Highlights

Managing human involvement in an energy community: application to a subway station

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- Cooperation between an energy community and the municipality is envisioned
- A recommendation strategy is proposed to manage the usage of a subway station
- The behaviour of passengers is modelled according to preferences and flexibility
- The strategy minimises the net energy exchanged with the grid and the dissatisfaction

Managing human involvement in an energy community: application to a subway station

Mircea Stefan SIMOIU[a,b], Ioana FAGARASAN[a], Stéphane PLOIX[b] and Vasile CALOFIR[a,*]

[a]Department of Automatic Control and Industrial Informatics, Faculty of Automatic Control and Computers, University Politehnica of Bucharest, 313 Splaiul Independentei, 060042, Bucharest, Romania

[b]Univ. Grenoble Alpes, CNRS, Grenoble INP, G-SCOP, 38000 Grenoble, France

A B S T R A C T

Energy communities become increasingly diverse, as sharing mechanisms and artificial intelligence become an important component of the cooperation between people and energy systems. This cooperation can play an important role at municipality level, where transportation systems that consume huge quantities of energy (i.e. subway networks) could become more efficient and sustainable, with the active involvement of people. In this context, we propose a method to manage the involvement of people in the cooperation mechanism established between an energy community and a subway station. The method relies on a multi-objective recommendation strategy that provides the members the optimal times to commute in order to provide a positive environmental and economical impact at municipality level, while also considering human dissatisfaction. The strategy is simulated in a multi-agent model, where agents represent commuting passengers. Results show that important economical and environmental performances may still be obtained when both the system performance and human dissatisfaction are minimised.

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

1. Introduction

Intelligent computational systems become increasingly important in society, an aspect that can be noticed frequently in infrastructure related developments at city level. A special focus in placed upon developments of transportation and energy systems for future districts and smart cities, since efficient and sustainable mobility is still an important challenge in world where cities are growing while aiming to satisfy the needs of people.

Furthermore, with the newly developed concept of energy communities (European Comission, 2022), we can imagine in many ways the development of future cities from an infrastructure point of view, not just by synthetically aiming for a permanent improvement of efficiency in systems, but considering a profound synergy between systems and citizens. To this aspect, energy communities represent organisations in which people voluntarily organise themselves to obtain a certain environmental, economical or social benefit through the usage of renewable energy sources. The most intuitive example of a community would be related to a residential neighborhood, where citizens would share the available photovoltaic (PV) production between themselves, while also sharing the benefits in a democratic manner. Interestingly enough, energy communities can be composed of both citizens who own or do not own renewable energy capabilities. This aspect emphasises the importance of cooperation at community level between people, but also the cooperation between energy systems and people, too.

On a different note, at city level, subway networks represent the largest energy consumers among known transportation services. In our view, subway networks represent a key instrument in developing the "15 minute city" concept (see Laurie (2022)) as a fast, reliable transportation service. The challenge is, however, related to the idea that humans represent a crucial component in the development of future transportation services and therefore they cannot be ignored. In our vision, people should play an active part in sustainable developments, as an increase in energy sobriety (also emphasised in Veolia) is definitely needed. While also considering energy communities, it would be

*Corresponding author

Email addresses: mircea_stefan.simoiu@upb.ro (M.S. SIMOIU); ioana.fagarasan@upb.ro (I. FAGARASAN); stephane.ploix@grenoble-inp.fr (S. PLOIX); vasile.calofir@upb.ro (V. CALOFIR)

ORCID(s): 0000-0001-7511-2910 (M.S. SIMOIU)

interesting to investigate, from the perspective of a simulation model, the potential impact of the synergy between an energy community and a subway station that plays the role of an urban transportation service.

In this context, we propose a method for managing the cooperation between people (as energy community members) and the energy system of a subway station. We consider that we have a PV plant that provides renewable energy for a subway station and the respective transportation company aims to capitalize on the available renewable resources. With this in mind, our proposed method relies on the implementation of an intelligent recommendation system that guides community members in choosing the most favourable times to commute so that the energy consumption inferred in a subway station's energy system is shifted. The desired consequence would be an increase in the self-consumption and self-sufficiency of the energy system of the subway station, while still accounting for the dissatisfaction of community members relative to their work schedule. In return for their active involvement, the subway transportation company may provide various benefits to the community members (for example free tickets). From a technical perspective, the main contribution of the paper reflects the implementation of a multi-agent simulation model, where community members (modeled as agents) react to recommendations according to a specific behaviour. The recommendations are developed based on a multi-objective optimisation model that accounts for both the performances of the system and the dissatisfaction of people.

2. State of the art

Management in an energy community represents the next important step towards an effective implementation of these organisations.

Currently, simulation models are developed to investigate the potential outcome of different sharing mechanisms, emphasising the economical and environmental benefits of organising in a community (Fina et al., 2022). In Ceglia et al. (2022), an environmental and economical analysis on an energy community is proposed based on the HOMER simulation software, evaluating the self-consumption at collective level. In Mehta and Tiefenbeck (2022), the authors evaluate an energy community based on self-sufficiency and net-present value. Accounting for these criteria, researchers have noted that flexibility plays an important part in increasing the economical and environmental benefit (Pinto et al. (2022)). Specifically, in Twum-Duah et al. (2022) the authors identify the need for flexibility in a community by investigating the contribution of energy storage with different capacities. Similarly, self-consumption and net-present value are used for evaluation. As a consequence, in most cases, optimisation models (Fan et al., 2022), multi-agent models (Lai et al., 2022) and game-theory models (Tushar et al., 2019) are used to simulate the energy sharing in different communities.

In terms of management, optimisation problems (Sima et al., 2022) are mostly used to manage an energy community. Even though optimisation may be used in the design stage too (Chen et al., 2021; Rafique et al., 2018; Iturriaga et al., 2021), it is also widely used in management strategies (Bartolini et al., 2020; Tomin et al., 2022), along with rules based energy management (Manso-Burgos et al., 2022). It is important to note that frequently, these strategies often do not take into account the social component of a community.

Typically, human involvement is simulated in a stochastic manner, especially in relation to occupancy. For example, in Norouziasl (2020), the authors propose a multi-agent model where occupancy is modeled in a stochastic manner. The simple presence of occupants in a residential area can be estimated using various techniques (Cretu et al., 2021; Stamatescu and Chitu, 2021). In Chapman et al. (2018), the authors emphasize that stochastic behaviour modeling improves the efficiency in energy systems at district level. However, there are also other method to model the behaviour of people relative to energy systems. In Perger et al. (2022), the authors propose a stochastic model to model the willingness to join an energy community. For example, Social Value Orientation theory is used to model the intention of people to join a community in different scenarios (Fouladvand, 2022). However, the difficulty to model human behaviour in an energy community still represents a challenge in relation to novel artificial intelligence solutions.

In other works, the main criteria was investigated for economical and environmental benefit quantification in energy systems (Simoiu et al., 2021a). These criteria were used to develop optimal management strategies for energy communities Simoiu et al. (2021b), exploring flexibility provided by storage. Additionally, building on the idea of sobriety and active human cooperation with energy systems, the same authors investigated the idea of an intelligent recommendation system that provides recommendation based on a stochastic model of the willingness of people to participate in the community life (Simoiu et al., 2022). Based on these works and considering other works in the literature, in this paper the authors make a step forward and propose the following solutions:

Table 1
Terminology

Abbreviation	Description
c_{grid}	grid tariff
$\mathsf{DIS}_{exp}^{norm,community}$	normalised expected community dissatisfaction
$\mathsf{DIS}_{morning,t}^{norm}$	normalised community dissatisfaction during hour t in the morning
$\mathsf{DIS}_{afternoon,t}^{norm}$	normalised community dissatisfaction during hour t in the afternoon
Δt	sampling time [h]
$\Delta t_{fav,j}$	preferred duration to stay at office of member j [h]
G	Incident solar radiation $[W/m^2]$
G_{STC}	Incident solar radiation at standard temperature conditions $[1kW/m^2]$
g_{h_i}	members who prefer to commute at time h_i
h_i	preferred time to go to work indexed by i
IPP	inferred power per passenger [W]
$\mathsf{IPP}_{morning}$	average IPP during the morning in a working day [W]
$\mathsf{IPP}_{afternoon}$	average IPP during the afternoon in a working day [W]
j	index for community members
MPGE	money payed for energy from the grid
$m_{est}^{commuting}$	estimated number of commuting passengers
n	number of PV modules
NEEG	net energy exchanged with the grid
$\mathsf{NEEG}_{exp}^{norm,community}$	normalised expected community NEEG
PV	Photovoltaic
$p_{exp,Load}^{community}$	expected community power [W]
$p_{sim,Load}^{community}$	simulated community power [W]
$p_{est,Load}^{subway,morning}$	average power of the subway station in the morning [W]
$p_{est,Load}^{subway,afternoon}$	average power of the subway station in the afternoon [W]
$p_{est,PV}^{community}$	estimated community PV power
p_{module}	rated power of a module [W]
$p_{est,morning}^{g_{h_i}}$	estimated power of a group h_i during the morning
SS	self-sufficiency
SC	self-consumption
t	index for hours
τ	PV production correction factor [%]
$w_{\mathsf{NEEG}}, w_{\mathsf{DIS}}$	weights associated to normalised NEEG and DIS
$x_{g_{h_i},t}$	decision for group h_i to commute at hour t

- a recommendation strategy that aims to both improve the economical and environmental benefits of an energy community, while also taking into account the social dimension of such an organisation - comparing to works such as Ceglia et al. (2022); Manso-Burgos et al. (2022); Fan et al. (2022), we consider the dissatisfaction of community members as an important criteria in developing the management strategy. Comparing to Oraiopoulos et al. (2023), we analyse an energy community considering the behaviour of community members. The model of the community member dissatisfaction represents another important contribution.

- a multi-agent model to simulate the involvement of community members in relation to the energy system of a subway station - comparing to works that deal with human actors modeled from a multi-agent approach (Lai et al., 2022; Norouziasl, 2020), we propose a model for the passengers that commute according to different flexibility profiles. This model is developed in the line set by the authors here (Simoiu et al., 2022); however, the model proposed in this paper is tailored to the context of a community that aims to contribute to the municipality.

