PV}_{peak\_inf}$	inferior limit for PV peak period
$\tau^{PV}_{peak\_sup}$	superior limit for PV peak period
i	hour index
j	community member index
$x^{\sim}$	decision variable to maintain consumption
x^{+}_{strong}	decision variable to strongly increase consumption
x^{+}_{mod}	decision variable to moderately increase consumption
x^{-}_{strong}	decision variable to strongly decrease consumption
x^{-}_{mod}	decision variable to moderately decrease consumption
$p_{prod,k}$	produced power at sample k
$p_{load,k}$	consumption at sample k
MILP	Mixed Integer Linear Programming
CBC	COIN-OR Branch and Cut Solver
IRS	Intelligent Recommendation System

the energy that is either injected or extracted from the grid (as defined in Simoiu et al. (2021a)). In this way, we evaluate the environmental impact through how much of the produced energy is consumed internally by the system (self-consumption - SC) and the degree of autonomy for the community (self-sufficiency - SS).

In this paper, we propose a simulation instrument for assessing the energy and humans collective impact of a renewable energy community that is actively guided by an intelligent recommendation system, maximising the local usage of energy provided by an owned PV plant. The instrument is based on a multi-agent model, while the intelligent recommendation system represents an entity that computes relevant recommendations based on the willingness of community members (or agents) to modify their consumption by increasing their flexibility. Furthermore, the objective of the optimal recommendation at collective level is to minimise the net-energy-exchanged-with-the-grid, thus maximising self-consumption and self-sufficiency. Further details on why minimising NEEG is equivalent to maximising self-consumption and self-sufficiency can be found in our previous research work (Simoiu et al., 2021a). In this way, considering the work in (Bonino et al., 2012), we provide a solution that aims to encourage citizens to become more flexible of their behaviour towards energy consumption by setting small psychological 'goals' in the form of recommendations. Several community configurations are investigated, considering different types of users depending on their willingness to modify consumption according to recommendations. Comparing to other works, we propose a model that is suitable for simulating the autonomous behaviour towards energy consumption of community members and that it can be used to assess the economical and environmental impact at collective level.

2. State of the art

A multi-agent simulation model for an energy community could be regarded as a relatively novel concept, especially considering the recent interest at international level in sobriety and flexibility in human consumption. However, there are some interesting research works that address relevant topics related to internal mechanisms that could be found in an energy community.

Peer-to-peer trading is identified as a possible activity in an energy community (Bokkisam and Selvan, 2021). (Soto et al., 2021) states that energy trading through peer-to-peer mechanisms is a relatively new topic and more research is needed for implementing a real world model. Moreover, cooperative models are investigated in order to see how individuals could cooperate for collective benefit. Nevertheless, the unpredictable deterministic behaviour of humans towards energy consumption represent the main difficulty in such simulation models. (Liu et al., 2017) also underlined that energy sharing between citizens could be more beneficial at collective level than targeting individual profit (see Lorenzo et al. (2021)). The authors further provided an optimization model for scheduling tasks between prosumers based on a centralized energy sharing structure that is governed by an entity defined as energy sharing provider. Furthermore, the work also investigated the willingness of prosumers to shift their consumption. Both the centralized nature of the energy sharing structure and the consumption shifting concept represent important starting points in simulating a community. Thus, in our work we provide extended autonomy to members through a multi-agent framework, but we also consider the same centralized principle to develop an IRS that may support the community members in adjusting daily activities to the community needs. Other works (Khorasany et al., 2021) also investigate peer-to-peer trading, but focus is usually placed on individual profit, rather cooperative relationships. Consequently, more research is needed to investigate whether collective action is beneficial and in what manner.

From a practical point of view, multi-agent system represent interesting simulation instruments, especially for investigating systems that have multiple autonomous entities that interact with each other. For example, decision support systems in other sectors such as solid waste recycling rely on multi-agent frameworks, allowing a deep understanding of the behaviour of people under different policies (Chen and Gao, 2021). In the energy management sector, (Zhou et al., 2018) proposes a multi-agent framework to investigate the impact of a peer-to-peer trading mechanism. Moreover, an optimisation model at individual level indicates the relevant schedule for energy consumption in order to maximise profit. Other works propose multi-agent frameworks combined with neural networks (Yue et al., 2020), or multi-agent frameworks at microgrid resource level (Xiong et al., 2020) to minimize the energy bill and optimize power quality. Nonetheless, there are two considerations that should be taken into account from these works: in most cases, human behaviour towards energy consumption is difficult to model in a conventional way and multi-agent systems usually have a coordination mechanism employed based on a central support entity. (Reis et al., 2020) provides a very interesting solution based on these principles, with the aim to schedule the operation of several loads in order to minimise the operational cost of energy in an energy community modeled as a multi-agent system. However, from a practical point of view, controlling different loads in residential homes can pose a certain discomfort for users, especially in unplanned situations.

Regarding human behaviour towards energy consumption, different approaches are investigated in specialized literature. Some works classify this behaviour through transient and persistent events (Chen et al., 2020), while other works investigate causality between impact of actions and energy efficiency through multi-objective optimisation models (Pal et al., 2019). However, as stated in (Hong et al., 2016), dependency between human actions can be easily ignored, thus increasing the difficulty of modeling energy consumption related behaviour. Several studies (Azar and Menassa, 2012; Gaetani et al., 2016) focus on occupancy estimation and offer relevant insights regarding models that can be used to reduce "the performance gap" between simulated and actual people behaviour. In (Chapman et al., 2018), the authors present a review of stochastic models that are used for modeling the energy behaviour of people, taking into account correlations between observed behaviour and specific events. Furthermore, it is concluded that a stochastic approach could reflect a more realistic energy demand pattern at district level.

Nevertheless, we consider that intelligent recommendation systems represent important instruments that can actively and positively influence the human behaviour towards consumption. In (Onile et al., 2021), the authors state that personalized recommendation systems are essential to increase sustainability and with personalized suggestions, the behaviour and responsibility of people can improve. Other instruments such as social interactions, real time representation of data analytics and feedback are also important, while it is also important to include an economical aspect in the global incentive mechanism. Moreover, agent based systems have already been used for occupancy estimation problems Norouziasl et al. (2020) that may further infer energy savings through sensors and efficient lighting system operation.

Energy communities represent, from a theoretical point of view, a suitable setting for developing and improving consumer behaviour through collective action. We can see in (Stephant et al., 2021) a simulation framework thorough a game theory approach, where a distributed optimisation model is employed to maximise the benefit of community members (although the respective work shows a non-cooperative game theory approach). In other works (Vand et al., 2021; Coignard et al., 2021; Chen and Gao, 2021; Sima et al., 2022), energy sharing is simulated with the aim to optimize the operational cost of energy. The importance of data driven solutions and forecasting models in energy communities is emphasised in Kazmi et al. (2021). Furthermore, optimization models are often implemented to determine the size of PV plants and energy storage systems in an energy communities (Weckesser et al., 2021; Simoiu et al., 2021b; Fina et al., 2020).

