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Added value services suite v1

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Executive Summary

This document is the first version of the D^2EPC Added Value Services Suite. D4.2 provides a thorough description of the main components that comprise the Added Value Services Suite, namely, the RoadMapping Tool, the AI-driven Performance Forecasts, and the Performance Alerts and Notifications. Furthermore, it provides information about their current development status, describing the work that has been carried out up to this point (M25) in the project. The interconnection between the examined sub-modules and other core components of the D^2EPC architecture is also analysed.

In the first part of this deliverable, a literature review is presented, analysing state-of-the-art methods and best practices with regard to the three sub-modules. Some of these methods are selected and experimented towards investigating whether they present a good fit for the D^2EPC ecosystem.

The second part provides the reader with more specific information about the applied methodologies along with software-specific implementation details. The document provides information about aspects such as the required inputs and the necessary preprocessing that is applied to the collected data, as well as, the general workflow of these tools in order to achieve the desired results.

In the case of the RoadMapping Tool, the already existing building documentation from the Building Digital Twin module is leveraged to diagnose the building's current state and strategically recommend the right renovation actions to increase the asset's energy efficiency. The analysis is performed both in terms of the building's envelope as well as of the installed technical systems that serve the asset's requirements. Finally, the tool examines the use of Renewable Energy Sources to reach net zero energy consumption goals.

The operational characteristics and behaviour profiles in terms of the asset's energy consumption and indoor conditions are examined by the AI-driven Performance Forecasts. The module relies on temporal data, namely the day of the week and the month of the year, weather data such as the daily average, maximum and minimum temperature, and historical consumption data. It becomes evident that the successful integration of these modules will be aligned with the data quality that they receive, and the techniques that will be deployed to tackle the issue of missing or corrupted data.

The Performance Alerts and Notification tool further facilitates the end-user's interaction with D^2EPC's certification and monitoring platform. The document reports the tool's articulation and its basic functionalities. Furthermore, there is an analysis of the tool's interoperability with the rest of the platform's submodules according to the D^2EPC Framework Architecture.

The third and final part of this report illustrates the application of the first two developed sub-modules. Both applications are based on CERTH's nZEB Smarthouse pilot building. The results are presented both in a qualitative and quantitative manner. The main conclusions drawn from the tools' development and application indicate the best practises and future improvements that need to be implemented in the progress of the D^2EPC.

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List of Acronyms and Abbreviations

Term	Description
AI	Artificial Intelligence
AR	Asset Rating
BIM	Building Information Model
CNN	Convolutional neural network
DNN	Deep Neural Network
EC	European Commission
ELM	Extreme Learning Machine
EMD	Empirical Mode Decomposition
EPC	Energy Performance Certificate
EPBD	Energy Performance of Buildings Directive
DHW	Domestic How Water
DNN	Deep Neural Network
GRU	Gated recurrent units
LSTM	Long-short term memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MS	Member States
MTLF	Mid-term load forecast
NCPE	National Integrated Energy and Climate Plan
nZEB	Nearly zero-emission building
PV systems	Photovoltaic systems
RBF	Radial Basis Function
RES	Renewable Energy Systems
ResNet	Residual Network
RMSE	Root mean square error
RNN	Recurrent Neural Networks
STC	Solar Thermal Collector Systems
STLF	Short term load forecasting

U-value	Thermal Transmittance value
XGBoost	extreme gradient boosting
Web	World Wide Web

1 Introduction

1.1 Scope and objectives of the deliverable

This deliverable aims to provide an overview of the D^2EPC Added Value Services Suite. The purpose of the document is to report and expand the building's current state by integrating three unique tools for an energy performance upgrade (Roadmapping tool), prediction of the month ahead energy consumption (AI-driven performance forecasts) for optimal operational behaviour combined with alerts and notifications for excess energy consumption warnings.

This report provides a theoretical rationale for the three tools that are part of this module and an analytical description of the implemented methodologies. Moreover, the connection between the theoretical background and the actual implementation is emphasized along with the technical challenges that have come up during the initial phase of this task T4.2.

1.2 Structure of the deliverable

The Added Value Services Module's main goal is to provide recommendations for energy performance upgrades, and energy consumption forecasting for the operational functionality of the building with early notifications to the end user. In order to achieve the aforementioned targets, the report is organised into the following chapters:

- **Chapter 2** includes methodology and theoretical background, which contains a literature review to identify the current approaches to every submodule and the presentation of the D2EPC approach.
- **Chapter 3** refers to the implementation of every submodule. A technical report is created for every submodule, which describes the implemented technologies and challenges during the development of the Added Value Services Suite.
- **Chapter 4** refers to the presentation of results for each submodule and their application to the pilot cases.
- **Chapter 5** is the summary of this deliverable. It describes the overall work that has been reported in this deliverable and potential next steps for functionality improvement of the modules.

1.3 Relation to other tasks and deliverables

Task 4.2 whole rationale and methodology are based on the developed architecture of deliverable 1.4 and its updated version of D1.7, named "D^2EPC Framework Architecture and specifications." As a technical development task, T4.2 cooperates with T4.1 "Building Performance Module" to acquire calculation results. More specifically, the Roadmapping tool is based on the Asset Rating Module and the AI-driven performance forecasts rely on the outputs of the Operational Rating Module. It is worth mentioning that the needed input for T4.2 results from the work performed in T3.3, where a BIM-file is translated into accessible data that will be used by tools for processing. Finally, T4.2 results will be used as input to T4.3, and T4.4 to increase the functionality of the D^2EPC Web Platform. The Roadmapping tool output will be related to T6.3 "Linking EPCs with building passports and renovation roadmaps". The second version of this deliverable is expected by M36.

2 Methodology and theoretical background

2.1 Roadmapping tool

As climatic change sharpens, different approaches and strategies have been developed to minimize the environmental impact across Europe. Europe's building stock tends to be old and energy inefficient. Europe's building stock is responsible for 40% of energy consumption and 36% of energy-related carbon dioxide emissions [1]. The implementation of holistic building renovation roadmaps is mandatory for the achievement of Europe's decarbonization targets.

A step towards decarbonization is the Renovation Wave Strategy [2], published by the European Commission (EC) in October 2020. The aim of the Strategy is to improve the energy performance of buildings and at least double the renovation rates in the next ten years. An essential part of the Strategy is also the revision of the Energy Performance of Buildings Directive (EPBD) [3], published in December 2021, where ambitions are set out on how to achieve a zero-emission and fully decarbonised building stock by 2050. The proposed measures focus on the increased renovation rates of low-performance buildings. In the EPBD, the term Building Renovation Passport is introduced, as a clear and tailored roadmap with timing and scope of interventions for the building owners and investors who are planning a staged renovation for significant improvement of the building's energy performance. According to the revised EPBD's Article 10, the EC shall establish a common European framework for the renovation passports by December 2023 and each member state shall introduce a scheme of renovation passports by 2024. The requirements for the renovation passports include a renovation roadmap indicating a sequence of renovation steps toward zero-emission building by 2025 while indicating the expected benefits in terms of energy savings, emissions, and benefits related to health and comfort, etc.

Regarding the renovation roadmap, different approaches are suggested by national energy policies or research papers based on each country's unique conditions. The common approach is the envelope renovation of roofs, floors, walls, windows, and doors [4] as it is the most effective way to reduce thermal losses and operational carbon dioxide emissions [5]. Moreover, each country has developed its own renovation approach based on its needs. For example, in Germany is highlighted the need for an upgrade of heating systems and integration with a boiler for Domestic Hot Water (DHW) needs [6]. In Greece and Cyprus, the governments have published a technical guide, which includes renovation measures for heating, cooling, lighting, DHW, and Renewable Energy Systems (RES) [7], [8]. Lithuania's national renovation guideline includes measures for heating, DHW, ventilation, and solar collectors (photovoltaic for electricity loads and solar thermal collectors for DHW needs) systems with indicative costs and the economic lifecycle of each renovation action[9]. Regarding the Netherlands' housing stock, a study suggests a classification of thermal energy renovation measures. The classification is based on the renovation action type (envelope or building technical systems) and quantity (e.g. upgrade of one heating system or simultaneous upgrade of heating, DHW, and ventilation system) [10]. Also, it is recommended the transition of fossil gas to a sustainable heating alternative [11]. Another study showed that in the National Integrated Energy and Climate Plan (NCEP) for decarbonization of Spain's existing residential building stock, priority is given to the building's envelope to reduce the demanded thermal load and to avoid the oversizing of heating systems [12].

There are several ongoing EU-funded projects, which are in some parts working on the development of renovation roadmaps. One of such is also the BIM-SPEED project[13], a "Harmonised Building Information Speedway for Energy-Efficient Renovation". One of the tasks within the project is focusing on the definition of semantic design rules and tools for deep renovation design, presented in deliverable 7.3[14]. A specific BIM-based model checker was developed which allows the design team to automatically compare the model against the design rules of a country regarding thermal and acoustic standards, fire safety, and accessibility requirements in residential renovation projects. The tool assesses the elements and points out the ones that do not comply with the design rules, which allows the design team to easily plan the renovation of the building.

One of the added value services within the D^2EPC platform is a Roadmapping tool for performance upgrades. The purpose of the tool is to evaluate and assess the building as a whole in terms of energy performance, emission, and cost carrier in order to provide building-specific recommendations and user-centred suggestions. The suggestions can further enhance the building's energy performance and upgrade its EPC classification within an indicative timeframe. This BIM-based decision support tool identifies the optimal course of action toward improved energy efficiency and can further feed the relevant building renovation passport, as seen in Figure 1.

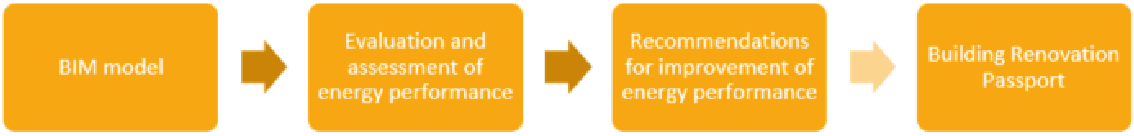

Figure 1: Roadmapping tool description

In the case of the Roadmapping tool within the D^2EPC project, the process of evaluation and assessment of the building's energy performance based on the BIM model can be divided into three main steps or categories.

1. Firstly, the **envelope** state is considered based on the thermal transmittance (U-values) of the individual elements, such as walls, roof, windows, doors, and floor. Based on that, the recommendations are formed indicating which elements and in which order should be improved in order to increase the EPC classification.
2. In the next step, the **building systems** can be improved, by replacing the heating or cooling system
3. As the third step, the Roadmapping tool considers the **renewable energy sources** and whether they can be installed or improved in order to increase the EPC of the building.

The important criteria of the Roadmapping tool are that this 3-step evaluation can be universally applied within all Member States (MS), however, there are different national legislations, defining minimum requirements for the U-values per element per country. In order to maintain the relevance of the tool, national regulations had to be investigated. This way the actual U-values of elements or systems efficiency could be evaluated by comparing them to the defined minimums. For example, if the U-value of walls is lower than what is indicated in the national legislation, then the improvement of wall insulation is considered mandatory.

The overall workflow can be described in Figure 2, where the main objective of improving the EPC classification can be achieved through three main categories. Each category consists of several actions to improve the building's energy efficiency. The diagnosis procedure includes the identification of the element and the element's specific characteristics. The technical characteristics of each building element category (e.g., U-values of walls) are compared with the respective values of specified standards. In the case that there is a "Violation of Standards," the diagnosis ends, and a renovation action is proposed as indicated in Figure 2: Workflow of the Roadmapping toolFigure 2.

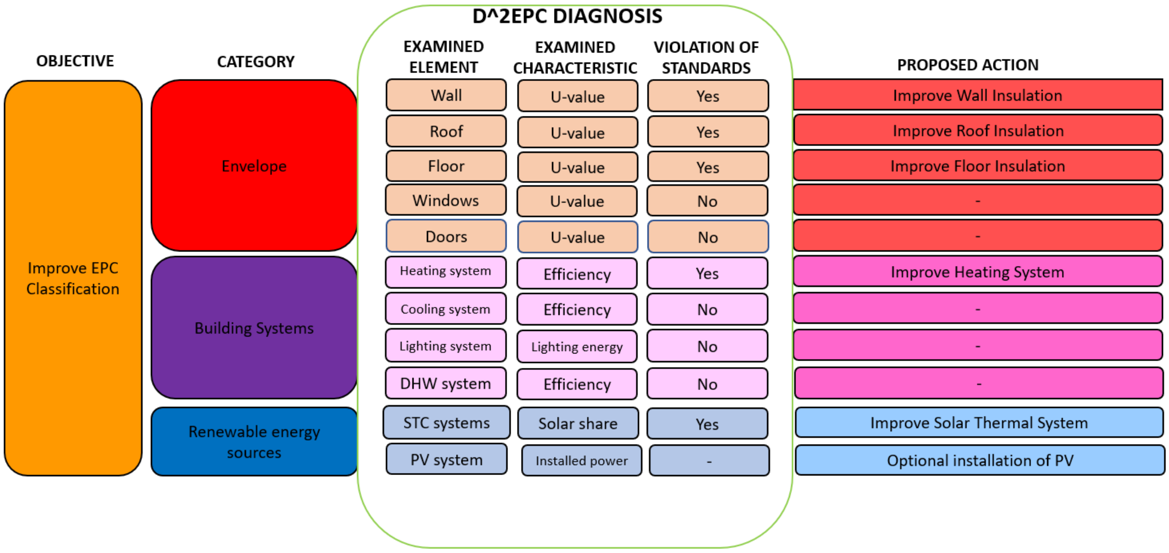

Figure 2: Workflow of the Roadmapping tool

Once the relevant actions are identified, they need to be evaluated regarding the effect they have on the improvement of the EPC classification. This means that for each action, a scenario is generated to evaluate how much the energy performance has improved. Based on that, a priority list is formed, indicating which action will result in the highest performance improvement with the deepest economic depreciation. Such prioritisation is valuable information for the user as it provides a guideline for energy and economically efficient EPC improvement.

