eneuron

optimising local energy communities

Development of the methodology for optimal design and operation of an energy hub within energy communities of energy islands

WP4, Deliverable 4.2

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Technical References

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[1] PU = Public
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Summary

This report is the second of three deliverables on the topic of "Analysis, design and operation optimization of the local energy systems: emergence of energy hubs" under WP4 in the Horizon 2020 project eNeuron.

Following the completion of the previous deliverable [1] with the "Identification and analysis of the multi-objective problem and the innovative approach of Energy Hub", this report presents the general methodology approach for optimal design and operation of an Energy Hub.

The first part of this report presents the eNeuron toolbox concept diagram with a detailed description of the different phases in the *Energy Hub* (EH) and *micro–Energy Hub* (mEH) levels. The second part of the report provides the definition of long-term optimisation objectives based on use cases developed under Task 3.3, "Use Cases and Innovative Business models for the eNeuron pilots". The third part of this report provides a description of the activities undertaken by project Task Forces. The first stage of the Task Force activities involved the determination of required inputs from Integrated Local Energy Communities (ILECs) and various energy carriers and the definition of short-term optimization inputs and objectives. The second stage involved the development of long-term optimization problems considering inputs and objectives and analysis of short-term optimization problems. The final part of the report presents an overview of work carried out on the formulation of a feedback loop between the long and short-term optimisation problems to complete the overall methodology development.

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Abbreviations and acronyms

Acronym	Meaning	Acronym	Meaning
AC	Air Conditioning	**FC**	Fuel Cell
ACK	Acknowledgement Code	**G2V**	Grid-to-Vehicle
AChil	Absorption Chiller	**gRPC**	Google Remote Procedure Call
AI	Artificial Intelligence	**H2020**	Horizon 2020
API	Application Programming Interface	**H2SS**	Hydrogen Storage System
BESS	Battery Energy Storage System	**HHS**	House Heating System
CAPEX	Capital Expenditure	**HP**	Heat Pump
CCGT	Combined-Cycle Gas Turbine	**ICE**	Internal Combustion Engine
CCHP	Combined-Cycle Heat and Power plant	**I.E.**	Information Exchanged
CHP	Combined Heat and Power plant	**ILEC**	Integrated Local Energy Community
CHP FC	Combined Heat and Power with a Fuel Cell as prime mover	**LTO**	Long-Term Optimisation
CHP NG ICE	Combined Heat and Power with an Internal Combustion engine as prime mover	**mCHP**	Micro-Combined Heat and Power
CHP NG MTG	Combined Heat and Power with a Micro Gas Turbine as prime mover	**mEH**	Micro Energy Hub
CI	Carbon Intensity	**MILP**	Mixed-Integer Linear Programming
CO_2	Carbon Dioxide	**MQTT**	Message Queuing Telemetry Transport
CRF	Capital Recovery Factor	**MTG**	Micro-Turbine Generator
DA	Day-Ahead	**NFCD**	Non-Flexible Cooling Demand
DAM	Day-Ahead Market	**NFEL**	Non-Flexible Electric Load
DB	Database	**NFH2D**	Non-Flexible Hydrogen Demand
DEOS	Deepgrid Embedded OS	**NFHL**	Non-Flexible Heating Load
DER	Distributed Energy Resource	**NFNGD**	Non-Flexible Natural Gas Demand
DHN	District Heating Network	**NFNGL**	Non-Flexible Natural Gas Load
DSO	Distribution System Operator	**NG**	Natural Gas
DTO	Data Transfer Object	**NGB**	Natural Gas Boiler
EH	Energy Hub	**NPV**	Net Present Value
eNeuron	greEN Energy hUbs for local integRated energy cOmmunities optimizatioN	**O&M**	Operation and Maintenance
EV	Electric Vehicle	**OPEX**	Operational Expenditure
EZ	Electrolyser	**P2P**	Peer-to-Peer

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PEV	Plug-in Electric Vehicle	**TF**	Task Force
PV	Photovoltaic	**THD(I)**	Total Harmonic Distortion Current
PWM	Pulse Width Modulation	**THD(V)**	Total Harmonic Distortion Voltage
PyMCDM	Python Multi-criteria Decision Making	**TOPSIS**	Technique for the Order of Prioritisation by Similarity to Ideal Solution
RES	Renewable Energy Sources	**TRL**	Technology Readiness Level
REST API	Representational State Transfer Application Programming Interface	**TSEL**	Time-Shiftable Electric Load
RMS	Root Mean Square	**TSS**	Thermal Storage System
SOC	State Of Charge	**V2G**	Vehicle-to-Grid
ST	Solar Thermal	**WE**	Water Electrolyzer
STO	Short-Term Optimisation	**WP4**	Work Package 4
T3.3	Task 3.3	**WT**	Wind Turbine
TES	Thermal Energy Storage		

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1 Introduction

This report is the second in a series of three deliverables on the topic of "Identification of the analysis, design and operation optimization of the local energy systems: emergence of energy hubs" in WP4 of the Horizon 2020 project eNeuron. The main objectives of this activity are:

- To build the eNeuron toolbox concept diagram. The toolbox consists of a set of integrated tools aiming at the optimal design and operation planning of integrated local energy communities (ILECs)
- To define the long-term optimization objectives based on use cases from T3.3 and then determine the required inputs from ILEC and various energy carriers and definition of short-term optimization inputs and objective(s)
- To develop long-term optimization problems considering inputs together with objectives and develop short-term optimization problems. The main goal of the long-term optimization problems is the optimal design of the ILEC, whereas the main goal of the short-term optimization problems is the optimal day-ahead and real-time of the ILEC.

1.1 eNeuron in a nutshell

The main goal of the eNeuron (greEN Energy hUbs for local integRated energy cOmmunities optimizatioN) project is to develop innovative tools for the optimal design and operation of ILECs, integrating distributed energy resources (DERs) and multiple energy carriers at different scales. This goal will be achieved by considering all the potential benefits realisable for the different actors involved and by promoting the Energy Hub (EH) and micro-Energy hub (mEH) paradigms as a conceptual model for controlling and managing multi-carrier and integrated energy systems in order to optimize their architecture and operation. To ensure both the short-term and the long-term sustainability of this new energy concept and support effective implementation and deployment, economic and environmental aspects will be considered in the optimisation tools through a multi-objective approach. eNeuron's proposed tools enable tangible sustainability and energy security benefits for all the stakeholders in the ILEC. Local prosumers (e.g., households, commercial, and industrial actors) will benefit through the reduction of energy costs while leveraging local, low-carbon energy. Developers and solution providers will find new opportunities for technologies as part of an integrated, replicable operational business model. Distribution System Operators (DSOs) benefit from avoiding grid congestion and deferring electrical network investments. Policymakers benefit from increasingly sustainable and reliable energy supply systems. eNeuron is a high Technology Readiness Level (TRL) project in line with the Work Program (Call: H2020-LC-SC3-2018-2019-2020 (building a low-carbon, climate-resilient future: secure, clean and efficient energy)) by developing innovative approaches and methodologies to optimally plan and operate ILECs through the optimal selection and use of multiple energy carriers and by considering both short- and long-run priorities. By optimally coordinating all energy carriers, cost-effective and low-carbon solutions

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will be provided to foster the deployment and implementation of this new energy paradigm at the European level.

1.2 Structure of the document

The remainder of this deliverable report is structured as follows:

- **Section 2** presents the eNeuron toolbox concept diagram with a detailed description of the EH and mEH levels and market and operative phases involved (planning, operational analysis, and real-time operation phases).
- **Section 3** presents the definition of long-term optimization objectives based on use cases developed in Task 3.3.
- **Section 4** outlines the task force (TF) activities. Firstly, the determination of the required inputs from ILEC and various energy carriers and the definition of short-term optimisation inputs and objectives were provided for the four TFs (TF1 System Design, TF2 Day-Ahead Operation Scheduling, TF3 Peer-to-Peer Market Design and TF4 Real-time Operation Design). Secondly, the development of the long-term optimisation problem considering inputs and objectives and the analysis of the short-term optimisation problem is outlined through a detailed description and formulation of the problems.
- **Section 5** presents the formulation of a feedback loop between long and short-term optimisation problems to complete overall methodology development.
- Conclusions for the deliverable are presented in **Section 6**.

2 eNeuron toolbox concept diagram

The eNeuron project aims to provide smart and optimal solutions for integrated local energy communities (ILECs) with long-term planning and short-term operational purposes. The solutions will be provided at the Energy community level (energy hub (EH) level) but also at the peers' level (micro-energy hub (mEH) level) to ensure that the levels can seamlessly collaborate with each other. Figure 1 provides the general concept diagram of the eNeuron toolbox architecture. The two levels of operation, EH and mEH, are supported by tools and functionalities that constitute the eNeuron toolbox.

The eNeuron project proposes the EH as the main architectural and operational solution for coupling multiple energy carriers while mEHs represent the prosumers (industrial, commercial or residential) within the community. Each mEH represents a multi-carrier energy system consisting of multi-energy generation, conversion and storage technologies to satisfy its own energy needs. The EH promotes local balancing as well as strategic exchanges with electrical external grids through coordination of exchange. In this way, the EH will always have interactions with larger systems, sustaining access to the largest pool of external resources, while leaving open the possibility of local resource optimization. The connection to the larger system allows for residual demand requirements to be met, excess energy to be sold, the procurement of energy shortfalls, and/or providing system services to the grid. In addition, the mEHs cooperate by coordinating and sharing with all energy carriers, with the aim of satisfying the energy needs of the entire ILEC.

The toolbox considers different time horizons from long-term planning to real-time operation. Moreover, it operates on two hierarchical levels, namely the EH and mEH levels. At the EH layer, the optimal design and day-ahead scheduling is performed, whereas at the mEH layer, the real-time operation optimization is carried out. The two layers complement each other with the mEHs interacting with the upper layer through day-ahead optimal scheduling while dealing with the real-time operation optimization. mEH operation is realized through a peer-to-peer (P2P) market established so that they can implement the day-ahead optimal scheduling through considerate decisions.

At the higher EH level, different tools contribute to two main processes: the planning phase, shown in blue in Figure 1, and the operational analysis phase, indicated in red. In the planning phase, the time series data is first processed under the "Data Processing" function (the function is the block in the eNeuron toolbox concept diagram) to meet the requirements of the "Optimization of System Design" block, where the optimal planning phase of the EH level takes place. The output from the planning phase is going to affect and be potentially affected by the "Operational Analysis" block from the operational phase shown in red. The Operational Analysis block, which does a more in-depth analysis of optimal dispatching and day-ahead scheduling of the EH for given system designs under the multi-objective economic/environmental approach, considers the uncertainties related to renewable energy resources (RES), energy loads and energy prices. Therefore, before handling the optimal operation and scheduling program, the generation of scenarios and forecasting of these uncertain parameters are carried out by the "Scenario Generation" based on historical data that generate potential operational scenarios to analyse system operation under various conditions, and "Forecasting" blocks, respectively. As the last step at the EH level, the Operational Analysis block

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provides the optimal scheduling of distributed energy resources (DERs) in the ILEC, that are required for the operation of the mEH level.

At the lower mEH level (highlighted in green), the real-time operation of each mEH is carried out with a multi-carrier structure. The mEHs are optimally managed and can participate in the local market via the peer-to-peer (P2P) market mechanism shown in the “P2P Market” block. The P2P concept will enable market participants to profit from providing flexibility according to the optimal EH dispatch while preserving critical private information. The core of the mEH level is the “Cloud-Based Solver” block that executes the optimal real-time scheduling for the mEH based on a multi-objective approach (economic/social approach). Furthermore, this block needs to receive initial forecasting data from the “Forecasting” block (RES and load profiles) that also needs to run in real-time. In order to apply the optimal set points of the control device, it is necessary to deploy the “Hardware Device Control” block, which is also responsible for providing the cloud-based solver toolbox with feedback from the functioning state of the devices interactively in real-time. The “forecasting” function provides additional information to the cloud-based solver.

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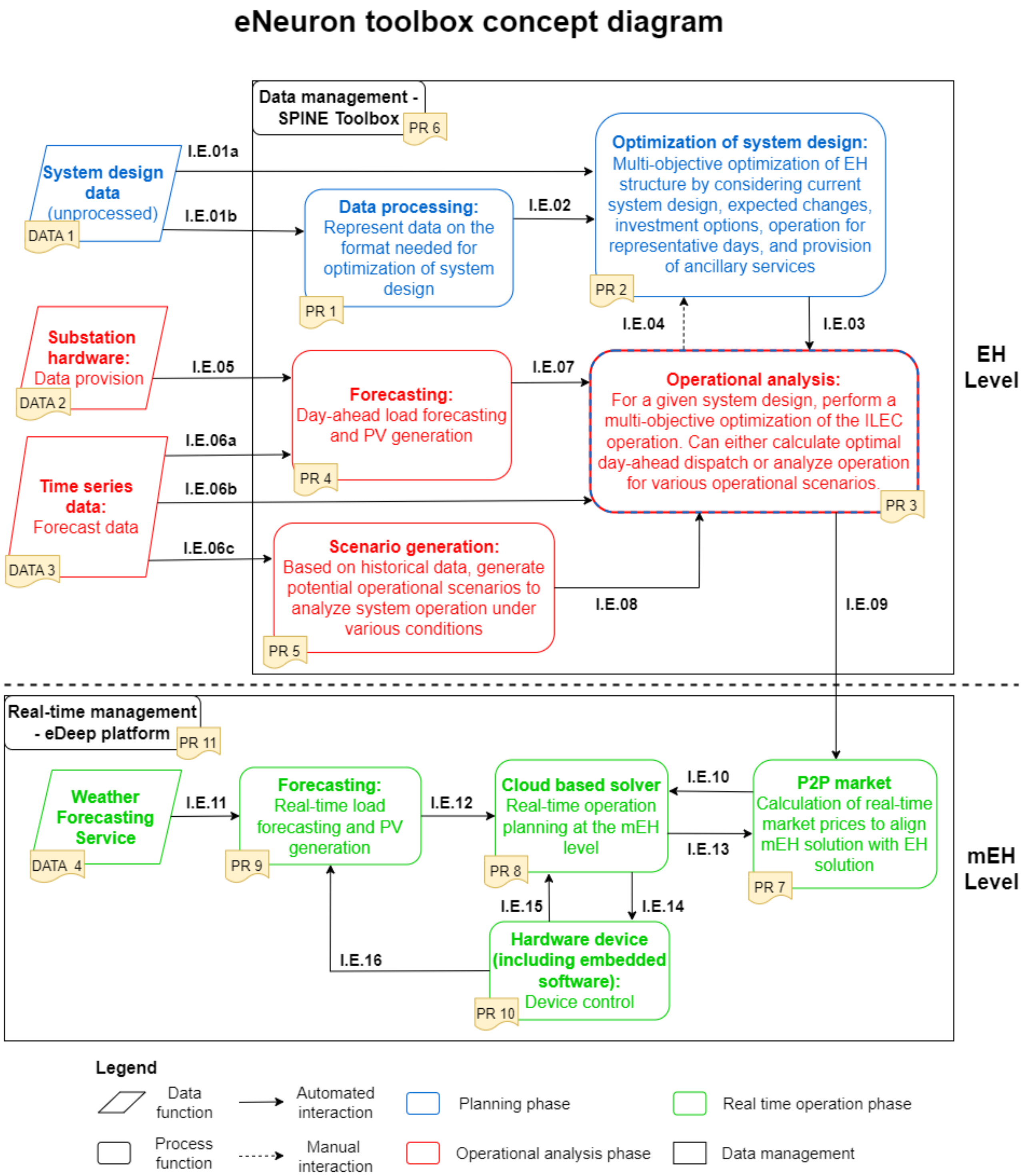

Figure 1 eNeuron toolbox concept diagram

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In Table 1, the tools name and tool providers used in eNeuron project are listed for the involved functions.

Table 1 Tool name and providers for all the functions in the eNeuron toolbox concept diagram

Function	Tool name	Responsible partners
PR 1	• Data processing tool	SINTEF
PR 2	• Integrate • Design optimization of multi-energy systems with multi-objective approach	SINTEF ENEA
PR 3	• Operation optimization of multi-carrier energy systems with multi-objective approach • Optimal management of EVs in multi-carrier energy systems with multi-objective approach	ENEA
PR 4	• PV forecasting • Deepgrid forecasting	FOSS ENEIDA
PR 5	• Data processing tool	SINTEF
PR 6	• SPINE	EPRI
PR 7	• P2P Platform	TECNALIA
PR 8	• mEH optimal operation scheduling real-time	TU/e
PR 9	• Electricity/Thermal Load Forecasting • PV forecasting	ENEA FOSS
PR 10	• DEOS: Deepgrid embedded OS	ENEIDA
PR 11	• Deepgrid	ENEIDA
DATA 3	• Deepgrid • knmi-api	ENEIDA TU/e
DATA 4	• Deepgrid	ENEIDA

The info exchanged (I.E) in details are described in the sections 4.2.2 of this deliverable and summarised in Table 2.

Table 2 Information exchanged in the eNeuron toolbox concept diagram.

Information exchanged	Description
I.E.01a	• RES output and load profiles data
I.E.01b	• Market prices
I.E.02	• Optimal configuration of the energy system on the Pareto frontier • Net-present value of costs and OPEX optimization
I.E.03	• Representative periods/clusters
I.E.04	• Information about any infeasible and/or undesirable system configurations that should be avoided
I.E.05	• Energy delivered per street per phase
I.E.06a	• Energy demand profiles for electricity, heating and cooling
I.E.06b	• Day-ahead market prices
I.E.06c	• Historical data related to the weather, including wind speed, direction and solar irradiance
I.E.07	• Day-ahead solar irradiance profiles and wind velocity

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I.E.08	• Scenarios for generation profiles, energy demand profiles and energy market prices
I.E.09	• Optimal hourly operation strategies on the Pareto frontier • Energy market prices
I.E.10	• Local P2P market electricity price.
I.E.11	• Weather information and weather historical data
I.E.12	• Demand and weather forecasting
I.E.13	• Aggregated quarter-hourly power profiles of the mEHs
I.E.14	• Real-time power setpoints of technologies in the mEH based on the optimal scheduling of appliances and the P2P interaction
I.E.15	• Technology specification of household appliances, preferences and device status
I.E.16	• Historical data of load consumption for different users

2.1 Energy Hub (EH) level

This section discusses the EH level of the eNeuron concept diagram in further detail. First, it is necessary to identify the objectives and incentives for developing the EHs. Accordingly, thanks to market deregulation in different energy sectors, it has become an urgent matter to pay further attention to optimal energy consumption. Also, state-of-the-art technologies can enable the integration of different energy carriers, which can potentially lead to techno-economic and environmental benefits as well as dealing with the energy crisis. The eNeuron project aims to develop solutions for the optimal design and operation of multi-carrier systems under the energy community concept, by exploiting the synergies coming from the interplay of multiple energy carriers and related technologies, thereby reducing primary energy consumption and environmental impacts and increasing of resilience of energy supply.

As illustrated in Figure 1 and summarized above, the operation of EH level consists of two phases: the planning phase to provide optimal energy system expansion pathways or optimal system design configurations for the establishment of ILECs and the operational phase for analysing different operational scenarios and performing day-ahead scheduling of the DER in the ILEC. Each phase will be described in further detail in the following sections.

2.1.1 Planning phase

In this phase, the long-term planning of EH is designated by considering the multiple carriers with a multi-objective framework. The core block in this phase is the “Optimization of System Design”, which adopts the “Integrate” and “Design optimization of multi-energy systems with multi-objective approach” tools to handle the process of determining the optimal system design.

The “Design optimization of multi-energy systems with multi-objective approach” tool starts with a pre-defined superstructure of the ILEC in terms of candidate technologies and energy interactions among them to satisfy the ILEC multi-energy demand. The objective is to minimize weighted sum of

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total annual cost and total annual CO_2 emissions. The outcome of the multi-objective function is the determination of the optimal selection of candidate technologies in the multi-carrier energy system with their optimal sizes and operation strategies in the representative season days. Hence, based on a preliminary superstructure, for given input data, the tool determines an optimal combination of technologies, including factors such as type, number, and size. In addition, the best corresponding operation strategies through economic and environmental assessments are also determined.

Regarding the "Integrate" tool functionality, it can provide investors with optimal investment strategies for developing the local energy system [2]. Furthermore, it optimises the expansion planning of the local energy system by considering (if applicable) an existing system configuration or a configuration determined by the other tool in case of a new system. Future developments of the system constitute projections for energy demand, energy prices, and the different investment possibilities for energy supply, conversion between energy carriers, distribution, storage, end-use measures, and restrictions on CO_2 emissions. The tool includes a graphical user interface and utilizes a cloud-based solution for optimizing the system. The Integrate software takes investment packages with given capacities as input and, therefore, may utilize the output from the "multi-energy system" tool, which can optimise capacities as input to define these packages. Furthermore, the functionality of the "Optimization of System Design" block is subject to the input data provided by the "Data Processing" block as well as the input signal coming from the operational phase layout that constitutes the current systems configuration. Once the optimal investment scenario with the technical specification of the installations and technologies is determined by the "Optimisation of System Design" block, the operational analysis can be carried out in the next phase under the "Operational Analysis" block.

As a complementary functionality, the "Data Processing" block employs the "Data processing tool" to cluster historical time series data into a set of representative days to be used by the "Optimisation of System Design" block. In particular, the data processing for generating representative days related to energy loads, energy prices and RES availability, used by the optimisation of system design tools is carried out by the "Data processing" tool. This will allow for clustering time series into representative periods as necessary for the tools optimizing the system design. Therefore, the tool will enable the data workflow and ensure data coherence across models.

2.1.2 Operational analysis phase

The core part of this phase is the "Operational analysis" block. Based on the system design, technologies, and their characteristics in the planning phase, it optimizes the dispatch of multi-carrier EH by pursuing multiple objectives when analysing the various operational scenarios or day-ahead dispatch. It is to be noted that the "Operational analysis" block can also work as a stand-alone block by directly interacting the toolbox user, that, with a given ILEC configuration, wants to investigate operational analysis of the ILEC.

More specifically, the "Operational analysis" block involves two tools, "Operation optimization of multi-carrier energy systems with multi-objective approach" and "Optimal management of EVs in

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multi-carrier energy systems with multi-objective approach" tools. With regards to the functionality of the first tool, it obtains (through a scenario-generation approach or forecasting tools as input) the optimal expected hourly operation strategies of the technologies in the multi-carrier systems by minimizing the weighted sum of total daily costs and CO_2 emissions. Therefore, by adopting a multi-objective stochastic optimization framework, given the input data, such as user demand, local climate data, energy prices, and technical information of the energy technologies, the tool determines the optimal operation scheduling of the multi-energy system by considering the uncertainties related to RES, energy prices and energy loads.

As a supplementary tool, the second "Optimal management of EVs in multi-carrier energy systems with multi-objective approach" tool is providing charging/discharging strategies for EVs in the context of multi-carrier energy systems, aiming at maximizing the ILEC's profit while also reducing CO_2 emissions. This tool provides a comprehensive multi-objective optimization model for optimally managing EVs with G2V and V2G technologies.

According to the concept diagram, prior to the optimal operational analysis, it is necessary to prepare data and make them compatible with the "Operational Analysis" block. Two approaches are included to determine RES generation and load profiles:

- Forecasting: To forecast data for the next day, required for scheduling the day-ahead operation of the system. Here, essential data is collected by the "Substation Hardware" block from the substations for the day-ahead scheduling and "Time series data" function.
- Scenario generation: Generation of scenarios to be analysed in order to verify a given system configuration under various operational conditions.

The tools in the "Forecasting" block are used to determine operation conditions for the next day. A specifically designed tool, the "PV forecasting" tool, can forecast PV production 24 hours ahead or an hour ahead based on parameters such as PV system position, size of the PV system, and the technology of the PV panels. Furthermore, the "Deepgrid forecasting" tool takes input from the substation hardware to forecast load profiles. Time series data are also directly used for the operational analysis function.

The tools in the "Scenario generation" block are employed to generate operation scenarios for stochastic optimization under the "Operational analysis" block. Accordingly, a "Data processing tool" can cluster time series for RES generation, loads and energy prices, based on historical data into representative scenarios along with their probability of occurrence. Such scenarios will help assess the system's operation under various conditions to assess the feasibility of potential system designs.

2.1.3 Data management at EH level

The tools at the EH level need to exchange data because of their complementary functionalities. Hence, to perform all aspects of the analysis, some output will also be used as input data for other tools. Since the focus is on analysis, data interaction between tools at the EH level is not sensitive to latency issues and can, therefore, be organized through shared data storage. A promising option

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that is being pursued in the eNeuron project is the SPINE framework, which provides facilities to organize and store data for energy system analyses involving multiple tools [3]. This builds on the idea that each tool works independently, but tools communicate through a common platform to exchange data in the overall toolbox concept. Because the EH-level tools are run for system analysis and not real-time operation, potential time lags between the execution of the different parts will not be a problem. Hence, tool synchronization will be manual, which is acceptable because the workflow is not executed for real-time applications. A motivating factor for choosing this architecture is that some tools are closed-source or based on licensed programs, and this data platform enables efficient interaction between them in accordance with these limitations.

2.2 Micro-energy hub (mEH) level

The EH layer is connected to mEH through the calculation of real-time market prices to align mEH and EH solutions in the P2P market. At the mEH level, the assumption of a centrally controlled system is relaxed as each mEH has control of the operation of its individual energy-related assets through their own optimization tool "mEH optimal operation scheduling real-time". The mEHs act as peers and respond to the local market price, which is determined based on mEH responses and the optimal dispatch determined at the EH level. The operational time domain of this level is real-time, with a resolution of 15 minutes, and it will set the operational setpoints of the energy technologies in different types of mEHs, e.g., residential, commercial, etc. As mentioned before, this level is coupled to the EH level through the "P2P Market" block, where the "P2P platform" tool is adopted as a P2P market platform to settle energy transactions among peers (mEHs) in a decentralized manner.

2.2.1 Real-time phase

More specifically, the "P2P platform" tool implements a peer-to-peer energy-sharing mechanism based on a deterministic approach in which a central coordinator modifies the day-ahead electricity price using an upper and a lower boundary derived from a threshold criterion over the expected day-ahead net power profile in order to incentivise the prosumers to change their power patterns. In this sense, the P2P coordinator is in charge of calculating the price signals to be sent to the prosumers to match the day-ahead optimal dispatch provided by the "Operational Analysis" as closely as possible on a real-time basis, i.e., in control cycles of 15 minutes.

To perform the above-mentioned, the "P2P market platform" operates interactively with the "Cloud-Based Solver" function, which can be considered the energy management core unit of every mEH. This block handles the real-time scheduling of each multi-carrier mEH by considering the energy prices broadcasted from the "P2P Market" block, forecasted load and RES production profiles provided by the "Forecasting" block, as well as the control status of hardware devices. Furthermore, multi-objective optimisation shall be used to accomplish the environmental, security and economic objectives. The tool implementing this functionality is 'mEH optimal operation scheduling real-time'.

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Under the "Cloud-Based Solver" block, the "mEH optimal operation scheduling real-time" tool schedules the flexibility allocation for the mEH. More specifically, it is a prosumer energy management system for multi-carrier energy systems which use the ε-constraint method[1] for multi-objective functions. The goal is to minimize the consumption costs while considering the CO_2 production as well as the security preserving objectives. The appliances allocated for such a multi-carrier system are based on the schemes and scenarios determined in the planning phase. They can include WT, PV, BESS, CHP, EV with V2G capability, AC, heat pump, fuel cell, electric boiler, and thermal storage systems. Given a variety of (uncertain) prices (Day-ahead and Intraday), flexibility markets, and direct control incentives, e.g., from DSOs, the tool calculates the expected optimal allocation of flexibility over a rolling horizon (e.g., a day length) within 15 min resolution such that the expected profit of the mEH is maximised.

The "P2P platform" tool also implements the required auxiliary functions between the "Cloud-based Solver" and the "P2P market" to make this mechanism work. These functions mainly include:

- Communications with the "Cloud-based solver":
  - Define the data model for the exchange of information
  - Define the sequence of messages and interaction logic
  - Define the API for the exchange of messages
- Implementation of the required convergence criteria of the P2P market mechanism at the coordinator level.

The real-time forecasting of the loads and RES generation is carried out by the "Forecasting" toolbox. The tools in this block are "Electricity/Thermal Load Forecasting" and "PV forecasting". To this end, the first one, as a thermal and electric load forecasting platform, can predict the load in the short term (up to 1-hour ahead). It used the load data in a time window and, eventually, some date/time features (e.g., weekday, holiday, etc.) for the forecasting purpose. Also, a medium-term (24 hours ahead) forecast can be attained by using a 1-hour ahead forecasting model in a recursive way. This data is provided through the "Deepgrid" tool. As an additional tool, the "PV forecasting" tool is adopted to forecast the PV generation profile 24 hours ahead or one hour ahead based on the preliminary parameters such as PV system position, the size of the PV system, and the technology of the PV panels.