- an estimation method for the collective impact of commuting passengers to the energy system of a subway station - the impact is quantified through an inferred estimated consumption profile that is developed according to the members preferred time to commute.

3. Improving energy efficiency in systems involving humans

To define the research problem of this paper, we consider that we have a renewable energy community (European Regional Development Fund, 2018) that is placed near a subway station - an external energy system. The subway station is connected to a PV plant. The plant provides renewable PV production that is available for the subway station, so, implicitly, the objective of the municipality is to modify the electricity consumption of the station to capitalize on the available production. The PV panels may be placed on adjacent residential buildings, as we consider the possibility that community members may agree to share the PV production with the subway station resulting in a PV virtual plant. Alternatively, PV panels may be installed on the roof of other municipality structures such as parking buildings.

An important requirement in this problem is reflected by the measure of how effective the actions of people would be in 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 both.

In this context, one can begin the investigation by considering an example related to minimising the energy consumption when transporting a number of passengers from station A to station B. Hence, we assume that we have n passengers to be transported and they can be partitioned in p subsets. Considering that each set has a size defined as n_i, the following constraints can be derived:

- the sum of all subsets' sizes equals n
- the maximum size of subset is limited by the capacity of one train (defined as c)

We can further model the energy consumption of the transportation process as:

$$E_{AB} = E_{AB}^{train} + mE_{AB}^{passenger} \tag{1}$$

where E_{AB}^{train} is the consumption of an empty train which transports the passengers from the current station "A" to the next station "B", $E_{AB}^{passenger}$ is the energy consumption to transport one passenger and m is the number of passengers to be transported. However, since passengers are grouped in p subsets and all p subsets need to be transported, Eq. 2 becomes:

$$E_{AB} = E_{AB}^{train} \cdot p + \sum_{i}^{p} n_i \cdot E_{AB}^{passenger} \tag{2}$$

We also remember that n_i is a fraction of n, so:

$$n_i = \rho_i n; \quad \sum_{i} \rho_i = 1 \tag{3}$$

So, in the end:

$$E_{AB} = E_{AB}^{train} \cdot p + (\sum_{i \in 1}^{p} \rho_i) n \cdot E_{AB}^{passenger} = E_{AB}^{train} \cdot p + n \cdot E_{AB}^{passenger} \tag{4}$$

In the energy consumption minimisation problem, one must therefore minimise the number of trips p, considering the lower bound $p = ceil(n/c)$. Consequently, empty trains or under-loaded trains will yield extra energy consumption.

Therefore, the ideal scenario is to have trains loaded with c passengers and therefore to have a match between the passenger traffic and the train traffic peaks.

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. Moreover, considering the potential for cooperation between the community and the transportation company, a possible solution would involve a community of commuting passengers who coordinate their actions to commute mainly during specific intervals, so that consumption match the PV production. This approach would require a train schedule that ensures the capacity of the trains matches the passenger demand. However, a challenge would be first to estimate the impact of people in the energy system of the subway station and then to effectively manage this impact so that the transportation company capitalizes on the available PV production.

The consequence is the development of an energy community that is unified in scope and objective rather then being limited by physical boundaries. Overall, this could also represent an indirect approach for people to contribute to the environment without specifically owning renewable energy capabilities, but still providing an impact through the collective action of energy communities.

Considering these assumptions, the research problem we try to address is to manage the usage of the subway station by community members in a manner that allows the subway station to capitalize the available PV production, without incurring a certain dissatisfaction to the people. Needless to say, community members that contribute to this objective would obtain a certain benefit in return from the subway transportation company.

This problem can be decomposed in four sub-problems:

- quantifying the global energy impact of community members as passengers that use a subway train in a business-as-usual scenario.
- defining the flexibility needs at station level - reflecting the desired behaviour that is expected from community members. It will lead to an energy consumption modification that is favourable relative to the objective of the subway company.
- proposing a solution at community level to manage the involvement of people towards satisfying the flexibility requirements at station level
- investigating the solution and the resulting collective impact in a comparison with the estimated initial impact identified in the business-as-usual scenario.

4. Proposed solution

Our solution is defined around the idea of developing an additional system denoted as "community manager", which acts as an intermediary between the community members and the subway station by providing recommendations in the form of favourable times to use the subway. This additional system represents a key element of an energy community, as it is shown in other research works that a community manager service could be an effective way to manage a residential community (Simoiu et al., 2021c, 2022).

During the previously defined favourable time periods, the subway energy system capitalizes on the available PV production. The potential economical benefits that might be obtained by the subway company by using PV energy instead of grid energy can be further returned to the passengers in suitable ways (for example through free tickets). The resulting cooperation can be investigated in Fig. 1.

In Fig. 1, the subway company has a specific objective to obtain some sort of economical/environmental benefit. This objective must be appealing for the community members since people voluntarily join the community and therefore must be motivated to contribute to the municipality instead of following other objectives. In a way, the objectives of the subway transportation company indirectly become the objectives of the community.

Inside the community, the manager "translates" the objectives into suitable requirements and provides dedicated recommendations to satisfy these requirements. Of course, given the cooperation context that is already in place, members have certain preferences/restrictions related to using subway transportation for their own needs. For example, some people might need to use the subway to commute to work at specific hours, while some other people might not use the subway for several days at all. Nevertheless, the manager needs to have a certain idea of how these preferences are shaped, since they are fundamental for the satisfaction of community members.

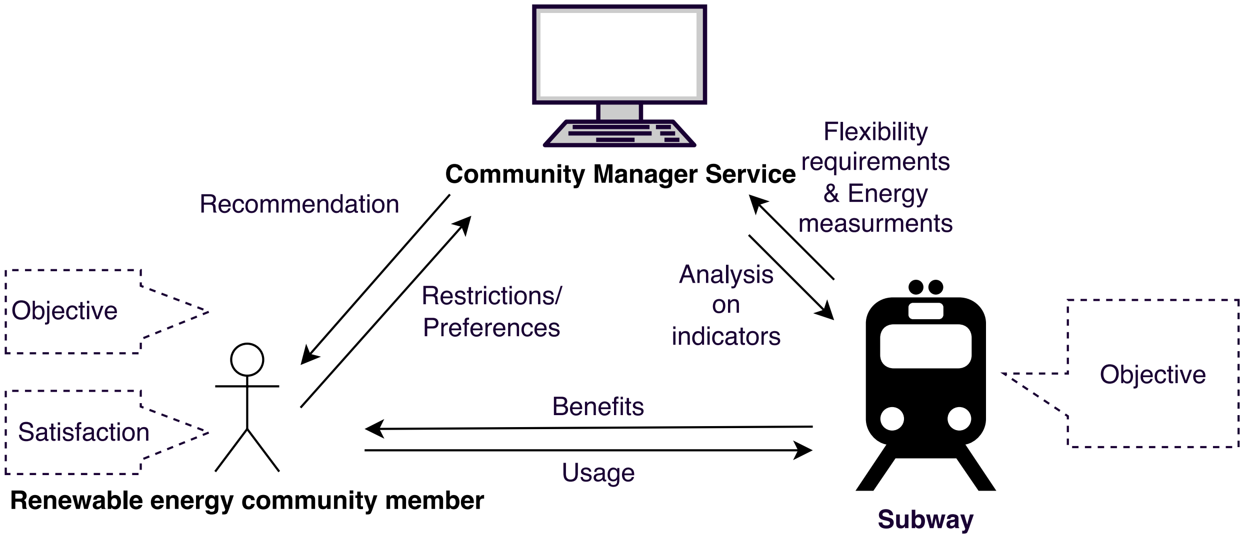


Figure 1: The cooperation between the energy community and the subway station

The collective effect of the community on the energy consumption of the subway station is measured by the manager, who provides a certain analysis on the degree to which the initial performance objectives have been fulfilled. This analysis will help the subway transportation company to return some benefits to the community members.

4.1. Multi agent simulation principle

To simulate the proposed solution, we consider a multi-agent framework. Specifically, the community manager and members are modeled as agents who interact during a simulation. The communication between agents allows us to model both the state of the energy community prior to receiving recommendations, as well as the performances of the community after the recommendations were given and members have individually reacted to them.

The proposed framework can be investigated in Fig. 2. The simulation works in time slots Δt of 1 hour each. A time slot is composed of two specific action slots: an action slot corresponding to the community manager service and an action slot corresponding to the community members.

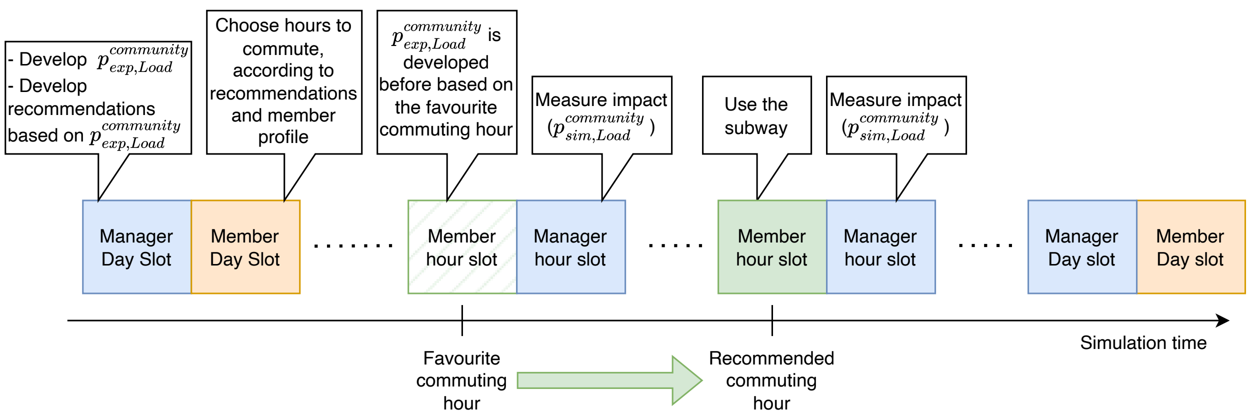
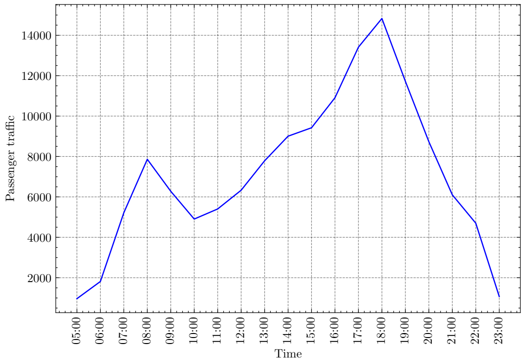
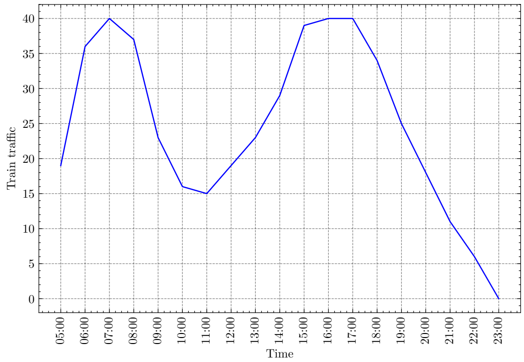


