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DATA DRIVEN FRAMEWORK TO SELECT BEST RETROFITTING STRATEGIES

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Abstract

EU building sector consists mainly of outdated and inefficient properties with high energy consumption. Hence, building retrofit is being emphasized as a feasible alternative for addressing existing challenges, taking lots of time, effort, resources, and expertise in its traditional form. Conventional case-based retrofit scenarios fail to deliver quick and objective solutions for massive datasets.

This research benefits from Artificial Intelligence, particularly clustering techniques, to enhance strategic decision-making for building retrofit and solve the shortcomings of conventional methods. It connects the dispersed Italian databases (CENED and TABULA) and determines desired building technology and retrofit strategy to obtain an optimum energy label.

Keywords: Building Retrofit, Artificial Intelligence, Clustering, Energy Saving, Decision Support Systems

Introduction

The construction sector accounts for nearly 40% and 36% of total energy consumption and CO_2 emissions in the EU, which makes Europe a consolidated continent in need of massive refurbishments (EU-Energy, 2018). Residential buildings, consisting of 85% of the EU building stock floor area, are on average extremely old and inefficient. In most EU countries, about 50% percent of the residential properties are constructed before the first thermal regulations, which results in increased consumption of fossil fuels, air pollution, and increased energy demand (Aldhshan et al., 2021). As a result, in order for the EU to meet its decarbonization targets by 2050 and to realize the EU green deal to double current rates of renovation of public and private buildings (European Commission, 2019), building retrofit is being emphasized as a viable approach to address building sector issues by the EU (Seghezzi and Masera, 2017). Hence, tools to assist local governments in promoting cost-effective retrofit measures for existing structures are critical in the ongoing transition to low-carbon cities (Delmastro, Mutani, and Corgnati, 2016).

The situation is even more critical in Italy. 49 percent of dwellings are over 50 years old, compared to 35 percent in Europe, which results in poor energy performance, given the average age of the residential building (Di Pilla et al., 2016). Moreover, systematic and data-driven decision-making tools for solving these challenges are lacking.

Building Retrofit is one of the most important strategies for accomplishing built-environment sustainability and resilience goals. In general, there are various types of retrofits, e.g. Seismic and Energy retrofits. Energy retrofit is the process of making operational or physical changes to a building, its energy-consuming systems, or the behavior of its occupants to reduce energy consumption (Jafari and Valentin, 2018). It is proved to be significantly beneficial in practice; the ZEBRA2020 EU project consortium (ZEBRA2020, 2020) estimated that a building's final heating energy demand can be lowered by 50 to 80 percent with considerable upgrades (range depending on the country and defined by national experts according to the current efficiency of the building stock).

Although imposing additional investment expenses, retrofitting the building envelope and thermal plants can dramatically reduce energy consumption and associated operational costs. (Lohse, Staller, and Riel, 2016). Aside from energy efficiency, additional factors driving building rehabilitation and retrofitting include fire safety, seismic concerns, indoor comfort, and outside aesthetics. Retrofitting existing buildings, in addition to reducing building energy consumption and carbon footprints, provides a significant opportunity to increase occupant comfort and well-being while also reducing world energy consumption and greenhouse gas emissions (Xu, Loftness, and Severnini, 2021).

Although their numerous advantages, retrofit projects are frequently marked by significant degrees of uncertainty and risk due to the complexity of the tasks and lack of information (Juan, 2009). Moreover, the decision-making process contains various competing interests, such as social and heritage-related tasks, financial investment limits, and environmental concerns (Nair, Gustavsson, and Mahapatra, 2010). Therefore, decision-support tools are highly beneficial to help designers, investors, and policymakers choose the most profitable and efficient retrofit solution.

This study intends to design a data-driven decision support system using Artificial Intelligence and open data, clustering residential structures in the Lombardy region of Italy based on their energy metrics and construction period. This model identifies a given building's construction technology and materials based on its energy parameters and records in national databases and accordingly determines the most optimum retrofit strategy to obtain a particular more energy-efficient label. Based on a massive amount of registered and approved data, this model can serve as a reference point for energy retrofit strategic decision making and planning on a building or urban scale.

Background

Conventional retrofit decision support tools can be classified in terms of the type of building (residential or service; refurbished or new) and their principal purposes (economic and environmental) (Ferreira, Pinheiro, and Brito, 2013). Moreover, they can be grouped in one of the a) general methods; b) improve energy and/or CO_2 emission performance; c) purely economic analysis; d) Life Cycle Analysis methods; e) sustainable assessment methods groups (Kolokotsa, et al., 2009). The knowledge gap regarding these methods is that they are mostly implemented in single case studies. Hence, they are engaged with the intrinsic complexities and technical aspects of the problem, not applicable to huge databases.