The new operation mode computed by the Cloud-base Solver (CBS) will be delivered to the installed technologies, by the "mEH Device" block under the DEOS (Deepgrid embedded OS) tool or by the Energy Management System (EMS) controlling the asset (installed technologies). In this last scenario, the "Deepgrid" tool can interface the CBS and the EMS. The associated main functionality of the mEH device is based on DTVI OS[2], which is an operating system based on Linux optimized for running Docker containers on embedded devices[3]. This interface runs on the necessary inputs, such

[1] ε-constraint methodology keeps one of the objectives as the main objective function with some modifications. Then, its constraints the other objectives as the additional constraints of the whole problem. The problem is solved for different grid points [33].

[2] DTVI Operating System. DTVI is ENEIDA Smart sensor for LV feeder pillars, to measure currents and voltage and performs Network Power Quality analysis.

[3] A Docker container is a lightweight, standalone, executable package of software that includes everything needed to run an application and can be run directly on the device [34]

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as system configuration and sensor signals indicating currents, voltages, and digital inputs of the devices. Moreover, this tool's output signals include the measured root mean square (RMS) values, alarm events, and other data (processed or raw), which will be directed to the "Cloud-Based Solver" block as the feedback signals. The mEH device can also produce commands to be directed to the Installed technologies as the control signal. The mEH is equipped with digital outputs (relay operated and PWM) to directly control the assets.

2.2.2 Data management at the mEH level

An application programming interface (API) is a way for two or more computer programs to communicate with each other. APIs are going to be developed for the seamless collaboration of the tools and the efficient exchange of data among them.

"Deepgrid" platform communicates with other systems via the Deepgrid REST API (Representational State Transfer Application Programming Interface) and a Broker (Kafka and RabbitMQ) [4]. The Broker is responsible for distributing and delivering internal asynchronous messages to the specific eNeuron tools that will handle them. In the case that synchronous requests are needed, gRPC (Google Remote Procedure Call) services are also available to be used.

It uses PostgreSQL to manage assets and devices [5], influxDB to manage RT data [6], and MongoDB [7] to store AI (Artificial Intelligence) Reports and Exports generated by the "Deepgrid" tool.

The mEH device is connected to the Cloud-based solver and has different communication means that can be used with different Low-carbon assets or systems. Measurements are transmitted to the Cloud-base Solver or to "Deepgrid" tool through Kafka DTO (Data transfer object) [8], the Deepgrid REST API or MQTT Sparkplug (MQTT is the communication broker, and sparkplug is a message and topic structure to make communication between multiple sources consistent and flawless) [9]. As a common practice, by receiving an ACK (Acknowledgement Code) from the other tool, the mEH device erases data already transmitted from its own memory. The acknowledgment code serves to validate the communication was done without flaw. If there is a problem in the transmission and the data is not sent correctly, the data needs to be sent again. If the mEH device does not receive the ack it sends the data again, until it receives the ack, meaning the data was passed on correctly and it can be erased from internal memory.

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3 Definition of long-term optimization objectives based on use cases

The chapter presents the long-term objective functions based on the use cases that were previously developed during the activities of T3.3 “Use Cases and Innovative Business Models for the eNeuron pilots” [10]. The objective of this activity is to develop a methodology for designing the optimal resource mix within an ILEC. The methodology aims to consider all aspects of the ILEC, including existing infrastructure and capacity, current and future load requirements from all energy carriers, and available resources and associated costs. Based on these inputs, a long-term (i.e., multiple years) optimisation can then be performed to determine the optimal system design for the EH to satisfy a number of objectives, including minimisation of costs and environmental impacts.

3.1 Identified Long-term Optimization Objectives

The first step in this activity was to identify the long-term optimization objectives. Table 3 presents the identified long-term optimization objectives along with the corresponding references which included previous eNeuron deliverables on the development of use cases and business models (T3.3 [10]) and the energy hub concept and multi-objective programming approach (T4.1 [1]).

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Table 3 Objective functions for long-term optimization

Source	Objective Functions	Short description	Reference
Task 3.3	Maximization of RES share in the EH	Maximization of the RES share in the local generation mix.	•Pilot use cases T3.3
	Maximization of mEHs efficiency and reduction of the imported energy carriers	Improvement of the energy efficiency of the mEHs with a consequent reduction of energy carriers amounts imported.	•Pilot use cases T3.3 •Background reports T4.1 •Article [11] - Innovation Report 18 T4.1 •Article [12] - Eqs. 5, 6 - Background Report 2 T4.1
Task 4.1	Minimization of CO_2 emissions	Minimization of CO_2 emissions in the ILEC.	•Background reports T4.1
Task 4.2	Minimization of the total system costs	The objective function of SpineOpt expresses the minimization of the total system costs associated with maintaining and operating the considered energy system.	•SpineOpt [3] •Article [13] - Eq.2 - Background Report 2 T4.1
Task 4.3	Minimization of net present value of total costs.	The Integrate (formerly eTransport) tool minimizes the discounted total costs (OPEX + CAPEX) of the system. The cost minimization is carried out in two steps: - *Step 1*: Optimisation of system operation for all potential system designs in current and future years. Optimised as a MILP problem for each representative day. The cost for a given year is then calculated as the weighted sum of the representative days. Operational cost for each system design in the various years is then considered by step 2. - *Step 2*: Find optimal investment strategies by considering operational costs from Step 1 along with investment costs and obeying any imposed restrictions on investment combinations.	Integrate tool [2]

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4 Task forces activities

Four Task Force (TF) teams were set up in order to collectively and simultaneously carry out the activities of the design of the eNeuron toolbox. The four TF teams were generally aligned with the main phases of the overall eNeuron concept diagram: TF 1 on System Design, TF 2 on Day-Ahead Operation Scheduling, TF 3 on Peer-to-Peer Market Design, and TF 4 on Real-time Operation Design. Figure 2 provides an overview of the TF groups along with a summary of the main tasks that were addressed.

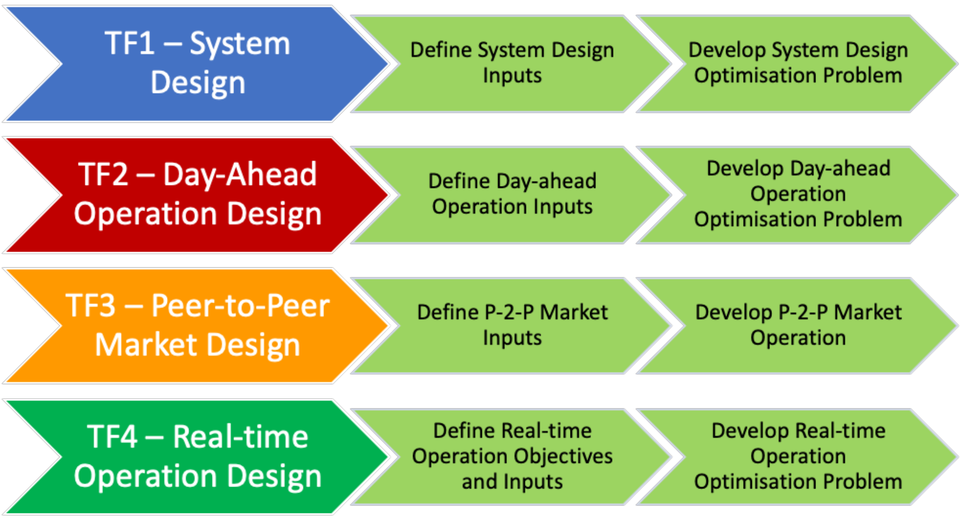

Figure 2 The T4.2 Task Forces and their activities

Each of the TF teams set out to define the required inputs for their respective sections of the overall methodology and develop the relevant optimization problem/operational mechanisms. A summary of each of the TF activities is provided as follows:

System Design (TF 1) was responsible for the overall design of the energy system under the ILEC concept. This subtask involved a comprehensive approach to identify the system design inputs and develop the system design optimisation problem for both existing and new energy structures of ILECs.

Day-Ahead Operation Scheduling (TF 2) focused on the development of the optimization problem for the day-ahead operation scheduling at the ILEC level. The initial task was to determine the necessary inputs for day-ahead operation optimization. This involved identifying data on demand forecasts, generation capacity, market prices, etc. These inputs are crucial for creating an accurate and efficient day-ahead scheduling optimization model. Once the inputs were identified, TF 2 worked on defining the optimization objectives. This included setting objectives such as minimizing costs and minimizing environmental impact. The TF then proceeded to develop the operation optimization model that leverages these inputs and objectives.

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Peer-to-Peer Market Design (TF 3) focused on the design of a peer-to-peer energy market. This was achieved by identifying the necessary inputs from ILEC's EH and mEH layers. These inputs include information on consumer (mEH) profiles, energy storage capabilities, pricing strategies, etc. Once the inputs were determined, TF 3 worked on defining short-term optimization inputs and objectives for the peer-to-peer market. These objectives include optimizing energy trading among consumers, ensuring fairness and transparency, and promoting renewable energy adoption while ensuring seamless collaboration between the two ILEC layers. The TF then delved into the design of the peer-to-peer market system, including algorithms for energy trading, pricing, and settlement.

Real-time Operation Design (TF 4) focused on the real-time operation scheduling of the energy system at the mEH layer. The work was initiated by identifying the required inputs from ILECs and energy carriers for real-time operations. These inputs typically involve real-time data on demand, generation, forecasting, market conditions and users' preferences. After identifying the inputs, TF 4 defined short-term optimization objectives for real-time operations. These objectives include ensuring minimal user discomfort while maximizing profits. The TF then proceeded to design the real-time operation framework. This involved developing algorithms to enable real-time decision-making at the mEH level while coordinating with market operations.

In summary, the Task Forces first focused on identifying the necessary inputs from ILECs and energy carriers for their respective subtasks. They then defined optimization inputs and objectives specific to each subtask. Finally, they designed the systems, models, and frameworks needed to address these objectives and offer the holistic optimization of an ILEC.

Detailed information on the TF activities and outcomes is provided in the remaining sections of this chapter. The information captured in the next section includes a description of the functions (blocks in the toolbox concept diagram), a list of inputs/outputs related to the functions, a description of the exchanged information with the other functions, energy carriers involved, the optimisation objectives, temporal resolution (e.g., hourly), and time horizon. The energy carriers involved are:

- Gas
- Hydrogen
- Electricity
- Heating
- Cooling

along with the following technologies:

- Combined heat and power (CHP) with different types of prime movers (internal combustion engine, micro-gas turbine, fuel cell)
- Electrolyser
- Natural gas boiler
- Solar PV
- Solar thermal

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- Reversible heat pump
- Absorption chiller
- BESS (battery energy storage system)
- Thermal storage for heating and cooling
- Hydrogen storage
- EVs
- House heating system (HHS).

The second part of the TF activity involved development of the long-term optimisation problem considering inputs and objectives and analysis of the short-term optimization problem. In this activity, all the main characteristics for the formulation of the optimisation problem were identified. An initial general description was first given to present the optimisation problem. This was followed by the problem formulation (e.g., mixed-integer linear programming (MILP), linear programming, etc.) and the types of constraints considered. The objective functions (e.g., minimization of CO_2, minimization of costs, thermal comfort, etc.) and the optimisation method used to solve the formulated problem were established. Finally, the identification of energy carriers (e.g., heating, cooling electricity etc.), energy technologies (e.g., CHP, PV etc.), system balance equations for the energy carriers involved, specification of the tools to solve the problems, the temporal resolution and time horizon were defined. For the EH layer and for each mEH, different sets of objectives are triggered.

The following section presents a summary of the tools to carry out the required functions. In some cases, more than one tool could be used to solve the related function problem (i.e., the blocks in the eNeuron toolbox concept diagram).

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4.1 Determination of ILEC and energy carrier inputs and definition of short-term optimization inputs and objectives

As the first part of TF activities, the determination of required inputs from ILEC and various energy carriers and the definition of short-term optimization inputs and objective(s) are provided. In this first part of the activities, the information exchanged, and the functions involved in the eNeuron toolbox concept diagram were analysed and described in detail. In the next section, the approach followed is described.

The approach followed was to analyse, per each task force, all the included functions in the eNeuron toolbox concept diagram. A common template including the description of the function, information exchanged to and from the functions, data format, energy carriers involved, temporal resolution, time horizon and optimisation objectives of the function were described per each function in the four task forces (TF-1 System design, TF-2 Day-Ahead Operation Scheduling, TF-3 Peer-to-Peer Market Design, TF 4 Real-time Operation Design).

4.1.1 TF 1 - System design

This section provides and overview of the functions operating under TF1 - System Design. Figure 3 shows the included functions from the eNeuron concept diagram.

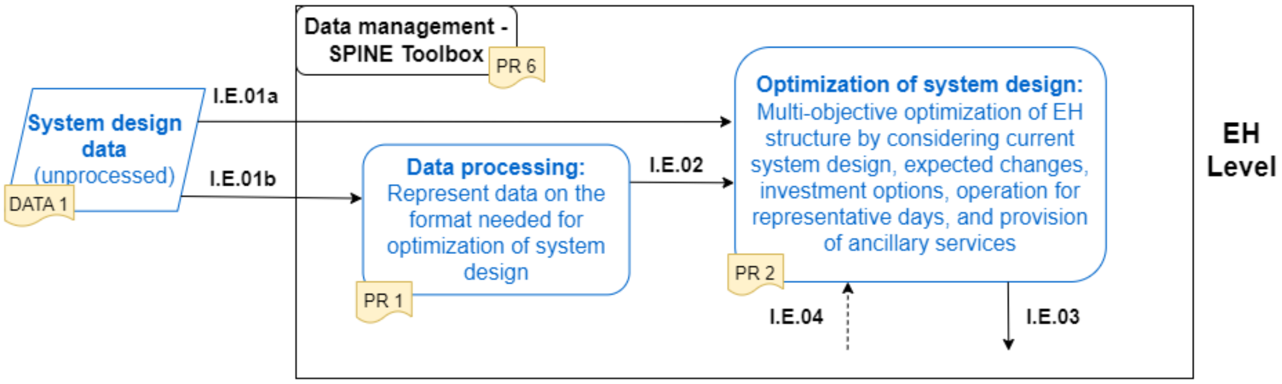

Figure 3 TF1 System design diagram

The following tables provide detailed descriptions of each function in the system design phase.

Function in the eNeuron toolbox concept diagram
DATA 1 – System design data
Description of the function
Sorting and formatting historical data for wind speed, solar irradiance, electricity/gas demand, and hourly profiles for energy demand (electricity, heating, and cooling)

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List of outputs from this function
I.E.01a: • *Hourly profiles for energy demand (electricity, heating and cooling) in representative season days* • *Hourly profiles for solar irradiance and wind velocity in representative season days* • *Preliminary superstructure of the EH (with energy flows among technologies in each mEH and among EHs)* • *Average efficiency of candidate technologies* • *Specific capital cost of candidate technologies* • *Specific O&M costs of candidate technologies* • *Gas and electricity (hourly profiles) prices in representative season days* • *Carbon intensity of gas and electricity from the grids.* *I.E.01b:* • *Time-series of parameters needed (loads, electricity prices, generation output, etc)* • *Number of representative periods* • *Length of representative periods* • *Clustering method to be used*
Data format
• *xlsx, csv*
Energy carriers involved
• *Electricity, natural gas, district heating and/or cooling, hydrogen.*
Temporal resolution
• *Hourly.*
Time horizon
• *User-defined.*

Function in the eNeuron toolbox concept diagram
PR 1 - Data processing (Data processing tool for integrating multi-energy systems tool)
Description of the function
Intermediate processing step to convert time series from other tools to representative periods used in Integrate tool using a clustering algorithm. The tool could also be adapted in a more general framework to other parts of the workflow where clustering can be used, for example, to reduce the number of scenarios generated by the Tools from TU/e.
List of inputs to this function
I.E.01b: • *Time-series of parameters needed (loads, electricity prices, generation output, etc)* • *Number of representative periods* • *Length of representative periods* • *Clustering method to be used*
List of outputs from this function
I.E.02: • *Representative periods/clusters* • *Relative weight of each cluster* • *Cluster correspondence to the original data*

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Data format
• *csv*
Energy carriers involved
N/A
Temporal resolution
Hourly (but could be adapted to other resolutions)
Time horizon
User-defined

Function in the eNeuron toolbox concept diagram
PR 2 - Optimization of system design (Design optimization of multi-energy systems with multi-objective approach)
Description of the function
Based on a preliminary superstructure of the ILEC, given the input data, such as user hourly demand, local climate data, energy prices and technical and economic information of the candidate energy technologies, the tool allows to obtain their optimized combination (types, number and sizes), and the corresponding operation strategies in representative season days through economic and environmental assessments [14].
List of inputs to this function
From user: • *Value of assigned weight for the economic objective function.* • *Number of prosumers (mEH) in the ILEC.* • *Type of load(s) (electricity and/or thermal and/or cooling) to consider for the optimal design.* *I.E.01a:* • *Carbon intensity of gas and electricity from the grid* *I.E.02:* • *Hourly profiles for energy demand (electricity, heating and cooling) in representative season days* • *Hourly profiles for solar irradiance in representative season days* • *Gas and electricity (hourly profiles) prices in representative season days* *I.E.04 (only if the operational analysis phase shows unfeasible solutions):* • *Optimal hourly operation strategies of energy technologies in the mEHs composing the ILEC*
List of outputs from this function
I.E.03: • *Pareto frontier (economic/environmental objective functions).* • *Optimal configuration of the EH in terms of types of energy technologies* • *Optimal sizing of energy technologies* *To user:* • *Pareto frontier (economic/environmental objective functions).* • *Optimal configuration of the EH in terms of types of energy technologies* • *Optimal sizing of energy technologies* • *Optimal operation strategies in representative season days*

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Energy carriers involved
• *Electricity, Natural gas, Hydrogen, Heating/Cooling.*
Optimisation objectives in this function
• *Economic objective: Minimization of total annual cost for the ILEC (sum of total annualized investment cost for all installed technologies, total O&M costs and total energy costs)* • *Environmental objective: Minimization of annual CO_2 emissions associated with the operation of the ILEC*
Temporal resolution
• *Hourly - Considering representative days for every year.*
Time horizon
• *One year*

Function in the eNeuron toolbox concept diagram
PR 2 - Optimization of system design (Integrate tool)
Description of the function
Finding the best investment strategies in terms of CAPEX and OPEX. Integrate tool is a software system for the optimisation of integrated energy systems. It can be used to optimise the development of an energy system while taking into account the projections in energy demand and the different technological possibilities for energy supply, conversion between energy carriers, distribution, storage, end-use measures and restrictions on CO_2 emissions. Investment packages need to be defined with given capacities, and these may originate from the optimal design of multi-energy systems with multi-objective approach tool or external sources.
List of inputs to this function
• *I.E.02: Current system configuration, e*xpected future development of loads and planned system development, potential investment options, and technology-specific parameters for current and potential system assets. • *I.E.04 (only if the operational analysis phase shows unfeasible solutions): Optimal hourly operation strategies of energy technologies in the mEHs composing the ILEC*
List of outputs from this function
• *I.E.03: CAPEX, OPEX, NPV, Cost-optimal investment strategies,* optimal operation for all representative days in all years considered by the OPEX optimization.
Energy carriers involved
• *Electricity, heat, cooling, natural gas, hydrogen*
Optimisation objectives
• *Minimize NPV of CAPEX and OPEX*
Temporal resolution in this function (e.g., hourly)
• *Hourly*
Time horizon in this function
• *10-50 years.*

Function in the eNeuron toolbox concept diagram
PR 6 - Data Management EH level (SPINE)

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Description of the function

Collect and process data from Data 1, 2, and 3 and orchestrate workflow between all blocks included in the EH level in order to give as output the optimal day-ahead dispatch in a suitable data form for PR7.

List of inputs to this function

I.E.01a:

- *Hourly profiles for energy demand (electricity, heating and cooling) in representative season days*
- *Hourly profiles for solar irradiance and wind velocity in representative season days*
- *Preliminary superstructure of the EH (with energy flows among technologies in each mEH and among EHs)*
- *Average efficiency of candidate technologies*
- *Specific capital cost of candidate technologies*
- *Specific O&M costs of candidate technologies*
- *Gas and electricity (hourly profiles) prices in representative season days*
- *Carbon intensity of gas and electricity from the grids*

I.E.01b:

- *Time-series of parameters needed (loads, electricity prices, generation output, etc.)*
- *Number of representative periods*
- *Length of representative periods*
- *Clustering method to be used*

I.E.05:

- *Active Power,*
- *Voltages and currents, RMS, min, max and angles*
- *Frequency,*
- *Reactive Power, Apparent Power and power factor*
- *THD(I) and THD(V).*

I.*E.06a*

- *Historical data of the PV production for at least 6 months with a granularity of 30 minutes*
- *Weather historical data (Irradiance, Temperature), if available*
- *Location (Latitude, Longitude)*
- *Installed capacity*
- *Year of manufacture*

I.E.06b

- *Day-ahead energy market prices (electricity, gas) (daily profiles for electricity with 1 hour as a time step)*

I.E.06c:

- *Time-series of parameters needed (loads, electricity prices, generation output, etc.)*
- *Number of representative periods*
- *Length of representative periods*
- *Clustering method to be used*

List of outputs from this function

I.E.09:

- *Pareto frontier*

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- *Daily ILEC's profit and CO_2 emissions in the various points of the Pareto frontier*
- *Optimal hourly operation strategies of energy technologies*
- *Optimal hourly bidding strategies of the ILEC on the day-ahead market*
- *Optimized strategies for PEV management during the parking period: (a) SOC of PEVs in the EHs; (b) Optimized charging/discharging strategies of EVs in the EHs*
- *Aggregated hourly energy generation profiles for EH*
- *Energy market prices (there are input also for Optimal management of EVs in multi-carrier energy systems with multi-objective approach tool but will be transferred to P2P market)*

4.1.2 TF 2 - Day-ahead operation scheduling

This section presents a detailed overview of the functions developed under TF2 – Day-Ahead operation scheduling. Figure 4 shows the relevant functions as depicted in the eNeuron concept diagram.

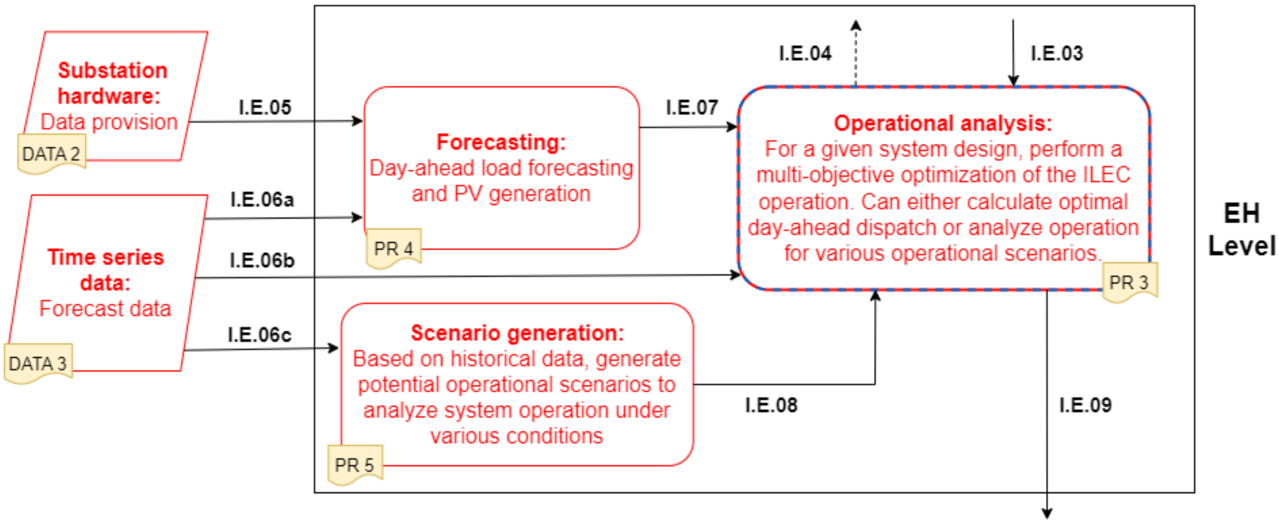

Figure 4 TF2 Day-Ahead operation scheduling diagram

The following tables provide detailed descriptions of each function in the day-ahead operation scheduling phase.

Function in the eNeuron toolbox concept diagram
DATA 2 - Substation Hardware
Description of the function
Characterization of the active power in each substation outgoing circuit.
List of outputs from this function
I.E.05: *- Active Power* *- Voltages and currents, RMS, min, max and angles* *- Frequency* *- Reactive Power, Apparent Power and power factor* *- THD(I) and THD(V)*

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Data format
MQTTS (Sparkplug) *HTTPS (JSON ENEIDA REST API)*
Energy carriers involved
Electricity
Temporal resolution
10 ms
Time horizon
5 minutes

Function in the eNeuron toolbox concept diagram
DATA 3 - Time series data Forecast Data (Deepgrid)
Description of the function
Deepgrid tool will make available weather forecasting services that will serve as an input to the energy forecasting tools. Specifically, the Deepgrid tool subscribes to Solcast (or a similar service) to collect the needed data and store them in an internal database. *This data will be available in Deepgrid. EH tools can call a Deepgrid API to get the data. These data become available on the following refreshing basis: 1 Data Request per day per place. One place per pilot (2 km x 2 km cells).*
List of outputs from this function
I.E.06a: • *Irradiance profiles* • *Energy demand profiles for electricity, heating and cooling*
Data format
- csv file (begin date Time/end date Time) *- Data (Eneida JSON format) By date Time"*
Describe the energy carriers involved in this function
Electricity, heating and cooling
Temporal resolution in this function (e.g., hourly)
1 hour
Time horizon in this function
1 day (at least)

Function in the eNeuron toolbox concept diagram
DATA 3 - Time series data Forecast Data (knmi-API tool)
Description of the function
The technical name of the tool is KNMI-API, which emerges meteorological data from 53 weather stations in the Netherlands [15].
List of outputs from this function
I.E.06c is the output of this tool, providing all types of historical data related to the weather, including wind speed, direction and solar irradiance.
Data format
It can be CSV, JSON, or pandas data frame

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Energy carriers involved
N/A, as this is weather station-related
Temporal resolution
From 10 minutes
Time horizon
1 Day

Function in the eNeuron toolbox concept diagram
PR 3 - Operational analysis (Operation optimization of multi-carrier energy systems with multi-objective approach)
Description of the function
Optimal scheduling of DER (daily profiles with 1 hour as a time-step) in the mEHs composing the ILEC based on a multi-objective approach by minimizing daily energy costs and CO_2 emissions [16] [17] [18] [19].
List of inputs to this function
Stochastic approach (working with scenario generation tools as input): *I.E.03 or user-defined* • *Structure of the ILEC (mEHs) with technologies and energy flows among technologies* • *Technical data of energy technologies in the ILEC (average energy efficiency and sizes)* • *Carbon intensity of input energy carriers* *I.E.08* • *Scenarios for solar irradiance profiles, wind velocity with related probability of occurrence (daily profiles with 1 hour as time step)* • *Scenarios for energy demand profiles (electricity, heating and cooling) with related probability of occurrence (daily profiles with 1 hour as a time step)* • *Scenarios for energy market prices (electricity, gas) with related probability of occurrence (daily profiles for electricity with 1 hour as a time step)* *Day-ahead scheduling (working with forecasting tools as input):* *I.E.03 or user-defined* • *Structure of the ILEC with energy flows among technologies* • *Technical data of energy technologies in the ILEC (average energy efficiency and sizes)* • *Carbon intensity of input energy carriers* *I.E.07* • *Day-ahead solar irradiance profiles and wind velocity (daily profiles with 1 hour as a time step)* • *Day-ahead energy demand profiles (electricity, heating and cooling) (daily profiles with 1 hour as a time step)* *I.E.06b* • *Day-ahead energy market prices (electricity, gas) (daily profiles for electricity with 1 hour as a time step)*
List of outputs from this function

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I.E.09 • *Pareto frontier* • *Daily energy cost and CO_2 emissions in the various points of the Pareto frontier* • *Optimal hourly operation strategies of energy technologies in the mEHs composing the ILEC* • *Amount of electrical and thermal energy shared among mEHs composing the ILEC* • *Aggregated hourly energy generation profiles for mEH* • *Energy market prices (there are input also for ENEA-4 but will be transferred to the P2P market)* *I.E.04 (only if the operational analysis phase shows unfeasible solutions): Optimal hourly operation strategies of energy technologies in the mEHs composing the ILEC*
Energy carriers involved in this function
Electricity, Natural gas, Hydrogen, Heating, Cooling.
Optimisation objectives
• *Economic objective: Minimization of daily energy costs associated with the energy carrier's input to the ILEC.* • *Environmental objective: Minimization of daily CO_2 emissions associated to the energy carriers input to the ILEC.*
Temporal resolution
1 hour
Time horizon
1 day

Function in the eNeuron toolbox concept diagram
PR 3 - Operational analysis (Optimal management of EVs in multi-carrier energy systems with multi-objective approach)
Description of the function
Optimal energy management of the ILEC in the presence of plug-in electric vehicles (PEVs), with the aim to combine maximization of ILEC's profit with the minimization of CO_2 emissions.
List inputs to this function
Day-ahead scheduling (working with forecasting tools as input): *I.E.03 or user-defined* • *Structure of the ILEC with energy flows among technologies* • *Technical data of energy technologies in the ILEC (average energy efficiency and sizes)* • *Technical data of PEVs in each EH of the ILEC (number of PEVs, capacity of batteries, parking duration (arrival and departure time), SOC (initial at parking arrival and desired at departure)* • *Carbon intensity of input energy carriers* *I.E.07:* • *Day-ahead solar irradiance profiles and wind velocity (daily profiles with 1 hour as a time step)* • *Day-ahead energy demand profiles (electricity, heating and cooling) (daily profiles with 1 hour as a time step)* *I.E.06b*

