ENPOWER
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# D3.2 - Interactive tool for consumers ‘activation’ and energy community planning (second version)

CARTIF
February 2025

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement Nº 101096354

# Energy Activated Citizens and Data-Driven Energy-Secure Communities for a Consumer-Centric Energy System

| Grant Agreement Number | 101096354 | Acronym | ENPOWER |
|---|---|---|---|
| **Full Title** | Energy Activated Citizens and Data-Driven Energy-Secure Communities for a Consumer-Centric Energy System | | |
| **Topic** | HORIZON-CL5-2022-D3-01: Sustainable, secure, and competitive energy supply | | |
| **Funding scheme** | HORIZON Innovation Actions | | |
| **Start Date** | 1st September 2023 | Duration | 36 months |
| **Project Coordinator** | NTUA | | |
| **Deliverable** | D3.2 - Interactive tool for consumers 'activation' and energy community planning (second version) | | |
| **Work Package** | WP3 - Plan: 'Interactive tool for consumer activation and aggregation' | | |
| **Delivery Month (DoA)** | February 2025 | Version | |
| **Actual Delivery Date** | 28 February 2025 | | |
| **Nature** | Report | Dissemination Level | Public |
| **Lead Beneficiary** | CARTIF | | |
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## Disclaimer

# Copyright Message

# Preface

ENPOWER will design, develop, and demonstrate SSH-driven methodologies, interactive and closed-loop tools, and data-driven services for energy-activated citizens and energy-secure cross-sector communities towards a citizen-centric energy system. We combine leading-edge ICTs with social/behavioural dimensions and with sharing economy and value stacking business models to deploy: 1) a Social Science Framework for energy citizens activation and innovative multidimensional incentives for citizens' participation in energy markets; 2) AI-based consumers clustering and segmentation algorithms; 3) interactive tools and facilitation services for energy community planning; 4) Energy Data Space adaptation to support community-level data-driven activation and interoperable automated privacy and sovereignty-preserving Demand Response (DR); 5) P2P DLT/Blockchain digital marketplace for tokenized energy and non-energy assets reciprocal compensation; 6) data-driven services and apps for energy efficiency and activation performance management; 7) ICT services and Digital Twins for community-level energy optimization and aggregated flexibility management to trade off local self-consumption against grid service provisioning, while boosting a beyond-energy community social welfare; 8) Edge monitoring hubs for automated DR; 9) Business Sandbox for novel sharing economy and social innovation-based business models; 10) methodologies for evaluating different energy community setups, upscaling and replication. ENPOWER framework will be validated along 4 Front Runners energy communities pilots and further replicated in 2 Early Adopters, covering different levels of maturity of communities, to demonstrate increased RES local self-consumption and consumers participation to the energy markets, while nurturing increased local security of supply. ENPOWER Leadership Programme and blueprints will support EU-wide replication and advice regulatory bodies on communities-friendly enabling frameworks.

# Executive summary

The ENPOWER project aims to facilitate the transition from a centralized energy system to a more decentralized and consumer-driven model by enabling energy citizens and communities through Social Sciences and Humanities (SSH)-driven methodologies, interactive tools, and data-driven services. Leveraging ICT technologies such as AI, IoT, big data, and blockchain, ENPOWER fosters a decentralized, consumer-centric energy model.

Key Objectives:

- Activate energy citizens and enhance their participation in energy markets.
- Digitally empower energy consumers and communities with interactive tools.

This deliverable presents the development of ENPOWER's interactive decision support tool or Planning Tool [1], designed to optimize energy community planning and management. Section 2 outlines the Planning Tool's architecture, detailing its structure, key modules, and system interactions that support energy optimization. Section 3 describes INESC TEC's optimization tool, which minimizes energy costs through mixed-integer linear programming (MILP), optimally sizing PV panels and batteries while incorporating clustering techniques and metaheuristic approaches like Particle Swarm Optimization (PSO) for enhanced computational efficiency. Section 4 explains the database structure, linking energy assets, buildings, and members, enabling scenario simulations and KPI calculations through a FastAPI-based API to support renewable energy planning and impact assessments. Section 5 presents a proof-of-concept by using Granada (ES), one of ENPOWER's pilot sites, as a case study, to showcase the tool's ability to integrate renewable energy, optimize heat pump and PV system capacities, and reduce reliance on conventional energy sources, achieving significant cost and emissions reductions. Section 6 defines the user interface, offering two tailored views: a citizen view for intuitive engagement and a stakeholder view for technical decision-making. The UI follows a structured design system incorporating UX best practices, interactive dashboards, and multilingual support, ensuring accessibility and effective decision-making for energy communities.

## Who we are

| No | Participant Name | Short Name | Country | Role |
|---|---|---|---|---|
| **1** | National Technical University of Athens | NTUA | GR | Coordinator |
| **2** | Engineering Ingegneria Informatica Spa | ENG | IT | Technology providers |
| **3** | INESC TEC - Institute for Systems and Computer Engineering, Technology and Science | INESC TEC | PT | |
| **4** | Fundación CARTIF (CARTIF Technology Center) | CARTIF | ES | |
| **5** | COMSENSUS D.O.O. | COMS | SL | |
| **6** | European Dynamics Luxembourg SA | ED | LU | |
| **7** | Audencia Business School | AUDENCIA | FR | Business modelling |
| **8** | Regulatory Assistance Project | RAP | BE | Regulatory assistance |
| **9** | ICLEI Europasekretariat GmbH | ICLEI | DE | Policy & capacity |
| **10** | University of Basel*(associated partner)* | UNIBAS | CH | Social framework |
| **11** | Blueprint Energy Solutions GMBH | BLUEPRINT | AT | Pilot 1 - Austria (Front runners) |
| **12** | OurPower Energiegenossenschaft SCE | OurPower | AT | |
| **13** | Cooperativa de Desenvolvimento Sustentável, CRL | COOPERNICO | PT | Pilot 2 - Portugal (Front runners) |
| **14** | WATT-IS SA | WATT-IS | PT | |
| **15** | Cooperativa Eléctrica do Vale D'Este CRL | CEVE | PT | |
| **16** | Energy Community of Chalki'Chalkion' | ChalkiON | GR | Pilot 3 - Greece (Front runners) |
| **17** | Hellenic Association for Energy Economics | HAEE | GR | |
| **18** | Green Energy Aggregator Services SA | GEARS | GR | |
| **19** | Parity Platform P.C. | PARITY | GR | |

| | | | | |
|---|---|---|---|---|
| **20** | Electric Power Research Institute Europe DAC | EEU | IE | Pilot 4 - Ireland<br><br>(Front runners) |
| **21** | University College Cork (MaREI Centre for Energy, Climate and Marine, Environmental Research Institute) | UCC | IE | |
| **22** | DC Six Technologies Limited | DCSix | IE | |
| **23** | MOL TEIC - Dingle Hub | DINGLE HUB | IE | |
| **24** | ESB Innovation ROI Limited | ESB | IE | |
| **25** | Békéscsaba Energia ESCO Kft. | BCS | HU | Pilot 5 - Hungary (Early adopters) |
| **26** | Enasco Cleantech Alliance LLC. | ENASCO | HU | |
| **27** | Montajes Eléctricos Cuerva SL | CUERVA | ES | Pilot 6 - Spain<br><br>(Early adopters) |
| **28** | VERGY COMMUNITY S.L. *(affiliated partner)* | VERGY | ES | |

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## List of acronyms

| | |
|---|---|
| **AI** | Artificial Intelligence |
| **CAPEX** | CAPital EXpenditure |
| **DES** | Decentralized Energy Sources |
| **DLT** | Distributed Ledger Technology |
| **DR** | Demand Response |
| **DHW** | Domestic Hot Water |
| **EC** | European Commission |
| **EnC** | Energy Communities |
| **EPSO** | Evolutionary Particle Swarm Optimization |
| **GDPR** | General Data Protection Regulation |
| **HP** | Heat Pump |
| **ICT** | Information and Communication Technologies |
| **IoT** | Internet of Things |
| **KPI** | Key Performance Indicator |
| **MILP** | Mixed Linear Integer Programming |
| **OPEX** | OPerational EXpenditure |
| **PSO** | Particle Swarm Optimization |
| **PV** | Photovoltaics |
| **REC** | Renewable Energy Community |
| **RES** | Renewable Energy Source |
| **SSH** | Social Sciences and Humanities |
| **UI** | User Interface |
| **UX** | User Experience |
| **WP** | Work Package |

# 1 Introduction

Empowered citizens and data-driven, energy-secure communities are introducing significant challenges to energy system operations and electricity markets. Consequently, there is a growing push to transition the electricity market from a centralized, supplier-focused model to a more decentralized, consumer-centric structure. Energy communities, in this context, refer to groups of individuals who collaborate to produce and manage their own energy. Citizens actively participate from the inception of these communities, anticipating economic benefits and environmental advantages through renewable energy sources. Additionally, energy community initiatives enhance cooperation, strengthen social ties, and cultivate a collective sense of purpose among members by pursuing shared objectives.

ENPOWER aims to design, develop, and demonstrate methodologies based on Social Sciences and Humanities (SSH) combined with interactive, closed-loop tools and services. This supports engaged citizens and data-driven, energy-secure communities, ultimately fostering a consumer-centric energy market.

The project leverages advanced Information and Communication Technologies (ICT) —such as the Internet of Things (IoT), AI, big data, and Distributed Ledger Technology/blockchains—along with social and behavioural insights, governance frameworks, and business models rooted in the sharing economy and value stacking.

Thus, the aim of the project is twofold:

1. Transform traditional passive energy citizens into active ones “energy-activated citizens”;
2. Convert energy consumers and/or communities into digitally-enhanced entities.

To achieve the first objective, an interactive decision-support tool (henceforth referred to as "Planning Tool") will provide essential information and data to citizens, offering a multi-carrier energy perspective. **The Planning tool will facilitate the assessment of an individual's or a community's readiness to join an energy community and determine the optimal sizing of such communities**. It will also evaluate the implications of participation. However, delivering both comprehensive simulation capabilities and an intuitive user experience tailored to varying levels of expertise presents a challenge in past tools. The Planning Tool aims to bridge this gap by assisting energy communities in the planning and design phases of their energy systems. It will illustrate both technical and non-technical benefits of community participation in contrast to individual efforts. The tool's design will prioritize user-centricity, integrating interactive and intuitive features to simplify complex data and processes. Therefore, the planning tool aims to:

- Visualize their current status (baseline);
- Calculate and compare different future scenarios to improve their energy system;
- Provide related-energy communities’ information about their countries to learn and make informed decisions.

## 1.1 Relation with other tasks:

To achieve these objectives, synergies identified during project development, mainly with WP2, include:

- Use cases (Blueprint): Use cases defined by Blueprint can be included in the database to provide insights for users in the information hub.
- Regulatory framework (RAP): Country-specific regulations analysed by RAP can be added to the database to inform users and define system restrictions in the modelling phase.

- Member/consumer segmentation in energy communities (UNIBAS): Segmentation data can enhance the User Experience (UX) of the Planning Tool.
- Incentive mechanisms (WP2): Defining KPIs related to monetary and non-monetary incentives.
- Business models (AUDENCIA): Including feasible business models in energy community assessments or informing users about potential models.

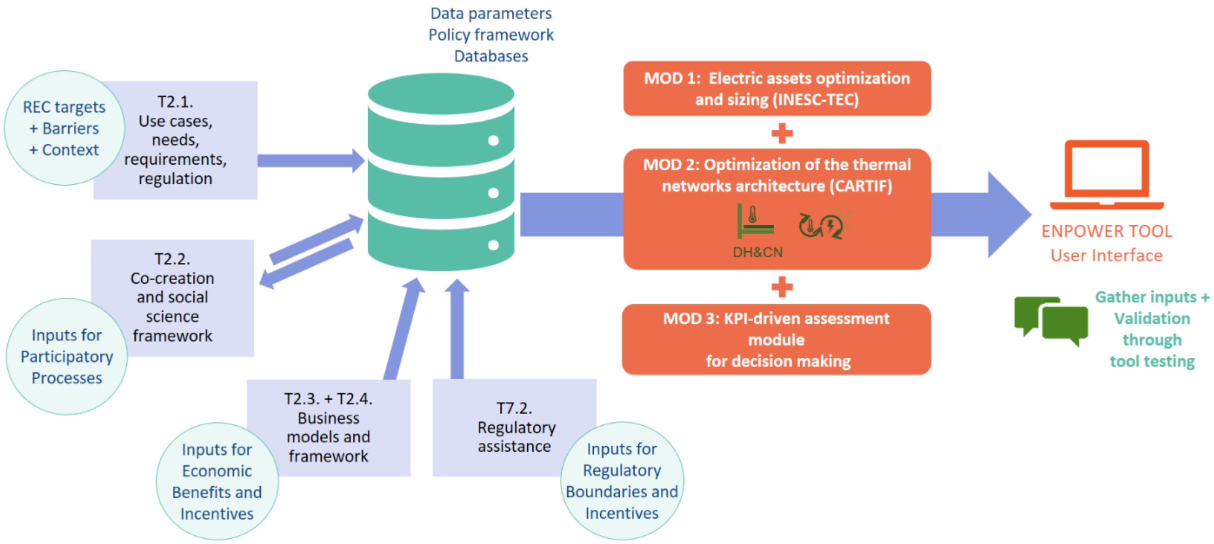


**Figure 1. Relationships among tasks (from WP3 perspective) [1].**

## 1.2 Structure of the document

In addition to this introduction section, this document is structured as follows:

Section 2 describes the tool's architecture, key modules, and interactions, including asset sizing, thermal optimization, and KPI evaluation. It explains database integration, scenario analysis, and optimization for energy planning.

Section 3 presents advancements made on the SITEC tool, the optimization tool using MILP and clustering to minimize energy costs in energy communities. New advancements include the integration of heat pump modeling, metaheuristics, and flexibility planning for efficient energy management.

Section 4 outlines the database structure, detailing the framework that connects energy assets, buildings, and users. It enables scenario simulations and KPI analysis to support informed decision-making.

Section 5 describes the user interface, designed to be accessible for both citizens and stakeholders. It ensures usability and effective interaction for energy planning and decision-making

Section 6 presents a proof of concept using one of ENPOWER pilot sites, Fornes, located in Granada (ES) as a case study; showcasing the tool's ability to optimize renewable energy integration and reduce costs in a real-world scenario.

# 2 Planning tool architecture

This section presents the overall structure, following the definitions outlined in *D3.1 - Interactive tool for consumers 'activation' and energy community planning* [1], where it details the design, organization of modules, and interaction between the tool's components, incorporating the latest development updates, that are already uploaded to a Github repository, on the following links.

The main modules are:

- **Sizing module for electrical assets**: Determines optimal configurations for energy assets (e.g., PV panels, batteries) based on energy profiles and interactions with other assets such as thermal storage. This module is being developed in the national Digital CER Portuguese P2020 project.
- **Optimisation module for thermal networks and heating and cooling assets**: optimizes thermal networks and heating/cooling assets for different community scenarios, leveraging the flexibility offered by digitalized local energy systems. An open-source simulation engine will be used for scenario modelling.
    - Available here: Github link
- **KPI module** to evaluate the different scenarios offered to prosumers and energy communities. The module is divided into sub-modules that can be standalone. For example, for the **calculation of energy demand, creation of new scenarios or calculation of KPIs**.
    - Available here: Github link

The tools modules will interface with the database and user repository hosted on CARTIF servers. Key inputs include the following categories presented in Table 1.