Figure 2: Multi-agent simulation framework

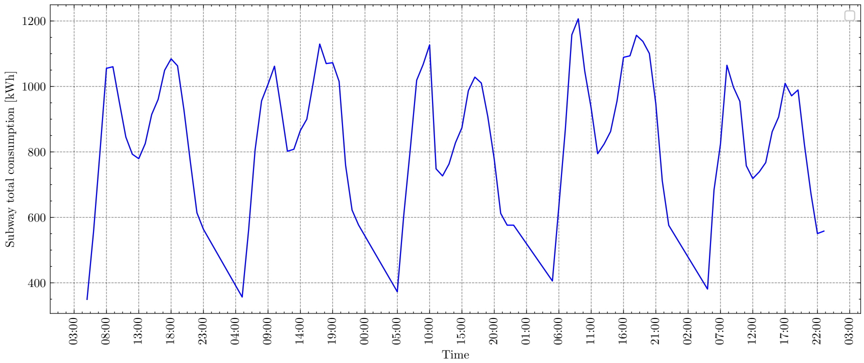
At the beginning of a simulation day, the manager develops the expected community power $p^{community}_{exp,Load}$. This expected level of consumption should reflect, in a realistic manner, the behaviour of people using the subway trains. In other words, the manager service estimates the consumption levels that are generated by passengers while using the



(a) 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.



(b) Train traffic through the station - the number of trains that pass through a specific station during each hour of a working day



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

Figure 3: Available data

subway, considering personal restrictions or preferences such as a favourite commuting hour. This power profile can be generated using historic data, or through other estimation methods.

Based on this expected consumption, the manager chooses what are the best hours to use the subway, considering the expected PV production. Consequently, the members in the simulation receive this recommendation and, as a reaction, they choose the time to use the subway transportation services. This actions represent the real actions of the community members, as a reaction to the recommendation. In the multi-agent simulation, these real actions yield a simulated power profile $p^{community}_{sim,Load}$, reflecting the real consumption of the community after receiving recommendations. This "real" impact is measured by the manager to properly evaluate the performances of the community at the end of the day and to compute the benefits that are due to the community members.

4.2. Modeling the community members

As mentioned before, in the first state (before recommendations) of the proposed solution, each community member has a certain expected behaviour that infers an expected level of consumption. To model this, we first have to look at the available data that was measured for a subway station in Bucharest, Romania. This data (Fig. 3) will be the fundamental step in developing the member profile, as well as the expected consumption levels.

In Figs. 3c, 3a, 3b we can see the available measured data for this study. This data was collected from a typical subway station in Bucharest, Romania, during 5 working days in October, between 05:00 and 23:00 - the interval in which the subway services are available for the general public.

By considering a real working day, we can imagine that various types of people pass through the access gates of a subway station. This aspect represents a challenge, since it becomes difficult to exclusively quantify the energy impact of the energy community members relative to the subway transportation company objective. So, we must make a further

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

Table 2
Regression analysis between the available passenger data and the subway consumption

statement to properly bound the community, both in size and in geographical limits. If we consider the passenger profile in 3a, it can be noticed that there are two peaks, correlated to the times when people mostly use the subway to commute to work. This observation paves the path for splitting the potential passengers between two categories: people who use the subway services to commute to work, twice per day and other people who simply pass through the access gates for various reasons (such as traveling just once per day, or even subway company employees who travel between stations).

Consequently, we consider a renewable energy community that is composed only from people who live near the subway station and use the subway transportation services daily to commute to work. This community choice allows us to also define certain benefits, since commuting passengers are represented by people who frequently use the subway station, so they can obtain a certain benefit for their contribution (possibly tickets with a certain discount).

Another important aspect to note is a significant correlation between the energy consumption and the passenger traffic. This correlation was also noted in the paper Simoiu et al. (2021a), a matter which allowed us to estimated the subway consumption for one year based on the passenger traffic profile.

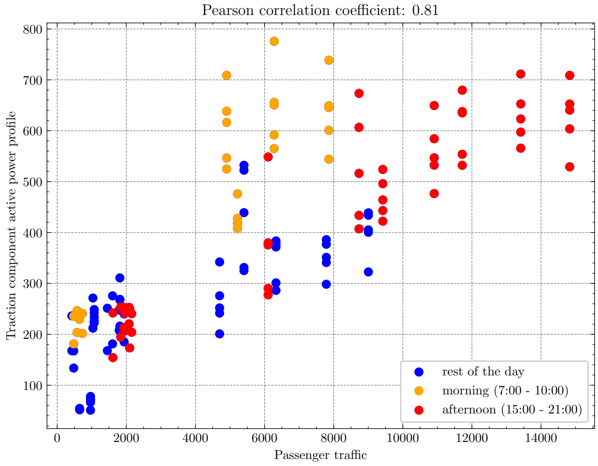
To emphasise this correlation, a regression analysis was conducted upon the data (Table 2). Specifically, a regression model was obtained for several scenarios in which the independent variable x was alternated with additional features, such as temperature[1], time of day, day of the week, or hour of 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 data. The closer the value of r^2 is to 1, the better the fit between the regression model's estimation and the actual parameter. As it can be noticed in Table 2, 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.

Additionally, a correlation analysis was conducted upon the available data (Fig. 4). 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.

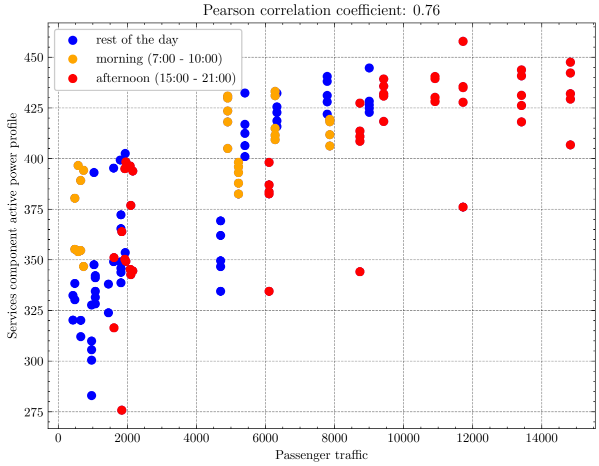
On the proposed analysis, one can see in Figs. 4b, 4a, 4c that there is a significant correlation between the passenger and the consumption of the subway station, as the passenger traffic is correlated to both the services component and the traction component. Moreover, we can see that the train traffic 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.

The correlation between passenger traffic and subway station consumption allows us to estimate the impact of each passenger in the power profile of the station. Moreover, a more precise estimation is obtained considering the dependency on the time of day (morning and afternoon, as it is shown in Table 2). Since the community is composed by members who use the subway services to commute, then during the morning (and each afternoon, implicitly) each member infers an indirect energy consumption in the subway station energy system. We further define this quantity of energy as *inferred power per passenger* (IPP) depending on the two commuting periods - morning and afternoon:

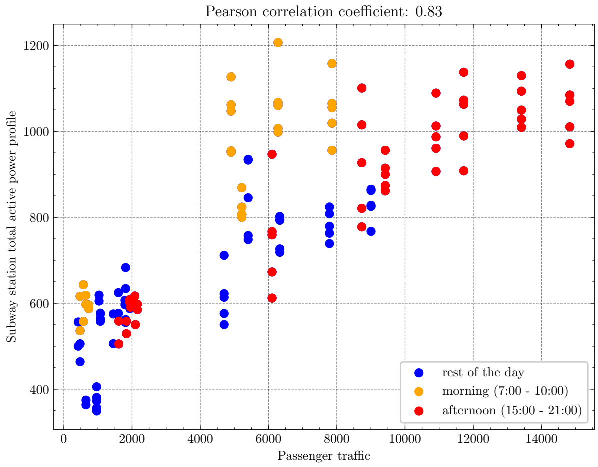
[1] The temperature data was obtained from *Openweathermap.org* for Bucharest, during the time period of the subway consumption measurements.



