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# Assessing energy demands of building stock in railway infrastructures: a novel approach based on bottom-up modelling and dynamic simulation

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ABSTRACT

In this paper the implementation and application of a novel methodology for the estimation of the energy demand of the railway building stock is presented. To this aim, a bottom-up modelling approach implemented in a simulation tool is developed to assess the energy footprint and potential savings of railway buildings. The tool is intended to support operators and decision-makers in the planning of systematic energy retrofit necessary to up to date the railway infrastructure.

The developed methodology is applied to the Italian railway building stock with a bottom-up approach, identifying several groups of similar stations (*archetypes*) that are clustered according to real data collected. Afterwards, a data-driven model is derived from the detailed dynamic simulations of physic-based models representing the whole building heritage. As a demonstration of the validity of the proposed methodology and its capability to be exploited in real applications, some energy-saving strategies are simulated, and a comprehensive analysis is conducted on the considered stations.

The surrogate data-driven model shows $R^2$ coefficients always above 0.93 compared to physic-based model in predicting heating, cooling and electricity demand. Depending on the size of the stations, the mean relative error is in the range 5.9–15.0%. Furthermore, the surrogate model turns out to be an easy-to-use tool to analyse retrofit scenarios and take informed decisions, while the methodology is easily extensible and scalable to other contexts.

As demonstrated, the most impactful measure among the ones investigated is the adoption of high-performance lighting systems which entail an overall primary energy saving up to 26%, with very low pay back periods (∼1 year).



## 1. Introduction

Tackling climate change issues calls for the implementation of energy efficiency measures and policy for the sustainable transition of our economy. Urgent actions are necessary to reduce the transport sector energy demands, playing a crucial role in global energy consumptions and associated greenhouse gas emissions. To promote the clean energy transition, it is crucial to cut the energy consumptions of buildings and transportation sectors, which have a huge impact on the air quality of urban areas and accounts for two third of the global energy consumption and of worldwide GHG emissions (Rail, 2020). Rail infrastructures are responsible only for the 3% of the global transport energy demand, a modest value compared with the share that railways take in the entire transport activity.

Between 2005 and 2015, the European passenger rail activity increased by 8.9%, of which high-speed rail is responsible for 84%. In the same period, China registered a huge increase in railway traffic, passing from 7 billion of passengers per km in 2005 to 386 billion passengers per km in 2015 (Railway Handbook, 2017). This rapid development led to a higher attention to the carbon footprint related to the whole rail industry. Consequently, energy efficiency of non-traction infrastructures such as station buildings, depots and sub-stations are also gaining importance to reduce their energy demand. This segment of the entire rail industry accounts for the 10% of the total energy used in the sector (RSSB, 2017) which is even higher within urban areas (Galaï-Dol et al., 2016). At the same time, with the increase of living standards, passengers are demanding increased comfort and greater services in building stations, representing a difficult challenge for the railway industry and transportation sector in general (AD Bank, 2015). Accommodating passengers' needs, providing comfortable environment in waiting halls and high

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quality services can significantly encourage the adoption of rail transports, with significant benefits for the environment (Brons et al., 2009). Several scientific works focused on the passengers' comfort aspect (Jia et al., 2021), and the related energy consumption due to the Heating, Ventilation and Air Conditioning systems (HVAC) (Lv et al., 2021; Barone et al., 2021b; Zhao et al., 2020; Yang and Xia, 2015) or electrical equipment (Ma et al., 2009). However, while new stations are being built to high standards and very efficiently, the existing building stock of the railway infrastructure is often outdated and does not meet the most modern efficiency standards.

Improving services for passengers in a significant way requires important renovations that can also contribute to reduce the carbon footprint of railway stations. Of course, energy retrofits enable significant cost savings as well, allowing money to be directed back into improving customer experience and overall company performance (RSSB, 2017). For this reason the railway operators plan to renew their facilities; it is the case of the Italian company Rete Ferroviaria Italiana RFI that planned important investments on the infrastructure between 2022 and 2026 exploiting funds allocated by means of the National Recovery and Resilience Plan (Piano Nazionale di Ripresa e Resilienza, PNRR) by the Italian government (RFI, 2021). In this framework, benchmarking activities of building stations energy consumption are of significant to railways authorities to develop informed energy efficiency plans.

*Studies on energy consumption of railway stations*

Unlike other building typologies such as residential or commercial (Mata et al., 2014), train stations' energy consumptions are poorly investigated on medium or large scale. Moreover, the overall impact of stations on the entire regional or national rail network energy use is rarely considered even in precise studies of the sector, mainly focused on trains' energy consumption (Martínez Fernández et al., 2019; Barone et al., 2020b). The assessment of their energy/environmental footprint strongly depends on availability of detailed data of both construction and technological plants. As an example, within a study on the carbon footprint and environmental impact of a Railway-Infrastructure (RI) (Tuchschmid et al., 2011), a synthetic and fast estimation of energy consumption and other environmental indices are provided for 5 relevant building typologies, without providing details about calculation assumptions and building features. Similarly, a large energy consumption survey on traffic buildings in China was conducted in ref. Lin et al. (2020). The authors analysed airports, railway and subway stations. As regards railway stations, the ones located in the hot summer and cold winter area are the most consuming buildings with an average Energy Use Intensity (EUI) of 147 kWh/m$^2$ year, followed by the hot and warm winter area with an EUI of 122 kWh/m$^2$ year.

With the aim of identifying the most impacting parameters on energy consumption and provide a benchmarking tool, a Multiple Linear Regression (MLR) was applied for the energy consumption data collected from 80 large stations in China (Su and Li, 2019). Both for heating and cooling energy consumption, the authors identified the building area, number of passenger and regional Gross Domestic Product (GDP), as well as other construction characteristics, as the main influencing factors. With $R^2$ values greater than 0.609, their model was found to be reliable and applicable. The study, however, mainly focuses on large railway stations and does not consider small or medium ones, which could limit the model applicability in such circumstances. Train station complexes are also analysed in ref. Ahn (2019), where the multiple variable dependent regression model (similar to Su and Li (2019)) was developed to provide a design tool. In addition, the impact of the user typologies in the station complex was also considered adopting both measured and simulation data of typical building usages. A methodology used to estimate both the energy consumption and the $CO_2$ emission of the Chinese High-Speed Railway infrastructure (HSR) during its life cycle was presented in Wang et al. (2021). The proposed model consists of 3 blocks: Infrastructure cycle, HSR train cycle and operation cycle. It also accounts for the buildings and stations of the network since, "*the energy consumption and carbon emissions during the HSR operation cycle mainly come from the operation of HSR and daily operation of HSR stations*". The paper proves that accurate models are fundamental to reliable Life Cycle Analysis (LCA) in this field.

*Modelling approaches of building stock*

In general, simplified models to evaluate energy consumption of buildings are recognized as useful tools to adopt in the early design stage (Liu et al., 2021; Grillone et al., 2020). Moreover, they are of great importance in decision-making processes since accurate models may provide technical support and data evidence to define informed plans for construction and/or renovation of the entire building stock, including railway stations. Nevertheless, models estimating performance of buildings on large scale rely on availability of on-site measurements or precise energy-related information that are often inadequate (Zhao et al., 2016). Several and different approaches to represent performance of building stocks and overcame the lack of energy consumption data have been developed either at urban or national level (Luddeni et al., 2018; Barone et al., 2020a). The most adopted one is the bottom-up analysis that is based on identification of representative buildings to reflect a large population of buildings (Goy et al., 2021; Ghiassi and Mahdavi, 2017). Otherwise, using a top-down approach, groups of buildings are treated as an aggregated energy entity, where energy consumption is correlated to some top-level variables (GDP or other economic indices, weather etc.) (Swan and Ugursal, 2009). Between the two approaches, the bottom-up analysis better reflects the spatial distribution of energy consumption and allows more accurate and detailed calculation. Nevertheless, the effort to develop the model is higher due to the need of defining a number of building *archetypes* that will be simulated and allocated in predefined building set. Usually, single *archetypes* are simulated by physics-based models to dynamically calculate their energy consumption (Li et al., 2020; Barone et al., 2020c; Smyth et al., 2020).

In this context, several urban building energy modelling procedures and tools based on the most used state-of-the-art Building Energy Modelling (BEM) software (i.e. EnergyPlus, Modelica, TRNSYS, etc.) have been developed (Ferrando et al., 2020; Prataviera et al., 2021). Such tools require building geometry, location, construction types, HVAC system and operation patterns, control logics (Buonomano et al., 2017), and weather data as input (Bellia et al., 1998) and provide hourly or sub-hourly energy consumption profiles (Barone et al., 2019a; Vassiliades et al., 2022b; Forzano, 2019). By parametrization of *archetypes*, urban BEM tools has the capability of good representing the building diversity, thus, investigating energy management strategies and retrofit plans for cities or districts. To support the spread of the urban BEM methodology, new data format such as CityGML (Consortium, 2022) or GeoJSON (GeoJSON, 2022) have been developed to facilitate urban building modelling and create standards for 3D building shape implementation (Abolhassani et al., 2021). However, although open-source Geographical Information Systems (GIS) databases are rich of information, they lack comprehensive building data. Therefore, it is still required a big effort for urban modellers to define geometry and physical properties of *archetypes* (Dabirian et al., 2022). In order to bridge this gap, some projects aiming at identify and classify building typologies of European countries were developed to support building experts (Loga et al., 2016; Ballarini et al., 2014).

*Considerations and aim of the work*

As reported in Carnieletto et al. (2021), the majority of the current studies in the field of building stock energy analysis focus on residential sector. Only few studies addressed office buildings or non-residential buildings, which is understandable since homes represent most of the built environment. Furthermore, according to our literature review, no studies were carried out by considering a whole building stock, and specifically the railway stations building stock, and none of them proposes a combined approach based on BEM and archetypes to derive data driven models (Johari et al., 2020). Defining a baseline and benchmarking stations energy demand – whether these are small regional stations or large terminal for national or international traffic – is fundamental for railway authorities to develop a sustainable plan and reduce both expensive waste of energy and harmful greenhouse gas emission.