**Table 1. Tool modules categories.**

| Category | Details | Additional Information |
|---|---|---|
| **User-provided data** | Includes location, building count, and any available details (e.g., occupancy, construction year). | Helps create more tailored energy solutions based on location and building specifics. |
| **Energy consumption profiles** | Derived from the database, representing each community energy usage patterns. | Critical for optimizing energy allocation and system design. |
| **Energy system specifications** | Assigned for each building, using default values unless specified by the user. | Ensures that energy systems are properly sized for each building's needs. |
| **Technical and scenario parameters** | Includes asset specifications, operational constraints, and efficiency metrics.<br>Covers factors like geography, regulations, limitations, financing, and user preferences. | Important for determining system feasibility and performance.<br>Key for simulating realistic and adaptable energy scenarios. |
| **Expected outputs** | Optimized energy system configurations: Suggestions for the size and operation of electrical and thermal systems. | Focuses on maximizing energy efficiency and cost-effectiveness. |

| Category | Details | Additional Information |
|---|---|---|
| | Scenario analysis: Provides comparisons of different energy setups, analyzing demand, savings, and environmental impacts. | Helps stakeholders make informed decisions on the most sustainable and economical solutions. |

The GitHub repository for the ENPOWER decision support tool is structured to facilitate energy system modeling, scenario evaluation, and community participation analysis.

- The **data** directory stores input data for simulations, analysis results, and generated output plots.
- **data_packages** contains scripts for processing and converting input data into structured outputs.
- **helpers** includes all utility functions used by the main scripts.
- The **kpi_module** is responsible for Key Performance Indicator (KPI) calculations to evaluate different energy scenarios.
- **model_configurations** holds configuration files that define parameters and settings for various model scenarios.
- The **models** directory implements different energy assets modelled within the tool, such as PV systems, heat pumps, and storage. scenario_generator/ is responsible for generating alternative future energy scenarios for assessment.

Additional several key files support the repository. The LICENSE file specifies the licensing terms of the project. README.md provides an overview and instructions for using the tool. Simple_ES_PV_HP_v2.py implements a simple energy system model that includes photovoltaic (PV) and heat pump (HP) components. Simple_Energy_System_sens.py is used for performing sensitivity analysis on energy system configurations. With_Context_HP_data_m2_v2.py analyses heat pump (HP) data within different energy contexts. The classes_database.py file defines the database structure and relevant classes. documentation_classes.md documents the classes and modules within the repository. module_integration.py manages interactions between different modules of the tool. pyproject.toml is the configuration file defining dependencies and project settings, while requirements.txt lists the necessary Python libraries for running the tool.

**Further documentation of the modules and how to use them will be made available in D3.3, once the modules are finalised.** Furthermore, a user interface will be developed, including two different views that will be further explained in Section 6, namely:

- **Citizens/consumers-oriented view**
- **Value chain energy stakeholders-oriented view**

# 3 SITEC

## 3.1 General description

SITEC is the INESC TEC tool for planning electrical assets in energy communities described in detail in *D3.1 - Interactive tool for consumers 'activation' and energy community planning* [1]. It runs a mixed linear integer programming problem (MILP) to minimize the total costs of the energy communities, considering the operation costs derived from the opportunity costs of the members of the community, and the costs of investing in new electricity assets such as PV panels and batteries and the associated tariffs for the contracted power needed. The opportunity costs of the community members are the costs related to buying energy from their suppliers or selling their surplus to the aggregators.

The optimization model determines the optimal capacity of both PV panels and batteries to be installed by each member of the Energy Communities (EnC). To account for uncertainty and seasonality, a full year of data would be advisable, but since this can lead to computational issues, in case large data sets are provided as input, data clustering can be used to reduce computational times and memory requirements. SITEC has implemented the K-medoids algorithm, a more robust variation of the K-means.

## 3.2 New Resources

Heat Pumps (HP) have been recognized for their capability to maintain indoor thermal comfort and emerged as a significant category of energy-intensive loads. The current models developed for heat pumps advance the understanding and optimization of heat pump operations, particularly in the context of demand-side flexibility. The current model focuses on precise indoor temperature regulation, with future expansions planned to incorporate the domestic hot water (DHW) supply, thereby increasing its practical relevance and applicability for providing flexibility to the energy communities.

Two distinct heat pump technologies, i.e., thermostat-based and inverter-based systems, have been systematically analysed within the framework. Both models capture the dynamic behaviour of temperature control strategies, ensuring a realistic representation of system operations. The model parameters have been carefully calibrated using a real-world dataset, and the methodology is designed to be adaptable for parameter selection across diverse datasets, enhancing its scalability and robustness.

The key aspect of the developed models is the possibility of integrating the capabilities of Demand Response (DR), where the flexibility potential of heat pumps is explicitly modelled in response to dynamic price signals. This feature enables a more efficient alignment between energy consumption cost and flexibility provision capabilities, contributing to an integrated flexibility provision at the energy community level. Ultimately, this model serves as a foundation for optimizing heat pump performance and reducing operating costs, while maintaining thermal comfort for the households and leveraging the flexibility provision capabilities of smart homes.

Thermal comfort is expressed as a tight and flexible limit that can be adjusted in response to energy prices. The heat pumps, in this case, control the indoor temperature to maintain the comfort level defined by the end-user.

Thermal comfort is expressed as a dynamic balance between human preferences, outdoor temperature, and the energy efficiency of the installed heat pumps. Rather than being a rigid threshold, the heat pump can be operated by adjusting adaptable ranges that respond to both individual comfort needs and external factors such as energy prices and demand for flexibility provision. In this context, heat pumps serve as thermal control systems, dynamically regulating indoor temperatures within the user-defined comfort limits. It should be highlighted that the flexibility provision in the developed models may need to slightly widen the acceptable temperature range to reduce energy consumption costs, while still ensuring a comfortable indoor environment. Conversely, when energy prices are low or when renewable energy availability is high, the system can adjust the power consumption by changing the desired setpoint and conserving energy. Overheating the concrete structure during off-peak periods is a practical solution to minimize energy demand during peak hours, and it has been considered in the developed model.

The developed models effectively contribute to flexibility provision in the local energy communities, reducing peak load demand and encouraging the use of cleaner energy sources.

### 3.2.1 Input data description

**Table 2. Indices and sets.**

| Indices/sets | Descriptions | Units |
|---|---|---|
| $\boldsymbol{t} \in \boldsymbol{T}$ | Set of time intervals/slots over the operation period. | - |
| $\boldsymbol{t} \in \boldsymbol{T}^{96}$ | Subset of time intervals/slots comprised by end-of-day steps, operational planning horizon is one day, with 15-min resolution | - |
| $\boldsymbol{n} \in \boldsymbol{N}$ | Set of CPEs. | - |
| $\boldsymbol{i} \in \boldsymbol{I}$ | Set of operating mode of inverter | - |
| $\boldsymbol{s} \in \boldsymbol{S}$ | Set of stationary batteries | - |

**Table 3. Parameters.**

| Service parameters | Descriptions | Units |
|---|---|---|
| $\boldsymbol{\alpha_n}$ | Building heat transfer capability. | $h^{-1}$ |
| $\boldsymbol{\beta_n}$ | Power to heat exchange coefficient. | °C/kWh |
| $\triangle \boldsymbol{t}$ | Time step. | 15-min |
| $\boldsymbol{\theta_{n,0}^{in}}$ | Initial indoor temperature ($t$=1). | °C |
| $\boldsymbol{\theta_{n,T}^{in}}$ | Final indoor temperature ($t$=$T$). | °C |
| $\boldsymbol{\hat{\theta}_{n,t}^{in,min}}$ | Minimum desired indoor temperature at $t$. | °C |
| $\boldsymbol{\hat{\theta}_{n,t}^{Th,min}}$ | Deviation threshold for changing the minimum acceptable range | °C |
| $\boldsymbol{\hat{\theta}_{n,t}^{in,max}}$ | Maximum desired indoor temperature at $t$. | °C |
| $\boldsymbol{\hat{\theta}_{n,t}^{Th,max}}$ | Deviation threshold for changing the maximum acceptable range | °C |
| $\boldsymbol{\hat{\lambda}_{n,t}}$ | Hourly energy tariff | €/kWh |
| $\boldsymbol{\hat{\lambda}_{n,t}^{Th,min}}$ | Minimum price for initiating new temperature setting | €/kWh |
| $\boldsymbol{\hat{\lambda}_{n,t}^{Th,max}}$ | Maximum price for initiating new temperature setting | €/kWh |
| $\boldsymbol{M}$ | A very big number (e.g., 1E6). | - |
| $\boldsymbol{\hat{P}_{n}^{HP,Rated}}$ | Rated power of heat pump $n$. | kW |

**Table 4. Variables.**

| Decision Variables | Descriptions | Units |
|---|---|---|
| $\theta_{n,t}^{in}$ | Indoor temperature controlled by heat pump *n*, at *t*. | °C |
| $\delta_{i,n,t}^{HP}$ | Binary variable corresponding to inverter operation modes | - |
| $E_{n,t}^{HP}$ | Energy consumed by heat pump *n*, at *t*. | kWh |
| $I_{n,t}^{HP}$ | Binary decision variable corresponding to heat pump operation | - |
| $I_{n,t}^{Th,min}$ | Binary variable for assigning new minimum temperature | - |
| $I_{n,t}^{Th,max}$ | Binary variable for assigning new maximum temperature | - |
| $J_{n,t}^{HP}$ | Auxiliary binary variable for thermostat-based control strategy | - |
| $K_{n,t}^{HP}$ | Auxiliary binary variable for thermostat-based control strategy | - |
| $P_{n,t}^{HP}$ | Heat pump power consumption for inverter-based model | kWh |

The end-users can express thermal comfort by choosing their minimum and maximum acceptable indoor temperatures. Violating this range will result in thermal discomfort. In the case of maintaining the temperature using heat pumps, the indoor temperature will be controlled in a closed-loop cycle. The air-to-water heat pumps can also serve the hot water demand, using a hot water tank as a thermal storage unit to support the hot water demands. Figure 2 illustrates the indoor temperature setting that can be chosen by the end-users. It should be noted that this range must comply with the temperature limits specified in the heat pump infrastructure's user manual.


**Figure 2. Comfort thermal range for indoor temperature control by heat pump.**

The operation of heat pumps in maintaining indoor thermal comfort can be categorized into two main control strategies: thermostat-based hysteresis control and inverter-driven variable-speed control, i.e., thermostat-based and inverter-based modes, respectively. In a conventional thermostat-based system, the heat pump operates in an on/off mode with a predefined hysteresis band, where it turns on when the temperature drops below the minimum threshold and turns off once the upper-temperature limit is reached. This cyclic operation can lead to temperature fluctuations and potential inefficiencies due to frequent compressor cycling, and such an operating mode has a dead band in the temperature control functionality. The hysteresis cycle in the thermostat-based control strategy is demonstrated in Figure 3. The first cycle (I) corresponds to the on-mode operation, and it continues with rated power to reach the maximum threshold; then, the heat pump switches to turn-off mode, and it stays in the second cycle (II) to reach the minimum acceptable range.

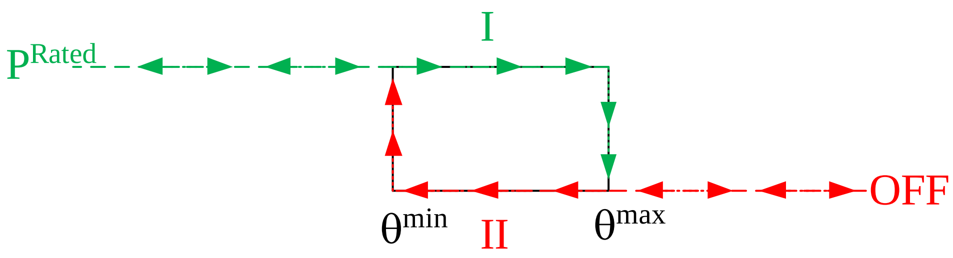


**Figure 3. Thermostat-based model to control the indoor temperature considering ON-mode cycle (I) and OFF-mode cycle (II).**

The model for thermostat-based heat pump has been developed using a mixed-integer linear programming approach and the transitions between on-off modes have been considered as a set of constraints.

**Table 5. Thermostat-based Heat Pumps (No-Flexibility).**

| Constraints | Sets | Identifications |
|---|---|---|
| $E_{n,t}^{HP} = \widehat{P}_{n}^{HP,Rated}.\triangle t. I_{n,t}^{HP}$ | $\forall\, t \in T, n \in N$ | (3.2.A1) |
| $\theta_{n,t}^{in} + M. I_{n,t}^{HP} \geq \widehat{\theta}_{n,t}^{in,min}$<br>$\theta_{n,t}^{in} - M.\left(1 - I_{n,t}^{HP}\right) \leq \widehat{\theta}_{n,t}^{in,max}$<br>$\theta_{n,t}^{in} - M. J_{n,t}^{HP} \leq \widehat{\theta}_{n,t}^{in,min}$<br>$\theta_{n,t}^{in} + M. K_{n,t}^{HP} \geq \widehat{\theta}_{n,t}^{in,max}$ | $\forall\, t \in T, n \in N$ | (3.2.A2) |
| $J_{n,t}^{HP} + K_{n,t}^{HP} - I_{n,t-1}^{HP} + I_{n,t}^{HP} \leq 2$<br>$J_{n,t}^{HP} + K_{n,t}^{HP} + I_{n,t-1}^{HP} - I_{n,t}^{HP} \leq 2$ | $\forall\, t \in T, n \in N$ | (3.2.A3) |
| $\theta_{n,t}^{in} = \theta_{n,0}^{in}$ | $\forall\, t = 1, n \in N$ | (3.2.A4) |
| $\theta_{n,t}^{in} = \theta_{n,t-1}^{in} + \alpha_n\left[\theta_{n,t-1}^{out} - \theta_{n,t-1}^{in}\right] \triangle t + \beta_n. P_{n,t-1}^{HP}. \triangle t. I_{n,t-1}^{HP}$ | $\forall\, t \in T \backslash t = 1, n \in N$ | (3.2.A5) |
| $\theta_{n,t}^{in} \geq \theta_{n,T}^{in}$ | $\forall\, t = T, n \in N$ | (3.2.A6) |

**Table 6. Descriptions of constraints of thermostat-based Heat Pumps (No Flexibility).**

| Constraints | Descriptions |
|---|---|
| **(3.2.2)** | Net consumption constraint |
| **(3.2.A1)** | Energy consumed by the thermostat-based heat pump |
| **(3.2.A2)** | Minimum and maximum range of the indoor temperature and the corresponding auxiliary binary variables associated with the thermostat model |
| **(3.2.A3)** | Transition from turn-on to turn-off modes according to the functionality of the thermostat |
| **(3.2.A4)** | Initial indoor temperature |
| **(3.2.A5)** | Indoor temperature control model using heat pump |
| **(3.2.A6)** | Final indoor temperature at the end of operational planning |

The initial range can be adjusted to activate the flexibility that the heat pumps can provide. For instance, whenever the electricity price is lower than a specific threshold, the heat pump can consume more power to overheat the temperature. On the contrary, the lower temperature limit can be adjusted while the energy price is higher than the specified threshold. It should be noted that the user can also define this deviation as not experiencing thermal discomfort. The adaptive settings can be applied in response to the renewable energy surplus in the community as well. Figure 4 depicts the adaptive temperature control strategy for the thermostat-based model to provide flexibility in the operational planning stage.