2.2 AI-driven performance forecasts

In the last couple of years, great strides have been made towards increasing the accuracy and the algorithmic complexity of Artificial Intelligence methods that aim to predict the energy consumption or the electrical load of residential and industrial buildings. These methods can be categorised as short-term, mid-term, and long-term energy consumption forecasting.

In [15] the authors propose a Deep Neural Network (DNN) using a Long Short-Term Memory (LSTM) architecture. They tried to predict the short-term load for residential buildings in a publicly available dataset having two hidden layers with 20 LSTM nodes each. They observed that the mean absolute percentage error was high for individual customers (44%) while when they aggregated the load for all the customers, or when aggregating the forecasts, this error decreased significantly to 8-9%.

In [16] they proposed a method using Gated Recurrent Units (GRU) with the attention of an attention layer. They too had 2 hidden layers with 20 nodes each and they aimed to tackle the problem of short-term load forecasting in industrial buildings, mainly offices. Their method showed promising results as they had better metrics when tested with similar methods across the board ranging from 5-15% MAPE based on the day they forecasted and 7-29% depending on the months the forecasts took place.

The aforementioned methods use Recurrent Neural Networks (RNN) for the forecasting problem. In [17] the authors used a popular architecture called Residual Networks (ResNet) for short-term load forecasting, at a power system level, instead of per building level. ResNets are stacked architectures using the ResNet block, which in turn has as a core component convolutional layer. Although these models are mainly aimed at Computer Vision tasks, their experiments showed promising results in a large dataset, beating the previous state-of-the-art method on that dataset.

In [18] there was an attempt at fusing the features from convolutional neural networks (CNNs) and LSTMs. They tested their model on very short-term forecasting (hourly), short-term (day ahead) mid-term (weekly), and long-term forecasting (month ahead). By comparing their method with other state-of-the-art models, they showed that their methodology was superior to the other methods across all the datasets they used, and it was better in almost every metric (MAPE, MAE, RMSE) for each one of the forecasting problems they tried to solve (STLF, MTLF, etc.).

[19] is another attempt to tackle the forecasting problem with the use of feature fusion, in a fully convolutional architecture, where they had two branches, one for the external factors (e.g. weather conditions) and another one called the forecasting branch, which had the historical load as the input. The features from the two branches were merged in order to produce a more robust model output.

Apart from Deep Learning methodologies, there are tree-based methods that have shown extremely good results and generalisation ability. For example, in [20] and [21] the authors used a robust method called eXtreme Gradient Boosting (XGBoost) for the forecasts. Tree-based ensembled methods are based on decision trees, each tree making a prediction, and the final prediction is the aggregation of those predictions based on a rule. The XGBoost algorithm creates a new tree at a time and fixes errors in the previous trees by fitting their residuals. The outputs of the trees are then aggregated as in (1), where $\hat{y}$ is the final prediction, N is the total number of trees, and f_n is the function of the n-th tree, containing its tree's structure and weight.

$$\hat{y} = \sum_{n=1}^{N} f_n(x) \qquad (1)$$

Similarly, in [22] and [23] they used the XGBoost algorithm in conjunction with RNNs to retain a part of the temporal information. More specifically, in [22] they used LSTMs and XGBoost for the prediction of energy consumption, having two streams, one for the LSTM method and one for the XGBoost. The predictions were combined based on a weighted formula, depending on the MAPE of each stream. In [23] it was proposed to use GRUs with the XGBoost algorithm, the information flow was similar to the one that was mentioned in [22].

In [24] the authors proposed an Empirical Mode Decomposition (EMD) strategy to remove randomness and noise from the load data. They then used an Extreme Learning Machine (ELM) using a Radial Basis Function (RBF) kernel to predict the load in households, for the next day, week, and month.

2.3 Performance alerts and notifications

Because of climate change, a global focus on reducing residential energy demand has become critical. Continuous feedback to end users is required to better inform and raise their awareness of energy issues in order to reduce energy demand. Feedback referred to the structural investments, which include a more energy-efficient system and renovations, or to the curtailments of daily energy behaviour [25]. To increase energy efficiency, feedback is suggested to be combined with either commitment or goal-setting targets of the end-users [26]. Studies have shown that a change in a daily energy habit can lead to a reduction of 20 % of home energy demand based on the returned feedback without the loss of thermal comfort [27]. Furthermore, it is mentioned that a lack of user awareness can increase energy consumption by one-third [28].

The most effective way to raise user awareness is by providing real-time feedback with the usage of metering and sub-metering systems in order to depict the impact (economic and environmental) of electrical consumption on the end-users [29][30].

In this direction, IoT systems have been deployed in order to depict an occupant's energy behaviour for optimal energy control [31]. Although IoT systems depict the energy consumption of an electrical device, due to the random behaviour of each end-user, the development of AI algorithms to personalise the returned feedback is crucial for efficient interaction. The depiction of behavioural patterns through IoT devices is distinguished by AI algorithms for optimal interaction between the data of a smart home and the end-user [31],[32]. However, the integration of AI is facing some challenges, like the definition of anomalous power consumption and annotated datasets [33].

Different kinds of applications have been implanted in order to inform the end-user about potential energy savings. A study has developed a smartphone application with real-time feedback from IoT systems, which informs the end-user of unnecessary energy consumption in a university office building [34].

In the D^2EPC project, the Alerts and Notifications sub-component seeks to provide notifications or alerts to the end-user. Notifications provide a simplified and personalized message to the end-user through the Web-Platform. The context of the Notification depends on the interaction with the Roadmapping tool or AI-driven Performance and Alerts. Interaction with the Roadmapping tool message contains information about optimal energy performance recommendations. In contrast, the AI-driven performance forecast provides a depiction of the impact of end-users' energy behaviour.

3 Added value services suite implementation

The Added value services suite component consists of 3 different subcomponents with different objectives. The first subcomponent, the Roadmapping tool, is responsible for creating potential recommendations related to the building's asset-based data. The second subcomponent, AI-driven performance forecast is responsible for building operational suggestions based on monthly load predictions. The final subcomponent, the Alerts and Notifications Module provides alerts and notifications to the end-user based on the results of the Roadmapping tool and AI-driven performance forecast.

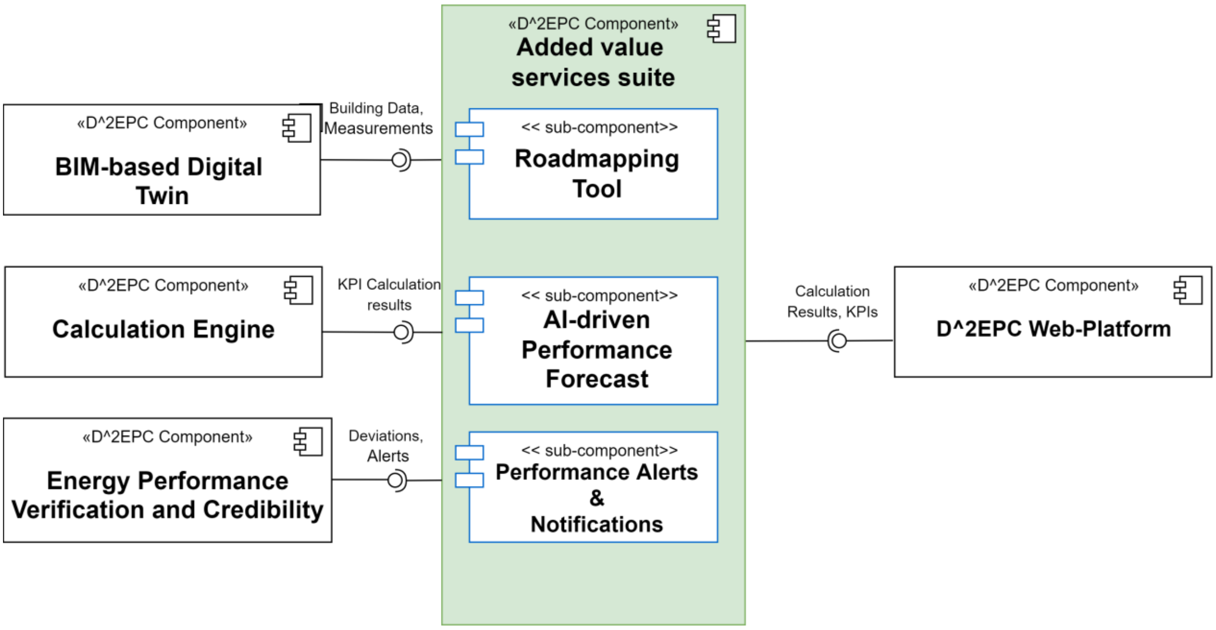

Figure 3: Added value services suite - Architectural view

3.1 Roadmapping tool Module

Roadmapping tool's main purpose in the D^2EPC project is to provide renovation action for energy performance upgrade with the integration of environmental and economic indicators for optimal strategy-making of the Web Platform end-user. Regarding the building's lifecycle Roadmapping tool can be mainly used during the operation and maintenance phase but it can also assist in the pre-design phase by providing different scenarios for optimal material and system selection.

Roadmapping's tool operation is enriched with Asset Rating (AR) Module calculations, which are described in D4.1. Asset Rating provides a Roadmapping tool with crucial feedback for energy performance indicators. Therefore, Roadmapping's tool strategy making is based on asset-based data, which is retrieved from the BIM-based Digital Twin.

The main purpose of this section is to present the tool's required input, operational workflow, and technical requirements for the development of the tool.

3.1.1 Roadmapping tool input

In order to provide the recommendation for an energy performance upgrade, the tool must acquire the national minimum requirements for the relevant EU country. The violation of the minimum requirement indicates the necessity of the renovation action. In the D^2EPC the examined countries are Cyprus, Germany, Greece, Lithuania, the Netherlands, and Spain. The boundaries are referred to as the minimum thermal transmittance value for each country's climatic zone, minimum efficiency standards for heating and cooling systems, and the minimum solar share of Solar Thermal Collector (STC) technical systems' attributes.

Indicatively, Table 1 documents the minimum thermal transmittance requirements (U-value) for the Greek climatic zone C, where CERTH's nZEB Smarthouse is located.

Table 1: Minimum U values of Greece per climatic zone

Climatic zone	External wall	Window	Floor	Roof	Door
A	0.6	3.2	0.5	0.5	3.2
B	0.5	3	0.45	0.45	3
C	0.45	2.8	0.4	0.4	2.8
D	0.4	2.6	0.35	0.35	2.6

Table 2 presents the minimum efficiency requirements for the various heating systems. The minimum efficiency for cooling systems has a value of 3.0. Finally, regarding the STC systems, the threshold of solar share is 0.6.

Table 2: Minimum efficiency of heating systems

HEATING SYSTEM	Minimum efficiency
Oil boiler	0.85
Natural gas boiler	0.95
Biomass boiler	0.82
Heat pump	3.3

It is worth mentioning that BIM-based Digital Twin provides the demanded input to the Roadmapping tool to complete the evaluation process. The data include:

i. Area of each thermal zone
ii. Thermal characteristics (e.g. U-value) for each envelope element
iii. Technical systems efficiency and nominal power

3.1.2 Roadmapping tool Operation Workflow

This section constitutes 2 sub-sections to describe holistically the operation workflow of the Roadmapping tool. The first sub-section describes the general workflow of the tool for all renovation measures and the second part explains the rationale for each specific renovation measure.

3.1.2.1 General Workflow of Roadmapping tool

This sub-section will present the general operational workflow of Roadmapping, which is applicable to all renovation measures. Roadmapping general workflow can be summarised in the following steps:

A. The first stage before scenario generation starts is the creation of a building instance with current characteristics and no renovation actions. Building's instance is used as an input to AR Module. AR provides different calculations that will be used for comparison with the calculation of renovated building instances. AR provides the following calculations of the current building's state:
    a. Total primary energy
    b. Total carbon emissions from carbon dioxide
    c. The total cost of all energy carriers
    d. Total energy for lighting use
    e. Solar share of Solar Thermal Collector (STC) Systems for DHW need, if STC system exists
    f. Electrical energy from photovoltaic systems (PV), If a PV system exists
B. A digital copy of the building is created for each renovation measure.
C. Identification of the examined attribute per renovation category. For example, for a building's envelope, the examined attribute is the thermal transmittance value.

D. The examined attribute is used as input to a diagnosis procedure to identify the need for a renovation action. The need for a renovation action is defined as mandatory in the event that any of the examined attributes violate national guidelines. If renovation action is mandatory, the scenario generation starts and the building's digital copy is modified according to suggested recommendations. In the case of a building's digital copy that does not violate national guidelines, its context remains immutable.
E. The modified copy of the building is used as an input to the AR Module for energy calculations.
F. All energy calculation results are integrated with an indicative renovation cost in a final table.
G. The final table is sorted by payback years.
H. Non-modified building instances are integrated into the final table to depict the final Renovation Roadmap to the end-user.

The general operational workflow is shown in Figure 4.