In this framework, this paper proposes a novel approach to assess the energy consumption and the potential energy retrofit actions for the railway stations building heritage. The approach adopted is based on the dynamic simulation of detailed physic-based building models, conducted by means of a BEM tool. The investigated stations are owned by the main Italian railway operator, Rete Ferroviaria Italiana (RFI), that manages more than 2000 stations spread throughout the Italian peninsula. According to the available data, several *archetypes* are defined by clustering similar stations, following a bottom-up approach. The developed physic-based model was then used to develop a *surrogate* mathematical model to provide an easy-to-use tool for the interested stakeholders to estimate the end-use energy consumption of the station buildings.

Finally, the capability of the developed tool was tested by analysing some retrofit scenarios such as envelope or HVAC system improvement, and reduction of electric loads. A comprehensive energy and economic analysis of the Italian railway building stock is also presented. The analysis has a twofold aim, such as: (i) proving the feasibility and scalability of the methodology to be applied to other cases and building stocks, and (ii) supporting the investment planning of the Italian railway operator (RFI) as part of the National Recovery and Resilience Plan (Piano Nazionale di Ripresa e Resilienza, PNRR) which amounts to 24 billion of euros.

The paper also aims of defining a framework for railway authorities and researchers to collect useful energy-related data to support the necessary renovation of railway stations. The study is part of a wider research effort to provide guidelines for net zero energy transport infrastructures.

## 2. Materials and method

This section includes the description of the key steps of the proposed methodology, structured by following the actual workflow adopted to carry out the study. Starting from the analysis of the selected railway infrastructure, the simulation model was built with a bottom-up approach involving building *archetypes,* extrapolated from the available data (Italian stations, 2021; RFI stations, 2021). All those phases are schematically summarized in Fig. 1 and described in detail in the following subsections.

In Sections 2.1, the analysed case of the Italian passenger stations and the procedure to gather the available data and classify the stations are respectively presented. Afterwords, building archetypes modelling and mathematical formulation of the developed surrogate model are described in Sections 2.2 and 2.3, while the economic and energy performance assessment method is reported in Section 2.4. The proposed methodology was exploited to also provide a graphical visualization of energy indexes, by showing the geographical distribution of the impact of the renovation measures.

### 2.1. Case study: the Italian railway building stock

The main Italian national railway network is entirely managed by RFI and runs through all the Italian regions and their provinces. In 2020, RFI registered 16 782 km of active rail lines (mostly electrified, 72%), of which 1467 km of high-speed rails (RFI, 2020).

Circa 2200 passenger stations serve the rail network. As shown in Fig. 2, Italian stations are distributed throughout the national territory, however, a higher concentration is recorded in the north side or near the most populated cities, i.e. Rome, Milan, Naples and Turin. RFI owns and operates over 2000 stations, while the rest are operated by regional or local authorities. Due to the lack of data, stations of regional or local operators are excluded from the analysis.

Although there are several modern stations from an architectural point of view, most of them have a typical style and construction typology that have been reproduced when built since the 20th century.

Currently, the Italian railway authority is involved in an innovation process and places its commitment against climate change and waste energy reduction as one of the priority objectives of its business model.

Data availability is one of the main challenges of building stock analyses and urban energy modelling. This study is based on the official information provided by RFI and other public databases (Italian stations, 2021; RFI stations, 2021). Specifically, data related to each of the 2070 considered stations are retrieved by an automated procedure. Specifically, a Matlab routine was suitably developed to query the abovementioned open databases, reducing the time and effort of data collection. The following data were collected: station ID, geographic coordinates, and the types of services provided to passengers.

The information available allowed to define a clusterization criteria to group stations in order to also provide results and graphical visualization of energy indexes, by showing the geographical distribution of the impact of the renovation measures. The aggregation of similar stations was defined according with the official administrative subdivision of the Italian territory (ISTAT, 2022).

Moreover, RFI identifies stations on the basis of a classification system that is based on passengers traffic, station attraction, interchange capacity and commercial services quality (RFI Network statement, 2021). Four categories are defined:

- *Bronze*. The facilities consist of small stations and stops that may be unstaffed, with the passenger building closed to public, and equipped with services only for regional or local traffic. Generally, the average number of users is <500 daily users.
- *Silver*. Medium-to-small facilities that may be unattended, equipped only with urban, sub-urban or metropolitan services. The average number of users is >2500 daily users (sometimes >4000 daily users).
- *Gold.* Medium or large plants equipped with high quality services to travellers for long, medium and short distances. Specific services for non-travelling visitors are generally guaranteed. The average number of users is >10 000 daily users.
- *Platinum*. Large plants equipped with high quality passenger services for long, medium and short distances and High Speed train. Specific services for non-travelling visitors are always guaranteed. The average number of users is >25 000 daily users.

It should be underlined that the classification system adopted by the Italian railway operator does not account for any energy or sustainability indices or protocols. The sole grouping criteria

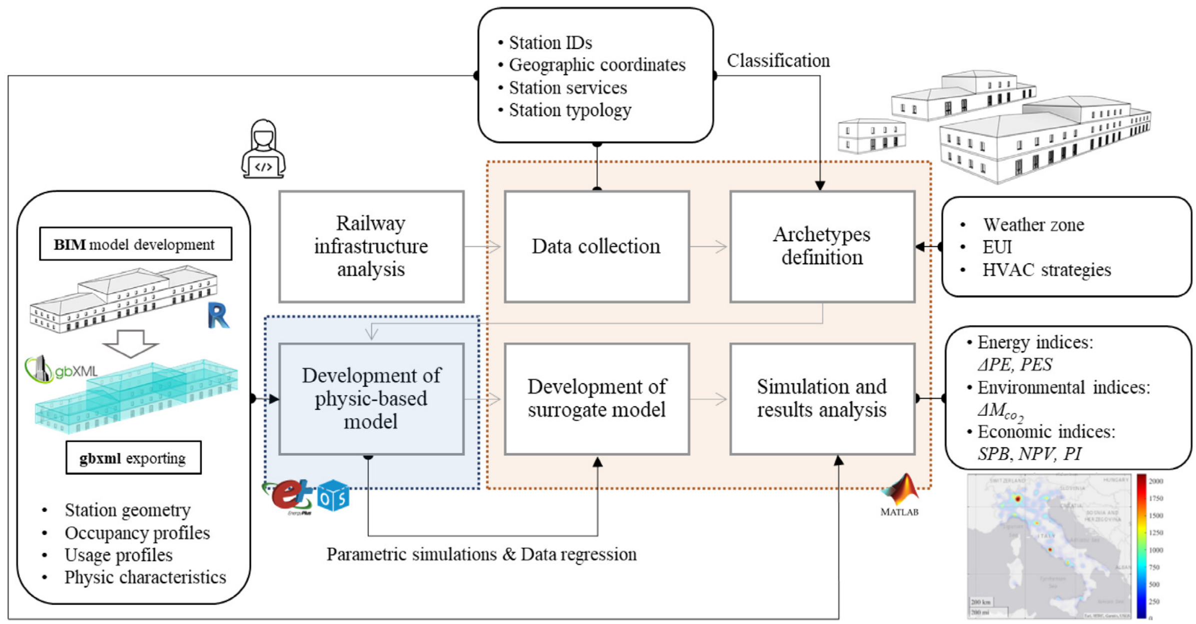


**Fig. 1.** Schematic workflow of the methodology adopted.


**Fig. 2.** Geographic distribution of Italian railway stations. *Source:* Data from Italian stations (2021) and RFI stations (2021).

adopted are the relevance and the size of the stations. Hereinafter, the same nomenclature adopted by RFI is considered for the classification in the proposed methodology. Specifically, the four considered categories are referred to as stops (*Bronze*), small stations (*Silver*), medium stations (*Gold*), and large stations (*Platinum*).

**Table 1**
Services provided by the station facility.

| | Services | ID number and typology | |
|---|---|---|---|
| Accessibility | Track accessibility | – | – |
| | Assistance services for people with disabilities | – | – |
| | Accessible toilets | – | – |
| | Parking with reserved places | – | – |
| | Sound public information systems | 1 | E |
| | Visual public information systems | 2 | E |
| | Accessible ticket office | – | – |
| Services | Ticket office | 3 | E |
| | Toilet | 4 | E |
| | Spaces for waiting | 5 | – |
| | Bar, cafeteria, restaurant | 6 | C, E |
| | Vending machines for snacks and drinks | 7 | E |
| | Tobacco | 8 | C, E |
| | Newsstand | 9 | C, E |
| | Tourist/ cultural information points | 10 | C, E |
| | Shopping | 11 | C, E |
| | Travel services | 12 | C, E |
| | Luggage storage | 13 | E |
| | Security | 14 | C, E |
| | Supermarkets, groceries, minimarkets | 15 | C, E |
| | Pharmacy | 16 | C, E |
| | Library | 17 | C, E |
| | Financial and postal services | 18 | C, E |
| Integrated mobility | Local public transport | – | – |
| | Bike | – | – |
| | Auto Motorcycle | – | – |
| | Direct connection with the airport | – | – |

As mentioned above, stations services (reported in Table 1) are also provided for each station of the network. This information reflects the importance of the considered facility and is useful to define its specific energy consumption. It is worth noticing that in Fig. 2 the marker size of RFI stations is proportional to the number of services provided by the station facilities. Furthermore, the number of stations facilities that offers specific services are reported in Fig. 3. Services are also marked with the symbols E (Energy consuming services) and C (Commercial services) for classification purpose.