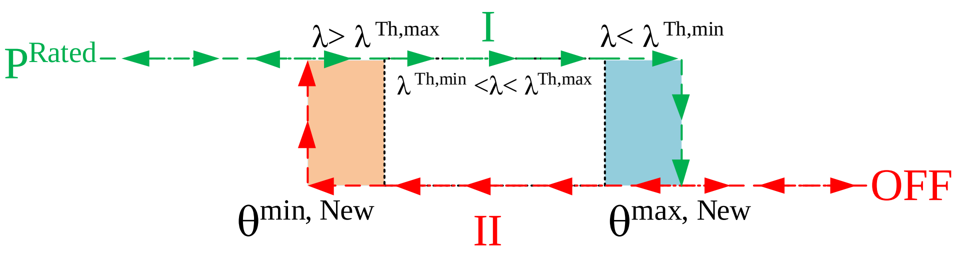


**Figure 4. Thermostat-based model with flexible thermal ranges responding to price thresholds.**

**Table 7. Thermostat-based Heat Pumps (Providing Flexibility).**

| Constraints | Sets | Identifications |
|---|---|---|
| $E_{n,t}^{HP} = \hat{P}_n^{HP,Rated}.\triangle t. I_{n,t}^{HP}$ | $\forall\, t \in T, n \in N$ | (3.2.B1) |
| $\theta_{n,t}^{in} + M.I_{n,t}^{HP} \geq \hat{\theta}_{n,t}^{in,min} - \hat{\theta}_{n,t}^{Th,min} I_{n,t}^{Th,min}$<br>$\theta_{n,t}^{in} - M.\left(1 - I_{n,t}^{HP}\right) \leq \hat{\theta}_{n,t}^{in,max} + \hat{\theta}_{n,t}^{Th,max} I_{n,t}^{Th,max}$<br>$\theta_{n,t}^{in} - M.J_{n,t}^{HP} \leq \hat{\theta}_{n,t}^{in,min} - \hat{\theta}_{n,t}^{Th,min} I_{n,t}^{Th,min}$<br>$\theta_{n,t}^{in} + M.K_{n,t}^{HP} \geq \hat{\theta}_{n,t}^{in,max} + \hat{\theta}_{n,t}^{Th,max} I_{n,t}^{Th,max}$ | $\forall\, t \in T, n \in N$ | (3.2.B2) |
| $J_{n,t}^{HP} + K_{n,t}^{HP} - I_{n,t-1}^{HP} + I_{n,t}^{HP} \leq 2$<br>$J_{n,t}^{HP} + K_{n,t}^{HP} + I_{n,t-1}^{HP} - I_{n,t}^{HP} \leq 2$ | $\forall\, t \in T, n \in N$ | (3.2.B3) |
| $\hat{\lambda}_{n,t}^{Th,max} - \hat{\lambda}_{n,t} + M.I_{n,t}^{Th,min} \geq 0$<br>$\hat{\lambda}_{n,t}^{Th,max} - \hat{\lambda}_{n,t} - M.\left(1 - I_{n,t}^{Th,min}\right) \leq 0$ | $\forall\, t \in T, n \in N$ | (3.2.B4) |
| $\hat{\lambda}_{n,t} - \hat{\lambda}_{n,t}^{Th,min} + M.I_{n,t}^{Th,max} \geq 0$<br>$\hat{\lambda}_{n,t} - \hat{\lambda}_{n,t}^{Th,min} - M.\left(1 - I_{n,t}^{Th,max}\right) \leq 0$ | $\forall\, t \in T, n \in N$ | (3.2.B5) |
| $\theta_{n,t}^{in} = \theta_{n,0}^{in}$ | $\forall\, t = 1, n \in N$ | (3.2.B6) |
| $\theta_{n,t}^{in} = \theta_{n,t-1}^{in} + \alpha_n\left[\theta_{n,t-1}^{out} - \theta_{n,t-1}^{in}\right] \triangle t + \beta_n.P_{n,t-1}^{HP}. \triangle t. I_{n,t-1}^{HP}$ | $\forall\, t \in T \backslash t = 1, n \in N$ | (3.2.B7) |
| $\theta_{n,t}^{in} \geq \theta_{n,T}^{in}$ | $\forall\, t = T, n \in N$ | (3.2.B8) |

**Table 8. Descriptions of constraints of thermostat-based Heat Pumps (Providing Flexibility).**

| Constraints | Descriptions |
|---|---|
| **(3.2.2)** | Net consumption constraint |

| | |
|---|---|
| **(3.2.B1)** | Energy consumed by the thermostat-based heat pump |
| **(3.2.B2)** | Flexible minimum and maximum range of the indoor temperature with the capability of responding to the electricity prices. The new ranges are associated with new auxiliary binary variables to change the thermostat settings. |
| **(3.2.B3)** | Transition from turn-on to turn-off modes according to the functionality of the thermostat |
| **(3.2.B4)** | Activating higher power consumption while the price is lower than the minimum threshold by changing the maximum allowed temperature |
| **(3.2.B5)** | Changing the minimum acceptable temperature into a lower temperature while the price is higher than the maximum price threshold |
| **(3.2.B6)** | Initial indoor temperature |
| **(3.2.B7)** | Indoor temperature control model using heat pump |
| **(3.2.B8)** | Final indoor temperature at the end of operational planning |

The inverter-based model for controlling the indoor temperature in heating mode is illustrated in Figure 5. The indoor temperature control strategy of the inverter-based model is more favourable for maintaining thermal comfort, as it eliminates the dead band in the temperature regulation mechanism. Unlike traditional thermostat-based systems with an on/off hysteresis mode, which results in temperature fluctuations within a predefined range, the inverter-based heat pump smoothly adjusts its compressor speed to match the real-time heating or cooling demand. Such performance can be achieved through a semi-continuous power consumption strategy, where the heat pump does not cycle on and off abruptly but instead modulates its output dynamically. The heat pump can maintain a stable indoor temperature with minimal deviations from the setpoint, avoiding sudden drops or overshoots that typically occur in hysteresis-controlled systems. This feature enhances thermal comfort, improves energy efficiency, and minimizes the compressor's wear and tear. If the indoor temperature falls below the lower comfort limit, the heat pump will activate at full power to restore and maintain thermal comfort within the predefined range.

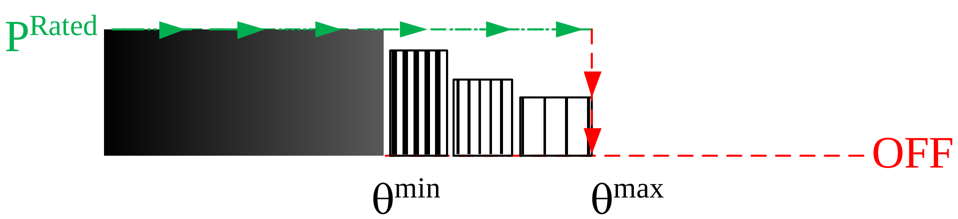


**Figure 5. Inverter-based model to control the indoor temperature.**

**Table 9. Inverter-based Heat Pumps (No Flexibility).**

| Constraints | Sets | Identifications |
|---|---|---|
| $E^{HP}_{n,t} = P^{HP}_{n,t} . \triangle t$ | $\forall\, t \in T, n \in N$ | (3.2.D1) |

| | | |
|---|---|---|
| $\boldsymbol{P^{HP}_{n,t} = \sum_{i=1}^{I} i.\delta^{HP}_{i,n,t}.\frac{\hat{P}^{HP,Rated}_{n}}{I}}$ | $\forall\, t \in T, n \in N$ | (3.2.D2) |
| $\boldsymbol{\sum_{i=1}^{I} \delta^{HP}_{i,n,t} \leq 1 \quad , \quad \delta^{HP}_{i,n,t} \in \{0,1\}}$ | $\forall\, t \in T, n \in N$ | (3.2.D3) |
| $\boldsymbol{\hat{\theta}^{in,min}_{n,t} \leq \theta^{in}_{n,t} \leq \hat{\theta}^{in,max}_{n,t}}$ | $\forall\, t \in T, n \in N$ | (3.2.D4) |
| $\boldsymbol{\theta^{in}_{n,t} = \theta^{in}_{n,0}}$ | $\forall\, t = 1, n \in N$ | (3.2.D5) |
| $\boldsymbol{\theta^{in}_{n,t} = \theta^{in}_{n,t-1} + \alpha_n\left[\theta^{out}_{n,t-1} - \theta^{in}_{n,t-1}\right] \triangle t + \beta_n.P^{HP}_{n,t-1}.\triangle t}$ | $\forall\, t \in T \backslash t = 1, n \in N$ | (3.2.D6) |
| $\boldsymbol{\theta^{in}_{n,t} \geq \theta^{in}_{n,T}}$ | $\forall\, t = T, n \in N$ | (3.2.D7) |

**Table 10. Descriptions of constraints of inverter-based Heat Pumps (No Flexibility).**

| Constraints | Descriptions |
|---|---|
| **(3.2.2)** | Net consumption constraint |
| **(3.2.D1)** | Energy consumed by the inverter-based heat pump |
| **(3.2.D2)** | Discretization of the operation of inverter-based heat pump using auxiliary binary variables associated with the operation mode of the inverter |
| **(3.2.D3)** | Selection of operation mode, maximum one of the auxiliary binary variables will be chosen |
| **(3.2.D4)** | Minimum and maximum indoor temperature selected by end-user |
| **(3.2.D5)** | Initial indoor temperature |
| **(3.2.D6)** | Indoor temperature control model using heat pump |
| **(3.2.D7)** | Final indoor temperature at the end of operational planning |

Like the thermostat-based control model, the adaptive range can be defined for the inverter-based control model, respecting the price signal or renewable energy surplus at the community level. The adjustment can provide a broader range of flexibility without additional penalties to the objective function. This feature is demonstrated in Figure 6.

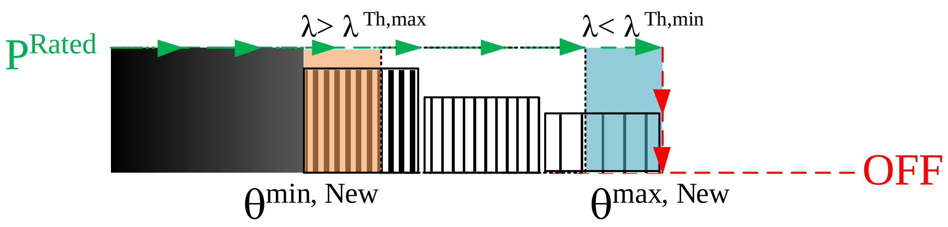


**Figure 6. Inverter-based model with flexible thermal ranges responding to price thresholds.**

**Table 11. Inverter-based Heat Pumps (Providing Flexibility).**

| Constraints | Sets | Identifications |
|---|---|---|
| $\boldsymbol{E^{HP}_{n,t} = P^{HP}_{n,t}.\triangle t}$ | $\forall\, t \in T, n \in N$ | (3.2.E1) |

| | | |
|---|---|---|
| $P^{HP}_{n,t} = \sum_{i=1}^{I} i.\delta^{HP}_{i,n,t}.\frac{\widehat{P}^{HP,Rated}_{n}}{I}$ | $\forall\, t \in T, n \in N$ | (3.2.E2) |
| $\sum_{i=1}^{I} \delta^{HP}_{i,n,t} \leq 1 \quad , \quad \delta^{HP}_{i,n,t} \in \{0,1\}$ | $\forall\, t \in T, n \in N$ | (3.2.E3) |
| $\widehat{\theta}^{in,min}_{n,t} - \widehat{\theta}^{Th,min}_{n,t} I^{Th,min}_{n,t} \leq \theta^{in}_{n,t} \leq \widehat{\theta}^{in,max}_{n,t} + \widehat{\theta}^{Th,max}_{n,t} I^{Th,max}_{n,t}$ | $\forall\, t \in T, n \in N$ | (3.2.E4) |
| $\hat{\lambda}^{Th,max}_{n,t} - \hat{\lambda}_{n,t} + M.I^{Th,min}_{n,t} \geq 0$<br>$\hat{\lambda}^{Th,max}_{n,t} - \hat{\lambda}_{n,t} - M.(1 - I^{Th,min}_{n,t}) \leq 0$ | $\forall\, t \in T, n \in N$ | (3.2.E5) |
| $\hat{\lambda}_{n,t} - \hat{\lambda}^{Th,min}_{n,t} + M.I^{Th,max}_{n,t} \geq 0$<br>$\hat{\lambda}_{n,t} - \hat{\lambda}^{Th,min}_{n,t} - M.(1 - I^{Th,max}_{n,t}) \leq 0$ | $\forall\, t \in T, n \in N$ | (3.2.E6) |
| $\theta^{in}_{n,t} = \theta^{in}_{n,0}$ | $\forall\, t = 1, n \in N$ | (3.2.E7) |
| $\theta^{in}_{n,t} = \theta^{in}_{n,t-1} + \alpha_n\left[\theta^{out}_{n,t-1} - \theta^{in}_{n,t-1}\right] \triangle t + \beta_n . P^{HP}_{n,t-1} . \triangle t$ | $\forall\, t \in T \backslash t = 1, n \in N$ | (3.2.E8) |
| $\theta^{in}_{n,t} \geq \theta^{in}_{n,T}$ | $\forall\, t = T, n \in N$ | (3.2.E9) |

**Table 12. Descriptions of constraints of inverter-based Heat Pumps (Providing Flexibility).**

| Constraints | Descriptions |
|---|---|
| **(3.2.2)** | Net consumption constraint |
| **(3.2.E1)** | Energy consumed by the inverter-based heat pump |
| **(3.2.E2)** | Discretization of the operation of inverter-based heat pump using auxiliary binary variables associated with the operation mode of the inverter |
| **(3.2.E3)** | Selection of operation mode, maximum one of the auxiliary binary variables will be chosen |
| **(3.2.E4)** | Flexible minimum and maximum range of the indoor temperature with the capability of responding to the electricity prices. The new ranges are associated with new auxiliary binary variables to change the thermostat settings. |
| **(3.2.E5)** | Activating higher power consumption while the price is lower than the minimum threshold by changing the maximum allowed temperature |
| **(3.2.E6)** | Changing the minimum acceptable temperature into a lower temperature while the price is higher than the maximum price threshold |
| **(3.2.E7)** | Initial indoor temperature |
| **(3.2.E8)** | Indoor temperature control model using heat pump |
| **(3.2.E9)** | Final indoor temperature at the end of operational planning |

### 3.2.2 Simulation Results of Heat Pumps

In this section, the simulation studies for the proposed models are presented, dealing with the models' performance and addressing each model's limitations. The first case demonstrates the performance of the thermostat-based heat pump functionality in indoor temperature control. Figure 8 shows the daily operational planning of the heat pump in heating mode.

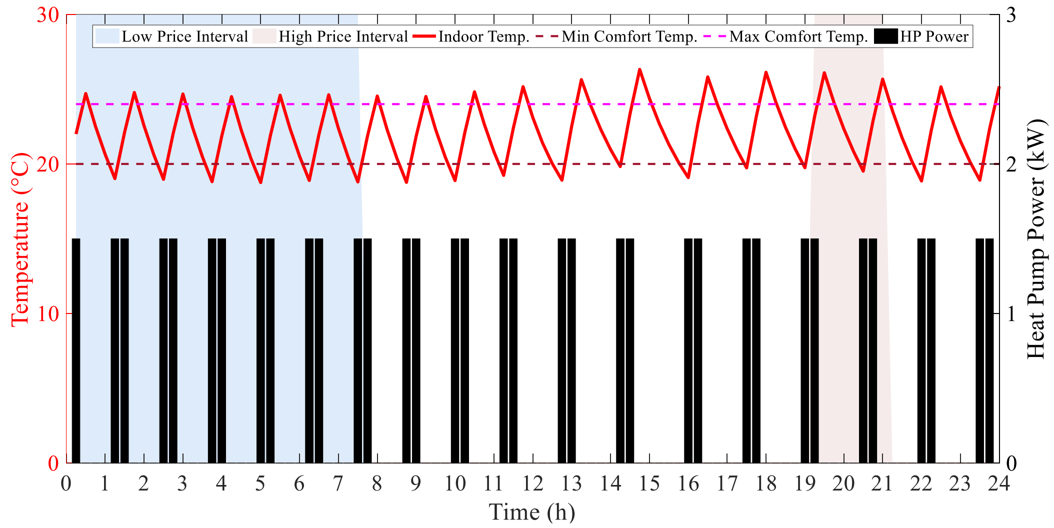


**Figure 7. Indoor temperature control strategy using thermostat-based heat pump without flexibility.**

The results illustrate the behaviour of the thermostat-based indoor temperature control strategy without flexibility provision. The indoor temperature fluctuates within the predefined comfort range of 20–24°C, governed by a hysteresis-based on/off control mechanism. This control strategy inherently leads to periodic temperature swings, as the heat pump only activates when the temperature reaches the lower threshold and deactivates upon reaching the upper limit.

