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Deliverable D4.1

Autonomous Building Digital Twins

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Deliverable D4.1

Autonomous Building Digital Twins

Deliverable number	D4.1
Deliverable name	Autonomous Building Digital Twins
Lead beneficiary	CERTH
Description	This deliverable is directly linked to the activities foreseen in Task 4.1 and Task 4.2, consolidating all foreseen technical developments on situation awareness, forecasting and autonomous decision-making mechanisms at building level. This report is considered as the first version of D4.2.
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Main author	Iakovos Michailidis (CERTH) Georgios Karatzinis (CERTH) Georgios Vougiatzis (CERTH)
Contributors	Vincent Chanal-Bertaud (CEA) Eric François (CEA) Fathia Karoui (CEA) Sophie Dourlens-Quaranta (R2M) MojtabaMaktabifard (R2M) Igor Perevozchikov (R2M) Raphaelle Papa (IESRD) Alessandro Sorce (UNIGE) Per Pedersen (NEOGRID) Ioannis Zornatzis (CERTH)

Document history

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EXECUTIVE SUMMARY

This deliverable consolidates the technical developments and achievements of Tasks 4.1 and 4.2 within the EVELIXIA project. As the first version of D4.2, it integrates advancements in building situation awareness, forecasting, and autonomous decision-making mechanisms at the building level. These developments aim to enhance building-to-grid interaction through digital twin technologies and advanced decision-support systems.

The activities under Task 4.1 focus on creating the Building Awareness and Forecasting Toolbox, a comprehensive platform that integrates a state-of-the-art simulation engine, real-time sensory data, and hybrid models to enable advanced forecasting and situation assessment. Key components include indoor air quality monitoring, demand forecasting, flexibility prediction, and simulation-based building energy modelling. The outcome is a multi-dimensional digital tool capable of assessing several building vectors and dimensions, serving as a virtual testbed for validating various control scenarios.

Under Task 4.2, the Autonomous Building Decision Support Toolbox has been developed to provide stakeholders with actionable insights for energy optimization, demand planning, and investment evaluation. Leveraging the simulation capabilities of the Building Digital Twin resulted from Task 4.1, this task integrates innovative approaches such as reinforcement learning, multi-timescale model predictive control, and ensemble decision-tree models. These methods support services such as day-ahead demand planning, real-time load control, and investment planning, rendering the digital twin autonomous in its decision-making capabilities.

The deliverable also details the individual service implementations (IS1-IS7 and IS9-IS10), including their current initial version towards achieving the described goals. These services address critical aspects such as:

Indoor Air Quality Monitoring (IS1): Energy costs optimization while ensuring acceptable indoor environmental conditions (CO_2 and temperature) taking into account occupant's window-opening behaviour.
Energy Assets Maintenance (IS2): Maintenance scheduling and failure anticipation for the battery cooling system, from the chiller to the emitters, including the room containing the batteries (IS2-1). Detection of limescale deposits in hot water tanks, whether equipped with electrical heaters or heat exchangers (IS2-2).
Monitoring and forecasting of battery state-of-health and remaining life of the battery providing (IS2-3).
Demand Forecasting (IS3): Prediction of electricity, heating and gas networks consumption and production especially for non-dispatchable plants.
Flexibility Forecasting (IS4): The service will be used for proactively assessing and forecasting the levels of demand flexibility – focusing on both thermal and electricity demand - at the building level.
Building Energy Modelling and Simulation (IS5): The simulation engine (modelled multi-vector energy digital twin) uses real-time data and BIM to create

hybrid digital twins, combining physics-based and data-driven models for scalable energy and performance analysis across buildings.
Building Investment Planning Assistant (IS6): Performs real-time LCA and LCC analyses, optimizing CAPEX, OPEX, and environmental benefits to support strategic energy investments and grid decongestion.
SRI Advisor (IS7): Offers tailored recommendations to improve SRI scores, analyzing upgrades and flexibility scenarios for cost-effective energy efficiency and comfort enhancements.
Proactive Demand Planning (IS9): This service reshapes day-ahead demand using episodic reinforcement learning and cost-benefit matrices, enabling energy cost savings without compromising efficiency.
Continuous Energy Performance Management (IS10): Real-time operational control to optimize energy supply-demand matching and grid stability. IS10b is dedicated to control the buildings HVAC systems with the constraint of ensuring the thermal comfort.

The outcomes of this deliverable demonstrate potential for replication across various building types and operational scenarios. The generalization of models, coupled with advanced simulation and data-driven methods, ensures adaptability and scalability. While case-specific customizations are necessary for factors such as climate conditions, building systems and stakeholder needs, the methodologies and tools are broadly applicable.

The barriers encountered include data integration challenges, service interconnections, and operational variability. Requirements for implementation include access to real-time data, computational resources for simulation and decision support, and stakeholder engagement to ensure adoption. The primary channels to promote these solutions include technical workshops, policy advisory groups, and publications in scientific and industry forums.

By addressing key European goals in energy efficiency, sustainability, and smart grid integration, this deliverable sets the foundation for innovative and autonomous building management solutions with important potential for real-world impact.

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ABBREVIATIONS

Abbreviation	Name
ABDSF	Autonomous Building Decision Support Framework
ABDT	Autonomous Building Digital Twins
aFRR	Automatic Frequency Restoration Reserve
BAFF	Building Awareness and Forecasting Framework
BAUNs	Buildings as Active Utility Nodes
BESS	Battery Energy Storage System
B2G	Building-to-Grid
COP	Coefficient Of Performance
DH	District Heating
DHW	Domestic Hot Water
DSO	Distribution System Operator
DT	Digital Twin
DTS	Dynamic Thermal Simulation
EER	Energy Efficiency Ratio
EMS	Energy Management System
FCR	Frequency Containment Reserve
HVAC	Heating, Ventilation & Air Conditioning
HWT	Hot Water Tank
HX	Heat eXchanger
IAQ	Indoor Air Quality
IS	Innovative Solution
IP	Innovation Pathway
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LCI	Life Cycle Inventory
MILP	Mixed Integer Linear Programming
ML	Machine Learning
MMS	Microgrid Maintenance Service
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Sources
RUL	Remaining Useful Life
SBS	Sick Building Syndrome
SOH	State of Health
SRI	Smart Readiness Indicator
SRIA	SRI Advisor tool
VE	Virtual Environment
WP	Work Package

1. INTRODUCTION AND OBJECTIVES

1.1. Scope and objectives

This deliverable, D4.1, is part of Work Package 4 (WP4) within the EVELIXIA project, consolidating the initial developments under Tasks 4.1 and 4.2. As the first version of Autonomous Building Digital Twins report, D4.1 provides an alpha-stage framework for building-level situation awareness, forecasting, and autonomous decision-making mechanisms. It establishes the foundation for subsequent iterations and refinements, culminating in D4.2 (final-updated version). An overview diagram placing Tasks 4.1 and 4.2 within the EVELIXIA project is depicted in **Figure 1**.

The scope of D4.1 is focused on conceptual design and early technical developments of the tools and methodologies needed to enhance building-to-grid interactions. This includes the development of initial algorithms, simulation models, and service architectures for energy forecasting, flexibility assessment, and decision support at the building level. While implementation and real-time data integration are planned for future stages, this version prioritizes establishing theoretical underpinnings and defining technical requirements alongside with initial stages of results.

The objectives of D4.1 are to:

- Lay the groundwork for the **Building Awareness and Forecasting Toolbox** (Task 4.1) by creating initial models, simulation engine and methodologies for energy performance assessment, air quality monitoring, and demand forecasting.
- Define the architectural and methodological framework for the **Autonomous Building Decision Support Toolbox** (Task 4.2), focusing on decision-support strategies such as demand planning and energy cost-benefit evaluation.

These early developments set the stage for future validation and implementation phases, aligning with EVELIXIA's long-term objectives of energy efficiency, grid flexibility, and smart building integration.

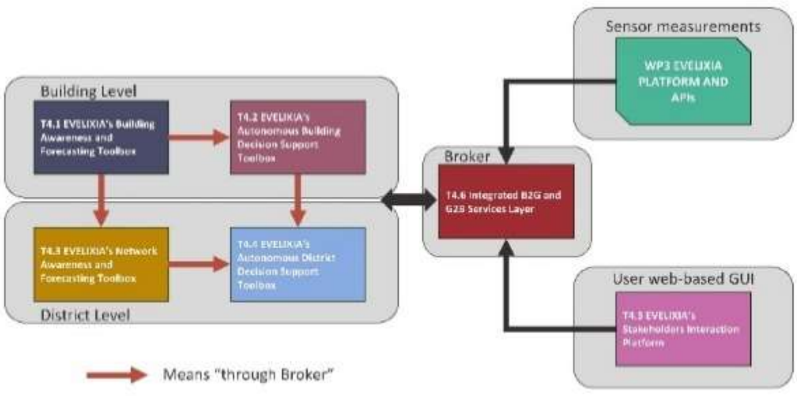


Figure 1. Overview Diagram

1.2. Structure

The structure of this deliverable reflects its alpha-stage focus, emphasizing the theoretical and conceptual foundations for the tools and methodologies to be developed in Tasks 4.1 and 4.2. The report is organized as follows:

- **Introduction and Objectives**: Provides the context, scope and objectives of D4.1 along with its alignment with project goals.
- **EVELIXIA'S Building Awareness and Forecasting Toolbox:** Outlines the technical framework of the alpha-stage version of the involved services in Task 4.1 (IS1-IS5),including their targeted functionality and roles within the project framework.
- **EVELIXIA'S Autonomous Building Decision Support Toolbox**: Outlines the technical framework of the alpha-stage version of the involved services in Task 4.2 (IS6-IS7 and IS9-IS10), including their targeted functionality and roles within the project framework.
- **Conclusions**: Summarizes the acquired knowledge while also the planned activities for future iterations, focusing on the transition from conceptual models to implementation and validation in D4.2.

1.3. Relation to Other Task and Deliverables

D4.1 is directly linked to Tasks 4.1 and 4.2 under WP4, serving as the initial version that consolidates early developments and frameworks for the Building Awareness and Forecasting Toolbox and the Autonomous Building Decision Support Toolbox. Task 4.1 focuses on the conceptual design of tools for energy modelling, demand forecasting, and flexibility assessment. These outputs form the basis for Task 4.2, which extends the toolbox to include decision-support mechanisms. Both tasks offer the Building-level structure of EVELIXIA's project.

This deliverable is pivotal for guiding future project activities, as it defines the technical requirements and architecture for subsequent iterations. While D4.1 does not yet include real-time data or implementation but instead provides a foundation for these aspects to be integrated in D4.2. The outcomes of D4.1 will inform further developments across WP4 and other work packages, ensuring alignment with the EVELIXIA project's broader objectives.

Additionally, D4.1 sets the stage for collaboration and knowledge sharing among project partners, facilitating the transition to the next validation and implementation phases. The deliverable represents a first step toward achieving the established goals of WP4, contributing to a cohesive and scalable framework for building-to-grid interactions.

2. EVELIXIA'S BUILDING AWARENESS AND FORECASTING TOOLBOX

2.1. Introduction

EVELIXIA's **Building Awareness and Forecasting Framework (BAFF)**, developed under **Task 4.1**, serves as a key component within the Innovation Pathway 1 (IP1):**Building-to-Grid (B2G) Services**, aiming to enhance the interaction between buildings and the energy grid. The BAFF is designed to provide a comprehensive suite of services that enable detailed building energy profiling, advanced forecasting capabilities, and improved situational awareness. By integrating real-time data from building sensors, static information (such as BIM data), and external environmental parameters, the BAFF supports the development of **Autonomous Building Digital Twins (ABDT)** that accurately reflect building operations and energy behaviour.

The toolbox operates in synergy with the **Autonomous Building Decision Support Framework (ABDSF),** enabling intelligent, model-based and data-driven decision-making that aligns with occupant preferences, operational requirements, and grid demands. Together, BAFF and ABDSF form the backbone of EVELIXIA's strategy to transform buildings into **Buildings as Active Utility Nodes (BAUNs)**—dynamic, responsive entities capable of participating in energy markets, optimizing consumption, and enhancing grid stability.

Task 4.1 focuses on the development, integration, and demonstration of five Innovative Solutions (ISs)within the BAFF. Each solution targets a distinct aspect of building energy awareness and forecasting:

- **IS1 - Indoor Air Quality (IAQ) Service:**Optimizes energy costs while ensuring acceptableindoor environmental conditions (CO_2, humidity, temperature) taking into accountoccupant'swindow-opening behaviour.
- **IS2 - Energy Assets Maintenance:** Evaluates operational performance, equipment health, and battery aging to schedule timely maintenance and to optimize microgrid-connected assets.
- **IS3 - Local Energy Consumption and Generation Forecasting:** Provides predictive analytics for electricity, heating, and gas loads at both building and district scales.
- **IS4 - Thermal and Electricity Flexibility Forecasting:** Assesses the flexibility potential of shiftable loads, supporting demand response and grid-interactive operations.
- **IS5 - Building Energy Modelling and Simulation:** Utilizes physics-based and data-driven models to develop hybrid digital twins, enabling energy performance simulations, demand flexibility analysis, and seamless integration with other EVELIXIA services.

Each of these ISs is described in detail in the following subchapters, outlining their objectives, methodologies, current results and next steps.

2.2. Indoor Air Quality forecast (IS1)

The current innovative solution so-called IS1 is an original tool developed by the CEA through the EVELIXIA project. The IS1 developed by CEA intends to forecast the CO_2 concentration in the building for the near future, taking into account a realistic window-opening behaviour of occupants using a machine learning approach, while respecting the thermal comfort and minimizing the energy costs. The IS1 can also be used to provide flexibility by reducing the ventilation rate.

2.2.1. Objectives

Indoor Air Quality as IAQ has been a major concern in buildings for decades with the emergence of the Sick Building Syndrome (SBS). However, IAQ is also strongly correlated with the energy bill, and the earliest B+ or Net-Zero buildings led to a drop in IAQ levels due to over-tightness and poor air change. This ambiguity raises the problem of how to reduce the energy consumption while ensuring the thermal comfort and air quality in the context of global warming.
As part of the EVELIXIA project, CEA is developing a predictive IAQ model. In this innovative solution IS1, the main challenge is to anticipate the occupants' behaviour in terms of window opening in response to weather and indoor conditions, among other factors. The aim is to offer flexibility based on heating, ventilation and air conditioning (HVAC) systems and to enable better optimization with an energy management system (EMS), for example the innovative IS10b solution developed in the same project.

2.2.2. Methodology

CEA is developing a predictive IAQ model in Python. The model encompasses four different items:

- A **predictive window-opening model** based on a Machine Learning approach and on the scikitlearn library in Python. This predictive model aims to emulate the window-opening behaviour over a short time-horizon (a few days). The window-opening model is based on a Logistic Regression approach. It is trained repetitively with historical data from the field to be adapted to the season and occupant changes, before coupling with the Mixed Integer Linear Programming (MILP)optimization model (see Figure 2).
- A **building model dedicated to estimate the air change** across the building when the windows are opened and the indoor air temperature as function of the window-opening scenario. A first step is to identify the thermal features of the building when the openings are closed and the rated mechanical ventilation is running. The building model can be either a simple model based on an electric analogy, also called RC-type model developed in Python or Matlab (see in section 3.5.2), or a DTS model such as the Building VE supported by the IS5 "Building Energy Modelling and Simulation" within the project.
- A **model is implemented to calculate the indoor CO_2 exposure** depending on the CO_2 sources from outdoors and indoors, the occupancy schedule and the air change ratio (mechanical and natural).

- At last, **an optimization model, Mixed-Integer Linear Programming (MILP)**, to enable minimizing a cost function depending on IAQ including indoor CO_2exposure, thermal discomfort, as well as the energy cost. This tool is intended to draw the trajectory of a window-opening schedule consistent with occupants' behaviour and the energy consumption throughout the HVAC systems. The predictive trajectory will be planned regularly over the horizon time of two or three days. This sub-model embeds two other programs as follows: the RC-type building model also calibrated on thermal features and air change rate, the CO_2 predictive model. It is coupled to the window-opening model trained previously.

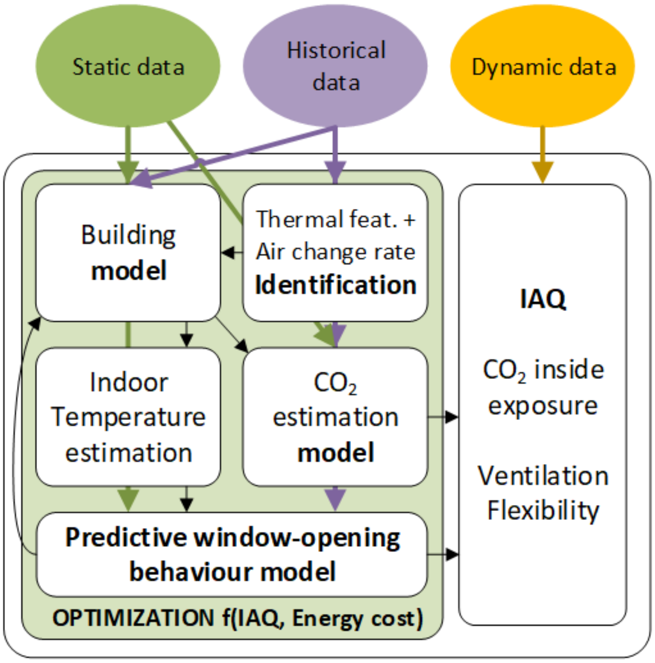


Figure 2. IS1 work flow

The training data necessary for the machine learning methodology comprises explanatory variables such as outdoor temperature, rainfall, wind speed and direction, indoor temperature, indoor relative humidity, indoor CO2 exposure, without any order of importance. In parallel, the following variables set the contextual: window state (opening or closed), window orientation, movement detection sensed to represent the occupancy, considered office, season, time of the day. The time step for calibrating the window-opening behaviour is 10 minutes maximum. The predicted variable may be either the window state (open or closed) or the action (opening or closing the window), deduced from the same explanatory window state variable. Obviously, the training data for both of these problems suffer from an imbalanced amount of data between each position or action. CEA is testing “class_weight” and “under sampling” solutions to fix this recurrent issue in machine learning methodology. CEA continues fine-tunning the model to improve the window-opening behaviour predictions. CEA also intends to go more in depth using the “ShuffleSplit” and “cross_val_predict” tools.

The building model could be a RC type model 5R1C for 5 resistances + 1 heat capacity (see in section 3.5.2) or a DTS model. It will be featured with the static data defined in the standard ISO 13790:2008, such as the conditioned floor area, the total area that is the addition of all surfaces (walls and floors) facing the building zone considered, the effective mass area, the heat capacity class of the building, ceiling height. All the data needed to create the DTS model is expected to be found in the IS16 “Digital Building Logbook”. The building model will be used to identify at a first step, the thermal characteristics of the building or office, in particular the heat transfer coefficients of the model. This calibration requires to feed the model with historical data as time series: solar heat gain based on the effective collecting areas of the building under consideration and corrections due to solar shading caused by the surrounding masks, internal heat gain due to activity inside the building, outdoor dry air temperature and supply air temperature if an energy recovering system exists, the mechanical ventilation rate across the building, indoor temperature setpoints for each time step, energy consumption, the occupancy and CO2 flow rate from hypothetic sources. Calibration of the building’s thermal behaviour must be carried out using data from periods when all windows are closed.

At a second stage, the model will be reversed to estimate its ventilation-related heat transfer coefficient, and thus the air change rate, according to the thermal characteristics identified at the previous stage and to the variation of indoor air temperature. The building’s air change rate must be identified when several windows are open. Consequently, the building model can be configured to predict the indoor air temperature and natural ventilation rate for the near future. An alternative to this method might be to calculate the air change rate based on historical data showing drops of CO2 concentration when windows are open. It might be more accurate but requires the considered rooms, offices to be equipped with CO2 sensors. Then, the optimization model set up with the aforementioned identified parameters can run, coupled to the window-opening model, to determine the indoor air temperature time series obtained with realistic window-opening behavior, and thus minimize the objective function such as the sum of energy costs, discomfort costs and CO2 exposure costs by leveraging temperature and CO2 difference potentials from the outside. The building energy consumption variable enables to solve this optimization problem, such as for the EMS described in section 3.5.2 (see IS10b).
Afterwards, the estimated air change rate is sent, during the window opening-periods to the brick model calculating the predictive CO2 concentration in the rooms. The calculation of indoor CO2 exposure is deduced from the general formula:

$$\frac{dC}{dt} + \frac{Qe + Qi}{V} \times C - \frac{(Ce \times Qe + Qi)}{V} = 0$$

where: Ce is the pollutant concentration of the air ventilated across the volume V with the flow rate Qe, Qi is the indoor pollutant source flow rate and C is the pollutant concentration into the volume V at each time step t.
Dynamic data are necessary to initialize the various calibration steps and to detect any deviations by comparison with the results of the predictive IAQ model.
This predictive IAQ model will allow for the possibility of shutting down the building ventilation system in the near time horizon in compliance with the thermal comfort and IAQ.

2.2.3. Evaluation & Results

The predictive window-opening model in development has been trained with historical data measured in the so-called HELIOS, CEA office building, located in Le Bourget-du-lac (F-Savoie) and cooled by cross-ventilation. The data set used for the machine learning predictive window-opening model covers the year 2022. After training the machine learning model on all this period, CEA tested to split the year 2022 into different seasons, with best results in particular for mid-season periods.

```
## TODO: SELECT THE PERIOD (date start and date end) OF THE YEAR TO FEED THE MODEL
dstart = datetime(2022, 3, 21)
dend   = datetime(2022, 6, 21)
dfc    = dfc[(dfc.index >= dstart) & (dfc.index < dend)]
```

CEA also addresses the time of day as a factor that influences window opening.

```
dfc['DAYTIME'] = dfc['DAYTIME'].where(~dfc.index.hour.isin([19, 20, 22, 23, 0, 1, 2, 3,
                                      4, 5, 6]), 'Out')
dfc['DAYTIME'] = dfc['DAYTIME'].where(~dfc.index.hour.isin([7, 8, 9, 10, 11, 12, 13, 14,
                                      15, 16, 17, 18]), 'In')
```

This parameter can be fine-tuned according to the type of occupant (residential or office buildings). It also allows to filter the data by considering only the period when the building is assumed to be occupied, in case of a lack of occupancy information. CEA has been continuously monitoring its offices for many years. At this stage, CEA used real data from three offices among its premises.

```
## TODO: SELECTION OF OFFICES TO BE INVESTIGATED AMONG '3033'(CLIMATISE),
'3071'(ATRIUM), '3072', '3105'
N_office = ['3071', '3072', '3105']
```

Various sets of training data have been tested. The explanatory factors used in this approach are as follows without any order of importance (see the results below): outdoor temperature, indoor air temperature, wind speed, rainfalls, time of the day and office reflecting both the occupant behaviour and the exposure of the office. The last two are contextual categories, while the predicting variable is the window status.

```
# ['CO2 AMBIANT', 'DIRECTION DU VENT', 'T AMBIANTE', 'T EXTERIEURE', 'VITESSE DU VENT',
#  'PLUIE', 'RAINFALL', 'RAINS', 'INFO PORTE OUVERTE', 'SEASON', 'DAYTIME', 'OFFICE#']
dfcc = dfcc.drop(columns = ['CO2 AMBIANT', 'DIRECTION DU VENT', 'PLUIE', 'RAINS',
                 'INFO PORTE OUVERTE', 'SEASON'])
In [59]: y.name
Out[59]: 'INFO FENETRE OUVERTE'
```

CEA set a “class_weight” attribute to alleviate the imbalanced window states problem.

```
# log_reg = LogisticRegression(class_weight = 'balanced', random_state = 0).fit(X_train_scaled, y_train)


log_reg = LogisticRegression(class_weight = {0:1, 1:2}, random_state = 0).fit(X_train_scaled, y_train)
```

It is relevant to notice that the prediction results are more accurate with the class_weight ratio (= 2), rather than with the close-to-open ratio (> 5) calculated from the imbalanced field of data.

In order to assess the efficiency of the machine learning model, CEA calculates the following indicators:

- The real ratio of closed status over the open status compared to the predicted ratio on the same period by the calibrated model.
- The global score defined as the number of predicted status events fitting the actual ones, for the training data only, the data for testing the model and for the whole period, also called primary test period
- The f1scores that give the numbers of matches for both window open and closed status, for the training data and the data for testing the model

A logistic regression was used for this application whose coefficients are as follows:

```
LogisticRegression coeff:

Index(['T AMBIANTE', 'T. EXTERIEURE', 'VITESSE DU VENT', 'RAINFALL', 'DAYTIME', 'OFFICE#'],

    dtype='object'):

[-0.67434053  1.26866081 -0.09063199 -0.07607217  0.35091588 -0.81611395]
```

This result shows that the parameters that most influence the window-opening behaviour are, in decreasing order of importance, outdoor temperature, office category and indoor temperature, respectively with a positive and negative influence for the last two on the window opening status. It is important to note that the “office category” parameter of influence includes the occupant’s sensibility and behaviour, as well as the thermal features and orientation of the occupied office. The wind speed, the rainfalls and the time of day look less decisive factors. However, there is a bias due to the indoor temperature and the data management. The training data explored tend to force the predictive model to learn situations regardless of occupancy. The absence of occupancy information in the training dataset does not rule out situations where the indoor temperature rises due to the inability to manipulate windows in the absence of occupants for varying periods of time. This misleads machine learning.

```
ratio of closed to open - actual states:
0.6825396825396826
scores for train period :
0.7296175220660347
scores for test period :
0.7307792887029289
scores for primary test period :
0.7298498875464198
ratio of closed to open - simulated states:
0.6078431372549020
f1scores for train period %C, %O :
[0.79052805 0.61876008]
f1scores for test period %C, %O:
[0.79174674 0.61933814]
f1scores for primary test period %C, %O:
[0.7907721 0.61887544]
```

Obviously, all the attempts carried out to train the predictive model entailed to better prognosis for closing status rather than for window opening status, due to the imbalanced question that is raised.

In this case, it is noticeable that the predictive model tends to overestimate slightly the opening status. **Figure 3** presents the gap between the window-opening real status versus predicted (simulated) status. As some literature references emphasize([1]; [2]), our predictive window-opening tends to overestimate the status of opening compared to the measured reality. The over-prediction is visible in the next figures and raises the question of how to account for vacancy during the summer period.

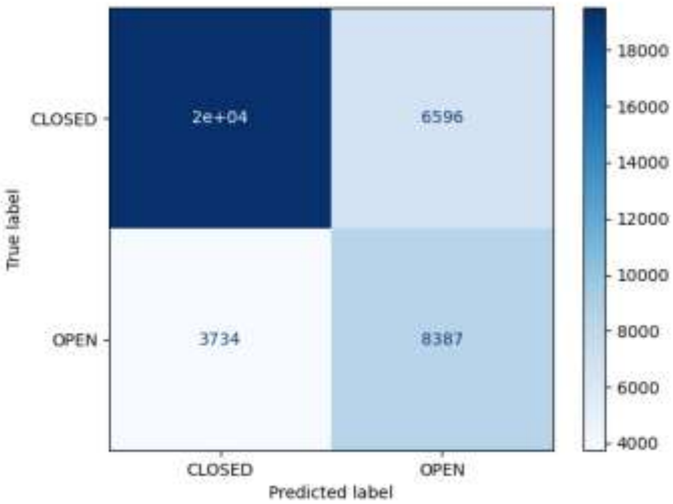


Figure 3.Confusion matrix using Logistic Regression

Figure 3 shows several discrepancies between the predicted window-opening status and the real ones.
CEA carried out different tests to train the model:

- Logistic regression
- Decision tree
- Random forest

CEA also performed several ways to set the training data and to split it, as shuffle and cross validation Kfold. The Random Forest approach for a single office '3072' and on the same season produced some fairly valuable results. By considering the traditional or activity-related vacancy periods and also by transposing the results to a macro-level granulometry to focus on opening predictions of a sufficient duration (it could be more than one hour), it seems possible to obtain a useful digital tool.

```
## TODO: SELECTION OF OFFICES TO BE INVESTIGATED AMONG '3033'(CLIMATISE), '3071'(ATRIUM), '3072', '3105'

N_office = ['3072']

rand_for = RandomForestClassifier(max_depth=4, random_state=0, class_weight={0:1, 1:2})  # 1:int(c_o_ratio)


In [64]: X.columns

Out[64]:

Index(['T AMBIANTE', 'T. EXTERIEURE', 'VITESSE DU VENT', 'RAINFALL', 'DAYTIME'],

    dtype='object')


In [66]: y.name

Out[66]: 'INFO FENETRE OUVERTE'
```

Figure 4 below shows the roles of each explanatory variable in the window opening prediction using the Random Forest approach.

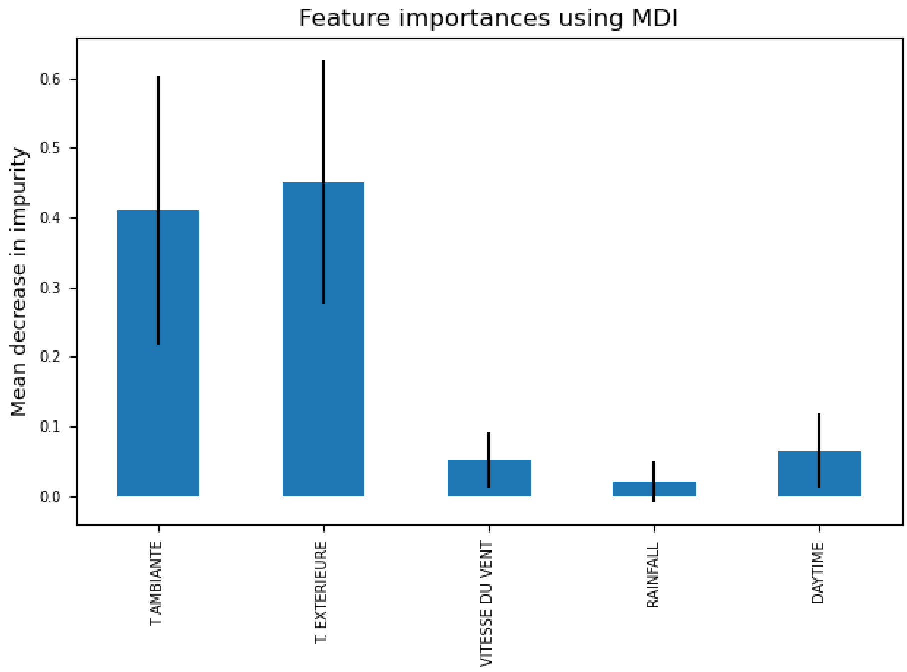


Figure 4.Feature importances using Random Forest

```
#Train accuracy : 0.803
Test accuracy : 0.813
ratio of closed to open - actual states:
0.7067448680351907
scores for train period :
0.803452332448725
scores for test period :
0.8133333333333334
scores for primary test period :
0.80542915424468
ratio of closed to open - simulated states:
0.6753246753246753
f1scores for train period %C, %O :
[0.85775128 0.6821066 ]
f1scores for test period %C, %O :
[0.8664422  0.69010417]
```

In this example, it can be noticed that the French traditional holidays at the end of May result in an absence of window openings, whereas the model, which is fairly effective even though it is not yet trained with occupancy data, predicts more manipulations. The confusion matrix (**Figure 5**) between the true values of all the recorded situations and the predicted with the Random Forest is as follows:

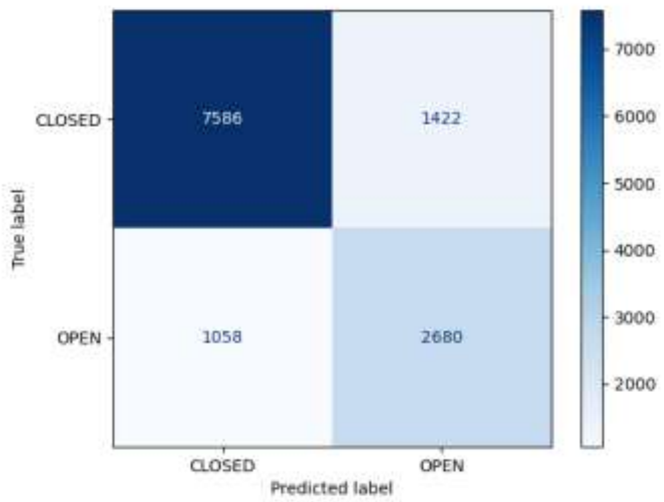


Figure 5.Confusion matrix using Random Forest

2.2.4. Next Steps

In order to improve the accuracy of the predictive window-opening model, CEA plans to work on another data set from the same existing office building. Otherwise, depending on the results to be obtained within the tool implementations at the pilot sites, CEA will endeavor to take a step forward by considering:

- The gliding outdoor temperature in order to take into account the adaptive comfort and therefore the occupant's behaviour, as an influencing dynamic parameter. This parameter will be calculated from the last few weeks and the successive average daily outdoor temperatures.
- The day of the week, the orientation of the window in each monitored office and the vacancy periods, as influencing contextual parameters.
- The use of indoor CO_2 concentration and the temperature gap between indoors and outdoors as potential influencing factors.
- Testing the Nearest Neighbours method as an alternative to Random Forest.
- Further development of the "ShuffleSplit" and "cross_val_predict" functions and also the use of "under sampling" methods to improve the fit of the predictive window-opening model
- Identification of the coefficient accounting the ventilation heat transfer in the building model.
- The generalization of the method for estimating the air change rate to each office or room under consideration.

Another opportunity is to transform the predicted opening status into flexibility potential. Considering start-up and shut-down times of the system, it could make sense to flag up the flexibility potential when long enough time intervals for a stable window state are detected. For instance, it seems reasonable to consider an opening prediction of at least 30 minutes to authorize shutdown of the ventilation system. Finally, CEA aims to calibrate a multivariate model for each office analyzed separately. Regular calibrations are also planned, at a frequency yet to be defined (possibly monthly). This work is still in progress, with the objective of establishing a distributable methodology for obtaining predictive window opening model specifically fitted to the building under consideration. CEA is now looking forward to testing and training the model with real data coming from the pilot sites. A step further would be to add another component to this digital tool, evaluating the air change rate according to the weather conditions, and wind patterns in particular. As a last step, CEA will test the coupling between the energy management optimization tool and the window-opening behaviour model.

2.3. Energy Assets Maintenance(IS2)

2.3.1. Battery cooling system monitoring (IS2-1)

The current innovative solution so-called IS2-1 is an original tool developed by the CEA through the EVELIXIA project. The IS2-1 developed by CEA aims to anticipate any failure of the battery cooling system and to schedule timely maintenance by keeping a watchful eye on the entire system, from the chiller to the emitters, including the room containing the batteries.

2.3.1.1. Objectives

The IS2-1 is designed to monitor the state-of-health of the battery cooling systems, in particular those for battery containers that are charged to support the grid with Frequency Containment Reserve (FCR) or Automatic Frequency Restoration Reserve (aFRR). These services are crucial to the stability of electrical grids and require high level of availability and reliability. More generally, it is worthwhile to maintain a watchful eye on any battery energy storage system (BESS) that provides flexibility to the buildings or systems it powers' is developing an IS that covers the entire cooling system, from the cooler to the emitters, including the ancillaries such as pumps and fans, as well as the temperature evolution monitoring of the battery room or container in its environment. Using its tool, CEA endeavors to detect deviations in the temperature of the air inside the room, gaps in the energy efficiency ratio (EER) of the chiller, and discrepancies in the energy consumption of all the equipment involved. Using this innovative IS2-1 solution should help operators and owners to schedule the maintenance operations and to anticipate critical failures.

2.3.1.2. Methodology

The IS2-1 solution relies on the following participating programs, developed in Matlab coding language (see **Figure 6**):

- An RC-type building model for simulating the thermal behaviour of the battery container or room housing the battery (see more details in section 3.5.2). It is necessary to identify the thermal characteristics of this model on real data, before using the model to predict indoor air temperature variations in the course of the numerical resolution. The calibration operation will be reiterated continuously at a frequency yet to be defined (monthly or seasonally).
- A chiller model based on standardized and proven data (from manufacturers' data sheets) and on data measurement from the field. This model constitutes the table containing the reference efficiency values for various temperatures at both sides of the cooler, evaporator and condenser.
- Another part of the code consists in keeping a close watch on the energy consumption of the various items of equipment, and on any potential deviation from expected energy flows.

The need to anticipate a maintenance operation will be triggered by one of the following indicators. Energy consumption and cooling output are used to calculate the EER of the chiller at each time step. The calculated value is compared with the EER deducted from the chiller's reference efficiency table. A difference between the calculated EER and the expected value, derived from table interpolation, signals to the operator the need to schedule a maintenance. A drop in the measured value relative to the expected effectiveness can result from various causes, such as: a lack of heat transfer fluid flow in the evaporator, a lack of refrigerant due to leakage, a fault on the compressor or on expansion valve.
The gap between the indoor air temperature calculated by the container model (RC-type) and the actual recorded temperature is likely to reveal a malfunction in the cooling chain, from the chiller outlet to the room housing the batteries and inverters. Such a deviation may be caused by a lack of heat transfer fluid, cooling transmission problems, a lack of air circulation in the container, leakage, mixing valve issues, rotative machine failures. Other indicators such as discrepancies between the actual energy consumed by the ancillary devices and the energy expected according to data sheets or power-pressure-flow curves can inform the operator of a partial or total malfunction of the rotating machines (fans and pumps).

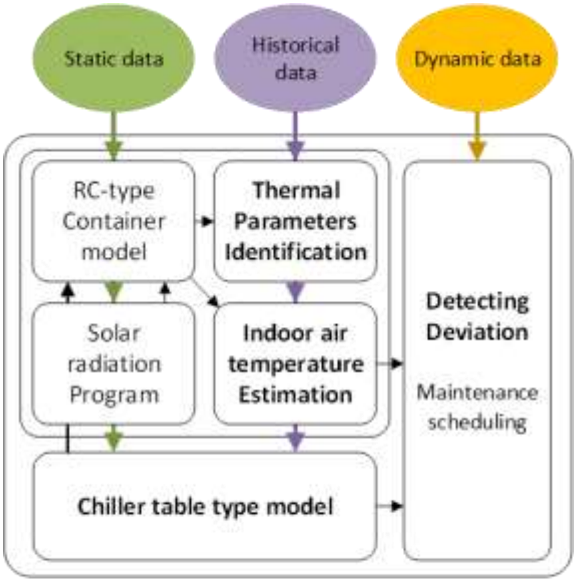


Figure 6.IS2-1 work flow

The physics or data-based models required for the IS2-1 are fed by static and historical data provided by the pilot sites partners and by the equipment manufacturers. The RC-type model for the battery container will be set up with static data and calibrated with historical data on the indoor air temperature measured on the field. See the list of data below:

- Static data related to the size, the structure and the thermal features of the 40' container available
- Outdoor air temperature
- Solar radiation received hour-per-hour by the individual surfaces of the container depending on its orientation and surroundings. The time series of solar radiation will be derived from meteorological data using our home-made MATLAB program for thermal behaviour of buildings with a simple shape like the parallelepipedic container. The weather data needed will be retrieved from the Photovoltaic (PV) plant's output or from the nearest weather station.
- Energy flow supplied by the cooling system to the container inside.
- Other internal loads due to the battery cells and inverters during charging or discharging, as well as heat gains from the transformer.
- Air temperatures inside the container are additional historical data needed to identify the parameters of the container's thermal behaviour model. Sensors must be installed in various parts of the container.

The IS2-1 chiller model also requires static and historical data to be adapted to the use cases on each pilot site interested in and to operate properly. The following list of data is taken from the French pilot site, but a few less data among the continuous data would not be prohibitive:

- Static data on the chiller is available but EER for different working conditions (evaporation and condensation temperatures) are still lacking. This information might be provided by CIAT or failing that, CEA will train a simulation model of the chiller based on historical data. This data-driven model should be a Linear Regression model.

- The historical and continuous data of the cooling system are as such: currents on each phase, apparent, active and reactive power of the chiller and of different groups of equipment (fans in particular), inlet and outlet temperatures and pressures, flow rate of the heat transfer fluid. CEA is still waiting for the conversion efficiency of inverter and of the transformer in order to estimate the energy flow transmitted inside the container or room.

The outputs of the IS2-1 will be to inform end-users and owners of any deviations between measurements, performances and consumptions based on model predictions.

2.3.1.3. Evaluation & Results

At this stage, CEA is adapting the building model to the French pilot site for the 40' long following battery container (see **Figure 7**).There is not yet concrete results to show. However, the container model, the chiller model and the program to translate the meteorological data into solar radiations inputs are ready to adaptation.

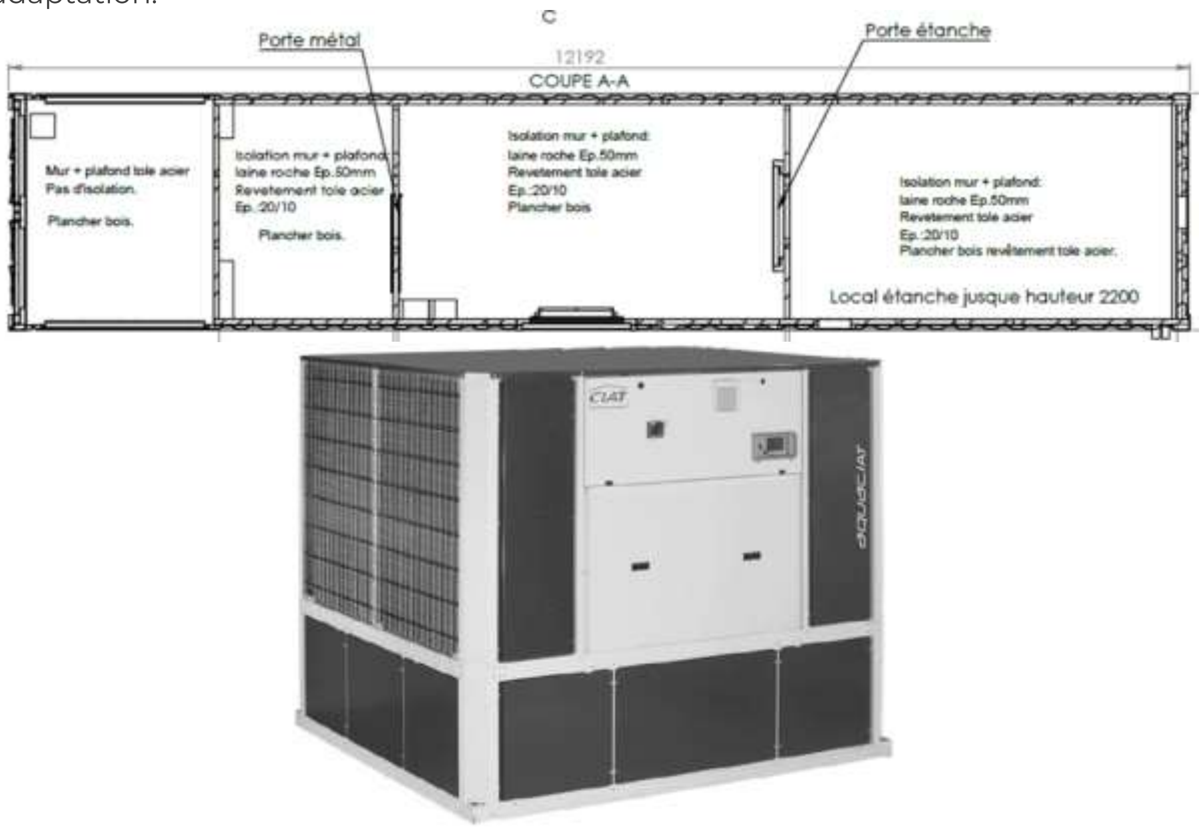


Figure 7.Section plan of the battery container (upper part) and image of the cooling system (lower part) – French pilot site

CEA has already experienced with monitoring the Coefficient Of Performance (COP) of heat pump systems for heat supply applications, in a similar way to the EER to be supervised for battery energy storage cooling systems in the EVELIXIA project **Figure 8**, resulting from the so-called "iBECOME" European project (see https://ibecome-project.eu/) shows the deprecation of the COP over the time, produced by the heat pump model trained on dummy realistic data. This model is a linear regression model based on four explanatory variables: fluid temperatures at the evaporator inlet and outlet, outdoor temperature and compressor power consumption.

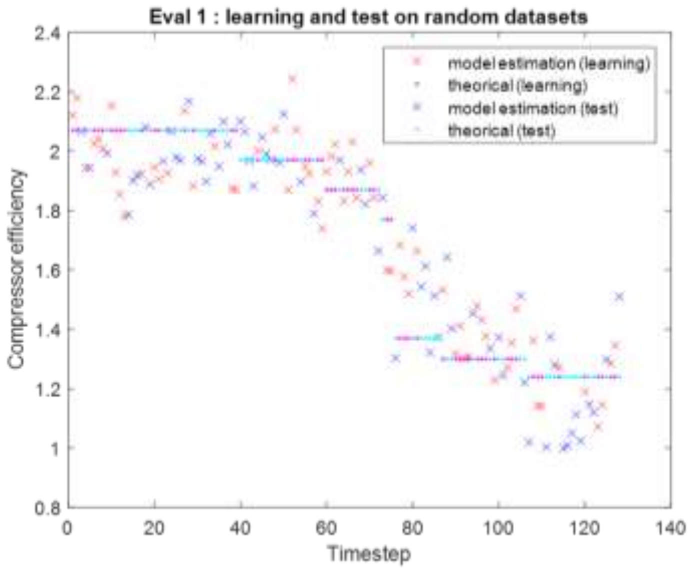


Figure 8.Drop in coefficient of performance of heat pump over time – iBECOME European project

2.3.1.4. Next Steps

CEA is currently collecting the static and historical data to fine-tune the RC model and the chiller models. The historical data and a few static data are still to be recovered from the pilot site manager or from the chiller's manufacturer, even though various types and a large amount of data already exist. CEA will set up the container model according to the assets of the French pilot site in March 2025, fine-tuning the program to build the time series of solar radiations received by the container from the meteorological data. At the same time, CEA will also create the cooling system model from the manufacturer's data sheet or from the historical data collected on the field. The first tests are expected to run in the spring 2025.Another looming task is to identify the parameters that represent the thermal characteristics of the container. This work will be carried out between March and April 2025 and will aim at monitoring the battery cooling system on the French pilot.

2.3.2. Limescale deposits detection in hot water tank (IS2-2)

The current innovative solution so-called IS2-2 is an original tool developed by CEA through the EVELIXIA project. This innovative solution is meant to detect faults caused by limescale deposits on an electrical heating resistor or on the outside surface of a heat exchanger or fouling inside a heat exchanger coil.

2.3.2.1. Objectives

The idea is to detect scale formation by monitoring the heating elements performance, rather than "seeing" the scale deposit with X-rays or such methods.
When water in the tank heats up, calcium and magnesium ions dissolved in water precipitate by reacting with dissolved acid gases such as CO_2, thus forming calcium or magnesium carbonate. The higher the temperature, the easier the scale formation [3].Scale accumulated on heat exchanger surfaces prevents heat transfers between the primary fluid and the water because it acts as an insulation, adding an extra thermal resistance. The heat exchanger efficiency is thus reduced, leading to a slower water heat up for the same heat flux coming from the primary side [4]. Likewise, fouling on the primary fluid side, i.e., inside the heat exchanger, adds a similar additional layer of insulation leading to the same decrease in efficiency. Moreover, fouling can also create pressure drops leading to a reduced flow rate on the primary side, which in turn hinders the heat transfer.
When scale forms on an electrical heater, the insulation shell that it creates induces the generated heat to diffuse more hardly to the water, increasing the peak temperature reached by the heater. This can cause the thermostat safety threshold to trip and force the heater to shut down. It also damages the heater, which contributes to reducing its lifetime. However, if the deposit is not thick enough to overheat the device, it works in normal operation and the heating power remains unchanged, since all the generated power eventually diffuses into the water [5], [4].
Within the EVELIXIA project, IS2-2 could be used to monitor the real-time performances of on-site hot water tank (HWT) and plan their upcoming maintenance. Changes of actual performance and maintenance requirements can further be transferred to other innovative solutions such as an energy management system (EMS) or IS10b that deals with the predictive control of the energy loads inside the buildings. The IS2-2 might also offer potential flexibility to IS4 or IS10.

2.3.2.2. Methodology

The hot water storage tank model is based on the TH-BCE 2012 calculation method. It represents a storage tank along its vertical axis, assuming longitudinal symmetry. It can include a heat exchanger, an electric heater, or both as heating sources, and accounts for heat losses through the tank's walls. It is made of several nodes, each of them defining a water layer. In practice, four nodes are most commonly used. **Figure 9** represents the HWT layout as it is modelled.