Consequently, the main contributions presented in this paper are:

- the development of a multi-agent model for simulating energy communities. Comparing to (Reis et al., 2020) and other multi-agent solutions (Zhou et al., 2018; Xiong et al., 2020), our focus is to provide community members a certain degree of flexibility by defining their willingness to shift consumption instead of controlling shiftable loads or resources, the stochastic decision process to change the consumption is entirely depending on the agents behaviour, considering the recommendation received. Thus, by developing different stochastic-based profiles (enthusiastic, non-enthusiastic community members), we could simulate different behaviour patterns and analyze the collective impact. Comparing to other works that refer to the design stage of an energy community Herenčić et al. (2022); Bartolini et al. (2020); Karunathilake et al. (2019); Rafique et al. (2018), the present work focuses on simulating the daily active operation of a community.

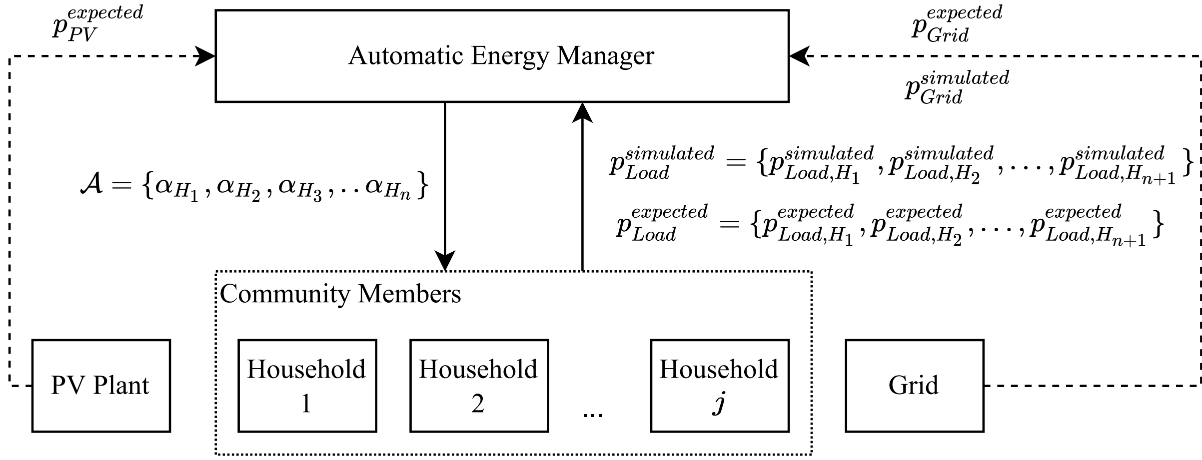

Figure 1: Energy community communication architecture

- we propose an intelligent recommendation system implemented as an automatic community manager. This recommendation system determines the best theoretical consumption related measures in order to minimise the collective net-energy-exchanged-with-the-grid, thus maximising self-consumption and self-sufficiency. Comparing to other solutions (Reis et al., 2020) from a practical point of view, the optimization of a single objective at central level through Mixed-Integer-Linear-Programming is more favourable in terms of speed and precision towards a global optimum then solving multi-objective problem through genetic algorithms. Moreover, in the energy community related context, through focusing on both self-consumption and self-sufficiency, we focus also on providing environmental benefit to the community by aiming to increase the PV energy consumed instead of focusing individually on economical aspects emphasised by trading mechanisms (Bokkisam and Selvan, 2021; Khorasany et al., 2021).
- we propose a way to model and simulate energy consumption behaviour of people and willingness to consume in a more flexible way, in the context of a personalized recommendation system. By assuming *a priori* that there is a profound unpredictability in the behaviour of people, we instead focus on their willingness to change consumption and use a different approach then other stochastic methods in literature (Chen et al., 2020).

3. Problem statement

We consider an energy community based on electricity sharing, where n residential households $\mathcal{H} = \{H_1, H_2, ...H_n\}$ can join as community members, with an automatic energy manager as central entity. There is a PV plant, possibly distributed, owned by community members and instead of using the available production for personal use, they allow the community to manage the renewable energy source. Consequently, we can assume that the energy community is connected to a unified PV plant. Thus, given the characteristics of energy communities defined at European level (Frieden et al. (2019)), we propose a solution envisioning a Citizen Energy Community (Figure 1), focused on electricity, that is open for the voluntary participation of members, with or without production capabilities.

Generally, in a typical daily scenario the manager knows the expected PV production for the community $p_{PV}^{expected}$ and the expected consumption of each community member $p_{Load,H_j}^{expected}$. Then, the manager provides a set of recommendations $\mathcal{A}$ to the members and then checks to see if the members have followed the recommendation or not by measuring their actual consumption (in this case we denote the actual consumption $p_{Load}^{simulated}$).

We estimate the PV production for the energy community with the following HOMER model:

$$p_{PV}^{expected} = n \cdot \eta \cdot p_{module} \cdot \frac{G}{G_{STC}} \quad [W] \tag{1}$$

where $p_{PV}^{expected}$ defines the expected PV production, p_{module} defines the module rating power, n defines the number of PV panels, η represents an estimation factor for the power losses due to temperature, partial shading or transmission through connection wires, G represents the incident solar irradiance on the panel and G_{STC} defines the irradiance at standard temperature conditions (1 kW/m^2).

At the beginning of the day, the manager computes the optimal recommendation based on the community configuration. More specifically, by understanding the willingness of users to change their consumption, the manager determines the recommendation based on an expected consumption profile $p_{Load}^{expected}$ which reflects the impact of the