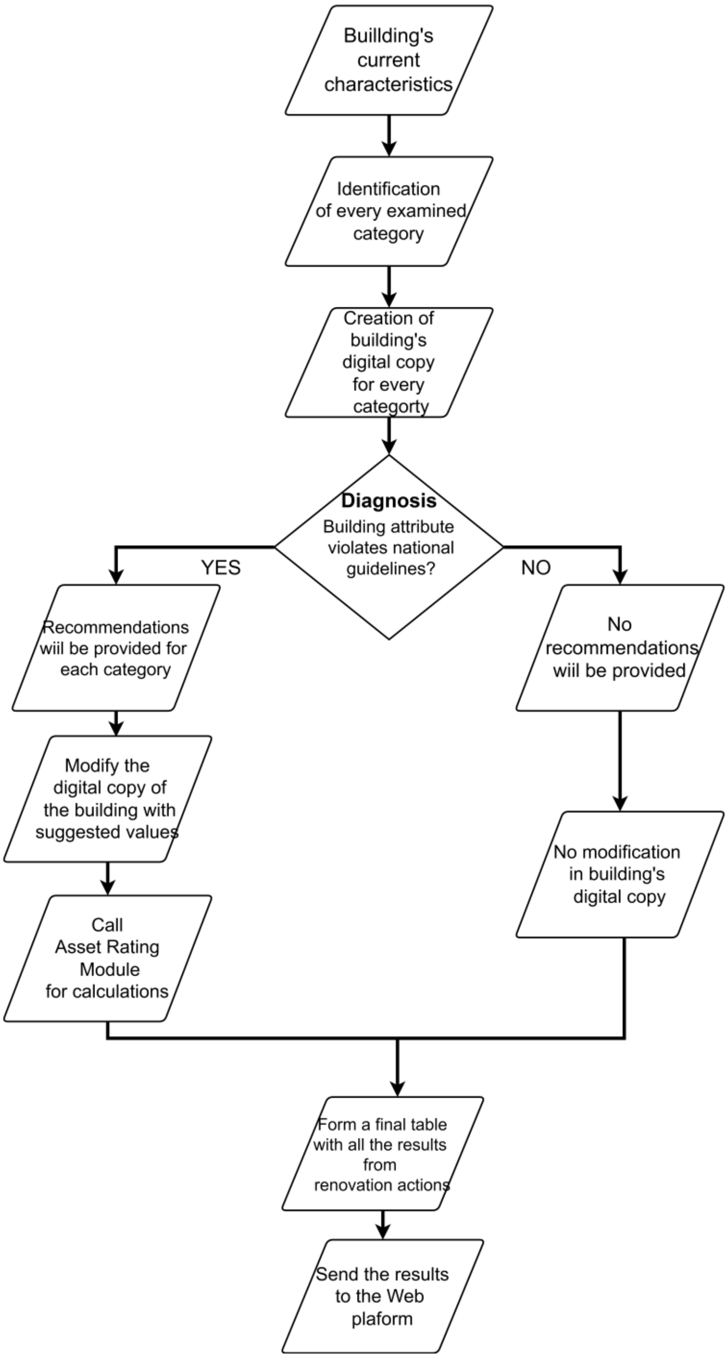

Figure 4: Roadmapping tool General Workflow

3.1.2.2 Renovation measures for energy performance upgrade

Apart from the general operational description, a brief description is made for each renovation measure. For the development of the tool, three main renovation categories were studied. For each renovation category, different renovation measures. More specifically, regarding the building's envelope, the external insulation of elements in contact with the external air was examined. In the category of technical systems, the heating, cooling, lighting, and Domestic Hot Water (DHW) systems were taken into consideration. Regarding Renewable Energy Sources (RES), Solar Thermal Collectors (STC) and Photovoltaic systems, finalise the renovation roadmap of the end-user. The order of the renovations is developed based on the renovations' measure efficiency and the fulfillment of the needs, which increases the standard of living of the end-user.

The following paragraphs provide the rationale for each renovation measure. Specifically:

I. The building's external insulation is referred to as the external insulation measure, which is implemented in elements that are in contact with the external air. The examined elements are external walls, roofs, floors, doors, and windows. For each element, the average thermal transmittance value and the total area are calculated. The average thermal transmittance value is compared with national minimum thermal transmittance values. If the average value is greater than the national minimum value, then each element of the building is assigned the minimum value. With the knowledge of the total element's area, the renovation cost of the external insulation is measured in $€/m^2$.

II. Heating systems are defined as the systems that are used during the predefined heating period. The examination of heating systems includes the identification of system type (boiler or heat pump), and current heating fuel (oil, biomass, natural gas, electricity). After identification, checking will be conducted to examine if the heating system's efficiency per heating zone meets minimum national guidelines. In case of national guidelines violation, a new heating system is proposed based on the heating zone area. More specifically, the heating zone area defines the efficiency and the nominal thermal power of the heating system. The total renovation cost of the heating system results from the nominal thermal power.

III. Cooling systems are defined as the systems, which are used during the cooling period. Similarly, to the heating system, it is examined if the cooling system efficiency per cooling zone is meeting the national standards. In case of renovation, a system is proposed based on the cooling zone area and the system's efficiency. The cooling zone area defines the required system's cooling power and consequently, the cooling power defines the renovation cost.

IV. Solar Thermal Collector (STC) systems include the system that partly covers DHW load with the harnessing of solar energy. The tool identifies the need for STC system installation, the non-existence of the system, or an upgrade of the current system for the specific thermal zone. The renovation action is mandatory in case the solar share of the STC system does surpass a solar share threshold. Solar share is described by the following equation:

$$solar\ share = \frac{Delived\ energy\ by\ the\ STC\ system}{Total\ demanded\ energy\ for\ DHW} \tag{2}$$

STC system proposal is based on the increase of the solar thermal collector's area until the satisfaction of the solar share threshold. The renovation cost is defined by the solar thermal collector's area.

V. DHW systems consist of units that will cover the remaining portion of the STC DHW load for every DHW zone. DHW production is based on the heating system, and the examination of the system follows the minimum efficiency standards for heating according to national guidelines. The examined attributes are production unit type (boiler or heat pump), fuel type (electricity, gas, or oil), and efficiency. The proposed DHW production unit can also be incorporated as a heating system.

VI. An examination of lighting systems is being conducted for non-residential and conditioned thermal zones. Based on the usage of the lighting zone, the demanded lux is defined. With knowledge of the total lighting zone area and the demanded lux, the total lumen per lighting zone is calculated. The proposed lamps have specific bright performance, which is measured in Lumen/Watt, and in combination with the total lumen, the total lighting installed power is calculated. Then, a calculation of the total number of lamps and the total lighting installed power is made. The lighting examination finishes with the comparison of lighting energies between the current building and the lighting-renovated building. In the case of renovation, the cost is calculated on the number of lamps.

VII. A photovoltaic (PV) system examination provides a suggestion about a PV system in order to minimise electrical demand. The proposed system is sized considering parameters like the building's location and its annual amount of energy demand. Finally, the installation cost is calculated based on the dimensioned PV system.

3.1.3 Development of Roadmapping tool

Roadmapping tool sub-module is written in the Python programming language in the Python 3.8 version. The whole tool is structured as a Python package to achieve interoperability among other services. The following libraries were used for the development of the tool:

- Pandas version 1.4.2[1]
- Joblib version 1.1.0[2]
- Collection version 3.3[3]

3.2 AI-driven performance forecasts

In the context of D^2EPC, the main idea is to implement a method for long-term load forecasting with monthly intervals. To that end, various architectures were tested using GRUs, LSTMs, Fully Connected Layers, and the XGBoost algorithm. For the experiments, a dataset taken from CERTH's smart home metering data was used, covering the period between November 2020 to November 2021. The data had a 15-minute granularity for the consumed energy, so it had to be preprocessed to extract the daily energy that was consumed.

Apart from energy consumption, we used weather and temporal data. The weather data were obtained from the meteostat[4] API. For the initial experiments, the data that we used can are:

- The energy consumption
- The average outdoor temperature
- The maximum outdoor temperature
- The minimum outdoor temperature
- The day of the week
- Binary mask for weekends
- The month of the year
- The precipitation

For the experiments with DNNs the weather and energy information had to be normalized using equation (3), while for the temporal info apart from the binary mask for weekends, they were transformed into sine and cosine form, with equations (4) – (7). The XGBoost algorithm does not necessarily need the weather and energy data to be normalized, but we still used equations (3) – (6) for the temporal information transforms. The day parameter ranges between 0 and 6, Monday being 0 and Sunday 6, and the $month$ parameter ranged from 1 through 12, January being 1 and December 12.

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{3}$$

$$day_{sin}' = \sin(day * 2 * \frac{pi}{7}) \tag{4}$$

$$day_{cos}' = \cos\left(day * 2 * \frac{pi}{7}\right) \tag{5}$$

[1] https://pandas.pydata.org/docs/index.html

[2] https://joblib.readthedocs.io/en/latest/

[3] https://docs.python.org/3/library/collections.html

[4] https://meteostat.net/en/

$$month'_{sin} = \sin(month * 2 * \frac{pi}{12}) \tag{6}$$

$$month'_{cos} = \cos\left(month * 2 * \frac{pi}{12}\right) \tag{7}$$

The experiments with DNNs were conducted using TensorFlow[5] with Keras's[6] backend. We used the regression eXtreme Gradient Boosting implementation provided by scikit-learn[7] .

Regarding the pre-processing, the sliding window technique was deployed. Temporal windows were generated with their length being twice the days we were forecasting. The first half of the window for energy consumption was the historical consumption input of the models. In the second half, the energy consumption was used as the target variable and the temporal and weather data were added to the energy consumption from the first half of the window as input. In total there were around 360 data points. The last month was used for validation and testing.

For the LSTMs and GRUs, an architecture with 2 hidden layers was tested, with varying nodes in them. It was observed that higher nodes were not beneficial for the models, it is possible that due to data scarcity the models could not learn well enough when they were too large. As such LSTMs and GRUs with 64 nodes in each hidden layer were deployed. We also tried using an attention mechanism after the 2 hidden LSTM layers, which did not improve the model's forecasting ability. In order to increase the forecasting ability of these methods a gaussian layer was placed after the input to data that added gaussian noise to the data distribution, thus augmenting the original dataset.

Furthermore, experiments were conducted with convolutional neural network (CNN) architectures and a CNN-LSTM hybrid architecture, where the CNN part was used to extract features from the temporal and weather data and the LSTM for the consumption data. Then the outputs were merged, and a final prediction was made with a fully connected layer handling the aforementioned outputs. In Figure 5, the architecture of the said mode is provided.

The same applied when experimenting with the Multi-Layer Perceptron using fully connected layers. As such the nodes in each hidden layer were set at 64. The networks had Adam as their optimizer and between the hidden layers and the output, we added dropout layers with a 50% to 70% chance of dropping that node during training. The models were trained for 60 epochs. The batch size was set at 4 to 6 and the optimal learning rate was 0.0003.

The XGBoost algorithm seemed to be more robust than the DNN architectures. After experimenting with its hyperparameters, the ones that yielded the best results were as follows: the number of estimators was 420, the maximum tree depth was 4 and the learning rate was set at 0.08. All the methods had a mean squared error as their loss function, except for the XGBoost which had a mean absolute error as its optimization function.

After the initial phase of the experiments, it was observed that there was residual noise in the data points. Thus, the 2-sigma rule was applied on the lower end of the data distribution to eliminate outliers due to incorrect measurements, power outages, etc. After that, via a grid search cross validation scheme, the optimal parameters for the XGBoost, Random Forest, and Extra Trees methods were estimated.

In D^2EPC the goal of this module is to forecast the energy consumption of the following month, its output will be forwarded to the Operational Rating module, defined in D4.1, where it will estimate how much the excess or lesser energy consumption will impact the building's Operational Rating in a 6-month window. As the Operational Rating is under development this connection has not been established yet. In addition to that, since the prediction of a single building's energy consumption needs a quite large dataset, we have integrated a self-learning mechanism, which retrains the models each month, making use of the newly available data that have been added to the D^2EPC database.

A limitation that we have currently observed is the lack of publicly available APIs for month-ahead weather forecasting. This is not a limitation during the training phase, but it will cause issues when it is used in production

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[5] https://www.tensorflow.org/

[6] https://keras.io/

[7] https://scikit-learn.org/stable/

since the weather data for the coming month are needed for the predictions. In M36 when the second and final iteration of this task is due, the document will be updated with the necessary steps to tackle this issue.

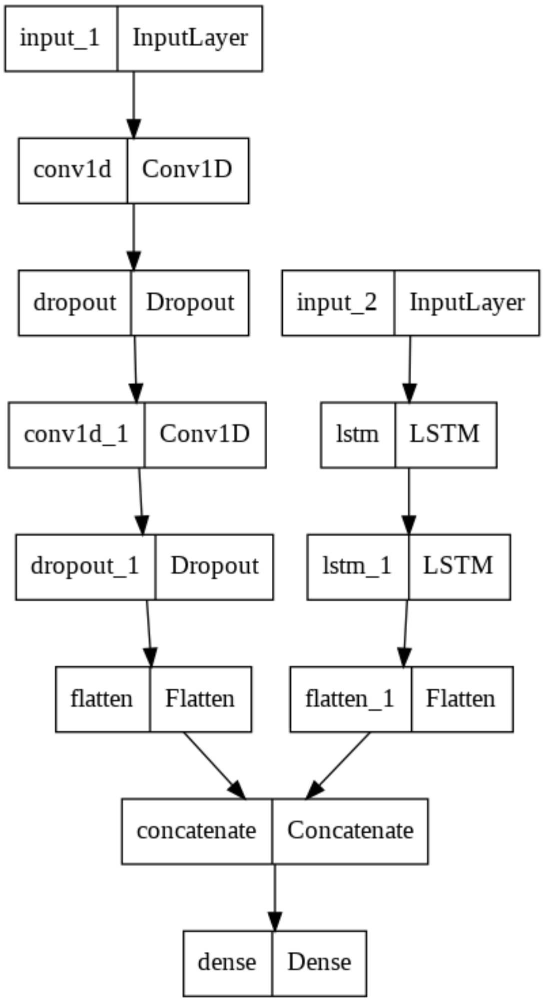

Figure 5: Hybrid CNN-LSTM architecture

3.3 Performance alerts and notifications Module

The functional diagram of the Performance Alerts and notification tool, as documented in D1.7, is shown in Figure 6. It includes two main sub-components, namely the recommendation engine and the communication client. As the component requires the advanced definition of the output of other components, as well as an initial integration among them and in the overall D^2EPC platform, a preliminary description of its basic functionalities is included herein.