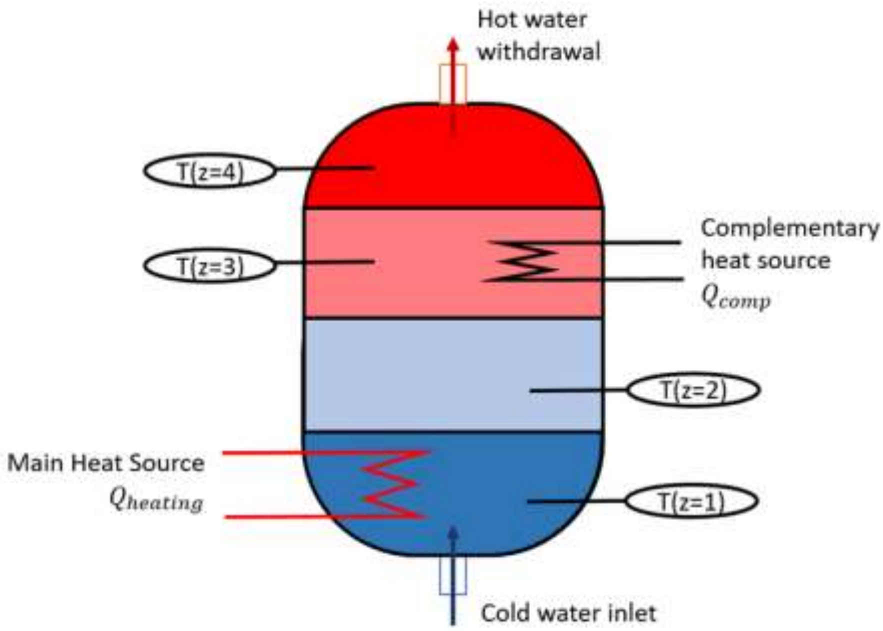


Figure 9.Sketch of the hot water storage tank as defined in the model

A simulation consists of three main actions being hot water withdrawal, cold-water heat-up and temperature mixing between layers. During a withdrawal, hot water is discharged from the top to the bottom, and cold water replaces hot water, entering from the bottom. The temperature around the heater / heat exchanger then decreases, and if it reaches a lower threshold, the heat source switches on. While the heat source is on, the water in the layer where it is located heats up as:

$$T_w(t) = \frac{Q_{heating}(t) - Q_{loss}(t)}{\rho_{water} \cdot c_{v,water} \cdot V_{hwt}} \times dt$$

Where $Q_{heating}$ is either the heater power for an electric heater or is calculated from solving the HX energy balance equation for a Heat exchanger.
At each time step, when the water in the heat source layer becomes hotter than its upper neighbor, they mix and average their temperatures, and so on for all the layers above. This means that the model assumes perfect mixing inside the tank at the end of each time step (one minute in our simulations).The data required to conduct the present method are as follows. Data must be collected all along the operation. Sensor data should be provided, as far as possible, as time series with the shortest time step between values (ideally 1 minute).
Required sensor data (provided as time series):

- HWT temperature(s) (on as many locations as possible)
- Electric heater instantaneous power
- HWT withdrawal mass/volumetric flow rate
- HX primary fluid mass flow, inlet and outlet temperatures
- Cold water temperature
- Ambient air temperature

Required static data:

- Hot water tank dimensions (at least volume and height)
- HWT temperature setpoint

- If presence of an electric heating resistor, its rated power
- Heat exchanger dimensions (at least height) and location inside the HWT
- UA_{HX}, given by the manufacturer (if possible)
- Specific heat capacity of the primary heat transfer fluid circulating in the HX

The first step of applying this method to a real HWT is to characterize it. The parameters that need to be characterized are the heat transfer coefficients. The losses coefficient, UA_{HWT},can be identified when the tank is at rest, i.e., it is not subjected to any heating nor withdrawal. During this period, the rate of the temperature drop is given by the heat losses coefficient. Sample measurements during periods when the tank is at rest followed by a linear regression (or another method such as Particle Swarm Optimization(PSO) should yield an approximation of this coefficient. The characterization can be performed regularly (weekly, or monthly to be defined yet) and the results averaged to obtain a more accurate value.

Then, the scale detection is conducted as follows. For the heat exchanger, the expected fault symptom is a reduced heat transfer between the primary fluid and the stored water leading to lower heating power exchanged. The reduced heat transfer must be determined during a heat-up phase achieved by the heat exchanger only.
There are then two cases. The first option is to monitor the following data: heat transfer fluid inlet and outlet temperatures and flow rate. Scale formation can then be detected by monitoring the HX heat transfer coefficient, UA_{HX},and comparing it to its reference value. UA_{HX} is defined in Equation (1) where $T_{tank,mean}$ is the mean temperature just above the HX, assumed homogeneous.

$$Q_{HX} = LMTD * UA_{HX} = \frac{T_{primary,in} - T_{primary,out}}{ln\left(\frac{T_{primary,in}-T_{tank,mean}}{T_{primary,out}-T_{tank,mean}}\right)} * UA_{HX} \qquad (1)$$

The primary side data give the heat flux transmitted to the stored hot water over the time steps, $Q_{HX}(t)$, according to Equation (2) , assuming the heat losses have been previously characterized. T_w represents the average temperature inside the tank.

$$Q_{HX}(t_i) = rho * c_{pf} * V * \frac{T_w(t_{i+1}) - T_w(t_{i-1})}{2 * dt} + Q_{loss}(t_i) \ \forall i \in [[2, n_t - 1]] \qquad (2)$$

Assuming $T_{tank,mean}$is approximated by the hot water temperature measurement of the probe that is the closest to the HX, the same data give the LMTD, Equation (1). With enough measurement samples, plotting Q_{HX} versus LMTD should give a scatter plot that can be approximated by a straight line with a slope equal to UA_{HX}, Equation (1). A linear regression should yield the expected value.

The second option is that no primary side measurement is available and only hot water temperature measurements exist. In this case,UA_{HX}cannot be determined. Instead, only the heat flux exchanged through the HX, Q_{HX}, can be monitored. A “day-1 measurement” of Q_{HX} versus time for a set temperature rise is determined and will be used as the reference value. $Q_{HX}$is then calculated regularly and compared to the reference. Alternatively, a trend can also be analysed. $Q_{HX} = f(t)$ is determined from Equation (2). This should ideally be repeated for several temperature rises of different values in order to have multiple samples that can be compared to future similar measurements during the scale detection phase. In either case, monitoring a possible divergence of UA_{HX} or $Q_{HX}(t, T_w)$ from their reference values should be a sign of HX degradation, and either will be used as a first fault indicator.

For an electric heater, its heat flux transferred to the water is supposed to not be influenced by scale in theory, since it only depends on the power supplied to heater that does not change. Nevertheless, as the heater's temperature increases, its electrical resistance should also increase, since resistivity depends on temperature. This should consequently lower the power consumed by the heater, since$P_{elec} = U^2/R$, where U is constant and equal to 230V. This power decrease, although possibly small, should still be detected via measurements of supplied electrical power. Since it is still uncertain whether this depends on the initial and final temperature of the heat-ups or not, heat up times will instead be monitored and associated to their corresponding initial and final heat-up temperatures in a table. The variation of $P_{elec}(T_{init}, T_{final})$ over the months will then be monitored for an electric heater, being the first indicator for an electric heater. Besides, in the early stage of scale build-up around the heat source, a visible effect should then be the appearance of a delay between the resistor start-up and the rise in water temperature. This also happens in a fault-free HWT, especially for an electric heater, since it needs to warm up itself during a transient state, but the phenomenon should be amplified due to the scale layer acting as an extra heat capacity between the heater and the water. This capacity needs to accumulate heat before transmitting it to the water during a transient phase. The transient phase duration can therefore be a second indicator, since it should increase as limescale accumulates on the heat source surface. **Figure 10** illustrates this phenomenon.

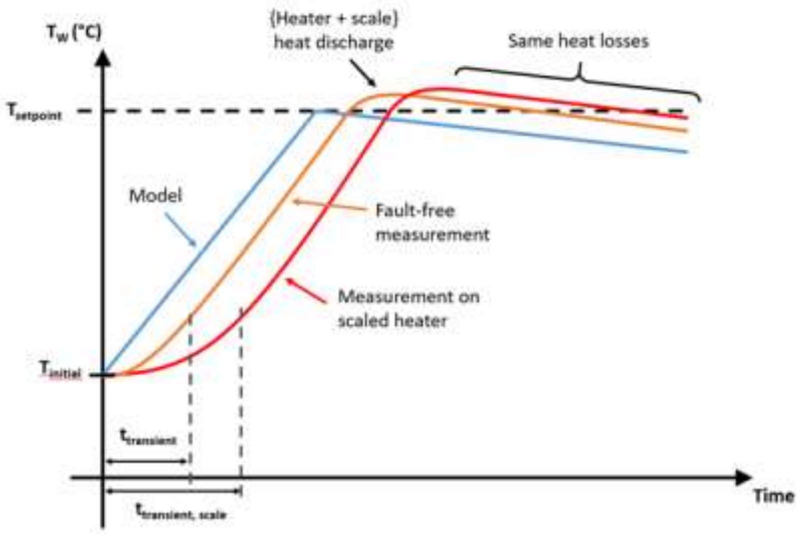


Figure 10. Expected temperature rises during the heater operation from the model (in blue), a real fault-free heater (orange) and a real scaled heater (red).

Finally, if the control thermostat is located close enough to the heat source, it might also be influenced by the scale deposits. The scale deposits could slow down the heat transfer from the heat source to the stored water, but not to the control thermostat. If so, the thermostat could prematurely shut down the heat source before the top of the tank actually attains the temperature setpoint. Once the heat has diffused into the water, the thermostat should restart the heat source until a next, possibly anticipated again, shutdown, and so on. Therefore, an excessive number of heaters starts and stops should be a third indicator of heater malfunction. This number can be compared to the model outputs that is run with the measurements of initial temperature, withdrawal profile and static data as inputs. The three above-mentioned indicators are calculated every day and compared to their reference values, which are either the model output or their values determined with historical data or during the first days of operation if no historical data are available. In practice, scale detection will be carried out thanks to a Matlab script that will compare the measured data (preferably previously converted into .csv or .txt format) with the reference values, for the above-mentioned variables. The resulting differences will be stored in a memory, and if they are greater than a set threshold several times, then an alarm will be triggered. The threshold still has to be defined.

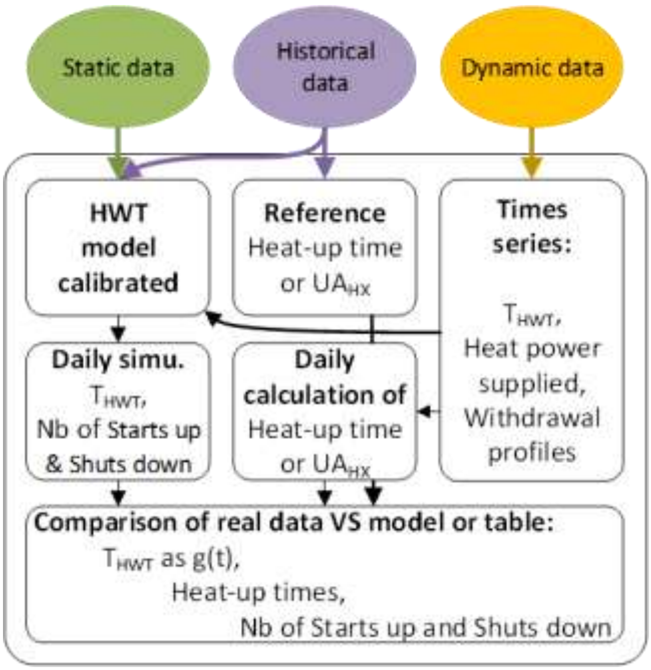


Figure 11.IS2-2 work flow

2.3.2.3. Evaluation & Results

Figure 12 presents some of the model outputs for a fault-free HWT.

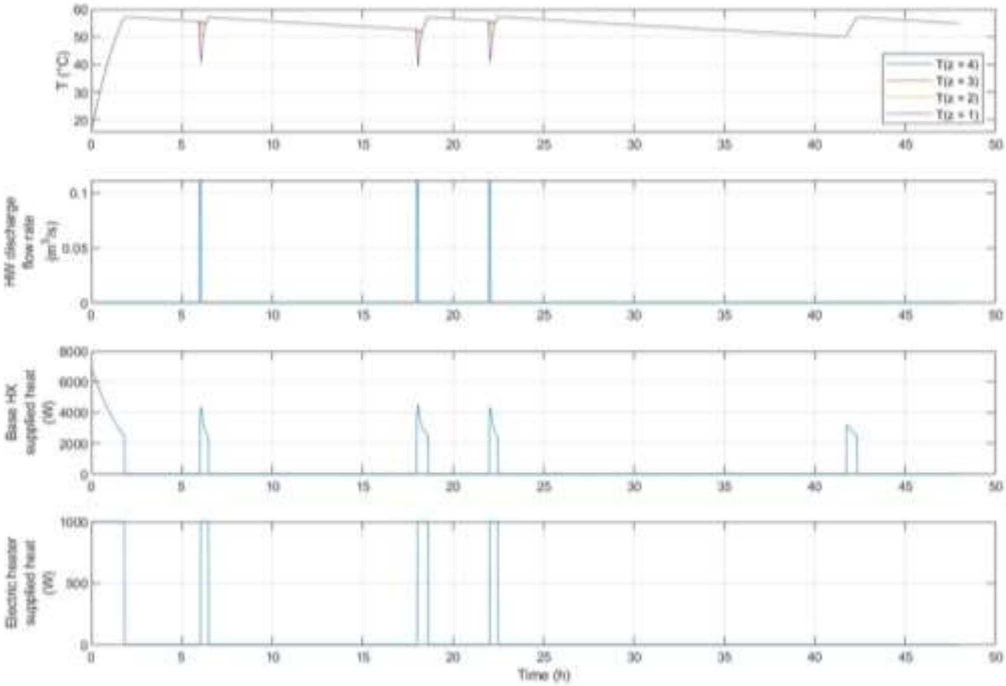


Figure 12.Model outputs for a fault-free HWT. From top to bottom, graphs show HWT temperature at four linearly spaced heights, DHW discharge, HX supplied heat and electric heater supplied heat

Artificial data were created with the model to test the fault detection script. The data consist of the HWT temperatures during heat-up phases with variable heat exchanger heat transfer coefficients (UA_{HX}). It is considered that four temperatures probes are available and linearly placed along the tank's height. They were lightly altered with random noise and some short delay in order to mimic real-life measurements. Additionally, it is considered here that primary-side data are also available, in particular a time series for the HX outlet temperature.

The data is fed to the fault detection script that performs the calculation of UA_{HX} according the steps presented in the Methods. **Figure 13** presents the resulting Q_{HX} calculated according to the first step of the Method. Blue circles represent Q_{HX} derived from the hot water temperatures only, whereas orange crosses represent Q_{HX} derived from the primary side data.

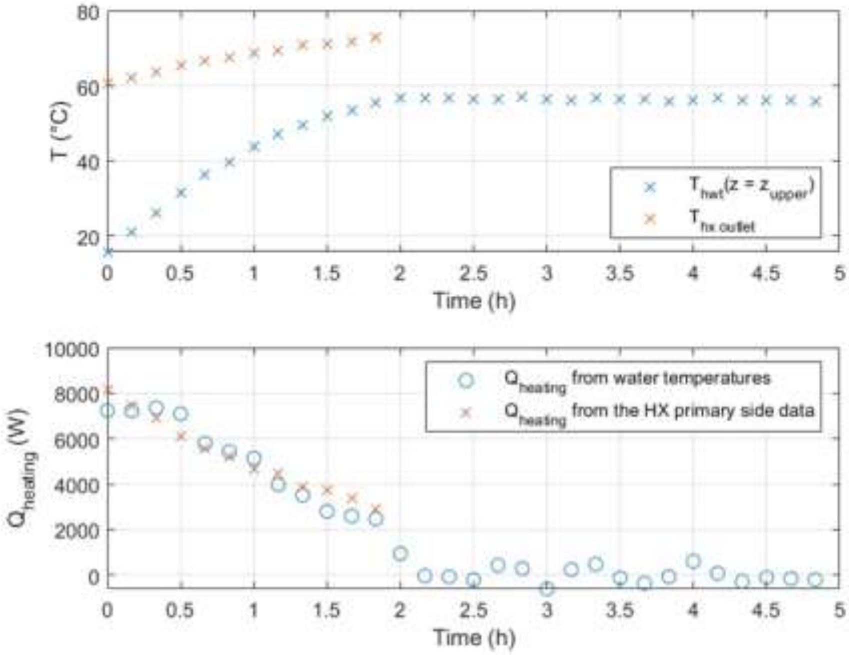


Figure 13.Measured temperatures and derived Q_{HX}

Subsequently, LMTD is calculated for each sample, according to the second step from the Methods, and a linear regression is carried out on Q_{HX} vs LMTD for both options. This finally yields UA_{HX} as the slope of the resulting line.

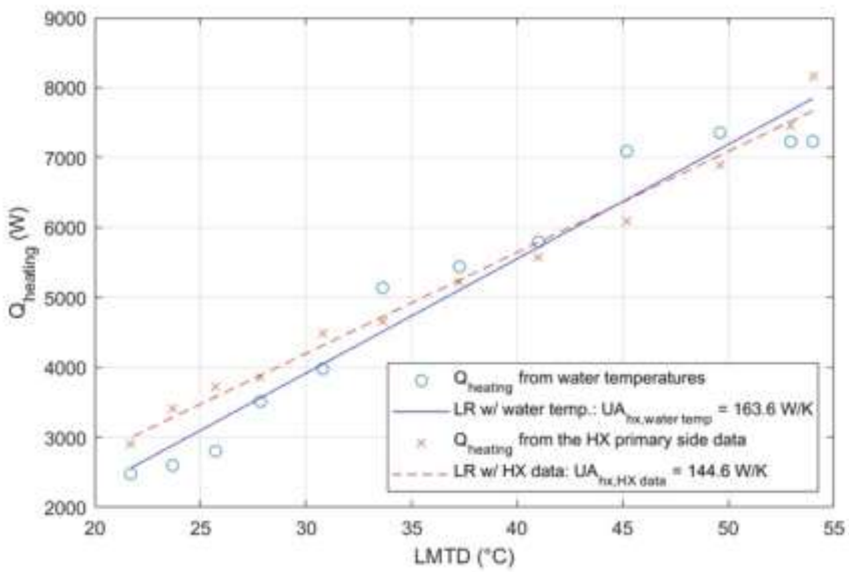


Figure 14.Heat flux from the heat exchanger vs LMTD for both methods and a linear regression made on each results to derive UA_{HX}

In this example case, measurement data were generated using UA_{HX}= 150 W/K. Despite the noise introduced, the program manages to approximate the value correctly with a 10% for the method using only hot water temperatures, and a 4% error for the method using HX data. This confirms that having HX primary data available will improve the detection accuracy. If this is not the case, only $Q_{HX}(t)$will be considered.This measurement (UA_{HX} or $Q_{HX}(t)$) will be stored in memory for future comparison. Assuming that the initial measurements, on day one, gave a value of 200 W/K, and that the threshold was defined as a loss of 20% of original efficiency (or a loss of 40 W/K), this threshold will be triggered for the present measurement. If this value is found again during new detection phases (in the following days), for a certain number of times in a row, an alert will be sent to the user.

Artificial data were also generated to simulate a faulty hot water tank equipped with an electric heater. To do so, the heater is forced to shut off after a certain time of operation, in some cases a shorter time than required to reach the temperature set point. Then, after some more time, the heater starts again, simulating a cool down in the zone where the control thermostat is located, due to the heat diffusing slowly into the tank. This results in an intermittent heater operation as it can be seen in **Figure 15**. The temperature consequently increases in a staircase shape, although the actually sensor measurements should show a smoother curve. The detection can be carried out on these curves by counting the number of starts and stops and comparing it to that of the fault-free model. Then, the average slope of each temperature rise can also be calculated and compared to the expected heater rated power, or the power measured during the implementation of IS2-2. Finally, transient state delay should be observable and measurable on the temperatures rises curves.

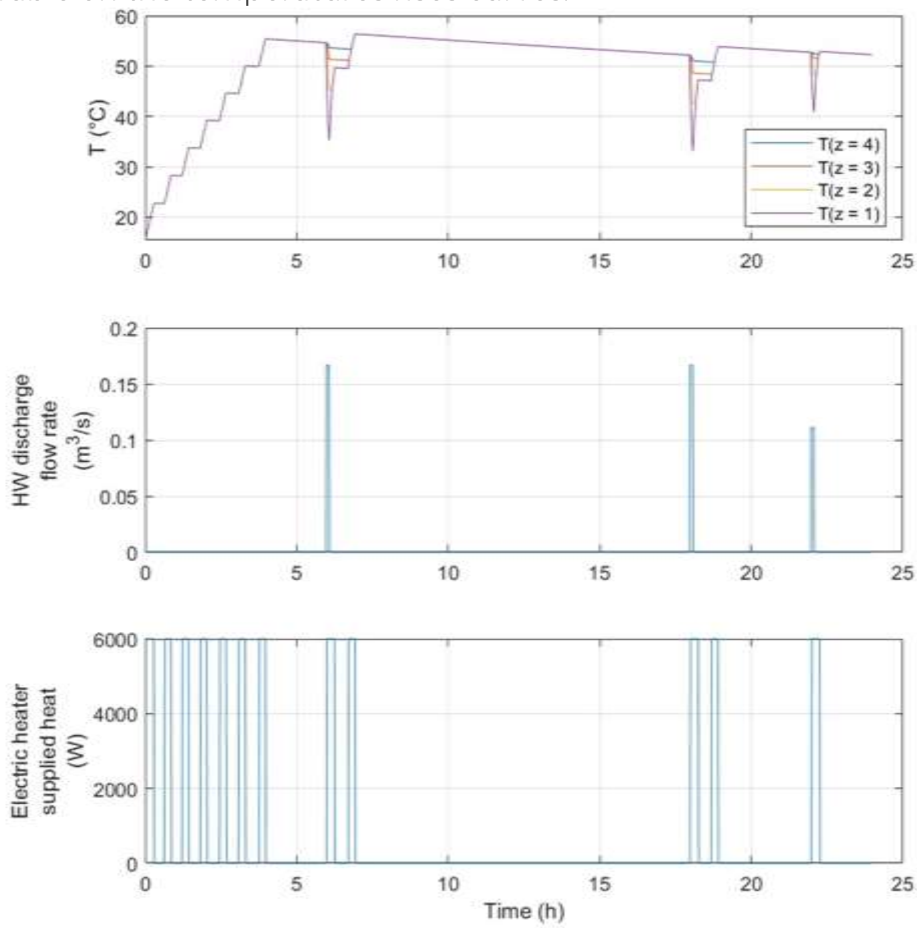


Figure 15.Simulation of scale. From top to bottom, graphs show the water temperatures at four heights, DHW withdrawal, power delivered over time

2.3.2.4. Next Steps

The IS needs to be tested on real-life data. UA_{HX} identification can easily be performed on HWT tank data during a heat-up phase. CEA has some sort of such data. Some online data are also available since extensive research has been carried out on different aspects of water heating systems [6].The issue comes up regarding faulty (affected by a lot of scale) hot water tanks since available real-life fault-related data is scarce. Datasets of both fault-free and faulty HVAC systems exist, but they mainly include gas boilers [7], [8] which is not exactly what we are considering in the present analysis. Therefore, we hope to find experimental data of scaled or fouled HWT in the upcoming weeks or months in order to test our solutions. Perhaps the pilot sites will provide us with such data. Another aspect worth considering is the temperature stratification in hot water storage tanks. In fact, the present HWT model considers perfect heat mixture between each layer of the tank during the heat-up phase (if a lower layer is hotter than its upper neighbor is, they mix and average their temperatures). In practice, in some cases, hot water heated up by the heating element tends to rise and accumulate at the top of the tank, due to its lower density and this with little mixture. Layers appear where the hot water is concentrated in the upper layers, and the cold water remains at the bottom. This is clearly showcased by [6] who highlight in their experimental testbed a high degree of stratification in the tank and that tends to persist over time, both during the heat up and the cool down phases. However, other studies show rather the opposite phenomenon, as showcased in, e.g., [9], in cases B, C and particularly case A, in which no stratifier is used. The question remains on whether stratification will occur in the pilot sites tanks. If so, and if few temperature sensors are available, these few sensors might give a mistaken idea of the temperature field inside the tank, especially in the case where only one temperature sensor is available. Finally, CEA is also considering testing a home-made model allowing to evaluate the withdrawn volume through the hot water tank, only using the following information: temperatures metered inside the tank and the energy consumed by the heater or the heat exchanger.

2.3.3. Battery ageing prognosis (IS2-3)

The current innovative solution so-called IS2-3 is an original tool developed by the CEA through the EVELIXIA project. The IS2-3 developed by CEA provides in real time the state-of-health and remaining life of the battery under surveillance.

2.3.3.1. Objectives

The Energy Assets Maintenance – Battery ageing prognosis (IS2-3) aims to calculate the battery state of health (SOH) and remaining useful life (RUL) in order to help the planning of battery maintenance.

2.3.3.2. Methodology

The IS2-3 uses battery operation data. Data processing is a key step in the development of advanced approaches for systems analysis. In a first step, an acquisition of the monitoring data shall be performed automatically. Then, a data processing structures the raw data and extracts the key indicators using statistical techniques and data-driven algorithms. Six families of indicators can be proposed as indicated in **Figure 16**. Within the EVELIXIA project, CEA is focusing on health indicators: diagnosis of the current SOH of the BESS and prognosis of its future SOH and RUL.

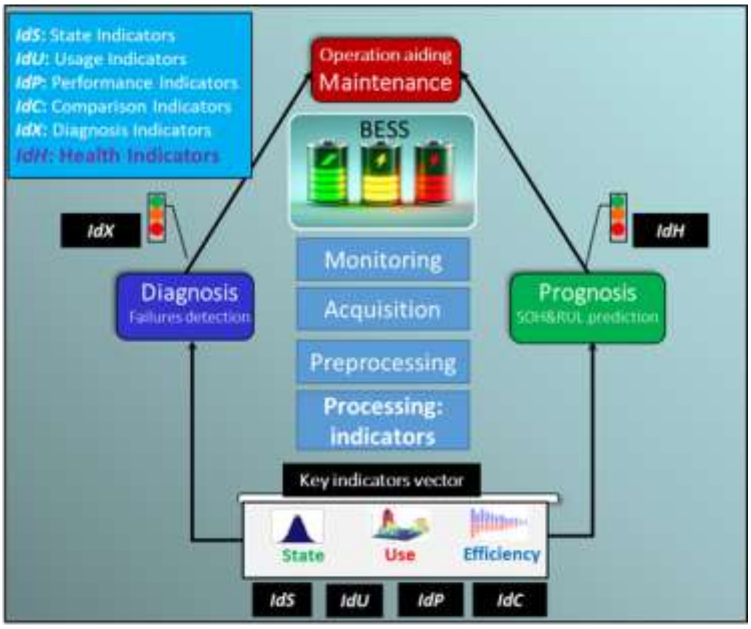


Figure 16.Architecture for BESS diagnosis / prognosis

The SOH and RUL can be calculated using Calendar and Cycling degradations. SOH degradation can be dissociated by cycling and calendar contribution (respectively SOHcycandSOHcal). With simplified cumulative linear approach and considering similar past/future use, this repartition can be expressedas:

$$SOH_{EOL} = SOH_{BoL} - \widetilde{\boldsymbol{\theta}_{cal}}.RUL - \widetilde{\boldsymbol{\theta}_{cyc}}.FEC$$

with$\widetilde{\boldsymbol{\theta}_{cal}}$ the average calendar degradation rate expressed as ΔSOH_{cal}per year, $\widetilde{\boldsymbol{\theta}_{cyc}}$the average cycling degradation rate expressed as ΔSOH_{cyc} per FEC, FEC the Full Equivalent Cycles, BoL is Beginning of Life, EoL is End of Life. **Figure 17** shows the cumulative degradations inducing battery SOH decrease.

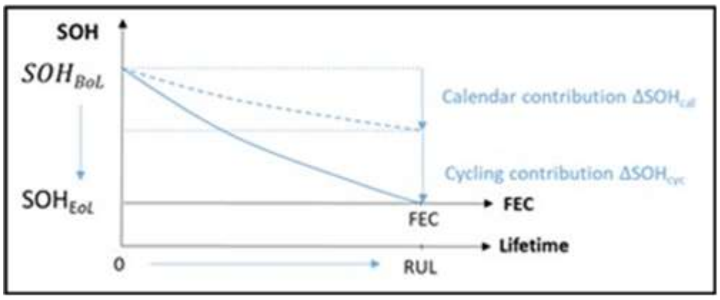


Figure 17.SOH and RUL calculation vs Calendar and Cycling degradations

CEA has developed two approaches for the prognosis of battery aging. The first one relies only on operation data and does not need a pre-calibrated battery aging model. This approach is shown in **Figure 18**. The second approach needs a pre-calibrated battery aging model and is shown in **Figure 19**.

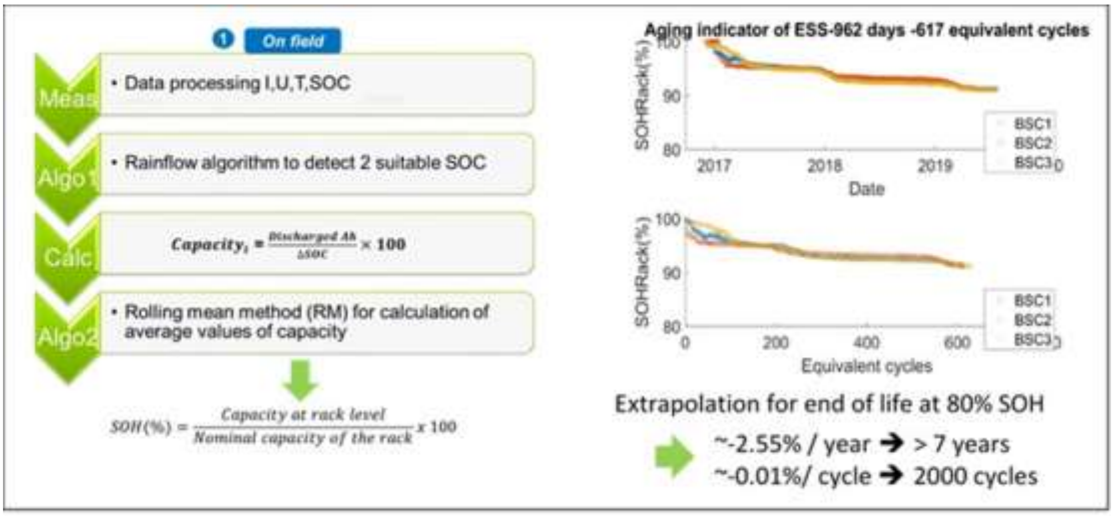


Figure 18.Diagram and example for approach 1: Battery SOH prediction without pre-calibrated model

The Inputs for the first approach are Battery nominal Energy (Wh)/capacity (Ah) from battery supplier. Current (I), voltage (U), temperature (T), state of charge (SOC) given by the BMS and if possible, SOH given by the BMS from data acquisition on the BESS.

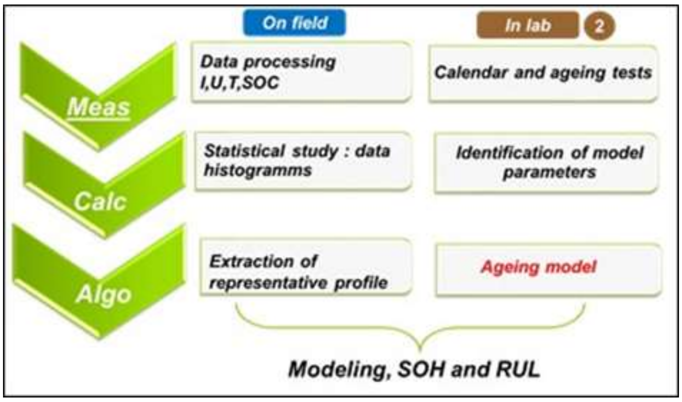


Figure 19. Diagram of 2nd Approach: Battery SOH prediction using pre-calibrated aging model

The second approach can be applied for EVELIXIA only if we have complete datasheet allowing to pre-calibrate an aging model or if model on similar technology would be available. In addition to the operation data, detailed information about the battery system: cell supplier, cell datasheet and BESS architecture (parallel and series) are needed.

2.3.3.3. Evaluation & Results

CEA conducted meetings with two pilot sites (PS6: Spanish and PS7: Finnish) in order to work on the useful data from the BESS. The datasheet given by PS6 indicates that the batteries are either VRLA (Valve Regulated Lead Acid Battery) or NiCd (Nickel Cadmium battery). The use of IS2-3 on these battery chemistries needs a lot of new development that cannot be done during EVELIXIA Project.

VRLA and NiCd need for example overcharge and have secondary reactions and their aging is very different from Li-ion batteries. IS2-3 is calibrated on Lithium-Ion batteries. Thus, finally IS2-3 tool will be used only on PS7, which has Lithium-Ion batteries. IS2-3 development task in EVELIXIA project allows continuing the development of CEA battery diagnosis and prognosis tools. For example, the calculation of full equivalent cycles using operation data have been improved recently. The CEA has not yet data from pilot sites to give results on these BESS.

Figure 20 below shows results on three BESS in a power plant from which the CEA got data for 7 years during a previous project (in the context of a call from the French Commission for Energy Regulation). This figure shows that the SOH given by the BMS is higher than the one given by the A4 - RM algorithm, which is higher that the SOH given by the aging model. The BMS does not detect that the battery capacity is lower at the beginning of the operation due to calendar aging. The difference between the A4-RM algorithm and the aging model results is less than 3 % for BESS1 and BESS3 and about 4 % for BESS2.

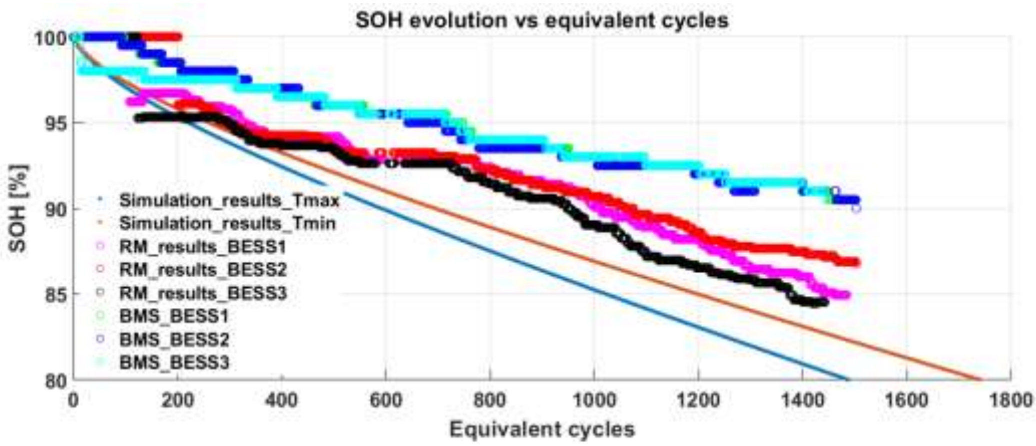


Figure 20.SOH evolution versus the number of equivalent cycles using A4 RM algorithm, an empiric ageing model and SOH from the BMS

2.3.3.4. Next Steps

Regarding IS2-3, CEA will work on the integration of one or two BESS in the tool presented in **Figure 16**. CEA will pre-calibrate aging model if the available data allows this. Thus, CEA will simulate the SOH and RUL using both approaches described in **Figure 18** and **Figure 19**. Detailed results will be given later when CEAreceives enough data from pilot sites.

2.4. Demand Forecasting (IS3)

EVELIXIA's Innovative Solution 3 (IS3) "Demand Forecasting" developed by CERTH/CPERI, is a critical component of the "Building Awareness and Forecasting Toolbox". IS3 supports evaluating different control scenarios (e.g., efficient resource planning, load balancing, energy trading) by utilizing predictive algorithms for local energy production and consumption across various vectors (electricity, heating, gas) and scales (building, district) through Machine Learning (ML) and Deep Learning (DL) techniques. During EVELIXIA, IS3 contributes to the development of a multi-dimensional toolbox with modelling functionalities that support B2G services. To achieve this, CERTH/CPERI advances the tool's capabilities to a) autonomously determine the most promising algorithm for several network types (ANN, SVR, LSTM, GBT, ARIMA) and topologies (two-stage, ensembled, hybrid) based on a set of attributes and metrics to ensure optimal forecasting accuracy under varying conditions (see Section 2.4.2.4), and b) integrate a clustering component based on generic-purpose clustering algorithms, such as K-means and the Density-based clustering of applications with noise (DBSCAN). In support of a broad range of interested stakeholders (i.e., building managers, energy planners, consultants, aggregators, grid operators), IS3 offers a refined understanding of energy consumption and production patterns and complements the data-driven forecasting capacity of a) the Building Energy Modelling and Simulation (IS5), and b) the Multi-Vector Grids Energy Modelling and Simulation (IS15) by enabling multi-dimensional forecasting.

2.4.1. Objectives

IS3 - Technical Objective "TRL5 to TRL7": Originally validated in the relevant environment of several past EU-funded projects (e.g. SMILE GA No. 731249, RENAISSANCE GA No. 824342) Demand Forecasting is introduced to EVELIXIA at Technology Readiness Level (TRL) 5. Advancing towards TRL6, a working version of IS3 is tested in the controlled, operational environment of the Greek Pilot Site (GR-PS). Testing is conducted using simulation data generated by IS5 - "Building Energy Modelling and Simulation" (see Section 2.6) for the CPERI office building (see Section 2.4.3). Upon integration of the EVELIXIA platform within GR-PS and establishment of its API connection with IS3, hour-ahead forecasting using sensor data sourced from the platform will be performed to complete testing. Progressing towards TRL 7 until the end of the project, future efforts and refinements of the tool target demonstration of the technology across all EVELIXIA pilot sites and end-user validation to expand its real-world applicability.

IS3 - Scientific Objective "Energy consumption and generation forecasting":
Develop and implement advanced, accurate, data-driven energy demand and local production forecasting services across EVELIXIA's Pilot Sites (PS) through the autonomous selection of suitable algorithms and the integration of clustering techniques. These services assist facility managers and aggregators of large building portfolios in energy management, with accurate forecasting and B2G service delivery (e.g. demand shifting and voltage regulation).

2.4.2. Methodology

2.4.2.1. Data extraction

To source the required input data, IS3 connects through the respective APIs of the energy modeling tools for building- and grid-level analysis developed by IES, namely:

- IS15-intelligent Virtual Network (iVN), a high-level district modelling tool for performing simulations of city or community-level commodity distribution networks
- IS5-iSCAN, a powerful data acquisition and monitoring system designed to streamline energy management processes, facilitating real-time data extraction, storage, and analysis

The automation exchange involves configuring in-house Python-based scripts, providing access to historical and real-time energy consumption values, and efficient data collection and transformation. The integration significantly enhances forecasting efficiency, as it eliminates errors, and the manual effort required for data handling and collection and ensures that models are trained and tested on the most relevant, up-to-date energy consumption data. This streamlined process establishes a continuous pipeline of forecasting updates, facilitating real-time adaptations of predictions.

2.4.2.2. Dataset

To perform hour-ahead forecasting based on a given dataset, a new column ("Next Hour") is created by shifting the energy consumption values forward by one time step. This column serves as the target variable that the forecasting models aim to predict. Several pre-processing steps are then applied to the initial dataset to ensure data quality and enhance model performance.

- A normalization occurs to the time series to scale the data between 0 and 1, preventing bias toward larger numerical values.
- To capture temporal dependencies, lag features incorporate past energy values, along with a rolling mean feature to smooth short-term fluctuations.
- Missing values resulting from these transformations are dropped to maintain consistency.
- The dataset is divided into training (90%) and testing (10%) sets, ensuring the models are trained on historical data while being evaluated on unseen future values.
-

These preprocessing steps formulate the Baseline Model and enhance the predictive power of the models by incorporating historical trends and reducing noise in the dataset.

2.4.2.3. Models Benchmarked

A set of predictive models are integrated into the analytical framework of IS3 to ensure precise forecasting. All selected models are executed as part of the analysis, ensuring a robust and concurrent evaluation of building energy dynamics. This approach is essential for capturing the heterogeneous nature of building energy data, optimizing computational efficiency, and tailoring the framework to the specific requirements of the EVELIXIA project, particularly regarding non-dispatchable plants. The rationale for employing such a diverse set of models for EVELIXIA is twofold. Firstly, it provides a comprehensive benchmark of predictive performance across different algorithmic paradigms, thereby ensuring reliability in forecasting outcomes Secondly, it brings adaptability and versatility when accommodating to various operational scenarios and data characteristics encountered in diverse real-world applications. This strategy is integral to achieving the EVELIXIA goal of enhancing building awareness and supporting advanced grid services across PSs. The selected predictive models are:

- Baseline (Persistence) Model: Assumes the current hour's value is the same as the next day's value.
- LSTM (Long Short-Term Memory): A Recurrent Neural Network (RNN) designed to handle sequential data and long-term dependencies, capable of capturing complex temporal patterns.
- Gradient Boosting (GBM): An ensemble technique that builds models sequentially, optimizing errors at each step. Highly flexible, it delivers strong predictive performance but can be prone to overfitting if not properly tuned.
- Random Forest: An ensemble method that combines multiple decision trees to improve accuracy and reduce overfitting. It is robust to noise and works well for both classification and regression tasks.
- XGBoost (Extreme Gradient Boosting): An ensemble learning method based on gradient boosting, designed for speed and performance. It is widely used for structured data problems and excels in handling missing values and complex patterns.
- LightGBM (Light Gradient Boosting Machine): A gradient boosting framework optimized for efficiency and scalability. It uses a leaf-wise tree growth strategy, making it faster and more memory-efficient than traditional boosting models.
- CatBoost (Categorical Boosting): A gradient boosting algorithm that is highly optimized for categorical data. It automatically handles categorical variables without extensive preprocessing, reducing the risk of overfitting.

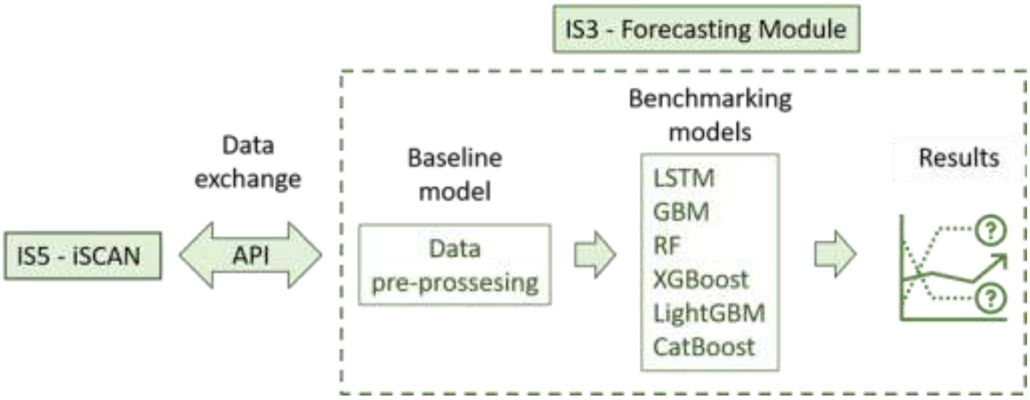


Figure 21. Synopsis of the IS3 workflow

2.4.2.4. Evaluation Metrics

To assess the predictive performance of the selected models within the IS3 framework for EVELIXIA, widely used evaluation metrics that capture different aspects of forecasting accuracy and reliability are employed. These metrics quantify errors in both absolute and relative terms, highlight the significance of large deviations, facilitate standardized comparisons across varying forecasting tasks, and validate reliable and efficient delivery of B2G services. Model evaluation is based on the following performance metrics:

Mean Absolute Error (MAE): Measures average absolute error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Root Mean Squared Error (RMSE): Penalizes large errors.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Mean Absolute Percentage Error (MAPE): Provides a relative error percentage.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100$$

2.4.3. Evaluation & Results

For the purposes of this initial test run, the evaluation regards evaluation algorithm selection for forecasting methods at the building level following a manual approach and allowing for the incorporation of domain expertise and specific performance criteria. Future work will focus on developing the planned automated selection mechanisms to dynamically optimize model choices based on evolving data characteristics and operational needs. The retrieved dataset comprises of hourly values of the energy consumption profile generated by IS5-iSCAN (**Figure 22**) for the CERTH office building of the GR-PS labeled as "Total system energy."

The resulting key performance metrics for each model are summarized in **Table1**. Random Forest and Gradient Boosting demonstrate the highest predictive accuracy, achieving the exceptionally low MAPE values of 0.03% and 0.05%, respectively. These results underscore that tree-based ensemble methods are highly effective for short-term energy forecasting, as they adeptly capture complex interactions among lagged energy consumption values without the need for extensive data preprocessing. Such precision is critical for EVELIXIA's aim of supporting demand shifting and voltage regulation. Conversely, LSTM, despite its robust capability to model sequential dependencies, exhibits a high error rate (MAPE = 0.90%). This disparity is mainly attributed to the limited size of the dataset, suboptimal hyperparameter tuning, or insufficient training iterations. Another key observation is that LightGBM and CatBoostperform well overall with MAPE values of 0.14% and 0.34%, respectively. However, these models exhibit some smoothing effects, a characteristic that indicates lower responsiveness to abrupt fluctuations in energy demand, in consistency with gradient boosting algorithms that prioritize overall prediction accuracy.

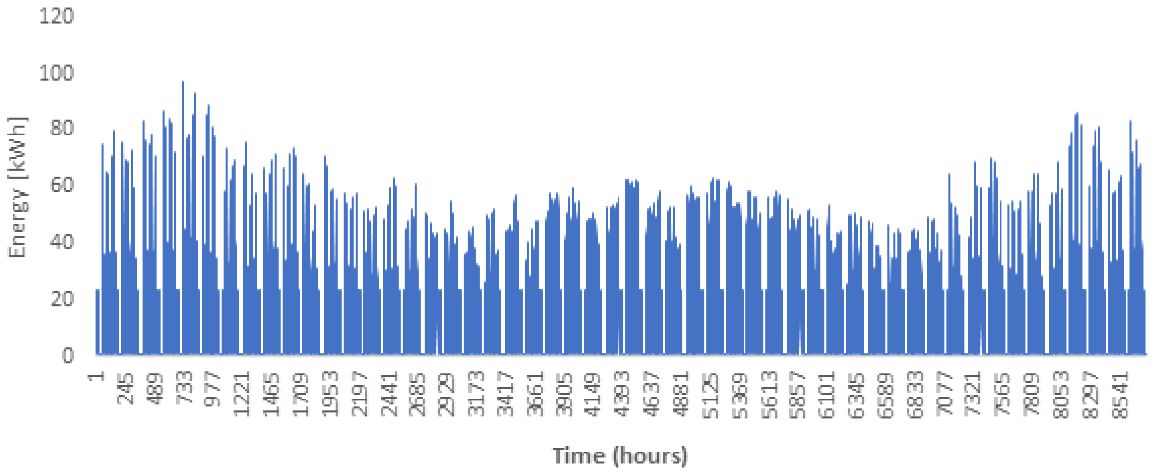


Figure 22. Total system energy examined dataset

Table 1. Resulting performance metrics

Model	MAE	RMSE	MAPE (%)
Baseline	0.0692	0.1406	30.5
LSTM	0.00197	0.00315	0.90
XGBoost	0.00035	0.00086	0.12
LightGBM	0.00046	0.00222	0.14
CatBoost	0.00082	0.00138	0.34
Random Forest	0.00008	0.00048	0.03
Gradient Boosting	0.00019	0.00053	0.05

Figure 23 presents the resulting MAE for all models. While the Random Forest model outperforms the others, it is important to point out that all models produced forecasts with acceptable accuracy (MAPE < 1.0%) in the context of energy management. These forecasts can facilitate other services, such as demand response optimization, voltage regulation, and predictive maintenance. By ensuring reliable short-term predictions, the models contribute to the efficient operation of distributed energy resources (DERs) and enhance the overall stability of the power system.