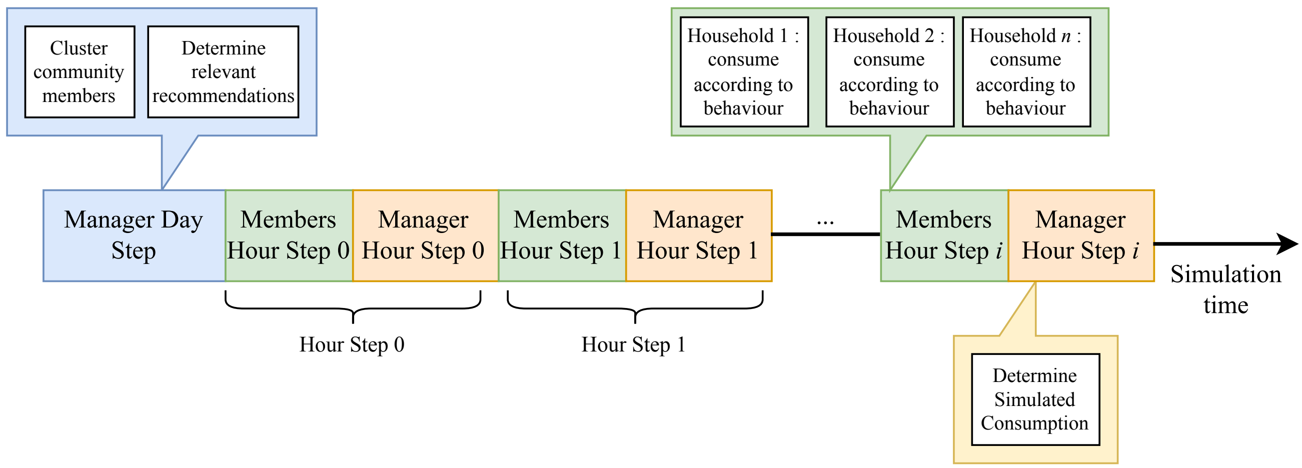

Figure 2: Schedule for a day in the simulation

users' consumption change. The expected power profile is developed based on the estimated consumption profile $p_{Load}^{estimated}$ and the behaviour of agents relative to possible recommendations.

So, based on the community expected power profile $p_{Load}^{expected}$, the expected PV production $p_{PV}^{expected}$ and the expected grid power $p_{Grid}^{expected}$, the energy manager computes a set of recommended actions in order to fit as much as possible the community consumption with the PV production. The recommendations for each period are further transmitted to the community members at the beginning of the day so that they know how to approach the day in terms of energy consumption activities.

During the day, at individual level, the consumption $p_{Load}^{simulated}$ is determined for each house and is further transmitted at the end of the day to the automatic energy manager. In a practical implementation, $p_{Load}^{simulated}$ would be equivalent to the actual measured consumption. In this way, the manager can determine whether the agent has followed the recommendation or not. At the end of the day, the manager also provides information regarding collective net-energy-exchanged-with-the-grid, emphasising how close the community was to fit consumption with production. In other words, the members know how much grid-dependent the community is.

To implement this energy community model, a multi-agent system is proposed, having the following possible agents:

- the *Community Member* agent - a representation of a community member, with his own individual stochastic decision-making process
- the *Automatic Energy Manager* agent - an unique agent that computes the optimal recommendations and communicates them to the community members

This approach is used to emphasize that members have particular attributes and actions, while the community manager has different characteristics and is responsible with providing the optimal recommendations.

Thanks to the multi-agent approach, we investigate the behaviour of members and their impact on the community through simulations. A simulation is represented as a number of hour time steps every day. During each model step, each agent executes its own particular step, according to a specific schedule.

Thus, a typical day in the simulation (Figure 2) begins with a particular *Manager Day Step*, a stage when the manager separates community members into clusters, according their willingness to change consumption. Then, he determines a personalised recommendation set for each cluster. During the day, at each hour step, each member consumes energy based on a specific model that is developed according to the estimated consumption profile $p_{Load}^{estimated}$ and the personalised recommendation (*Members Hour Step*). This 'real' consumption profile is equivalent to the simulated profile $p_{Load}^{simulated}$. Furthermore, at each hour step, the manager records this simulated profile so he can periodically evaluate the performance of the community (*Manager Hour Step*).

3.1. Modeling the community members with stochastic decision processes

Considering that the main objective of the community is to fit as much as possible the consumption with own PV production, we propose two different recommendation types: Δp_{strong} for a strong change in consumption (to cover significant differences between production and consumption), Δp_{mod} for a moderate change in consumption (for "fine tuning"). Both variables stand for percentages of the estimated community member consumption $p_{Load}^{estimated}$. The two possible modifications in the consumption of one typical member are illustrated in Figure 3.

Table 2
Community Member profiles

Member type	Description	probability to follow recommendation	probability to consume as expected
ideal	follow any given recommendation	$P_{\Theta_0}(Y) = 1$	$P_{\Theta_0}(N) = 0$
enthusiastic	increased willingness to change consumption	$P_{\Theta_1}(Y) = 70\%$	$P_{\Theta_1}(N) = 30\%$
normal	equally willing to change consumption and consume the same	$P_{\Theta_2}(Y) = 50\%$	$P_{\Theta_2}(N) = 50\%$
non-enthusiastic	decreased willingness to change consumption	$P_{\Theta_3}(Y) = 30\%$	$P_{\Theta_3}(N) = 70\%$

Consequently, the possible actions of an agent during the *Hour Step* are presented in Table 3.

Table 3
Possible agent actions

Possible action	$p^{simulated}_{Load,i}$
maintain consumption as expected	$p^{estimated}_{Load,i}$
moderately increase consumption	$(1 + \Delta p_{mod})p^{estimated}_{Load,i}$
strongly increase consumption	$(1 + \Delta p_{strong})p^{estimated}_{Load,i}$
moderately decrease consumption	$(1 - \Delta p_{mod})p^{estimated}_{Load,i}$
strongly decrease consumption	$(1 - \Delta p_{strong})p^{estimated}_{Load,i}$

We further start from the assumption that a day ahead estimation of the community power profile $p^{estimated}_{Load}$ exists for the desired simulation time and is determined *a priori* from an accurate prediction of the community consumption, thus reflecting the community energy needs.

Furthermore, we consider that a single recommendation may infer a certain increase or decrease in consumption denoted Δp as a fixed value for each hour, value that is further considered constant for the whole simulation experiment. However, choosing the value of Δp for a whole simulation experiment might represent a challenge from a more practical point of view. If the recommendation is to lower consumption according to a significant Δp value, energy consumers might find it difficult to adapt their behaviour according to this context. However, if Δp is too low, the collective benefit might be too small. As an alternative, we defined two Δp so that, if there is significant PV energy surplus, we may recommend specifically for that period a strong increase in member consumption, while in other periods we may recommend a moderate increase. Nevertheless, it is important to take into account that a recommendation system is effective if the long-term behaviour of users is improving, so an equilibrium between several and numerous recommendations must be found. Thus, through this "coaching" approach, we choose a fixed value for Δp for the whole experiment to accommodate community members with a certain flexibility request.