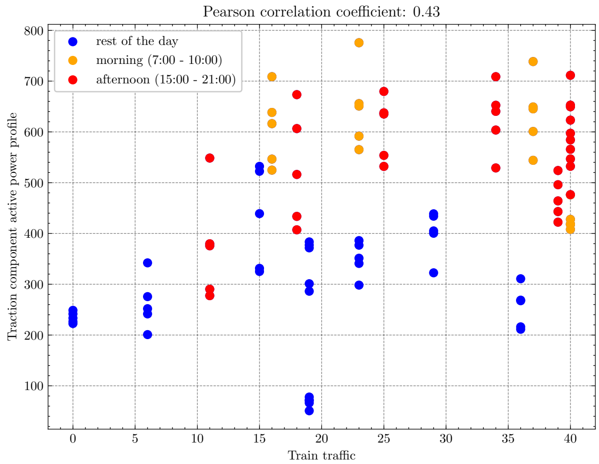
(a) Passenger traffic vs. Traction consumption



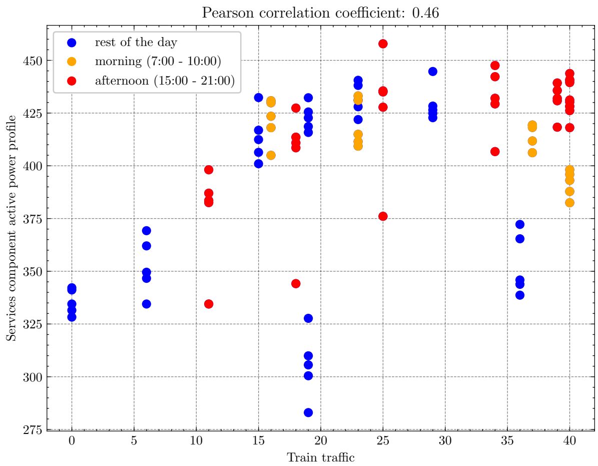
(b) Passenger traffic vs. Services consumption



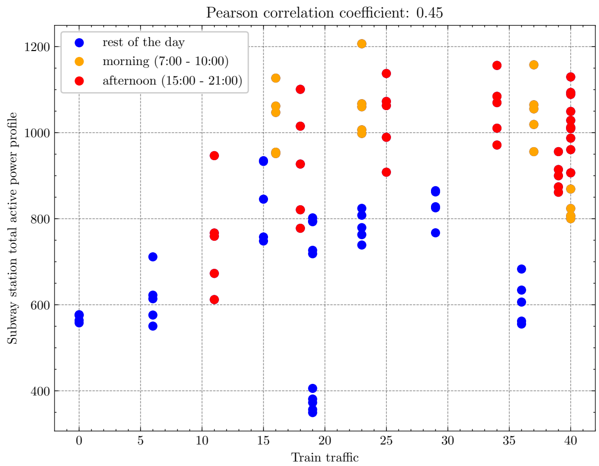
(c) Passenger traffic vs. Station consumption



(d) Train traffic vs. Traction consumption



(e) Train traffic vs. Services consumption



(f) Train traffic vs. Station consumption

Figure 4: Correlation analysis on the subway station available data

$$\mathrm{IPP}_{morning} = \frac{p^{subway,morning}_{est,Load}}{m^{commuting}_{est}}$$
$$\mathrm{IPP}_{afternoon} = \frac{p^{subway,afternoon}_{est,Load}}{m^{commuting}_{est}} \tag{5}$$

where $p^{subway,morning}_{est,Load}$ and $p^{subway,afternoon}_{est,Load}$ represent the average power of the subway station during morning and afternoon commuting periods. $m^{commuting}_{est}$ represents an estimated number of the commuting passengers for the respective day.

To estimate the subway station power based on the passenger profile for long periods of time, a regression model was used:

$$\hat{y} = 0.05x + 534.48 \tag{6}$$

where x represents the hourly measured number of passengers accessing the respective station and $\hat{y}$ represents the estimated hourly power profile. However, to determine the IPP based on Eq. 5, we will consider a constant average value during each period. We do this since, if we consider again the measured data in Fig. 3, even if we can estimate the hourly subway consumption based on the passenger profile, to estimate the hourly IPP might not be such a simple task. This is because IPP is dependent on the train traffic too and there is a difference between the passenger peak (located at 8 a.m.) and the number of trains peak (located at 7 a.m.). This can be noticed in Fig. 5, for example, where we can see that the IPP varies in times, especially in the morning when the train asynchronicity phenomena is noticed. Moreover, one can observe in Fig. 5 two particular time moments where the maximum values of the IPP are noticed: 05:00 and 23:00. These values indicate situations where the trains are typically empty and therefore each passenger traveling at the respective times yield a significant consumption level in the subway energy system. Therefore, considering the variations in the IPP, we will use the average value over a period instead of using the hourly value.

Besides the estimated consumption that a community member may infer to the subway energy, we need to determine the times when the member uses the subway station, as well as the duration during which the member is away at work. Consequently, we defined the following community member features:

- the preferred time to go to the office h_i of a member j
- the preferred duration to stay in office $\Delta t_{fav,j}$

It is important to note that we defined these parameters as "preferred", however they may express even restrictions that people have considering the nature of the job, as well as the rules of various employees.

The accuracy of the estimation is strongly dependent on these parameters. For the proposed case study in this paper, we do not aim to obtain a strong estimation accuracy score, we want to use an estimation that reflects the reality in an acceptable manner. Thus, we consider that typically each community member stays at work around 8 hours ($\Delta t_{fav,j} = 8$ for each member j) and we have the following configuration (based on the subway power peaks in Fig. 3c):

- 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. ($h_i = 10$)

The last element we need to find to develop the multi-agent simulation and, implicitly, to completely model the estimated behaviour of the community members is represented by the estimated number of commuting passengers $m^{commuting}_{est}$. This number may be estimated from the type of transportation tickets and more associated data that may be collected from such a ticket when the validation at the station access gate occurs. In this paper, we obtain this number from the tickets sales reported by the subway transportation company (Fig. 6, Metrorex (2017)) .

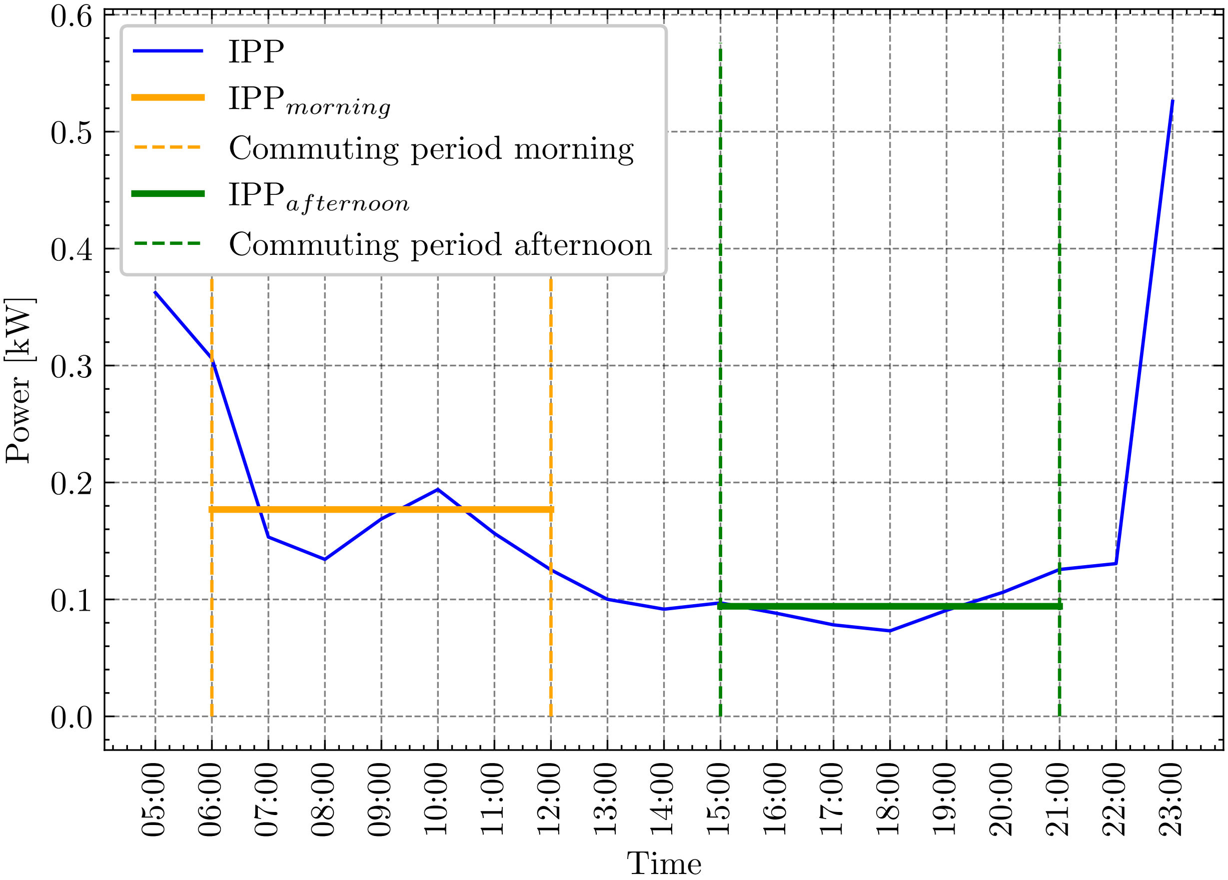


Figure 5: IPP evolution in time for measured data, during one typical working day

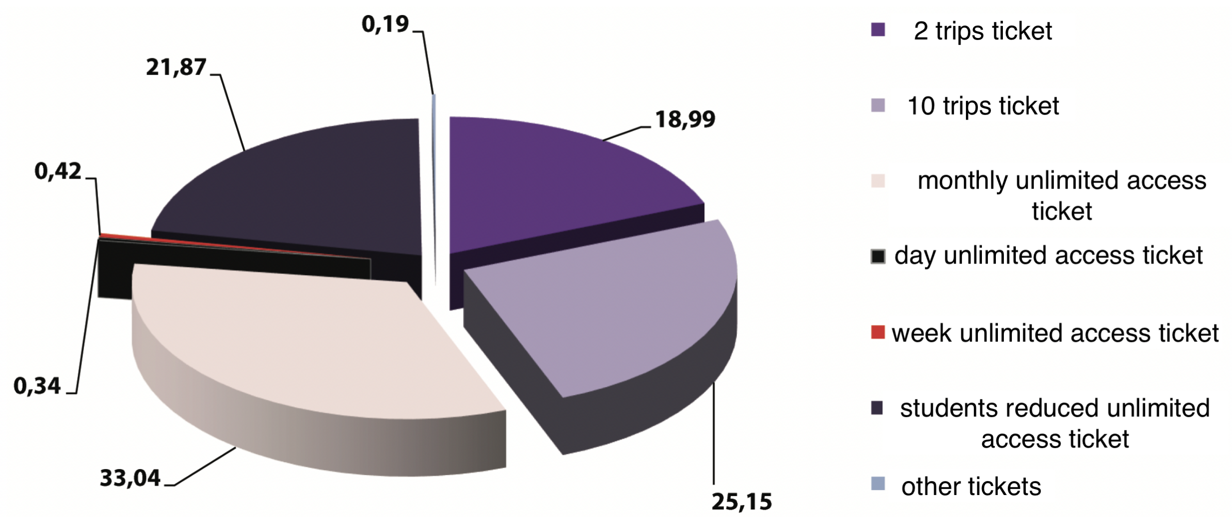


Figure 6: Ticket sales ration during 2017

We can further assume that commuting passengers use either monthly unlimited tickets or student unlimited tickets. So, we can consider an average value between the percentage of tickets sold as monthly tickets and the percentage of tickets sold as student tickets. This would result in an average value of 27%.