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• *Day-ahead energy market prices (electricity, gas) (daily profiles for electricity with 1 hour as a time step*
List outputs from this function
I.E.09: • *Pareto frontier* • *Daily ILEC's profit and CO2 emissions in the various points of the Pareto frontier* • *Optimal hourly operation strategies of energy technologies* • *Optimal hourly bidding strategies of the ILEC on the day-ahead market* • *Optimized strategies for PEVs management during the parking period: (a) SOC of PEVs in the EHs; (b) Optimized charging/discharging strategies of EVs in the EHs* • *Aggregated hourly energy generation profiles for EH* • *Energy market prices (there are input also for ENEA-5 but will be transferred to the P2P market)* *I.E.04 (only if the operational analysis phase shows unfeasible solutions): Optimal hourly operation strategies of energy technologies in the mEHs composing the ILEC*
Energy carriers involved in this function
Electricity, Natural gas, Hydrogen, Heating, Cooling, mobility
Optimisation objectives
• *Economic objective: ILEC's profit consists of the following terms: (1) revenue for selling the electricity provided by distributed technologies in the ILEC into the wholesale market; (2) revenue for selling the electrical flexibility collected from PEVs in V2G mode into the wholesale market; (3) cost for the input energy carriers; and (4) cost of buying electricity from PEV owners in V2G mode.* • *Environmental objective: Minimization of daily CO_2 emissions*
Temporal resolution
1 hour
Time horizon in this function
1 day

Function in the eNeuron toolbox concept diagram
PR 4 - Forecasting (Deepgrid forecasting tool)
Description of the function
Forecasting the demand and the production in each substation outgoing circuit to promote market opportunities between EH and the grid.
List of inputs to this function
Forecasting the demand and the demand constraints in each substation outgoing circuit: *I.E.05 (historical of 6 months and 10-min aggregated, updated every 10-min):* • *Real-time substation voltage vectors* • *Real-time outgoing circuits' current vectors* • *Synchronized, locally computed, power-quality data.* *I.E.06a (Historical of 6 months and 1-hour aggregated, updated every day)* • *Outdoor temperature data* • *Rainfall data*

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Forecasting the production in each substation outgoing circuit: *I.E.05 (Historical of 6 months and 10-min aggregated, updated every 10-min):* • *Real-time substation voltage vectors* • *Real-time outgoing circuits' current vectors* • *Synchronized, locally computed, power-quality data.* *I.E.06a (Historical of 6 months and 1-hour aggregated, updated every day)* • *Solar irradiance data*
List of outputs from this function
Forecasting the demand and the demand constraints in each Substation outgoing circuit: *I.E.07 (computed every 6 hours):* • *2 days ahead, hourly power demand per Substation outgoing circuit* • *2 days ahead, hourly, demand constraints alerts, per Substation outgoing circuit* *Forecasting the production in each Substation outgoing circuit:* *I.E.07 (computed every 6 hours):* • *2 days ahead, hourly power production per substation outgoing circuit* • *2 days ahead, hourly Reverse Power flows alerts per substation outgoing circuit*
Energy carriers involved in this function
Electricity – this function has the objective of characterising stressed grids due to the fact of a continuously growing demand and reverse flows. For that reason, it has a higher fit on the electricity grid. *Nevertheless, it is based on available real-time data. In that sense, it can be applied to different energy carriers.*
Temporal resolution
1 hour
Time horizon
48 hours

Function in the eNeuron toolbox concept diagram
PR 4 - Forecasting (PV forecasting tool)
Description of the function
Day-ahead PV forecasting tool
List inputs to this function, describing then the exchanged information with the other functions
I.E. 05 and I.E. 06a • *Historical data of the PV production for at least 6 months with a granularity of 30 minutes* • *Weather historical data (irradiance, temperature), if available* • *Location (latitude, longitude)* • *Installed capacity* • *Year of manufacture*
List of outputs from this function

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I.E. 07 • *PV production forecast. csv file with the forecasted data for the next day (48 values of the forecasted PV production for the next day)*
Energy carriers involved
Electricity
Temporal resolution
30 minutes
Time horizon
1 day

4.1.3 TF 3 - Peer-to-Peer market design

This section describes the function developed under TF3 – Peer-to-Peer market design. Figure 5 shows the function as depicted in the eNeuron concept diagram.

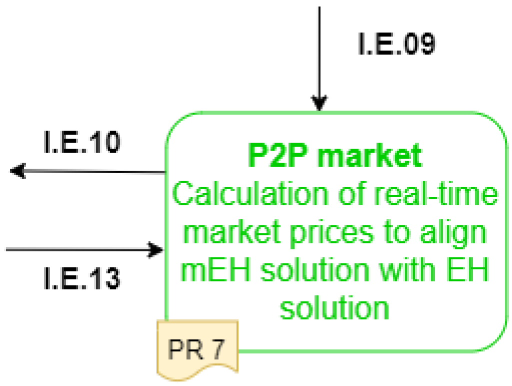

Figure 5 TF3 Peer-to-Peer Market Design diagram

The following table provides a detailed description of the Peer-to-Peer market function components.

Function in the eNeuron toolbox concept diagram
PR 7 - P2P Market (P2P Platform tool)
Description of the function
In this function, the P2P coordinator is in charge of calculating the internal P2P market price signals and sending them back to the mEHs to match in real-time the day-ahead dispatch provided by the "Operational Analysis" function as closely as possible. During each control cycle, an iterative process occurs to match the final local energy price for the mEHs. The P2P market platform operates interactively with the "Cloud-Based Solver" block, which handles the real-time scheduling of each multi-carrier mEH by considering the energy prices broadcasted from the "P2P Market" function. Each iterative process (executed every 15 minutes) has the following steps: *1. P2P Market sends day-ahead market price profile to the mEHs "Cloud-Based Solver" blocks.*

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2. *Each mEH “Cloud-Based Solver” block optimizes the energy resources of the mEH and sends back to the P2P Market its optimized consumption and generation profiles (aggregated at the mEH level).*
3. *The P2P Market checks whether the EH energy profile (aggregation of mEH profiles) matches the desired EH objective profile or whether there have not been significant changes in the power profile since the last iteration. If any of the mentioned checks are true, the iterative process ends; if not, the process continues to step 4.*
4. *The P2P Market calculates a new price profile to incentivize mEHs to change their energy profiles so that the EH energy profile is better aligned with the objective profile.*
5. *The new price profile is sent to the mEHs so that they can proceed with step 2.*
 	
This function also implements the required auxiliary functions between the “Cloud-based Solver” and the “P2P market” to make this mechanism work. These mainly include:
- Set up the required communications with the “Cloud-based solver”:
    o Data model for the exchange of information
    o Sequence of messages and interaction logic
    o API for the exchange of messages
- Define the required convergence criteria of the P2P market mechanism

List of inputs to this function

• *I.E.09 (provided by the “Operational Analysis” function at the EH level):*
    o *Day-ahead energy market prices [€/kWh]*
    o *Aggregated hourly energy generation profile for EH*
    o *Aggregated hourly demand profile for EH (base demand, EV, remaining technologies)*
• *I.E.13 (provided by the “Cloud Based Solver” function at the mEH level):*
    o *Aggregated quarter-hourly power profiles of the mEHs*

List of outputs from this function
• *I.E.10 (sent to the “Cloud Based Solver” function at the mEH level): Local P2P market electricity price.*
Energy carriers involved
Electricity
Optimisation objectives
Maximization of the welfare of the mEHs
Temporal resolution
15 minutes/1 hour
Time horizon in this function
1 day

4.1.4 TF 4 - Real-time operation design

This section presents detailed descriptions of the functions developed under TF 4 – Real-time operation design. Figure 6 shows the included functions as shown in the eNeuron concept diagram.

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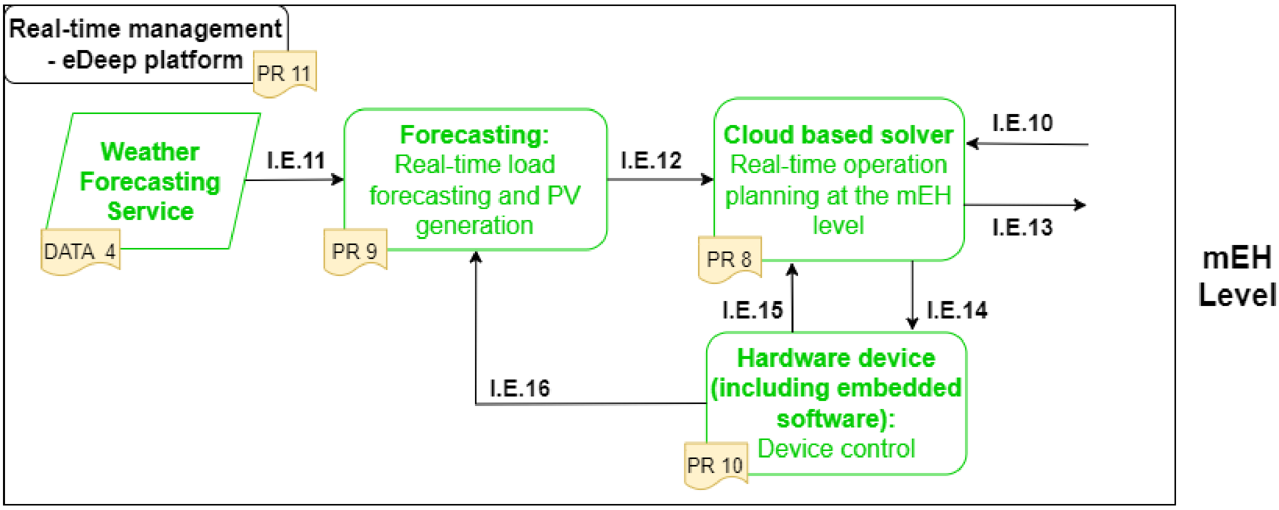

Figure 6 TF4 Real-time Operation Design diagram

Detailed descriptions of each function in the real-time operation design phase are presented in the following tables.

Function in the eNeuron toolbox concept diagram
DATA 4 - Weather Forecasting Service (Deepgrid tool)
Description of the function
Deepgrid tool will make available weather forecasting services that will serve as an input to the energy forecasting tools in the next. Specifically, the Deepgrid tool subscribes to Solcast to collect the needed data and stores them in an internal database. *This data will be available in Deepgrid. Electricity/Thermal Load Forecasting and/or PV forecasting tools can call a Deepgrid API to get the data.* *These data become available on the following refreshing basis: 1 Data Request per day per place. One place per pilot (2 km x 2 km cells).*
List of outputs from this function
I.E.11: Both weather information and weather historical data to feed both Electricity/Thermal Load Forecasting and PV forecasting tools as follows: *Regarding the first tool mentioned before, two phases need to be considered:* *- in the learning phase, the tools need the same time horizon of historical data of load consumption, but usually, at least 1 year of historical data is necessary to have a model with acceptable results.* *- in the operational phase, the tool needs past data in a time window that could vary from the last 24 h to the last 2 weeks. At this moment, we could give a clear indication of the dimension of the past window because it is a hyperparameter that has to be tuned once we have access to real data.* *The PV forecasting tool needs historical data from the previous 6 months of PV system production (if the system is already installed and in operation). It would be good if a sliding window of historical data could be provided for better accuracy.*

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Typical data to be acquired: Temperature [°C], Humidity [%], Solar Irradiance [W/m2], Pressure [hPa], Wind Speed [m/s], Wind Direction [°], Rain [mm]) for a previous window time (e.g., the previous 24 hours) and Weather prediction for the considered horizon (e.g., 1 or 24)
Data format
csv file (begin dateTime/end dateTime) *Data (Eneida JSON format) By dateTime*
Energy carriers involved
N/A
Temporal resolution
1 h
Time horizon
1 day ahead and the previous 1 day to 2 weeks

Function in the eNeuron toolbox concept diagram
PR 8 - Cloud-based solver (mEH optimal operation scheduling real-time tool)
Description of the function
The optimal energy management of a micro-Energy Hub (mEH) connected to the multi-carrier energy system is carried out via a cloud-based solver. The technologies can run on electricity, heat, gas and hydrogen energy carriers by taking into account the minimization of water consumption. Moreover, a multi-objective MILP is adopted to maximize the comfort of house residents, minimize greenhouse gas production, and minimise costs.
List of inputs to this function
I.E.10 multi-sector energy prices (dynamic electricity prices from P2P market. Gas price is fixed) and convergence restrictions from P2P market platform *I.E.12 Demand and weather forecasting, including* o *Electricity load forecast* o *Thermal load forecast* o *Solar irradiance forecast* o *Wind velocity forecast* o *Ambient temperature forecast* *I.E.15 Technology specification of household appliances, preferences and device status, i.e., EV, FC, BESS, PV, mCHP, etc.* • *Internal data of the "Cloud-based solver" function:* o *Technical information on energy technologies* o *Preferences of the end-user (e.g., comfort temperature)*
List of outputs from this function
• *I.E. 13 (sent to the "P2P Market" function at the mEH level): optimal power schedule for the mEH* - Iterative energy block offer signals submitted to the P2P market • *I.E.14 (sent to the "Hardware device" function at the mEH level): Real-time power setpoints of technologies in the mEH based on the optimal scheduling of appliances and the P2P interaction.*
Energy carriers involved
Electricity, Heat, Cooling, Gas, water, hydrogen.

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Optimisation objectives
Minimize household cost *Minimize CO_2 emissions cost* *Maximize resident comfort*
Temporal resolution
5-15 min
Time horizon
1 day

Function in the eNeuron toolbox concept diagram
PR 9 - Forecasting (Electricity/Thermal Load Forecasting tool)
Description of the function
Electricity/Thermal Load forecasting tool. It is a Machine Learning-based forecasting tool that provides short-term load forecasting (1h ahead) or medium-term load forecasting (24h ahead) using a 1 h ahead forecasting model in a recursive way. Two different phases have to be considered: the learning phase and the inference phase. In the learning phase, the model is trained using historical data; in the inference phase, the model is used using real-time information observed in a time window [20] [21].
List of inputs to this function
<u>During the learning phase:</u> *I.E.16 Dataset containing the historical data of load consumption for different users (at least 1 year, hourly based, for each user)* *I.E.11 Historical weather data (Temperature [°C], Humidity [%], Solar Irradiance [W/m^2], Pressure [hPa], Wind Speed [m/s], Wind Direction [°], Rain [mm]) for the related area (same time horizon of historical data of load consumption)* *<u>During the inference phase:</u>* *I.E.16 Load consumption (hourly based) for a previous window time (e.g. previous 24 hours)* *I.E.11 Weather information (Temperature [°C], Humidity [%], Solar Irradiance [W/m^2], Pressure [hPa], Wind Speed [m/s], Wind Direction [°], Rain [mm]) for a previous window time (e.g., previous 24 hours) and Weather prediction for the considered horizon (e.g., 1 or 24 h)*
List of outputs from this function
I.E.12. Short Term (1h ahead) load forecasting: return the next one value of load consumption or Medium Term (24h ahead) load forecasting: return the next 24 values of load consumption
Energy carriers involved
Electricity, Thermal
Temporal resolution
1 h
Time horizon in this function
1. Short Term: 1 h *2. Medium Term: 24 hours*

Function in the eNeuron toolbox concept diagram
PR 9 - Forecasting (PV forecasting tool)

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Description of the function
Hour-ahead PV production forecasting tool
List of inputs to this function
I.E. 11 and I.E. 16 • *Historical data of the PV production for at least 6 months with a granularity of 30 minutes* • *Weather historical data (Irradiance, Temperature), if available* • *Location (Latitude, Longitude)* • *Installed capacity* • *Year of manufacture* *Basically, the PV forecasting tool needs historical data from the previous 6 months of PV system production (if the system is already installed and in operation). It would be nice if a sliding window of historical data could be provided from a hardware device (I.E. 16). Furthermore, with weather historical data (from I.E. 11), the forecasts will be more accurate but are not mandatory if not available.*
List of outputs from this function
I.E. 12 • *PV production forecast. csv file with the forecasted data for the next one or two hours or for the next day (48 values of the forecasted PV production for the next day)*
Energy carriers involved
Electricity data to be used for the optimal system design
Temporal resolution
Adjustable with the input data (30 minutes, 1 hour, …)
Time horizon
• *One hour to two hours ahead (real-time)* • *Day ahead*

Function in the eNeuron toolbox concept diagram
PR 10 - Hardware device (including embedded software): device control (DEOS: Deepgrid embedded OS tool)
Description of the function
Monitoring and Control Device - it can work as an electricity meter when connected to electricity carrier assets and as a controller of Energy Assets, defining the asset's operation setpoints.
Input data format
T MQTTS (Sparkplug) *HTTPS (JSON ENEIDA REST API)* *(It is also able to measure Voltage and Current and compute NPQ parameters, and Eneida developed an SDK to build new embedded Apps (including third party Apps) to serve the use cases)*
Output data format
MQTTS (Sparkplug). *HTTPS (JSON ENEIDA REST API).* *It is also able to Control 3rd party devices through Digital outputs, both Relay and PWM (Voltage, current, power (P, S, Q), power factor, energy, THDi, THDv, and temperature are parameters computed by the device)*

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Energy carriers involved
Electricity, others (the device can control energy assets irrelevantly of the carrier to which they belong. Depending on the use cases of the pilots, the HW device can be installed in CHP units, Boilers etc.)
Temporal resolution
1 s. The device can handle different transmission services as a way of seamlessly interacting with the other tools at the mEH level. So, it can handle services to the Cloud-based Solver with a periodicity 1, to the Forecasting service with a periodicity 2, publishing data to a broker with a periodicity 3, and others.
Time horizon
5 min

Function in the eNeuron toolbox concept diagram
PR 11 - Real-time management (Deepgrid tool)
Description of the function
The Eneida Deepgrid is a web platform to manage Energy assets and provide visibility of the system behaviour, its historical and the day ahead forecasting. *Data ingestion is made in two phases. In the first phase, a proper Translator handles the messages that are received via HTTP or MQTT to be translated. Once the message is in the Deepgrid Format (JSON), it is posted in the Broker. In the second phase, the Broker handles all the messages in the queues and delivers them to all DB pipelines and services that are subscribing to such data.*
List of inputs to this function
MQTTS (Sparkplug) *HTTPS (JSON ENEIDA REST API)* *direct connection to the databases*
List of outputs from this function
MQTTS (Sparkplug) *HTTPS (JSON ENEIDA REST API)* *direct connection to the databases*

4.2 Analysis and development of the long-term optimization problem

The next stage of the TF activities involved the analysis and development of the long-term optimisation problem considering the inputs and objectives. The approach followed was to perform a detailed analysis of the formulation of the optimisation problem for each of the TF phases.

As part of the analysis, the main information captured for each of the phases was as follows:

- Description of the considered optimisation problem
- Formulation of the optimisation problem in terms of which approach has been used (e.g., MILP)
- Constraints considered in the optimisation problem (also reporting the formulas, e.g., design or operation constraints)
- Objective function(s) of optimisation problem and the relative formulations (economic and/or environmental objective functions)
- Optimisation method used to solve the formulated problem (e.g., weighted-sum method)
- Energy carriers and technologies involved
- Formulation of system balances equation for energy carriers involved
- Tool(s) used to solve the problem
- Time horizon and temporal resolution.

For TF 1 - *System design*, two LTO problems in the planning phase have been developed. The first one is related to the tool for the optimal design of multi-energy systems with a multi-objective approach, while the second one is related to the same problem, but the Integrate tool is used to solve it. These two tools are different and solve the related problems in TF1.

For TF 2 - *Operation optimization of multi-carrier energy systems with multi-objective approach* and *Optimal management of EVs in multi-carrier energy systems with multi-objective approach* tools are described for the formulation of the problems.

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4.2.1 Design optimization of multi-energy systems with multi-objective approach

Optimisation problem
LTO problem in Planning phase – *Optimal design of multi-energy systems with multi-objective approach tool*
Description of the considered optimisation problem
Based on a preliminary superstructure of the ILEC, in terms of potential candidate energy technologies to be installed and energy flows among them, given the input data, such as user loads with the hourly resolution, local climate data, and techno-economic data of the technologies and energy prices, the proposed optimization model allows obtaining the optimized combination of those energy technologies, in terms of types, number and sizes, and the corresponding operation strategies in representative season days, through economic and energetic/environmental objectives [14] [22]. With the weighted sum of two objective functions, the goal is to determine the optimal design and operation strategies for representative days on the Pareto frontier, i.e., the ILEC configurations and the corresponding optimized operation strategies for representative days according to the economic and sustainability priorities. The superstructure of the ILEC used for the optimization problem is shown in Figure 7. The ILEC under consideration is assumed to be equipped with a set of technologies for the generation, conversion and storage of electrical and thermal energy to satisfy end-user demand. The generation technologies can include Combined Heat and Power (CHP) systems with micro gas turbines, internal combustion engines or fuel cells as the prime mover (where the fuel cell is fed by an electrolyser), gas-fired boilers, solar PV systems and solar thermal collectors. The conversion technologies can include reversible electric heat pumps and single-stage absorption chillers. The storage technologies can include batteries, thermal energy storage (TES) for heating and cooling purposes and H_2 storage. The ILEC can consist of multiple mEHs, each of them representing a prosumer, namely a multi-energy system equipped with the generation, conversion and storage technologies mentioned above. It is assumed that there is a mEH *j* to satisfy the multi-energy demand associated with user *u.* Moreover, the electrical and thermal energy provided by CHPs can be exchanged among the mEHs, where the thermal energy is shared by using the heating pipeline network to be designed. The distance between the mEH *j* and its end-user u (i.e., *j=u*) is assumed null, while the distance among different mEHs is assumed known.

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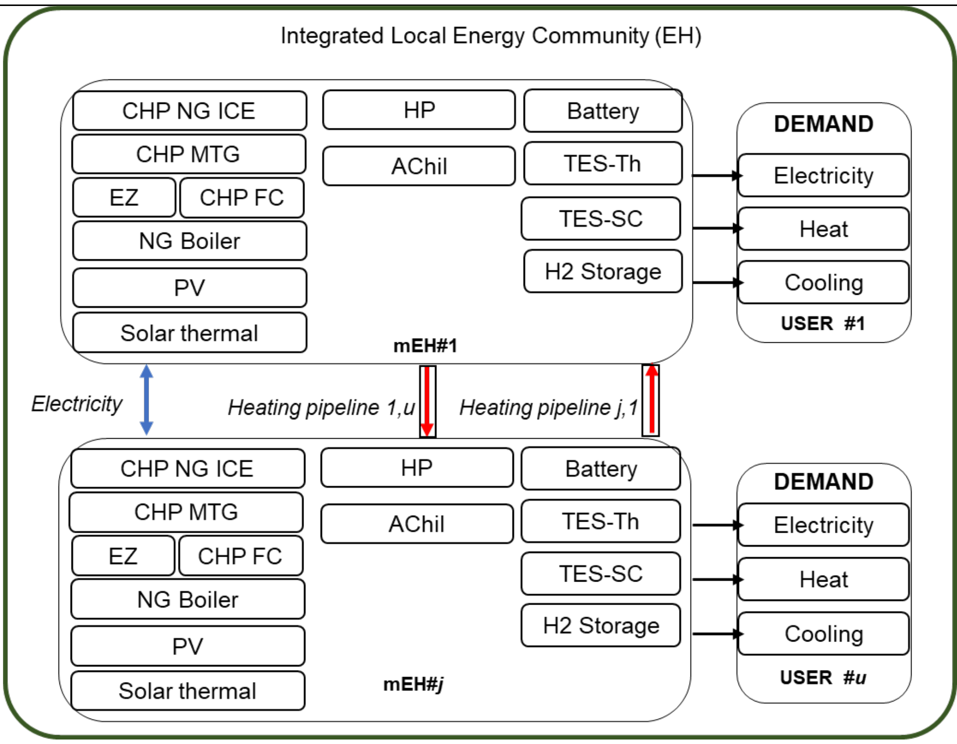

Figure 7 Scheme of the ILEC used for the optimization problem.

Formulation of the optimisation problem

The problem is formulated through a MILP approach. It must be mentioned that, from the analysis carried out in T4.1 [1], it emerged that MILP formulations are the most widely used in the literature for the design optimization of EHs, being these a good compromise between model fidelity and complexity of the optimization process, by also taking advantage of powerful MILP solution methods as branch-and-cut.

The optimization problem is linear and involves both discrete (binary) and continuous variables. The binary decision variables are the existence and the operation on/off status of the energy technologies, whereas the continuous decision variables include the size of the energy technologies with the corresponding energy rate provided (power, heating and cooling), the capacity of storage systems, with charging/discharging rate, and power taken from the grid. All the other variables can be classified as dependent variables.

Constraints considered in the optimisation problem

The optimization problem constraints mainly consist of three types of constraint, i.e.:

1. Design constraints
2. Operation constraints
3. System balance constraints

1. Design constraints

Design constraints ensure that the designed size of each energy technology *i* installed in mEH *j* (a continuous decision variable) should be within the minimum and maximum size values available in the market:

$$S_i^{min} x_{i,j} \leq S_{i,j} \leq S_i^{max} x_{i,j}, \forall i, j \quad (1)$$

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The binary decision variable, $x_{i,j}$ is equal to 1 if the technology is chosen to be part of the mEH configuration.
The design constraint for the PV is formulated below:

$$A_{PV\,j} \leq A_{PV\,j}^{max}, \forall j \tag{2}$$

which ensures that the total designed area is lower than the available one for each mEH. A similar constraint is formulated for solar thermal collectors.

2. Operation constraints

The common operation constraint for generation and conversion technologies in the ILEC is the technology capacity constraint. It is formulated below by taking the natural gas internal combustion engine-based CHP (CHP NGICE) as an example:

$$E_{CHP\ NGICE\,j}^{min} x_{CHP\ NGICE\,j,d,hr} \leq E_{CHP\ NGICE\,j,d,hr} \leq E_{CHP\ NGICE\,j}^{max} x_{CHP\ NGICE\,j,d,hr}, \forall j,d,hr \tag{3}$$

This constraint ensures that for each *h* of the representative season day *d*, the power provided by the CHP in each mEH *j* is limited by its minimum part load and the size, if the technology is on, i.e., the binary decision variable $x_{CHP\ NGICE\,j,d,hr}$ is equal to 1.

The minimum and maximum output of each CHP can be obtained based on its designed capacity, as in [23].

In the following, the additional operation constraints for generation and conversion technologies, as well as the constraints for storage, are presented.

Operation constraints for generation technologies

Combined heat and power systems

The prime mover of the CHP could be an internal combustion engine (ICE), a micro-turbine (MTG), or a fuel cell (FC). Taking the CHP with an ICE as an example, the ramp rate constraint limits the power generation change between two successive hours to be within the ramp-down and ramp-up rates expressed as a percentage of the designed CHP size, i.e.:

$$DR_{CHP\ NGICE\,j} \leq E_{CHP\ NGICE\,j,d,hr} - E_{CHP\ NGICE\,j,d,hr-1} \leq UR_{CHP\ NGICE\,j}, \forall j,d,hr \tag{4}$$

The amount of natural gas required by the prime mover to produce the power is formulated as:

$$G_{CHP\ NGICE\,j,d,hr} = \frac{E_{CHP\ NGICE\,j,d,hr}}{\eta_{e,CHP\ NGICE} LHV_{NG}}, \forall j,d,hr, \tag{5}$$

where $\eta_{e,CHP\ NGICE,}$ is the electrical efficiency of the CHP and LHV_{NG} is the lower heat value of natural gas.

The thermal energy recovered from the prime mover is formulated as:

$$H_{CHP\ NGICE\,j,d,hr} = \frac{E_{CHP\ NGICE\,j,d,hr}\eta_{th,CHP\ NGICE}}{\eta_{e,CHP\ NGICE}}, \forall j,d,hr, \tag{6}$$

where $\eta_{th,CHP\ NGICE}$ is the thermal efficiency of the CHP. This thermal energy can be used to satisfy the thermal demand and to activate absorption chillers to produce cooling energy.

$$H_{CHP\ NGICE\,j,d,hr} = H_{CHP\ NGICE\,j,d,hr}^{Th} + H_{CHP\ NGICE\,j,d,hr}^{SC}, \forall j,d,hr, \tag{7}$$

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Beyond the capacity constraint as in Eq. (3) and ramp-rate constraint as in Eq. (4), the additional operation constraints to consider for the fuel cell CHP and electrolyser are presented below [23].

$$H2_{CHP\ FCj,d,hr} = \frac{E_{CHP\ FCj,d,hr}}{(\eta_{e,CHP\ FC} LHV_{H2})}, \forall j, d, hr, \quad (8)$$

$$E^{req}_{EZj,d,hr} = \frac{H2_{CHP\ FCj,d,hr} LHV_{H2}}{(\eta_{e,EZ})}, \forall j, d, hr, \quad (9)$$

Eq. (8) allows calculating the amount of hydrogen needed by the CHP FC to produce power and depends on the electrical efficiency of the FC. Eq. (9) allows calculating the power required by the electrolyser to produce hydrogen and depends on the electrical efficiency of the electrolyser

The thermal energy recovered from the FC is formulated as in Eq. (6) and is subject to the constraint in Eq. (7).

