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Energy refurbishment planning of Italian school buildings using data-driven predictive models

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HIGHLIGHTS

- Time-consuming simulations are required for energy refurbishment of buildings.
- Simplified methodologies may support the energy requalification of buildings.
- The results of refined energy analyses of existing school buildings are considered.
- A Multiple Linear Regression (MLR) model is trained to obtain a predictive tool.
- A framework for a preliminary design of energy refurbishment interventions is proposed.

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ABSTRACT

In the current practice, the design of energy refurbishment interventions for existing buildings is typically addressed by performing time-consuming software-based numerical simulations. However, this approach may be not suitable for preliminary assessment studies, especially when large building portfolios are involved. Therefore, this research work aims at developing simplified data-driven predictive models to estimate the energy consumption of existing school buildings in Italy and support the decision-making process in energy refurbishment intervention planning at a large scale. To accomplish this, an extensive database is assembled through comprehensive on-site surveys of school buildings in Southern Italy. For each school, a Building Information Modelling (BIM) model is developed and validated considering real energy consumption data. These BIM models serve in the design of suitable energy refurbishment interventions. Moreover, a comprehensive parametric investigation based on refined energy analyses is carried out to significantly improve and integrate the dataset. To derive the predictive models, firstly the most relevant parameters for energy consumption are identified by performing sensitivity analyses. Based on these findings, predictive models are generated through a multiple linear regression method. The suggested models provide an estimation of the energy consumption of the "as-built" configuration, as well as the costs and benefits of alternative energy refurbishment scenarios. The reliability of the proposed simplified relationships is substantiated through a statistical analysis of the main error indices. Results highlight that the building's shape factor (i.e., the ratio between the building's envelope area and its volume) and the area-weighted average of the thermal properties of the building envelope significantly affect both the energy consumption of school buildings and the achievable savings through retrofitting interventions. Finally, a framework for the preliminary design of energy refurbishment of buildings, based on the implementation of the herein developed predictive model, is proposed and illustrated through a worked example application.

Worth noting that, while the proposed approach is currently limited to school buildings, the methodology can conceptually be extended to any building typology, provided that suitable data on energy consumption are available.

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Nomenclature

Acronyms

3-D	Three Dimensional
AI	Artificial Intelligence
ANN	Artificial Neural Network
BEM	Building Energy Model
BIM	Building Information Modelling
CO2	Carbon dioxide
D.L.	Decreto Legge
D.M.	Decreto Ministeriale
DL	Deep Learning
ETICS	External Thermal Insulation Composite Systems
GBRT	Gradient Boosting Regression Trees
LCT	Life Cycle Thinking
ML	Machine Learning
MLR	Multiple Linear Regression
NPV	Net Present Value
NZEB	Nearly Zero Energy Building
RC	Reinforced Concrete
SVM	Support Vector Machine
SVR	Support Vector Regression

MLR parameters

y_i	i-th independent variable
x_i	i-th predictor variable
β_0	intercept of the regression
β_i	i-th regression coefficient
ε	error of the prediction

Error and performance parameters

MAPE	Mean Absolute Percentage Error
R^2	Coefficient of determination
σ	Root-mean-square error
R	Linear correlation coefficient

Parameters

S	External envelope area [m^2]
V	Gross heated volume [m^3]
S/V	Shape factor [m^{-1}]
$\%S_g$	Percentage of the vertical glazed surface [%]
S_{vo}	Vertical opaque surface [m^2]
S_g	Surface of the glazed component [m^2]
S_{ho}	Horizontal opaque surface [m^2]
S_{vo}/S	Normalized vertical opaque surface [−]
S_g/S	Normalized surface of the glazed component [−]
S_{ho}/S	Normalized horizontal opaque surface [−]
S_o/S	Normalized opaque surface [−]
U	Thermal transmittance [W/m^2K]
U_{vo}	U-value of the vertical opaque envelope [W/m^2K]
U_g	U-value of the glazed building envelope [W/m^2K]
U_{ho}	U-value of the horizontal opaque envelope [W/m^2K]
U*	Area-weighted average U-values of the building envelope[1] [W/m^2K]
HDD	Heating Degree Days [K day]
BOR	Building Occupancy Rate [ppl/m^2]
SP	Heating setpoint temperature [°C]
HDD	heating degree days [°C]

Output parameters

$EP_{gl,nren}$	non-renewable global energy performance index [−]
$Q_{h,nd}$	Heating Energy Demand [KWh/y]
CI	Cost of Intervention [euro]
$\Delta Q_{(h,nd)}$	Heating Energy Demand Savings [KWh/y]
Qph	Primary heating energy demand [KWh/y]

Cost-benefit analysis parameters

r	leading interest rate of energy [−]
g	real interest rate of energy [−]
N	period of investment [year]

1. Introduction and motivation

The recent sustainability requirements at the international level (e.g., [1]) have led to growing focus on enhancing the energy performance of existing buildings. It is now widely acknowledged that the built environment is responsible for 36% of global final energy end-use and 37% of energy-related carbon dioxide (CO2) emissions [2]. Therefore, curbing the significant environmental impact of the building sector during each stage of the building life cycle, thus moving towards a carbon-neutral and eco-friendly society, is being recognized as a critical socio-economic need and challenging objective. According to the European Green Deal [3] plan, Europe aspire to be the world's first climate-neutral continent by 2050. To achieve this goal, all 27 EU Member States are obliged to reduce CO2 emissions and energy consumption by at least 55% by 2030, compared to 1990 levels.

Considering the Italian scenario, the recent financial incentives for energy refurbishment (i.e., "Eco-Bonus" and "Superbonus110%") and seismic retrofitting (i.e., "Sisma-bonus") interventions on existing buildings introduced by the Italian government represent a unique opportunity for an overall requalification of the Italian building stock [4]. Indeed, in earthquake-prone countries, environmental sustainability alone is deemed inadequate for developing a resource-efficient economy [5], as even low-intensities earthquake events can damage and compromise the performance of energy interventions such as External Thermal Insulation Composite Systems (ETICS) and rooftop solar power systems. Consequently, several past studies in the literature have stressed that energy refurbishment and seismic retrofitting should rather be designed and implemented through an integrated multi-performance approach (e.g., [6,5,7,8,9,10,11,12,13]). To achieve the objective of upgrading the national building stock, the first step is to establish a prioritization plan, based on both the life safety and economic-energy savings that can be achieved with integrated retrofit intervention. However, the inherent complexity in gathering existing building data at national level, including the relevant data to perform both energy and seismic assessment and retrofit analyses, is often viewed as a significant barrier for the implementation of such an ambitious national requalification plan. Thus, simplified and standardized procedures, built on adaptive and updatable frameworks and tools, are needed to support both the seismic vulnerability assessment [14,15] and the large-scale evaluation of building energy performance.

When shifting the focus to the building energy assessment, it is widely understood that numerous factors affect building energy performance. These include material thermophysical properties (e.g., conductivity, density and heat capacity), weather conditions, building shape (e.g., opaque surface, grazed component surface, and the shape factor) intended use, lighting density, building occupancy, and heating/cooling set points. Additionally, data regarding the actual energy consumption of the building under analysis (i.e., gas and electricity consumption) are necessary for model calibration, validation of the building energy assessment results, and to design energy refurbishment interventions and conduct cost-benefit evaluations. In current practice, the energy performance of buildings is typically assessed using ad-hoc energy software, performing time-consuming simulation analyses on refined three-dimensional (3-D) numerical models and validating the results through an iterative approach. Given the complexity of the problem, predicting building energy consumption can present significant challenges [16]. This issue is further highlighted when dealing with large building portfolios or applications at the territorial scale. Recent large-scale investigations based on statistical census data have confirmed that traditional energy refurbishment interventions, such as building envelope insulation, may represent a cost-effective measure to guarantee a high-energy-performance, CO2-eq emission reduction, comfortability and energy savings over the building life (e.g., [17] for the Albanian's buildings stock). Yet, suitable and practical methodologies to define prioritization schemes for the actual implementation of a national qualification plan are missing. Towards this end, the use of simplified, yet reliable, predictive models should be pursued as effective support tools.

In recent decades, several simplified models have been proposed in the literature, typically built on extensive building data collections and regression-based analyses applying machine learning (ML) and artificial intelligence (AI) techniques. However, as detailed further in Section 2, these methods are greatly influenced by the characteristics of the building portfolio under analysis. In the case of existing school buildings, there is a lack of actual data related to both the energy consumptions and the energy savings achievable through refurbishment interventions. Ultimately, a standardized methodology designed to assist the decision-making process in planning energy refurbishment for (Italian) school buildings is still missing in the current literature. In this context, the UEFA/ELENA research project [4] aimed to provide a reference framework for the execution of integrated seismic and energy retrofitting interventions of an extensive number of school buildings located in the province of Foggia, in Southern Italy. The project, whose methodology is described in Section 3, incorporated a comprehensive data collection drawn from both desktop study and on-site investigations, and employed refined and validated 3D BIM models to generate and compare a variety of integrated retrofit strategies. A very insightful school buildings database, containing information about the buildings' geometry, the characteristics of the envelope, the climatic zone, the building usage, the energy performance, and, finally, the costs and benefits of possible alternative retrofit interventions, was developed during the project. This paper presents predictive models, based on the implementation of a Multiple Linear Regression (MLR) method, to estimate a) the energy performance of existing school buildings in Italy, as well as b) the benefits and costs associated with different energy retrofitting intervention scenarios. The primary goal is to provide various stakeholders with a rapid, updatable, and simplified methodology that can support decision-making in energy refurbishment planning at a large scale. This methodology leverages and builds on an extensive database, originally developed in the aforementioned UEFA/ELENA project, and further integrated to include real data as well as extensive energy simulation results of school buildings in the Province of Foggia, Southern Italy. To appropriately train the predictive models, the database has undergone a suitable preprocessing through parametric simulations and specific variable selection. Furthermore, the stages involved in the proposed design-planning methodology are demonstrated through an application on a case-study archetype school.

The structure of the paper is outlined as follows. Section 2 provides an overview of available predictive models for energy consumption of buildings and refurbishment intervention. Section 3 reports a description of the utilized database, which includes the results of refined energy assessment analyses and refurbishment interventions. Section 4 presents the methodology employed for the development of the predictive model. This section also discusses in detail the parametric analysis of the calibrated energy models, the sensitivity analysis, the MLR approach adopted and the limitations of the adopted methodology. The results of the MLR model are reported and examined in Section 5, while Section 6 presents a simplified framework for the preliminary design of energy refurbishment of school buildings. Finally, Section 7 draws conclusions. Furthermore, although beyond the primary scope of this paper, Appendix A offers a practical overview of potential integrated energy and seismic interventions, including specific recommendations for construction details.

2. Overview of predictive models for energy consumption of buildings and energy retrofit savings

As discussed in the previous section, there has been an increase in initiatives to raise the energy efficiency of buildings. This trend has catalysed the development of innovative data-driven tools able to effectively predict energy consumption. From a historical point of view, Parti and Parti [18] were arguably the first to propose a regression-based model to assess the electricity demand in households. The study was based on an extensive database including data from 5286 households in San Diego County. Many research studies resumed and compared various works providing machine learning (ML) and artificial intelligence (AI) predictive models in this context (e.g., [19,20,21,22,23,24,25,26]). Among others, Amasyali and El-Gohary [20] observed that different ML techniques were under development and/or adopted in current research work: 47% incorporated Artificial Neural Networks (ANNs), 25% made use of Support Vector Machines (SVMs), 24% capitalized on other statistical methods and the remaining 4% employed decision tree algorithms. These findings have stimulated critical comparison and discussions on the most appropriate methods, including merits and shortcomings.

Focusing on supervised machine learning methods, multiple linear regression has been adopted by Bianco et al. [27] to forecast the Italian gross domestic electrical energy product based on historical consumption data. Kialashaki and Reisel [28] proposed an energy-demand model to predict the energy requirements in the residential sector of the United States (US). The authors applied both the artificial neural network (ANN) technique and the multiple linear regression (MLR) method to develop the predictive energy-demand model, using available statistical data for the US scenario. Aydinalp-Koksal and Ugursal [29] investigated the use of traditional regression-based methods for modelling the energy consumption of the Canadian residential sector. The study was based on the extensive database of the 1993 Survey of Household Energy Use (SHEU) [30]. In Ciulla and D'Amico [16], the use of multiple linear regression to predict building heat demand was detailed and showcased. The regression model was trained with a dataset of 1560 energy simulations, obtained from the parametric modelling of a singular non-residential "Base Case Study" and across varied boundary conditions and building geometric properties. Moreover, Ciulla et al. [31] explored alternative prediction methods, addressing the same problem through the Buckingham π theorem. In this research work, the database obtained from parametric simulations involved 2184 samples, representative of non-residential building stock designed according to modern energy requirements. The same researchers [32] also investigated the use of ANNs for the same task. They concluded that ANN can be used as a reliable alternative method for solving a traditional building energy balance, as well as for assessing the building energy demand.

Other studies implied and compared the use of Support Vector Regression (SVR) for predicting building energy requirements. In Wang et al. [33], four AI models, including three ANNs and one SVR, were employed to predict the hourly residential space heating electricity use. According to the authors, the SVR model outperformed the others. Furthermore, the authors pointed out that the dynamic nature of human behaviour negatively impacted on the prediction performance, stressing the need for improved occupant behaviour data integration in future models.

Some studies developed methodologies that use optimized ML approaches or combine several ML models. In Seyedzadeh et al. [34], Gradient Boosting Regression Trees (GBRTs) and SVMs were demonstrated to be effective for predicting building energy loads. Wang et al. [35] introduced a novel model for predicting building energy consumption by combining various models to enhance prediction accuracy, generalization, and robustness. In Li et al. [36], an extreme Deep Learning (DL) approach was used and compared with other ML techniques, among which NN and MLR, for predicting buildings' energy consumption; the potential of DL methods to extract better features was thus highlighted.

In general, despite the significant advances, review and comparison studies agree that each model has its unique strengths and weaknesses, making the selection of a definitive predictive strategy/method a complex exercise. Amasyali and El-Gohary [20] concluded that even though specific methods seem more accurate than others, each approach is deemed valuable; consequently, the selection of the most suitable method, primarily relies on the application context. Indeed, in Deng et al. [37], a comparative assessment among various predictive models for US commercial building energy usage revealed that ML methods can nudge linear regression methods in some cases. Yet, the need for more variables, particularly those tied to thermal performance and occupant behaviour, was also emphasized. In this context, D'Amico et al. [38] investigated the optimal predictive model for building energy demand through a Multiple Criteria Assessment. The authors compared various predictive models based on multiple unique criteria across four stages of model training and use pre-processing, implementation, post-processing, and use. The findings highlighted that the selection of a predictive tool inevitably and significantly relies on the aims of the application.