The last element of the behavioral model of community members is related to their flexibility related to the work schedule at the office. Considering other works that identify behavioral patterns Cruz et al. (2021), but also the fact that there are various jobs with different requirements for the employees, we can distinguish three main employee categories:

- fully flexible people - people who have full flexibility regarding the duration spent at the office from day to day; in other words, people who can arrive and can leave the work place at any time since they can continue their work remotely
- semi-flexible people - people who have freedom to arrive at the office whenever they want, but must complete 8 hours at the office in a working day.
- people with no flexibility - people who must be at a specific hour at work (in our method this hour is represented by h_i) and must complete 8 hours at the office every day.

We propose these categories to depict in a realistic manner the possible ways people could react to a recommendation.

4.3. Modelling the community manager

The community manager represents the system that provides recommendations to commute at favourable times, so that the objectives of both the community and the subway transportation company are met.

However, the commuting times cannot be chosen arbitrary during the day, since people can usually slightly adjust their work schedule. As a consequence, we propose two flexibility periods defined by two time periods during a day. We choose these periods specifically to encapsulate the commuting periods, so that only small variations can be obtained around the typical commuting time (Fig. 7).

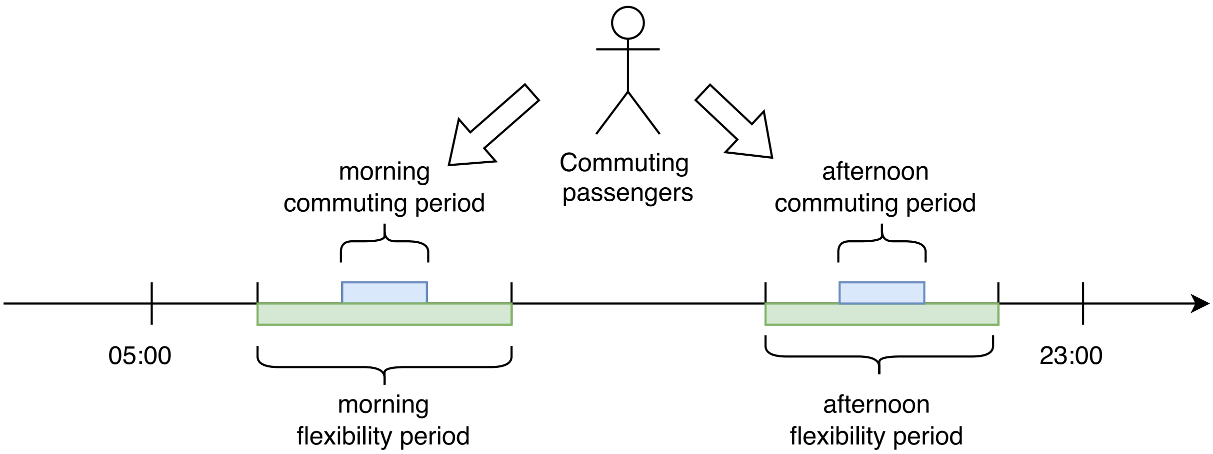


Figure 7: Flexibility periods relative to the commuting periods

The recommendations will be given mainly based on the comparison between estimated load and estimated production. To estimate the PV production, we can use the following model:

$$p^{community}_{est,PV,t} = n \cdot \tau \cdot p_{module} \cdot \frac{G_t}{G_{STC}} \tag{7}$$

where n represents the number of PV panels, p_{module} represents the power rating of a module, τ represents a correction factor to account for inverter efficiency, partial shading and other similar phenomena, G represents the total incident radiation at time t and G_{STC} represents the radiation at Standard Temperature Conditions ($1kW/m^2$).

For these flexibility periods, we propose two recommendation strategies:

- an "informative" recommendation strategy: where the manager would simply highlight the favourable 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.

The "informative" strategy simply compares at each hour t the expected community load $p^{community}_{exp,Load,t}$ with the estimated community PV power $p^{community}_{est,PV,t}$. If $p^{community}_{exp,Load,t} > p^{community}_{est,PV,t}$, then the recommendation given to the whole community is to commute, else the recommendation is not to commute during that specific hour.

The multi-objective recommendation strategy has the following objective:

$$\min \quad \omega_{\mathrm{NEEG}} \cdot \mathrm{NEEG}^{norm,community}_{exp} + \omega_{\mathrm{DIS}} \cdot \mathrm{DIS}^{norm,community}_{exp} \tag{8}$$

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

The net-energy-exchanged-with-the-grid represents an indicator reflecting the absolute quantity of energy that is either injected or extracted from the grid. Here (Simoiu et al., 2021a), the utility of this indicator was emphasised from an optimisation perspective, since minimising the net-energy-exchanged-with-the-grid is equivalent to maximising the self-consumption and self-sufficiency of the system.

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

$$\mathrm{NEEG}^{community}_{period} = \sum_{t} |p^{community}_{exp,Load,t} - p^{community}_{exp,PV,t}|\Delta t \tag{9}$$

To develop the expected level of consumption, we assume that the manager knows the preferred hour and preferred time duration to be spent at work of each community member. In a real implementation of such a system, the members could communicate directly their preferences at the beginning of each month/year, through an application integrated in the recommendation system. With this information, the manager to split the community members in several groups g_{h_i}, depending on the preferred hour of each member j. More specifically, since we mentioned in the previous section that we have 4 commuting hours $h_i \in \{7, 8, 9, 10\}$, we assume we have 4 groups $g_{h_i} \in \{g_7, g_8, g_9, g_{10}\}$, where g_7, for example, represents the group of people who prefer to go to work at 07:00 A.M.

Typically, if a group commutes at a certain hour, then it infers a certain consumption in the subway energy system. So, for the four groups, we have the following sets:

$$p_{est,morning} \in \{p^{g_7}_{est,morning}, ..., p^{g_{10}}_{est,morning}\} \tag{10}$$

and

$$p_{est,afternoon} = \{p^{g_7}_{est,afternoon}, ..., p^{g_{10}}_{est,afternoon}\} \tag{11}$$

where, for example, $p^{g_7}_{est,morning}$ represents the estimated power of the group that prefers to commute at 07:00 A.M. and $p^{g_7}_{est,afternoon}$ represents the estimated power for the same group when returning from work at 15:00 A.M. We note here that we have two sets since we already assumed that we will use two different IPP average values, one for each period (Eq. 5).

In the optimisation problem (Eq.8), the recommendations will be given to groups. Conversely, each group will have a recommended time to commute in the flexibility period. We can model this with a set boolean decision variables $x_{g_{h_i},t}$ for each group, for each hour in the flexibility period. For example, if we recommended that the group with the favourite

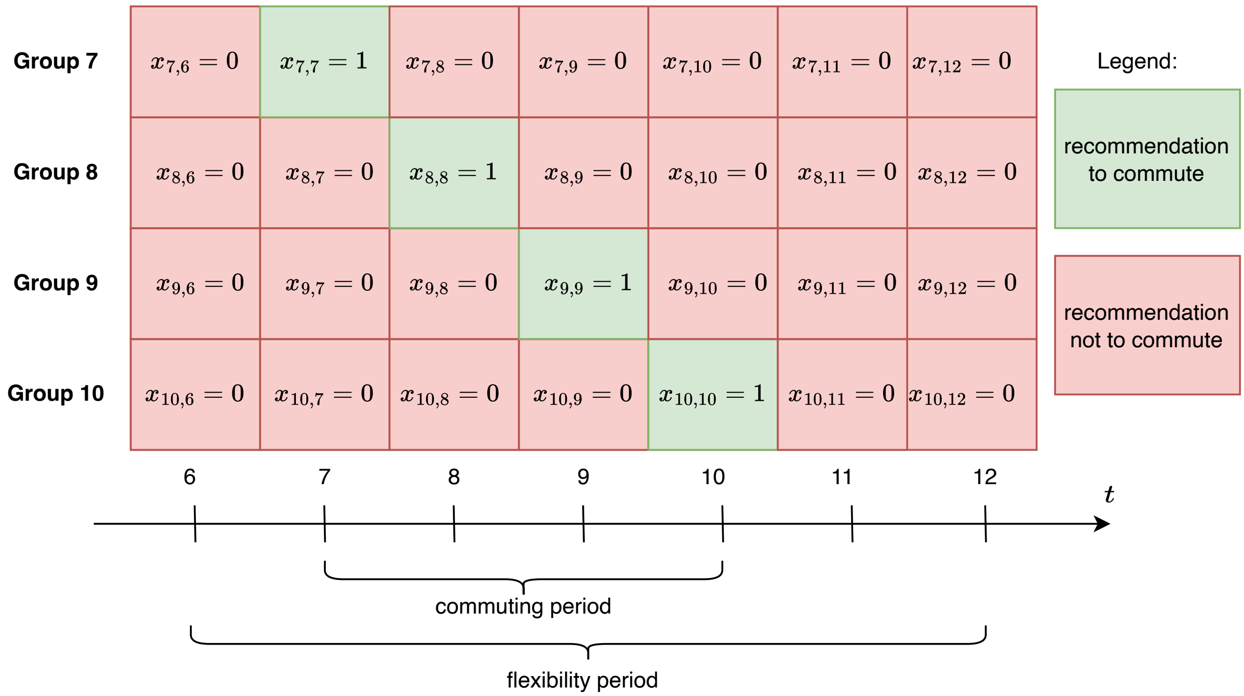


Figure 8: This figure shows an example of the proposed optimization model using boolean decision variables to describe the recommendation mechanism. The horizontal time axis includes commuting and flexibility hours, and the values for the decision variable $x_{g_{h_i},t}$ are presented for each group g_{h_i}. In this example, the recommendation is to commute during each group's favorite hour ($t = h_i$).

hour to commute 08:00 to go to work to 07:00, then $x_{g_8,7} = 1$ and all other variables in the corresponding set for g_8 are equal to 0. To better depict this, considering the commuting and flexibility periods defined before, we show a simple example in Fig. 8, where we recommend to each group to commute during their favourite commuting time.