As for the electrolyser, the following constraints are formulated:

$$E^{min}_{EZ} x_{EZj,d,hr} \leq E^{req}_{EZj,d,hr} \leq E^{max}_{EZ} x_{EZj,d,hr}, \forall j, d, hr, \quad (10)$$

$$E^{req}_{EZj,d,hr} = E^{EZ}_{PVj,d,hr}, \forall j, d, hr. \quad (11)$$

Eq. (11) ensures that the power required by the electrolyser is equal to the share of power from PV in mEH j allocated for usage in the electrolyser to ensure that only green hydrogen is used in the ILEC.

Natural gas boilers

Similarly to (5), the amount of natural gas required by the boilers can be formulated based on the heat rate provided by the boiler (a continuous decision variable) and the thermal efficiency. The same as CHPs, the thermal energy provided by the boilers can be used to satisfy the thermal demand and to activate absorption chillers to produce cooling energy.

Solar technologies

Solar PV and solar thermal collectors can be used to satisfy the electricity demand and the thermal demand, respectively. The power provided by a PV system is formulated as:

$$E_{PVj,d,hr} = A_{PVj} \eta_{PV} I_{d,hr}, \forall j, d, hr, \quad (12)$$

where η_{PV} is the efficiency of the PV system, $A_{PV,j}$ is the area of PV installed (a continuous decision variable) and $I_{d,hr}$ is the hourly solar irradiance. The heat rate provided by the solar thermal collectors can be formulated in a similar way.

Operation constraints for conversion technologies

Reversible heat pumps

Reversible heat pumps can be used to satisfy the thermal or cooling demand in the heating or cooling mode, respectively. Considering the heating mode, the heat rate (a continuous decision variable) provided by a heat pump is formulated as:

$$E^{HM,req}_{HPj,d,hr} = \frac{H_{HPj,d,hr}}{COP^{HM}_{HP}}, \forall j, d, hr, \quad (13)$$

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which links the electricity required by the heat pump to the heat rate provided through its coefficient of performance. The constraint is similar for the heat pump operating in cooling mode.

Absorption chillers

In each mEH *j*, the absorption chillers can be used to meet the cooling demand and be powered by the CHPs and boilers installed in the same mEH, and by the CHPs installed in the other mEHs through the heating pipeline (if installed). The cooling rate provided by an absorption chiller is thus formulated as:

$$C_{AChil j,d,hr} = \Bigg[\sum_{CHP\ NGICE} H^{SC}_{CHP\ NGICE j,u,d,hr} + \sum_{CHP\ NGMTG} H^{SC}_{CHP\ NGMTG j,u,d,hr} + \sum_{CHP\ FC} H^{SC}_{CHP\ FC j,u,d,hr} + \sum_{NG\ Boiler} H^{SC}_{NG\ Boiler j,d,hr} + \sum_{j,j\neq u} x_{pipe,u,j} \Bigg(\eta_{pipe,j,u} \Bigg(\sum_{CHP\ NGICE} H^{SC}_{CHP\ NGICE j,u,d,hr} + \sum_{CHP\ NGMTG} H^{SC}_{CHP\ NGMTG j,u,d,hr} + \sum_{CHP\ FC} H^{SC}_{CHP\ FC j,u,d,hr} \Bigg)\Bigg)\Bigg] COP_{AChil},$$

$\forall j = u, \forall d, hr$ (14)

where $H^{SC}_{CHP\ NGICE j,u,d,hr}$ $H^{SC}_{CHP\ NGMTG j,u,d,hr}$ and $H^{SC}_{CHP\ FC j,u,d,hr}$ are the heating rates for cooling purposes provided by CHPs in mEH j to user u.

Operation constraints for storage technologies

Batteries

The operation constraints for a battery in mEH j are formulated below:

$$0 \leq E^{Ch}_{Bat j,d,hr} \leq x^{Ch}_{Bat j,d,hr} E^{Ch,max}_{Bat j,d,hr}, \forall j, d, hr, \quad (15)$$

$$0 \leq E^{Disch}_{Bat j,d,hr} \leq x^{Disch}_{Bat j,d,hr} E^{Disch,max}_{Bat j,d,hr}, \forall j, d, hr, \quad (16)$$

$$x^{Ch}_{Bat j,d,hr} + x^{Disch}_{Bat j,d,hr} \leq 1, \forall j, d, hr, \quad (17)$$

$$SOC_{Bat j,d,hr} = SOC_{Bat j,d,hr-1} + \frac{E^{Ch}_{Bat j,d,hr} \eta^{Ch}_{Bat} Dt}{Cap_{Bat j}} - \frac{E^{Disch}_{Bat j,d,hr} Dt}{\eta^{Dis}_{Bat} Cap_{Bat j}}, \forall j, d, hr, \quad (18)$$

$$SOC^{min}_{Bat j} \leq SOC_{Bat j,d,hr} \leq SOC^{max}_{Bat j}, \forall j, d, hr. \quad (19)$$

The battery charging/discharging power limits are enforced in Eqs. (15) - (17). The battery state-of-charge (SOC) dynamics are modelled in Eq. (18), and the upper and lower limits of SOC are enforced by Eq. (19).

Thermal energy storage systems

As for the thermal storage system for heating, the state dynamic is formulated as:

$$H_{TES-Th j,d,hr} = H_{TES-Th j,d,hr-1}\big(1 - \varphi_{TES-Th}(Dt)\big) + (H^{Ch}_{TES-Th j,d,hr} - H^{Disch}_{TES-Th j,d,hr}) Dt, \forall j, d, hr$$

(20)

meaning that the energy stored at hour *hr* depends on the non-dissipated energy stored at hour *hr -1* (based on the loss fraction of the storage), and on the net energy flow. The constraint for the thermal storage system for cooling is similar.

H_2 storage systems

The operation constraints for a H_2 storage in mEH *j* are formulated below:

$$0 \leq H2^{Ch}_{H2stoj,d,hr} \leq H2^{Ch,max}_{H2stoj} x^{Ch}_{H2stoj,d,hr}, \forall j, d, hr, \quad (21)$$

$$0 \leq H2^{Disch}_{H2stoj,d,hr} \leq H2^{Disch,max}_{H2stoj} x^{Disch}_{H2stoj,d,hr}, \forall j, d, hr, \quad (22)$$

$$x^{Ch}_{H2stoj,d,hr} + x^{Disch}_{H2stoj,d,hr} \leq 1, \forall j, d, hr, \quad (23)$$

$$H2^{sto}_{H2stoj,d,hr} = H2^{sto}_{H2stoj,d,hr-1}\eta_{H2sto} + \left(H2^{Ch}_{H2stoj,d,hr} - H2^{Disch}_{H2stoj}\right)Dt, \forall j, d, hr. \quad (24)$$

where $x^{Ch}_{H2stoj,d,hr}$ and $x^{Disch}_{H2stoj,d,hr}$ are binary decision variables that are equal to 1 if the charging and discharging process is active, respectively. Eqs. (21) and (22) allow the charging and discharging processes, respectively, taking place between a minimum and a maximum value. Eq. (23) ensures that the charging and discharging processes do not take place simultaneously, whereas Eq. (24) relates the amount of hydrogen stored at time *hr* of day *d* with the one stored at previous time *hr-1* of the same day that depends on the efficiency of the hydrogen storage.

Operation constraints for heating network

The mEHs in the ILEC are interconnected from the energetic point of view through a pre-existing local grid and a heating network to be designed.

The heating pipeline, if installed (e.g., binary decision variable $x_{pipe,j,u}$ =1), allows the exchange of thermal energy among the mEHs through their CHPs with thermal losses increased with the distance among the systems [24]. From the mEH *j* to user *u*, the efficiency of the heat pipeline is formulated as:

$$\eta_{pipe,j,u} = 1 - \beta d_{j,u} x_{pipe,j,u}, \forall j, j \neq u. \quad (25)$$

where β is a parameter which represents the thermal loss per meter. If *j=u*, then $d_{j,u}$=0, and there are no heat losses.

Moreover, each installed heating pipeline allows the heat delivery only in one direction, and the connection is allowed only in one direction:

$$x_{pipe,j,u} + x_{pipe,u,j} \leq 1, \forall j, j \neq u \quad (26)$$

Objective function(s) of optimisation problem

The proposed tool allows to find the optimal design of the ILEC by determining the types, numbers and sizes of the generation, conversion and storage technologies, while considering short- and long-term objectives.

Economic objective function

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The short-term objective is the economic objective to minimize, representing the investment, O&M and energy costs of the ILEC as a whole.
In detail, the economic objective is to minimize the total annual cost C^{Tot} of the ILEC, that is formulated as:

$$C^{Tot} = C^{INV} + C^{O\&M} + C^{Energy} \quad (27)$$

The investment cost function C^{INV} consists of the following terms:

$$C^{INV,tech} = \sum_i \sum_j CRF_i\left(C_{c,i} S_{i,j}\right), \quad CRF_i = r(1+r)^{N_i}/[(1+r)^{N_i} - 1] \quad (28)$$

$$C^{INV,pipe} = \sum_j \sum_u CRF_{pipe}\left(C_{pipe} d_{j,u} x_{pipe,j,u}\right), \quad CRF_{pipe} = r(1+r)^{N_{pipe}}/[(1+r)^{N_{pipe}} - 1] \quad (29)$$

The total annualized investment cost of all technologies is represented in Eq. (28). For technology *i*, the total annualized investment cost is calculated as the product of the capital recovery factor (CRF) (a parameter depending on the lifetime of the technology and the interest rate), the capital cost (a parameter) and its designed size. The total annualized investment cost of pipelines is in Eq. (29), calculated as the product of the CRF of the pipeline, the capital cost of the pipeline (a parameter), the distance between the mEH *j* and user *u*, and the indicator $x_{pipe,j,u}$ whether the heating pipeline is installed between *j* and *u*.
The total annual O&M cost of the integrated energy system is formulated as:

$$C^{O\&M} = \sum_i \sum_j \sum_d \sum_{hr} OM_i R_{i,j,d,hr} D_t \quad (30)$$

For technology *i*, the total annual O&M cost is calculated by multiplying its O&M specific cost (a parameter) by its generation level *R* at hour *hr* of day *d*, and the length of the time interval (1 hour). For storage systems, the O&M costs are calculated through their capacities.
The total energy cost is formulated as:

$$C^{Energy} = \sum_{i\in\{CHP\ NGICE, CHP\ NGMTG, NG\ Boiler\}} \sum_j \sum_d \sum_{hr} Pr_{NG,d} G_{i,j,d,hr} Dt + \sum_j \sum_d \sum_{hr} Pr_{PG,d,hr} E_{PGj,d,hr} D \quad (31)$$

It is the sum of the total cost of gas calculated by multiplying the gas price (a parameter) by the total amount of gas consumed by the CHPs and boilers in the ILEC and the total cost of buying grid power calculated by multiplying the time-varying unit price of grid power (a parameter) and the total amount of electricity taken from the grid.

Environmental objective function

The environmental objective is to minimize the total annual CO_2 emissions, consisting of the sum of the following functions:

$$Env^{Tot} = Env^{NG} + Env^{PG} \quad (32)$$

$$Env^{NG} = \sum_{i\in\{CHP\ NGICE, CHP\ NGMTG, NG\ Boiler\}} \sum_j \sum_d \sum_{hr} G_{i,j,d,hr} CI_{NG} LHV_{NG} Dt \quad (33)$$

$$Env^{PG} = \sum_j \sum_d \sum_{hr} E_{PGj,d,hr} CI_{PG} Dt \quad (34)$$

In Eq. (33), the total CO_2 emission associated with the gas consumed by the CHPs and auxiliary boilers in the ILEC depends on the carbon intensity (CI) of gas, whereas in Eq. (34), the total CO_2 emission associated with the grid power depends on the carbon intensity of the power grid, which the ILEC is connected to.

Optimisation method used to solve the formulated problem

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With the economic and environmental objectives formulated above, the planning problem has two types of objective function to be minimized. To solve this multi-objective optimization problem, the weighted-sum method is used to have a single objective function formulated as: $Fobj = c\omega C^{TOT} + (1-\omega)Env^{Tot},$ (35) where c is a constant scaling factor to keep the two objectives at the same order of magnitude, and ω is the weight for the total annual cost C^{Tot} varying in the range of 0-1. When ω = 1, it is to find the solution that minimizes the total annual cost of the whole ILEC, and when ω = 0, it is to find the solution that minimizes the total environmental impact of ILEC. When varying the weight ω in the range of [0, 1], the Pareto front between economic and environmental objectives can be found. The problem formulated in Eqs. (1)-(43) is linear and involves both discrete and continuous variables. To solve the problem efficiently, branch-and-cut, which is powerful for MILP problems, is used.
Energy carriers involved
Gas, hydrogen, electricity, heating, cooling.
Energy technologies involved

• CHP with different types of prime movers:
    o Internal combustion engine
    o Micro-gas turbine
    o Fuel cell
• Electrolyser
• Natural gas boilers
• Solar PV
• Solar thermal
• Reversible heat pump
• Absorption chiller
• Battery
• Thermal storage for heating and cooling
• Hydrogen storage

Formulation of system balances equation for energy carriers involved
3. System balance constraints ***Power balance*** In the ILEC, for each user u, the electrical demand and the electricity required by the heat pumps (either in the heating or cooling mode) and electrolysers installed in the associated mEH j, must be met by the sum of the electricity provided by the CHPs in all energy hubs, by the electricity provided by PV and the battery in the associated mEH, and by the grid power: $E_{dem,u,d,hr} + \sum_{HP} E^{req}_{HPj,d,hr} + \sum_{EZ} E^{req}_{EZj,d,hr} = \sum_j \sum_{CHP\ NGICE} E_{CHP\ NGICEj,u,d,hr} + \sum_j \sum_{CHP\ NGMTG} E_{CHP\ MTGj,u,d,hr} + \sum_j \sum_{CHP\ FC} E_{CHP\ FCj,u,d,hr} + E_{PVj,d,hr} + E_{PGj,d,hr} + \sum_{Bat} E^{Disch}_{Batj,d,hr} - E^{Ch}_{Batj,d,hr}, \forall u, j = u, \forall d, hr$ (36) where $E_{CHP\ NGICEj,u,d,hr}$, $E_{CHP\ MTGj,u,d,hr}$ and $E_{CHP\ FCj,u,d,hr}$ represent the power provided by CHPs associated with mEH j to user u, which are involved in the following CHP electricity balance constraints: $E_{CHP\ NGICEj,d,hr} = \sum_u E_{CHP\ NGICEj,u,d,hr}, \forall j, d, hr$ (37) $E_{CHP\ MTGj,d,hr} = \sum_u E_{CHP\ MTGj,u,d,hr}, \forall j, d, hr$ (38)

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$E_{CHP\ FC j,d,hr} = \sum_u E_{CHP\ FC j,u,d,hr}\ , \forall j, d, hr$ (39) ***Thermal energy balance*** In the ILEC, for each user *u*, the thermal demand must be met by the total thermal energy provided by the CHPs, boilers, heat pumps, and the thermal storage installed in the associated mEH *j*, and by the total thermal energy provided by CHPs installed in the other mEHs, through the heating pipeline (if installed): $H_{dem,u,d,hr} = \sum_{CHP\ NGICE} H_{CHP\ NGICE j,u,d,hr} + \sum_{CHP\ NGMTG} H_{CHP\ NGMTG j,u,d,hr} + \sum_{CHP\ FC} H_{CHP\ FC j,u,d,hr} + \sum_{NG\ Boiler} H_{NG\ Boiler j,d,hr} + \sum_{HP} H_{HP j,d,hr}^{HM} + H_{ST j,d,hr} + \sum_{TES-Th} H_{TES-Th j,d,hr}^{Disch} - H_{TES-Th j,d,hr}^{Ch} + \sum_{j,j\neq 1}[\eta_{pipe,j,u}(\sum_{CHP\ NGICE} H_{CHP\ NGIC j,u,d,hr} + \sum_{CHP\ NGMTG} H_{CHP\ NGMTG j,u,d,hr} + \sum_{CHP\ FC} H_{CHP\ FC j,u,d,hr})], \forall u, j = u, \forall d, hr$ (40) where $H_{CHP\ NGICE j,u,d,hr}$, $H_{CHP\ NGMTG j,u,d,hr}$ and $H_{CHP\ FC j,u,d,hr}$ are the heating rates provided by CHPs associated with mEH *j* to user *u*, which are involved in the following CHP thermal balance constraints, $H_{CHP\ NGICE j,d,hr} = \sum_u (H_{CHP\ NGICE j,u,d,hr} + C_{CHP\ NGICE j,u,d,hr})\ , \forall j, d, hr$ (41) $H_{CHP\ NGMTG j,d,hr} = \sum_u (H_{CHP\ NGMTG j,u,d,hr} + C_{CHP\ NGMTG j,u,d,hr})\ , \forall j, d, hr$ (42) $H_{CHP\ FC j,d,hr} = \sum_u (H_{CHP\ FC j,u,d,hr} + C_{CHP\ FC j,u,d,hr})\ , \forall j, d, hr$ (43) The thermal balance for the cooling demand can be formulated similarly.
Tool(s) used to solve the problem
Optimal design of multi-energy systems with multi-objective approach tool
Temporal resolution
Hourly resolution for four representative season days
Time horizon
1 year

Nomenclature

Decision Variables	
$A_{PV j}$	Installed area of PV (m^2)
$C_{AChil j,d,hr}$	Cooling rate provided by absorption chiller (dependent variable) (kW)
C^{Energy}	Total annual energy cost (€)
C^{INV}	Total annualized investments cost (€)
$C^{O\&M}$	Total annual O&M cost (€)
C^{Tot}	Total annual cost (€)
$Cap_{Bat j}$	Capacity of battery (kWh)
$DR_{CHP\ NGICE j}$	Maximum ramp-down rate of CHP NG ICE (dependent variable) (kW)
$E_{Bat j,d,hr}^{Ch,max}$	Maximum charging power of battery (dependent variable) (kW)
$E_{Bat j,d,hr}^{Ch}$	Charging power for battery (kW)
$E_{Bat j,d,hr}^{Disch,max}$	Maximum discharging power of battery (dependent variable) (kW)
$E_{Bat j,d,hr}^{Disch}$	Discharging power for battery (kW)
$E_{CHP\ FC j,d,hr}$	Power provided by CHP FC (kW)
$E_{CHP\ NGICE j,d,hr}$	Power provided by CHP NG ICE (kW)
$E_{CHP\ NGICE j}^{max}$	Maximum load of CHP NG ICE (dependent variable) (kW)

$E_{CHP\ NGICE j}^{min}$	Minimum part load of CHP NG ICE (dependent variable) (kW)
$E_{EZ j,d,hr}^{req}$	Power required by the electrolyser (dependent variable) (kW)
E_{EZ}^{max}	Maximum part load of EZ (dependent variable) (kW)
E_{EZ}^{min}	Minimum part load of EZ (dependent variable) (kW)
$E_{HP j,d,hr}^{req}$	Power required by the heat pump (dependent variable) (kW)
$E_{PG j,d,hr}$	Grid power (kW)
$E_{PV j,d,hr}$	Power provided by PV (kW)
$E_{PV j,d,hr}^{EZ}$	Share of power from PV allocated for usage in the EZ (kW)
Env^{NG}	Total annual CO2 emission related to gas consumption (kgCO2)
Env^{PG}	Total annual CO2 emission related to grid power consumption (kgCO2)
Env^{Tot}	Total annual CO2 emissions (kgCO2)
$G_{CHP\ NGICE j,d,hr}$	Gas volumetric flow rate consumed by CHP NG ICE (dependent variable) (Nm^3/h)
$H2_{H2sto j,d,hr}^{Ch}$	H2 charging for H2 storage (m^3/h)
$H2_{H2sto j,d,hr}^{Disch}$	H2 discharging for H2 storage (m^3/h)
$H2_{H2sto j,d,hr}^{sto}$	H2 stored in H2 storage (m^3)
$H2_{H2sto j}^{Ch,max}$	Maximum H2 charging for H2 storage (dependent variable) (m^3)
$H2_{H2sto j}^{Disch,max}$	Maximum H2 discharging for H2 storage (dependent variable) (m^3)
$H_{\mathrm{TES-Th} j,d,hr}^{\mathrm{Disch}}$	Discharging heat rate from TES (kW)
$H_{\mathrm{TES-Th} j,d,hr}^{\mathrm{Ch}}$	Charging heat rate to TES (kW)
$H_{CHP\ NGICE j,d,hr}$	Heat rate provided by CHP NG ICE (dependent variable) (kW)
$H_{HP j,d,hr}$	Heat rate provided by the heat pump (kW)
$H_{NG\ Boiler j,d,hr}$	Heat rate provided by natural gas boiler (kW)
$H_{TES-Th j,d,hr}$	Thermal energy stored in TES (kWh)
$SOC_{Bat j}^{max}$	Maximum SOC battery (dependent variable)
$SOC_{Bat j}^{min}$	Minimum SOC battery (dependent variable)
$S_{i,j}$	Designed size of the technology (kW – kWh)
$UR_{CHP\ NGICE j}$	Maximum ramp-up rate of CHP NG ICE (dependent variable) (kW)
$x_{Bat j,d,hr}^{Ch}$	Binary variable for usage of battery for charging process
$x_{Bat j,d,hr}^{Disch}$	Binary variable for usage of battery for discharging process
$x_{CHP\ NGICE j,d,hr}$	On/off status of CHP NG ICE
$x_{EZ j,d,hr}$	On/off status of EZ
$x_{H2sto j}^{Ch}$	Binary variable for usage of H2 storage for charging process
$x_{H2sto j}^{Disch}$	Binary variable for usage of H2 storage for discharging process
$x_{i,j}$	Binary variable for the choice of technology
$x_{pipe,j,u}$	Binary variable for the choice of installation of heating pipeline between mEH *j* and user *u*
$\eta_{pipe,j,u}$	Efficiency of heating pipeline (dependent variable)
c	Constant in *Fobj* (kgCO2/€)
$Fobj$	Objective function of the multi-objective optimization problem
$H2_{CHP\ FC j,d,hr}$	Volumetric flow rate of hydrogen (m^3/h)
$SOC_{Bat j,d,hr}$	Battery SOC
ω	Weight value in *Fobj*
Parameters	
$A_{PV j}^{max}$	Maximum area for PV installation (m^2)

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CI_{NG}	Carbon intensity of natural gas (kgCO2/Nm^3)
CI_{PG}	Carbon intensity of power grid (kgCO2/kWh)
COP_{HP}^{HM}	COP of heat pump in heating mode
CRF_i	Capital recovery factor
$C_{c,i}$	Specific capital cost (€/kW)–(€/kWh)–(€/m^2)
$E_{dem,u,d,hr}$	Time-varying power demand of mEH (kW)
$H_{dem,u,d,hr}$	Time-varying heat rate demand of mEH (kW)
$I_{d,hr}$	Hourly solar irradiance (kW/m^2)
LHV_{NG}	Lower heat value of natural gas (kWh/Nm^3)
OM_i	Specific O&M cost (€/kWh)
$Pr_{NG,d}$	Natural gas price (€/Nm^3)
$Pr_{PG,d,hr}$	Time-varying unit price of grid power (€/kWh)
$R_{i,j,d,hr}$	Generation level (kW) – (kWh)
S_i^{max}	Maximum size of technology in the market (kW)
S_i^{min}	Minimum size of technology in the market (kW)
$d_{j,u}$	Distance between mEH *j* and user *u* (m)
η_{Bat}^{Ch}	Efficiency of charging process for battery
η_{Bat}^{Dis}	Efficiency of discharging process for battery
η_{H2sto}	Efficiency of H2 storage
η_{PV}	Electric efficiency of PV
$\eta_{e,CHP\ FC}$	Electric efficiency of CHP FC
$\eta_{e,CHP\ NGICE}$	Electric efficiency of CHP NG ICE
$\eta_{e,EZ}$	Electric efficiency of EZ
$\eta_{th,CHP\ NGICE}$	Thermal efficiency of CHP NG ICE
φ_{TES-Th}	TES storage loss fraction
Dt	Length of the time interval (1 hour)
N_i	Lifetime (years)
r	Interest rate
LHV_{H2}	Lower heat value of hydrogen (kWh/m^3)
β	Parameter representing the thermal loss per meter in heating pipeline
Subscripts/Superscripts	
d	Index of representative season day
HM	Heating mode
hr	Index of hour in representative season day
i	Index of technology
j	Index of mEH
pipe	Heating pipeline
SC	Space cooling purposes
ST	Solar thermal
tech	Technology
Th	Thermal purposes
u	Index of user

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4.2.2 Integrate tool

Optimisation problem
LTO problem in the Planning phase – *Integrate*
Description of the considered optimisation problem
Integrate (previously known as eTransport) [2] is a software system for the optimisation of integrated energy systems. It can be used to optimise the development of an energy system while considering the projections in energy demand and the different technological possibilities for energy supply, conversion between energy carriers, distribution, storage, end-use measures, and restrictions on CO_2 emissions. Integrate represents a spatially confined area and determines cost-optimal energy system investment strategies based on predefined investment options. Multiple energy carriers, energy uses, and technologies are considered. The competition and synergies between different energy carriers and technology solutions are part of the optimisation. The structure of the energy system modelled in Integrate is highly flexible and given as user input, as depicted in Figure 8. The user controls the placement of and connection between the different components. Here, the components connected by a dashed line are investment options, while those with a whole line are the existing system.

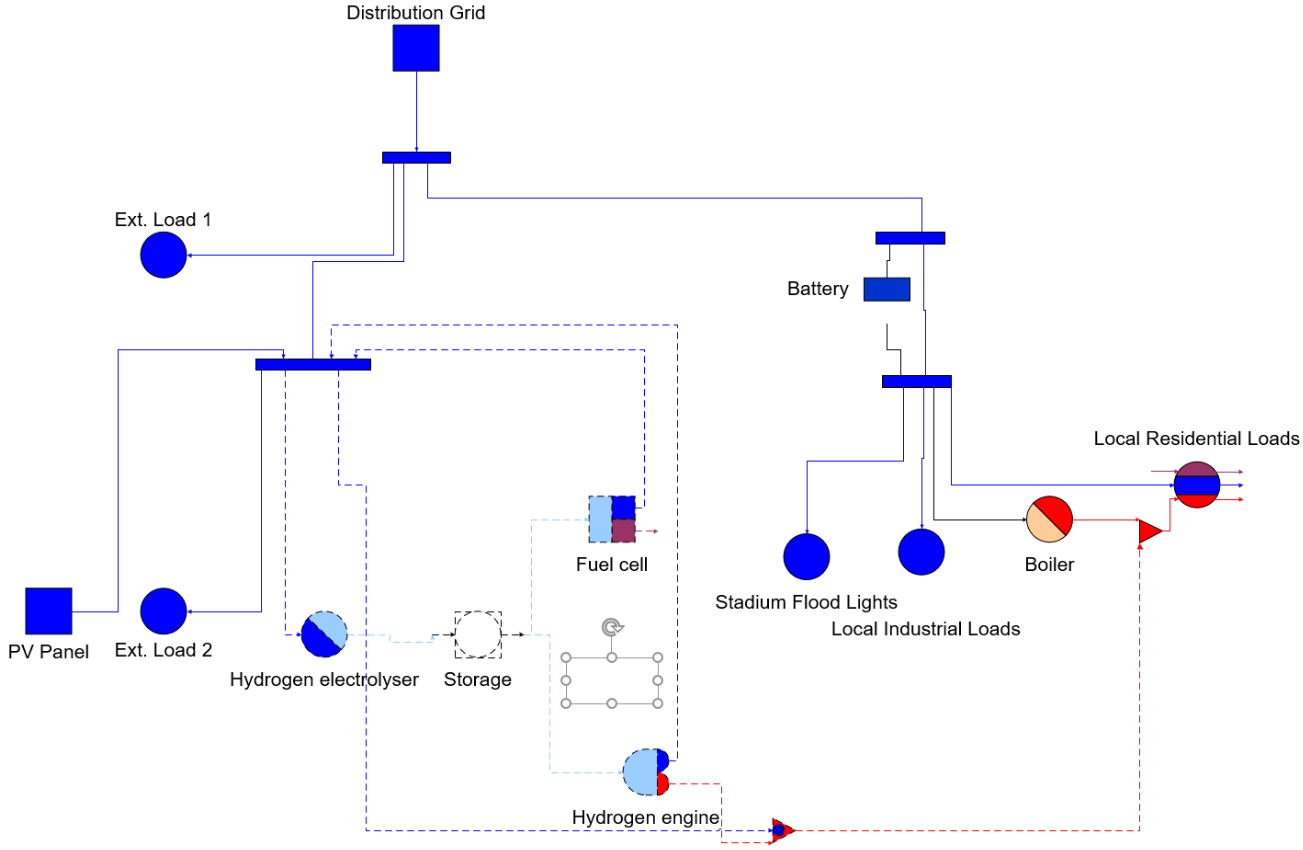

Figure 8 Example of an energy system model in Integrate

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Formulation of the optimisation problem

The optimisation problem is formulated as a two-step procedure, as depicted in Figure 9. The short-term operational analyses and the long-term investment decisions are decoupled to allow a fine resolution of the operational optimisation (e.g., 1h) while also optimizing for a 20–50-year horizon. Without decoupling the investment and operational problems, the problem size would render it infeasible.