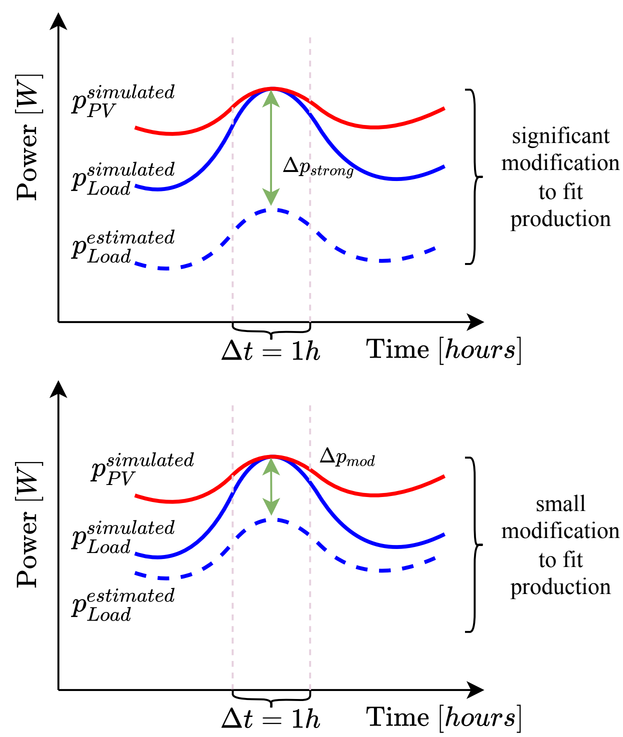

Figure 3: The two possible modifications in consumption for one member

Focusing on the value of Δp, we consider it to be a certain fraction of the member estimated consumption at a given time step. In this way, by recommending users to lower or increase their consumption by a fraction, the system provides the users a certain degree of freedom in choosing what appliances to use or not use, avoiding sensible situations where users are restricted to use some appliances or situations involving remote appliance control (Reis et al., 2020).

From a practical point of view, people may have a different affinity towards contributing to the community life. Some people may be more enthusiastic to follow the recommendations, while others may not change their consumption

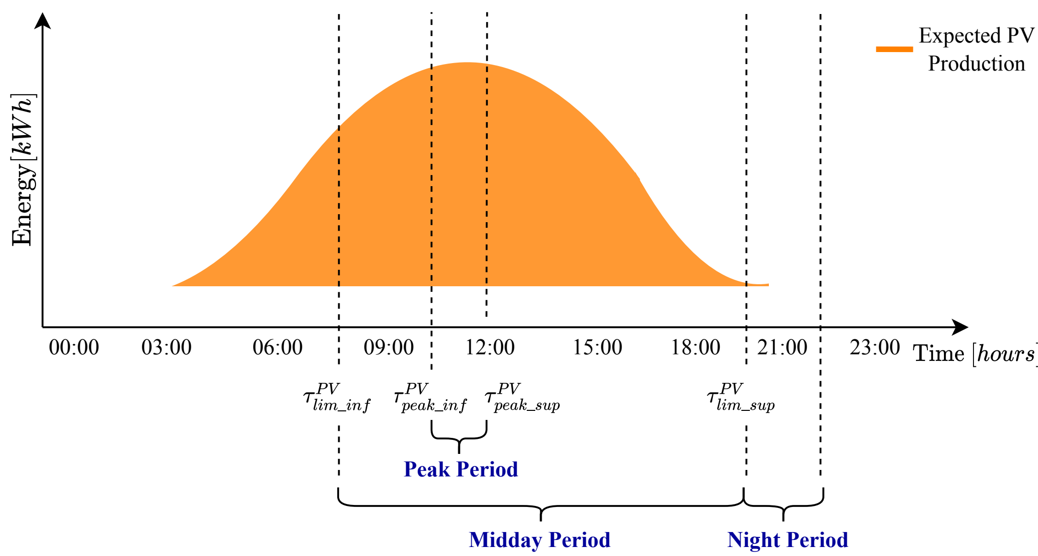

Figure 4: An illustration of how a typical simulation day is decomposed in periods

Table 4
Recommendation periods definition

Period	Inferior limit	Superior limit	Description
Midday	$\tau^{PV}_{lim\_inf}$	$\tau^{PV}_{lim\_sup}$	automatically set by the manager considering the expected PV production for the respective day $p^{expected}_{PV}$
Peak production	$\tau^{PV}_{peak\_inf}$	$\tau^{PV}_{peak\_sup}$	represented by one hour where we have maximum production (or two or three consecutive hours around this hour, if they are at least 80% of the maximum value). If there is only a maximum value, then $\tau^{PV}_{peak\_inf} = \tau^{PV}_{peak\_sup}$.
Morning period	08:00	$\tau^{PV}_{lim\_inf}$	optionally, we use the morning period if there is no PV production between 08:00 and $\tau^{PV}_{lim\_inf}$
Night period	$\tau^{PV}_{lim\_sup}$	23:00	a period in the day where we do not have PV production

so easily for different personal reasons. Thus, we propose to cluster members in the categories presented in Table 2. So, at each *Member Hour Step* i, each member from a cluster m decides whether to follow the recommendation (a probability denoted by $P_{\Theta_m}(Y)$) or to consume as estimated (a probability denoted by $P_{\Theta_m}(N)$). This decision is developed in a stochastic manner, through several member profiles (Table 2).

3.2. Modeling the community manager

To compute relevant recommendations, we propose an optimisation model that the manager uses every day to find the actions that minimise the collective net-energy-exchanged with-the-grid.

In an intuitive way, since the recommendation is given for a single hour i, the manager may provide a different recommendation at every hour during a calendar day, including the night. However, since we aim to propose a method that encourages people to improve their behaviour towards energy consumption, the proposed strategy will provide the same recommendation for each hour, for representative periods of the day. More specifically, we define a period to be a time interval in which the same recommendation is given for a category of community members.

Consequently, we propose to split a simulation day in periods (Figure 4) according to the rules described in Table 4.

So, instead of providing 24 recommendations for each hour of the day, the manager determines a personalised recommendation for each period, resulting in 4 or 5 recommendations in total per day for each category of members.

Setting the number of periods and the length of each period is a fundamental aspect that significantly affects the performances of the community from a quantitative point of view. We can intuitively consider that increasing the number of periods (and the number of recommendations) will also improve performances due to the higher accuracy in capturing the ever-changing energy profile in residential homes. Since in (Bonino et al., 2012) the consumption goals are set for a complete day, we infer that providing too many recommendations during one day would result in a troublesome experience for citizens. Moreover, a relatively low number of recommendations may be easier to implement by people, thus improving the chances that community members adopt these recommendations in their daily behaviour. Nevertheless, we consider that 4 or 5 recommendations per day represent an adequate choice.