Regarding the energy retrofit intervention on buildings, the potential of ML and AI to support the understanding of the associated benefits and costs has been only partially addressed. In a comprehensive review study, Grillone et al. [39] highlighted a critical obstacle limiting the growth of energy renovation programs: the lack of information about retrofitting impacts. This emphasises the paramount importance of data collection for enhancing building portfolio management through data-driven approaches. A compelling study [40] has shown the potential of regional approaches to retrofitting school buildings. They utilize Building Information Modelling (BIM) to gather and transfer information to their Building Energy Model (BEM). Several other studies have explored the application of ML and AI in this field. Among these, Platten et al. [41] concluded that ML methods can enrich building databases with relevant building characteristics for energy retrofitting, improving estimates of national energy-saving potentials. A data-driven approach to predict future saving potential, aimed at assisting retrofit planning, was proposed by Xu et al. [42] utilizing a portfolio of 550 federal buildings in the US. The authors pointed out that significant savings can be achieved and suggested a series of future improvements to enhance the usability of the proposed method. Other studies have proposed data-driven frameworks based on a combination of ML, multi-objective optimization, and multi-criteria decision-making techniques. Such frameworks typically aimed to evaluate the energy performance of buildings and provide optimal retrofit plans (e.g., [43]).

In general, the above-mentioned studies agree that, while ML and AI can provide valuable insights into the cost-benefit analysis of energy retrofit interventions on buildings, fewer studies on retrofitting can be attributed to a data collection problem. Indeed, while it is theoretically a relatively straightforward task to access (if permissions are granted) a specific building's consumption data through the relevant bills, it is a much more complex and unusual task to construct a dataset derived from designing detailed large-scale energy interventions. For this reason, the authors believe that predicting costs and benefits achievable with energy retrofit interventions is a critical aspect to be further investigated and developed from research to practice. Such an action will arguably contribute to facilitate the implementation of a widespread energy refurbishment plan at a territorial scale.

3. The UEFA/ELENA research project

The UEFA/ELENA research project [4] aimed at supporting the implementation of integrated seismic and energy retrofitting interventions at a large scale, providing a reference framework for the decision-making process in the design phase, in line with the motivations discussed in the first section. This research project involved a large data collection on school buildings located in the province of Foggia (Southern Italy), consisting of 81 buildings, which can be grouped into 59 school buildings, 19 gyms, 2 offices and 1 laboratory. Fig. 1 shows the buildings' location at the territorial level together with the climatic zones. Specifically, it is worth reminding that the Italian territory is subdivided into 6 different climatic zones (from “Zone A" to “Zone F", [44]), based on specific ranges of heating-degree-days (HDD). The province of Foggia is characterized by 3 different climatic zones, namely “Zone C" ($900 < HDD \leq 1400$), “Zone D" ($1400 < HDD \leq 2100$), and “Zone E" ($2100 < HDD \leq 3000$).

The adopted methodology of the project is summarized in the flowchart in Fig. 2. Each step of the methodology will be discussed in further detail in the next sections below, along with a brief description of the main results.

3.1. Data collection and description of the case-study buildings

The first key step of the research project was the data collection on the case-study buildings. This task was performed through both a desktop study (in the first phase of the project) and in-situ surveys. The former (i.e., the desktop study) is deemed critical in the data acquisition process as it allows to collect the first relevant information on the case-study buildings and support the in-situ investigations, possibly suggesting localized screening tests and/or specific in-situ inspections. Therefore, during the first phase of the project, all available information about the case-study buildings was collected, e.g. satellite images, cadastral maps and plans, construction period, history of the buildings, and photos. Moreover, through a collaboration with the Technical Office of the Province of Foggia, it was possible to collect the energy and electricity consumption data related to the past three years, as well as digital architectural drawings and (only in a few cases) existing energy assessment reports.

Concerning the in-situ surveys, an ad-hoc energy data acquisition form and an interview form for school principals were developed. A particular focus during the in-situ inspections was given to the building envelope for both transparent and opaque components; for the latter, endoscopic investigations were performed to define the external walls stratigraphy. The geometric measurements then allowed the technical drawings of the buildings to be either confirmed or developed/integrated through simulated design and further in-situ inspections. Heating and cooling systems and the number and location of heating/cooling terminal units and lighting lamps were investigated. In addition, a photographic survey was conducted for each building investigated. This documentation has been used to collect information on the typology of the heating and cooling system, the heating/cooling terminal units, the facade’ glazed components and possible degradation phenomena. Finally, any difference observed during in-situ inspections compared to the data collected through the preliminary desktop study has been properly documented.

The main results of the data collection process are herein presented to give an idea of the building database. Fig. 3a shows the construction period of the analysed buildings; this information is deemed critical when compared to the historical evolution of the building energy codes in Italy (Fig. 3c), in order to preliminary assess the expected energy performance of case-study buildings. From a historical point of view, the first Italian building code addressing the energy efficiency of buildings is represented by the Law 373 [45]. This document introduced some provisions related to the heating systems and the insulation of the building envelope. Later on, in the early 1990s, the enforcement of Law 10 [46] and DPR 412 [44] defined the national regulations for the energy design/assessment of buildings. These documents introduced a technical report, still mandatory nowadays, describing the energy performance of the building system, i.e. the so-called “Relazione energetica

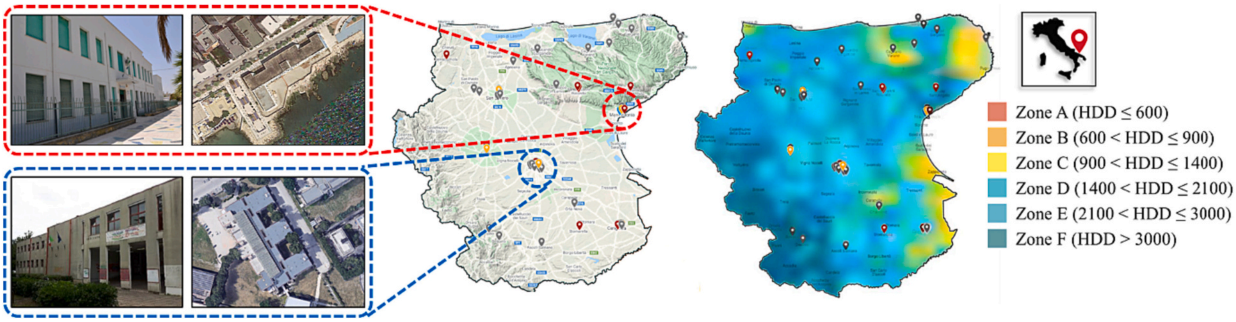


Fig. 1. Building location at territorial level and heating degree days in the province of Foggia.

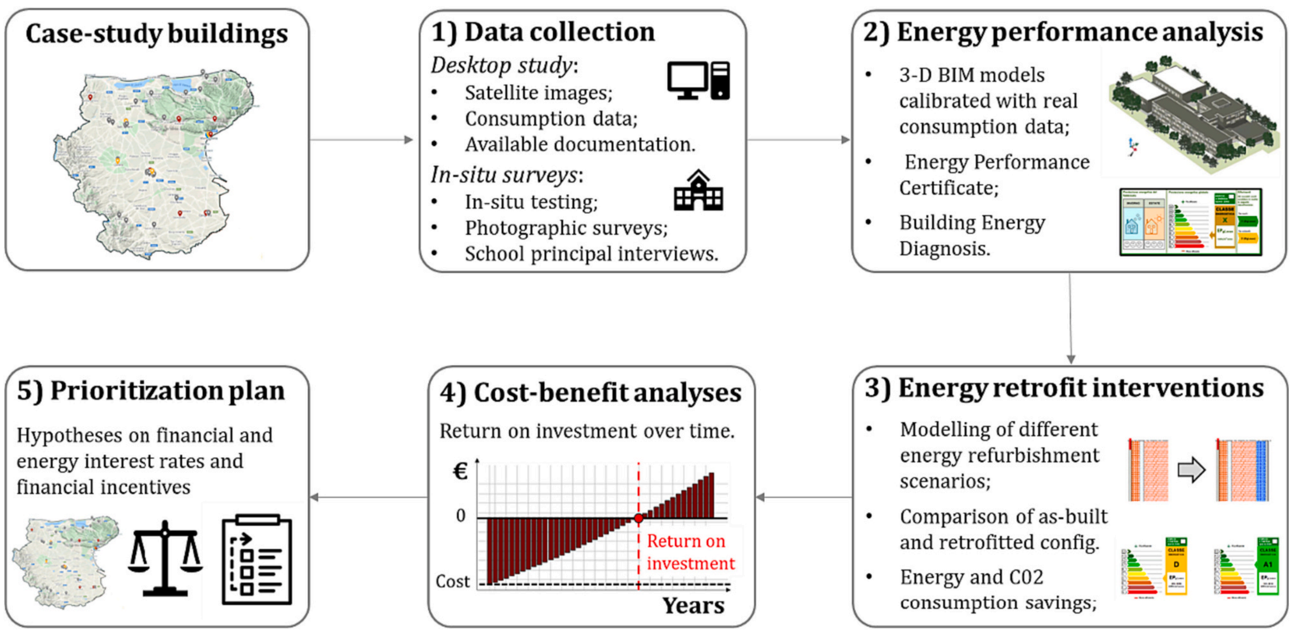


Fig. 2. Flowchart of the UEFA-ELENA Research Project methodology for large-scale energy refurbishment investigations.

(ex legge 10)" in Italian. Further improvements have been introduced by DL 192 [47], DL 311 [48], and DPR 59 [49], building on the European Directive 2002/91/EC [50]. Through these documents, the minimum requirements for energy efficiency for newly designed and retrofitted buildings were defined, as well as the methodology for the building energy performance assessment. The concept of Nearly Zero Energy Building (NZEB) was introduced by DL 63 [51]. Finally, the DM 26/06/2015 [52] defined the new methodologies to assess the energy performance of buildings and the minimum energy efficiency requirements for new and retrofitted buildings. Moreover, this document provided the guidelines for the development of the Energy Performance Certificate ("Attestato di Prestazione Energetica", in Italian), introduced by the DL 63 [51].

Therefore, looking at Fig. 3a, it can be noted that almost 48% of the case-study buildings were built before Law 373 (i.e., pre-1976) and 32% in the subsequent period range 1976–1991; on the other hand, only a few buildings were built in the period range 1992–2005 (13%) or after 2005 (4%). The most recent school in the database was built in 2008.

The subdivision in terms of construction material is illustrated in Fig. 3b. The largest part of the database is characterized by Reinforced Concrete (RC) frames (83%); masonry buildings are 7% of the total, as well as mixed masonry-RC buildings; on the other hand, steel structures are only 2%.

Concerning the opaque building envelope, the external walls stratigraphy was defined through in-situ endoscopic investigations. The main observed typologies are single-layer and cavity wall, while only one multi-layer wall typology and one cavity wall filled with cementitious materials ("muratura a sacco" in Italian, typical of pre-1900s buildings) are observed (Fig. 4a). The presence of insulation material is also accounted for, as it strongly affects the thermophysical properties of the building envelope. Fig. 4 shows the distribution of the building envelope typologies and the percentage of observed insulation materials.

Moving towards a more detailed description level, the most frequent typology of wall/infill elements consists of hollow bricks, observed in both single-layer and cavity walls, followed by the combination of hollowed bricks and solid bricks in single-layer and multi-layer walls, while only few cases present single-layer wall with solid bricks. There are also cases, representing a lower percentage, of rubble stone, square stone, concrete panels, and concrete blocks.

Regarding the roof, the most frequent typology consists of composite cast-in-place RC and masonry floor systems without insulation (42 cases, Fig. 5a); only 2 cases of precast concrete roofs without insulation are observed. Moreover, some cases of pitched roofs are present, involving reinforced concrete and masonry floor systems (9 cases, Fig. 5b) and precast concrete floor systems (9 cases), both without insulation; a single case of a timber pitched roof is also collected. The presence of insulation material is observed in 17 cases of RC and masonry floor systems and in 1 case of precast concrete pitched roof.

Finally, looking at the glazed building envelope, the differences

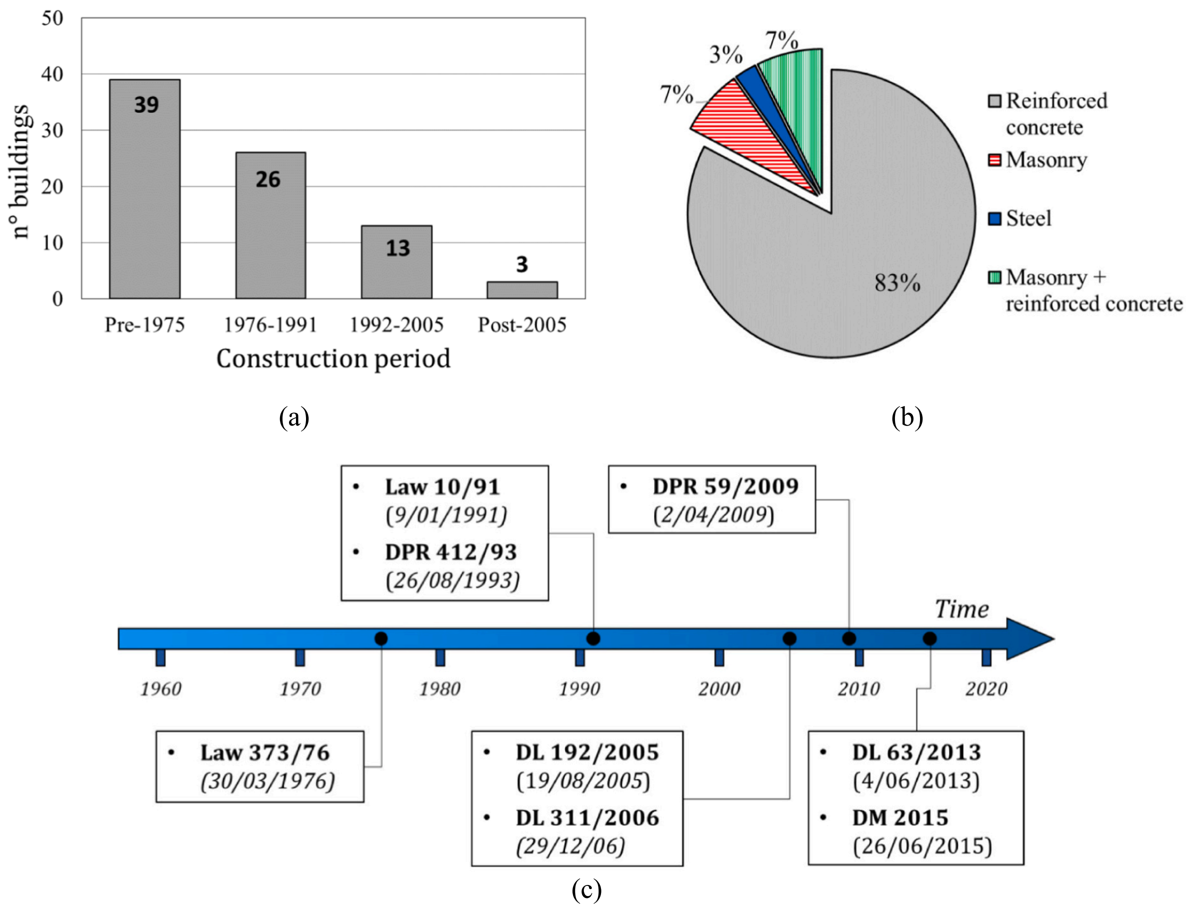


Fig. 3. (a) Construction period and (b) construction materials of the case-study buildings; (c) evolution of the building energy codes in Italy.