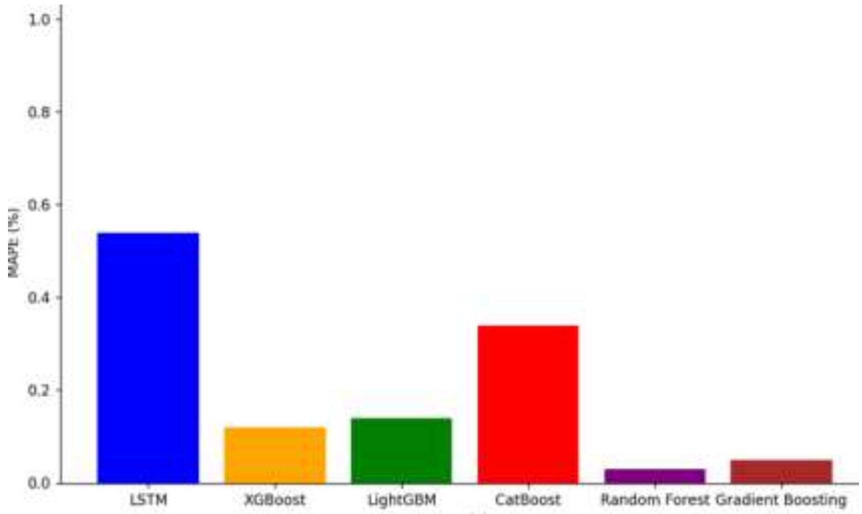


Figure 23. The Mean Absolute Percentage Error across models.

The evaluation of the predictive models highlights key differences in their forecasting performance, capturing trade-offs between accuracy, computational efficiency, and adaptability to different patterns in the data. Key observations across the predictive models reveal distinct strengths and limitations.

The **Baseline Model**(see2.4.2.2) serves as a simplistic benchmark, but performs poorly, exhibiting the highest RMSE.

LSTM effectively captures long-term dependencies but shows slight fluctuations due to sensitivity to noise. Occasionally lagging behind actual values, it is likely hindered due to training data limitations or suboptimal hyperparameter tuning.

XGBoost provides stable and precise predictions with minimal deviations but struggles with sudden trend shifts, a common limitation of tree-based models in sequential forecasting.

LightGBM delivers competitive accuracy with fast computation, adept at capturing short-term variations, but occasionally smoothing out rapid fluctuations due to its leaf-wise growth approach.

CatBoost performs well on structured data, balancing accuracy and efficiency, though it sometimes struggled to adapt to sharp peaks and troughs, likely due to its reliance on categorical transformations. **Random Forest** produces stable but overly smooth predictions, missing finer details due to the averaging effect of multiple decision trees, which reduces variance at the cost of responsiveness to abrupt changes.

Gradient Boosting effectively captures the overall trends but shows slight overfitting in some cases, making it less adaptable to dynamic shifts in the data.

Overall, the analysis underscores that no single model is universally superior; instead, the choice of model depends on the specific forecasting requirements, such as sensitivity to sudden changes, long-term trend detection, or computational constraints. By leveraging the strengths of each approach, energy management strategies can be optimized for improved forecasting accuracy and grid service efficiency.

Figure 24 resents the resulting forecasts of each model for an indicative day.

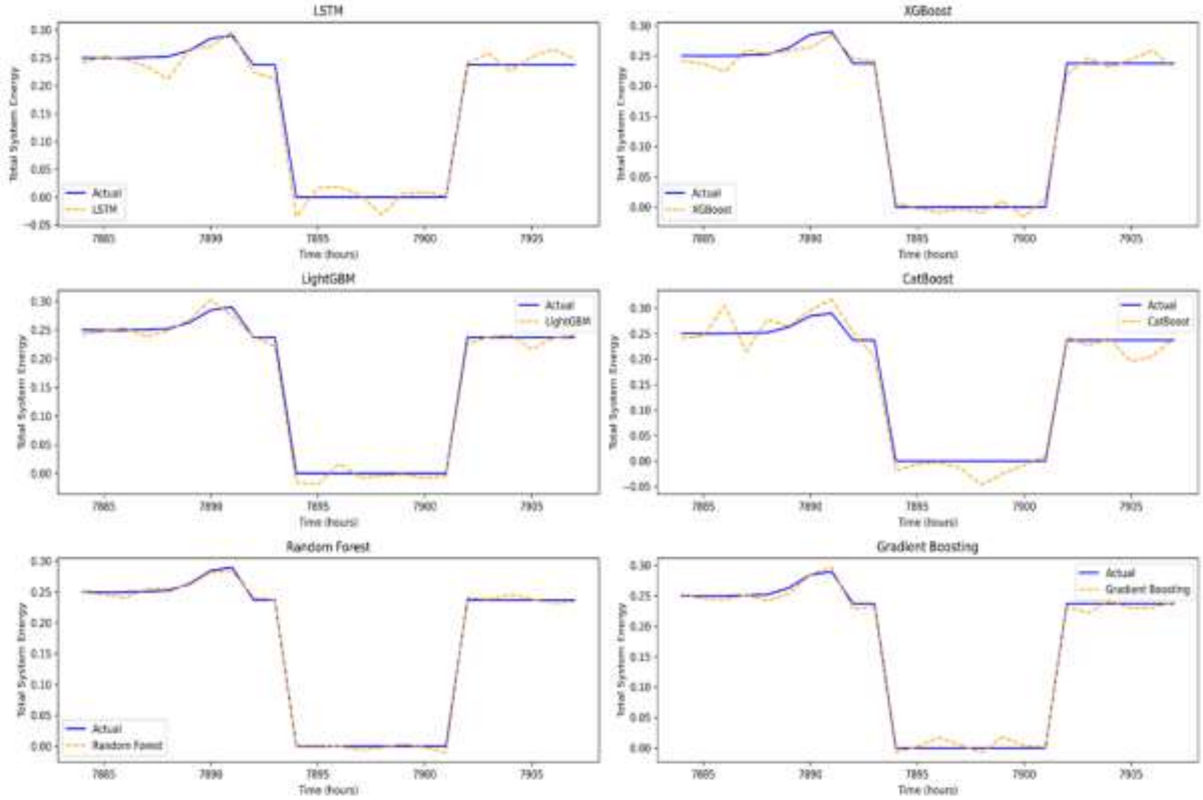


Figure 24. Resulting forecasts of each model compared to the actual time series for one day.

The resulting metrics indicate that a) ensemble-based tree models outperform traditional statistical approaches while requiring less computational cost compared to deep learning models like LSTM, and b) ML & DL models generally outperform classical statistical methods for day-ahead energy forecasting. Among the tested models in this initial test-run:

Random Forest and Gradient Boosting emerges as the best-performing models, achieving the lowest performance metrics.

The Tree-based models (i.e., XGBoost, LightGBM, CatBoost, and Random Forest) achieve significant accuracy, demonstrating strong predictive power and stability.

Random Forest exhibits the lowest performance metrics due to its ability to reduce overfitting through ensemble learning for the given dataset.

LSTM performs reasonably well, but had a slightly higher error rate, indicating that deep learning models require fine-tuning and a larger dataset to fully capture complex temporal dependencies.

Gradient Boosting and CatBoost return promising and competitive results, but they struggle with sudden changes in energy demand, highlighting the limitations of boosting models in highly volatile time series.

The results highlight the effectiveness of ML and DL models for short-term energy forecasting, demonstrating a significant advantage over traditional statistical methods. Among the evaluated models, a) Random Forest and Gradient Boosting exhibit the highest performance, achieving optimal accuracy with minimal error rates for the given dataset, and b) LSTM model shows potential in capturing sequential dependencies despite its limited performance, likely due to dataset size and training constraints. However, since model performance is inherently dependent on the characteristics of the dataset (such as feature distributions, sample size, and data quality), results may vary with changes in the dataset, potentially affecting predictive accuracy and generalizability as IS3 benchmark models take into account these particularities across scenarios.

2.4.4. Next Steps

In the forthcoming phase of the EVELIXIA project until M24, the main advancements and activities related to IS3 that are underway, pertain to:

- further streamlining data acquisition and preprocessing through IS5-iSCAN and IS15-iVN in parallel with the modelling progress, ensuring a robust and automated forecasting pipeline across EVELIXIA's PSs.
- exploring hybrid models that combine the sequential learning capabilities of LSTM with the structured feature selection strengths of tree-based models to develop an automatic model selection process that identify well-performing models based on the specific forecasting task and data availability, providing insights on accurate and reliable forecasting services
- employing hyperparameter optimization and feature selection techniques to further enhance predictive accuracy and adaptability across different energy system scenarios.

2.5. Flex Forecasting (IS4)

The Flex Forecasting (IS4) service focuses on proactively assessing and forecasting the levels of demand-side flexibility that could potentially be provided by distributed loads in buildings. In this way, IS4 will contribute to optimizing energy consumption and grid stability in buildings, particularly with the increasing integration of Renewable Energy Sources (RES). This can be achieved through the management of individual building systems (such as white goods, HVAC systems, etc.).By accurately predicting the availability and magnitude of this demand-side flexibility, building and grid managers can make informed decisions on energy allocation and load balancing, thus reducing energy cost and grid congestion and participating in Demand Response (DR) programs. This proactive approach allows for a more efficient and flexible energy system in buildings, maximizing the use of Renewable Energy Sources (RES) and minimizing dependence on peak generation resources. The foundation of the tool is in advanced algorithms and models considering historical building energy patterns, various factors that influence building energy consumption, including weather forecasts, occupancy patterns, building thermal characteristics and appliance operation.

2.5.1. Objectives

The primary objective of IS4 is to evaluate and forecast the demand-side flexibility limits at the building level, focusing on both thermal and electrical demand. This involves the development of advanced Machine Learning algorithms and models capable of quantifying the demand flexibility potential arising from the various building systems (HVAC systems, lighting, etc.). More specifically, IS4 predicts the amount of flexibility that a building has to either increase its energy consumption during periods of surplus energy production (up-flexibility bound) or reduce its energy consumption during time periods of energy production shortage or high demand (down-flexibility bound). By providing accurate predictions of building energy consumption patterns and demand-side flexibility limits, IS4 will contribute to optimizing energy management strategies, reducing peak demand, increasing the economic benefits for residents and integrating RES into the grid. In addition, IS4 also promotes a detailed scientific framework for analyzing and utilizing demand-side flexibility within the buildings by establishing reliable methodologies and performance metrics that quantitatively assess the demand flexibility limits. This approach integrates data analytics methods, Machine Learning techniques in order to estimate and predict the demand side flexibility in buildings and optimize the load response, thus contributing to grid stability. IS4 promotes the transition to sustainable energy practices by providing smart energy systems within the buildings and supporting the active participation of buildings in the flexibility markets.

2.5.2. Methodology

For the technical development of IS4, the necessary data were collected through the building simulation model provided by IS5 (see Section 2.6). In this way, it was ensured that the solutions proposed by IS4 will be fully aligned with the needs and requirements of the EVELIXIA project. More specifically, historical energy and weather data for one year were used regarding the Greek Pilot site, which includes the offices of CERTH and Mpodosakeio Hospital. Furthermore, the results obtained from IS4 could be directly applicable to the Greek Pilot site, supporting the integration of the various ISs in WP4 (EVELIXIA's Intelligent B2G and G2B Services).The analysis of historical energy consumption patterns is critical and necessary for the technical development of IS4, as they contribute to the understanding of the energy behavior and the overall energy and operational efficiency of a building. **Figure 25** and **Figure 26** represent the boxplots of one year's energy consumption for the Greek Pilot site which were extracted from IS5. In particular, each boxplot shows the distribution of energy consumption by hour within the year, allowing visual comparison of energy patterns and understanding hourly variations in energy consumption allowing for periods of high or low consumption, which are critical for planning energy strategies.

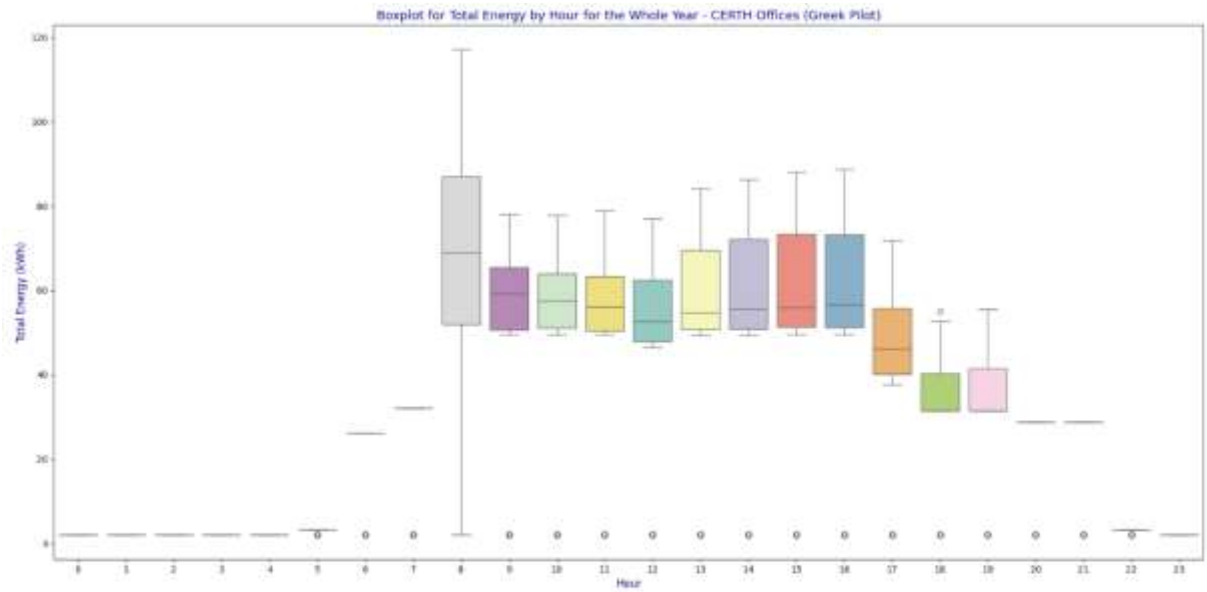


Figure 25. Boxplot of total building energy consumption for a year - CERTH Offices (Greek Pilot site)

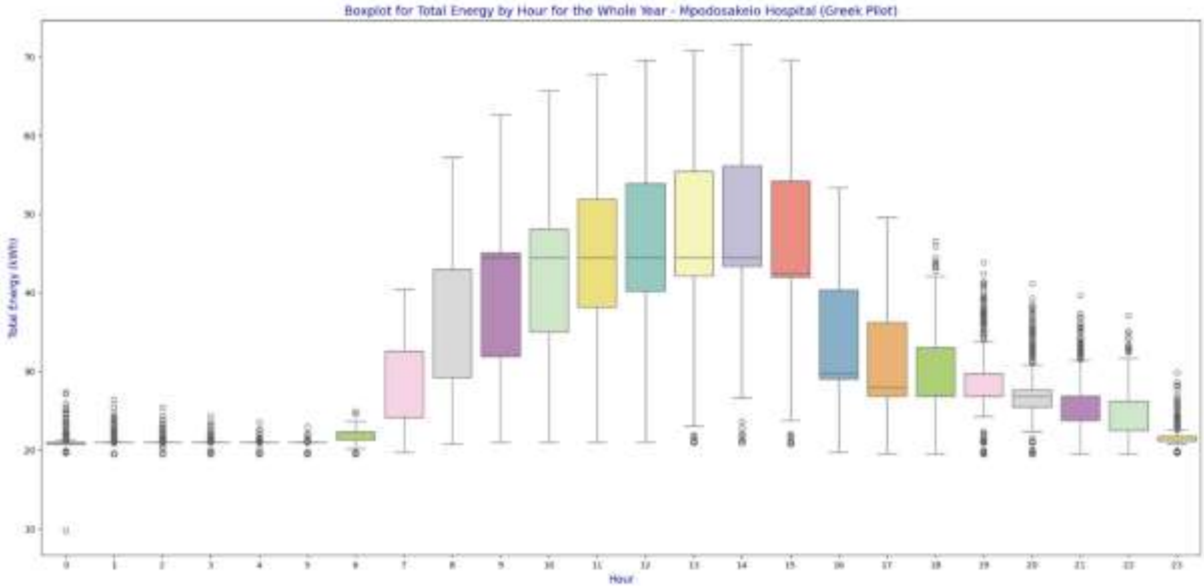


Figure 26. Boxplot of total building energy consumption for a year - Mpodosakeio Hospital (Greek Pilot site)

For the technical development of IS4, a detailed approach was used utilizing k-Means algorithms to study and classify historical energy consumption patterns and determine the demand-side flexibility limits for the Greek Pilot site. By creating groups of consecutive two-day periods within the year and using static analysis metrics (mean value and standard deviation) for the annual energy consumption data, considering the outdoor temperature, k-Means was used to classify similar energy behaviors. The choice of two consecutive days allows for the recording and analysis of short-term changes in energy consumption, which may be influenced by external factors such as external temperature and the behavior of occupants and contributes to provide overview of daily energy patterns and improve the accuracy of energy demand forecasts.

More specifically, this methodology involves two clustering stages:

- The first step of k-Means clustering for the outdoor temperature,
- In the second step, k-Means clustering is applied to the building energy consumption data within each cluster obtained from the first stage, ensuring that energy consumption patterns are analyzed in relation to their corresponding outdoor temperature groupings/clusters.

In the first clustering step, the k-Means methodology was applied to the outdoor temperature data. In this way, days with similar temperature conditions were grouped together, thus creating clusters representing different temperature profiles. This analysis is critical as outdoor temperature has a significant impact on energy consumption. **Figure 27** and **Figure 28** present that the best classification of the data based only on outdoor temperature of all two consecutive days of the year is in 2 clusters for the Greek Pilot site since it has the highest silhouette score.

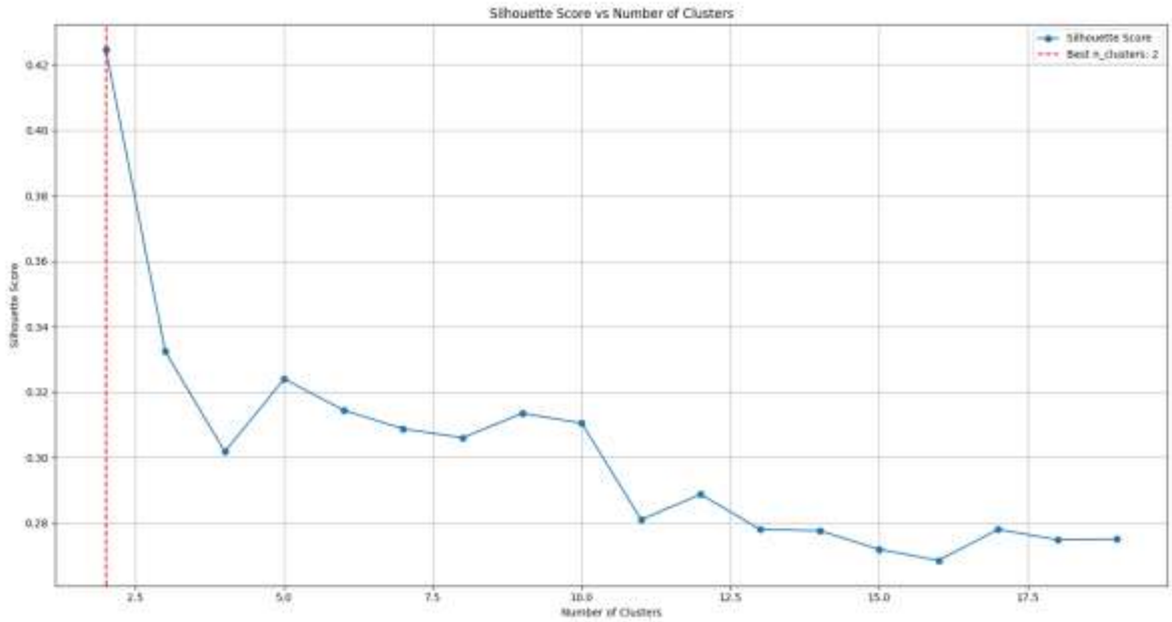


Figure 27. Silhouette scores of outdoor temperature clustering - CERTH Offices (Greek Pilot site)

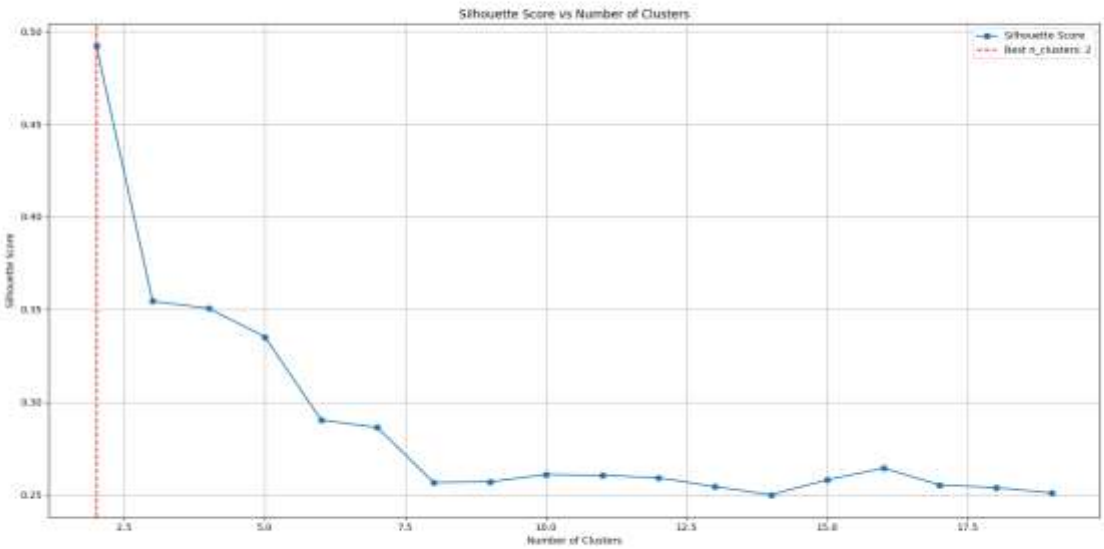


Figure 28. Silhouette scores of outdoor temperature clustering – Mpodosakeio Hospital (Greek Pilot site)

In the second stage, within each of the above 2 clusters resulting from the outdoor temperature analysis, k-Means was applied to the corresponding energy consumption data contained in them. In this way, energy consumption patterns that are similar under specific outdoor temperature conditions were identified. **Figure 29** shows that the first outdoor temperature cluster contains 4 energy consumption sub-clusters, while **Figure 30** indicates that the second cluster includes 2 sub-clusters regarding the CERTH offices (Greek Pilot site).

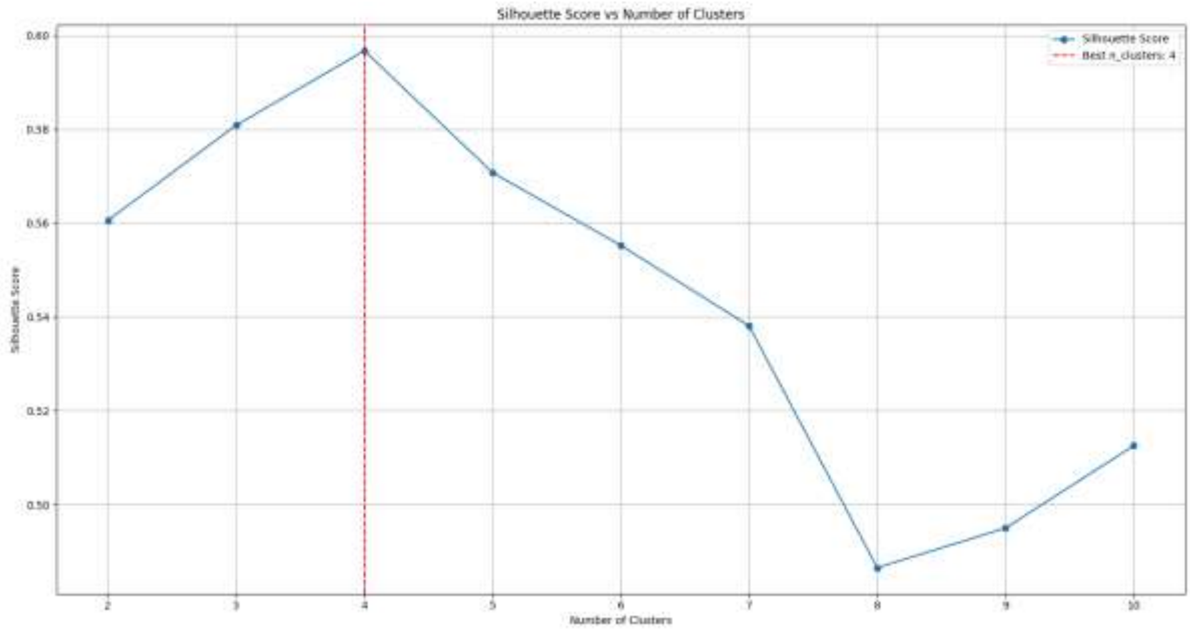


Figure 29. Silhouette scores of building energy consumption clustering in the first outdoor temperature cluster - CERTH Offices

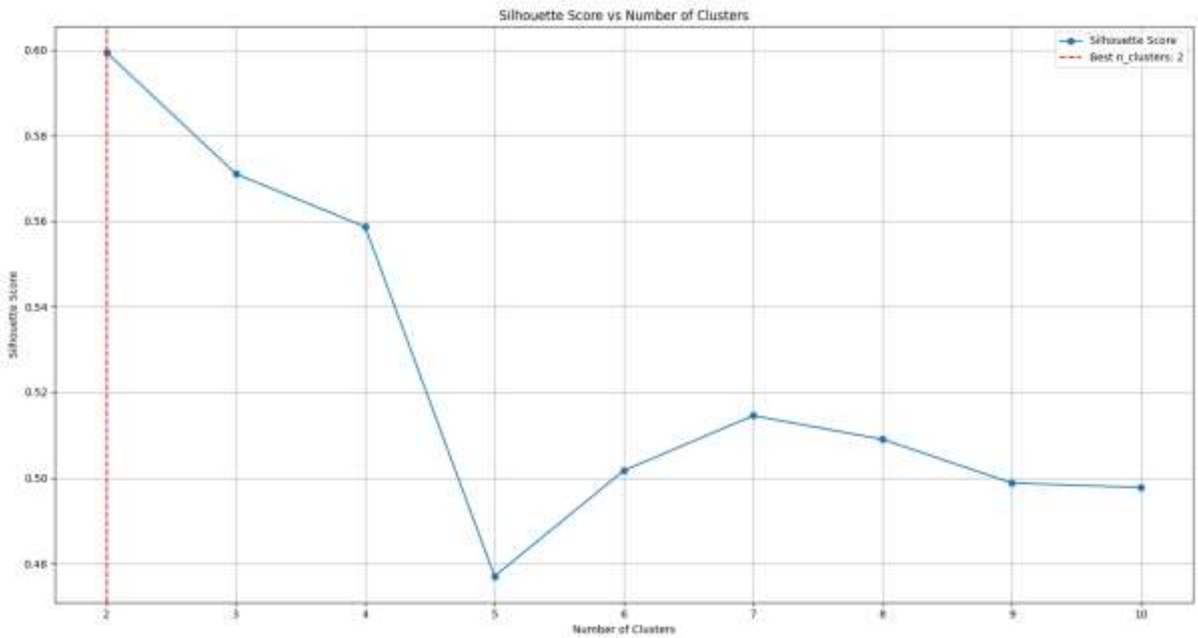


Figure 30. Silhouette scores of building energy consumption clustering in the first outdoor temperature cluster - CERTH Offices

Therefore, applying the same analysis to the two resulting groups of external temperature for Mpodosakeio Hospital (Greek Pilot Site), **Figure 31** shows that there are 7 energy consumption sub-clusters based on the highest silhouette score, while **Figure 32** shows that there are involved 6 sub-clusters.

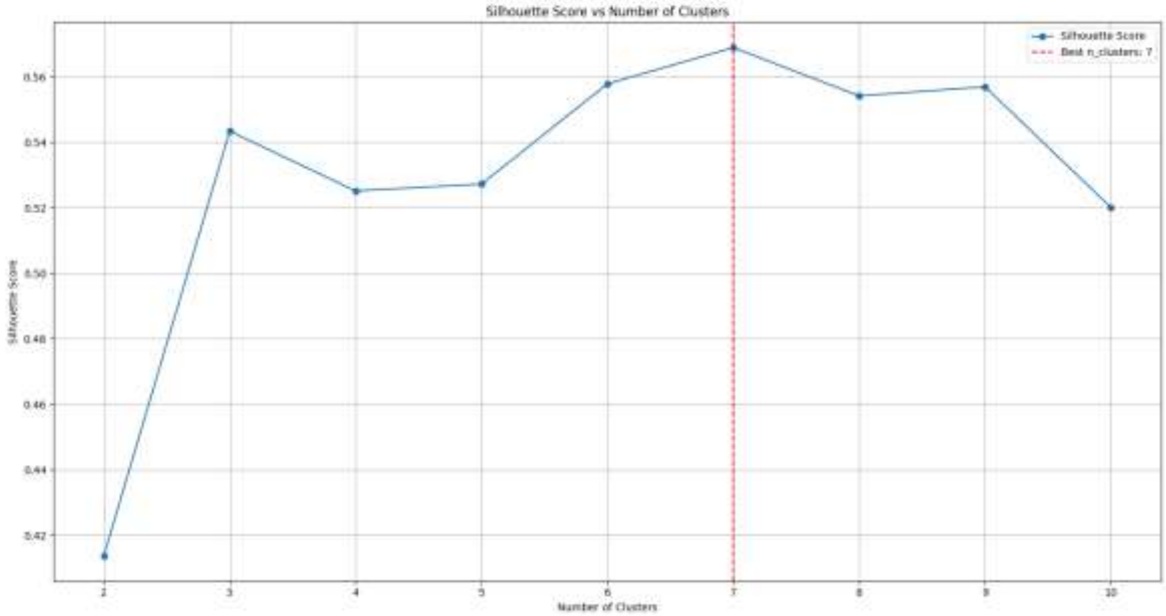


Figure 31. Silhouette scores of building energy consumption clustering in the first outdoor temperature cluster –Mpodosakeio Hospital

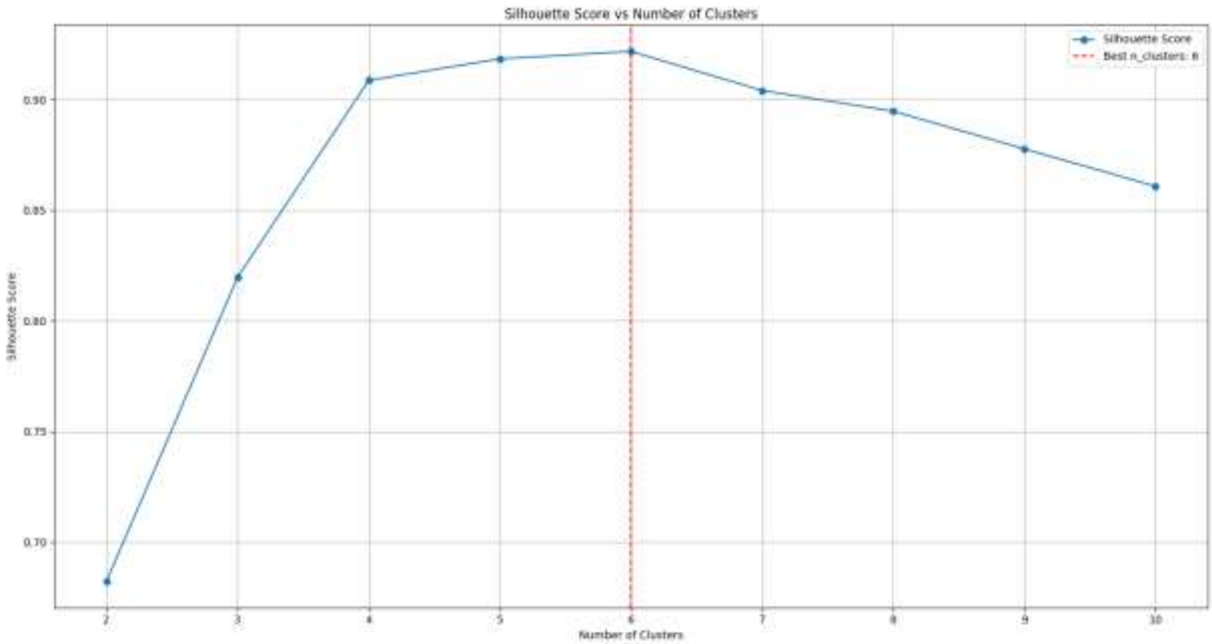


Figure 32. Silhouette scores of building energy consumption clustering in the outdoor temperature cluster – Mpodosakeio Hospital

Following the k-Means clustering process, IS4 is able to predict the demand side flexibility bounds. The predicted energy consumption, weather conditions and the corresponding data of the previous day are given as input to IS4. The service then classifies the forecast into the appropriate cluster. Using the historical energy data from buildings with the most similar and non-similar behavior within that cluster being classified, the required flexibility limits are determined. The predicted demand-side flexibility bounds will be discussed in more detail in the next section (Section 2.5.3).

2.5.3. Evaluation & Results

For the technical development of IS4, as mentioned before, historical energy consumption data as well as outdoor temperature data for one year were collected through IS5 for the Greek pilot area, allowing a detailed analysis of the energy behaviour and performance of the buildings in EVELIXIA. **Figure 33** shows the outdoor temperature data during the simulation period during which they were collected, as well as the cluster from the k-Means process with different colours in different colours (red and blue) for the CERTH Offices (Greek Pilot site).

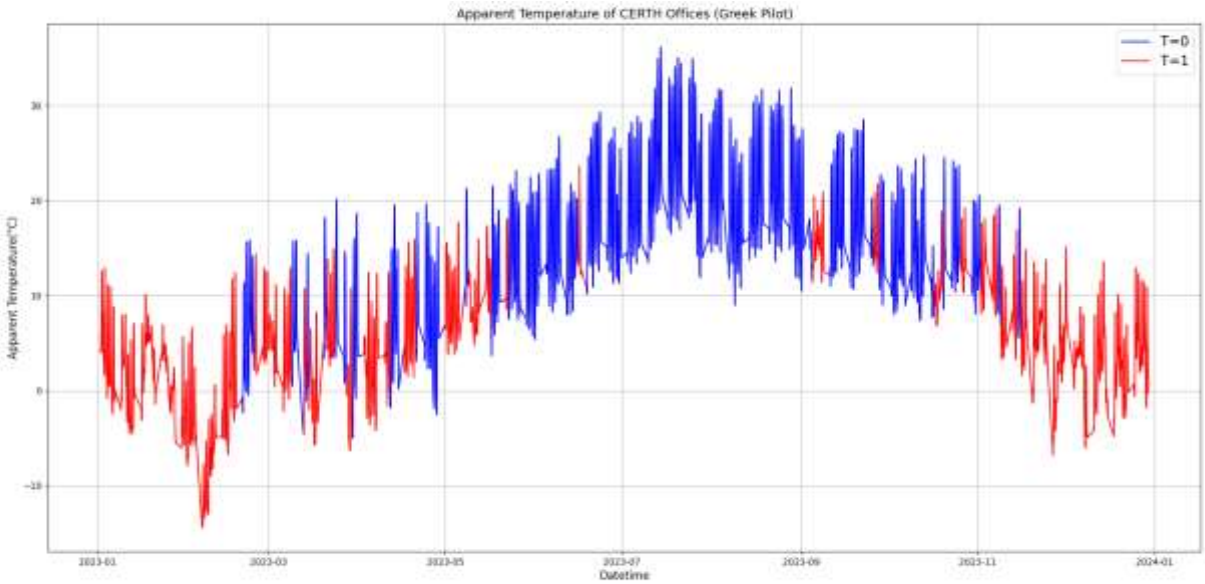


Figure 33. Outdoor temperature data for the CERTH Offices according to the clustering procedure (first cluster-blue and second cluster-red)

Also, **Figure 34** and **Figure 35**present the energy consumption data for the CERTH offices where the different classification for each of the two above mentioned clusters of the outdoor temperature is shown in different colours.

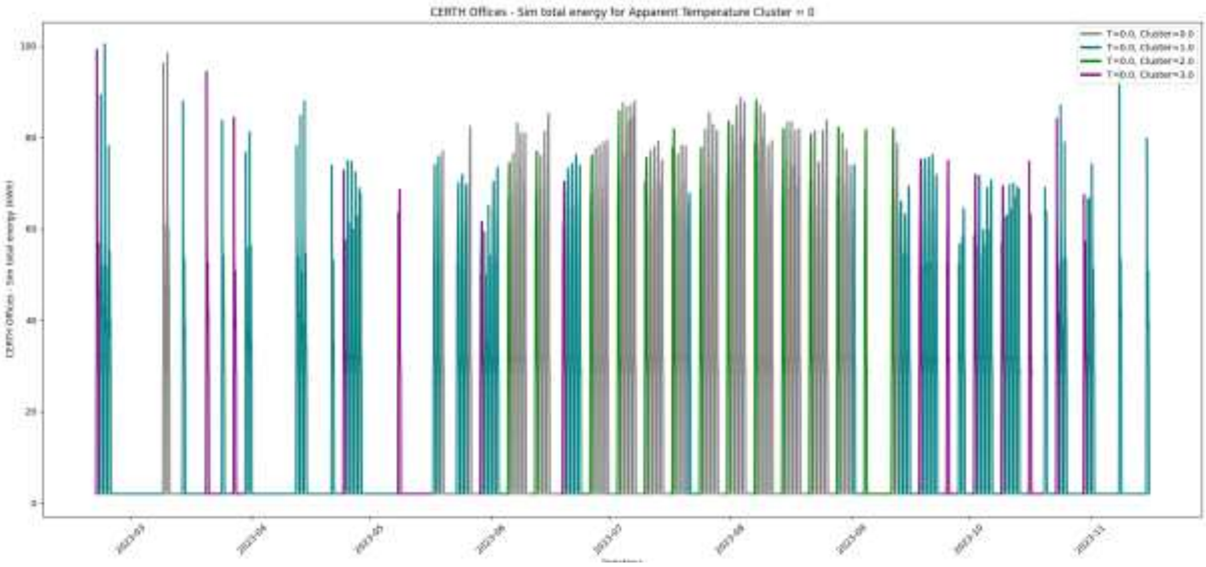


Figure 34. Energy consumption data for CERTH Offices according to the first outdoor temperature cluster

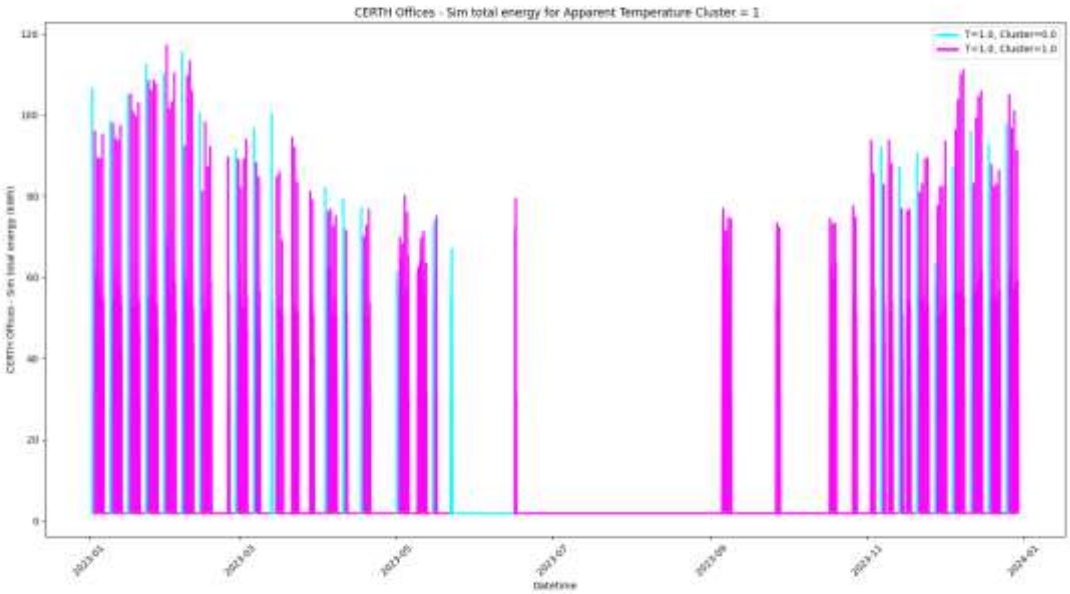


Figure 35. Energy consumption data for CERTH Offices according to the second outdoor temperature cluster

Regarding the Mpodosakeio Hospital (Greek Pilot site), **Figure 36** presents the outdoor temperature data during the simulation period in which they were collected, as well as the cluster from the k-Means process with different colours (red and blue). In addition, **Figure 37** and **Figure 38** indicate the energy consumption data for the Mpodosakeio Hospital where the different classification for each of the two above-mentioned clusters of the outdoor temperature is shown in different colours.

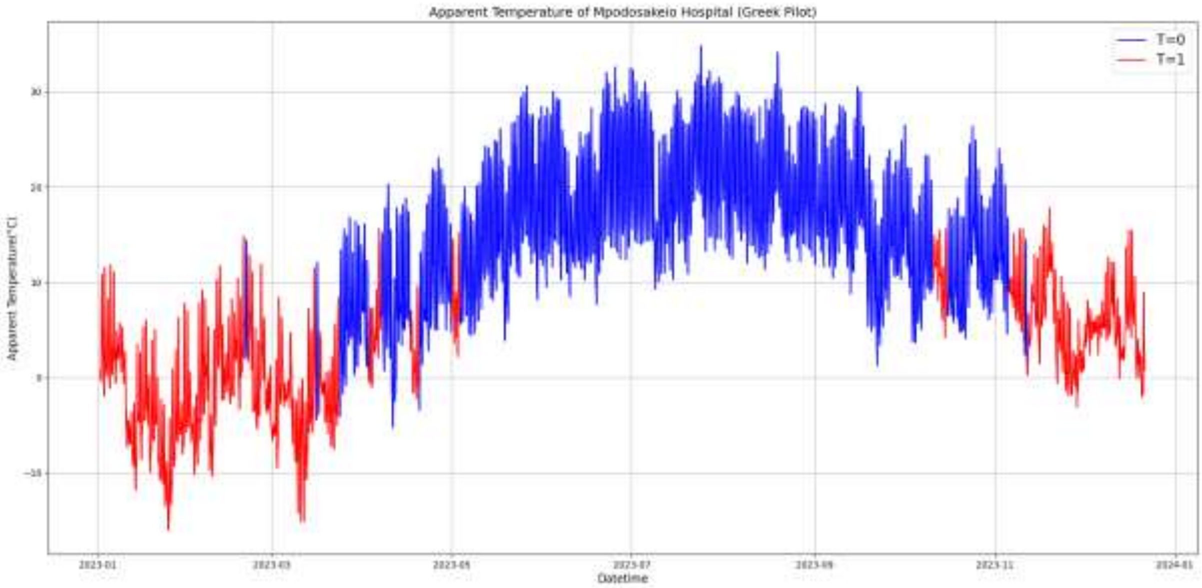


Figure 36. Outdoor temperature data for the Mpodosakeio Hospital according to the clustering procedure (first cluster-blue and second cluster-red)

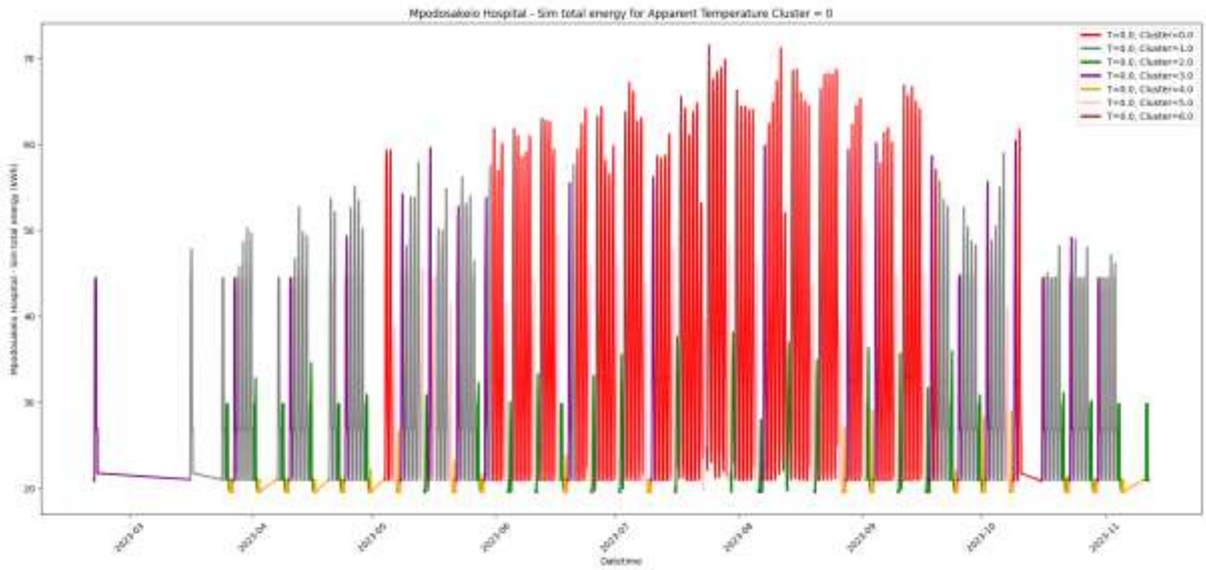


Figure 37. Energy consumption data for Mpodosakeio Hospital according to the first outdoor temperature cluster

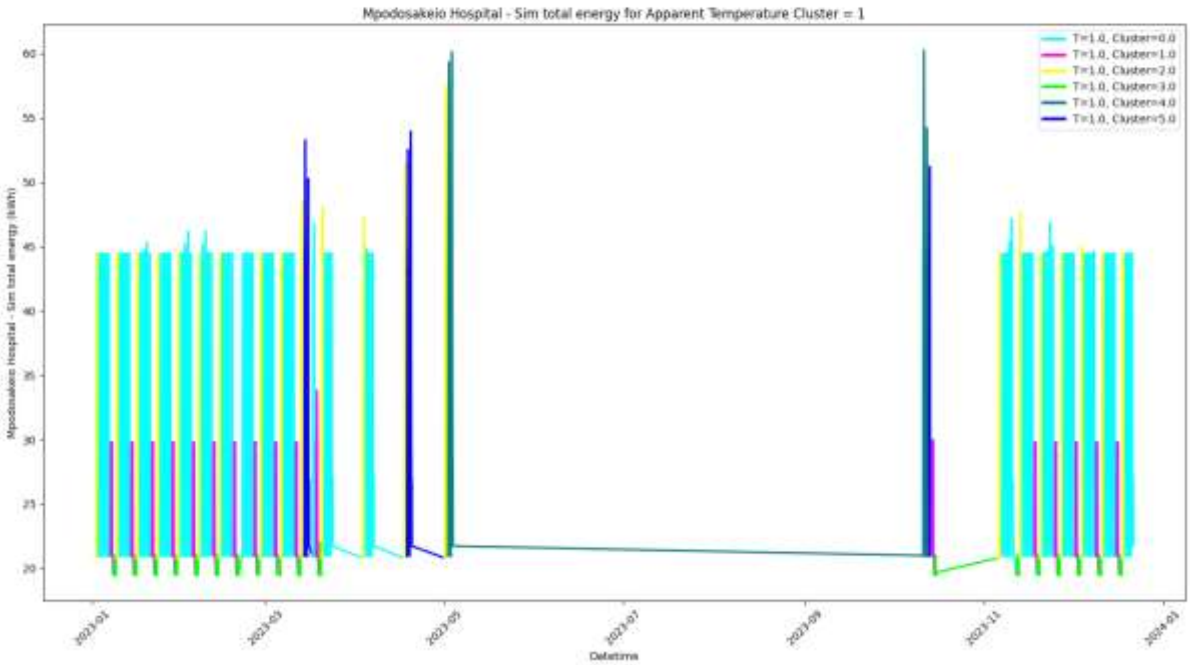


Figure 38. Energy consumption data for Mpodosakeio Hospital according to the first outdoor temperature cluster

Predictions of energy consumption and corresponding outdoor temperature based on the IS5 model simulation data were usedto present the predicted demand-side flexibility limits. More specifically, the procedure followed involves using data from the IS5 dataset, considering them as forecasts in order to be used in the analysis and calculation of demand side flexibility bounds. This approach allows the accurate analysis and management of energy demand, considering changes in weather conditions and energy consumption patterns for the future days. The forecasted energy consumption, weather conditions and the corresponding data from the previous day are given as input to IS4. This tool classifies the forecast into the appropriate cluster using the above k-Means clustering methodologies. Then using the historical simulated energy data from the Greek Pilot site that exhibit the most similar and non-similar energy behaviour within the cluster being classified, the required flexibility limits are determined by calculating the mean value of the above energy consumption data. **Figure 39** presents the indicativeforecasted demand-for the first energy consumption sub-clusters for CERTH offices **Figure 40** respectively for the first energy consumption sub-cluster of Mpodosakeio Hospital.