The optimisation problem is formulated in a Mixed-Integer-Linear-Programming form. The objective is to determine the best recommendations for each category of members, to minimise the collective NEEG of each period. We start by formulating the objective for the whole community, where each agent is indexed by j:

$$\min_{\substack{x^{\sim}_{\Theta_m}, x^{+}_{\Theta_m,strong}, x^{-}_{\Theta_m,strong},\\ x^{+}_{\Theta_m,mod}, x^{-}_{\Theta_m,mod}}} \sum_{i=1}^{N} | \sum_{j\in\Theta_m} p^{expected}_{Load,i,j} - p^{expected}_{PV,i} | \quad (2)$$

where i represents the hour, N represents the number of hours in the period, $p^{expected}_{Load,i,j}$ represents the expected load for each member j during the hour i, $p^{expected}_{PV,i}$ represents the expected PV power generated for the whole community at hour i and Δt represent the sampling time ($\Delta t = 1h$). $x^{\sim}_{\Theta_m}, x^{+}_{\Theta_m,strong}, x^{-}_{\Theta_m,strong}, x^{+}_{\Theta_m,mod}, x^{-}_{\Theta_m,mod}$ represent binary decision variables for each possible recommendation: maintain consumption, strongly increase consumption, strongly decrease consumption, moderately increase consumption, moderately decrease consumption for each category of members Θ_m ($m = 0$ for ideal, $m = 1$ for normal, $m = 2$ for enthusiastic and $m = 3$ for non-enthusiastic members).

Is is assumed that the manager knows the profile of each member in the community (possibly from historic data). So, by substituting $p^{expected}_{Load}$ in Eq. 2 with the estimated power profile and considering the possible actions (Table 3) and profile (Table 2) of each category of members Θ_m, the optimisation problem to determine the relevant recommendations for a specific time period can be defined according to Eq. 3.

$$\begin{aligned}
\min_{\substack{x^{\sim}, x^{+}_{strong}, x^{-}_{strong},\\ x^{+}_{mod}, x^{-}_{mod}}} \quad & \sum_{i=1}^{N} | \sum_{j\in\Theta_m} p^{estimated}_{Load,i,j} \Bigg\{ \underbrace{x^{\sim}_{\Theta_m}}_{\text{same consumption}} + \\
& \underbrace{x^{+}_{strong}\left[P_{\Theta_m}(Y)(1+\Delta p_{strong}) + P_{\Theta_m}(N)\right]}_{\text{strongly increase consumption}} + \\
& \underbrace{x^{-}_{strong}\left[P_{\Theta_m}(Y)(1-\Delta p_{strong}) + P_{\Theta_m}(N)\right]}_{\text{strongly decrease consumption}} + \\
& \underbrace{x^{+}_{mod}\left[P_{\Theta_m}(Y)(1+\Delta p_{mod}) + P_{\Theta_m}(N)\right]}_{\text{moderately increase consumption}} + \\
& \underbrace{x^{-}_{mod}\left[P_{\Theta_m}(Y)(1-\Delta p_{mod}) + P_{\Theta_m}(N)\right]}_{\text{moderately decrease consumption}} \Bigg\} - \\
& p^{expected}_{PV,i} | \\
\text{subject to:} \quad & x^{\sim}_{\Theta_0} + x^{+}_{\Theta_0,strong} + x^{-}_{\Theta_0,strong} + x^{+}_{\Theta_0,mod} + \\
& + x^{-}_{\Theta_0,mod} = 1 \\
& x^{\sim}_{\Theta_0}, x^{+}_{\Theta_0,strong}, x^{-}_{\Theta_0,strong}, x^{+}_{\Theta_0,mod}, \\
& x^{-}_{\Theta_0,mod} \in \{0,1\}
\end{aligned} \quad (3)$$

As it is depicted by the second constraint, it is important to note once again that the decision variables represent binary values reflecting the recommended actions of a specific category of members j for an hour i. With periods, the same recommendation is given for all the hours in the respective period. More specifically, if the optimal recommendation for any category members Θ_m during the morning period should be to strongly decrease consumption, then the solution would be $x^{-}_{\Theta_m,strong} = 1$ and all other decision variables for the category Θ_m would be 0 (hence the first constraint imposed to the optimisation problem).

4. Case Study

The methodology has been implemented in the multi-agent framework MESA in Python (see MESA). Simulations were further conducted based on real consumption data from the IRISE database, collected through the REMODECE project. More specifically, consumption data for almost 1 year with a sample time of 1h for 20 residential homes from France have been used. This data are considered as estimated levels of consumption for the community members, with the previously mentioned assumption that these profiles reflect the community energy needs. A power diagram of the community can be analysed in Figure 5, where *simulated* reflects the real consumption/production levels exchanged in the system (we assume $p^{simulated}_{PV} = p^{expected}_{PV}$).

The simulation scenarios are executed for a time interval from 16 February 1999 to 1 January 2000 (as per available data). The expected PV power for the year $p^{expected}_{PV}$ is estimated with the model in Eq. 1, with a configuration $n = 150$ panels, $p_M = 500W_p$ and $\eta = 75\%$. The chosen slope is 60° and the direction is South, yielding maximum power for the respective coordinates. Weather data has been obtained from the weather platform *OpenWeatherMap* based on the location defined in the consumption database. Irradiance was further obtained from a solar model (see (buildingenergy) and Ploix et al. (2021)). Moreover, the strong increase/decrease in consumption is chosen $\Delta p_{strong} = \pm 0.8$, while the moderate increase/decrease is $\Delta p_{mod} = \pm 0.5$, as we discovered after several simulations (Simoiu et al.) that these values would provide the best performances for the available dataset. Furthermore, two cases are presented for each simulation scenario: February and July. In this way, a comparison can be made between a month with very low PV production and a month with peak production.

The MILP optimisation problem is resolved using the Coin-or-Branch-and-Cut Solver (CBC) from Python. We executed several simulation scenarios for different community configurations (Table 5). In each scenario, we split the total member count (20 houses equivalent to 20 members) between categories, thus simulating different community configurations which are rather interesting from both performances and realism points of view. For example, in scenario 1, we simulate a community with only ideal agents, thus the member count for ideal agents is 20. For all scenarios, we show in Table 5 the collective NEEG per day computed for the whole simulation period with and without the