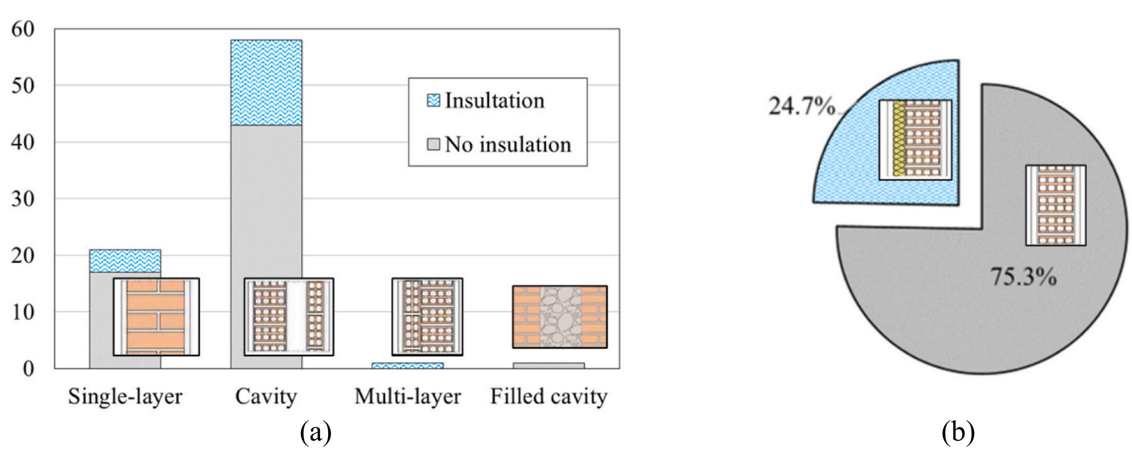


Fig. 4. (a) Typologies of the opaque building envelope and (b) presence of insulation.

between the observed windows typologies involve different window frames and the number of layers of glass (Fig. 6). Specifically, the observed window typologies are: windows with aluminium frames (53 double-pane windows and 14 single-pane windows), windows with wooden frame (4 double-pane windows and 2 single-pane windows), and 8 double-pane windows with PVC (polyvinyl chloride) frame.

3.2. Building energy analyses and refurbishment interventions

The data collection process (both through a desktop study and in-situ surveys) allowed the development of BIM numerical models, used to perform energy performance analyses. Specifically, the models were implemented through the software TerMus BIM – DIM (ACCA software S.p.a). It is worth noting that, for the considered database, in some cases, two or more independent buildings are served by the same thermal system (e.g., school building and adjacent gym). This leads to 66 energy models and analyses starting from the 81 independent buildings. The main steps of the performed energy analyses are discussed below.

(a) (b)

Fig. 5. Example of composite cast-in-place RC and masonry floor systems for (a) flat and (b) pitched roof.

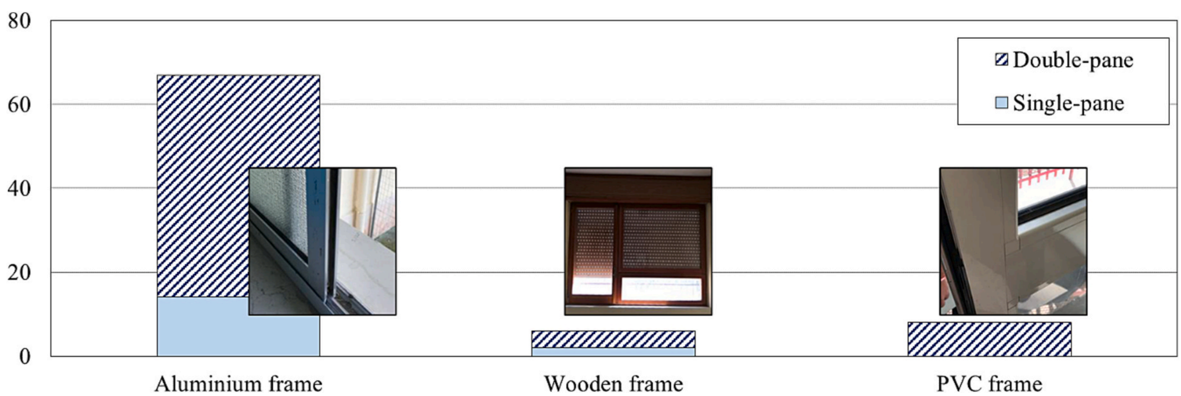


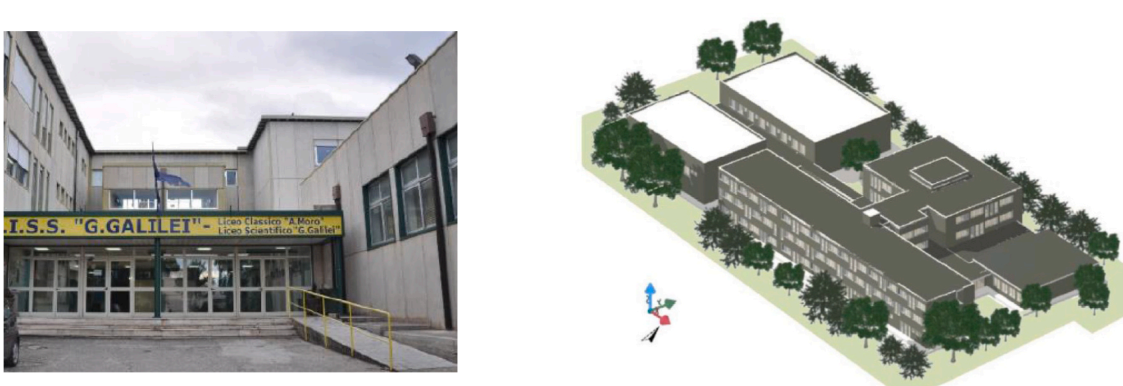
Fig. 6. Typologies of the transparent building envelope (windows).

3.2.1. Modelling approach

A detailed 3-D BIM model was implemented for each analysed case-study building. Heated and cooled areas were identified by data collected through in-situ surveys, together with the building occupancy, daily schedules regarding the utilization of equipment and heating/cooling set points. Heating and cooling systems were modelled considering their performance, i.e., their efficiency and nominal power, according to the documentation available for each case study. The building envelope was modelled considering the thermos-physical properties of each component (i.e., vertical and horizontal, opaque and transparent). Specifically, the stratigraphy of each envelope component was defined to evaluate the thermal properties of the building envelope. Since the buildings under investigation are mainly schools, a closure period from 1st August to 31st August (summer holidays in Italy) and from 23rd December to 6th January (Christmas holidays in Italy) was considered; weekends were also not accounted for in the analyses. Finally, almost 8–10 h per day were assumed based on the school occupancy rate as well as on the information collected during the in-situ surveys. An example of a case-study school building and the BIM model implemented in TerMus BIM–DIM is reported in Fig. 7.

Energy analyses were performed through a semi-stationary approach, in line with the Italian standards [53]. This procedure is based on the use of monthly average values for environmental temperature, solar radiation values and relative humidity. The energy balance of the building is thus defined by the following Eq. (1) and Eq. (2), for the building's annual heating and cooling energy demands, respectively:

$$Q_{h,nd} = Q_{h,ht} - \eta_{h,gn} Q_{gn} = \left(Q_{h,tr} + Q_{h,ve}\right) - \eta_{h,gn}\left(Q_{int} + Q_{sol}\right) \quad (1)$$



(a) (b)

Fig. 7. Example school building and its BIM model implemented in the software TerMus BIM – DIM.

$$Q_{C,nd} = Q_{gn} - \eta_{C,ls} Q_{gC,ht} = (Q_{int} + Q_{sol}) - \eta_{C,ls} (Q_{C,tr} + Q_{C,ve}) \quad (2)$$

where $Q_{h,tr}$ and $Q_{C,tr}$ represent the transmission heat exchange for heating and cooling seasons, respectively; $Q_{h,ve}$ and $Q_{C,ve}$ are the ventilation heat exchange for heating and cooling seasons, respectively; Q_{int} represents the internal gains, while Q_{sol} represents the solar gains; $\eta_{h,gn}$ is the heating utilization factor and $\eta_{C,ls}$ is a reduction factor for transmission heat loss.

For each case-study building, a fundamental step in the modelling process was the calibration and validation of the predicted gas/energy and electricity consumptions through real data, derived from the actual energy bills. For each school the numerical model was thus calibrated and validated against the available (gas and electricity) consumption data targeting an error threshold lower than 5%. Furthermore, for each case-study building, the Energy Performance Certificate ([50], "Attestato di Prestazione Energetica", APE, in Italian) was obtained as an output of the validated BIM models leading to a benchmarked and standard/codified assessment of the energy class. It is worth noting that the Energy Performance Certificate was performed after the model calibration and validation through actual consumption data, even if this is not mandatory for Italian regulations. Therefore, these results are deemed more accurate than traditional Energy Performance Certificate analyses.

3.2.2. Building energy performance results

A brief overview of the building energy performance results is given in this section. Firstly, the Energy Performance Certificate has been evaluated for each case-study building, according to the UNI/TS 11300. Although this asset rating methodology provides approximate results, it is deemed useful to preliminary assess and compare the entire building portfolio in terms of building energy class. The Italian energy certification involves ten energy classes, from class "A4" (i.e., most energy-efficient class) to "G" (i.e., worst energy-efficient class); the energy classes are evaluated through a comparison of the non-renewable global energy performance index $EP_{gl,nren}$ value and the one of the so-called "reference building". More specifically, according to DM 26/06/2015 [52] procedure, the reference building is a benchmark building equal to the real one in terms of geometry (i.e., surface, volume, location, orientation, and building use), but with a code-compliant envelope (in terms of either energy and thermal properties). The $EP_{gl,nren}$ ranges for the Italian building energy classification are listed in Table 1.

Results of the Energy Performance Certificate (APE in Italian), in terms of building energy classes for each analysed case-study building are shown in Fig. 8.

Most of the analysed buildings are assessed as "D" class (26 buildings) and "C" class (20 buildings); only a few buildings show a relatively good energy performance (2 buildings in "A1" class; 8 buildings in "B" class). The remaining ones belong to the "E" class (5 buildings), the "F" class (4 buildings) and the "G" class (1 building). Results shown in Fig. 8 highlight, on one hand, an expected low energy performance of the building portfolio and, on the other hand, the need to investigate possible energy refurbishment interventions. In that direction, a more advanced "tailored rating" approach was also adopted for each building by performing a Building Energy Diagnosis ("Diagnosi Energetica", in Italian). As mentioned before, a validation process was performed through a model calibration, in order to achieve an error lower than 5% with respect to the real consumption data for each analysed building. These calibrated and validated BIM models were used to investigate possible energy refurbishment interventions through a cost-benefit analysis. More details on this are given in the next sections. The results of the Building Energy Diagnosis analyses are shown in Fig. 9.

Table 1
Definition of the Italian building energy classes [52].

Class A4		$EP_{gl,nren}$	$\leq 0.4\ EP_{gl,nren,ref.building}$
Class A3	$0.4\ EP_{gl,nren,ref.building} <$	$EP_{gl,nren}$	$\leq 0.6\ EP_{gl,nren,ref.building}$
Class A2	$0.6\ EP_{gl,nren,ref.building} <$	$EP_{gl,nren}$	$\leq 0.8\ EP_{gl,nren,ref.building}$
Class A1	$0.8\ EP_{gl,nren,ref.building} <$	$EP_{gl,nren}$	$\leq 1.0\ EP_{gl,nren,ref.building}$
Class B	$1.0\ EP_{gl,nren,ref.building} <$	$EP_{gl,nren}$	$\leq 1.2\ EP_{gl,nren,ref.building}$
Class C	$1.2\ EP_{gl,nren,ref.building} <$	$EP_{gl,nren}$	$\leq 1.5\ EP_{gl,nren,ref.building}$
Class D	$1.5\ EP_{gl,nren,ref.building} <$	$EP_{gl,nren}$	$\leq 2.0\ EP_{gl,nren,ref.building}$
Class E	$2.0\ EP_{gl,nren,ref.building} <$	$EP_{gl,nren}$	$\leq 2.6\ EP_{gl,nren,ref.building}$
Class F	$2.6\ EP_{gl,nren,ref.building} <$	$EP_{gl,nren}$	$\leq 3.5\ EP_{gl,nren,ref.building}$
Class G		$EP_{gl,nren}$	$> 3.5\ EP_{gl,nren,ref.building}$

From Fig. 9a it can be noted, as expected, a relatively high correlation between the heating energy demands and the volume of the buildings, i.e., the higher the volume the higher the heating energy demands. Therefore, it seems reasonable to normalize the results to the volume of the buildings. However, a correlation between the $Q_{h,nd}/V$ values and other key energy metrics are not straightforward. As an example, Fig. 9b shows the $Q_{h,nd}/V$ values vs. heating degree days HDD cloud data. Although the physics of the problem would suggest that higher $Q_{h,nd}/V$ values should be related to higher HDD values, the results are characterized by a severe dispersion and a reliable trend cannot be defined. This is mainly due to the other (numerous) metrics affecting the energy performance assessment of buildings, such as the shape factor S/V, the thermal properties of the envelope, the internal setpoint etc. These (lack of) results prompted the need to investigate the adoption of a multiple linear regression approach as a basis for a simplified and practical methodology to predict the energy performance of school buildings, as reported in the following Section 4, 5.