A reliable modelling of station *archetypes* needs detailed data about construction typologies, building size and facility operation

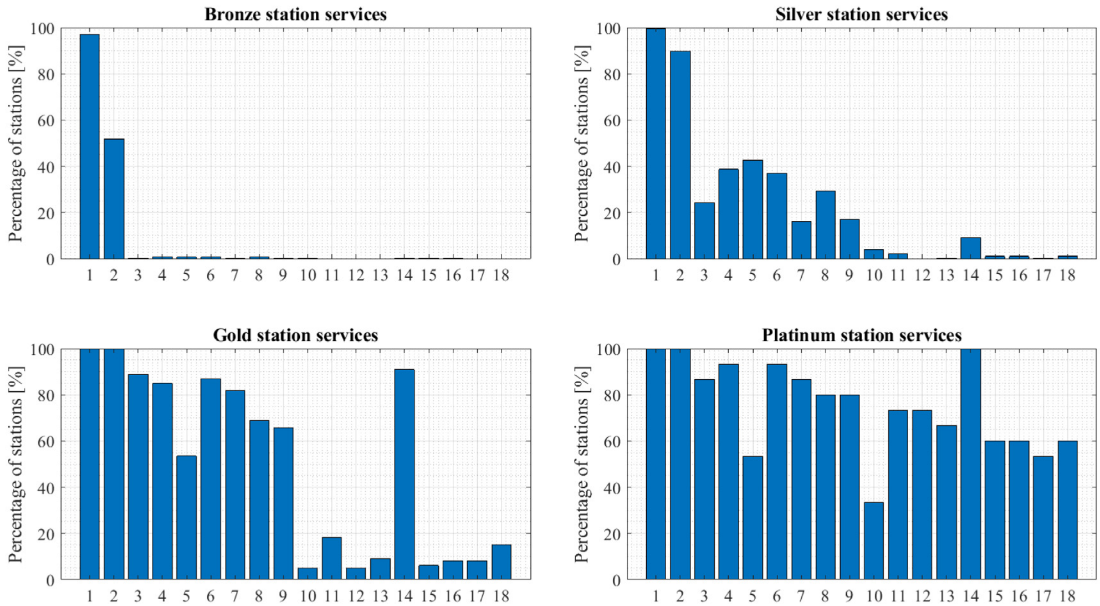


**Fig. 3.** Services of stations (the corresponding ID number of services is reported in Table 1).

in order to derive typical stations that represent a larger group of stations. However, as no GIS data about size and characteristics of the stations are provided, the procedure to define *archetypes* was made by observations of satellite images. Specifically, due to the large population of buildings considered in the study (*Bronze (Stops)*, 1043; *Silver (Small)*, 802; *Gold (Medium)*, 99; *Platinum (Large)*, 15), the 10% of each station category has been randomly sampled to statistically represent the entire population of the category (*Bronze (Stops)*, 104; *Silver (Small)*, 80; *Gold (Medium)*, 10; *Platinum (Large)*, -). Then, satellite images of the station sample were detailed analysed to identify one or more common building prototypes which may faithfully feature the station category. Their volumes were evaluated by measuring both the footprint areas and the building elevations. Three building prototypes were identified to respectively represent the *Bronze*, *Silver* and *Gold* stations. They have been built based on the average volumes estimated respectively as high as 1200 m$^3$, 3000 m$^3$ and 15 000 m$^3$ for the *Bronze (Stops)*, *Silver (Small)* and *Gold (Medium)* stations. It is worth noticing that *Platinum (Large)* stations were excluded from the analysis because they are extremely heterogeneous and require careful considerations. Based on the three selected building prototypes, different *archetypes* are identified by considering the following assumptions:

1. 5 climatic conditions according to Italian weather zones, classified by Heating Degree Days (*HDD*) and Cooling Degree Days (*CDD*): Zone B, $600 \le HDD \le 900$; Zone C, $901 \le HDD \le 1400$; Zone D, $1401 \le HDD \le 2100$; Zone E, $2101 \le HDD \le 3000$; Zone F, $HDD > 3000$;
2. 4 heating and cooling strategies (no HVAC systems, HVAC only in waiting halls, HVAC only in workplaces/services room, HVAC both in waiting halls and in workplaces/services rooms);
3. 4 different electric load intensities (5, 10, 15, 20 W/m$^2$).

By combining these parameters, 80 different archetypes are generated starting from each building *prototype*. In Fig. 4, the 3D models of the selected prototypes, as well as a logical scheme of the described workflow are reported.

### 2.2. Energy modelling of archetypes

Once defined both station prototypes and all *archetypes*, the physic-based energy models are developed. The three-dimensional models were carried out by means of the BIM (Building Information Modelling) software Autodesk Revit. It allows to create, and export through *gbxml* format (Runge and Zmeureanu, 2019), a detailed energy model leveraging all the energy-related information inputted in the BIM model, such as geometry, construction materials, zones, occupancy schedules, lighting, setpoint temperatures, ventilations, etc. So, after the three station prototypes (*Bronze (Stops)*, *Silver (Small)* and *Gold (Medium)*) are modelled, the energy models of the prototype were exported in *OpenStudio* environment to further manipulate the model and define the basis for *archetypes* simulations in EnergyPlus. The data transfer from BIM to BEM software relying on *gbxml* format is a completely automated process performed by means of the *Revit Systems Analysis*, which is a built-in feature of *Autodesk Revit 2021* (Barone et al., 2021b).

In Fig. 5, the BIM and BEM models of the *Gold* stations are shown. Here, it is also possible to see the space types that have been considered. For simulation purposes, each space has been defined as an independent thermal zone. According to building *archetypes* defined in the previous section, the thermal zones conditioned by HVAC systems are Offices, Waiting hall and Services. *Bronze* and *Silver* stations are not reported for the sake of brevity since their modelling is quite similar. As concern thermal zones, the only difference in the *Gold* stations is the presence of office spaces on the upper floor that are not considered in the other building prototypes. The parameters inputted in the energy model for conditioned thermal zones are summarized in Table 2. Please note that other space types/thermal zones shown in Fig. 5 are not conditioned, however, they are occupied so lighting and equipment power densities are also considered.

As regards to the air-conditioning plants modelling, the simulations are performed by considering the station buildings equipped with ideal HVAC systems to estimate the heating and cooling energy demands. Then, the primary energy required is calculated by means of performance coefficients of real systems such as heating boilers or heat pumps/chillers, according to Eq. (6). Given the purpose of the research study and to keep the analysis as less case specific as possible, the HVAC systems is not modelled in detail, whereas the surrogate model is derived from the physics-based building heating and cooling demands (as described in Section 2.3). The developed model is intended to be

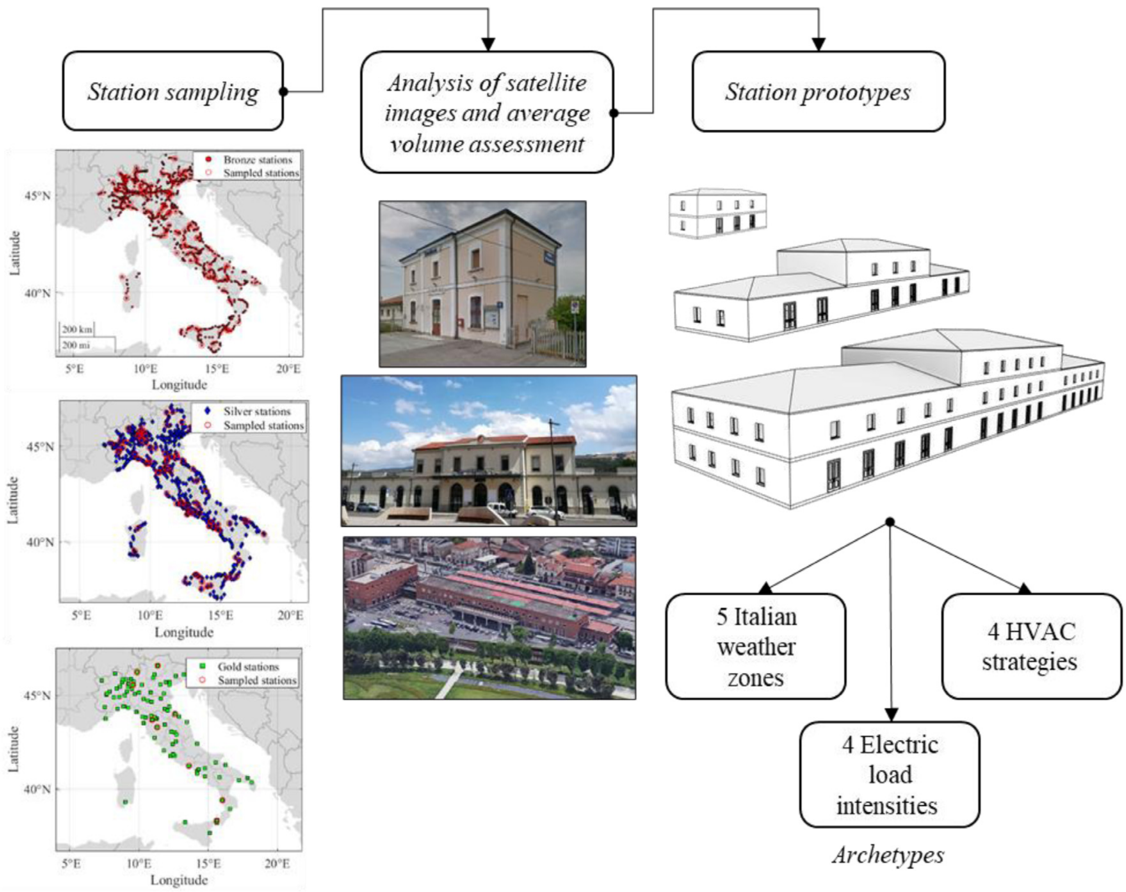


**Fig. 4.** Archetypes identification workflow.

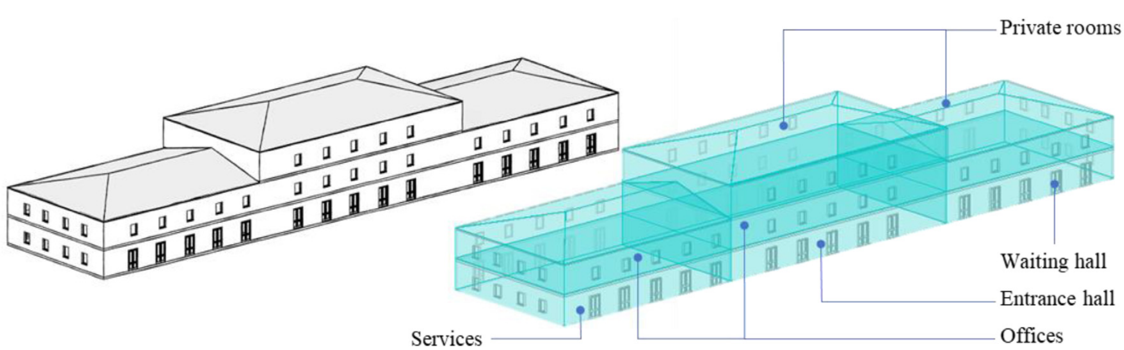


**Fig. 5.** Energy model and zoning.

a general tool for analyses in a wider domain than that of a single building, useful in planning and life cycle analysis.