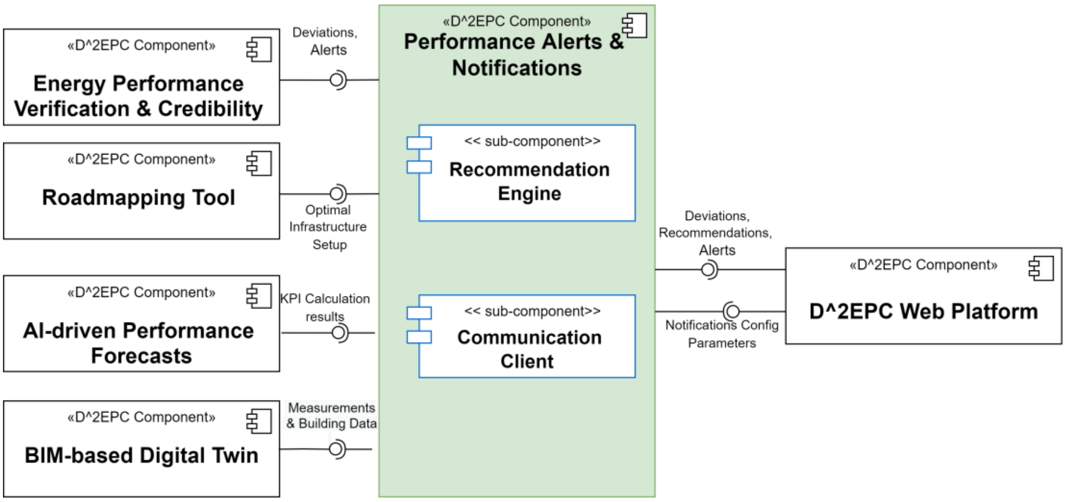

Figure 6: Performance Alerts and Notification - Architectural view

The tool functions as a common service that extracts and visualises through the Web Platform important information that is provided by the output of other tools. The component collects available data (both the most recent and historical) from the D^2EPC Repository, which have been stored as results from other components, and, through the incorporated recommendation engine, compiles meaningful alerts/notifications that are presented to the user, in order to provide insights and, depending on the case, to suggest possible actions.

The collection and visualisation of available notifications is based on periodic HTTP requests to the component. This asynchronous design stems from the fact that the output of the tools, based on the gathered real-time and static data, is not expected to be updated in high frequency, rather than over a wider timeframe. This design will be re-evaluated upon further development of the D^2EPC tools and a better definition of their expected outputs.

The operation of the tool can be adjusted by the user through the D^2EPC Platform in terms of:

- Frequency of notifications issuance: the user is able to select the minimum time interval between displayed notifications
- Notification sources: the user can select against which data sources (tools' outputs) alerts can be generated

The expected operation of the component and its information exchange with other components is illustrated in Figure 7.

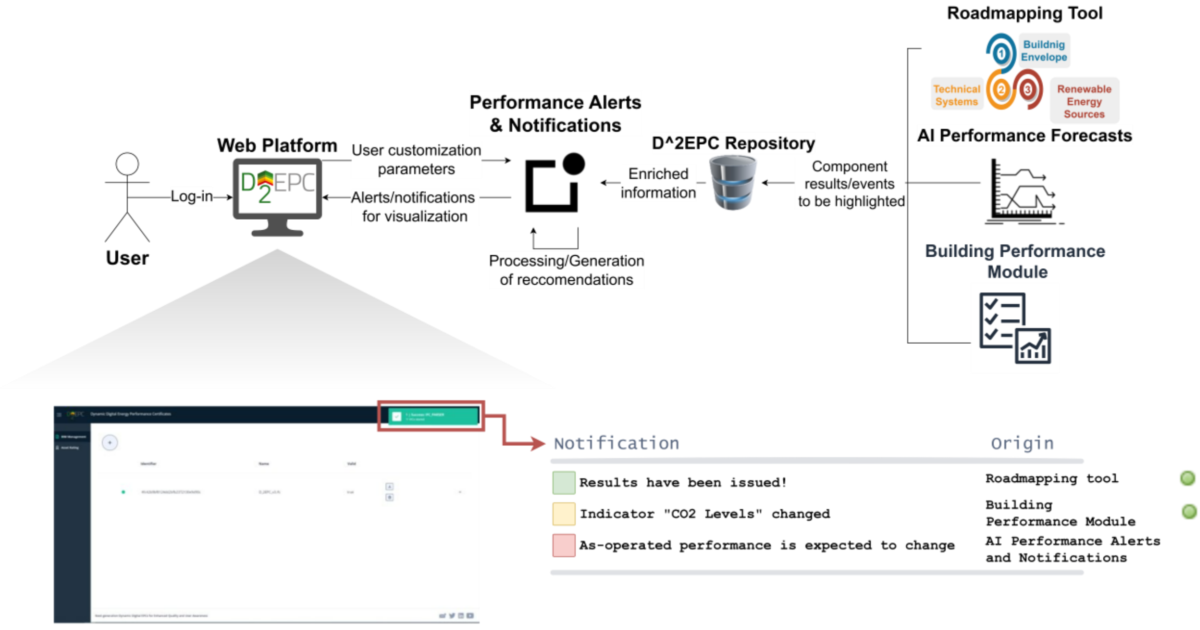

Figure 7: Performance Alerts & Notifications component interactions

Based on the current tools' design, the content of the alerts/notifications that are planned to be provided to the user includes the following:

Roadmapping Tool:	• Issuance of new renovation suggestions with high efficiency that are expected to have a direct impact on the building's performance (either on user demand or automatically) • Improvement of the set of suggestions in regard to the last one provided, based on new inputs
AI Performance Forecasts:	• Issuance of an updated forecast of the building's as operated energy performance (either on user demand or automatically) • Predicted alteration of the buildings as operated energy performance (upgrade/downgrade) in regard to the one included in the last issued EPC
Building Performance Module:	• Issuance of an updated set of calculated static or dynamic indicators (either on user demand or automatically) • Significant alteration of the newly calculated indicators in regard to the previous ones calculated

4 Added value services suite validation

4.1 Roadmapping tool

The Roadmapping tool has been tested for CERTH's nZEB Smart House. However, Smart House contains state-of-the-art technologies and an ideal envelope in comparison with regular buildings. To test every renovation measure of the Roadmapping Tool, Smart House properties were modified in order to violate national standards. This section demonstrates the results of the Smart house with major property modifications and the official examination of CERTH's nZEB Smart Home.

The final result of the Roadmapping tool is a complete renovation roadmap to guide the end-user about the environmental and economic impact of the renovation action. After energy and renovation cost calculations, all data are gathered per renovation action in a table, which has the format of the Python Pandas library Dataframe.

A typical table, which informs the end-user, is shown in Table 3. The index of the table describes the implemented renovation action and varies accordingly to the renovation measure. In the cases of heating (

Table 4), cooling, DHW (

Table 5), and lighting (

Table 6) the index refers to the renovation action and the examined zone. In contrast, STC (Table 7) and PV (Table 8) systems index indicates the existence or absence of the systems. The table depicts the values of total primary energy, primary energy saving percentage, total cost carrier, total cost carrier percentage, total emissions, total emission percentage, total renovation cost, and payback years. The last step is renovation scenario prioritisation based on the payback years. All the tables below, refer to the modified version of the Smart Home.

Table 3: Renovation of building's envelope

RENOVATED ELEMENT	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
Roof	79,016	24.3	5,752.4	24.3	67,163.6	24.3	4,126.7	2.2
Wall	78,699.3	24.6	5,729.3	24.6	66,894.4	24.6	12,557.8	6.7
Floor	88,357	15.3	6,432	15.3	75,103	15.3	8,062	6.9
Door	96,926.6	7.1	7,056.3	7.1	82,387.6	7.1	3,829.3	7.1
Window	98,807.6	5.3	7,193.2	5.3	83,986.5	5.3	27,051.8	67

Table 4: Renovation of heating systems

RENOVATED SYSTEM/ THERMAL ZONE	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
Heat pump/Residential	26,021.8	16.2	1,961.3	20.2	18,588.1	16.1	10,800	21.7
Heat pump/Office	28,431.6	8.5	2,200	10.5	17,305	8.1	8,150	31.5
Gas boiler/ Residential	28,870.6	7.1	2,550	3.7	16,912.6	5.6	4,000	43.7
Gas boiler/ Office	29,935.5	3.6	2,505.6	1.9	16,475.5	2.9	4,000	85
Biomass boiler/ Residential	29,960.5	3.6	2,361.3	4	15,969.2	0.3	9,800	100.7

Biomass boiler/ Office	3,049.63	1.8	2,408.5	2	15,990.1	0.1	8,650	172.8

Table 5: Renovation of DHW systems

RENOVATION ACTION	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
Upgrade of DHW system	21,279.6	19.9	1,549.2	19.9	18,087.6	19.9	12,500	32.4

Table 6: Renovation of lighting systems

RENOVATION ACTION/ LIGHTING ZONE	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
Upgrade of lighting system /Office	26,071.4	45.2	1,898	45.2	22,160.7	45.2	196	0.1

Table 7: Renovation of STC SYSTEMS

RENOVATION ACTION	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
With STC system	22,459.9	15.5	1,635.1	15.5	19,090.9	15.5	1,700	5.7

Table 8: Renovation of PV SYSTEMS

RENOVATION ACTION	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
With a PV system with a panel area 90 s.m	578.3	98.8	42.1	98.8	491.5	98.5	19,800	5.8

If a renovation action is not mandatory because there is no violation of the national guidelines, then the context of the table will be the values of primary energy, total emissions, and total cost carrier, and the index will adjust accordingly. The results are shown in Table 9.

Table 9: No renovation of the building's cooling systems table

RENOVATION ACTION/ COOLING ZONE	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
NO COOLING UPGRADE /RESIDENTIAL	19,774.7	0	1,436.6	0	16,808.5	0	0	0
NO COOLING UPGRADE /OFFICE	19,774.7	0	1,436.6	0	16,808.5	0	0	0

The final table, which will assist the end-user in optimal decision-making is shown in Table 10.

Table 10: Roadmapping tool final table

RENOVATION ACTION	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
Roof	149,727.4	27.7	12,971.5	26.7	18,055.3	52.4	4,126.7	0.9
Upgrade of DHW system	103,562.6	50	8,671.7	51	28,327	25.3	12,500	1.4
Heat pump/Residential	135,036.3	34.8	10,665.4	39.7	70,771	86.6	10,800	1.5
Floor	158,500	23.5	13,418	24.2	35,640	6	8,062	1.9
Wall	140,184.3	32.3	11,988.6	32.3	25,140.4	33.7	12,557.8	2.2
Heat pump/Office	172,994.2	16.5	14,379.6	18.8	52,897.3	39.5	8,150	2.5
COOLING UPGRADE /OFFICE	198,616.5	4.1	17,079.6	3.5	30,666.3	19.1	1,700	2.7
COOLING UPGRADE /RESIDENTIAL	200,607.7	3.2	17,224.6	2.7	32,358.8	14.7	1,700	3.6
With STC system	202,440	2.3	17,358	1.9	33,916.3	10.6	1,700	5
Doors	196,443.1	5.2	16,955.3	4.2	27,034.6	28.7	3,829.3	5.1
Biomass boiler/ Residential	185,700.8	10.4	15,809.4	10.7	37,084.8	2.2	9,800	5.2
Gas boiler/ Residential	171,680.4	17.1	18,237.5	3	49,219.1	29.8	4,000	7.5
Biomass boiler/ Office	197,124.5	4.8	16,816.8	5	37,530.4	1	8,650	9.8
Gas boiler/ Office	190,570.6	8	17,951.8	1.4	43,202.6	13.9	4,000	16
Windows	190,260.4	8.2	16,213.8	8.4	37,143.8	2.1	27,051.8	18.2
A PV upgrade with 85 s.m. panel area	213,873.7	3.2	12,949.6	26.8	6,643.8	82.5	187,000	39.4
NO LIGHTING UPGRADE	207,151.9	0	17,701	0	37,921.4	0	0	0

The table contains all the possible renovation actions prioritized by payback years. For the total number of renovated actions, the visualization of the table is conducted with graphs. Graphs contain the values for each renovation action about a specific field like primary energy or renovation cost. The following graphs contain values from specific renovation action of Table 10. The graphs describe the primary energy(Figure 8), energy saving(Figure 9), annual energy cost(Figure 10), annual cost saving(Figure 11), CO_2 emissions(Figure 12), CO_2 emissions saving (Figure 13), renovation cost (Figure 14), and payback years(Figure 15).