So, taking into account the recommendations for all groups at each hour t, we can rewrite the NEEG as:

$$\text{NEEG}_{period}^{community} = \sum_t |p_{PV,t} - \sum_{g_{h_i}} x_{g_{h_i},t} p_{est,period}^{g_{h_i}}|\Delta t \tag{12}$$

where by the $\sum_{g_{h_i}} x_{g_{h_i},t} p_{est,period}^{g_{h_i}}$ element we take into account the decisions for all groups g_{h_i} during the hour t.

To properly include the NEEG in the multi-objective optimisation problem, we need to normalize the value between 0 and 1. We can do this by referring to the maximum value of the energy that is either consumed ($\sum_i p_{est_{period}}^{g_{h_i}}$)) or produced ($p_{PV,t}$) during an hour t. After normalizing Eq. 12, we obtain:

$$\text{NEEG}_{period}^{norm,community} = \sum_t \left| \frac{p_{PV,t} - \sum_{g_{h_i}} x_{g_{h_i},t} p_{est,period}^{g_{h_i}}}{max(p_{PV,t}, \sum_{g_{h_i}} p_{est_{period}}^{g_{h_i}})} \right| \tag{13}$$

Based on the preferences of members, we can develop the dissatisfaction indicator. However, since we group the members according to their preferred hour, we can first define the dissatisfaction considering all groups, for a specific hour t:

$$\begin{aligned} \mathrm{DIS}_{morning,t} &= \sum_{h_i} |h_i - x_{g_{h_i},t} \cdot t| \\ \mathrm{DIS}_{afternoon,t} &= \sum_{h_i} |h_i + \Delta t_{fav,j} - x_{g_{h_i},t} \cdot t| \end{aligned} \tag{14}$$

If we consider the length of the flexibility period T, we can normalise this indicator in the following manner:

$$\begin{aligned} \mathrm{DIS}^{norm,g_{h_i}}_{morning,t} &= \sum_{h_i} \frac{|h_i - x_{g_{h_i},t} \cdot t|}{T} \\ \mathrm{DIS}^{norm,g_{h_i}}_{afternoon,t} &= \sum_{h_i} \frac{|h_i + \Delta t_{fav,j} - x_{g_{h_i},t} \cdot t|}{T} \end{aligned} \tag{15}$$

Conversely, at community level, for a period:

$$\mathrm{DIS}^{norm,community}_{period,t} = \sum_t \mathrm{DIS}^{norm,g_{h_i}}_{period,t} \tag{16}$$

Lastly, we impose a constraint that each member should commute only once during the morning and only once during the afternoon. As such, for a a group g_{h_i} during a period:

$$\sum_t x_{g_{h_i},t} = 1 \tag{17}$$

4.4. Collective impact evaluation

In each case, we evaluate the impact at community level according to the following metrics:

- NEEG per day - the average net-energy-exchange-with-the-grid at community level per day.
- Money paid for grid energy (MPGE) - how much money the subway transportation company has to pay for grid energy:

$$\mathrm{MPGE} = (\sum_t p^{community}_{Load,t} \Delta t) \cdot (1 - \mathrm{SS}) \cdot c_{grid} \tag{18}$$

  where $p^{community}_{Load}$ represents the community load over the simulation period, where each hour is indexed by t, SS represents the self-sufficiency (Simoiu et al., 2021a) over the same simulation period and c_{grid} represents the grid energy tariff.

- average community dissatisfaction ($\mathrm{DIS}^{community}$) for the simulation.
- Self-Consumption (SC) - a metric with values between 0 and 1, showing how much of the of the PV production is internally consumed by the system (Simoiu et al., 2021a). This metric is useful in the evaluation since the closer the SC index is to 1, the higher the quantity of renewable energy is. Indirectly, this represents a benefit for the environment.

With these metrics, we evaluate the collective impact from three perspectives: the economical (MPGE and NEEG per day), environmental (SC) and social ($\mathrm{DIS}^{community}$) perspectives. In a real implementation of the system, these metrics may be presented to the community members from time to time through an application, in order to offer them a form of feedback related to their actions and community impact.

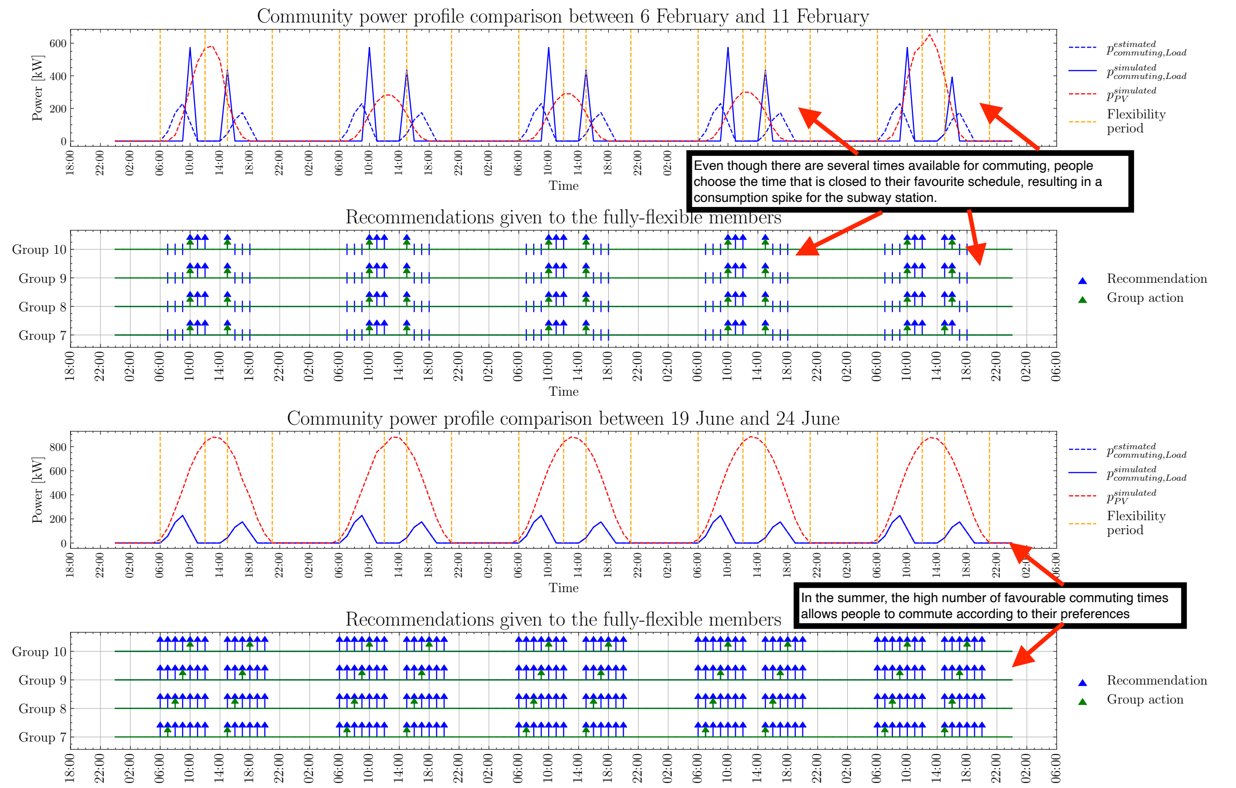


Figure 9: Collective impact of the informative recommendation strategy on a community with fully-flexible community members (Extreme case). **Note:** in the recommendations plot for each month, there is a plot line corresponding to each group described by a preferred hour (ex: Group 7 is the group of passengers who prefer to commute at 07:00). Attached to this plot line we may see three symbols: 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. 10, 12, 13.

5. Case Study

The proposed method was implemented in a multi-agent framework developed in Python for simulating renewable energy communities. The model is based on the MESA framework (see Project Mesa Team (2021)). We have considered an energy community of 4000 residential community members, each one 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) are set around the passenger traffic peaks (Fig. 3a) 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 estimated community power $p_{est,Load}^{community}$ is developed based on the estimated $\text{IPP}_{morning}$ and $\text{IPP}_{afternoon}$ (as described in the previous sections), for one year in 2017, considering the available passenger data. Consequently, as a preliminary stage for developing the IPP (with Eq. 5), the subway station consumption has been estimated for one year using the regression model in Eq. 6.

The estimated PV production $p_{est,PV}^{community}$ is developed according to the model presented in Eq. 7, 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, we used the solar model developed in the *buildingenergy* project (Ploix, 2021). To infer maximum production, the PV panels are directed towards South, with a slope of 60°.

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, we assume the community manager knows the preferred hour and preferred working duration of each community member i.e. $p_{exp,Load} = p_{est,Load}$.

The multi-objective optimisation problem (Eq. 8) has been formulated as a Mixed Integer Linear Programming problem. In each simulation, the problem is solved using the Coin-or-Branch-and-Cut Solver (CBC) from Python.