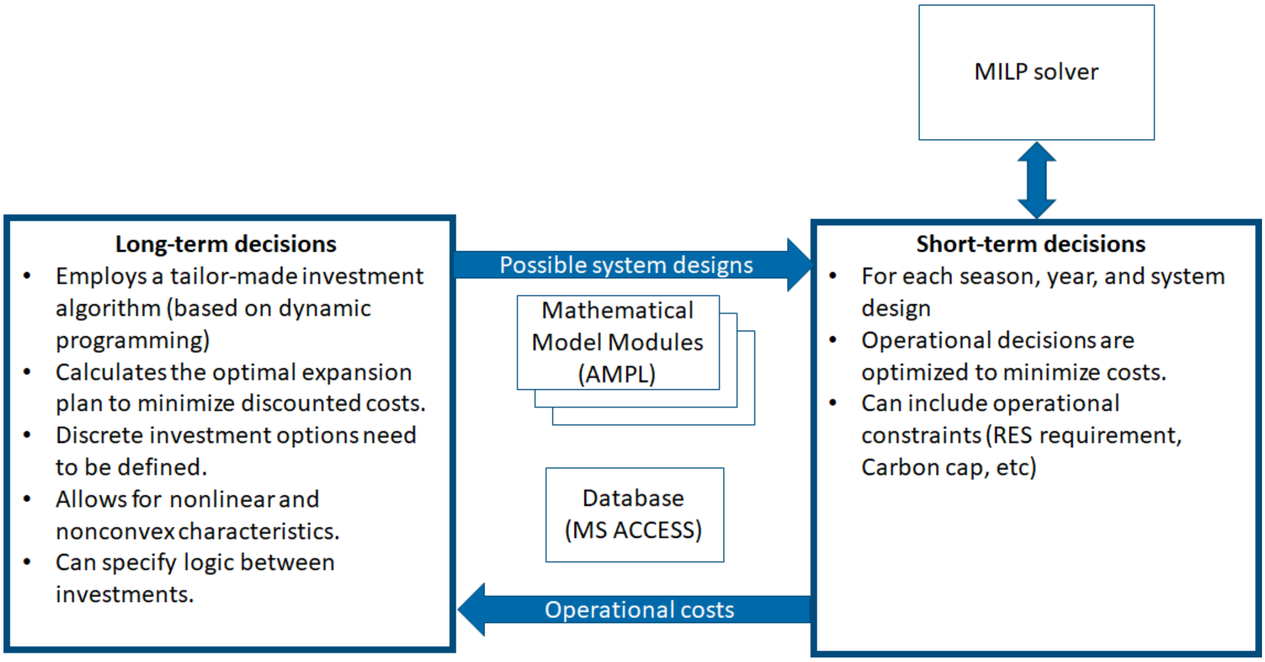

Figure 9 Integrate optimisation framework

Constraints considered in the optimisation problem

The optimization problem constraints mainly consist of three types of constraint:

1. Design constraints
2. Operation constraints
3. System balance constraints

1. Design constraints

The user defines a set of investment alternatives that are represented by set D, where each investment alternative typically consists of several physical components with predefined connections to the rest of the energy system. If *n* investment alternatives are defined by the user, the model must in principle, account for 2^n different states. Processing could be computationally costly/could have a high computational cost, if many investment alternatives have been defined. However, many states are usually irrelevant combinations that can be skipped. The computational time can be significantly reduced if the user specifies the following type of information to form design constraints:

- **Mutually exclusive alternatives:** any pair of investment alternatives are assumed to be mutually exclusive unless the user specifies that they are not.
- **Time window for investments:** a first and a final relevant year for each investment alternative.
- **Dependent alternatives:** a part/subset of the alternatives are relevant only if some other alternatives are also carried out. For instance, a district heating network is relevant only if a heat central is also included (e.g., one of the two competing alternatives ‘’boiler’’ and ‘’CHP’’). Several sets of dependent alternatives can be specified for each investment.

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- **Necessary alternatives:** a set of investment alternatives where at least one of the alternatives must be carried out within a specified year. Several sets of necessary alternatives can be defined for each year.

2. Operation constraints

The mathematical formulations for all the modules are combined to form a single linear problem for each operational analysis to be carried out. The operational constraints are inequality and equality constraints specific to each technology. The formulations for the optimal design of multi-energy systems with multi-objective approach tool provide some examples of the general structure of such constraints that are also valid for the Integrate tool.

3. System balance constraints

All modules are connected through system balance constraints. This is elaborated further in the section about system balance equations.

Objective function(s) of the optimisation problem

The overall objective for the model is to identify an investment plan that minimizes the discounted net present value of all operational and investment costs:

$$minimize_{\{I_{td}\}} \left\{ \sum_{t \in T} \delta^{t-t_{start}} \left\{ \sum_{\tau \in \{1,\ldots,T_{step}\}} \delta^{\tau-1} c_t^{ope} + c_t^{inv} \right\} - \delta^{t_{end}+T_{step}-t_{start}} \Phi \right\} \tag{1}$$

The investment cost during period t is given by:

$$c_t^{inv} = \sum_{d \in D} c_d^{inv} I_{td} \tag{2}$$

Here, c_d^{inv} is the investment cost for project d specified by the user. If, for instance, investment u and v is carried out in period t, then $I_{tu}, I_{tv} = 1$ and $c_t^{inv} = c_u^{inv} + c_v^{inv}$.

The operation cost during period t is given by:

$$c_t^{ope} = minimize \sum_t \sum_k c_{kt} x_{kt} \tag{3}$$

The operation costs are determined before the investment planning is initiated. Operational costs include costs for energy procurements to the system subtracted revenue for energy exports. Some technologies may also have specific costs directly related to their operation. The sequential optimization methodology is further elaborated in the next section.

The scrapping value at the end of the planning horizon is given by:

$$\Phi = \sum_{t \in T, d \in D} c_d^{inv} I_{td} \cdot max \left\{ 0, 1 - \frac{t^{end} - t + T^{step}}{L_d} \right\} \tag{4}$$

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Optimisation method used to solve the formulated problem

The model performs a system optimization, minimizing the total present value of all costs. The energy system costs are minimized by considering both investment costs (CAPEX) and operational costs (OPEX). Integrate has a two-step approach to calculate optimal investment strategies.

The optimisation is carried out using a two-step procedure as depicted in Figure 9:

1) Operational optimization is carried out to determine OPEX
2) Investment optimisation considers OPEX from step 1 + CAPEX.

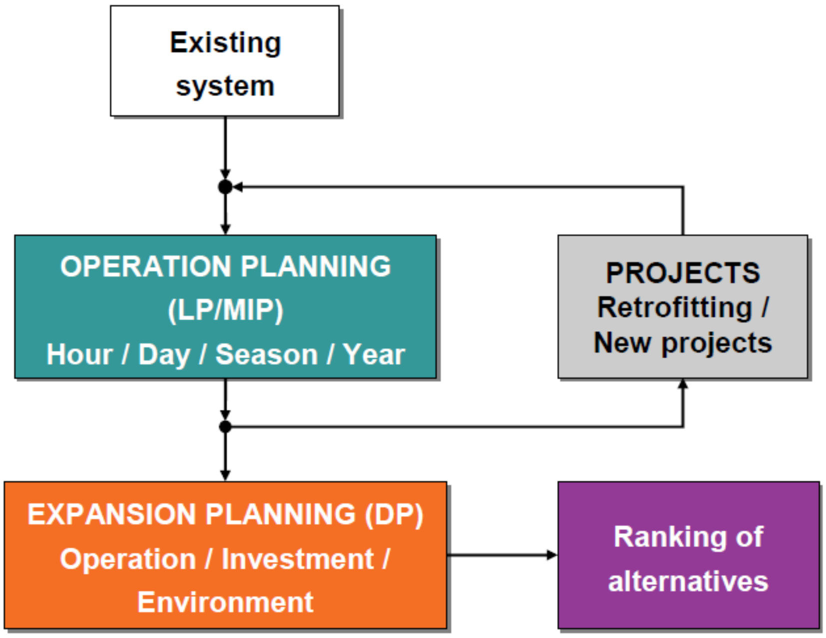

Figure 10 Structure of optimization process in Integrate

The first step optimises the operation by formulating a Mixed-Integer Linear Problem (MILP) for each combination of season, year, scenario, and energy system design. The seasons are represented by user-selected representative periods with a duration usually between one day and one week.

The second step, investment optimisation, is executed after the first step is completed. This happens as the OPEX for the different system configurations is needed. The investment optimisation is performed using a dynamic programming algorithm.

In the second step, the optimized OPEX of all possible system configurations for every year is forwarded to the investment algorithm to provide information about how investments will affect operational costs. The optimization of investments is then performed via dynamic programming (DP), considering all costs and logic between investment packages. Each dot in Figure 3 represents the annual operating costs for a given energy system design and year as calculated by the operational part of the model, where the green arrows and red dots represent the optimal investment pathway. See [25] for further details on the methodology.

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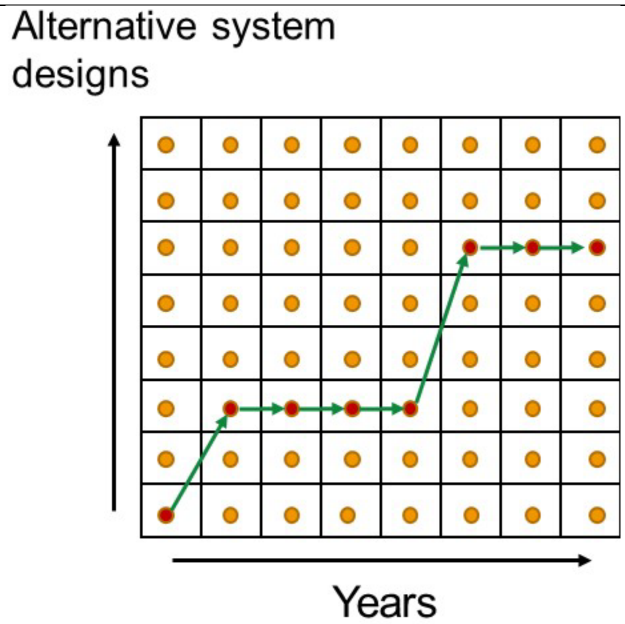

Figure 11 Optimization of investment strategy in Integrate

Energy carriers involved

Electricity, heating, hydrogen, biomass, gas, oil, waste, cooling.

Energy technologies involved

Conversion technologies:

- Boiler (can utilise various energy carriers)
- Heat pump
- Combined heat and power plant (CHP)
- Combined-cycle gas turbine (CCGT)
- Combined-cycle heat and power plant (CCHP)

Electricity:

- Power line
- Busbar
- Source (can represent, e.g., wind, photovoltaics, etc.)
- Load
- AC/DC converter
- Electricity market
- Battery
- Residential area
- Grid import

District heating

- Production plant
- Load junction
- Heat market
- Network junction
- Heat load
- Water heater

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- Warm water load
- Heat source
- Pipeline
- Heat storage
- Seasonal storage

Hydrogen:

- Hydrogen market/load
- Electrolyser
- Reformer
- Pipeline
- Hydrogen combustion
- Bulk transport
- Fuel cell

Cooling:

- Cold load
- Cold supply
- Pipeline
- Input point
- Junction point
- Load point
- Heat sink (condenser)
- Compression chiller
- Heat supply

Waste:

- Waste supply

Oil:

- Oil supply

Gas:

- Gas source
- Gas market
- Gas load
- Compressor
- Gas node
- Gas network pipe
- Valve
- Gas storage

Biomass:

- Biomass supply
- Biomass market
- Biomass bulk transport

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Formulation of system balances equation for energy carriers involved
The sub-models for different technologies are connected by general energy flow variables that identify the flow between energy sources (*Supply_points*), network components for transport, conversion and storage (*Network_nodes*) and energy sinks like loads and markets (*Load_points*). The connections between supply points, network nodes and load points are case-specific and given by the user. The connections are identified by sets of pairs where each pair shows a possible path for the energy flow between technology component types: - *Supply2net*: Set of pairs (*i, j*), where *i* ∈ *Supply_points* and *j* ∈ *Network_nodes* - *Supply2load*: Set of pairs (*i, j*), where *i* ∈ *Supply_points* and *j* ∈ *Load_points* - *Net2net*: Set of pairs (*i, j*), where *i, j* ∈ *Network_nodes* - *Net2load*: Set of pairs (*i, j*), where *i* ∈ *Network_nodes* and *j* ∈ *Load_points* Energy flow variables are defined over the energy system structure to account for the actual energy flow between different technology components (except for internal flows modelled within each technology). These general variables are included and restricted by the various modules, and they are the link between the different system components: - $Supply\_flow_{ijt}$: Energy flow from *i* to *j* at *t*, where (*i, j*) ∈ *Supply2net* and *t* ∈ *Time_steps* - $Local\_flow_{ijt}$: Energy flow from *i* to *j* at *t*, where (*i, j*) ∈ *Supply2load* and *t* ∈ *Time_steps* - $Net2net\_flow_{ijt}$: Energy flow from *i* to *j* at t, where (*i, j*) ∈ *Net2net* and *t* ∈ *Time_steps* - $Load\_flow_{ijt}$: Energy flow from *i* to *j* at *t*, where (*i, j*) ∈ *Net2load* and *t* ∈ *Time_steps*
Tool(s) used to solve the problem
Integrate
Temporal resolution
User-defined and hourly resolution is most usual.
Time horizon
User-defined, and 20-50 years is typical.

Nomenclature

Variables	
c_t^{ope}	Variable for annual operating costs in time-step t
c_t^{inv}	Variable for investment costs in time-step t
Φ	Variable for the scrap value of investments
I_{td}	Binary variable that identifies investments. I_{td} = 1 if the investment project d ∈D has been carried out in period t, and I_{td} = 0 otherwise.
x_{kt}	Decision variable for the operation of technology k in time-step t.
Parameters	
t_{start}	Parameter for the first year in the first time-step in the planning period
t_{end}	Parameter for the first year in the final time step in the planning period
T_{step}	Parameter for the number of years in each time step
δ	Parameter for the annual discount factor; δ =1/(1+ r)
c_d^{inv}	Investment cost for investment package d specified by the user
c_{kt}	Variable operation cost of technology k in time-step t.
L_d	Lifetime of investment package d.
r	Parameter for annual interest rate

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Indices and sets	
t	Index for time-steps; $t \in T$
τ	Index for the year within a time-step; $\tau \in \{1, \ldots, T_{step}\}$
T	Set for the planning period; $T = \{t_{start}, t_{start} + T_{step}, \ldots, t_{end}\}$
d	Index for investment alternatives; d $\in$D
D	Set of investment alternatives
k	Set of technologies

4.2.3 Operational analysis phase

Optimisation problem
Optimisation problem for operational analysis phase – 1. *Operation optimization of multi-carrier energy systems with multi-objective approach tool* 2. *Optimal management of EVs in multi-carrier energy systems with multi-objective approach tool*
Description of the considered optimisation problem
Based on the system design, technologies, and their characteristics in the planning phase, the optimisation problem for the operational analysis phase allows for the dispatch of the multi-carrier EH by pursuing multiple objectives when analysing the various operational scenarios or day-ahead dispatch. More specifically, the “Operational analysis” toolbox involves two tools: Operation optimization of multi-carrier energy systems with multi-objective approach and optimal management of EVs in multi-carrier energy systems with multi-objective approach tool. With regards to the functionality of the operation optimization of multi-carrier energy systems with multi-objective tool, it obtains (through a scenario-generation approach or forecasting tools as input) the optimal expected hourly operation strategies of the technologies in the multi-carrier systems by minimizing the weighted sum of total net daily costs and CO_2 emissions. Therefore, by adopting a multi-objective framework, the tool determines the optimal operation scheduling of the multi-energy system in the following modes: 1. **Stochastic approach**: in this case, the optimization problem is stochastic and allows determining the expected daily operation strategies of the ILEC by considering uncertainties related to RES, users’ loads and energy prices through a scenario-generation procedure that defines a set of scenarios related to uncertain parameters with related probability of occurrence that represent input data for the stochastic optimisation problem. In detail, the related input data for the stochastic optimisation problem are: a. Scenarios for solar irradiance profiles with related probability of occurrence (daily profiles with 1 hour as a time step) b. Scenarios for energy market prices (electricity, gas) with related probability of occurrence (daily profiles for electricity with 1 hour as a time step) c. Scenarios for energy demand profiles (electricity, heating, and cooling) with the related probability of occurrence (daily profiles with 1 hour as a time step). In order to simplify the stochastic optimization problem resolution and reduce the computational complexity, scenarios are combined such that there will be only two sets of scenarios, namely: - s_{sup}: set of supply sides scenarios obtained through combining scenarios of solar irradiance and energy market prices (electricity and gas)

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- s_{dem}: set of demand side scenarios obtained through combining scenarios of electricity, thermal and cooling demand hourly profiles.

In this way, the total number of scenarios will be given by $s_{sup} \times s_{dem}$.

2. **Deterministic approach**: in this case, the optimization problem is deterministic and uses as input data for RES generation, users' loads, and energy prices the day-ahead forecasted data as specified below:
   a. Day-ahead solar irradiance profiles and wind velocity (daily profiles with 1 hour as a time step)
   b. Day-ahead energy demand profiles (electricity, heating and cooling) (daily profiles with 1 hour as a time step)
   c. Day-ahead energy market prices (electricity, gas) (daily profiles for electricity with 1 hour as a time step).

The other input data that are common for both approaches are indicated below:
- Structure of the ILEC (and mEHs) in terms of installed technologies and energy flows among technologies within each mEH and among mEHs
- Technical data of energy technologies in the ILEC (average energy efficiency and installed sizes)
- Carbon intensity of input energy carriers.

As a supplementary tool, the optimisation problem related to optimal management of EVs in multi-carrier energy systems with multi-objective approach tool is providing charging/discharging strategies of EVs that allow for minimizing the ILEC's net daily energy cost while also reducing CO_2 emissions. This tool provides a multi-objective optimization model for optimally managing EVs with G2V and V2G technologies. The tool is based on a deterministic approach and can be only used for the daily optimal scheduling of the technologies in the ILEC and the daily management of charging/discharging strategies of EVs, with forecasting tools for solar irradiance, energy prices and energy load profiles as input.

The input data for this tool are the same as those for the operation optimization of multi-carrier energy systems with multi-objective tool. The additional input data are related to plug-in electric vehicles (PEVs), as indicated below.
Technical data of PEVs in each mEH of the ILEC:
   a. number of PEVs
   b. capacity of PEV batteries
   c. parking duration (arrival and departure time)
   d. SOC (initial at parking arrival and desired at departure)

The optimisation problem below is formulated for the operation optimization of multi-carrier energy systems with multi-objective tool in relation to the stochastic approach. It must be mentioned that this problem can be easily adapted to the deterministic approach, by not considering the dependence of variables on scenarios.

Additional equations are added with reference to the optimal management of the EVs tool.
In detail, the ILEC consists of multiple mEHs, each of them representing a prosumer, namely a multi-energy system equipped with the generation, conversion and storage technologies

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designed in the planning phase. It is assumed that each mEH *j* satisfies the multi-energy demand associated with user *u* and can also sell electricity back to the grid. The generation technologies include Combined Heat and Power (CHP) systems with micro gas turbines, internal combustion engines or fuel cells as the prime mover (where the fuel cell is fed by an electrolyser), gas-fired boilers, solar PV systems and solar thermal collectors. The conversion technologies include reversible electric heat pumps and single-stage absorption chillers. The storage technologies include batteries, thermal energy storage (TES) for heating and cooling purposes and H_2 storage. Moreover, the electrical and thermal energy provided by CHPs can be exchanged among the mEHs, where the thermal energy is shared by using the heating pipeline network designed in the planning phase. The distance between the mEH *j* and its end-user u (i.e., *j*=*u*), is assumed null, while the distance among different mEHs is assumed known [16] [19] [23] [26].
Formulation of the optimisation problem
The problem is formulated through a MILP approach. It must be mentioned that, from the analysis carried out in T4.1 [1], it emerged that MILP formulations are the most widely used in the literature for the design optimization of EHs, being these a good compromise between model fidelity and complexity of the optimization process, by also taking advantage of powerful MILP solution methods as branch-and-cut. The optimization problem is linear and involves both discrete (binary) and continuous variables. The binary decision variables are the operation on/off status of the energy technologies, whereas the continuous decision variables include the energy rate (power, heating or cooling) provided, the charging/discharging rate, and power taken from the grid. All the other variables can be classified as dependent variables.
Constraints considered in the optimisation problem
The optimization problem constraints mainly consist of two types of constraint, i.e.: 4. Operation constraints 5. System balance constraints **1. Operation constraints** The common operation constraint for generation and conversion technologies in the ILEC is the technology capacity constraint. It is formulated below by taking the natural gas internal combustion engine-based CHP (CHP NGICE) as an example. $$E^{min}_{CHP\ NGICE\,j} x_{CHP\ NGICE\,j,s_{sup},s_{dem},hr} \leq E_{CHP\ NGICE\,j,s_{sup},s_{dem},hr} \leq E^{max}_{CHP\ NGICE\,j} x_{CHP\ NGICE\,j,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr \quad (1)$$ This constraint ensures that for each scenario s_{sup} and s_{dem}, for each *hr* of the day, the power provided by the CHP in each mEH *j* is limited by its minimum part load and the size, if the technology is on, i.e., the binary decision variable $x_{CHP\ NGICE\,j,s_{sup},s_{dem},hr}$ is equal to 1. In the following, the additional operation constraints for generation and conversion technologies, as well as the constraints for storage are presented.

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Operation constraints for generation technologies

Combined heat and power systems

The prime mover of the CHP could be an ICE, MTG, or FC. Taking the CHP with an ICE as an example, the ramp rate constraint limits the power generation change between two successive hours to be within the ramp-down and ramp-up rates, i.e.:

$$DR_{CHP\ NGICEj} \leq E_{CHP\ NGICEj,s_{sup},s_{dem},hr} - E_{CHP\ NGICEj,s_{sup},s_{dem},hr} \leq UR_{CHP\ NGICEj}, \forall j, s_{sup}, s_{dem}, hr$$
(2)

The amount of natural gas required by the prime mover to produce the power is formulated as:

$$G_{CHP\ NGICEj,s_{sup},s_{dem},hr} = \frac{E_{CHP\ NGICEj,s_{sup},s_{dem},hr}}{\eta_{e,CHP\ NGICEj} LHV_{NG}}, \forall j, s_{sup}, s_{dem}, hr, \quad (3)$$

where $\eta_{e,CHP\ NGICEj}$ is the electrical efficiency of the CHP in mEH j and LHV_{NG} is the lower heat value of natural gas.

The total power supplied by the CHP NG ICE is equal to the sum of that sold on the day-ahead market (DAM) and that used for self-consumption in the ILEC (both decision variables), i.e.:

$$E_{CHP\ NGICEj,s_{sup},s_{dem},hr,s,t} = E^{sell}_{CHP\ NGICEj,s_{sup},s_{dem},hr,s,t} + \sum_u E^{self}_{CHP\ NGICEj,u,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr \quad (4)$$

The thermal energy recovered from the prime mover is formulated as:

$$H_{CHP\ NGICEj,s_{sup},s_{dem},hr} = \frac{E_{CHP\ NGICEj,s_{sup},s_{dem},hr} \eta_{th,CHP\ NGICEj}}{\eta_{e,CHP\ NGICEj}}, \forall j, s_{sup}, s_{dem}, hr, \quad (5)$$

where $\eta_{th,CHP\ NGICEj}$ is the thermal efficiency of the CHP in mEH j. This thermal energy can be used to satisfy the thermal demand and to activate absorption chillers to produce cooling energy.

$$H_{CHP\ NGICEj,s_{sup},s_{dem},hr} = H^{Th}_{HP\ NGICEj,s_{sup},s_{dem},hr} + H^{SC}_{HP\ NGICEj,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr, \quad (6)$$

Beyond the capacity constraint as in Eq. (1) and ramp-rate constraint as in Eq. (2), the additional operation constraints to consider for the fuel cell CHP and electrolyser are presented below [4].

$$H2_{CHP\ FCj,s_{sup},s_{dem},hr} = \frac{E_{CHP\ FCj,s_{sup},s_{dem},hr}}{(\eta_{e,CHP\ FC} LHV_{H2})}, \forall j, s_{sup}, s_{dem}, hr \quad (7)$$

$$E^{req}_{EZj,s_{sup},s_{dem},hr} = \frac{H2_{CHP\ FCj,s_{sup},s_{dem},hr} LHV_{H2}}{\eta_{e,EZj}}, \forall j, s_{sup}, s_{dem}, hr \quad (8)$$

Eq. (7) allows calculating the amount of hydrogen needed by the CHP FC to produce power and depends on the electrical efficiency of the FC. Eq. (8) allows calculating the power required by the electrolyser to produce hydrogen and depends on the electrical efficiency of the electrolyser.

The thermal energy recovered from the FC is formulated as in Eq. (5) and is subject to the constraint in Eq. (6).

As for the electrolyser, the following constraints are formulated:

$$E^{min}_{EZj} x_{EZj,s_{sup},s_{dem},hr} \leq E^{eq}_{EZj,s_{sup},s_{dem},hr} \leq E^{max}_{EZj} x_{EZj,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr, \quad (9)$$

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$$E^{req}_{EZj,s_{sup},s_{dem},hr} = E^{EZ}_{PVj,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr. \quad (10)$$

Eq. (10) ensures that the power required by the electrolyser is equal to the share of power from PV in mEH j allocated for usage in the electrolyser to ensure that only green hydrogen is used in the ILEC.

Natural gas boilers

Similarly to (3), the amount of natural gas required by the boilers can be formulated based on the heat rate provided by the boiler (a continuous decision variable) and the thermal efficiency. The same as CHPs, the thermal energy provided by the boilers can be used to satisfy the thermal demand and to activate absorption chillers to produce cooling energy.

Solar technologies

Solar PV and solar thermal collectors can be used to satisfy the electricity demand and the thermal demand, respectively. The power provided by a PV system is formulated as:

$$E_{PVj,s_{sup},hr} = A_{PVj}\eta_{PVj}I_{s_{sup},hr}, \forall j, s_{sup}, hr \quad (11)$$

where η_{PVj} is the efficiency of the PV system in mEH j, $A_{PV,j}$ is the installed area and $I_{s_{sup},hr}$ is the hourly solar irradiance in scenario s_{sup}. The electrical power supplied by the PV can be divided into the rate sold on the DAM that supplied for self-consumption of the ILEC and that used for EZ in each mEH, both continuous decision variables (as in Eq. 4).

The heat rate provided by the solar thermal collectors can be formulated as in Eq. (11).

Operation constraints for conversion technologies

Reversible heat pumps

Reversible heat pumps can be used to satisfy the thermal or cooling demand in the heating or cooling mode, respectively. Considering the heating mode, the heat rate (a continuous decision variable) provided by a heat pump is formulated as:

$$E^{HM,req}_{HPj,s_{sup},s_{dem},hr} = \frac{H_{s_{sup},s_{dem},hr}}{COP^{HM}_{HPj}}, \forall j, s_{sup}, s_{dem}, hr, \quad (12)$$

which links the electricity required by the heat pump to the heat rate provided through its coefficient of performance. The constraint is similar for the heat pump operating in cooling mode.

Absorption chillers

In each mEH *j*, the absorption chillers can be used to meet the cooling demand and be powered by the CHPs and boilers installed in the same mEH, and by the CHPs installed in the other mEHs through the heating pipeline (if installed). The cooling rate provided by an absorption chiller is thus formulated as:

$$C_{AChilj,s_{sup},s_{dem},hr} = \Big[H^{SC}_{CHP\ NGICEj,u,s_{sup},s_{dem},hr} + H^{SC}_{CHP\ NGMTGj,u,s_{sup},s_{dem},hr} + H^{SC}_{CHP\ FCj,u,s_{sup},s_{dem},hr} + H^{SC}_{NG\ Boilerj,u,s_{sup},s_{dem},hr} + \eta^{th}_{pipe}\Big(H^{SC}_{CHP\ NGICEj,u,s_{sup},s_{dem},hr}\Big|_{j\neq u} + H^{SC}_{CHP\ NGMTGj,u,s_{sup},s_{dem},hr}\Big|_{j\neq u} + H^{SC}_{CHP\ FCj,u,s_{sup},s_{dem},hr}\Big|_{j\neq u}\Big)\Big] COP_{AChilj}, \forall j = u,\ \forall s_{sup}, s_{dem}, hr \quad (13)$$

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where $H^{SC}_{CHP\ NGICEj,u,s_{sup},s_{dem},hr}$ $H^{SC}_{CHP\ NGMTGj,u,s_{sup},s_{dem},hr}$ and $H^{SC}_{CHP\ FCj,u,s_{sup},s_{dem},hr}$ are the heating rates for cooling purposes provided by CHPs in mEH j to user u.

