



Human-centered control systems : application to energy communities

Mircea Simoiu

► To cite this version:

Mircea Simoiu. Human-centered control systems : application to energy communities. Automatic Control Engineering. Université Grenoble Alpes [2020-..]; Universitatea politehnica (Bucarest), 2023. English. NNT : 2023GRALT060 . tel-04416509

HAL Id: tel-04416509

<https://theses.hal.science/tel-04416509>

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THÈSE

Pour obtenir le grade de

DOCTEUR DE L'UNIVERSITÉ GRENOBLE ALPES et de l'UNIVERSITE POLITEHNICA BUCHAREST

École doctorale : École doctorale Électronique, Électrotechnique, Automatique, Traitement du Signal (ED EEATS)

Spécialité : Automatique - productique (AP)

Unité de recherche : Laboratoire G-SCOP

Systèmes de contrôle centres sur l'homme : application aux communautés énergétiques

Human - centered control systems: application to energy communities

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HUMAN-CENTERED CONTROL SYSTEMS: APPLICATION TO ENERGY COMMUNITIES

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A Thesis Submitted to
the Doctoral School of the Faculty of Automatic Control and Computers,
University Politehnica of Bucharest
and to the Doctoral School of Electronics, Electrical Engineering,
Automation, Signal Processing
University Grenoble Alpes
in Partial Fulfillment of the Requirements for the Degree.

DOCTOR OF PHILOSOPHY

BUCHAREST, ROMANIA

2023

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To my father.

ACKNOWLEDGMENTS

Firstly, I would like to express my profound gratitude to my family for their exceptional support over the years. Specifically, I owe a great deal to my parents, who have made significant sacrifices to foster my education and growth. I also want to acknowledge my sister, Ana, who has consistently believed in me. Lastly, I am grateful to my in-laws for their encouragement and faith in me during these past years.

I would also like to extend my deepest and warmest thanks to my wife, Mădălina. She has stood by my side through the most challenging and stressful times, believing in me and supporting me even during periods when we were separated while I was working in France as part of a joint PhD agreement and she was in Romania. This work would not have been possible without her unwavering support.

Secondly, I would like to express my gratitude to the professors from my research team at University Politehnica of Bucharest, namely Sergiu Iliescu, Ioana Făgărășan, Vasile Calofir, Nicoleta Arghira, Iulia Stamatescu, and Grigore Stamatescu. Their support, encouragement, and guidance over the years have been instrumental in my academic development. Each of them, in their unique way, has contributed to my growth as a researcher. Professor Iliescu's approach to problem-solving, Professor Făgărășan's innovative thinking, Vasile Calofir's meticulous attention to detail, Nicoleta Arghira's passion for teaching, and Iulia and Grigore Stamatescu's dedication to research have all left an important mark on my journey.

Finally, I want to convey my deepest appreciation to Stephane Ploix, my thesis co-director from France. Professionally, he has been an inspiration to me in terms of values, research vision and creativity. On a personal level, he has believed in me and guided me through an amazing journey in France, during which we both gained a deeper understanding of each other. He has changed my life by shaping me into the young researcher I am today, and for this, I will forever be indebted to him.

ENGLISH SUMMARY

This research study explores control strategies for energy systems, giving due consideration to human involvement and personal preferences, dissatisfaction, and motivation. The aim is to create a paradigm shift from traditional approaches where control strategies often overlook the behaviour of people. As an alternative, this study introduces the actor-service- system paradigm, a novel approach for designing innovative energy systems that significantly incorporate human actors.

The proposed solution, applied in the context of energy communities, refers to a recommendation system acting as a service that facilitates the interaction between people acting as community members and the pure technical system consuming or producing energy. Several proposed service implementations demonstrate how optimization problems may be shaped to provide solutions that maximize system performance and minimize user dissatisfaction when adhering to recommendations. Since in energy communities people voluntarily join to share energy and foster environmental benefits, the recommendation system capitalises on the potential psychological, motivational and social aspects that may be involved in such an organisation. Subsequently, several interaction and behaviour models are proposed, along with associated recommendation strategies developed on optimisation principles. The idea is to demonstrate how stochastic models or Hidden Markov models may represent suitable solutions for describing how people react to recommendations in their daily energy consumption behaviour, while interaction models implemented as multi-agent systems represent a way of organising the community around the recommendation system. Altogether, these elements harmonise human effort and comfort to achieve various objectives set by the community in terms of energy performance.

The effectiveness of the proposed methods is demonstrated through several case studies. These studies show concrete examples of the recommendation system's impact on contrasting communities and highlighting the actor-service-system paradigm common role. The recommendation system embodies the core idea of future control techniques, positioning the service as a decision-aiding assistant and emphasising the psychological significance of recommendations in enhancing performance or fostering long-term sustainable behaviours.

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CHAPTER I

INTRODUCTION

1.1 Role of humans in the energy transition

Technology evolves around us with incredible speed, as innovation in the digital world grows exponentially. We can notice that we have abundant digital services available at a glance, thanks to incredibly complex data-center infrastructures. Urban services are embracing digital transformation, as the communication between cities and citizens becomes strongly facilitated by informational technologies. Around us at home we notice various so called intelligent devices, ready to help us in our every-day routine.

However, everything comes at a price. Even though these services may seem accessible in terms of cost, the energy (especially electricity) consumed to keep everything up and running is sometimes wrongfully neglected. By embracing comfort, people tend to forget about indirect implications of their actions in terms of energy consumption. This is because, traditionally, we focus more on the economical evaluation of products and services. While the purchasing power grows, the focus shifts from the economical evaluation of services and products to other priorities, while energy demand constantly grows. As the lifestyle of people improves, their energy demands (electric heating) concurrently grow, while energy consumption is often disregarded. One should not mistake that high values for economical indicators such as purchasing power are definitely desired, however in a permanently evolving environment in terms of demand, attention should always be paid on how energy is consumed.

Efficient energy consumption becomes an additional objective of the global aim to reduce global carbon emissions. In the European context, this challenge is clearly addressed in the European Green Deal (European Commission. Directorate-General for Energy, 2012), emphasising that there is clear need for more effort in making cities, housing or transportation systems significantly

more long-term sustainable. This is not an easy challenge, as simple infrastructure investments or building retrofitting might not have the expected impact. Often it is noted that there is typically a performance gap between the desired energy performances established during the design stage and the actual operational performances obtained when the buildings are inhabited.¹ It is clear that people have increased their comfort requirements and become less aware of the energy they consumed.

¹ In Germany, it is noted that a major building retrofitting effort did not lead to effective reduction in thermal energy consumption, as values decreased from 131 kWh/m^2 in 2010 to just 130 kWh/m^2 in 2018 (Cécile Boutelet, 2020)

1.2 Energy communities - a possible solution

As systems are not able to achieve performances alone, the focus gradually shifted towards human behaviour. In Guillard (2021), the concept of "energy sobriety" is mentioned as the idea of adapting our behaviour for consuming energy in a more efficient conscious manner. This concept envisions a possible objective that may be achieved as a consequence of various contributing actions, such as: conscious efficient energy consumption, prioritisation of energy consumption related activities (or appliances), and others.

Another concept proposed by European forums (still connected to energy sobriety by the social component) is represented by energy communities. A typical energy community is a form of organisation voluntarily formed by people or small businesses in which renewable energy is produced and consumed, with the aim to obtain environmental, economical or social benefits (Frieden et al., 2019). As an important rule, decisions are established in the community in a democratic manner regarding all aspects: specific objectives, the manner in which benefits are shared between community members.

There may be two community types: renewable energy communities must be limited geographically and are generally opened to all types of energy (European Parliament and Council of the European Union, 2018), while citizen energy communities are focused on electricity and may not be limited geographically (European Parliament and Council of the European Union, 2019). Aside the technical aspects related to energy, there is an important idea behind energy communities: the social component. By relying on voluntary participation, it is expected that people who are somehow motivated towards sustainable energy consumption gather around together under a specific goal.² In the same way, it is expected that people become more aware of how the energy is consumed since they participate voluntarily, they are motivated and their social image is open towards other community members.

² Whether this goal is environmental or economical, people should decide together and renewable energy must be involved in some way.

1.3 Potential challenges

Most of the research works in the domain of energy systems automation rely on controlling appliances and renewable resources (often defined as "systems"). It is clear that a change of direction is needed since the systems alone, as designed, cannot achieve the a priori established performances when people are actively involved in the operational phase. Many energy systems involve humans, from grid to homes with all the intermediate scales. In a human-system cooperation involving energy consumption, the final decision should always be at the side of people, since they reflect the true, unconditioned demand. So, efficient energy consumption should ideally come as a consequence of purely motivated, uncontrolled behaviour. With this in mind, this work carefully addresses the issue of automation and the involvement of systems in human life, since it is desired that systems sufficiently aid people in developing their behaviour and becoming better in their own energy consuming actions.

Another challenge is related to the efficient usage of renewable energy through flexibility. As storage systems are available, it is still difficult to integrate them with households and other systems as economical and dimensional problems arise. It would be interesting to investigate whether people, with their energy consumption behaviour, can provide energy flexibility when needed. The potential outcome may be represented by cities with energy systems designed and operated in a more profound, human-centered manner, with renewable energy sources that are exploited to their potential by conscious human behaviour.

1.4 The thesis

Given the current challenges in terms of energy sobriety, sustainability and the future of energy consumption, the problem investigated in this thesis is how to manage the human involvement in systems such as an energy community. Specifically, in a context where renewable resources such as photovoltaic (PV) panels are available, the challenge is to influence a distributed system (reflected by community members and their autonomous energy consumption behaviour) to act in a manner that capitalizes on the available renewable production. The problems investigated in this work have the potential to uncover a way in which both systems and humans may act in coordination, with the voluntarily participation of people having a decisive impact on improving the system performance.

The main contribution of this work is reflected in a recommendation system, a solution that takes into account cognitive aspects of human behaviour to guide people in their daily actions so that they may improve their energy consumption behaviour. The system is integrated in several models and controlling principles for influencing energy communities and to properly evaluate the impact of such an organisation. This work is expected to be a small stepping stone at the foundation of a new paradigm, in which systems are designed considering the human impact as a significant, contributing partner in achieving the desired performance. Consequently, this work can envision a future where technology must be shaped so that humans cooperate with systems in a coordinated, uniform manner, so that people improve their behaviour, acquire knowledge, prioritize what is meaningful to them and fulfill their objectives. With the models, the controlling principle and the simulation tools presented in this work, one may catch a glimpse into the potential of collective action, where people are guided and sometimes cooperate with the surrounding systems to obtain environmental and economical benefits, taking individual decisions that affect both the performance of the community, but also have an impact in terms of human effort.

CHAPTER 2

STATE OF THE ART REVIEW

2.1 Energy flexibility

An energy system based on renewable energy is typically composed of consumers, renewable energy sources and the grid. Typically, in the operational phase, consumers rely on the renewable energy (if available) and on the grid in other cases. However, two consequent situations may be observed here: firstly, there are times when there is excessive renewable production that is often wasted, since consumer demand is not high enough and secondly there are other times when demand is significantly higher than renewable production. In this case, energy flexibility can be interpreted as the capacity of the system to adapt its consumption and production to achieve energy balance.

Energy flexibility is subject of many research works, given the ongoing development of renewable sources that are frequently dependent on weather conditions, and therefore generate power in a more or less unpredictable manner³. In residential and urban local levels, flexibility may be achieved through the usage of storage systems in different forms: batteries, electrical vehicles, etc. This implies that there is a certain control mechanism employed for the charge/discharge process to occur in a robust manner, aiming for maximum benefits. Azevedo and Santos (2021) present a residential-specific energy system with PV panels and storage capabilities. Although a typical low-power system is presented, the authors indicate that the cost of batteries may represent a problem in other situations. Dongol et al. (2018) propose a model predictive controller that manages a storage system for balancing the consumption and production in a residential scenario. Similarly as Azevedo and Santos (2021), the authors indicate that as prices might fluctuate, operational costs of the system might be higher than expected. van der Meer et al. (2021) propose a model predictive controller for a residential storage system, which is

³ For example PV energy production is influence by temperature, partial shading phenomena, solar irradiation direction, etc.

⁴ Self-consumption measures how much of the available production is internally consumed in the energy system over a period of time.

⁵ Self-sufficiency indicates how much of the energy consumption is covered by the energy produced internally by the system

⁶ Here, "sizing" may refer to the physical size in terms of space, but it may also refer to other relevant technical characteristics of the systems, such as peak power.

⁷ For example, the criteria might be economical (operational costs, grid energy costs), environmental (carbon emissions), or any other metric that is relevant for the stakeholders, including even the human actors' satisfaction.

⁸ Given a multi-criteria optimisation problem, Pareto solutions are equally optimal, non-dominated, solutions that cannot be better in one objective without penalising the others

evaluated in terms of self-consumption ⁴ and self-sufficiency ⁵. As a future research perspective, the authors note that flexibility for a system with distributed buildings (instead of the traditional individual scenario) could pose an interesting research problem. Engels et al. (2019) present an analysis for a storage system investment, aiming for revenues maximisation using an evolutionary optimisation algorithm.

For economical and environmental evaluations, there are two situations often investigated in research works:

- the design stage of an energy system - often referring to optimally sizing ⁶ renewable resources and energy storage systems such as initial investment cost is minimised.
- the operational stage of an energy system - referring to a system that is already deployed, but the challenge is to find the optimal energy management strategy that minimises a certain criteria considering a predicted behaviour of the system for a certain period of time ⁷.

As for the design stage, techno-economical analysis involving various factors such as degradation and cost (Maheshwari et al., 2020) or charge-discharge cycles (M. Cao et al., 2020) are taken into account. Degradation and other criteria are often included in a Pareto analysis ⁸ along with traditional economical criteria, letting a human decision maker choose a favourite strategy among possible Pareto candidates.

There are also studies related to district level integration of storage systems (Sameti and Haghighat, 2018), even as electrical vehicles (Fanti et al., 2017), in order to minimise the costs. In the same way as Maheshwari et al. (2020), Pareto analysis is developed to present multi-objective optimisation problem solutions between criteria such as cost and CO₂ emission minimisation.

Overall, storage systems represent interesting and useful solutions for providing energy flexibility, however several important aspects should still be subject to subsequent research:

- deployment of storage systems might be difficult in residential areas, due to various safety and economical concerns;
- long-term analysis of such investments (including pay-back periods) are still to be investigated, considering the fluctuating nature of prices or degradation costs;
- environmental impact of such solutions is still evaluated from a preliminary perspective, with the focus being typically placed on economical impact;

- investment costs may be too high;
- more research is needed to assess the impact of storage systems in a distributed architecture.

On the other hand, another possibility to obtain energy flexibility is represented by involving people in load shifting mechanisms or consumption increase/decrease. Despite involving electrical vehicles, transportation systems (Groppi et al., 2021) or storage systems as a means to provide flexibility and further to improve performances, involving humans in energy flexibility represents a solution with significant potential.

2.2 Energy communities

As the aforementioned challenges are yet to be addressed even for individual situations, a greater challenge is to improve flexibility at district or city level. Moreover, given the potential of people to adapt their consumption behaviour and thus to provide energy flexibility, the social component becomes increasingly important, besides the technical performances that are traditionally considered.

To this aspect, energy communities projects are being developed. The European Union has launched several platforms to support the implementation of energy communities in various contexts such as islands ("Clean Energy for EU Islands" European Commission, n.d.-a) or towards the transition to smart cities ("Smart Cities Marketplace" European Commission, n.d.-b). A list of notable projects includes the COME-RES Project (come-res.eu, n.d.), aimed to foster development of energy communities in several European countries and the COMPILE project (compile-project.eu, 2018), where some of the main results refer to support tools for energy communities economical evaluation and development. These projects represent fundamental steps in developing energy communities and familiarising people with the idea of shared renewable energy, however management solutions that reflect an active cohesion between people and the energy system ⁹ are yet to be proposed in an implementable form. As it is emphasised in different research papers (Gjorgievski et al., 2021), barriers such as community members willingness to participate in community life, the impact of human behaviour or the necessity for flexibility as a consequence of variable renewable production, research works have pointed out potential modeling and simulation tools to identify the best possible management solutions. These solutions refer mainly to decision making models such as optimisation frameworks or multi-agent systems. In the following sections, the most relevant research related to these pillars will be presented.

⁹ Energy system refers to the renewable energy sources, storage systems, the grid and other infrastructure components.

2.3 Optimisation models

Optimisation models for energy communities can be classified in two categories: models typically used in the design phase of the energy system that will be integrated in the energy community and models for optimised management of the energy system during the operational phase.

For the design stage, we can see a relevant example provided by Fina et al. (2020), where the authors describe an optimisation model to find the optimal PV capacity for several community configurations. Interestingly, the authors note that energy communities should be implemented at neighbourhood level first, as trust in the energy system is significantly relevant. Weckesser et al. (2021) investigate the economical impact of different communities configurations, with different storage capabilities optimally managed to provide flexibility. Bartolini et al. (2020) present a mixed integer linear programming optimisation model for minimising costs when installing and operating renewable resources for electricity or heat in an energy community. Fan et al. (2022) describe a multi-objective optimisation design model for a community with storage systems, evaluating the results with a Pareto analysis. The criteria involved were both related to economical evaluation (annual total cost and grid interaction), as well as environmental cost (annual carbon emission). Another example is presented by Sima et al. (2022), where a university campus is considered an energy community and a techno-economical analysis based on optimisation of costs is developed. X. Chen et al. (2021) recognise that deployment space might be an issue when implementing storage systems, besides describing an optimisation model for the design stage of an energy community. Braeuer et al. (2022) describe a design method for energy communities based on several criteria such as self-consumption, self-sufficiency, autonomy or net-present value.

Regarding the operational phase of an energy community, by using estimated individual or collective consumption and production data, researchers analyse potential activities involving energy sharing that could take place in an energy community. Of such activities, peer-to-peer trading is frequently investigated. Soto et al. (2021) present several energy sharing models, emphasising that cooperation in distributed energy systems is yet to be explored since most models focus on individual profit for each member involved. Bokkisam and M.P. (2021) present an energy trading model coordinated by a central operator who determines internal trading prices. The objective is individual profit of community members, as members could buy electricity inside the community at a more advantageous price. Khorasany et al. (2021) describe a peer-to-peer trading model with storage and PV panels for each community member, where

each member aims to maximise its own utility function. Again, it is noted that a coordinator governs the informational exchange at community level. Tomin et al. (2022) describe a bilevel optimisation model for an internal market of a community, with an operator at supervisory level that aims to minimise operating costs. N. Liu et al. (2017) present a dynamical pricing scheme, with a virtual entity who coordinates energy sharing activities between prosumers. From a more practical perspective, Di Lorenzo et al. (2021) describe a power sharing model between community members. There are also multi-objective optimisation methods such as the one presented by J. Liu et al. (2021), where the authors aim to design a net-zero energy system with electric vehicles and hydrogen storage. The criteria used for evaluation are self-consumption, annual electricity bill and carbon emission. Flexibility in the operational phase of an energy community remains a recurrent topic in research, as Manso-Burgos et al. (2022) describe different energy storage systems integrated in an energy community, with the aim to maximise economic savings and self-consumption. It is stated here that human organisation and collective behaviour within the community are yet to be explored. Similarly, Li et al. (2022) present an optimisation model for an energy community that takes into account weather forecasts and various scenarios, noting that human behaviour might profoundly influence the community performances. Aside from these models, Xiong et al. (2020) propose an optimisation model for an energy community that allows users to choose their own consumption mode between several choices, providing users a decision to whether opt for green energy or energy bill minimisation. This concept suggests the idea that people should be deeply involved in the control of the community.

Overall, there are two important aspects that can be identified in most research works:

- Most optimisation models do not take into account the human behaviour and thus represent an "ideal" representation of communities. Therefore, before successfully implementing energy communities with a set of performance objectives, knowledge of human behaviour must be thoroughly accounted for in models and simulation scenarios.
- There is often identified a central figure (community operator, community coordinator, etc.) that coordinates the activity in the community, often employing direct control over community resources/loads. When referring to the social component, excessive control could yield a certain discomfort for community members.

Since an energy community can be interpreted as a distributed system where each community member is autonomous, multi-agent systems might represent suitable models for representing the decision-making process of each community member, as noted by Xiong et al. (2020).

2.4 Multi-agent systems

Aside from the aforementioned works, multi-agent models may represent a suitable solution for assessing the collective impact of an energy community as a distributed system. We can see for example the idea of community member profiles that is addressed by Fouladvand (2022), where a thermal energy-based energy community is investigated, with each member having a profile developed according to the Social Value Orientation theory. Lai et al. (2022) describe an energy community modeled as a multi-agent system with storage and reinforcement learning for agents. We can also notice another similar aspect, a central entity in the form of the community aggregator who is involved in appliance scheduling.

From a practical point of view, multi-agent systems represent interesting simulation instruments, especially for investigating case with multiple autonomous entities that interact with each other and an informational exchange is identified between agents. For example, L. Chen and Gao (2021) propose an example in the solid waste recycling sector, where a multi-agent framework allows a deep understanding of the collective behaviour and imperfection of people under different policies. Zhou et al. (2018) propose a multi-agent model for a peer-to-peer trading mechanism that is evaluated according to the self-sufficiency of the whole system. Once again, it is stated that imperfections of human behaviour should be thoroughly taken into account in the future. Another multi-agent model (described in Reis et al., 2020) is integrated with a scheduling mechanism for shiftable loads, aiming to minimise the operational costs.

By analysing these solutions involving distributed systems, we can notice that energy flexibility can be obtained from either storage systems or controllable shiftable loads. As a consequence, human behaviour, preferences or comfort are not sufficiently considered in such collective organisation.

2.5 Recommendation systems

From a general perspective, recommendation systems collect information and, according to the preference profile of the user, develop a list of items that are

ranked according to a certain model, as it was proposed by Quijano-Sánchez et al. (2020). However, in the energy sector, recommendation systems are rather viewed as guidance systems which provide certain goals for people to follow, given the complex nature of energy consumption, generation and transmission. Specifically, recommendation systems represent a way to provide simple and concise information to people in order to help them to achieve their objectives in terms of energy efficiency and sustainability. These systems represent an interesting alternative to the excessively technical and automation-oriented solutions that focus on shiftable loads or storage infrastructure. Moreover, as technology evolved, it became increasingly easier to present insights, feedback and other information in an understandable manner so that people accept it and use it in their decision making process.

There are few examples describing recommendation systems in the energy sector. Starke et al. (2015) conduct an online survey and ask participants to identify energy saving measures, in an effort to raise awareness towards the impact of energy consumption. Pinto et al. (2019) describe a recommendation system which identifies patterns in energy consumption and tries to provide energy-efficient recommendations according to previous scenarios. Some other examples such as the INVOLVED project (considered in (Alyafi, 2019)) has shown that Persuasive Interactive Systems (PIS) could be used to effectively improve human behaviour. The idea is to assist people in their daily activities to increase both efficiency and comfort. Still related to the same project, the same principle could be identified by Pal et al. (2019), while Laurillau et al. (2018) emphasise how people can interact with energy management tools through simple interfaces, in order to become aware about the best energy management approach.

It is noted, however, by Onile et al. (2021) that very few recommendation systems have found real validation. Furthermore, it is stated that recommendations could represent a concrete way to enhance sustainability and energy efficiency. For this approach to have a positive effect, people should always receive information regarding the impact of their action in the form of a feedback mechanism.

2.6 Deterministic vs. stochastic modeling of human behaviour

Integrating human behaviour in energy management strategies represents an important and difficult challenge. Besides using stochastic approach for different aspects of energy systems such as network availability (Prince Agbodjan

et al., 2021, Prince Agbodjan et al., 2020), some other research works referring to stochastic models have been considered as a good alternative in modeling uncertainty characterising human behaviour.

S. Chen et al. (2020) propose a classification of human energy consumption behavior in two categories (persistent and transient behaviours), emphasising the importance of energy consumption behaviour in operational optimisation of energy management. Pal et al. (2019) investigate the impact of actions and energy efficiency through multi-objective optimisation models. Interestingly, in this work more focus is put on the human component through thermal and air quality dissatisfaction evaluation. In (Hong et al., 2016), the authors identify a framework for modeling occupant behaviour in several steps, starting from a model between human needs and subsequent actions and further going to simulating the impact of actions in the system. In (Azar and Menassa, 2012), the authors investigate the issue with "the performance gap" inferred by the unpredictable nature of human behaviour, indicating that more attention should be given on how people are educated to consume energy, rather than labeling the energy crisis as "purely technological". Another works address the performances gap (Chapman et al., 2018), emphasising that stochastic modeling could represent an adequate approach for developing more consistent and realistic consumption models at collective level. Stochastic modeling is also used in modeling the willingness to participate in a community (Perger et al., 2022). Although in (Norouziasl et al., 2020) occupancy is estimated from a stochastic point of view, it is emphasised that modeling the human impact in building performance still needs to account for multiple factors, therefore it represents a critical challenge for researchers.

By analysing these works, it becomes evident that the research community is increasingly acknowledging the influence of human energy consumption behaviour on overall building performances. However, it's important to note that only certain aspects of human behaviour can be modeled in a deterministic manner, while others are more aptly captured through stochastic modeling. Specifically, while some small elements of human behaviour can be predicted with a high degree of certainty and thus be modeled in a deterministic manner, the stochastic elements involve a degree of randomness and unpredictability that is usually associated with time, context and the variety of situations an actor can find itself in. Thus, a persistent challenge that remains is determining the optimal frontier between deterministic and stochastic modeling. This involves discerning which aspects of human behaviour can be reliably predicted and which are subject to variability, in order to effectively integrate this knowledge into the development of energy-efficient systems.

2.7 Conclusions

From a conceptual point of view, in the context of renewable energy sources becoming affordable and increasingly popular among residential and industrial sectors, one can notice that the need for energy flexibility becomes critical. One specific example could refer to production being variable due to weather conditions and other external factors, leading to uncertainty in the overall system. It is up to the local energy systems to manage the energy flexibility properly so that the dependency of the grid is at a minimum, the system is up and running and all the stakeholder needs are met. Since the energy communities concept proposed by the European forums is quite permissible, one could also notice there is significant space for creative solutions to be developed among the international research space to increase energy flexibility.

Consequently, specialised literature describe peer-to-peer trading mechanisms, energy sharing models between residential energy consumers, locally deployed storage systems and electrical vehicles as possible activities and solutions to be found in energy communities. Typically, it could be also noticed that there is a local central entity in charge of managing the energy flow inside the respective system, a solution that may potentially lead to increased automation through direct control of appliances and subsequently to increased discomfort among people.

However, the underlying principle of energy communities is to actively involve people in the community life, to increase the awareness towards how energy is consumed and produced. To this aspect, very few solutions try to shape the role of human behaviour in such an organisation. Although stochastic modeling, optimisation models or multi-agent systems offer a technical perspective on how the infrastructure in a community could be managed, **it is clear that research must not consider the "system" as a the unique problem to be solved in an energy community, but how the cooperation "human and system" could be managed in a way that the human counterpart is equally important.** The immense potential of such a cooperation in the energy sector is yet to be discovered. In order to have control on modern energy systems, new paradigms should be proposed by the sciences of system control.

CHAPTER 3

ACTOR - SERVICE - SYSTEM: A NEW PARADIGM FOR DEFINING ENERGY COMMUNITY MODELING REQUIREMENTS

Since energy communities are often linked to residential homes and renewable energy consumption, it's important to note that building systems are especially unique. This is primarily because inhabitants interact with the system on a daily basis, resulting in a synergy of actions and effects based on human beliefs, desires, and intentions (Bratman, 1987), which continuously evolve over time. As a result, designing appropriate energy systems presents a complex research challenge, especially as we transition towards a distributed organization such as an energy community.

Before stating the research problem investigated in this work, it is assumed that there is a renewable energy community based on electricity (as defined in European Parliament and Council of the European Union, 2018), with people being members as a consequence of voluntary participation. Although electricity is the sole focus of this study, the proposed solutions may be applied in scenarios with other sources of renewable energy.

In this context, the research problem investigated in this work refers on how to effectively manage the collective human impact of an energy community so that energy flexibility and energy sobriety are increased as the community fulfills its objectives in terms of economical, environmental and social benefits. This

research problem may be further split in several 4 sub-problems (according to Fig. 3.1)

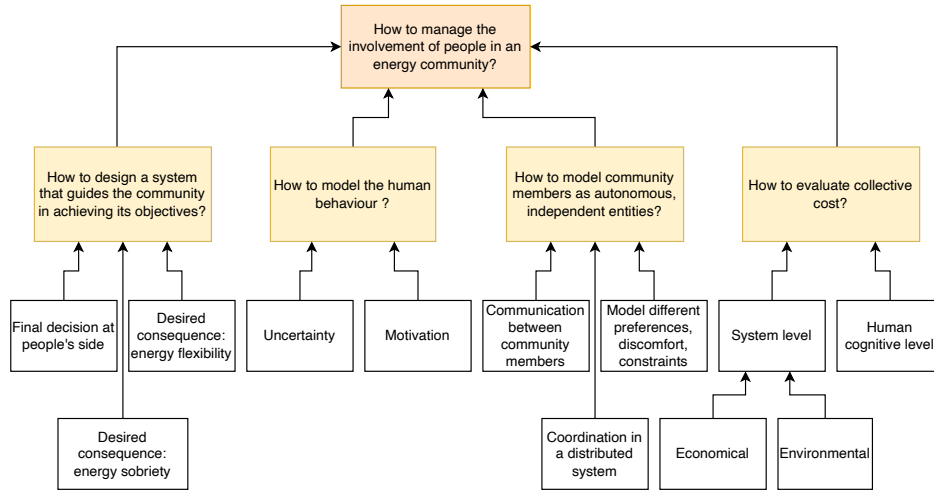


Figure 3.1: Research problem top-down view

The first sub-problem refers to developing a method for actively involving people in the community life. More specifically, by acknowledging that human behaviour has an important impact in the energy consumption of a building (as it is also emphasised in Azar and Menassa, 2012; S. Chen et al., 2020; Norouzi et al., 2020; Pal et al., 2019), the challenge is to focus on this impact and provide a technical solution that rather guides this impact towards fulfilling the objectives of the community. Nonetheless, we use the term "to guide" specifically because actual decisions that influence consumption should be taken by people. The consequence of control system taking decisions and directly acting on appliances excludes the human from the decision process and may possibly interfere with the true needs of people, thus causing discomfort which decreases the trust in the system¹⁰. Moreover, trust in the proposed solution is of significant importance. Considering that the energy sharing mechanisms that may appear in an energy community can be quite complex to be understood by community members in their daily activities, at all times people should use additional systems or services as tools and actively use this information in their lives to adapt and improve their behaviour. Moreover, if the action of the system is precise and in complete accordance with the objectives of the community, long-term trust in the service would definitely foster beneficial, sustainable behaviours and also better awareness towards energy consumption.

The second sub-problem refers to proposing a model of the human behaviour and its subsequent impact in the energy community. This sub-problem mainly refers to an effective way to represent the uncertainty and the unpre-

¹⁰ This reflects the case of excessive automation, where systems have a significant, intrusive impact in households - for example limiting the usage of a certain appliance to a certain period of time that may overlap with the user not being at home, an aspect that may increase discomfort

dictable nature of the human behaviour, in relation to energy consumption. Moreover, an important aspect to be considered is human motivation. One should not consider that motivation here does refer to whether people are motivated to participate in the community or not (such is the case in Perger et al., 2022), but to the fact that people are already voluntarily in the community and they have different motivational levels towards actively participating in the community. Moreover, this active participation should be considered from a two-fold, temporal perspective: a short term perspective referring to the willingness to participate in the community life and provide energy flexibility specifically when needed and a long-term perspective in which community members are expected to become aware of their impact and thus they become more motivated, they become more comfortable with the idea of voluntary participation and thus energy sobriety increases ¹¹.

¹¹ By fostering trust in the partnership with the system, people develop beneficial habits that would prove to become useful in the future. Consequently, the force of habit will render the attention of the user towards the importance of energy consumption in daily activities.

The third sub-problem refers to finding a way to view the community as a real distributed system. Specifically, community members should be represented by autonomous entities, since it is evident that each community member has its own particular perception, referring (but not only) to preferences, interests, discomfort. From a practical point of view, this representation would allow different models to be implemented, and therefore multiple configurations of communities could be investigated as a consequence. Moreover, it is clear that an informational exchange level is to be expected as part of the solution, since members may coordinate their actions between themselves, or could interact with a specialised entity (a recurrent idea in several research works Lai et al., 2022; N. Liu et al., 2017; Zhou et al., 2018). A distributed model would facilitate the implementation of such a level, considering the fact that not only human-human communication should be clear in daily collaboration, but human-system communication should be equally important ¹².

¹² Clear communication is a fundamental step in developing a trust-based relationship.

The forth and final sub-problem refers to the collective evaluation of the community. Besides typical measures of economical cost, environmental impact and grid dependence, it is important to account for the human effort in an equal manner. From a first point of view, system related performances such as cost or environmental impact have the aim to show whether the whole community is managed in the right direction, according to the members' preferences. These metrics would also reflect the economical and environmental benefits that are expected when developing energy communities (Frieden et al., 2019). However, a difficult challenge would be to identify and define what would be the most relevant metrics to evaluate human impact from a cognitive point of view. This evaluation is equally necessary because it would reflect a potential "cost" of the human involvement in the community life. For example, it would

be important to quantify the sacrifice of people who would not go to work in order to contribute to the energy community, or the effort of people who would restrain themselves in using some home appliances for the sake of collective community benefit. Considering human effort as an equally important metric such as system performance would be a significant step in counterbalancing the impact of excessive automation is such a system that should be naturally focused on people.

Overall, the research problem may be conceptually encapsulated in an Actors-Service-System paradigm, as it is proposed in Fig. 3.2. This paradigm reflects three main abstract directions around which solutions may be developed in the future.

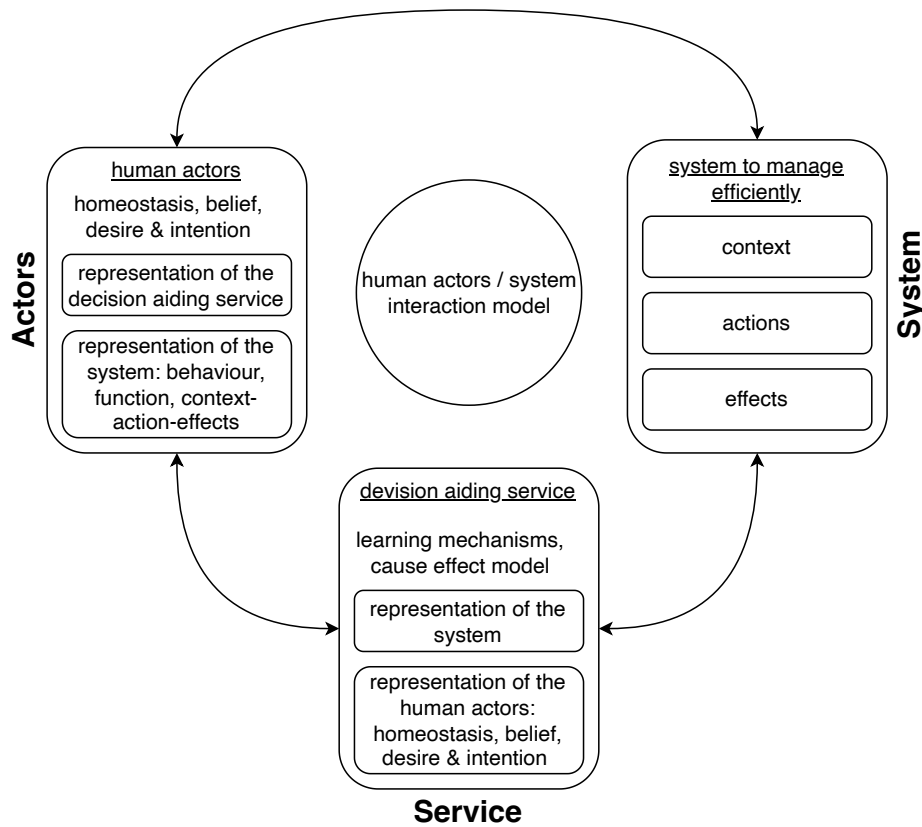


Figure 3.2: The Actors-Service-System paradigm

The first, common, direction is represented by the system to be managed efficiently, an entity described by a context, which is often governed by causality, where actions¹³ from other external systems have certain internal or external effects. As automation has evolved, so have the techniques to command and control various components of systems in order to increase efficiency or achieve certain objectives.

¹³ Often viewed, from a system engineering perspective, as "inputs."

From a completely different perspective, the second pillar is represented by human actors who are characterised by beliefs, act according to various intentions or motivations and, in the context of energy systems, are typically excluded from management problems. However, it is important to notice that people perceive the systems around them in various ways which are profoundly influenced by beliefs and motivation. As it is the case in this paradigm, people perceive the system according to its function, its behaviour when fulfilling that function and its surrounding environment. While this perception may not fully understand the particularities and complexity of the system¹⁴, it gradually becomes necessary to consider another additional conceptual pillar, the service.

¹⁴ This aspect can be easily noticed with energy systems, since people are not fully aware of the complex process that occur at grid/district level, with management of various renewable energy resources, in order to ensure that each building has a quality, persistent energy supply.

¹⁵ In literature, solutions in this framework are often described as artificial intelligence systems.

¹⁶ For people, the service simply represents another external, complex, system.

The decision aiding service should be developed as a "mirror" to the typical human actor¹⁵, with learning mechanisms, decision making models, and, most importantly, its own perception of the other pillars. The perception on the system must be characterised by a certain completeness, as the decision aiding service should have the capability to understand and process the complexity of the system in a superior manner to the one specific to human actors. On the other hand, the perception on the actors is meant to understand the beliefs and motivation of people so that it may provide adequate decision-making support. One must not forget that as people have a perception of the system, they similarly have a perception on the service¹⁶. As it is clear that this perception cannot be directly controlled, it can be certainly influenced by developing the decision-aiding service in a transparent, truthful way, governed by human-centered mechanisms and with clear, simple communication lines, allowing people to set the objectives and have the final decision in every situation so that a certain level of trust develops.

By developing new modern systems implementing this paradigm, we can ensure that we obtain modern human-system interaction models, with a truthful and clear focus on the human actors and their behaviour. In the context of energy, where systems have evolved independently and at a rapid pace, this paradigm has the potential to establish a truly meaningful connection between people and energy in a manner that has not been seen until now.

Additional information

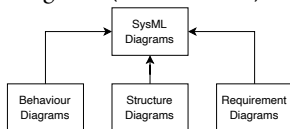
The work presented in this chapter is further detailed in:

Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2021). General Considerations About Simulating Energy Communities. *2021 11th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, 1126–1131. <https://doi.org/10.1109/IDAACS53288.2021.9661053>

CHAPTER 4

SIMULATING ENERGY COMMUNITIES: AN INTEGRATED FRAMEWORK FOR PREDICTING HUMAN BEHAVIOUR

¹⁷ To completely model a system, the SysML modeling paradigm proposes that diagrams may be categorised between Structure Diagrams, Behaviour Diagrams and Requirements Diagrams (Wasson, 2016).



Therefore, to completely describe a management solution for an energy community, one should investigate how the community is structured, the main system requirements and relevant behavioural aspects

Considering the conceptual aspects of the Actor-Service-System paradigm 3.2, a uniform way of modeling the entities in an energy communities must be developed. These representation are particularly useful for the entities involved (namely the *actors*, *service* and *system*) to develop *actions* and quantify the *effects* of these actions in the energy community context. Additionally, a behavioural community description is further required as a complementary perspective ¹⁷.

This chapter advances the discussion by proposing a comprehensive framework for modeling the entities within an energy community, adhering to the actor-service-system paradigm. It further describes the core structure of the solution proposed in this thesis, designed to address the challenge of managing energy systems involving human interactions effectively.

The proposed framework advocates for three primary models to be addressed to fully characterize an energy community, each with its unique characteristics:

- **The community member model** - this model should authentically depict the behavior of a community member, including their possible preferences, restrictions, motivations, and beliefs. It should also encapsulate the member's perception of the decision-support service and the physical system.

- **The community service model** - this model should describe how the decision aiding mechanism is implemented based on the representation of the human actors. It should also illustrate how the community's objectives are evaluated through performance indicators.
- **The energy community interaction model** - this model should describe firstly the manner in which the community is organised and secondly the manner in which the interactions in the community are conducted.

Referring back to the problem statement from Fig. 3.1 defined in Chapter 3, where the primary research problem was divided into four sub-problems, this chapter addresses two key challenges:

- how to model community members as autonomous entities in the coordinated organisation represented by the energy community;
- what metrics can be effectively used for evaluating the collective impact of actions from a system and human cognitive perspectives, while also identifying relevant metrics that may act as relevant tools for the *service* in its daily behaviour.

As this chapter will sequentially address the member model, the service model and the energy community model, this chapter will also provide a concise overview of one of the main contributions described in this work, which is how the service can effectively support community members in their daily activities to achieve the collective objectives of the community.

4.1 Modeling human behaviour of community members

The focus on an energy community assisted by a decision support system provides a well-defined, bounded, context suitable for effectively modeling user behaviour.

Specifically, the term "system" in this context pertains to the energy system, and consequently, user behaviour translates to their energy consumption patterns when interacting with the system. It, therefore, becomes apparent that the behaviour of a given member i is intricately linked to a power profile (or a consumption profile), denoted as $p_{Load,i}$.

In terms of the relationship between community members and the decision support service, the process of offering specific advice suggests an inherent

sequential logic within the interaction model between the individuals and the service. Specifically, two primary temporal dimensions can be defined: the 'business-as-usual' dimension, where individuals operate independently of the decision support service, and the outcome which outlines the behaviour of individuals after receiving recommendations.

In terms of energy consumption i.e. the behaviour impact in the system, the consumption profiles are further defined as:

- $p_{Load,i}^{estimated}$ - the estimated hourly load of a community member i , reflecting their business-as-usual consumption profile relative to the system. This power profile may be determined through observations or other estimation techniques, without involving recommendations. It should be noted that this profile aims to represent the behavior of a community member **without the involvement of the recommendation system** and is **internal to the member**.
- $p_{Load,i}^{real}$ - the hourly power profile obtained **after the community member i has reacted to the recommendations**. It captures the change in consumption produced as the member has responded to a recommendation.

Without the recommendation system, $p_{Load}^{estimated}$ would not exist and p_{Load}^{real} would represent the actual consumption profile. However, in the context of the recommendation system, $p_{Load}^{estimated}$ must be introduced by considering two standpoints. Firstly, from a technical point of view, $p_{Load}^{estimated}$ represents the internal consumption profile of a member, as it was previously presented. Secondly, from a conceptual viewpoint, it serves as a reference for calculating indicators, allowing the community manager service to accurately assess the collective impact of recommendations by referencing this profile.

However, given that $p_{Load}^{estimated}$ is internal to the member model, it could potentially present a challenge to the decision support service. The service's responsibility is to aid the community in achieving its goals, and the effectiveness of its recommendations depends significantly on the accuracy of the community member representation that is being developed within the service.

Consequently, an additional measure is introduced, the expected level of consumption $p_{Load,i}^{expected}$. This measure shapes the **internal representation of community members' behaviour as perceived by the service**. Ideally, a comprehensive understanding of the community behaviour would yield an ideal platform upon which the service might provide recommendations, signifying that $p_{Load,i}^{expected} = p_{Load,i}^{estimated}$. Altogether, $p_{Load,i}^{real}$, $p_{Load,i}^{expected}$ and $p_{Load,i}^{estimated}$ will be further considered in this study as hourly power profiles. This aspect

is associated to the role of the decision aiding service, as providing recommendations based on minute-scaled time frames could prove ineffective for energy communities with people¹⁸, whereas employing hourly profiles facilitates the examination of larger time periods composed of multiple hours.