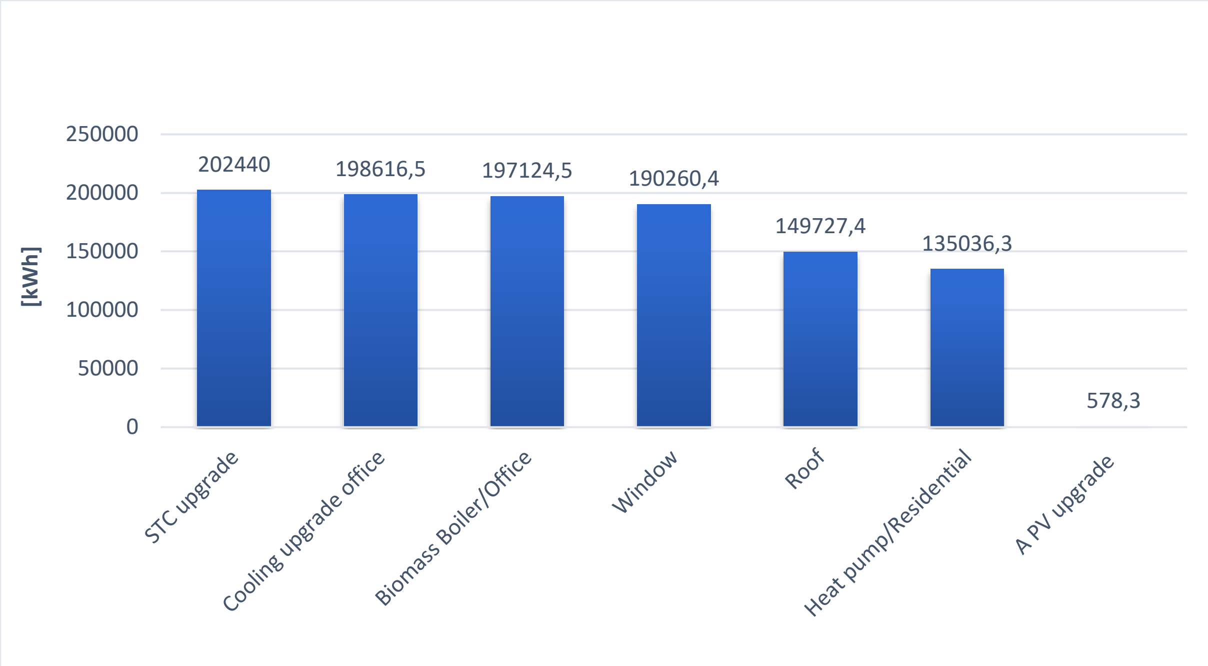

Figure 8: Primary energy

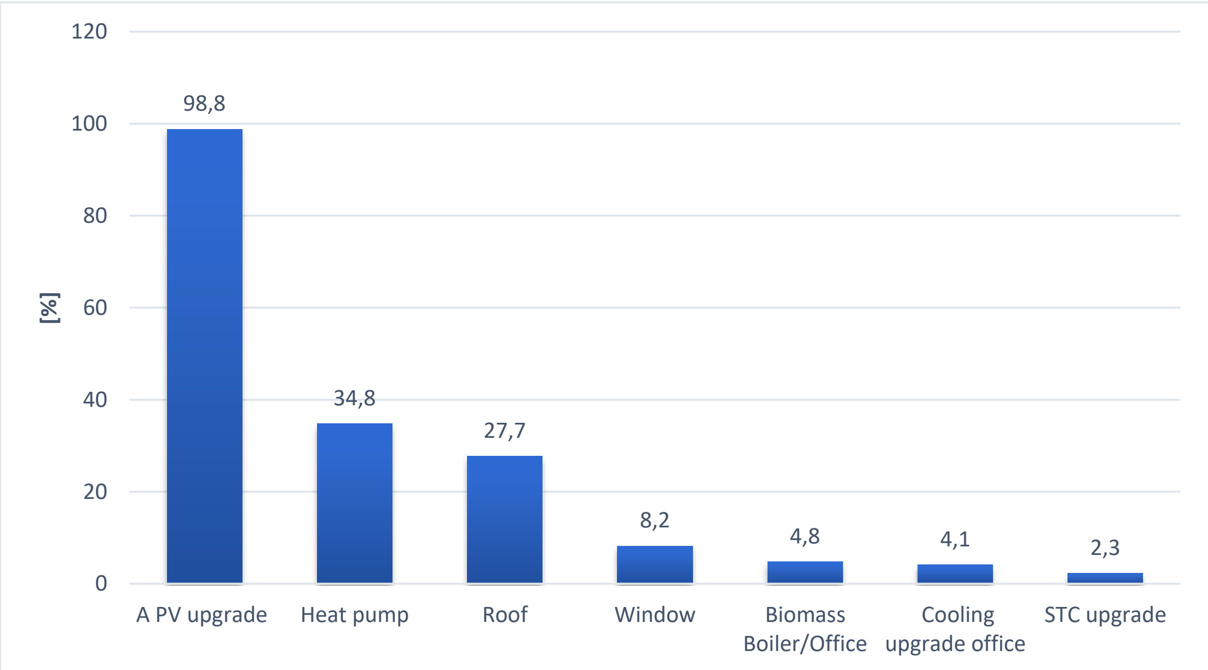

Figure 9: Energy saving

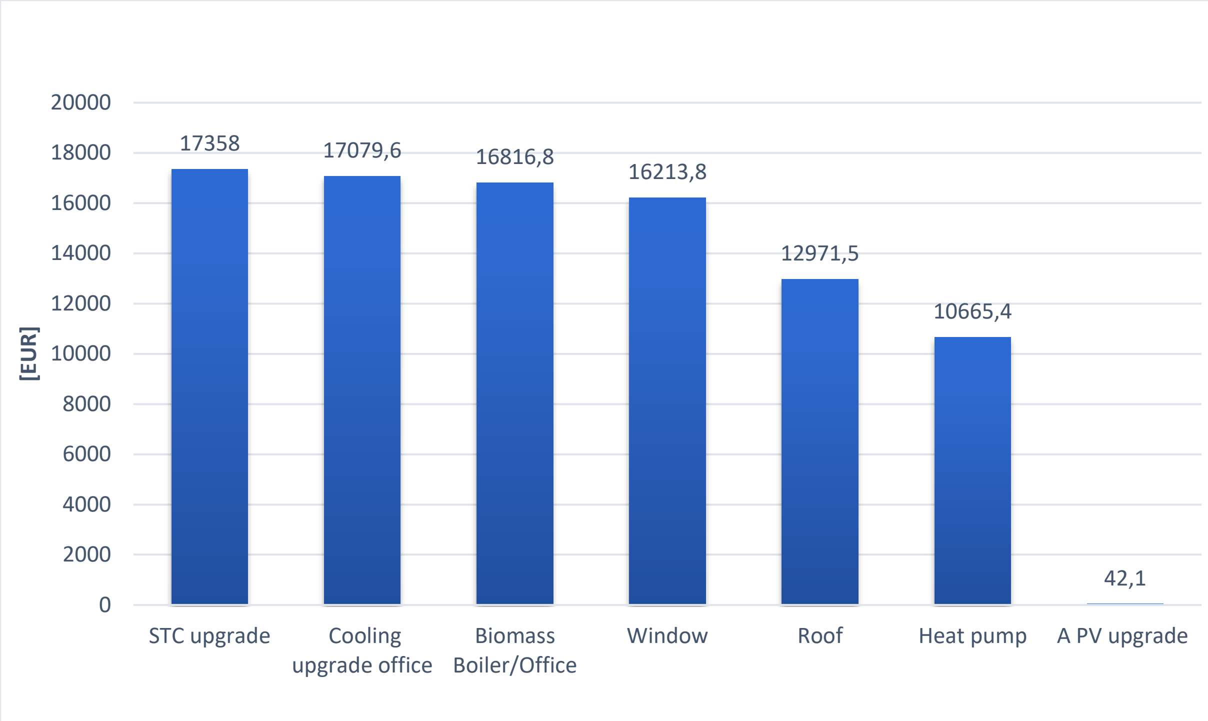

Figure 10: Annual cost of energy bills

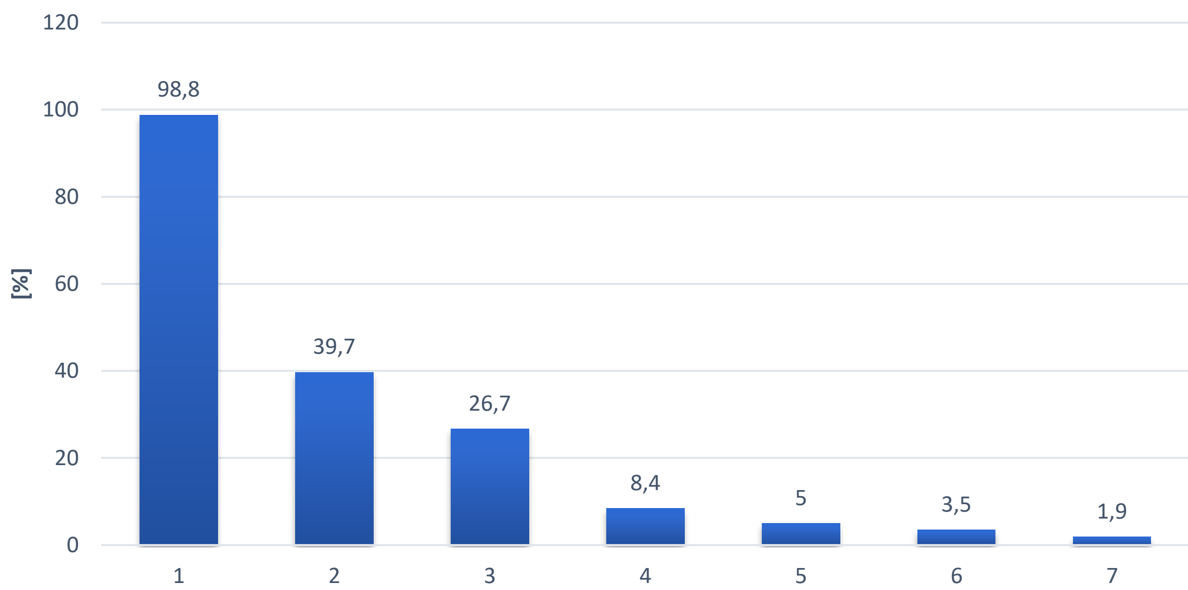

Figure 11: Annual cost saving

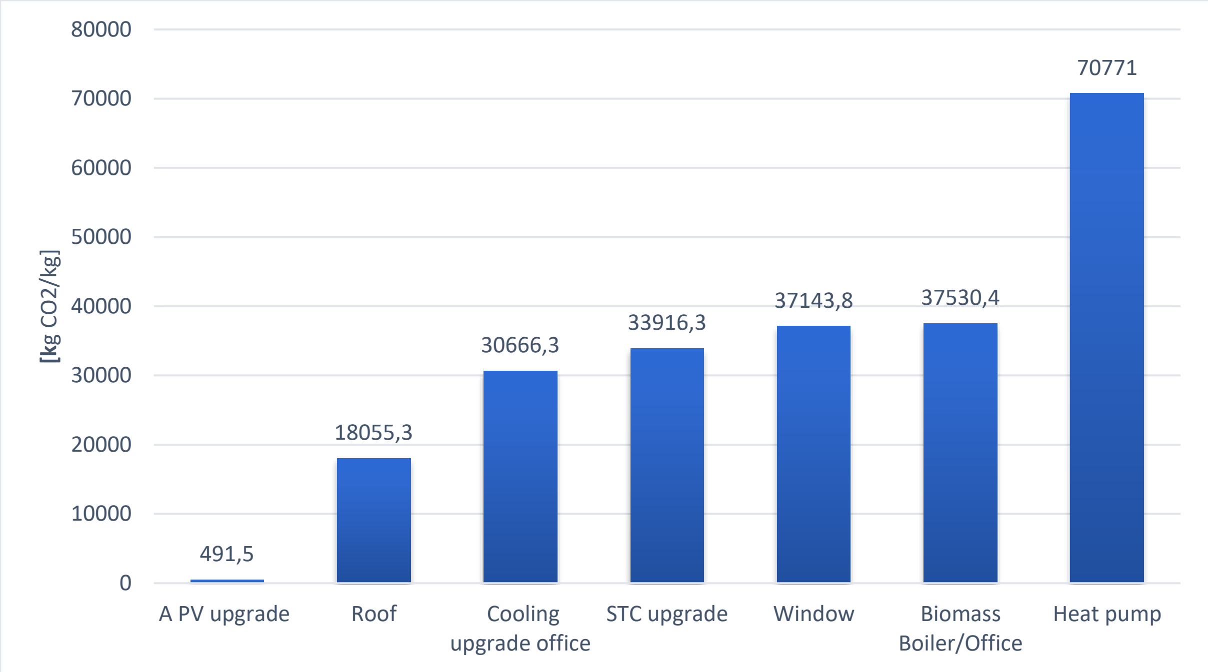

Figure 12: CO2 Emissions

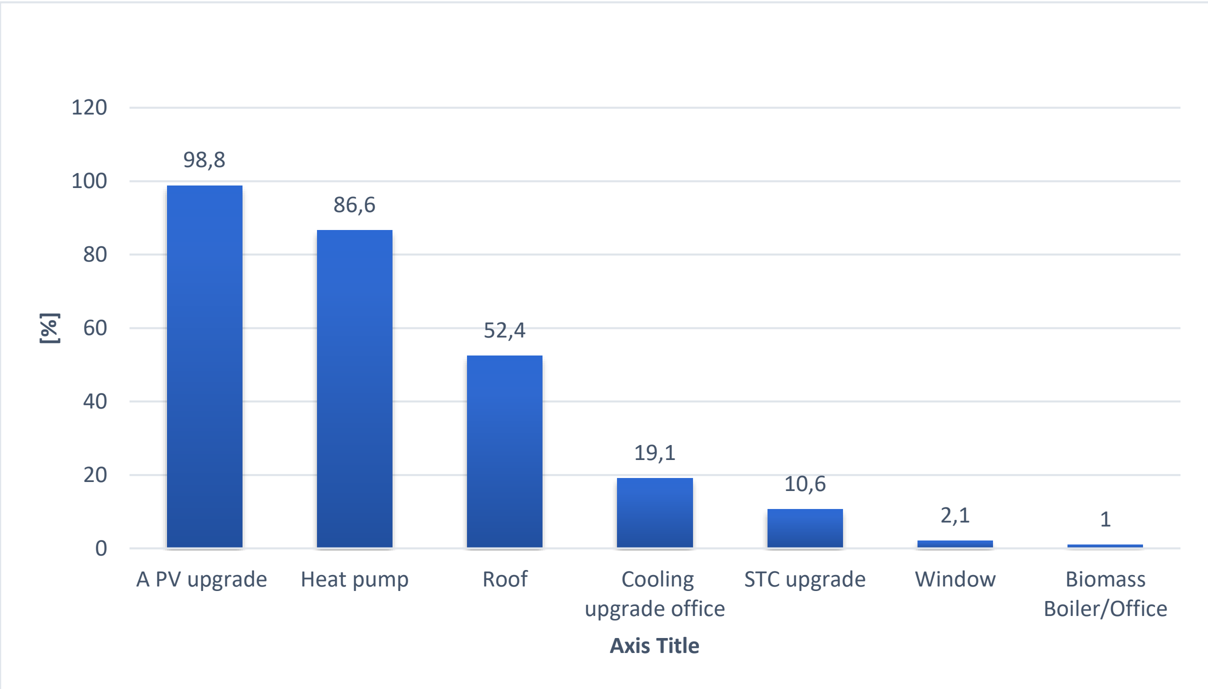

Figure 13: CO2 Emissions saving

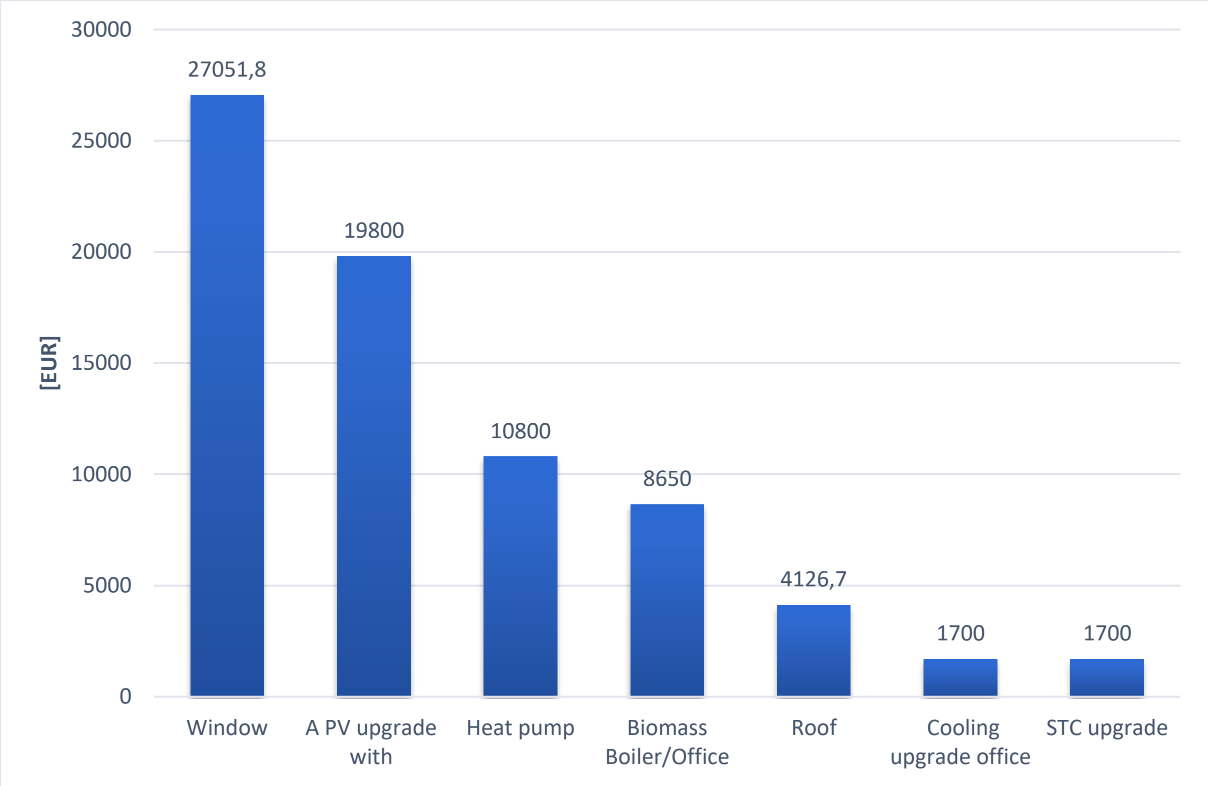

Figure 14: Renovation cost

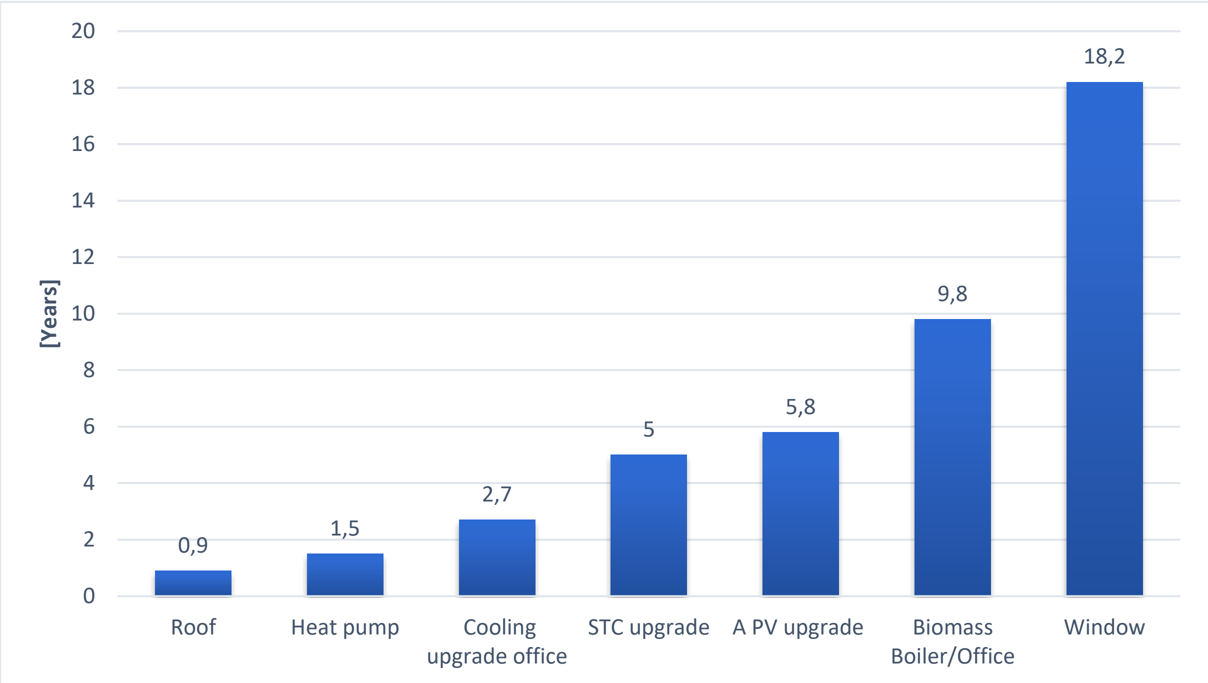

Figure 15: Payback years

The end-user information can be achieved with ball graphs. Figure 16 shows a bubble chart, where in the x-axis is the renovation cost, in the y-axis is the payback years. The diameter of each bubble depends on the energy saving, and inside the ball depicts the name of the renovation action.

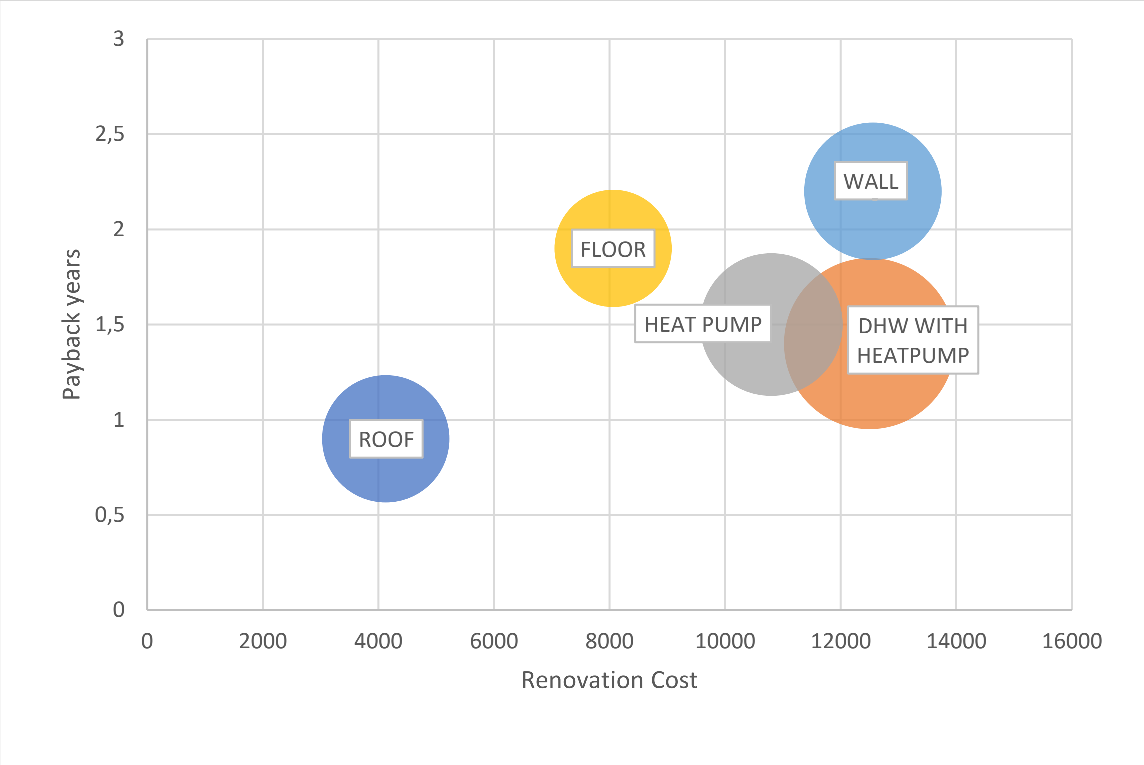

Figure 16: Ball graph for renovation depiction

Finally, the Roadmapping tool was tested in CERTH'S nZEB Smart House (Pilot Case Study 1). Smart home's BIM file contains all the necessary information for the operation of the tool. However, Smart House is a state-of-the-art building, which includes a reinforced envelope, high-efficiency systems, and electrical production from a PV system as described in D5.3. It implies that Roadmapping tool can only make suggestions regarding photovoltaic systems, which is an optional recommendation. The final results of the tool are shown in Table 11.

Table 11: Roadmapping tool results for CERTH's nZEB Smart House

RENOVATION ACTION	Primary Energy [kWh]	Energy saving [%]	Cost [EUR]	Cost saving [%]	Emissions [kg CO_2/kg]	Emissions saving [%]	Renovation Cost [EUR]	Payback years
PV system with panel area 90 m^2	3,924.4	7,040	285.7	80.2	3,335.7	80	7,040	6.1
NO RENOVATION OF WALL	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO RENOVATION OF WINDOWS	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO RENOVATION OF DOORS	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO RENOVATION OF ROOF	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO RENOVATION OF FLOORS	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO HEATING UPGRADE /OFFICE	19,774.7	0	0	1,439.6	0	16,808.5	0	0