3.2.3. Energy refurbishment interventions

Different energy refurbishment interventions were considered in the research project, mainly aiming to improve the energy performance of the building envelope (both opaque and transparent) in line with a "passive" approach. Specifically, the considered interventions were: (a) thermal insulation of opaque vertical walls, (b) floor and roof insulation, and (c) replacement of windows and external glass doors. The typology of intervention was defined in line with the building characteristics and other possible constraints. For instance, concerning the thermal insulation of opaque vertical walls, when considering school buildings with architectonic constraints, internal thermal insulation composite systems were deemed as a more suitable intervention than external insulation techniques. Each intervention was implemented to achieve the performance thresholds and requirements defined by the Italian code [52] for each Italian climate zone. The replacement of the heating systems with more performing solutions was also considered a possible energy refurbishment intervention (when suitable), in line with the "active" energy retrofitting technique. On the other hand, no active interventions such as those involving solar photovoltaic technologies were implemented in this study, as they can be at any time, during the design process, and easily considered as additional/optional scenarios.

Different energy retrofitting scenarios were thus investigated, based on a combination of the retrofit energy techniques discussed above. Although the UEFA/ELENA research project involved 12 different scenarios, in this research work only three scenarios, deemed as the most effective and suitable for practical purposes, were investigated, as shown in Fig. 10.

It can be noted that the selected scenarios involve a combination of different energy refurbishment interventions. Specifically, *Scenario 1* is the more complete retrofitting scenario, involving the thermal insulation of opaque vertical walls, as well as of the ground floor and roof, and the replacement of windows and external glass doors. *Scenario 2* is similar to *Scenario 1*, with no replacement of the transparent building envelope (i.e., windows and glass doors). Finally, *Scenario 3* represents a single intervention scenario, involving only the replacement of the transparent building envelope.

For each analysed case-study building, the proposed energy retrofitting scenarios were investigated through a cost-benefit analysis.

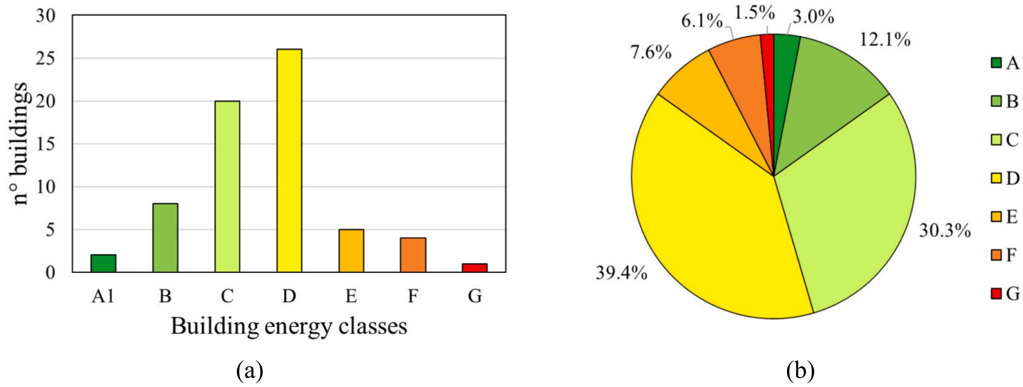


Fig. 8. Results of the Energy Performance Certificate (APE in Italian): (a) number and (b) the percentage of buildings belonging to the same energy class.

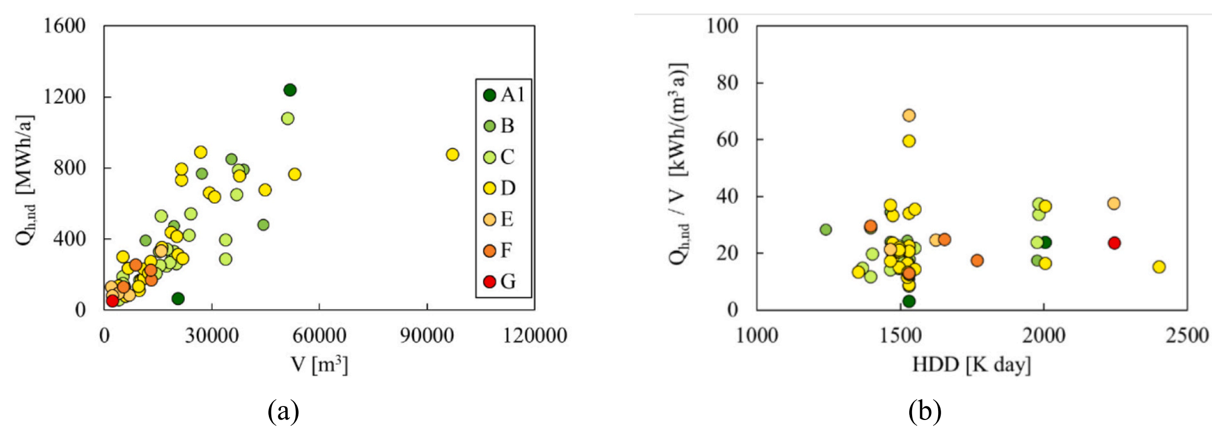


Fig. 9. Results of the Building Energy Diagnosis analyses: (a) heating energy demands $Q_{h,nd}$ vs. volume V and (b) heating energy demands normalized to the volume of the building $Q_{h,nd}/V$ vs. heating degree days.

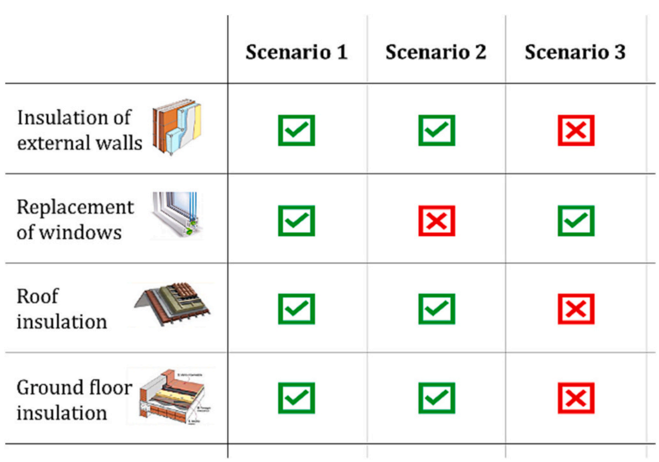


Fig. 10. Conceptual definition of energy refurbishment scenarios.

Specifically, the cost of each energy refurbishment intervention was evaluated according to two main price list documents for Southern Italy [54,55]. The cost-benefit analysis considered, for each energy refurbishment scenario, the annual energy consumption savings and, thus, the related economic savings. The payback time of the investment over time was then evaluated under different assumptions on the following parameters: interest rates on loans, real interest rates on energy, and financial incentives (currently available in Italy). Following this approach, a prioritization plan for the energy renovation of the analysed building portfolio was developed, taking into account, for each building, its original consumption, the investment costs, and the payback time of the intervention. For the sake of brevity, the results regarding the priority plan are herein not reported, but a worked-example showing how to calculate the above results is given in Section 6.

4. Building energy performance prediction model

The methodology described in the previous section provided a dataset consisting of 66 energy models, based on real case-study school buildings, containing information about: geometric properties, climate exposure, thermal properties and usage of the school buildings. These data are further associated with the results of the energy performance simulations and energy retrofit analyses. The database is used to develop predictive models for the energy performance of school buildings as well as for assessing the costs and benefits of retrofit interventions, according to the energy refurbishment techniques described in the previous section. A sensitivity analysis is conducted to highlight the most relevant parameters in both results and to reduce the number of variables of the predictive model. The dataset characteristics and manipulation, the results of the sensitivity analysis and the multiple linear regression (MLR) method used to obtain the predictive models are described in this section.

4.1. The multiple linear regression model

Data on energy consumption for both the as-built and retrofitted configuration are used to define MLR model, in order to preliminary assess both the building energy requirements and the energy consumption savings through a simplified and easy-to-apply tool. This regression model is selected among others because it is deemed one of the most used and intuitive approaches of prediction [16], allowing one to develop simplified relationships without excessive computational effort.

The MLR model defines a relationship between the dependent variable and several independent variables (or predictor variables) through a linear combination of the latter. The general equation of an MLR model is (Eq. (3)):

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p + \varepsilon \quad (3)$$

Where y represents the independent variable; x_i is the i-th predictor variable (input); β_0 is the intercept (constant) of the relationship, while β_i is the i-th regression coefficient; finally, ε is the (random) error related to prediction (disturbance term or error variable). The latter follows a normal distribution with a mean of zero. The MLR model is fitted using the least square method, based on minimizing the sum of the squares of the residuals (i.e., the difference between the expected and predicted outputs). Moreover, different measures of accuracy of the predictive method are also evaluated in this study, namely: the Mean Absolute Percentage Error (MAPE), the coefficient of determination (R^2), and the root-mean-square error (or standard deviation, σ). The mathematical formulations of each error measure are listed in Table 2 (Eqs. (4)–(6)).

4.2. Dataset description and parametric simulation

Among the 66 models, which represent a broad range of building typologies, including concrete and masonry structures, 31 were selected in order to homogenize the dataset and provide effective predictive models. This selection is intended to exclude buildings with exceptional peculiarities. Among these are: public buildings that are not used as schools (e.g., municipality buildings), historical masonry buildings, and buildings characterized by exceptions in either the thermal properties of the envelope (e.g. overall heat transfer coefficient, U-value), or the geometry (e.g. volume). The list of parameters, with the relative upper and lower bound, that make up the considered database is presented in Table 3. Moreover, when it is deemed relevant, Table 3 also contains statistical metrics (i.e., means and standard deviation) of the selected parameters.

Concerning the energy retrofitting, in line with the methodology adopted in the UEFA/ELENA research project, the costs and benefits associated with each implemented scenario have been expressed in terms of CI/V and $\Delta Q_{(h,nd)}/V$. The related dataset has been derived from the original 31 by considering only the case studies for which all the analysed scenarios have been implemented. It is worth noting that, as previously mentioned in Section 3.2.3, in the UEFA/ELENA research project the refurbishment interventions have been selected according to the characteristic of the analysed buildings, thus some scenarios may have not been implemented since it has been deemed not suitable (e.g., for schools with glazed components with good performance, no replacement of windows has been considered). This decreases the dataset from 31 to 25 samples.

To improve the results in the predictive model for the energy performance assessment, the dataset has been increased by generating new energy models through a modification of some relevant parameters from the original ones. Specifically, the new energy models are generated by modifying the following building envelope and usage parameters: $\%S_g \in [20\%, 25\%]$; $U_{vo} \in [0.5, 0.6, 0.7, 0.8]$; $SP \in [20^\circ]$. A sample size of 275 is thus obtained for the energy analysis dataset. Differently, no intervention scenarios have been implemented for the additional models obtained through the parametric simulations.

The main output considered for the energy simulation is the heating energy demand normalized by the building volume $\left(Q_{h,nd}/V\right)$, while, concerning the retrofit analysis, both cost of the intervention normalized by the building volume (CI/V), and heating energy savings normalized by the building volume $\left(\Delta Q_{h,nd}/V\right)$ are considered. For the sake of clarity, it is remarked that the output data for the refurbishment interventions (i.e., CI/V and $\Delta Q_{h,nd}/V$) have been obtained following three main steps: i) design of the intervention (including costs); ii) implementation in the BIM model; and iii) comparison between the as-built and the retrofitted configurations.

4.3. Sensitivity analysis and variable selection

A sensitivity analysis is carried out comparing the linear correlation coefficient R (Eq. 7), between the dataset parameters (Table 3) and the results of both energy performance analyses (i.e., $Q_{h,nd}/V$) and energy intervention analyses (i.e., $\frac{\Delta Q_{h,nd}}{V}$ and CI/V).

$$R = \frac{\sum\left[(x_i - \underline{x})\left(y_i - \underline{y}\right)\right]}{\sqrt{\sum (x_i - \underline{x})^2 \bullet \sum \left(y_i - \underline{y}\right)^2}} \quad (7)$$

The objective of the sensitivity analysis is to identify the most influent parameters for each result, thus making a selection of variables to be adopted in the training of the predictive models through the multiple linear regression method. Correlation coefficients among parameters of the energy analysis dataset are shown through a heatmap in Fig. 11; for the sake of simplicity, the following parameters have already been excluded from the analysis, as they are considered to be redundant with the others: $V, S, S_{vo}, S_g, S_{ho}, S_o/S, \%S_g$.

It is worth noting that variables are sorted in descending order from the absolute values of the correlation coefficient with respect to the normalized total energy exchange for space heating $Q_{h,nd}/V$, thus highlighting those that mostly affect its evaluation (from left to right in the first raw of the heatmap in Fig. 11). Observing Fig. 11, it can be seen that the product of the average U-value and the shape factor $(U^* \bullet S/V)$ is the most correlated variable with the annual energy consumption (Q_h/V); arguably, it can be considered the most representative parameter for the building energy performance, as it includes information about both the geometry and envelope thermal properties. Thereafter, the parameters identified as most influential are those related to the geometric characteristics of the building (i.e., $S_{ho}/S; S_{vo}/S; S_g/S$) and some envelope characteristics (i.e., U_{ho}), followed by thermal demand parameters of the site (HDD) and building usage ($Occupancy\ rate; Setpoint$). It can also be noted that the infill walls' transmittance (U-value) is weakly correlated with energy consumption ($R = 0.03$), and in particular is less than the glazing ($R = 0.21$) and floor ($R = 0.43$) ones; this aspect could be ascribed to the school building typology, characterized by wide windows and horizontal surfaces. The variables' selection process for the MLR model should avoid collinearity between the multiple predictor variables (e.g., S_{vo}/S vs. S_{ho}/S leads to $R = 0.98$), as this can undermine the stability of the model. For this reason, correlation coefficients among the variable of the database are also shown in Fig. 11.

Sensitivity analysis is therefore carried out also for the energy intervention dataset. For the sake of brevity, only the correlation coefficient of parameters concerning the cost of the intervention (CI/V) and energy consumption savings $(\Delta Q_{h,nd}/V)$ are reported in Table 4.

Table 2
Mathematical formulations of the adopted measures of prediction accuracy of the predictive method.

$MAPE = 100 \bullet \frac{1}{N}\sum_{i=1}^{N}\frac{\lvert x_i - y_i\rvert}{x_i}$	$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N}(x_i - \widetilde{x}_i)^2}$	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2}$
(4)	(5)	(6)

Note: x_i = i-th observed output; y_i = i-th predicted output; $\widetilde{x}$ = mean of the observed data; N = number of samples.

Table 3
Database of the school building parameters (31 schools; μ = mean; σ = standard deviation).