Operation constraints for storage technologies

Batteries

The operation constraints for a battery in mEH *j* are formulated below:

$$0 \leq E^{Ch}_{Batj,s_{sup},s_{dem},hr} \leq x^{Ch}_{Batj,s_{sup},s_{dem},hr} E^{Ch,max}_{Batj,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr, \quad (14)$$

$$0 \leq E^{Disch}_{Batj,s_{sup},s_{dem},hr} \leq x^{Disch}_{Batj,s_{sup},s_{dem},hr} E^{Disch,max}_{Batj,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr, \quad (15)$$

$$x^{Ch}_{Batj,s_{sup},s_{dem},hr} + x^{Disch}_{Batj,s_{sup},s_{dem},hr} \leq 1, \forall j, s_{sup}, s_{dem}, hr, \quad (16)$$

$$SOC_{Batj,s_{sup},s_{dem},hr} = SOC_{Batj,s_{sup},s_{dem},hr-1} + \frac{E^{Ch}_{Batj,s_{sup},s_{dem},hr}\eta^{Ch}_{Batj}Dt}{Cap_{Batj}} - \frac{E^{Disch}_{Batj,s_{sup},s_{dem},hr}Dt}{\eta^{Dis}_{Batj}Cap_{Batj}}, \forall j, s_{sup}, s_{dem}, hr, \quad (17)$$

$$SOC^{min}_{Batj} \leq SOC_{Batj,s_{sup},s_{dem},hr} \leq SOC^{max}_{Batj}, \forall j, s_{sup}, s_{dem}, hr. \quad (18)$$

The battery charging/discharging power limits are enforced in Eqs. (14) - (16). The battery state-of-charge (SOC) dynamics are modelled in Eq. (17), and the upper and lower limits of SOC are enforced by Eq. (18).

Thermal energy storage systems

As for the thermal storage system for heating, the state dynamic is formulated as:

$$\mathrm{H_{TES-Thj,s_{sup},s_{dem},hr}} = \mathrm{H_{TES-Thj,s_{sup},s_{dem},hr-1}}\left(1 - \varphi_{\mathrm{TES-Th}}(\mathrm{Dt})\right) + (\mathrm{H^{Ch}_{TES-Thj,s_{sup},s_{dem},hr}} - \mathrm{H^{Disch}_{TES-Thj,s_{sup},s_{dem},hr}})\mathrm{Dt}, \forall \mathrm{j}, \mathrm{s_{sup}}, \mathrm{s_{dem}}, \mathrm{hr} \quad (19)$$

meaning that *for each set of scenarios, the energy stored at hour* hr *depends on the non-dissipated energy stored at hour* hr -1 *(based on the loss fraction of the storage), and on the net energy flow. The constraint for the thermal storage system for cooling is similar.*

H2 storage systems

The operation constraints for a H_2 storage in mEH *j* are formulated below:

$$0 \leq H2^{Ch}_{H2stoj,s_{sup},s_{dem},hr} \leq H2^{Ch,max}_{H2stoj} x^{Ch}_{H2stoj,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr, \quad (20)$$

$$0 \leq H2^{Disch}_{H2stoj,s_{sup},s_{dem},hr} \leq H2^{Disch,max}_{H2stoj} x^{Disch}_{H2stoj,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr, \quad (21)$$

$$x^{Ch}_{H2stoj,s_{sup},s_{dem},hr} + x^{Disch}_{H2stoj,s_{sup},s_{dem},hr} \leq 1, \forall j, s_{sup}, s_{dem}, hr, \quad (22)$$

$$H2^{sto}_{H2stoj,s_{sup},s_{dem},hr} = H2^{sto}_{H2stoj,s_{sup},s_{dem},hr-1}\eta_{H2sto} + H2^{Ch}_{H2stoj,sup,s_{dem},hr} - H2^{Disch}_{H2stoj,s_{sup},s_{dem},hr}, \forall j, s_{sup}, s_{dem}, hr. \quad (23)$$

where $x^{Ch}_{H2stoj,s_{sup},s_{dem},hr}$ and $x^{Disch}_{H2stoj,s_{sup},s_{dem},hr}$ are binary decision variables that are equal to 1 if the charging and discharging process is active, respectively for each scenario set. Eqs. (20) and

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(21) allow the charging and discharging processes, respectively, taking place between a minimum and a maximum value. Eq. (22) ensures that the charging and discharging processes do not take place simultaneously, whereas Eq. (23) relates the amount of hydrogen stored at time *hr* with the one stored at previous time *hr-1* of the same day that depends on the efficiency of the hydrogen storage.

Modelling of PEVs (valid for ENEA-5 tool)

The PEVs in the ILEC are supposed to be divided into clusters, each of them characterized by a specific number of PEVs and specific values for: (1) battery capacity (2) arrival and departure times at/from the charging stations, (3) the SOC at the arrival time; and (4) the SOC desired at the departure time. The PEVs can work in both G2V and V2G modes.

Before the arrival and after the departure at/from the charging stations, they can be modelled as:

$$\begin{cases} E^{Ch}_{PEV_p,k,hr} = 0 \\ E^{Disch,self}_{PEV_p,k,hr} = 0, \text{ If } hr < hr^{arrival}_{p,k}, and\ hr > hr^{departure}_{p,k}, \forall p,k \\ E^{Disch,sell}_{PEV_p,k,hr} = 0 \end{cases} \quad (24)$$

where $E^{Ch}_{PEV_p,k,hr}$ is the charging power for the PEV *p* in cluster *k*; $E^{Disch,self}_{PEV_p,k,hr}$ and $E^{Disch,sell}_{PEV_p,k,hr}$ are the discharging power rates for the PEV *p* in cluster *k* for self-use in the ILEC and for selling to the wholesale market, respectively; and $hr^{arrival}_{p,k}$ and $hr^{departure}_{p,k}$ are the arrival and departure times, respectively, at/from the charging stations for the PEV *p* in cluster *k.*

During the parking period, the PEVs can be modelled as:

$$\begin{cases} SOC_{PEV_p,k,hr|hr=hr^{arrival}_{p,k}} = SOC^{initial}_{PEV_p,k} \\ SOC_{PEV_p,k,hr} = SOC_{PEV_p,k,hr-1} + \dfrac{E^{Ch}_{PEV_p,k,hr}\eta^{Ch}_{PEV_p,k}Dt}{Cap_{PEV_p,k}} - \dfrac{\left(E^{Disch,self}_{PEV_p,k,hr} + E^{Disch,sel}_{PEV_p,k,hr}\right)Dt}{\eta^{Disch}_{PEV_p,k}Cap_{PEV_p,k}} \\ SOC^{Ch}_{PEV_p,k,hr|hr=departure} \geq SOC^{Desired}_{PEV_p,k} \end{cases}$$

(25)

if $hr^{arrival}_{p,k} < hr < hr^{departure}_{p,k}, \forall p,k$

where $SOC_{PEV_p,k,hr}$ is the state-of-charge of the battery of PEV *p* in cluster *k*; $SOC^{initial}_{PEV_p,k}$ is the state-of-charge of the battery at arrival time at charging station; $\eta^{Ch}_{PEV_p,k}$ and $\eta^{Disch}_{PEV_p,k}$ are the charging and discharging efficiencies, respectively; $Cap_{PEV_p,k}$ is the battery capacity of PEV; and $SOC^{Desired}_{PEV_p,k}$ is the desired state-of-charge at departure time from the charging station.

Operation constraints of PEVs (valid for ENEA-5 tool)

In addition to the PEV operating mode expressed in Eqs (24)-(25), additional operation constraints for PEVs are defined below:

$$\begin{cases} 0 \leq E^{Ch}_{PEV_p,k,hr} \leq x^{Ch}_{PEV_p,k,hr}E^{Ch,max}_{PEV_p,k,hr} \\ 0 \leq E^{Disch,self}_{PEV_p,k,hr} + E^{Disch,sell}_{PEV_p,k,hr} \leq x^{Disch}_{PEV_p,k,hr}E^{Disch,max}_{PEV_p,k,hr} \\ x^{Ch}_{PEV_p,k,hr} + x^{Disch}_{PEV_p,k,hr} \leq 1 \\ SOC^{min}_{PEV_p,k} \leq SOC_{PEV_p,k,hr} \leq SOC^{max}_{PEV_p,k} \end{cases}, \text{ if } hr^{arrival}_{p,k} < hr < hr^{departure}_{p,k}, \forall p,k \quad (26)$$

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which allow to limit the charging and discharging power for the PEV's battery and the battery SOC.
Objective function(s) of optimisation problem
The proposed tool allows to find the optimal expected operation strategies of the ILEC while considering short- and long-term objectives. **Economic objective function (for *operation optimization of multi-carrier energy systems with multi-objective tool*)** The short-term objective is the economic objective to minimize, representing the total net daily energy costs to minimize: $F_{obj,eco} = \sum_{i\in\{CHP\ NGICE,CHP\ NGMTG,NG\ Boiler\}} \sum_j \sum_{s_{sup}} \sum_{s_{sup}} \sum_{hr} (\pi_{sup}\pi_{dem}) \left(Pr_{NG,s_{dem}} G_{i,j,s_{sup},s_{dem},hr} + Pr_{PG,s_{dem},hr} E_{PGj,s_{sup},s_{dem},hr} - Pr_{PG,s_{dem},hr} E^{sell}_{j,s_{sup},s_{dem},hr} \right) Dt$ (27) It is the sum of the total cost of gas calculated by multiplying the gas price (a parameter) by the total amount of gas consumed by the CHPs and boilers in the ILEC, and the total cost of buying grid power calculated by multiplying the time-varying unit price of grid power (a parameter) and the total amount of electricity taken from the grid, minus the profit for selling electricity from CHPs and PVs in the ILEC on DAM. In Eq. (27), π_{sup} and π_{dem} are the probability of occurrence of scenarios s_{sup} and s_{dem}, respectively. **Economic objective function (for optimal management of EVs in multi-carrier energy systems with multi-objective approach tool) / deterministic approach** The short-term objective is the economic objective to minimize, representing the total net daily energy cost to minimize: $F_{obj,eco} = \sum_{i\in\{CHP\ NGICE,CHP\ NGMTG,NG\ Boiler\}} \sum_j \sum_{hr} (Pr_{NG} G_{i,j,hr} + Pr_{PG,hr} E_{PGj,hr})\, Dt - (\sum_k \sum_p \sum_{hr} Pr_{PG,hr}\, E^{Disch,sell}_{PEV_p,k,hr} Dt + \sum_j \sum_{hr} (Pr_{PG,s_{dem},hr} E^{sell}_{j,s_{sup},s_{dem},hr})\, Dt)$ (28) **Environmental objective function** The environmental objective is to minimize the total annual CO_2 emissions, consisting of the sum of the following functions: $F_{obj,env} = Env^{NG} + Env^{PG}$ (29) $Env^{NG} = \sum_{i\in\{CHP\ NGICE,CHP\ NGMTG,NG\ Boiler\}} \sum_j \sum_{s_{sup}} \sum_{s_{sup}} \sum_{hr} (\pi_{sup}\pi_{dem}) \left(G_{i,j,s_{sup},s_{dem},hr} CI_{NG} LHV_{NG} \right) Dt$ (30) $Env^{PG} = \sum_j \sum_{s_{sup}} \sum_{s_{sup}} \sum_{hr} (\pi_{sup}\pi_{dem}) \left(E_{PGj,s_{sup},s_{dem},hr} CI_{PG} \right) Dt$ (31) In Eq. (30), the total CO_2 emission associated with the gas consumed by the CHPs and auxiliary boilers in the ILEC depends on the carbon intensity (CI) of gas, whereas in Eq. (31), the total CO_2 emission associated with the grid power depends on the carbon intensity of the power grid, which the ILEC is connected to.
Optimisation method used to solve the formulated problem
With the economic and environmental objectives formulated above, the operation optimization problem has two types of objective function to be minimized. To solve this multi-objective optimization problem, the weighted-sum method is used to have a single objective function formulated as:

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$Fobj = c\omega F_{obj,eco} + (1-\omega)F_{obj,env}$, (32) where c is a constant scaling factor to keep the two objectives at the same order of magnitude, and ω is the weight for the economic objective function varying in the range of 0-1. When ω = 1, it is to find the solution that minimizes the total daily energy cost of the whole ILEC, and when ω = 0, it is to find the solution that minimizes the total daily environmental impact of ILEC. When varying the weight ω in the range of [0, 1], the Pareto front between economic and environmental objectives can be found. The problem formulated for both tools is linear and involves both discrete and continuous variables. To solve the problem efficiently, branch-and-cut, which is powerful for MILP problems, is used.
Energy carriers involved
Gas, hydrogen, electricity, heating, cooling, mobility.
Energy technologies involved

• CHP with different types of prime movers:
  o Internal combustion engine
  o Micro-gas turbine
  o Fuel cell
• Electrolyser
• Natural gas boilers
• Solar PV
• Solar thermal
• Reversible heat pump
• Absorption chiller
• Battery
• Thermal storage for heating and cooling
• Hydrogen storage
• PEVs (only for Optimal management of EVs in multi-carrier energy systems with multi-objective approach tool)

Formulation of system balances equation for energy carriers involved
4. System balance constraints ***Power balance (valid for operation optimization of multi-carrier energy systems with multi-objective tool)*** In the ILEC, for each user u, for each scenario set, the electrical demand and the power required by the heat pumps (either in the heating or cooling mode) and electrolysers installed in the associated mEH j, must be met by the sum of the electricity provided by the CHPs in all energy hubs, the electricity provided by PV together with the battery in the associated mEH and the power grid: $E_{dem,u,s_{dem},hr} + \sum_{HP} E^{req}_{HPj,s_{sup},s_{dem},hr} + \sum_{EZ} E^{req}_{EZj,s_{sup},s_{dem},hr} = \sum_j \sum_{CHP\ NGICE} E^{self}_{CHP\ NGICEj,u,s_{sup},s_{dem},hr} + \sum_j \sum_{CHP\ NGMTG} E^{self}_{CHP\ MTGj,s_{sup},s_{dem},hr} + \sum_j \sum_{CHP\ FC} E^{self}_{CHP\ FCj,s_{sup},s_{dem},hr} + E^{self}_{PVj,s_{sup},hr} + E_{PGj,s_{sup},s_{dem},hr} + \sum_{Bat} E^{Disch}_{Batj,s_{sup},s_{dem},hr} - E^{Ch}_{Batj,s_{sup},s_{dem},hr}, \forall u, j = u, \forall s_{sup}, s_{dem}, hr,$ (33)

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where $E^{self}_{CHP\ NGICE j,u,s_{sup},s_{dem},hr}$, $E^{self}_{CHP\ MTG j,s_{sup},s_{dem},hr}$ and $E^{self}_{CHP\ FC j,s_{sup},s_{dem},hr}$ represent the power provided by CHPs associated with mEH *j* to user *u* for each scenario set, which are involved in the following CHP electricity balance constraints:

$$E_{CHP\ NGICE j,s_{sup},s_{dem},hr} = E^{sell}_{CHP\ NGICE j,s_{sup},s_{dem},hr,s,t} + \sum_u E^{self}_{CHP\ NGICE j,u,s_{sup},s_{dem},hr}\ , \forall j, s_{sup}, s_{dem}, hr$$
(34)

$$E_{CHP\ MTG j,s_{sup},s_{dem},hr} = E^{sell}_{CHP\ MTG j,s_{sup},s_{dem},hr,s,t} + \sum_u E^{self}_{CHP\ MTG j,,u,s_{sup},s_{dem},hr}\ , \forall j, s_{sup}, s_{dem}, hr$$
(35)

$$E_{CHP\ FC j,s_{sup},s_{dem},hr} = E^{sell}_{CHP\ FC j,s_{sup},s_{dem},hr,s,t} + \sum_u E^{self}_{CHP\ FC j,u,s_{sup},s_{dem},hr}\ , \forall j, s_{sup}, s_{dem}, hr \qquad (36)$$

$$E_{PV j,s_{sup},hr} = E^{sell}_{PV j,s_{sup},hr} + E^{EZ}_{PV j,s_{sup},s_{dem},hr} + \sum_u E^{self}_{PV j,u,s_{sup},hr} \qquad (37)$$

Power balance (valid for optimal management of EVs in multi-carrier energy systems with multi-objective approach tool) / deterministic approach

$$E_{dem,u,hr} + \sum_{HP} E^{req}_{HP j,hr} + \sum_{EZ} E^{req}_{EZ j,hr} = \sum_j \sum_{CHP\ NGICE} E^{self}_{CHP\ NGICE j,u,hr} + \sum_j \sum_{CHP\ NGMTG} E^{self}_{CHP\ MTG j,hr} + \sum_j \sum_{CHP\ FC} E^{self}_{CHP\ FC j,hr} + E^{self}_{PV j,hr} + E_{PG j,hr} + \sum_{Bat} E^{Disch}_{Bat j,,hr} + \sum_k \sum_p E^{Disch,self}_{PEV_p,k,hr} - E^{Ch}_{Bat j,s_{sup},s_{dem},hr} - \sum_k \sum_p E^{Ch}_{PEV_p,k,hr}\ , \forall u, j = u, \forall p, k, hr \qquad (38)$$

Eqs. (34-37) are valid also for this tool.

Thermal energy balance

In the ILEC for each user *u*, the thermal demand must be met by the total thermal energy provided by the CHPs, boilers, heat pumps, and the thermal storage installed in the associated mEH *j*, and by the total thermal energy provided by CHPs installed in the other mEHs, through the heating pipeline (if installed):

$$H_{dem,u,s_{dem},hr} = \sum_{CHP\ NGICE} H_{CHP\ NGICE j,u,s_{sup},s_{dem},hr} + \sum_{CHP\ NGMTG} H_{CHP\ NGMTG j,u,s_{sup},s_{dem},hr} + \sum_{CHP\ FC} H_{CHP\ FC j,u,s_{sup},s_{dem},hr} + \sum_{NG\ Boiler} H_{NG\ Boiler j,s_{sup},s_{dem},hr} + \sum_{HP} H^{HM}_{HP j,s_{sup},s_{dem},hr} + H_{ST j,s_{sup},hr} + \sum_{TES-Th} H^{Disch}_{TES-Th j,s_{sup},s_{dem},hr} - H^{Ch}_{TES-Th j,s_{sup},s_{dem},hr} + \sum_{j,j\neq 1} \left[\eta_{pipe,j,u} \left(\sum_{CHP\ NGICE} H_{CHP\ NGICE j,u,s_{sup},s_{dem},hr} + \sum_{CHP\ NGMTG} H_{CHP\ NGMTG j,u,s_{sup},s_{dem},hr} + \sum_{CHP\ FC} H_{CHP\ FC j,u,s_{sup},s_{dem},hr}\right)\right], \forall u, j = u, \forall j, s_{sup}, s_{dem}, hr$$
(39)

where $H_{CHP\ NGICE j,u,s_{sup},s_{dem},hr}$, $H_{CHP\ NGMTG j,u,s_{sup},s_{dem},hr}$ and $H_{CHP\ FC j,u,s_{sup},s_{dem},hr}$ are the heating rates provided by CHPs associated with mEH j to user u for each scenario set, which are involved in the following CHP thermal balance constraints,

$$H_{CHP\ NGICE j,s_{sup},s_{dem},hr} = \sum_u \left(H_{CHP\ NGICE j,u,s_{sup},s_{dem},hr} + C_{CHP\ NGICE j,u,s_{sup},s_{dem},hr}\right), \forall j, s_{sup}, s_{dem}, hr$$
(40)

$$H_{CHP\ NGMTG j,s_{sup},s_{dem},hr} = \sum_u \left(H_{CHP\ NGMTG j,u,s_{sup},s_{dem},hr} + C_{CHP\ NGMTG j,u,s_{sup},s_{dem},hr}\right), \forall j, s_{sup}, s_{dem}, hr \qquad (41)$$

$$H_{CHP\ FC j,s_{sup},s_{dem},hr} = \sum_u \left(H_{CHP\ FC j,u,s_{sup},s_{dem},hr} + C_{CHP\ FC j,u,s_{sup},s_{dem},hr}\right), \forall j, s_{sup}, s_{dem}, hr$$
(42)

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The thermal balance for the cooling demand can be formulated similarly.
Tool(s) used to solve the problem
Operation optimization of multi-carrier energy systems with multi-objective approach and optimal management of EVs in multi-carrier energy systems with multi-objective approach in multi-carrier energy systems with multi-objective approach tools
Temporal resolution
Hourly resolution
Time horizon
1 Day

Nomenclature

Decision Variables	
$C_{AChilj,hr}$	Cooling rate provided by absorption chiller (dependent variable) (kW)
$E_{PEV_p,k,hr}^{Ch}$	Charging power for the PEV (kW)
$E_{PEV_p,k,hr}^{Disch,self}$	Discharging power rate for the PEV for self-use in the ILEC (kW)
$E_{PEV_p,k,hr}^{Disch,sell}$	Discharging power rate for the PEV for selling to wholesale market (kW)
$E_{Bat j,hr}^{Disch}$	Discharging power for battery (kW)
$E_{Bat j,d}^{Ch}$	Charging power for battery (kW)
$E_{CHP\ FCj,hr}$	Power provided by CHP FC (kW)
$E_{CHP\ NGICEj,hr}$	Power provided by CHP NG ICE (kW)
$E_{EZj,hr}^{req}$	Power required by the electrolyser (dependent variable) (kW)
$E_{HPj,hr}^{req}$	Power required by the heat pump (dependent variable) (kW)
$E_{PGj,hr}$	Grid power (kW)
$E_{PVj,hr}$	Power provided by PV (kW)
$E_{PVj,d,hr}^{EZ}$	Share of power from PV allocated for usage in the EZ (kW)
Env^{NG}	Total daily CO2 emission related to gas consumption (kgCO2)
Env^{PG}	Total daily CO2 emission related to grid power consumption (kgCO2)
$F_{obj,eco}$	Economic objective function (€)
$F_{obj,env}$	Environmental objective function ($kgCO_2$)
$G_{CHP\ NGICEj,hr}$	Gas volumetric flow rate consumed by CHP NG ICE (dependent variable) (Nm^3/h)
$H2_{H2stoj,hr}^{Ch}$	H2 charging for H2 storage (m^3/h)
$H2_{H2stoj,hr}^{Disch}$	H2 discharging for H2 storage (m^3/h)
$H2_{H2stoj,hr}^{sto}$	H2 stored in H2 storage (m^3)
$H_{\mathrm{TES-Th}j,hr}^{\mathrm{Disch}}$	Discharging heat rate from TES (kW)
$H_{\mathrm{TES-Th}j,hr}^{Ch}$	Charging heat rate to TES (kW)
$H_{CHP\ NGICEj,hr}$	Heat rate provided by CHP NG ICE (dependent variable) (kW)
$H_{HPj,hr}$	Heat rate provided by the heat pump (kW)
$H_{NG\ Boilerj,hr}$	Heat rate provided by natural gas boiler (kW)
$H_{TES-Thj,hr}$	Thermal energy stored in TES (kWh)
$SOC_{PEV_p,k,hr}$	PEV battery SOC
$x_{PEV_p,k,hr}^{Ch}$	Binary variable for charging PEV
$x_{PEV_p,k,hr}^{Disch}$	Binary variable for discharging PEV
$x_{Batj,hr}^{Ch}$	Binary variable for usage of battery for charging process
$x_{Batj,hr}^{Disch}$	Binary variable for usage of battery for discharging process
$x_{CHP\ NGICEj,hr}$	On/off status of CHP NG ICE
$x_{EZj,hr}$	On/off status of EZ

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x_{H2stoj}^{Ch}	Binary variable for usage of H2 storage for charging process
x_{H2stoj}^{Disch}	Binary variable for usage of H2 storage for discharging process
c	Constant in *Fobj* (kgCO2/€)
$Fobj$	Objective function of the multi-objective optimization problem
$H2_{CHP\ FCj,hr}$	Volumetric flow rate of hydrogen (m^3/h)
$SOC_{Batj,hr}$	Battery SOC
ω	Weight value in *Fobj*
Parameters	
$hr_{p,k}^{arrival}$	Arrival time of PEV to charging station (hr)
$hr_{p,k}^{departure}$	Departure time of PEV from charging station (hr)
A_{PVj}	Installed area of PV (m^2)
CI_{NG}	Carbon intensity of natural gas (kgCO2/Nm^3)
CI_{PG}	Carbon intensity of power grid (kgCO2/kWh)
COP_{HP}^{HM}	COP of heat pump in heating mode
$Cap_{PEV_p,k}$	PEV battery capacity (kWh)
Cap_{Batj}	Capacity of battery (kWh)
$DR_{CHP\ NGICEj}$	Maximum ramp-down rate of CHP NG ICE (kW)
$E_{PEV_p,k,hr}^{Ch,max}$	Maximum charging power for PEV battery (kW)
$E_{PEV_p,k,hr}^{Disch,max}$	Maximum discharging power for PEV battery (kW)
$E_{Batj,d,hr}^{Ch,max}$	Maximum charging power of battery (kW)
$E_{Batj,d,hr}^{Disch,max}$	Maximum discharging power of battery (kW)
$E_{CHP\ NGICEj}^{max}$	Maximum load of CHP NG ICE (kW)
$E_{CHP\ NGICEj}^{min}$	Minimum part load of CHP NG ICE (kW)
E_{EZ}^{max}	Maximum part load of EZ (kW)
E_{EZ}^{min}	Minimum part load of EZ (kW)
$E_{dem,u,d,hr}$	Time-varying power demand of mEH (kW)
$H2_{H2stoj}^{Ch,max}$	Maximum H2 charging for H2 storage (m^3)
$H2_{H2stoj}^{Disch,max}$	Maximum H2 discharging for H2 storage (m^3)
$H_{dem,u,d,hr}$	Time-varying heat rate demand of mEH (kW)
$I_{d,hr}$	Hourly solar irradiance (kW/m^2)
LHV_{NG}	Lower heat value of natural gas (kWh/Nm^3)
$Pr_{NG,d}$	Natural gas price (€/Nm^3)
$Pr_{PG,d,hr}$	Time-varying unit price of grid power (€/kWh)
$R_{i,j,d,hr}$	Generation level (kW) – (kWh)
$SOC_{PEV_p,k}^{Desired}$	Desired PEV battery SOC at departure time from charging station
$SOC_{PEV_p,k}^{initial}$	PEV SOC at arrival time at charging station
$SOC_{PEV_p,k}^{max}$	Maximum PEV battery SOC
$SOC_{PEV_p,k}^{min}$	Minimum PEV battery SOC
SOC_{Batj}^{max}	Maximum SOC battery
$UR_{CHP\ NGICEj}$	Maximum ramp-up rate of CHP NG ICE (kW)
$\eta_{PEV_p,k}^{Ch}$	Charging efficiency of PEV battery
$\eta_{PEV_p,k}^{Disch}$	Discharging efficiency of PEV battery
η_{Bat}^{Ch}	Efficiency of charging process for battery
η_{Bat}^{Dis}	Efficiency of discharging process for battery
η_{H2sto}	Efficiency of H2 storage
η_{PV}	Electric efficiency of PV
$\eta_{e,CHP\ FC}$	Electric efficiency of CHP FC
$\eta_{e,CHP\ NGICE}$	Electric efficiency of CHP NG ICE

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$\eta_{e,EZ}$	Electric efficiency of EZ
$\eta_{pipe,j,u}$	Efficiency of heating pipeline
$\eta_{th,CHP\ NGICE}$	Thermal efficiency of CHP NG ICE
π_{dem}	Probability of occurrence of scenario s_{dem}
π_{sup}	Probability of occurrence of scenario s_{sup}
φ_{TES-Th}	TES storage loss fraction
Dt	Length of the time interval (1 hour)
LHV_{H2}	Lower heat value of hydrogen (kWh/m^3)
Subscripts/Superscripts	
HM	Heating mode
hr	Index of hour
i	Index of technology
j	Index of mEH
k	Index of PEVs cluster
p	Index of PEV
SC	Space cooling purposes
s_{dem}	Index of scenario in scenario set s_{dem}
self	Self-use
sell	Sold
s_{sup}	Index of scenario in scenario set s_{sup}
ST	Solar thermal
Th	Thermal purposes
u	Index of user

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4.3 Analysis and development of the short-term optimization problem

A similar approach to the one that was applied to the LTO problem was taken for the analysis and development of the short-term optimization (STO) problem. However, in the optimisation problem related to the P2P market, the information captured is different to the other phases due to the nature of the specific problem.

For TF 3 - *Peer-to-Peer Market Design*, development and analysis of the STO problem in the P2P Market is solved by the P2P platform tool and details of the formulation are provided.

Finally, for TF 4 - *Real-time Operation Design*, the STO problem in the real-time operation phase is solved through the mEH optimal operation scheduling real-time tool, and the relative formulation of the problem is presented.