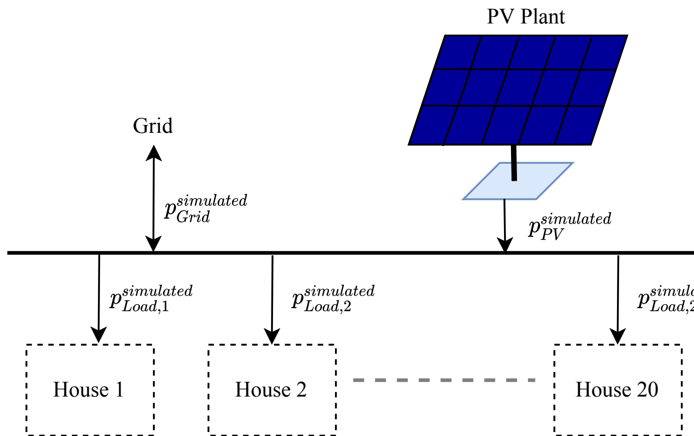

Figure 5: Energy community investigated in the case study

IRS. In terms of economical evaluation, we show the self-sufficiency index (defined in Simoiu et al. (2021a)) showing the percentage of the community energy bill that is reduced with and without IRS. We assume that the community does not obtain income from injecting energy into the grid and we calculate the saved amount with IRS v_{saved} obtained by reducing the grid dependency over the period with an average tariff for households of $c_{grid} = 0.185$ EUR/kWh (as it was recorded in France by GlobalPetrolPrices.com in 2021). Thus:

$$v_{saved} = \sum_j p_{Load,j}^{simulated} \cdot SS^{simulated} * c_{grid} \tag{4}$$

For the most interesting scenarios, we illustrate in Figs. 6, 7, 8 and 9 two comparisons for each category of members in the respective scenario:

- a power load profile comparison between the expected consumption of the respective category of members (marked with dashed blue plot), the real consumption of the respective category of members, (marked with continuous blue plot) and the expected PV production (marked with continuous red production).
- an action-recommendation comparison, depicting the real actions of the first agent (marked with blue), as well as the recommendations for his category (marked with green).

It is important to mention that in Figs. 6 and 7, since we have scenarios with only one category of members, the community simulated/expected consumption is equivalent to the category simulated/expected consumption. However, in Figures 8 and 9, since we have multiple categories, we show the two aforementioned comparisons for each category, while also illustrating a power profile comparison for the whole community. Furthermore, for each Figure and scenario we provide observations in Table 5.

Overall, we can see that the classification in different categories depending on the willingness to change consumption is fundamental for providing the manager a better understanding of the nature of the community to properly compute the recommendations. As it can be noticed both in Figure 6 and Table 5, the best performances in terms of simulated NEEG can be obtained with an ideal community. However, since this case cannot be achieved realistically speaking, we consider both Scenarios 4 and 5 with a mixture of enthusiastic and standard members to illustrate the best, feasible, results.

Moreover, the IRS (combined with the aforementioned classification system) is able to significantly increase the performances of the community in comparison with the expected performances provided by a community without a decision support mechanism. This aspect can also be noticed by analysing the performances of scenario 8 in comparison with scenario 2 in Table 5, where the impact of the non-enthusiastic agents is limited as a result of the actions of normal and enthusiastic members, guided by an optimal recommendation that is computed accordingly. From an economical point of view, even if energy communities are not focused on financial profit (Frieden et al. (2019)), we see that in each scenario the community saves an important amount per year. This aspect provides opportunities for the community, such as investing in a shared energy storage capacity or reducing the payback period of the investment.

Finally, splitting the production period in sub-periods based on a potential 'peak production time' can have an important effect in adequately matching the production with consumption. Consequently, better performances are obtained in such days. Long-term, coaching people with several recommendations per day can have a positive impact in their energy consumption behaviour.

Table 5
Results comparison

Scenario	Fig.	Member count: ideal	Member count: enthusiastic	Member count: normal	Member count: non-enthusiastic	NEEG without IRS [kWh/day]	NEEG with IRS [kWh/day]	SS without IRS [%]	SS with IRS [%]	v_{saved} with IRS [EUR]	Observations
1 (100% ideal members)	6	20	0	0	0	329.23	229.82	37	56	7908	• reflects the optimal case • absolute theoretical extent in terms of performances • simulated consumption remarkably fits the production • strong increase in consumption noted in July • almost 30% NEEG reduction comparing to the expected case • energy bill reduced by 19% comparing to the expected case
2 (100% normal members)	7	0	0	20	0	329.23	274.63	37	47	6926	• adequate fit of consumption and production • the stochastic behaviour impacts performances • in July, consumption increase is not significant during the day • almost 17% NEEG reduction comparing to the expected case • energy bill reduced by 10% comparing to the expected case
3 (100% non-enthusiastic members)	-	0	0	0	20	329.23	295.23	37	43	6494	• decrease by 10% in NEEG comparing to the expected case • energy bill reduced by 6% comparing to the expected case
4 (50% normal and 50% enthusiastic members)	8	0	10	10	0	329.23	264.2	37	49	7144	• overall consumption change is impacted by collective consumption of each category • thus, some production peaks may not be perfectly covered • the manager relies more on enthusiastic agents for important consumption modifications • almost 20% NEEG reduction comparing to the expected case • energy bill reduced by 12% comparing to the expected case
5 (25% enthusiastic members and 75% normal members)	-	0	5	15	0	329.23	268.96	37	48	7036	• almost 19% NEEG reduction with just 5 enthusiastic members • energy bill reduced by 11% comparing to the expected case
6 (25% enthusiastic members, 50% normal members and 25% non-enthusiastic members)	9	0	5	10	5	329.23	273.9	37	47	6901	• scenario similar to reality • normal and enthusiastic members provide an important contribution • during high production periods for raising consumption • during these periods, we can also notice the differences in contribution by member type • non -enthusiastic members are required to reduce consumption most of the time • performances-wise, the simulated NEEG is similar to scenario 2 • enthusiastic members compensate for the impact of non-enthusiastic members • energy bill reduced by 10% comparing to the expected case