During the middle of the day, power consumption is reduced due to higher outdoor temperatures, which naturally decreases heating demand. As a result, the heat pump operates less frequently, improving its efficiency during this period. However, after 13:00h, the impact of the dead band becomes more pronounced, causing exaggerated temperature deviations. This occurs because the system waits for the indoor temperature to hit the lower threshold before activating, leading to perceptible drops in comfort levels.

Moreover, with a rated capacity of 1.5 kW, the heat pump operates at full power when engaged, leading to abrupt cycling between the 'on' and 'off' states rather than a smooth modulation of heating output. This operational pattern results in inefficient energy use and potential discomfort due to temperature overshoots and undershoots. These findings highlight the limitations of traditional thermostat-based control strategies, particularly in maintaining a more stable indoor climate and optimizing energy efficiency. However, the computational burden of this model is less than that of the inverter-based control strategy, which has a vast range of binary decision variables.

The thermostat-based control strategy adapts to dynamic electricity prices, optimizing energy consumption while maintaining indoor comfort and contributing to flexibility provision in response to the electricity price signals. The heating system prioritizes operation during low-price periods and reduces energy consumption during peak hours to minimize costs. Figure 8 illustrates the response of the heat pump with adjustable comfort zones.

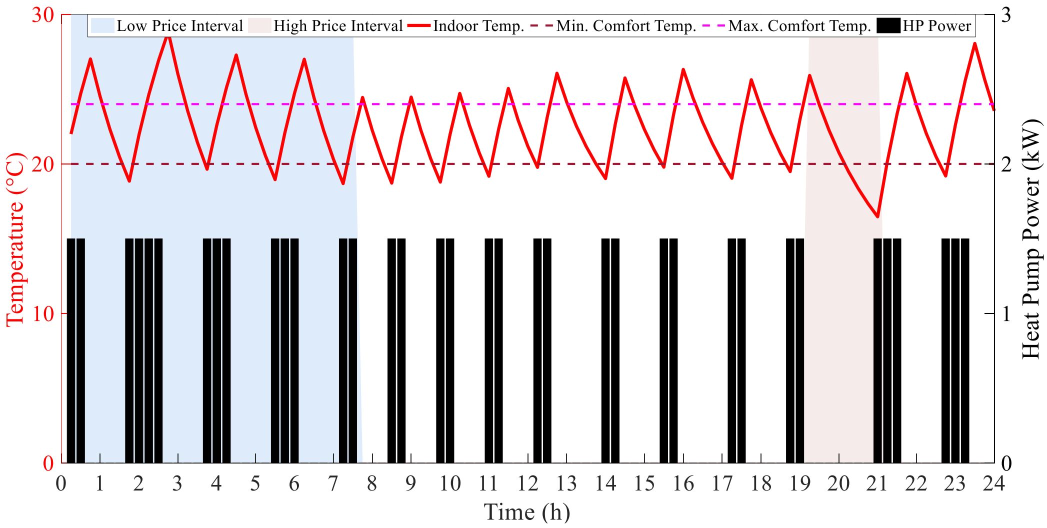


**Figure 8. Indoor temperature control strategy using thermostat-based heat pump considering flexible temperature control and demand response.**

During the low-price interval (00:00 - 07:30h), the system preheats the indoor space, allowing temperatures to rise within the comfort range. This proactive heating approach leverages lower energy costs and enhances thermal storage, reducing the need for heating later in the day. Compared to the normal operation strategy, energy consumption during this period is 0.75 kWh higher than the normal operation strategy. Conversely, during the peak-price interval (19:30 - 21:00h), the heat pump operates less frequently to limit electricity expenses. As a result, the indoor temperature gradually declines but remains within acceptable comfort levels (±3°C) due to the stored thermal energy from prior heating. According to the results of this study, the energy consumption during the peak period is 0.75 kWh less than the normal mode operation.

By shifting heating demand away from expensive periods, this strategy reduces overall energy costs while maintaining thermal comfort. Unlike traditional thermostat-based control, which follows a rigid hysteresis cycle, this approach introduces flexibility, improving both efficiency and maintaining the user's comfort.

The inverter-based heat pump operates with continuous modulation rather than on-off cycling, allowing smoother temperature control. Unlike thermostatic control, this system adjusts heating power incrementally to maintain indoor temperatures within the comfort range of 20–24°C. Figure 10 provides the indoor temperature control results for the inverter-based heat pump.

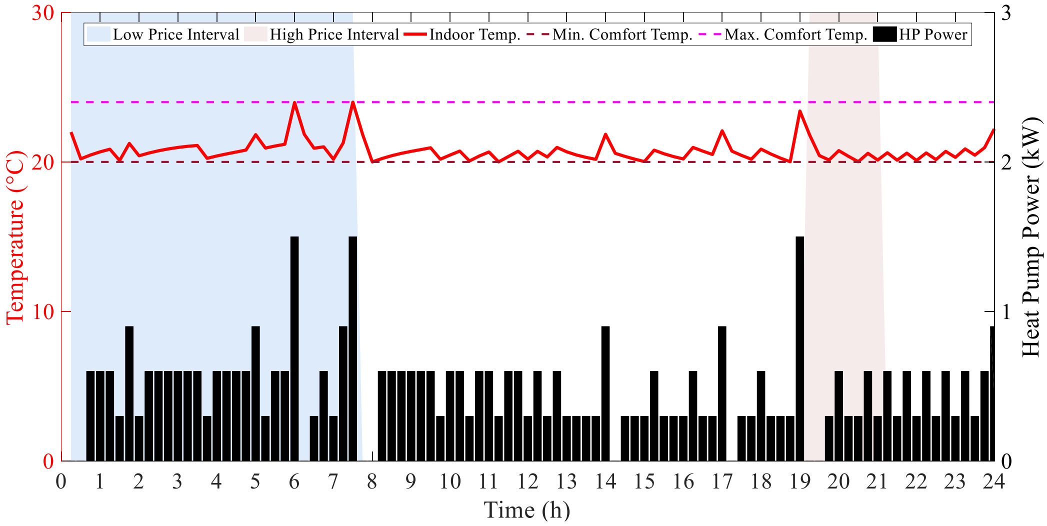


**Figure 9. Indoor temperature control strategy using inverter-based heat pump without flexibility.**

During midday, heating demand decreases due to rising outdoor temperatures, leading to a natural reduction in power consumption. The inverter-based system optimizes energy consumption by running at lower capacities rather than completely turning off. It should be highlighted that the inverter-based system considers the energy prices during off-peak and peak periods. For instance, between 6:00 to 7:30, the heat pump increases the temperature, avoiding violating the comfort levels to reduce the power consumption afterward. In addition, at 19:45 the heat pump operates at the maximum rated power to leverage the indoor temperature to the maximum range.

Without flexibility provision, the system does not exceed the thermal comfort level. This results in steady operation even during the peak-price interval (19:30 - 21:00h), leading to higher energy costs. However, compared to hysteresis-based control, this approach minimizes abrupt temperature swings, improving comfort levels. While the lack of flexibility increases operational costs, the inverter-based strategy enhances temperature stability and energy efficiency by avoiding excessive cycling.

Figure 10 provides the results of the heating system, which actively adjusts its operation in response to electricity price signals, trading off between energy costs and thermal comfort. In this case, the temperature band is widened, allowing for controlled variations in indoor temperature to maximize cost savings without significantly impacting comfort.

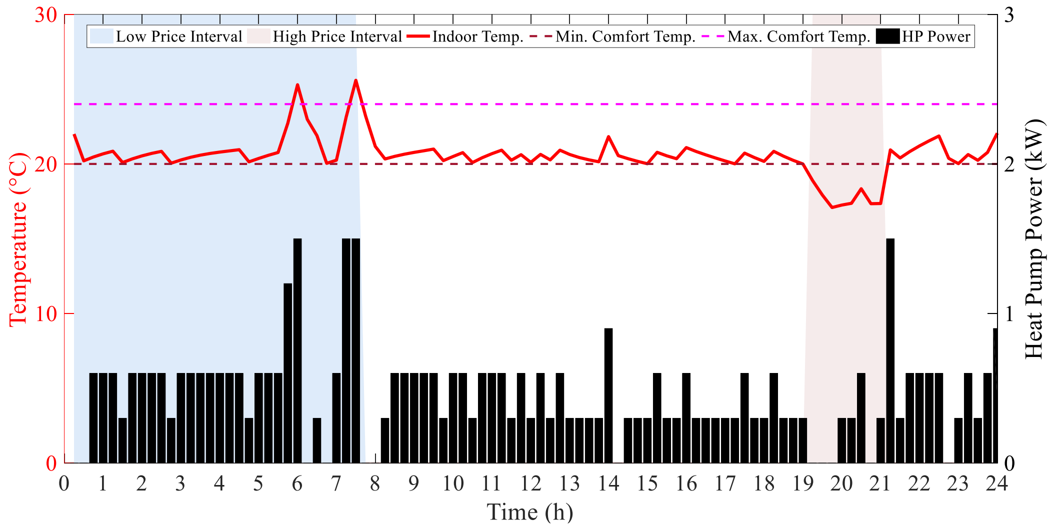


**Figure 10. Indoor temperature control strategy using inverter-based heat pump considering flexible temperature control and demand response.**

During the low-price interval (00:00 - 07:30h), the system raises the indoor temperature above the standard comfort range, preheating the space efficiently by consuming 0.15 kWh more energy compared to the normal operation case. This proactive heating reduces the need for energy consumption during expensive hours. In addition, as electricity prices rise, particularly during the peak-price interval (19:30 - 21:00h), the system lowers the temperature band, allowing indoor temperatures to drop while remaining within the acceptable range (±3 °C). This limits heat pump operation during peak-cost periods, significantly reducing energy expenses. Compared to the previous case, the energy saving during the peak period is 0.225 kWh for the studied day.

## 3.3 Clustering approach to reduce computational effort

The SITEC tool can be computationally demanding and memory-intensive, especially for simulations that involve large volumes of data. To mitigate this challenge, data clustering techniques are applied to optimize computational efficiency and reduce memory consumption while preserving the essential patterns within the dataset [2]. The K-medoids algorithm is applied, a more robust variation of the widely used K-means method [3]. By grouping similar data points, K-medoids allows for an efficient and reliable representation of energy profiles and opportunity costs, facilitating improved decision-making within the EnC framework.

Clustering is an unsupervised machine learning technique used to partition datasets into groups (or clusters) based on similarity measures. The fundamental goal is to represent a large dataset with a reduced set of representative elements, minimizing intra-cluster dissimilarities while maximizing inter-cluster differences. In this context, clustering is particularly valuable for simplifying high-resolution time series data, making it more manageable for the optimization.

Among clustering methods, K-medoids is a partitioning-based algorithm that minimizes the sum of dissimilarities between data points and their assigned cluster centers (medoids). Unlike K-means, which uses the average of the cluster members as the cluster representative, being more sensitive to outliers, K-medoids selects actual cluster members as cluster representatives, enhancing its robustness [3], and avoiding the smoothing effect that averages, which can be especially inadequate for sizing problems. Given the seasonal and uncertain nature of energy consumption, production and opportunity costs in EnCs, K-medoids provides a more reliable clustering approach, ensuring that representative days retain realistic variability and statistical properties. By applying K-medoids here, the idea is to construct a reduced yet representative dataset that captures the key temporal patterns in EnC energy data and prices. This enables computationally efficient modelling and analysis while maintaining some degree of accuracy in system performance evaluations [2].

Using clustering to reduce data sets has direct implications on the computational time but also on the accuracy of the results, and a careful analysis of this trade-off is needed.

### 3.3.1 K-medoids clustering for SITEC

This implementation leveraged the sklearn_extra [4] python library's K-Medoids clustering algorithm to efficiently partition energy-related time series data into a user-defined number of clusters. The clustering process groups daily patterns to create a reduced yes representative dataset, improving computational efficiency while preserving key energy consumption, generation and opportunity cost trends.

**Data Structure**

The input dataset must be structured with a fixed, yet configurable time step, expressed in multiples of 1 day. Each day must contain four distinct time series:

- Generation PV factor: a normalized factor representing the PV generation;
- Consumption (kWh): the energy consumed per day;
- Buying opportunity cost (€/kWh): the cost of purchasing electricity from the grid;
- Selling opportunity cost (€/kWh): the price at which the electricity can be sold to the grid.

By clustering this data, the model identifies representative days that effectively characterize the variability of energy patterns throughout the dataset.

**Input Parameters**

The function receives a Python dictionary containing:

- Data to be clustered: a time series dataset structured as described above;
- Time step of the data;
- Number of days in the dataset: specifies the total duration covered by the dataset;
- Desired number of clusters: the number of representative days to extract from the dataset.

**Output Parameters**

The function returns a dictionary containing:

- Medoids (representative days): the cluster centres (actual days from the dataset) separated by data series;
- Cluster labels: a mapping of each day to its assigned cluster label;
- Inertia Parameter: a measure of the total intra-cluster distance, indicating clustering compactness;
- Number of days per cluster: the count of days assigned to each cluster providing an overview of distribution.

### 3.3.2 Testing: clustering, time and accuracy

Several tests are being performed to address the trade-off between accuracy and computational time. As an example, Figure 11 shows the result of a case example based on an energy community with 4 members, when sizing is performed without considering flexibility provision. Sizing is performed for a varying number of clusters, from 1 to 365. Since the data used corresponded to one year, when the number of clusters is 365, the problem uses all data, and no clustering reduction is applied. As can be seen, when the number of clusters increases, the accuracy, understood as the difference of the current number of clusters compared with the no clustering case decreases, but computational time increases. It is a clear challenge to select an appropriate number of clusters since this approach depends directly on the complexity and size of the EnC structure and even on the numerical data that describes the energy behaviour of the members and their opportunity costs and is clearly a matter of further research.

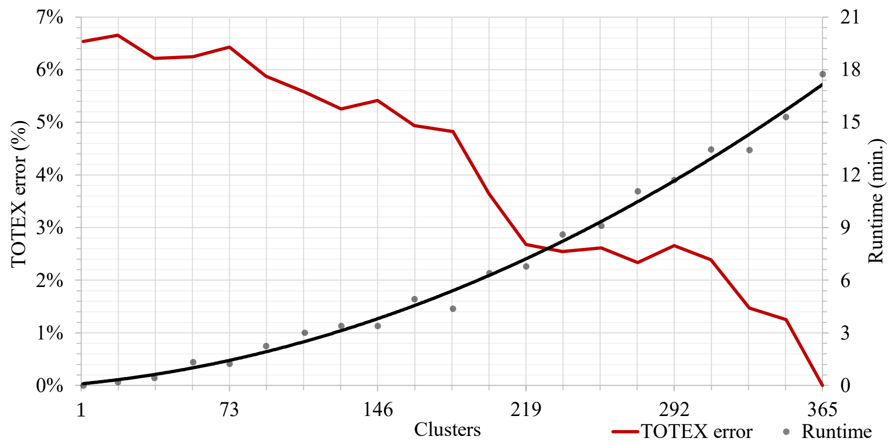


**Figure 11. Clustering and the trade-off between accuracy and computational time.**

## 3.4 Metaheuristics

As already mentioned, computational efficiency is a critical factor in optimizing the sizing and operation of EnC, where complex, large-scale, and sometimes nonlinear decision-making problems must be solved effectively. Traditional optimization methods may struggle with these challenges due to high computational costs or difficulty in finding global optima. In contrast, metaheuristic approaches offer flexible and efficient solutions by navigating large search spaces and avoiding local optima, making them well-suited for EnC optimization.