- Blue color represents the building's flexibility to increase energy consumption (up-flexibility bound).
- Red color indicates the predicted limit for reducing energy consumption (down-flexibility bound).
- Green color shows the forecasted energy consumption(baseline).

The following results represent a one-day forecast with hourly granularity and at the points where the three waveforms overlap, there is no available flexibility.

IS4 Annex provides all the indicative predicted demand side flexibility bounds for each of the aforementioned building energy consumption sub-clusters for both CERTH Offices and Mpodosakeio Hospital (Greek Pilot site).

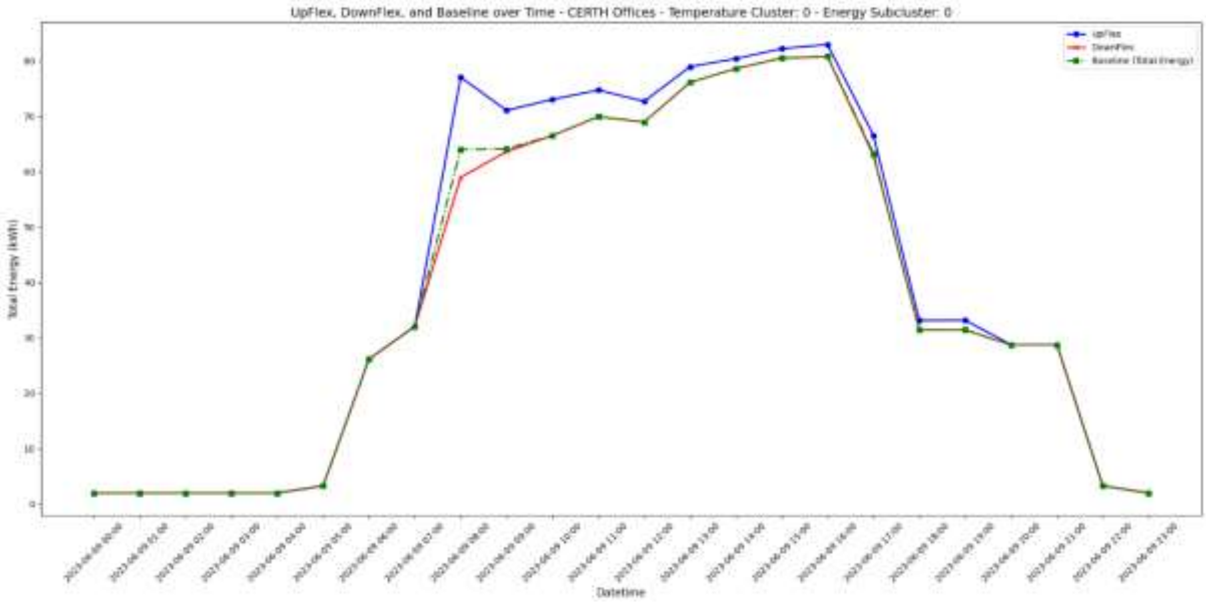


Figure 39. Predicted Demand side flexibility bounds for the first energy consumption sub-cluster of CERTH Offices (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

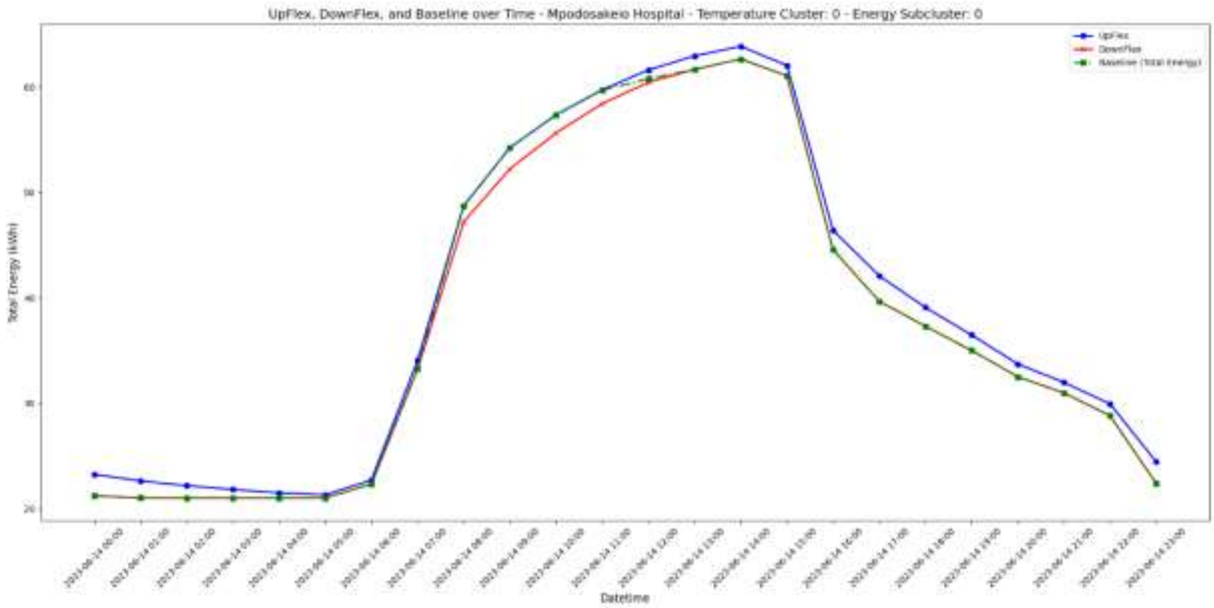


Figure 40. Predicted Demand side flexibility bounds for the first energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

2.5.4. Next Steps

Regarding the next steps of the IS4 technical development, it is intended to further improve the effectiveness of IS4 by incorporating additional metrics during the process of classifying the building's energy behavior (such as photovoltaic (PV) generation, intra-day energy cost values, integration of EV chargers, etc.). These steps are expected to improve the accuracy and reliability of IS4's predicted demand-side flexibility limits, contributing to optimizing the building energy consumption and supporting the grid stability. In addition, the forecasts provided by the demand forecasting tool (IS3) will be used as baseline in order to estimate and predict the limits of demand-side flexibility. At the same time, it is planned to integrate IS4 into the whole WP4 through T4.6 by month M24 of the project, contributing to the integration of the different ISs into EVELIXIA (D5.1). In conclusion,IS4 will be also deployed in other EVELIXIA's Pilot Sites either through the IS5 simulation model or by receiving either historical or real-time data through T4.6.

2.6. Building Energy Modelling and Simulation (IS5)

The **Building Energy Modelling and Simulation tool (IS5)** is built upon the **IES Virtual Environment (VE)** tool, a comprehensive simulation software widely used for energy performance analysis, building design optimization, and sustainability assessments. VE enables detailed modelling of buildings by integrating physics-based simulations with real-world operational data, facilitating informed decision-making across the entire building lifecycle. The software's core simulation engine, **Apache**, performs advanced thermal and energy analyses, allowing users to evaluate various designs and operational scenarios with high accuracy.

IS5 extends traditional digital twin (DT) functionalities by combining **physics-based** and **data-driven** modelling approaches. A key innovation within EVELIXIA is the development of **VE-based hybrid DT which leverage real-time data from IoT devices, smart meters, and external sources (e.g., weather platforms).** This enables the creation of calibrated and refined digital twins that more accurately reflect the actual operational behaviour of buildings. Additionally, IS5 will introduce **load disaggregation** and the **deployment of virtual sensors** to enhance building performance insights across interconnected networks, supporting **sector coupling services**.

To ensure seamless integration within the broader EVELIXIA ecosystem, IS5 is being configured for **machine-to-machine (M2M) communication and semantic interoperability through APIs to the project's central server**. This will enable **automated data exchange** with other ISs and tools, allowing IS5 to function not only as a standalone energy modelling tool but also as an integrated component of the EVELIXIA **Building-to-Grid services layer**, supporting a more efficient and interoperable energy management ecosystem.

As of **M17**, during the preparation of this deliverable, the **methodology is being defined and tested within the Greek pilot**. The results and refinements from this phase will inform the **replication across the remaining six pilot sites by M24**, with final outcomes to be reported in D4.2.

2.6.1. Objectives

The primary technical and scientific objectives of IS5 within the EVELIXIA context include:

- **Enhance Building-to-Grid Services:** Develop and deploy a simulation engine that will facilitate the integration of buildings with grid services, specifically focusing on energy flexibility and demand response capabilities.
- **Hybrid DT:** Create digital twins that combine both physics-based models and data-driven models for more accurate simulations of building performance, enabling precise demand response management.
- **Interoperability with Other ISs:** Ensuring seamless data exchange across different systems, including integration with other ISs within **T4.1**(**IS1**(Indoor Air Quality Service),**IS2** (Microgrid Maintenance Service),**IS4** (thermal/electricity flexibility forecasting) and **IS3** (local energy consumption/generation forecasting)), and support for the decision-making and forecasting services developed within **T4.2**. The outputs from IS5 will feed into the **Building Awareness Toolbox** (T4.1) and the **Autonomous Building Decision Support Toolbox** (T4.2), enabling more informed and proactive forecasting, demand planning, and energy performance management.

2.6.2. Methodology

The development of IS5 involves the integration of several methodologies, focusing on **simulation**,**DT modeling**, and **data interoperability**. The general methodology is divided into the following phases:

1. Data Collection, Baseline DT Model Preparation and Calibration
To accurately model the seven pilots in the EVELIXIA project, a **structured data collection process** was established. An Excel file was prepared and circulated among the pilot leaders, requesting all necessary information to build the baseline models for each pilot building. This included:

- **General Building Characteristics:** Location, year of construction, building type, and occupancy patterns.
- Architectural & Geometric Data: Floor plans, elevations, and construction details.
- **HVAC & Energy Systems:** Heating, cooling, ventilation, lighting, and energy storage.
- **Metering & Sensor Data:** Available IoT devices, smart meters, and energy monitoring systems.
- **Weather & Environmental Data:** Local climate conditions from on-site and off-site sources.
- **Operational Data:** Historical energy consumption, load profiles, and maintenance schedules.

In case of lack of data availability, assumptions are made to fill in missing information based on standard building codes (e.g. ASHRAE), benchmark data, and expert judgment.

Once the data are collected, each **pilot's DT is developed using IES Virtual Environment (VE).** This process includes:

- **3D Geometry Construction:** Using the provided architectural drawings to create an accurate representation of the buildings.
- **Zoning & Thermal Segmentation:** Dividing the buildings into thermal zones based on occupancy and usage patterns.
- **Envelope Properties Assignment:** Inputting wall, roof, window, and insulation properties to reflect real-world performance.

Finally, in this initial phase the model **is calibrated using historical real data** to ensure the accuracy of the simulations. So, simulation outputs (e.g., energy consumption, indoor temperatures) are compared with available real energy use data from the pilots.

2. Simulation, Integration and Interoperability

Once the baseline models are developed and preliminarily calibrated, extensive simulation processes are conducted to evaluate energy performance, demand flexibility, and comfort levels. This phase includes:

- **Baseline Performance Simulations:** Running simulations under typical operating conditions to assess baseline energy consumption, indoor comfort metrics, and potential flexibility capacities.
- **Scenario Analysis:** Evaluating different operational strategies, demand response scenarios, and grid interaction capabilities. These simulations help identify how buildings can adjust consumption patterns to support grid services while maintaining occupant comfort.
- **Integration with iSCAN Platform:** Simulation results are exported to iSCAN for data visualization, collaborative analysis with partners, and further validation. This step enables stakeholders to assess building performance through an interactive platform that supports exploratory data analysis.
- **API Development for Interoperability:** APIs are developed to facilitate data exchange between IS5, iSCAN, and the EVELIXIA project server. This enables automated data sharing with T4.1 and T4.2 components like IS1 (Indoor Air Quality Service), IS2 (Microgrid Maintenance Service), IS3 (local energy forecasting) and IS4 (flexibility assessment).

2.6.3. Evaluation & Results

The **first development phase (M4-M16)** of IS5 focused on defining the methodology and workflow for the development, planning and validation of the VE's capabilities expenditure in terms of B2G services enhancement, hybrid DT creation, and interoperability with the other ISs within EVELIXIA.

In particular, it has been decided to focus firstly only on the creation of the **baseline building DT model** of one pilot, the **Greek Demo Site**, assessing its accuracy in simulating building energy performance, and exporting its outputs into iSCAN platform for visualization, analysis and data exchange through API to the EVELIXIA platform and other ISs. This process was crucial in understanding the building's energy flexibility potential and ensuring seamless interaction with other EVELIXIA services. Once validated, the process will be replicated to the other 6 Pilot Sites.

1. Overview of the Greek Pilot DT Model

The Greek pilot serves as the **first implementation** of IS5, providing a reference framework for future replications in other pilots. The pilot is composed of 2 buildings: Mpodosakeio Hospital and the CERTH/CPERI Office building, making it an ideal testbed for evaluating energy demand patterns and flexibility potential.
The baseline DT model was created in IES VE, integrating the following information from D1.3 and provided by the pilot leaders:

- **Architectural and thermal properties** from **CAD** sources.
- **HVAC system representation**, including heating, cooling, and ventilation configurations.
- **Lighting and occupancy schedules** to reflect real usage patterns.
- **Renewable energy sources** (e.g., PV panels, battery storage).
- **Weather conditions and external influences** using historical climate data.

Figure 41. CERTH building google maps view

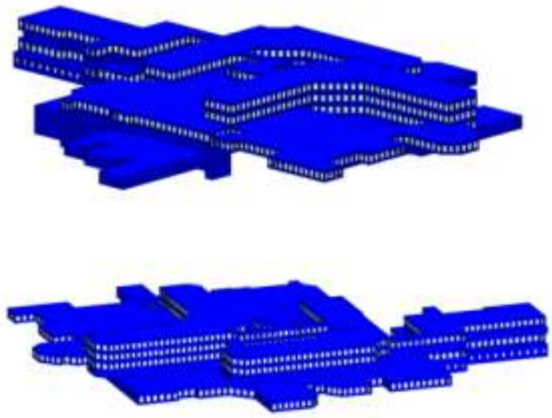


Figure 42. Mpodosakeio Hospital building in VE

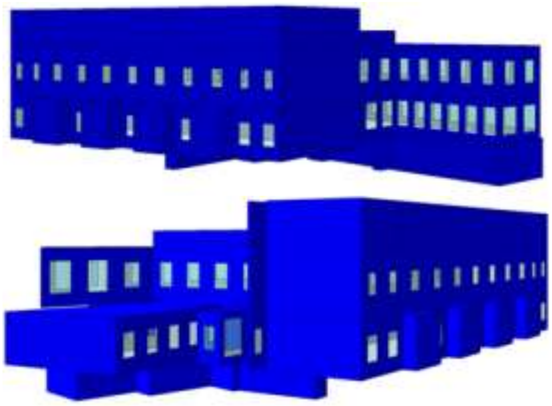


Figure 43. CERTH/CPERI building in VE

To ensure accuracy, the simulation models were calibrated against real data obtained from the pilot site leader. The calibration process involved comparing simulated vs. actual energy consumption for heating, cooling, and electricity, and adjusting occupancy schedules and internal heat gains to match real usage trends.

- The **CERTH/CPERI Office building** was validated against an annual total electricity consumption of 275.02 MWh for the year 2022. The VE simulation returned a yearly total electricity consumption of 247.22MWh, with a difference of less than 10%compared to the metered consumption.
- **Mpodosakeio Hospital** was validated both yearly and monthly for its electricity consumption, and only yearly from the thermal energy aspects as no monthly metered energy data of the District Heating Network were available. The results showed a minor deviation between simulated and actual metered values of 6.8% in yearly thermal energy, 5.7% in yearly electricity consumption, and an overall 6.3% deviation in total energy.

2. iSCAN for Data Visualization and Data Exchange through API

To further analyse results, the simulated data were exported to the iSCAN platform (**Figure 44**), enabling partners to interactively explore building performance metrics, and to enable real-time communication between the digital twin and the EVELIXIA project's central server API were developed. This enables automated data sharing with the other ISs, and real-time updates to support decision-making in T4.2's Autonomous Building Decision Support Toolbox.

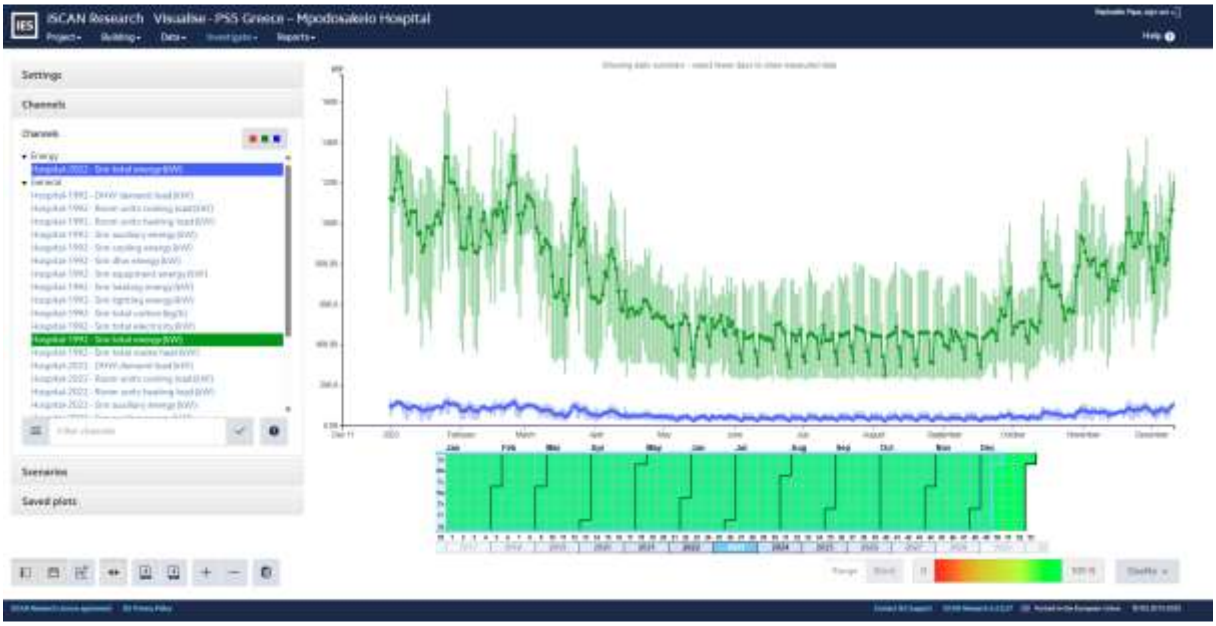


Figure 44. Baseline Digital Twin model results visualized in iSCAN platform

2.6.4. Next Steps

Building on the progress achieved so far, the upcoming months will focus on **further refining IS5** and ensuring its **seamless integration** with other EVELIXIA services. The key next steps include:

- **Scaling and Replicating the Methodology:** Expanding the **baseline digital twin approach** to **additional pilot sites** beyond Greece.
- **Enhancing Model Calibration:** Integrating **real-time sensor data** into the digital twin to improve the model's accuracy.
- **Strengthening Interoperability & Advancing Data Exchange:** Expanding the **API infrastructure** to establish direct, **standardized communication** between IS5, iSCAN, and the **central EVELIXIA project server**. Implementing **secure, scalable data-sharing mechanisms** to support **real-time analytics and control strategies**.
    - Ensuring interoperability with **IS1 & IS2** for building awareness (T4.1), **IS3 & IS4** for local energy forecasting and flexibility assessment (T4.1), and **IS9 & IS10** for demand planning and energy performance optimization (T4.2).
    - Facilitating the **integration of all services** into the **EVELIXIA platform**, allowing **real-time data flows, cross-service interactions, and automated decision-making**.

These advancements will **significantly enhance the automation, interoperability, and overall effectiveness** of IS5, ensuring it fully supports **EVELIXIA's mission of integrating buildings with grid services**.

3. EVELIXIA'S AUTONOMOUS BUILDING DECISION SUPPORT TOOLBOX

3.1. Introduction

This chapter describes the tools described in Task 4.2, including the Building Investment planning assistant service (IS6), the SRI Advisor (IS7), the Proactive Demand Planning Service (IS9) and the Continuous Energy Performance Manager Service (IS10). The latter service is unfolded into 3 sub-services, i.e., IS10a, IS10.b, IS10.c which include distinct optimization methods that will be applied in different pilots.

3.2. Building Investment Planning Assistant (IS6)

EVELIXIA's Innovative Solution 6 (IS6) "Building Investment Planning Assistant" is a critical component of the "Autonomous Building Decision Support Toolbox" that leverages the robust framework and advanced analytic capabilities of VERIFY, a web-based platform developed by CERTH/CPERI. VERIFY consists of two software suites, VERIFY-Buildings (VERIFY-B) for building-level, and VERIFY-District (VERIFY-D) for district-level analysis respectively. Building upon VERIFY-B, IS6 holistically performs dynamic Life Cycle Assessment (LCA) and a Life Cycle Costing (LCC) of energy systems at the building level from manufacturing to operation taking into account a) location-specific climate conditions, b) thermal properties of the building envelope, and c) the users' energy profile. IS6's modular architecture (**Figure 45**) integrates diverse data streams on energy prosumption, environmental impact and financial information for all types of energy carriers (e.g. electricity, heating, cooling), coupling VERIFY's Life Cycle Inventory (LCI) with both static and dynamic external parameters (e.g. operational time series, regional emission factors, fuel prices, interest rates, and others). Both suites employ an internal energy modelling module (INTEMA) that can generate synthetic energy profiles with hourly granularity (8,760 values per year) through an automated process. Both suites are able to calculate pre-defined Key Performance Indicators (KPIs) such as Lifetime Primary energy Demand, Lifetime Global Warming Potential and Lifecycle Costs for a user-defined analysis period that is generally recommended to be equal or greater than the expected lifespan of the installed systems. During EVELIXIA, CERTH/CPERI will adapt its energy performance, environmental impact, and financial returns analytics capabilities to contribute to the development of a digital building twin with modelling functionalities that support investment planning and evaluate the provision of flexibility services. VERIFY's capabilities will be extended to a) utilize and fuse data from multiple data resources (i.e., its own Postgres relational database, European grid emissions factors observatories, its own data lake and lifecycle inventory, the EVELIXIA platform and the data sourced by its constituent components), and b) dynamically evaluate key financial variables (such as NPV, IRR, ROI, etc.) relevant to the specific context of EVELIXIA's Pilot Sites (PS). In support of a broad range of stakeholders (i.e., building managers, energy planners, consultants, aggregators, regulatory bodies), IS6 informs decision-making by assessing building-level energy system investments in terms of financial benefit, taking into account not only the expected costs and savings associated with the installation of new technologies, but also any direct profits from supplying the grid with renewable energy. This allows a comprehensive evaluation of these investments' economic viability.

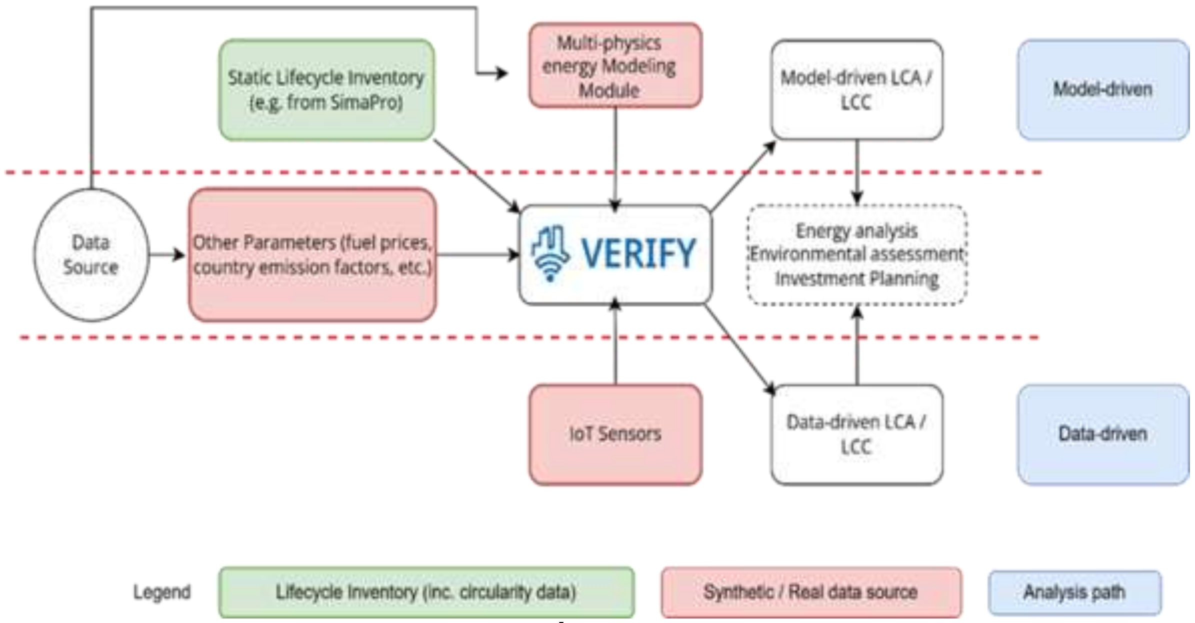


Figure 45. IS6/VERIFY Architecture

3.2.1. Objectives

IS6 - Technical Objective "TRL5 to TRL7": Originally validated in the relevant environment of several past EU-funded projects (e.g., RENplusHOMES GA No.101103450, REHOUSE GA No.101079951, IANOS GA No.957810, REEFLEX GA No.101096192, ENFLATE GA No. 101075783) VERIFY is introduced to EVELIXIA as a tested tool at Technology Readiness Level (TRL) 5. Following the implementation of the aforementioned project-specific advancements, a working version of IS6 is tested using data obtained from the operational environment of the Greek pilot site (GR-PS), advancing towards TRL6. Testing is conducted using static data (provided by the GR-PS Manager) and simulated dynamic data (exported from IS5-iSCAN) for the CPERI office building. Upon integration of the EVELIXIA platform within GR-PS and establishment of the EVELIXIA platform's API connection with IS6 testing will be completed using dynamic data related to operational energy consumption/generation sourced from the platform, enabling real-world, scenario-based analysis of investment strategies. Progressing towards TRL 7 until the end of the project, future efforts and refinements target end-user validation to expand its real-world applicability, offering a responsive, advanced energy-investment planning tool that is accessible to diverse ecosystem actors.

IS6 - Scientific Objective "Computation of real-time life cycle metrics": IS6 is advanced to dynamically compute environmental and economic KPIs across EVELIXIA's Pilot Sites (PSs), which are designed and equipped with the necessary energy generation, management and control systems to provide grid services.

VERIFY-B source code will be refined to update the calculation methods of its default KPIs and modified appropriately to integrate additional equations for non-default, EVELIXIA-specific KPIs, namely Net Present Value (NPV), Internal Rate of Return (IRR) and Return on Investment (ROI). The cumulative list of quantitative metrics derived from IS6 (see Section 3.2.2.5) applies across PSs. Provided they correspond to a common analysis period, the VERIFY's results can be aggregated either at the PS-level or at project-level to be used in the evaluation, impact assessment, and validation processes, confirming the attainment of EVELIXIA's targets and long-term impact based on the upgrade scenarios that will be implemented per PS.

3.2.2. Methodology

IS6 operates through an online platform, eliminating the need for local software installations, making it accessible from any location with internet connectivity and stimulating ease of deployment and navigation. At the time of writing of the present deliverable, two approaches for the integration of IS6 with the overall EVELIXIA platform are considered:

- **Computational integration**: This approach involves the integration of VERIFY's computational back-end with the EVELIXIA platform, where visualization is provided by IS17 (the Visual Analytics Engine, VAE). In this case, the EVELIXIA platform will use VERIFY's API to make analysis requests for specific scenarios. VERIFY will respond with a corresponding JSON file with the outcomes of the analysis, which will then be presented to the VAE users. Integration will be achieved through an encrypted interface used by the platform to communicate with CERTH's computational back-end servers.

- **Full web application integration**: In this approach, VERIFY's web application will be adapted to the EVELIXIA users' needs, containerized and integrated as a separate module of the EVELIXIA platform's visual interface. To protect CERTH's IP, the computational back-end used will remain on CERTH's computational cluster, with encrypted communications taking place between the two applications.

In both cases, the user is initially redirected through EVELIXIA platform to the designated page. Access to the page is managed through the platform's SSO mechanism, which will regulate which user roles have access to the specific facilities. The remainder of this chapter refers to the potential implementation of the second integration option (full-web) using VERIFY's current user interface to provide guidance for further integration activities. It should be noted that, as part of VERIFY's EVELIXIA adaptation activities, some non-essential elements of the UI may be hidden from view to simplify the users' interaction with the application. In addition, some parameters/options may be simplified to adapt to the specific application usage scenarios pertinent to EVELIXIA.

3.2.2.1. Application entry

The point of entry to the application will be the VERIFY's EVELIXIA dedicated dashboard (**Figure 46**) and the user will be prompted to select the "My Buildings" option (**Figure 46**, Choice 1). Subsequently entering the VERIFY-B Suite, the user may add a new building entry (**Figure 46**,Choice 3). Once created, the building entry is automatically saved, and the user may review, edit, clone, or delete it at any given time (**Figure 46**, Choice 2).

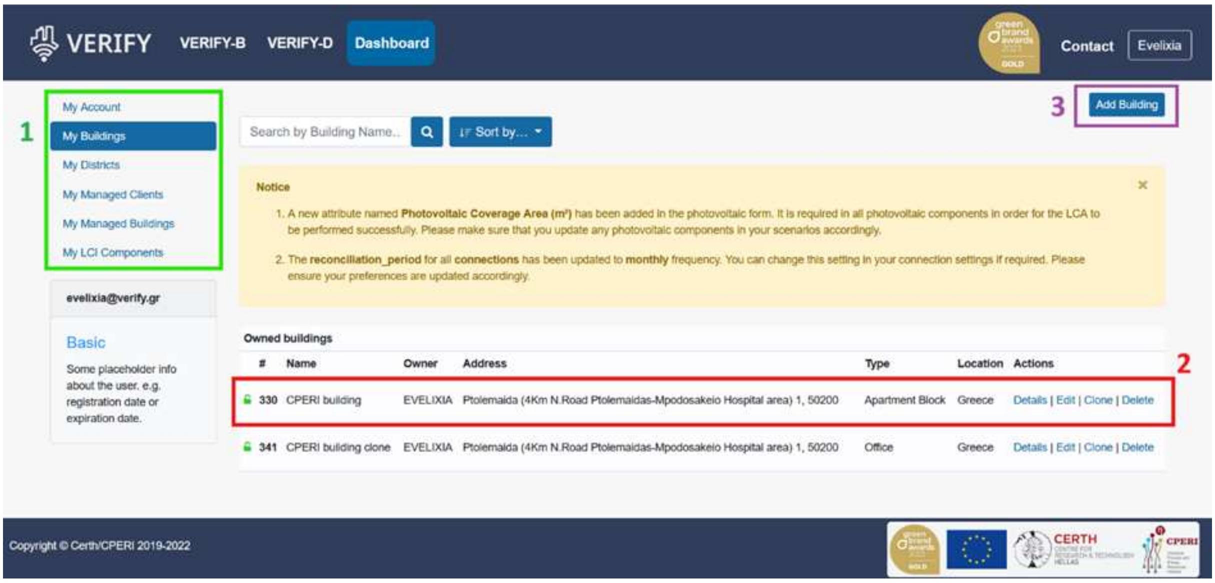


Figure 46. VERIFY - Dashboard page

When the user selects a listed building entry, a building-specific view is enabled, displaying all its details and characteristics (**Figure 47**).

Figure 47. VERIFY - building-specific view

3.2.2.2. Building definition

The LCA/LCC analysis in VERIFY-B begins with the building definition. The user is requested to insert building-level static data necessary for generating the building model:

- **Building attributes:** type, outer dimensions, number of floors, floor area & per façade: glazing area, external wall area, type of glazing, type of insulation, orientation
- **Location details:** address, zip code, country, altitude, coordinates
- **External factors:** temperature set points (winter/summer), occupancy profiles, cost of energy per energy source type

3.2.2.3. Scenario definition

VERIFY conducts real-time, scenario-based LCA/LCC analyses comparing user-specific investment scenarios per building entry prior and after the implementation of EVELIXIA's solutions (**Figure 48**). The user may create a new scenario (**Figure 48**, Choice 2), edit an existing scenario (**Figure 48**, Choice 1), or clone an existing scenario to generate a new one in a simplified manner. Upon creation, each scenario is automatically saved.

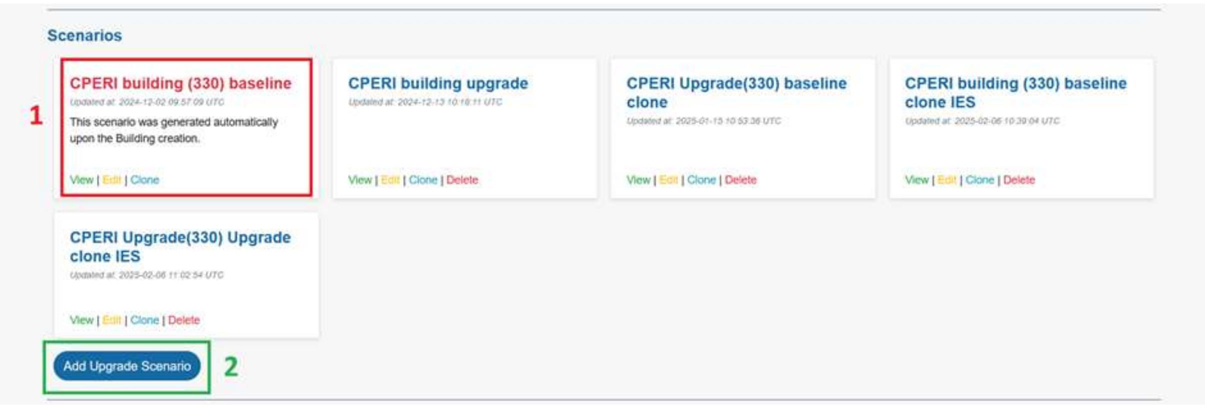


Figure 48. VERIFY - Scenario definition

The user may further refine those scenarios by selecting energy efficiency measures, adjusting system components, and modifying financial assumptions tailored to user-specific needs and goals. Prior to the LCA/LCC analysis, user can select which scenarios to include and compare, regardless of the number of scenarios created (**Figure 49**).

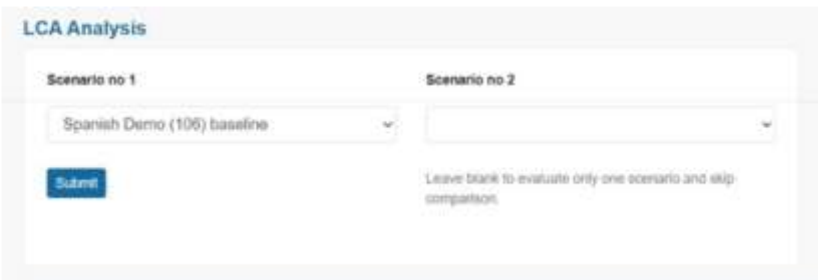


Figure 49. VERIFY - Scenario selection

3.2.2.4. Component definition

For each newly added scenario, user has to specify the component information, both static and dynamic, provided from the list of component groups (**Figure 50**, Choice 1). Upon selecting each tabbed group (**Figure 50**, Choice 2), the user may insert the relative information (incl. component type, power rating, installation year, efficiency factors, technical specifications per type, CAPEX and OPEX, interest rates, usage hours, emission coefficients, etc.).

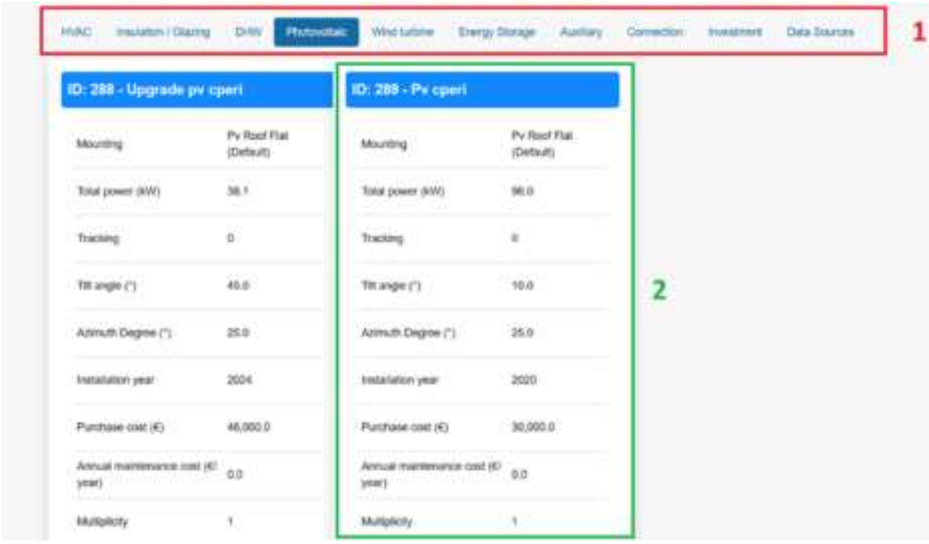


Figure 50. VERIFY - Component Tabs

VERIFY's interoperability is supported by independent messaging protocols and APIs. The required back-end operations are already in place, which allow seamless data exchange with third-party data platforms and external systems such as SCADA, EMS, and BEMS. As soon as the EVELIXIA platform is operational, the necessary back-end modifications of IS6 will take place to ensure the centralized and consistent data flow, making use of API and MQTT-based communication.
The dynamic data per component can be provided through various data streams (i.e., manual entry, API Call, MQTT Queue) and formats (i.e., .csv, .json) via the "Data Sources" Component Tab (**Figure 51**). The minimum requirements need timeseries with at least hourly timespan and spanning over a full calendar year.

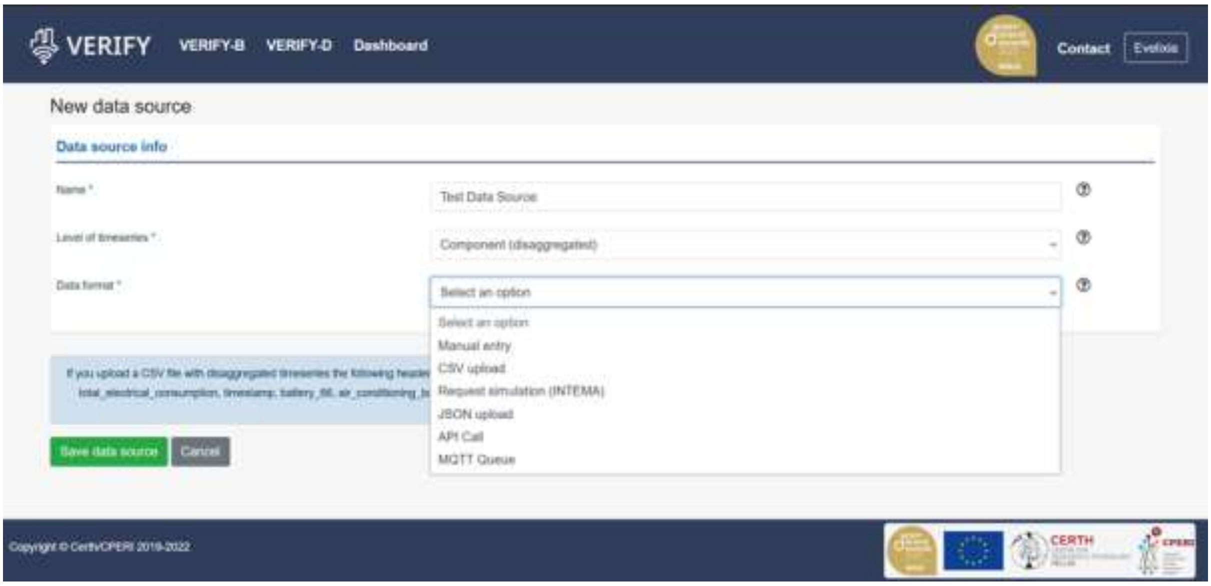


Figure 51. VERIFY -Data Sources

To counter issues of incomplete datasets due to data scarcity, measurements inaccuracies, technical problems, and sensor sensitivity, VERIFY generates synthetic data through INTEMA, its internal simulation engine that employs predictive energy modelling. In case of total absence of data or mere building-level values provided by the user (e.g., annual energy consumption for connected grids), INTEMA performs an on-demand disaggregation process, utilizing VERIFY's LCI to infer detailed, time-resolved data per component (**Figure 52**).

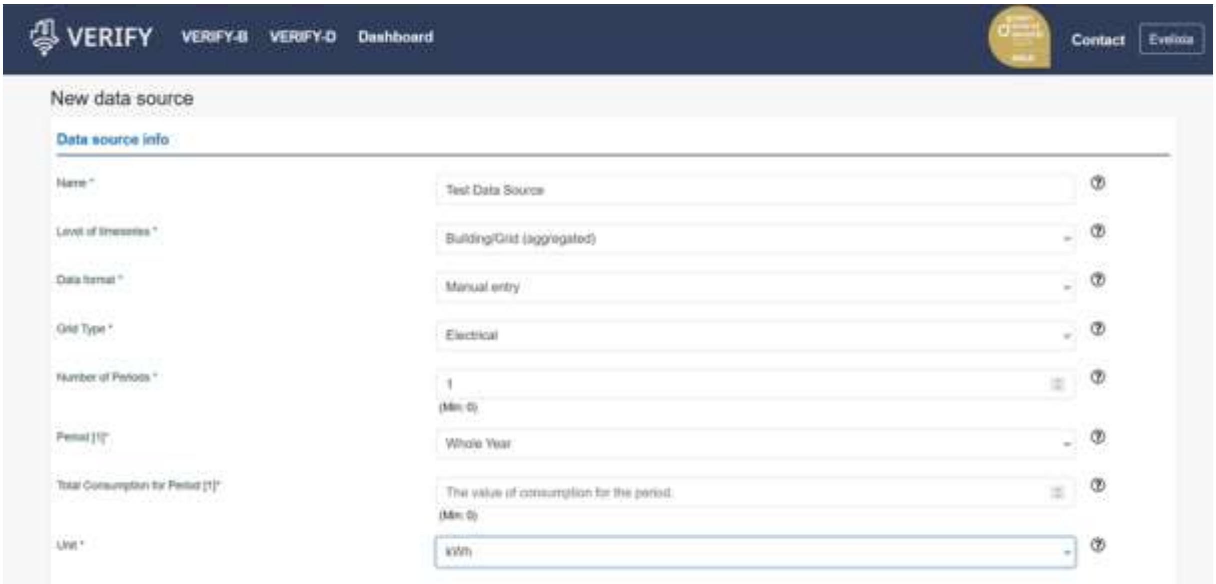


Figure 52. VERIFY - Data source info for data disaggregation

3.2.2.5. LCA/LCC Analysis

The combined model-driven and data-driven approach of IS6 uses physics-based simulations that incorporate passive features, active systems and environmental factors and financial information. IS6 backend functionality is structured to align with ISO standards (ISO 14040/14044 for LCA, ISO 15686-5 for LCC, ISO 16745-1 for determining and reporting carbon metrics) and EU-wide frameworks (Level(s), Energy Performance for Building Directive (EPBD)). Based on the detailed, real-time LCA/LCC analysis of the resulting energy prosumption profile per building via VERIFY-B, IS6 generates the following KPIs:

Environmental
- Lifetime Primary Energy Demand (PED)
- Lifetime Global Warming Potential (GWP)

Economic
- Lifecycle Costs (LCC)
- Pay Back Time (PBT)
- Levelized Cost of Electricity (LCOE)
- Net Present Value (NPV)
- Internal Rate of Return (IRR)
- Return on Investment (ROI)

The respective definitions, formulas & calculation methods for all the above KPIs are presented in Annex 6.1.

3.2.2.6. Data Storage, Security & GDPR

VERIFY securely stores all data within CERTH's data center, utilizing structured access protocols to ensure confidentiality and integrity. Data generated within VERIFY can be exported in multiple formats (e.g.,.csv,.json) and made available to interested partners upon request through EVELIXIA platform. Controlled access to scenarios will be managed through EVELIXIA's user access control system, with each user having access to specific buildings and scenarios. The details of the access rules will be determined during the platform's integration. VERIFY does not process personal data subject to GDPR. It exclusively handles non-personal data related to the energy performance of facilities and their billing arrangements.

3.2.3. Evaluation & Results

The results of IS6 can be disseminated in three primary formats, depending on the integration option adopted in EVELIXIA:
- cumulative list & graphs (online)
- exportable time series
- exportable report

KPI	CPERI building (330) baseline		CPERI Upgrade(330) baseline clone		Difference
	Total	Annual avg.	Total	Annual avg.	
Lifetime Primary Energy Demand (kWh)	21,773,889	435,478	22,066,752	441,335	1.35%
Lifetime Primary Energy Demand Per m² (kWh/m²)	5,745.09	114.9	5,822.36	116.45	
Lifetime Global Warming Potential ($kgCO_2$-eq)	4,056,913	81,138.26	4,189,196	83,783.92	3.26%
Lifetime Global Warming Potential per m² ($kgCO_2$-eq/m²)	1,070.43	21.41	1,105.33	22.11	
GHG emissions payback period (years)					No payback
Life Cycle Costs (€)	6,204,466	124,089	5,899,259	117,985	-4.92%
Life Cycle Costs Per m² (€/m²)	1,637.06	32.74	1,556.53	31.13	
Whole Life Costs (€)	6,197,988	123,960	5,887,741	117,755	-5.01%
Whole Life Costs Per m² (€/m²)	1,635.35	32.71	1,553.49	31.07	
Payback time (years)					1.6181193744731583

Figure 53. VERIFY - Indicative list of KPIs in the results page

VERIFY's own online results page offers a detailed tabulated list (**Figure 53**) alongside dedicated visualization plots (**Figure 54**). These plots incorporate cumulative curves that extend over the entire project lifespan, thereby providing a comprehensive long-term perspective on energy performance, emissions reductions, and cost evolution. The availability of exportable time series data further supports detailed post-analysis and integration with other external analytical tools.

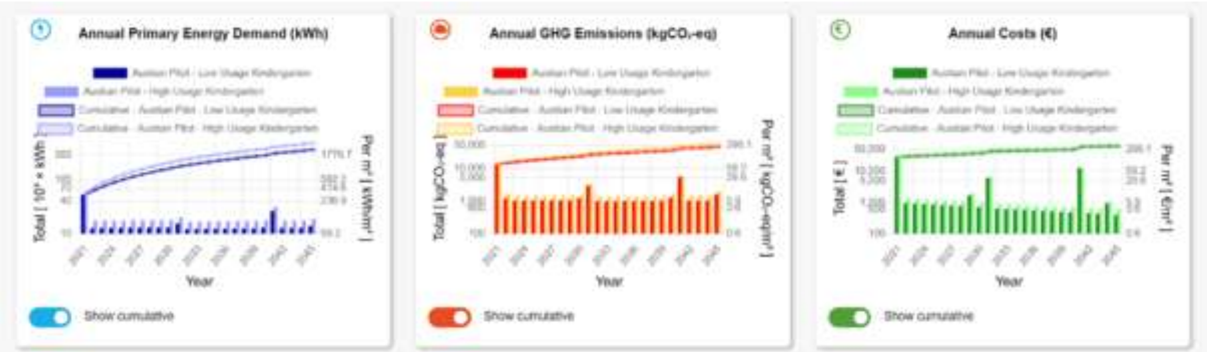


Figure 54. VERIFY - Indicative resulting plots of KPIs

The evaluation of the IS6 development is conducted through a dual-path test run (**Figure 55**)) to ensure reliability of results, applied to a Case Study for CPERI office building of the Greek PS. In the first approach, the building's annual energy consumption is generated from iSCAN module of IS5 - "Building Energy Modelling and Simulation" (see2.6). This input is uploaded into VERIFY to disaggregate into component-specific information for both baseline and upgrade scenarios and calculate the KPIs (iSCAN-approach). Concurrently, the total energy consumption is also generated internally through INTEMA to disaggregate the building-level input data into component-level consumption series for each scenario.