Artificial Intelligence

Data-driven tools applied for seismic and energy retrofit or renovation research are BIM (Scherer and Katranuschkov, 2018) and Multi-Criteria Decision-Making (Asadi, Salman, and Li, 2019). Decision Support Systems for choosing the best retrofit strategies have been proposed using an MCDM-BIM integrated framework (Caterino et al., 2021) and for purposes like emissions reduction (Håkansson et al., 2013). Moreover, BIM has provided an affordable computation platform for Virtual Retrofit Model (VRM) (Woo and Menassa, 2014) for energy simulation, agent-based modeling, and multi-criteria decision support systems that support streamlined decision-making for building retrofit projects. Some specific studies in Italy have examined retrofit alternatives using detailed numerical models (Carofilis et al., 2020).

Despite their many benefits, the previously mentioned techniques cannot be implemented in a wide range of projects at once in a quick manner. Artificial Intelligence techniques, which have prompted a massive shift toward digitalization in the construction industry, seem to be the ideal solution to this problem due to their ability to provide accurate results in uncertain, dynamic, and complex environments and when dealing with them with massive data (Yaseen et al., 2020). AI techniques benefit from previous data by learning the relationship between input variables and their effect on the outcome to generalize the rule to new projects for automatic prediction. AI's application in built environment management is increasing due to asset-related digital information (Ling et al., 2018). Its application in the building retrofit process, on the other hand, is a relatively new and unadvanced direction.

Fig 1 presents the co-occurrence keyword network of the systematic search conducted in Scopus on the topic of building retrofit and AI, which is analyzed and depicted using the Bibliometrix package in R and the Biblioshiny library.

CENED Database

Various countries have prepared building stock databases based on Census data or survey data applying different methodologies (Ali et al. 2020) and describing properties with relevant or irrelevant features (Famuyibo, Duffy, and Strachan 2012). Hence, choosing proper databases and feature selection for reducing model input dimensions, computational loads, and enhancing the model performance are of high importance (Fan et al. 2019).

This paper aims to use AI, particularly the clustering techniques, to exploit the massive data in an Italian public databases for future building retrofit decision-making. When evaluating and planning for national energy savings and energy retrofitting, building databases are valuable assets. However, databases often lack information on building attributes essential to assess the viability of specific energy conservation measures. Similar approaches conducted in other countries like Sweden (Von Platten et al., 2020) and Ireland (Ali et al. 2020) are proved to be beneficial, and serve as a benchmark for this research's application in Italian building stock.

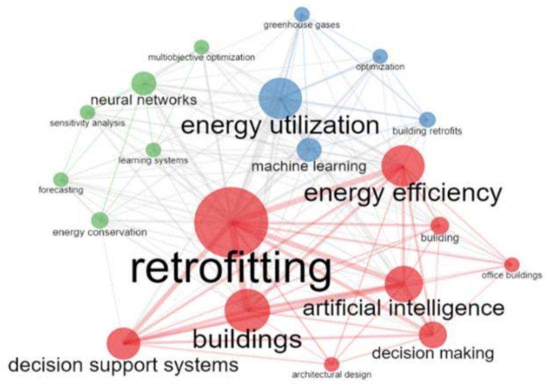


Fig 1. Co-occurrence network of keywords in the building retrofit cost literature

As a result of a change in the Italian Laws on energy efficiency ('D. Lgs. 19 August 2005 n. 192', 2005), several Italian regions, including the Lombardy Region, have adopted a series of regional legislative measures on building energy efficiency. Lombardy Region entrusted a public company, the Centre for Technological Development, Energy and Competitiveness (CESTEC), with the role of Regional Accreditation Body (RAB), a role taken over in 2013 by Finlombarda, which now has among its responsibilities the management of the CENED database (DB) (energy cadastral of buildings in Lombardy Region)(Regione Lombardia, 2019). The open DB encompasses data about building energy performances (i.e., both primary energy and net energy), geometric information (e.g., volume, gross and net surface, etc.), and installed technologies (i.e., mainly the average thermal transmittance of building components and information about thermal plants' global efficiency) (Re Cecconi et al., 2020).