As said, *archetypes* are generated by varying HVAC operation strategies, electric load intensities and weather conditions. A suitable algorithm developed in Matlab programmatically modified the *EnergyPlus* input data file (*idf*). To do so, the *idf* generated from the *OpenStudio* models were manually modified to define the varying parameters (e.g. U-value and internal thermal loads) that are then parsed by the purposely developed *Matlab* routine. The 5 weather files that represents the considered weather zones are collected from the public repository "Gianni De Giorgio" (IGDG). Specifically, the weather files of Palermo, Bari, Roma, Milano and Tarvisio were used for the weather zones B, C, D, E and F, respectively.

Finally, dynamic simulations of all the *archetypes* are performed with a timestep of 0.25 h, providing accurate results of building energy needs. The outputs of the dynamic simulations are then integrated on annual basis obtaining the heating $E_{nd,h}$, cooling $E_{nd,c}$, and electricity $E_{nd,el}$ demands. As *archetypes* are derived from the simplification of the entire station building stock, the $E_{nd,h}$, $E_{nd,c}$, and $E_{nd,el}$ indices, which refer to a specific *archetype*, are assumed to represent all the stations with similar characteristics (same *archetype*), as typically occurs in bottom-up modelling approaches.

It worth of noticing that *archetypes* are simulated according to the prescriptions of the Appendix G of ASHRAE Standard 90.1 to provide building energy consumptions that are neutral to building orientation.

**Table 2**
Input parameters of energy model.

| | Parameter | Services | | Waiting hall | | Offices | |
|---|---|---|---|---|---|---|---|
| | | Settings | Value | Settings | Value | Settings | Value |
| Bronze (Stops) | Occupancy schedule [h] | 6:00–21:00 | 1 [people/m$^2$] | 6:00–21:00 | 1 [people/m$^2$] | – | – |
| | Lighting schedule [h] | 18:00–9:00 | 12 [W/m$^2$] | 18:00–9:00 | 12 [W/m$^2$] | – | – |
| | Appliances schedule [h] | 0:00–24:00 | 5, 10, 15, 20 [W/m$^2$] | 0:00–24:00 | 6 [W/m$^2$] | – | – |
| | HVAC system | Ideal loads air system | ON; OFF | Ideal loads air system | ON; OFF | – | – |
| | Heating set-point [h] | 6:00–21:00 | 20 [°C] | 6:00–21:00 | 20 [°C] | – | – |
| | Cooling set-point [h] | 6:00–21:00 | 26 [°C] | 6:00–21:00 | 26 [°C] | – | – |
| | Ventilation | Outdoor air flow air changes per hour | 8 [ACH] | Outdoor air flow air changes per hour | 8 [ACH] | – | – |
| Silver (Small) | Occupancy schedule [h] | 6:00–21:00 | 1 [people/m$^2$] | 6:00–21:00 | 1 [people/m$^2$] | – | – |
| | Lighting schedule [h] | 18:00–9:00 | 12 [W/m$^2$] | 18:00–9:00 | 12 [W/m$^2$] | – | – |
| | Appliances schedule [h] | 0:00–24:00 | 5, 10, 15, 20 [W/m$^2$] | 0:00–24:00 | 6 [W/m$^2$] | – | – |
| | HVAC system | Ideal loads air system | ON; OFF | Ideal loads air system | ON; OFF | – | – |
| | Heating set-point [h] | 6:00–21:00 | 20 [°C] | 6:00–21:00 | 20 [°C] | – | – |
| | Cooling set-point [h] | 6:00–21:00 | 26 [°C] | 6:00–21:00 | 26 [°C] | – | – |
| | Ventilation | Outdoor air flow air changes per hour | 8 [ACH] | Outdoor air flow air changes per hour | 8 [ACH] | – | – |
| Gold (Medium) | Occupancy schedule [h] | 6:00–21:00 | 1 [people/m$^2$] | 6:00–21:00 | 1 [people/m$^2$] | 6:00–21:00 | 0.12 [people/m$^2$] |
| | Lighting schedule [h] | 18:00–9:00 | 12 [W/m$^2$] | 18:00–9:00 | 12 [W/m$^2$] | 18:00–9:00 | 12 [W/m$^2$] |
| | Appliances schedule [h] | 0:00–24:00 | 5, 10, 15, 20 [W/m$^2$] | 0:00–24:00 | 6 [W/m$^2$] | 0:00–24:00 | 6 [W/m$^2$] |
| | HVAC system | Ideal loads air system | ON; OFF | Ideal loads air system | ON; OFF | Ideal loads air system | ON |
| | Heating set-point [h] | 6:00–21:00 | 20 [°C] | 6:00–21:00 | 20 [°C] | 6:00–21:00 | 20 [°C] |
| | Cooling set-point [h] | 6:00–21:00 | 26 [°C] | 6:00–21:00 | 26 [°C] | 6:00–21:00 | 26 [°C] |
| | Ventilation | Outdoor air flow air changes per hour | 8 [ACH] | Outdoor air flow air changes per hour | 8 [ACH] | Outdoor air flow air changes per hour | 8 [ACH] |

### 2.3. Surrogate model

Detailed physic-based building energy models require a high number of input parameters and it is a very time-consuming task. Therefore, simplified models based on data regression may be useful tools for designers and benchmark purposes (Fumo et al., 2021; Deb and Schlueter, 2021; Barone et al., 2019b).

To define a reliable and a simple surrogate model to be used as an alternative to the detailed model, a linear regression approach was adopted. Heating and cooling needs of *archetypes*, $E_{nd,h}$ and $E_{nd,c}$, resulted from the physics-based model, were fitted by a first-order equation function of *HDD* and *CDD*. Afterwards, correlation coefficients were adjusted to take into account the effect of fraction of conditioned volume (heated and cooled volume to total volume ratios, $V_h/V$ and $V_c/V$), the wall *U-value*, and the electric equipment load intensity ($I_{el,loads}$). Furthermore, a linear equation depending on total electric light load intensity $I_{el,lights}$ and the total electric equipment load intensity $I_{el,equipment}$ is derived to calculate the total electricity demand $E_{nd,el}$. The progressive steps of the data regression procedure, which leads to Eqs. (1), (2) and (3), are summarized in Fig. 6. Curve fitting was carried out by the *cftool* in Matlab environment.

$$E_{nd,el} = a_{el} \cdot I_{el,lights} + b_{el} \cdot I_{el,equipment} \tag{1}$$

$$E_{nd,h} = \left(\left(c_{h,1} + c_{h,2} \cdot \frac{V_h}{V}\right) \cdot \left(c_{h,3} + c_{h,4} \cdot U\right) + \left(c_{h,5} + c_{h,6} \cdot \frac{V_h}{V}\right) \cdot \left(c_{h,7} + c_{h,8} \cdot U\right) \cdot HDD\right) \cdot \left(c_{h,9} + c_{h,10} \cdot I_{el,loads}\right) \tag{2}$$

$$E_{nd,c} = \left(\left(c_{c,1} + c_{c,2} \cdot \frac{V_c}{V}\right) \cdot \left(c_{c,3} + c_{c,4} \cdot U\right) + \left(c_{c,5} + c_{c,6} \cdot \frac{V_c}{V}\right) \cdot \left(c_{c,7} + c_{c,8} \cdot U\right) \cdot CDD\right) \cdot \left(c_{c,9} + c_{c,10} \cdot I_{el,loads}\right) \tag{3}$$

The accuracy of the surrogate model was evaluated by the coefficient of determination ($R^2$) which is an index of the goodness of how the surrogate model approximates observations (Ciulla and D'Amico, 2019). $R^2$ is function of the ith expected output $x_i$, the ith predicted output $y_i$, and the average value of all the expected output $\bar{x}$. It is calculated by Eq. (4).

$$R^2 = 1 - \frac{\sum_i (x_i - y_i)^2}{\sum_i (x_i - \bar{x})^2} \tag{4}$$

The surrogate model will be used to calculate energy consumption of the entire Italian stations building stock according to the available data described so far. In addition, the mean relative error $e$ was calculated according to Eq. (5), which is the mean percentage deviation between surrogate and physic-based models:

$$e = \frac{1}{N} \sum_i \frac{(x_i - y_i)}{x_i} \tag{5}$$

### 2.4. Energy, economic and environmental assessment

To calculate the energy and economic performance of the system, several indices are calculated for both the proposed system and the reference one (Barone et al., 2021c).