Category	Parameter	Notation	Unit	Lower bound	Upper bound	μ	σ
Geometry	External envelope area	S	[m^2]	1012	35,913	8175	6772
	Gross heated volume	V	[m^3]	2250	97,062	20,133	18,402
	Shape factor	S/V	[m^{-1}]	0.29	0.65	0.44	0.09
	Percentage of the vertical glazed surface	$\%S_g$	[%]	0.11	0.31	0.19	0.06
	Vertical opaque surface	S_{vo}	[m^2]	636	6648	2646	1570
	Surface of the glazed component	S_g	[m^2]	92	2365	680	505
	Horizontal opaque surface	S_{ho}	[m^2]	275	27,503	4851	5163
	Normalized vertical opaque surface	S_{vo}/S	[–]	0.17	0.69	0.37	0.13
	Normalized surface of the glazed component	S_g/S	[–]	0.03	0.16	0.09	0.03
	Normalized horizontal opaque surface	S_{ho}/S	[–]	0.15	0.80	0.54	0.14
	Normalized opaque surface	S_o/S	[–]	0.84	0.97	0.91	0.03
Thermal properties	U-value of the vertical opaque envelope	U_{vo}	[W/m^{2}K]	0.47	0.92	0.73	0.14
	U-value of the glazed building envelope	U_g	[W/m^{2}K]	1.80	6.15	4.16	1.09
	U-value of the horizontal opaque envelope	U_{ho}	[W/m^{2}K]	0.63	1.85	1.27	0.33
	Area-weighted average U-values of the building envelope[1]	U*	[W/m^{2}K]	0.84	1.72	1.31	0.23
	Average U-value multiplied by the shape factor	U*•S/V	[W/m^{3}K]	0.34	0.82	0.57	0.11
Location and usage	Heating Degree Days	HDD	[K day]	1353	2400	–	–
	Building Occupancy Rate	BOR	[ppl/m^2]	0.05	0.60	–	–
	Heating setpoint temperature	SP	[°C]	18	21	–	–

[1] According to Kwag et al. [56].

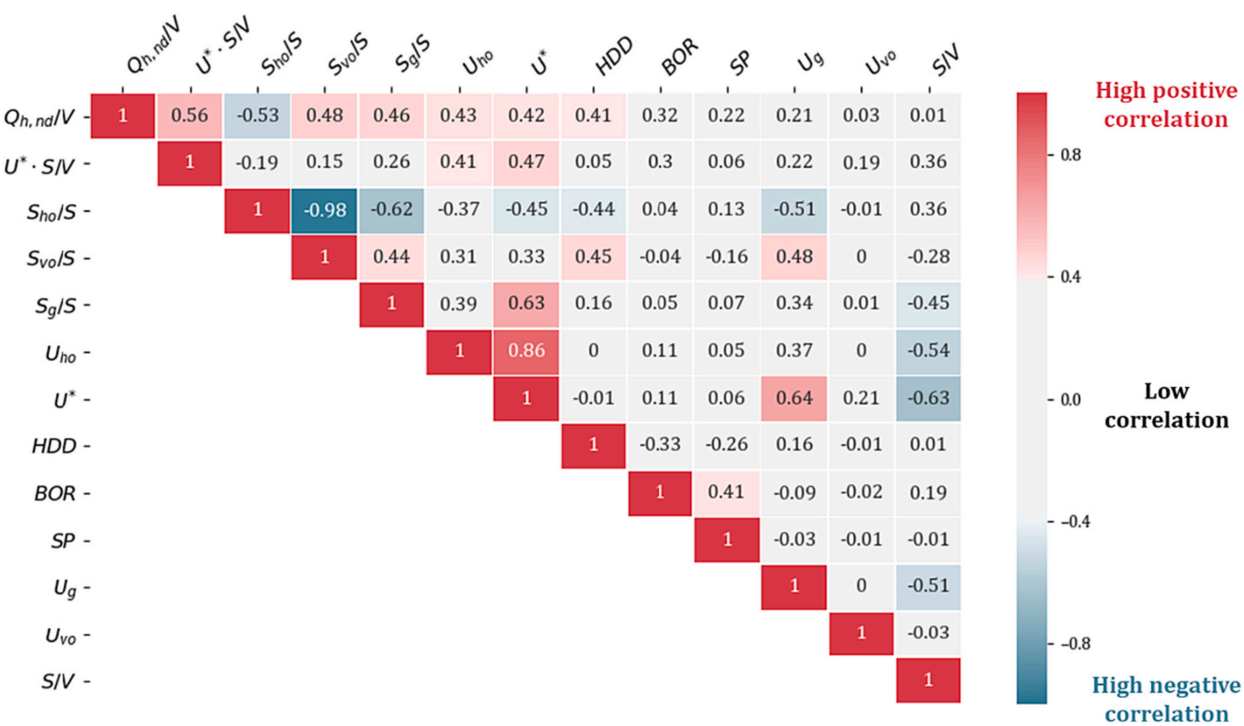


Fig. 11. Heatmap for correlation coefficient R for the energy analysis dataset.

Table 4 confirms that the parameter $U^* \bullet S/V$ has a strong influence with respect to both the cost of intervention and the annual savings in energy consumption achieved. Other useful observations towards the variables selection as well as for energy retrofit intervention choice can be made: (i) geometrical parameters are particularly relevant in determining the cost of intervention, and (ii) the correlation of U_v with energy savings still shows how glazed facade components might represent a weakness in the envelope of school buildings. Is the opinion of the authors that these findings may already be considered an important suggestion for the choice of energy improvement interventions, as they highlight that the intervention on the glazed components only (i.e. Scenario 3) could be very effective in many cases.

Predictive models' variables selection is based on correlation coefficient analysis. For each forecast model, the parameters with the highest correlation coefficients were selected; then mutual dependence between the variables is avoided by excluding quantities that were physically dependent on each other (e.g., clearly, when the product $U^* \bullet S/V$ is chosen, both S/V and U^* variables are excluded in the regression analysis), and by excluding variables affected by high collinearity (i.e., $R > 0.5$). The final choice of variables is summarized in Table 5.

5. Result and discussion

The results of predictive models for the normalized total energy exchange for space heating ($Q_{h,nd}/V$), normalized costs for energy retrofit intervention (CI/V), and normalized savings for the total energy exchange for space heating ($\Delta Q_{h,nd}/V$) achieved by the intervention, obtained using the variables selected in the previous section and resumed in Table 5, are herein presented. Validation of the energy performance predictive model, whose dataset has a sample size of 275, is performed

Table 4
Correlation coefficient R for energy intervention analysis (higher correlations are in bold).

Parameters	Correlation coefficient R					
	Scenario 1		Scenario 2		Scenario 3	
	CI/V	$\Delta Q_{h,nd}/V$	CI/V	$\Delta Q_{h,nd}/V$	CI/V	$\Delta Q_{h,nd}/V$
U_{vo}	−0.04	−0.09	−0.06	−0.19	0.07	0.06
S/V	**0.66**	0.43	**0.63**	0.47	0.45	0.26
U_g	−0.04	**0.59**	−0.07	0.51	0.21	**0.53**
HDD	0.24	0.23	0.30	0.11	−0.03	0.31
Occupancy rate	0.10	0.06	0.06	0.07	0.20	0.03
Setpoint	0.10	0.24	0.02	0.32	0.26	0.08
U_{ho}	−0.09	−0.16	−0.03	−0.11	−0.31	−0.20
U* • S/V	**0.63**	**0.55**	**0.57**	**0.57**	**0.52**	0.39
U*	−0.02	0.16	−0.05	0.11	0.09	0.19
S_{vo}/S	**0.56**	0.16	**0.56**	0.07	0.32	0.24
S_g/S	0.33	0.24	0.16	0.03	**0.76**	0.42
S_{ho}/S	**−0.58**	−0.20	**−0.55**	−0.07	−0.45	−0.31

Table 5
Selected variables for the predictive models.

Case-study configuration	Dependent variable	Independent variables
As-built configuration	$Q_{h,nd}/V$ [kWh/m^3]	U*•S/V, HDD, BOR, SP, S_g/S
Energy Retrofit intervention SC1	CI_{SC1}/V [€/m^3] $\Delta Q_{h,nd,SC1}/V$ [kWh/m^3]	S/V, S_{oo}/S, S_g/S U_{vt}, S/V, S_g/S, HDD, SP
Energy Retrofit intervention SC2	CI_{SC2}/V [€/m^3] $\Delta Q_{h,nd,SC2}/V$ [kWh/m^3]	S/V, S_{vo}/S U*•S/V, SP, HDD
Energy Retrofit intervention SC3	CI_{SC3}/V [€/m^3] $\Delta Q_{h,nd,SC3}/V$ [kWh/m^3]	S_g/S, S/V, U_g U_g, S_g/S, S/V, HDD

Table 6
MLR analysis results for Energy demand, savings and intervention costs.

Configuration	Regression Model		MAPE	R^2	σ_{res}
As-built	$\frac{Q_{h,nd}}{V} = -54.7728 + 23.7512\,U^* \bullet \frac{S}{V} + 0.0117\,HDD + 10.9238\,BOR + 1.7572\,SP + 44.0452\frac{S_g}{S}$	(8)	12.51%	0.65	2.86
Energy refurbishment SC1	$\frac{\Delta Q_{h,SC1}}{V} = -58.5 + 3.0158\,U_g + 23.7656\frac{S}{V} + 41.3787\frac{S_g}{S} + 0.0047\,HDD + 1.8546\,SP$	(9)	20.24%	0.71	2.59
	$\frac{CI_{SC1}}{V} = 14.2565 + 171.7411\frac{S}{V} - 80.4705\frac{S_{ho}}{S} + 155.4090\frac{S_g}{S}$	(10)	15.16%	0.73	11.36
Energy refurbishment SC2	$\frac{\Delta Q_{h,SC2}}{V} = -26.9103 + 14.2723\,U^* \bullet \frac{S}{V} + 1.1635 SP + 0.0024\,HDD$	(11)	28.44%	0.42	2.27
	$\frac{CI_{SC2}}{V} = -47.3886 + 136.5590\frac{S}{V} + 90.6233\frac{S_{vo}}{S}$	(12)	19%	0.64	11.86
Energy refurbishment SC3	$\frac{Q_{h,SC3}}{V} = -13.3574 + 1.3072\,U_g + 40.9671\frac{S_g}{S} + 8.4371\frac{S}{V} + 0.0027 HDD$	(13)	29.07%	0.63	1.5
	$\frac{CI_{SC3}}{V} = -23.5081 + 197.5633\frac{S_g}{S} + 41.0909\frac{S}{V} + 1.1450\,U_g$	(14)	16.52%	0.88	2.15

by splitting it into train and test with a 70/30 ratio. Furthermore, k-fold cross-validation is carried out on the train set by using $k = 5$ and a value of $R^2 = 0.6$ is obtained.

On the other hand, for the intervention analyses the dataset for each scenario has a sample size of 25. Thus, considering the limited number of samples, for intervention scenarios the validation of the predictive model is carried out by comparing actual and predicted values over the entire dataset, without splitting into train and test. Table 6 shows the linear equations (Eq. 8–14) determined through MLR methodology for each predictive model, along with the selected regression accuracy indices (previously described in Table 2).

The results of the regression analyses over the "test" set, in terms of predicted vs. observed heating energy demand values comparison and the residual analyses for the as-built configuration, are shown in Fig. 12. In the latter, the probability density function of residuals' distribution, assumed as Gaussian, is superimposed.

Moreover, the results of MRL analyses for each energy refurbishment scenario, in terms of energy consumption savings and costs of intervention are shown in Fig. 13 and Fig. 14, respectively.

Considering school buildings that fall within the application range defined in Table 3, the proposed MLR models (Table 6; Eqs. (8)–(14)) allow one to preliminary evaluate both the heating annual energy consumptions of the analysed building and the costs and benefits that can be achieved by implementing the intervention scenarios presented in Section 3. Although these predictive models are affected by uncertainties, it is worth noting that these are obtained from real case-study school buildings and using refined 3-D models calibrated and validated on the real energy consumption data, following a rigorous methodology of assessment.

It is worth highlighting that these models are validated, and thus considered effective, when applied to buildings within the database ranges defined in Table 3. For buildings outside this range, the proposed equations listed in Table 6 could be misleading. Furthermore, any error between the actual energy consumption and the consumption predicted by the models (<5%) was, for simplicity, overlooked in the training of the predictive model. The power of the proposed predictive models lies in the simplicity of their application, as they are a function of a few variables that can be easily determined through a preliminary desk and on-site study. By fixing some discrete values for the parameters related to the location (e.g., heating degree day) and the building use (e.g., occupancy density and setpoint) it is possible to provide a three-dimensional (3-D) graphical illustration of the proposed predictive formulations, as shown in Fig. 15; for the sake of brevity, only the MLR model of the heating energy demand for the as-built configuration is reported in Fig. 15.

In the following section, the usefulness of the models for the preliminary design of energy refurbishment of school buildings, as well as for supporting decision-making for large-scale building portfolios is discussed.

6. Framework for preliminary design of energy refurbishment of school buildings

The proposed simplified predictive model can be adopted for the preliminary energy assessment of school buildings at a large scale, as well as to support the decision-making in the energy refurbishment process (i.e., the selection of suitable requalification strategies and the adequate amount of investment based on cost-benefit analysis). Conceptually, in a preliminary design process of energy refurbishment interventions, the methodology illustrated previously in Fig. 2, based on

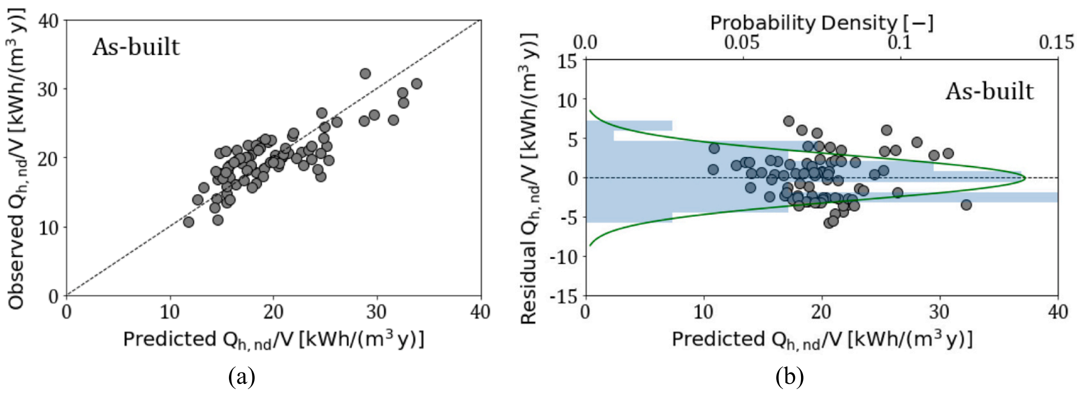


Fig. 12. Results of the MLR predictive model in terms of annual energy consumption: (a) predicted vs. observed values and (b) residual analysis (note: only the results on the test dataset are shown).

refined (but time-consuming) software-based energy analyses of both the as-built and energy-retrofitted building, can be supported by the proposed MLR model, as shown in the framework in Fig. 16.