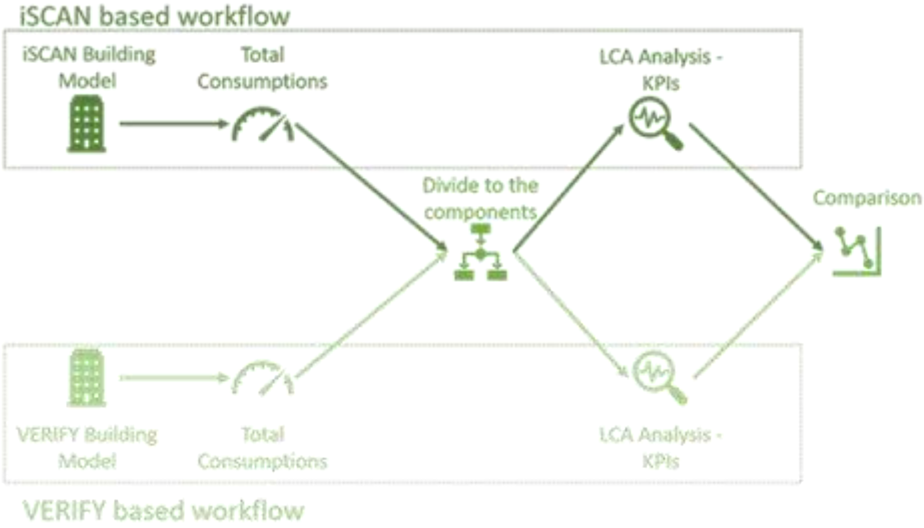


Figure 55. Overview of the dual-path test run for IS6

The two approaches perform an annual analysis that refers to different calendar year (2022 for iSCAN-approach and 2023 for INTEMA-approach) due to respective availability of historical data, resulting in different energy profiles. Moreover, significant deviations in the estimated annual (total) energy consumption and minor deviations across KPIs are further attributed to inherent energy modeling differences in distinct assumptions and computational frameworks employed between the two simulation engines. However, the comparative analysis examines the relative difference between the baseline (prior to EVELIXIA), and the upgrade scenario (following the implementation of EVELIXIA's solutions) of each approach.
As a distinct parameter for a comparative analysis for the two approaches, the Lifetime Primary Energy Demand (PED) KPI is selected due to its intuitive and clear definition as a benchmark to validate the accuracy of the estimations of the simulated data generated IS5-ISCAN in comparison to the ones retrieved from the default internal simulation engine (INTEMA). This comparison is limited for the purposes of the initial test run, as no further calibration process is integrated into the tool. During implementation dynamic data will be sourced either directly from the EVELIXIA platform or via the IS5-ISCAN in case of simulated/synthetic data. PED is calculated using the following formula:

$$L_{PE} = I_{PE} + \sum_{i=1}^{N} (O_{PE}^{[i]})$$

Where:

L_{PE} is the Lifetime PE Demand of the project;

I_{PE} is the Infrastructure (embodied) PE Demand;

$O_{PE}^{[i]}$ is the Operational PE demand of the building's components in year i.

The resulting values for PED between approaches (**Figure 56**) demonstrate a high degree of qualitative alignment, while quantitatively remaining within the same order of magnitude (39% difference), indicating a similar data handling and processing functions. The same outcome applies to all KPIs, based the range of the deviation of their relative difference, resulting in 0.9%-1.21% deviation for Environmental KPIs and a 26.19% difference in for Cost Savings (more sensitive to the total energy consumption by definition, yet correlated with the difference in PED). These results reveal that the KPI values reveal a consistent pattern in both approaches, regardless of the original input. A comprehensive tabulation of the cumulative results across KPIs, covering both scenarios for each approach, and the relative differences and deviations are presented in Annex 6.1.

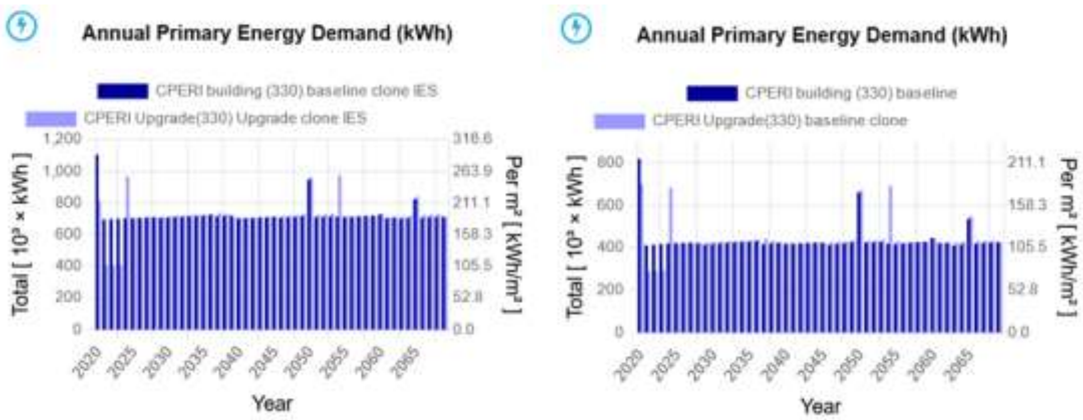


Figure 56. Lifetime Primary Energy Demand for the baseline scenario (left: iSCAN-approach, right: INTEMA-approach)

3.2.4. Next Steps

In the forthcoming phase of the EVELIXIA project until M24, the following key advancements and initiatives pertaining to IS6 are underway:

- **Static Data Collection for Energy Models:** Static data will be systematically collected for all buildings across all EVELIXIA Pilot Sites (PS) to support the development of accurate energy models. In close collaboration with T4.2, T5.2, WP4, and WP5 Leaders, PS managers will be iteratively engaged to provide all necessary static building information for building model generation within IS6 and discuss mitigation strategies for potential data shortages, thereby ensuring data integrity and enhancing model reliability.

- **Interconnection with the EVELIXIA Platform:** In parallel with the upcoming deployment and integration of EVELIXIA's platform, CERTH/CPERI will work closely with the relevant task leaders to establish a) an automated dynamic data exchange mechanism via API, eliminating the need for human intervention, enhancing communication reliability and enabling real-time calculations that are essential for dynamic system performance, and b) the re-direction process to the dedicated domain of VERIFY through EVELIXIA platform in the case of the full-web integration, solidifying the accessibility of the solution

The collective work performed thus far, together with the planned actions in the months to come, delineate the roadmap for delivering an advanced tool designed to support building-level investment strategies that cater to project-specific targets. IS6 underpins the development of multi-utility services and viable, adaptive investment strategies, ultimately contributing to the enhancement of the Autonomous Building Digital Twin with self-decision-making capabilities.

3.3. SRI Advisor (IS7)

The SRI Advisor tool (SRIA) aims to provide tailored recommendations on how to improve the SRI class of a building. Rather than a "push-button" tool delivering automated recommendations, the SRIA is intended to be a decision-support tool determining a short list of the most cost-effective smartness upgrades adapted to the building and its owner's priorities. This list should be critically analyzed by the user of the tool (SRI assessor) before being discussed with their client (building owner or manager). The final recommendations to be implemented in the building will then be co-designed with the client. The tool includes the following components as showed in **Figure 56**:

1) A questionnaire to understand building characteristics and its owner's priorities,
2) An SRI calculation engine using the building features,
3) A cost database gathering all the possible smartness upgrades' CAPEX and OPEX,
4) An optimization engine determining the most cost-effective smartness upgrades adapted to the building features and the owner's priorities,
5) An interactive interface presenting the short list of the most cost-efficient smartness upgrades, among which the user can select the preferred ones.

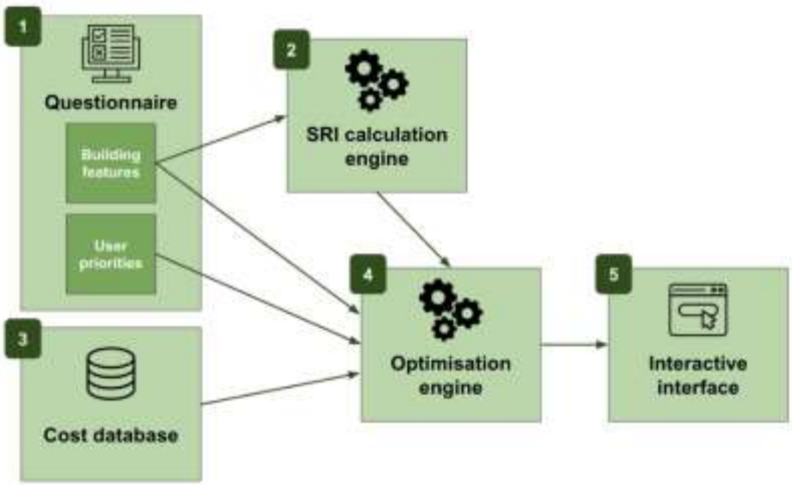


Figure 57. SRIA Components Diagram

At this stage of the project, the methodology is fully developed (including the user questionnaire), the cost database is partially populated, and the development of the optimization engine and interactive interface has started.

3.3.1. Objectives

The SRIA tool advances the state of the art by supporting users in prioritizing actions to improve their SRI score in a cost-efficient manner. SRIA simplifies the optimization calculations, providing clear recommendations to building owners. The cost database within the tool gives assessors a clear view of upgrade package prices in different regions, so they can suggest reliable estimates.
In comparison with state-of-the-art solutions such as easySRI Technical and Financial indicators for SRT[1] and SRI-ENACT Decision support tool for supporting decisions regarding the smart-ready upgrades[2], SRIA brings the following advances:

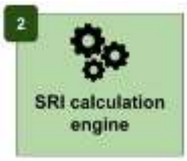
- SRIA includes data for the 56 SRI services defined in the generic SRI technical framework (method A and method B),
- SRIA's cost database covers 30 countries (EU27 + Norway, Switzerland and United Kingdom),
- SRIA covers the whole SRI scope (7 impact criteria), not limited to energy savings,
- SRIA considers real building characteristics and user preferences.

3.3.2. Methodology

A single questionnaire is developed to collect at once:

- **The building features needed to determine which smart-ready services apply to the building**. For instance, if the building has no cooling system, the services included in the cooling domain are not applicable and do not need to be assessed by the SRI engine. Similarly, if the heating system of the building counts one single gas boiler, the services related to heat pumps are not applicable, as well as the service related to sequencing in the case of different heat generators.
- **The building features needed to determine the cost of smartness upgrades**. For instance, the number of air-handling units will determine the cost of upgrading the ventilation system of the building; the number of rooms in the building will determine the cost of installing occupation detection sensors; the number of windows will determine the cost of upgrading the building envelop systems; etc.
- **Users' preferences in terms of smartness ambition and perspective**. Some building owners may want to level up the SRI class of their building by one, and others by two or more letters. Some may consider the SRI score overall, while others may want to improve more particularly one of the three key functionalities addressed by the SRI. If the user selects no specific preferences, by default the SRIA tool will propose users to level up the overall SRI score by one class at the lowest possible price.

The full questionnaire can be found in IS7 Annex 1 - SRIA questionnaire.



SRIA is equipped with a SRI calculation engine, developed according to the updated SRI calculation methodology (V4.5), to help the end user calculate the SRI score of the existing building. It makes use of the building features needed to determine which smart-ready services apply to the building, collected in the previously mentioned questionnaire. Based on the functionality level of each service, it calculates the SRI score of the building and the detailed scoring matrix.

The unit cost of smartness upgrades is needed for each smart-ready service and each functionality level (e.g., cost of installing thermostatic valves and cost of motorizing blinds). Within the generic SRI technical framework3, there are 178 pairs [service, upgrade] to be considered (56 services, multiplied by 2, 3, or 4 possible upgrades, depending on the number of functionality levels). For each of these 178 pairs, 3 cost components must be identified, the first two forming the CAPEX and the third one corresponding to the yearly OPEX:

- average price of the products enabling the upgrade,
- cost of the corresponding installation service, and
- in some cases, yearly operational and maintenance costs.

These cost components should be adapted to each of the **30 countries** targeted by the tool. Therefore, in total, the cost database to be built should have a size of 16,020 cost items, which need to be identified (178 x 3 x 30).
The following choices are adopted to reduce the size of the cost database:

- **Single upgrades enabling levelling up the functionality level of several services**: In practice, a single intervention can allow upgrading at once the functionality level of several services, typically those related to heating and cooling, or those associated with the presence of occupancy sensors. In this way, from the initial list of 178 pairs [service, upgrade], 33 pairs can be discounted. The list of upgrades considered by the SRIA tool, their links with smart-ready services functionality levels and the type of professionals needed to implement each action can be found in IS7 Annex 2 - Example of smartness upgrades implemented in the SRIA.
- **Geographical differentiation of installation service cost vs. single product cost**: Most products needed to upgrade smart-ready services are available at the EU level from international manufacturers and distributors. Therefore, in the cost database, for each product only one price is considered, applying to our 30 countries. National differences (e.g., taxes) are neglected. By contrast, the cost for the installation services of these devices is obviously different from one country to another. In order to build a consistent database, it has been decided to estimate this cost as follows:

Estimated number of hours needed to install the device in question	**x**	**Number of devices to be installed**	**x**	**Average hourly rate of a professional installer**
(same value for all buildings and all countries)		*(depends on the building's characteristics)*		*(depends on each country)*

Therefore, only the average hourly rate of a professional installer must be identified for each country. An estimation of these rates per country is calculated by using an average rate for a given country (e.g., France, where the R2M team is located), and by multiplying it with a country coefficient based on the average GDP per capita in order to derive hourly rates in the other countries.

- **Yearly operational costs**: As OPEX are not expected to be very significant, a flat OPEX rate is applied by default, corresponding to 5% of the CAPEX. In specific cases, for which OPEX are expected to be more expensive, specific research is conducted to identify the corresponding value.
- **Low-impact upgrades**: As demonstrated by a sensitivity analysis (see below), upgrading some services has a very low impact on the SRI score. Therefore, these upgrades are very unlikely to be short-listed by the SRIA, whatever their actual cost is. As a result, resources may not be wasted in assessing their cost with precision.

Concerning the **data sources for the cost database**, a combination of different sources is used to populate the cost database reliably: (i) desk research, (ii) collecting input from EVELIXIA's partners and (iii) conducting interviews with external market experts.

Starting from the SRI assessment of a building, the optimization engine seeks to identify, amongst all possible upgrades, the ones which have the lowest cost per % of improvement of the SRI score. In mathematical terms, the function F to be minimized is the following:

$$F = \frac{C}{I} = \frac{\sum_{n=1}^{N} \frac{C_n}{(1+r)^n} + C_0}{SRI_f - SRI_i}$$

Where:

- **C** is the total cost of an action aiming at improving the SRI score, with the following parameters:
- **N** represents the number of years during which the calculation applies; it can typically be the lifespan of the investment (e.g., 20 years);
- **r** represents a discount rate used to determine the present value of future cash flows (e.g., 3%);
- $\mathbf{C_n}$ represents the yearly costs in year n of the action (e.g., yearly operational expenditures or OPEX);
- $\mathbf{C_0}$ represents the cost of the initial investment (e.g., capital expenditure or CAPEX).
- **I** is the impact of this action on the SRI score expressed in percentage, calculated as the difference between the SRI score after this action is implemented ($\mathbf{SRI_f}$) and the initial SRI score ($\mathbf{SRI_i}$).

The calculation should be run several times to identify the optimal upgrades one by one to establish a short list of the most cost-efficient upgrades.

The outcomes of the tool include (see **Figure 57**):

- **A short-list of upgrades**, sorted by increasing order of their cost per % of improvement on the SRI score (most cost-efficient actions first). Via an interactive interface, the SRIA user (SRI assessor) should be able to choose the actions they wish to include in the upgrade package proposed to their client (the building owner or manager) to level up the SRI score of their building by one class. They may choose, if relevant in a specific situation, to skip an action even though it is in theory more cost-efficient than the next one.
- **For each upgrade**, their cost and their impact on the SRI score.
- **The overall resulting SRI score**, sub-scores per key functionality, impact criterion and technical domain, and the detailed scoring matrix.
- **An invitation to simulate different scenarios**, such as more ambitious upgrade packages (e.g., to level up the SRI score by two classes), or the focus on one of the three key functionalities of the SRI.

Figure 58. **SRIA output mockup**

3.3.3. Evaluation & Results

The complete SRIA tool, being still under development, has not been tested yet. However, a preliminary step has been achieved concerning the SRI calculation itself: a calculation structure has been designed to highlight **the impact on the SRI score of the upgrade of each service by one level**, which the usual calculation sheet[4] does not allow. This structure is fully in line with the description of the SRI calculation steps in Annex I of the Commission Delegated Regulation (EU) 2020/2155. As a result, a percentage is associated to each pair [service, upgrade].

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As illustrated at the Table 2, different shades of green allow quickly identifying the upgrades that have the higher impact; and in the last column, different shades of pink allow identifying the most impactful services (assuming the starting point is level 0 for all services, and the end point the smartest level). In this example, the three services with the most significant impact on the overall SRI score are H-1C "Storage and shifting of thermal energy" (10.4%), H-1a "Heat emission control" (8.6%) and MC-25 "Smart Grid Integration" (8.5%).

***Table 2.* Impact of each service upgrade for a residential building in Northern Europe, with a single boiler for heating, and no cooling system; assessment with method A; interest in the impact on the overall SRI score**

0

Applicability according to building characteristics	Domain	Code	Service	Expected impact 0 to 1	Expected impact 1 to 2	Expected impact 2 to 3	Expected impact 3 to 4	SRI score upgrade if service is improved from level 0 to the smartest level
	Heating	H-1a	Heat emission	2,8%	2,8%	1,7%	1,2%	8,6%
	Heating	H-1c	Storage and	5,2%	5,2%			10,4%
	Heating	H-2a	Heat generator	1,9%	1,9%			3,8%
Not applicable	Heating	H-2b	Heat generator					
	Heating	H-3	Report information	2,9%	0,3%	0,3%	3,1%	6,6%
Not applicable	Domestic	DHW-1a	Control of DHW					
	Domestic	DHW-1b	Control of DHW	1,8%	3,4%			5,3%
	Domestic	DHW-3	Report information	1,1%	0,3%	0,3%	0,7%	2,3%
Not applicable	Cooling	C-1a	Cooling emission					
Not applicable	Cooling	C-2a	Generator control					
Not applicable	Cooling	C-3	Report information					
Not applicable	Cooling	C-4	Flexibility and grid					
	Ventilation	V-1a	Supply air flow	2,4%	1,7%	2,4%	0,7%	7,2%
	Ventilation	V-6	Reporting	2,7%	1,0%	1,2%		5,0%
	Lighting	L-1a	Occupancy control	1,0%	1,0%	0,1%		2,2%
	Dynamic	DE-1	Window solar	1,1%	1,2%	1,9%	1,5%	5,6%
	Dynamic	DE-4	Reporting	0,5%	0,3%	0,3%	0,4%	1,5%
	Electricity	E-2	Reporting	1,5%	0,3%	0,3%	0,9%	2,9%
	Electricity	E-3	Storage of (locally	2,7%	2,3%	0,0%	2,3%	7,4%
	Electricity	E-11	Reporting	1,5%	0,3%	0,3%	0,9%	2,9%
	Electricity	E-12	Reporting	0,3%	0,8%	1,5%	1,4%	4,0%
	Electric	EV-15	EV Charging	0,2%	0,2%	0,2%	0,0%	0,6%
	Electric	EV-16	EV Charging Grid	2,2%	1,2%			3,5%
	Electric	EV-17	EV charging	0,8%	0,9%			1,7%
	Monitoring	MC-13	Central reporting	2,6%	1,8%	1,8%		6,3%
	Monitoring	MC-25	Smart Grid	4,9%	3,7%			8,5%
	Monitoring	MC-30	Single platform	1,3%	1,2%	1,2%		3,7%

The list of most impactful service upgrades mentioned in the previous example and the corresponding impact on the SRI score depend on each building. For a different climate zone, a different building type and different settings in terms of applicable services, the ranking of impactful upgrades will be different. However, it is likely that upgrading some services will be impactful in all cases; and upgrading some others might have a very little impact in all cases. This is why a sensitivity analysis has been conducted.

To do so, to always consider the same list of services, all services from the catalogue A or B are considered applicable (which is a virtual situation, as some services are mutually exclusive). The corresponding impacts of each service upgrade from 0 to the next level, up to the smartest ones is considered for 40 cases, each case being defined by: **(1) The focus chosen by the user** (4 possibilities): Impact on overall SRI score, or impact on one of the three key functionalities (efficiency, occupant, flexibility); **(2)The building type** (2 possibilities): residential or non-residential; **(3) The climate zone** (5 possibilities):

Northern Europe (NE), Western Europe (WE), Southern Europe (SE), North-Eastern Europe (NEE) or South-Eastern Europe (SEE).

- **Concerning method A (simplified service catalogue)**, upgrading services H-1a, H-2b, V-1a and MC-13 from 0 to the smartest level always have a high impact, for all climate zones and building types. Upgrading services H-1c, H-3, C-4 and MC-25 from 0 to the smartest level also have high impact in most cases. By contrast, upgrading services L-1a, DE-4, EV-15, EV-16 and EV-17 from 0 to the smartest level always have a very low impact on the overall SRI score, for all climate zones and all building types, even more so for incremental upgrades from level 0 to level 1, level 1 to level 2, etc. As a result, it is quite unlikely that upgrading these services will be advised to level up the overall SRI score - except if all other services already score very high or if these upgrades prove to be extremely cheap.
- **Concerning method B (detailed service catalogue)**, the list of service upgrades with the highest impact is also quite stable. Indeed, upgrading from 0 to the smartest level the services H-1a, H-2b, H-2d, H-3 and H-4 in the heating domain, and MC-3, MC-4, MC-9 and MC-13 in the monitoring & control domain, always have a high impact, for all climate zones and building types. Upgrading services H-1b and H-1f from 0 to the smartest level also have high impact in most cases. By contrast, upgrading services H-1c, H-1d, H-2a, C-1c, C-1d, C-1f, C-2a, C-2b, C-3, V-1c, L-1a, DE-2, DE-4, EV-15, EV-16 and EV-17 always have a very low impact (< 1%) on the overall SRI score, for all climate zones and all building types. As a result, it is quite unlikely that upgrading these services will be advised to level up the overall SRI score - except if all other services already score very high or if these upgrades prove to be extremely cheap. Finally, there is a significant difference in the impact of upgrading services in the electricity domain depending on the building type (residential or non-residential).

The detailed results of the sensitivity analysis are presented in IS7 Annex 3 - Sensitivity analysis for the SRIA.

Concerning the evaluation of the performance of the SRIA tool, the following indicators will be used:

- Average number of actions listed to level up the SRI class by one,
- Average number of professionals needed to level up the SRI class by one,
- Average cost efficiency of the proposed upgrade package to level up the SRI class by one (unit: €/ sqm / % of SRI score increase).

In addition, the following aspects will be assessed:

- User-friendless, evaluated using the System Usability Scale (SUS) score, described in the D1.5.

3.3.4. Next Steps

The development of the first prototype of the SRIA tool will be implemented according to the following schedule:

- The development of the functionality for calculating the SRI score upgrade per functionality level includes the creation of a dataset indicating the upgrade impact per case, as well as the implementation of filtering algorithms and tool features to guide the end user toward the most optimal actions. A first complete version of the above is expected by M20.

- In parallel, the calculation of costs per recommendation requires both the development of the cost database and the implementation of functions to enable cost estimation based on building characteristics. Both functionalities are expected to be completed by M22. The cost database will be periodically updated with data related to technical equipment and labor costs, as this is an ongoing task that will continue until the end of Task 4.2 (M34).
- The user interface is a key component, reflecting the core functionalities of the tool's engine. Therefore, its development will proceed in parallel with the back-end development. A first version is expected by M22 and will be periodically updated in line with progress on the core functionalities.
- The testing phase will begin after M22, during which the SRIA tool prototype will undergo thorough testing by R2M. Feedback loops will be established with CERTH's development team to ensure iterative improvements. Testing will cover a variety of building types, ranging from simple to complex, culminating in the evaluation of the tool at the EVELIXIA pilot sites in Spain and Denmark.

3.4. Proactive Demand Planning (IS9)

Energy demand in buildings has steadily increased over the years, necessitating advanced strategies to ensure energy efficiency and cost savings while maintaining user comfort. Proactive demand planning plays a crucial role in balancing electricity consumption, mitigating demand peaks, and optimizing energy usage in a way that benefits both end-users and energy providers. By strategically shaping energy demand ahead of time, buildings can reduce dependency on costly peak-hour electricity, enhance renewable energy integration by promoting self-consumption, and contribute to grid stability. Additionally, maintaining thermal comfort can be achieved by leveraging user-defined preferences or extrapolating historical comfort behavior, ensuring that demand adjustments align with occupant needs.

The proactive demand planning service (IS9) is designed to reshape day-ahead electricity demand providing user-based recommendations, ensuring an optimized balance between energy savings and user comfort. The tool will be responsible to reshape the aggregated building demand for the day-ahead, based on i) the different expected OPEX from multiple cross-vector energy systems' operating conditions (e.g., boilers, multiple type of heat pumps, solar thermal collectors, PVs and storage technologies), ii) the forecasted energy prices (historical data retrieved from relevant databases e.g., ENTSO-E APIs), iii) the forecasted aggregated demand flexibility (considering convenience) - based on the Flex Forecaster module output, and iv) the forecasted local RES/storage profiles; iv) the selected user comfort preferences; Unlike traditional demand response methods that react to grid signals, this approach anticipates energy needs and adjusts consumption patterns accordingly. This enables buildings to shift demand intelligently, avoiding high-cost periods and reducing unnecessary energy expenditure while sustaining indoor thermal comfort levels. A key component of this service is its ability to evaluate cost-benefit trade-offs at the building level. By leveraging cost-benefit matrices, the system ensures that energy efficiency measures do not compromise user satisfaction or operational needs. This approach fosters a more resilient and adaptive energy management strategy, making buildings not just passive consumers, but active participants in energy optimization.

3.4.1. Objectives

The main objectives of IS9 within the EVELIXIA context are:

- Sustaining thermal comfort for building occupants while reshaping electricity demand.
- Maximizing energy efficiency by leveraging flexibility in electricity consumption.
- Reducing monetary costs by avoiding peak-hour electricity charges and optimizing energy usage.
- Enhancing the integration of renewable energy sources by aligning demand with availability.
- Encapsulating and providing cost-benefit evaluations to ensure optimal trade-offs between cost savings and comfort.
- Alleviate the optimization problem by incorporating cost-benefit matrices while also enhancing the transparency and interpretability elements of the adopted intelligent solution.

These objectives aim to establish a proactive, cost-effective, and user-centric energy demand planning service at building level, ensuring that energy savings do not come at the expense of occupant well-being.

3.4.2. Methodology

IS9 considers the development of a proactive demand planning service, responsible for day-ahead demand reshaping based on novel episodic RL methods by CERTH and cost-benefit matrices by UNIGE to enable energy cost-savings without jeopardizing energy efficiency at building level.

3.4.2.1. Cost benefit matrices

The Cost/Benefit Matrices are built to summarize and easily represent the cost associated to the operational expenditure including the effect of flexibility margins on the real components off-design performance in order to provide the RL agent with thermodynamically accurate information including non-linear ones. Moreover, those matrixes can be used for an easy representation of the cost, that after the RL agent execution can be used for debug and verification by not expert, providing an element of transparency of the calculation, increasing the user acceptance. An example of off-design behavior, that should be taken into account when solving the optimization, is related to the HVAC systems as function of two parameters: ambient temperature and relative load, is presented in **Figure 59**.

In order to implement the cost Benefit Matrices two kind inputs are required daily internal and external:

Internal: Cost Optimized Base Line [1,24] from IS3 and Updated Flex Constraints [2,24] from IS4 (i.e. the vectors of hourly $f_t^{up}$and f_t^{down}. Those values are fitted within a [2n+1,24] constant size matrix, created by dividing the admissible load variation into the same number of n points for both flexibility directions and made non dimensional based on the BL value. So for each hour the existence space of admissible solution will be, expressed as with Matlab syntax:

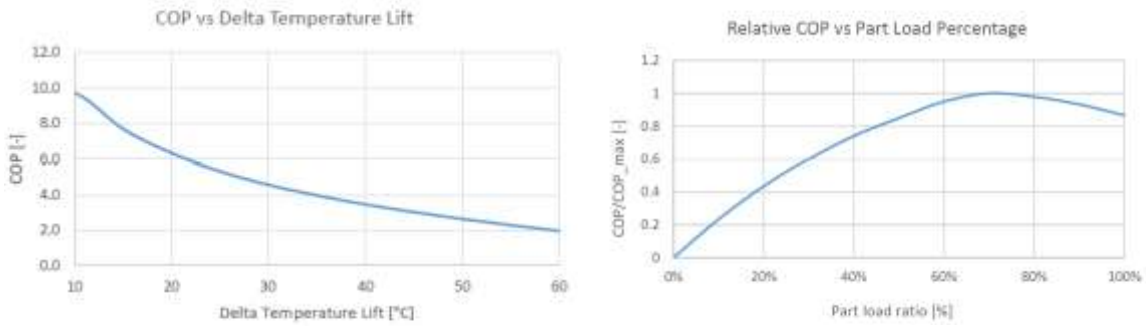

Figure 59. Example of the effect of temperature lift (left) and relative load (right) on the Coefficient of Performance of a Heat Pump

$$[f_t^{up}:\frac{(f_t^{up}-BL)}{n}:BL; BL+\frac{(BL-f_t^{up})}{n}:\frac{(BL-f_t^{up})}{n-1}:f_t^{up}]/.BL$$

This matrix of investigated space is then reflected into the output effect evaluated as the super position of the effect of the m-th appliances (e.g. HVAC, White Goods) that are involved in the optimization. The results matrixes provides: efficiency values, consumption effect as energy (kWh) or expenditure (€), and environmental impact as CO_2 Emissions. The effect of each element remain available for future investigation.

External: Price tariffs (time series). These are the energy consumption prices for each country based on the Entsoe API, which are better discussed in the next paragraph.

3.4.2.2. Day-Ahead Retail Energy Prices

Implicit Demand-Side Flexibility depends on the access of customers to market-related retail pricing. Electricity retailers, including default providers, should offer price plans that allow consumers to choose hourly, or where applicable shorter time-interval pricing, that reflect the actual market conditions and create incentives for consumers to align their demand with system conditions. According to [10], in 2019, only eight countries have implemented dynamic electricity prices: Denmark, Estonia, Finland, Norway, Spain, Sweden, The Netherlands and The United Kingdom. However, Directive (EU) 2019/944 of 5 June 2019, on common rules for the internal market for electricity and amending Directive 2012/27/EU, introduces new provisions that entitle all final customers who have a smart meter installed to conclude a dynamic electricity price contract so a wide application is expected.

Actual analyses rely on Electricity Wholesale price, as retrieved day ahead from ENTOSE via API. This represents a pure dynamic price where no impact of fixed mark-up or cost and proportional taxation (i.e., VAT) is present. The first element increases the average price without affecting the distance among peak and valley prices. This reduces the percentage impact of the savings with respect to the whole energy cost. The latter effect, a proportional increase, even maintaining the same average price of electricity, increases the absolute difference between peak and off-peak energy prices, magnifying the impact of Implicit Demand-Side

Flexibility including the usage of Storage. For this reason, the data of Eurostat based on semester excluding and including taxes and levies were retrieved to setup the scenario analysis for different EU countries.

3.4.2.3. Proactive Demand Planning using RL

A Markov Decision Process (MDP) is a mathematical framework for decision-making under uncertainty, where an agent interacts with an environment to maximize cumulative rewards. An MDP is defined by the tuple $M = (S, A, P, R, \gamma)$, where $\boldsymbol{S}$ is the state space representing all possible states of the environment; $\boldsymbol{A}$ is the action space representing the set of all possible actions an agent can take; $\mathrm{P}(s' \mid s, \alpha)$ is the transition probability function, defining the probability of moving from state s to state s' given action α; $R(s, a)$ is the reward function, which gives a numerical reward for taking actionα in state s; $\gamma \in [0,1]$is the discount factor, which determines the importance of future rewards; At each timestep t, the agent: observes a state $s_t \in \mathrm{S}$, then selects an action $a_t \in \mathrm{A}$ and based on that action receives a reward $r_t = R(s_t, a_t)$ and finaly transitions to a new state $s_{t+1} \sim \mathrm{P}(s' \mid s_t, a_t)$. The agent's goal is to learn a policy $\pi(\alpha|s)$ that maximizes the expected cumulative reward $J(\pi) = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)]$.

The state space consists of all relevant variables that define the current status of the environment and for the energy management problem, the state space is given by the following state vector $s_t = [P_t \quad B_t \quad U_t \quad D_t \quad P_{t+1} \quad P_{t+2} \quad \cdots \quad P_{t+23} \quad RD_t]$, where P_t is the electricity price at time t, B_t is the baseline consumption at given time t, U_t and D_t are the upper and lower flexibility bounds respectively defining the acceptable consumption ranges sustaining thermal comfort preferences, $P_{t+1:t+24}$ are the price predictions within the day since those values are available under a day ahead pricing concept and RD_t defines the remaining energy demand to be balanced offering the residual of pre and post demand management operation or the residual between the recommended decision/action and the baseline consumption profile as an alternative conceptual representation of energy balance. Note that all states are normalized. From the action space point of view, the action space defines the possible decisions the agent can make and for the energy optimization problem, the action a_t is the recommended energy consumption profile at each timestep such that $a_t \in \mathbb{R}$which is the normalized adjustment to energy consumption, i.e.,$a_t \in [0,1]$and the action should be preferably bounded by flexibility constraints to sustain thermal comfort.

The reward function describes the defined objectives of the under-examination problem and its simplest form encapsulates thermal comfort and monetary cost as follows: $reward = -\{\alpha \cdot Energy + \beta \cdot Cost\}$ which practically unfolds the inherent trade-off between energy consumption and electricity bill through the two weighting factors. After exploring and evaluating different policies, the reward function is designed to incorporate a set of individual objectives like monetary cost reduction, residual demand minimization and maximization of flexibility bounds satisfaction:

$$R(s_t, a_t) = R_{residual}(s_t, a_t) + R_{cost}(s_t, a_t) + R_{flex}(s_t, a_t)$$

where the first penalty term is given by:

$$R_{residual}(s_t,a_t)=\begin{cases} par1\cdot\left|\frac{RD_t}{\sum_{t=0}^{23}B_t}\right|, RD_t>0\\ par2\cdot\left|\frac{RD_t}{\sum_{t=0}^{23}B_t}\right|, RD_t<0\\ 0, RD_t=0\end{cases}$$

where par1 and par2 are penalty factors and this term penalizes any residual energy balance at the end of the day, so t in this case is the final time step of the day, i.e., T^{last}=23. Residual demand at time t, denoted as RD_t, represents the **difference between the baseline energy consumption and the energy action taken by the agent** and it is given by: $RD_t = RD_t + B_t - a_t$. In respect to the second penalization order, its form is given by:

$$R_{cost}(s_t,a_t)=\begin{cases} par3\cdot\left(\frac{a_t-D_t}{\sum_{t=0}^{23}B_t}\right)^2, P_t>\frac{1}{6}\sum_{k=t}^{t+6}P_k\\ par4\cdot\left(\frac{a_t-U_t}{\sum_{t=0}^{23}B_t}\right)^2, otherwise\end{cases}$$

where par1 and par2 are still design parameters and this penalty term prompts the agent to consume the least amount of energy if current price is higher than the expected one in the near future intraday (mean of next 6 hours), otherwise produces a recommendation closer to the upper flexibility bound to extrapolate the lower current price in respect to the expected one within the predefined horizon. Note that the horizon is also a design parameter and in practice affects the response speed of the agent since the price profile of the day based on the possible fluctuations formulate this behaviour. Carefully adjustment is needed for the future implementations and it is possible to have different horizons for individual inter-country cases based on the trends that emerge in different regions. Regarding the third penalty term:

$$R_{flex}(s_t,a_t)=\begin{cases} par5\cdot\left(\frac{a_t-U_t}{\sum_{t=0}^{23}B_t}\right)^2, a_t>U_t\\ par6\cdot\left(\frac{a_t-D_t}{\sum_{t=0}^{23}B_t}\right)^2, a_t<D_t\\ 0, D_t\le a_t\le U_t\end{cases}$$

where again par5 and par6 are design parameters. Note that the similarity in the mathematical formulation of $R_{cost}(s_t,a_t)$and $R_{flex}(s_t,a_t)$ arises from the shared principle of penalizing deviations from an optimal energy consumption level. However, each term serves a distinct purpose in guiding the agent's decision-making:

1. $R_{cost}(s_t,a_t)$ **– Incentivizing Cost-Efficient Energy Consumption**
    - This term encourages the agent to **adjust its consumption based on predicted price trends**.
    - If the **current price is high** compared to the expected average over the next six hours, the agent is penalized for consuming too much and should **reduce consumption** (closer to D_t).
    - If the **current price is low**, the agent is encouraged to **consume more** (closer to U_t) to exploit the economic benefit of lower electricity costs.
    - The penalty is **quadratic**, meaning **larger deviations** from the suggested optimal consumption result in **greater penalties**.

2. $R_{flex}(s_t, a_t)$– **Ensuring Flexibility Constraints Are Respected**
   - While $R_{cost}(s_t, a_t)$ incentivizes energy consumption adjustments based on pricing, $R_{flex}(s_t, a_t)$ **enforces physical and operational constraints**.
   - The agent is **penalized** if it **exceeds the upper bound** U_t **or falls below the lower bound** D_t like adding an extra layer of penalization to guarantee that the agent will deviate within the preferred thermal comfort bounds.
   - This term ensures that energy recommendations are **feasible and do not violate thermal comfort preferences or grid constraints**.
   - The quadratic penalty form **acts as a strict deterrent**, reinforcing adherence to operational boundaries.

3.4.3. Evaluation & Results

In order to evaluate the performance of the proactive demand planning tool that is formulated using Reinforcement Learning, we utilised data from the Greek pilot as a proof-of-concept. More specifically, 5 consecutive days were used for training the adopted methodology and 1 day for testing. The under-examination period concerns heating-demand season with similar energy demands for the considered building. **Figure 60** presents the resulted performance of the proactive demand planning tool for an indicative day in a day-ahead setting. Notations of *Baseline*, *Up* and *Down* denote the predictions of baseline energy consumption and the corresponding flexibility bounds respectively. Note that these serve as input variables (states) for the RL formulated agent (in this example, those are simulated trajectories but eventually they will be the direct predictions given by IS3 and IS4 after integration part is done) alongside the pricing profile that is provided daily before midnight for the next day in country-level electricity markets. At later stages, the pricing profile will be formulated to be closer to the retail price that customers pay in electricity bills. However, even with the Entso-e day-ahead included prices, the rationale remains valid in demonstrating the functionalities of the developed tool. As it can be observed, the agent (*Decision*) provides a trajectory which recommends higher energy consumption during lower pricing periods of the day. Three primal metrics are measured in order to assess the energy efficiency consumption (this is the residual demand that shows the deviation of the total energy consumed for the day between decision and baseline), cost (this is the monetary cost as a direct projection of the electricity bill) and the thermal comfort deviation (this is to show how much is the thermal comfort penalization). **Table 3** shows the percentage difference between baseline energy consumption and the decision recommendation produced by the RL agent. Basically, the agent produced a day-ahead trajectory that consumes 1.31% less energy and 2.51% less costly in terms of Euros compared to the baseline. Lastly, there was penalization on thermal comfort bounds.

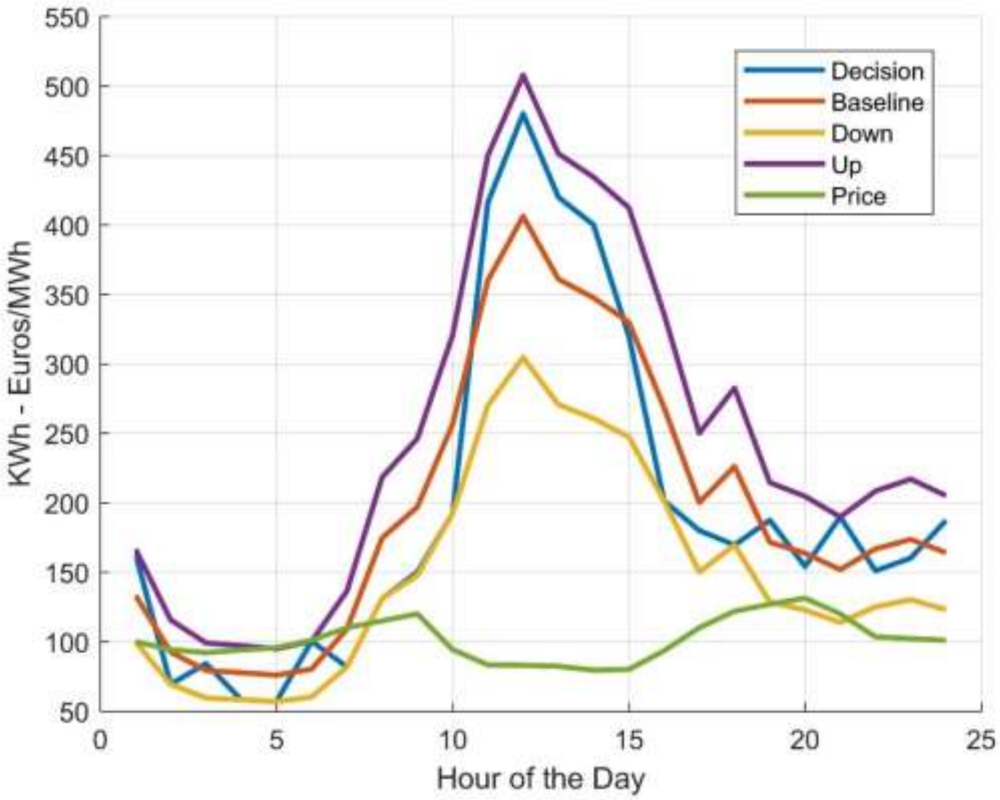

Figure 60. Proactive demand planning performance for an indicative day

Table 3. Resulted performance in terms of energy, cost and convenience metrics

Residual Energy	Monetary Cost	Thermal Comfort Deviation
1.31%	2.51%	0%

3.4.4. Next Steps

Building upon the current implementation of the Proactive Demand Planning tool, the next phase of development will focus on refining and expanding its capabilities to enhance decision-making, optimize trade-offs, and improve real-world applicability. The key directions for future work include:

- **Reward Function Reformulation**: The current reward function balances residual energy minimization, cost reduction, and flexibility satisfaction. To further refine decision-making, we will explore alternative weighting schemes that enable dynamic trade-offs among these objectives. This will allow for scenario-specific adaptations where energy efficiency, monetary savings, or thermal comfort constraints may take priority depending on user preferences, energy market conditions, or operational requirements.
- **Integration of Additional Pilot Data**: The current evaluation relies on data from the Greek pilot. Moving forward, we will incorporate data from other pilots, particularly leveraging simulation models from IS5, to assess the generalizability and adaptability of the RL approach across different

building types, climate conditions, and energy market structures. This will support the validation of the methodology across diverse scenarios.

- **Modification of RL with Cost-Benefit Matrices**: To enhance transparency and decision interpretability, we plan to integrate cost-benefit matrices into the RL framework. This will provide a structured way to quantify trade-offs between energy efficiency, cost savings, and thermal comfort deviation, ensuring that optimization objectives align with stakeholder priorities.
- **Utilization of Real-World Data**: While the current study relies on simulated trajectories, future iterations will incorporate real-world operational data from pilot buildings. This transition to real data will refine the RL agent's performance by capturing realistic variability in energy consumption, pricing fluctuations, and user preferences. It will also enable a more accurate assessment of practical implementation challenges.
- **Integration with Task 4.6**: The next phase will also focus on integrating the proactive demand planning tool within the broader framework of Task 4.6 (Integrated B2G and G2B Services Layer), ensuring alignment with the overarching energy management strategies.

These advancements will further strengthen the proactive demand planning methodology, making it more robust, adaptive, and suitable for real-world deployment.

3.5. Continuous Energy Performance Management (IS10)

3.5.1. Continuous Energy Performance Management (IS10a)

Modern buildings consume a significant portion of global energy, with heating, ventilation, and air conditioning (HVAC) systems being among the primary contributors. Achieving an optimal balance between energy efficiency, user comfort, and operational convenience remains a challenge due to the dynamic nature of building environments. Factors such as fluctuating occupancy patterns, external weather conditions, and varying user preferences make traditional rule-based or model-based control strategies less effective in real-world settings. To address these limitations, advanced control techniques that can adapt and optimize energy performance in real-time are essential.

The Continuous Energy Performance Manager Service (IS10) is designed to enhance building operations by implementing data-driven control strategies that optimize energy consumption while ensuring occupant comfort. By leveraging black-box policy optimization, the system learns from historical and real-time data to make intelligent control decisions without requiring an explicit physical model of the building. This approach enables a more flexible and scalable solution that can be deployed across diverse building types and configurations. Through automated adaptation, the system can continuously improve performance, reducing energy waste and operational costs while maintaining a high level of indoor environmental quality.

3.5.1.1. Objectives

The main objectives of IS10.a within the EVELIXIA context are:

- Optimizing building operations by implementing intelligent control strategies that enhance energy efficiency while maintaining user comfort.
- Employing black-box policy optimization to enable adaptive and self-learning control, reducing reliance on explicit physical models and improving scalability across diverse buildings.
- Minimizing energy consumption and operational costs by dynamically adjusting system settings in response to real-time conditions and external factors such as occupancy and weather variations.
- Integrating data-driven decision-making by leveraging real-time sensor data and historical trends to continuously refine control strategies and improve system performance.
- Supporting renewable energy integration by aligning energy consumption with the availability of on-site and grid-supplied renewable sources, maximizing self-consumption and reducing grid dependency.

These objectives aim to establish a proactive, self-adaptive, and cost-effective energy management service that ensures efficiency, comfort, and sustainability while reducing operational complexity in building systems.

3.5.1.2. Methodology

The Continuous Energy Performance Manager Service (IS10.a) utilizes a Black-Box Model Predictive Control (MPC) framework to optimize building system operations while balancing energy efficiency, user comfort, and convenience. Instead of relying on explicit physics-based models, IS10 employs a neural network-based system model trained on historical and real-time building data to predict future states, such as indoor temperature and energy consumption. These predictions allow the system to optimize control actions over a finite prediction horizon, ensuring proactive and adaptive decision-making. This enables an adaptive control strategy that accounts for uncertainties and complex building dynamics without requiring a manually developed mathematical model.

At each time step, the MPC controller collects the current state estimate from an estimator, which filters sensor measurements and handles missing data. The neural network model then forecasts the system's evolution based on the applied control inputs and external disturbances (e.g., weather conditions, occupancy). An optimization solver computes the optimal sequence of control actions while respecting system constraints, such as comfort limits and actuator restrictions. Only the first control action is applied, and the process repeats in a receding horizon fashion. This approach enables real-time adjustments to varying conditions, ensuring energy-efficient building operations while maintaining user-defined comfort preferences.
More specifically, the methodology follows a receding horizon control approach, as illustrated in **Figure 61**, where:

- Sensor measurements from the building (e.g., indoor temperature, energy consumption) are processed by an estimator to remove noise and handle missing data.
- The neural network model predicts the next system state based on current conditions, disturbances (e.g., weather, occupancy), and control inputs:

$$\hat{\boldsymbol{x}}_{k+1} = f_\theta(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k, \boldsymbol{d}_k)$$

where $\hat{\boldsymbol{x}}_k$ is the estimated state, $\boldsymbol{u}_k$ is the control action, $\boldsymbol{d}_k$ represents the external disturbances like weather conditions and occupancy profiles and f_θ is the neural network trained on historical and real-time data.

- An optimization solver determines the best sequence of control inputs by minimizing a cost function while satisfying system constraints:

$$\min_{u_0,\cdots,u_{N-1}} \sum_{k=0}^{N-1} \ell(\boldsymbol{x}_k, \boldsymbol{u}_k) + \ell_N(\boldsymbol{x}_N)$$

subject to:

$$\boldsymbol{x}_{min} \le \boldsymbol{x}_k \le \boldsymbol{x}_{max}, \boldsymbol{u}_{min} \le \boldsymbol{u}_k \le \boldsymbol{u}_{max}$$

ensuring that states and control actions remain within safe operating limits.

- Only the first control action u_0 is applied to the building, and the process repeats at the next time step, shifting the horizon forward.

This closed-loop control strategy allows IS10.a to dynamically adjust to variations in building conditions, occupancy patterns, and external disturbances, achieving efficient, real-time energy management. **Figure 61** visually represents this process, showing how the estimator, neural network model, optimization solver, and building system interact to form a continuous control loop.