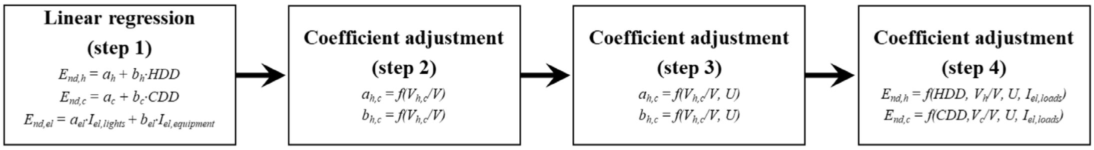


**Fig. 6.** Schematic procedure of the surrogate model development.

The primary energy ($PE$) is calculated by considering the primary energy conversion factors $\eta_{el}$, $\eta_h$ and $\eta_c$ for electricity, heating, and cooling, as:

$$PE = \frac{E_{nd,el}}{\eta_{el}} + \frac{E_{nd,h}}{\eta_h} + \frac{E_{nd,c}}{\eta_c} \tag{6}$$

The primary energy saved ($\Delta$PE) and the primary energy saving ($PES$) of the proposed scenarios respect to the reference case, are calculated as:

$$\Delta PE = PE_{reference} - PE_{proposed} \tag{7}$$

$$PES = 1 - \frac{PE_{proposed}}{PE_{reference}} \tag{8}$$

To assess the economic profitability the Simple Pay Back period ($SPB$) is calculated as:

$$SPB = \frac{I_0}{\Delta C} \tag{9}$$

where $I_0$ is the investment cost and $\Delta C$ are the cost difference between reference and proposed scenarios. At last, net present value ($NPV$) and profit index ($PI$) are also evaluated as:

$$NPV = \Delta C \cdot \left\{ \frac{1}{p} \cdot \left[ 1 - \frac{1}{(1+p)^N} \right] \right\} - I_0 \tag{10}$$

where $p$ is the interest rate and $N$ is the time span.

$$PI = \frac{NPV}{I_0} \tag{11}$$

Finally, the environmental performance is assessed by the $\Delta MCO_2$ index that represents the total equivalent $CO_2$ emitted. The indicator is calculated by:

$$\Delta M_{CO_2} = E_{el} \cdot F_{el} + E_g \cdot F_{ng} \tag{12}$$

Eq. (12) involves the energy consumption provided by electricity $E_{el}$ and natural gas $E_g$, as well as the related emission factors $F_{el}$ and $F_{ng}$.

## 3. Results and discussion

In this section, both the data regression procedure and simulation results of the carried analysis are presented and discussed.

The surrogate model is defined by Eqs. (1), (2) and (3) that are fully characterized by means of several constant coefficients for each station category, reported in Table 3. Users are required to input 3 input variables to calculate heating and cooling needs, and 2 input variables for electricity demand, which are much fewer inputs compared to detailed physics models such as the ones developed for *archetypes*.

The surrogate model provides very accurate results and reflects with good agreement the outputs of the physic-based model as shown in the charts of Fig. 7. Specifically, here both the heating (Fig. 7a) and cooling needs (Fig. 7b) calculated by the surrogate model for different station *archetypes* are plotted against the same outputs of the physic model. The relative errors are mostly within the range ±20% with some exceptions for low $E_{h,nd}$ and $E_{c,nd}$ values. However, the mean relative errors, calculated by means of Eq. (5) taking into account all the *archetypes* of the considered station typologies (*Bronze (Stops)*, *Silver (Small)*, *Gold (Medium)*), are equal to 15.0%, 6.7%, and 5.9% for $E_{h,nd}$, while 6.2%, 7.7%, and 9.8% for $E_{h,nd}$. As expected, the higher error is registered for *Bronze (Stops)* stations as $E_{h,nd}$ values are lower compared to the other station categories.

The determination coefficient $R^2$, calculated by Eq. (4), is also reported for each station category. It should be noted that $R^2$ is greater than 0.97 in case of *Bronze (Stops)* and *Silver (Small)* stations, while it is equal to 0.93 in predicting the cooling demand of *Gold (Medium)* stations. In this case, the lower value of determination coefficient is due to the increasing complexity of the station building compared to the simplicity of the surrogate model. The high obtained values of $R^2$ prove the validity of the proposed approach.

The simplified calculation method is not intended to replace neither detailed building energy models nor dynamic simulations of HVAC systems in the design process. BEM is still the most convenient state-of-the-art method to investigate passive and active energy saving strategies for complex buildings (Barone, 2020) or renewables integration (Barone, 2019). However, it requires significant efforts, so that a surrogate model can be successfully adopted as decision support tool to analyse building energy demand on a large scale. We demonstrate its viability by a suitable analysis of retrofit actions on the over 2000 Italian railway stations. Specifically, three different systematic energy retrofit actions have been analysed: the envelope performance improvement, the renovation of HVAC systems, and the implementation of more efficient lighting systems. Such interventions have been individually investigated both on the entire building stock and on part of it. They consist in the reduction of U-value factor to 0.60 (*Bronze*), 0.51 (*Silver*) and 0.44 (*Gold*), the switching to highly efficient heat pumps ($SCOP = 4.0$) and chillers ($SEER = 4.0$), and the reduction of lighting power density to 3.4 W/m$^2$.

The potential benefit of the investigated strategies has been evaluated by comparing their related energy consumptions to the one of the baseline. The latter is calculated according to the following assumptions:

- *HDDs* and *CDDs* are taken by the Italian regulation (Allegato A of DPR 412/93 (Dpr412/93, 1993));
- $V_h/V$ is calculated by the number of conditioned thermal zones defined in station *archetypes*. It depends on whether stations provide commercial services (marked as C in Table 1), or waiting halls, or both;
- $U$ is as high as 1.8, 1.6 and 1.4 respectively for *Bronze*, *Silver* and *Gold* stations.
- $I_{el,loads}$ depends on the total number of energy-consuming services $N_{services}$ (marked as E in Table 1): if $N_{services} \leq 2$ then $I_{el,loads} = 5$ W/m$^2$; if $2 < N_{services} \leq 6$ then $I_{el,loads} = 10$ W/m$^2$; if $6 < N_{services} \leq 12$ then $I_{el,loads} = 15$ W/m$^2$; if $N_{services} > 12$ then $I_{el,loads} = 20$ W/m$^2$;
- Heating system: Gas Boiler ($\eta_{gb} = 0.9$); Cooling system: Split System ($SEER = 3.0$);
- Primary energy consumption calculation is performed taking into account the average Italian electricity conversion efficiency of $\eta_{ce} = 0.46$.

**Table 3**
Surrogate model coefficients.

| | Bronze | | Silver | | Gold | |
|---|---|---|---|---|---|---|
| Heating demand | $c_{h,1}$ | −0.134 | $c_{h,1}$ | 0.366 | $c_{h,1}$ | 4.896 |
| | $c_{h,2}$ | −33.808 | $c_{h,2}$ | −10.052 | $c_{h,2}$ | 18.507 |
| | $c_{h,3}$ | 1.056 | $c_{h,3}$ | 1.137 | $c_{h,3}$ | 0.908 |
| | $c_{h,4}$ | −0.058 | $c_{h,4}$ | −0.164 | $c_{h,4}$ | 0.123 |
| | $c_{h,5}$ | 0.000 | $c_{h,5}$ | 0.000 | $c_{h,5}$ | 0.011 |
| | $c_{h,6}$ | 0.171 | $c_{h,6}$ | 0.209 | $c_{h,6}$ | 0.194 |
| | $c_{h,7}$ | 0.911 | $c_{h,7}$ | 0.970 | $c_{h,7}$ | 0.971 |
| | $c_{h,8}$ | 0.093 | $c_{h,8}$ | 0.036 | $c_{h,8}$ | 0.039 |
| | $c_{h,9}$ | 1.073 | $c_{h,9}$ | 1.054 | $c_{h,9}$ | 1.015 |
| | $c_{h,10}$ | −0.006 | $c_{h,10}$ | −0.004 | $c_{h,10}$ | −0.001 |
| Cooling demand | $c_{c,1}$ | 0.044 | $c_{c,1}$ | −0.209 | $c_{c,1}$ | −1.072 |
| | $c_{c,2}$ | −6.789 | $c_{c,2}$ | −2.659 | $c_{c,2}$ | −3.669 |
| | $c_{c,3}$ | 0.908 | $c_{c,3}$ | 0.908 | $c_{c,3}$ | 0.946 |
| | $c_{c,4}$ | 0.096 | $c_{c,4}$ | 0.096 | $c_{c,4}$ | 0.073 |
| | $c_{c,5}$ | 0.001 | $c_{c,5}$ | 0.001 | $c_{c,5}$ | −0.008 |
| | $c_{c,6}$ | 0.423 | $c_{c,6}$ | 0.336 | $c_{c,6}$ | 0.201 |
| | $c_{c,7}$ | 0.910 | $c_{c,7}$ | 0.910 | $c_{c,7}$ | 1.011 |
| | $c_{c,8}$ | 0.094 | $c_{c,8}$ | 0.094 | $c_{c,8}$ | 0.015 |
| | $c_{c,9}$ | 0.797 | $c_{c,9}$ | 0.807 | $c_{c,9}$ | 0.974 |
| | $c_{c,10}$ | 0.016 | $c_{c,10}$ | 0.015 | $c_{c,10}$ | 0.002 |
| Electricity demand | $a_{el}$ | 3.968 | $a_{el}$ | 3.968 | $a_{el}$ | 3.968 |
| | $b_{el}$ | 6.308 | $b_{el}$ | 6.308 | $b_{el}$ | 6.308 |