Each step of the proposed simplified framework is discussed in detail below through an illustrative application. For the sake of simplicity, the application is limited to an archetype school building in order to show the step-by-step procedure to preliminary assess the heating energy demand as well as the cost-benefit analysis of potential energy-refurbishment interventions. Nevertheless, it is worth underling once again that the simplicity of the model allows one to perform preliminary large-scale analyses, as conceptually shown in Fig. 16.

6.1. Step 1a: preliminary data collection

The simplified framework can (and should) be implemented starting from a preliminary data collection process, i.e., using the building information obtained from a desktop study only and before the in-situ surveys. In the preliminary energy assessment phase, geometrical information and global dimensions of the building can be easily estimated from satellite images, photographic reports or available documentation. Moreover, information about the building occupancy, setpoint and time of service can be collected by interviewing the school principals through either phone calls or ad-hoc forms that can be sent by email. On the other hand, the identification of the building envelope stratigraphy (both vertical and horizontal) as well as of the thermal properties of the glazed surface may require specific in-situ surveys/testing, unless advanced technical documentation is available for the case-study structure. However, in the case of limited data collection scenarios, the missing building information can be preliminarily assumed based on the construction period (often available on the web page in the case of school buildings), in line with the building characteristics and the construction practice of that period (e.g., following the TABULA - Typology Approach for Building stock Energy Assessment - research project methodology, [57]). To better understand this concept, an illustrative application is herein presented.

The selected archetype case-study building is a pre-1970s school located in San Marco in Lamis (province of Foggia, south Italy; Zone "D", HDD = 1981), with global dimension as shown in Fig. 17a.

Based on this information (i.e., the global dimension and the construction period), potentially available from a desktop study, the relevant building data for energy performance evaluation can be obtained/assumed, i.e., volume $V = 9000m^3$, shape factor $S/V = 0.34$. The glazed surface is assumed equal to $Svt = 312m^2$ (78 windows with dimensions equal to 2x2m). Concerning the thermal properties of the building envelope, the selected typologies for the vertical and horizontal opaque envelope, as well as of the glazed surfaces are shown in Fig. 17b, together with their thermal transmittance values. These envelopes are assumed according to the building typology classification provided by the TABULA research project [57]. Moreover, the most observed window typology is chosen for this illustrative application, i.e., double-pane windows with aluminium frames. Finally, assumptions are needed for the building occupancy index and the setpoint; in a preliminary assessment, the occupancy can be assumed equal to $0.45\,people/m^2$ (standard values for school buildings in Italy), while the latter (i.e., the setpoint) can be assumed equal to 20 °C (typically adopted value).

6.2. Step 1b: refined data collection

In addition to the data obtained through the initial desktop study, more refined information can be collected through in-situ surveys. Nevertheless, this task could be informed by the preliminary investigation performed using the proposed MLR model (*Step 2*, discussed in detail in the next paragraph), suggesting further localized screening tests and/or specific in situ inspections. The results of the predictive model can be easily updated if more refined data are collected (double-ended arrow in Fig. 16), thus providing an adaptive and updatable tool for the energy assessment of buildings.

6.3. Step 2: simplified energy analyses

The proposed MLR model can be used to perform a preliminary assessment of the energy performance of the investigated building portfolio. This analysis can be performed using either the analytical formulations provided by the regression model or the same results in the form of design/assessment charts. Examples of possible energy performance assessment charts are shown in Fig. 18 and applied to the archetype case-study building for illustrative purposes.

The simplified MLR model allows one to preliminary assess the heating energy demand of the building in its as-built configuration (Fig. 18a), as well as the heating energy demand savings by implementing the investigated energy refurbishment interventions (Fig. 18b-d). The results in their absolute values (i.e., multiplied by the volume) are listed in Table 7 for the as-built configuration and each considered energy refurbishment scenario. Moreover, the proposed MLR regression model can provide also a preliminary evaluation of the expected cost of each intervention scenario; these values are also listed in Table 7.

6.4. Step 3: cost-benefit analyses

The results obtained through the simplified MLR model (listed in Table 7) can be used to perform a cost-benefit evaluation of the considered energy refurbishment scenarios. It is worth underlying that this task does not require any numerical (software-based) simulation since it can be carried out through analytical formulation. In that direction, the Net Present Value (NPV) of the investment over the years can be evaluated through Eq. (15).

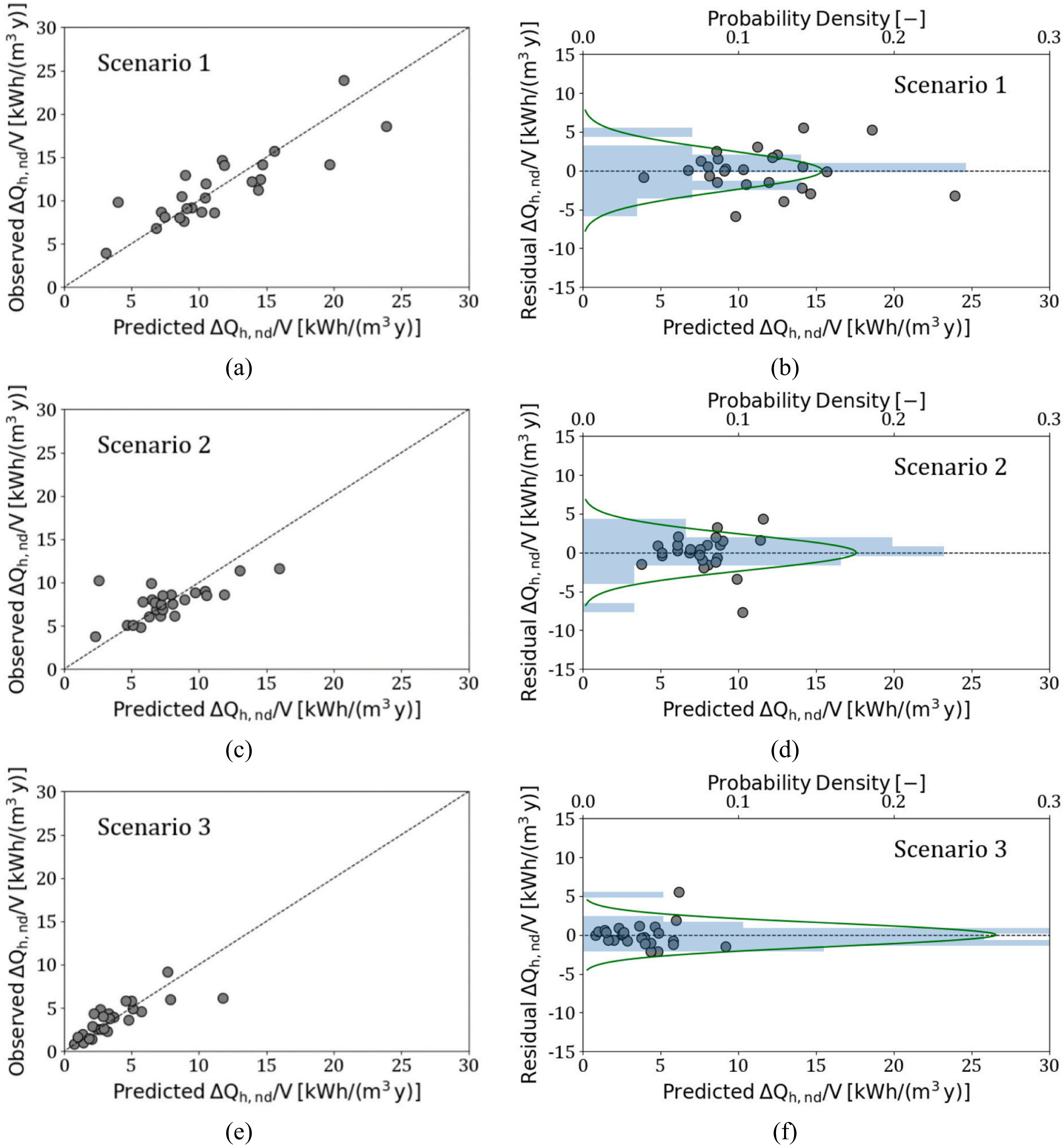


Fig. 13. Results of the predictive MLR predictive model in terms of annual energy consumption savings: predicted vs. observed values and residual analysis for (a, b) Scenario 1, (c, d) Scenario 2, and (e, f) Scenario 3.

$$NPV = CI + S\frac{1}{r-g}\left[1-\left(\frac{1+g}{1+r}\right)^N\right] \tag{15}$$

In Eq. (15) CI is the investment cost, which may include possible financial incentives, and S is the energy annual saving; r and g are the leading interest rate and the real interest rate of energy respectively; finally, N is the period of the investment.

In order to evaluate the NPV of the investment over time, the heating energy demand needs to be converted into natural gas consumption. Thus, the primary heating energy demand Q_{ph} can be evaluated assuming an efficiency value of the heating system and assessing the equivalent natural gas consumption. Information about the heating systems may be collected through either a desktop study, interviewing the school principals and/or in-situ inspections. In this application, for illustrative purposes, an efficiency value equal to 0.95 is assumed. The cost-benefit analysis is carried out considering a leading interest rate of $r = 2\%$ and a real interest rate of energy $g = 1.47\%$. Moreover, the actual (i.e., 2022) cost of natural gas in Italy is considered, i.e., 0.976 €/Sm^3. Clearly, different choices can be made based on the investigation and the requirements of the stakeholders. Payback times are thus defined as the period corresponding to $NPV = 0$; for the case-study archetype building, the cost-benefit analysis is performed considering either the absence or presence of financial incentives, fixed equal to 65% of the cost of the intervention according to the Italian regulation (i.e., the so-called "Conto Termico 2.0", in Italian). The results of the cost-benefit analysis are shown in Fig. 19 and listed in Table 8.

As expected, the financial incentives strongly affect the results of the cost-benefit analysis, leading to break-even points significantly lower for each scenario if compared to the ones without financial incentives. However, it is worth remembering that this is only a preliminary evaluation, aiming to support the best choice of refurbishment intervention and giving an idea of the related investment. In that direction, for the

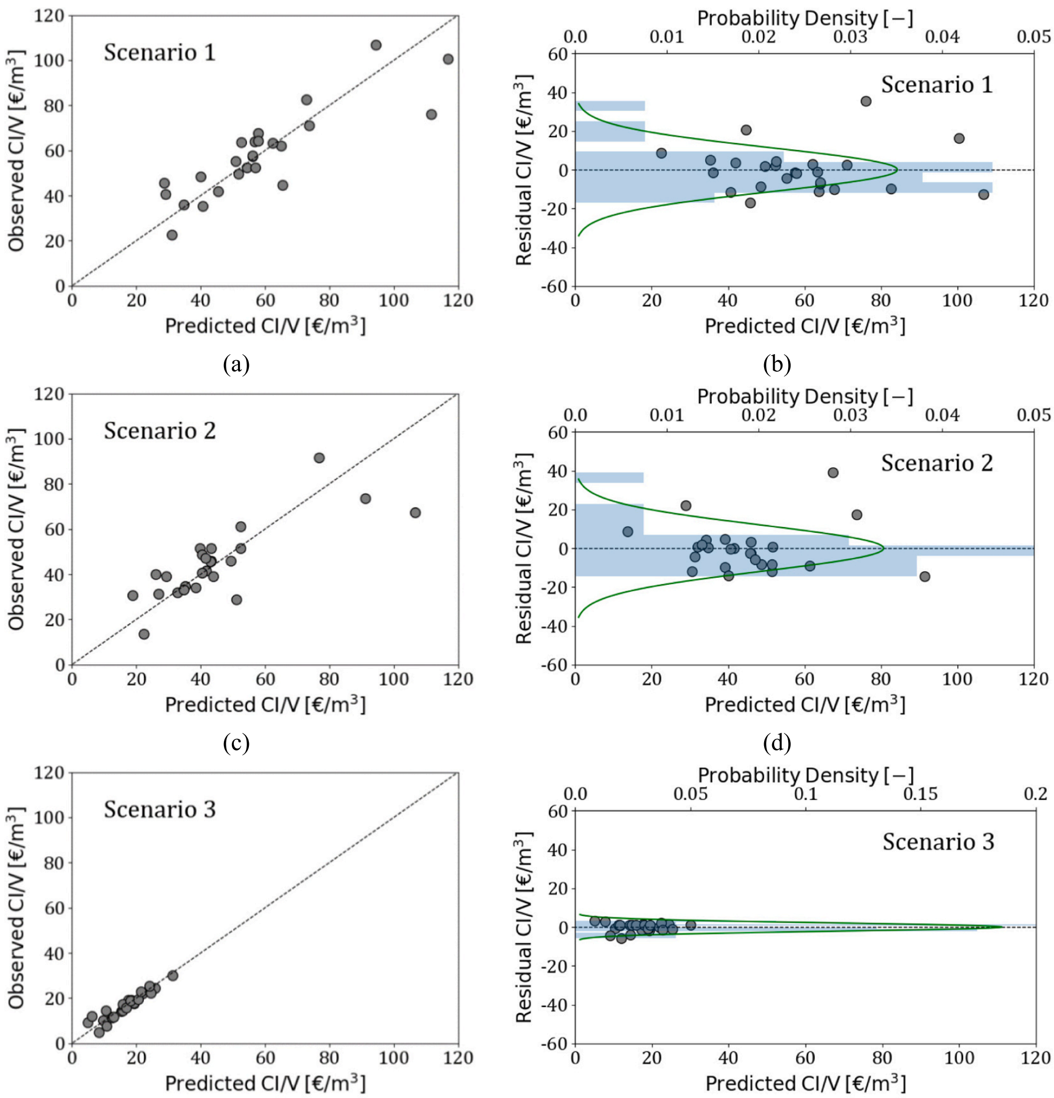


Fig. 14. Results of the predictive MLR predictive model in terms of cost of intervention: predicted vs. observed values and residual analysis for (a, b) Scenario 1, (c, d) Scenario 2, and (e, f) Scenario 3.

case-study building, no significative differences are observed in terms of break-even points for each scenario. On the other hand, among the others, Scenario 1 can provide a significative return on the investment in the 50 years of serviceability life of the building. Nevertheless, the choice of the best energy refurbishment scenario should be made accounting for different variables, such as the budget and the needs of the owners/stakeholders.