The recommendation strategies previously defined have been tested in several simulation scenarios (Table 3). Besides performances, in Table 3 we included a dedicated column with several observations for each scenario.

In implementing the case study, our first objective was to investigate the extreme potential of the proposed method to obtain maximum environmental and economical profit, in which we use fully flexible members and demand maximum effort ($w_{\text{NEEG}} = 1$ and $w_{\text{DIS}} = 0$ in the optimisation problem defined in Eq. 8). This objective is equivalent to minimising solely the NEEG. Our next objective was to evaluate a realistic community, with a mixture of members normally distributed between flexibility profiles: 20% members with no flexibility, 20% fully-flexible members and 40% semi-flexible members. For each simulation scenario in Table 3, we emphasise:

- the economical and environmental benefit, quantified through the NEEG per day in the business-as-usual variant (NEEG_{est} per day) and the NEEG per day after the recommendation (NEEG_{sim} per day)
- an explicit economical profit obtained in a comparison between money payed to the grid in the business-as-usual scenario (MPGE_{est}) and the money payed after the recommendation system takes effect (MPGE_{sim}). In this case, we compute the MPGE according Eq. 18, considering a grid tariff of 0.2 EUR for a kWh - the grid tariff used by the subway transportation company to buy energy in during 2022 (Romanian Gouvernment Control Body, 2022).
- the average community dissatisfaction, quantifying the average dissatisfaction of all community members over the simulation period.

In Fig. 12, 9, 13 and 10, we show the actions of representative community members, as well as the overall collective impact over the energy consumption. Even though we simulate and evaluate performances for one year, we will illustrate the behaviour of community members only during two weeks: 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, we show two plots:

- a plot with a power profile comparison, where the estimated community power (the blue dashed line) is compared with the simulated community power (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. 9 and 12, since we have only fully flexible members, we show only one action-recommendation related plot. In Figs. 10 and 13, since we have a mixture of member types, we show an action-recommendation plot for each flexibility category.

Overall, regarding the informative strategy we 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_{DIS}=0.5), this recommendation strategy may prove the best solution in a realistic scenario with people having various working schedule restrictions. Additionally, if we analyse the proposed simulation scenarios in a 2D objective space described by the average dissatisfaction and simulated NEEG (Fig. 11), we can see

Table 3
Results comparison

Scenario	Fig	NEEG_{est} per day	NEEG_{sim} per day	MPGE_{est}	MPGE_{sim}	$\text{DIS}^{community}$	SC_{est}	SC_{sim}	Observations
Fully flexible members, M.O. strategy, $w_{\textbf{NEEG}} = 1, w_{\textbf{DIS}} = 0$	12	4467.07	4169.45	13,966,500.4	3,103,666.76	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, $w_{\textbf{NEEG}} = 1, w_{\textbf{DIS}} = 0$	-	4467.07	4382.75	13,966,500.4	10,862,833.65	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, $w_{\textbf{NEEG}} = 0.5, w_{\textbf{DIS}} = 0.5$	13	4467.07	4340.61	13,966,500.4	9,311,000.27	0.06	0.11	0.12	- adequate NEEG improvement, but an important decrease in dissatisfaction
Fully flexible members, Informative strategy	9	4467.07	4454.92	13,966,500.4	13,449,222.61	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	13,966,500.4	19,139,278.33	0.1	0.11	0.09	- in this case, the restrictions of semi-flexible members significantly decrease the performances
Mixed members, informative strategy	10	4467.07	4451.02	13,966,500.4	13,449,222.61	0.08	0.11	0.11	in a realistic community, the performances are not so significant, and the dissatisfaction is still noticeable

that the balanced strategy with $w_{\text{NEEG}} = 0.5$, w_{DIS}=0.5 is the closest to the ideal origin point where both dissatisfaction and NEEG are at an absolute minimum.

It can also be noticed that the environmental benefit emphasised by self-consumption does not increase significantly, as a consequence of the large PV production available. This aspect represents an opportunity, as the excess PV production may be used somewhere else (possibly inside the energy system of the subway station, thus increasing the self-consumption, or simply to become available for consumption inside a residential community). Future research may further address this topic.

6. Conclusions

This paper proposes a novel method to manage the involvement of people in an energy community as part of an active association with the municipality. Specifically, we propose recommendations strategies to guide the community members to use a subway station at favourable times for the energy system of the transportation company, thus inferring an indirect economical and environmental benefit that can be later returned in the form of free tickets, for example.

The main contribution of the work is reflected in the multi-objective optimisation model that provides a tailored recommendation that takes into account both the performances of the system and the dissatisfaction of people. In this way, we propose a method that creates flexibility for the energy system of the subway station through the active participation of people. This also implies that people become more sober towards energy consumption and more conscious regarding the impact of their actions in the life of the city.

Another contribution is related to modeling the behaviour of community members as commuting passengers based on characteristics such as preferred time to commute. Along with the time segmentation related to commuting periods and flexibility periods, we show that it is possible to form a different type of energy community that is rather related to a common aim (i.e. contributing to the municipality) rather then a typical geographical setting.

We identified two interesting improvements for this study. The first one is related to the available subway consumption and passenger traffic data, which has allowed us to model a basic estimation of the IPP. With more data, a more accurate estimation of the IPP, as well as the total number of commuting passengers could be obtained. Another one is related to the assumption that the community manager knows the preferred time and preferred working duration of people - an aspect that can be determined in time through observation, estimation or by people directly providing their preferences to the manager. We aim to address these improvements in the future, when we also aim to develop more complex situations in which the manager knows very little information about the community, rendering a more realistic simulation model.

Code availability

The simulation framework used for the case study presented in this paper is available at Simoiu (2022).

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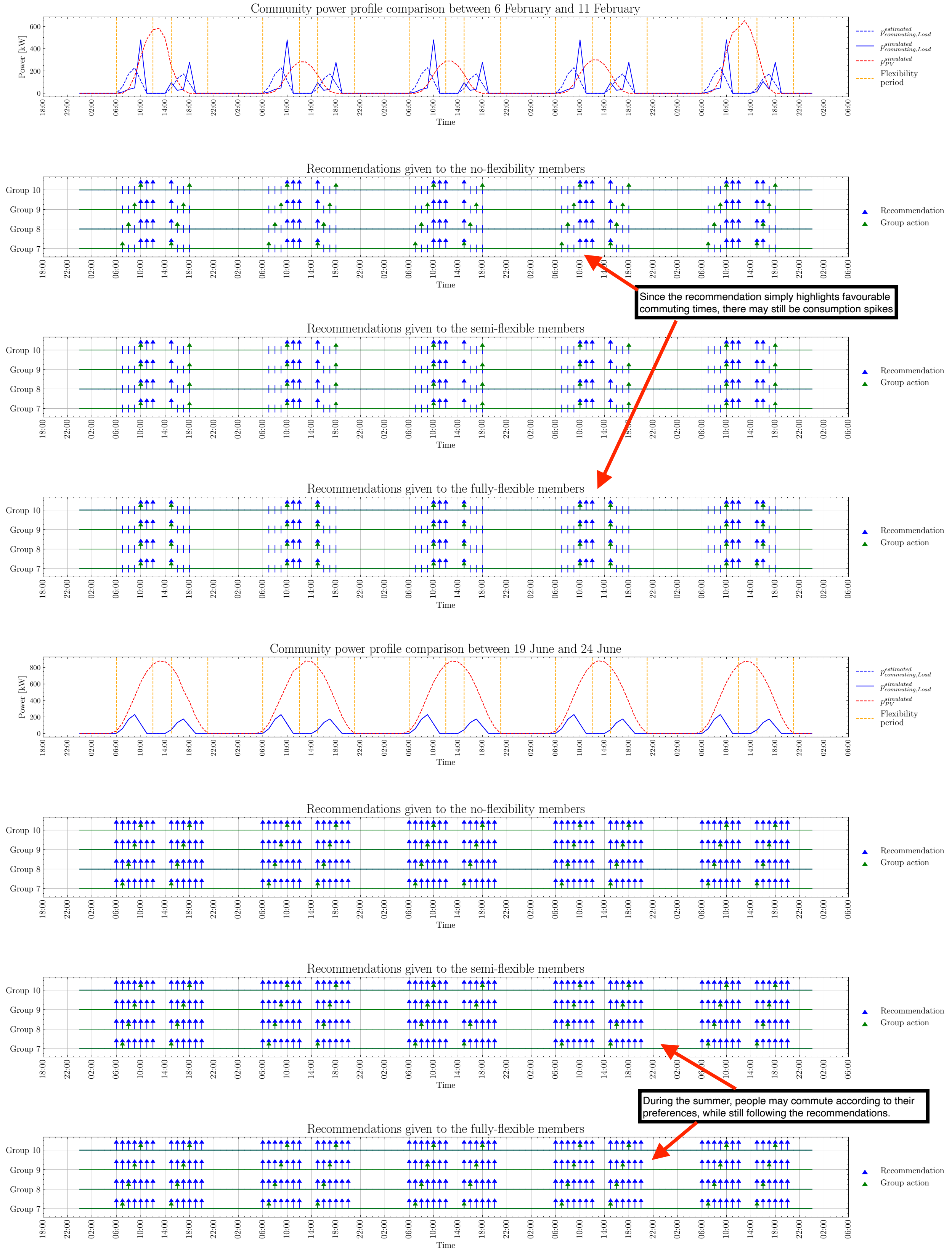

Figure 10: Collective impact of the informative recommendation strategy on a community with mixed community members (Realistic case)