Metaheuristic algorithms, such as Particle Swarm Optimization (PSO), have emerged as powerful alternatives to traditional optimization methods, offering flexible and efficient approaches to handling these challenges. This section presents the application of PSO for EnC optimization while also exploring the potential of Evolutionary Particle Swarm Optimization (EPSO), a variant that remains underexplored in the existing literature. By leveraging these metaheuristics, this section aims to assess the potential improvement in computational performance while maintaining or enhancing solution quality.

A key objective is to compare EPSO with traditional Mixed-Integer Linear Programming (MILP) methods and standard PSO, a widely used metaheuristic algorithm. Metaheuristics are particularly valuable for their ability to navigate complex, high-dimensional search spaces and escape local optima, making them well-suited for EnC optimization problems. The goal is to assess the speed, solution quality, and robustness of PSO and EPSO in comparison to the deterministic approach, to provide valuable insights into its potential advantages and disadvantages for EnC planning and operation.

Metaheuristic algorithms are advanced optimization techniques designed to efficiently solve complex problems that traditional methods, such as gradient-based techniques, struggle with due to non-linearity, non-differentiability, or high-dimensionality. By leveraging randomness and iterative search strategies, metaheuristics explore vast solution spaces to identify near-optimal solutions within a reasonable computational time. These methods are particularly effective in accelerating the optimization of large-scale problems, especially those involving extended time horizons, where conventional approaches may become computationally prohibitive. Their ability to balance exploration and exploitation makes them well-suited for solving dynamic, multi-period optimization challenges, such as those encountered in SITEC. Considering this, two optimization techniques are being explored as an alternative to the original MILP problem formulated in SITEC, namely PSO and EPSO. PSO and EPSO are briefly described in the next subsections.

### 3.4.1 PSO

PSO is a computational method used to find optimal solutions to complex problems by simulating a group-based search process. Instead of evaluating every possible solution individually, PSO allows a set of candidate solutions—called particles—to explore the solution space collectively. Each particle adjusts its position based on both its own progress and insights gained from the best-performing solutions in the group. This approach makes PSO an efficient alternative to traditional optimization methods, especially for problems with large or complex search spaces. Formally, each particle is characterized by the following components [5]:

- Position ($x_i^t$): Represents the current solution at iteration.
- Velocity ($v_i^t$): Determines the direction and magnitude of movement in the solution space.
- Personal best position ($p_i$): The best solution the particle has discovered so far.
- Global best position ($g$): The best solution found by any particle in the swarm.

The velocity and position updates in PSO are governed by key equations that balance three fundamental components: inertia, cognitive influence, and social influence. These components enable the algorithm to dynamically explore the solution space while converging toward optimal solutions.

The velocity of a particle at iteration $t + 1$ is updated using the following equation:

$$v_i^{t+1} = w * v_i^t + c_1 * r_1 * (p_i - x_i^t) + c_2 * r_2 * (g - x_i^t) \quad (3.4.1)$$

where:

- $w$ is the inertia weight, controlling the influence of the previous velocity to balance exploration and exploitation.
- $c_1$ *and* $c_2$ are acceleration coefficients that determine the relative importance of the cognitive and social components.
- $r_1$ *and* $r_2$ are random numbers uniformly distributed in [0,1], introducing stochasticity to the search process.
- $p_i$ is the personal best position of the particle, representing the best solution found by the particle so far.
- $g$ is the global best position found by the entire swarm.

After updating the velocity, the new position of the particle is determined by:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (3.4.2)$$

This iterative process allows particles to navigate the solution space dynamically, adjusting their trajectories based on their own experience and the collective knowledge of the swarm. By fine-tuning the parameters $w$, $c_1$and $c_2$, PSO can be adapted to different optimization problems, striking a balance between global exploration and local exploitation.

### 3.4.2 EPSO

EPSO improves the standard PSO by integrating evolutionary mechanisms—mutation, recombination, and selection—to enhance adaptability, maintain diversity, and prevent premature convergence. These mechanisms dynamically adjust the swarm's parameters, enabling better exploration and exploitation of the solution space [5].

**Mutation**: Introduces random perturbations to the parameters of the particles, enhancing exploration:

$$\theta_i^{new} = \theta_i^{new} + Gaussian\ Noise\ (\mu, \sigma) \tag{3.4.3}$$

**Recombination**: Combines parameters from two particles to create new candidate solutions, promoting diversity:

$$\theta_i^{new} = \alpha * \theta_{i1} + (1 - \alpha) * \theta_{i2} \quad \alpha \in [0,1] \tag{3.4.4}$$

**Selection**: Ensures that only the fittest particles are retained by applying mutation to the recombined parameters:

$$\theta_i^{t+1} = \theta_i^t + Mutation(Recombination(\theta_i^t)) \tag{3.4.5}$$

The evolved parameters are then incorporated into the velocity update equation, refining the swarm's movement:

$$v_i^{t+1} = \theta_{w,i} * v_i^t + \theta_{c1,i} * r_1 * (p_i - x_i^t) + \theta_{c2,i} * r_2 * (g - x_i^t) \tag{3.4.6}$$

**Preliminary results**

**Table 13. Metaheuristics comparison between objective function values.**

| | Spring | Summer | Autumn | Winter |
|---|---|---|---|---|
| **MILP [€]** | 292,55 | 291,43 | 294,91 | 297,41 |
| **EPSO [€]** | 293,13 | 298,15 | 297,54 | 299,77 |
| **PSO [€]** | 438,26 | 440,45 | 439,74 | 448,85 |

Preliminary results (Table 13.) on an EnC with four members, and representative days of each season, incorporating the flexibility of EVs and EWHs, highlight key trade-offs between optimization methods. The MILP model remains the best approach, delivering optimal results but at the cost of high computational demands. In contrast, EPSO provides a practical alternative, achieving a balance between accuracy, computational efficiency, and economic feasibility, making it well-suited for real-world EnC applications.

While PSO offers certain heuristic advantages, its performance in this context is hindered by slow convergence and suboptimal results, making it less effective than both MILP and EPSO. These limitations suggest that further refinements to PSO, such as parameter tuning or hybridization with other techniques, may be necessary to improve its applicability.

The PSO's performance could be enhanced, particularly by addressing its slow convergence and suboptimal solutions. Additionally, extending the test duration to encompass multiple seasons or a full year would improve the analysis by capturing seasonal variability and dynamic behaviour, enabling a more comprehensive evaluation of the optimization algorithms' robustness and adaptability in real-world EnC applications.

## 3.5 Planning with flexibility

When planning with flexibility, SITEC will implement 2 stages, as shown in Figure 12. Flexibility provision and baselining are based on the work described in [6] for the operation process, where the baseline corresponds to the optimal behaviour of the EnC without providing flexibility.

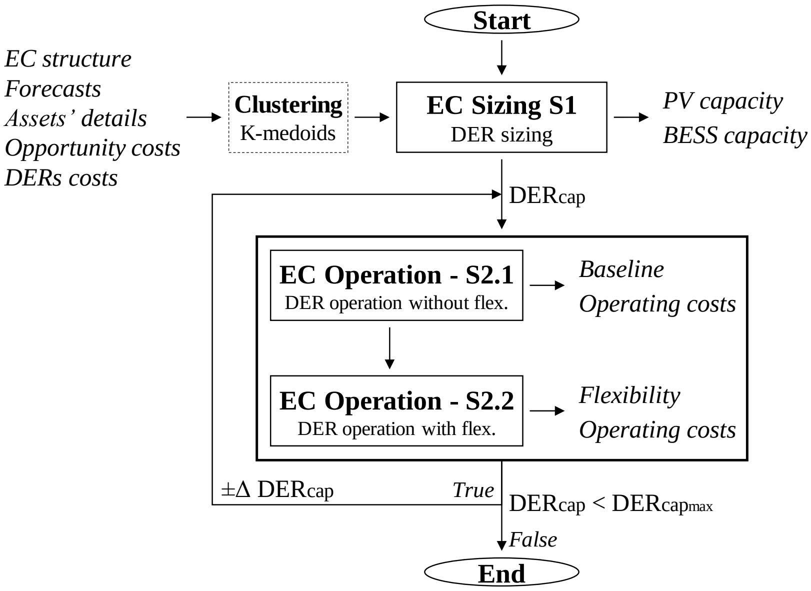


**Figure 12. Planning with flexibility provision.**

As shown in Figure 12, the methodology proposed for EnC planning with flexibility provision relies on two main stages. Stage S1 is used to compute the optimal DER investment without the provision of flexibility. As described in D3.1, these optimal assets are computed based on the EnC business model, past consumption and generation data, existing energy and cross-sector assets (such as electric vehicle or thermal loads), members' opportunity costs, and DERs investment costs.

From these initial PV and BESS capacities, stage S2 is used to assess how to modify these initial values to further minimize the EnC costs by profiting from the provision of flexibility. This approach was selected since sizing DER with flexibility provision involves computing the optimal capacities given a baseline that depends on these optimal capacities. This modifies the initial MILP, leading to a complex possible bilevel problem where both, the size of the assets and the baseline are decisions to be taken simultaneously. The first simplified approach for S2 is using a grid to assess different combinations of size variations from the capacities without flexibility. However, metaheuristic approaches could also be considered.

S2 is then divided into two sub-stages. The first sub-stage S2.1 computes the optimal schedule of the EC flexible assets without flexibility provision, using the capacities from S1, and therefore providing the baseline from which the flexibility to be offered is computed in S2.2. Then, the second sub-stage S2.2 re-schedules the flexible EC's assets considering the expected incomes from providing flexibility. It is assumed that the typical hours where the flexibility is requested, its sense (upwards or downwards) and price are known and given to S2.2 as inputs. Then, the flexibility to be offered is the difference between the EC's net consumption in S2.2 and the baseline obtained in S2.1. In addition, as proposed in [6], in periods where no flexibility is required, the EC is allowed to deviate from the baseline within a predefined tolerance. Figure 14 shows the processes involved in S2. As can be seen, from the capacities without flexibility, new solution candidates are considered when providing flexibility from a grid or with some metaheuristic approach. The assessment of the final cost allows selecting, from the solutions candidate, those that provide the lower energy cost to the EnC.

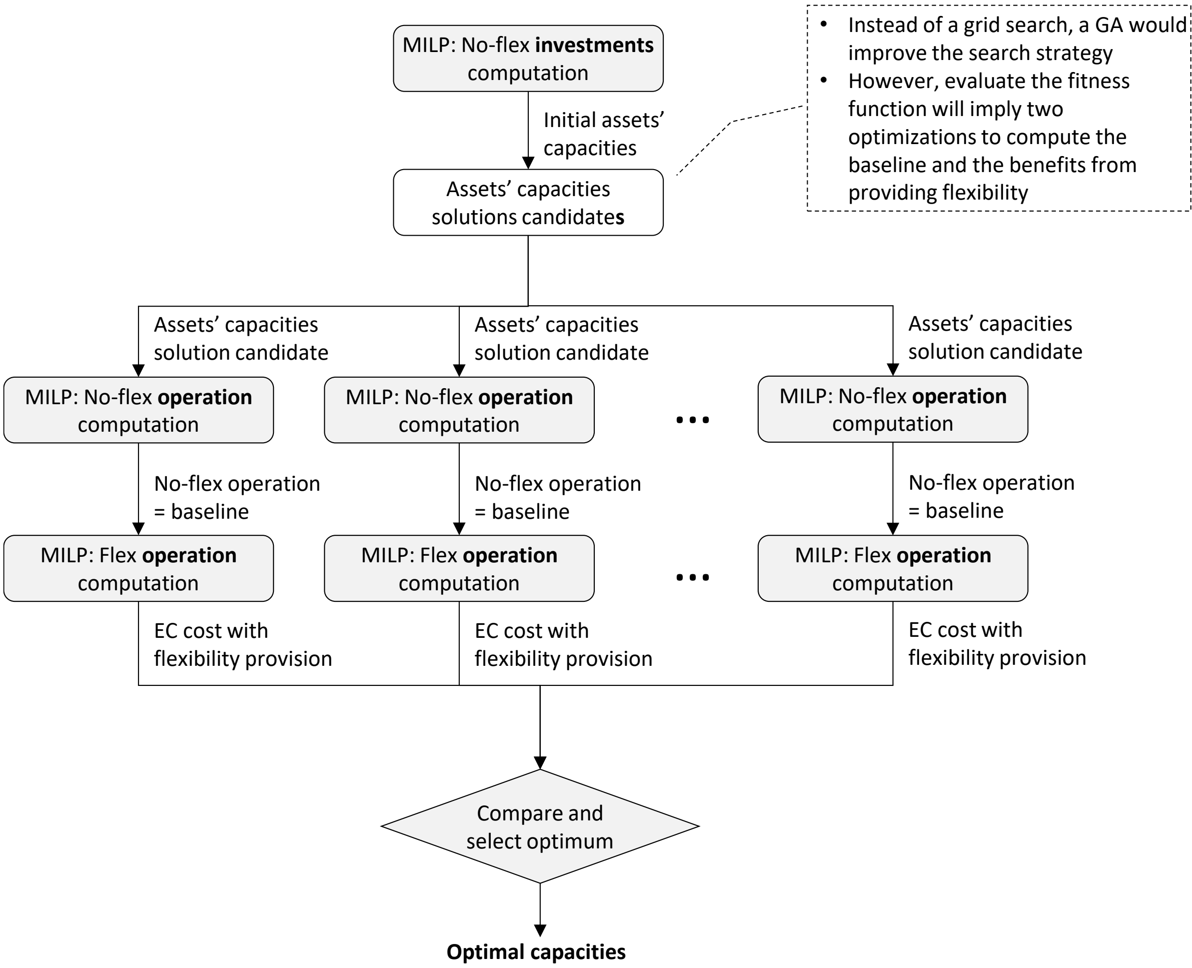


**Figure 13. Stage S2 when planning with flexibility provision.**

## 3.6 API

The API to access the SITEC service is built using FastAPI [7] as the backend framework, with Uvicorn [8] serving as the Asynchronous Server Gateway Interface for handling requests. The API was adapted from another project [9] and still needs further modifications to fully align with this project's requirements. Data validation and serialization are managed by Pydantic [10], ensuring strict type enforcement and structured input handling. Background processing of MILP models is achieved using Python's threading module. Logging is implemented with Loguru [11], providing detailed logs to both the console and files. API documentation is available through Swagger UI [12] at the */docs* endpoint and ReDoc at /redoc.

### 3.6.1 API general architecture

The diagram in Figure 14 illustrates the architecture of SITEC API handling client requests, database interactions, and API documentation. FastAPI serves as the backend, processing requests and interfacing with various components, including clients, external systems, and the database. The database stores and retrieves data as requested by FastAPI, containing meter data and sizing computation results. The client represents end-users that send HTTP requests to the FastAPI server to fetch or submit data.

Swagger provides interactive API documentation, allowing developers to test endpoints directly via a web interface. The data flow begins when a client sends a request to the FastAPI server, which processes it and may interact with the database to retrieve relevant data. The response is forwarded to SITEC to size the resources and compute the EnC set points. Meanwhile, API documentation remains accessible through Swagger to facilitate development and debugging.