Another aspect that is embedded in the human behaviour and must be accounted for in the modeling process is related to human dissatisfaction. As it might be relatively straightforward to focus on the performances of the system (Manso-Burgos et al., 2022; Soto et al., 2021), human dissatisfaction might be an influencing factor that accounts as a penalty in the system performances and should be accounted for, as it was noted in performance-gap situations such as (Li et al., 2022). Furthermore, in the energy community context, service should not treat community members as pure technical systems, but should instead account for their habits, personal privacy, annoyance levels, and other personal behavior traits that may conflict with the recommendation mechanism's purpose. Specifically, the idea of a penalty should reflect that people have their own habits that may be associated with a reference direction, and they may not want to deviate too much from this direction. The personal motivation for joining an energy community can help in this regard, as individuals who are motivated to contribute may be more willing to accept the community manager's involvement than those who do not want to be involved.

As the behaviour of people in terms of energy consumption might be characterised by uncertainty, from an external standpoint, it becomes increasingly difficult to model human dissatisfaction. When considering the internal measures of $p_{Load,i}^{real}$ and $p_{Load,i}^{estimated}$, an intuitive (but mistaken) approach would be to consider that every change in the real consumption which comes as a consequence of recommendations can be interpreted as an indicator for dissatisfaction. However, this is not always the case, since human behaviour evolves in time and effort might be reduced if it is accompanied by motivation¹⁹. Moreover, as the service provides recommendations based on $p_{Load,i}^{expected}$, this measure may not entirely capture the internal behaviour of individuals as reflected by $p_{Load,i}^{estimated}$. Therefore, considering that the service should incorporate dissatisfaction when formulating advice, the discrepancy between the representation of individuals within the service and the representation of the service within actors may both present complications when establishing certain dissatisfaction metrics. Consequently, it becomes clear that, to develop dissatisfaction indicators that relate to the behaviour of community members, one may begin from the particularities of the respective decision aiding service and include additional knowledge about the potential preferences, restrictions, habits of the people in the community.

¹⁸ This is a differentiating aspect comparing to pure technical systems, where using a smaller sampling period could sometimes be effective.

¹⁹ Motivation is a critical factor in an energy community. This is also indirectly stated by the European Directives European Parliament and Council of the European Union, 2018, 2019, as they suggest that people should voluntarily take part in energy communities.

Finally, these measures ($p_{Load,i}^{expected}$, $p_{Load,i}^{estimated}$ and $p_{Load,i}^{real}$) and the interpretation on dissatisfaction pave the way for an appropriate approach to modeling human behavior in energy systems. This approach refers to modeling only the reaction and its implicit dissatisfaction to recommendations, rather than the entire complexity of the behavior of community members. Such focused approach allows for a more precise and targeted analysis of the impact of recommendations on energy consumption.

4.2 The dual role of community service: providing recommendations and assessing community impact

An important requirement defined in the paradigm in Fig. 3.2 was related to the idea that both the actors and the service have an internal representation of the other elements of the structure. From a *service* point of view, the representation is useful in developing recommendations, while for the *actors* point of view the representation is useful for developing trust in the overall cooperation mechanism and further improving one's behaviour.

To establish the necessary framework for the service to deliver recommendations, $p_{PV}^{expected}$ is further defined to outline the expected profile of the photovoltaic (PV) production associated to the corresponding community. It is noteworthy that while this study regards PV production as a form of renewable energy, the same methodology could be employed for other renewable energy communities comprising other renewable energy sources. Similarly, the PV plant yields an hourly expected production profile denoted as $p_{PV}^{expected}$, considering location and whether data for the respective time interval.

Recommendations represent an important solution from two perspectives: commitment theory (Bonino et al., 2012) and feedback importance (Seligman and Darley, 1977). From a commitment standpoint, breaking a significant goal such as consuming energy more efficiently into smaller sub-goals such as recommendations can help people feel that the objective is achievable by following small steps. Complementing this aspect, feedback theory emphasizes the importance of people knowing the impact of their actions as they progress towards specific goals. Feedback increases the trust that individuals are on the right path to achieving their objective.

Additionally, recommendations represent the advises in the form of *actions* that the human actors should do in order to influence the system. These actions may come in various forms:

- Color signals: the manager service may employ a signaling mechanism in the community to emphasize what the community members should do and when. For example, in a residential community context, a recommendation to decrease consumption would be reflected by the color RED, while the recommendation to increase consumption would be reflected by the color GREEN.
- Specific changes in consumption: the manager service may send specific values to reflect the required changes in power, compared to the business-as-usual scenario. For example, in a residential community context, the community manager may require at times that the overall consumption should be lowered by a moderate change (Δp_{mod}) or during other times by a strong change (Δp_{strong}).
- Time moments: the manager service may simply emphasize the time moment when it is favorable for community members to employ a certain action. For example, in an energy community for commuting passengers, the manager service would transmit time slots for commuting members when it is favorable to commute.

In summary, these recommendations encapsulate the expected impact that the actors should exert on the system. Specifically, they could represent a time span during which agents should produce a certain effect, or they might depict a particular modification in the consumption profile that the members are anticipated to achieve. Alternatively, they could be encoded in a specific manner (i.e., color signals), a simplified agreement between the community members and the service, to symbolize distinct demands that the members are expected to fulfill.

However, recommendations themselves are subject to the perspective of community members, especially if one refers to the actor-service-system paradigm. For example, the members receive the recommendation in some form, but they may not understand it, may not be capable of following it or simply may choose to ignore it due to other contextual or internal factors. This discrepancy can cause confusion if the members' perspective does not align with that of the decision-aiding service. Therefore, it is crucial that recommendations are formulated in a way that ensures comprehensive understanding by the people. This contribution complements the perspective of the service, which possesses a more thorough understanding of the system due to the installed measurement devices. Accordingly, the collaboration between the decision-aiding service and community members is established, with this collaboration deeply depending on the shared knowledge between the involved parties.

In addition to providing recommendations, the service must also possess the capability to assess their impact. The previous section elucidated how dissatisfaction indicators relate to the community member model. This section will extend the discussion to indicators that evaluate system performance. Specifically, these indicators are designed to determine whether the community achieves its economic, environmental, or social benefits, using measures such as $p_{Load}^{expected}$, p_{Load}^{real} , or $p_{PV}^{expected}$.

In these study, three performance indicators will be used: self-consumption, an indicator that is used to evaluate the environmental impact, self-sufficiency, an indicator that is used to evaluate the economical benefits and the net-energy-exchanged-with-the-grid, a novel indicator that can evaluate both the environmental and economical impact, but it can also be successfully used in developing recommendation strategies.

4.2.1 Self-sufficiency

After providing recommendations, the community manager service evaluates their collective impact on the *system*²⁰. The service aims to quantify the environmental and economic benefits obtained, as well as to determine whether following the recommendations has caused any dissatisfaction among the community.

One suitable economic indicator to be used for evaluation is represented by **self-sufficiency** (SS) (M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2021b). Self sufficiency indicates how much of the total load is covered by the energy produced and consumed internally²¹. In a general discrete form, the SS index can be defined by Eq. 4.1.

$$SS = \frac{\sum_k^T \min(p_{PV,k}, p_{Load,k}) \Delta t}{\sum_k^T p_{Load,k} \Delta t} \quad (4.1)$$

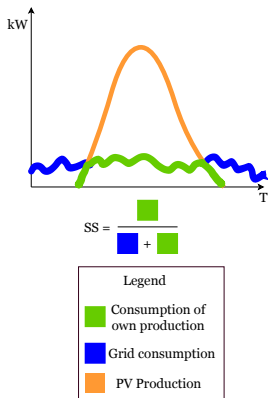
where $p_{PV,k}$ represents the average power produced from PV panels over the k^{th} interval Δt (which represents the sampling time), $p_{Load,k}$ represents the average load over the same interval and T represents the total time period.

Self-sufficiency can be used to quantify the economical benefits. A self-sufficiency index of 1 over a time period indicates that all the consumption is covered by internal production, while a self-sufficiency index of 0 reflects the situation when all the consumption is satisfied by grid energy.

While self-sufficiency may be suitable for economical evaluation, it may not always be suitable as a criteria for developing recommendations. For example, in design problems, an infinite number of PV panel may be the optimal solution for maximising self-sufficiency. In the context of the recommendation system

²⁰ This evaluation may take place during a Manager Day Step, as shown in Figure 4.3

²¹ A graphical representation of self-sufficiency.



implemented in a residential community, maximising self-sufficiency would be synonymous with keeping all the appliances off most of the day.

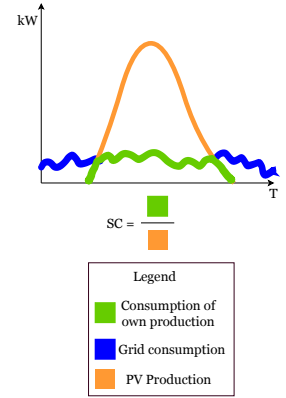
4.2.2 Self-consumption

From an environmental point of view, **self-consumption** (SC) can be used as an indicator (M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2021b). Self-consumption quantifies how much of the PV energy produced is consumed internally by the system ²². The value of the SC is between 0 and 1 and, while 0 indicates that no energy produced by the PV is consumed internally, 1 emphasizes that all energy produced is consumed internally. The SC index in discrete form can be defined as:

$$SC = \frac{\sum_k^T \min(p_{PV,k}, p_{Load,k}) \Delta t}{\sum_k^T p_{PV,k} \Delta t} \quad (4.2)$$

Both self-consumption and self-sufficiency are appropriate metrics to evaluate the benefits of an energy community. As an example for the energy community context, one can evaluate these indicators by comparing the expected consumption $p_{Load}^{expected}$ and production $p_{PV}^{expected}$ at the collective level with the real values $p_{Load}^{real}, p_{PV}^{real}$ obtained after the community has followed the recommendations. Additionally, although the indicators typically show values between 0 and 1, they can be easily adapted to show either a quantity of energy or a quantity of money.

²² A graphical representation of self-consumption.



4.2.3 The net-energy-exchanged-with-the-grid

The idea of proposing a new metric to maximise environmental and economical benefits has developed as a consequence of two associative relationships: the relationship between self-consumption and production and the relationship between self-sufficiency and consumption. As self-consumption and self-sufficiency are commonly employed in energy system evaluation, both in design (Braeuer et al., 2022) and operational (J. Liu et al., 2021; Manso-Burgos et al., 2022) stages, the problem consists in finding the optimal configuration that maximises both criteria, considering physical constraints related to PV module characteristics.

Additionally, it would be interesting to see if an equivalent criterion could be determined that may address be suitable in the maximisation problem and whether this criterion could be used to identify a globally optimal solution.

Consequently, as a first step, the following case study is considered: the problem of sizing a suitable PV plant for a specific consumer, a subway station.

The design stage would consist in an optimisation problem that accounts for both the predicted PV production and the estimated system consumption over a time period.

Referring to the PV production, it is assumed we have four PV module categories indexed by j , as described in Table 4.1 (M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2021b). Power rating limits $p_{M_{lim_inf,j}}$ and $p_{M_{lim_sup,j}}$ for each category have been considered (see pvXchange Trading GmbH, 2020), along with an associated cost-per-watt peak power $c_{wp,j}$ for year 2020.

Table 4.1: PV modules techno-economic specifications

Category	$p_{M_{lim_inf,j}}$	$p_{M_{lim_sup,j}}$	$c_{wp,j}$	Description
<i>High Efficiency</i>	330 W	500 W	0.31 €/Wp	crystalline modules
<i>All Black</i>	290 W	390 W	0.32 €/Wp	modules with black sheets and frames
<i>Standard</i>	275 W	325 W	0.22 €/Wp	mainstream modules with 60 multicrystalline cells
<i>Low Cost</i>	0 W	275 W	0.16 €/Wp	modules representing factory seconds, limited warranty products with a lower lifetime (around 10 years) and low power output

Given the known parameters of the PV module, and considering the estimated consumption over a year as additional input parameters for computing self-consumption and self-sufficiency, the aim is to determine the optimal size of a PV plant. This refers to the number of panels and nominal output power of a panel that maximizes both the system's self-consumption and self-sufficiency. The sizing problem is consequently formulated as a multi-objective optimisation problem:

$$\max \quad SC \quad (4.3a)$$

$$\max \quad SS \quad (4.3b)$$

$$\text{where } n_{lim_inf,j} < n < n_{lim_sup,j} \quad (4.3c)$$

$$p_{M_{lim_inf,j}} < p_M < p_{M_{lim_sup,j}} \quad (4.3d)$$

where the decision variable is composed of the number of PV modules n and the power of a module p_M . These decision variables are used in developing the PV production profile, which is used in both SC and SS. The consumption profile can be interpreted as a constant.

The evaluation horizon is determined for a year. The PV production profile is estimated with Eq. 4.4 (HOMER, n.d.), combined with a solar/weather model:

$$p_{PV,t} = p_M \cdot n \cdot \tau \cdot \frac{G_t}{G_{T_{STC}}} \quad [\text{kW}] \quad (4.4)$$

where p_M represents the power rating for a module, n represents the number of modules, τ represents a scaling factor for real world conditions such as power losses in electrical wiring and shading. G_t represents the estimated total incident radiation over the panels at time t and $G_{T_{STC}}$ is the incident radiation at Standard Temperature Conditions ($1\text{kW}/\text{m}^2$). The incident radiation is obtained according to a solar model (Ploix, 2021) that accounts for the exposure, outdoor temperature and slope (Duffie et al., 2020), while geo-specific parameters and weather data have been obtained from *OpenWeatherMap.org*.

The subway station consumption is estimated for one year using the measured data from M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2021b and a linear regression model between the passenger traffic and subway consumption (more details in Appendix B).

To solve the multi-objective optimisation problem in Eq. 4.3, the heuristic method named *Differential Evolution* is used. This genetic algorithm is used to find the Pareto efficient solutions that dominate other candidate solutions in the multi-objective space²³. The Pareto-Front is the set of all the non-dominated solutions of the problem and represent a decision platform upon which a solution may be chosen based on higher-order information or external criteria.

So, for the optimisation problem defined in Eq. 4.3, the results depicting the Pareto front for each category of panels are presented in Fig. 4.1 (M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2021b). One can notice that in each plot, the solution labeled as "Best Value" represents the solution that is closest to the ideal point defined by $SC = 1$ and $SS = 1$ (the maximum values for SC and SS). In a real implementation, a system with $SC = 1$ and $SS = 1$ is a system with PV production, where the load profile over the evaluation period perfectly matches the PV profile. Thus, maximising SC and SS over an interval T is equivalent to minimising:

$$NEEG = \sum_k^T |p_{PV,k} - p_{Load,k}| \Delta t \quad [\text{kWh}] \quad (4.5)$$

Eq. 4.5 represents the net-energy exchanged-with-the-grid, a novel metric that describes the absolute quantity of energy that is either injected or extracted from the grid. So, maximising self-consumption and self-sufficiency is equiv-

²³ A solution composed of multiple objective functions values $f_i(x^*)$ dominates another solution $f_i(x)$ if there is at least a value $f_i(x)$ that is strictly greater in the objective space (see Price et al., 2005). Consequently, a solution for a multi-objective optimisation problem is Pareto-Efficient if there is no other solution that dominates it (thus, being called non-dominated solution).

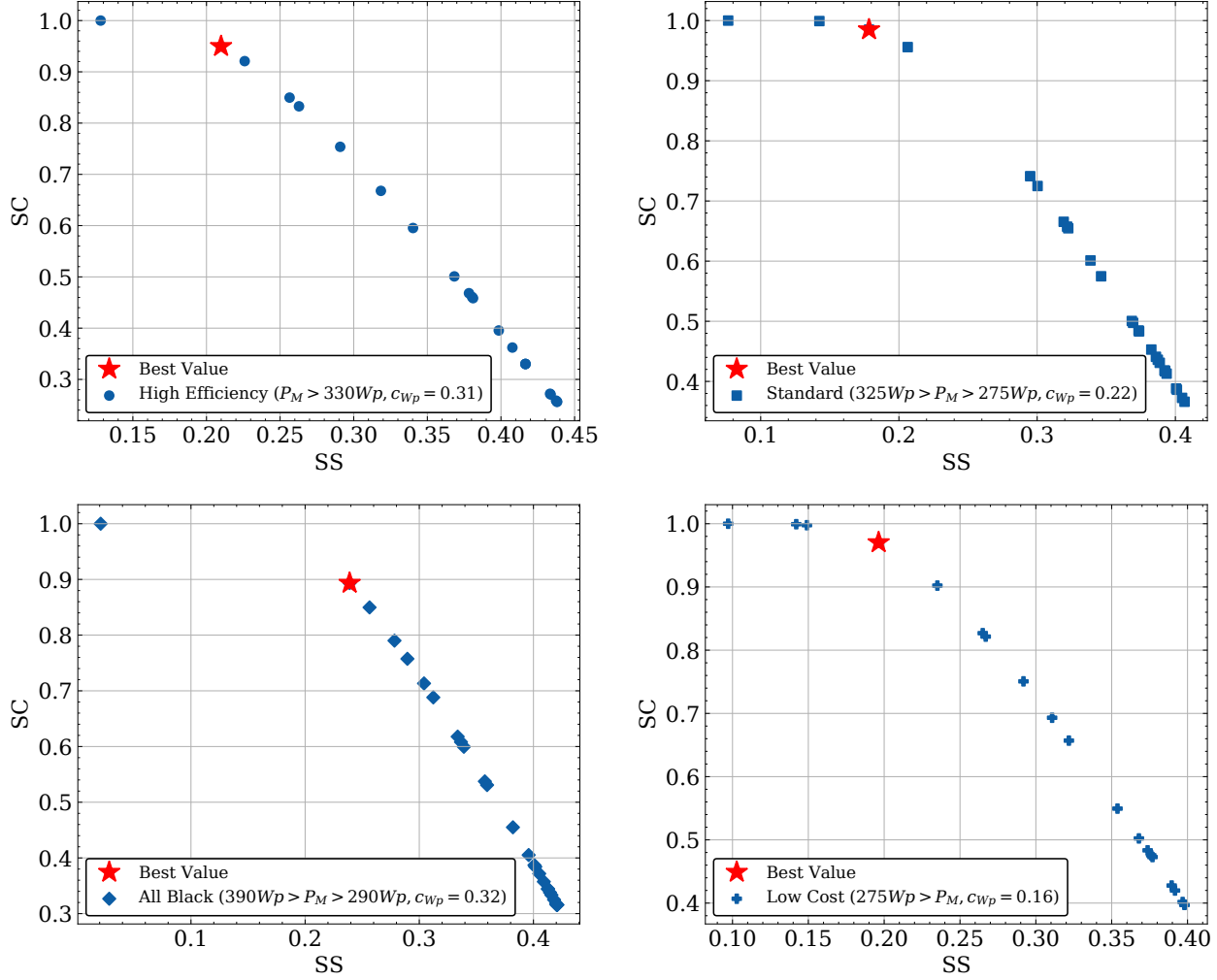


Figure 4.1: Pareto Set for the SS-SC multi-objective optimisation problem

alent to minimising the NEEG, thus obtaining a solution that matches the consumption and production profiles for a time interval. A graphical depiction of this equivalency is presented in (M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2021b), while a more detailed proof is presented in Appendix A.

Overall, from an evaluation standpoint, self-consumption and self-sufficiency are more relevant than NEEG when evaluating community performances. However, since both self-consumption and self-sufficiency are non-linear, it can be difficult to consider them in optimization problems. For instance, heuristic methods like *Differential Evolution* cannot guarantee finding the global minimum, and can be computationally expensive. On the other hand,

NEEG can be used effectively as an objective in a single-objective optimization problem that is formulated in a suitable linear manner. Therefore, NEEG may be more useful from an optimization perspective.

4.3 Energy communities modeled as multi-agent systems: proposing an interaction model

To develop the coordinated approach for modeling the interaction between community members, the service and the system, as they were presented before, one can begin from a static, structural community architecture that briefly depicts the main interactions between entities in a typical energy community. (Fig. 4.2).

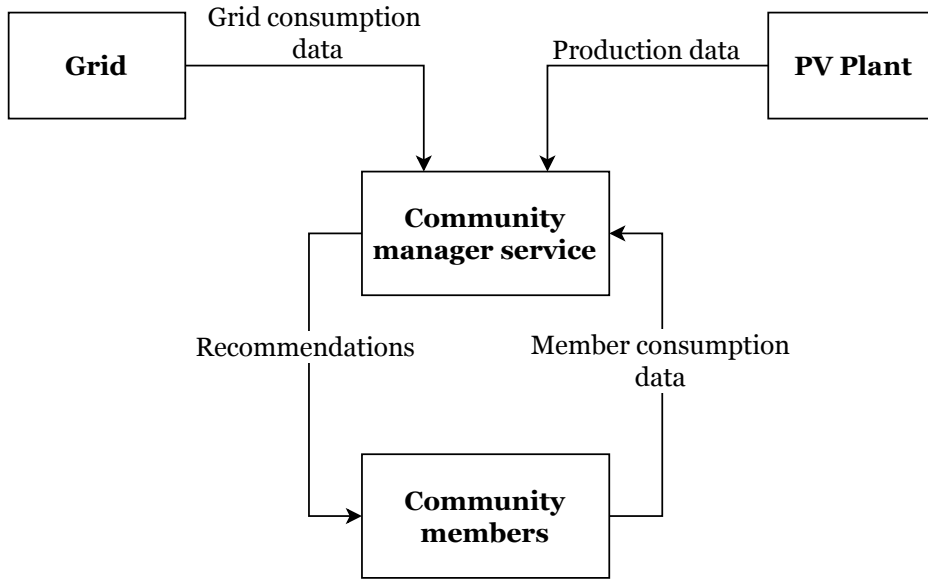


Figure 4.2: Proposed communication framework for modeling and simulating energy communities

As it can be noticed, the main entities can be still associated with the main pillars defined in Fig. 3.2. From a modeling perspective, a suitable framework may be represented by multi-agent systems²⁴, a model where entities are represented conceptually as agents (or practically as software applications) who act autonomously according to a certain behaviour and communicate in an organised manner.

A novelty included in this architecture is represented by the definition of the community manager service²⁵, which sends recommendations to community members. This service is responsible for implementing the aiding process

²⁴ In some specialised literature, multi-agent systems are often referred to as distributed systems.

²⁵ The community manager service represents a realization of the *service* from Fig. 3.2

by sending personalized recommendations to community members based on the expected consumption and the overall community expected production. As time passes, members may react to the recommendations with varying intensity, or they may not react at all. This aspect depends on several associated attributes such as their behavior, motivation level, availability, and so on, which are integrated in the community member model. The service measures the reaction in terms of consumption modification, to establish whether the members have followed the recommendations or not, and to quantify the economic and environmental impact accurately. Overall, the recommendation process represents a proper implementation of the interaction between the behavior of the service and the behaviour of the actors.

As the multi-agent system implies a coordinated manner in which agents communicate, a general representation of the interaction model is proposed in Fig. 4.3.

The figure shows that a typical simulation is split into d days, with each day being divided into several agent interactions. This interaction model comes as a consequence of the multi-agent organisation. Specifically, this organisation places the community service in the role of the coordinator agent, while the other agents interact exclusively with the coordinator agents, without interacting between themselves. This type of organisation is a variant of other similar multi-agent model in recent literature (Khorasany et al., 2021; Lai et al., 2022; Zhou et al., 2018), where typically there is a central coordinator agent with a management function, among other distinct agent that behave and act towards a certain individual objective.

As it is presented in Fig. 4.3, a typical day can be interpreted from the following perspective: at the beginning of each day, the manager and community members have two dedicated interaction slots assigned specifically for daily tasks, such as data collection, recommendation proposal or analysis.

Then, during each hour t , there is a sequence of interactions, starting with a manager interaction followed by a community member interaction. During a typical manager interaction, the manager may act according to its behavior, such as providing recommendations or measuring consumption. During the dedicated interactions for the community members, they react to recommendations based on their behavior and send additional information to the manager that may be required for developing the recommendations.

A particular feature of the interaction model depicted in Fig. 4.3 is the representation of specific events where agents perform certain functions, termed 'interactions'. An interaction may represent an exchange of information between the manager service and the members, or simply a self-interaction, the

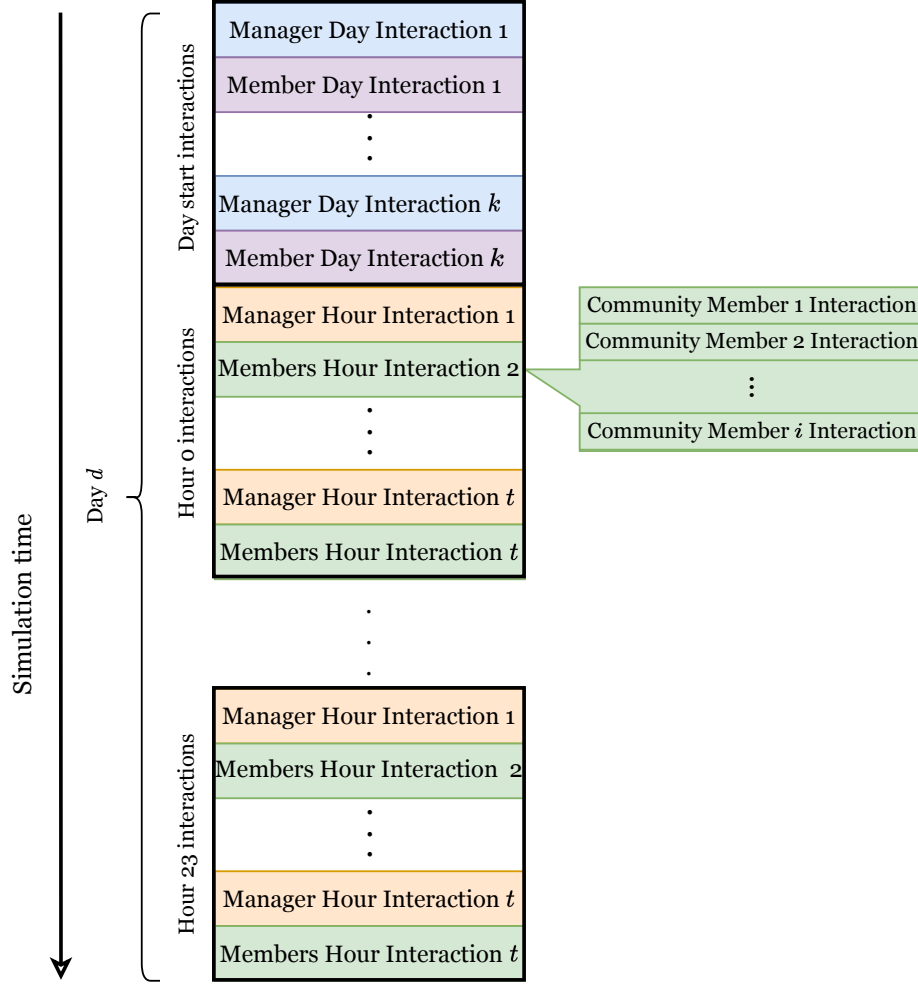


Figure 4.3: Proposed interaction model for a typical day in the multi-agent simulation framework

implementation of an internal function by either the manager or the members, depending on the type of interaction (manager interaction/member interaction). These interactions could correspond to distinct times of the day (day interactions, for instance at the beginning or end of the day) or be associated with particular hours (hour interactions). This modeling representation for a typical day is proposed to offer flexibility, signifying that while designing energy communities of varied contexts, there is a degree of freedom in selecting and modeling the time-frame connected to the interaction model. For instance, if a member interaction and a manager interaction are tied to an hour, the spe-

cific moments when these interactions occur can be determined by the user, depending on the application.

However, in these regard, there are three additional features that restrict the flexibility of the user and therefore can be regarded as limitations of this model:

- the manager-member interaction succession, identifiable at either a daily or hourly level. This factor does not represent a limitation per se, but is rather an organizational aspect, mirroring the coordinating profile associated with the manager.
- the day interactions, which are more representative to the idea that the manager evaluates the community daily, offering a suitable framework for developing recommendation strategies that are associated to one day.
- grouping interactions by one-hour intervals - the fundamental principle behind the proposed hourly time-segmentation approach is related to the development of recommendations. As stated in previous chapters, recommendations should be simple signals with an appropriate time frequency and requested action intensity, to ensure that community members do not feel discomfort as they gradually adapt their energy consumption behavior. Additionally, choosing an hour as time sample related also to the behaviour impact of community members in the system, specifically to the hourly consumption and production profiles that are considered in developing the community member and service models. As it was mentioned, these measures represent key components of the human behavior model, since each agent is portrayed individually as an autonomous entity, so $p_{Load,i}^{estimated}$ and $p_{Load,i}^{real}$ are strictly related to the agent i .

Returning to Fig. 4.3, the simulation is divided into d days to consider the impact of daily recommendations (as demonstrated in (Seligman and Darley, 1977)) and the importance of periodicity in developing specific behaviors. Additionally, hours are associated to interactions to allow community members necessary time to react to recommendations according to their preferences and restrictions. The pairing of manager interactions and member interactions reflects a key element: as the manager provides recommendations and measures their effects to provide feedback, a feedback mechanism is implemented at a deep, granular level. In a real-world implementation, people could have mobile devices such as tablets installed in their homes and could receive both recommendations and feedback throughout the day.

The proposed interaction model has been implemented as a framework in Python (M. S. Simoiu, 2023), based on the multi-agent model MESA (Project Mesa Team, 2021). The framework can be effectively used to develop models for energy communities following the proposed approach. The simplified²⁶ core part of this framework is depicted as a UML class diagram in Fig. 4.4.

²⁶ The diagram includes only the attributes and methods of each class that are relevant for the topic of the chapter.

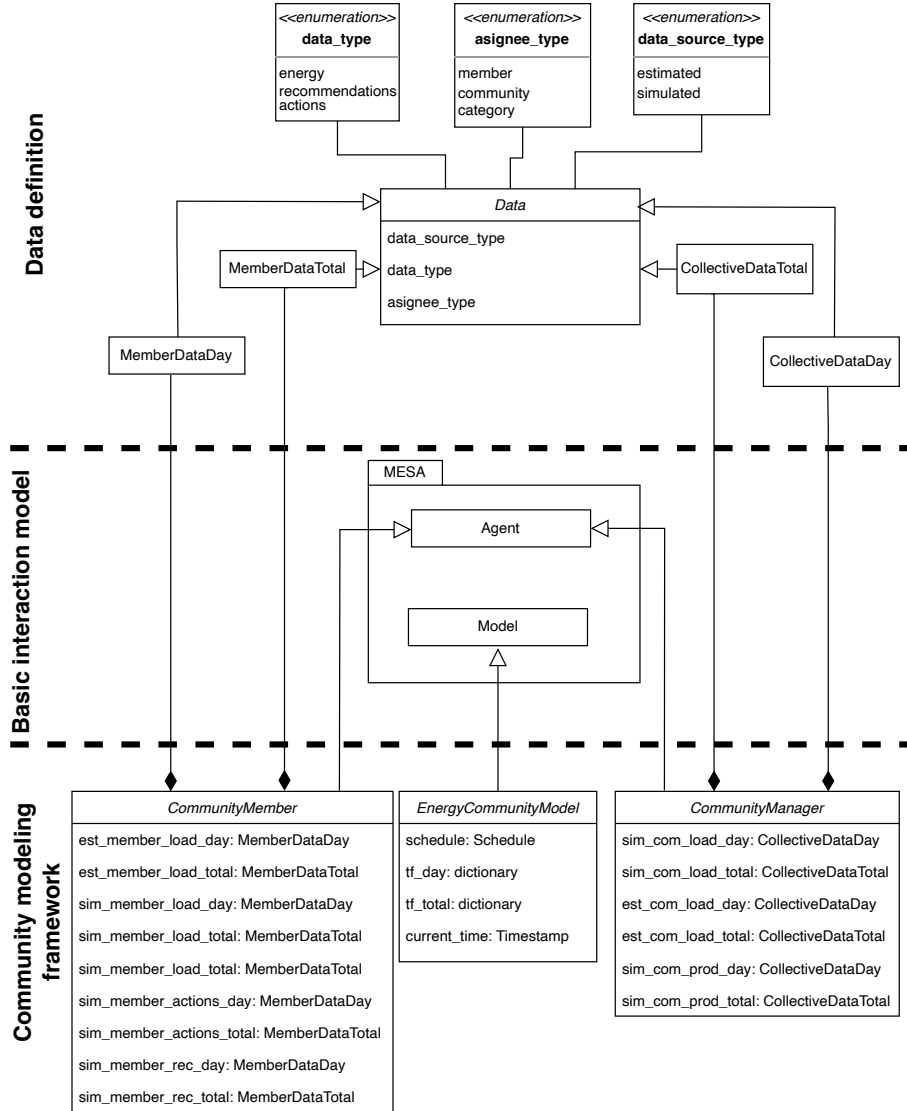


Figure 4.4: UML class diagram depicting the core framework for modeling energy communities; Keyword legend: est = estimated; sim = simulated; tf_day = time frame day; tf_total = time frame total. **Note:** simulated here corresponds to the final power profile of a community member $p_{Load,i}^{real}$, after receiving recommendations.

As depicted in Fig. 4.4, the framework comprises three distinct levels: a data definition level, where various system measures are established, a basic

²⁷ As this model represents the core implementation of the concepts defined in this chapter, the following chapters will explore different community configurations and will be described in a more specific manner how the community manager, community members and energy community model are adapted to depict different communities.

interaction model encapsulating the principal entities of the MESA project, and the community specialised models, which are constructed based on the two aforementioned tiers and represent a platform for developing even more specialised, contextual models for various community types.²⁷

Comparing to other work regarding multi-agent frameworks for energy communities (such as Lai et al., 2022), the proposed multi-agent framework provides increased flexibility in designing how community members interact with the community manager. However, it also provides a certain precision by focusing on time segments for each day in the simulation rather than analysing the behaviour of large periods (Fouladvand, 2022).

Additionally, the proposed framework is suitable for modeling a wide range of human-centered energy communities applications, representing a more general approach than studies that focus on a specific community type (such as Fina et al., 2020; Sima et al., 2022).

A limitation deduced from the proposed model relates to the depth of the social dimension among community members. Specifically, the interaction model proposed in this study does not capture the interactions between community members and the resultant impact on system performance. While cooperation among members at a collective level is determined by their commitment to participate in the community and utilize the community manager service as a decision-support tool, modeling the perception of community members about their fellow participants is not integrated in the scope of this work.

4.4 Conclusion

Based on the problem statement outlined in Chapter 3, the current chapter presents a comprehensive solution for modeling energy communities. Initiated from the definitions offered within the actors-service-system paradigm, this chapter advances the discussion, furnishing a more comprehensive explanation of models which may be employed to articulate the interactions, attributes, and unique aspects of an energy community. Through the establishment of models for community members, community managers, and a collective interaction model for the community, this chapter suggests solutions to a variety of sub-problems defined in Chapter 3. These include the challenge of devising a decision-aiding service, the issue concerning the portrayal of community members as autonomous, independent entities, and the task of modeling evaluative indicators.

Firstly, this chapter proposes that an energy community should be modeled as a multi-agent system, with the behavior of community members embedded

in agents who act autonomously. At the community level, the *service* is represented by a community manager, which is another individual agent. All agents act in a coordinated manner, as shown in Fig. 4.3. Additionally, the community manager service implements a recommendation mechanism to support community members in their daily activities. The description of this mechanism in this chapter provides a brief overview of the main solution proposed in this work, a solution that aims to effectively manage the involvement of people in community life.

Secondly, the role and importance of indicators is discussed in this chapter. Several indicators are proposed for both evaluating *system* performances and representing support instruments in the recommendation development process. Moreover, since human involvement related indicators are characterised by a certain complexity and depend in certain way on the *actor-service* contextual relationship of each particular case study, several requirements have been proposed to serve as a framework for the solutions to be presented in the next chapters.

A depiction of the overall solution proposed in this chapter can be analysed in Fig. 4.5.

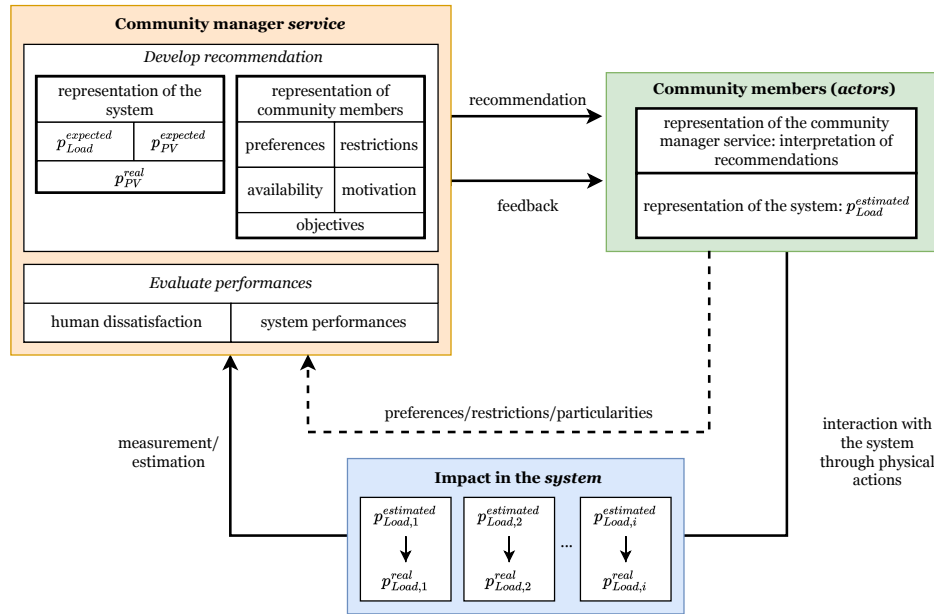
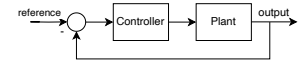


Figure 4.5: Recommendation mechanism - interaction between the community manager service and community members considering indicators

It can be observed that Fig. 4.5 bears some similarity to the feedback control loop of classical control theory²⁸. However, it should not be assumed that the purpose of this architecture is to represent a control mechanism, as an en-

²⁸ The classical feedback control loop, where the controller provides an input to a plant so that the difference between the output and a desired reference is minimised.



ergy community is not solely a technical system. The main difference lies in the fact that the community service provides recommendations to community members, with the understanding that the system is associated with people and therefore the desired effect of recommendations may be uncertain. As a complementary step, the manager service measures community activity to determine how objectives can be achieved and to further enhance the recommendation mechanism.

An additional characteristic depicted by Fig. 4.5 refers to the internal representations of both the manager service and the community members. Community members possess their own comprehension of the recommendations received, yielding a quantifiable impact on the system, denoted by $p_{Load}^{estimated}$ in a typical scenario. After receiving recommendations, the reflection of the behaviour in the system is represented by p_{Load}^{real} . Conversely, the community manager service must develop an adequate interpretation of the community, encompassing aspects such as preferences, motivation to adhere to recommendations, or willingness to contribute to the community. This is why in Fig. 4.5 the interpretation of preferences and restrictions is marked with a dashed line rather than with a continuous line, emphasising the distinction between the manager's representation of the system and the manager's representation of community members. Furthermore, the community manager service is obligated to issue recommendations that align with and facilitate the community's objectives. Hence, indicators serve dual purposes: to assess the community's performance in the system, and to measure member dissatisfaction. This aspect underlines the fact that the proposed solution is human-centered, setting it apart from similar solutions that are purely technical in nature (Li et al., 2022; Soto et al., 2021).

Another contribution of this chapter is represented by the framework implementation in Python of the proposed solution, implementation that is available as an open-source software here: (M. S. Simoiu, 2023). The implementation serves as a platform for developing energy community models, considering the concepts and principles presented in this work.

Referring to the proposed interaction model, this approach represents a step further from other similar multi-agent frameworks (such as Reis et al., 2020). This distinction can be conceptually observed, as the illustration of the recommendation mechanism (Fig. 4.5) presents a method for managing systems that genuinely consider human actors and their decisions, rather than merely treating agents as small-scale systems that operate based on optimization.

Additional materials provided to the scientific community

The work presented in this chapter is further detailed in the following papers:

Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2021b). Optimising the self-consumption and self-sufficiency: A novel approach for adequately sizing a photovoltaic plant with application to a metropolitan station. *Journal of Cleaner Production*, 327, 129399. <https://doi.org/10.1016/j.jclepro.2021.129399>

Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2021a). Sizing and Management of an Energy System for a Metropolitan Station with Storage and Related District Energy Community. *Energies*, 14(18), 5997. <https://doi.org/10.3390/en14185997>

The modeling and simulation instrument is available here:

Simoiu, M. S. (2023, October). RENO - a multi-agent simulation tool for a renewable energy community [Language: en]. <https://doi.org/10.5281/zenodo.8424333>

CHAPTER 5

CONTRASTING RESIDENTIAL ENERGY COMMUNITIES: A STUDY ON POSSIBLE CONFIGURATIONS

Energy communities can be implemented in a wide range of contexts, from isolated landscapes such as islands or small villages to complex and diverse urban environments. Furthermore, these communities can form cooperative relationships with other entities, such as the municipality, landowners, or external systems, which enables the achievement of specific and sometimes more complex economic or environmental objectives. However, defining and modeling energy communities can be complex due to their open nature and the variety of factors that influence their objectives and operations. Consequently, the process of defining energy communities and their objectives requires careful consideration of multiple factors.

Furthermore, an energy community must have its own objectives in terms of environmental and economic improvement, which are shaped by the community but can also be influenced by external entities through cooperation. This type of cooperation represents an opportunity for communities, particularly when considering future smart cities where citizens are more involved in city life in an organized manner. For example, energy communities could cooperate with transportation systems, such as EVs, underground or surface transportation. However, this type of cooperation is marked with dotted lines because it is optional since it may imply that external entities contribute to both the system element and objectives element of the community, in a manner which complies with the directives stated in (Frieden et al., 2019).

In this chapter, as a starting point for applying the modeling framework proposed in Chapter 4, two possible community configurations are investigated. These case-studies will be further described in this chapter from several perspectives:

- The physical perspective, from which the community's constituent energy system-related elements are described. This perspective focuses on the particularities, constraints, and opportunities related to physical function, placement, as well as other social or economic characteristics.
- The philosophical perspective, emphasising the manner in which the respective community is developed within the paradigm proposed in Fig. 3.2.

The aim of this chapter is to provide an introductory depiction of two possible energy communities, a starting platform upon which the modeling framework proposed in Chapter 5 may be applied. Furthermore, this chapter emphasises how respective framework can apply in contexts where both the structure of the system, and the objectives can vary. It shows how the same principles stated in the previous chapter are suitable, even if external municipalities are involved in cooperation mechanisms with the energy community.

5.1 Residential PV community representation and characteristics

The first community configuration depicts a residential energy community composed of households from Grenoble, France. The physical architecture of such a community can be seen in Fig. 5.1.

From a physical perspective, the community depicted in Figure 5.1 represents a residential community with members indexed by i , with each household associated with an individual community member. In this case, the aggregated consumption of the community is associated with the system, as it is composed of the individual electricity consumption profiles of each household. Each household's power profile is represented by $p_{Load,i}$.