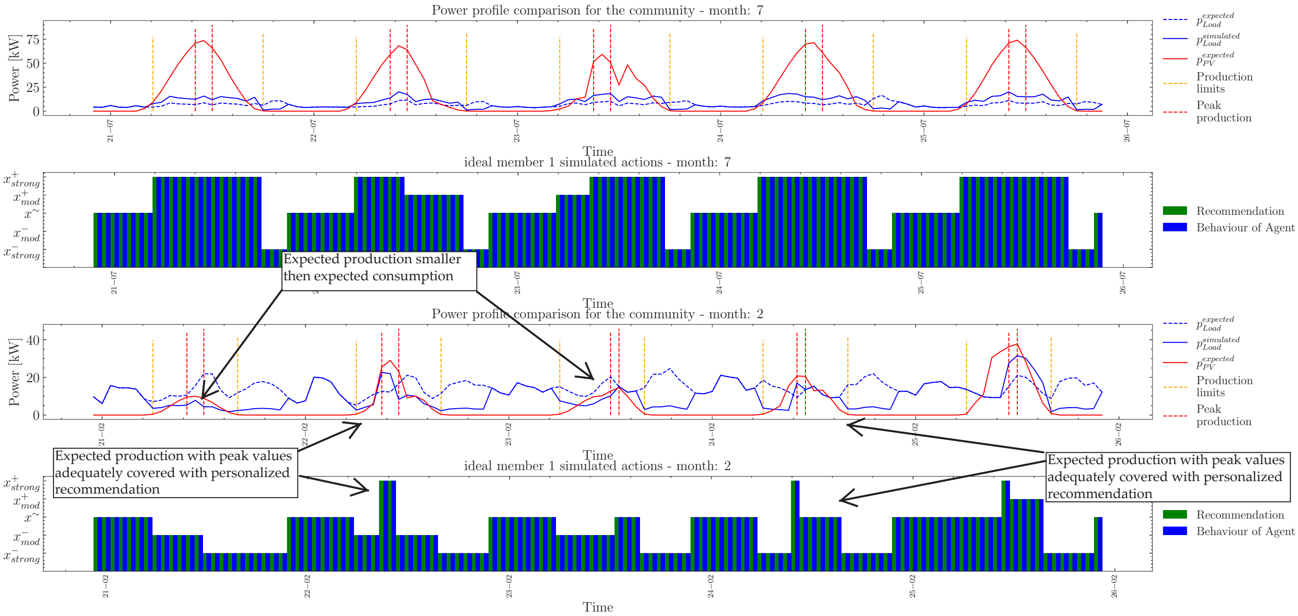

Figure 6: Energy community exclusively composed of agents from the ideal category

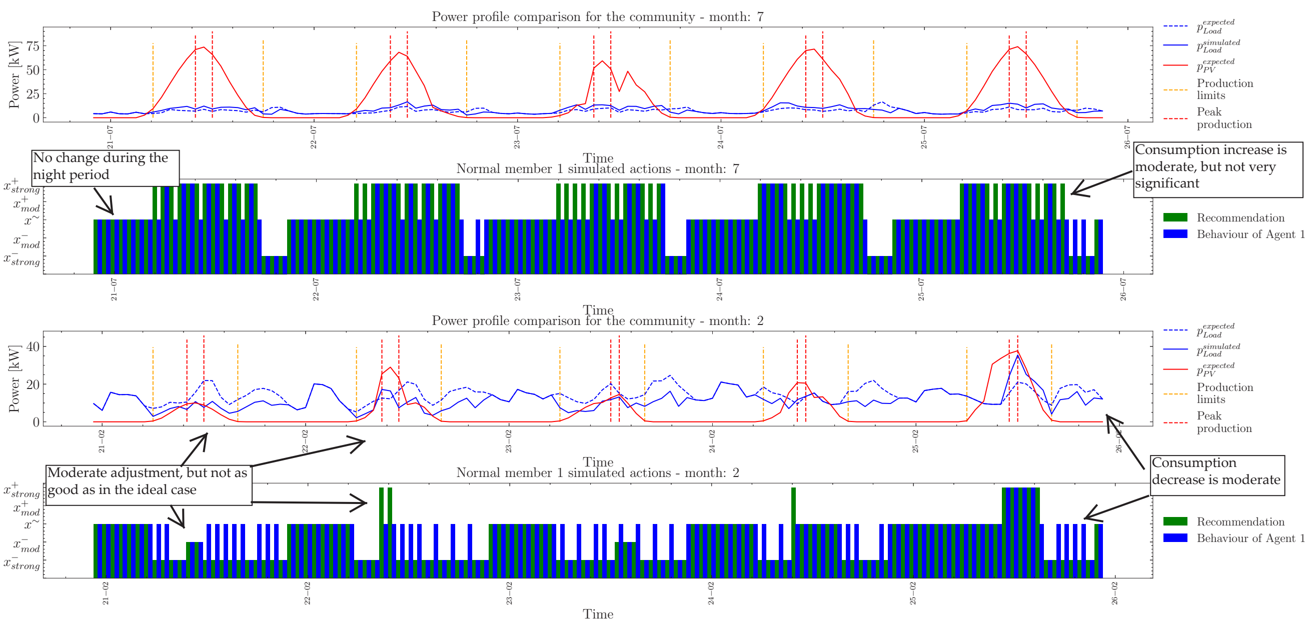

Figure 7: Energy community exclusively composed of agents from the normal category