This study implements the clustering technique on the CENED database provided by Lombardy Region. Clustering is an important tool for data mining and pattern recognition. This method aims to group items into classes or clusters where objects in the same cluster are similar enough to infer they are of the same type, while objects in different clusters are different enough to infer they are of different types (Pfitzner, Leibbrandt, and Powers, 2009).
Clustering, not imposing particular weights on variables, enables for a more accurate and unbiased building stock segmentation of the building stock compared to traditional classification procedures producing an unbiased grouping outcome (Tardioli et al. 2020).
This method is generally implied for three main purposes: a) to identify underlying structure, b) to conduct natural classification based on the degree of resemblance, c) to do compression for summarizing data based on cluster prototypes (Jain, 2010).
The steps to implement the clustering technique on the datasets and obtain optimum retrofit strategies are presented in the methodology section.

Methodology

To benefit from open data, and when working with huge portfolios and databases, the clustering technique is used to identify and select properties with similar characteristics. The features based on which the clustering can be selected based on the type of analysis (data-driven or engineering), retrofit purpose (Energy, Seismic, etc.), significance and variance of the features (Stone et al. 2014). However, this study chose the features that were common in both CENED and TABULA databases, for better interoperability and connection of the results, as well as for not over complicating the model. Clustering for status quo analysis is the first step and foundation for future decision-making. Since the number of buildings to be analyzed in the CENED database is huge, it is possible to locate properties contemporaneously constructed with nearly similar materials and technologies. The clusters were computed using the Gaussian mixture partitional model (GMM) in this study. GMM uses a mixture of multivariate normal distributions to model the probability density of a numeric space. Supervised learning of multimedia data and pattern recognition are applications of GMM algorithms (Crouse et al., 2011). Figure 2 presents the general workflow of the research scheme, documents used in each phase, and current and future steps. In this paper we progress till the Retrofit Strategy choice and Retrofit Strategy phases.
First step is the data cleaning. In CENED database there are 1.52 million records registered, each containing an energy label described by 45 parameters. Among these, the most relevant to this research are: a) the energy label, b) the gross and net heated surface, c) the gross and net volume, d) the envelope surface, e) the ratio between opaque and transparent envelope surface, f) the average walls, windows, and roof thermal transmittance, and g) the primary energy for heating (EP_H).
However, since the CENEB data has been collected by many persons, the reliability is low and data cleaning is required. After data cleaning, 956,143 records remained from the initial 1.52 million records in the database. It is worth mentioning that only residential assets in the DB were selected. Once only records referring to residential properties were selected, the data were cleaned by removing records containing obvious errors, like assets with the primary Energy for Heating Index (EP_H) <= 0 kWh/m^{2}y or a heated floor area of less than 20 m^2. Finally, properties built before 1800 and after 2021 have been deleted because either they don't need an energy retrofit (new assets) or they are too peculiar (historical heritage).
Second step is properties grouping. The DB properties have eight different energy labels (EL) for residential properties: A+, A, B, C, D, E, F, G. Moreover, the construction year intervals are: "Before 1930", "1930-1945", "1946-1960", "1961-1976", "1977-1992", "1993-2006" and "After 2006". According to the seven classes of Year of construction (YoC) and the eight energy labels, records in the CENED DB are classified into 56 groups (EL). To eliminate outliers, the mean and standard deviation of various columns of the DB (average thermal transmittance of walls U_{walls}, windows U_{win}, and roofs U_{roof}) were calculated for each pair of YoC and EL. Figure

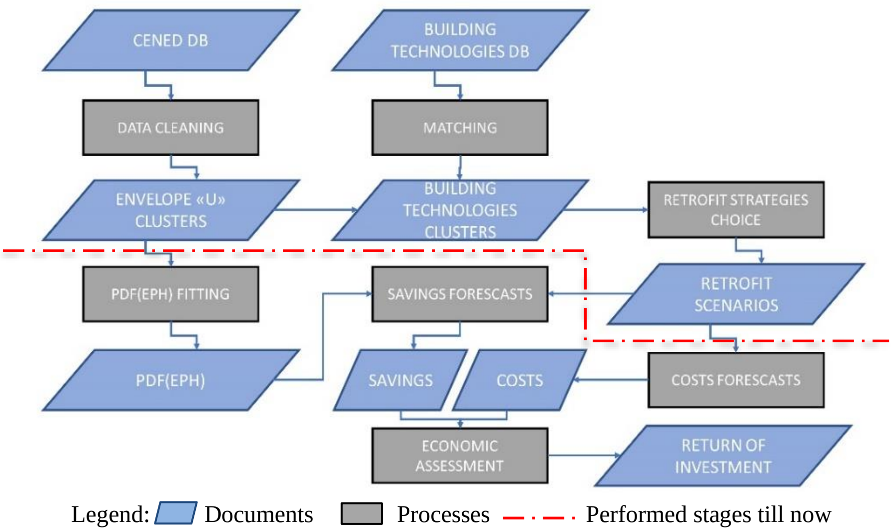
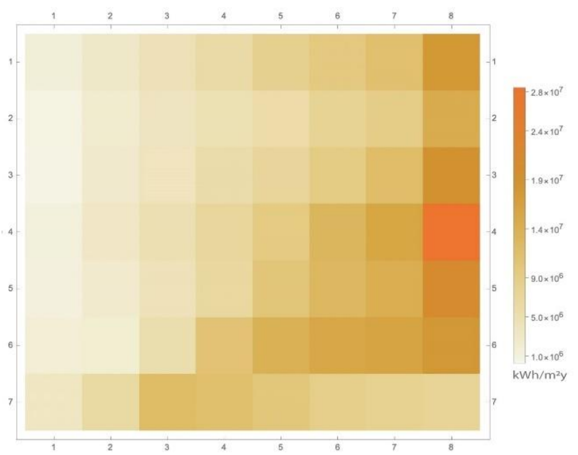