Regarding renewable energy production, some houses may have PV panels mounted on their rooftops, or the whole community may be connected to a standalone PV plant placed nearby. For this work, it is considered that there is a standalone shared PV plant with an associated production of p_{PV} which supplies the community.

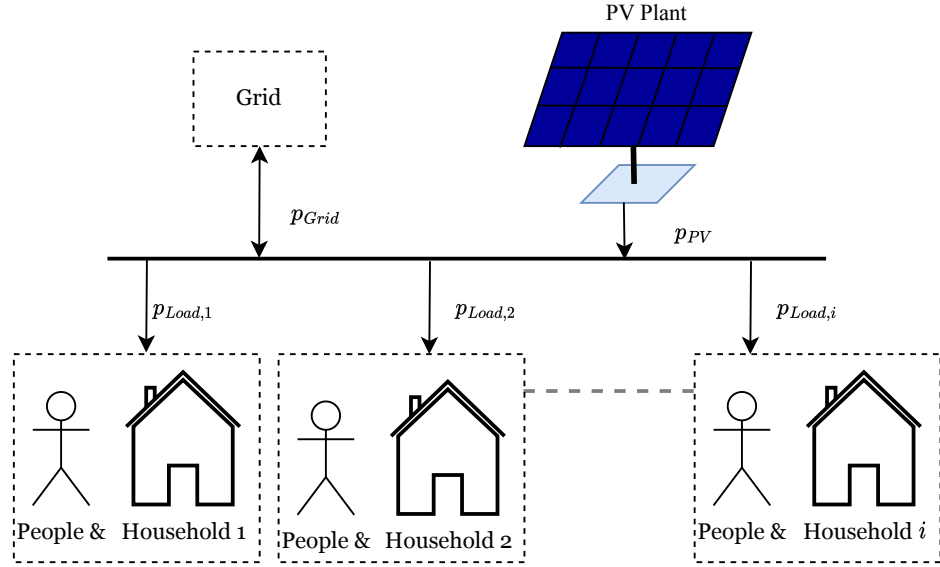


Figure 5.1: Residential energy community physical architecture

From the philosophical perspective, the renewable PV production p_{PV} , the aggregated community consumption p_{Load} and the grid energy system responsible with maintaining stability in the energy balance (defined as p_{Grid}) represent *the system*. The community members, or *actors*, influence with their household-related energy consumption behaviour the aggregated community consumption, thus producing a certain effect in the system that is either beneficial or acts as a penalty towards the objectives²⁹. The *objectives* of the community would be in this case to capitalize on the renewable energy production available and to reduce the dependency of the households on the grid. In this manner, both environmental and economical benefits are obtained. These benefits would be used afterwards for reducing the payback period for the initial community infrastructure investment, they may alternatively be invested in new infrastructure, or they may be simply shared between community members.

To completely represent the system, one must model the energy consumption, production and the grid contribution. The energy consumption of each house is reflected in an energy consumption profile, which can be estimated in each residential building. In this study, the estimated energy consumption $p_{Load}^{estimated}$ for each house is obtained from the IRISE consumption database that was gathered as a part of the REMODECE project (REMODECE, n.d.).

For the PV production, the PV power is estimated with the following model Duffie et al., 2020:

²⁹ For additional context, the reader can check again Fig. 3.2, in which it was depicted that actors may influence the system with their actions, causing certain system-related effects.

$$p_{PV,t} = \eta_{PV} \cdot A_{PV} \cdot G_t \quad [\text{kW}] \quad (5.1)$$

where A_{PV} represents the area of the PV plant, η_{PV} represents the efficiency of the plant and G_t represents the total irradiation incident on the PV modules that accounts for geographical coordinates, local time, outdoor temperature, nebulosity, time, cloudiness, slope and exposure.

This data are used to model the behaviour of people and the expected renewable energy production associated to the community. Regarding the community service, it would represent an instrument with the objective to aid the community members towards matching their consumption with the production. This would imply that the service develops an internal representation of the expected behaviour of the community in terms of energy consumption. Based on this expected behaviour and considering the dissatisfaction of people, the service would aim to provide recommendations, trying to influence people to modify their consumption so that the real and final consumption and production are better matched. The outcome would result in reduced grid dependency, which may be further associated with economical and environmental benefits.

Overall, this community configuration has significant potential. Firstly, it can be easily adapted to any urban context, regardless of the type of energy production. For example, in a more realistic scenario, only several households may have PV panels installed, and the associated community members could agree to share the PV production with the whole community, resulting in a virtual PV plant. Secondly, as the PV production is shared by the community, households without renewable energy sources can also benefit from the community's shared energy production. However, the challenge is to identify a meaningful way for community members to contribute to the community life, guided by the community-owned service and considering system-related constraints.

5.2 An energy community as a sustainable solution for metropolitan transportation

The second configuration investigated in this work is related to an energy community composed of people who live near a subway station and typically use the subway to commute to work.

From the physical point of view, the community architecture can be visualised in Fig. 5.2.

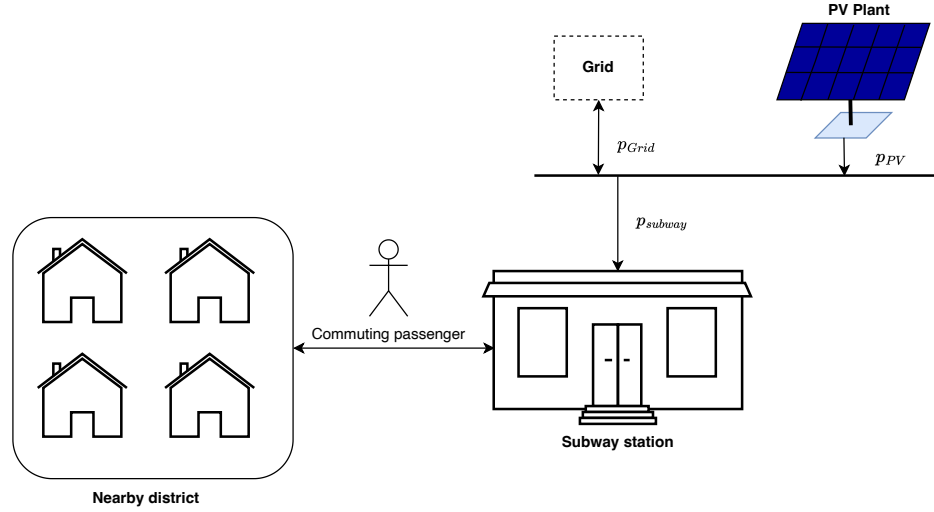


Figure 5.2: Residential energy community physical architecture

³⁰ One can consider that the PV plant may be owned by community members and they can all agree to share the energy with the subway station, or it can be a standalone PV plant directly connected to the subway station, situated, for example, on the roof of a large parking.

The *system* in this case is represented by the energy system of the subway station (with its associated load p_{subway}), the PV plant, and the grid ³⁰. It is important to note that, compared to the previous residential community configuration, this community does not consider the aggregate consumption of households but the consumption of a particular subway station, an *external system* that is not owned by the community.

From a philosophical standpoint, this case study reflects a situation in which a cooperation mechanism is implemented between the community and another entity, in this case, the subway transportation company. As a consequence, the *system* (as initially defined in the paradigm from Fig. 3.2) may now be composed of both community-owned components, such as the PV plant, and external components, such as the energy system of the subway station. This cooperation implies that there are several shared *objectives* between the community and the municipality-administered company, specifically related to environmental and economic benefits.

The subway station is connected to a nearby PV plant, and it directly benefits from the available PV production. However, the energy consumption of the subway station is mostly influenced by the traction part, especially during peak traffic hours. Additionally, the consumption of trains is directly influenced by the number of passengers inside a train. Therefore, people who specifically use the subway to commute to work may adjust their commuting times so that a portion of the traction energy consumption inside the station is shifted. Con-

currently, the subway transportation company may shift the train schedule so that passenger traffic peaks are matched with train traffic peaks. Thus, the role of each passenger is directly related to the community's objective of producing a certain environmental and economic benefit. The work notably focuses on the commuting passengers, as other people who occasionally use the subway such as tourists, for example, may be not have the necessary motivation to take part in the community, as they may not be so easily rewarded for their involvement.

5.2.1 Modeling the behaviour impact of community members as commuting passengers

Comparing to the previous configuration, in this case the community members' actions inside their households do not influence the energy consumption of the *system*, they must opt for other possible actions, such as adjusting the times they interact with the *system*. In the case of a subway station, one can consider that commuting passengers may change the time intervals when they commute to work, according to some rules. By changing their commuting times, people may influence the energy consumption of the trains, which would directly affect the consumption of the station. In return for their active involvement, the subway transportation company may provide concrete benefits for the community members, such as free nominal tickets to the respective community members.

An important requirement in this problem is reflected by the measure of how effective the *actions* of people are in relation to the possible *effects* on the energy system of the subway station. Specifically, it is important to determine what are the main parameters that influence the energy consumption of a subway station and whether these parameters include the passenger traffic, the train traffic or both³¹.

The work presented in this research study focuses on a typical subway station from Bucharest, Romania. Consequently, all the data further depicted is limited between 05:00 and 23:00, as during this interval the subway station is open to public. To model the energy consumption of the subway station, one can begin by analysing the power flow in a typical station (Fig. 5.3, M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2021b). As it can be noticed, the energy system can be conceptually divided in two parts:

- **The traction component** : responsible for powering the rolling stock; DC power is supplied to trains, based on two AC/DC transformer points (GTR₁ and GTR₂).
- **The services component**: responsible for powering the lighting systems, the ventilation systems etc. These systems are typically powered at 230V

³¹ There may be some other factors such as train individual efficiency or train schedule that may influence the consumption in a more significant manner than the passengers. This would result in a situation where community members' actions have no effect in the behaviour of the system.

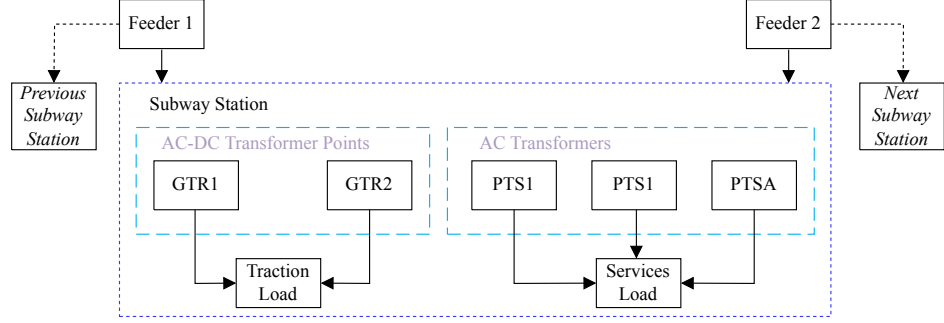


Figure 5.3: Subway station power flow

AC, so several transformers (PTS_1 , PTS_2 , $PTSA$) are used to ensure the transition from the city level (represented by Feeder 1,2) to this power rating.

The data used in this work has been obtained from an energy measurement study conducted by the respective subway transportation company on a specific subway station for the duration of a week in October, in which consumption has been measured for all power transformers presented in Fig. 5.3.

The average power level of the subway station can be thus analysed in Fig. 5.4c. This profile has been obtained by aggregating the measurement of power profiles for each transformer (both services, Fig. 5.4a, and traction Fig. 5.4b) in a single power profile, thus obtaining the overall power evolution for the station.

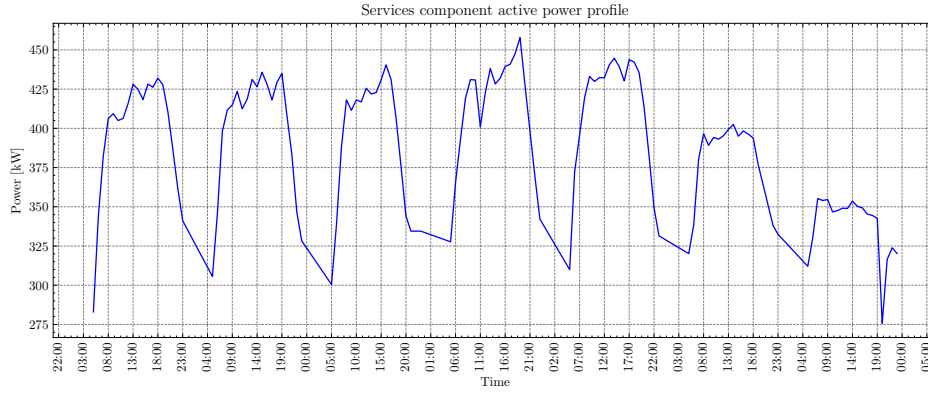
By analysing the consumption profiles in Fig. 5.4, one can notice there are two consumption peaks related to the train traction load, one in the morning and one in the afternoon. These two peaks are correlated with typical periods when people commute to work. Although these peaks are yielded by the traction consumption, they have a significant impact in the total subway consumption profile ³².

³² This is not the case for the weekend, as it can be noticed the consumption profile level significantly drops.

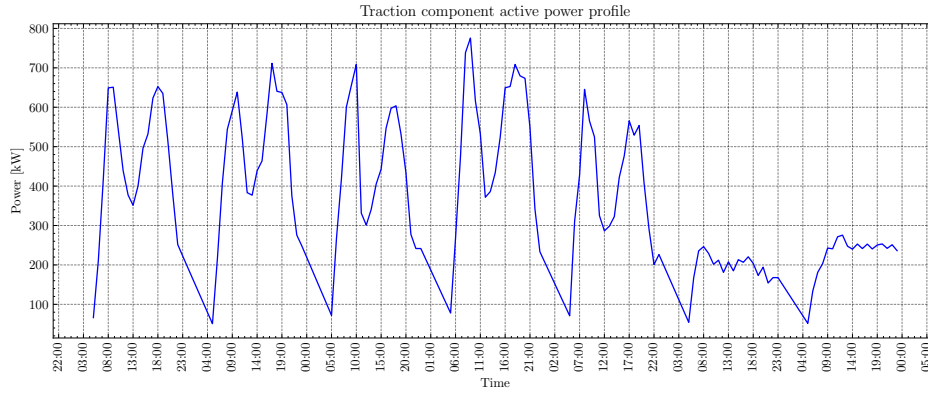
On another hand, to determine the passenger profile, one can look at the number of passages through the access gates of the respective subway station. As per the available data and considering the same analysis period, the average passenger profile can be analysed in Fig. 5.5.

Additionally, the number of trains passing through the station in the same time period can be analysed in Fig. 5.6.

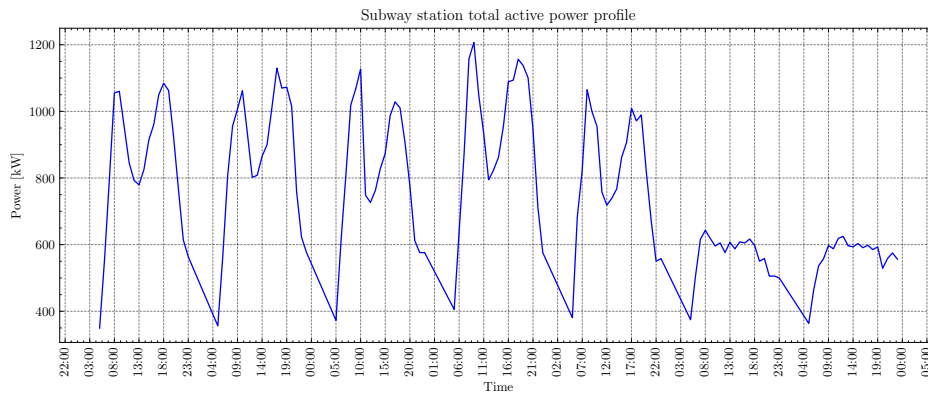
To identify the key factors that affect energy consumption in a subway station, one can start by focusing on traction energy consumption, as this is the primary energy expenditure when trains are used to transport people, including



(a) Services average consumption profile - hourly average data was computed for 5 working days during October.



(b) Traction average consumption profile - hourly average data was computed for 5 working days during October.



(c) Subway station average consumption profile - hourly average data was computed for 5 working days during October.

Figure 5.4: Available consumption data for a subway station, measuring during 5 working days in October

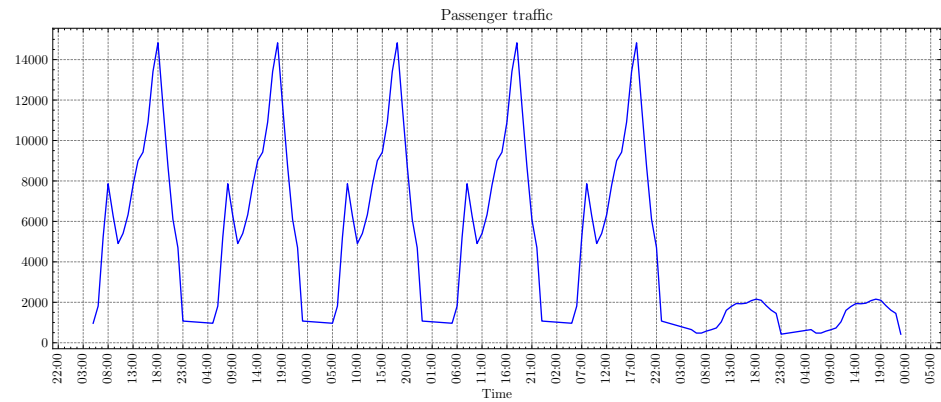


Figure 5.5: Average passenger profile - the passenger profile reflects the number of passing during each hour through the access gates of a specific subway station, during a working day.

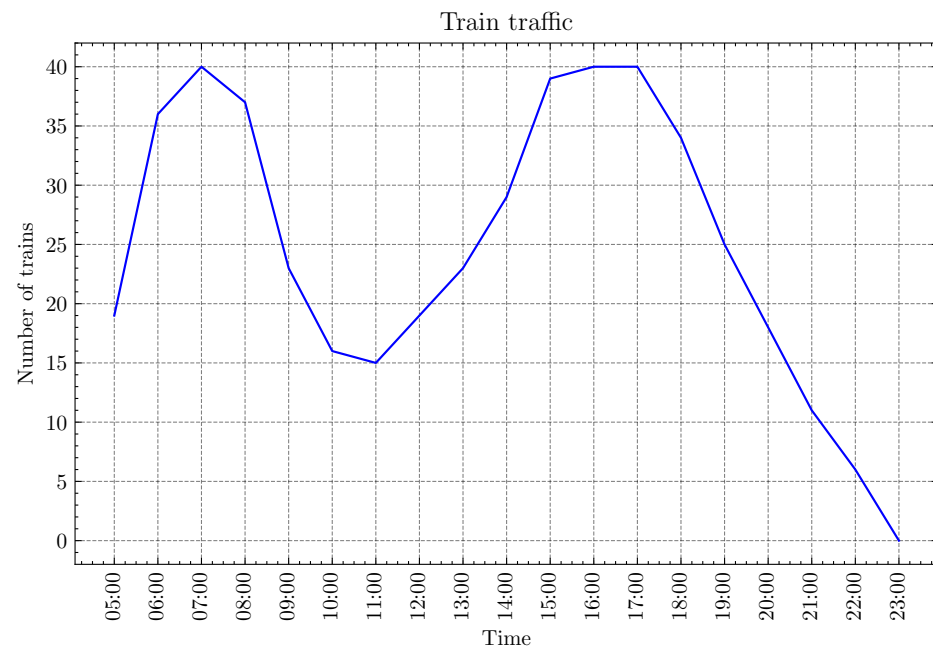


Figure 5.6: Train traffic through the station - the number of trains that pass through a specific station during each hour of a working day

the community members under study in this section. The aim is to minimize this energy consumption when transporting a specific number of passengers from Station A to Station B.

One can begin by assuming there is a total of N_{total} passengers to be transported, and they can be divided into P_{trips} groups. Each group has a size defined as N_{group} , and therefore the following constraints can be derived:

- The sum of all group sizes equals N_{total} .
- The maximum size of a group is limited by the capacity of one train, defined as C_{train} .

One can further model the energy consumption of the transportation process for one trip as:

$$E_{total,i} = E_{empty_train} + N_{group,i} \cdot E_{per_passenger} \quad (5.2)$$

Here, $E_{total,i}$ is the total required energy for one trip i , E_{empty_train} is the energy consumption of an empty train traveling from Station A to Station B, $E_{per_passenger}$ is the energy consumption to transport one passenger, and $N_{group,i}$ is the number of passengers to be transported in trip i .

However, since passengers are grouped into P_{trips} groups and all P_{trips} groups need to be transported, the equation becomes:

$$E_{total} = E_{empty_train} \cdot P_{trips} + \sum_{i=1}^{P_{trips}} N_{group_i} \cdot E_{per_passenger} \quad (5.3)$$

It is also important to remember that N_{group_i} is a fraction of N_{total} , so:

$$N_{group_i} = \rho_i \cdot N_{total} \quad , \text{ where } \sum_{i=1}^{P_{trips}} \rho_i = 1 \quad (5.4)$$

Therefore, the total energy consumption equation simplifies to:

$$E_{total} = E_{empty_train} \cdot P_{trips} + N_{total} \cdot E_{per_passenger} \quad (5.5)$$

In this energy consumption minimization problem, the goal is to minimize the number of trips P_{trips} , considering the lower bound $P_{trips} = \text{ceil}(N_{total}/C_{train})$. This is because empty or under-loaded trains result in extra energy consumption. The ideal scenario is to have each train fully loaded with C_{train} passengers, aligning passenger traffic with train traffic peaks to minimize energy consumption.

Within the energy community context, influencing passenger traffic is of particular interest, as the train traffic schedule is an aspect that can be easily controlled by the transportation company. Specifically, the company has the capacity to adjust the schedule in response to passenger demand. However, when renewable energy sources are incorporated, the company may also wish to optimize the use of available renewable energy production. This can be challenging, as the involvement of individuals can significantly impact the overall balance of energy consumption.

One potential solution to this issue involves the voluntary participation of regular subway commuters. Due to their consistent use of this mode of transportation, these individuals can form an energy community and can further collaborate with the transportation company to influence the station's energy consumption. Recognizing the importance of this community and its impact on traction energy consumption, the company may agree to reward them with the economical benefits that may potentially emerge as a consequence of the community's coordinated actions.

In this newly formed tripartite cooperative mechanism, community members are encouraged to commute primarily during specific intervals determined by the community service.³³

The transportation company, on the other hand, should implement a train schedule that ensures the capacity of the trains aligns with passenger demand. Additionally, the company should provide appropriate rewards to individuals for their participation.

Finally, the community service plays a crucial role in supporting the community to meet objectives regarding commuting during specific intervals. This might not be an easy task, as the internal representation of the behaviour of each community member is crucial in developing a realistic model of the collective community impact. For the community service, a realistic representation of community behaviour, including individual preferences, restrictions and dissatisfaction, provides a solid foundation for developing precise, personalized support that can further assist the community in fulfilling its role within the cooperative mechanism.³⁴

With this representation, the service can develop an overall consumption profile, which is a specific depiction of people's behaviour within the system. By providing recommendations related to commuting times, the service can further influence this consumption profile to align with renewable energy production. This alignment leads to a reduction in grid energy usage, resulting in economic benefits that will be subsequently distributed among the members, who are the primary actors in this mechanism.

³³ This is particularly relevant when the subway station is connected to a PV plant, as commuting times would ideally align with periods of available renewable energy production.

³⁴ Fig. 3.2 can be used once again for reference, since it was already mentioned that the *service* should have a proper representation of the *actors* and their potential impact in the *system*.

5.2.2 Passenger traffic and subway consumption correlation analysis

To determine whether the station's consumption is truly influenced by passenger traffic, a correlation analysis was conducted upon the available data (Fig. 5.7). In each plot, either the passenger traffic or the train traffic is plotted vs. each consumption component, emphasizing the two key commuting periods (morning and afternoon) during a day. Moreover, the Pearson correlation coefficient is computed for each analysis.

On the proposed analysis, one can see in Figs. 5.7b, 5.7a, 5.7c that there is a significant correlation between the passenger and the consumption of the subway station, as the passenger traffic is correlated to both the services component and the traction component. Moreover, we can see that the train traffic is not significantly correlated to the consumption, since the train schedule seems not to match the demand represented by the passenger traffic. The consequences show that there are some incomplete trains that yield additional consumption to the overall station profile.

Additionally, a regression analysis was conducted upon the data (Table 5.1). Specifically, a regression model³⁵ was obtained for several scenarios in which the independent variable x was alternated with additional features, such as temperature³⁶, time of day, day of the week, or hour of the day. The dependent variable y was the subway consumption. All scenarios were evaluated according to the r^2 score, an indicator with values between 0 and 1 that shows how well the regression model obtained fits the data³⁷. As it can be noticed, the regression analysis shows that features like temperature or day of the week do not reflect a significant change in the subway consumption estimation, as the most significant improvement is reflected by the time of the day. This aspect supports the idea that passenger traffic represents an important factor that impacts the consumption of the subway station, with commuting passenger traffic accounting for the most significant influence in the overall consumption.

5.2.3 The inferred consumption per passenger

The correlation between passenger traffic and subway station consumption enables the estimation of the impact of each passenger in the power profile of the station. Considering the dependency between the subway consumption profile and the passenger traffic, the following model is proposed:

$$IPP(t) = \frac{P_{Load}^{subway}(t)}{n^{passengers}(t)} \quad (5.6)$$

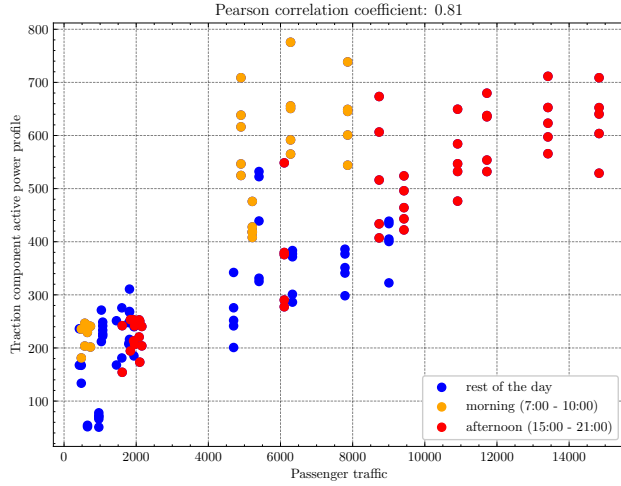
³⁵ A typical regression model has the form

$$\hat{y} = ax + b$$

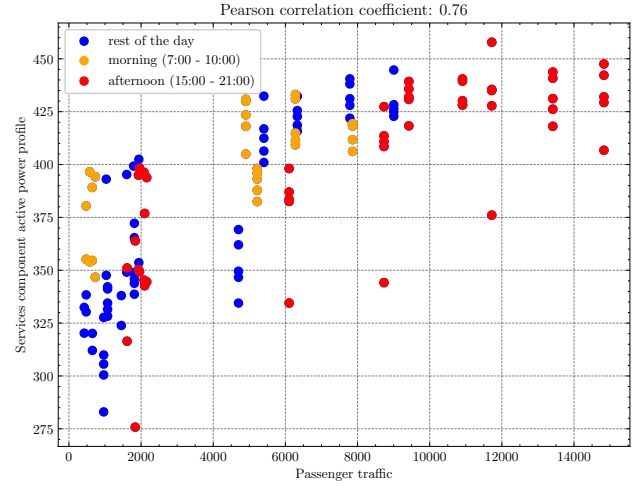
, where $\hat{y}$ represents the dependent variable to be estimated based on x , the independent variable. As x can be composed of several parameters (often called features), the goal is to estimate the values of the coefficients or parameters (a, b) that describe the relationship between the dependent and independent variables.

³⁶ The temperature data was obtained from *Openweathermap.org* for Bucharest, during the time period of the subway consumption measurements.

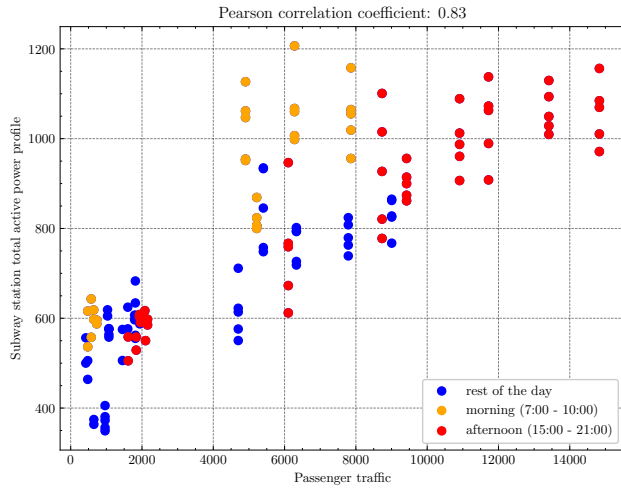
³⁷ The closer the value of r^2 is to 1, the better the fit between the regression model's estimation and the actual parameter.



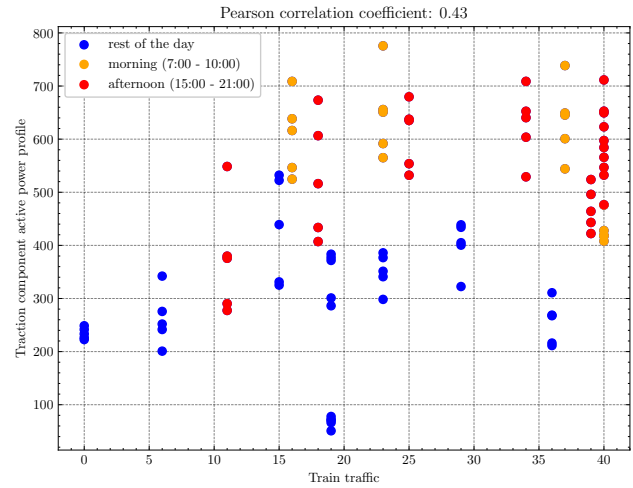
(a) Passenger traffic vs. Traction consumption



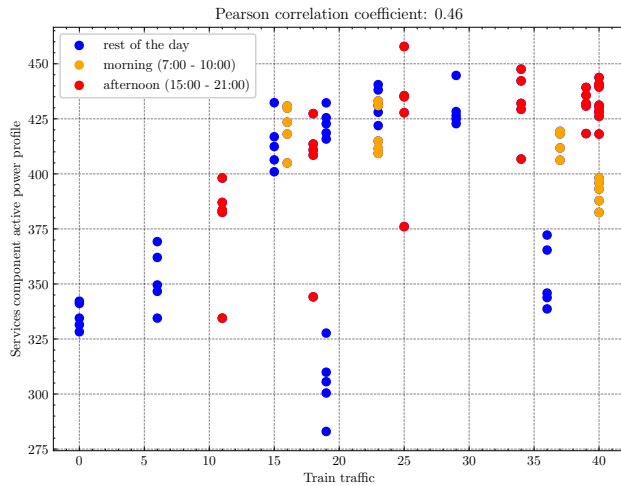
(b) Passenger traffic vs. Services consumption



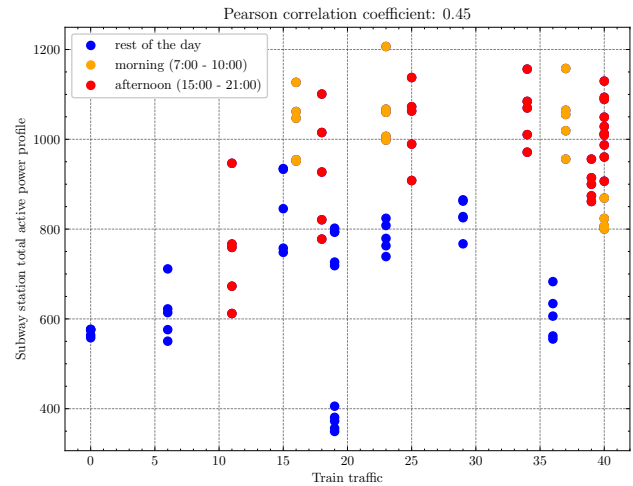
(c) Passenger traffic vs. Station consumption



(d) Train traffic vs. Traction consumption



(e) Train traffic vs. Services consumption



(f) Train traffic vs. Station consumption

Figure 5.7: Correlation analysis on the subway station available data

Table 5.1: Regression analysis between the available passenger data and the subway consumption. Passenger traffic represents the number of passing through the access gates, train traffic represents the number of trains passing through the station. Subway station power is measured in kW.

Independent Variable(s)	Dependent Variable	r^2 score
Passenger traffic	Subway station power	0.76
Passenger traffic, Train traffic	Subway station power	0.78
Passenger traffic, Temperature	Subway station power	0.77
Passenger traffic, Time of day	Subway station power	0.8
Passenger traffic, Day of week	Subway station power	0.76
Passenger traffic, Hour of day	Subway station power	0.76

where IPP represents the *inferred power per passenger*, p_{Load}^{subway} represents the subway station consumption profile, and $n^{passengers}$ represents the passenger traffic profile.

As a brief example, for the measured data depicted in Figs. 5.4c, 5.5, the subway station consumption has been divided by the passenger traffic, as indicated by the model in Eq. 5.6. The results for one working day can be analysed in Fig. 5.8.

In Fig. 5.8, one can see that the IPP varies in time. Based on the correlation analysis from the previous section, it can be considered that there are several influencing factors that contribute to the IPP variation in time, factors such as train traffic and the time of the day. However, the value are relatively similar during morning and afternoon, the relevant periods of the day for the community passengers.

Consequently, since the impact is important only during the morning and the afternoon for the respective energy community, the IPP profile can be estimated using Eq. 5.6. Then, to develop the power profile which depicts the behaviour of commuting passengers, the average value can be considered for each hour during one period of interest (morning or afternoon).

Overall, the IPP could determine the significance of the impact that community members have on the *system*. Although the accuracy of the estimation depends on the size of the available dataset, the IPP, along with the number of commuting passengers and a model of their associated behavior, could potentially provide a reliable representation for the service to guide the community towards fulfilling their objectives effectively.

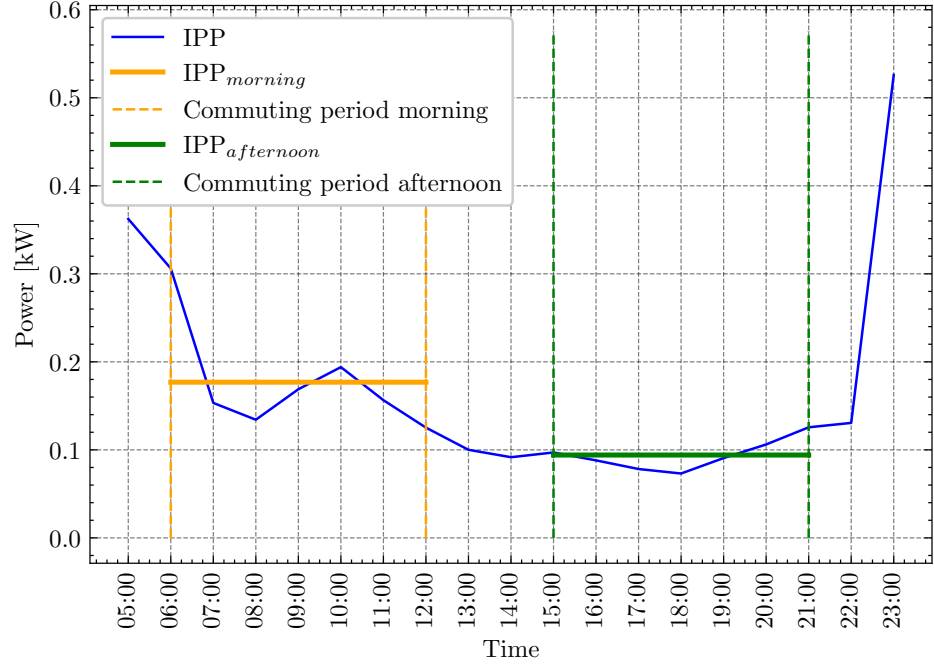


Figure 5.8: Inferred power per passenger profile for one working day, with average values emphasised for each period of interest: morning (06:00 - 12:00) and afternoon (15:00 - 21:00).

5.3 Conclusion

In this chapter, two possible energy community configurations were presented as a starting point for applying the modeling framework proposed in Chapter 4.

The first configuration is represented by a residential energy community where community members are household owners, and the *system* comprises household appliances, the grid and an external PV plant. Furthermore, the community uses the service to obtain guidance on adapting their energy consumption *actions* in their households, aiming to align consumption with the available PV production. This approach produces a certain environmental and economic *effect*, yielding benefits such as increased self-consumption and self-sufficiency.

The second configuration refers to an energy community comprising people who commute via the subway and live near a particular subway station. In this case, the *system* is composed of the energy system of the subway station and an external PV plant. By adjusting their commuting *actions*, under the

guidance of the *service*, people can influence the energy consumption of the subway station and align it with the available production from the PV plant. This approach can yield an *effect* with economic benefits for the transportation company, which can be passed on to the commuting passengers who contribute to the energy-saving actions.

These two configurations reflect two contrasting scenarios. Firstly, one can notice that even that the two communities may be similar from a *system* point of view, the objectives may differ. This is especially because external entities might be involved (in the second configuration, the external entity is represented by the transportation company), resulting in a newly developed *system* with new particularities, so the community objectives might require adaptation³⁸. Secondly, it is important to notice the potential complexity of the *actions* that community members may take in relation to the *system*. While in the first configuration, the *actions* depend on time, behavior, and household appliance usage, in the second configuration, the *actions* are more specific, referring only to the choice of commuting times. Thirdly, the cooperation mechanism shown in the second configuration reflects significant potential, as even more benefits may be obtained when several parties are involved and cooperate in a coordinated manner. However, it becomes clear that as the complexity of the system increases, the requirement for an effective and trustworthy *service*, with a realistic representation of both the *system* and the community members, becomes crucial.

³⁸ Nevertheless, EU forums Frieden et al., 2019 suggest that large companies should not be included in energy communities, as they might enforce their own objectives. However, with municipality, the community may maintain a certain degree of autonomy, as the primary objective of the municipality is to serve the citizens.

Additional information

The work presented in this chapter is further detailed in:

Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2021b). Optimising the self-consumption and self-sufficiency: A novel approach for adequately sizing a photovoltaic plant with application to a metropolitan station. *Journal of Cleaner Production*, 327, 129399. <https://doi.org/10.1016/j.jclepro.2021.129399>

Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2021a). Sizing and Management of an Energy System for a Metropolitan Station with Storage and Related District Energy Community. *Energies*, 14(18), 5997. <https://doi.org/10.3390/en14185997>

Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2023). Managing human involvement in an energy community: Application to a subway station. *Sustainable Cities and Society*, 95, 104597. <https://doi.org/10.1016/j.scs.2023.104597>

CHAPTER 6

CASE STUDY: MANAGING HUMAN INVOLVEMENT IN RESIDENTIAL ENERGY COMMUNITIES

6.1 Modeling a typical residential community

As both the multi-agent framework and the relevant indicator adoption are set, the last two requirements defined in Fig. 3.1 emphasise, at the same time, the most important aspects of human involvement management in an energy community. These aspects refer, firstly, to how recommendations are developed and how the objectives of the community are formulated considering the *actors* involvement in the *system* and secondly refer to how the behaviour of community members is modeled.

This chapter addresses these requirements from a simple residential community standpoint, as it was defined in Chapter 4. Specifically, several recommendation strategies are proposed as a concrete solution to influencing systems with humans. Additionally, several human-related indicators will be proposed according to the context and actor-service relationship described by the community configuration. Finally, the simulation strategies will be evaluated in a case study, where several relevant scenarios are further analysed.

6.2 Community manager service recommendation strategies

In developing suitable recommendation strategies, the main reference is represented by the simulation framework depicted in Fig. 4.3, as the actions of manager and the community members must be suitably adapted to the time segmentation of each day. As a standalone research objective, several aspects should be defined for each recommendation strategy:

- **the nature of the recommendation**, whether it is a color signal, a textual information or other form of representation;
- **the target period for the recommendations**, reflecting the period during which the community members are required to be involved;
- **time coordinates**, emphasising when the recommendations are given and how often.
- **the intensity of the recommendation**, reflecting the commitment that is required from the community members
- **the targeted community members** - whether the recommendations are aimed at all community members, or recommendations are personalised for groups or even if recommendations are to be given to individuals.

Moreover, as the previous chapter proposed several metrics that could both contribute towards developing and evaluating recommendation strategy from a system performance standpoint, additional metrics should be proposed for evaluating discomfort.

In terms of nature of recommendation, for the case study of a residential energy community as it was envisioned in Chapter 4, the solution proposed in this chapter refers to developing recommendations as simple colored signals. As such, the following recommendation dictionary is proposed to describe the recommendations and expected outcomes from the service standpoint (Table 6.1).

By analysing the proposed recommendations in Table 6.1, one can notice that each recommendations deals either with an expected level of consumption developed internally by the manager $p_{Load}^{expected}$, or a true consumption profile p_{Load}^{real} that has been measured at a previous time step.

As a starting point, recommendations will be the same for all community members, without focusing on individuals or groups characterised by preferences or motivation. From a practical point of view, one may consider that

Table 6.1: Recommendation dictionary and expected outcomes

Recommendation	Description	Expected outcome
WHITE	The community is expected to consume energy as in their business as usual scenario.	$p_{Load}^{real} = p_{Load}^{expected}$
RED	The community is expected to decrease consumption.	$p_{Load}^{real} < p_{Load}^{expected}$
STRONG RED	The community is expected to strongly decrease consumption.	$p_{Load}^{real} \ll p_{Load}^{expected}$
BLINKING RED	The community is expected to additionally decrease consumption. This signal may be used by the manager when he has discovered an additional contribution is needed, as the initial outcome was not met.	$p_{Load,final}^{real} < p_{Load,initial}^{real}$ where the keywords <i>initial</i> and <i>final</i> mark the respective member contributions.
GREEN	The community is expected to increase consumption.	$p_{Load}^{real} > p_{Load}^{expected}$
STRONG GREEN	The community is expected to strongly increase consumption.	$p_{Load}^{real} \gg p_{Load}^{expected}$
BLINKING GREEN	The community is expected to additionally increase the consumption.	$p_{Load,final}^{real} > p_{Load,initial}^{real}$

community members have portable devices that show the respective recommendations during the day, along with other relevant indicators.

Based on the premise that energy sobriety should be increased and people should reduce their energy consumption over time, the timing for providing recommendations becomes important. As people are typically less active at night, the "flexibility period" is defined as the time between 7:00 AM and 11:00 PM, during which recommendations can be communicated to the community. Specifically, the term "flexibility period" is used to refer to the time when people can modify their energy consumption directly or indirectly in response to the recommendation mechanism, thereby providing flexibility to the overall energy system.

The importance of using color-coded recommendations is twofold. Firstly, these recommendations are simple and community members can easily understand what impact is required of them. Secondly, there is significant freedom for members to choose how they want to follow the recommendations, as they are not restricted to use certain appliances or change their consumption according to a set quantity.

As the nature of recommendations is set, the actor-service relationship is conceptually defined. This aspect allows the development of two evaluation indicators for dissatisfaction:

- **Recommendation deviation rate (RDR)** - assuming the recommendation at each hour t in a time interval T has a certain rating r_{color} for quantifying intensity, the recommendation deviation rate is represented by Eq. 6.1.

$$\text{RDR} = \frac{1}{\max(r_{\text{color}})} \sqrt{\frac{\sum_t^T (r_{\text{color},t} - r_{\text{white}})^2}{T}} \quad (6.1)$$

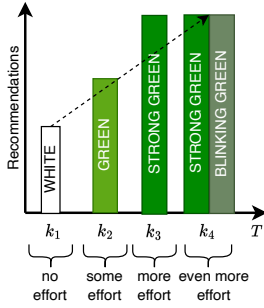
where r_{white} is the rating for the white color and must be equal to 0.