NO HEATING UPGRADE /RESIDENTIAL	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO COOLING UPGRADE /OFFICE	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO COOLING UPGRADE /RESIDENTIAL	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO RENOVATION IS NEEDED FOR RES_SOLAR SYSTEMS	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO STC SYSTEMS UPGRADE	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO DHW SYSTEMS UGRADE	19,774.7	0	0	1,439.6	0	16,808.5	0	0
NO LIGHTING UPGRADE	19,774.7	0	0	1,439.6	0	16,808.5	0	0

4.2 AI-driven performance forecasts

4.2.1 Ensemble Methods

The tree-based methods that we have tested are the XGBoost, Random Forest, and Extra Trees regressors. A grid search cross validation scheme was deployed in order to find the optimal parameters for these methods, which are presented in Table 12 and provided next to ease the reader. For the XGBoost algorithm, the number of estimators is set to 420, the maximum tree depth at 4, the learning rate at 0.08, the loss function is the mean absolute error, and the criterion is the Friedman MSE. For the Random Forest algorithm, the number of estimators is set at 60 and the maximum tree depth is 8, the criterion is mean squared error, while for the Extra Trees Regressor, the number of estimators is equal to 300, the maximum tree depth is 9 and the criterion is also mean squared error.

Figure 17 through Figure 19 illustrate the predictions for the month ahead forecasting on a daily basis for the XGBoost, Random Forest, and Extra Trees Regressor. Figure 20 demonstrated the comparison of these results side by side. Table 13 summarizes the metrics of the three applied methods, namely the Daily mean absolute percentage error (MAPE), the Monthly MAPE, and the actual and predicted consumption.

The main metric of interest for the D^2EPC ecosystem is the monthly percentage error since the summation of the 30 predicted values for the month ahead forecasting will be given as input into the operational rating module, to predict the change in the building's operational rating. This study has reached the conclusion that the XGBoost algorithm performs significantly better than the other tested ensemble methods.