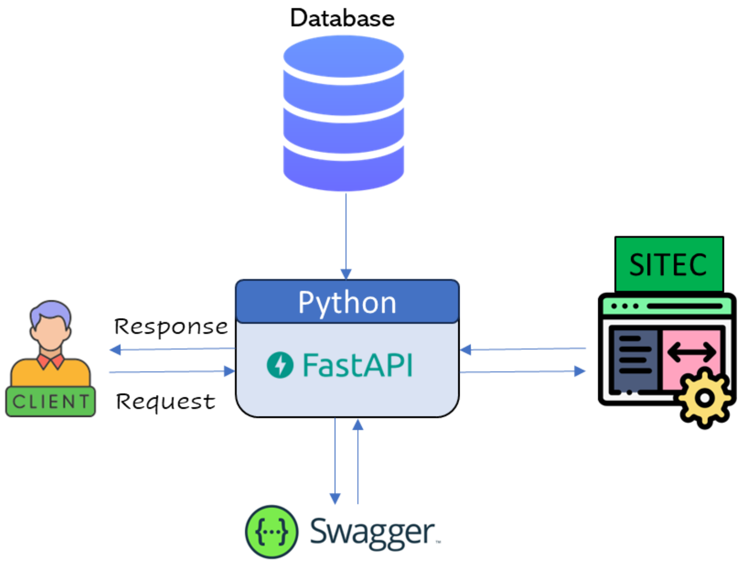


**Figure 14. SITEC API framework.**

### 3.6.2 Endpoints

This API provides a set of endpoints designed to facilitate energy-related operations, including locating meters within a geographical area and performing energy sizing computations.

**Sizing Operations**

- Sizing without shares assets:
  - Initiates an energy sizing computing for selected meter IDs.
  - Stores the request in the database and process it in a background thread.
- Sizing with shares assets:
  - Similar to the previous endpoint but includes a shared meter ID.
  - Ownership percentages must be defined, ensuring the total equals 100%.

**Results retrieval**

- Get sizing results:
  - Returns the results of a sizing computation based on the provided order ID.
  - Handles multiple states: pending, successful, or error (e.g., missing meter data)

## 3.7 Next steps

The next phase will focus on integrating SITEC with the optimization module for thermal networks and heating and cooling assets. Ensuring seamless data integration is essential to meet the requirements of both tools. The key priorities will include:

- **Assess Data Availability and Feasibility:** Evaluate the accessibility of existing data and determine the viability of integrating an additional database containing critical service-related information.
- **Define Data Exchange Process:** Establish clear guidelines for data transfer, specifying formats, protocols, and expected interactions to ensure seamless integration between SITEC and CARTIF.
- **Enhance System Capabilities:** Develop and implement new endpoints with the necessary input parameters to support expanded data requirements and resource integration.

Building on our earlier overview of the SITEC API, the following section describes the database structure that supports these interactions.

# 4 Database structure

This section describes the overall database structure, which is composed of the following data table in Figure 15:

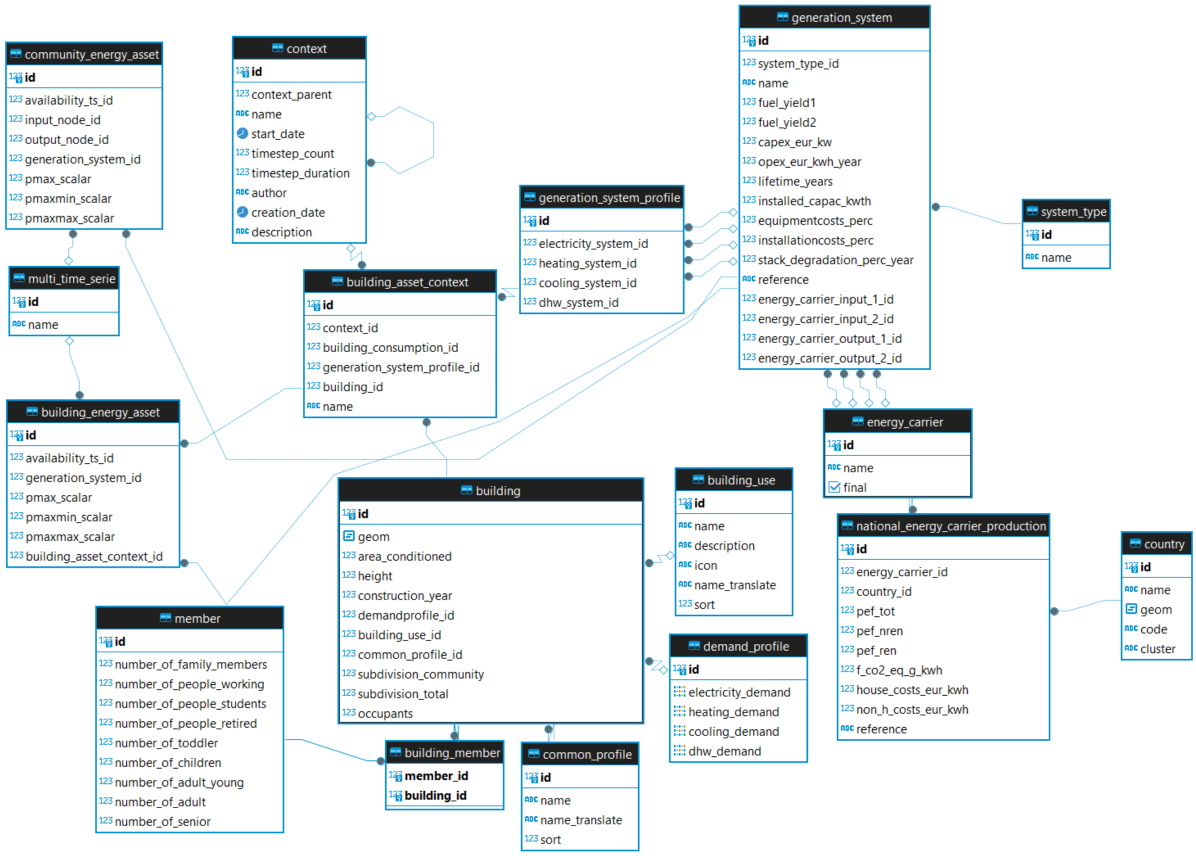


**Figure 15. Database structure.**

- **Context**: Central table connecting many other tables, serving as the main entry point for defining different contexts such as time periods (of the simulation, e.g. 8760h), list of buildings, or list of community energy assets. It has the following fields: context_id, start_date, timestep_count, timestep_duration, and descriptive metadata.
- **Community Energy Asset**: Represents energy assets owned by a community. This table records availability (availability_ts_id), and operational characteristics, such as node (geometry point), and scaling factors for energy generation (the bounds of the optimisation: maximum capacity to be installed pmaxmax, minimum pmaxmin_scalar and the actual install capacity in pmax_scalar).
- **Generation System**: contains detailed information of an energy generation systems. Includes fields for system types (system_type_id), fuel yields (efficiency), capital and operational expenditures (capex, opex), and associated lifetime (lifetime_years). This module is connected to public.energy_carrier for specifying energy input and output types, e.g. electricity (energy carrier 12), or heat (energy carrier 11).
- **Building**: Stores static information about buildings in the energy community. Attributes include building area, height, construction year, and geometry data for spatial representation. Linked to public.demand_profile and public.building_use for characterizing energy consumption and building types.

- **Building Asset Context**: It contains the list of buildings. It is a table connecting many other tables, serving as the main entry point to retrieve information from a building. Defines specific assets within buildings, likely related to energy systems installed in those buildings. Connected to the public.building_energy_asset table that contains data on individual building-level energy generation or storage units to be optimised.
- **Member**: Represents members or participants of the energy community. Contains demographics such as the number of family members, adults, children, and retirees, potentially used for demand estimation.
- **Energy Carrier**: Defines the type of energy carriers, such as electricity, natural gas, or heat. Fields include energy_carrier_id and descriptive labels. It is connected to national energy carrier production, which contains key information to calculate KPIs.
- **National Energy Carrier Production**: Provides data on primary energy factors, greenhouse gas emission factors, and other data dependent on the country. It is connected to energy carrier types and country-specific details (public.country).
- **Demand Profile**: Contains energy demand information for different profiles, including electricity, heating, cooling, and domestic hot water demands. These profiles are assumed when no geometry data is selected.
- **System Type**: Defines the type of systems providing a service, e.g. heating, cooling, domestic hot water (DHW) or electricity systems. Storage is also a type.

FastAPI (Python) is used for communicating data to the SITEC module to calculate further scenarios. All community-related data transfer to the DB is achieved through a REST API. This API allows the client to:

- List the contexts of a given community;
- Retrieve the information of a given context (list of buildings, associated equipment consumption and production load curves);
- Get the results of a simulation of a given context.

This database is highly useful for planning, optimizing, and managing local energy systems within the context of Renewable Energy Communities (RECs). It provides a structured and relational foundation for:

- Simulation of energy scenarios: enables simulations of annual or hourly energy generation, consumption, and storage patterns. For example, simulating 8760 hours to determine how much electricity a community can self-generate versus how much it needs to import from the grid. It also supports the exploration of various renewable energy scenarios using baseline data and user-defined inputs.
- The database was designed to support planning tools for energy optimization, helping to simulate different energy scenarios for buildings and communities (as outlined in LocalRES deliverables such as D2.2 [13], D2.4 [14], and D2.3 [15]).
- Provides detailed building-level data to optimize individual energy systems and aggregate community performance.
- Demand profiles: supports estimation of electricity, heating, cooling, and domestic hot water demand profiles, even when building geometry data is unavailable.
- Member demographics: uses demographic data (e.g., number of family members, children, and retirees) to better estimate residential energy demand patterns.

- Environmental and economic KPIs: facilitates the calculation of key indicators such as energy efficiency, greenhouse gas emissions, and economic performance of different energy systems. Integrates country-specific data for accurate KPI calculations, enabling the comparison of decarbonization scenarios.
- The geometry data allows for the spatial representation of buildings and energy assets, useful for visualizing community layouts and energy flows.
- It is integrated into a web-based planning tool with interactive dashboards for visualizing and managing energy system performance.
- The results are presently presented at the community level, where the demand from community users is aggregated and addressed collectively using community assets. Future enhancements to the tool will explore the possibility of visualizing results at the building level; however, the data will continue to be processed in the same manner. KPIs could be assessed at the building level and subsequently but at this step they are aggregated for community-level presentation. Presenting the results as a community aggregate is more beneficial as it provides a clearer overview of energy consumption patterns and optimization opportunities across the entire community, rather than focusing on individual buildings. This approach enables more efficient and effective planning, resource allocation, and system management, ensuring a holistic and scalable energy strategy.

# 5 Preliminary definition of the user interface view

The ENPOWER tool will have two views: the citizen and stakeholder views.

Regarding the citizen view, the ENPOWER interactive tool is designed to empower citizens within energy communities by providing an intuitive, user-friendly digital interface that supports informed decision-making regarding their local energy systems. This tool simplifies the process of understanding and engaging with energy community planning while fostering awareness of best practices for energy production, consumption and efficiency.

The tool offers an accessible interface for scenario planning that presents relevant data, visualizations and participative actions which allow citizens to shape their community's energy future.

Main considerations for the citizen view may include making use of user experience best practices such as consistency, hierarchy and usability.

## 5.1 Usability

- **Complex data, simplified interface**: The tool translates data-driven models into easy-to-understand visuals, actions and path-flows, ensuring that non-experts can explore different energy scenarios without feeling overwhelmed. Graphs, charts, interactive elements and one-action screens guide users naturally toward insights.
- **Clear design elements**: To improve readability and clarity, the interface uses contrasting colours, appropriate font sizes, and distinct visual cues. A consistent colour scheme and iconography help users quickly grasp important information.
- **User centric design**: The tool follows a UX-led process, making energy community planning both straightforward and insightful for citizens.
- **Language**: The tool supports most spoken languages in ENPOWER's demo countries. Additionally, it uses clear and accessible terminology, even for technical concepts, to ensure understanding among all users.
- **Responsive layout**: The interface adapts to various devices (e.g., smartphones, tablets, desktops) so that citizens can engage with the tool anytime, anywhere, ensuring inclusivity and broad participation.

## 5.2 Consistency

### 5.2.1 Style guide

To maintain a consistent and scalable design system, a structured approach to style guides and design tokens has been implemented. These elements ensure uniformity across all visual components and streamline collaboration between designers and developers.

### Colour styling

The colour palette blends cool blues and teals with vibrant pinks and magentas, reflecting ENPOWER's visual identity. Buttons, input fields, and containers follow a standardized system of shapes and sizes, with rounded corners creating a welcoming and user-friendly interface. The consistent sizing of buttons, icons, and typography ensures a well-balanced layout, with larger elements signifying primary actions and smaller elements for secondary interactions.

By integrating these structured style guides and tokens, the ENPOWER design system remains scalable, cohesive, and efficient, reinforcing a seamless user experience.


**Figure 16. ENPOWER brand palette.**

### Token categories

The Figma plugin **Token Studio**[1] has been used to centralize and manage design tokens efficiently as shown in Figure 18 and Figure 18. This approach allows for seamless updates across the entire system, reducing errors and improving cross-platform consistency. By defining tokens for colours, typography, spacing, and components, the tool ensures that changes are automatically propagated throughout the interface, supporting a modular and maintainable design.

The ENPOWER design system is structured into six key token categories:

- **Core tokens**: Define fundamental design values such as spacing, typography, and grid systems, forming the foundation of the design system.
- **Semantic tokens**: Assign meaning to design elements (e.g., "primary" or "alert" instead of specific colours) to allow for flexible global updates.
- **Style tokens**: Cover general visual properties like shadows, borders, and font sizes to maintain aesthetic consistency.
- **Component tokens**: Control the styling of reusable UI elements such as buttons, cards, and input fields, ensuring uniformity across the tool.
- **Brand tokens**: Manage design elements representing ENPOWER's identity, including colours, fonts, and logos, while allowing flexibility for branding adjustments.
- **Language tokens**: Accommodate different language-specific elements, such as typography choices and spacing variations to support multilingual requirements.

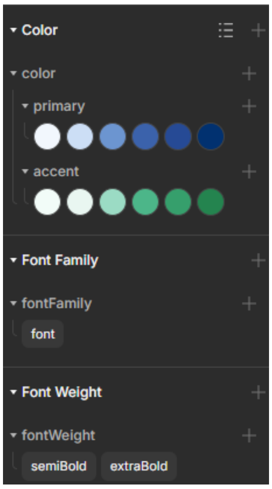


**Figure 17. Token Studio screenshot (Figma plugin).**

[1] Figma plugin Token Studio. https://www.figma.com/community/plugin/843461159747178978/tokens-studio-for-figma


**Figure 18. Example of a complete token set for a surface colour (application on a button).**

## Typography

The tool adopts **Roboto**, a modern and legible font, ensuring readability across different screen sizes. A clear **typographic hierarchy** is maintained through standardized font sizes, weights, and colours for headings, subheadings, body text, and labels.

## Illustrations and icons

**Figure 19. Example set of EXPOWER illustrations library.**

Custom illustrations making use of the ENPOWER's style consistently convey concepts like planning, community collaboration or building types. This helps users develop a visual reference for core features and actions within the tool.

The ENPOWER tool features a consistent iconography system to enhance usability and visual clarity. Standard icons represent common actions such as settings, navigation, and notifications, ensuring users can quickly recognize key functions.

To reflect the platform's focus on energy communities, a set of custom energy-related icons was developed, illustrating concepts like solar panels, wind turbines, battery storage, and energy consumption. Designed with uniform stroke weight, size, and colour treatments, these icons (Figure 20) integrate seamlessly with the general UI while maintaining distinctiveness for energy-specific content. This consistency minimizes confusion and reinforces the tool's thematic identity.