The rating system defined by r_{color} is meant to measure the effort in following recommendation from the community members' perspective. It is therefore chosen by community members according to their appreciation of the intensity of each recommendation, depending on their collective intentions towards obtaining environmental and economical benefits. In this work, the rating system used is described in Table 6.2, an extension of Table 6.1 as each recommendation has an associated rating.

Table 6.2: Rating system for the intensity of each recommendation

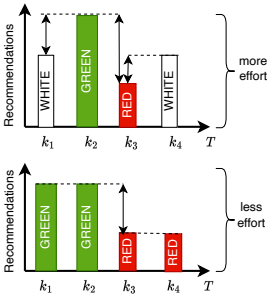
Recommendation	r_{color}
BLINKING RED	-1
STRONG RED	-0.75
RED	-0.5
WHITE	0
GREEN	0.5
STRONG GREEN	0.75
BLINKING GREEN	1

³⁹ The increase in recommendation intensity is associated with more effort and discomfort from community members.



⁴⁰ One should note that if the community members choose the rating system between 0 and 1, the term $\frac{1}{\max(r_{\text{color}})}$ disappears.

⁴¹ If the members must frequently change their behaviour, it might represent a certain discomfort for them as the recommendations might be in conflict with their current activities



This metric aims to determine how far the recommendation system is requiring community members to deviate from their usual behaviour (reflected by the WHITE signal)³⁹, since it is important to quantify the magnitude of the effort required by community members to follow the recommendations at each time step. The metric is also normalised to the maximum value for the set⁴⁰ so that the value 0 over a time interval indicates that people were always given the WHITE recommendation, while 1 means people were always requested to deviate from their usual energy consumption behaviour.

- **Contribution Change Rate (CCR)**

$$\text{CCR} = \frac{C}{T} \quad (6.2)$$

where C represents the number of changes in recommendations from one hour to another and T represents the time interval. This indicator is equal to 0 if the recommendation is the same every hour and equal to 1 if the recommendation changes every hour⁴¹.

In contrast to the recommendation deviation rate, the contribution change rate aims to quantify how frequently community members are required to modify their energy consumption. This metric is essential because residential energy consumption can be highly variable, and the recommendations given may also be characterized by chaotic fluctuations. Therefore, it is crucial for community members to have a certain level of predictability, so they are not asked to make radical changes to their energy consumption from one hour to the next.

In addition to these metrics, another one may also be considered: the average contributions per day. This final metric aims to determine an average number of contributions, with one contribution defined in the same manner as previously specified for the contribution change rate.

The fundamental principles behind these metrics rest on the relationship between the manager service and the community members, focusing specifically on the individual perspectives developed by each entity. To illustrate, if the manager issues a recommendation every hour, then from their viewpoint, a contribution is required for that respective hour. This required contribution is subsequently communicated to the members, who interpret recommendations according to their own, personal perspectives. These perspectives are independent and may differ from the manager's viewpoint. For example, if a member only receives GREEN recommendations throughout a day, they may infer that they need to make a unique contribution during the entire period (which is to increase consumption). This is a different perspective from the manager, who has requested the member to assist the community every hour.

Considering there might be a discrepancy between the manager's perception and human perception, the aforementioned metrics have been designed to best capture the members' viewpoints. They address both the perceived intensity of the recommendation (Recommendation Deviation Rate) and the perceived duration of a contribution (Contribution Change Rate). In evaluation, to get a comprehensive picture of the human effort and dissatisfaction that may arise when following a recommendation, it's important to consider both of these metrics in an integrated manner.

Considering these aspects, this work will further discuss several recommendation strategies that may be implemented in the residential context.

6.2.1 The *one-turn informative* strategy

The first recommendation strategy proposed in this work is defined as *one-turn informative* and is further depicted in Fig. 6.1. The figure represents an UML Sequence diagram, adapted to the multi-agent framework described in Fig. 4.3.

At the beginning of the flexibility period, the manager computes the expected consumption of the community. Then, during the day, considering the expected production, the manager provides a recommendation each hour. Subsequently, after each member reacts to the recommendation, the manager measures the real consumption profile before going to the next hour.

The objective of this strategy is to minimise the NEEG (Eq. 4.5), that is to match the community consumption with the production. The name of the strategy is proposed considering two aspects ⁴²:

⁴² These aspects may also be notice in Fig. 6.1

- the manager provides the recommendations once per hour (*one turn*), in the Manager Hour Interaction slot. In this manner, the target time period for generating recommendations is set equal to the data's time step, as considered in Chapter 5. This choice represents a first step in achieving a balance between good system performance and increased cognitive annoyance associated with receiving frequent recommendations. Specifically, even if the recommendations remain consistent over several hours, the manager service has the flexibility to provide a different recommendation each hour, effectively adapting to the context of the energy system. Concurrently, individuals are given a brief, albeit adequate, window to respond to the recommendation and adjust their consumption accordingly.
- the term *informative* refers to the method the manager uses - a straightforward rule-based algorithm - with the aim of minimizing the NEEG. Specifically, if the expected consumption is less than the anticipated production, the recommendation is to increase consumption, and vice versa. The manager's role involves comparing the expected effects of the system members' usual business operations with the predicted production. Subsequently, a recommendation is provided, which acts independently of any member-associated knowledge such as preferences or motivation towards following recommendations.

An important aspect to note here is related to the perception of the manager regarding the member impact in the system performances. As $p_{Load}^{expected}$ is determined by the manager as a estimated power profile when trying to capture

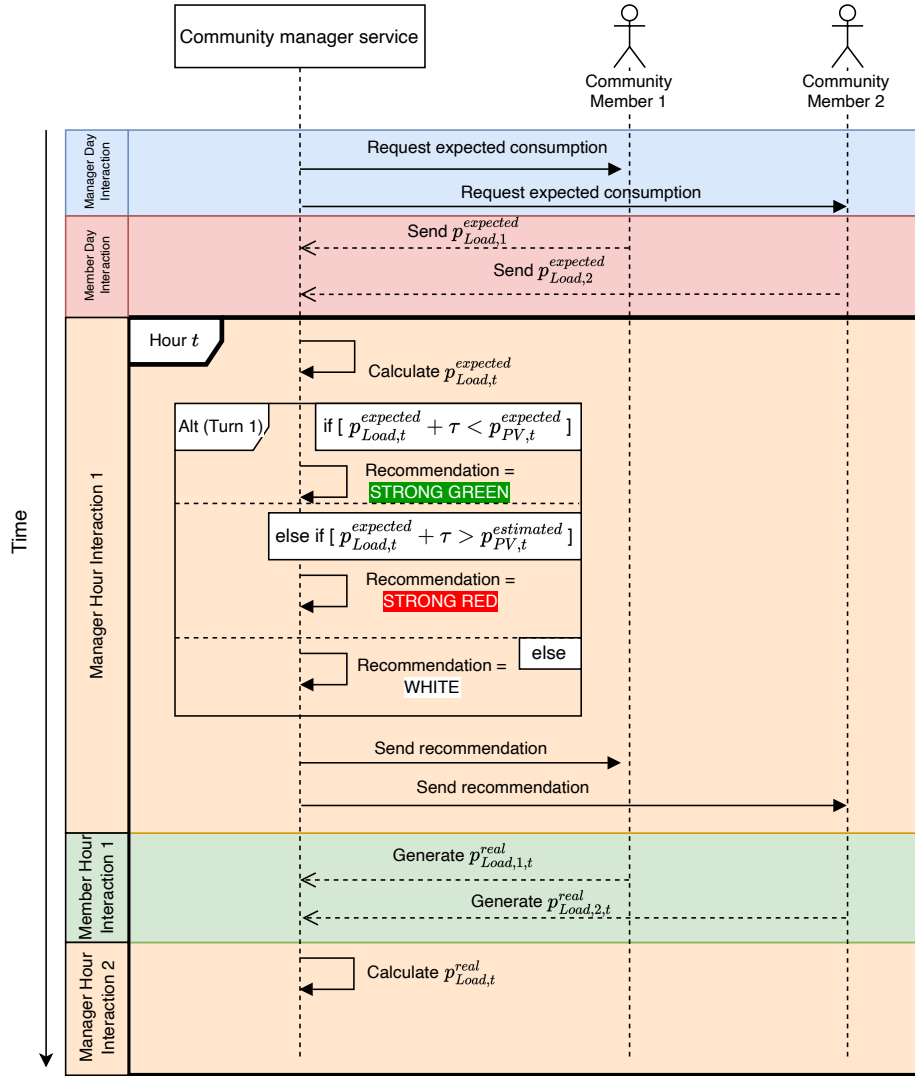


Figure 6.1: One-turn informative recommendation strategy; $p_{Load}^{expected}$ represents the expected community consumption, $p_{PV}^{expected}$ represents the expected production and p_{Load}^{real} is the consumption generated after recommendations. The formalism used is UML Sequence Diagram.

the collective behaviour prior to receiving recommendations, the respective profile might closely align to the estimated production in a manner that providing recommendations might yield inadequate performances at the expense of the community members' effort. Consequently, a "comfort" parameter τ is introduced. This comfort parameter is meant reduce the number of times when the member is required to contribute and can be adjusted according to preferences of the community (M. Ş. Simoiu et al., 2023).

In a practical implementation, the manager could develop its own expected community consumption profile at the beginning of the flexibility period of each day, accounting for each community member. In doing so, the estimation window could accurately capture daily repetitive patterns of human behavior. Afterwards, the manager provides the recommendations to the community for the whole day as a list of indications, reflecting the expected impact over the day. During the day, the manager measures the final consumption profile p_{Load}^{real} after each time the community members react to the given recommendations, so he may capture the collective impact of the behaviour in the system and further compute and update the system performances according to the relevant indicators.

6.2.2 The *two-turns informative* strategy

The second strategy defined as *two-turns informative* can be analysed in Fig. 6.2. The term *two turns* emphasises that the manager may give recommendations twice during an hour as a reinforcement, once in the Manager Hour Interaction 1 slot and once in the Manager Hour Interaction 2 slot. However, this doesn't occur every hour, since the manager provides an additional recommendation only if it considers the initial recommendation has not achieved the desired impact. In this manner, the manager exhibits a "reactive" behaviour by closely monitoring the members impact in the system performances and providing interventions during the day with a certain sense of urgency.

This process means that the manager measures actual consumption twice: initially after the first round of recommendations, to evaluate performance and assess the necessity for additional recommendations, and then again following the second round (if applicable), to calculate the final collective performance .

Compared to the strategy shown in Figure 6.1, this strategy may provide recommendations twice during each hour. Specifically, after the manager measures the impact of the initially sent recommendations, it may intervene again by providing a blinking recommendation (either red or green) if the desired impact is not achieved. This strategy aims to achieve a higher level of precision in matching consumption and production, but it requires more effort from community members as the manager updates its recommendation during the same hour it was initially given.

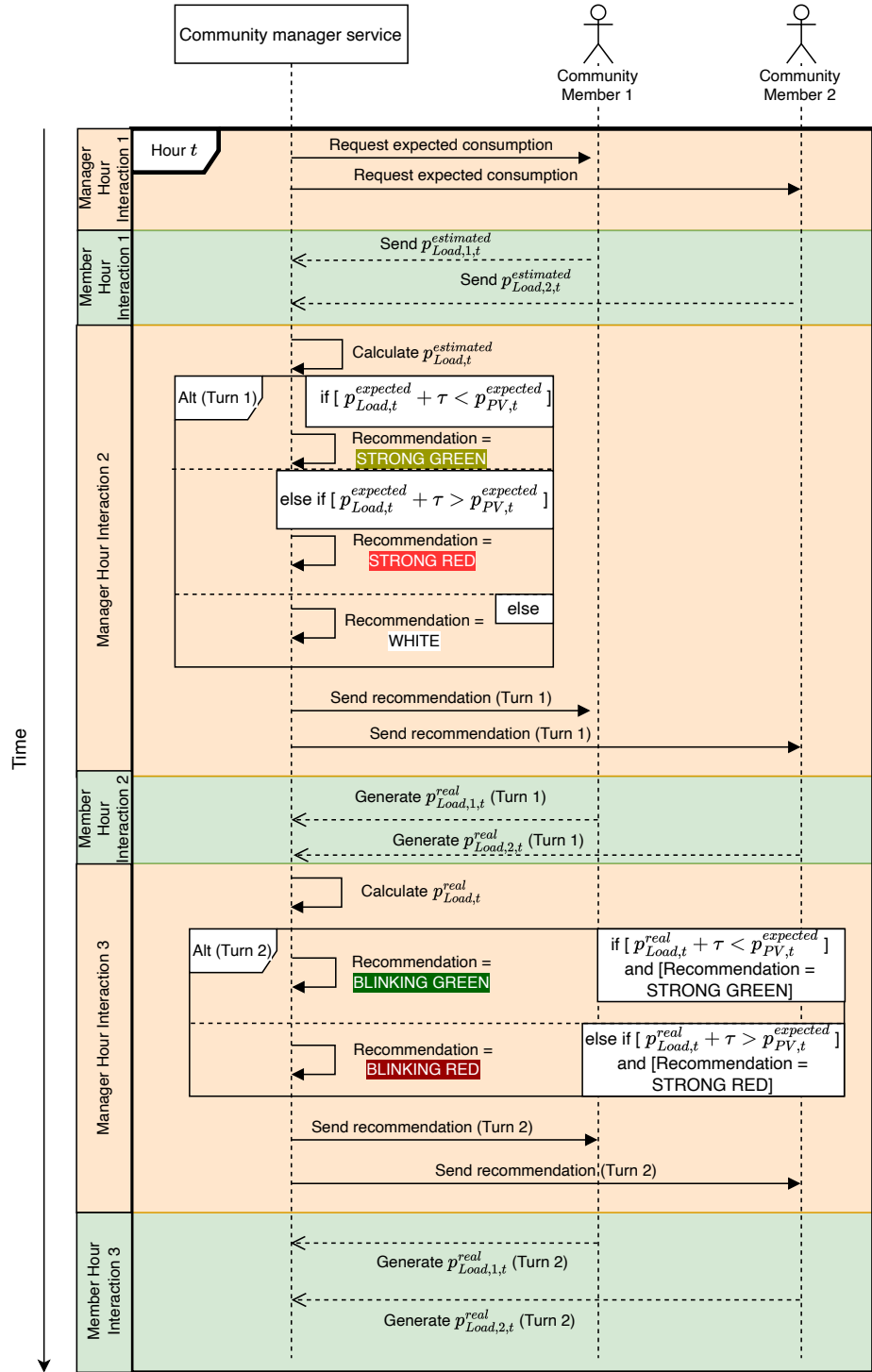


Figure 6.2: *Two turns informative* strategy. The formalism used is UML Sequence Diagram.

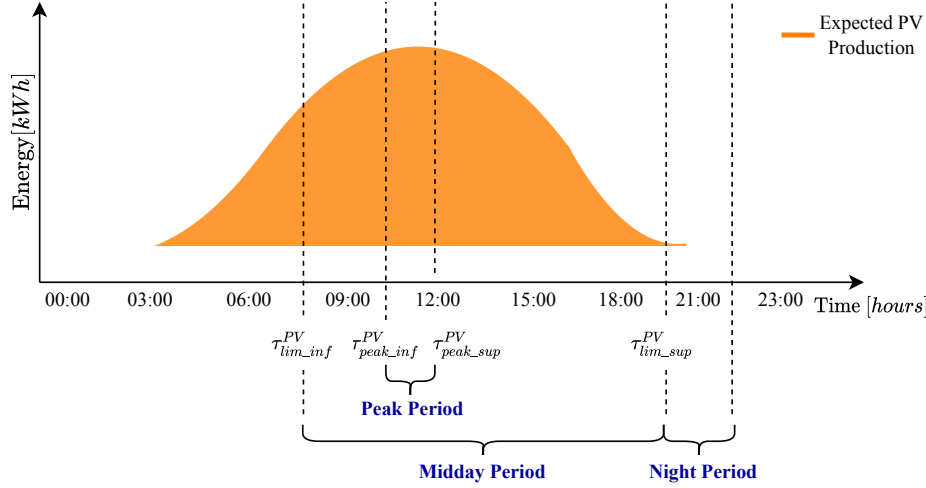


Figure 6.3: An illustration of how a typical simulation day is decomposed in periods

6.2.3 The *one-turn coaching* strategy

As it could be noticed in the first two strategies, since the recommendation is given for a single hour k , the manager may provide a different recommendation at every hour during a calendar day. However, since the objective is to propose a method that encourages people to improve their behaviour towards energy consumption, the *coaching* strategy will provide the same recommendation for each hour, for representative periods of the day. More specifically, a *period* is defined as a time segment of the flexibility period of one day, in which the same recommendation is given during each hour.

Consequently, the flexibility period of a simulation day is further split in periods (Figure 6.3, M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2021b) according to the rules described in Table 6.3.

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

Setting the number of periods and the duration of each period is a fundamental aspect that significantly affects the performances of the community from a quantitative point of view. One 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

Table 6.3: Recommendation periods definition

Period	Inferior limit	Superior limit	Description
Midday	$\tau_{lim_inf}^{PV}$	$\tau_{lim_sup}^{PV}$	automatically set by the manager considering the expected PV production for the respective day $p_{PV}^{expected}$
Peak production	$\tau_{peak_inf}^{PV}$	$\tau_{peak_sup}^{PV}$	represented by one hour where there is 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 $\tau_{peak_inf}^{PV} = \tau_{peak_sup}^{PV}$.
Morning period	08:00	$\tau_{lim_inf}^{PV}$	optionally, the model considers the morning period if there is no PV production between 08:00 and $\tau_{lim_inf}^{PV}$
Night period	$\tau_{lim_sup}^{PV}$	23:00	a period in the day where there is no PV production

are set for a complete day, one can 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, it is assumed that 4 or 5 recommendations per day represent an adequate choice.

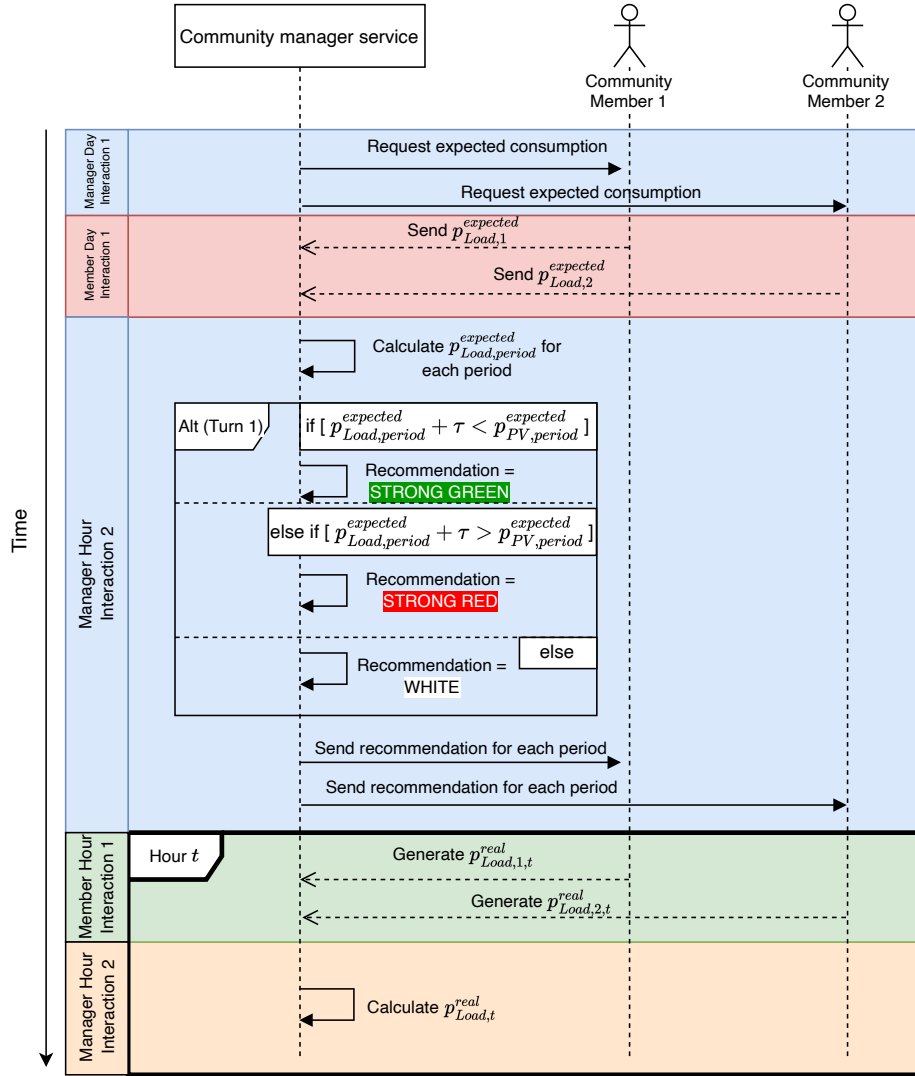


Figure 6.4: *One turn coaching* strategy. The formalism used is UML Sequence Diagram.

6.3 Markov Chain model to simulate energy community member reactions to recommendations

Focusing on the *actor* component of the energy community, the behaviour of community members should be modeled in a way that reflects uncertainty. However, it is important to note that only the reaction to recommendations should be modeled, not the entire energy consumption behaviour of people. To this aspect, Hidden Markov Models can be used as suitable models.

The concept of using Hidden Markov Models to account for uncertainty is not considered novel. However, it is important to identify the specific process that uncertainty represents. For instance, in human behavior towards energy consumption, it might be challenging to conceptualize the source of uncertainty from a broader perspective. Nevertheless, when implementing the recommendation system, the problem's scope narrows to whether the recommendation is followed or not. In other specialized literature (Lin et al., 2022), Markov models are employed in contexts where the scope is limited to a human-robot interaction process. In (Chung and Liu, 2008), the authors propose a Hidden Markov model for understanding the uncertainty in human behaviour. In (Zhao et al., 2023), the authors use a Hidden Markov model embedded in a multi-agent system to predict how the collective intelligent of a team of humans and machines will evolve in time. In occupancy problems for examples, Hidden Markov Models can be used to estimate occupancy as a step in designing energy management strategies (Soudari et al., 2016). Uncertainty in behaviour can be also related to transportation systems, as researchers try to enhance the energy performances of a building based on the recognition of the EV parking process using Markov chains (L. Cao et al., 2021).

Considering these literature examples, Hidden Markov models have been used to model the uncertainty specifically related to the daily process of following recommendations. Generally, a Hidden Markov Model λ is characterised by 3 elements: the transition matrix A reflecting the probability distribution to change states, the emission matrix B depicting the probability distribution to generate observations and the initial states probability distribution π .

When modeling the community members' reaction to recommendations, the proposed model presented and further used in this study is composed of two hidden states: **Attentive** and **Inattentive**, reflecting the potential state of a community member as he reacts to a recommendation. This is because community members focus on the recommendation received, thus consuming

energy in the manner suggested by it (attentive), while in some other cases the community member may respect the recommendation or not, while not being specifically aware of the recommendation received (inattentive).

The transition matrix A , characterising the probability distribution to transition from one state to another (Rabiner, 1989). In the proposed case with two hidden states (attentive, inattentive), the transition matrix becomes Eq. 6.3.

$$A = \begin{array}{c|cc} & \text{Attentive} & \text{Inattentive} \\ \hline \text{Attentive} & a & 1 - a \\ \text{Inattentive} & b & 1 - b \end{array} \quad (6.3)$$

Here, a and b are the probabilities of remaining in the same state for the "Attentive" and "Inattentive" states, respectively.

The emission matrix B , characterising the probability distribution to generate observations given the current state (Rabiner, 1989). Since the two possibilities in relation to the recommendations are "Follow recommendation" and "Not follow recommendation", the emission matrix can be defined as Eq. 6.4

$$B = \begin{array}{c|cc} & \text{Follow} & \text{Not follow} \\ \hline \text{Attentive} & \alpha & 1 - \alpha \\ \text{Inattentive} & \beta & 1 - \beta \end{array} \quad (6.4)$$

Here, α and β are the probabilities of the "Follow" observation given the "Attentive" and "Inattentive" states, respectively.

An important property of Hidden Markov Models is that the current state depends only on the immediate previous state of the system. This aspect relates to certain patterns in human behaviour, particularly when people adhere to their daily routines. For instance, sequences such as "have breakfast" followed by "have coffee" and then "go to work" represent routines, making them suitable for representation by Hidden Markov Models.

Addressing this, the previously proposed model described by Eqs. 6.3 and 6.4 can be seen as a "low resolution" model, since it does not try to capture in too much detail particularities of human behaviour. Instead, this model comprised of only two states attempts to encapsulate human behaviour related to following recommendations in a general sense, while still preserving the properties inherent to Hidden Markov Models.

In relation to the energy consumption behaviour context, the choice of the two hidden states relies on several fundamental aspects. Firstly, the attentive state encapsulates the concept of energy sobriety that has been discussed in previous chapters and, as such, represents a crucial criterion to consider when

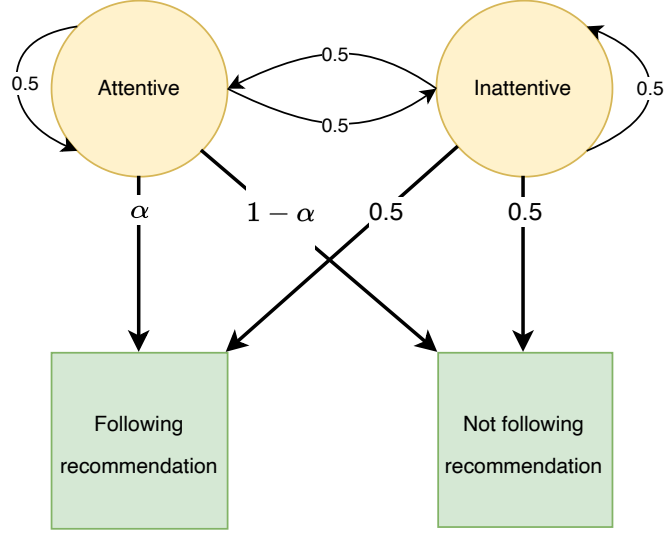


Figure 6.5: Hidden Markov chain for modeling the reaction of community members

modeling community members. Secondly, the introduction of the inattentive state allows the model to incorporate factors such as presence or availability to follow recommendations, two important aspects in terms of building energy performance and at an informational level for the manager. Lastly, by opting for a small number of states, the model reflects simplicity, and its stochastic nature could be suitable for a wide spectrum of scenarios in residential homes, regardless of the number of occupants, diversity of appliances, or other factors.

The general parameters of the model are described by Fig. 6.5. The parametrisation shown in Fig. 6.5 has been chosen based on several aspects. Firstly, due to the high degree of uncertainty, a member may either maintain their current hidden state or switch to the other one with equal probabilities. This principle can be observed on the transition probabilities. Alternatively, these probabilities may be adapted to obtain different attentiveness profiles. For example, a highly attentive member would have $A = \begin{pmatrix} 0.8 & 0.2 \\ 0.8 & 0.2 \end{pmatrix}$.

Secondly, regarding the emission probabilities, there are two scenarios to consider. Firstly, if a member is inattentive, they may follow or not follow the recommendation with equal probability. This is because the change in consumption could either be an increase or decrease. Secondly, if a member is attentive, the parameter α is proposed to allow for variations within the Markov chain. For instance, a community with enthusiastic members (characterised by

a high α , such as 0.8) should perform better than a community with 'reluctant' members (characterised by a lower α , such as 0.3).

In the context of this research, Hidden Markov Models (HMMs) are particularly valuable for their generative capabilities. In the multi-agent model of an energy community, different community member behaviours will be generated according to the aforementioned model. However, if more data becomes available (possibly from a field study), this model could be refined to better reflect the actual behaviour of people using a community aiding service, such as the one proposed in this study.

Regarding the intensity of the community members' reaction, it is assumed that one can model this in the stochastic manner described by Eq. 6.5.

$$p_{Load,i,t}^{real} = \begin{cases} \mathcal{U}(0, 0.5) \cdot p_{Load,i,t}^{estimated} & \text{if recommendation}_t = \text{BLINKING RED} \\ \mathcal{U}(0, 1.2) \cdot p_{Load,i,t}^{estimated} & \text{if recommendation}_t = \text{STRONG RED} \\ \mathcal{U}(0.8, 1.2) \cdot p_{Load,i,t}^{estimated} & \text{if recommendation}_t = \text{WHITE} \\ \mathcal{U}(0.8, 3) \cdot p_{Load,i,t}^{estimated} & \text{if recommendation}_t = \text{STRONG GREEN} \\ \mathcal{U}(1.5, 3) \cdot p_{Load,i,t}^{estimated} & \text{if recommendation}_t = \text{BLINKING GREEN} \end{cases} \quad (6.5)$$

where $\mathcal{U}(a, b)$ reflects a uniform probability choice between a and b .

This choice explicitly shows that there is another level of uncertainty regarding human actions when aiming to preserve privacy of people. Alternatively, a deeper understanding of the possible changes in consumption could be formed, at the cost of identifying and measuring the individual impact of each appliance. Moreover, these values are adequately chosen to cover a certain interval of change in consumption (between 0% and 300%), in a manner which does not rely on using a wider range of signals (or colors) to account for simplicity. Although, for this work it is assumed that these values are known, they may be recorded in an future alternative field study.

6.4 Simulation scenarios

The strategies have been evaluated in a case-study on 5 residential homes from Grenoble, for a period of almost one year. The consumption data for each community member has been obtained from the IRISE database (see chapter 4). This consumption data represents the business-as-usual representation $p_{Load}^{estimated}$ for each community member. In this work, it is assumed that $p_{Load}^{expected} = p_{Load}^{estimated}$, meaning that the manager have a very good expectation of what the business as usual scenario means for the community members. Although $p_{Load}^{expected}$ can be alternatively determined through estimation techniques

or by adequately choosing observation days and measuring the consumption of community members, this aspect is not in the scope of this work.

The PV production $p_{PV}^{expected}$ is obtained using the model in Eq. 5.1. The chosen surface is $A = 100m^2$, with a PV efficiency of 13%. The solar irradiance G_t was obtained using the model implemented in the *buildingenergy* project (Ploix, 2021), for a slope of 30 degrees towards South for maximum power output, with the geographical coordinates set for Grenoble.

Results are evaluated in terms of self-consumption, self-sufficiency, the net-energy-exchanged-with-the-grid normalised to the estimated consumption of the community, the recommendation deviation rate and the contribution change rate.

The simulation scenarios are further clustered in two groups. One group consists of the simulation scenarios involving only ideal members, reflecting an "extreme", ideal case, while the other group aims to design a community that is as realistic as possible.

6.4.1 The extreme case

The extreme case focuses on community members that always follow the recommendations, hence $\alpha = 1$ and are always in the attentive state. The aim of these scenarios is to show the maximum potential impact of recommendations, similarly to the case of optimising a pure technical system.

The purpose of the simulation scenarios is to evaluate the impact of each previously proposed strategy on a community with ideal members, both in terms of system performance and human effort. This evaluation is done under different comfort parameters, denoted by τ ⁴³. As such, each simulation scenario uses a distinct value of τ .

The results can be analysed comprehensively in Table 6.4 and graphically Fig. 6.6, offering a clear view of changes across scenarios. The results are presented in terms of Recommendation Deviation Rate, Contribution Change Rate, and Average Contributions per Day to obtain a complete image of the potential human discomfort that may appear when following recommendations. Furthermore, concerning energy system performance, the results provide a comparison between estimated self-consumption and self-sufficiency, reflecting performance prior to recommendations, and real self-consumption and self-sufficiency, reflecting system performance after using the recommendation system. In addition, although this indicator is primarily used for optimisation purposes, a version of the net-energy-exchanged-with-the-grid indicator (NEEG) is also included. This version is normalised to the initial estimated NEEG.

⁴³ The reader can check again the recommendation strategies in Figs. 6.1 6.2 and 6.4 to see the role of τ .

Table 6.4: Results for a residential community, the extreme case; The green rows mark the best solutions, considering system performances, human involvement and the average number of contributions per day; est.: estimated, SC: self-consumption, SS: self-sufficiency, NEEG: Net-Energy-Exchanged-with-the-Grid, RDR: Recommendation Deviation Rate, CCR: Contribution change Rate

ID	Scenario	est. SC	est. SS	real SC	real SS	NEEG	RDR	CCR	Avg. contrib. per day
1	one turn informative with $\tau = 0$	0.49	0.38	0.53	0.43	0.89	0.5	0.13	3.17
2	one turn informative with $\tau = 100$	0.49	0.38	0.54	0.43	0.89	0.5	0.15	3.64
3	one turn informative with $\tau = 500$	0.49	0.38	0.53	0.43	0.89	0.47	0.22	5.17
4	one turn informative with $\tau = 1000$	0.49	0.38	0.53	0.43	0.9	0.43	0.26	6.14
5	one turn informative with $\tau = 1500$	0.49	0.38	0.53	0.42	0.92	0.39	0.28	6.83
6	two turns informative with $\tau = 0$	0.49	0.38	0.86	0.6	0.55	0.95	0.31	7.37
7	two turns informative with $\tau = 100$	0.49	0.38	0.86	0.61	0.53	0.93	0.33	8.02
8	two turns informative with $\tau = 500$	0.49	0.38	0.88	0.64	0.47	0.88	0.41	9.9
9	two turns informative with $\tau = 1000$	0.49	0.38	0.86	0.63	0.49	0.79	0.49	11.65
10	two turns informative with $\tau = 1500$	0.49	0.38	0.84	0.6	0.55	0.68	0.45	10.77
11	one turn coaching with $\tau = 0$	0.49	0.38	0.53	0.42	0.92	0.5	0.1	2.44
12	one turn coaching with $\tau = 100$	0.49	0.38	0.53	0.42	0.92	0.5	0.1	2.44
13	one turn coaching with $\tau = 500$	0.49	0.38	0.53	0.42	0.92	0.49	0.11	2.7
14	one turn coaching with $\tau = 1000$	0.49	0.38	0.52	0.42	0.93	0.45	0.14	3.36
15	one turn coaching with $\tau = 1500$	0.49	0.38	0.52	0.41	0.94	0.4	0.15	3.54

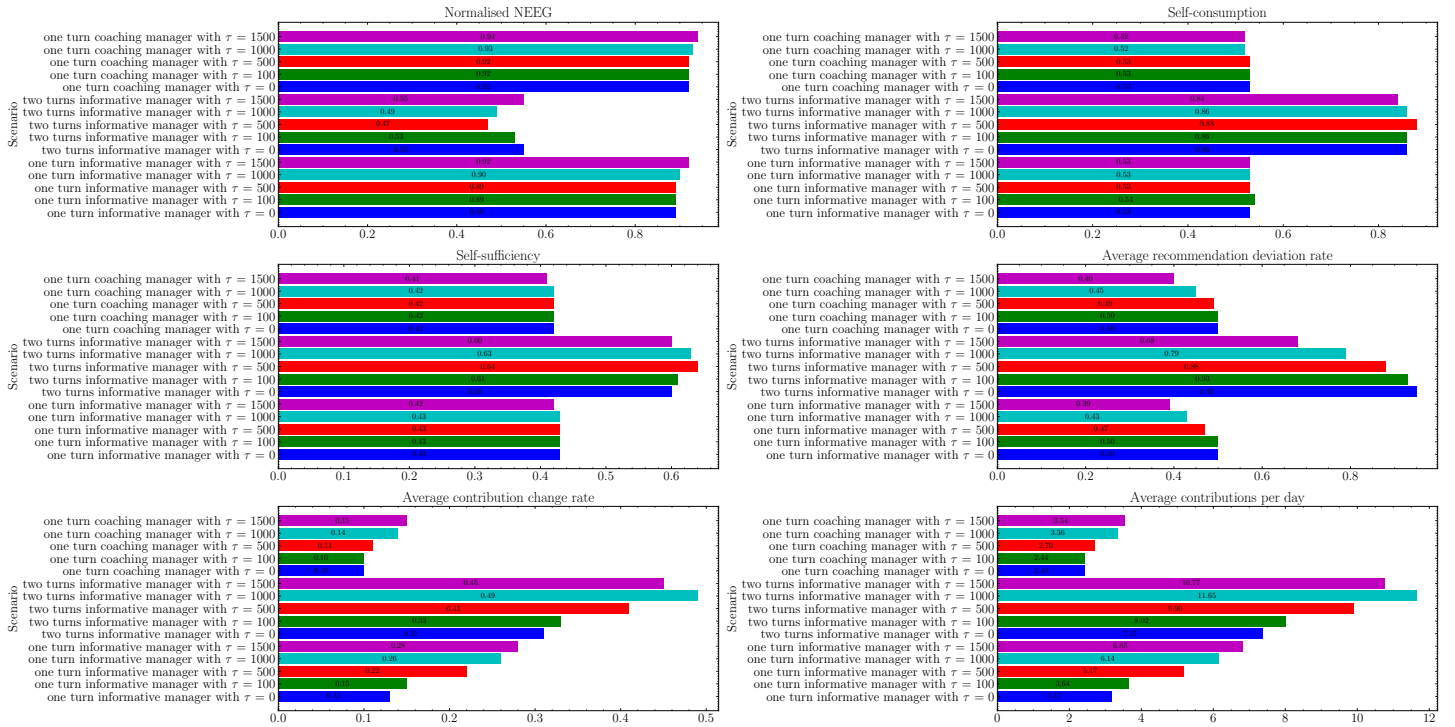


Figure 6.6: Graphical representation of the results obtained in the extreme case (Table 6.4). While the two-turn informative strategy yields the best performance at the cost of increased effort, the coaching strategy delivers similar results to that of the one-turn informative approach. The Jupyter notebook used to generate this figure can be accessed here. Implementation in M. S. Simoiu, 2023

With or without recommendations: an overall analysis

In terms of performances, especially self-consumption, self-sufficiency, and net energy exchanged with the grid, there is a certain improvement compared to the estimated, business-as-usual scenario. For instance, it is clear that using a two-turn strategy, where the service provides additional recommendations during the day, is the clear choice when the community is very demanding in terms of performance. Even though one should take into account that the community is composed of ideal agents and a realistic community might yield different results, it is important here to emphasise the perception of the agents. It is clear that an urgent, 'blinking' recommendation yields better performances than other more straightforward recommendations.

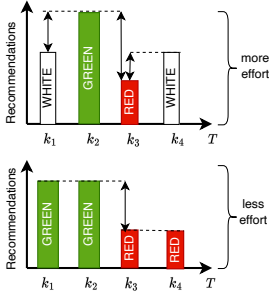
In contrast to the system's performance, it can be noticed that the intensity of recommendations is significantly higher than in the case of one-turn strategies, suggesting that the manager often requires the community members to adapt their usual behaviour. This aspect is also reflected in the Contribution Change Rate⁴⁴.

Interestingly, it should be noted that *one-turn informative* and *one-turn coaching* systems provide similar performance, despite requiring different levels of effort from the community. This aspect comes as an additional argument that the human perception should be accounted for, especially when defining what a contribution should be. Specifically, it would be beneficial for both community members and the system to provide recommendations for certain period rather than every hour, as similar performances can be achieved at a lower effort reflected by almost 2-3 recommendations per day.

The impact of the comfort parameter

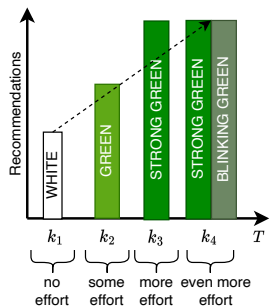
Regarding the impact of the comfort parameter⁴⁵, τ , it is noticeably reflected in both the Recommendation Deviation Rate⁴⁶ and the Contribution Change Rate. While it is evident that an increased comfort parameter reduces the intensity of recommendations, leading to a lower Recommendation Deviation Rate, the same cannot be said for the Contribution Change Rate. This effect is particularly evident in the *one-turn-informative* strategy and the *two-turn-informative* strategy, where recommendations are given hourly. In these two scenarios, given the comfort parameter, the manager frequently transitions between recommendations, which results in increased effort for the community members. However, with the coaching strategy, the change in the Contribution Change Rate due to modifications in τ is not as pronounced. This is because,

⁴⁴ It is worth noting again that the Contribution Change Rate quantifies how frequently people are required to modify their energy consumption.



⁴⁵ As described before, τ represents a power threshold for not providing recommendations when there is only a very small difference between the expected consumption and production.

⁴⁶ It is worth noting again that the Recommendation Deviation Rate captures the intensity of recommendations.



in this case, recommendations are provided for more than just an hour and the overall consumption over the period becomes the main evaluation criteria.

System performance vs. discomfort: a Pareto analysis on the main indicators

Overall, a better perspective upon the impact of each strategy can be achieved by selecting the Net-Energy-Exchanged-with-the-Grid, the Recommendation Deviation Rate, and the Contribution Change Rate as the most pertinent indicators in terms of system performance and perceived effort. Specifically, Fig. 6.7 displays a two-by-two graphical representation of the results for the investigated simulation scenarios, where a Pareto plot is drawn for each combination.

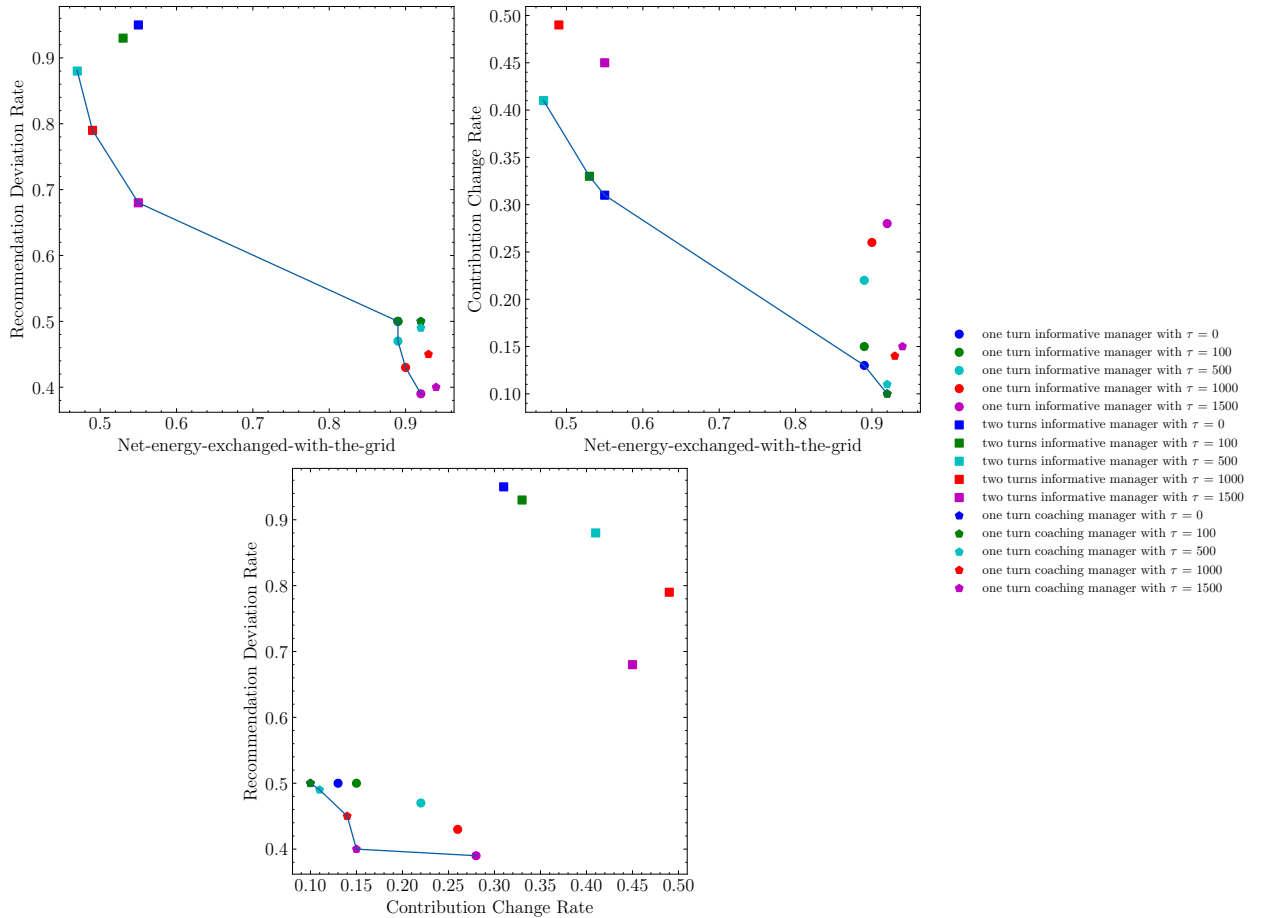


Figure 6.7: The extreme case - Pareto evaluation over the three most relevant indicators. The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

As it can be seen in Fig. 6.7, in the first two plots involving the Net-energy-exchanged-with-the-grid, the values associated to the *two-turns informative*

⁴⁷ As previously discussed, if a day is divided into significant periods based on PV production, the one-turn coaching strategy's goal is to provide one recommendation per period, rather than offering a recommendation every hour as done in the *one-turn informative* strategy.

strategy are mostly associated to increase performance and effort and therefore are usually grouped in a corner. On the other hand, the values associated to the other two strategies are similar in terms of performances and can be noticed relatively in the same area. Additionally, in the last plot involving only effort-related indicators, it can be seen that the *one-turn coaching*⁴⁷ strategy associated results are dominating the other two strategies.