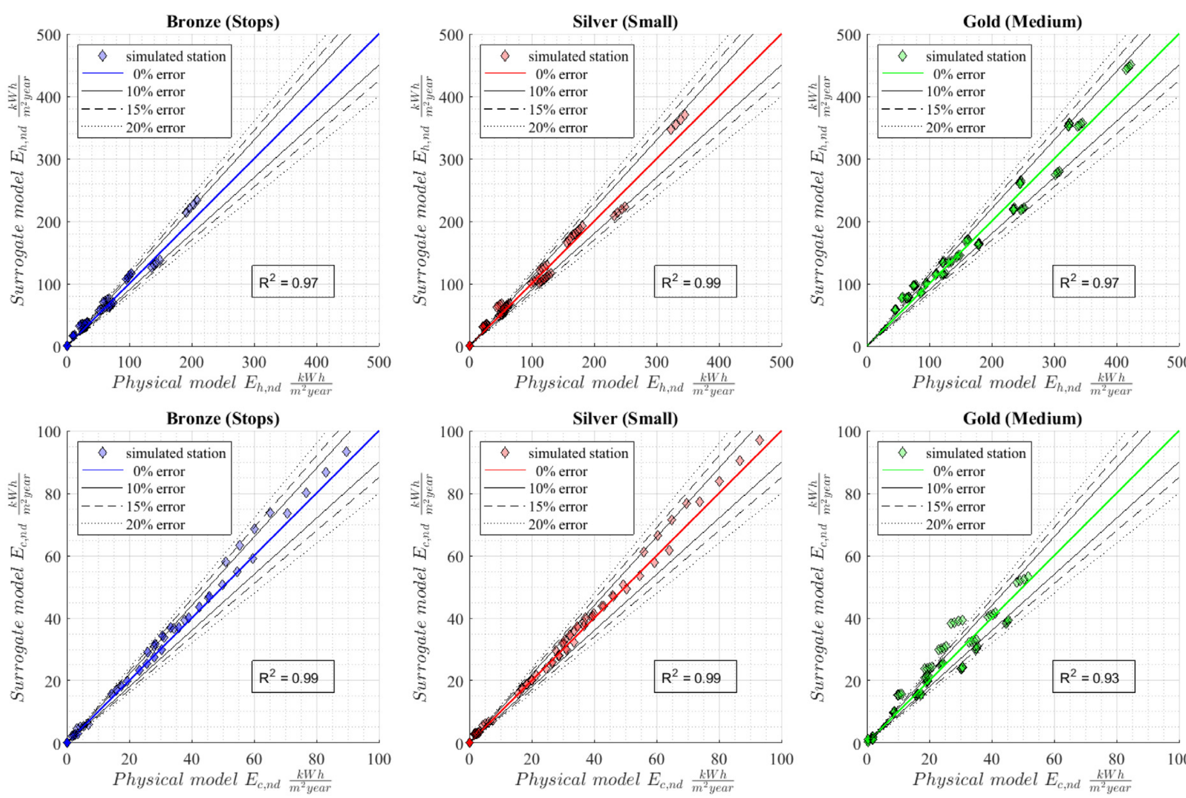


**Fig. 7.** Model accuracy comparison, (a) heating needs and (b) cooling needs.

A graphical visualization of primary energy consumption is reported in Fig. 8, where all contributions due to electricity, heating and cooling are compared for both baseline and renovation scenarios. This figure also shows how the proposed methodology can be exploited to provide a graphical visualization of energy indexes, by showing the geographical distribution of the impact of the renovation measures.

The Electric loads reduction strategy turns out to be the most impactful solution from an energy point of view, providing a *PES* of ∼26.0%, followed by the System efficiency improvement (14.3%) and Envelope improvement (1.2%) strategies. The building stock of railway stations is mainly composed of small or medium passenger buildings, which are often unconditioned. Therefore, the overall greater impact of electricity consumption compared to the one related to air conditioning is understandable. However, this might not be true for the specific stations within the stock and, especially, for the *Platinum (Large)* stations that should be investigated by means of customized analyses.

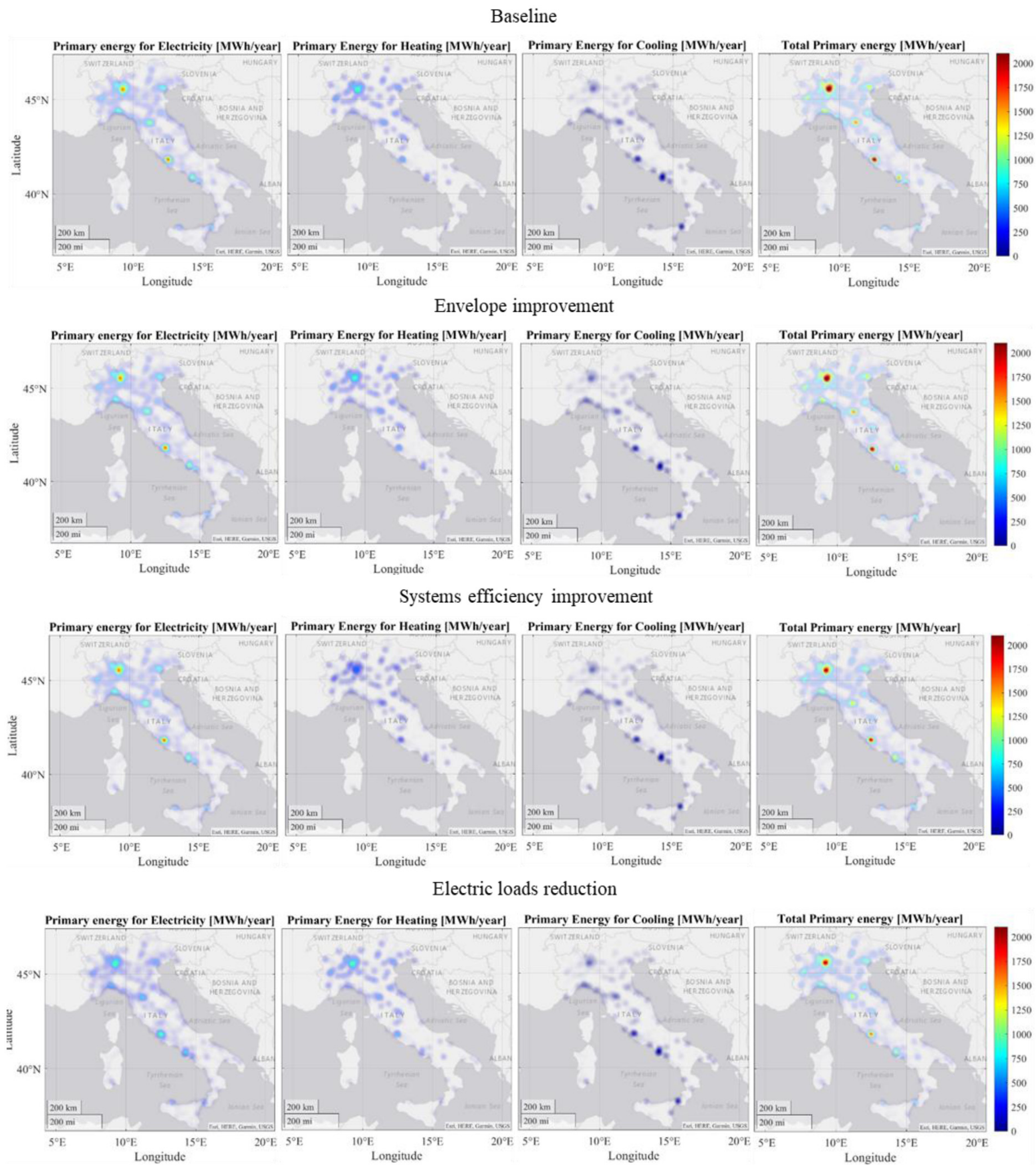


**Fig. 8.** Overall impact of systematic energy retrofit actions.

System improvements show significant effect on the stations energy performance mostly during the heating season due to the higher efficiency enhancement of heating generators compared to the cooling ones. Only 3.5% of the annual *PES* is due to higher *SEER* of chillers while the heat pumps are responsible for the rest of primary energy reduction.

Building envelope improvement such as insulation of external walls or substitution of low-performance windows enable a minor reduction in primary energy consumption, resulting to be the less interesting energy efficiency measure to implement on the investigated building stock. Indeed, station buildings are modelled with high air change rates (8 ACH according to Italian standard UNI 10 339 (Impianti, 1995)) to reflect intrinsic characteristics of terminals, i.e. high infiltrations, high outdoor air requirement, etc. As a result, the impact on thermal loads and demands due to the heat transfer through the envelope is low if compared to the ventilation.

As expected, the different station typologies have different impacts in terms of potential energy savings. Although there are fewer *Gold (Medium)* stations, these contribute more to limit primary energy consumption in case of retrofitting envelope (75%) and plants (79%). *Silver (Small)* stations cover a smaller share instead, as high as 24% and 20% for the envelope and system efficiency improvement respectively. These solutions have no impact (1%) on *Bronze*-type stations since only a very small number of stations were considered air-conditioned. This behaviour is also depicted in Fig. 9 where the shares of primary energy saved for station types are shown. Furthermore, the figure also reports the

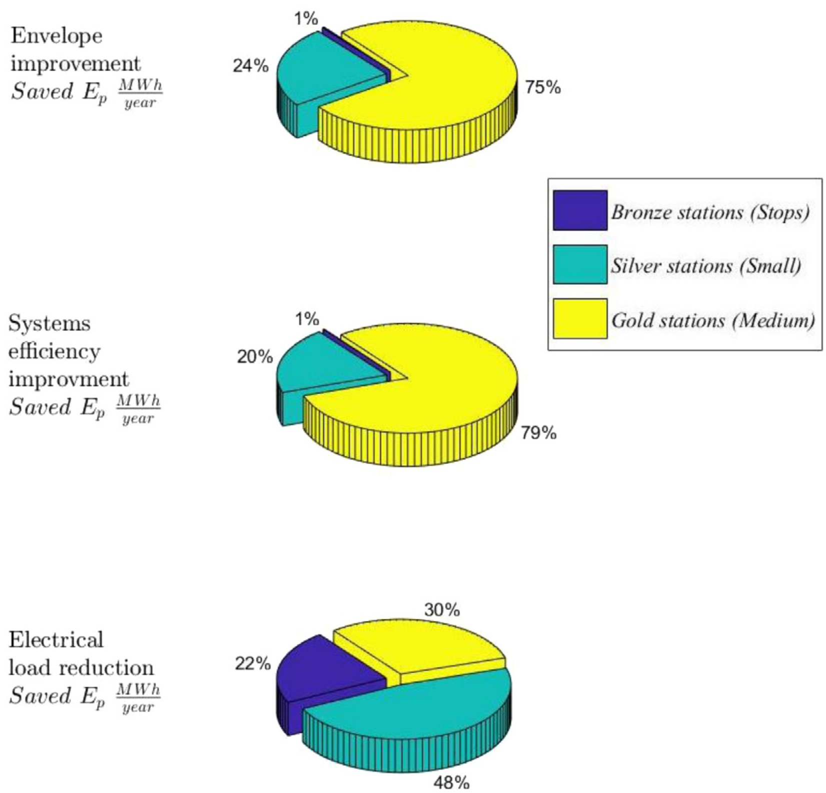


**Fig. 9.** Impact of systematic energy retrofit actions by station typologies.

station typology contributions in case of the electric load reduction. Here, *Bronze (Stops)* stations gain importance (22%). Nevertheless, the *Silver (Medium)* stations bring the greatest savings accounting for 48%.