4.3.1 P2P market (P2P platform)

Optimisation problem
Peer-to-Peer market - coordinator framework – *P2P platform*
Description of the considered optimisation problem
The P2P coordinator is in charge of calculating the internal P2P market price signal and sending it back to the mEHs to match as closely as possible in real-time the day-ahead dispatch at the EH level, which is given in the operational analysis phase. During each control cycle, an iterative process occurs to match the final local energy price for the mEHs. In this framework, the P2P coordinator operates interactively with the "Cloud-Based Solver" block, which handles the real-time scheduling of each mEH by considering the energy prices broadcasted from the P2P Market. In order to select the best day-ahead schedule from the Pareto frontier derived from the EH level to initialise the P2P module, the multi-criteria decision-making technique named TOPSIS (Technique for the Order of Prioritisation by Similarity to Ideal Solution) will be employed through the PyMCDM (Python Multi-criteria Decision Making) library described in [27].
Formulation of optimisation problem
The P2P market framework has been defined so that the P2P coordinator only assists the bidding process and computes the internal price without taking control of the energy resources in the mEH.
Objective function(s) of the optimisation problem
As the P2P market framework is not an optimisation model itself, it does not follow a specific optimisation function. Instead, it is an iterative mechanism that seeks to reduce the error, in each iteration, between the aggregated optimal energy profiles from all mEHs in real-time ($\mathrm{E}_{\mathrm{hr}}^{\mathrm{bid}}$) and the aggregated day-ahead energy profile of all mEHs ($\mathrm{E}_{\mathrm{hr}}^{\mathrm{da}}$). **1. Aggregation of mEH's net power profiles** In order to quantify the net power profile of the EH in the day ahead and the real-time operation, it is necessary to add up all mEH profiles ($\mathrm{e}_{\mathrm{i,hr}}^{\mathrm{net,da}}$) resulting from the ENEA-4 and ENEA-5 tools and

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the mEH profiles ($e_{i,hr}^{net,rt}$) resulting from the cloud-based solver. Note that the day-ahead net power profile at the EH level is selected from the Pareto frontier based on the TOPSIS multi-criteria decision-making technique. This approach is also employed to select the best candidate solution per mEH at each iteration.

$$E_{hr}^{da} = \sum_{i \in EH} e_{i,hr}^{net,da} \quad \forall hr \in \mathcal{T} \tag{1}$$

$$E_{hr}^{bid} = \sum_{i \in EH} e_{i,hr}^{net,rt} \quad \forall hr \in \mathcal{T} \tag{2}$$

2. Power boundaries

In order to generate a new internal price profile for the mEHs at the coordinator level, it is required to compute an upper (E_{hr}^{upper}) and a lower (E_{hr}^{lower}) power boundary at each time step using a deviation threshold based on the day-ahead operation.

$$E_{hr}^{lower} = \begin{cases} (1-e) \cdot E_{hr}^{da}, & E_{hr}^{da} > 0 \\ (1+e) \cdot E_{hr}^{da}, & E_{hr}^{da} < 0 \end{cases} \quad \forall hr \in \mathcal{T} \tag{3}$$

$$E_{hr}^{upper} = \begin{cases} (1+e) \cdot E_{hr}^{da}, & E_{hr}^{da} > 0 \\ (1-e) \cdot E_{hr}^{da}, & E_{hr}^{da} < 0 \end{cases} \quad \forall hr \in \mathcal{T} \tag{4}$$

3. Imbalance ratio

The imbalance ratio aims to quantify the maximum deviation of all mEHs' net power with respect to day-ahead operation at each time step. Later, the internal energy price is modified according to this criterion.

$$IR_t = \frac{\left|E_{hr}^{da} - E_{hr}^{bid}\right|}{\max\left\{E^{da}\right\}}, \quad \forall hr \in \mathcal{T} \tag{5}$$

3. Internal energy price

Once the IR is calculated at each time step, the internal energy price at the coordinator level is computed proportionally upward or downward.

$$Pr_{hr}^{int} = \begin{cases} Pr_{PG,hr}, & E_{hr}^{lower} \leq E_{hr}^{bid} \leq E_{hr}^{upper} \\ Pr_{PG,hr} \cdot (1+IR), & E_{hr}^{bid} > E_{hr}^{upper} \\ Pr_{PG,hr} \cdot (1-IR), & E_{hr}^{bid} < E_{hr}^{lower} \end{cases} \quad \forall hr \in \mathcal{T} \tag{6}$$

Because all mEHs are allowed to change their net power pattern at each iteration, the change in power demand or generation within the EH may be too large, provoking the internal price to oscillate heavily and making it more challenging to find convergence in the simulation. Therefore, to achieve such convergence, it is necessary to employ a constraint at the mEH level (i.e., the Cloud-Based Solver), which in this case is called "step length control". This constraint limits the ramping rate of the changing energy bids to increase the chance of finding the convergence and try to avoid the "oscillation" (i.e., iterative large changes) between the bids and the internal price.

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Optimisation method used to solve the formulated problem
Although the P2P market framework is not an optimisation model itself, it follows an iterative methodology to update the internal energy price, as follows. 1. The P2P coordinator sends the day-ahead market price profile to the mEHs in the Cloud-Based Solver block. 2. Each mEH optimises its energy resources and sends back to the P2P coordinator the resulting optimal energy profiles of all technologies. Then, at the coordinator level, the TOPSIS technique is applied to select the best solution from the Pareto frontier. Later, the P2P coordinator adds all the mEH net energy profiles, i.e., the difference between the aggregated consumption and generation. 3. The P2P coordinator checks whether the aggregation of mEH power profiles from the real-time operation matches the aggregation of the day-ahead mEH power profiles or whether there have not been significant changes in the aggregated real-time power profile since the last iteration. If any of the mentioned checks are true, the iterative process ends; otherwise, the process continues to step 4. Note that the day-ahead schedule at the EH level is selected based on the TOPSIS multi-criteria decision-making technique. 4. The P2P coordinator computes a new internal energy price profile to incentivise mEHs to change their energy profiles, so that the EH's energy profile is better aligned with the day ahead EH profile. 5. The new internal energy price profile is sent to the mEHs, so that they can proceed with step 2.
Energy carriers involved
The P2P coordinator is based only on electricity prices, as it is only considered the electrical power of the gas, heating and cooling-based technologies.
Energy technologies involved
The P2P coordinator does not operate directly on the technologies. It only receives the optimised consumption and generation profiles of each mEH from the Cloud-Based Solver. Therefore, the technologies will be the ones in the Cloud-Based Solver.
Tool(s) used to solve the problem
The P2P coordinator framework is developed in the Python environment.
Temporal resolution
The P2P market model can be executed every 15 minutes. It must be aligned with the time resolution of the real-time optimisation block.
Time horizon
It will be a rolling time horizon for 24 hours of the representative day.

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Nomenclature

Variables	
E_{hr}^{da}	Aggregated day-ahead net power profile (kW)
E_{hr}^{bid}	Aggregated net bidding power profile (kW)
π_{hr}^{ini}	Initial energy cost per time interval (€)
$\pi^{T,ini}$	Total initial energy cost (€)
π_{hr}^{eq}	Energy cost per time interval by following E_t^{da} (€)
π_{hr}^{up}	Energy cost per time interval by demanding/supplying more energy than E_t^{da} (€)
π_{hr}^{down}	Energy cost per time interval by demanding/supplying less energy than E_t^{da} (€)
$\pi^{T,eq}$	Total energy cost by following E_t^{da} (€)
$\pi^{T,up}$	Total energy cost by demanding/supplying more energy than E_t^{da} (€)
$\pi^{T,down}$	Energy cost per time interval by demanding/supplying less energy than E_t^{da} (€)
α^{up}	Scaling up factor (p.u.)
Pr_{hr}^{int}	Internal energy price per time step (€/kWh)
Parameters	
$e_{i,hr}^{net,da}$	Net day-ahead power profile per mEH from ENEA-4 tool (kW)
$e_{i,hr}^{net,rt}$	Net bid power profile per mEH from the cloud-based solver (kW)
$Pr_{PG,hr}$	Time-varying unit price of grid power (€/kWh)
$Pr_{PG,hr}^{up}$	Upwards day-ahead energy price profile (€/kWh)
$Pr_{PG,hr}^{down}$	Downwards day-ahead energy price profile (€/kWh)
α^{down}	Scaling down factor (p.u.)

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4.3.2 Real-time operation phase

Optimisation problem
STO problem in real-time operation phase - *Optimal multi-carrier and objective* - mEH optimal operation scheduling real-time.
Description of the considered optimisation problem
Renewable energy sources (RES) and state-of-the-art conversion technologies such as micro-combined heat and power (mCHP), fuel cells (FC) and storage systems are being adopted in the smart buildings that formulate an mEH, to participate in demand response programs and provide flexibility to the integrated local energy communities (ILEC). This work proposes a model based on MILP to implement the mEH optimal operation scheduling real-time working as a cloud-based solver for mEH in real-time with multiple energy carriers considering multiple objectives. Accordingly, the bi-directional energy exchange is made available for the mEHs to trade their excess energy upstream. Moreover, the multi-objective optimization methodology is based on the augmented epsilon-constraint (AUGMECON) method to solve the problem and map the Pareto frontier. The objectives are both optimizing the costs and maximizing user comfort for the mEH optimal operation scheduling real-time tool as a micro-energy hub (mEH). In order to successfully reach the set objectives, the problem considers the interaction with the peer-to-peer (P2P) market via a decentralized mechanism as well.
Formulation of optimisation problem
The optimization problem is formulated as a MILP problem where the first-order linear equations of the technologies are adopted with the help of the binary variables. This method will guarantee the global optimality of the problem in a short period of time. Especially since the mEH problem is supposed to be operational in the real-time domain, the lower computational burden will lead to a faster solution found. Furthermore, the DA scheduling of the assets at the EH level is projected to the real-time scheduling via the P2P market. In other words, the real-time scheduling of the flexible energy technologies is the superposition of the DA scheduling as a parameter and real-time deviation variable from that to be decided by the mEH optimal operation scheduling real-time.
Constraints considered in the optimisation problem
The model involves technologies involved in modern and sustainable homes/mEHs, which can run on single or multiple energy carriers. Accordingly, the constraints, in general, can be categorized into the following types: • Energy conversion and operational constraints of the technologies • Correlation of the energy carriers via a specific technology • Energy balance equations The constraints for involving technologies in the model are the following. **1. Plug-in EV:** The PEV in mEH acts as a battery, serving either to absorb energy from the mEH or to inject power back into it when needed. When the PEV is unavailable, its charging or discharging power can be set to zero. This allows us to formulate the mathematical model of the PEV. $$E^{Ch}_{PEV,j,t} = E^{Ch,DA*}_{PEV,j,t} + \Delta E^{Ch}_{PEV,j,t}, \ \forall j,t \quad (1)$$

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$$E_{PEV,j,t}^{Disch} = E_{PEV,j,t}^{Disch,DA*} + \Delta E_{PEV,j,t}^{Disch},\ \forall j,t \quad (2)$$

$$SOC_{PEV,j,t} = SOC_{PEV,j,t-1} + \eta_{PEV,j}^{Ch} E_{PEV,j,t-1}^{Ch} Dt - E_{PEV,j,t}^{Disch} Dt,\ \forall j,t \in \left(t^{arrival}, t^{departure}\right] \quad (3)$$

$$SOC_{PEV,j,,t} = 0,\ \forall j,t \in \left(t^{departure}, t^{arrival}\right) \quad (4)$$

$$SOC_{PEV,j,t} = SOC_{PEV,j}^{initial},\ \forall j,t \in t^{initial}, t^{final} \quad (5)$$

$$SOC_{PEV,j,t} = SOC_{PEV,j}^{arrival},\ \forall j,t = t^{arrival} \quad (6)$$

$$SOC_{PEV,j,t} \geq SOC_{PEV,j}^{departure},\ \forall j,t = t^{departure} \quad (7)$$

$$SOC_{PEV,j}^{min} \leq SOC_{PEV,j,t} \leq SOC_{PEV,j}^{max}, \forall j,t \quad (8)$$

$$0 \leq E_{PEV,j,t}^{Ch} \leq E_{PEV,j}^{Ch} x_{PEV,j,t}, \forall j,t \in \left[t^{arrival}, t^{departure}\right] \quad (9)$$

$$E_{PEV,j,t}^{Ch} = 0,\ \forall j,t \in \left(t^{departure}, t^{arrival}\right) \quad (10)$$

$$0 \leq E_{PEV,j,t}^{Disch} \leq E_{PEV,j}^{Disch}\left(1 - x_{PEV,j,t}\right),\ \forall j,t \in \left[t^{arrival}, t^{departure}\right] \quad (11)$$

$$E_{PEV,j,t}^{Disch} = 0,\ \forall j,t \in \left(t^{departure}, t^{arrival}\right) \quad (12)$$

$$E_{PEV,j,t}^{Disch,self} = E_{PEV,j,t}^{Disch,self,DA*} + \Delta E_{PEV,j,t}^{Disch,self},\ \forall j,t \quad (13)$$

$$E_{PEV,j,t}^{Disch,sell} = E_{PEV,j,t}^{Disch,sell,DA*} + \Delta E_{PEV,j,t}^{Disch,sell},\ \forall j,t \quad (14)$$

$$E_{PEV,j,t}^{Disch,self} + E_{PEV,j,t}^{Disch,sell} = \eta_{PEV,j}^{Disch} E_{PEV,j,t}^{Disch},\ \forall j,t \quad (15)$$

In real-time optimal operation, the scheduling of the PEV may deviate from the DA schedule as a result of changes in arrival or departure times or differences in expected input parameters. This deviation is illustrated in equations (1) and (2). Changes in the real-time schedule will affect the PEV SOC, as given in equation (3). The remaining equations express operational constraints and limitations related to the PEV. The assumption for PEV is that it can sell a portion of its discharge energy to the ILEC or neighbouring mEHs, as expressed in equation (15), by considering the possible deviation from the DA scheduling equations (13) and (14) are provided for RT scheduling.

2. **Battery Energy Storage System:**

$$\mathrm{E}_{\mathrm{Bat},j,t}^{\mathrm{Ch}} = \mathrm{E}_{\mathrm{Bat},j,t}^{\mathrm{Ch,DA*}} + \Delta \mathrm{E}_{\mathrm{Bat},j,t}^{\mathrm{Ch}},\ \forall j,t \quad (16)$$

$$\mathrm{E}_{\mathrm{Bat},j,t}^{\mathrm{Disch}} = \mathrm{E}_{\mathrm{Bat},j,t}^{\mathrm{Disch,DA*}} + \Delta \mathrm{E}_{\mathrm{Bat},j,t}^{\mathrm{Disch}},\ \forall j,t$$

$$\mathrm{SOC}_{\mathrm{Bat},j,t} = \mathrm{SOC}_{\mathrm{Bat},j,t-1} + \eta_{\mathrm{Bat},j}^{\mathrm{Ch}} \mathrm{E}_{\mathrm{Bat},j,t-1}^{\mathrm{Ch}} \mathrm{Dt} - \frac{\mathrm{E}_{\mathrm{Bat},j,t-1}^{\mathrm{Disch}} \mathrm{Dt}}{\eta_{\mathrm{Bat},j}^{\mathrm{Disch}}},\ \forall j,t \quad (17)$$

$$\mathrm{SOC}_{\mathrm{Bat},t} = \mathrm{SOC}_{\mathrm{Bat},t}^{\mathrm{initial}}, \forall t \in t^{\mathrm{initial}}, t^{\mathrm{final}} \quad (18)$$

$$\mathrm{SOC}_{\mathrm{Bat},j}^{\min} \leq \mathrm{SOC}_{\mathrm{Bat},j,t} \leq \mathrm{SOC}_{\mathrm{Bat},j}^{\max}, \forall j,t \quad (19)$$

$$0 \leq \mathrm{E}_{\mathrm{Bat},j,t}^{\mathrm{Ch}} \leq \mathrm{E}_{\mathrm{Bat},j}^{\mathrm{Ch,max}} \mathrm{x}_{\mathrm{Bat},j,t}, \forall j,t \quad (20)$$

$$0 \leq \mathrm{E}_{\mathrm{Bat},j,t}^{\mathrm{Disch}} \leq \mathrm{E}_{\mathrm{Bat},j}^{\mathrm{Disch,max}}\left(1 - \mathrm{x}_{\mathrm{Bat},j,t}\right),\ \forall j,t \quad (21)$$

$$\mathrm{SOC}_{\mathrm{Bat},j}^{\min} \leq \mathrm{SOC}_{\mathrm{Bat},j,t} \leq \mathrm{SOC}_{\mathrm{Bat},j}^{\max}, \forall j,t \quad (22)$$

Similar to the PEV, according to (16) and (17) the charging and discharging power of BESS in RT scheduling is going to be different from the one determined in the DA scheduling. The difference equation of the charged energy in the BESS is expressed in (17). The remaining equations indicate the initial SOC and boundaries for the safe operation of BESS. Also, it is assumed that all the discharged energy from the BESS is used internally by the mEH.

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3. House heating system (HHS):

In the EH level formulation, the heating demand for the HHS was implicitly forecasted and embedded in the overall base heating demand. However, for each mEH it is necessary to express the formulation of HHS explicitly. (23) implies that the ambient temperature in RT will be different from the DA scheduling. Therefore, the thermodynamic equation of the indoor space temperature can be expressed as in (24). It should be noted that the $H_{HHS,j,t}$ is derived from the heating network of the mEH which acquires the heating energy from the CHP, ST, HP, NGB, TSS and DHN. The parameter ϵ_j^{in} is the allowed temperature deviation from the set point.

$$T_{j,t}^{out} = T_{j,t}^{out,DA*} + \Delta T_{j,t}^{out},\ \forall j,t \tag{23}$$

$$T_{j,t}^{in} = \left(1 - \frac{Dt}{R^{in}C^{in}}\right) T_{j,t-1}^{in} + \left(\frac{T_{j,t-1}^{out}}{R^{in}C^{in}} + \frac{H_{HHS,j,t-1}}{C^{in}}\right) Dt,\ \forall j,t \tag{24}$$

$$T_{j,hr}^{in} = T_j^{in,initial},\ \forall j, hr^{initial} \tag{25}$$

$$T^{in,min} - \epsilon_j^{in} \le T_{j,hr}^{in} \le T^{in,max} + \epsilon_j^{in},\ \forall j, hr \tag{26}$$

4. Time-shiftable electric load (TSEL):

The technologies such as washing machine or dishwasher, which their operation can automatically be shifted in time, are generally called TSEL. The operation of TSEL is not considered in the DA scheduling, but it is modelled as a predicted general electricity demand. However, in the RT, this will be explored in detail. Constraint (27) indicates the sum of power consumed in each operational phase of the TSEL. (28) indicates that the operation of one phase is allowed at a time, while (29) states the duration of each phase from start to finish i.e. $T_{TSEL,j,n,ph}^{dur}$. The operation phase in the previous and current time-step certainly changes the start and ending statuses of the device as implied by (30). Eventually, (31) enforce the operational consistency until the last phase and (32) limits the maximum number of times that the device should be turned on during a day which is set to 1 in our study.

$$E_{TSEL,j,n,t} = \sum_{ph} x_{TSEL,j,n,ph,t} E_{j,n,ph}^{ph},\ \forall j,n,t \tag{27}$$

$$\sum_{ph} x_{TSEL,j,n,ph,hr} \le 1,\ \forall j,n,hr \tag{28}$$

$$y_{TSEL,j,n,ph,hr} = z_{TSEL,j,n,ph,\left(hr+T_{TSEL,j,n,ph}^{dur}\right)},\ \forall j,n,ph,hr \tag{29}$$

$$\begin{aligned} y_{TSEL,j,n,ph,hr} - z_{TSEL,j,n,ph,hr} \\ = x_{TSEL,j,n,ph,hr} - x_{TSEL,j,n,ph,hr-1},\ \forall j,n,ph,hr \\ - \{hr^{initial}, hr^{final}\} \end{aligned} \tag{30}$$

$$z_{TSEL,j,n,ph,hr} = y_{TSEL,j,n,ph+1,hr}\ \forall j,n,ph - \{ph^{final}\}, hr \tag{31}$$

$$\sum_{hr} y_{TSEL,j,n,ph,hr} = N_{TSEL,j,n},\ \forall j,n,ph \tag{32}$$

5. PV:

The DA forecast of solar irradiance affecting PV energy production could potentially be different form the RT production. A deviation $\Delta I_{j,t}$ is added to the DA scheduling to constitute the RT scheduling. Accordingly, we can expect that the proportions of power produced by PV and used internally in the mEH and sold to the ILEC could change in RT, (35)-(38). Moreover, part of PV production is fed to the WE to generate clean hydrogen this is implied in (38).

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$$I_{j,t} = I_{j,t}^{DA,*} + \Delta I_{j,t}, \forall j, t \quad (33)$$

$$E_{PV,j,t} = A_{PV,j} I_{j,t} \eta_{PV,j}, \forall j, t \quad (34)$$

$$E_{PV,j,t}^{self} = E_{PV,j,t}^{self,A*} + \Delta E_{PV,j,t}^{self}, \forall j, t \quad (35)$$

$$E_{PV,j,t}^{sell} = E_{PV,j,t}^{sell,DA*} + \Delta E_{PV,j,t}^{sell}, \forall j, t \quad (36)$$

$$E_{PV,j,t}^{EZ} = E_{PV,j,t}^{EZ,DA*} + \Delta E_{PV,j,t}^{EZ}, \forall j, t \quad (37)$$

$$E_{PV,j,t} = E_{PV,j,t}^{self} + E_{PV,j,t}^{sell} + E_{PV,j,t}^{EZ}, \forall j, t \quad (38)$$

6. Heat pump (HP)

Heat pumps are one of the high-performance energy convention technologies with a COP of generally hight than a unit. It absorbs the heat from the ambient and feeds it to the heating network, storage, or area. This technology is explicitly formulated in the EH DA scheduling. Therefore, we can expect deviation from its scheduled value in the RT, expressed in (39). Furthermore, the operation of HP is considered reversible which means instead of heating it can generate cooling but either of the operation is allowed at a time. This fact is mathematically expressed by help of a binary variable in (43) and (44).

$$\mathrm{H}_{\mathrm{HP,j,t}}^{\mathrm{H}} = \mathrm{H}_{\mathrm{HP,j,t}}^{\mathrm{H,DA*}} + \Delta \mathrm{H}_{\mathrm{HP,j,t}}^{\mathrm{H}}, \forall \mathrm{j, t} \quad (39)$$

$$\mathrm{H}_{\mathrm{HP,j,t}} = \mathrm{COP}_{\mathrm{HP,j}}^{\mathrm{H}} \mathrm{E}_{\mathrm{HP,j,t}}^{\mathrm{H}}, \forall \mathrm{j, t} \quad (40)$$

$$\mathrm{C}_{\mathrm{HP,j,t}} = \mathrm{C}_{\mathrm{HP,j,t}}^{\mathrm{DA*}} + \Delta \mathrm{E}_{\mathrm{HP,j,t}}^{\mathrm{C}}, \forall \mathrm{j, t} \quad (41)$$

$$\mathrm{C}_{\mathrm{HP,j,t}} = \mathrm{COP}_{\mathrm{HP,j}}^{\mathrm{C}} \mathrm{E}_{\mathrm{HP,j,t}}^{\mathrm{C}}, \forall \mathrm{j, t} \quad (42)$$

$$0 \le \mathrm{E}_{\mathrm{HP,j,t}}^{\mathrm{H}} \le \mathrm{x}_{\mathrm{HP,j,t}} \mathrm{E}_{\mathrm{HP}}^{\mathrm{H,max}}, \forall \mathrm{j, t} \quad (43)$$

$$0 \le \mathrm{E}_{\mathrm{HP,j,t}}^{\mathrm{C}} \le \left(1 - \mathrm{x}_{\mathrm{HP,j,t}}\right) \mathrm{E}_{\mathrm{HP}}^{\mathrm{C,max}}, \forall \mathrm{j, t} \quad (44)$$

7. CHP:

The CHP technology is dispatched in DA and in RT operation it can experience deviation from its schedule values. This deviation should be accounted for both electricity (45) and heating (52) generation. In the proposed ILEC model, CHP is one of the technologies that its energy generation is used for internal demand of mEH and the excess is sold within the ILEC. Therefore, we can expect that the DA scheduling for the sold and self-used energy of CHP in mEH can be different in RT. This is indicated in (49)-(51) and (54)-(56), respectively for electricity and heating. The reminder of the equations is set for safe operation of the CHP.

$$E_{CHPNGICE,j,t} = E_{CHPNGICE,j,t}^{DA*} + \Delta E_{CHPNGICE,j,t}, \forall j, t \quad (45)$$

$$E_{CHPNGICE,j,t} = G_{CHPNGICE,j,t} \eta_{e,CHPNGICE} LHV_{NG}, \forall j, t \quad (46)$$

$$E_{CHPNGICE,j}^{min} x_{CHPNGIC,j,hr} \le E_{CHPNGICE,j,t} \le E_{CHPNGICE,j}^{max} x_{CHPNGIC,j,t}, \forall j, t \quad (47)$$

$$DR_{CHPNGICE,j} \le E_{CHPNGICE,j,t} - E_{CHPNGICE,j,t-1} \le UR_{CHPNGICE,j} \ \forall j, t \quad (48)$$

$$E_{CHPNGICE,j,t}^{self} = E_{CHPNGICE,j,t}^{self,DA*} + \Delta E_{CHPNGICE,j,t}^{self}, \forall t, j \quad (49)$$

$$E_{CHPNGICE,j,t}^{sell} = E_{CHPNGICE,j,t}^{sell,DA*} + \Delta E_{CHPNGICE,j,t}^{sell}, \forall t, j \quad (50)$$

$$E_{CHPNGICE,j,t} = E_{CHPNGICE,j,t}^{self} + E_{CHPNGICE,j,t}^{sell}, \forall j, t \quad (51)$$

$$H_{CHPNGICE,j,t} = H_{CHPNGICE,j,t}^{DA*} + \Delta H_{CHPNGICE,j,t}, \forall j, t \quad (52)$$

$$H_{CHPNGICE,j,t} = \frac{E_{CHPNGICE,j,t} \eta_{th,CHPNGICE,j}}{\eta_{e,CHPNGICE,j}}, \forall j, t \quad (53)$$

$$H_{CHPNGICE,j,t}^{self} = H_{CHPNGICE,j,t}^{self,DA*} + \Delta H_{CHPNGICE,j,t}^{self}, \forall t, j \quad (54)$$

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$$H^{sell}_{CHPNGICE,j,t} = H^{sell,DA*}_{CHPNGICE,j,t} + \Delta H^{sell}_{CHPNGICE,j,t}, \forall t, j \quad (55)$$
$$H_{CHPNGICE,j,t} = H^{self}_{CHPNGICE,j,t} + H^{sell}_{CHPNGICE,j,t}, \forall j, t \quad (56)$$

8. Natural Gas Boiler:

The optimal DA scheduling of NGB is also carried out in EH level. However, the changes in the RT demand will change the optimal behaviour of NGB; therefore, the operational constraints of the NGB can be updated as follows.

$$\mathrm{H_{NGBoiler,j,t}} = \mathrm{H^{DA*}_{NGBoiler,j,t}} + \Delta\mathrm{H_{NGBoiler,j,t}}, \forall \mathrm{j, t} \quad (57)$$
$$\mathrm{H_{NGBoiler,j,t}} = \mathrm{G_{NGBoiler,j,t}}\eta_{\mathrm{NGBoiler,j}}\mathrm{LHV_{NG}}, \forall \mathrm{j, t} \quad (58)$$
$$\mathrm{H^{min}_{NGBoiler}} \leq \mathrm{H_{NGBoiler,j,t}} \leq \mathrm{H^{max}_{NGBoiler}}, \forall \mathrm{j, t} \quad (59)$$

9. Absorption Chiller:

The core element of the cooling carrier of each mEH is the AC, which runs on heating energy and generates cooling. The operational constraints could be developed accordingly, as follows.

$$C_{AChil,j,t} = C^{DA*}_{AChil,j,t} + \Delta C_{AChil,j,t}, \forall j, t \quad (60)$$
$$C_{AChil,j,t} = H_{AChil,j,t} COP_{AChil,j}, \forall j, t \quad (61)$$
$$0 \leq H_{AChil,j,t} \leq H^{max}_{AChil,j}, \forall j, t \quad (62)$$

10. Solar thermal:

The RT solar irradiance deviation from the DA is already expressed in PV modelling section. Therefore, the heating produced in RT can be indicated as in (63).

$$H_{ST,j,hr} = A_{ST,j} I_{j,hr} \eta_{ST,j}, \forall j, hr \quad (63)$$

11. Thermal Storage System (TES):

The state of energy stored in the TES is associated with the energy loss due to imperfect isolation of the TES and the heating energy absorbed or fed to the TES at a certain time. This will lead to the difference equation of the TES (66). Considering that the charging and discharging heating energy of the TES could differ in RT from the value scheduled in DA as indicated by (64) and (65). The rest of the constraints are associated with the initial energy state of the TES, minimum and maximum charging or discharging rate and capacity. Also (69) makes sure that the TES is either charging or discharging at a time.