These aspects emphasise again that the coaching strategy might be a good choice for a recommendation strategy that takes into account people discomfort. Specifically, with only a few, adequately developed recommendations per day, the economic and environmental benefits for the energy community could be enhanced. However, as demonstrated in the case of the *two-turn informative* strategy, the actors' perceptions and the intensity of their reactions are the primary distinguishing factors between a minor overall performance improvement and a substantial one.

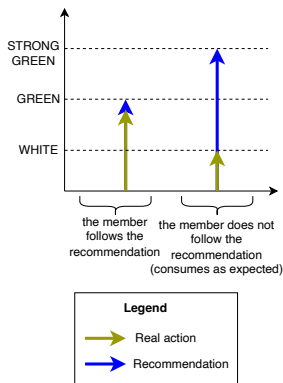
Finally, the two strategies that yield overall good results in terms of system performance, while still considering human effort, are highlighted in green in Table 6.4. These two scenarios are also marked considering that the average number of contributions per day is similar, thus ensuring a fair comparison in terms of recommendation efficiency when analysing both scenarios.

An in-depth analysis on the collective impact

Alternatively, for a more in-depth view of the impact of recommendations at individual and collective level, an analysis for each strategy can be seen in Figs. 6.8, 6.10, 6.9. In each figure, there are six subplots, grouped three by three. Each group refers to a representative period in the year. The first group refers to March, a period in the year with not so much PV production, while the second group refers to June, when there is significant PV production.

As for the structure of each group, the first subplot in each group shows a comparison between power profiles, namely the profiles before the recommendations ($p_{community, Load}^{estimated}$ and $p_{PV}^{estimated}$) marked with dashed lines, and the consumption profile obtained after the members have reacted to recommendations ($p_{community, Load}^{real}$), marked with a continuous blue line. In the second subplot, there are two distinctive arrow plots, associated with the labels on the 'y' axis representing the recommendations. Specifically, the blue arrows represent the recommendations given and the green arrows represent the real actions of a representative member randomly chosen from the community. As an example, at an hour t if the green arrow is very close to the blue arrow, then it is considered that the respective member has followed the recommendation⁴⁸. In

⁴⁸ For a comparative analysis on recommendations (expected impact) and real member reaction, the following plot is proposed:



the third subplot, the state evolution of the representative community member is depicted.

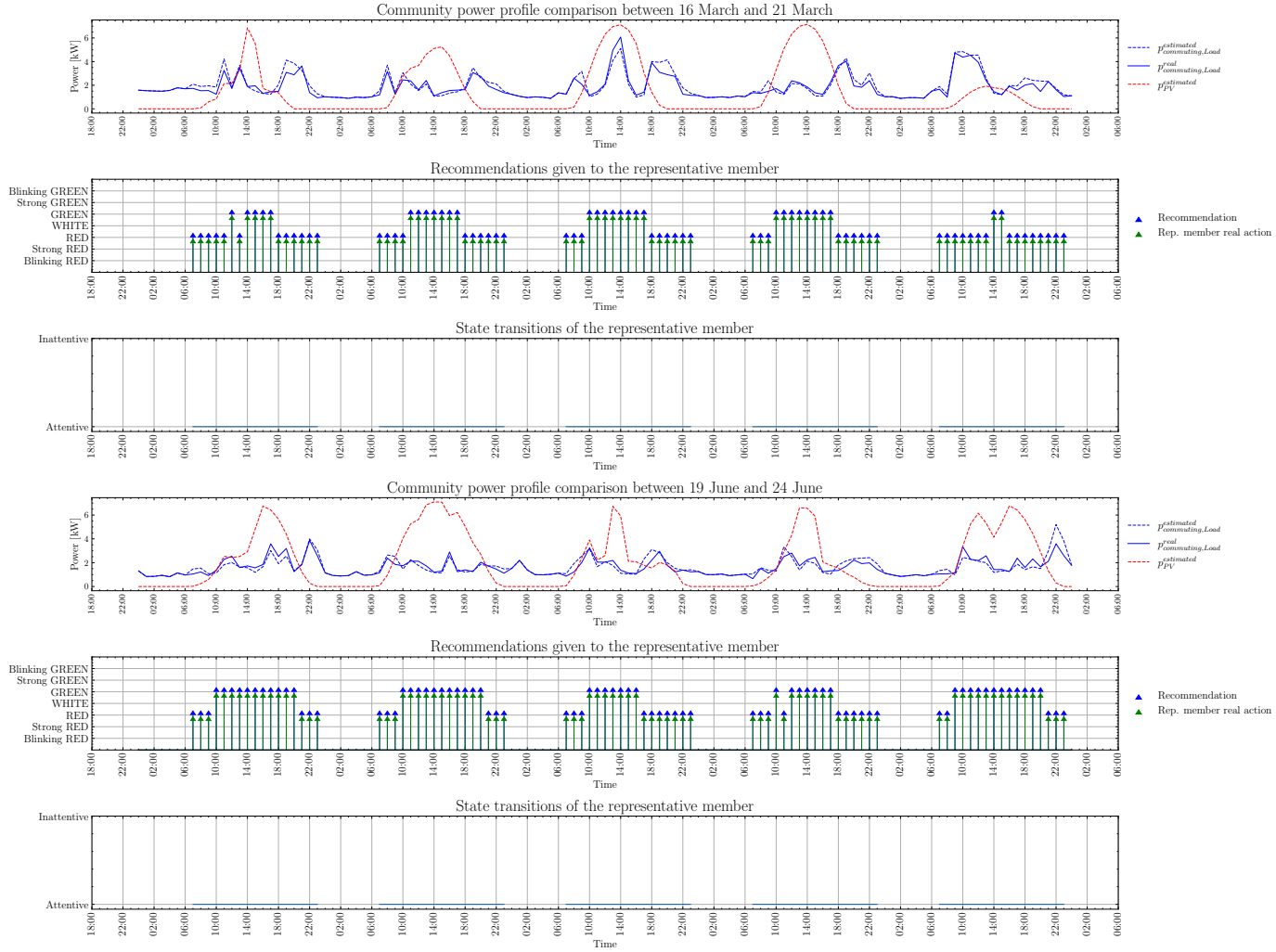


Figure 6.8: Collective impact analysis - *one turn informative* strategy for a community with ideal members, with $\tau = 0$. **Note:** in the state transitions of the representative member plot, there are two possible values, corresponding to the two states: attentive and inattentive. At each hour, the member may find itself in a certain state, so the plot generally follows the evolution between states. In this scenario (and also in Figs. 6.10, 6.9), the extreme case is characterised by ideal members who are considered to be always attentive. The Jupyter notebook used to generate this figure can be accessed here. Implementation in M. S. Simoiu, 2023

In Fig. 6.8, for example, it can be observed that the informative strategy has the desired impact at the collective level, with the community's actual consumption increasing relative to the estimated consumption levels obtained prior to the integration of the recommendation system. Moreover, from a members' perspective, the contributions do not seem to vary greatly from one hour to another, a behaviour that resembles the coaching strategy where recommendations are given for extended periods. This is attributable to the often significant

differences between consumption and production in the depicted case. In an alternative scenario where the difference is smaller, the informative strategy might be more effective at "fine-tuning" the alignment between consumption and production, given the frequency of issuing recommendations.

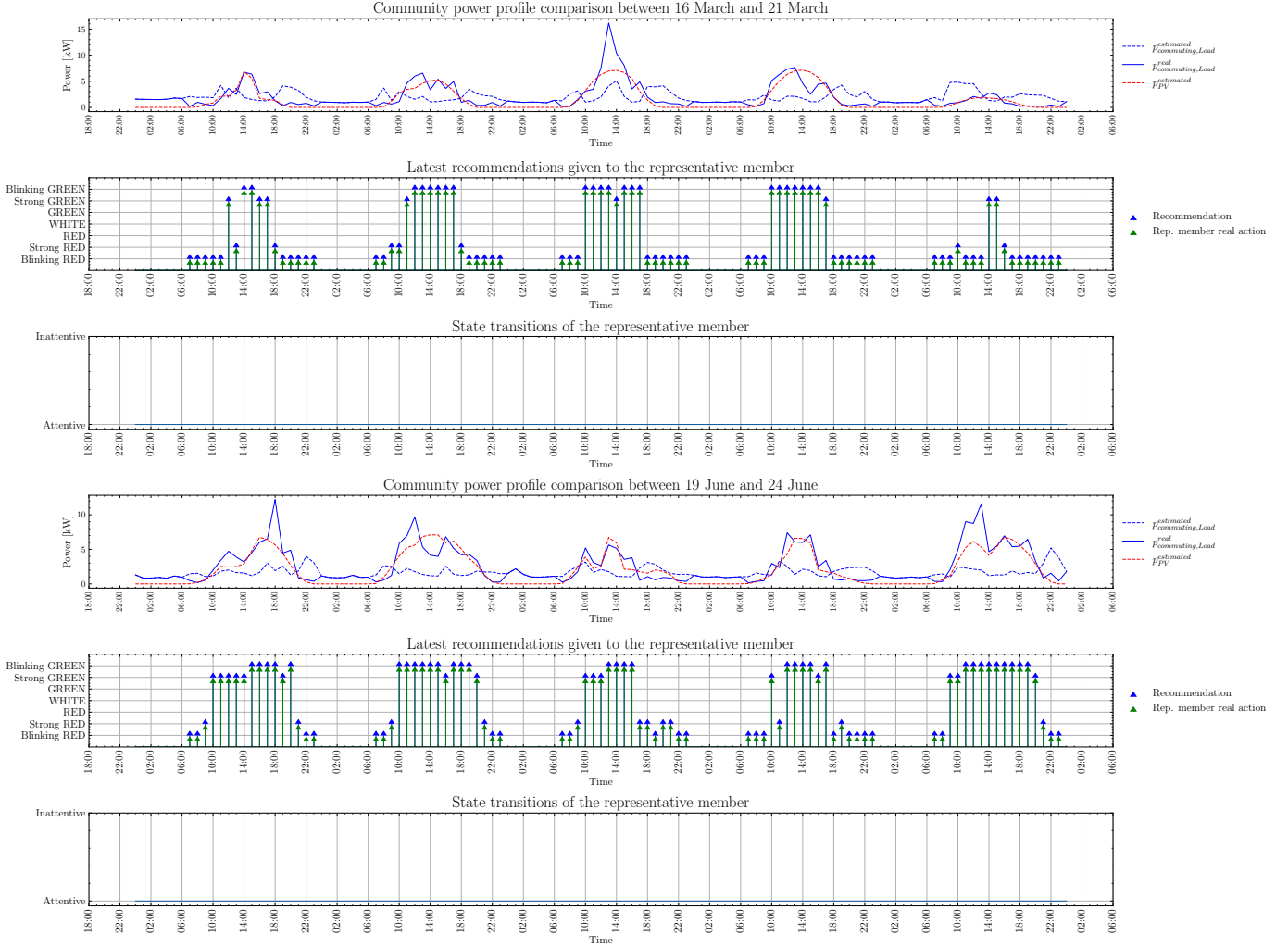


Figure 6.9: Collective impact analysis - *two turns informative* strategy for a community with ideal members, with $\tau = 0$ The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

With regard to the two-turns informative strategy (Fig. 6.9), it can be primarily observed that consumption more closely aligns with the production profile, thus providing a clear argument for the very good system performances that were noted in Table 6.4. However, there are certain situations where consumption greatly surpasses production, a result that might be deemed unfavorable, given the importance of promoting energy sobriety. This is primarily because of the blinking recommendations that reflect a sense of emergency and require

a significant involvement from community members, but also because the manager service does not have comprehensive knowledge of the community when issuing recommendations. Therefore, in a context of an ideal community where members consistently follow recommendations with considerable involvement, it is critically important to provide accurate, tailored recommendations, possibly based on a more in-depth understanding of the community members.

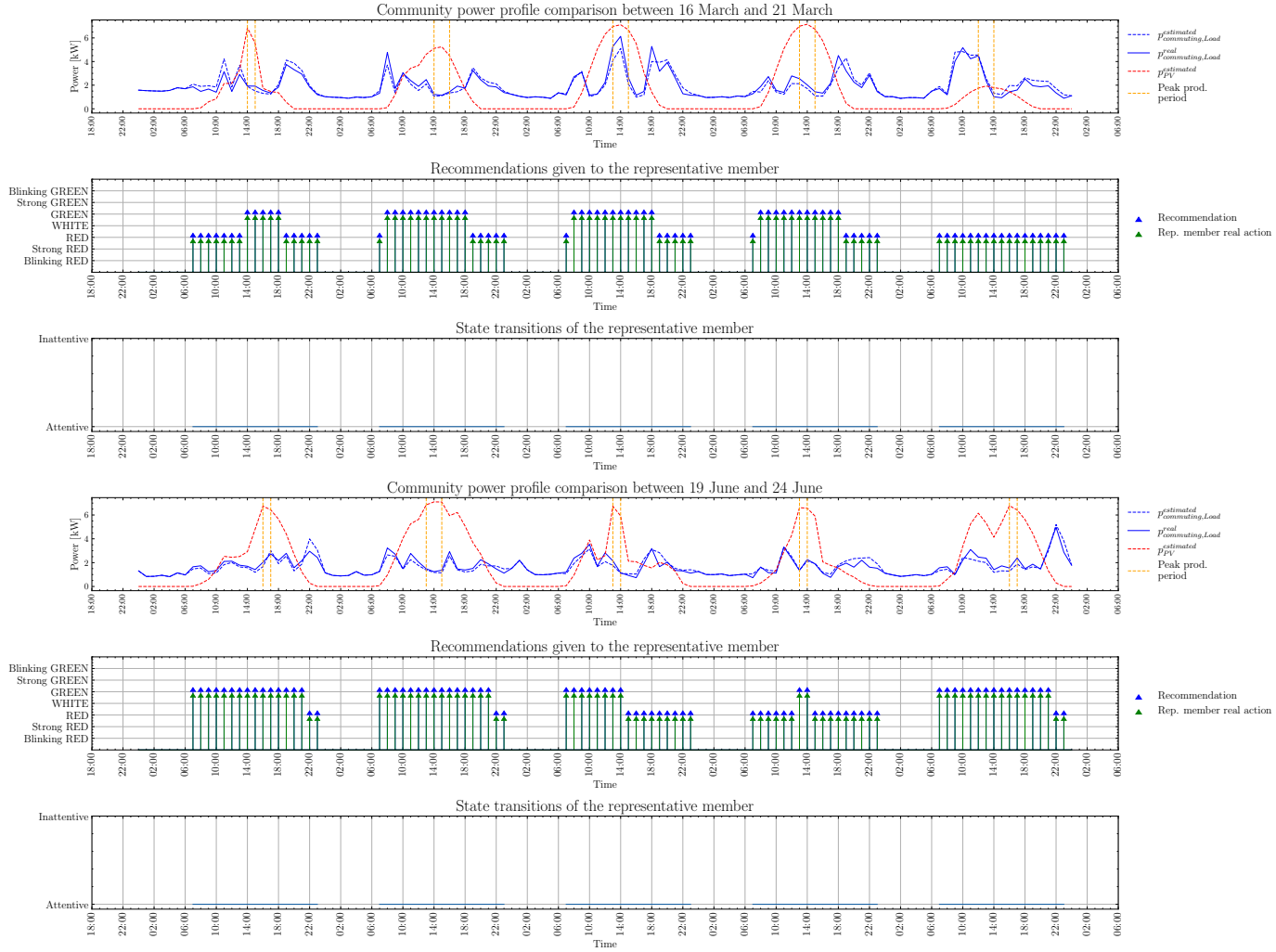


Figure 6.10: Collective impact analysis - *one turn coaching* strategy for a community with ideal members, with $\tau = 0$. **Note:** the yellow dotted lines reflect the peak production period, as it was defined in Table 6.3. The Jupyter notebook used to generate this figure can be accessed here. Implementation in M. S. Simoiu, 2023

Finally, in terms of issuing recommendations, the *one-turn coaching* strategy indeed creates a suitable environment for individuals to become accustomed to the concept of recommendations. In Fig. 6.10, from a member's perspective, it can be seen that typically 2 or 3 contributions are required per day, and these contributions are associated with moderate intensity signals (Green or Red). It

could also be considered that, for a typical community member, having a simple schedule to follow based on these recommendations may be a more favourable, realistic solution for contributing to the collective benefit. Therefore, dividing the day into periods based on estimated production and issuing recommendations accordingly might serve as a good general starting point for residential energy communities.

6.4.2 The realistic case

For simulating a realistic scenario, the transition matrix for each member is $\begin{pmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{pmatrix}$ and the emission matrix is determined by the random uniform choice of the parameter α , for each member, considering the Hidden Markov Model structure in Fig. 6.5. This selection of transition matrix implies a balanced proportion between attentive and inattentive states, reflecting a truly random behavior that might be displayed by households with several inhabitants, diverse schedules, or availability patterns. On one hand, this could be viewed as a pessimistic scenario since energy communities generally consist of motivated individuals who actively want to contribute to the environment. However, considering the random nature of this model and a simulation period of nearly a year, the subsequent simulation scenarios will reveal whether benefits can be derived even under unfavorable conditions. Similar to the extreme case, each scenario is associated to a comfort parameter τ .

With or without recommendations: an overall analysis

For the realistic case, the results can be seen in Table 6.5. A graphical depiction of these results can be analysed in Fig. 6.11.

While there is small difference (around 1-2%) for the one-turn informative and coaching strategies, there is a notable larger difference for the two-turn strategy. This is because a larger number of recommendations implies that members are requested to react more frequently, so an ideal member who always follows the recommendation yields a significantly bigger performance a member with a different motivation level.

The impact of the comfort parameter

Compared to the extreme case, the comfort parameter τ generally has a similar impact across all recommendation strategies. This suggests that the energy community should tailor this parameter according to their preference for the recommendation deviation rate or the contribution change rate. For instance, a $\tau = 0$

Table 6.5: Results for a residential community, the realistic case; The green rows mark the best solutions, considering system performances, human involvement and the average number of contributions per day; est.: estimated, SC: self-consumption, SS: self-sufficiency, NEEG: Net-Energy-Exchanged-with-the-Grid, RDR: Recommendation Deviation Rate, CCR: Contribution change Rate

ID	Scenario	est. SC	est. SS	real SC	real SS	NEEG	RDR	CCR	Avg. contrib. per day
1	one turn informative with $\tau = 0$	0.49	0.38	0.51	0.41	0.95	0.5	0.13	3.17
2	one turn informative with $\tau = 100$	0.49	0.38	0.52	0.41	0.94	0.5	0.15	3.64
3	one turn informative with $\tau = 500$	0.49	0.38	0.51	0.41	0.95	0.47	0.22	5.17
4	one turn informative with $\tau = 1000$	0.49	0.38	0.52	0.41	0.94	0.43	0.26	6.14
5	one turn informative with $\tau = 1500$	0.49	0.38	0.51	0.4	0.96	0.39	0.28	6.83
6	two turns informative with $\tau = 0$	0.49	0.38	0.68	0.52	0.72	0.97	0.24	5.81
7	two turns informative with $\tau = 100$	0.49	0.38	0.74	0.55	0.66	0.96	0.28	6.82
8	two turns informative with $\tau = 500$	0.49	0.38	0.72	0.55	0.67	0.91	0.35	8.38
9	two turns informative with $\tau = 1000$	0.49	0.38	0.71	0.54	0.7	0.82	0.42	10.01
10	two turns informative with $\tau = 1500$	0.49	0.38	0.68	0.52	0.73	0.72	0.42	10.19
11	one turn coaching with $\tau = 0$	0.49	0.38	0.51	0.4	0.95	0.5	0.1	2.44
12	one turn coaching with $\tau = 100$	0.49	0.38	0.51	0.4	0.95	0.5	0.1	2.44
13	one turn coaching with $\tau = 500$	0.49	0.38	0.51	0.4	0.95	0.49	0.11	2.7
14	one turn coaching with $\tau = 1000$	0.49	0.38	0.51	0.4	0.97	0.45	0.14	3.36
15	one turn coaching with $\tau = 1500$	0.49	0.38	0.51	0.4	0.97	0.4	0.15	3.54

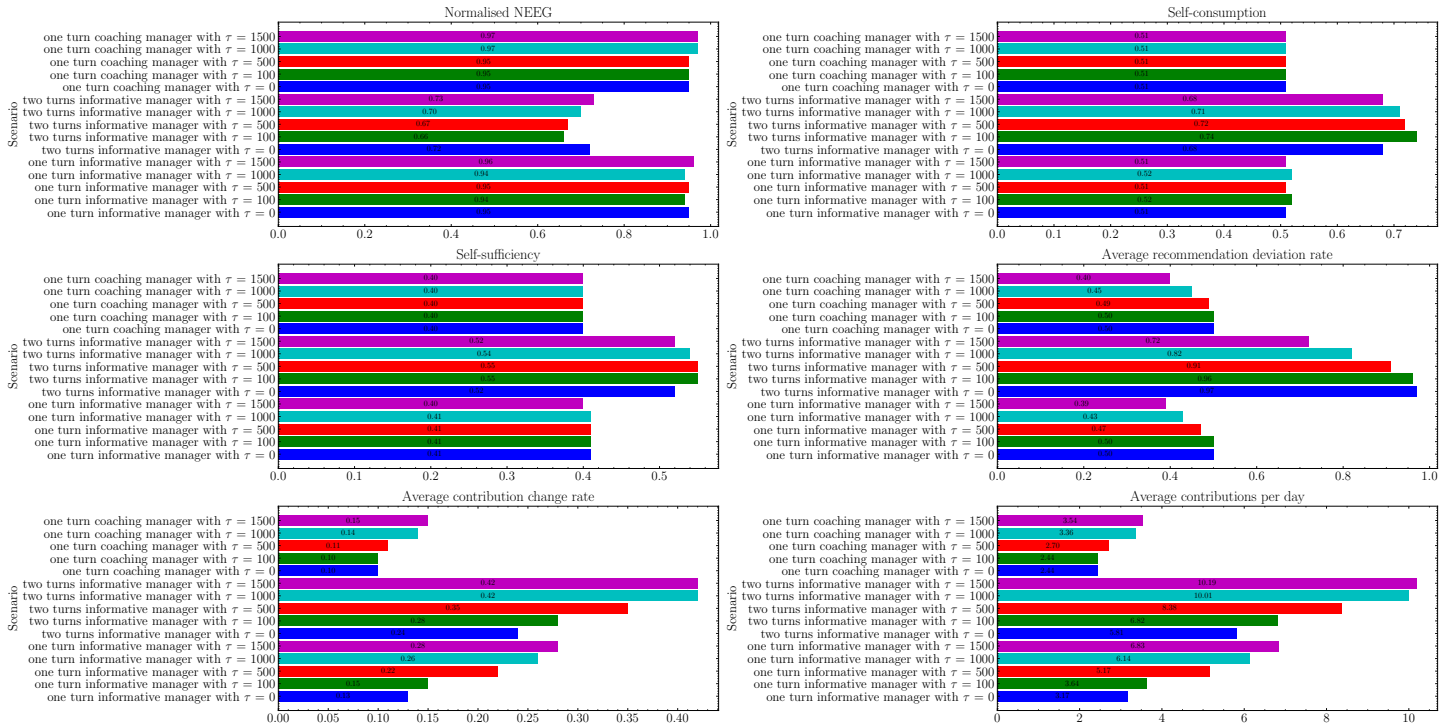


Figure 6.11: Graphical representation of the results obtained in the extreme case (Table 6.5). The Jupyter notebook used to generate this figure can be accessed here. Implementation in M. S. Simoiu, 2023

would be suitable for those who favor receiving numerous demanding Green or Red recommendations, which would result in a high Recommendation Deviation Rate over several consecutive hours and, in turn, a low Contribution Change Rate. Conversely, if τ is set to a significant value, it would result in a manager that doesn't place excessive demands on the community as he generally provides the White recommendation, thus leading to a low Recommendation Deviation Rate. This would be excepted during critical periods when the difference between consumption and production is substantial, which would trigger an increased Contribution Change Rate.

System performance vs. discomfort: a Pareto analysis on the main indicators

Analogous to the extreme case, a Pareto plot is presented for each combination of the most relevant indicators (Fig. 6.12). By analysing the Pareto plot, it can be observed that the change in terms of the Net-Energy-Exchanged-with-the-Grid does not profoundly affect the dominance relationship between strategies. Some small differences do appear, for example, in the first plot between NEEG and RDR, where the results associated with the informative and coaching strategies appear more clustered, further emphasizing the similarity in terms of energy performance between the two strategies.

An in-depth analysis on the collective impact

Figures 6.13, 6.14, and 6.15 offer a collective analysis of the profiles associated with the community over significant periods during the simulation. These figures are correlated with the responses of a representative member who has been arbitrarily chosen from the community.

For example, in Fig. 6.13, the impact of the hidden states in the behaviour of the representative member can be noticed in his reaction to recommendations. Comparing to the extreme case, it is evident here that the member may occasionally fail to follow the recommendation given the state he is in. Some interesting situations are also observed, for example cases when the member is inattentive all day, potentially reflecting a case where people are away from home.

In Fig. 6.14, which illustrates the analysis over the two-turn strategy, the impact of human behavior is most easily noticeable. However, since the members are no longer ideal, there are very few to almost no instances where real consumption exceeds the estimated production. This is due to the fact that at any given moment, there may be at least one member who is inattentive or does

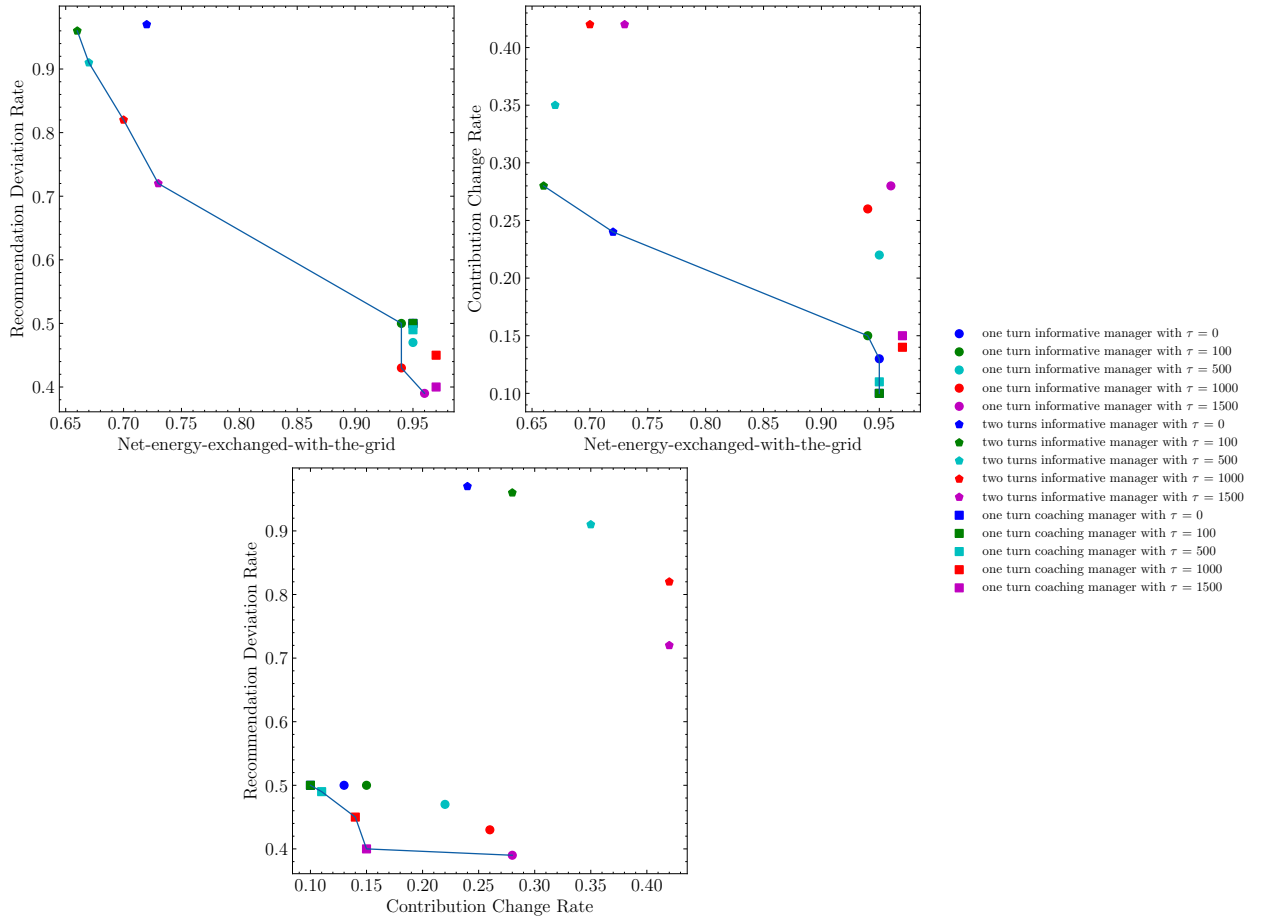


Figure 6.12: The realistic case - Pareto evaluation over the three most relevant indicators. In comparison to the extreme case (Fig. 6.7), the dominance relationship is maintained across strategies. The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

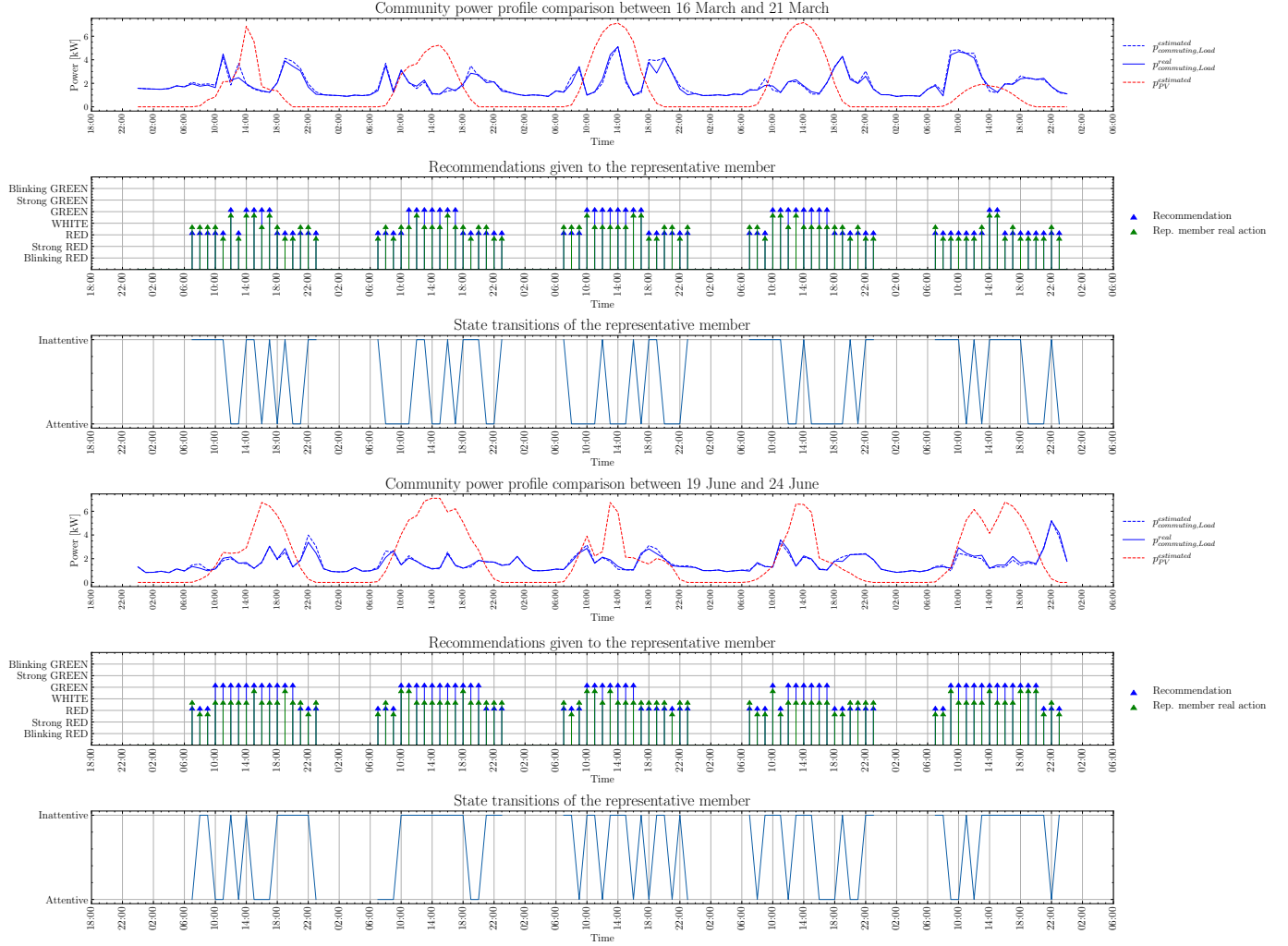


Figure 6.13: Collective impact analysis - *one turn informative* strategy for a realistic community, with $\tau = 0$. **Note:** in the state transitions of the representative member plot, there are two possible values, corresponding to the two states: attentive and inattentive. At each hour, the member may find itself in a certain state, so the plot generally follows the evolution between states. The same is considered for Figs. 6.14, 6.15. The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

not adhere to the provided recommendation, in contrast to the extreme case where every recommendation was followed.

Regarding the coaching strategy (Fig. 6.4), the changes in performances are similar to the ones obtained as a consequence of the *one-turn informative* strategy.

An interesting aspect that can be noted in both scenario groups (extreme and realistic) refers to the overall difference between the consumption and pro-

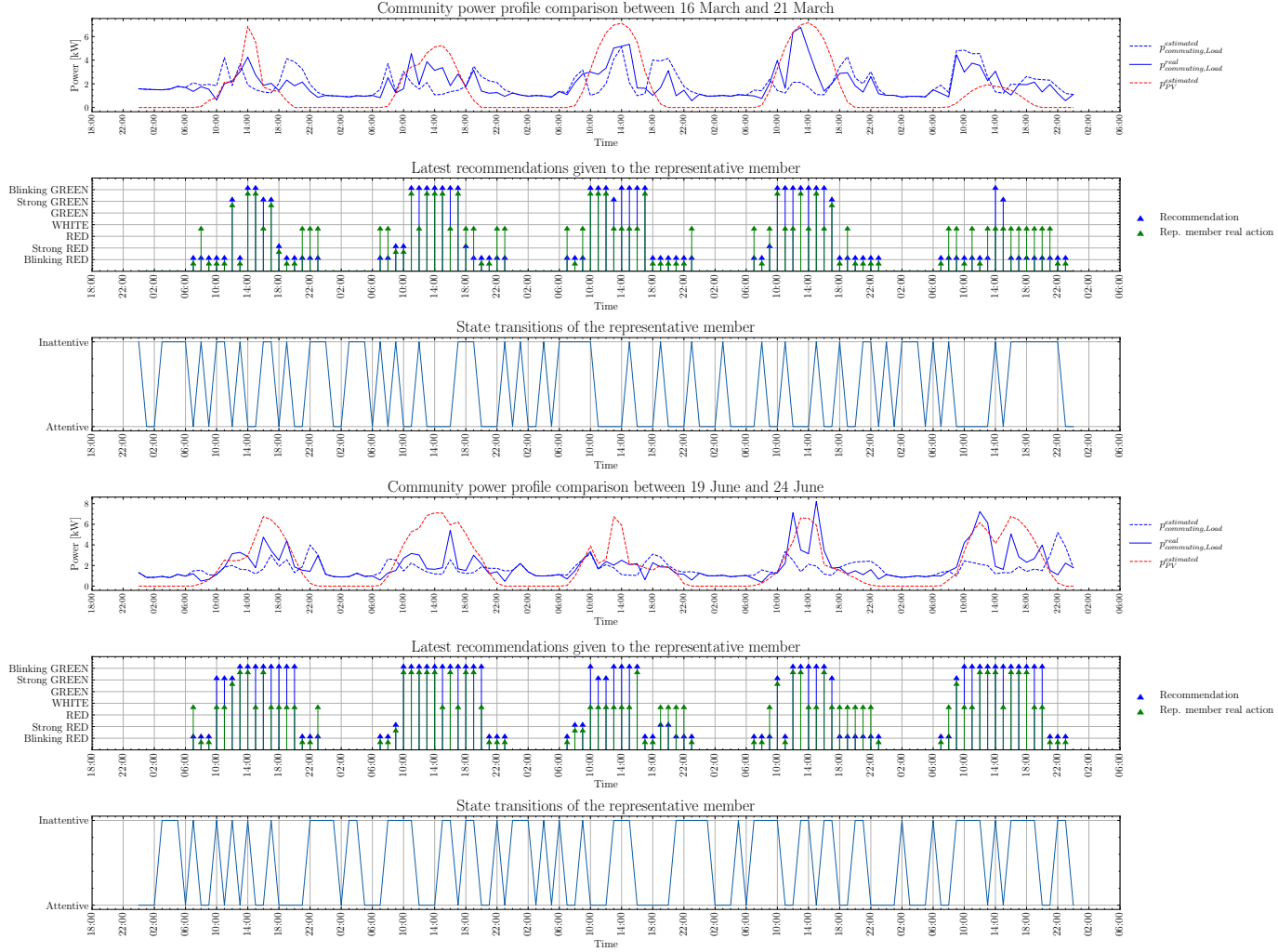


Figure 6.14: Collective impact analysis - *two turns informative* strategy for a realistic community, with $\tau = 0$. The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

duction profiles and its relationship to the comfort parameter τ . Given that the power profiles are relatively similar, the overall impact of τ is significant as it limits the manager's ability to issue demanding recommendations. However, if the PV output were significantly larger than the collective consumption, then the impact of τ would generally be minimal over the course of the year, possibly with exceptions during the winter months.

Overall, one can notice also that the realistic scenario is not so significantly different from the extreme case. This is because the Markov Chain model proposed (Fig. 6.5) adequately represents the availability of community members.

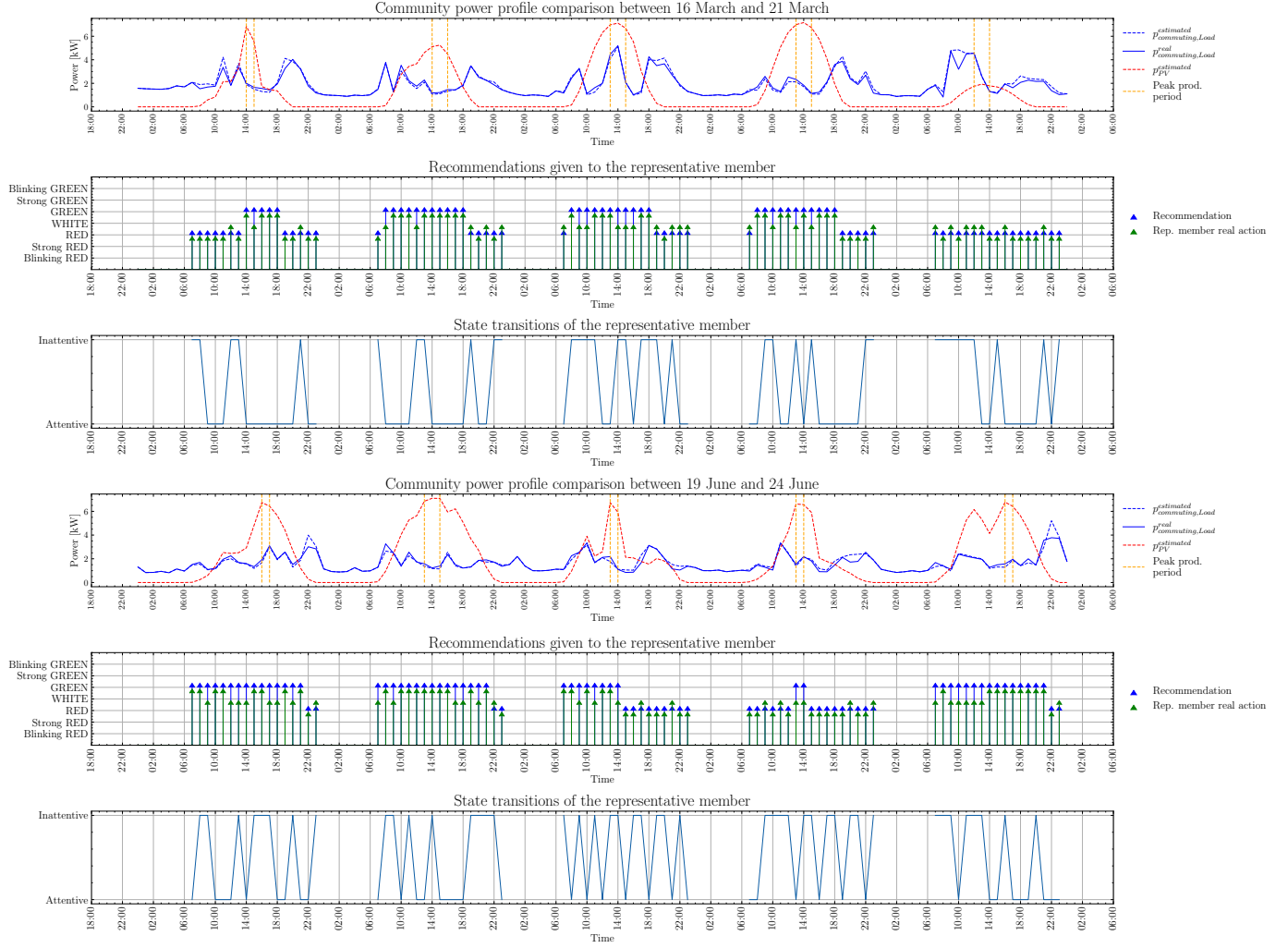


Figure 6.15: Collective impact analysis - *one turn coaching* strategy for a realistic community, with $\tau = 0$. **Note:** the yellow dotted lines reflect the peak production period, as it was defined in Table 6.3. The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

From a future perspective, this may be considered an optimistic outcome, since a realistic scenario with a mixture of community members with different motivations can obtain relatively good performances comparing to a system that is rather considered fictional.