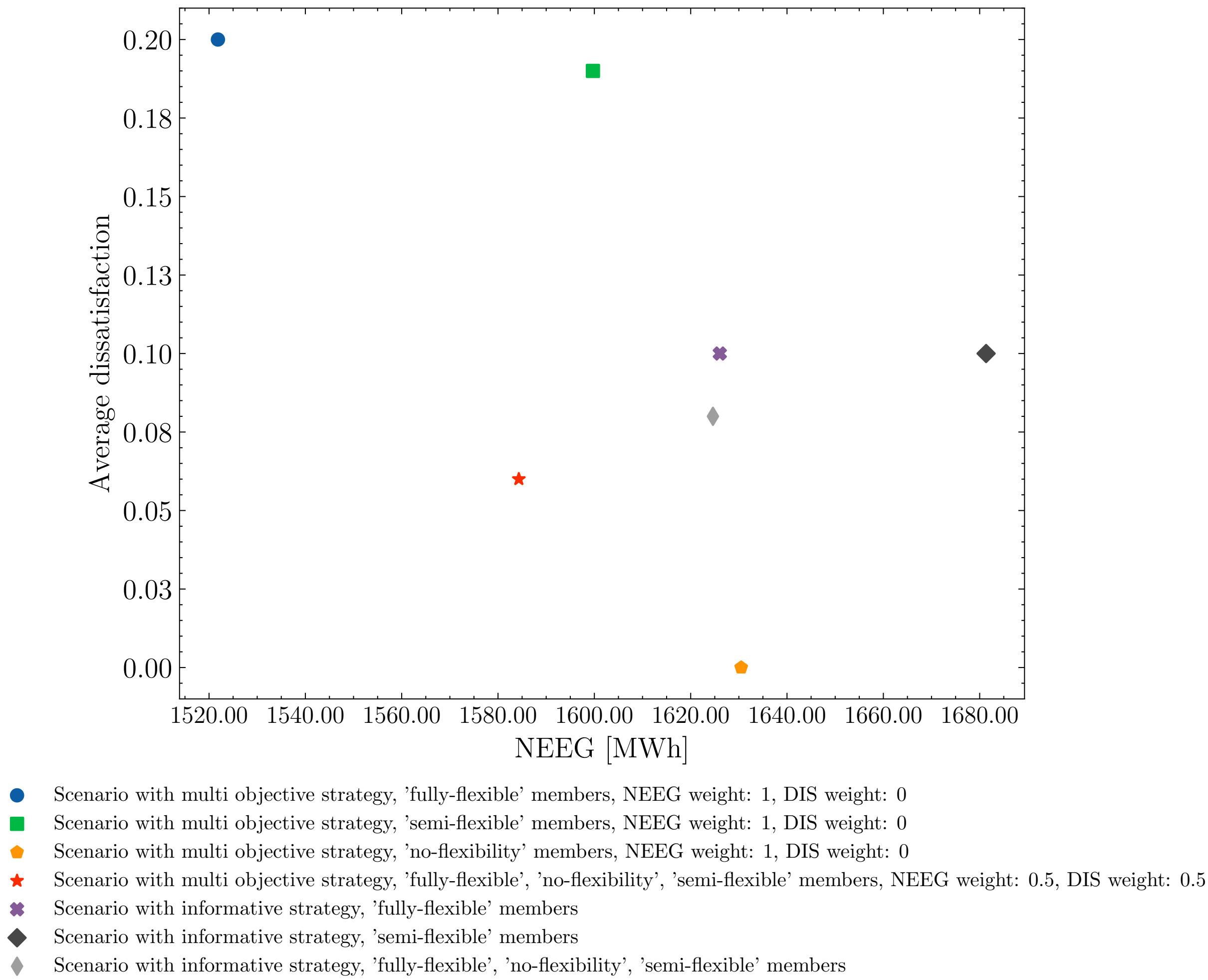

Figure 11: Strategy comparison in the objective space described by the NEEG and dissatisfaction

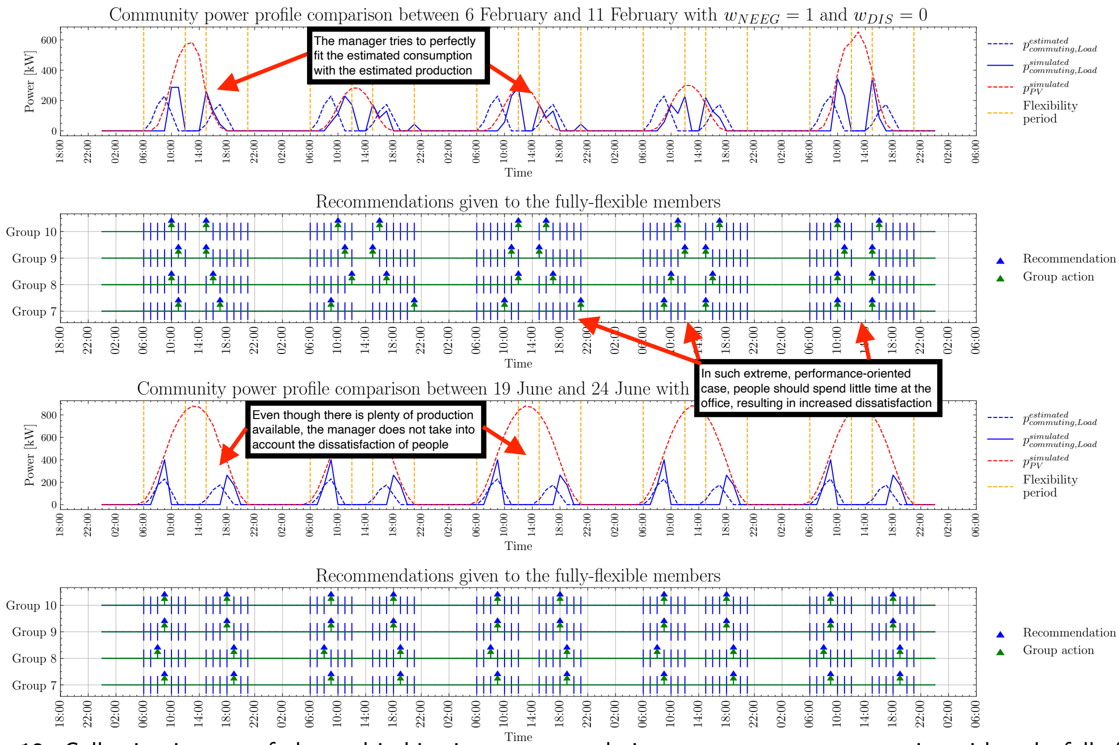

Figure 12: Collective impact of the multi-objective recommendation strategy on a community with only fully-flexible members (Extreme case)

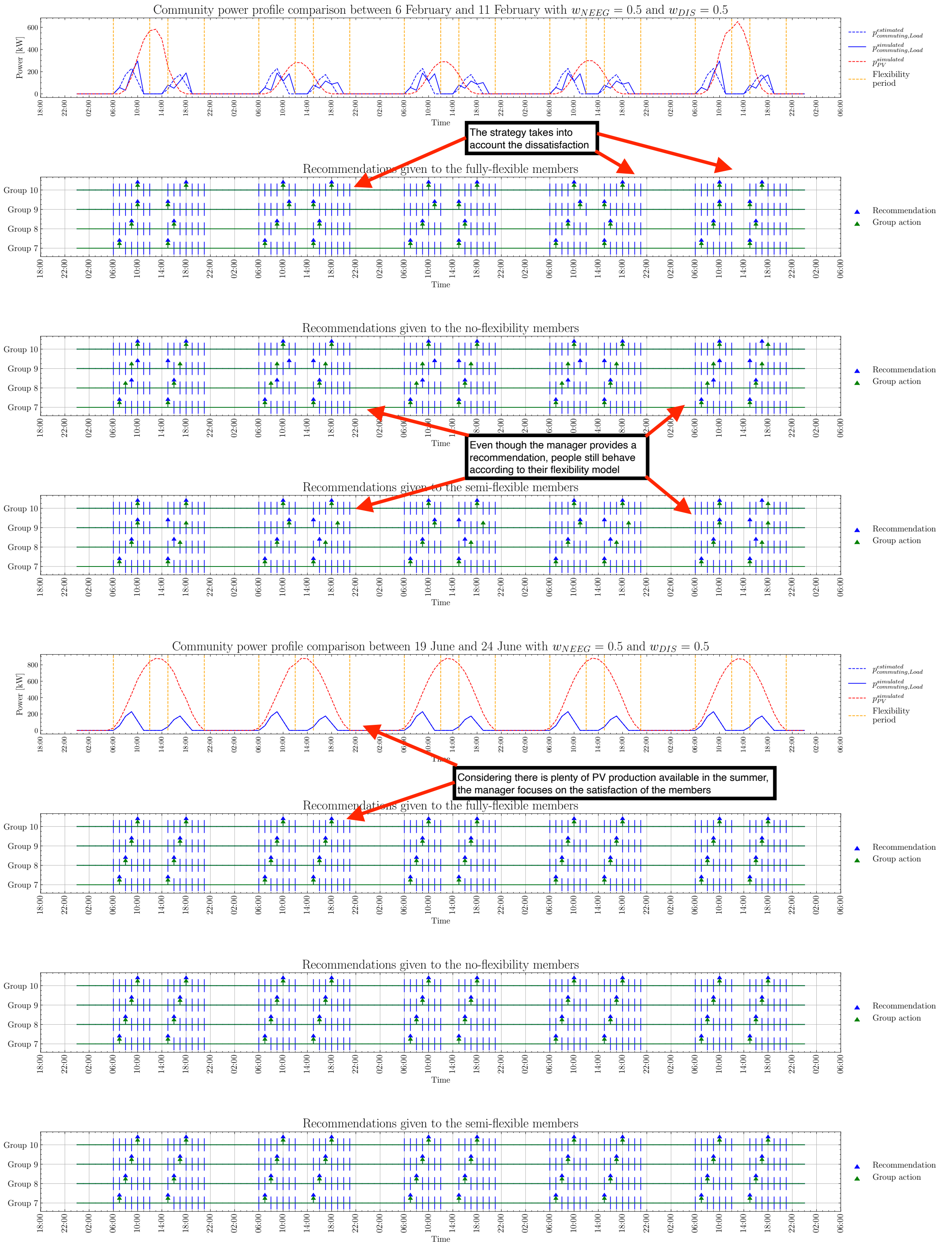

Figure 13: Collective impact of the multi-objective recommendation strategy on a community with mixed community members (Realistic case)