6.5. Step 4: prioritization plan

In the case of large-scale analyses, typically involving a large building portfolio, the results of the cost-benefit analyses can be used to select the most suitable energy refurbishment interventions and define a prioritization plan. Towards this goal, the proposed MLR model can provide fast and updatable cost-benefit evaluations for each involved building, even in the case of a limited data collection scenario. In fact, although these results are affected by uncertainties related to the simplicity of the analyses, they can support the decision-making process regarding the feasibility of the refurbishment intervention plan even from the early stages of the investigation. In other words, through the proposed simplified model, the prioritization plan can be considered a result of the preliminary design phase and not only the final output of the refined (but time-consuming) energy assessment and refurbishment of the building portfolio. It should also be emphasized that the results obtained from this fast and simplified procedure (i.e. as-built consumption, cost of the intervention, payback times) are extremely flexible with respect to the policy that the stakeholders intend to implement (e.g. refurbishing the maximum number of school buildings given a budget-cap or maximize long-term savings over a defined period). However, although the economic constraints are typically the most relevant parameter (and often obstacle) to the implementation of this task, it is worth mentioning that other variables can strongly affect the decision-making process, e.g., the invasiveness of the interventions and the business interruption. Thus, it is also suggested that this task should be addressed in a more holistic vision by implementing multi-criteria decision-making analyses.

6.6. Step 5: detailed design of energy refurbishment intervention

The results of the simplified MLR model can finally support and inform the detailed energy performance assessment and design of the refurbishment interventions for the analysed building portfolio. On one hand, the preliminary prioritization plan can indicate the most relevant school buildings for the aims of the investigation, suggesting the order to

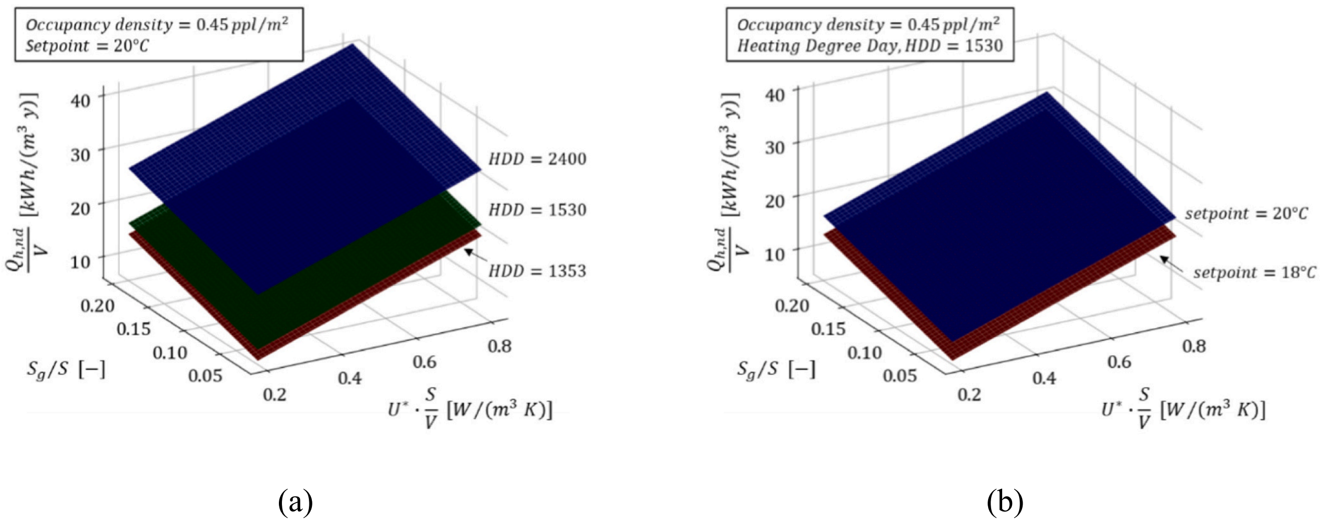


Fig. 15. 3D illustration of the predictive model considering fixed values of occupancy density and discrete values of either (a) the setpoint and (b)the heating degree day.

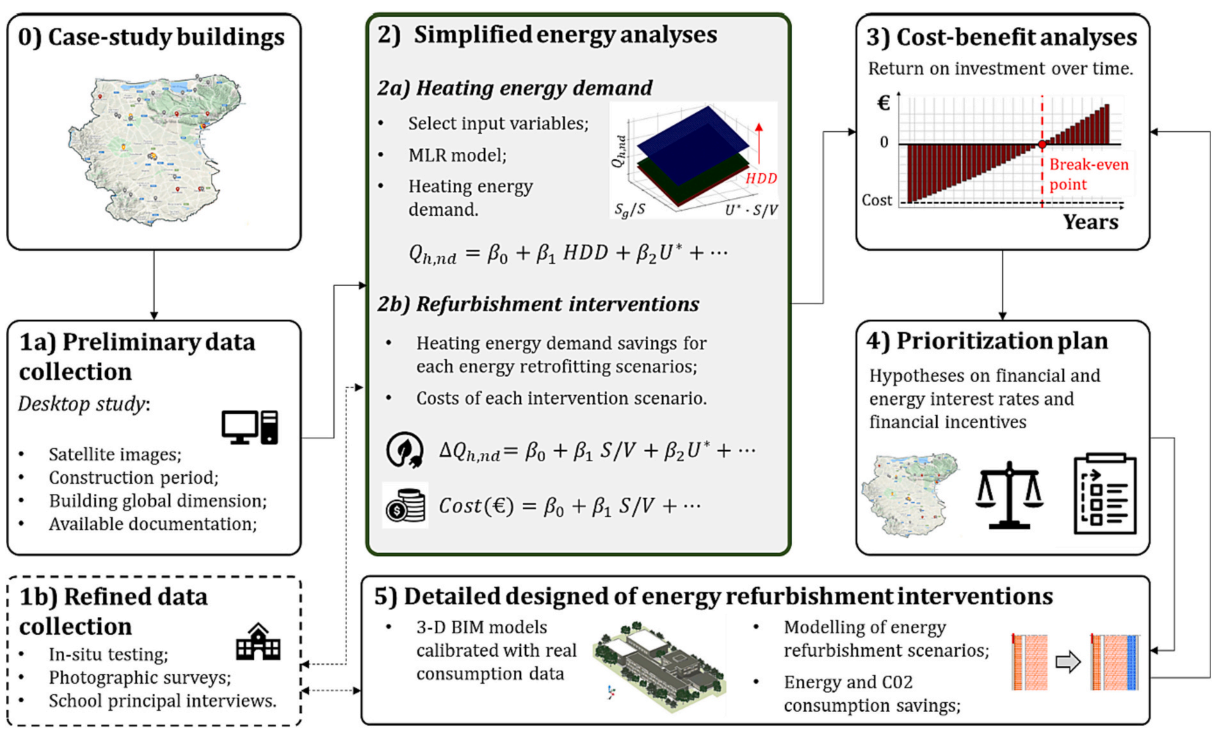


Fig. 16. Framework for preliminary design of energy refurbishment of school buildings based on the proposed simplified predictive model.

implement the refined investigations. On the other hand, the results of the simplified model in terms of heating energy demand and heating energy savings for the as-built and the retrofitted configuration, respectively, can be used as expected values to avoid possible errors in the more refined energy analyses, supporting the definition and implementation of the 3D advanced numerical models. It is worth highlighting once again that the proposed simplified model should not be used to replace the refined energy assessment evaluation process, but only as a supporting tool in the whole framework, as shown Fig. 16. Finally, even if this is the last step of the framework, the output of the refined analyses can be once again used to perform a cost-benefit analysis (*Step 3*) and define a final prioritization plan of implementation of the intervention scenarios (*Step 4*), as well as further train the predictive model.

7. Conclusion

In this research work, a framework is proposed for the preliminary design of energy refurbishment of school buildings, using simplified, regression-based predictive models. These models are applied for the initial assessment of the heating energy demand of school buildings and to identify suitable energy refurbishment intervention scenarios. The Multiple Linear Regression (MLR) method was used to develop the predictive model, drawing upon an extensive database comprised of results of detailed three-dimensional software-based energy simulations. The simulations pertain to school buildings in southern Italy, in both

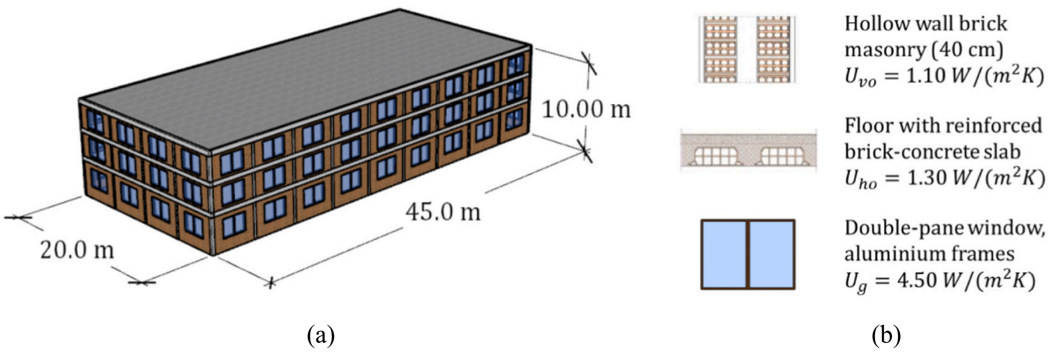


Fig. 17. (a) Global dimension of the analysed school building and (b) selected thermal properties of the building envelope.

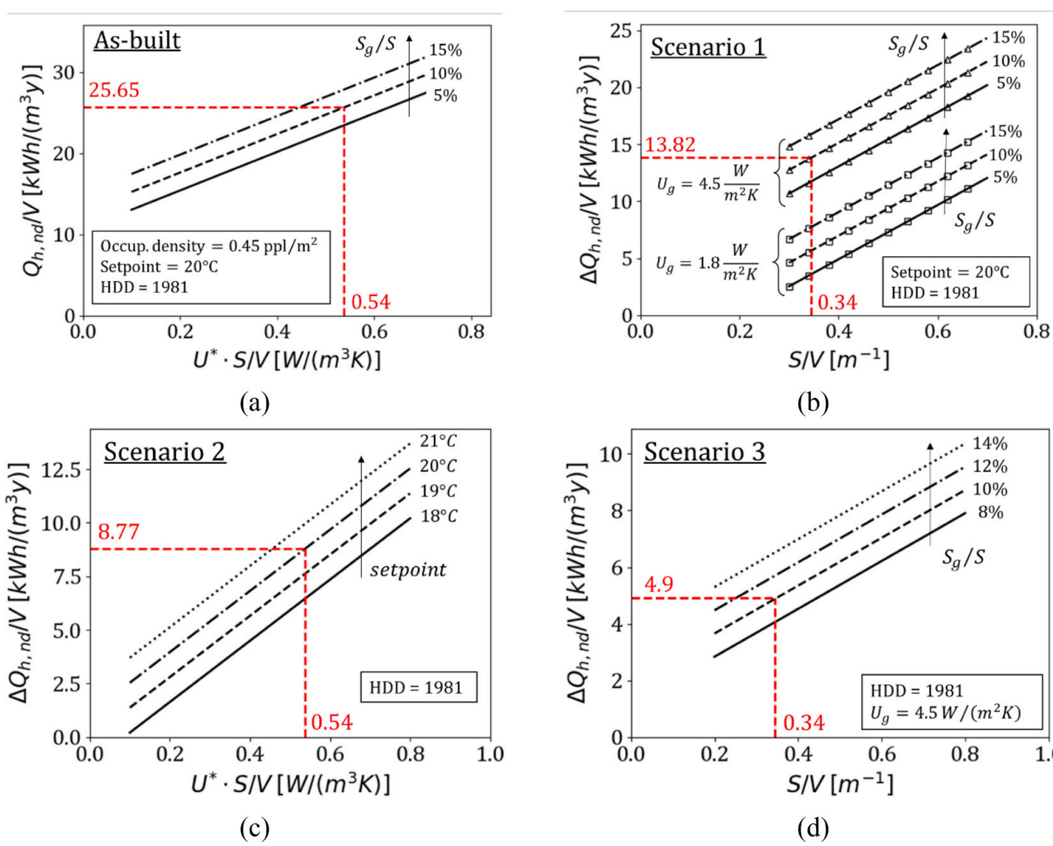


Fig. 18. Examples of possible charts for the energy performance assessment of school buildings and their illustrative application: (a) normalized heating energy demand of the as-built case-study school and expected heating energy saving through (b) Scenario 1, (c) Scenario 2, and (d) Scenario 3 interventions. Red lines represent the values obtained for the case-study building as an illustrative application. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7
Results of the MLR model in terms of heating energy demand for the as-built structure and the energy-retrofitted configurations and cost of the intervention scenarios.

Energy refurbishment scenarios	Heating Energy Demand Q_h [kWh/y]				Cost of interventions
	Ante operam	Post operam	Saving	% Diff.	
Scenario 1	230,815	106,397	124,419	−54%	380,953 €
Scenario 2	230,815	151,842	78,974	−34%	256,778 €
Scenario 3	230,815	186,689	44,127	−19%	141,135 €

their as-built and retrofitted configurations, carried out under the UEFA/ELENA research project.

The principal findings and significant conclusions are resumed and discussed below:

- Data collection was performed through both a preliminary desktop study and refined ad-hoc in-situ investigations. This allowed for the collection of essential information about the characteristics of school buildings in the province of Foggia, Southern Italy. Specifically, of the 81 analysed buildings, approximately 80% of these were constructed before 1991 (i.e., before the introduction of [46] and [44]). The majority of these feature RC infilled frame structures, accounting for nearly 83%. Concerning the building envelope, the most common typology includes cavity walls without insulation and cast-in-place

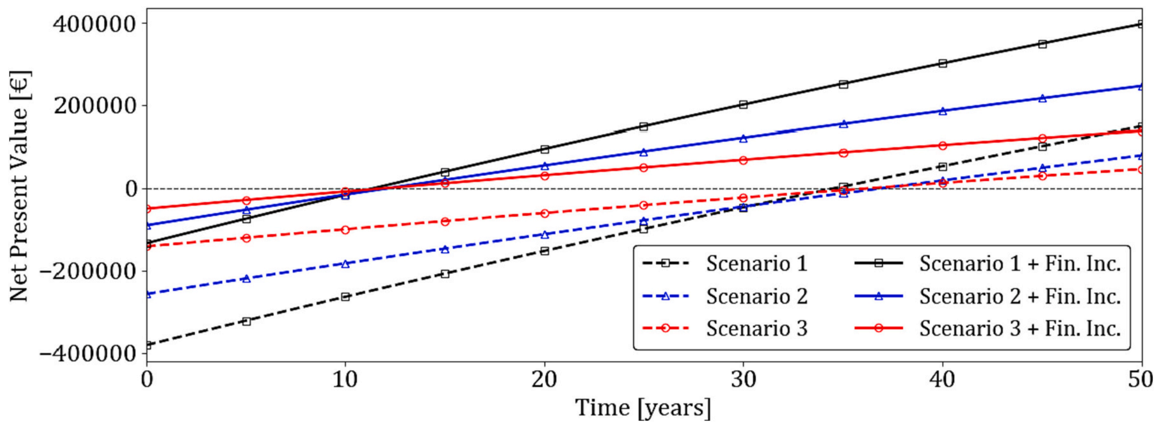


Fig. 19. Net Present Value (NPV) of the investment over time for each considered energy refurbishment scenario.