6.5 Conclusion

This chapter proposes a solution for effectively controlling the energy system of an energy community, considering the activity and contribution of the community members. Specifically, the solution refers to a recommendation system that provides colored signals to residential community members to influence the community's energy flow so that consumption is matched with the production.

The main contributions presented in this chapter are represented, firstly, by the indicators that evaluate the human effort in following recommendations. These indicators, namely the recommendation deviation rate and the contribution change rate, mainly address the issue that the service providing recommendations must always account for the human involvement in the community life, a contrasting scenario with the usual optimisation of technical systems. Although dissatisfaction indicators are typically employed in occupancy-related issues (Pal et al., 2019), or sometimes refer to effort as the work done by a specific agent (Zhao et al., 2023), the proposed indicators are developed within a different context, adhering to the same underlying principle: establishing a connection to the desired behavior of human actors. Moreover, the performances of the system are evaluated considering a significant involvement from interacting humans, a step forward in research involving energy in buildings.

Secondly, a case study is proposed to depict the activity of a community in a multi-agent simulation framework. The case study emphasises the performances that may be achieved in different scenarios, from an extreme case where it is assumed that members always follow the recommendations to a case that aims to be as close to reality as possible. Comparing to other works (Xiong et al., 2020; Zhou et al., 2018), the proposed solution represents a distinctive approach on how community members have an own behaviour model and act independently on other technical mechanisms.

In this chapter, another contribution is presented: the stochastic modeling of community members' behavior using Markov chains. By employing a simplified hidden state model, a precise approach is proposed to model community members' reactions to recommendations within a residential context characterized by deep uncertainty.

The proposed solution adheres to the fundamental principle which is also notice in other research works Lin et al., 2022 which is to model uncertainty within a limited, restricted scope. However, the approach also aims to address a distinct problem: modeling human behavior related to energy consumption.

Although previous studies have explored related domains such as occupancy (Soudari et al., 2016) or EVs (L. Cao et al., 2021) , the model introduces a novel application of Hidden Markov models, focusing on the interaction between human actors and an intelligent assistance service.

Furthermore, the model incorporates behavioral factors, such as motivation and availability to respond, enabling the development of various pessimistic and optimistic scenarios.

Additional information

A variant of the *one turn informative* strategy was described in the following work, in initial study on the comfort parameter:

Simoiu, M. Ș., Făgărășan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2023). A Recommendation Strategy Proposal for an Energy Community Modeled as a Multi-agent System [Series Title: Studies in Computational Intelligence]. In T. Borangiu, D. Trentesaux, & P. Leitão (Eds.), *Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry of the Future* (pp. 48–58, Vol. 1083). Springer International Publishing. https://doi.org/10.1007/978-3-031-24291-5_4

The day-segmentation mechanism considering the PV production profile has been described in:

Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2022). Modeling the energy community members' willingness to change their behaviour with multi-agent systems: A stochastic approach. *Renewable Energy*, 194, 1233–1246. <https://doi.org/10.1016/j.renene.2022.06.004>

The Hidden Markov Model structure was initially proposed in:

Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2023). Markov Chain model for energy community member reaction to recommendations: A multi-agent case study. *Proceedings of The 24th Conference on Control Systems and Computer Science, (Accepted, to be published)*

The simulation framework used for the work in this chapter is available here:

Simoiu, M. S. (2023, October). RENO - a multi-agent simulation tool for a renewable energy community [Language: en]. <https://doi.org/10.5281/zenodo.8424333>

CHAPTER 7

CASE STUDY: CONTROLLING THE ENERGY SYSTEM OF A SUBWAY STATION CONSIDERING HUMAN INVOLVEMENT

7.1 A divergent approach on energy community management

As the previous chapter showed the collective impact of an energy community guided by a recommendation system in the actor-service-system paradigm, this chapter focuses on presenting a contrasting case-study. Specifically, the focus is placed upon a residential community placed near a subway station which is composed from the people that commute daily using the underground transportation services.

From one point of view, this type of community differs from the previously presented case study as it involves the inclusion of an external entity as part of the *system*. The external entity in question is the subway transportation company, which contributes its energy system of a subway station to the energy system of the community. Thus, the resulting synergy is depicted in Fig. 7.1.

Through this mechanism, a new form of energy community is developed, as the subway transportation company exerts significant influence over community activity by contributing its energy system to the community's energy system. Moreover, the energy system of the subway station infers the main en-

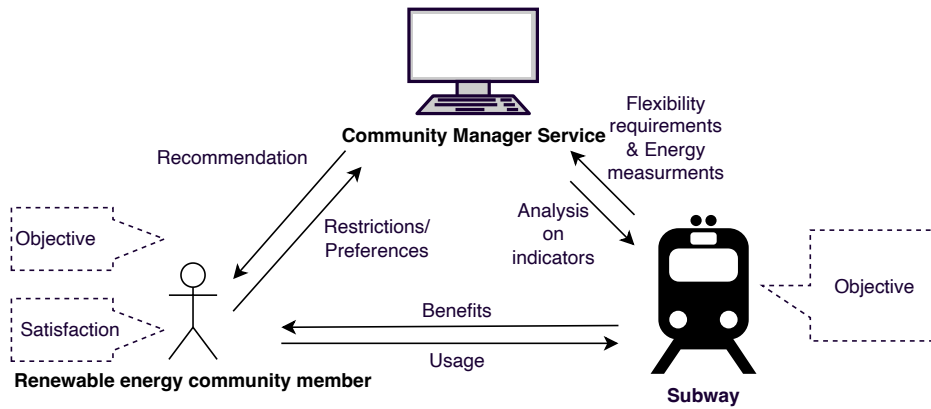


Figure 7.1: The cooperation between the energy community and the subway station

ergy efficiency problem, which is now a concern for both the transportation company and the energy community. As a consequence, the transportation company requires the involvement of external entities such as community members to help improve energy flexibility.

In a more practical interpretation of Fig. 7.1, one can consider that this new tripartite involvement is characterised by a different type of cooperation. This is because both the community members and the transportation company are interested and motivated⁴⁹ to increase the economical and environmental benefits of the energy system, so the energy community uses the community manager service to provide recommendations as a tool for their daily activities. The service also implements the typical functions of evaluation on indicators and user preference interpretation, as it was the case in the previous case study. In the end, the benefits obtained by the transportation company are adequately distributed between community members.

However, the aim of this chapter is to show that even if the application presented in this case study is practically different from the one presented in the previous chapter, the conceptual approach for managing the energy community remains the same.

Compared to other research works (Fan et al., 2022, Manso-Burgos et al., 2022, Ceglia et al., 2022), the proposed solution in this chapter addresses the management of an energy community while considering the dissatisfaction of community members. This approach entails a more profound consideration of human behavior, going beyond the conventional perspective of energy communities, as presented in (Oraiopoulos et al., 2023).

⁴⁹ Again, it must be emphasised that people join the energy community voluntarily.

7.2 Flexibility in the work schedule: a distinct approach for modeling community member involvement

As previously mentioned in chapter 4, it is important to properly develop the representation of the system in the community manager service based on observed patterns in subway station consumption and passenger traffic. Specifically, the expected consumption is determined using inferred behaviors derived from subway station consumption and passenger traffic data, as explained in detail in Chapter 4. Additionally, as noted in Chapter 4, a relevant metric for assessing the impact of each passenger is the inferred power per passenger

In the context of controlling the energy system of a subway station, the proposed solution presented in this work refers to an energy community composed of commuting passengers (of the respective subway station) as the main influencing actor. This approach is preferred from several standpoints:

- The community must be limited in scope, meaning that not all subway passengers are affected, only the commuting passengers. This is because a typical energy community is driven by motivation, so it cannot be assumed that all subway passengers are interested in participating in energy efficiency improvement mechanisms.
- The focus of the study is the energy system of a particular subway station, not the entire subway network. Therefore, the community must be geographically limited to reduce uncertainty and ensure that economic and environmental benefits can be appropriately distributed among community members. Additionally, studying a particular station provides a suitable starting point that can be scaled to other requirements later on.
- the IPP⁵⁰ is influenced by the time period of the day (an aspect that could be noticed in the regression analysis in Chapter 4). Therefore, IPP estimation techniques will be more effective if the focus is specifically on the period when it is known that people commute to work.

Besides the estimated consumption that a community member may infer to the subway energy, the model of a community member must be composed of the preferred time for commuting, along with the preferred duration for staying away at work. So, the following features are further defined:

- for a community member j , h_i represents the preferred time to go to the office

⁵⁰ The IPP refers to the Inferred Power per Passenger, as it was defined in Chapter 5

- the preferred duration to stay in office is represented by $\Delta t_{fav,j}$

These two parameters explicitly describe the interaction of community members with the system. Their meaning may be associated with personal preferences, however sometimes one can consider this preferences as restrictions imposed by the employer. For example, some people have the freedom to go to work whenever they prefer, as long as they work 8 hours, while some other people have a more strict working schedule.

In addition to obtaining a more detailed model of community members, the use of these two parameters enables a more realistic depiction of a community. Specifically, by taking into account the flexibility of community members in terms of changing their commuting times, it becomes possible to consider multiple member profiles. This approach is similar to the idea presented in (Cruz et al., 2021) and (M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2022).

As such, three categories are further proposed:

- **Fully flexible people** - These community members have complete flexibility in terms of the duration spent at the office from day to day. In other words, they are able to arrive and leave the workplace at any time. As a practical example, one can consider the people are able to continue their work remotely.
- **Semi-flexible people**: individuals who have the freedom to arrive at the office whenever they want but are required to complete eight hours of work in the office each working day.
- **People with no flexibility**: individuals who are required to be at work at a specific time (represented in our method by h_i) and must complete eight hours of work in the office every day.

Contrasting with other works that propose multi-agent methods for modeling human actors (Lai et al., 2022, Norouziasl et al., 2020), the proposed solution outlines a model for human actors as passengers commuting to work. This approach focuses on a specific type of community member, characterized by distinct actions and preferences.

As this chapter will maintain the same focus as the previous chapter, simulation scenarios will reflect both extreme and realistic simulation scenarios. Regarding $t_{fav,j}$ and h_i , these parameters may be alternatively measured in external field studies or may be chosen adequately to investigate different community variants. Consequently, it is further considered that typically each community member stays at work around 8 hours ($\Delta t_{fav,j} = 8$ for each member j).

From a multi-agent perspective, another essential component required for a comprehensive model of the energy community is the estimated number of commuting passengers, denoted as $m_{est}^{commuting}$. This parameter is important in accurately estimating the expected energy consumption of the community. As a proposed solution, this number can be estimated using data from transportation tickets and other relevant sources collected during the validation process at station access gates.

7.3 Smart commuting implemented through recommendation strategies

In contrast with the case study proposed in the previous chapter, the manager service represents in this case a system that provides recommendations to commute at favourable times, so that the objectives of both the community and the subway transportation company are met. One can notice that the nature of the recommendation is different: while in the previous case study recommendations were given as colored signals, in this case study the recommendations are represented by timestamps.

Furthermore, target period for recommendations, commuting times cannot be chosen arbitrarily throughout the day, since people can typically make slight adjustments to their work schedules. Consequently, two flexibility periods are proposed, defined by two specific time periods during the day. These periods are selected to encompass the typical commuting periods, allowing for only small variations in arrival and departure times (as shown in Fig. 7.2).

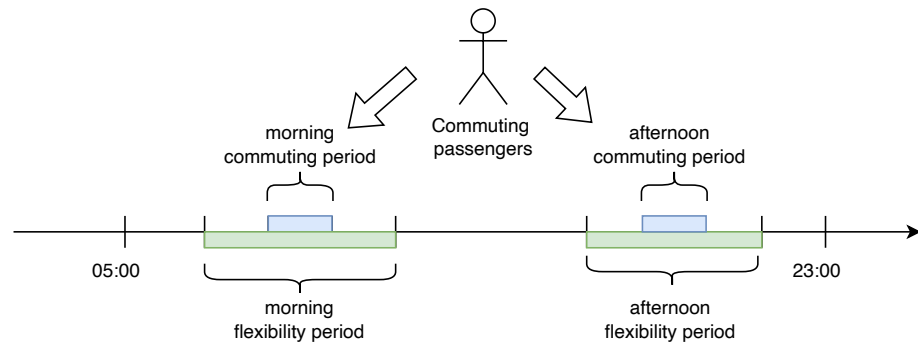


Figure 7.2: Flexibility periods relative to the commuting periods

Based on the information taken into account, one can distinguish two recommendation strategy types: recommendation strategies accounting only for consumption and production and recommendation strategies that additionally

account for community member preferences. Consequently, for each subsequent category, one strategy is proposed:

- an *informative* recommendation strategy: this strategy implies that the manager simply highlights the best commuting hours for the members.
- a *multi-objective* recommendation strategy, that takes into account both the performance-related objectives of the community and the dissatisfaction of the members relative to their preferences.

By referring to the multi-agent framework (Fig. 4.3), the sequence diagram depicting the impact of the recommendation strategy is represented in Fig. 7.3.

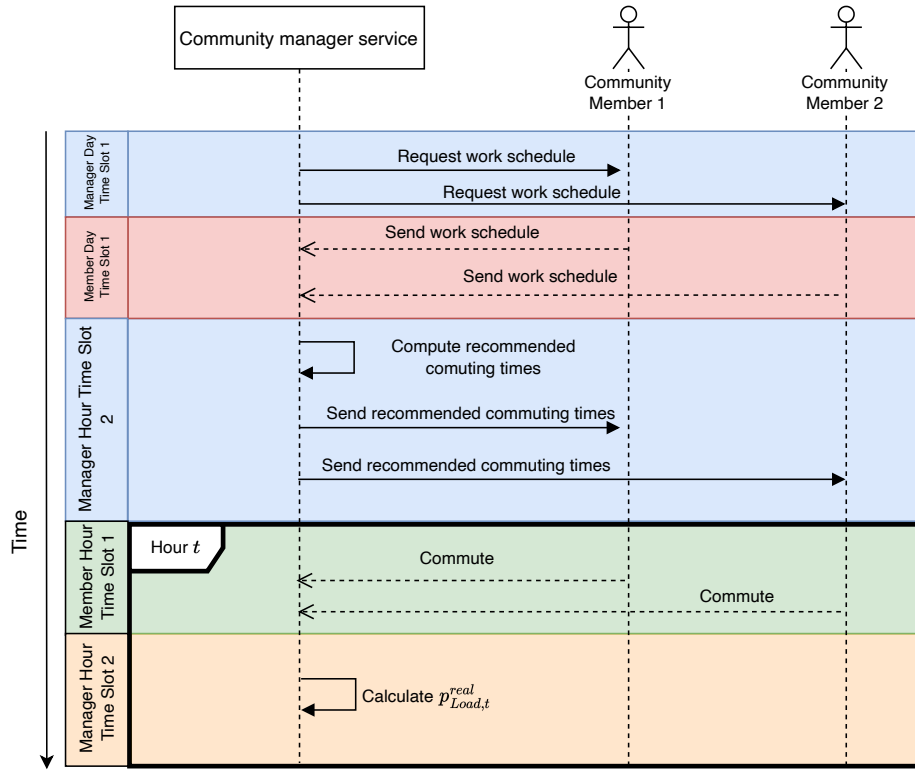


Figure 7.3: UML Sequence diagram representing the recommendation mechanism from a multi-agent perspective.

As the informative strategy is very similar to the one presented in the previous chapter, this section will further describe the impact of the multi-objective strategy. The objective of the optimisation problem is described by 7.1.

$$\min \quad w_{\text{NEEG}} \cdot \text{NEEG}^{\text{expected,norm}} + w_{\text{DIS}} \cdot \text{DIS}^{\text{expected,norm}} \quad (7.1)$$

where $NEEG^{expected,norm}$ represents the expected net-energy-exchanged-with-the-grid of the community, normalised between 0 and 1, $DIS^{expected,norm}$ represents the expected average community dissatisfaction, normalised relative to the flexibility period and w_{NEEG} , w_{DIS} represent weights that can be used to obtain several strategy variants (for example, a more performance-oriented strategy would have w_{NEEG} bigger than w_{DIS}).

From the community manager's perspective, the net-energy-exchanged-with-the-grid can be written for a period (either morning or afternoon):

$$NEEG_{period}^{expected} = \sum_t |p_{Load,t}^{expected} - p_{PV,t}^{expected}| \Delta t \quad (7.2)$$

To develop the expected level of consumption, it is assumed that the manager has access to the preferred arrival time and duration of work for each community member. In a real implementation, this information could be collected directly from members through an integrated application at the beginning of each month or year. Using this information, the manager can group community members into several groups g_{h_i} based on their preferred departing time h_i . Typically, if a group commutes at a certain hour, then it infers a certain consumption in the subway energy system. So, for each favourite hour, there would be an expected consumption profile for the morning $p_{morning}^{expected,g_{h_i}}$ and an expected consumption profile for the afternoon $p_{afternoon}^{expected,g_{h_i}}$. It should be noted that two periods are used (morning and afternoon), as it has been assumed that two different average values for the IPP are utilized - one for each period.

In the optimisation problem presented in Eq. 7.1, recommendations are provided to groups of individuals, with each group being assigned a recommended commuting time during the flexibility period. Boolean decision variables, denoted by $x_{g_{h_i},t}$, are used for each group and each hour in the flexibility period to model these recommendations.

For example, assuming four commuting hours from 7:00 A.M. to 10:00 A.M., four groups are considered (g_7 , g_8 , g_9 , and g_{10}) based on each group's preferred departing time, such as the group of people who prefer to depart at 8:00 A.M. is g_8 . If a recommendation is made for a group preferring to commute at 8:00 A.M. to shift to 7:00 A.M., the corresponding set g_8 will have $x_{g_8,7}$ set to 1 while all other variables in the set will be set to 0. To provide a better illustration, a simple example is presented in Figure 7.4, where each group is recommended to commute during their preferred commuting time, using the previously defined commuting and flexibility periods.

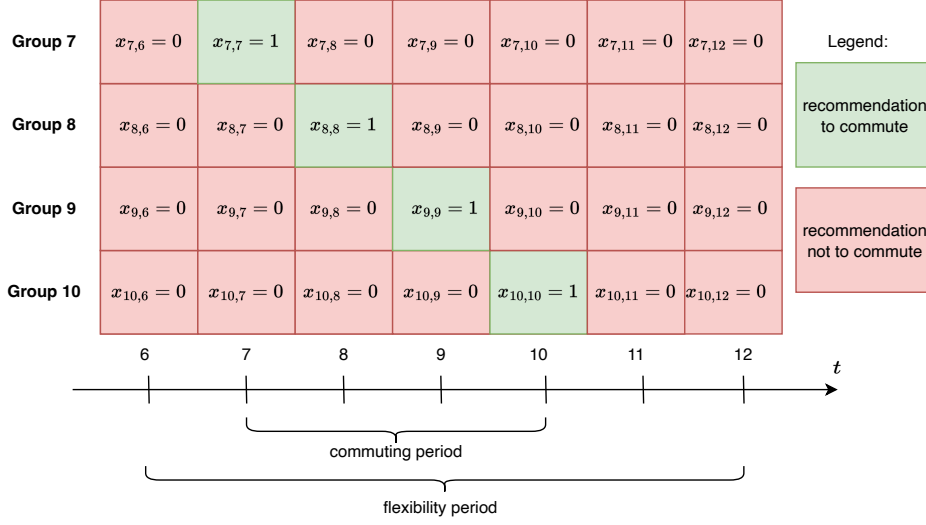


Figure 7.4: The presented figure provides an example of the solution of the proposed optimisation model utilizing boolean decision variables to represent the recommendation mechanism. The horizontal time axis includes commuting and flexibility hours, with the decision variable $x_{g_{h_i}, t}$ values shown for each group g_{h_i} . In this example, the recommendation is made for each group to commute during their preferred hour ($t = h_i$).

7.3.1 Developing strategies considering the system performances under the influence of community members

The multi objective optimisation problem in Eq. 7.1 allows as a preliminary step the development of recommendation strategies that are solely focused on system performances, excluding the human factor ($w_{DIS} = 0$). So, taking into account the recommendations for all groups at each hour t , the objective of the optimisation problem can be rewritten in terms of the expected NEEG:

$$NEEG_{period}^{expected} = \sum_t |p_{PV,t}^{expected} - \sum_{g_{h_i}} x_{g_{h_i}, t} p_{period}^{expected, g_{h_i}}| \Delta t \quad (7.3)$$

where by the $\sum_{g_{h_i}} x_{g_{h_i}, t} p_{period}^{estimated, g_{h_i}}$ element the decisions for all groups g_{h_i} during the hour t are accounted for.

To properly include the NEEG in the multi-objective optimisation problem, it is important to normalize to the maximum value of the energy that is

either consumed ($\sum_i p_{period}^{expected, g_{h_i}}$) or produced ($p_{PV,t}^{expected}$) during an hour t . After normalizing Eq. 7.3, the following equation can be considered:

$$NEEG_{period}^{expected, norm} = \sum_t \left| \frac{p_{PV,t}^{expected} - \sum_{g_{h_i}} x_{g_{h_i},t} p_{period}^{expected, g_{h_i}}}{\max(p_{PV,t}^{expected}, \sum_{g_{h_i}} p_{period}^{expected, g_{h_i}})} \right| \quad (7.4)$$

which is the final form of the NEEG as it is used in the optimisation problem.

7.3.2 Developing strategies considering the member dissatisfaction

Based on the preferences of members, a dissatisfaction indicator can be considered. In a general form that, for a specific hour t , the dissatisfaction indicator becomes:

$$\begin{aligned} DIS_{morning,t} &= \sum_{h_i} |h_i - x_{g_{h_i},t} \cdot t| \\ DIS_{afternoon,t} &= \sum_{h_i} |h_i + \Delta t_{fav,j} - x_{g_{h_i},t} \cdot t| \end{aligned} \quad (7.5)$$

If the length of the flexibility period is considered to be T , the dissatisfaction indicator can be normalised in the following manner:

$$\begin{aligned} DIS_{morning,t}^{norm, g_{h_i}} &= \sum_{h_i} \frac{|h_i - x_{g_{h_i},t} \cdot t|}{T} \\ DIS_{afternoon,t}^{norm, g_{h_i}} &= \sum_{h_i} \frac{|h_i + \Delta t_{fav,j} - x_{g_{h_i},t} \cdot t|}{T} \end{aligned} \quad (7.6)$$

Conversely, at community level, for a period:

$$DIS_{period,t}^{norm, community} = \sum_t DIS_{period,t}^{norm, g_{h_i}} \quad (7.7)$$

Lastly, a constraint is imposed such as each member should commute only once during the morning and only once during the afternoon. Consequently, for a group g_{h_i} during a period:

$$\sum_t x_{g_{h_i},t} = 1 \quad (7.8)$$

7.4 Simulation scenarios and results

Several simulation scenarios have been implemented in the same multi-agent framework proposed for the previous case study. The simulation scenario aims to reflect both the extreme case described mainly by fully-flexible members following recommendations that aim to maximise solely system performance and mixed community configures that try to depict realistic scenarios.

The number of community members is estimated from the tickets sales reported by the subway transportation company (Fig. 7.5, Metrorex, 2017) .

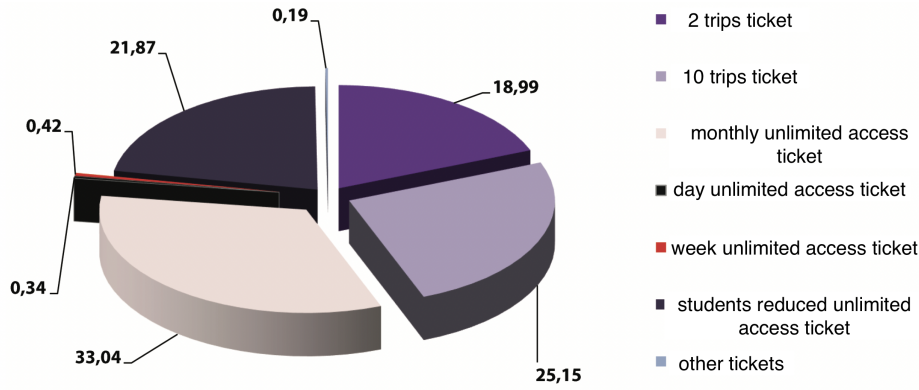


Figure 7.5: Ticket sales ration during 2017

Moreover, it is assumed that commuting passengers utilize either monthly unlimited tickets or student unlimited tickets. As a result, an average value can be calculated between the percentage of tickets sold as monthly tickets and the percentage of tickets sold as student tickets to estimate the percentage of commuters who use these ticket types. For instance, for a subway station in Bucharest, Romania, the estimated percentage of commuters who use monthly or student tickets would be 27%.

Consequently, an energy community of 4000 community members has been considered, each member having a preferred hour to commute between 7:00 AM and 10:00 AM, with a duration at the office of 8 hours. Thus, the commuting periods (as depicted in Fig. 7.2) are set around the passenger traffic peaks (Fig. 5.5) between 7:00 and 10:00 in the morning and 15:00 and 18:00 in the afternoon. The flexibility periods are set between 6:00 and 12:00 in the morning and 15:00 and 21:00 in the afternoon.

The expected community power $p_{Load}^{expected}$ is developed based on the estimated $IPP_{morning}$ and $IPP_{afternoon}$ (as described in Chapter 4), for one year in 2017, considering the available passenger data. Consequently, as a preliminary stage for developing the IPP (with Eq. 5.6), the subway station consumption

has been estimated for one year using the regression model provided in Annex B.

The expected PV production $p_{PV}^{expected}$ is developed according to the model presented in Eq. 4.4, with the following parameters: $n = 5000$ panels, $p_M = 325W_p$ and $\tau = 75\%$. The weather data used to develop the radiation has been extracted from <https://openweathermap.org> for the year 2017 for Bucharest. To estimate the incident radiation, the solar model developed in the *buildingenergy* project Ploix, 2021 was used. To infer maximum production, the PV panels are directed towards South, with a slope of 60° .

The community configuration used in every scenario is based on the subway power peaks shown in Figure 5.4:

- 10% of the community members typically commute at around 07:00 a.m. ($h_i = 7$)
- 30% of the community members typically commute at around 08:00 a.m. ($h_i = 8$)
- 40% of the community members typically commute at around 09:00 a.m. ($h_i = 9$)
- 20% of the community members typically commute at around 10:00 a.m. ($h_i = 10$)

As mentioned before, the preferences of each community member regarding the work schedule might be transmitted to the manager at convenient times or might be estimated through other techniques (possibly involving observation periods or other monitoring mechanisms). However, in each case study presented in this paper, it is assumed that the community manager knows the preferred hour and preferred working duration of each community member.

The multi-objective optimization problem presented in Equation 7.1 has been formulated as a Mixed Integer Linear Programming problem. To solve this problem, the Coin-or-Branch-and-Cut Solver from Python is utilized in each simulation (M. S. Simoiu, 2023).

The previously defined recommendation strategies have been evaluated in multiple simulation scenarios, as listed in Table 7.1. Alongside performance metrics, Table 7.1 also includes a dedicated column for several observations for each scenario.

In the case study implementation, the primary objective was to investigate the full potential of the proposed method in achieving maximum environmental and economical benefits, using fully flexible members and demanding maximum effort ($w_{NEEG} = 1$ and $w_{DIS} = 0$ in the optimization problem defined in

Table 7.1: Results comparison. **Note:** *exp.* refers to the expected case (without recommendations), while *real* refers to the behaviour after receiving recommendations.

Scenario	Fig	NEEG ^{exp.} per day	NEEG ^{real} per day	DIS ^{community}	SC ^{exp.}	SC ^{real}	Observations
Fully flexible members, M.O. strategy, $w_{NEEG} = 1, w_{DIS} = 0$	7.8	4467.07	4169.45	0.2	0.11	0.14	- represents the extreme case - the manager adequately chooses the favourable commuting times so that the consumption fits the production - people spend less time in office since favourable commuting times appear in the middle of the day - strong NEEG decrease, at the price of increased dissatisfaction
Semi flexible members, M.O. strategy, $w_{NEEG} = 1, w_{DIS} = 0$	-	4467.07	4382.75	0.19	0.11	0.12	- since the members must spend 8 hours at the office, there is an important impact in the NEEG - the dissatisfaction is still significant, since during the summer, the manager is solely focused on minimising the NEEG
Mixed members, MO strategy, $w_{NEEG} = 0.5, w_{DIS} = 0.5$	7.9	4467.07	4340.61	0.06	0.11	0.12	- adequate NEEG improvement, but an important decrease in dissatisfaction
Fully flexible members, Informative strategy	7.6	4467.07	4454.92	0.1	0.11	0.11	- a simple highlight of several favourable hours may result in significant consumption peaks - people tend to choose the favourable commuting time that is also in line with their preferences
Semi flexible members, Informative strategy	-	4467.07	4606.4	0.1	0.11	0.09	- in this case, the restrictions of semi-flexible members significantly decrease the performances
Mixed members, informative strategy	7.7	4467.07	4451.02	0.08	0.11	0.11	in a realistic community, the performances are not so significant, and the dissatisfaction is still noticeable

Equation 7.1). This objective is equivalent to minimizing solely the NEEG. The secondary objective was to evaluate a realistic community, comprising of members with different flexibility profiles, with 20% having no flexibility, 20% being fully flexible, and 40% being semi-flexible. Table 7.1 presents the simulation scenarios for each objective, with emphasis on:

- the economical and environmental benefit, quantified through the NEEG per day in the business-as-usual variant ($NEEG^{expected}$ per day) and the NEEG per day after the recommendation ($NEEG^{real}$ per day)
- the average community dissatisfaction, quantifying the average dissatisfaction of all community members over the simulation period.
- the explicit environmental benefit quantified through self-consumption before and after recommendations.

Figs. 7.8, 7.6, 7.9 and 7.7 depict the actions of representative community members, as well as the overall collective impact over the energy consumption. Even though the simulation spans for one year, the behaviour of community members during 2 weekes will be presented: a week in February (reflecting the comparison during a low-production month) and a week in June (reflecting the comparison during a high-production month). For each week, two plots are implemented:

- a plot with a power profile comparison, where the estimated community power (the blue dashed line) is compared with the simulated community power after recommendations (continuous blue line) and the estimated PV production (red dashed line) during the flexibility periods of each day (marked with yellow dashed lines).
- a plot with the recommendations (marked with blue arrows) and real actions (marked with green arrows) for each group defined by the preferred hour. For example, Group 10 refers to the group having the preferred hour for commuting at 10:00 A.M. Additionally, if the green arrow is place immediately under a blue arrow it means that the respective group has followed the recommendation and thus it has commute at that time.

Another important thing to note is that for Figs. 7.6 and 7.8, where fully flexible members are involved, only one action-recommendation related plot is presented. In Figs. 7.7 and 7.9, since there is a mixture of community members types, an action-recommendation plot is presented for each flexibility category.

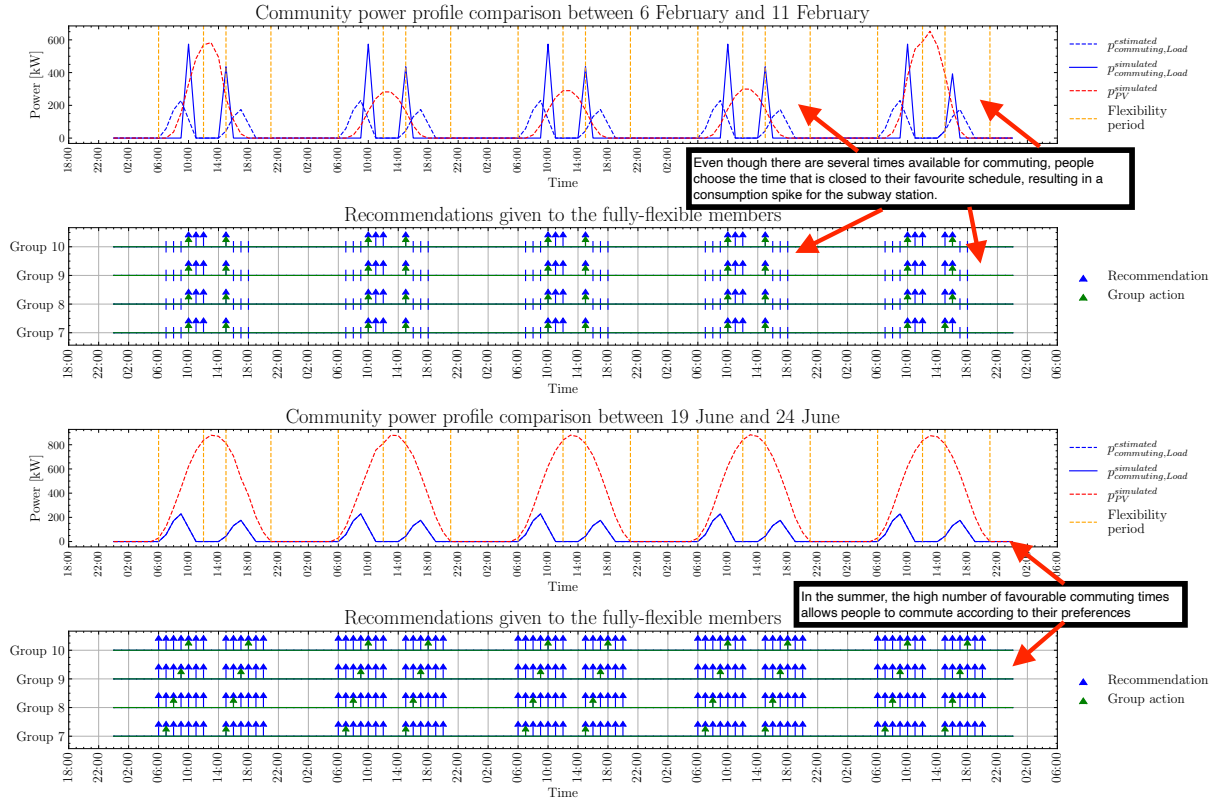


Figure 7.6: Collective impact of the informative recommendation strategy on a community with fully-flexible community member, extreme case (M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2023). **Note:** in the recommendations plot for each month, there is a plot line corresponding to each group described by a preferred hour (ex: Group 7 is the group of passengers who prefer to commute at 07:00). One may see three symbols attached to this plot line: a simple vertical line emphasising an hour in a flexibility period, a blue arrow depicting that it is recommended to commute during that respective hour and a green arrow indicating the hour when the members from the respective group have commuted to work. The same interpretation can be applied to Figs. 7.7, 7.8, 7.9. Moreover, *simulated* refers here to the "real" profile (after recommendations)



Figure 7.7: Collective impact of the informative recommendation strategy on a community with mixed community members (Realistic case)(M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2023)

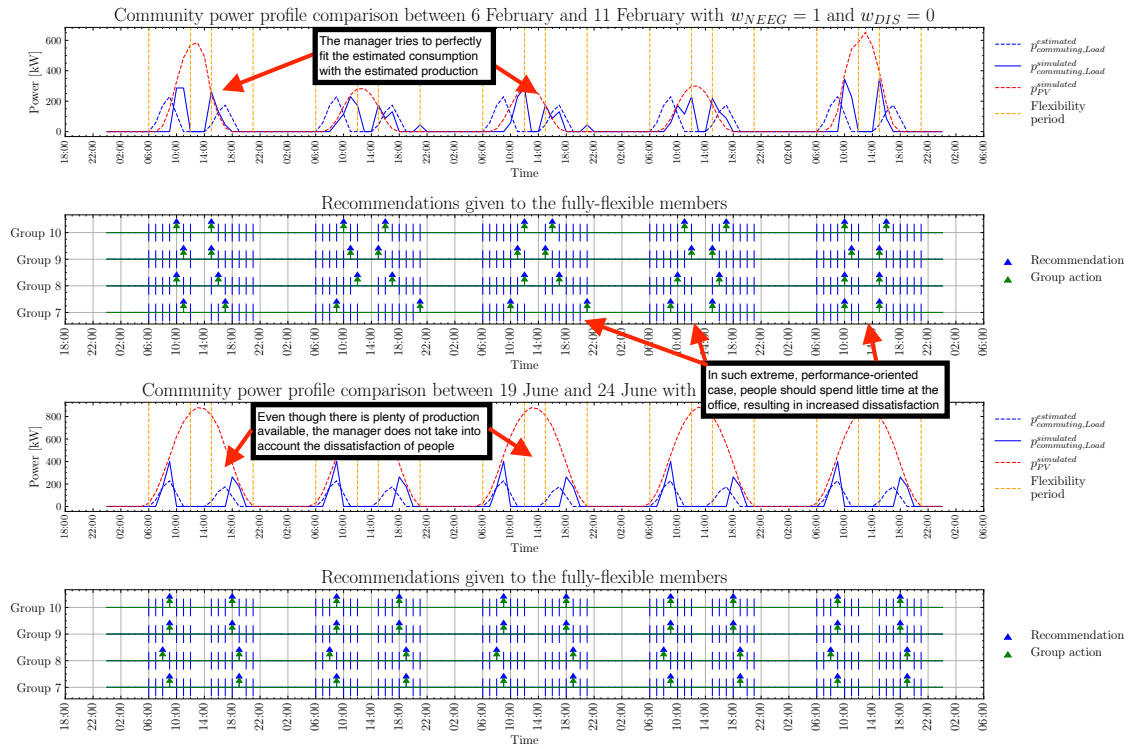


Figure 7.8: Collective impact of the multi-objective recommendation strategy on a community with only fully-flexible members (Extreme case) (M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2023)

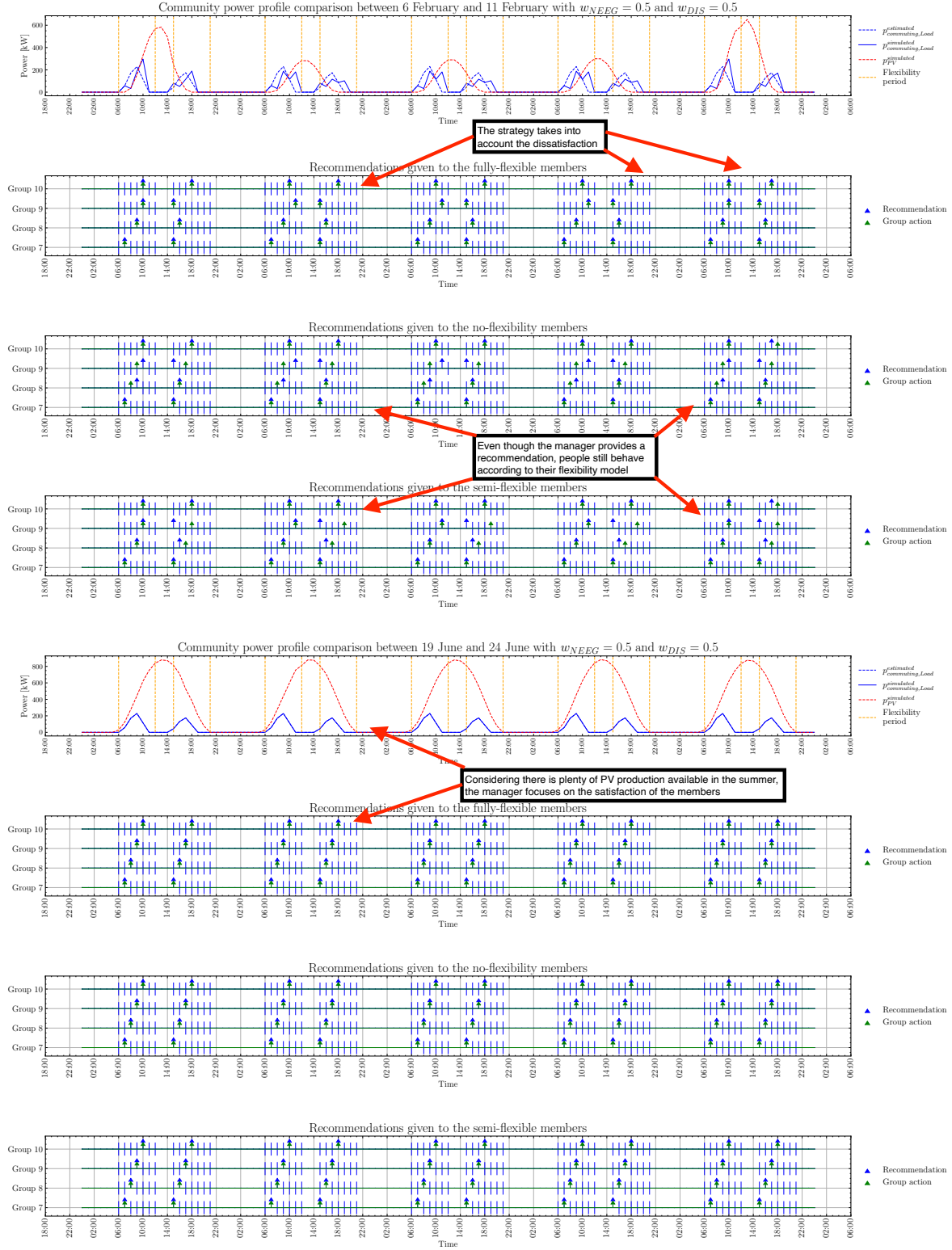


Figure 7.9: Collective impact of the multi-objective recommendation strategy on a community with mixed community members (Realistic case)(M. S. Simoiu, Fagarasan, Ploix, and Calofir, 2023)

Overall, regarding the informative strategy, one can notice that simply highlighting the favorable commuting times may sometimes result in unexpected consumption peaks. This aspect may pose some problems both logistically and in energy efficiency for the subway transportation company, people will be highly dissatisfied with the transportation service if it is too crowded. However, by providing several commuting times during the summer, the manager would provide increased freedom for people to choose their commuting time according to their preference, thus resulting a decreased collective dissatisfaction.