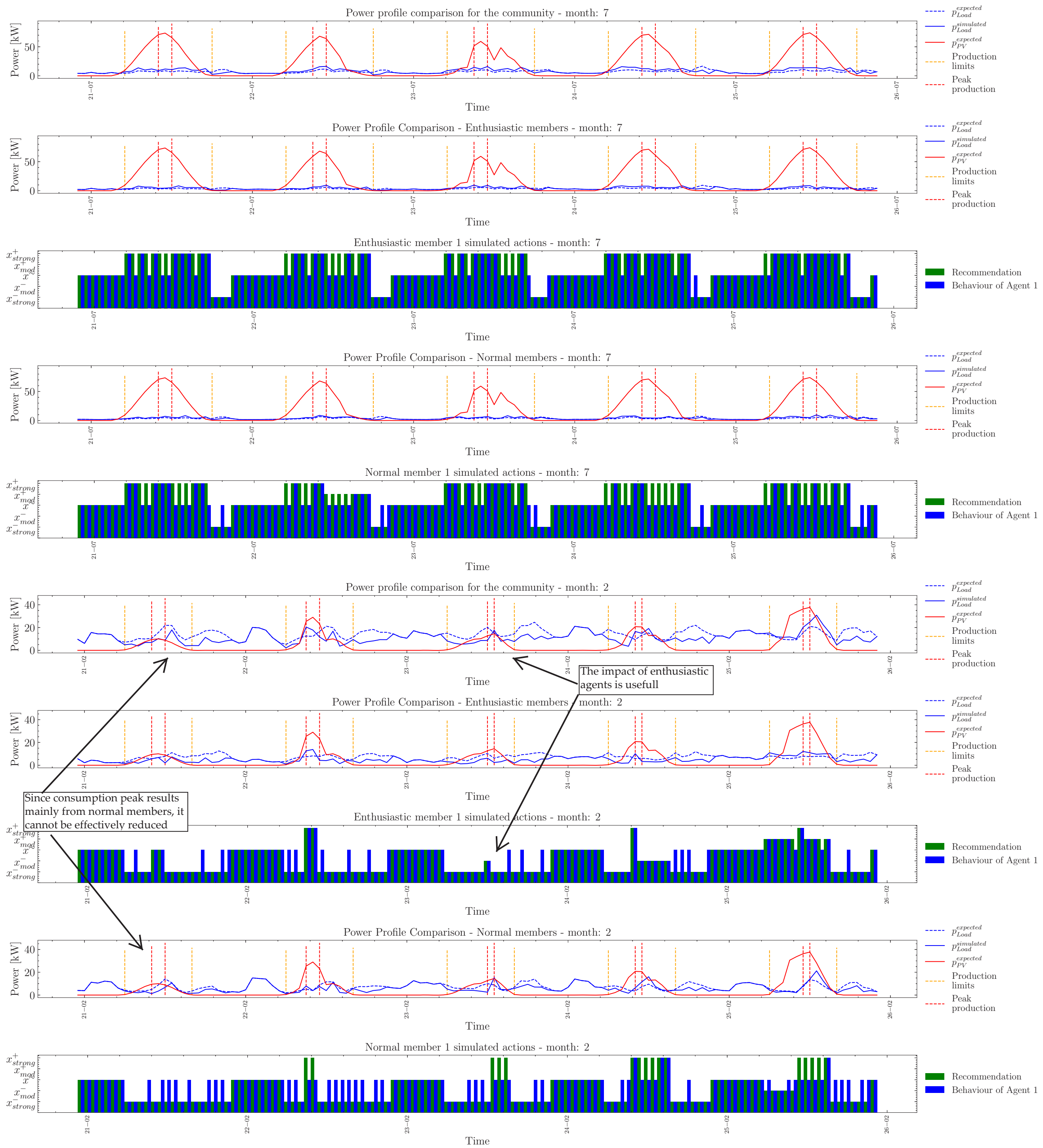

Figure 8: 50% Normal Agents and 50% Enthusiastic agents simulation results

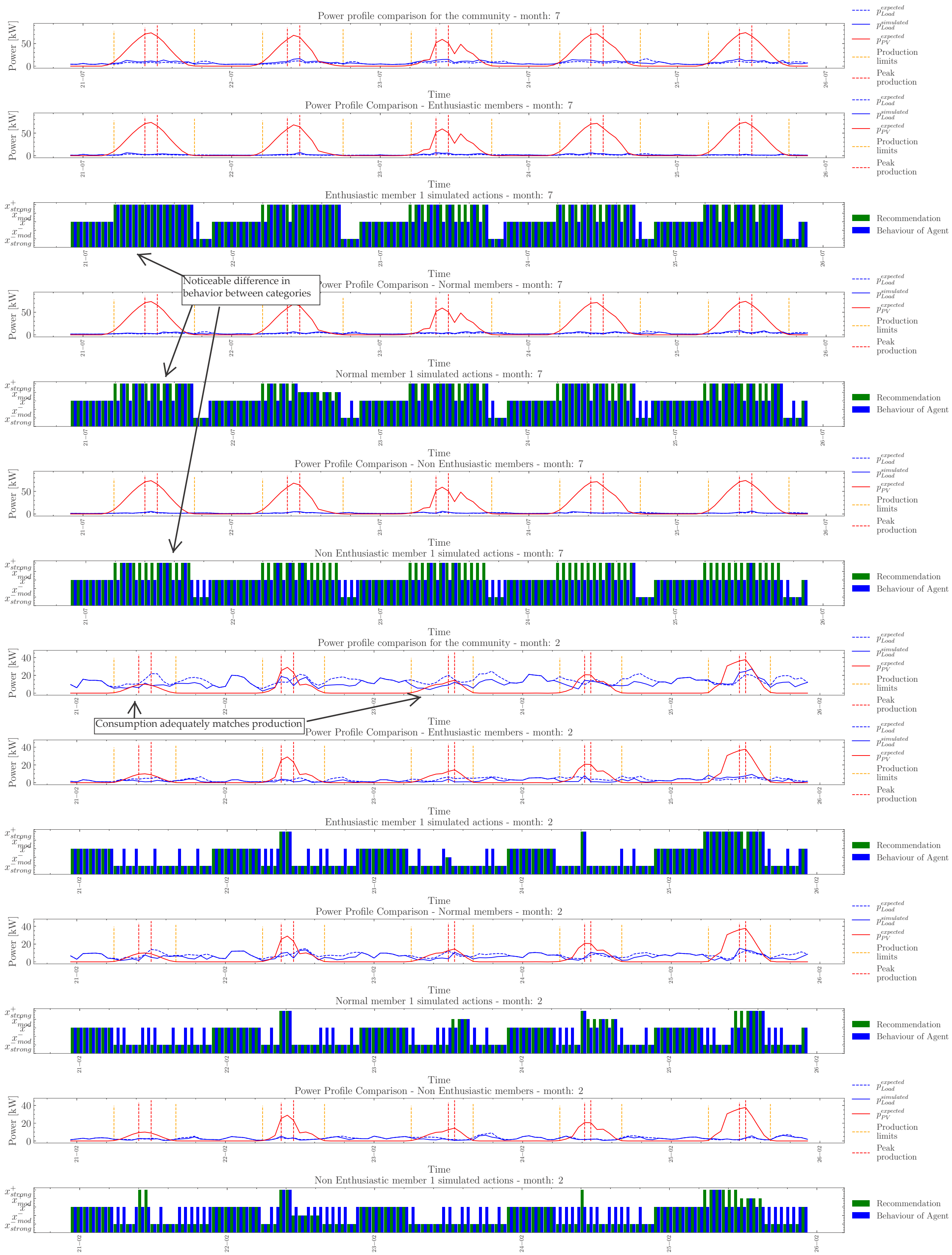

Figure 9: 50% Normal Agents, 25% enthusiastic agents and 25% non-enthusiastic agents simulation results

5. Conclusions

In this paper, we propose a method for simulating energy communities through multi-agent systems. The multi-agent framework represents a possible solution to model the collective action of community members who provide a certain flexibility to the energy system by modifying their consumption at specific times. Moreover, the multi-agent framework allows for a more realistic simulation community members since complex behaviours can be modeled inside agents.

A first contribution of this paper is reflected in the multi-agent model of a community of people, where the willingness to change consumption according to a personalised recommendation is modeled in stochastic manner, allowing agents to be clustered in several categories. Consequently, agents act autonomously in the simulation according to their own behaviour and the received recommendation, thus showing the possible impact from a collective point of view.

Another contribution that is presented in the paper is related to the intelligent recommendation system employed by the manager, who formulates personalised recommendations according to an expected view of the behaviour of people in the community. Moreover, the recommendation is given in an instructive way to improve the long-term behaviour of community members. Comparing to other works, instead of solely relying on an optimisation model Bartolini et al. (2020); Rafique et al. (2018); Tomin et al. (2022), we offer several insights into the potential daily involvement of people, thus providing flexibility.

Further research work will address developing possible mechanism for modeling the change in time of the willingness to modify consumption, due to the influence of different factors. In this way, we may see how non-enthusiastic members could become enthusiastic under the impact of recommendations.

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