A similar analysis was also carried out for geographical subareas which is shown in Fig. 10. While improvements on stations implemented in northern and central Italy reflect the performance at national level, in the South the weight of the small and medium stations is higher. Specifically, in Sicily and Sardinia, the share of primary energy saved of *Silver (Small)* stations reach 48, 35, and 57% respectively for the investigated scenarios, against 49, 64, and 16% of *Gold (Medium)* stations. Moreover, *Bronze (Stops)* stations in the South of the peninsula contribute for 26% when electric loads for lighting are reduced.

The primary energy saving (*PES*) strongly depends on the number of refurbished stations. However, only a limited number of stations should undergo renovation. Fig. 11 showing the *PES* value for different percentages of refurbished stations is provided as guidance for the reader. The index adopted is also useful to quickly obtain information on the percentage of avoided carbon dioxide emission since the two indexes are proportional. The results of a sensitivity analysis of the model are also reported in Fig. 11. Different values of parameters such as envelope heat transfer coefficients ($U$), system energy efficiency factors (*SCOP* and *SEER*), and lighting power densities ($I_{el,light}$) were considered. Specifically, the explored solutions are summarized in Table 4 reporting the value of the affecting variables as well as the unitary costs adopted for the economic assessment.

It is worth noticing that *PES* is always an increasing function of the number of stations refurbished in all the investigated scenarios (see Fig. 11). However, interventions such as Env.1, Env.2, and Env.3 or Sys.1, Sys.2, and Sys.3 do not entail further reductions of *PES* over certain percentages of renovation. This is evident in the case of the *Silver* stations since the maximum *PES* value occurs for an intervention on about 30% of the stock of the medium stations. As already mentioned, the savings of the smaller stations are negligible. On the other hand, Eui.1, Eui.2, and Eui.3 are the most interesting solutions as all building typologies have significant potential energy savings, regardless of the number of stations considered. Furthermore, due to the large number of small stations compared to medium and large ones, the *PES* values are higher if we consider the redevelopment of the *Bronze (Stops)* stations alone. It should be underlined that *PES* values are calculated considering the primary energy consumption of each building category instead of the entire stock (*Bronze PE*: 52.6 GWh; *Silver PE*: 148.3 GWh; *Gold PE*: 174.3 GWh).

The proposed strategies are also analysed from the financial point of view as well. The most relevant energy/environmental and economic indices that are calculated (i.e. $\triangle$PE, *PES*, $\triangle MCO_2$, *SPB*, *NPV*, and *PI*) are summarized in Table 5. Investment costs are evaluated by means of average unitary costs (shown in Table 4) such as insulation, heat pumps/chiller, and efficient lamps (Vassiliades et al., 2022a; Barone et al., 2021a). Similarly, running costs calculation involves the average cost of electricity (0.22 €/kWh) and natural gas (0.2 €/Sm$^3$), while the total equivalent $CO_2$ emissions are evaluated by means of the emission factors $F_e$ and $F_{ng}$, respectively equal to 0.480 and 0.202 t$CO_2$/MWh for electricity and natural gas (Maturo et al., 2021).

Finally, thanks to the proposed methodology, it is clear that systematic renovation of the envelope from an energy point of view is certainly not convenient. The high cost of investment and the low impact on energy consumption leads to a very high return of investment periods (from 146 to 170 years). Similarly, renovation of HVAC systems provides negative *NPVs* with no return of investment. However, this type of strategy could be taken into consideration at the end of the plant life cycle since

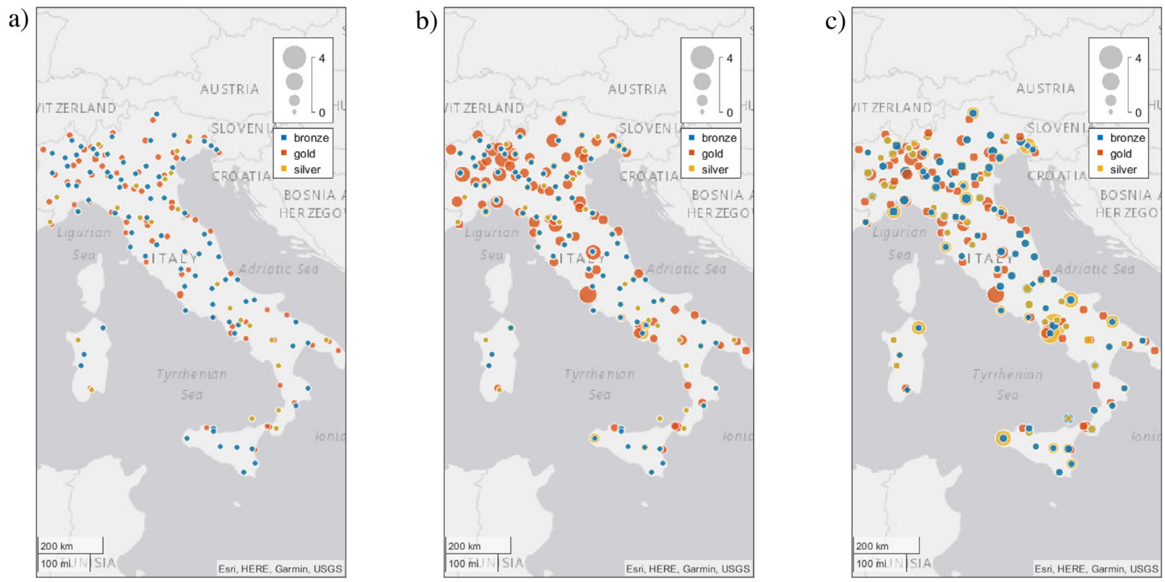


**Fig. 10.** Potential primary energy (GWh) saving by regional areas: (a) Envelope improvement; (b) System efficiency improvement; and (c) Electric load reduction.

**Table 4**
Investigated interventions on station building stock.

| | Intervention code | Bronze (Stops) | | Silver (Small) | | Gold (Medium) | |
|---|---|---|---|---|---|---|---|
| | | Unitary cost €/m$^2$ | Affecting variable U-value W/m$^2$ K | Unitary cost €/m$^2$ | Affecting variable U-value W/m$^2$ K | Unitary cost €/m$^2$ | Affecting variable U-value W/m$^2$ K |
| Envelope improvement | Env.1 | 60 | *0.60* | 60 | *0.50* | 60 | *0.44* |
| | Env.2 | 80 | *0.30* | 80 | *0.25* | 80 | *0.22* |
| | Env.3 | 40 | *0.90* | 40 | *0.75* | 40 | *0.66* |
| | Intervention code | Unitary cost €/kW | Affecting variable SCOP/SEER | Unitary cost €/kW | Affecting variable SCOP/SEER | Unitary cost €/kW | Affecting variable SCOP/SEER |
| System efficiency improvement | Sys.1 | 130 | 4 | 130 | 4 | 130 | 4 |
| | Sys.2 | 150 | 5 | 150 | 5 | 150 | 5 |
| | Sys.3 | 170 | 6 | 170 | 6 | 170 | 6 |
| | Intervention code | Unitary cost €/m$^2$ | Affecting variable $I_{el,lights}$ W/m$^2$ | Unitary cost €/m$^2$ | Affecting variable $I_{el,lights}$ W/m$^2$ | Unitary cost €/m$^2$ | Affecting variable $I_{el,lights}$ W/m$^2$ |
| Electric load reduction | Eui.1 | 7.7 | *3.4* | 7.7 | *3.4* | 7.7 | *3.4* |
| | Eui.2 | 5.3 | *5.7* | 5.3 | *5.7* | 5.3 | *5.7* |
| | Eui.3 | 3.6 | *7.9* | 3.6 | *7.9* | 3.6 | *7.9* |

**Table 5**
Summary of economic assessment of energy saving strategies.

| | Intervention code | ΔPE [GWh/y] | PES [%] | $\Delta M_{CO2}$ [$tCO_2 \times 10^3$/y] | $M_{CO2}$ [%] | Investment cost [M€] | Economic savings [M€/y] | SPB [y] | NPV [M€] | PI [%] |
|---|---|---|---|---|---|---|---|---|---|---|
| Envelope improvement | Env.1 | 4.7 | 1.2 | 0.95 | 1.2 | 21.4 | 0.13 | ∼170 | −19.7 | −92 |
| | Env.2 | 5.7 | 1.5 | 1.17 | 1.4 | 28.6 | 0.16 | ∼184 | −26.4 | −92 |
| | Env.3 | 3.6 | 1.0 | 0.74 | 0.9 | 14.3 | 0.10 | ∼146 | −12.9 | −90 |
| System efficiency improvement | Sys.1 | 53.6 | 14.3 | 10.0 | 12.3 | 21.6 | −2.6 | – | −59.0 | −272.6 |
| | Sys.2 | 64.8 | 17.3 | 12.4 | 15.3 | 25.0 | −1.5 | – | −46.3 | −185.6 |
| | Sys.3 | 72.3 | 19.3 | 14.1 | 17.4 | 28.3 | −0.8 | – | −39.0 | −137.8 |
| Electric load reduction | Eui.1 | 96.1 | 25.6 | 21.2 | 26.2 | 10.3 | 9.7 | ∼1.1 | 126.7 | 1225 |
| | Eui.2 | 68.6 | 18.3 | 15.2 | 18.7 | 7.2 | 6.9 | ∼1.0 | 90.7 | 1267 |
| | Eui.3 | 41.2 | 11.0 | 9.1 | 11.2 | 4.8 | 4.2 | ∼1.1 | 54.0 | 1130 |

it leads to significant energy savings and avoided equivalent $CO_2$ emissions. Railway authorities should certainly focus on reducing the electrical loads of lights and appliances, the adoption of highly-efficient lamps all over the stations is the cheapest and most impacting strategies of our analysis, providing a NPV up to 127 million euros after 25 years and preventing the emission of circa 21 × $10^3$ $tCO_2$ per year.