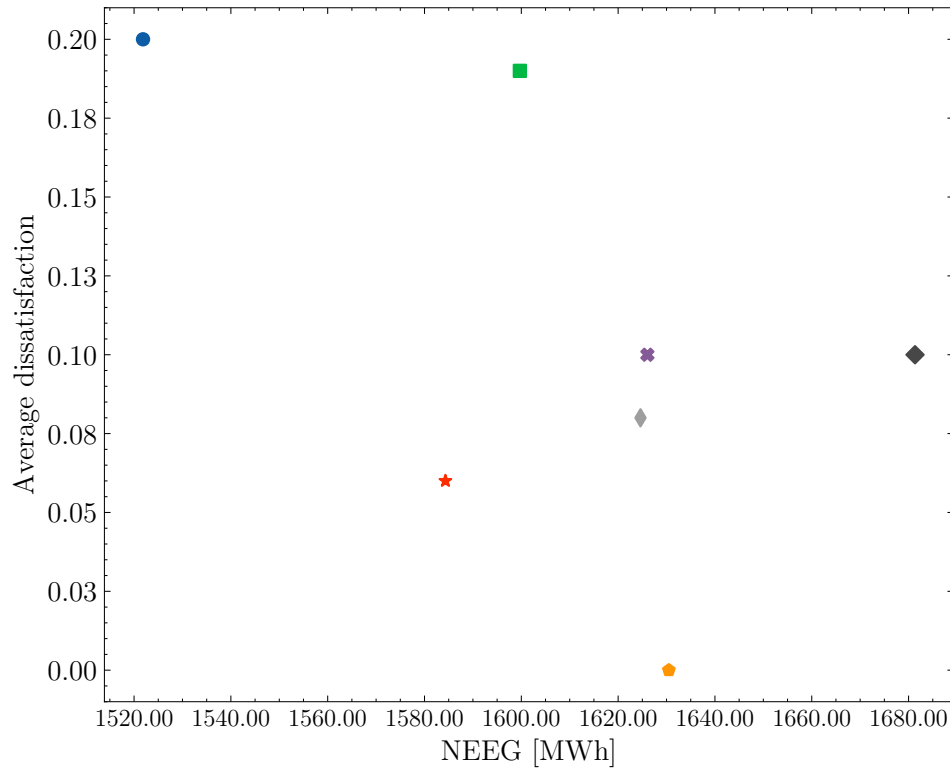
On another hand, at a first glance, the multi-objective strategy shows us the extreme case of extreme performances, along with its consequences in terms of social discontent. However, by addressing both performance and dissatisfaction in a balanced manner ($w_{\text{NEEG}} = 0.5$, $w_{\text{DIS}}=0.5$), this recommendation strategy may prove the best solution in a realistic scenario with people having various working schedule restrictions. Additionally, if one analyses the proposed simulation scenarios in a 2D objective space described by the average dissatisfaction and real NEEG (Fig. 7.10), it can also be seen that the balanced strategy with $w_{\text{NEEG}} = 0.5$, $w_{\text{DIS}}=0.5$ is the closest to the ideal origin point where both dissatisfaction and NEEG are at an absolute minimum.

Additionally, it can be observed that the environmental benefits highlighted by self-consumption do not significantly increase, owing to the large PV production available. This presents an opportunity to utilize the excess PV production elsewhere, such as in the energy system of the subway station, thereby increasing self-consumption, or making it available for consumption in a residential community. Future research can further explore this topic.

7.5 Conclusion and future perspectives

In this chapter, a case study on an energy community is presented, focusing on three distinctive characteristics in comparison to the study presented in the previous chapter: the cooperation mechanism between the transportation company and the community, the nature of recommendations, and the incorporation of a specific representation of community member dissatisfaction in the recommendation system.

The main contribution of this work is reflected in the proposed multi-objective optimization model, which provides tailored recommendations that take into account both the system's performance and the satisfaction of the community members. This approach creates flexibility for the energy system of the subway station through active participation of the community. Additionally, it promotes awareness among community members about their energy consump-



- Scenario with multi objective strategy, 'fully-flexible' members, NEEG weight: 1, DIS weight: 0
- Scenario with multi objective strategy, 'semi-flexible' members, NEEG weight: 1, DIS weight: 0
- ◆ Scenario with multi objective strategy, 'no-flexibility' members, NEEG weight: 1, DIS weight: 0
- ★ Scenario with multi objective strategy, 'fully-flexible', 'no-flexibility', 'semi-flexible' members, NEEG weight: 0.5, DIS weight: 0.5
- ✱ Scenario with informative strategy, 'fully-flexible' members
- ◆ Scenario with informative strategy, 'semi-flexible' members
- ◆ Scenario with informative strategy, 'fully-flexible', 'no-flexibility', 'semi-flexible' members

Figure 7.10: Strategy comparison in the objective space described by the NEEG and dissatisfaction

tion habits and the impact of their actions on the city's energy demand related to the transportation sector. Overall, this method encourages more responsible energy usage in the community.

Another contribution of this work is the modeling of community members' behavior as commuting passengers, based on characteristics such as their preferred time to commute. By segmenting time periods related to commuting and flexibility, the potential to form a unique type of energy community that is united by a common aim of contributing to the municipality emerges, rather than forming a community solely defined by geography. This novel approach has the potential to enhance community engagement and promote a sense of shared responsibility towards the energy system.

An important aspect to note is related to the preferences of community members. These preferences represent fundamental features upon which community member profiles may be developed. As it was the case in this chapter, with the knowledge of fully flexible and semi-flexible members, the community manager service was able to develop a more precise and effective recommendations. A future challenge is to develop methods that can infer these profiles and use specific community behaviour knowledge that is gathered in time.

Additional information

The work presented in this chapter has been published in:

Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2023). Managing human involvement in an energy community: Application to a subway station. *Sustainable Cities and Society*, 95, 104597. <https://doi.org/10.1016/j.scs.2023.104597>

The simulation framework used for the work in this chapter is available here:

Simoiu, M. S. (2023, October). RENO - a multi-agent simulation tool for a renewable energy community [Language: en]. <https://doi.org/10.5281/zenodo.8424333>

The results can be generated with the following Jupyter notebook.

CHAPTER 8

UNCOVERING UNCERTAINTY: PROVIDING PERSONALISED RECOMMENDATIONS CONSIDERING COMMUNITY MEMBER MOTIVATION

8.1 The importance of personalised recommendations in energy communities

The case studies presented in the previous chapters showed interesting results in terms of economical and environmental performances, even in situations where the focus was placed on minimising member dissatisfaction. However, one could notice that recommendations were generally characterised by increased privacy. Specifically, the community manager service provided the same recommendations for all members by focusing mostly⁵² on the energy-related characteristics of the community.

Moreover, even if the integration of a comfort parameter in developing strategies might be considered useful in minimising discomfort, choosing a value might not be easy due to the diversity of household appliances and individual household consumption.

Undoubtedly, privacy is of utmost importance, even in energy communities. While considering the actor-service-system paradigm (Figure 3.2), one can easily notice the possibility for the *service* to acquire increased knowledge, to a deep extent, in order to facilitate the interaction of the *actors* with the *system*.

⁵² The manager service accounted for member preferences only to consider dissatisfaction in the optimization problem, as shown in the case study of the community of commuting passengers.

In the context delineated by the proposed solution of this work, it is intuitively clear that recommendations would carry a more significant impact if the managerial service had a deeper understanding of the community members, their preferences, or motivations. The problem addressed in this chapter relates to the necessity of providing tailored recommendations to community members in a way that enhances system performance without causing undue discomfort.

In the context of an energy community, the challenge is to propose non-intrusive recommendation strategies that consider additional knowledge about community members, while relying on minimum knowledge. The subsequent idea is to potentially develop personalised individual recommendations that aim to increase the community performances, while taking into account the particularities and historic involvement of each community member. The potential outcome of such non-intrusive recommendation strategies should result in an improved service-actor interaction, enhanced system performance, and increased trust in the service due to its focus on privacy. By prioritizing privacy considerations in the development of personalized recommendations, community members are more likely to feel comfortable sharing information and participating in the community, ultimately leading to better overall results.

8.2 Developing adaptive strategies based on consumption profile analysis

To address this challenge, this work will consider the case of the simple residential community (previously presented in Chapters 4 and 6), with one community member who exhibits behaviour towards following recommendations according to a certain internal model, which is hidden from the community manager. The problem is that this model is unknown to the manager and might be characterised deeply by uncertainty and other hidden factors such as presence at home, availability to follow recommendations, the number of residents and so on.

One method for learning from the members' behavior and adapting the recommendation strategies accordingly, is by comparing their historic initial consumption profile $p_{Load}^{estimated}$ with the final consumption profile obtained after providing recommendations p_{Load}^{real} . For instance, when providing a recommendation, the manager can measure the difference afterwards $\Delta_{Load} = p_{Load}^{real} - p_{Load}^{estimated}$ and compute an average value associated with that recommendation. Naturally, a learning period is essential at the beginning so that the manager can properly initialize these average values.

For instance, the *one turn informative* strategy (Fig. 6.1) from Chapter 6 can be enhanced in this manner. The result would be an 'adaptive' strategy that takes into account both the expected future consumption and production and the previous average engagement of individuals in response to recommendations. The term 'adaptive' emphasises the fact that if the consumption profile of households changes over time due to an increase in appliances or even behavioral shifts resulting from recommendations, an adaptive recommendation strategy can capture these dynamics and provide a tailored recommendation

The *one turn adaptive informative* strategy is proposed in Fig. 8.1:

In this case, the manager starts by providing recommendations for 20 days using the basic version of the informative strategy. This initial learning period can be tailored to the community's needs, but it should not be significantly shortened to avoid inferring biases towards a particular behavior.

During these days, the average change in consumption for each recommendation, denoted by Δ_{Load}^{rec} , is calculated. After this learning period, the manager determines the recommendation that provides the best expected response when matching the expected consumption with the production while still accounting for the previous impact of Δ_{Load}^{rec} . Finally, if the required change surpasses the value of the comfort parameter τ , then the recommendation rec^{best} reflecting the best response is dispatched to the members. However, if the change is not significant enough, then the members are advised to consume energy as originally expected.

To evaluate the proposed method, a case study is proposed. The case study presents a comparison between the classic informative strategy, as it was proposed in Chapter 6 and the new *adaptive one turn informative* strategy. The simulation conditions are the same in terms of consumption data, with a PV plant area that is chosen at $A = 50m^2$.

To better emphasise the collective effect of the previously mentioned strategies, several community configurations are proposed:

- **a community composed of ideal community members**, who are always attentive and follow recommendations (similar to the extreme cases proposed in Chapter 6).
- **a community composed of normal community members**, having the following Hidden Markov Model:

$A_{balanced} =$		Attentive	Inattentive
		0.5	0.5
	Attentive	0.5	0.5
	Inattentive	0.5	0.5

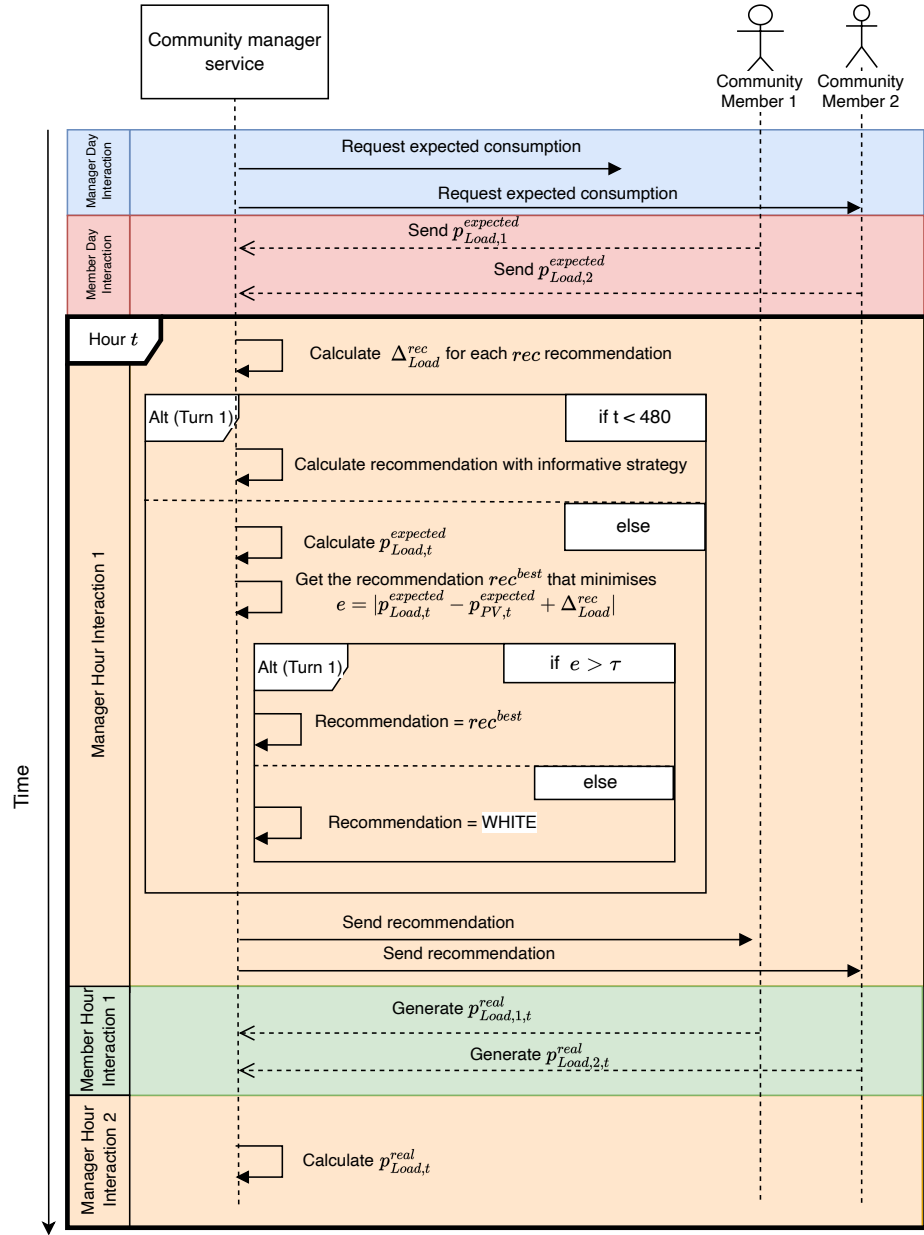


Figure 8.1: *One turn adaptive informative* recommendation strategy; $p_{Load}^{expected}$ represents the expected community consumption, $p_{PV}^{expected}$ represents the expected production and p_{Load}^{real} is the consumption generated after recommendations. Δ_{Load}^{rec} represents the average change in consumption associated to the recommendation rec . The formalism used is UML Sequence Diagram.

		Follow	not Follow
$B_{normal} =$	Attentive	0.5	0.5
	Inattentive	0.5	0.5

- **a community composed of attentive and enthusiastic community members**, having the following Hidden Markov Model:

		Attentive	Inattentive
$A_{attentive} =$	Attentive	0.8	0.2
	Inattentive	0.8	0.2

		Follow	not Follow
$B_{enthusiastic} =$	Attentive	0.8	0.2
	Inattentive	0.5	0.5

- **a community composed of inattentive and reluctant community members**, having the following Hidden Markov Model:

		Attentive	Inattentive
$A_{inattentive} =$	Attentive	0.8	0.2
	Inattentive	0.8	0.2

		Follow	not Follow
$B_{reluctant} =$	Attentive	0.8	0.2
	Inattentive	0.5	0.5

- **a mixed community**, with members having the following Hidden Markov Model:

		Attentive	Inattentive
$A_{inattentive} =$	Attentive	a	$1 - a$
	Inattentive	a	$1 - a$

		Follow	not Follow
$B_{reluctant} =$	Attentive	α	$1 - \alpha$
	Inattentive	0.5	0.5

with a and α chosen randomly.

Simulation scenarios have been executed for a period of almost one year, with the same conditions as in the case presented in Chapter 6. However, the comfort parameter τ is chosen to provide a good platform for comparison,

Table 8.1: Results for a residential community, comparison between basic and adaptive strategies; est.: estimated, SC: self-consumption, SS: self-sufficiency, NEEG: Net-Energy-Exchanged-with-the-Grid, RDR: Recommendation Deviation Rate, CCR: Contribution change Rate

ID	Scenario	est. SC	est. SS	real SC	real SS	NEEG	RDR	CCR	Avg. contrib. per day
1	One turn informative with ideal CMs	0.73	0.28	0.77	0.32	0.86	0.5	0.12	2.8
2	One turn informative with normal CMs	0.73	0.28	0.75	0.3	0.93	0.5	0.12	2.8
3	One turn informative with enthusiastic CMs	0.73	0.28	0.76	0.31	0.9	0.5	0.12	2.8
4	One turn informative with reluctant CMs	0.73	0.28	0.75	0.3	0.94	0.5	0.12	2.8
5	One turn informative with random CMs	0.73	0.28	0.76	0.31	0.91	0.5	0.12	2.8
6	One turn adaptive informative with ideal CMs	0.73	0.28	0.77	0.32	0.86	0.49	0.15	3.56
7	One turn adaptive informative with normal CMs	0.73	0.28	0.75	0.3	0.93	0.49	0.13	3.23
8	One turn adaptive informative with enthusiastic CMs	0.73	0.28	0.77	0.32	0.89	0.49	0.14	3.46
9	One turn adaptive informative with reluctant CMs	0.73	0.28	0.75	0.3	0.94	0.5	0.13	3.19
10	One turn adaptive informative with random CMs	0.73	0.28	0.76	0.31	0.92	0.49	0.14	3.29

with a relatively similar number of required contributions per day across all scenarios.

⁵³ Est. suggests that the respective indicator is computed for the date before recommendations.

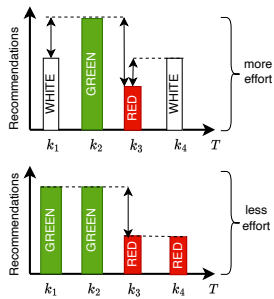
The results can be analysed in Table 8.1⁵³ and in Fig. 8.2. To provide a more detailed view on the effect that is provided in the system, a depiction of the hourly energy profiles of the reluctant community can be analysed in Fig. 8.3.

By analysing the results, it seems that the system performances in the adaptive case are generally the same as in the original one, the main differences being in the Contribution Change Rate⁵⁴ and the Recommendation Deviation Rate⁵⁵.

⁵⁴ It is worth noting again that the Contribution Change Rate quantifies how frequently people are required to modify their energy consumption.

The performances are somewhat similar because, in the original strategy case, the recommendation is developed by simply comparing consumption and production. In contrast, in the adaptive case, the recommendation is also developed according to the previous responses of the members. Therefore, if the average consumption change from previous responses is not significant, then the recommendations will be milder in the overall intensity. Additionally, excepting the extreme scenario, the average consumption change is expected to be minimal, as the Hidden Markov Model introduces additional uncertainty beyond that associated with the consumption change when following recommendations (Eq. 6.5).

On the other hand, given the limited range of recommendations associated with the informative strategy (only GREEN, RED and WHITE signals), the performances are favourable relative to the state before giving recommendations. This is also available in the case where the community is composed exclusively of reluctant inattentive members, which can be regarded as an optimistic result.



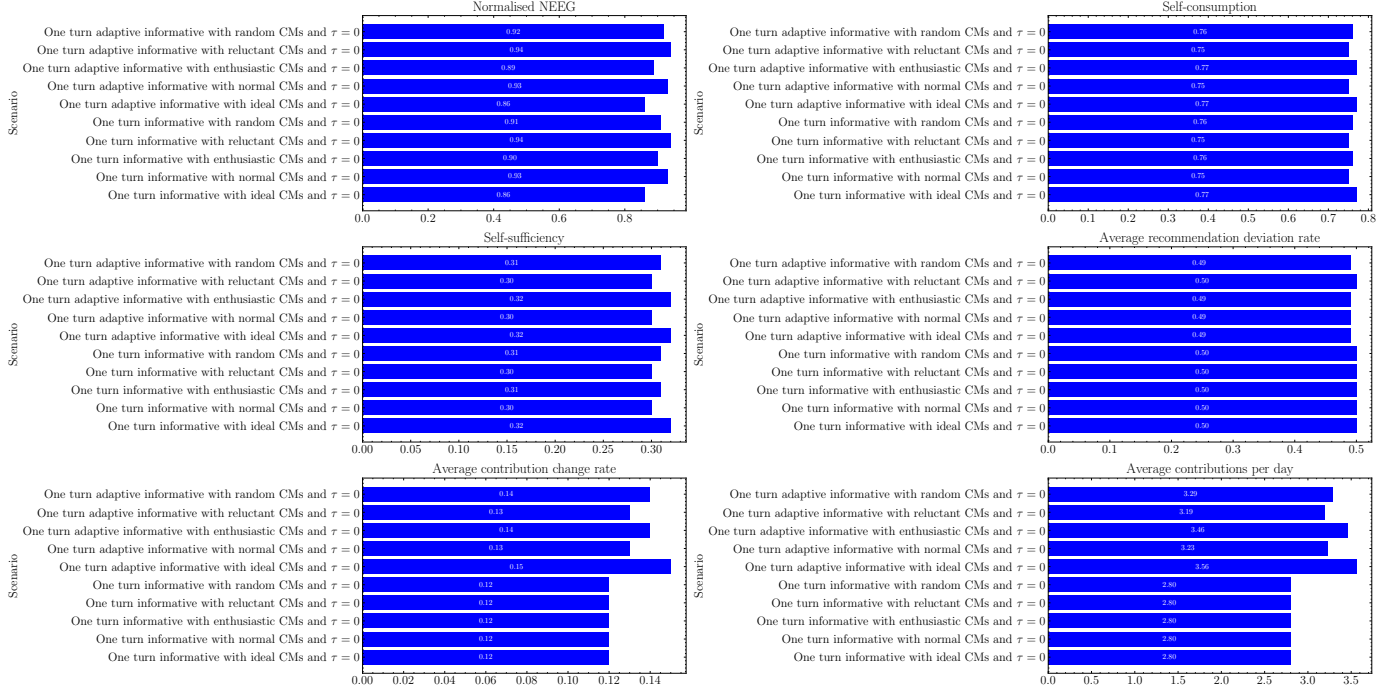
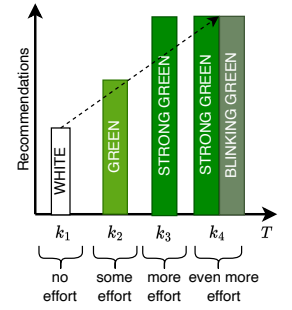


Figure 8.2: Graphical representation of the results obtained in Table 8.1. The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

Regarding the Recommendation Deviation Rate, a minor decrease can be observed, suggesting that more WHITE signals are given during the simulation (as it can be also noticed in Fig. 8.3). This aspect might be viewed favorably by individuals who prefer not to make drastic consumption changes. However, the Contribution Change Rate is increased compared to the traditional *one turn informative* strategy, suggesting that the recommendation system oscillates frequently (possibly hourly) between the spectrum of recommendations. This might cause discomfort for some people.

Overall, using the adaptive informative strategy can be useful as a more personalised alternative than simply using a global comfort parameter for the whole community. Given that households vary in the number of appliances and consumed power, people would likely prefer a more tailored and equitable strategy. Such a strategy would genuinely account for historic changes in consumption rather than relying on an arbitrarily set comfort parameter.

⁵⁵ It is worth noting again that the Recommendation Deviation Rate captures the intensity of recommendations.



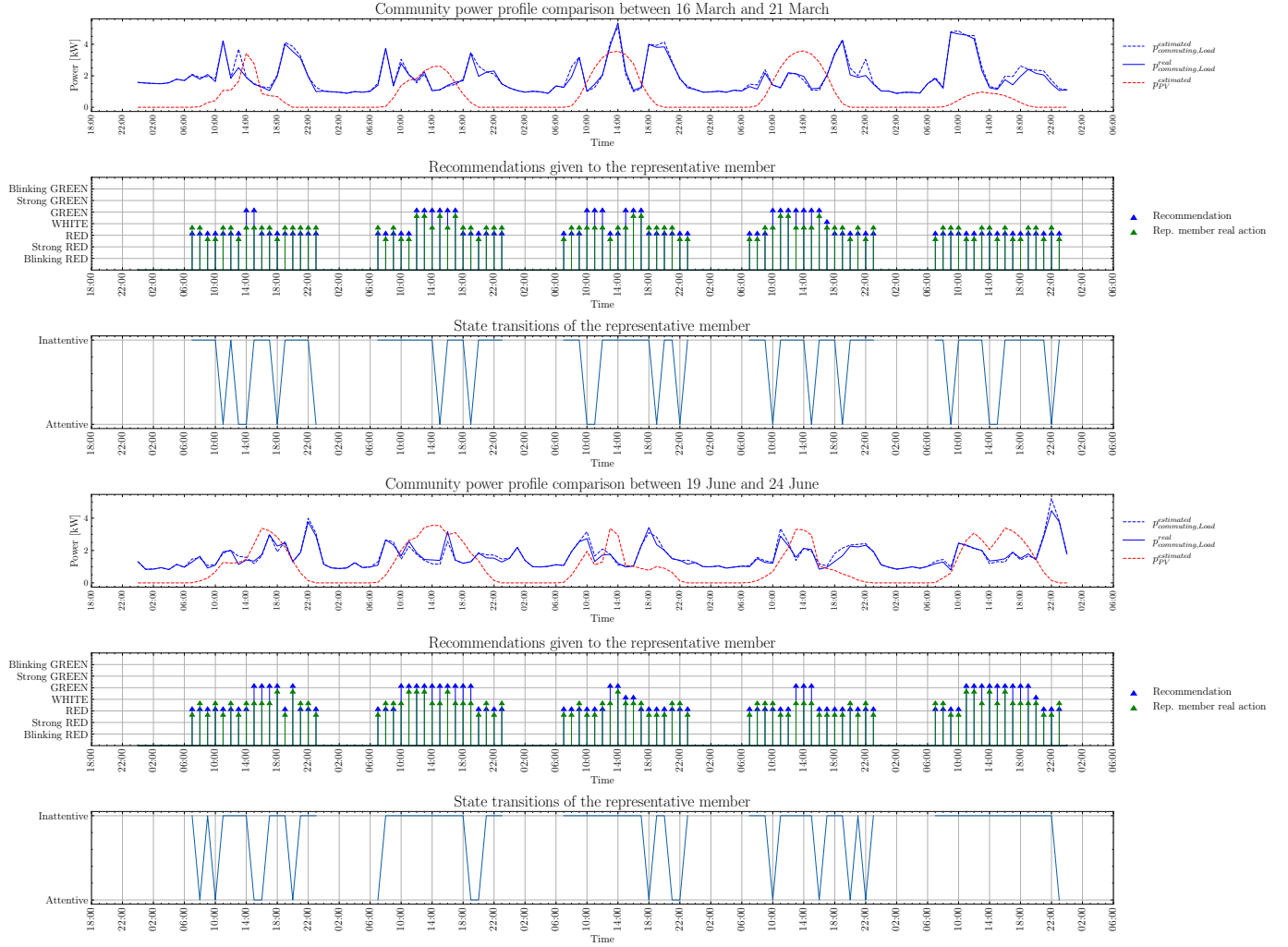


Figure 8.3: Collective impact analysis - *adaptive one turn informative* strategy for a community with reluctant members, with $\tau = 0$. The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

8.3 A personalised, adaptive coaching strategy

Reflecting on the results of Chapter 6, it can be observed that the *one turn coaching recommendation* strategy might be more preferable for energy communities given its solid performance and the potential for low dissatisfaction, as recommendations are provided for periods spanning several hours. Considering the problem of providing tailored recommendations, which is investigated in this chapter, it would be interesting to explore any potential improvements that could be made to the coaching strategy that may be associated to the current vision.

Another method for adapting and personalising recommendation strategies relies on the knowledge whether a member has followed a recommendation or not. This aspect can be determined with a local manager for example, a service that is associated specifically to one household and has a deeper visibility regarding the types of appliances, possible occupancy data or other knowledge that is relatively private and cannot be accessed by a central community manager.

By correctly approximating a sequence of observations $\mathcal{O} = \{\text{Follow, not Follow, Follow, ...}\}$ of length n , reflecting whether the member has followed or not followed the recommendation, a Recommendation Acceptance Ratio (RAR) can be defined as:

$$\text{RAR} = \frac{e_{\text{followed}}}{n} \quad (8.1)$$

where e_{followed} represents the number of events when the member has followed the recommendation. For long data-sets, this metric is equivalent to the probability to follow the recommendation $P_j(Y)$ of a member j .

With this information, the central manager service can provide a personalised recommendation to each member considering both the probability to follow a recommendation and the past changes in consumption associated to each recommendation, with minimum knowledge regarding personal details of the respective household. Consequently, the *adaptive one turn coaching* strategy can be further proposed.

The *adaptive one turn coaching strategy* represents a variant of the coaching strategy proposed in Chapter 6. This strategy involves providing recommendations to community members once per period, with each day being divided into several intervals based on the intensity of the PV production. However, given the fact that one recommendation per member is given for a period of several hours, this coaching strategy focuses on solving an optimization problem for each subsequent period, aiming to minimize the Net-Energy-Exchanged-

with-the-Grid for that period by considering past information related to each member.

So, the objective is to find a recommendation for each member j so that the overall community NEEG is minimised. The fundamental principle is that at each hour t , there is an absolute error between the expected consumption and the expected production. As the production cannot be modified, the expected consumption is the only measure that can be adapted considering the given recommendation and additional knowledge associated to each community member. Thus, the objective of the optimisation problem for one period can be intuitively written as follows:

$$\min_{\substack{x_j^{\text{WHITE}}, x_j^{\text{GREEN}}, x_j^{\text{RED}}, \\ x_j^{\text{STRONG GREEN}}, x_j^{\text{STRONG RED}}}} \sum_{t=1}^N \left| \sum_j p_{\text{Load},t,j}^{\text{expected}} - p_{\text{PV},t}^{\text{expected}} \right| \quad (8.2)$$

where t represents the hour, N represents the number of hours in the period, $p_{\text{Load},t,j}^{\text{expected}}$ represents the expected load for each member j during the hour t , $p_{\text{PV},t}^{\text{expected}}$ represents the expected PV power generated for the whole community at hour t . Additionally, $x_j^{\text{WHITE}}, x_j^{\text{GREEN}}, x_j^{\text{RED}}, x_j^{\text{STRONG GREEN}}, x_j^{\text{STRONG RED}}$ represent binary decision variables for each possible recommendation. Furthermore, a set of decision variables is associated for each member j , as each member receives a personalised recommendation. For example, if the personalised recommendation for any member j during the morning period is to strongly decrease consumption, then the solution would be $x_j^{\text{STRONG RED}} = 1$, and all other decision variables for the member j would be set to 0.

Starting from this objective, the aim now is to model the expected consumption considering the probability to follow recommendations and the average gas consumption change associated to each recommendation $\Delta_{\text{Load}}^{\text{rec}}$.

So, by substituting $p_{\text{Load}}^{\text{expected}}$ in Eq. 8.2 with the estimated power profile of each member, the optimisation problem to determine the personalised recommendations for a specific time period can be defined according to Eq. 8.3.

$$\begin{aligned}
& \min_{\substack{x_j^{\text{WHITE}}, x_j^{\text{GREEN}}, x_j^{\text{RED}}, \\ x_j^{\text{STRONG GREEN}}, x_j^{\text{STRONG RED}}}} \sum_{t=1}^N \left| \sum_j p_{\text{Load},t,j}^{\text{estimated}} \left\{ \underbrace{x_j^{\text{WHITE}}}_{\text{same consumption}} + \right. \right. \\
& \underbrace{x_j^{\text{STRONG GREEN}} \left[P_j(Y) \cdot \Delta_{\text{Load}}^{\text{STRONG GREEN}} + P_j(N) \cdot \Delta_{\text{Load}}^{\text{WHITE}} \right]}_{\text{strongly increase consumption}} + \\
& \underbrace{x_j^{\text{STRONG RED}} \left[P_j(Y) \cdot \Delta_{\text{Load}}^{\text{STRONG RED}} + P_j(N) \cdot \Delta_{\text{Load}}^{\text{WHITE}} \right]}_{\text{strongly decrease consumption}} + \\
& \underbrace{x_j^{\text{GREEN}} \left[P_j(Y) \cdot \Delta_{\text{Load}}^{\text{GREEN}} + P_j(N) \cdot \Delta_{\text{Load}}^{\text{WHITE}} \right]}_{\text{moderately increase consumption}} + \\
& \left. \underbrace{x_j^{\text{RED}} \left[P_j(Y) \cdot \Delta_{\text{Load}}^{\text{RED}} + P_j(N) \cdot \Delta_{\text{Load}}^{\text{WHITE}} \right]}_{\text{moderately decrease consumption}} \right\} - \\
& p_{PV,t}^{\text{expected}} \left| x_j^{\text{WHITE}} + x_j^{\text{STRONG GREEN}} + x_j^{\text{STRONG RED}} + x_j^{\text{GREEN}} + \right. \\
& \left. + x_j^{\text{RED}} = 1 \right. \\
& x_j^{\text{WHITE}}, x_j^{\text{STRONG GREEN}}, x_j^{\text{STRONG RED}}, x_j^{\text{GREEN}}, \\
& , x_j^{\text{RED}}, \\
& \left. x_{\Theta_0, \text{mod}}^- \in \{0, 1\} \right.
\end{aligned}
\tag{8.3}$$

subject to:

As depicted by the second constraint, it is important to reiterate that the decision variables represent binary values reflecting the recommended actions for a specific member j during an hour t . With periods, the same recommendation is given for all the hours within the respective period. Additionally, each member should receive only one recommendation. To model these aspects, the first constraint imposed on the optimization problem (Eq. 8.3).

The simulation scenarios have been devised in the same manner as those proposed for the informative strategies in the previous section, as the goal is to compare the adaptive coaching strategy with the initial coaching strategy across various community configurations. Similarly, the comfort parameter τ is omitted in this case since the aim is to compare strategies that issue the same relative number of recommendations per day.

Referring to the 20 days associated to the initial learning period, the *one turn coaching strategy* is employed. After these 20 days, the manager proceeds to compute personalised recommendations.

Results reflecting the comparison between strategies can be analysed in Table 8.2 and Fig. 8.4.

By analysing the results, both strategies provide an increase in system performances (self-consumption, self-sufficiency) comparing to the case without

Table 8.2: Results for a residential community, comparison between basic and adaptive strategies; est.: estimated, SC: self-consumption, SS: self-sufficiency, NEEG: Net-Energy-Exchanged-with-the-Grid, RDR: Recommendation Deviation Rate, CCR: Contribution change Rate

ID	Scenario	est. SC	est. SS	real SC	real SS	NEEG	RDR	CCR	Avg. contrib. per day
1	One turn coaching with ideal CMs	0.49	0.38	0.53	0.42	0.92	0.5	0.1	2.44
2	One turn coaching with normal CMs	0.49	0.38	0.51	0.4	0.96	0.5	0.1	2.44
3	One turn coaching with enthusiastic CMs	0.49	0.38	0.52	0.41	0.94	0.5	0.1	2.44
4	One turn coaching with reluctant CMs	0.49	0.38	0.51	0.4	0.97	0.5	0.1	2.44
5	One turn coaching with random CMs	0.49	0.38	0.51	0.4	0.96	0.5	0.1	2.44
6	One turn adaptive coaching with ideal CMs	0.49	0.38	0.52	0.41	0.94	0.45	0.14	3.26
7	One turn adaptive coaching with normal CMs	0.49	0.38	0.51	0.4	0.96	0.49	0.1	2.39
8	One turn adaptive coaching with enthusiastic CMs	0.49	0.38	0.52	0.4	0.96	0.48	0.11	2.69
9	One turn adaptive coaching with reluctant CMs	0.49	0.38	0.51	0.4	0.97	0.49	0.1	2.42
10	One turn adaptive coaching with random CMs	0.49	0.38	0.51	0.4	0.96	0.48	0.11	2.62

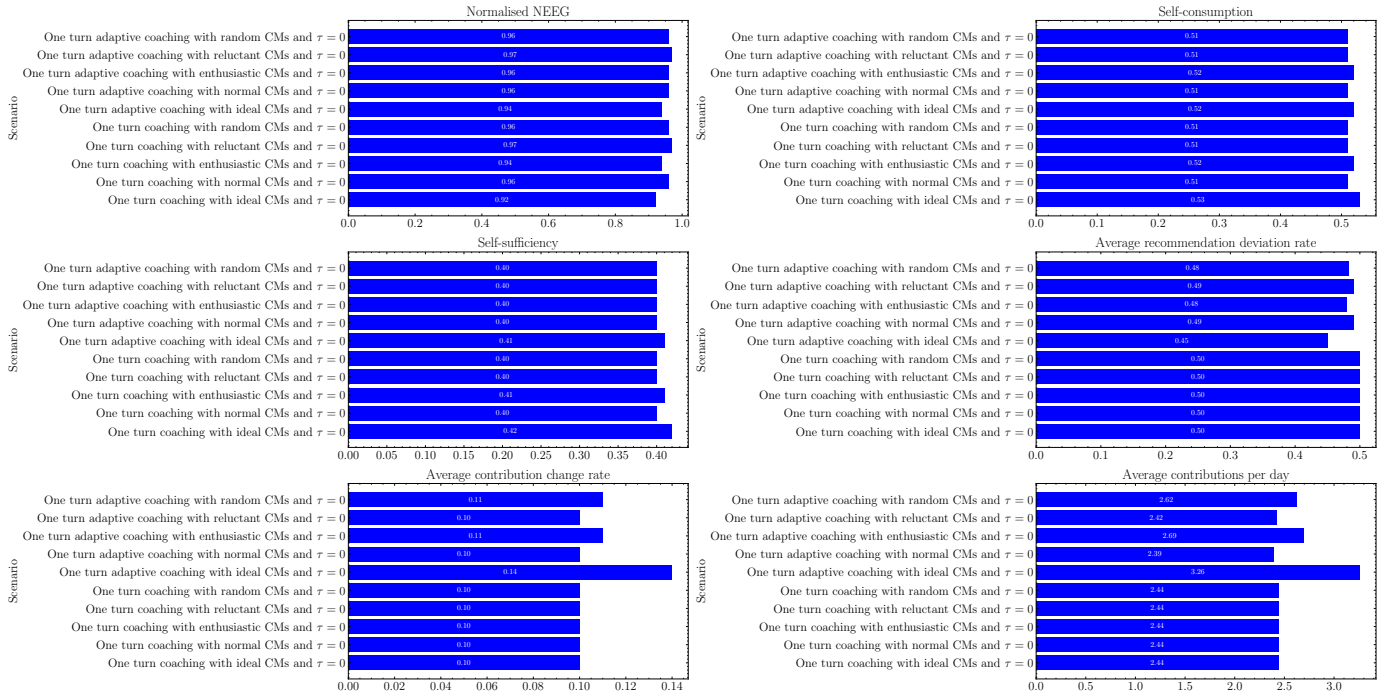


Figure 8.4: Graphical representation of the results obtained in Table 8.2. The Jupyter notebook used to generate this figure can be accessed here. Implementation in M. S. Simoiu, 2023

the recommendation system, across all scenarios. Similar to the informative strategy, the adaptive mechanism yields a decrease in the Recommendation Deviation Rate, as well as an increase in the Contribution Change Rate. In this case, however, given the fact that the recommendations are given for periods, the contribution change rate does not have a significant effect on the members. This conclusion is supported also by the average contributions per day, which remains around the same level as the initial coaching strategy.

As a simple example, results at day level can be analysed in Fig. 8.5 for a community of enthusiastic members.

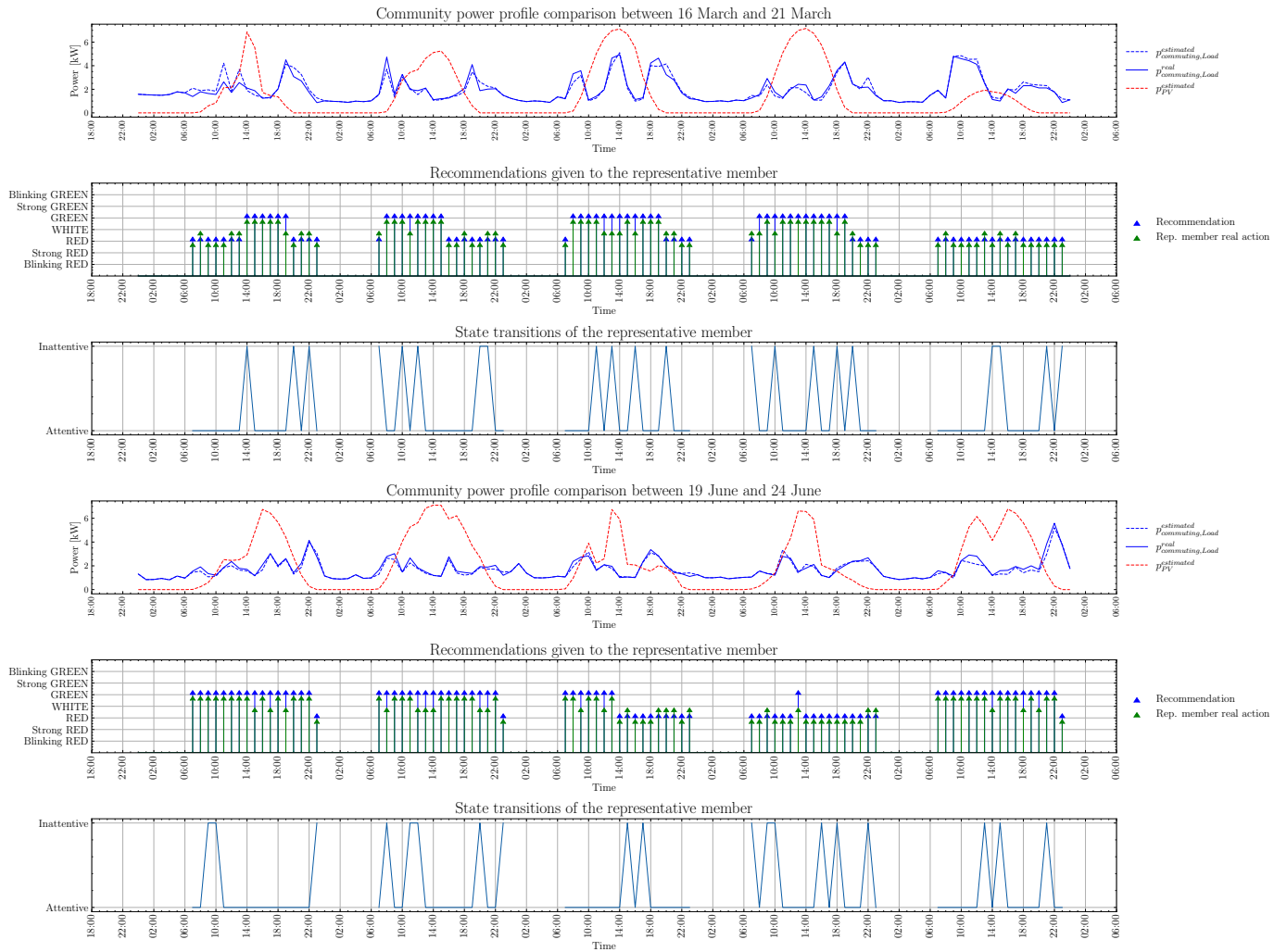


Figure 8.5: Collective impact analysis - *adaptive one turn coaching* strategy for a community with enthusiastic members, with $\tau = 0$. The Jupyter notebook used to generate this figure can be accessed [here](#). Implementation in M. S. Simoiu, 2023

At day level, it can be noticed that recommendations are grouped and associated to periods, as it is expected for the coaching strategy. However, the

manager's demand for intensity is moderate, as the majority of recommendations are either GREEN or RED instead of STRONG GREEN or STRONG RED. This is because the manager adjusts the expected load with both the probability of the member to follow recommendations and the previous average impact associated to each recommendation.

Overall, comparing to the classic variant of the *one turn coaching* strategy, the adaptive coaching strategy represents an even softer variant in terms of system performances. If the community members desire increased performance or recommendations that require more involvement, then other recommendation strategies such as the two turn informative strategy might be more suitable.

8.4 Conclusion

In this chapter, a novel strategy was proposed for providing personalized recommendations to energy communities, taking into account the motivational profile of each community member. In conjunction with this approach, an additional method is described to develop recommendations based on historic impact, in a non-intrusive manner.