Table 12: Grid Search optimal parameters

Method	Number of Estimators	Max Depth	Criterion	Loss	Learning Rate
XGBoost	420	4	Friedman MSE	MAE	0.08
Random Forest	60	8	MSE	-	-
Extra Trees	300	9	MSE	-	-

Table 13: Metrics with optimal parameters

Method	Daily error (MAPE)	Monthly error (MAPE)	Predicted Consumption (KWh)	Actual Consumption (KWh)
XGBoost	*21.8 %*	*2.9 %*	2,287	2,221.6
Random Forest	35 %	21.8 %	2,705.3	
Extra Trees	40 %	31.1 %	2,912.5	

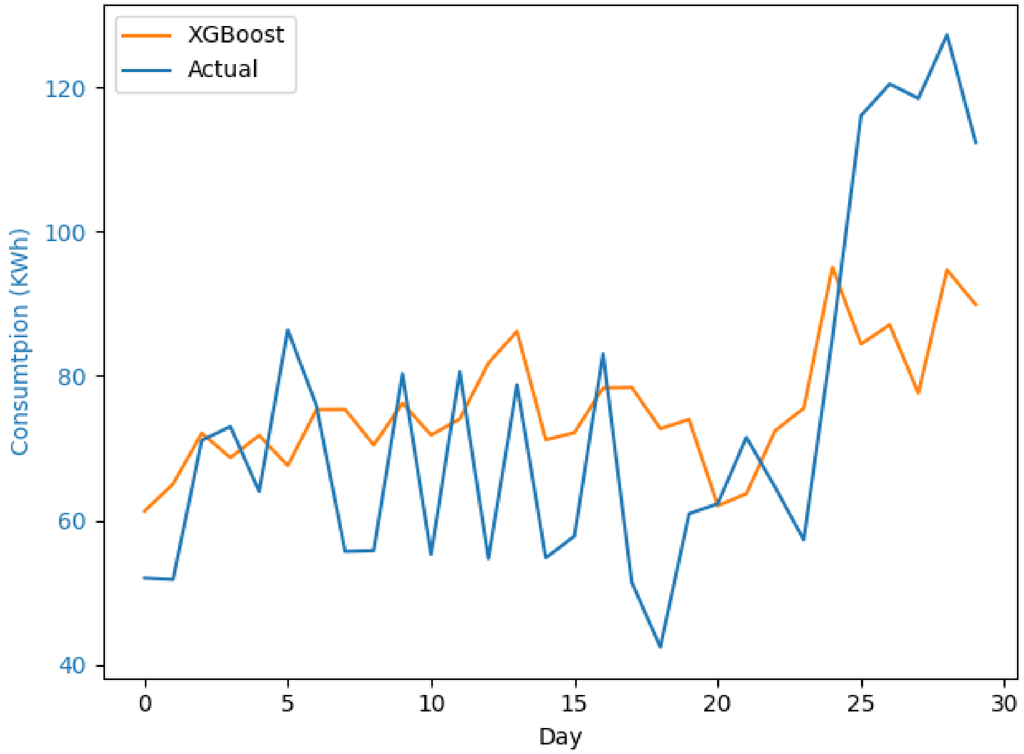

Figure 17: XGBoost - optimal parameters

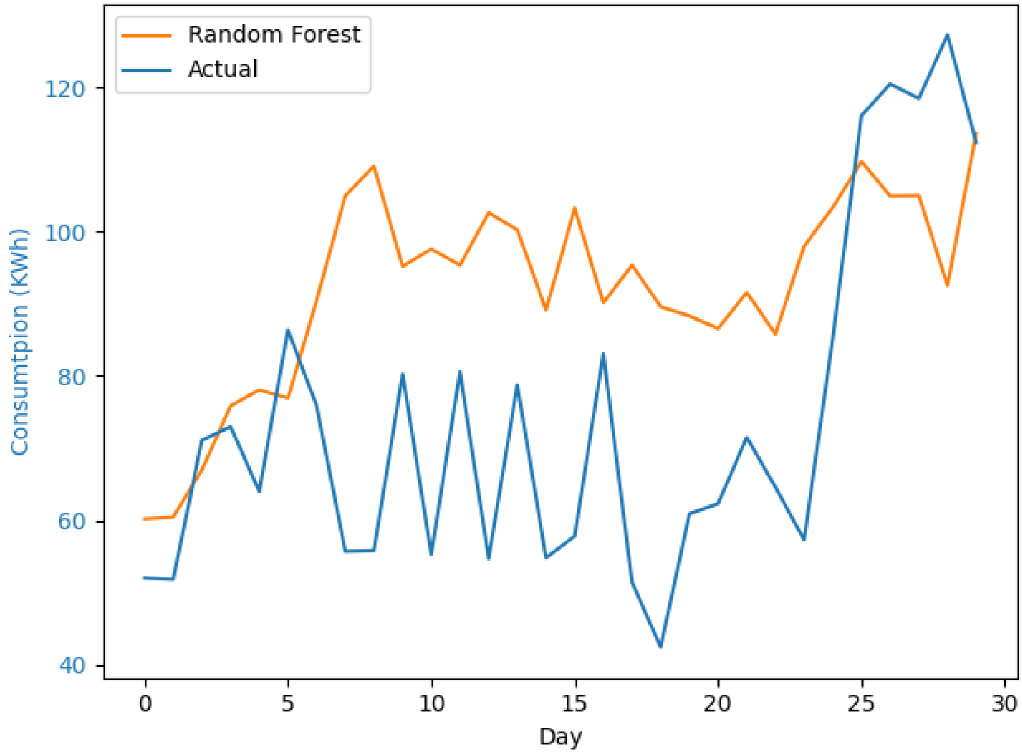

Figure 18: Random Forest - optimal parameters

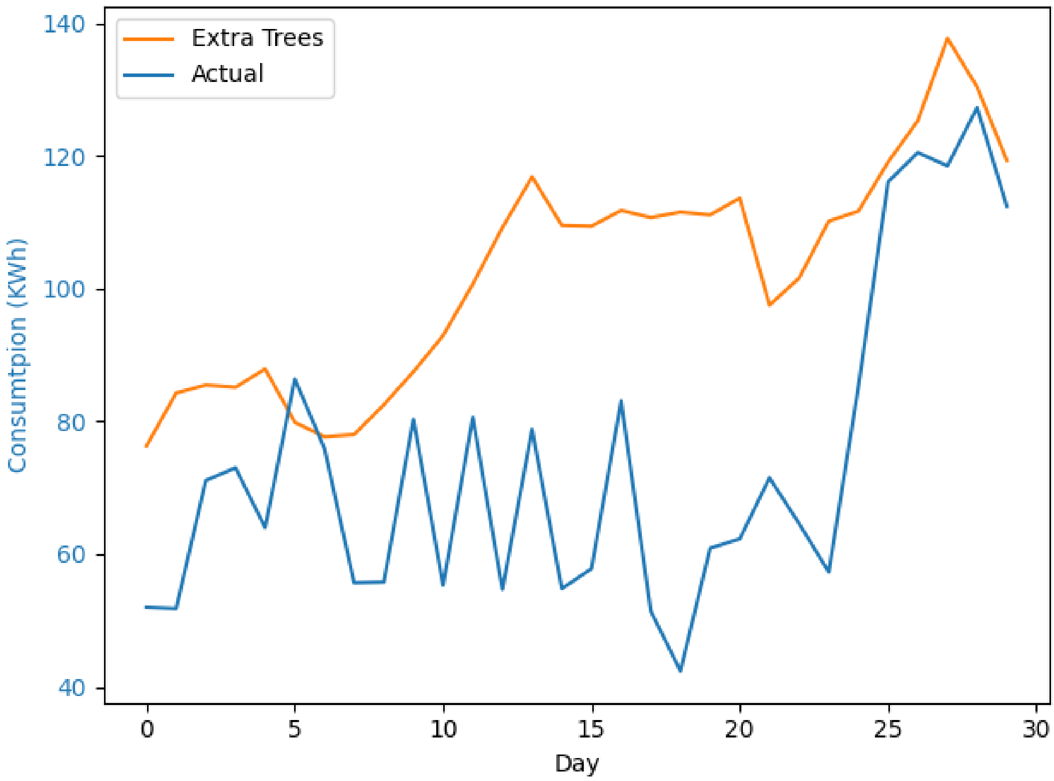

Figure 19: Extra trees - optimal parameters

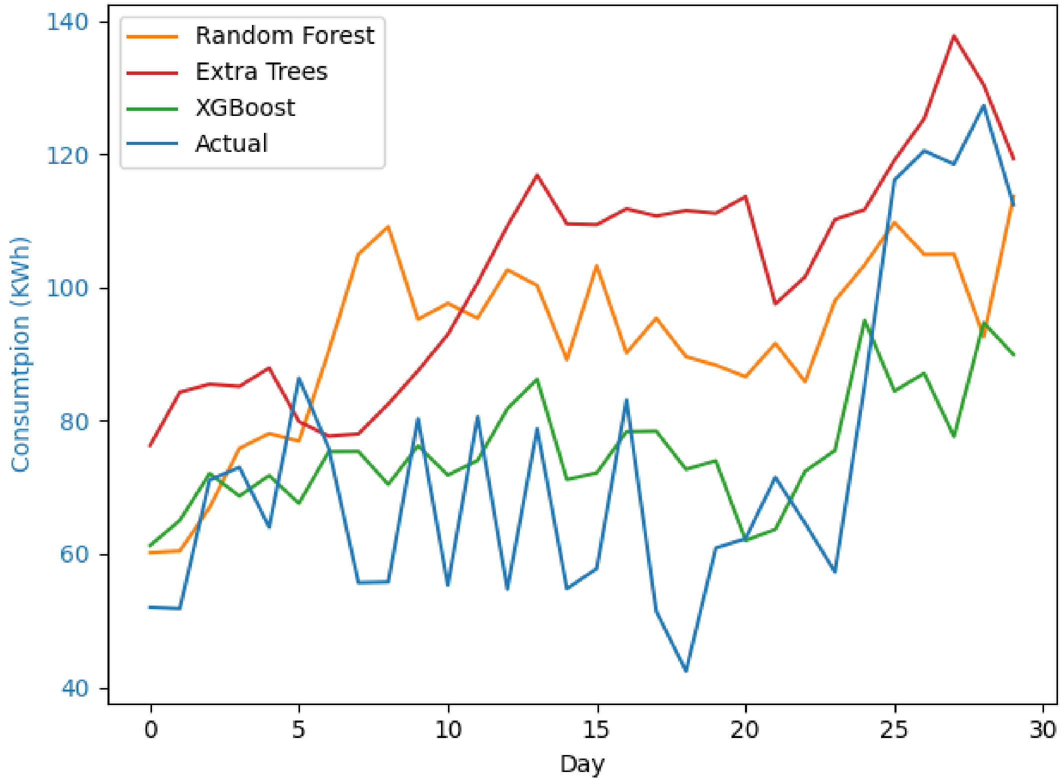

Figure 20: Side by side comparison

4.2.2 Deep Learning Methods

Several Depp Learning architectures have been experimented with, namely MLPs, CNNs, LSTMs, GRUs, and a hybrid CNN – LSTM architecture. Due to the small number of data points, it is essential to heavily regularize the developed deep learning architectures to prevent them from overfitting.

In general, the Neural Networks were not as successful as the XGBoost algorithm, for the prediction of the month ahead energy consumption, especially when predicting an energy consumption surge. This could be attributed to the dataset not being big enough for the methods to learn relevant information, too much noise in the data, e.g. large increases or drops in the total energy consumption in weekday to weekday without having much correlation with outside weather conditions (Figure 21).

On the other hand, they seem to learn better the periodical nature of energy consumption, weekdays tend to have more energy demand than weekends, as can be observed in Figure 22 through Figure 24, where the qualitative results for the CNN, LSTM, and CNN-LSTM hybrid architectures are provided. In Figure 25 the predictions are compared side by side.

As far as their metrics are concerned, the Hybrid CNN-LSTM architecture had the best performance regarding the monthly error, while the CNN had the lowest daily error (Table 14).

Table 14: DNN metrics

Method	Daily error (MAPE)	Monthly error (MAPE)	Predicted Consumption (KWh)	Actual Consumption (KWh)
CNN	24.1 %	3.9 %	2,134	2,221
LSTM	34.2 %	11 %	2,464	
Hybrid CNN - LSTM	*24.8 %*	*3.5 %*	2,299	