## 4. Conclusion

In this paper a novel approach based on large building stock energy modelling have been adopted to analyse the energy use intensity of railway stations heritage. The study was conducted on the case study of the Italian passenger stations (>2000 units), spread along the Italian peninsula. Furthermore, a simplified model was carried out to provide an easy-to-use tool for design

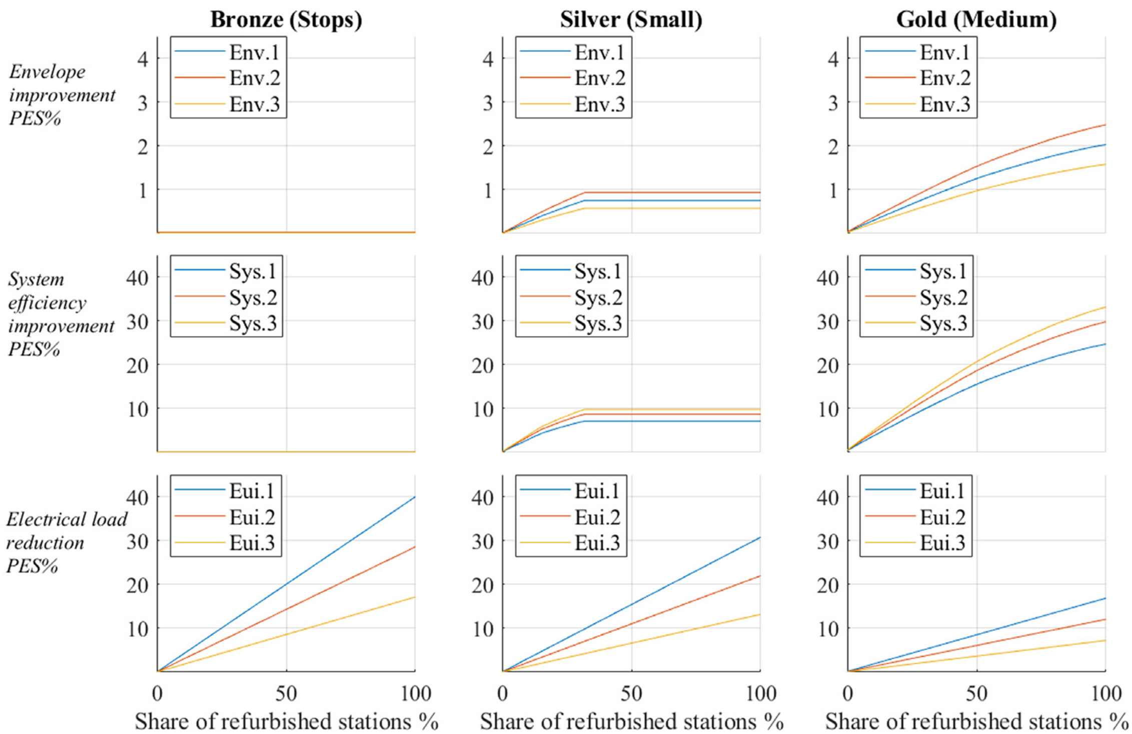


**Fig. 11.** Impact of systematic energy retrofit actions for different share of refurbished stations.

and decision-making purposes. Aiming at proving the effectiveness and potentials of the adopted methodology, some easy to implement energy retrofit actions were investigated to deduce useful insights, and potential energy and economic savings on the entire stations building stock.

The simplified model has been developed by linear regression of data obtained from simulations of detailed physic-based building models, developed by the BEM approach, which have been deduced from a randomly generated sample of real station buildings and data provided by the Italian railway operator. Several station archetypes were modelled and simulated by means of both BIM and BEM software such as *Autodesk Revit* and *OpenStudio/Energyplus*. Conditioned volume to total volume ratio, electric load intensity, envelope quality and weather conditions are the variable defining the station *archetypes*. The derived surrogate model for each *archetype* provides results that are in good agreement with physic-based building models which demonstrates the validity of the proposed approach. Useful insights can be extrapolated that can serve as guidance for railway operators:

- the major energy and economic benefits are obtained by the reduction of electric load intensities that are the most impacting energy consumptions. Systematic efficiency actions on lighting and appliances are highly encouraged. As demonstrated, an overall primary energy saving of 26% can be reached by adopting highly-efficient lighting systems (e.g. LED lamps) with very low pay back periods (∼1 year);
- energy measures such as envelope improvement and replacement of HVAC with more efficient systems have a lower impact on the station heritage as only a limited number of stations are equipped with air conditioning systems. In these scenarios, the primary energy savings are estimated as high as 1.2% for envelope improvement and 14.3% for HVAC system renovations. Nevertheless, it should be highlighted that negative net present values over 25 years were calculated;
- if partial actions on the building stock are taken into consideration, small and medium-sized stations have a greater impact on reducing electricity consumption (not related to air conditioning) given their higher number, while interventions on large stations provide the highest primary energy savings when envelope and system improvements are considered. Furthermore, contrary to what happens in northern and central Italy where large stations count more, in the South and on the islands the medium stations have greater potential energy savings;
- the renovation of the entire building stock of the Italian stations can avoid the emission of $21 \times 10^3$ t of equivalent carbon dioxide per year.

The authors would like to stress the fact that accuracy of both detailed and simplified models are limited by the lack of data on stations geometry and physical characteristics, as well as other energy-related information. The major uncertainty is due to the poor information on actual electric loads and operating schedules of stations, both affecting electricity consumption and thermal needs. Thus, the applicability of the model is limited in schematic or detailed design workflows. Nevertheless, the proposed methodology could result as a useful tool for railway operators in the planning of refurbishment measures.

Future development of the study will focus on the improvement of model accuracy taking into account specific energy-consuming processes required by the railway infrastructures such as conditioning of electric sub-station and air ventilation handling costs.

Open-source data would foster the development of more complex models, capable to provide high flexibility and greater accuracy of predictive tools as the one developed in this study.

## Nomenclature

| | |
|---|---|
| $\Delta C$ | Economic saving, M€ |
| $\Delta$PE | Primary Energy Saved, kWh/years |
| ACH | Air Change per Hour |
| BEM | Building Energy Modelling |
| BIM | Building Information Modelling |
| CDD | Cooling Degree Days |
| $E_{nd,c}$ | Cooling needs, kWh/m$^2$ |
| $E_{nd,el}$ | Electricity demand, kWh/m$^2$ |
| $E_{nd,h}$ | Heating needs, kWh/m$^2$ |
| EUI | Energy Use Intensity, kWh/m$^2$ |
| GDP | Gross Domestic Product |
| GIS | Geographical Information System |
| HDD | Heating Degree Days |
| HVAC | Heating, Ventilation and Air Conditioning systems |
| $I_0$ | Investment cost, M€ |
| $I_{el,equipment}$ | Electric equipment load intensity, W/m$^2$ |
| $I_{el,lights}$ | Lights load intensity, W/m$^2$ |
| $I_{el,loads}$ | Electric equipment load intensity of Service thermal zone, W/m$^2$ |
| MLR | Multiple Linear Regression |
| $N$ | time span, years |
| $NPV$ | Net Present Value, M€ |
| $P$ | interest rate, % |
| $PE$ | Primary Energy, kWh/years |
| $PES$ | Primary Energy Saving, % |
| $PI$ | Profit index, (−) |
| RFI | Rete Ferroviaria Italiana |
| RI | Railway Infrastructure |
| $SCOP$ | Seasonal Coefficient of Performance, (−) |
| $SEER$ | Seasonal Energy Efficiency Ratio, (−) |
| $SPB$ | Simple Pay Back, years |
| $U$ | Heat transfer coefficient through building envelope, (W/m$^2$ K) |
| UBEM | Urban Building Energy Modelling |
| $V_c/V$ | Cooling volume to total volume ratio, (−) |
| $V_h/V$ | Heated volume to total volume ratio, (−) |

## CRediT authorship contribution statement

**Giovanni Barone:** Conceptualization, Model development, Formal analysis, Methodology, Investigation, Data curation, Writing – original draft, Visualization, Writing – review & editing. **Annamaria Buonomano:** Conceptualization, Model development, Formal analysis, Methodology, Investigation, Data curation, Writing – original draft, Visualization, Writing – review & editing, Supervision. **Cesare Forzano:** Conceptualization, Model development, Formal analysis, Methodology, Investigation, Data curation, Writing – original draft, Visualization, Writing – review & editing. **Giovanni Francesco Giuzio:** Conceptualization, Model development, Formal analysis, Methodology, Investigation, Data curation, Writing – original draft, Visualization, Writing – review & editing. **Adolfo Palombo:** Conceptualization, Model development, Formal analysis, Methodology, Investigation, Data curation, Writing – original draft, Visualization, Writing – review & editing, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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