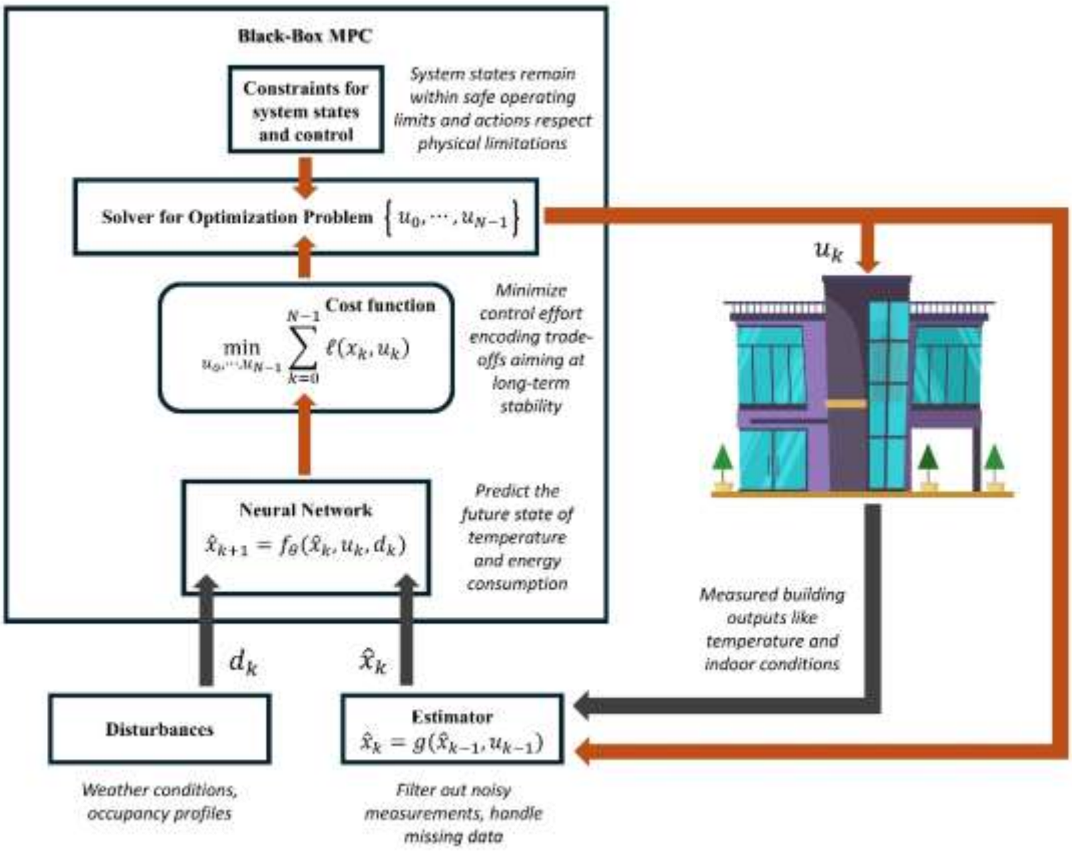

Figure 61. Black-Box MPC framework for building energy management.

The system continuously optimizes control inputs based on real-time sensor data, an estimator that refines state measurements, and a neural network model that predicts future states. An optimization solver determines the best control actions while respecting operational constraints, ensuring energy efficiency and user comfort.

3.5.1.3. Evaluation & Results

In order to evaluate the adopted approach, we use the hydronic heat pump model from BOPTEST environment. This testbed is a building with 192m^2 and includes a 15-kW air-to-water modulating heat pump which extracts energy from the ambient air to supply heat to the floor heating system The control signal is the heat pump modulation signal with range [0,1] dictating how much heating power the system provides. The cost function to be minimized becomes:

$$\min_{u_o,\cdots,u_{N-1}} \sum_{k=0}^{N-1} \left(W_1 \cdot s_k^2 + W_2 \cdot P_k \cdot pr_k + W_3 \cdot \Delta u^2\right)$$

Where s_k is the temperature deviation from the defined operational bounds, $P_k$is the electricity consumption, pr_k is the electricity price and W_1, W_2, W_3 are scalar weight factors. Note that this formulation encapsulates monetary cost, while a realization that prompts least energy usage could be $W_2 \cdot u_k$ excluding the direct connection with energy price. The last term penalizes oscillations on the change of control signal. Two streams of scenarios have been applied: the first represents a family setting with the corresponding occupancy profiles, while the second corresponds to an office work setting, as follows:

$$T^{family}(t) = \begin{cases} 21°C - 23°C, if\ 7{:}00 \leq t < 9{:}00\ (Weekday) \\ 18°C - 20°C, if\ 9{:}00 \leq t < 13{:}00\ (Weekday) \\ 21°C - 23°C, if\ 13{:}00 \leq t < 22{:}00\ (Weekday) \\ 17°C - 20°C, if\ 22{:}00 \leq t < 7{:}00\ (Weekday) \\ 21°C - 23°C, if\ 7{:}00 \leq t < 22{:}00\ (Weekend) \\ 17°C - 20°C, if\ 22{:}00 \leq t < 7{:}00\ (Weekend) \end{cases}$$

$$T^{office}(t) = \begin{cases} 17°C - 20°C, if\ 19{:}00 \leq t < 7{:}00\ (Weekday) \\ 21°C - 23°C, if\ 7{:}00 \leq t < 19{:}00\ (Weekday) \\ 17°C - 20°C, if\ 0{:}00 \leq t < 24{:}00\ (Weekend) \end{cases}$$

To further encapsulate the trade-off between thermal comfort deviations and monetary cost, we introduce the Weighted Bounds Penalty (%), which represents the average deviation from the defined comfort bounds. This metric is computed as the mean of the Upper Bound Deviation Mean (%) and Lower Bound Deviation Mean (%), effectively summarizing the overall deviation from the preferred thermal comfort range.

The Upper Bound Deviation Mean (%) quantifies how much, on average, the recommended energy consumption exceeds the upper flexibility limit set to ensure thermal comfort. Conversely, the Lower Bound Deviation Mean (%) measures the average deviation when the recommended energy consumption falls below the lower flexibility threshold, potentially leading to discomfort due to insufficient heating or cooling. Together, these two metrics provide insight into how well the control strategy maintains energy consumption within the predefined comfort range.

A lower Weighted Bounds Penalty (%) indicates that the control strategy better adheres to the predefined comfort constraints, minimizing deviations from the acceptable limits. A higher value, on the other hand, suggests greater deviations, implying that the control actions may not fully respect occupant comfort preferences. By incorporating this factor, the analysis provides a more interpretable assessment of the controllers' ability to balance cost savings with user comfort constraints. This allows for a more holistic evaluation of black-box MPC configurations across different prediction horizons and dominant trade-off objectives. The results indicate that configurations prioritizing comfort preservation generally exhibit lower Weighted Bounds Penalty (%), whereas those focused on monetary cost reduction tend to have higher deviations, reflecting the inherent trade-offs in optimizing energy consumption.

Table 4 and Table 5 present the comparative performance of Black-Box Model Predictive Control (MPC) and PID controllers under family and office occupancy profiles, respectively, for a 7-day testing period. The results showcase the trade-offs between total monetary cost (€/kWh), upper and lower bound deviations, and the weighted bounds penalty across different prediction horizons and optimization objectives.

Table 4. Performance comparison of Black-Box MPC and PID controllers under a family occupancy profile

Controller	N	Dominant Objective in a trade-off setting	Total Monetary Cost (€/kWh)	Upper Bound Deviation Mean (%)	Lower Bound Deviation Mean (%)	Weighted Bounds Penalty (%)
PID	-	-	56.21133461	1.546379334	0.377891052	0.962
Black-box MPC	12	Monetary Cost	**42.3799411**	**0.42278056**	0.860304355	0.642
	12	Comfort Preservation	43.85850917	0.465731612	**0.295795434**	**0.381**
	24	Monetary Cost	42.8216597	0.899254069	1.203720508	1.05
	24	Comfort Preservation	44.63397034	1.036208632	0.317788169	0.674
	48	Monetary Cost	42.86603132	0.599015822	1.388741299	0.995

Table 5. Performance comparison of Black-Box MPC and PID controllers under an office occupancy profile

Controller	N	Dominant Objective in a trade-off setting	Total Monetary Cost (€/kWh)	Upper Bound Deviation Mean (%)	Lower Bound Deviation Mean (%)	Weighted Bounds Penalty (%)
PID	-	-	57.03238467	1.373900464	0.259814341	0.817
Black-box MPC	12	Monetary Cost	**35.14754978**	**0.172165415**	1.939852886	1.06
	12	Comfort Preservation	38.88933668	0.201474917	0.402354007	**0.302**
	24	Monetary Cost	37.98396665	0.295603152	0.630709386	0.464
	24	Comfort Preservation	41.63770401	0.486369459	**0.130668254**	**0.309**
	48	Monetary Cost	40.42509569	0.564285574	0.304510056	0.435

The PID controller, included as a baseline, demonstrates higher total monetary costs compared to all Black-Box MPC configurations. The Black-Box MPC controller, evaluated under different prediction horizons (12, 24, and 48 steps with each step representing a 15-minute interval) and dominant objectives (monetary cost vs. comfort preservation), consistently outperforms PID in cost reduction while maintaining varying degrees of adherence to thermal comfort constraints. The dominant objective in a trade-off setting illustrates whether a particular configuration prioritizes monetary cost minimization or comfort preservation. As expected, configurations prioritizing monetary cost reduction tend to exhibit higher deviations from the comfort bounds, leading to an increased Weighted Bounds Penalty (%). Conversely, configurations focused on comfort preservation result in lower deviations but at the expense of slightly higher energy costs.

A comparison between **Table 4** and **Table 5** highlights the impact of different occupancy profiles on the control strategies. The family setting (**Table 4**) exhibits greater variability in deviation patterns due to more dynamic occupancy and energy demand fluctuations, whereas the office setting (Table 5) shows relatively lower deviations, likely due to more predictable and structured occupancy schedules. Overall, the results emphasize that the choice of prediction horizon and dominant objective significantly influences the trade-offs in energy cost and thermal comfort. The introduction of the Weighted Bounds Penalty (%) provides an abstract metric to quantify the comfort deviations, aiding in the assessment of optimal control strategies for different building usage scenarios.

The results presented in **Figure 62** and **Figure 63** compare the performance of PID and Black-Box MPC controllers under two different occupancy settings: family and office environments. Both cases utilize a 12-step prediction horizon (3 hours) with a configuration that prioritizes comfort preservation. In both scenarios, the Black-Box MPC demonstrates improved temperature regulation, maintaining indoor temperatures closer to the predefined comfort bounds while adapting control actions dynamically. The PID controller, in contrast, exhibits slower responsiveness and more deviation from the desired comfort range.

The heat pump control signals reveal that the MPC-based approach leverages predictive capabilities to adjust energy consumption proactively, avoiding unnecessary fluctuations and reducing control effort. The difference is particularly noticeable during transitions between heating cycles, where the MPC controller provides smoother adjustments compared to the more reactive nature of PID. An exception is observed during 5th day in the office case where the MPC approach produced high oscillation operation to thermal comfort bounds. In the family occupancy profile (**Figure 62**), variations in indoor temperature are more dynamic due to irregular occupancy patterns, leading to increased demand flexibility. The MPC controller effectively utilizes the available flexibility, reducing sharp deviations from comfort bounds. In the office occupancy profile (**Figure 63**), the environment exhibits more predictable energy demand. Here, the MPC approach maintains a stable and efficient control strategy, particularly during periods of lower occupancy, leading to smoother operation with fewer control variations. Overall, these results highlight the advantages of Black-Box MPC in balancing comfort preservation with energy efficiency, making it a more effective strategy than traditional PID control in dynamic building environments.

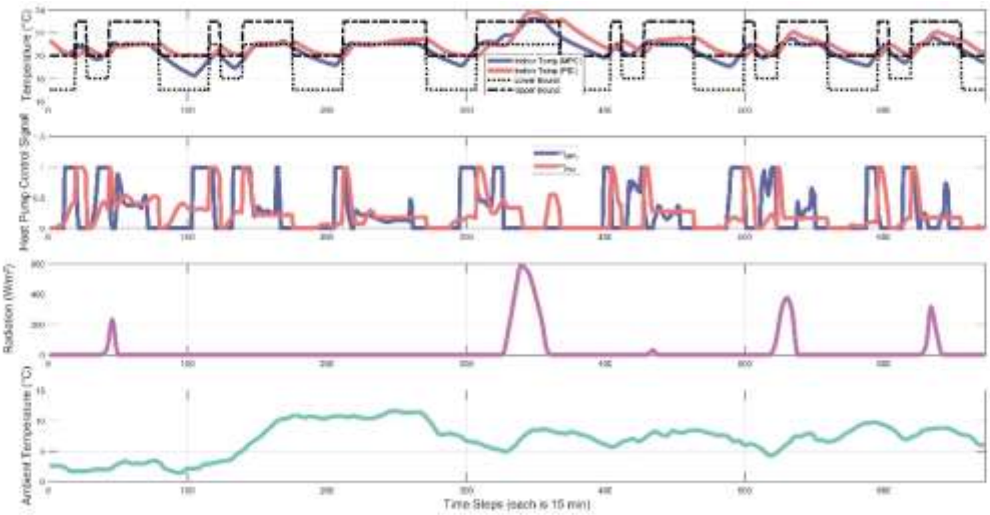

Figure 62. Comparison of PID {light red} and Black-Box MPC (12-step horizon, Comfort Preservation) {light blue}under a family occupancy profile.

The subplots present indoor temperature tracking, heat pump control signals, solar radiation, and ambient temperature variations. The MPC controller exhibits improved adherence to thermal comfort bounds while optimizing control effort.

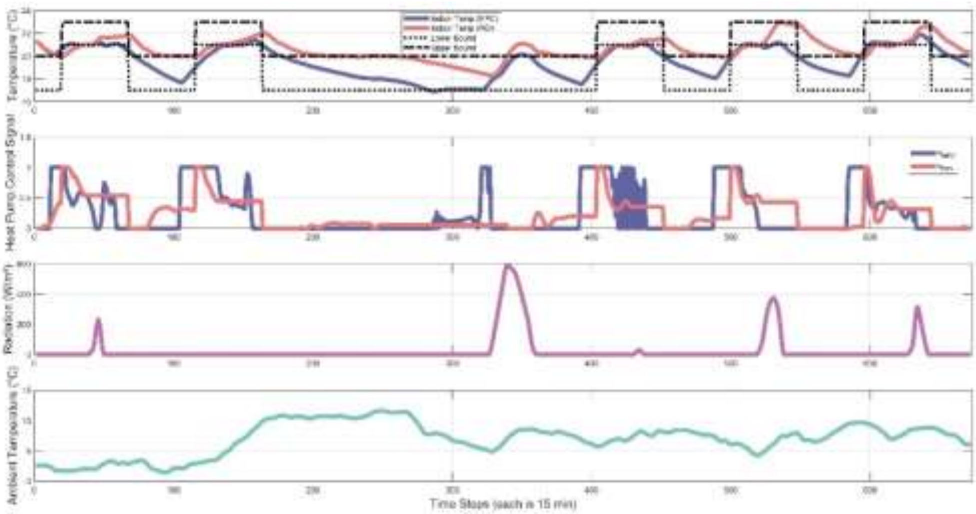

Figure 63. Comparison of PID {light red} and Black-Box MPC (12-step horizon, Comfort Preservation) {light blue} under an office occupancy profile.

The subplots depict indoor temperature tracking, control signals, solar radiation, and ambient temperature trends. The MPC controller shows improved control precision and responsiveness to external conditions compared to PID.

3.5.1.4. Next Steps

Future work will focus on enhancing the Black-Box MPC approach by refining its optimization framework and expanding its adaptability to different building conditions. A key direction is the integration of a simulation engine that emulates the behavior of pilot cases (from IS5), allowing for more representative training and testing environments instead of relying on publicly available testbeds. This will improve the controller's ability to generalize across different occupancy and energy demand scenarios while also to adapt on the actual pilot cases.

Additionally, the incorporation of real-world data from pilot buildings will further validate the model's performance under practical conditions, capturing dynamic interactions between occupancy patterns, HVAC operations, and external disturbances. The approach will also be aligned with Task 4.6, ensuring that the control strategy integrates seamlessly into the broader energy management framework.

3.5.2. HVAC Management System (IS10b)

The current innovative solution so-called IS10b is an original tool developed by CEA through the EVELIXIA project. Buildings can offer a degree of flexibility to connected energy networks (district heating and electric grid), such as load shifting, load shedding, thanks to their mass inertia, their RES capacity of production and the occupant's tolerance in term of comfort.IS10b developed by CEA dispatches the building's heating and air-conditioning power over the next two days, minimizing energy costs while respecting the thermal comfort of occupants, taking into account the evolution of energy prices, weather conditions and building activity.

3.5.2.1. Objectives

As part of the EVELIXIA project, CEA promotes a solution for managing the flexibilities of buildings and their heating and cooling systems over a few days ahead, depending on the specific use case to be run. This optimization tool, so called energy management system (EMS), requires an objective function to be implemented by users according to their own point of interest and the systems' features. The objective function may be, for example, to reduce the energy consumption as much as possible, to increase the share of Renewable Energy Sources (RES) in the necessary energy consumption or even, to reach the lowest energy cost over the period. The tool is built to compute the optimized trajectory under the constraint of ensuring the thermal comfort of the occupants. This tool also enables users to track the energy flow trajectories defined the day before by another optimization solution (such as IS9), if it exists, under the condition that it is fed with the optimized time series to be followed. The solution proposed by the CEA does not involve controlling the systems. It will produce outputs in the form of time series in .txt or .csg format and transmit them to the EVELIXIA platform. These results must be retrieved from the platform somehow and transformed into actions by operators in the field.

3.5.2.2. Methodology

The optimization core of the IS10b solution is implemented in a GAMS environment. It is based on a Mixed Integer Linear Programing (MILP) approach to ensure the optimum energy distribution of the HVAC and loads systems. CEA is used to developing and fine-tuning projects in this environment according to the wishes of its customers or partners. The necessary bricks around the optimization tool block were programmed in Matlab, specifically, the bricks dedicated to preparing the input data and to managing the dataflow.

The workflow in the IS10b solution is as follows:

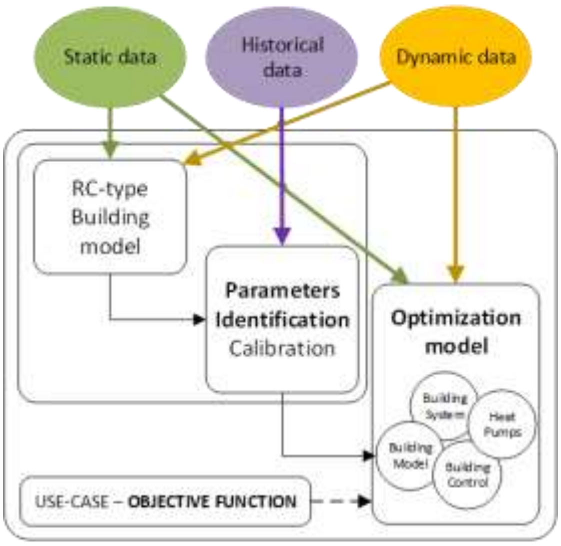

Figure 64.IS10b workflow

The IS10b solution relies on an electrical analogy RC-type model to simulate the thermal behavior of the buildings considered. The RC-type building model is based on the repealed standard ISO13790:2008, including 5 resistances and 1 capacity and several temperatures nodes θ_e, θ_{sup}, θ_{air}, θ_s, θ_m. The temperature nodes respectively denote the external temperature, the supply air temperature θ_{sup} that could be different of θ_e in case of energy recovering systems between fresh and exhaust air, indoor air temperature, star node temperature θ_s corresponding to the delta to star conversion and effective mass temperature θ_m representing the mean temperature of the building structure.

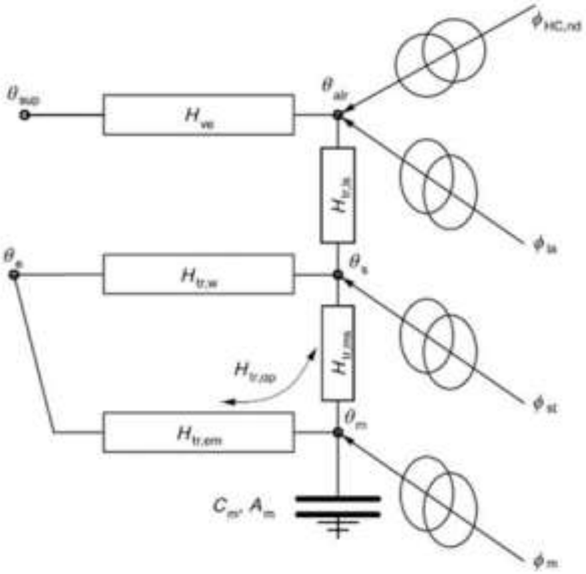

Figure 65. RC network heat flows (from abrogated std. ISO13790:2008)

In view of the RC building model, the IS10b solution also entails a program, as a second brick, dedicated to identifying the parameters H_{ve}, $H_{tr,w}$, $H_{tr,em}$, $H_{tr,is}$, $H_{tr,ms}$, C_m, A_m. The goal is to match the outputs of the building model to the measured air temperatures, considering the necessary measured inputs such as Φ_{sol}, Φ_{int}, $\Phi_{HC,nd}$ from which Φ_{ia}, Φ_{st}, $\Phi_m$are calculated. These six latter are the power flows representing respectively solar radiations on the total exposed external surfaces, internal heat gains distributed inside the building, heating/cooling power supplied to the building and the inputs deduced therefrom featuring the power flows transmitted to the indoor air temperature node, the star temperature node and the structure temperature node.

CEA designed the parameter identification tool based on the PSO (Particle Swarm Optimization) methodology that is powerful for estimating the optimum target although it does require some precaution in its handling and in parameter bounding. This calibration process of the model will be repeated as often as necessary to take into account the variations of building thermal behavior along the seasons and activities. Afterwards, the so-calibrated parameters are set into the optimization tool block. The EMS contains four different models that can be extended according to the scope of the use case and the assets considered (e.g. BESS, solar PV, loads):

- Building system model grouping the buildings under consideration into different groups and their relationship with the heat pumps involved (heating and cooling systems). This model ensures to comply with the energy matching balance at each building node and at each heat pumps node
- Building model based on repealed ISO13790:2008. The building model implemented in the optimization block calculates the power flow to ensure the air temperature target and thermal comfort.
- Building control model. This model deals with the strategy to control thermal comfort: manual or adaptive. It switches alternatively and automatically from one mode to the other.
- Heat pump model. The model can simulate any other types of heating or cooling systems as it is formulated on an energy efficiency ratio. It manages minimum and maximum power limitations. It can also consider limitations at the start-up and shut-down phases and consider fixed ramps to emulate the dynamic behavior of power variations. At this stage, there is no calibration of the heat pumps model, since heating and cooling systems are assumed to be well documented and maintained. That might be done in further developments.

According to what has already been mentioned, IS10b tool requires many inputs, static data, historical data, and dynamic data.

- Static data are gathering the information about buildings structure and thermal features, sizes including openings size and exposure, the power rate of heating, cooling, energy recovering systems and RES involved as well as the indoor air temperature set point and the ventilation air flow rate profile.
- Historical data supports the process of identifying the parameters of the building model. For instance, to identify the building's thermal characteristics, the RC-type model needs to be fed with solar radiation hitting the building's external surfaces at each time step. This recalculated data is expected from IS5 "Building Energy Modelling and Simulation".
- Dynamic data are used to feed the optimization model with forecasts and real-time information (indoor air temperature, energy market prices, air flow rate, weather, occupancy, load profiles, RES production if any, availability of HVAC systems).

IS10b optimization tool deals with the following flexibilities in terms of comfort:

- Indoor air temperature inferior gap profile.
- Indoor air temperature superior gap profile.
- Indoor air temperature set points depending on the comfort mode to be calculated and then applied (manual or adaptive).

Moreover, the comfort flexibility can be constrained by two additional parameters related to the variation limits of the air temperature set point:

- Indoor air temperature ramp up max.

- Indoor air temperature ramp down max.

It is relevant to notice that the building model can deal with the indoor air temperature as well as the indoor operative temperature, both at the end of each time step or for the mean value over each time step. The operative temperature is defined as the weighted average of indoor air temperature and radiative temperature from the inside walls (see the repealed ISO13790:2008). The two different weights to calculate the operative temperature are fine-tunable. For its part, the so-called HeatPumpMdl1 model is based on a thermal efficiency ratio approach. It encompasses the parameters as follows:

- Thermal power min: this is the lowest thermal power provided by the system.
- Thermal power max: this is the uppers thermal power provided by the system.
- Thermal start power max: this is the uppers thermal power that can be provided by the system at the starting stage.
- Thermal stop power max: this is the uppers thermal power allowing the system to shut down.

HeatPumpMddl1 model is also considering the thermal system inertia and dynamic with two additional parameters to be filled in:

- Thermal power increasing max.
- Thermal power decreasing max.

The heat pump model also emulates the type of emitters inside the building by considering this coefficient representing the convective part on total thermal exchanges from emitters (convective + radiative emissions).A run of IS10b is stepping as follows:

- Receiving the request from the building's owner, operator or user through the EVELIXIA platform.
- Getting the static and historical data from the EVELIXIA platform.
- Setting the parameters as regards the building model, building control model, thermal system.
- Identifying the thermal features of the buildings under consideration.
- Running the optimization computation.
- Collecting output time-series data on thermal and electrical power consumption for integration into the EVELIXIA platform and field application.

Each specific use case and asset requires CEA to discuss the objective function with the end-user.

3.5.2.3. Evaluation & Results

The IS10b test illustrated in the current section is not linked to any pilot site in the EVELIXIA project but it does represent a use case based on minimising the energy cost associated with the heating and air conditioning systems. This objective is well representing part of what EVELIXIA is striving to test and demonstrate.

CEA displays the IS10b results for a system of two buildings, with floor areas of 100 and 200 m²,respectively, building structure=medium and heavy according to the abrogated ISO13790:2008 (respective specific heat c_m = 165 and 260 kJ/m²) and two heating systems. The building #1 is heated by heating system #1 and the building #2 is heated by both heating systems #1 and 2. Each heating system has a power rating of 10 kW.

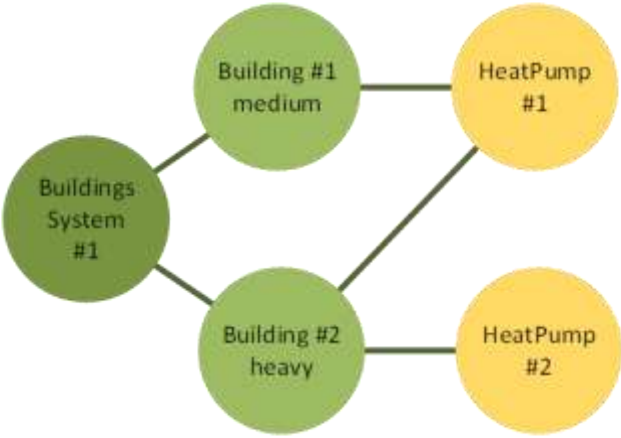

Figure 66. Demo's relationships between the buildings and heat pumps

Buildings features are the followings (all definitions in accordance with ISO13790:2008):

```
BuildingModel3_p_Af      = 100 * ones(1, Nbr_BuildingModel3_entities); % in m²
BuildingModel3_p_Af(1,2) = 200; % in m²
BuildingModel3_p_Atot    = 4.5*BuildingModel3_Params.BuildingModel3_p_Af;
BuildingModel3_p_Am      = 2.5 * BuildingModel3_p_Af; % Medium
BuildingModel3_p_Am(1,2) = 3 * BuildingModel3_p_Af(1,2); % Heavy
BuildingModel3_p_cm      = ones(Nbr_BuildingModel3_entities, N_TimeStep); % J/m²
BuildingModel3_p_cm(1,:) = (165000 / Wh_to_Joules); % Medium building structure
BuildingModel3_p_cm(2,:) = (260000 / Wh_to_Joules); % Heavy building structure
BuildingModel3_p_his   = 3.45 * ones(Nbr_BuildingModel3_entities, N_TimeStep);% W
BuildingModel3_p_hms   = 9.10 * ones(Nbr_BuildingModel3_entities, N_TimeStep);% W
BuildingModel3_p_H_em  =   90 * ones(Nbr_BuildingModel3_entities, N_TimeStep);% W
BuildingModel3_p_H_ve  =  100 * ones(Nbr_BuildingModel3_entities, N_TimeStep);% W
BuildingModel3_p_H_w   =  108 * ones(Nbr_BuildingModel3_entities, N_TimeStep);% W
```

In this experience, the last seven parameters have been chosen arbitrarily, but in the real performance of IS10b they must be identified thanks to the PSO methodology mentioned in the previous section. The weather time series comes from meteonorm database: LeHavre (France GPS cord.: 49.5 / 0.1).In this demonstration, solar radiations are those received at this GPS coordinates, on the level of ground without any calculation of the total radiations on each external walls and roof. It has been decided to rely on the building VE from IESRD to get this data for each time step. It will be applied in the coming month for the Greek and French pilot sites. Using the IS10b implies a previous stage to calculate the solar radiation received by the various building's areas depending on their orientation (see in section 3.5.2).

The first day of test horizon time is on December 21, 2050.

```
FirstDay_of_Horizon  = 21;
Month_of_Horizon     = 12;
Year_of_Data         = 2050;
```

1 hour is the time step, implying 72 steps time series to be handled and managed.

The internal heat gains are assumed to be known and fixed to: 200 W in each building for the demo.

For this test, the convective upon total emission coefficient is fixed as follows:

```
BuildingModel3_p_C1_ConvRadia= 0.5 * ones(Nbr_BuildingModel3_entities, N_TimeStep);
```

And the operative temperature is calculated respectively from the indoor air temperature and the internal wall surface temperature with the following weights:

```
BuildingModel3_p_C1_Theta_op = 0.3 * ones(Nbr_BuildingModel3_entities, N_TimeStep);
BuildingModel3_p_C2_Theta_op = 0.7 * ones(Nbr_BuildingModel3_entities, N_TimeStep);
```

The heating systems have been customized with these parameters in mind:

```
HeatPumpMdl1_p_COP_Heat        = 4*ones(Nbr_HeatPumpMdl1_entities, N_TimeStep);% Watt
HeatPumpMdl1_p_Pac_Heat_min       = 500*ones(1, Nbr_HeatPumpMdl1_entities);  % Watt
HeatPumpMdl1_p_Pac_Heat_max       = 2500*ones(1, Nbr_HeatPumpMdl1_entities); % Watt
HeatPumpMdl1_p_Pac_Heat_Start_max = 2500*ones(1, Nbr_HeatPumpMdl1_entities); % Watt
HeatPumpMdl1_p_Pac_Heat_Stop_max  = 2500*ones(1, Nbr_HeatPumpMdl1_entities); % Watt
```

These last two parameters are set at the same level as the power rating of the heating system. That means they have no impact on the thermal behaviour of the heat pump system during the optimization test. However, they can be between the Pac_Heat_min and the Pac_Heat_max, as a function of the considered heating system.

A horizon period of three days have been selected from the December 21, and the indoor air temperature set point is distributed as follows:
The temperature set points are corresponding to the indoor operative temperature aforementioned in section 3.5.2.

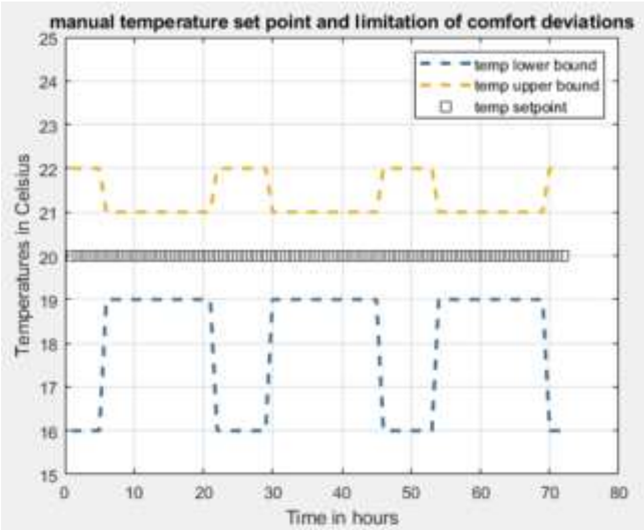

Figure 67.Operative temperature set point and limitations over the time horizon for the demo

The operative temperature manual set points were constrained between these two bounds:

```
BuildMod3Ctrl1_p_Theta_Manual_SetPoint_UB = 21 * ones(Nbr_BuildMod3Ctrl1_set, Nbr_Day_of_Horizon);   % Borne sup Consigneen mode manuel in Celsius

BuildMod3Ctrl1_p_Theta_Manual_SetPoint_LB = 20 * ones(Nbr_BuildMod3Ctrl1_set, Nbr_Day_of_Horizon);   % Borne inf Consigneen mode manuel in Celsius
```

For the current test, the initial indoor air temperature inside the two buildings is assumed to be 18 degrees Celsius when the primary indoor wall surface temperature is admitted to be 18.6 degrees Celsius.
In case of adaptive control mode, the temperature adaptive set points are compelled into the range of +2/-3 degrees Celsius around the gliding daily average temperature (see calculation in the RE2020 French regulation). Here it is relevant to mention that the gliding daily average temperature is calculated from the last height days.

As for the objective function, CEA programmed a cost function including the energy consumption over the period of three days in addition to the cost in term of discomfort represented by the gap between actual temperature and the set point. The electric energy prices in €/kWh and the prices of discomfort in €/K at are defined at each time step. For example, CEA has considered:

- 0 €/K when the actual temperature deviation is retained inside the tolerated range: between the upper and the lower bounds.
- 150 €/K when the temperature deviation is outside this admitted range.

For sure, the energy prices and comfort tolerances have to be defined with the support of the IS10b users (building owners, operators, occupants).

For the current demonstration of IS10b, CEA defined arbitrarily the electric energy prices:

```
BuildMod3Ctrl1_p_Theta_Manual_SetPoint_UB = 21 * ones(Nbr_BuildMod3Ctrl1_set,
Nbr_Day_of_Horizon);   % Borne sup Consigneen mode manuel in Celsius

BuildMod3Ctrl1_p_Theta_Manual_SetPoint_LB = 20 * ones(Nbr_BuildMod3Ctrl1_set,
Nbr_Day_of_Horizon);   % Borne inf Consigneen mode manuel in Celsius

% Prix achatelec :
Price_Elec              = 0.20 * 1e-3 * ones(1, N_TimeStep); % 0.2 €/kWh
%
Period_LowPrice_Elec       = [Periode3, Periode4, Periode6, Periode7, Periode9];
%
Price_Elec(Period_LowPrice_Elec) = 0.1 * 1e-3; % 0.1 €/kWh Low charge onto the grid
```

The following equations define the objective function to be tested:

```
eq_Cost_Elec(HeatPumpMdl1_set, k)
..
v_Cost_Elec(HeatPumpMdl1_set, k)
   =e=
      - p_Price_Elec(k) * HeatPumpMdl1_v_Pac(HeatPumpMdl1_set, k) * TimeStep(k)
;
*
eq_Obj_Cost
..
obj_Cost
 =e=
sum( (BuildMod3Ctrl1_set, k) , BuildMod3Ctrl1_v_Theta_CostGap (BuildMod3Ctrl1_set,
k) )
   +
sum( (HeatPumpMdl1_set,   k) , v_Cost_Elec                (HeatPumpMdl1_set,   k) )
```

The IS10b is up-and-running and the optimisation test is complete:

```
------------------ Status returned via gdx file --------------------
Solver Status : 1  -> must be equal to 1 for NORMAL COMPLETION
Model Status  : 8  -> see here : Model Status in Gams documentation
--------------------------------------------------------------------
Problem solved : in 36.042 seconds
```

The figures here after present the results of this IS10b test.

Figure 68 shows the indoor operative temperatures (end and average of time step) for the two buildings over the three-day horizon period. The operative temperatures are within the tolerance range.

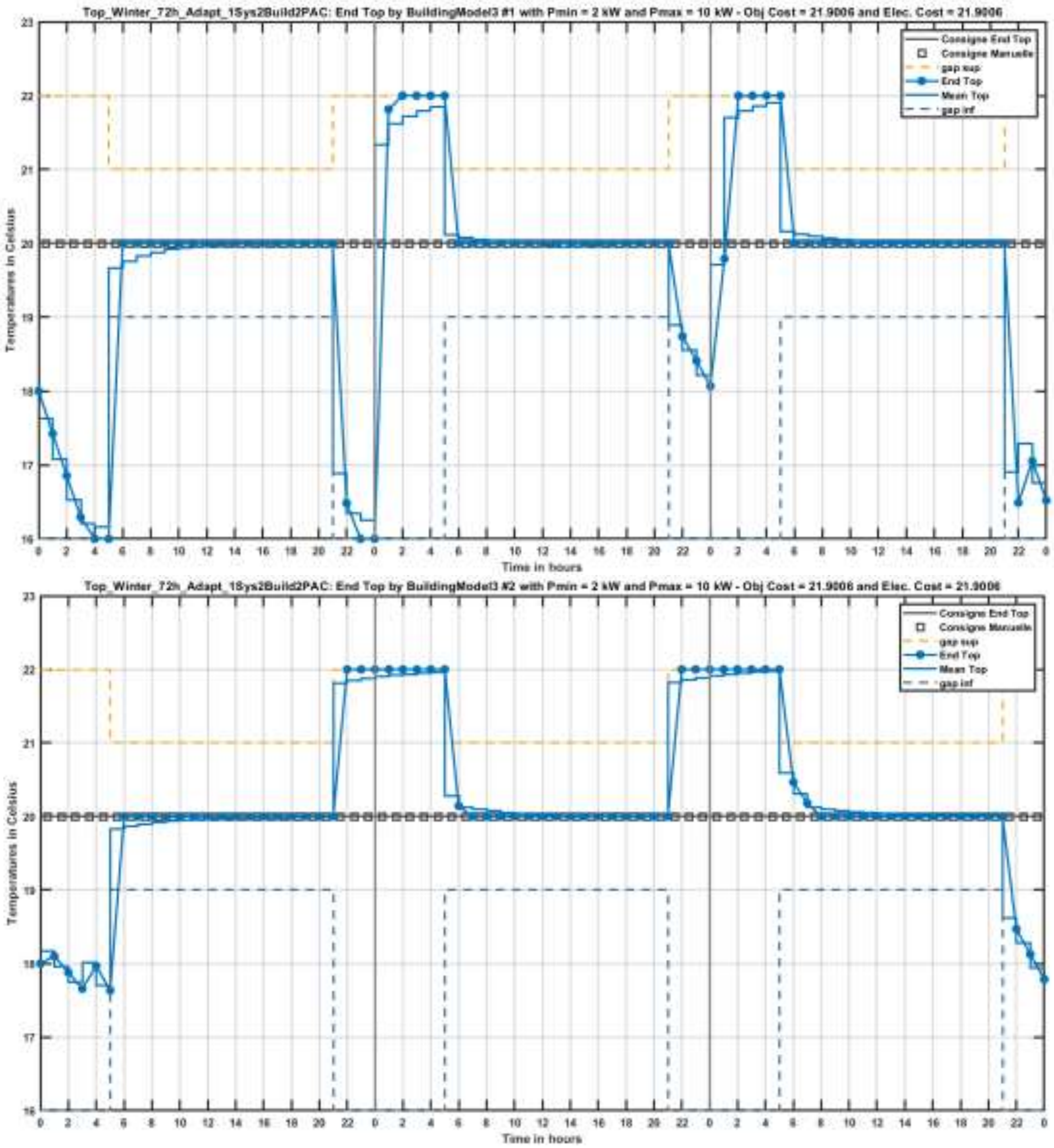

Figure 68. Operative temperature evolution after optimization by EMS

In addition, **Figure 69** illustrates the thermal power distribution from heating systems to the supplied buildings.

They also show the energy needs of the two buildings over the three-day horizon. As expected, building #2, which is larger and heavier than the building #1, anticipates the heating phases after the first day and the target temperature: 20 degrees Celsius. It requires higher peak energy when the energy prices are low, and lower thermal consumption at the end of days when electricity prices are still high.

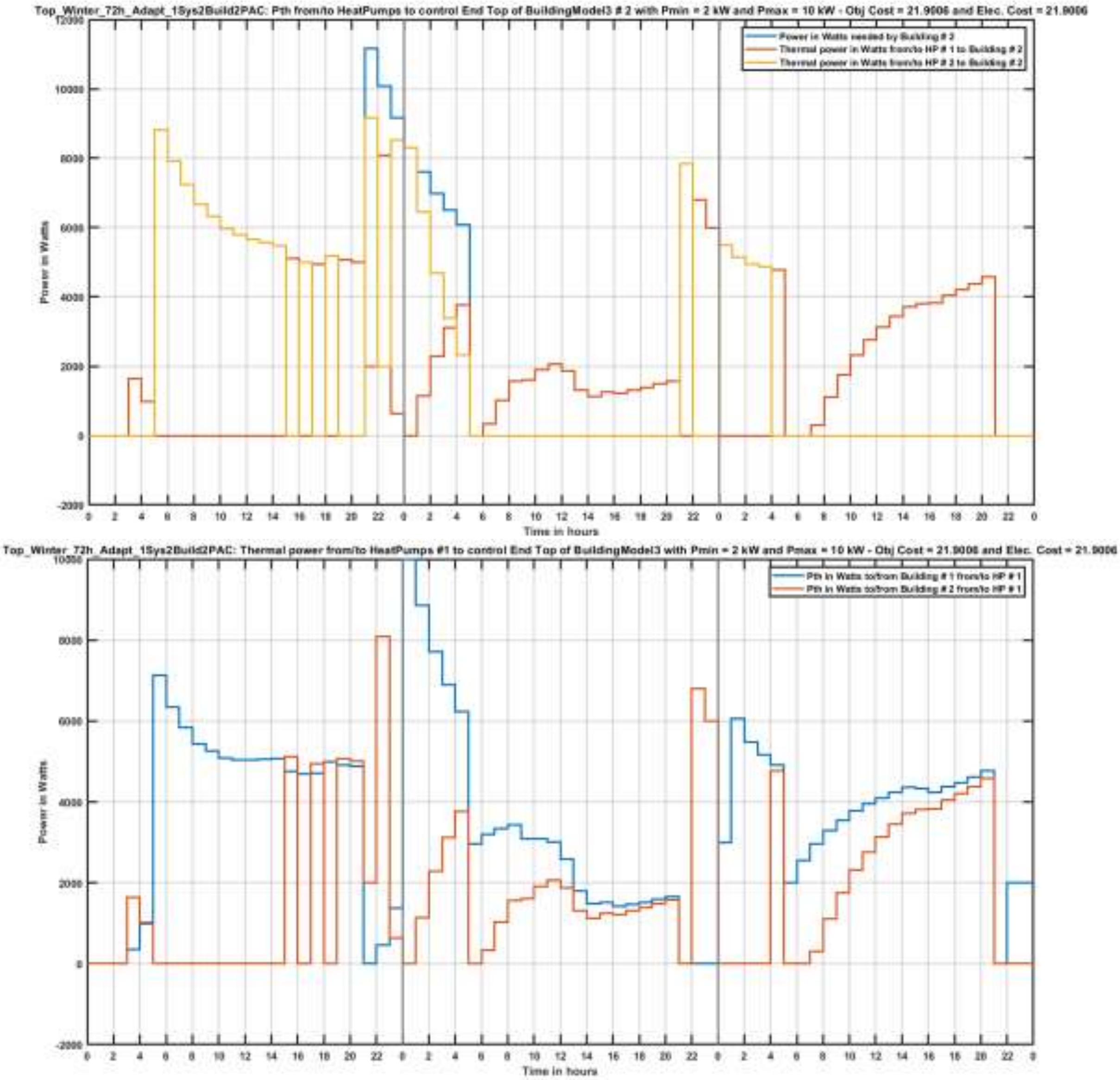

Figure 69. Distribution of heat power to buildings after optimization by EMS

The IS10b also calculates the electricity consumptions of the two heating systems under consideration to control the heating space air conditioning of the buildings. The optimized control of the heating systems discloses the priority of the heating system #1 when the heating system #2 is activated mainly to overcome the energy peaks required to heat the building #2.

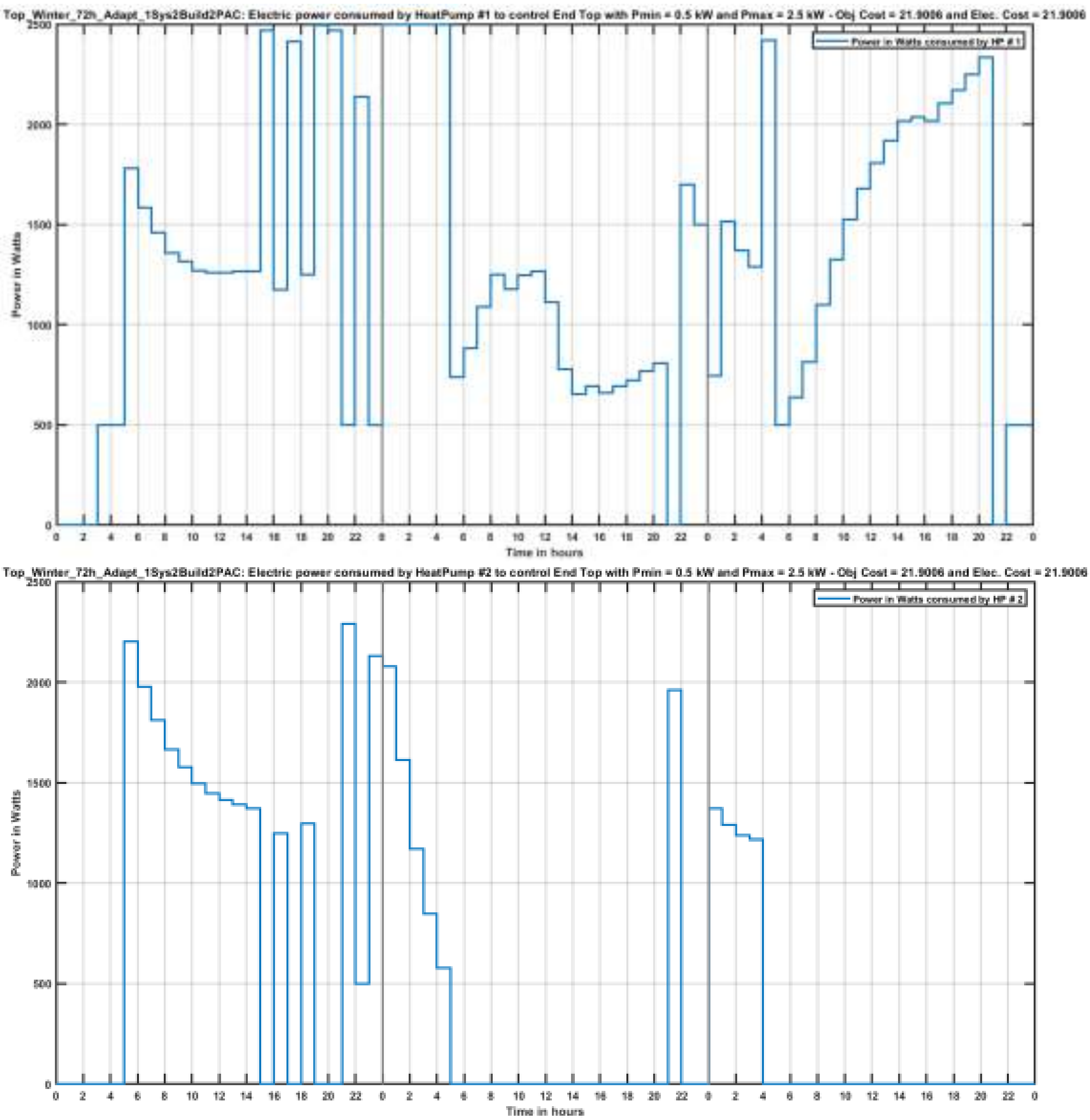

Figure 70.Power consumption of heat pumps for the demo

This section is intended to showcase the role of IS10b and the opportunity offered.

3.5.2.4. Next Steps

The ongoing task is to push this work on the CEA mOreGAMS simulation environment and to connect it to the EVELIXIA platform.
The IS10b can both be run to optimise the energy consumptions for space heating and air-conditioning or to follow intra-day the trajectory drawn the days before (from IS9 if any). Furthermore, it can also involve different loads (Hot water tanks, batteries, other loads related to indoor activities) or RES energy generation taking into account the variation of electricity prices induced.
CEA is now looking forward to connecting the IS10b solution to the interested pilot sites through the EVELIXIA platform. The input data are still required from other solutions (e.g. IS1, IS2, IS4, IS5, IS9, IS18).