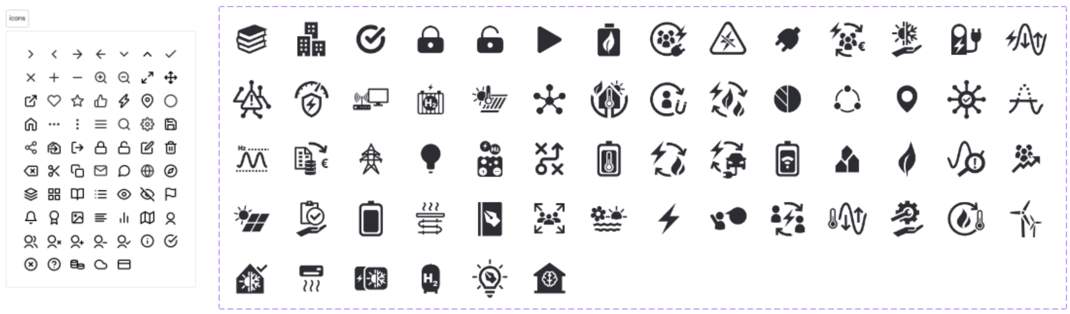

**Figure 20. Example set of EXPOWER icons library.**

### 5.2.2 Design system

To ensure functional consistency the tool follows a unified design. Built in Figma, the system defines reusable components like buttons, forms, and navigation elements, maintaining a cohesive user experience, shown in Figure 21.

To bridge design and development, the system was translated into CSS and HTML classes, ensuring a seamless transition from concept to implementation. By maintaining consistency, the tool enhances usability and reduces cognitive load, making interactions more intuitive.

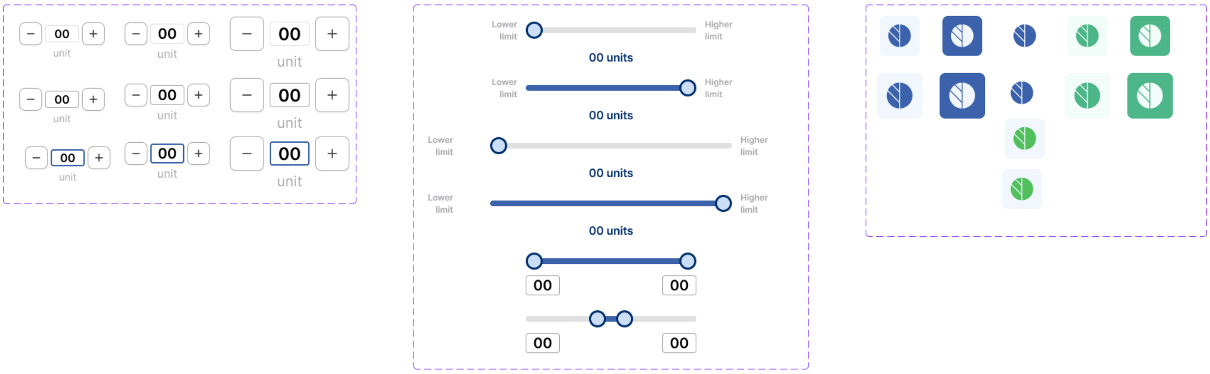


**Figure 21. Example set of EXPOWER functional components.**

## 5.3 User pathflow

A well-defined structure guides citizens through the tool's main areas, helping them quickly find and use features relevant to their energy community participation.

### 5.3.1 Create a community

Users initiate the creation of a new energy community, defining its main characteristics as the location, number of buildings and resident profiles. This data allows the tool to calculate energy-related KPIs, which will give valuable insights for community planning and improvement. The interface presents clear steps and guidelines, from initial setup to alternative planning.

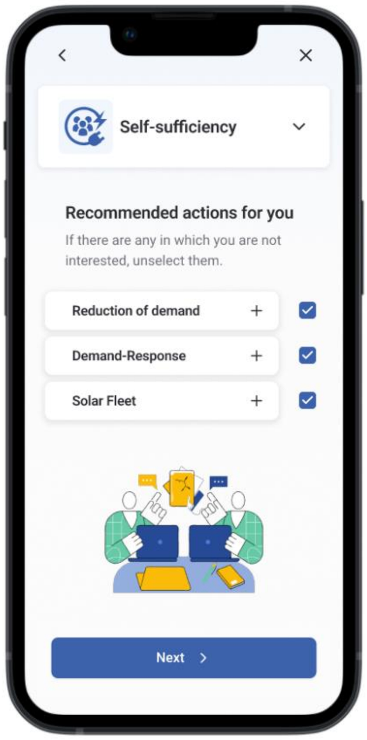


**Figure 22. Screen for selecting the goal for a scenario.**

### 5.3.2 Find a community

For individuals interested in exploring or joining existing energy communities, the tool provides a search function.

### 5.3.3 Academy

The Academy section provides educational resources on energy communities and related topics, including a glossary, articles, and materials from the ENPOWER project.

It features relevant documents from both ENPOWER and other initiatives to help users understand energy data and the benefits of participating in an energy community. Additionally, step-by-step tutorials and user guides on the platform will be available, including in the Value Chain/Stakeholder View.

A Frequently Asked Questions (FAQ) section will address key topics related to the ENPOWER project, its decision support tool, and general energy concepts, ensuring users have easy access to essential information.

### 5.3.4 Experts’ repository

A database of experts, consultants, and relevant stakeholders enables users to connect with energy professionals, allowing users to get support when needed and fostering business opportunities.

## 6 Proof of concept – Fornes, Granada

As a proof of concept, one of ENPOWER's pilot sites has been used as an example in the current version of the tool, the village of Fornes, located in Granada, Spain.

First, the desired location is identified on the map. This can be done by manually navigating the map or by entering an address or location into the search bar, as depicted in the Figure 23 below.

Next, a selection process helps determine the most common building type and profile in the area. To improve accuracy, an option can be chosen to specify details for each building individually. In that case, buildings are selected on the map, one at a time. Additional details can be provided, such as building type (e.g., multi-family, single-family, public), year of construction, and demographic information about the occupants (e.g., students, adults).

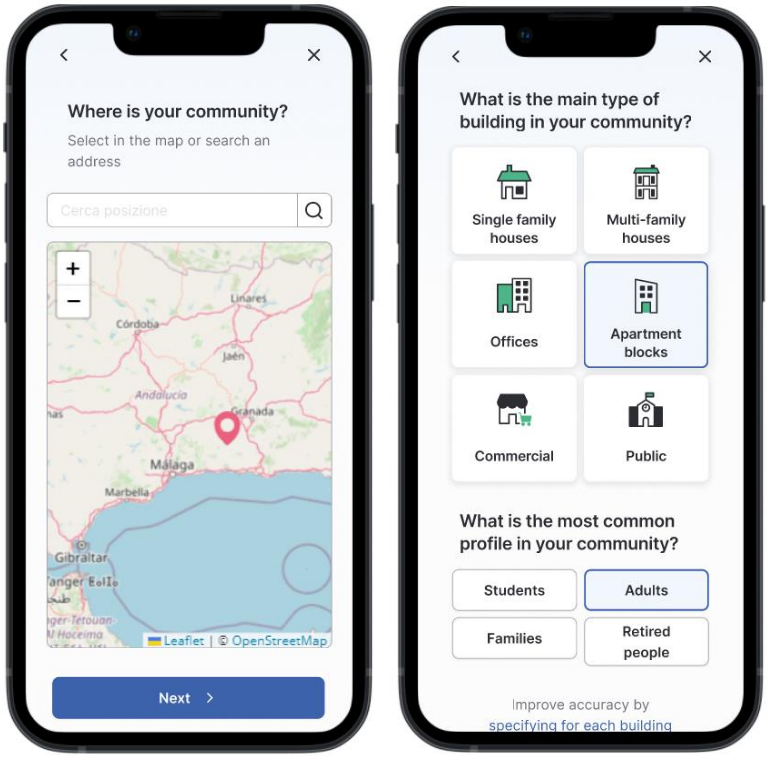


**Figure 23. Creation of an energy community.**

The initial community context has no building energy assets, and the systems are the average ones from the country (e.g., for Spain, gas boilers and electricity are provided by the grid). All the energy demand is imported from the national grid and heating and domestic hot water are provided with gas.

We aim to shift from a baseline with no renewable energy assets to a scenario focused on increasing renewable energy penetration. For the scenario, when selecting the goal (e.g., increasing renewables), recommendations are provided (e.g., installing a solar fleet). When the user selects the option of "solar fleet" to be studied in detail, the backend modifies the data model to:

- Add one photovoltaic system per household. The maximum area of the roof is obtained from the geometry, and a factor of 60% is applied to estimate the useful area in $m^2$. The useful area is then transformed to kWp to be installed. That's the maximum power of the photovoltaic system. The actual capacity installed is an output of the optimisation as *pmax_scalar*;

- Information from the PV system is also retrieved from the database, including data such as CAPEX, OPEX, and the electricity cost of Spain.

The data model is automatically transformed into an OEMOF model. For example:

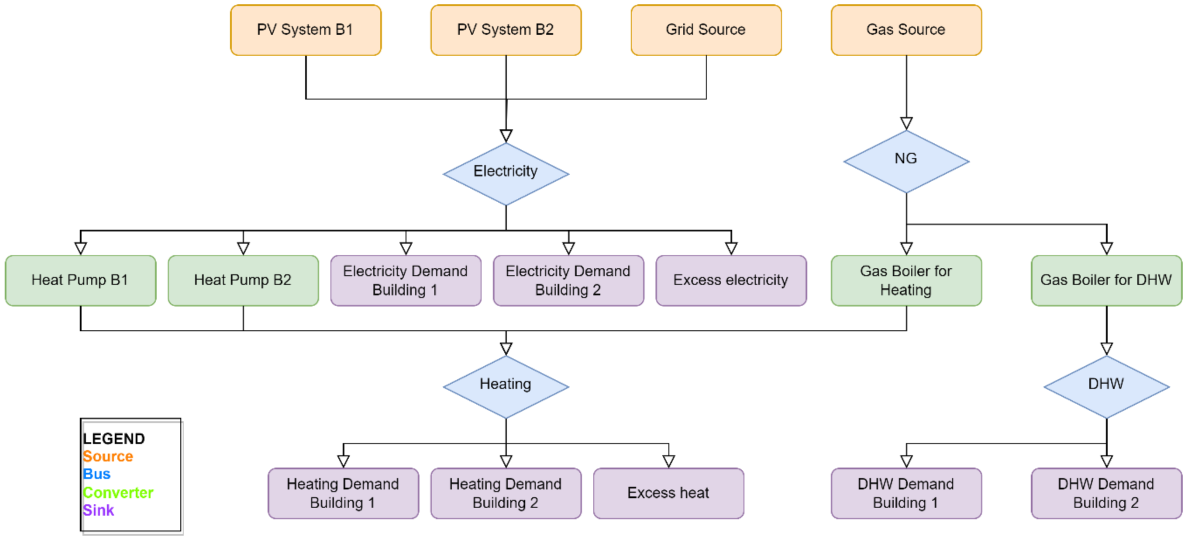


**Figure 24. Example of OEMOF model (automatically generated from the context data).**

The optimisation is run and the optimal capacity to be installed of the PV system is obtained. For now, the backend is able to solve this process for the following systems:

- Wind turbine. The maximum capacity of the system is set at 1MW for the whole community. The community energy asset is located in the centroid as proof of concept of the savings they could obtain. It does not mean they need to install it in that location, but it gives an estimation. The proper location will need to be found in a detailed engineering analysis in the next steps (not overseen in the project).
- Solar thermal panels. Similar to the PV system, the maximum solar thermal yield is estimated. Then, the system is added to OEMOF and optimised.

Heat pumps: for heat pumps, a special model is from oemof.thermal, considering an hourly COP value that depends on the source. For now, only air is considered, but in further steps, geothermal could be added.

After transforming the data into an OEMOF model, the backend runs an optimization to determine the ideal capacities for these systems to minimize costs and maximize renewable energy penetration.

The baseline scenario is characterized by 10.2 MWh/year from the grid and 64.7 MWh/year from gas, resulting in a total energy consumption of 74.9 MWh/year. The following Sankey diagram Figure 25 illustrates the energy flows in the baseline scenario:

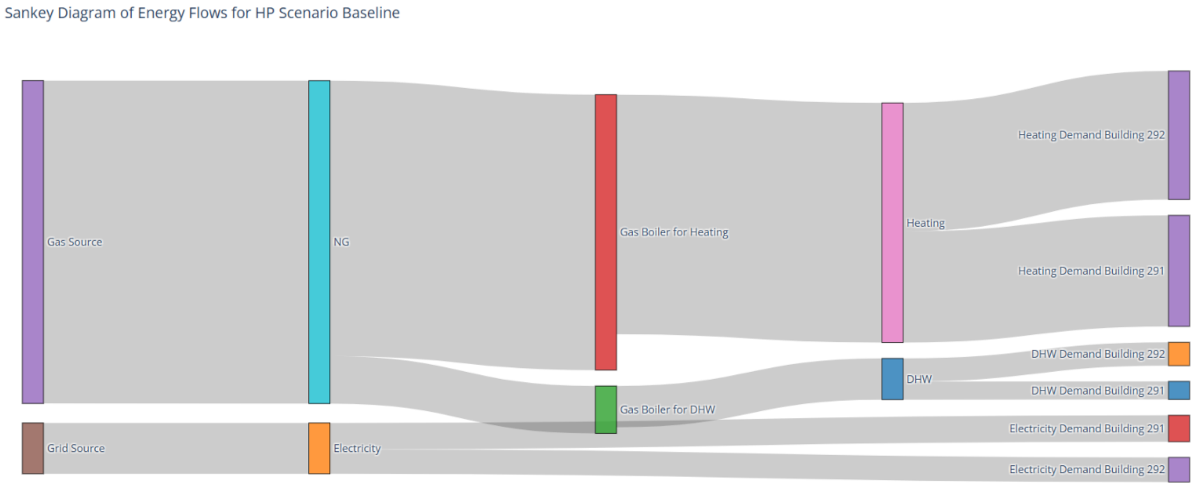


**Figure 25. Sankey Diagram of Energy Flows in the Baseline Scenario.**

With an optimal investment in heat pumps (HP), the selected capacities are:

- Heat Pump for Building 291: 2.79 kW
- Heat Pump for Building 292: 0.33 kW

In this optimized scenario, the energy flows change to 17.5 MWh/year from the grid and 44 MWh/year from gas, reducing total energy consumption to 61.5 MWh/year. This optimization achieves a reduction of 13.4 MWh/year (approximately 18%), while also shifting a greater share of energy consumption from gas to electricity. The following Sankey diagram Figure 26 represents the updated energy flows in the optimized scenario:

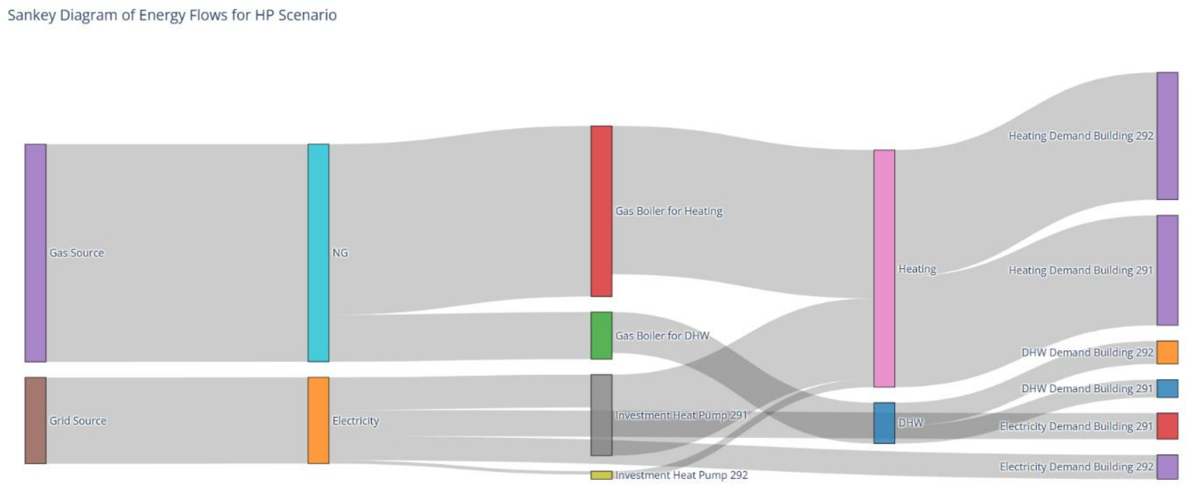


**Figure 26. Sankey Diagram of Energy Flows in the HP Scenario.**

To further enhance renewable energy integration, photovoltaic (PV) generation is introduced alongside heat pumps. In this new optimized scenario, energy flows shift to 12 MWh/year from the grid and 40.6 MWh/year from gas, while PV generation contributes 13.14 MWh/year, reducing the total purchased energy to 52.6 MWh/year. This optimization decreases the paid energy by 8.9 MWh/year (approximately 14.5%).