$$H^{Ch}_{TES,j,t} = H^{Ch,DA*}_{TES,j,t} + \Delta H^{Ch}_{TES,j,t}, \forall j, t \quad (64)$$
$$H^{Disch}_{TES,j,t} = H^{Disch,DA*}_{TES,j,t} + \Delta H^{Disch}_{TES,j,t}, \forall j, t \quad (65)$$
$$H_{TES,j,t} = H_{TES,j,t-1}\big(1 - \phi(Dt)\big) + H^{Ch}_{TES,j,t-1}Dt - H^{Disch}_{TES,j,t}Dt, \forall j, t \quad (66)$$
$$H_{TES,j,t} = H^{initial}_{TES,j}, \forall t \in t^{initial}, t^{final} \quad (67)$$
$$0 \leq H^{Ch}_{TES,j,t} \leq H^{Ch,max}_{TES,j} x_{TES,j,t}, \forall j, t \quad (68)$$
$$0 \leq H^{Disch}_{TES,j,t} \leq H^{Disch,max}_{TES,j}\big(1 - x_{TES,j,t}\big), \forall j, t \quad (69)$$
$$H^{min}_{TES,j} \leq H_{TES,j,t} \leq H^{max}_{TES,j}, \forall j, t \quad (70)$$

12. Water Electrolyzer:

In order to produce clean hydrogen, the EZ uses a portion of electricity produced by PV and generates hydrogen. EZ is another technology that is scheduled centrally in DA by the ILEC. Therefore, the H2 RT H2 production will be affected by DA scheduling according to (71). The

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efficiency and LHV of hydrogen are the main factors in the volume of hydrogen produced by EZ (73). Also, the nominal (maximum) power of the EZ is taken into account in (73).

$$H2_{EZ,j,t} = H2_{EZ,j,t}^{DA*} + \Delta H2_{EZ,j,t},\ \forall j,t \quad (71)$$

$$H2_{EZ,j,t} = \frac{E_{PV,j,t}^{EZ}\eta_{e,EZ,j}}{LHV_{H2}},\ \forall j,t \quad (72)$$

$$0 \leq E_{PV,j,t}^{EZ} \leq E_{EZ}^{max},\ \forall j,t \quad (73)$$

13. Hydrogen Storage System (HSS):

The HSS is modelled and dispatched in DA scheduling. Therefore, it is likely that the optimal operation of it in RT varies. This variation from the DA scheduling should be considered in the hydrogen charging and discharging volumes of the HSS, (74) and (75). The difference equation of the HSS (76) implies that the level of hydrogen stored in the tank is subject to the efficiency of the tank and hydrogen inflow and outflow at a certain time. To ensure the tank cannot charged and discharged simultaneously, the (79)-(80) are adopted by the contribution of a binary variable.

$$H2_{H2Sto,j,t}^{Ch} = H2_{H2Sto,j,t}^{Ch,DA*} + \Delta H2_{H2Sto,j,t}^{Ch},\ \forall j,t \quad (74)$$

$$H2_{H2Sto,j,t}^{Disch} = H2_{H2Sto,j,t}^{Disch,DA*} + \Delta H2_{H2Sto,j,t}^{Disch},\ \forall j,t \quad (75)$$

$$\begin{aligned} H2_{H2Sto,j,t}^{Sto} = {} & H2_{H2Sto,j,t-1}^{Sto}\eta_{H2sto,j} \\ & + \left(H2_{H2Sto,j,t-1}^{Ch} - H2_{H2Sto,j,t-1}^{Disch}\right)Dt,\ \forall j,t \end{aligned} \quad (76)$$

$$H2_{H2Sto,j,t}^{Sto} = H2_{H2Sto,j}^{initial},\ \forall t \in \{t^{initial}, t^{final}\} \quad (77)$$

$$H2_{H2Sto,j,t}^{Sto,min} \leq H2_{H2Sto,j,t}^{Sto} \leq H2_{H2Sto,j,t}^{Sto,max},\ \forall j,t \quad (78)$$

$$0 \leq H2_{H2Sto,j,t}^{Ch} \leq H2_{H2Sto,j,t}^{Ch,max} x_{H2Sto,j,t}^{Ch},\ \forall j,t \quad (79)$$

$$0 \leq H2_{H2Sto,j,t}^{Disch} \leq \left(1 - x_{H2Sto,j,t}^{Ch}\right),\ \forall j,t \quad (80)$$

14. Fuel Cell (FC) based CHP:

The operation of FC-based CHP is similar to the NG-based CHP except that it runs on hydrogen rather than natural gas. Therefore, the same explanation stands true for the operational constraints of this technology.

$$E_{CHPFC,j,t} = E_{CHPFC,j,t}^{DA*} + \Delta E_{CHPFC,j,t},\ \forall j,t \quad (81)$$

$$E_{CHPFC,j,t} = H2_{CHPFC,j,t}\eta_{e,CHPFC,j}LHV_{H2},\ \forall j,t \quad (82)$$

$$E_{CHPFC,j,t}^{min} x_{CHPNGIC,j,t} \leq E_{CHPFC,j,t} \leq E_{CHPFC,j,t}^{max} x_{CHPNGIC,j,t},\ \forall j,t \quad (83)$$

$$DR_{CHPFC,j} \leq E_{CHPFC,j,t} - E_{CHPFC,j,t-1} \leq UR_{CHPFC,j},\ \forall j,t \quad (84)$$

$$E_{CHPFC,j,t}^{self} = E_{CHPFC,j,t}^{self,DA*} + \Delta E_{CHPFC,j,t}^{self},\ \forall j,t \quad (85)$$

$$E_{CHPFC,j,t}^{sell} = E_{CHPFC,j,t}^{sell,DA*} + \Delta E_{CHPFC,j,t}^{sell},\ \forall j,t \quad (86)$$

$$E_{CHPFC,j,t} = E_{CHPFC,j,t}^{self} + E_{CHPFC,j,t}^{sell},\ \forall j,t \quad (87)$$

$$H_{CHPFC,j,t} = H_{CHPFC,j,t}^{DA*} + \Delta H_{CHPFC,j,t},\ \forall j,t \quad (88)$$

$$H_{CHPFC,j,t} = \frac{\eta_{th,CHPFC,j}\left(1 - \eta_{e,CHPFC,j}\right)}{\eta_{e,CHPFC,j}} E_{CHPFC,j,t},\ \forall j,t \quad (89)$$

$$H_{CHPFC,j,t}^{self} = H_{CHPFC,j,t}^{self,DA*} + \Delta H_{CHPFC,j,t}^{self},\ \forall j,t \quad (90)$$

$$H_{CHPFC,j,t}^{sell} = H_{CHPFC,j,t}^{sell,DA*} + \Delta H_{CHPFC,j,t}^{sell},\ \forall j,t \quad (91)$$

$$H_{CHPFC,j,t}^{DA*} = H_{CHPFC,j,t}^{self} + H_{CHPFC,j,t}^{sell},\ \forall j,t \quad (92)$$

Objective function(s) of optimisation problem
The primary objective at the mEH level is to minimize the cost of transactions while keeping the deviation of the DA scheduling close to zero. Since the environmental impact of the ILEC is already tackled in the EH DA scheduling at the mEH level, the second objective is to maximize the user's thermal comfort, as indicated in (94). Accordingly, if the mean ambient temperature is higher than 15°C, this will mean that the cooling system is on, and the indoor temperature should be regulated as close as to the set point temperature. On the contrary, if the ambient temperature is lower than 15°C, the heating system will be operational, and the maximum comfort for the user would be the higher indoor temperature. $$min\ Cost_j = \sum_t \{\Delta E^{buy}_{PG,j,t} Pr^{buy}_{PG,j,t} - \Delta E^{sell}_{PG,j,t} Pr^{sell}_{PG,j,t} + \Delta H^{buy}_{DH,j,t} Pr^{buy}_{DH,j,t} - \Delta H^{sell}_{DH,j,t} Pr^{sell}_{DH,j,t} + G^{buy}_{NG,j,t} Pr^{buy}_{NG,j,t}\} Dt\ ,\ \forall j \quad (93)$$ $$max \sum_t UC_{j,t} = \begin{cases} T^{in}_{j,t}, & mean(T^{out}_{j,t}) \leq 15 \\ -T^{in}_{j,t}, & mean(T^{out}_{j,t}) \geq 15 \end{cases} \forall j \quad (94)$$
Optimisation method used to solve the formulated problem
The problem will be formulated as a MILP problem with multiple objective functions. To solve such a multi-objective problem, the AUGMECON method will be adopted, which is the improved version of the epsilon-constraint method for mapping the non-dominates solutions of the Pareto frontier [28].
Energy carriers involved
Currently, the following carriers are integrated and operational: • Electricity • Heat • Gas • Hydrogen
Energy technologies involved
As the formulation regards, the following technologies are available for the time being. • EV • BESS • HHS • PV • CHP • Heat pump (HP) • Natural gas boiler (NGB) • Solar thermal (ST) • TSS • Water electrolyzer (EZ) • H2SS • FC • Absorption chiller
Formulation of system balances equation for energy carriers involved
The balance equations will incorporate electrical power, gas, heating, cooling, and hydrogen for the current version of the model as follows:

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1. Electric power balance

$$E_{PEV,j,t}^{Ch} + E_{Bat,j,t}^{Ch} + \sum_{n} E_{TSEL,j,n,hr} + E_{HP,j,t}^{H} + E_{HP,j,t}^{C} + E_{NFEL,j,hr} - E_{PEV,j,t}^{Disch,self} - E_{Bat,j,t}^{Disch} - E_{PV,j,t}^{self} - E_{CHPNGICE,j,t}^{self} - E_{CHPFC,j,t}^{self} = E_{PG,j,hr}^{buy,DA*} + \Delta E_{PG,j,hr}^{buy}, \ \forall j,t \tag{95}$$

$$E_{PEV,j,t}^{Disch,sell} + E_{PV,j,t}^{sell} + E_{CHPNGICE,j,t}^{sell} + E_{CHPFC,j,t}^{sell} = E_{PG,j,hr}^{sell,DA*} + \Delta E_{PG,j,hr}^{sell}, \ \forall j,t \tag{96}$$

$$0 \le E_{PG,j,hr}^{buy,DA*} + \Delta E_{PG,j,hr}^{buy} \le x_{PG,j,hr} \overline{E_{PG,j}^{buy}}, \ \forall j,t \tag{97}$$

$$0 \le E_{PG,j,hr}^{sell,DA*} + \Delta E_{PG,j,hr}^{sell} \le \left(1 - x_{PG,j,hr}\right) \overline{E_{PG,j}^{sell}}, \ \forall j,t \tag{98}$$

where NFEL stands for non-flexible electric load. Constraint (95) indicates the internal electricity balance of the mEH while (96) expresses the electricity aggregated in the mEH and sold to ILEC. To ensure the simultaneous electricity transaction between the mEH and the ILEC grid is prohibited, constraints (97) and (98) are adopted. Also, they set the maximum limitation of the electricity transferred at a time.

2. Heat balance:

$$H_{HHS,j,t} + H_{AChil,j,t} + H_{TES,j,t}^{Ch} + H_{NFHL,j,t} - H_{HP,j,t}^{H} - H_{CHPNGICE,j,t}^{self} - H_{NGBoiler,j,t} - H_{ST,j,hr} - H_{TES,j,t}^{Disch} - H_{CHPFC,j,t}^{self} = H_{DH,j,hr}^{buy,DA*} + \Delta H_{DH,j,hr}^{buy}, \ \forall j,t \tag{99}$$

$$H_{CHPNGICE,j,t}^{sell} + H_{CHPFC,j,t}^{sell} = H_{DH,j,t}^{sell,DA*} + \Delta H_{DH,j,t}^{sell}, \ \forall j,t \tag{100}$$

$$0 \le G_{NG,j,t}^{buy} \le \overline{G_{NG,j}^{buy}}, \ \forall j,t \tag{101}$$

$$0 \le G_{NG,j,t}^{buy} \le \overline{G_{NG,j}^{buy}}, \ \forall j,t \tag{102}$$

where NFHL stands for non-flexible heating load, the concept behind the energy balance for the heating carrier is similar to the electricity. Therefore, the same reasoning is developed here.

3. Cooling balance

$$C_{AChil,j,t} + C_{HP,j,t} = C_{NFCD,j,t}, \ \forall j,t \tag{103}$$

The only technologies contributing to the cooling generation are AC and HP and they are supposed to feed the cooling demand of the mEH.

4. Gas balance:

$$G_{CHPNGICE,j,t} + G_{NGBiler,j,t} + G_{NFNGD,j,t} = G_{NG,j,t}^{buy}, \ \forall j,t \tag{104}$$

$$0 \le G_{NG,j,t}^{buy} \le \overline{G_{NG,j}^{buy}}, \ \forall j,t \tag{105}$$

where NFNGL stands for non-flexible natural gas load. Also, there is no gas generation technology in the mEH; therefore, the gas balance constitutes the NG imported and consumed by the technologies.

5. Hydrogen balance:

$$H2_{EZ,j,t} + H2_{H2Sto,j,t-1}^{Disch} = H2_{H2Sto,j,t-1}^{Ch} + H2_{CHPFC,j,t} + H2_{NFH2D,j,t}, \ \forall j,t \tag{106}$$

In this model, there is no H_2 external carrier. Therefore, the clean hydrogen produced by the EZ or discharged from the H2SS is consumed by the FC, NFH2D and H2SS in charging mode.

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The perception in this model is that bi-directional energy transactions and trade are possible only for electricity and heating carriers.
Tool(s) used to solve the problem
The model is developed in the Python environment using the Pyomo package, and it is solved by the Gurobi solver.
Temporal resolution
The resolution can be 5 to 15 minutes, according to the user's preference. However, the coordination with the P2P market platform will be synchronized according to the P2P market time resolution.
Time horizon
It will be a rolling time horizon for 24 hours of representative day.

Sets	
t	Time index (15 minutes resolution)
j	mEH index
n	TSEL device
ph	BESS binary

Decision Variables	
$x_{Bat,j,t}$	BESS binary
$E_{Bat,j,t}^{Ch}$	BESS charge power [kW]
$E_{Bat,j,t}^{Disch}$	BESS discharge power [kW]
$SOC_{Bat,j,t}$	BESS state of energy [kWh]
$x_{CHPNGIC,j,t}$	CHP binary
$G_{CHPNGICE,j,t}$	CHP gas consumption [m^3]
$H_{CHPNGICE,j,t}$	CHP heat produced [kW]
$H_{CHPNGICE,j,t}^{sell}$	CHP heat sold [kW]
$H_{CHPNGICE,j,t}^{self}$	CHP heat used [kW]
$E_{CHPNGICE,j,t}$	CHP power produced [kW]
$E_{CHPNGICE,j,t}^{sell}$	CHP power sold [kW]
$E_{CHPNGICE,j,t}^{self}$	CHP power used [kW]
$z_{TSEL,j,n,ph,t}$	Ending binary variable for TSEL
$x_{PEV,j,t}$	EV binary
$E_{PEV,j,t}^{Ch}$	EV charging power [kW]
$E_{PEV,j,t}^{Disch}$	EV discharging power [kW]
$\mathrm{E}_{\mathrm{PEV},j,t}^{Disch,\mathrm{sell}}$	EV power sold [kW]
$\mathrm{E}_{\mathrm{PEV},j,t}^{Disch,\mathrm{self}}$	EV power used [kW]
$\mathrm{SOC}_{PEV,j,t}$	EV state of energy [kWh]
$H_{DH,j,t}^{buy}$	External heat bought [kW]
$H_{DH,j,t}^{sell}$	External heat sold [kW]
$E_{PG,j,t}^{buy}$	External power bought [kW]
$E_{PG,j,t}^{sell}$	External power sold [kW]

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$H^{sell}_{CHPFC,j,t}$	FC heat sold [kW]
$H^{self}_{CHPFC,j,t}$	FC heat used [kW]
$H2_{CHPFC,j,t}$	FC hydrogen consumed [m^3]
$E_{CHPFC,j,t}$	FC power produced [kW]
$E^{sell}_{CHPFC,j,t}$	FC power sold [kW]
$E^{self}_{CHPFC,j,t}$	FC power used [kW]
$x^{Ch}_{H2Sto,j,t}$	H2SS binary
$H2^{Ch}_{H2Sto,j,t}$	H2SS hydrogen inflow [m^3]
$H2^{Disch}_{H2Sto,j,t}$	H2SS hydrogen outflow [m^3]
$H2^{Sto}_{H2Sto,j,t}$	H2SS state of hydrogen [m^3]
$T^{in}_{j,t}$	Home inside temperature [°C]
$G_{NGBoiler,j,t}$	NGB gas consumed [m^3]
$H_{NGBoiler,j,t}$	NGB heat produced [kW]
$x_{TSEL,j,n,ph,t}$	Operational binary variable for TSEL
$E_{TSEL,j,n,t}$	Power consumed by TSEL [kW]
$E^{sell}_{PV,j,t}$	PV power sold [kW]
$E^{self}_{PV,j,t}$	PV power used [kW]
$\Delta(.)$	Real-time deviation from the DA scheduling
$y_{TSEL,j,n,ph,t}$	Staring binary variable for TSEL
$x_{TES,j,t}$	TSS binary
$H^{Ch}_{TES,j,t}$	TSS heat charged [kW]
$H^{Disch}_{TES,j,t}$	TSS heat discharged [kW]
$H_{TES,j,t}$	TSS state of heat [kWh]
$H2_{EZ,j,t}$	EZ hydrogen produced [m^3]
$E_{EZ,j,t}$	EZ power used [kW]
$E_{EZCmp,j,t}$	EZ power used for compressing hydrogen [kW]

Parameters	
$T^{out}_{j,t-1}$	Ambient temperature [°C]
$E^{Ch,max}_{Bat,j}$	BESS charge rate
$\eta^{Disch}_{Bat,j}$	BESS discharge efficiency
$SOC^{initial}_{Bat,hr}$	BESS initial state of energy [kWh]
$SOC^{min}_{Bat,j}$ $/SOC^{max}_{Bat,j}$	BESS min/max state of energy [kWh]
$\eta_{e,CHPNGICE,j}$	CHP electrical efficiency
$E^{min}_{CHPNGICE,j}$ $/E^{max}_{CHPNGICE,j}$	CHP max/min power [kW]
$\eta_{th,CHPNGICE,j}$	CHP thermal efficiency
$(.)^{DA*}$	Day ahead scheduling of the installations coming from EH level as parameters
$\eta_{EBoiler,j}$	EB efficiency

$H_{NGBoiler}^{min}$ $/H_{NGBoiler}^{max}$	EB min/max heat [kW]
$Pr_{PG,j,t}^{buy}$	Electricity buying price [€/kW]
$Pr_{PG,j,t}^{sell}$	Electricity selling price [€/kW]
C^{in}	Equivalent thermal capacitance of home
R^{in}	Equivalent thermal resistance of home
$\eta_{PEV,j}^{Ch}$	EV charging efficiency
$\eta_{\mathrm{PEV,j}}^{\mathrm{Disch}}$	EV discharge efficiency
$E_{PEV,j}^{Disch}$	EV discharge rate
$\mathrm{SOC}_{PEV,j}^{min}$ $/SOC_{PEV,j}^{max}$	EV min/max state of energy [kWh]
$\mathrm{SOC}_{PEV,j}^{arrival}$	EV state of energy at arrival [kWh]
$\mathrm{SOC}_{PEV,j}^{departure}$	EV state of energy at the departure time [kWh]
$\mathrm{SOC}_{\mathrm{PEV,j}}^{\mathrm{initial}}$	EV state of energy in the morning [kWh]
$\overline{H_{DH,j}^{buy}}$	External heat buying limit [kW]
$\overline{H_{DH,j,hr}^{sell}}$	External heat selling limit [kW]
$\overline{E_{PG,j}^{buy}}$	External power buying limit [kW]
$\overline{E_{PG,j}^{sell}}$	External power selling limit [kW]
$\eta_{e,CHPFC,j}$	FC electrical efficiency
$E_{CHPFC,j,t}^{min}$ $/E_{CHPFC,j,t}^{max}$	FC min/max power produced [kW]
$\eta_{th,CHPFC,j}$	FC thermal efficiency
$Pr_{NG,j,\mathrm{t}}^{buy}$	Gas buying price [€/m^3]
$\gamma_{H2Sto,j}^{Dsp}$	H2SS hydrogen dissipation
$H2_{H2Sto,j,t}^{Ch,max}$	H2SS hydrogen inflow rate [m^3]
$H2_{H2Sto,j,t}^{Disch,max}$	H2SS hydrogen outflow rate [m^3]
$H2_{H2Sto,j}^{initial}$	H2SS initial state of hydrogen [m^3]
$H2_{H2Sto,j,hr}^{Sto,min}$ $/H2_{H2Sto,j,t}^{Sto,max}$	H2SS min/max state of hydrogen [m^3]
$Pr_{DH,j,\mathrm{t}}^{buy}$	Heat buying price [€/kW]
$Pr_{DH,j,\mathrm{t}}^{sell}$	Heat selling price [€/kW]
$T^{in,min}/T_{j}^{in,max}$	Home min/max temperature [°C]
$Pr_{H2N,j,\mathrm{t}}^{buy}$	Hydrogen buying price [€/m^3]
LHV_{NG}	Low heat value of gas [kWh/m^3]
LHV_{H2}	Low heat value of hydrogen [kWh/m^3]
$\eta_{NGBoiler,j}$	NGB efficiency
$H_{NGBoiler}^{min}$ $/H_{NGBoiler}^{max}$	NGB min/max heat [kW]

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$\eta_{PV,j}$	PV efficiency
$E_{PV,j,t}$	PV power production [kW]
$A_{PV,j}$	PV total panel area [m^2]
$I_{j,t}$	Solar irradiance [kW/m^2]
$\eta_{ST,j}$	Solar thermal efficiency
$H_{ST,j,t}$	Solar thermal heat [kW]
$A_{ST,j}$	Solar thermal panel area [m^2]
$N_{TSEL,j,n}$	TSEL maximum number of operations per day
$E_{j,n,ph}^{ph}$	TSEL power consumption per phase
$H_{TES,j}^{Ch,max}$	TSS charging rate [kW]
$\eta_{TES,j}^{Disch}$	TSS discharge efficiency
$H_{TES,j}^{Disch,max}$	TSS discharging rate [kW]
$H_{TES,j}^{initial}$	TSS initial state of heat [kWh]
$H_{TES,j}^{min}/H_{TES,j}^{max}$	TSS min/max state of heat [kW/h]
$\eta_{EZCmp,j}$	WE compressor efficiency
$COP_{EZ,j}$	WE conversion coefficient
$\eta_{e,EZ,j}$	WE efficiency
$H2_{EZ}^{min}/H2_{EZ}^{max}$	WE min/max hydrogen production [m^3]

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5 Feedback loop between long-term and short-term optimisation problems

With the optimisation problems residing in the different layers of the ILEC, it is necessary to ensure that they are not conflicting with each other but are operating in harmony, fulfilling the objectives of the related stakeholders.

For this reason, a forward loop has been established through the P2P market to secure maximum convergence between the layers. An asynchronous feedback loop between the two layers will allow the ex-post analysis of the collaboration between the two layers. Through this loop, the aim is to identify any shortcomings, such as non-convergence, imbalance issues, etc., in extreme cases. Collected data from the different operations will give insights to both layers' tools to refine their functionalities.

5.1 Identification and processing of feedback loop data

Two main operations have been designed with the P2P market playing a central role, as this is the function that allows communication between the two layers:

- The P2P market secures that convergence is found in most operations as follows: At the EH level, the strategic decision for the preference of weights (in optimisation problem) is taken by the core user, i.e., the ILEC and thus, the sets of solutions are forwarded with a preference to the mEH level and specifically through the P2P market. The market is responsible for starting the iteration from the preferred solution and proceeding with other solutions in case a point of convergence is not found. To do so, a multi-criteria decision-making approach called TOPSIS (Technique for the Order of Prioritisation by Similarity to Ideal Solution) is employed through the PyMCDM library at the coordinator level. This approach is useful when dealing with a large set of optimal solutions to rank and present a narrower subset to facilitate selection. The method compares a set of alternatives through a decision matrix (alternative solution x objectives) that is normalised into a non-dimensional attribute matrix. The ILEC selects the set of weights to express the relative importance of each objective and the criteria type for each objective, i.e., 1 for benefits and -1 for cost.

- We identify the different data sets to be collected, and then we identify KPIs that will allow for the evaluation of the collaboration and operation of the two layers together. The processing of the related data is further analysed.

In the Table *4*, the data that are critical for the evaluation are presented.

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Table 4 Data identification

#	Data/Variable to be tracked	Units	Toolbox Level	Relevance to Toolbox Performance
	Name or description	*e.g., kW, etc.*	*EH or mEH*	*Brief description of why these should be tracked to assess performance*
1	mEH’s electricity import/export in DA	kW	EH to mEH	The DA scheduling of the assets belonging to the mEH is first dispatched in a centralized way at the EH level, and its quality is subject to the precise load and generation forecast in DA. This information needs to be broadcast to the mEH for RT operation.
2	mEH's electricity import/export in RT	kW	mEH	The optimal operation of the RT problem at the mEH level is subject to having full information on DA scheduling of energy import or export for the mEHs for every time step to keep the system balanced by possible re-scheduling the mEH assets. This index will help see how well the DA schedule is followed.
3	System-level operational costs	EUR/ year	EH	All these tools report costs for the optimized period. It could be useful to compare the outcomes to see how the modelling approaches impact the result.
4	Operational costs for each mEH	EUR/ period	EH and mEH	The main difference between the EH and mEH calculation is the modelling approach being centralized or decentralized. This will likely have an impact on the outcome for each mEH. Therefore, it would be interesting to compare the economic outcome for each mEH under these approaches.

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In Table 5, the relevant KPIs and the foreseen data processing are presented.

Table 5 Data processing

#	KPI of Feedback	Input Data required	Equation for Assessing KPI
	Short description of KPI for evaluating the efficiency in the collaboration of the two layers	*Specify Data*	*A detailed description of how the data should be processed, including any relevant equations*
1	The mismatch is provided by the difference between the hourly DA scheduling and the mEH RT scheduling	mEH's DA electricity import/export (I.E.09), mEH's RT electricity import/export (within TU/e-1)	The hourly time series of the data coming from mEH should be resampled in 15 15-minute resolution, and the gaps between hourly values should be filled linearly. A Python script using the Pandas library is given in the following: df_15min = df_hourly.resample('15T').interpolate(method='linear') Then, the mismatch between the RT optimal operation import/export and the DA scheduling is minimised.
2	The imbalances in RT re-scheduling lead to mismatches and their negative or positive contribution to the cost based on the RT incentives from the P2P market will be calculated.	Incentives (energy costs) in RT coming from the RT P2P market	The cost objective function of the RT operation for each mEH can be found in the mEH STO problem formulation
3	Comparing EH operational costs to mEH costs	EH operational costs and operational costs for all mEHs in the EH system	It can compare the deviation between the cost calculations. Relative terms describing mEH solution cost increase/decrease relative to the EH solution could be a good metric. In that case, the equation to calculate the percentage deviation becomes 100*((sum of mEH operational costs)-(EH operational costs))/(EH operational costs)

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6 Conclusions

This report presents the general methodology approach for the optimal design and operation of an energy hub. This task developed a methodology for designing the optimal resource mix within an ILEC. The methodology aimed to consider all aspects of the ILEC, including existing infrastructure and capacity, current and future load requirements from all energy carriers, and available resources and associated costs. Based on these inputs, a long-term optimisation was then developed to determine the optimal system design for the energy hub to satisfy a number of objectives, including minimisation of costs and environmental impacts over a multi-year time horizon. The resulting system design was then employed as an input to a short-term optimisation problem that calculated the optimal dispatch of resources in an operational time frame (e.g., minutes/hours), considering both the limitations and needs of the power system as well as the overarching objectives of the ILEC.

This task began with the construction of the eNeuron toolbox concept framework. The toolbox operates on two hierarchical levels, namely the EH level, which is the community itself, and the mEH level representing the single prosumer in the community. At the EH layer, the optimal design and day-ahead operation is performed, whereas at the mEH layer, the real-time operation optimization is carried out. The two layers complement each other with the mEHs interacting with the upper layer through day-ahead optimal scheduling while dealing with the real-time operation optimization of mEHs. The operation is realized through a P2P market established such that mEHs can implement the day-ahead optimal scheduling through considerate decisions. The toolbox was designed using a workflow approach, allowing for the possibility to integrate multiple existing tools in a modular way.

Following the development of the eNeuron toolbox concept framework, the long-term optimization objectives were defined based on the use cases and business models developed in Task 3.3 of the eNeuron project. With the long-term objectives identified, project task forces were established to determine the functional optimization inputs required at each of the toolbox phases. The analysis focused on each of the functional blocks within each phase to provide a detailed description of how that function will interact within the toolbox. The final stage of the Task Force activities developed detailed descriptions of the optimization problems for each of the phases within the EH and mEH layers of toolbox, including formulation of the problem, definition of the constraints, and energy carriers involved, etc.

Finally, the formulation of a feedback loop between the long-term and short-term optimization problems was developed to ensure that the optimization problems residing in the different layers of the ILEC do not conflict with each other. Data processes were identified along with Key Performance Indicators for evaluating the efficiency in the collaboration of the two layers.

The methodology for the optimal design and operation of energy hubs developed in this task will form the basis for the eNeuron toolbox development in Task 4.3 of the eNeuron project.

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