3.5.3. Building Aggregator Service, BAS (IS10c)

The Danish pilot site, located in Aabenraa, Southern Denmark, is part of the Kolstrup Housing Association. This pilot site is the demo site for developing and testing the innovative solution Building Aggregator Service, BAS. The pilot focuses on typical Danish housing association buildings from the 1970s, which were renovated in 2015 with photovoltaic (PV) panels, batteries and EV charging stations. The BAS enables cross sector coupling between electricity and district heating and leveraging the flexibility in heating and hot water production in an apartment building block.

3.5.3.1. Objectives

The BAS is the tool to be developed to fulfil the following objectives:

- Maximize local consumption of electricity generated from local PV.
- Optimize local electricity usage based on variable local tariffs and electricity prices.
- Utilize PV electricity to power an electric heater installed in a domestic hot water (DHW) tank.
- Test concepts and business cases for exporting energy to the district heating (DH) grid.
- Collaborate with the Distribution System Operator (DSO) to explore optimized grid load management and reduce grid bottlenecks.
- Evaluate the potential for delivering balancing services to Balance Responsible Parties (BRPs) and the Transmission System Operator (TSO).

In Denmark the TSO Energinet is currently procuring balancing services from large power plants and aggregated combined heat and power plants. The TSO and DSOs are also trying to establish a market for grid stability. However, these services are predominantly provided major players, with no local models available for community-level aggregators. The BAS is a tool where energy flows can be controlled and optimized according to price signals and relevant constraints.

3.5.3.2. Methodology

The following work break-down has been established to develop and test the BAS:

- Retrofit of Evelixia components on Pilot site
- Setup device connection, data collection, control and management
- Develop API support
- Create Energy forecast
- Create flexibility forecast
- Create optimizer, define constraints
- Develop tenant app
- Develop operation GUI
- Develop watchdog

3.5.3.3. Evaluation and Results

In the following section the various steps in the above work breakdown will be further elaborated and the first results listed.

There are 2 use cases defined for the Danish Pilot Site

Table 6: Danish Pilot Site UCs

ID	Use Case	Description
UC-DK#1	Electricity Optimization on Building Level	Optimized operation of inverter, battery, and possibly consuming assets, to minimize cost of electricity.
UC-DK#2	Optimization of District Heating Consumption and Production	Optimized operation of district heating assets, including conversion of surplus electricity to energy for district heating network.

The following description is mainly focusing on Use Case 1, UC-DK#1 as this will be the first to be implemented.

Re: Retrofit of Evelixia components on Pilot site
Both technique room and apartment upgrades are planned. This is part of the pilot site Denmark setup and detailed described in EVELIXIA'sD5.3 (Pilot Implementation Planning and Preparations).

Re: Setup device connection, data collection, control and management
Evelixia pilot site operation is planned to use the Neogrid platform framework with the following architecture:

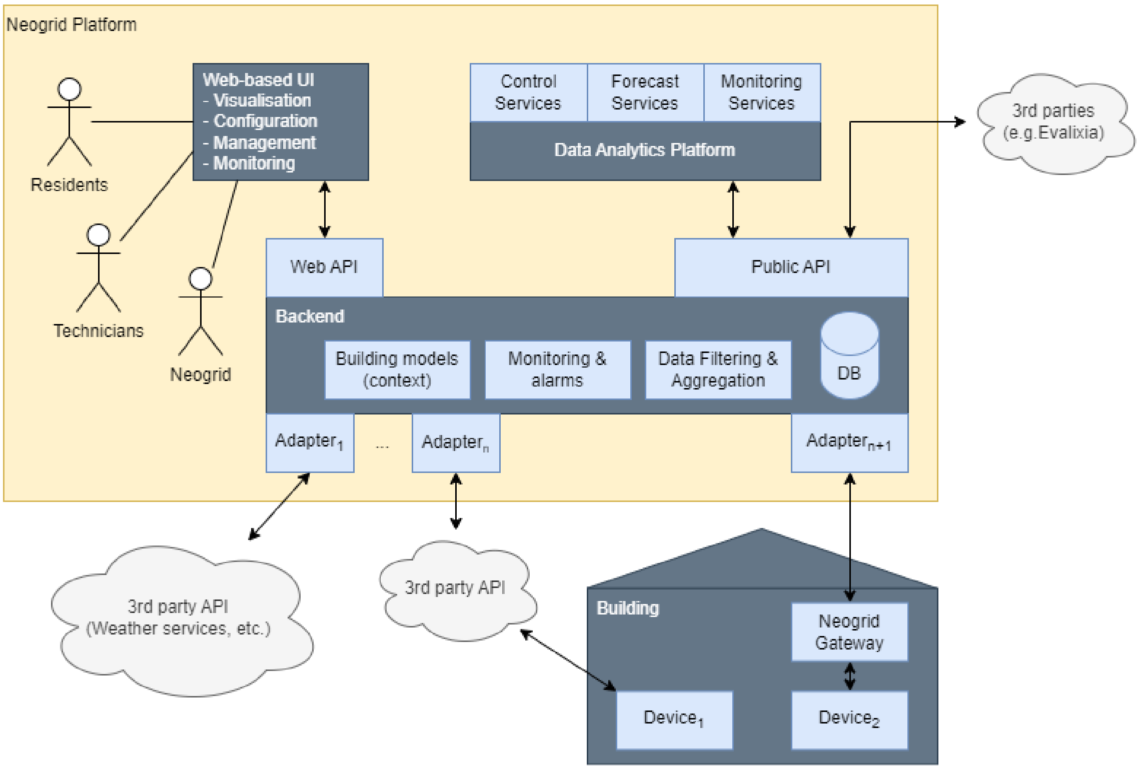

Figure 71. Neogrid platform framework

The main product running on Neogrids platform today is PreHEAT, a monitoring and control solution for energy installations in buildings. EVELIXIA plans to use the same connection between gateway and server as PreHEAT and this is shown below:

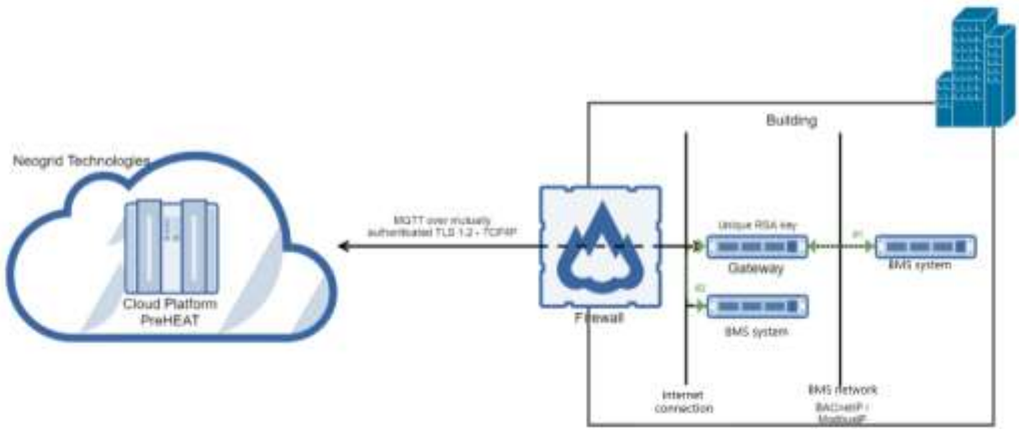

Figure 72. Connection between gateway and server

Re: Develop API support

Data on the cloud can be accessed by authorized users via an open web API based upon JSON. This API allows the following:

- Reading timeseries of measurements
- Reading of local weather data
  Sending setpoints to the controller (Forwarded by the gateway to the BMS system)

The specification of this public API is available on https://neogrid-technologies.gitlab.io/neogrid-api/. Moreover, a toolbox for Matlab and Python has been developed, which allows fast usage of the system without extensive prior knowledge of web API management, which can be found here: https://gitlab.com/neogrid-technologies-public.

Re: Create Energy forecast
Re: Create flexibility forecast
Re: Create optimizer, define constraints

Those steps here are part of the control for UC-DK#1. It can be further divided into activities before first control can be done, and then into daily and 5 minutes activities:

Initial activities before first start

- Setup data connection
  Connect electricity meters, PV battery and inverter
  Start collecting data
- Create energy forecaster
  Use hourly electricity consumption for buildings
- Define flexibility
  Operating range of battery
- Define constraints
  Battery size
  Battery charging and de-charging speed

Hourly activities

- Read future price data
  Hourly spot price
- Read battery status
- Estimate hourly energy consumption for coming day
- Optimize energy flow in- and out of battery

Instant interrupt activities

- Fallback operation of battery in case something unforeseen happens

Re: Develop tenant app

A tenant app will be developed and rolled out in the test buildings with features aimed at providing transparency, engaging tenants, and promoting efficient energy use. Here's a summary of the app's features:

- Apartment Data:
  Displays electricity and heating consumption, enabling tenants to monitor their usage.
- Price information & flexibility
  Provides information on electricity pricing and flexibility opportunities, helping tenants optimize their energy consumption.
- Nudging for Efficient Behavior
  Encourages tenants to adjust their consumption during periods of low prices and tariffs, while supporting co-sector coupling (e.g., between district heating and electricity).

Re: Develop operation GUI
This activity is to develop a GUI supporting the use case. The target is to support:

- Show actual status
- Show relevant KPIs
- Turn on and off application
- Adjust constraints

Re: Develop watchdog
This activity is to develop an independent program which checks the operation of the optimized operation.

3.5.3.4. Next Steps

For next steps (coming 6 months) the following activities are foreseen:

- Finalize first iteration of UC-DK#1
- Getting the retrofit installations on the two pilot sites done
- Setting up full data collection for all elements including api support
- Setting up specifications on tenant app and start development
- Further developing of UC-DK#2
    - Defining optimization criteria and constraints
    - Clarify DSO involvement
    - Clarify TSO and balancing services involvement
    - Clarify if DH connection will be real or simulated
- Securing data for other IS's to be tested out on the Danish pilot plant

The overall goal is to get as much functionality ready for heating season 2025/2026 and secure the Danish pilot plant delivers data to other IS's. IS10c is so far "only" intended to be used on the Danish Pilot plan.

4. CONCLUSIONS

This deliverable has presented the first version of D4.1, consolidating the outcomes of Tasks 4.1 and 4.2 within the EVELIXIA project, with a particular focus on enhancing building-to-grid (B2G) interaction through digitalisation and advanced control strategies. The work achieved under these tasks lays the foundation for a new generation of intelligent, autonomous building systems capable of dynamic participation in energy markets while ensuring energy efficiency, indoor comfort, and operational resilience.

Task 4.1 unfolded the development of building awareness and forecasting services formulating a comprehensive toolbox that integrates real-time sensory inputs, simulated data from the simulation environment engines, BIM-based static data and forecasting modules, to further enable accurate predictions of indoor air quality, energy demand, and flexibility potential, supporting both operational and strategic decision-making at the building level.

Task 4.2 introduced the autonomous building decision support framework, which builds upon the simulation and awareness capabilities of Task 4.1. Through the integration of reinforcement learning, multi-timescale model predictive control, and decision models, this toolbox offers intelligent support for tasks like day-added demand planning, real-time HVAC control and investment planning. This synergy enables compatibility with real time responses establishing the foundation for the next steps of integration with the real pilot cases, based on occupant needs, energy system dynamics and grid conditions.

Across both tasks, the development and preliminary implementation of Innovative Services IS1-IS7 and IS9-IS10 demonstrate the potential for cross-cutting and reliable solutions addressing key operational vectors: air quality, predictive analysis, energy flexibility potential, energy consumption forecasting, simulation of building behaviours in control responses, investment planning and control. The methodologies and tools described herein are designed for scalability and adaptability across building types. Nevertheless, successful deployment requires addressing several technical and operational challenges, including robust data integration, interoperability between services, and stakeholder engagement to support adoption and ensure relevance to end-user priorities.

Concluding, this deliverable serves as an important milestone in EVELIXIA's pursuit of smart and resilient building and district systems. It brings together state-of-the-art digital twin technologies, forecasting models, and autonomous decision support systems to create a unified and flexible platform towards next generation building energy management.

5. REFERENCES

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6. ANNEXES

6.1. IS6 Annex

6.1.1. Detailed list of KPIs

6.1.1.1. Lifetime Primary Energy Demand

The **Lifetime Primary Energy Demand (PED)**is a vital environmental KPI that measures the total primary energy demand of a project throughout its entire lifecycle. This KPI quantifies the energy used from raw material extraction to the operational and maintenance phases of the building or district. It provides a comprehensive overview of a project's total energy consumption and is essential for evaluating energy efficiency and identifying potential areas for energy savings.

The total PED is derived from two primary sources:

- Infrastructure (Product/Construction Stages) Energy Demand: This includes energy consumed during the production, transportation, and installation of building materials and components (Stage A of the component lifecycle). These energy requirements are considered embodied energy and are incurred when a component is installed for the first time.
- Operational & Maintenance (Stage B Use Stage) Energy Demand: This captures the energy used during the building's operational phase, such as for heating, cooling, lighting, and other energy-consuming activities. It also includes energy used for maintenance activities, including repair, replacement, and refurbishment of components.

The Lifetime PED is critical for assessing a project's long-term energy needs and efficiency. It helps stakeholders make informed decisions to optimize energy use, reduce reliance on non-renewable sources, and enhance overall sustainability.

The Lifetime PED is calculated in four versions, which include the total and average annual demand for the whole building, and the total and annual average demand per m^2 of useful building area. The basic equation for calculating the total building PE demand is:

$$L_{PE} = I_{PE} + \sum_{i=1}^{N} (O_{PE}^{[i]})$$

Where:

L_{PE} is the Lifetime PE Demand of the project;

I_{PE} is the Infrastructure (embodied) PE Demand;

$O_{PE}^{[i]}$ is the Operational PE demand of the building's components in year i.

As in the case of GWP, the equations for the per m² and annual averages are given by:

$$L_{PE}/_{m^2} = {L_{PE}}/_{(Useful\ area)}\ , \overline{L_{PE}} = {L_{PE}}/_{N}\ , and\ \overline{L_{PE}/_{m^2}} = {{L_{PE}}/_{m^2}}\Big/_{N}$$

The Infrastructure (embodied) PE demand is defined as:

$$O_{PE}^{[i]i} = \sum\nolimits_{\forall j \in Components} FE_j^{[i]} \cdot PEF_{fuel,j} + O_{PE,MN,j}^{[i]}$$

Where:

$FE_j^{[i]}$ is the Final Energy consumed by component in year, obtained from energy demand timeseries;

$PEF_{fuel,j}$ is the PE factor associated with the fuel consumed by component (this can differ depending on the project country and the energy mix), for year i. VERIFY uses the Primary Energy factors defined in "Support to Primary Energy Factors Review (PEF), Specific Tender ENER/B2/2021-593/2022-467, European Commission, DG ENER".

$O_{PE,MN,j}^{[i]}$ is the maintenance PE demand (inc. replacement \& EoL) of component j for year i.

Unless explicit values are provided, the maintenance Primary Energy (PE) demand is calculated as a percentage of a component's embodied PE. The End-of-Life (EoL) PE demand is determined based on the planned disposal or recycling of the component at the end of its useful life. If a component reaches the end of its life during the analysis period and is scheduled for replacement, the embodied PE demand for the replacement is added to the component's Operational PE Demand for that year

6.1.1.2. Lifetime Global Warming Potential

Lifecycle Global Warming Potential (GWP) is a critical environmental KPI that measures the total greenhouse gas (GHG) emissions produced throughout a project's lifecycle. It is expressed in terms of kilograms of CO_2-equivalent per square meter of the building's useful floor area. This indicator provides a comprehensive view of the carbon footprint associated with a project and helps evaluate its overall environmental performance.

The total GWP consists of the following components:

- Infrastructure (Embodied) GHG Emissions: These are emissions generated during the production and construction stages when a building component is installed for the first time. For renovation projects, any infrastructure costs incurred are allocated to the use stage, as outlined in the Level(s) framework.

- Operational & Maintenance GHG Emissions: Emissions produced during the use stage of the building. These include maintenance-related emissions (from repair, replacement, and refurbishment activities) and operational emissions (from energy consumption such as electricity or fuel).

GWP is calculated in four versions, which include the total and average annual demand for the whole building, and the total and annual average demand per m^2 of useful building area. The basis of the calculation is the GHG emissions over the lifetime of the entire project (assumed to be *N* years), which are calculated as the sum of the infrastructure (product / construction) emissions and use-stage emissions over the period of estimation, as shown in equation below:

$$L_{GHG} = I_{GHG} + \sum_{i=1}^{N} (O_{GHG}^{[i]})$$

Where:

$O_{GHG}^{[i]}$ is the Operational GHG emissions of the building's components in year i ;

L_{GHG} denotes the Lifetime GHG emissions of the project;

I_{GHG} denotes the Infrastructure (embodied) GHG emissions.

GWP (as per the definition used in Level(s) indicator 1.2) is then calculated as:

$$L_{GWP} = \frac{L_{GWP}}{Useful\ area}$$

The useful area is defined as the total building area that is heated or cooled. The value is calculated in units of *kgCO2-eq/m²*. The latter's equation can be written as:

$$\overline{L_{GWP}} = {}^{L_{GWP}}\!/_{N}$$

The Infrastructure (embodied) GHG emissions are defined as:

$$I_{GHG} = \sum\nolimits_{\forall j \in Components} I_{GHG,j}$$

where $I_{GHG,j}$are the GHG Emissions embodied in component *j* and include the emissions associated with the manufacturing, transportation and installation of the component (i.e. Stage A of its lifetime).

Note that infrastructure GHG emissions are taken into account only when components are installed at the beginning of a project and are not included in the calculation of this KPI for pre-existing components. Similarly, the components are assumed to remain in place (installed at the building) at the end of the analysis period, so end-of-life values are not added to the total.

The Total Operational annual GHG emissions are defined as:

$$O_{GHG}^{[i]} = O_{GHG,MN}^{[i]} + O_{GHG,FI}^{[i]}$$

And include:

Annual emissions due to component maintenance:

$$O_{GHG,MN}^{[i]} = \sum\nolimits_{\forall j \in Components} O_{GHG,MN,j}^{[i]}$$

Where $O_{GHG,MN,j}^{[i]}$: the annual GHG emissions required for the maintenance of component j in year i.

Whenever a component reaches its end-of-life, the assumption is that the component is replaced with an identical one. In this case, the associated end-of-life (Stage C) embodied GHG emissions are added to the maintenance costs for that year. This is because as far as the building as a whole is concerned, component replacement is part of its maintenance process.

Emissions generated due to fuel imports for operating the components considered (Stage B – Use Stage):

$$O_{GHG,FI}^{[i]} = \sum\nolimits_{\forall k \in Fuel} FI_k^{[i]} \cdot EF_k^{[i]}$$

Where:

$FI_k^{[i]}$ is the total Fuel Imports for fuel type k in year i, obtained from energy demand timeseries (in kWh);

$EF_k^{[i]}$is the GHG emission factor associated with fuel type k (this can differ depending on the project country and the energy mix) in year i. For electricity specifically, country emissions factors are based on hourly historical values obtained from this source (VERIFY's DB is updated annually).

6.1.1.3. Lifecycle Costs (LCC)

LCC calculated as the sum of all infrastructure costs (CAPEX), all operational costs of all the components and the residual values of components at the end of the project, as follows:

$$L_C = I_C + \sum_{i=1}^{N} O_C^{(i)} - V_R$$

6.1.1.4. Pay Back Time (PBT)

Payback Period is estimated as period Tp = TL + tr

TL is the last period before the following inequality holds:

$$\sum_{i=1}^{N} (O_{C,ren}^{(i)} - O_{C,bl}^{(i)}) > I_{C,ren}^{(0)}$$

And

$$t_r = 1 - \frac{\sum_{i=1}^{T_L} (O_{C,ren}^{(i)} - O_{C,bl}^{(i)})}{I_{C,ren}^{(0)}}$$

Where

$I_{C,ren}^{(0)}$= Initial renovation investment costs

$O_{C,ren}^{(i)}, O_{C,bl}^{(i)}$ = Renovation and baseline scenarios' operating costs, respectively.

6.1.1.5. Levelized Cost of Energy (LCOE)

The **Levelized Cost of Electricity (LCOE)** is an economic KPI that measures the average cost per unit of electricity generated over the duration of a project's lifetime, expressed in euros per kilowatt-hour (€/kWh). This KPI is essential for evaluating the cost- effectiveness of different energy generation systems, including renewable and non-renewable sources.

The LCOE consists of the following cost components:

- Infrastructure Costs (CAPEX): These are the capital expenditures incurred for the procurement, delivery, and installation of electricity generators. This cost is a one-time investment made at the beginning of the project or when new generators are installed.
- Operation and Maintenance Costs: These are recurring costs associated with the ongoing operation and maintenance of the electricity generators. They include regular upkeep, repairs, and inspections to ensure efficient operation throughout the project's lifespan.
- Fuel Costs: If the building or district has electricity generators that use fuel, the fuel costs incurred during electricity generation are included. This component is variable and depends on the type of fuel used, fuel prices, and the efficiency of the generators.

LCOE KPI provides a clear view of the financial performance of electricity generation systems, enabling stakeholders to compare different energy generation scenarios and select the most cost-effective option.LCOEis calculated using the following equation:

$$LCOE = \frac{\sum_{i=1}^{N} \frac{I_{C,GEN}^{[i]} + O_{C,GEN,MN}^{[i]} + O_{C,GEN.NEI}^{[i]}}{(1+r)^i}}{\sum_{i=1}^{N} \frac{SC^{[i]} + EX^{[i]}}{(1+r)^i}}$$

Where:

$I_{C,GEN}^{[i]}$ are the generator infrastructure costs (CAPEX) in year i;

$O_{C,GEN,MN}^{[i]}$ are the annual generator maintenance costs in year i (which include replacement costs, if the analysis period exceeds the generators' lifetime);

$O_{C,GEN.NEI}^{[i]}$ are the costs of fuel used for electricity generation in year i (applicable only in the case of electricity generators using other fuel);

$SC^{[i]} and\ EX^{[i]}$ are respectively the total energy that was self-consumed and exported by the building in year i;

r is the project discount rate.

The numerator of the fraction of the equation includes CAPEX of generators, maintenance costs of the generators and costs for fuels used for electricity generation.

6.1.1.6. Net Present Value (NPV)

NPV is defined as the sum of expected cashflows of all components included in the considered investment. The cashflow CF_{comp} for a component *k* is equal to:

$$CF_k^{(i)} = S_{k,func}^{(i)} + S_{k,residual}^{(i)} - C_{k,inf}^{(i)} - C_{k,mn}^{(i)} - C_{k,func}^{(i)} - C_{k,EOL}^{(i)}$$

Where:

$S_{k,func}^{(i)}$: functional savings of component *k* in year (*i*), calculated on the basis of the corresponding expenditure expected during a baseline scenario

$S_{k,residual}^{(i)}$: residual value of component *k* in year (*i*)

$C_{k,inf}^{(i)}$: is the infrastructure cost (CAPEX) of component *k*, incurred if the component is installed or replaced in year (*i*)

$C_{k,mn}^{(i)}$: maintenance cost of component *k* in year (*i*)

$C_{k,func}^{(i)}$: functional cost of component *k* in year (*i*). Note that if the component generates revenue (through, e.g. the sale of electricity to the grid), this value may be negative (i.e. the component will contribute to cash flows).

$C_{comp,eol}$: End-of-Life cost of the component *comp*, incurred if the component is replaced in year *i*.

The calculation of the NPV KPI is based on the equation:

$$\sum_{t=0}^{M-1} \frac{cashflow_t}{(1+rate)^t}$$

Where*rate*is the investment project's discount rate. As per Level(s) guidance, the default value is 4% (but can be configured to a different value). Here, $cashflow_t = \sum_{\forall components} CF^t$.

6.1.1.7. Internal Rate of Return (IRR)

IRR is used to quantify the profitability of an investment while taking into account the time value of money. Its calculation is based on the following formula:

$$\sum_{t=0}^{M} \frac{v_t}{(1+irr)^t} = 0$$

In this formula $v_t = [v_0, v_1, \ldots, v_M]$represent the expected future cashflow of the investment (marked as *cashflow* in NPV).

6.1.1.8. Return On Investment (ROI)

ROI is the cumulative sum of cashflow of the investment, with respect to the initial investment's total cost (I_{CAPEX})as follows:

$$ROI = \frac{cashflow.cumsum}{I_{CAPEX}}$$

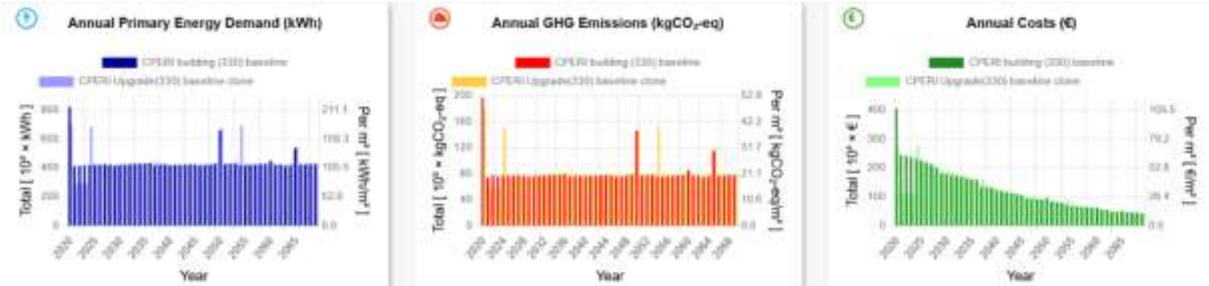
6.1.2. Results for the dual test-run approach

Resulting values of KPIs (INTEMA-approach)

	CPERI Building **Baseline Scenario**	CPERI Building **Upgrade Scenario**	Differencein resulting values (%)
Primary Energy Demand (kWh/m²/year)	111.88	117.39	4.68
GHG Emissions ($kgCO_2$-eq)/year/m²)	20.76	22.07	5.96
Payback Period (years)	No payback	No payback	-
Levelized Cost of Electricity (€/kWh/year)	-	0.051	-
NPV $_{t=50\ years}$ (k€)	-	-2.160,13	-
ROI $_{t=50\ years}$	-	-22.31	-
IRR $_{t=50\ years}$	-	No payback	-

Cost Savings (INTEMA-approach)

	$LCC_{upgrade}$ - $LCC_{baseline}$ (€/year)
Costs Savings	8047.38



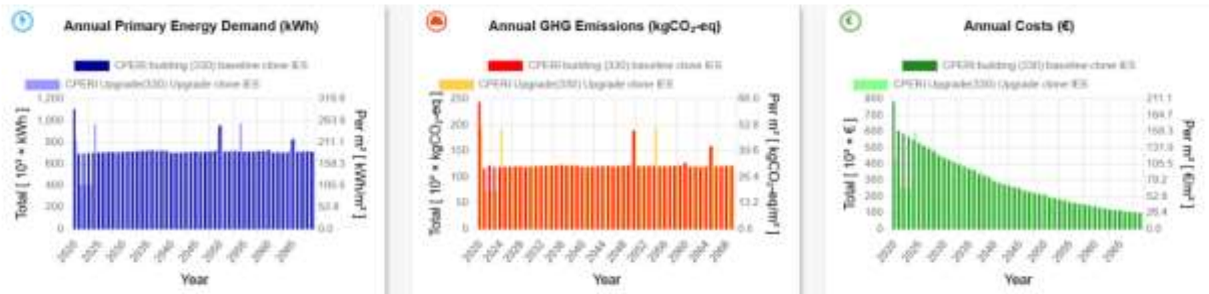
VERIFY - Comparative Plots for baseline and upgrade scenarios (INTEMA-approach)

Resulting values of KPIs (iSCAN-approach)

	CPERI Building **Baseline Scenario**	CPERI Building **Upgrade Scenario**	Difference in resulting values (%)
Primary Energy Demand (kWh/m²/year)	184.58	191.82	3.77
GHG Emissions ($kgCO_2$-eq)/year/m²)	31.66	33.24	4.75
Payback Period (years)	No payback	No payback	-
Levelized Cost of Electricity (€/kWh/year)	-	0.051	-
NPV $_{t=50\ years}$ (k€)	-	-5.918,41	-
ROI $_{t=50\ years}$	-	-61.12	-
IRR $_{t=50\ years}$	-	No payback	-

Cost Savings (iSCAN-approach)

	$LCC_{upgrade}$ - $LCC_{baseline}$ (€/year)
Costs Savings	10902.6



VERIFY - Comparative Plots for baseline and upgrade scenarios (iSCAN-approach)

6.1.3. Comparison of relative deviations the dual test-run approach

Deviation of relative difference between scenarios of Environmental KPIs between the two approaches

	Deviation of Relative Differences (%)
Primary Energy Demand	0.91
Global Warming Potential	1.21

Relative difference of Cost Savings between the two approaches

	Relative Difference (%)
Costs Savings	26.19

6.2. IS7 Annex

6.2.1. SRIA questionnaire

User preference among SRI functionalities and the assessment type	
Preference to improve the score of one key functionality in particular (optional)	
Energy performance and operation	☐
Response to the occupants' needs	☐
Energy flexibility	☐
Assessment preferences	
Do you want to use the detailed service catalogue or a simplified version?	☐ Detailed ☐ Simplified
Lowest cost to increase the SRI class by one level	☐ (default)
Lowest cost to increase the SRI class by <u>two</u> levels	☐
Lowest cost to increase the SRI class by <u>three</u> levels	☐
Buildings characteristics	
Select your country	☐ (among 30 countries)
Sector:	☐ Residential ☐ Non-residential
Floor area in m^2	(number)
Number of rooms or zones	(number)

Number of external windows	(number)
Building characteristics relevant to heating domain	
How many heat generators are there in this building?	(number)
What is the main heating system of your building?	☐ Heat pump ☐ Gas boiler ☐ Fuel boiler ☐ Wood boiler ☐ District heating network ☐ Other
Type of heating generator 1	☐ Heat pump ☐ Gas boiler ☐ District heating network ☐ Other
Function of heating generator 1	☐ Heating ☐ Cooling ☐ Both heating & cooling
Type of heating generator XX	☐ Heat pump ☐ Gas boiler ☐ District heating network ☐ Other
Function of heating generator XX	☐ Heating ☐ Cooling ☐ Both heating & cooling
Number of thermal storage units	(number)
Number of distribution pumps	(number)
Number of heating emitters	(number)
Type of heating emitter 1	☐ Radiator ☐ Fan coil ☐ TABS ☐ Heat pump
Function of heating emitter 1	☐ Heating ☐ Cooling ☐ Both heating & cooling
Type of heating emitter XX	☐ Radiator ☐ Fan coil ☐ TABS ☐ Heat pump
Function of heating emitter XX	☐ Heating ☐ Cooling ☐ Both heating & cooling
Building characteristics relevant to cooling domain	
Is cooling mandatory for this type of building in your country?	Yes/No
Is the building equipped with a cooling system?	Yes/No
What is the principal cooling system of your building?	☐ Heat pump ☐ District cooling network ☐ Other

How many cold generators are there in this building?	(number)
Type of cooling generator 1	☐ Heat pump ☐ District cooling network ☐ Other
Function of cooling generator 1	☐ Heating ☐ Cooling ☐ Both heating & cooling
Type of cooling generator XX	☐ Heat pump ☐ District cooling network ☐ Other
Function of cooling generator XX	☐ Heating ☐ Cooling ☐ Both heating & cooling
Number of distribution pumps	(number)
Number of cooling emitters	(number)
Type of cooling emitter 1	☐ Radiator ☐ Fan coil ☐ TABS ☐ Heat pump
Function of cooling emitter 1	☐ Heating ☐ Cooling ☐ Both heating & cooling
Type of cooling emitter XX	☐ Radiator ☐ Fan coil ☐ TABS ☐ Heat pump
Function of cooling emitter XX	☐ Heating ☐ Cooling ☐ Both heating & cooling
Building characteristics relevant to ventilation domain	
Number of air handling units (AHUs)	(number)
Type of AHUs control	☐ No ventilation ☐ Manual ☐ Automatic
Number of fan coils	(number)
Type of fan coils control	☐ No ventilation ☐ Manual ☐ Automatic
Number of air quality sensors	(number)
Building characteristics relevant to domestic hot water domain	
What is the principal DHW system of your building?	☐ Direct electric heating ☐ Integrated heat pump ☐ Hot water generation
Number of DHW generators	(number)
Type of DHW generator 1	☐ Direct electric heating ☐ Integrated heat pump

	☐ Hot water generation
Coverage of DHW generator 1	☐ Building ☐ Floor ☐ Apartment ☐ Room/zone
Type of DHW generator ZZ	☐ Direct electric heating ☐ Integrated heat pump ☐ Hot water generation
Coverage of DHW generator ZZ	☐ Building ☐ Floor ☐ Apartment ☐ Room/zone
Is the building equipped with solar collectors for DHW?	Yes/No
Building characteristics relevant to lighting domain	
Number of lighting points	(number)
Building characteristics relevant to dynamic building envelope domain	
Number of solar protection systems on windows	(number)
Building characteristics relevant to electricity domain	
Is the building equipped with an electricity production system (e.g., PV panels)?	Yes/No
Is the building equipped with an electricity storage system (e.g., battery)?	Yes/No
Is the building equipped with a combined heat and power (CHP- system)?	Yes/No
Number of electricity production units	(number)
Number of electricity storage units	(number)
Building characteristics relevant to EV charging domain	
Is the building equipped with parking spaces?	Yes/No
Number of parking slots	(number)

6.2.2. Example of smartness upgrades implemented in the SRIA

Domain	Smart-ready service	Functionality level upgrade FL0=>FL1		Functionality level upgrade FL1=>FL2		Functionality level upgrade FL2=>FL3		Functionality level upgrade FL3=>FL4	
		Upgrade action FL0=>FL1	Cost FL0=>FL1, €	Upgrade action FL1=>FL2	Cost FL1=>FL2, €	Upgrade action FL2=>FL3	Cost FL2=>FL3, €	Upgrade action FL3=>FL4	Cost FL3=>FL4, €
Cooling	C-1d: Control of distribution pumps in networks	Installation of a controller of pumps for heating like Thermador RA100 - 24V or equivalent	495	Replacement of on/off pump per a multi-stage distribution pump	1100	Installation of a speed variator on each distribution pump	1100	Installation of a speed variator on each distribution pump and connection to an external controller or a SCADA system	
Ventilation	V-1a: Supply air flow control at the room level	Installation of mechanically operated extract units with temporisation and humidity detectors	94	Installation of mechanically operated extract units with temporisation and occupancy detectors	95	Installation of single-flow MCV with flow regulation based on humidity and VOC pollution sensors integrated in the ventilator	345	Installation of control element with room temperature controller function, communication and CO2/moisture sensors installed locally by zone	436
Lighting	L-1a: Occupancy control for indoor lighting	Installation of a controller for control of lighting circuits and of an interruptor for manual On/Off	237	Installation of a motion or a presence detector with an integrated luminosity sensor	230	Installation of a lighting controller with a motion or a presence detector with integrated luminosity sensor	1258		
Dynamic building envelop	DE-1: Window solar shading control	Installation of motor and control button for sun shading devices	300	Installation of motor for solar shading devices, blinds controller and solar		Installation of motor for solar shading devices, light/blind/HVAC controller		Data collection of weather forecasts from a web service and installation of a system	

				irradiation and/or luminosity sensors for an automated control		and several ambient and outdoor sensors for an automated control of light/blind/ HVAC		from the level 3	
Electricity	E-2: Reporting information regarding local electricity generation	Installation of a PV panels' field with reporting of current generation data to final user		Installation of a PV panels' field with reporting of current generation and historical data to final user OR setup of data historisation functionality if the PV panels' field is already installed		Level 2 + weather forecast data collection from a web service + installation of AC and DC meters for performance evaluation		Level 3 + fault detection capacibility in order to identify problems of PV modules, strings or arrays	
Electrical vehicle charging	EV-15: EV charging capacity	Installation of an outdoor electrical plug for EV charging protected by a differential circuit breaker	184	Installation of IRVE charging point with communication, protections and eventually solar production control.	996	Installation of IRVE double charging station with communication, protections and eventually solar production control.	1639	Installation of IRVE double charging station with communication, protections and eventually solar production control.	1639
Monitoring and control	MC-9: Occupancy detection: connected services	Installation of occupancy detector for control of lighting OR fan coils	250	Installation of occupancy detector for control of lighting AND heating or fan coils	430				

6.2.3. Sensitivity analysis for the SRIA

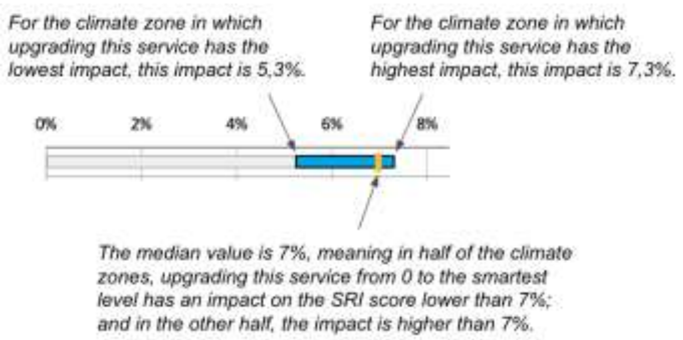
Methodology

In order to always consider the same list of services, all services from the catalogue A or B are considered applicable (which is a virtual situation, as some services are mutually exclusive).
The corresponding impacts of each service upgrade from 0 to the next level, up to the smartest ones is considered for 40 cases, each case being defined by:

- The focus chosen by the user (4 possibilities):
- 0. Impact on overall SRI score
- 1. Impact on key functionality 1 (efficiency)
- 2. Impact on key functionality 2 (occupant)
- 3. Impact on key functionality 3 (flexibility)
- The building type (2 possibilities):
- 1. Residential
- 2. Non-residential
- The climate zone (5 possibilities):
- Northern Europe (NE)
- Western Europe (WE)
- Southern Europe (SE)
- North-Eastern Europe (NEE)
- South-Eastern Europe (SEE)

The impact of smartness upgrades for each service is then calculated for every of the 40 cases considered and results are compared.
The sensitivity analysis is presented in the form of graphs, illustrating the range of the impact of upgrading each service from zero to the smartest level. In other words, the graphs show to which extent the impact of the upgrade of each service from 0 to the smartest level (2, 3 or 4) varies according to the 5 climate zones. The graphs read as follows.

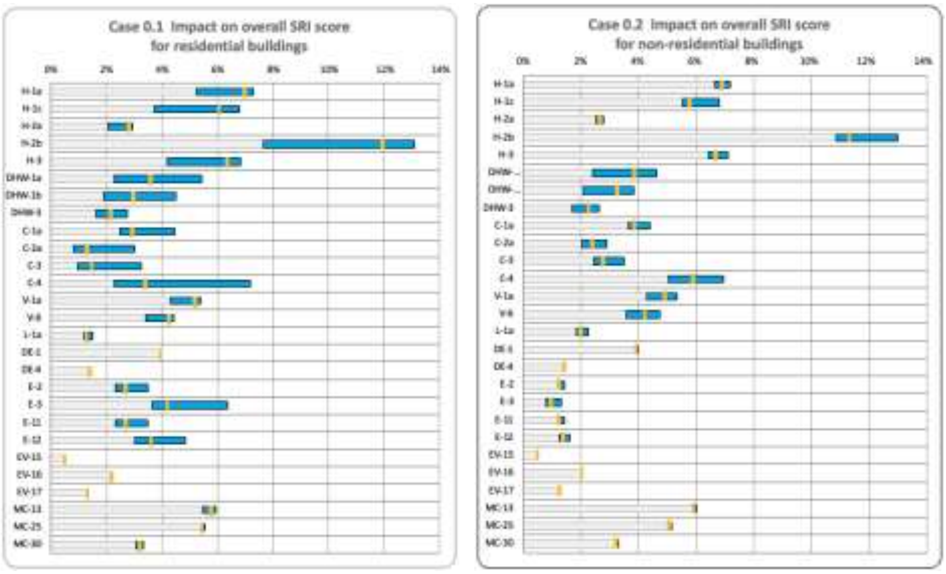
Figure 73. How to read the graphs in the sensitivity analysis



Results for service catalogue A

The figure below shows the impact on the overall SRI score of upgrading each service from zero to the smartest level. For instance, for a residential building, upgrading the service H-2b “Heat generator control (for heat pumps)” from 0 to 3 (highest level) has an impact of 7.7% on the overall SRI score in the South-Eastern Europe (SEE) climate zone, while it has an impact of 13.1% in the Western Europe (WE) climate zone. More generally speaking, and logically, the variations are higher for the domains related to climate aspects (heating, domestic hot water, cooling, electricity). Variations are also higher for residential buildings than non-residential ones.

Figure 74.Variability of the impact on the overall SRI score of the 0-to-smartest-level upgrade for each service of catalogue A for all climate zones, for residential buildings (left) and non-residential buildings (right)



However, despite this variability, the list of service upgrades with the highest impact is relatively stable.

Upgrading services H-1a, H-2b, V-1a and MC-13 from 0 to the smartest level always have a high impact, for all climate zones and building types. Upgrading services H-1c, H-3, C-4 and MC-25 from 0 to the smartest level also have high impact in most cases.

By contrast, upgrading services L-1a, DE-4, EV-15, EV-16 and EV-17 from 0 to the smartest level always have a very low impact on the overall SRI score, for all climate zones and all building types, even more so for incremental upgrades from level 0 to level 1, level 1 to level 2, etc. As a result, it is quite unlikely that upgrading these services will be advised to level up the overall SRI score - except if all other services already score very high.

Looking more particularly on upgrade impacts on each of the 3 key functionalities (see figure below), the following facts are observed from the data:

- There is a high variability in the results for the key functionality 1 on efficiency. However, upgrading the services H-1a, H-2a, H-2b, H-3, MC-13 and MC-30 most often has a high impact. By contrast, upgrading the services H-1c, DHW-1b, E-3, EV-15, EV-16 and EV-17 has zero or close-to-zero impact on this key functionality.

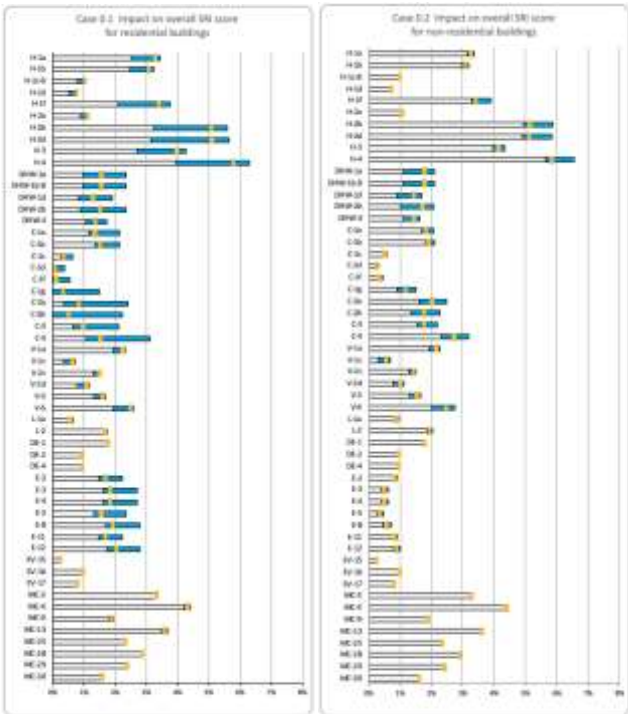
- The impact on the key functionality 2 on occupants is not sensitive at all to climate zones and building types (no variability in the corresponding graphs). Upgrading from 0 to the smartest level the services H-1a, DHW-3, C-4, V-1a, V-6, DE-1 and MC-13 always is impactful. By contrast, upgrading services H-1c, H-3, DHW-1a, DHW-1b, E-3, EV-15, EV-16 and MC-25 always have a very low impact on this functionality.
- There is a very high variability in the results for the key functionality 3 on flexibility. However, upgrading the services H-1c, H-2b, DHW-1a, DHW-1b, C-4, EV-16 and MC-25 most often has a high impact. By contrast, upgrading the services H-1a, H-2a, H-3, DHW-3, C-1a, C-3, V-1a, V-6, L-1a, DE-1, DE-4, E-2, E-11, E-12, EV-15, MC-13 and MC-30 has zero or close-to-zero impact on this key functionality.

Figure 75. Variability of the impact on each key functionality for each service of catalogue A

Results for service catalogue B

The next figure shows the impact on the overall SRI score of upgrading each service from zero to the smartest level, for catalogue B. As it was observed for catalogue A, the variations are higher for the domains related to climate aspects (heating, domestic hot water, cooling, electricity). Variations are also higher for residential buildings than non-residential ones.

Figure 76. ***Variability of the impact on the overall SRI score of the 0-to-smartest-level upgrade for each service of catalogue B for all climate zones, for residential buildings (left) and non-residential buildings (right)***



However, despite this variability, the list of service upgrades with the highest impact is relatively stable. Indeed, upgrading from 0 to the smartest level the services H-1a,H-2b, H-2d, H-3 and H-4 in the heating domain, and MC-3, MC-4, MC-9 and MC-13 in the monitoring & control domain always have a high impact, for all climate zones and building types. Upgrading services H-1b and H-1ffrom 0 to the smartest level also have high impact in most cases. By contrast, upgrading services H-1c, H-1d, H-2a, C-1c, C-1d, C-1f, C-2a, C-2b, C-3, V-1c, L-1a, DE-2, DE-4, EV-15, EV-16 and EV-17 always have a very low impact (< 1%) on the overall SRI score, for all climate zones and all building types. As a result, it is quite unlikely that upgrading these services will be advised to level up the overall SRI score - except if all other services already score very high. Finally, there is a significant difference in the impact of upgrading services in the electricity domain depending on the building type (residential or non-residential).

The next figures illustrate the impact of service upgrades on each of the 3 key functionalities. It is observed that:

- There is a high variability in the results for the key functionality 1 on efficiency. However, upgrading the services H-1a, H-1b, H-2d, H-3, MC-4, MC-9, MC-13, MC-25, MC-28, MC-29 and MC-30 always is impactful. In the electricity domain, upgrading services E-2, E-11 and E-12 always is impactful for residential buildings, but is never impactful for non-residential buildings. It is the opposite for service C-3, the upgrade of which being impactful on the efficiency score for non-residential buildings, but only in one region (SEE) concerning residential buildings.

- Concerning key functionality 2, as previously explained climate zones play no role in the impact of service upgrades. The services with the highest impact (≥ 4%) on this functionality are H-1b, C-1b, V-1a, V-6, L-2, DE-1, MC-4 and MC-13.
- Finally, concerning key functionality 3, a limited number of service upgrades impact the flexibility subscore, but in this case, the impact can be very high (> 10%); the concerned services are in the heating, DHW, cooling and M&C domains. However, there is a more significant variability of this impact in the residential sector than in the non-residential sector.