Beyond reducing reliance on gas, this scenario also significantly decreases electricity demand from the grid, as the PV system generates additional electricity to support both heating and other electricity needs.

With the new optimal investment in heat pumps and PV systems, the updated capacities are:

- PV System Capacity for Building 291: 1.78 kW;
- PV System Capacity for Building 292: 5.00 kW;
- Heat Pump Capacity for Building 291: 0.68 kW;
- Heat Pump Capacity for Building 292: 3.04 kW.

The following Sankey diagram Figure 27 illustrates the energy flows in this fully optimized scenario. Other calculated results include heating demand, representing the energy needs of each building Figure 28, as well as electricity demand per building before the integration of the heat pump Figure 29. Additionally, the results cover optimized heat pump energy Figure 30, which represents the energy delivered to meet heating needs, and optimized PV energy Figure 31, referring to the photovoltaic energy supplied to cover the building's energy requirements.

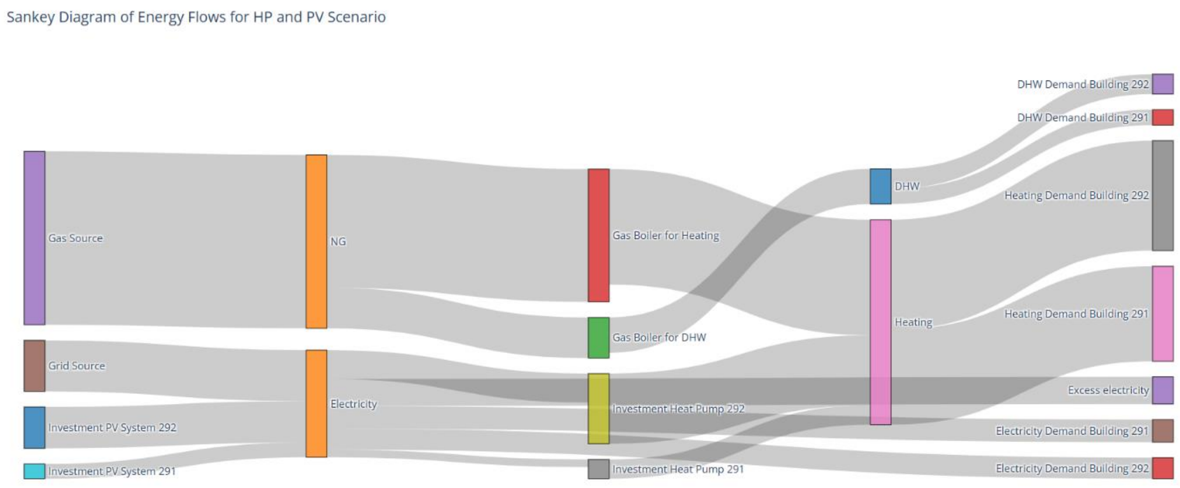


**Figure 27. Sankey Diagram of Energy Flows in the HP and PV Scenario.**

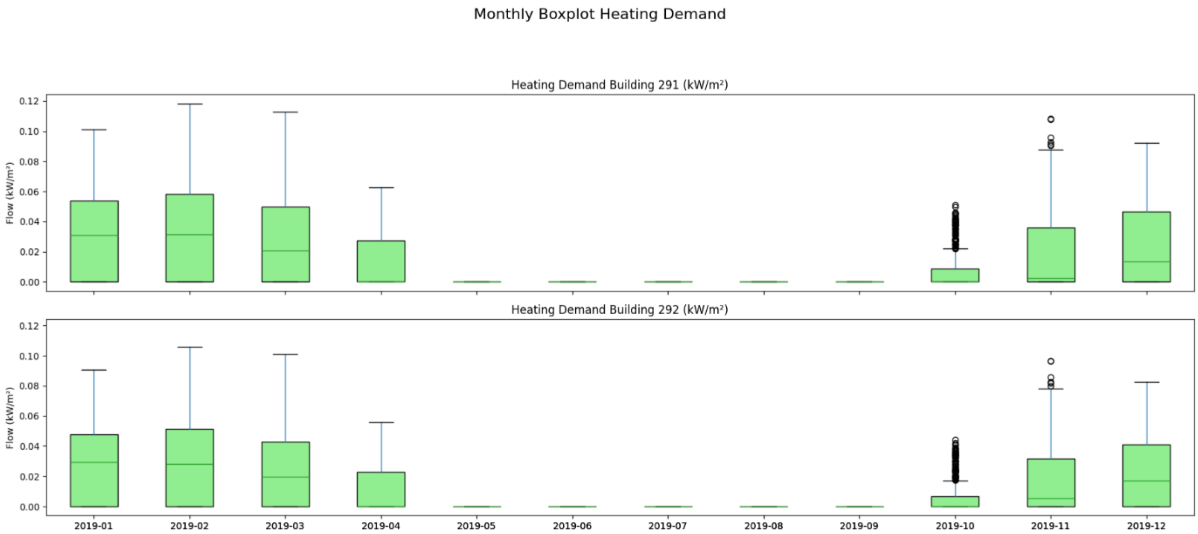


**Figure 28. Heating demand (energy needs) per building.**

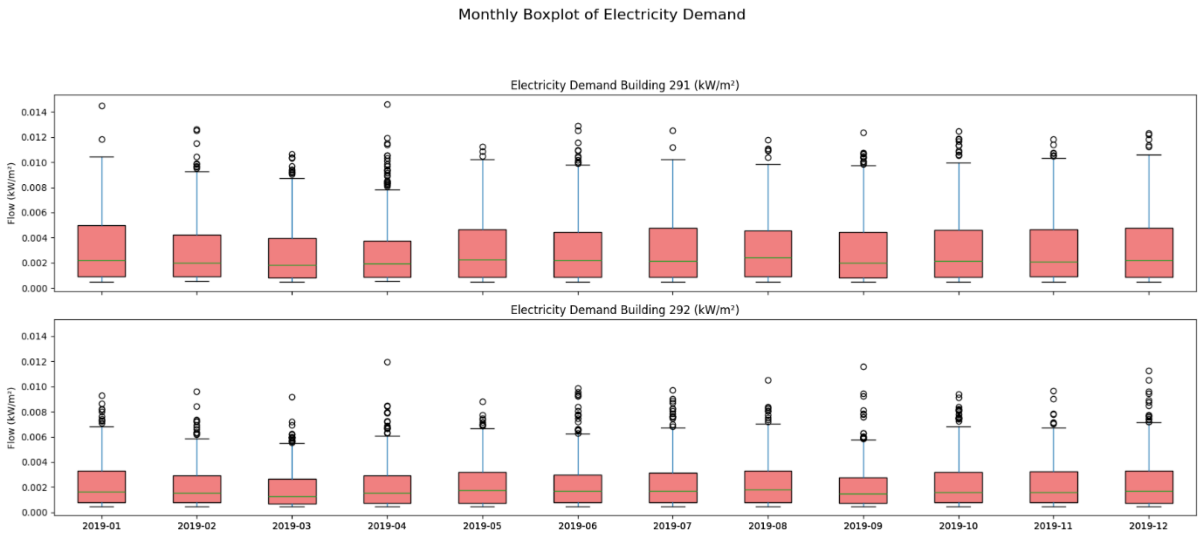


**Figure 29. Electricity demand per building (before heat pump).**

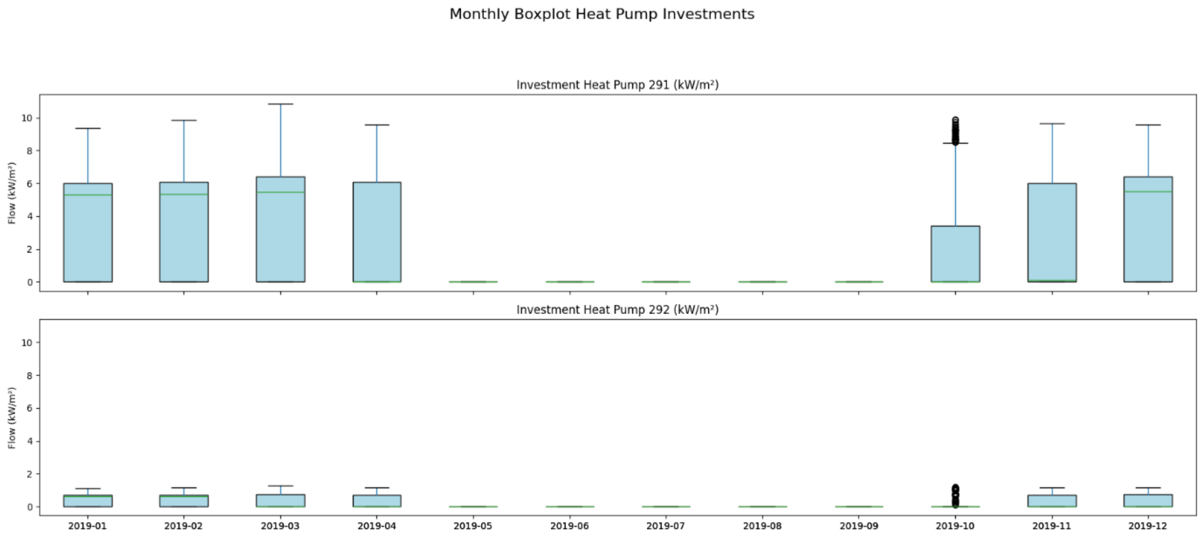


**Figure 30. Optimized Heat Pump energy delivered to supply needs per building.**

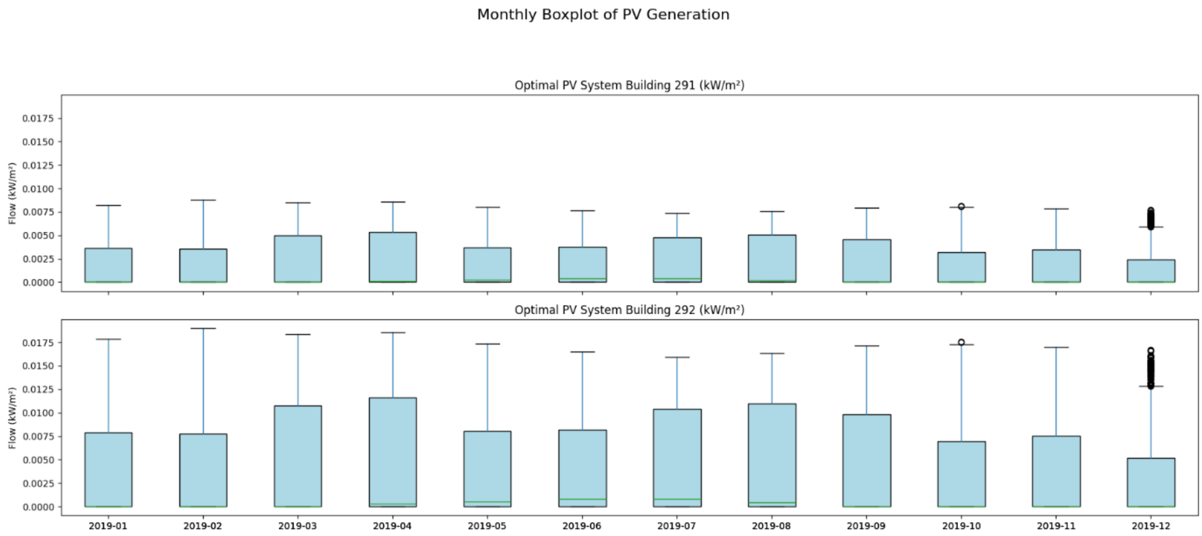


**Figure 31. Optimized PV energy delivered to supply needs per building.**

Next, Key Performance Indicators (KPIs) defined in D3.1 [1] are calculated for both baseline (pre-optimization) and optimized (post-optimization) scenarios. For example, metrics such as energy consumption, $CO_{2eq}$ emissions, and cost savings are generated before and after optimization to provide a clear comparison of performance improvements:

- Peak demand;
- Capacity to be installed (pmax_scalar);
- Primary energy consumption;
- $CO_{2eq}$ emissions;
- Costs and costs savings;
- Investments costs;
- Equivalent energy in the number of trees saved and pizzas that could be cooked in an oven thanks to the energy saved, etc.

This information is sent via API to the front-end to show it to the user.

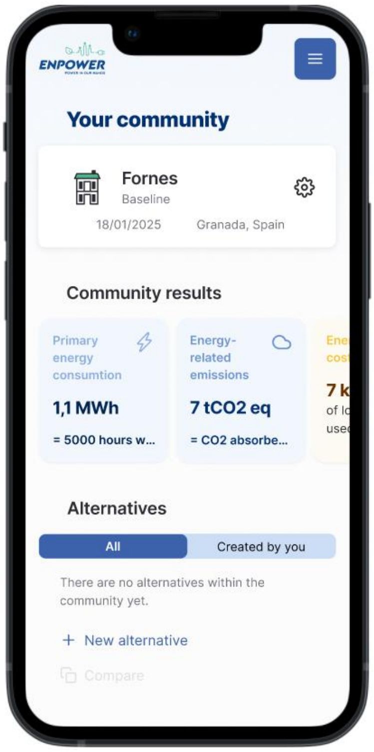


**Figure 32. Community results.**

By following this process, the community can evaluate moving from a baseline with gas and grid consumption to a more self-sufficient energy system powered by renewable energy. Each system is optimized to ensure maximum savings for the overall system. As can be seen on the Figure 32.

# 7 Conclusions and next steps

The ENPOWER project successfully integrates Social Sciences and Humanities (SSH) methodologies with advanced ICT technologies to empower energy citizens and optimize energy communities. Through the development of interactive tools, data-driven services, and innovative business models, ENPOWER facilitates the transition towards decentralized, consumer-driven energy markets.

The project has led to the creation of an interactive Planning Tool that supports energy community design and decision-making. By implementing AI-based consumer clustering and segmentation, energy efficiency and market participation have been enhanced. Optimization algorithms using Mixed-Integer Linear Programming (MILP) and metaheuristics have improved energy asset sizing and cost efficiency, further strengthening the tool's decision-support capabilities.

A user-friendly interface has been designed to cater to both citizens and stakeholders, ensuring accessibility and engagement in energy planning. The validation of these tools through a proof-of-concept case study in Granada has demonstrated tangible benefits, including renewable energy integration, cost reduction, and emissions savings.

Through these innovations, ENPOWER has laid the foundation for a consumer-centric energy ecosystem that enhances energy security, promotes sustainability, and fosters active participation from communities. The project's methodologies and tools have the potential to redefine the way energy communities operate, providing a scalable and replicable framework that can be adapted across diverse regions and regulatory landscapes.

The next phase will focus on integrating SITEC with the optimization module for thermal networks, ensuring seamless data exchange. Key priorities include refining CARTIF's databases, enhancing system capabilities, and implementing new features in the tool's modules. Additionally, scenario simulation and analysis will be expanded, user engagement will be supported through dedicated workshops, and the UI will be developed to ensure accessibility for both non-technical users and energy professionals, enabling reliable and effective decision-making.

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