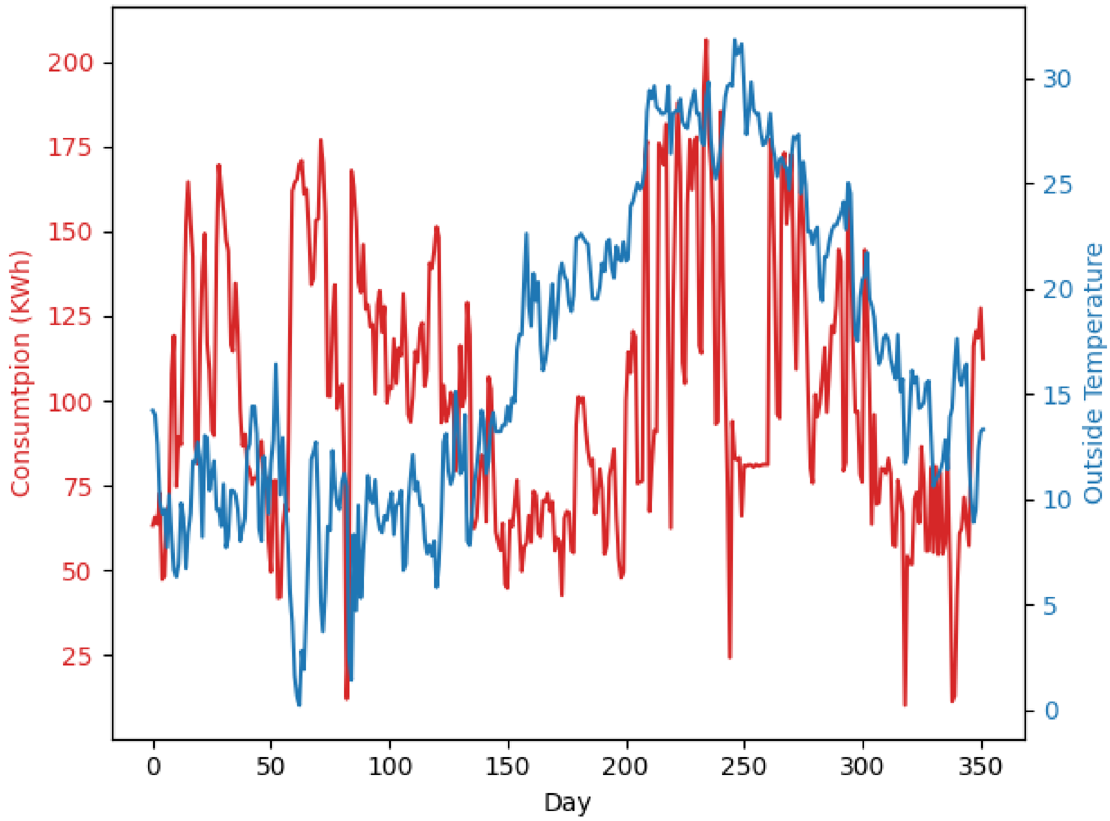

Figure 21: Average Outside Temperature – Consumption

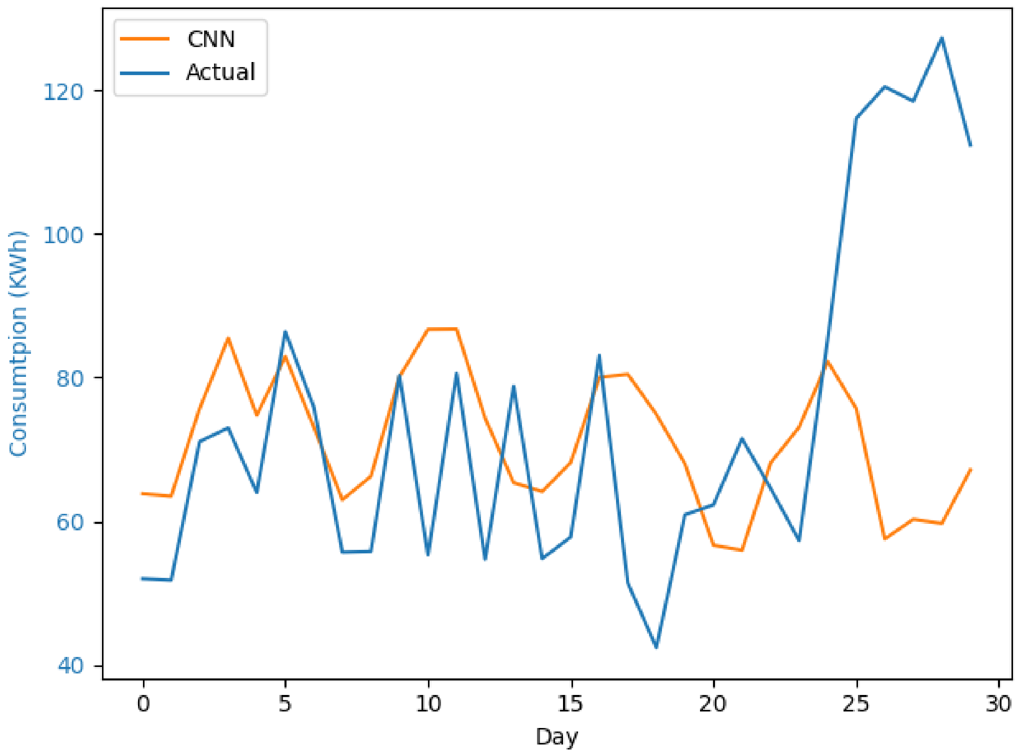

Figure 22: CNN prediction

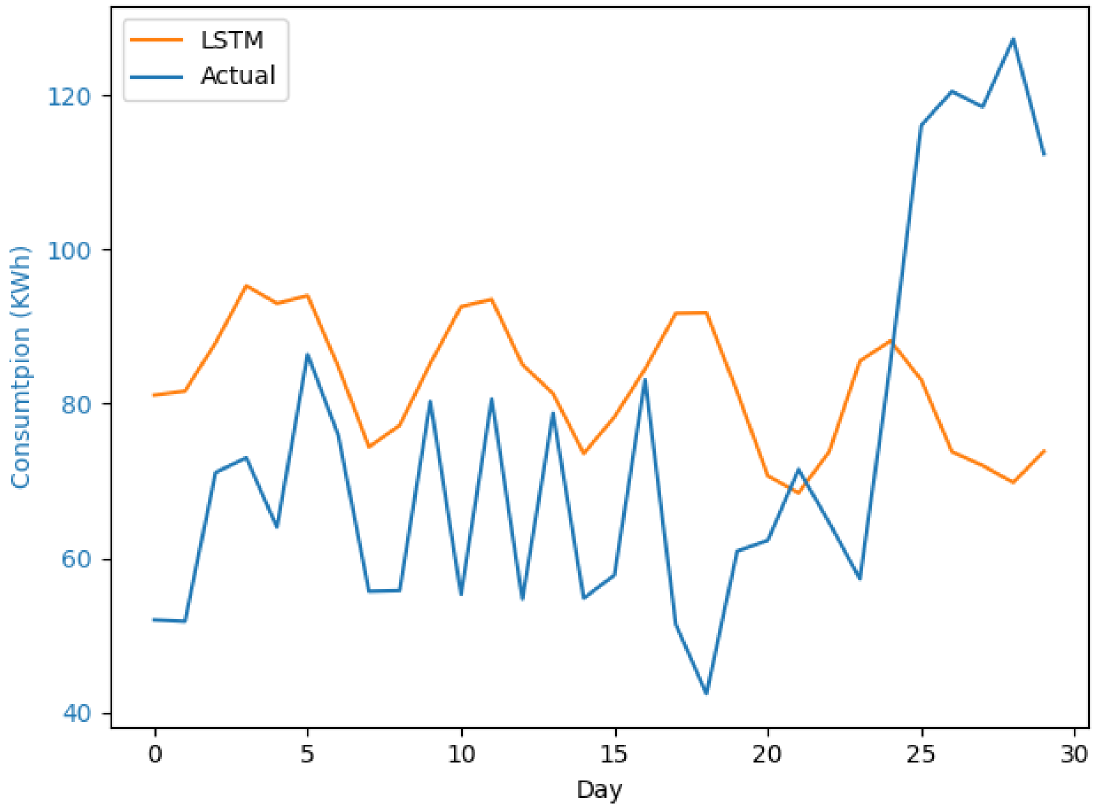

Figure 23: LSTM prediction

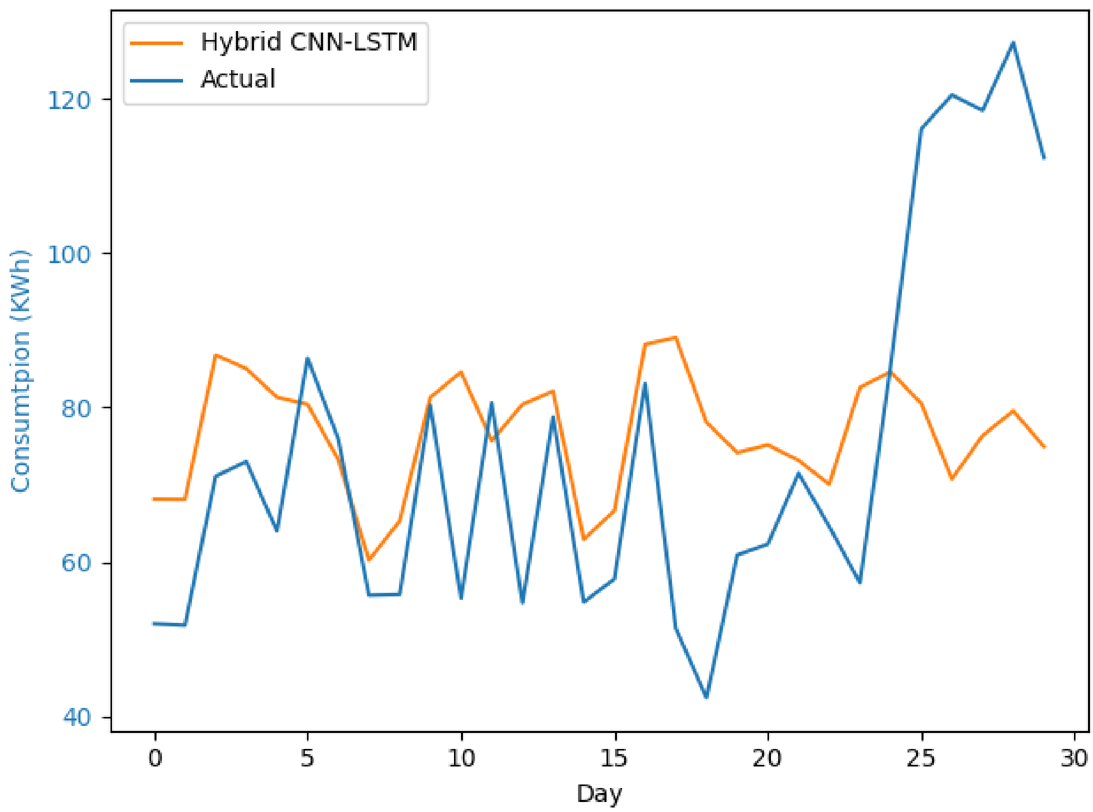

Figure 24: Hybrid CNN - LSTM prediction

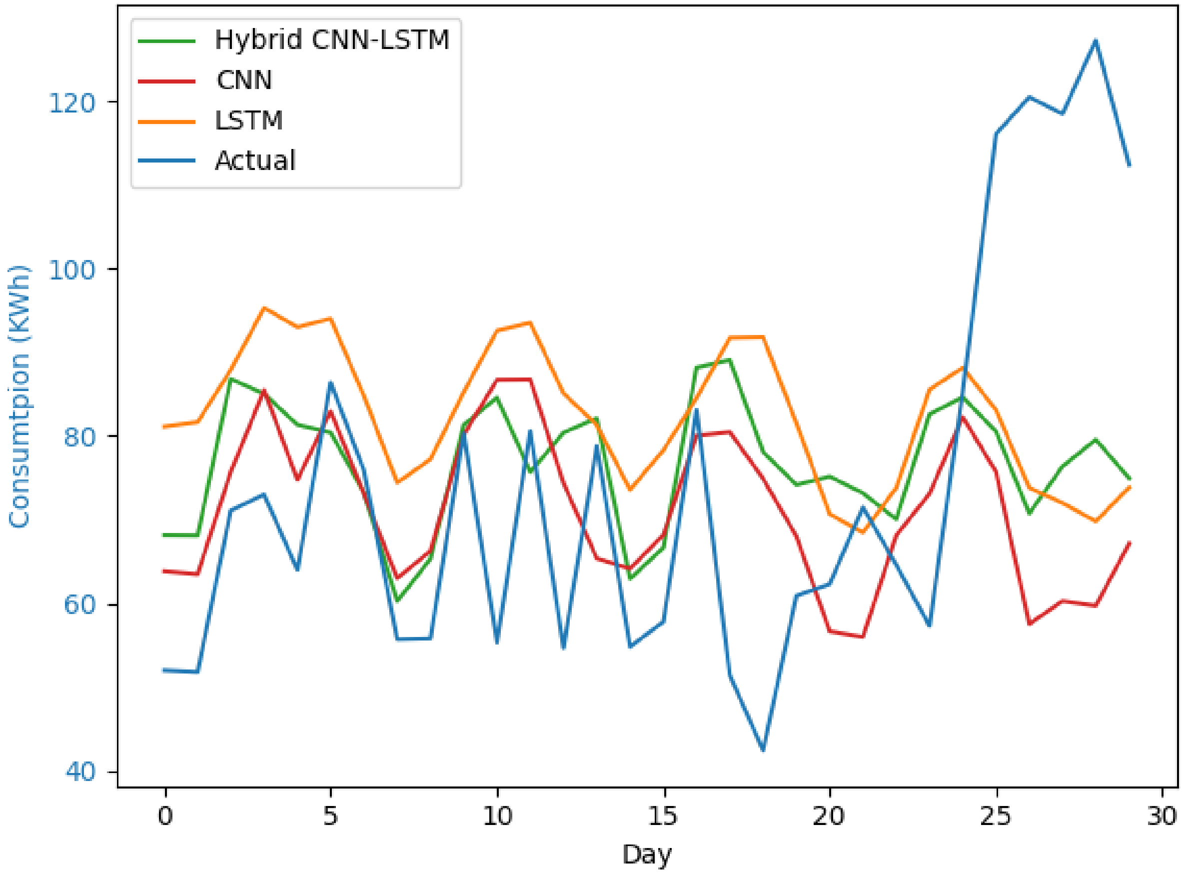

Figure 25: DNN comparison

5 Conclusions

This report describes the development procedure of the Added Value Services Suite and its application based on data collected from the project's Case Study 1. The module consists of three basic sub-components; the Roadmapping Tool, the AI-driven Performance Forecasts, and the Performance Alerts and Notifications. Each sub-component enriches the D^2EPC framework's functionalities by providing recommendations for building energy performance upgrades, forecasted energy consumption behaviour of the end-user, and creation of notifications.

Regarding the Roadmapping tool, a complete renovation roadmap is provided with all possible renovation actions that refer to the envelope, technical, and, RES systems. As the project is progressing, the tool will be furth tested with data from other pilot sites, to enhance its functionalities, covering a variety of building usages and the adaptability to various national guidelines.

From the work that has been carried out in T4.2.2 so far, the two dominant architectures that have emerged are the XGBoost algorithm and the hybrid CNN-LSTM, since they were the two with the lowest monthly error. Additional experiments should be conducted to finalize the method that will be chosen and used in the D^2EPC ecosystem. These experiments should investigate the behaviour of these methods in the other pilot sites, further hyper parameter tuning for the hybrid architecture and possibly training it with a large publicly available dataset and fine tuning it for the D^2EPC.

The main structure of the Performance Alerts and Notifications tool has been laid out, with main a focus on its interaction with the rest of the Added Value Services Suite components, as well as with other components of the D^2EPC architecture. This tool will be furtherly developed and finalized in parallel with the other two tools that have been analysed in this document. Elaborated results will be presented in the second version of this task D4.6 "Added Value Services Suite v2", which is due on M36.

Regarding the next version of this report in M36, Added Value Services Module will be integrated into the D^2EPC platform. This add-in will visualize each sub-component's results and reveal major modifications for seamless integration. In addition, testing with data from all pilot cases will be carried out, in order to increase the adaptability of the Module among different types of buildings and indicate possible improvements.

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