Table 8
Results of the cost-benefit analysis.

Energy refurbishment scenarios	Natural gas annual savings [Sm3]	Investment cost (including Fin. Inc.)	Break-even point [years]
Scenario 1	12,251.4	380,953 €	35
Scenario 2	7776.4	256,778 €	37
Scenario 3	4345.1	141,135 €	37
Scenario 1 + Fin. Inc.	12,251.4	133,334 €	12
Scenario 2 + Fin. Inc.	7776.4	89,872 €	13
Scenario 3 + Fin. Inc.	4345.1	49,397 €	12

Note: Fin. Inc. = financial incentives.

RC floor systems for the vertical and horizontal building envelopes, respectively. Double-pane windows with aluminium frames represent the most frequent typology of glazed components.

- Energy analyses conducted using detailed BIM models enabled the evaluation of the energy classes of the analysed school buildings. Results revealed that the majority of the case studies (almost 70%) are fall within energy class between "C" and "D", while 15% rank at energy class "E" or below. Although these results were obtained through an "asset rating" approach, they are deemed representative of the poor energy performance of the analysed building portfolio.
- A sensitivity analysis was conducted, centred around the evaluation of the linear correlation coefficient R, to select the most significant parameters for training the predictive models for both energy consumption and the costs/benefits of alternative refurbishment interventions. Regarding the consumption of the as-built configuration, the most relevant variable among those analysed is the product of the average U-value and the shape factor (i.e., $U^* \bullet S/V$), with $R = 0.56$. This is followed by the building's geometric characteristics (e.g., vertical and horizontal opaque surface, glazed surface), the heating day degrees of the site, and the building usage (i.e., occupancy rate and setpoint). It was also observed that the walls' transmittance has a weak correlation with energy consumption ($R = 0.03$), and this correlation is lower than those related to glazed components ($R = 0.21$) and floors ($R = 0.43$). Similar conclusions can be also extended to the energy refurbishment intervention scenarios.
- A statistical analysis of the primary error indices, namely, the Mean Absolute Percentage Error (MAPE), the coefficient of determination, and the standard deviation (σ), was conducted to evaluate the reliability of the proposed simplified relationships derived from the MLR method. Overall, a high level of accuracy was observed for the proposed simplified predictive model, with a coefficient of determination typically ranking between 0.65 and 0.88 for both the energy consumption and the costs and benefits of the alternative refurbishment intervention scenarios. In addition, a k-fold cross-validation (using k = 5) was also performed on the train set used for the energy consumption, yielding $R^2 = 0.6$.
- The potential application of the proposed predictive model within a framework for the preliminary design of energy refurbishment interventions for schools in Italy was discussed through an illustrative application. It was concluded that the proposed methodology serves as an effective, adaptive, and updatable tool. This aids studies involving large building portfolios towards defining a prioritization plan for intervention based on cost-benefit analyses.

It is worth mentioning that, at this stage, the procedure is tailored to school buildings that share similar characteristics with those in the analysed database. The applicability of the calibrated models to different building types is yet to be explored; indeed, for residential buildings, significantly different energy consumptions are expected due to the different construction characteristics and use of the building. Consequently, the results of the predictive model cannot be easily generalized. It is also important to highlight that the models can be refined for the buildings under study if more data become available. Furthermore, as the refurbishment planning methodology remains applicable, new predictive models for different building typologies can be developed using the same approach if new databases become available. The authors anticipate that this study will lay the foundation for further research on energy efficiency and renovation planning for school buildings. Acknowledging the effectiveness of Multiple Linear Regression in approximating energy consumption, the authors are aware of the potential of advanced AI methodologies. In fact, future developments will involve the application of AI to the unique collected dataset, with the objective of formulating an optimal strategy in the intervention planning through algorithmic decision making.

CRediT authorship contribution statement

Livio Pedone: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Filippo Molaioni:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrea Vallati:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Stefano Pampanin:** Writing – review & editing, Supervision, Project administration, Conceptualization.

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.

Data availability

Data will be made available on request.

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Appendix A. Integrated seismic and energy refurbishment interventions

The UEFA/ELENA research project has also placed significant emphasis on the technical solutions for integrated seismic and energy retrofitting of existing buildings. Although this paper specifically discusses the development of simplified methodologies for the energy consumption evaluation and the selection of suitable refurbishment interventions for schools in Italy, this appendix offers some insights on the seismic retrofit strategies/techniques and the implementation of integrated (i.e., seismic and energy) interventions.

Concerning the structural/seismic retrofitting of existing structures, two main retrofitting approaches are typically identified, based on either “local interventions” or “global interventions”. Considering RC frames structures (widely adopted in European building practice), local interventions aim to improve the seismic performance of the structure through local retrofit of structural members such as columns, beams, and joint panels, in order to establish a correct hierarchy of strength at the subassembly level (i.e., targeting the development of a plastic hinge in the beam; [14]) and avoid any possible brittle failures. Alternative local retrofit techniques may involve the use of fiber-reinforced polymer (FRP) (e.g., [58,59]), diagonal haunch (e.g., [60]) or the implementation of a “selective weakening” (e.g., [61]). In contrast, global interventions are typically adopted for drift-control strategy by increasing the stiffness/strength of the existing structure. Typical examples are the introduction of new lateral-load resisting systems, such as RC shear walls (e.g., [62]), steel braces (e.g., [63]), or exoskeleton systems (e.g., [64,65,66]).

In view of an integrated refurbishment intervention, particular attention should be given to the facade's “non-structural” components. Considering RC infilled frame structures, although masonry infill panels are typically designed to provide only thermal and acoustic insulation, they may have a strong interaction with the surrounding frame during seismic shaking, potentially leading to failures even for low-intensity earthquakes (e.g., [67]). Clearly, earthquake-induced damage to masonry infills can directly lead to loss of performance of energy retrofit solutions such as external thermal insulation composite systems. Therefore, suitable and practical retrofit strategies and techniques must also be implemented to reduce the negative effects of infill-frame seismic interaction. These solutions are typically based on either decoupling (e.g., [68,69,70]) or strengthening (e.g., [7,71]) approaches. Hybrid structural-plus-energy retrofitting solutions for non-structural components have also been proposed (e.g., [7]).

Conceptually, by coupling these seismic retrofitting techniques (for both structural and non-structural components) with the most widely implemented energy-efficiency refurbishment interventions (e.g., those listed in previous Fig. 10), alternative combined retrofit solutions can be defined (e.g., [10,12]), as shown conceptually in Fig. A1. Nevertheless, recent research have highlighted the attractiveness of exoskeleton solutions from an LCT perspective (e.g. standardization, demountability, reparability, and reusability; [11,66]). Notable advantages of this technique include the reduced invasiveness (i.e., the intervention can be entirely carried out from outside, thus minimizing the users' disruption) and the possibility to also implement a multi-performance “double-skin”, supported by the exoskeleton itself, for an integrated seismic-energetic-architectural upgrading. Moreover, advanced low-damage technologies, either in concrete (e.g., PREcast Seismic Structural System, PRESSS; [72]), steel (e.g., [73]) or eco-friendly materials like engineered timber (e.g., Prestressed Laminated Timber, Pres-Lam; [74]), as well as a combination of those (e.g., frames with concrete/steel columns and timber beams) can be employed for the exoskeletons, allowing for a multi-performance rehabilitation [65,13]. Additionally, low-damage technologies can also be applied to non-structural components (e.g., [75,76]) to implement an integrated high-performance retrofitting intervention (Fig. A2).

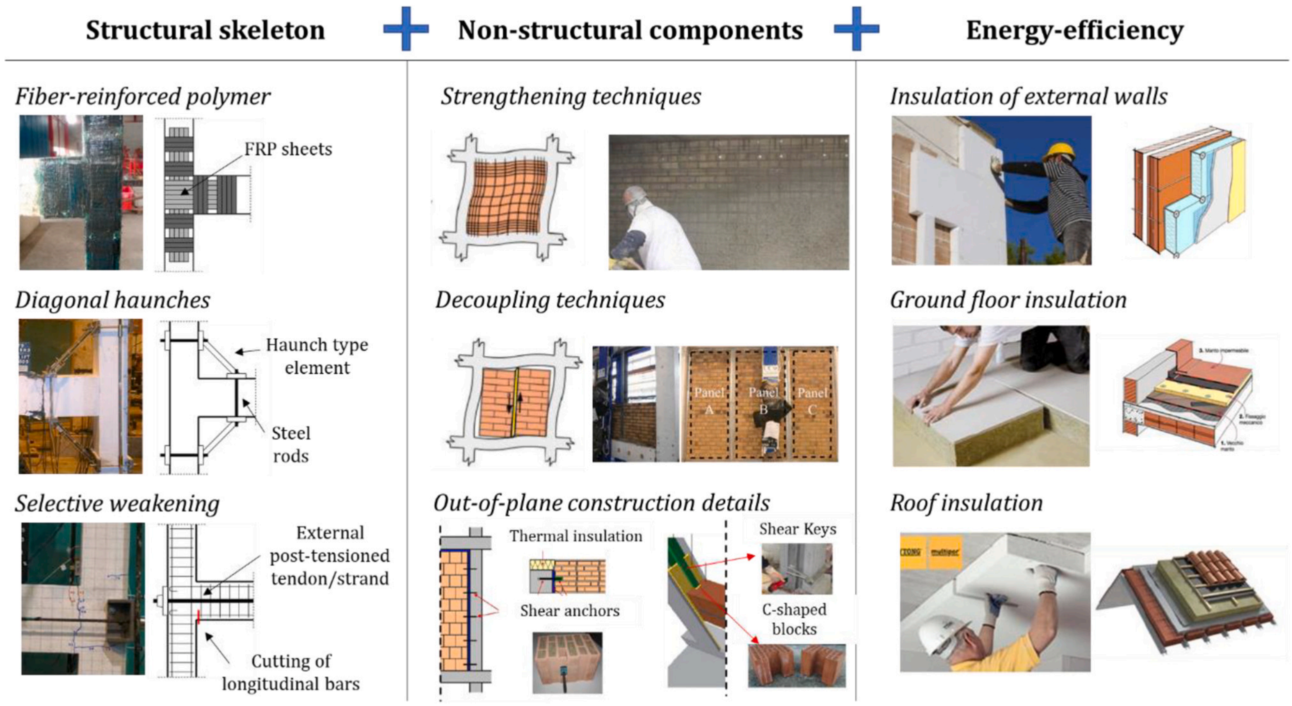

Fig. A1. Examples of possible combined seismic and energy retrofitting interventions (structural skeleton: adapted from [61,60]; non-structural components: adapted from [7,10,68,69,70]).

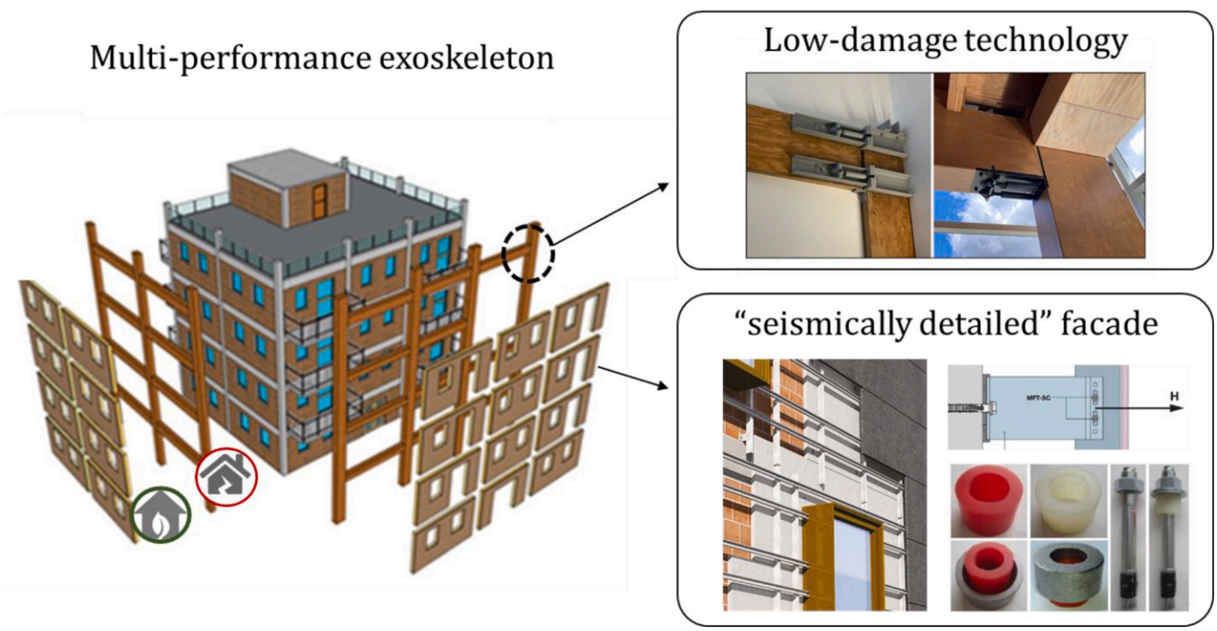

Fig. A2. Concept of multi-performance exoskeleton for integrated seismic and energy retrofitting (exoskeleton: adapted from [13]; EQ-Rod: adapted from [77]).

Finally, providing adequate seismic details is crucial to improve the overall performance of the building envelope. Therefore, best building practices recommend designing any energy-efficiency refurbishment intervention for facade elements to offer an appropriate displacement capacity. In this context, Pedone and Pampanin [78] proposed a methodology to assess the seismic displacement incompatibility between infill walls and the surrounding frames based on the concept of shape functions. The use of the proposed method to design construction details of both seismic and energy retrofit solutions has also been discussed and a possible operative flowchart for an integrated requalification of RC buildings has been introduced. Research effort has also been carried out to develop advanced high-performance post-installed fasteners to anchor non-structural components to concrete structures, e.g. the EQ-Rod [77]. Recent experimental investigations have shown that these solutions can reduce the acceleration to non-structural components, as well as the force to the anchor itself during seismic shaking [79]. Therefore, these technologies could also be employed for energy and architectural intervention, such as ventilated facades, to avoid earthquake-induced damage during seismic events (Fig. A2).

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