Figure 77. ***Variability of the impact on key functionality 1 of the 0-to-smartest-level upgrade for each service of catalogue B for all climate zones, for residential buildings (left) and non-residential buildings (right)***

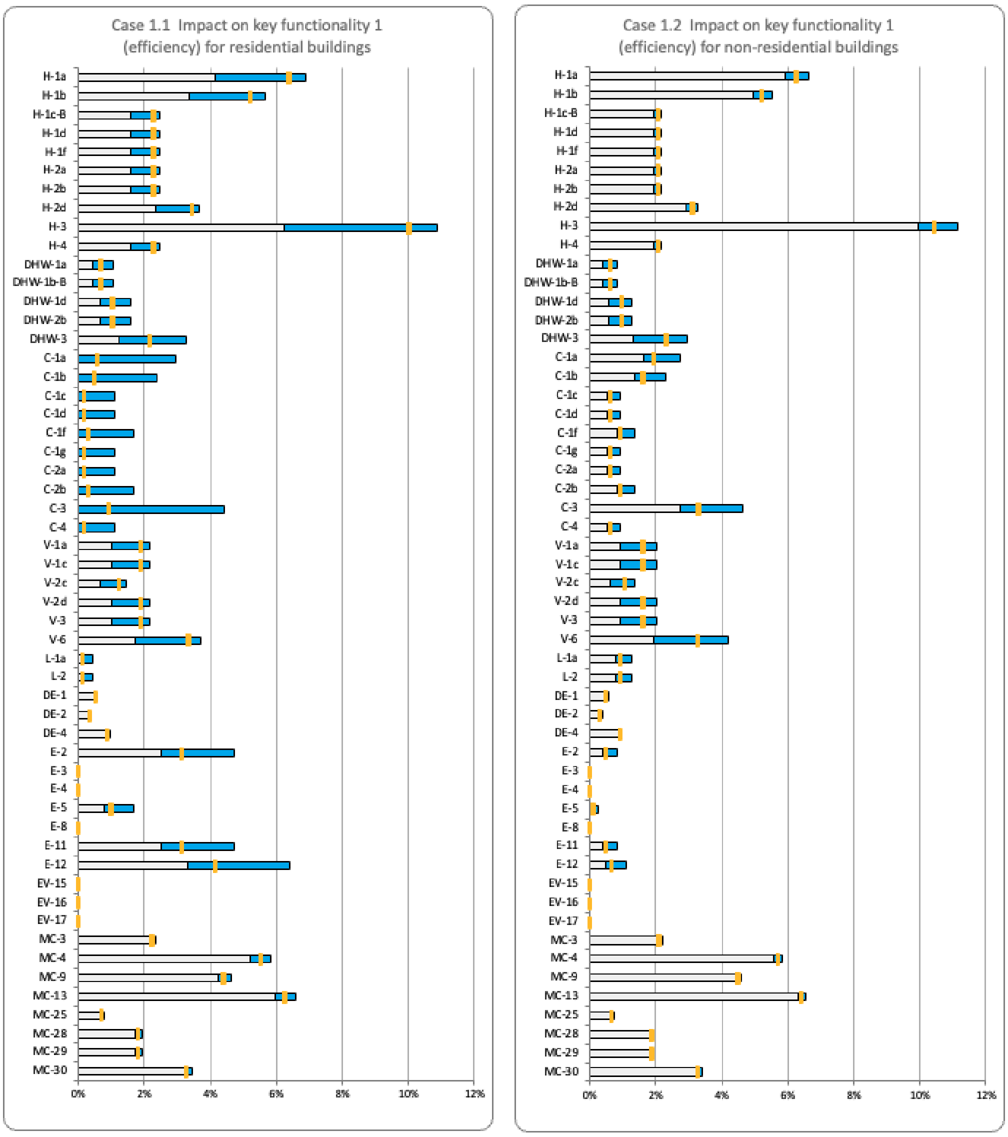


Figure 78. *Variability of the impact on key functionality 2 of the 0-to-smartest-level upgrade for each service of catalogue B for all climate zones, for residential buildings (left) and non-residential buildings (right)*

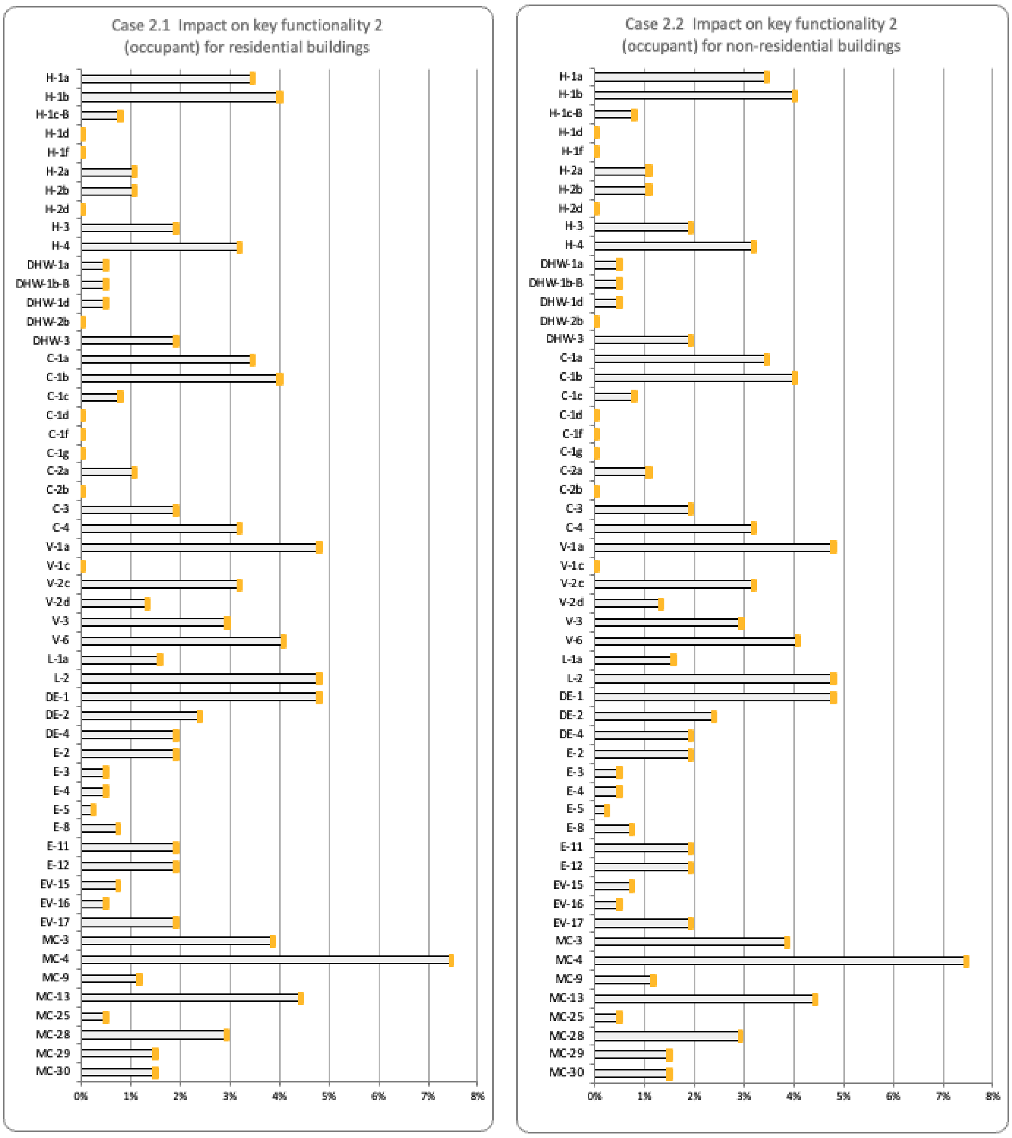
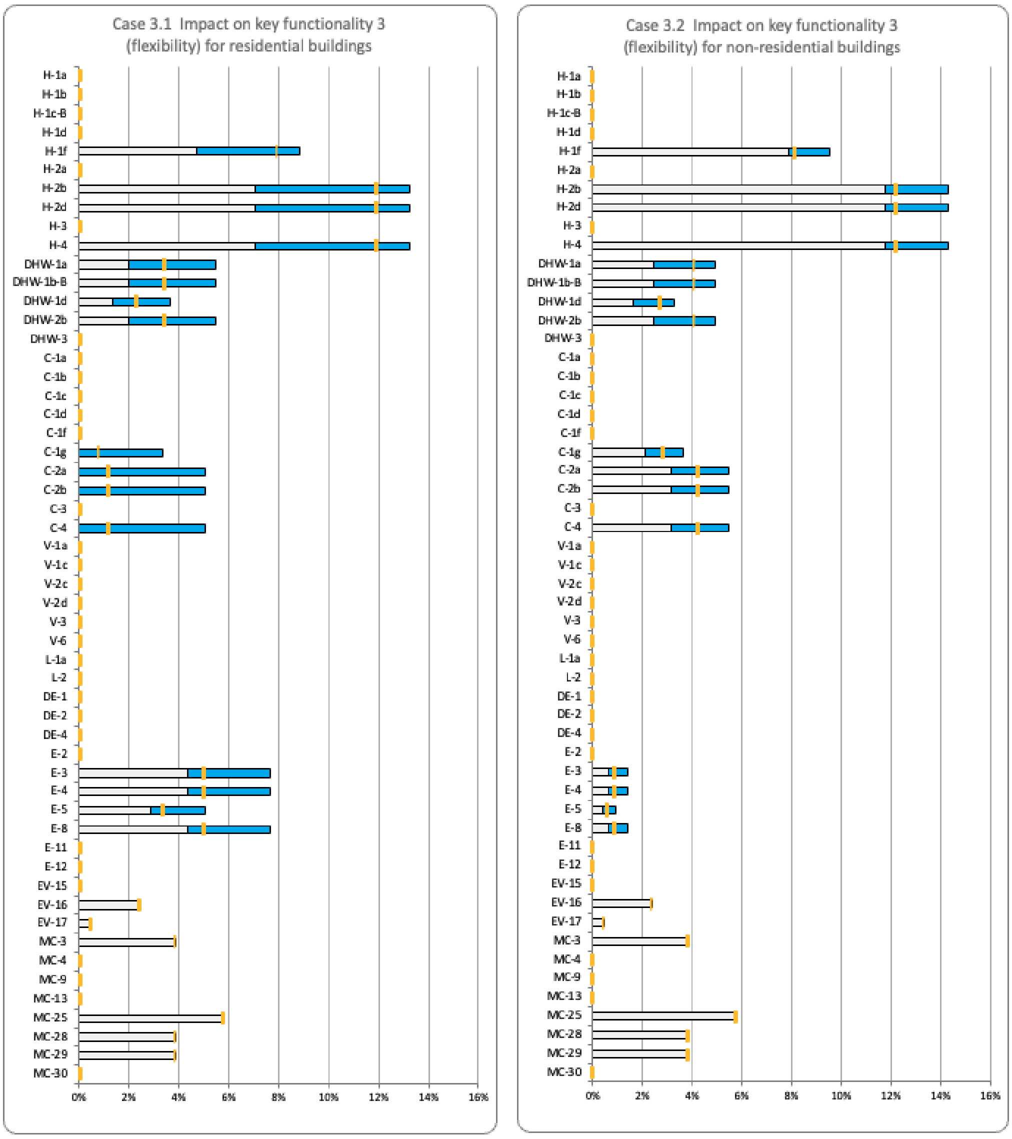


Figure 79. ***Variability of the impact on key functionality 3 of the 0-to-smartest-level upgrade for each service of catalogue B for all climate zones, for residential buildings (left) and non-residential buildings (right)***



6.3. IS4 Annex

This annex presents the indicative forecasts of demand-side flexibility limits for the energy consumption sub-clusters of CERTH offices and Mpodosakeio Hospital. These forecasts are generated by the IS4 system, which utilizes data on energy consumption, weather conditions, and corresponding data from the previous day. The following figures illustrate the flexibility limits for increasing (blue) and decreasing (red) energy consumption, as well as the forecasted energy consumption (green). These results represent a one-day forecast with hourly granularity. At points where the three waveforms overlap, there is no available flexibility.

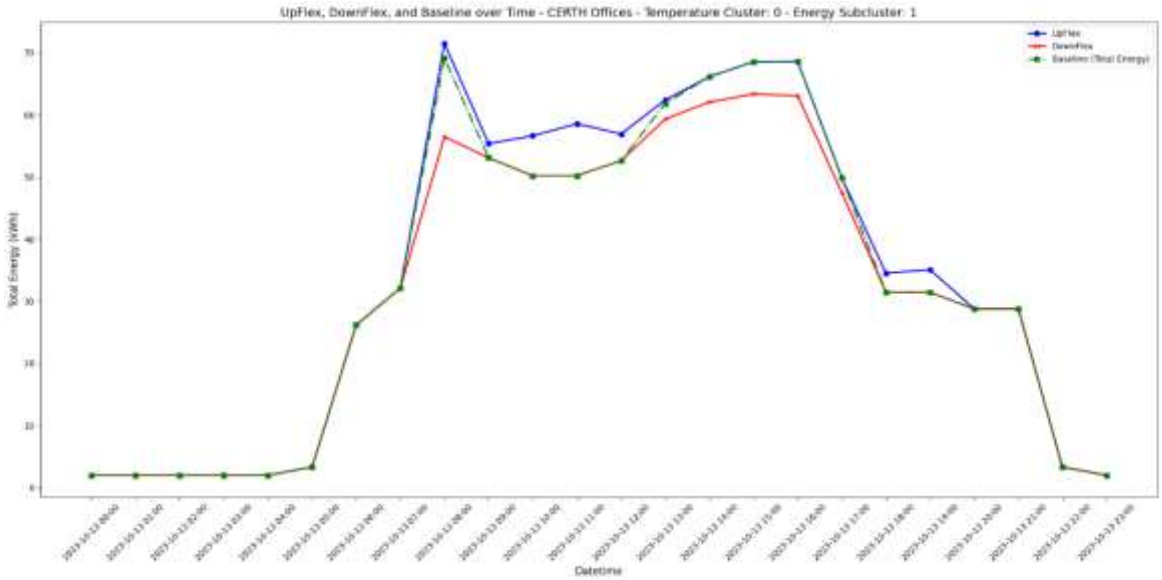


Figure 80:Predicted Demand side flexibility bounds for the second energy consumption sub-cluster of CERTH Offices (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

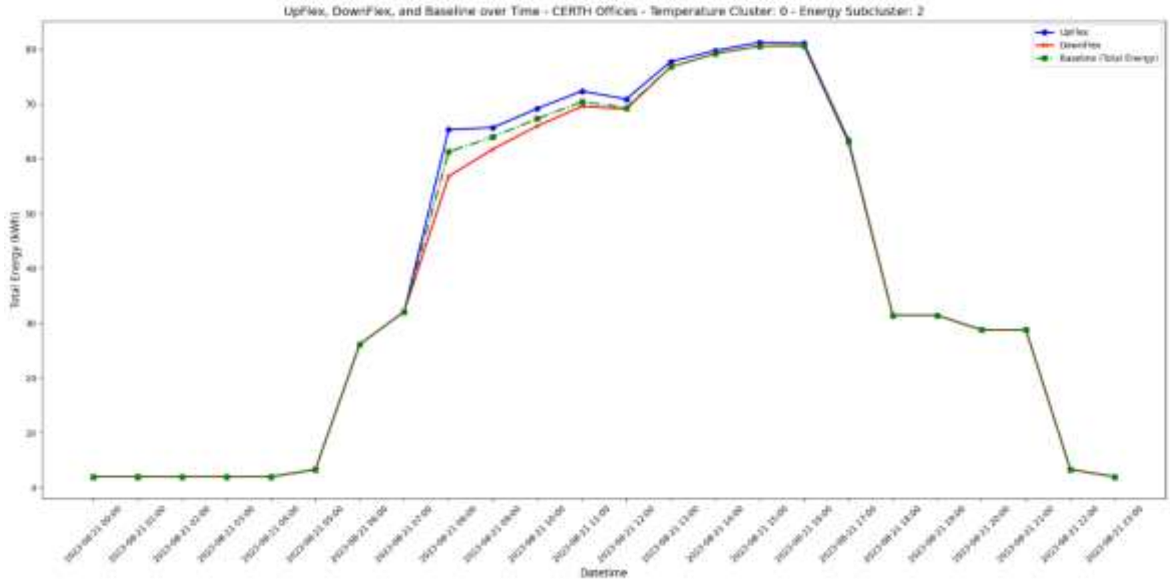


Figure 81: Predicted Demand side flexibility bounds for the third energy consumption sub-cluster of CERTH Offices (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

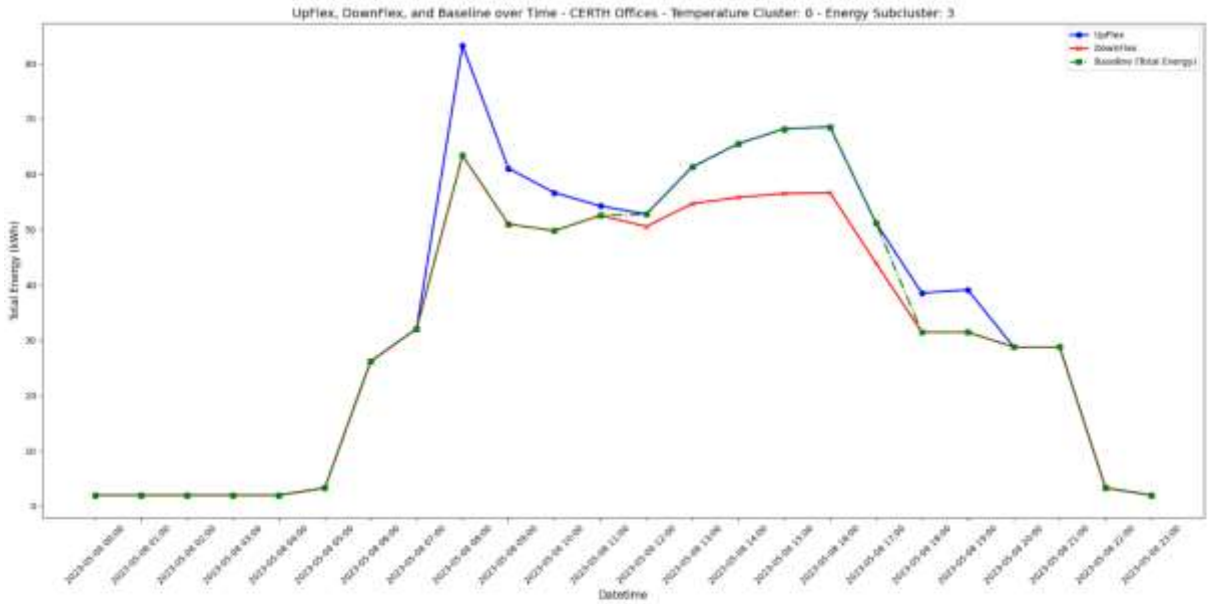


Figure 82. Predicted Demand side flexibility bounds for the fourth energy consumption sub-cluster of CERTH Offices (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

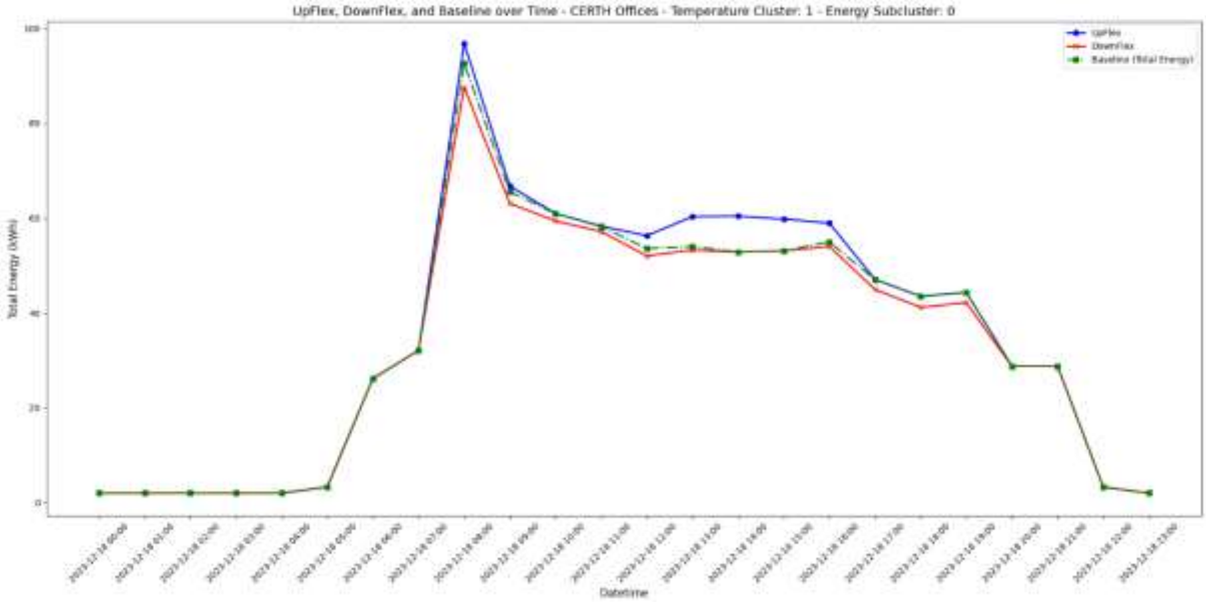


Figure 83. Predicted Demand side flexibility bounds for the fifth energy consumption sub-cluster of CERTH Offices (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

Figure 84: Predicted Demand side flexibility bounds for the sixth energy consumption sub-cluster of CERTH Offices (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

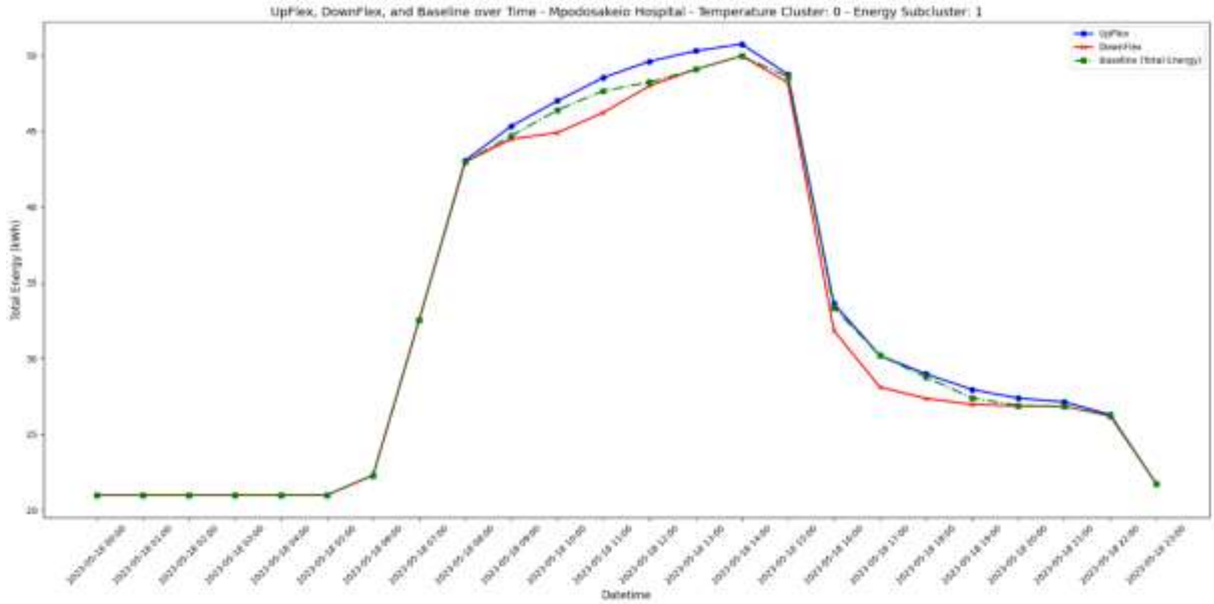


Figure 85:Predicted Demand side flexibility bounds for the second energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

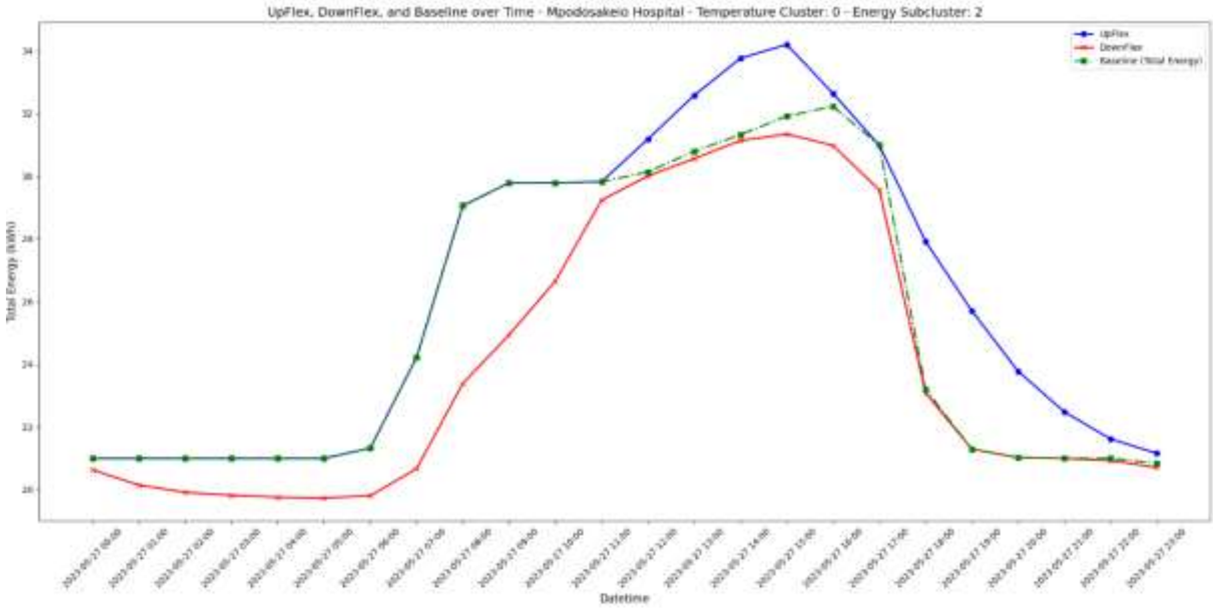


Figure 86:Predicted Demand side flexibility bounds for the third energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

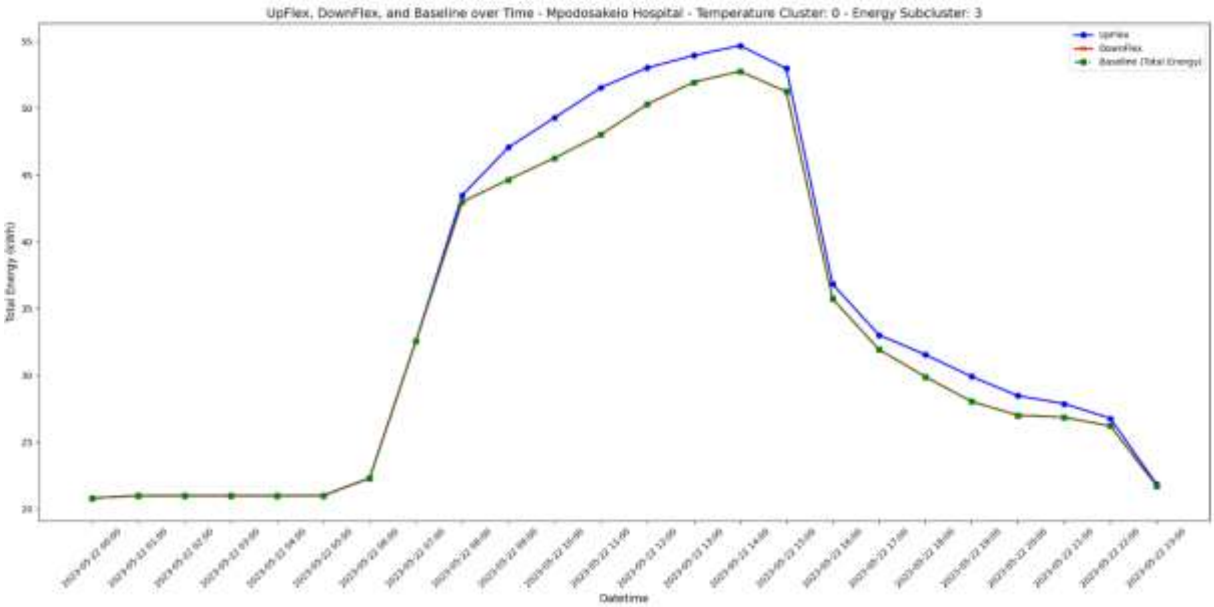


Figure 87:Predicted Demand side flexibility bounds for the fourth energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

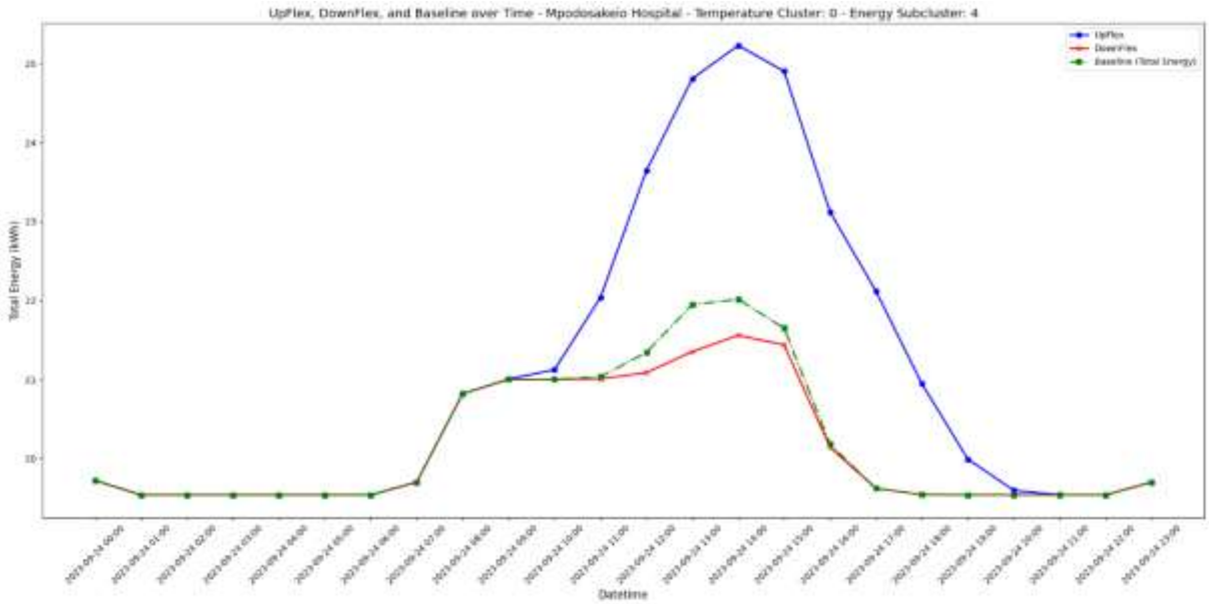


Figure 88:Predicted Demand side flexibility bounds for the fifth energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

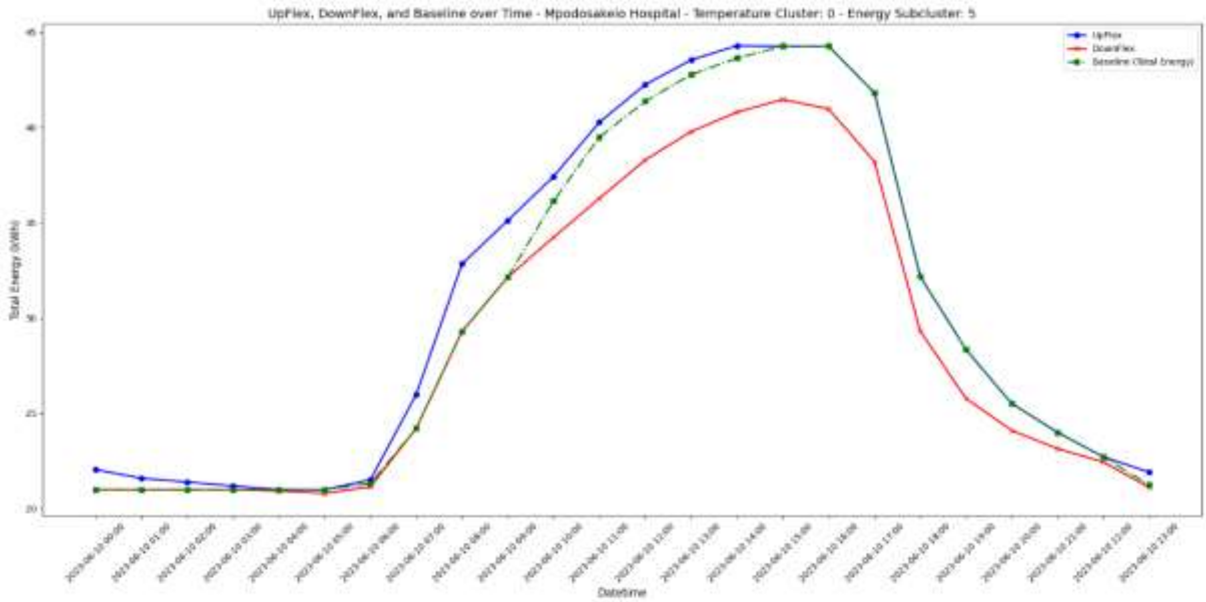


Figure 89:Predicted Demand side flexibility bounds for the sixth energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

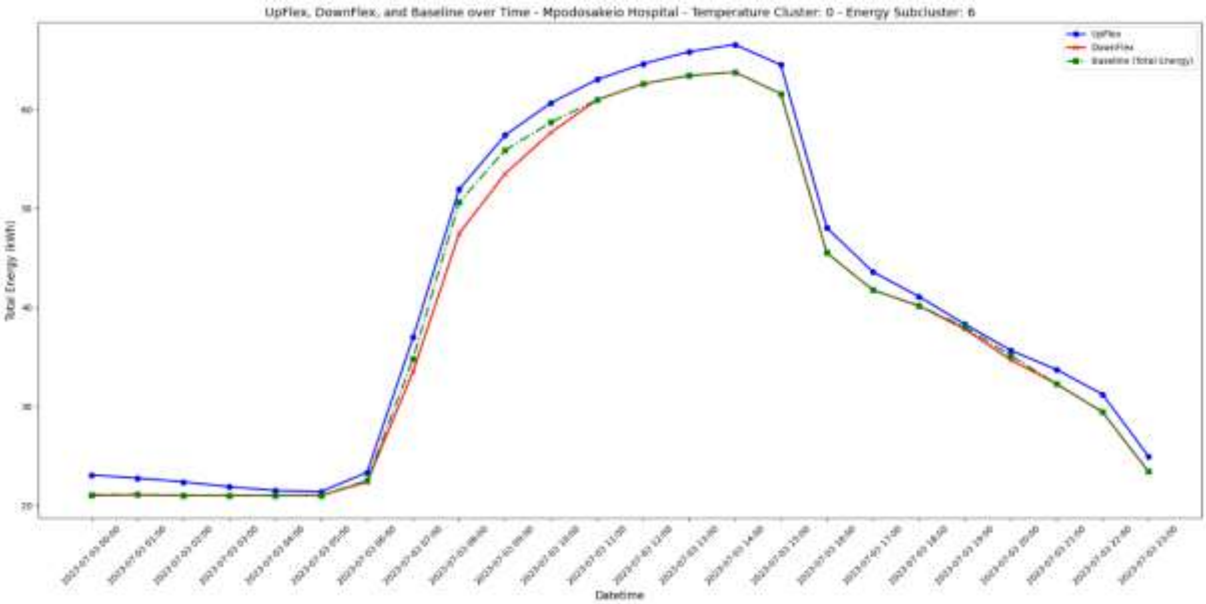


Figure 90:Predicted Demand side flexibility bounds for the seventh energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

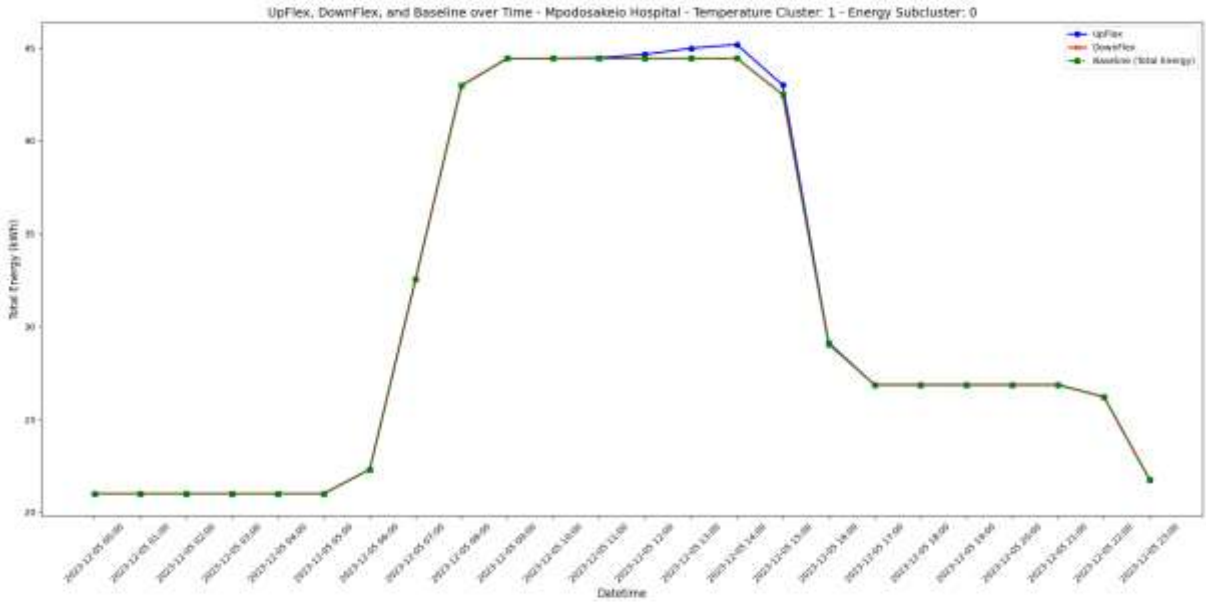


Figure 91:Predicted Demand side flexibility bounds for the eigth energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

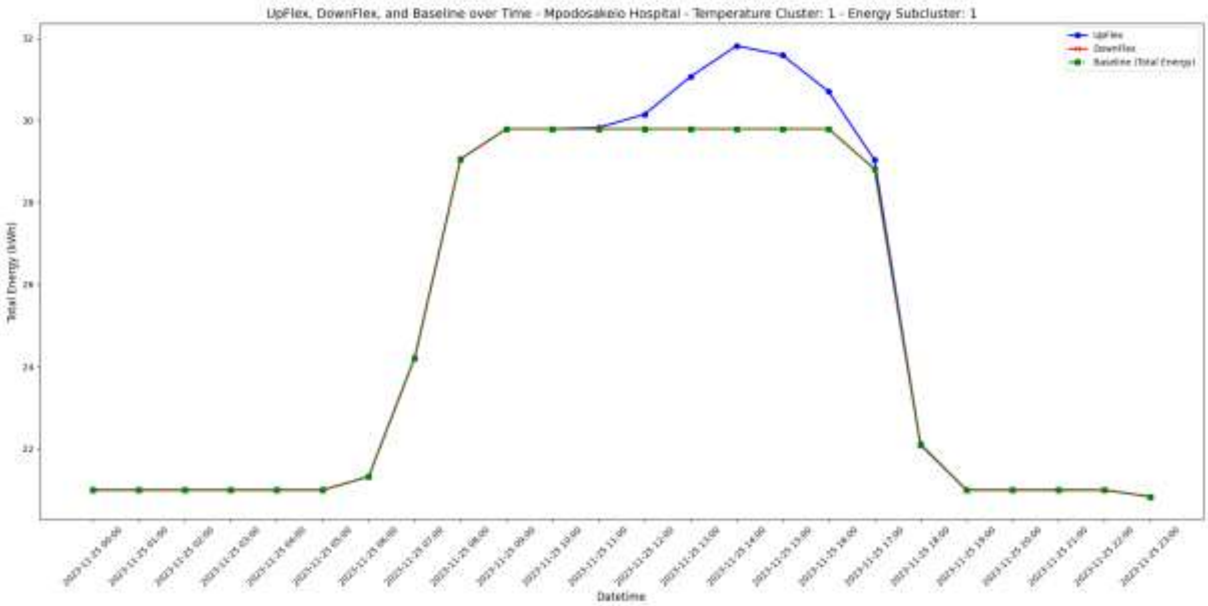


Figure 92:Predicted Demand side flexibility bounds for the ninth energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

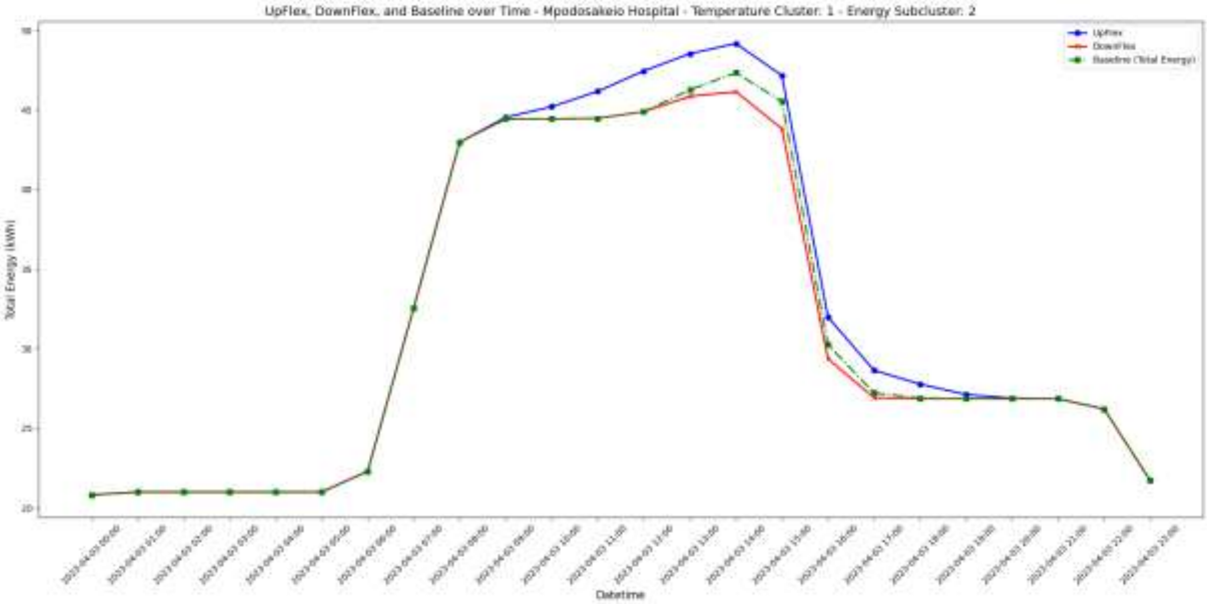


Figure 93:Predicted Demand side flexibility bounds for the tenth energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

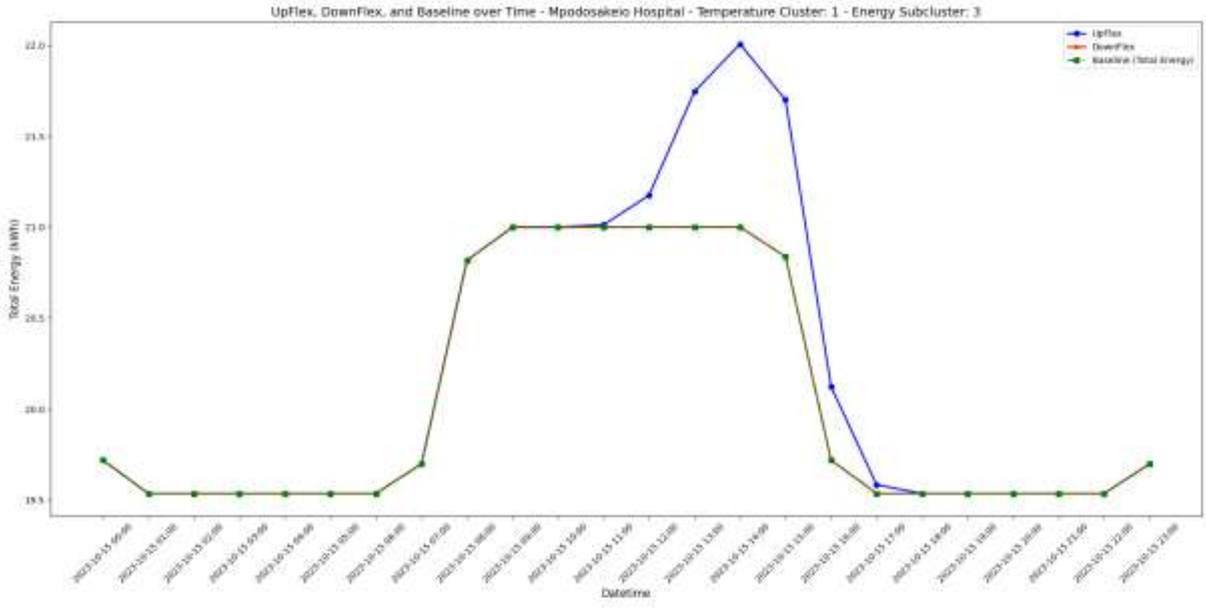


Figure 94:Predicted Demand side flexibility bounds for the eleventh energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

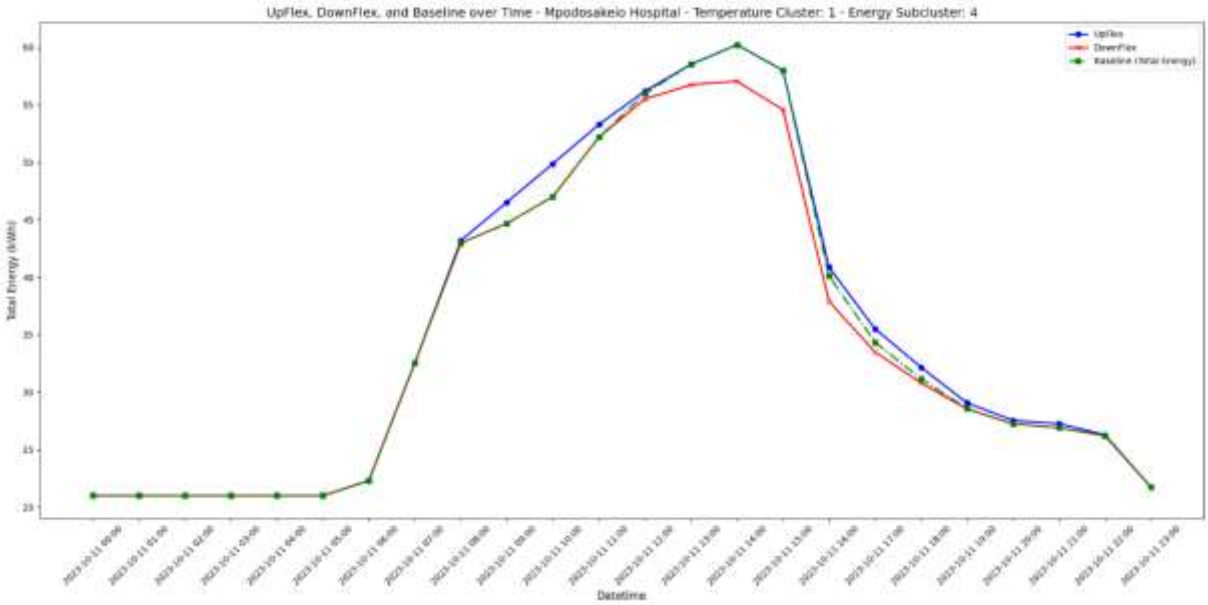


Figure 95:Predicted Demand side flexibility bounds for the twelfth energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))

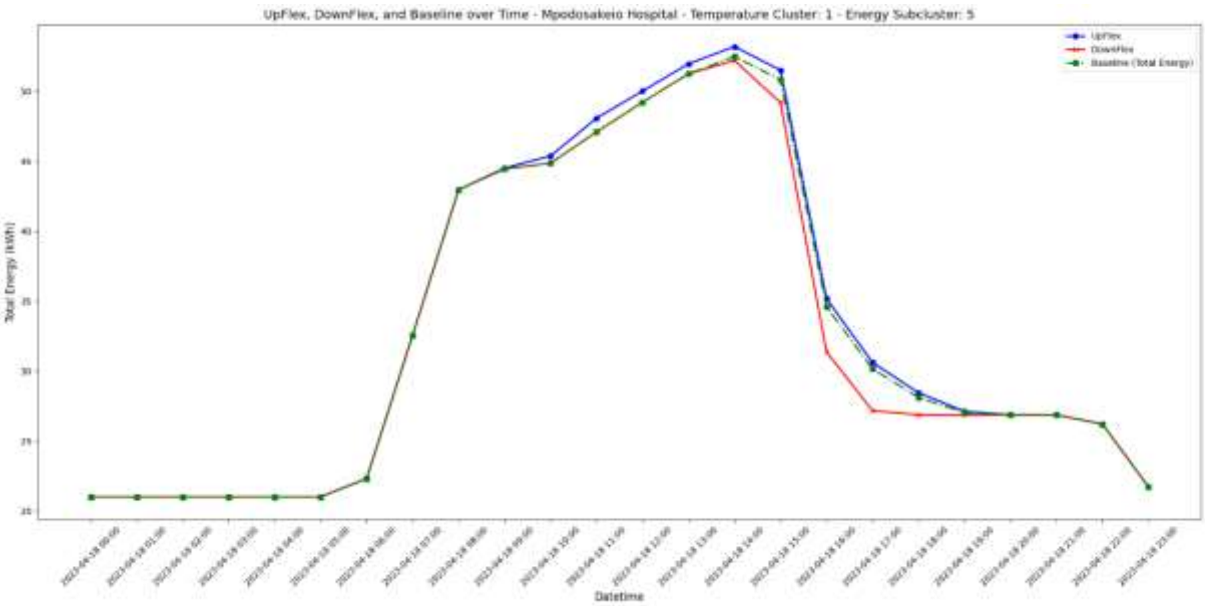


Figure 96:Predicted Demand side flexibility bounds for the thirteenth energy consumption sub-cluster of Mpodosakeio Hospital (up- flexibility bound (blue), down-flexibility bound (red), baseline (green))