The first contribution of this chapter is the adaptation of recommendation strategies, considering the historical average change in the consumption of community members. This proposed adaptation involves selecting the best recommendation that minimizes the net energy exchanged with the grid for the targeted period, taking into account the previous average change in consumption associated with each recommendation. In this way, the manager can provide recommendations that are more tailored to community members, requiring a reasonable level of involvement from them, rather than issuing strong recommendations that may lead to discomfort. Additionally, this method represents a potentially useful alternative to the arbitrary chosen comfort parameter that was introduced in Chapter 6.

A second contribution relates to the previously proposed optimal coaching strategy, a method based on a stochastic Mixed Integer Linear Programming optimization problem. This strategy minimizes the net-energy-exchanged-with-the-grid for specific periods during the day, taking into account the motivation profile of each member and an expected change in consumption, thereby addressing the uncertainty in human behavior.

In contrast to other works employing optimization models (Bartolini et al., 2020; Rafique et al., 2018; Tomin et al., 2022) for direct system control in a conventional manner or techno-economic analysis during the design stage, the proposed solution involves using an optimization model at the operational stage.

This approach continuously accounts for the uncertainty arising from human behavior, focusing on fostering sustainable energy consumption behaviors.

Regarding performance, the recommendation strategy yields improved results comparing to the initial scenario involving the already proposed coaching strategy (see Chapter 6), as the community manager service leverages the knowledge gained from previous changes in consumption to provide more accurate recommendations.

Two limitations have been identified in this study, which can be addressed in future research. Firstly, the adaptive coaching strategy is based on the assumption that there is a local community manager associated with each household who can provide a good estimation of the observation sequence related to that member. There are several potential methods for implementing this manager, including estimation using machine learning techniques, employing occupancy models, or even requiring people to provide input into the system about their perception of whether the recommendation was followed or not. Secondly, the other limitation refers to the evolutionary aspect of human behavior, which is not taken into account in both adaptive strategies. The idea is that if a regular member becomes more enthusiastic over time, then the historical impact of following recommendations would also change positively, requiring greater involvement in recommendations. This aspect might pose a problem when focusing on the other end of the spectrum, where reluctant members who become even more reluctant could potentially influence the recommendation system into providing inadequate recommendations. Therefore, balancing and considering the evolutionary behavior of individuals represents an intriguing challenge for future research.

Finally, a recommendation system can provide excellent recommendations if it has access to abundant data. However, if acquiring this data raises privacy concerns, then obtaining knowledge and offering precise recommendations becomes challenging. By analysing the changes in consumption, the uncertainty inferred from the consumption behavior of typical residential users can be significantly reduced, enabling the management service to become more competent and, consequently, assist community members more efficiently.

Additional information

A variant of the adaptive coaching strategy has been described in the following work:

Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2022). Modeling the energy community members' willingness to change their behaviour with multi-agent systems: A stochastic approach. *Renewable Energy*, 194, 1233–1246. <https://doi.org/10.1016/j.renene.2022.06.004>

Another recommendation strategy variant, based on an optimisation method, has been proposed in the following work, with focus on analysing the extreme case composed exclusively of ideal agents:

Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2022). Towards Energy Communities: A Multi-Agent Case Study. *2022 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR)*, 1–6. <https://doi.org/10.1109/AQTR55203.2022.9802060>

The simulation framework used for the work in this chapter is available here:

Simoiu, M. S. (2023, October). RENO - a multi-agent simulation tool for a renewable energy community [Language: en]. <https://doi.org/10.5281/zenodo.8424333>

CHAPTER 9

CONCLUSION AND FUTURE RESEARCH PERSPECTIVES

This study explores the effective control of energy systems, taking into account the active involvement and profound impact on system performances of humans, characterised by personal preferences, dissatisfaction and motivation. One of the roles of this work is to propose a change of paradigm from traditional control approaches, highlighting the critical role of people in shaping energy system performance. Thus, thorough consideration of humans is essential when designing and developing the operational management of the future energy systems.

9.1 Contributions

In Chapter 3, a first contribution of the work is the proposal of the human-actor-service paradigm, a depiction of the main paradigm in which the novel energy systems may be designed. The central element is the service, a computational component that interacts with both human actors and the system, based on its own representation of both entities. Likewise, human actors engage with the service, exerting an influence on the physical system. The work focuses on the cooperation between people and the service, depicting the manner in which this interaction influences this cooperation may influence the performances of the system.

Starting from this paradigm and the associated problem statement, the rest of the work focuses on energy communities, an energy system with humans, based on a novel European concept on how energy sharing mechanisms may be implemented to increase sustainability in urban environments. To this aspect, another contribution proposed in Chapter 3 in the form of a general set

of requirements that must be fulfilled when modeling energy communities according to the human-actors-service paradigm.

As a building platform for developing control solutions for such system, Chapter 4 further proposes a general framework comprising a general interaction model, the most relevant measures to quantify the actor's impact in the system and the general set of indicators for evaluating system performances. As a complementary contribution, a Python implementation of this framework has been developed and is further available as an open-source software.

Given the flexibility and potential applications offered by the concept of energy communities, Chapter 5 provides several technical models for two distinct energy communities: a typical residential community and a community of individuals who commute using subway transportation and wish to contribute towards more sustainable modes of transportation. The chapter emphasizes that, despite their differences from various perspectives technical and philosophical aspects, both communities can be linked to the human-service-paradigm.

For these energy communities, the following chapters explores several control solutions aligned with the previously mentioned framework. Among these, in each case an important contribution refers to a recommendation system, an embodiment of the service that facilitates the interaction between humans and the system. This study emphasizes the importance of recommendations as small goals proposed to community members. Through various proposed recommendation strategies, it demonstrates how these goals can be utilized to either enhance system performances from a collective perspective or foster long-term sustainable behaviors by considering member preferences, effort, or personal constraints. However, the key aspect of this contribution lies in its distinctiveness compared to existing state-of-the-art works, as well as in showcasing the main difference between traditional control and control in energy systems involving humans. This key aspect suggests that control should not be exerted directly on the system but rather indirectly, allowing individuals to decide how to interact with the system. In the energy community context, such an organisation should be the one to define the collective objectives and then to further use the service as an instrument to achieve a collaborative form of control that influences the performances of the energy system.

Another contribution refers to the conceptualization and further practical implementation of a multi-agent system, a software instrument (M. S. Simoiu, 2023) that depicts a concrete representation of the interaction between the community members and the service. Furthermore, compared to other research works, the proposed distributed model enables an interdependent depiction of each community member, complete with their individual behavior model,

encompassing preferences, personal motivation, restrictions, and willingness to follow recommendations. This simulation framework also allows the development of various simulation scenarios and collective evaluations, thus showing the concrete impact of the previously mentioned recommendation strategies.

Finally, for each community, another contribution involves proposing models that depict the dynamic human behavior in energy communities, behaviour which appears to be deeply characterized by uncertainty from an external perspective. These proposed models describe behaviors in communities with limited interaction between humans and the system (e.g., the community near a subway station) and in communities with diverse activities that cannot be fully recognized due to privacy concerns (e.g., the residential community case study). The models are developed to ensure sufficient knowledge exists for the service to provide precise and appropriate recommendations in situations that both aim to increase the system performances or other situations where human comfort is rather important.

9.2 A novel theoretical perspective

In retrospective, human-centered systems represent cooperative solutions involving technical systems, services and humans influencing the system. These systems take into account the satisfaction of people when improving performances.

9.2.1 Fundamental features of human-centered systems

Delving into the proposed theory, several key concepts can be emphasised.

The notion of **cooperation** evolves around the idea that people are part of the overall process of improving performances, as their knowledge is complemented by the knowledge of the service in daily activities. This could be noticed in the establishment of the main rule of this work's contribution, in which people have the final decision in whether to follow or not to follow the recommendations. As people set the overall objectives of the cooperation and the primary performances that need improvement, they are the ones making decisions, whether at a high or low level. The role of the service becomes most prominent when it transforms the collective, low-resolution objectives set by people, such as achieving environmental and economic benefits, into high-resolution goals expressed as recommendations.

In contrast with solutions developed until now, human-centered systems should deeply consider **human satisfaction**. By focusing on this aspect, cooperation between services and actors evolve in time as people develop a certain

trust in the services. Alongside this, the human capacity for engagement and their perception should always be seen as ways to enhance the effectiveness of services in the cooperative relationship. For instance, by offering recommendations as color codes or commute time intervals, individuals could receive specific, comprehensible advice to influence an otherwise complex energy system.

The importance of **learning** as a fundamental feature of human-centred systems is a underlying aspect that is emphasised by both the concepts of cooperation and human satisfaction. Firstly, this is important since it is relatively difficult to establish prior realistic models for the manager's perception on the actors without sufficient knowledge or carefully placed assumptions. Secondly, as the behaviour of individuals, the knowledge and their perception evolves in time, the services must permanently adapt and either learn from the influence of the actors in the systems, as was considered by the case-study involving adaptive recommendation strategies, or learn from the potential preferences of the actors, as it was the case with comprehending the work schedule of commuting passengers. Moreover, while this overall image deeply affects the performances of the system, privacy should always be considered as a necessary, fundamental right of the actors and thus the learning mechanism must be designed according to proper boundaries.

9.2.2 Comparison to classic control theory

In comparison to classic control theory, the theory of influencing human-centered systems depicts several distinct aspects.

From an overall standpoint, traditional control systems typically rely on a purely technical segregation of subsystems, signals, and subsequent dynamic relationships. This allows for a direct "divide and conquer" method of deriving a solution. In contrast to this approach, influencing human-centered systems depends largely on emergence and continuous performance adaptation, which are direct results of complex human behavior.

Additionally, in a purely technical system, knowledge is limited to the controlled process, while in human centered systems knowledge about the process could be considered as infinite in terms of the social dimension, culture or ergonomics.

In terms of the control signal, recommendations do not offer a deterministic effect and their effectiveness depends on the perception of the human actors on the service and overall cooperation mechanism.

When evaluating performances, the deterministic nature of some technical systems allows control to be employed and evaluated for very short time periods. However, due to the emergent nature, the performance of human-centered sys-

tems must be evaluated exclusively over a long-term period to genuinely capture the impact of the human-service cooperation and account for the complexity of human behaviour and its seemingly stochastic influence on the system.

What could be an interesting similarity between the two paradigms is related the desire for the ideal (or at least, the better). Fundamentally, control systems aim to guide towards a reference deemed ideal. Humans have shaped this theory in their own image, as we tend to meticulously organize our lives in pursuit of a state that is better, closer to the ideal. Consequently, human-centered systems should follow the same pattern, as a human-machine cooperation paradigm would represent the next step in the human quest for improving life in a sustainable manner. The potential of such cooperation would allow individuals to use services more efficiently in managing the complexity of the technical world.

9.3 Future research direction

Future research should focus on four primary directions. The first direction concerns enhancing the service's understanding of human behavior. This aspect originates from 8, where it is assumed that the manager knows whether members have followed the recommendations or not. Consequently, future research may explore models of a local service tailored to each community member. Such a local service could potentially gather enough information to enable the central community service to offer improved recommendations, while still preserving the privacy of individual members.

The second direction arises from the assumption in Chapters 6 and 8 that the expected consumption levels accurately represent the true energy needs of the community. In reality, this may not be the case, as human behavior evolves and energy needs change. Therefore, this direction will investigate methods that might rely on observation days when members do not receive recommendations and their behavior is simply monitored.

The third direction will focus on investigating the social dimension inferred by the cooperative mechanisms between members. This will firstly refer to validation scenarios that will involve a member trying to distinguish between reality and simulation scenarios and secondly by investigating the decision making process of each community member through a game theory approach. From this approach, new perspectives may emerge on, for example, how economical rewards are split between community members so that motivation is increased.

The fourth and final research direction will concentrate on modeling the dynamic changes in community members' behavior over time. This direction presents a challenge, as it is expected that factors such as the indirect influence of

coaching strategies have a quantifiable effect on the motivation and availability of community members. Specifically, it would be intriguing to examine how a reluctant community member might transition to a normal or even enthusiastic state, as well as the timeframe and circumstances under which such changes occur.

Nevertheless, cooperation between human and energy systems constitutes a vast research domain with much left to explore. The potential for adapting and developing new control techniques is seemingly limitless in an era where humans ought to capitalize on available technology to enhance their decision-making processes concerning environmental resources.

RELEVANT PERSONAL PUBLICATIONS

1. Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2022). Modeling the energy community members' willingness to change their behaviour with multi-agent systems: A stochastic approach. *Renewable Energy*, 194, 1233–1246. <https://doi.org/10.1016/j.renene.2022.06.004> - **Q1, Impact factor: 8.634**
2. Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2021b). Optimising the self-consumption and self-sufficiency: A novel approach for adequately sizing a photovoltaic plant with application to a metropolitan station. *Journal of Cleaner Production*, 327, 129399. <https://doi.org/10.1016/j.jclepro.2021.129399> - **Q1, Impact factor: 11.072**
3. Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2023). Managing human involvement in an energy community: Application to a subway station. *Sustainable Cities and Society*, 95, 104597. <https://doi.org/10.1016/j.scs.2023.104597> - **Q1, Impact factor 10.696**
4. Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2021a). Sizing and Management of an Energy System for a Metropolitan Station with Storage and Related District Energy Community. *Energies*, 14(18), 5997. <https://doi.org/10.3390/en14185997> - **Q3, Impact factor 3.252**
5. Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2021). General Considerations About Simulating Energy Communities. 2021 11th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), 1126–1131. <https://doi.org/10.1109/IDAACS53288.2021.9661053>
6. Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2022). Towards Energy Communities: A Multi-Agent Case Study. 2022 IEEE

International Conference on Automation, Quality and Testing, Robotics (AQTR), 1–6. <https://doi.org/10.1109/AQTR55203.2022.9802060>

7. Simoiu, M. Ș., Făgărășan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2023). A Recommendation Strategy Proposal for an Energy Community Modeled as a Multi-agent System [Series Title: Studies in Computational Intelligence]. In T. Borangiu, D. Trentesaux, & P. Leitão (Eds.), *Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry of the Future* (pp. 48–58, Vol. 1083). Springer International Publishing. https://doi.org/10.1007/978-3-031-24291-5_4
8. Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2023). Markov Chain model for energy community member reaction to recommendations: A multi-agent case study. *Proceedings of The 24th Conference on Control Systems and Computer Science, (Accepted, to be published)*

APPENDIX A

EQUIVALENCY BETWEEN MAXIMISING SELF-CONSUMPTION AND SELF-SUFFICIENCY AND MINIMISING THE NET-ENERGY-EXCHANGED- WITH-THE-GRID

The objective is to show that maximising SC and SS is equivalent to minimising NEEG.

As a prerequisite, average hourly consumption p_{Load} and production p_{Prod} profiles are considered for a time interval T , with each hourly value indexed by k .

Consequently, self-consumption and self-sufficiency are defined by Eq. A.1 and A.2 respectively.

$$SC = \frac{\sum_k^T \min(p_{Prod,k}, p_{Load,k})}{\sum_k^T p_{Prod,k}} \quad (A.1)$$

$$SS = \frac{\sum_k^T \min(p_{Prod,k}, p_{Load,k})}{\sum_k^T p_{Load,k}} \quad (A.2)$$

The net-energy-exchanged-with-the-grid is defined by Eq. A.3

$$\text{NEEG} = \sum_k^T |p_{Prod,k} - p_{Load,k}| \quad (\text{A.3})$$

For the demonstration NEEG (Eq. A.3) is considered as a starting point. One can split this sum according to two sets of indexes: $i \in X$ and $j \in Y$:

$$\sum_i^T |p_{Prod,i} - p_{Load,i}| = \sum_i^X (p_{Prod,i} - p_{Load,i}) + \sum_j^Y (p_{Load,j} - p_{Prod,j}) \quad (\text{A.4})$$

where X and Y are sets where the following rules apply:

$$\begin{cases} p_{Prod,i} \geq p_{Load,i} & , i \in X \\ p_{Load,j} > p_{Prod,j} & , j \in Y \end{cases} \quad (\text{A.5})$$

Specifically, X represents the set of time indexes associated to the periods where production is bigger then the consumption, while Y represents the set of time indexes associated to the periods where consumption is bigger then production.

If $p_{Prod,i} > p_{Load,i}$, then $\min(p_{Prod,i}, p_{Load,i}) = p_{Load,i}$. In a similar way, if $p_{Load,i} > p_{Prod,i}$, then $\min(p_{Prod,i}, p_{Load,i}) = p_{Prod,i}$.

So, considering this, one can rewrite Eq.A.4 as:

$$\begin{aligned} \sum_i^T |p_{Prod,i} - p_{Load,i}| &= \sum_i^X [p_{Prod,i} - \min(p_{Prod,i}, p_{Load,i})] + \\ &\quad \sum_j^Y [p_{Load,j} - \min(p_{Prod,j}, p_{Load,j})] \end{aligned}$$

One can go even further:

$$\begin{aligned} \sum_i^T |p_{Prod,i} - p_{Load,i}| &= \sum_i^X p_{Prod,i} - \sum_i^X \min(p_{Prod,i}, p_{Load,i}) + \\ &\quad \sum_j^Y p_{Load,j} - \sum_j^Y \min(p_{Prod,j}, p_{Load,j}) \end{aligned}$$

and then:

$$\sum_i^T |p_{Prod,i} - p_{Load,i}| = \sum_i^X p_{Prod,i} \left[1 - \frac{\sum_i^X \min(p_{Prod,i}, p_{Load,i})}{\sum_i^X p_{Prod,i}} \right] + \sum_j^Y p_{Load,j} \left[1 - \frac{\sum_j^Y \min(p_{Prod,j}, p_{Load,j})}{\sum_j^Y p_{Load,j}} \right]$$

which becomes, if one considers the initial notations defined in Eq.A.1 and Eq. A.2:

$$\sum_i^T |p_{Prod,i} - p_{Load,i}| = \sum_i^X p_{Prod,i} [1 - SC_X] + \sum_j^Y p_{Load,j} [1 - SS_Y] \quad (A.6)$$

Note: In Ec. A.6, SC_X is the self-consumption considered for indexes $i \in X$, so over the interval X . The idea is to consider SC over the whole time interval T , so this implies one also needs to consider SC_Y (which is self consumption computed over Y). The same can be said about SS_X and SS_Y .

But, for example, if one considers SC_Y :

$$\left. \begin{array}{l} \sum_j^Y p_{PV,j} [1 - SC_Y] \\ p_{Load,j} > p_{Prod,j} \quad , j \in Y \end{array} \right\} \min(p_{Prod,j}, p_{Load,j}) = p_{Prod,j} \quad (A.7)$$

So

$$\sum_j^Y p_{Prod,j} \left[1 - \frac{\sum_j^Y \min(p_{Prod,j}, p_{Load,j})}{\sum_j^Y p_{Prod,j}} \right] = \sum_j^Y p_{Prod,j} \left[1 - \frac{\sum_j^Y p_{Prod,j}}{\sum_j^Y p_{Prod,j}} \right] = 0 \quad (A.8)$$

The same applies for the situation involving SS_X and SS_Y .

So, returning to Ec. A.6, if SC and SS have maximum values (equal to 1), only then NEEG reaches its minimum value 0. This means that if the objective is to maximise SC and SS, one can instead minimise NEEG.

APPENDIX B

SUBWAY CONSUMPTION ESTIMATION MODEL

The subway consumption is estimated for 1 year based on the passenger traffic. A linear regression model is used to do this:

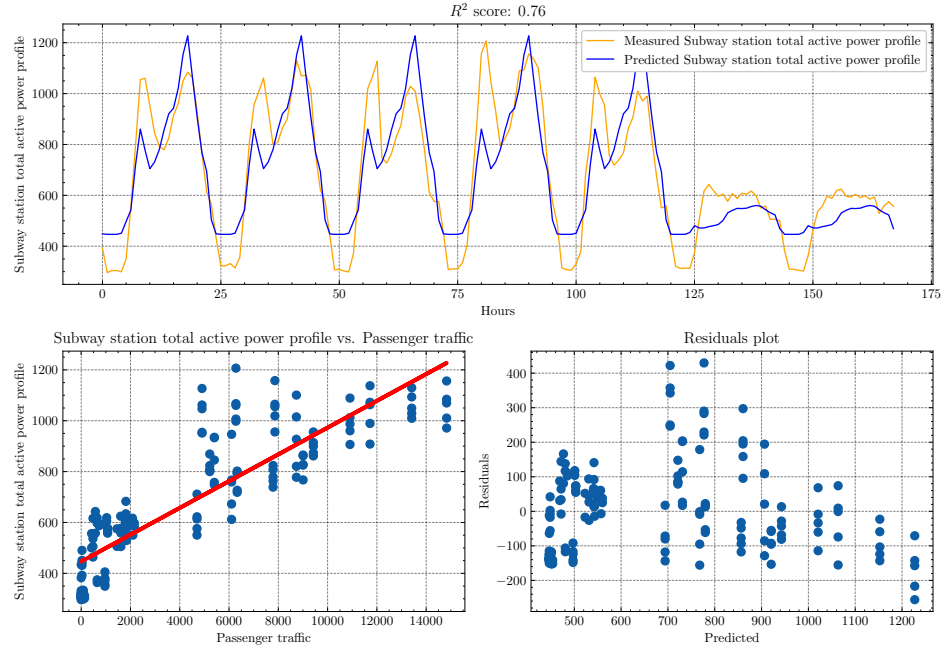


Figure B.1: Regression analysis for a linear regression model that estimates the subway consumption based on the passenger traffic

The model used is defined by Eq.

$$\hat{y} = 0.05x + 446.61 \quad (\text{B.1})$$

BIBLIOGRAPHY

- Alyafi, A. A. (2019). Generation of explanations for energy management in buildings.
- Azar, E., & Menassa, C. C. (2012). A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings. *Energy and Buildings*, 55, 841–853. <https://doi.org/10.1016/j.enbuild.2012.10.002>
- Azevedo, J. A., & Santos, F. E. (2021). A More Efficient Technique to Power Home Monitoring Systems Using Controlled Battery Charging. *Energies*, 14(13), 3846. <https://doi.org/10.3390/en14133846>
- Bartolini, A., Carducci, F., Muñoz, C. B., & Comodi, G. (2020). Energy storage and multi energy systems in local energy communities with high renewable energy penetration. *Renewable Energy*, 159, 595–609. <https://doi.org/10.1016/j.renene.2020.05.131>
- Bokkisam, H. R., & M.P., S. (2021). Effective community energy management through transactive energy marketplace. *Computers & Electrical Engineering*, 93, 107312. <https://doi.org/10.1016/j.compeleceng.2021.107312>
- Bonino, D., Corno, F., & De Russis, L. (2012). Home energy consumption feedback: A user survey. *Energy and Buildings*, 47, 383–393. <https://doi.org/10.1016/j.enbuild.2011.12.017>
- Braeuer, F., Kleinebrahm, M., Naber, E., Scheller, F., & McKenna, R. (2022). Optimal system design for energy communities in multi-family buildings: The case of the German Tenant Electricity Law. *Applied Energy*, 305, 117884. <https://doi.org/10.1016/j.apenergy.2021.117884>
- Bratman, M. (1987). *Intention, plans, and practical reason*. Harvard University Press.
- Cao, L., Huang, Y., & Liu, N. (2021). Optimal Scheduling of Building Integrated Energy System considering uncertainty of Human Behavior. *2021 3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST)*, 1893–1897. <https://doi.org/10.1109/IAECST54258.2021.9695655>

- Cao, M., Xu, Q., Qin, X., & Cai, J. (2020). Battery energy storage sizing based on a model predictive control strategy with operational constraints to smooth the wind power. *International Journal of Electrical Power & Energy Systems*, 115, 105471. <https://doi.org/10.1016/j.ijepes.2019.105471>
- Cécile Boutelet. (2020). En Allemagne, les rénovations énergétiques des bâtiments n'ont pas fait baisser la consommation. *Le Monde.fr*. Retrieved February 3, 2023, from https://www.lemonde.fr/economie/article/2020/10/04/en-allemande-les-renovations-energetiques-des-batiments-n-ont-pas-fait-baisser-la-consommation_6054715_3234.html
- Ceglia, F., Esposito, P., Faraudello, A., Marrasso, E., Rossi, P., & Sasso, M. (2022). An energy, environmental, management and economic analysis of energy efficient system towards renewable energy community: The case study of multi-purpose energy community. *Journal of Cleaner Production*, 369, 133269. <https://doi.org/10.1016/j.jclepro.2022.133269>
- Chapman, J., Siebers, P.-O., & Robinson, D. (2018). On the multi-agent stochastic simulation of occupants in buildings. *Journal of Building Performance Simulation*, 11(5), 604–621. <https://doi.org/10.1080/19401493.2017.1417483>
- Chen, L., & Gao, M. (2021). Formal or informal recycling sectors? Household solid waste recycling behavior based on multi-agent simulation. *Journal of Environmental Management*, 294, 113006. <https://doi.org/10.1016/j.jenvman.2021.113006>
- Chen, S., Wu, J., Pan, Y., Ge, J., & Huang, Z. (2020). Simulation and case study on residential stochastic energy use behaviors based on human dynamics. *Energy and Buildings*, 223, 110182. <https://doi.org/10.1016/j.enbuild.2020.110182>
- Chen, X., Xiao, J., Yuan, J., Xiao, Z., & Gang, W. (2021). Application and performance analysis of 100% renewable energy systems serving low-density communities. *Renewable Energy*, 176, 433–446. <https://doi.org/10.1016/j.renene.2021.05.117>
- Chung, P.-C., & Liu, C.-D. (2008). A daily behavior enabled hidden Markov model for human behavior understanding. *Pattern Recognition*, 41(5), 1572–1580. <https://doi.org/10.1016/j.patcog.2007.10.022>
- come-res.eu. (n.d.). COME-RES | Home. Retrieved February 6, 2023, from <https://come-res.eu/>
- compile-project.eu. (2018). The Compile Project. Retrieved February 6, 2023, from <https://www.compile-project.eu/>

- Cruz, C., Palomar, E., Bravo, I., & Aleixandre, M. (2021). Behavioural patterns in aggregated demand response developments for communities targeting renewables. *Sustainable Cities and Society*, 72, 103001. <https://doi.org/10.1016/j.scs.2021.103001>
- Di Lorenzo, G., Rotondo, S., Araneo, R., Petrone, G., & Martirano, L. (2021). Innovative power-sharing model for buildings and energy communities. *Renewable Energy*, 172, 1087–1102. <https://doi.org/10.1016/j.renene.2021.03.063>
- Dongol, D., Feldmann, T., Schmidt, M., & Bollin, E. (2018). A model predictive control based peak shaving application of battery for a household with photovoltaic system in a rural distribution grid. *Sustainable Energy, Grids and Networks*, 16, 1–13. <https://doi.org/10.1016/j.segan.2018.05.001>
- Duffie, J. A., Beckman, W. A., & Blair, N. (2020, March). *Solar Engineering of Thermal Processes, Photovoltaics and Wind* (1st ed.). Wiley. <https://doi.org/10.1002/9781119540328>
- Engels, J., Claessens, B., & Deconinck, G. (2019). Techno-economic analysis and optimal control of battery storage for frequency control services, applied to the German market. *Applied Energy*, 242, 1036–1049. <https://doi.org/10.1016/j.apenergy.2019.03.128>
- European Commission. (n.d.-a). Clean energy vision to clean energy action | Clean energy for EU islands. Retrieved February 6, 2023, from <https://clean-energy-islands.ec.europa.eu/>
- European Commission. (n.d.-b). Creating smart cities together | Smart Cities Marketplace. Retrieved February 6, 2023, from <https://smart-cities-marketplace.ec.europa.eu/>
- European Commission. Directorate-General for Energy. (2012). *Energy : Roadmap 2050*. Publications Office. Retrieved February 3, 2023, from <https://data.europa.eu/doi/10.2833/10759>
- European Parliament & Council of the European Union. (2018). DIRECTIVES DIRECTIVE (EU) 2018/2001 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 11 December 2018 on the promotion of the use of energy from renewable sources (recast) (Text with EEA relevance). <http://data.europa.eu/eli/dir/2018/2001>
- European Parliament & Council of the European Union. (2019). DIRECTIVE (EU) 2019/ 944 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL - of 5 June 2019 - on common rules for the internal market for electricity and amending Directive 2012/ 27/ EU. <http://data.europa.eu/eli/dir/2019/944>

- Fan, G., Liu, Z., Liu, X., Shi, Y., Wu, D., Guo, J., Zhang, S., Yang, X., & Zhang, Y. (2022). Energy management strategies and multi-objective optimization of a near-zero energy community energy supply system combined with hybrid energy storage. *Sustainable Cities and Society*, 83, 103970. <https://doi.org/10.1016/j.scs.2022.103970>
- Fanti, M., Mangini, A., Roccotelli, M., & Ukovich, W. (2017). District Microgrid Management Integrated with Renewable Energy Sources, Energy Storage Systems and Electric Vehicles * *This work is supported by the project Smart Cities and Communities and Social Innovation Pilot 2014-2016 - ASMAR. *IFAC-PapersOnLine*, 50(1), 10015–10020. <https://doi.org/10.1016/j.ifacol.2017.08.2035>
- Fina, B., Auer, H., & Friedl, W. (2020). Cost-optimal economic potential of shared rooftop PV in energy communities: Evidence from Austria. *Renewable Energy*, 152, 217–228. <https://doi.org/10.1016/j.renene.2020.01.031>
- Fouladvand, J. (2022). Behavioural attributes towards collective energy security in thermal energy communities: Environmental-friendly behaviour matters. *Energy*, 261, 125353. <https://doi.org/10.1016/j.energy.2022.125353>
- Frieden, D., Turek, Andreas, Roberts, Josh, d’Herbement, Stanislas, & Gubina, Andrej. (2019, June). *Collective self-consumption and energy communities: Overview of emerging regulatory approaches in Europe* (tech. rep.). https://www.compile-project.eu/wp-content/uploads/COMPILE_Collective_self-consumption_EU_review_june_2019_FINAL-1.pdf
- Gjorgievski, V. Z., Cundeva, S., & Georghiou, G. E. (2021). Social arrangements, technical designs and impacts of energy communities: A review. *Renewable Energy*, 169, 1138–1156. <https://doi.org/10.1016/j.renene.2021.01.078>
- Groppi, D., Pfeifer, A., Garcia, D. A., Krajačić, G., & Duić, N. (2021). A review on energy storage and demand side management solutions in smart energy islands. *Renewable and Sustainable Energy Reviews*, 135, 110183. <https://doi.org/10.1016/j.rser.2020.110183>
- Guillard, V. (2021). TOWARDS A SOCIETY OF SOBRIETY: Conditions for a change in consumer behavior.
- HOMER. (n.d.). HOMER PV Energy Model. Retrieved January 12, 2020, from https://www.homerenergy.com/products/pro/docs/latest/how_homer_calculates_the_pv_array_power_output.html
- Hong, T., Taylor-Lange, S. C., D’Oca, S., Yan, D., & Corngati, S. P. (2016). Advances in research and applications of energy-related occupant behavior

- in buildings. *Energy and Buildings*, 116, 694–702. <https://doi.org/10.1016/j.enbuild.2015.11.052>
- Khorasany, M., Razzaghi, R., & Shokri Gazafroudi, A. (2021). Two-stage mechanism design for energy trading of strategic agents in energy communities. *Applied Energy*, 295, 117036. <https://doi.org/10.1016/j.apenergy.2021.117036>
- Lai, B.-C., Chiu, W.-Y., & Tsai, Y.-P. (2022). Multiagent Reinforcement Learning for Community Energy Management to Mitigate Peak Rebounds Under Renewable Energy Uncertainty. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 6(3), 568–579. <https://doi.org/10.1109/TETCI.2022.3157026>
- Laurillau, Y., Nguyen, V.-B., Coutaz, J., Calvary, G., Mandran, N., Camara, F., & Balzarini, R. (2018). The TOP-slider for multi-criteria decision making by non-specialists. *Proceedings of the 10th Nordic Conference on Human-Computer Interaction*, 642–653. <https://doi.org/10.1145/3240167.3240185>
- Li, L., Wang, J., Zhong, X., Lin, J., Wu, N., Zhang, Z., Meng, C., Wang, X., Shah, N., Brandon, N., Xie, S., & Zhao, Y. (2022). Combined multi-objective optimization and agent-based modeling for a 100% renewable island energy system considering power-to-gas technology and extreme weather conditions. *Applied Energy*, 308, 118376. <https://doi.org/10.1016/j.apenergy.2021.118376>
- Lin, C.-H., Wang, K.-J., Tadesse, A. A., & Woldegiorgis, B. H. (2022). Human-robot collaboration empowered by hidden semi-Markov model for operator behaviour prediction in a smart assembly system. *Journal of Manufacturing Systems*, 62, 317–333. <https://doi.org/10.1016/j.jmsy.2021.12.001>
- Liu, J., Yang, H., & Zhou, Y. (2021). Peer-to-peer trading optimizations on net-zero energy communities with energy storage of hydrogen and battery vehicles. *Applied Energy*, 302, 117578. <https://doi.org/10.1016/j.apenergy.2021.117578>
- Liu, N., Yu, X., Wang, C., Li, C., Ma, L., & Lei, J. (2017). Energy-Sharing Model With Price-Based Demand Response for Microgrids of Peer-to-Peer Prosumers. *IEEE Transactions on Power Systems*, 32(5), 3569–3583. <https://doi.org/10.1109/TPWRS.2017.2649558>
- Maheshwari, A., Paterakis, N. G., Santarelli, M., & Gibescu, M. (2020). Optimizing the operation of energy storage using a non-linear lithium-ion battery degradation model. *Applied Energy*, 261, 114360. <https://doi.org/10.1016/j.apenergy.2019.114360>

- Manso-Burgos, Á., Ribó-Pérez, D., Gómez-Navarro, T., & Alcázar-Ortega, M. (2022). Local energy communities modelling and optimisation considering storage, demand configuration and sharing strategies: A case study in Valencia (Spain). *Energy Reports*, 8, 10395–10408. <https://doi.org/10.1016/j.egy.2022.08.181>
- Metrorex. (2017). Metrorex Activity Report - 2017. Retrieved May 6, 2022, from <http://www.metrorex.ro/Resurse/RaportActivitate/Raport%20code%20activitate-2017-RO.pdf>
- Norouziasl, S., Jafari, A., & Wang, C. (2020). An agent-based simulation of occupancy schedule in office buildings. *Building and Environment*, 186, 107352. <https://doi.org/10.1016/j.buildenv.2020.107352>
- Onile, A. E., Machlev, R., Petlenkov, E., Levron, Y., & Belikov, J. (2021). Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. *Energy Reports*, 7, 997–1015. <https://doi.org/10.1016/j.egy.2021.01.090>
- Oraiopoulos, A., Hsieh, S., & Schlueter, A. (2023). Energy futures of representative Swiss communities under the influence of urban development, building retrofit, and climate change. *Sustainable Cities and Society*, 91, 104437. <https://doi.org/10.1016/j.scs.2023.104437>
- Pal, M., Alyafi, A. A., Ploix, S., Reignier, P., & Bandyopadhyay, S. (2019). Unmasking the causal relationships latent in the interplay between occupant's actions and indoor ambience: A building energy management outlook. *Applied Energy*, 238, 1452–1470. <https://doi.org/10.1016/j.apenergy.2019.01.118>
- Perger, T., Zwickl-Bernhard, S., Golab, A., & Auer, H. (2022). A stochastic approach to dynamic participation in energy communities. *e & i Elektrotechnik und Informationstechnik*, 139(8), 644–661. <https://doi.org/10.1007/s00502-022-01069-2>
- Pinto, T., Faia, R., Navarro-Caceres, M., Santos, G., Corchado, J. M., & Vale, Z. (2019). Multi-Agent-Based CBR Recommender System for Intelligent Energy Management in Buildings. *IEEE Systems Journal*, 13(1), 1084–1095. <https://doi.org/10.1109/JSYST.2018.2876933>
- Ploix, S. (2021). Buildingenergy. Retrieved June 27, 2022, from <https://gricad-gitlab.univ-grenoble-alpes.fr/ploixs/buildingenergy>
- Price, K. V., Storn, R. M., & Lampinen, J. A. (2005). *Differential evolution: A practical approach to global optimization*. Springer.
- Prince Agbodjan, J.-J., Haessig, P., Bourdais, R., & Gheguen, H. (2020). Stochastic modelled grid outage effect on home Energy Management.

- 2020 *IEEE Conference on Control Technology and Applications (CCTA)*, 1080–1085. <https://doi.org/10.1109/CCTA41146.2020.9206157>
- Prince Agbodjan, J.-J., Haessig, P., Bourdais, R., & Gueguen, H. (2021). Integrating stochastic discrete constraints in MPC. Application to Home Energy Management System. *IFAC Journal of Systems and Control*, 17, 100168. <https://doi.org/10.1016/j.ifacsc.2021.100168>
- Project Mesa Team. (2021). Mesa: Agent-based modeling in Python 3+ — Mesa .1 documentation. Retrieved August 5, 2022, from <https://mesa.readthedocs.io/en/latest/>
- pvXchange Trading GmbH. (2020). Solar price index & Solar module price development. Retrieved May 1, 2020, from <https://www.pvxchange.com/Price-Index>
- Quijano-Sánchez, L., Cantador, I., Cortés-Cediel, M. E., & Gil, O. (2020). Recommender systems for smart cities. *Information Systems*, 92, 101545. <https://doi.org/10.1016/j.is.2020.101545>
- Rabiner, L. (1989). A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2), 257–286. <https://doi.org/10.1109/5.18626>
- Rafique, M. M., Rehman, S., & Alhems, L. M. (2018). Developing zero energy and sustainable villages – A case study for communities of the future. *Renewable Energy*, 127, 565–574. <https://doi.org/10.1016/j.renene.2018.04.087>
- Reis, I. F., Gonçalves, I., Lopes, M. A., & Antunes, C. H. (2020). A multi-agent system approach to exploit demand-side flexibility in an energy community. *Utilities Policy*, 67, 101114. <https://doi.org/10.1016/j.jup.2020.101114>
- REMODECE. (n.d.). REMODECE Project. Retrieved January 12, 2021, from <https://remodece.isr.uc.pt>
- Sameti, M., & Haghighat, F. (2018). Integration of distributed energy storage into net-zero energy district systems: Optimum design and operation. *Energy*, 153, 575–591. <https://doi.org/10.1016/j.energy.2018.04.064>
- Seligman, C., & Darley, J. M. (1977). Feedback as a Means of Decreasing Residential Energy Consumption. *Journal of Applied Psychology*, 62(4), 363–368.
- Sima, C. A., Popescu, C. L., Popescu, M. O., Roscia, M., Seritan, G., & Panait, C. (2022). Techno-economic assessment of university energy communities with on/off microgrid. *Renewable Energy*, 193, 538–553. <https://doi.org/10.1016/j.renene.2022.05.047>

- Simoiu, M. S. (2023, October). RENO - a multi-agent simulation tool for a renewable energy community [Language: en]. <https://doi.org/10.5281/zenodo.8424333>
- Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2021a). Sizing and Management of an Energy System for a Metropolitan Station with Storage and Related District Energy Community. *Energies*, 14(18), 5997. <https://doi.org/10.3390/en14185997>
- Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2021). General Considerations About Simulating Energy Communities. *2021 11th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, 1126–1131. <https://doi.org/10.1109/IDAACS53288.2021.9661053>
- Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2022). Towards Energy Communities: A Multi-Agent Case Study. *2022 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR)*, 1–6. <https://doi.org/10.1109/AQTR55203.2022.9802060>
- Simoiu, M. S., Fagarasan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2023). Markov Chain model for energy community member reaction to recommendations: A multi-agent case study. *Proceedings of The 24th Conference on Control Systems and Computer Science, (Accepted, to be published)*.
- Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2021b). Optimising the self-consumption and self-sufficiency: A novel approach for adequately sizing a photovoltaic plant with application to a metropolitan station. *Journal of Cleaner Production*, 327, 129399. <https://doi.org/10.1016/j.jclepro.2021.129399>
- Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2022). Modeling the energy community members' willingness to change their behaviour with multi-agent systems: A stochastic approach. *Renewable Energy*, 194, 1233–1246. <https://doi.org/10.1016/j.renene.2022.06.004>
- Simoiu, M. S., Fagarasan, I., Ploix, S., & Calofir, V. (2023). Managing human involvement in an energy community: Application to a subway station. *Sustainable Cities and Society*, 95, 104597. <https://doi.org/10.1016/j.scs.2023.104597>
- Simoiu, M. Ș., Făgărășan, I., Ploix, S., Calofir, V., & Iliescu, S. S. (2023). A Recommendation Strategy Proposal for an Energy Community Modeled as a Multi-agent System [Series Title: Studies in Computational Intelligence]. In T. Borangiu, D. Trentesaux, & P. Leitão (Eds.), *Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry*

- of the Future* (pp. 48–58, Vol. 1083). Springer International Publishing. https://doi.org/10.1007/978-3-031-24291-5_4
- Soto, E. A., Bosman, L. B., Wollega, E., & Leon-Salas, W. D. (2021). Peer-to-peer energy trading: A review of the literature. *Applied Energy*, 283, 116268. <https://doi.org/10.1016/j.apenergy.2020.116268>
- Soudari, M., Srinivasan, S., Balasubramanian, S., Vain, J., & Kotta, U. (2016). Learning based personalized energy management systems for residential buildings. *Energy and Buildings*, 127, 953–968. <https://doi.org/10.1016/j.enbuild.2016.05.059>
- Starke, A., Willemsen, M. C., & Snijders, C. (2015). Saving energy in 1-D: Tailoring energy-saving advice using a Rasch-based energy recommender system.
- Tomin, N., Shakirov, V., Kozlov, A., Sidorov, D., Kurbatsky, V., Rehtanz, C., & Lora, E. E. (2022). Design and optimal energy management of community microgrids with flexible renewable energy sources. *Renewable Energy*, 183, 903–921. <https://doi.org/10.1016/j.renene.2021.11.024>
- van der Meer, D., Wang, G. C., & Munkhammar, J. (2021). An alternative optimal strategy for stochastic model predictive control of a residential battery energy management system with solar photovoltaic. *Applied Energy*, 283, 116289. <https://doi.org/10.1016/j.apenergy.2020.116289>
- Wasson, C. S. (2016). *System Engineering Analysis, Design, and Development*. Wiley Series in Systems Engineering; Management.
- Weckesser, T., Dominković, D. F., Blomgren, E. M., Schledorn, A., & Madsen, H. (2021). Renewable Energy Communities: Optimal sizing and distribution grid impact of photo-voltaics and battery storage. *Applied Energy*, 301, 117408. <https://doi.org/10.1016/j.apenergy.2021.117408>
- Xiong, L., Li, P., Wang, Z., & Wang, J. (2020). Multi-agent based multi objective renewable energy management for diversified community power consumers. *Applied Energy*, 259, 114140. <https://doi.org/10.1016/j.apenergy.2019.114140>
- Zhao, M., Eadeh, F. R., Nguyen, T.-N., Gupta, P., Admoni, H., Gonzalez, C., & Woolley, A. W. (2023). Teaching agents to understand teamwork: Evaluating and predicting collective intelligence as a latent variable via Hidden Markov Models. *Computers in Human Behavior*, 139, 107524. <https://doi.org/10.1016/j.chb.2022.107524>
- Zhou, Y., Wu, J., & Long, C. (2018). Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework. *Applied Energy*, 222, 993–1022. <https://doi.org/10.1016/j.apenergy.2018.02.089>