Figure 2: AI-based Building Clustering and Retrofit Decision Making Framework

3 depicts a heatmap of the number of records in each group in the Lombardy Region, as defined by a YoC and an EL. As evident in Figure 3, which represents the heatmap of Total primary energy demand (EP_h in kWh/m^2y) based on YoC and EL, the density of buildings with "G" EL is highest before 1976, just before the first Italian Law on the energy performance of buildings. In 1976, just after the petroleum crisis, the first Law to lower buildings' energy demand was published in Italy. Sequentially, the most recent government legislation was adopted in 1992 and 2006. This figure analysis gives an insight on properties overall status quo and target properties for research application.

Properties constructed simultaneously and in the same period can be either in their original state or significant energy performance. Logically, it could be concluded that those properties with better energy performance have been retrofitted. Therefore, properties that are still in their original state, it is reasonable to assume that an energy retrofit will result in similar energy performance to those built at a similar time period but already retrofitted, which can be identified by better energy label.



Key	1	2	3	4	5	6	7	8
YoC	Before 1930	1930-1945	1946-1960	1961-1976	1977-1992	1993-2006	After 2006	-
EL	A⁺	A	B	C	D	E	F	G

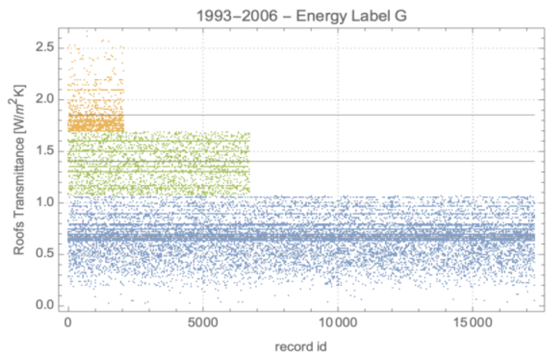
Figure 3: Total EP_h (kWh/m^2y) / of residential properties in the CENED DB according to the year of construction (YoC) and the energy label (EL)

Results

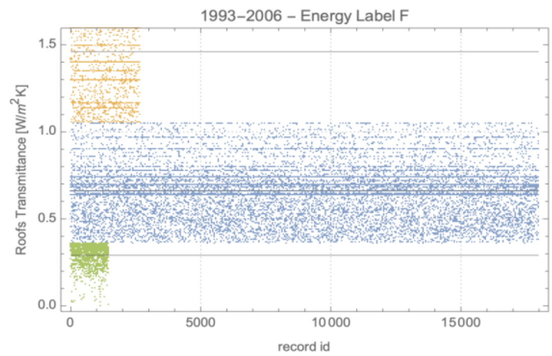
Records on each of the 56 groups identified by YoC and EL were clustered using three CENED DB columns: a) average walls transmittance (U_{wall}); b) average windows transmittance (U_{window}) and c) average roofs transmittance (U_{roof}). Therefore, the elements of a cluster will be residential properties built in the same time period, with the same energy label, i.e., similar energy consumption, and with the components of the building envelope having similar transmittance. It is reasonable to presume that all of a cluster's properties were built using the same building technologies. Figure 4 depicts the Roof clusters of the buildings constructed between 1993-2006 for "G", "F", and "A^{+}" ELs based on their U_{Roof}. The clustering process allows a better understanding of the contents of the DB. For instance, Figure 5 presents the correlation between Wall and Window thermal transmittance in the groups of 8 Els constructed between 1993-2006, where the poor performance of not retrofitted buildings is evident.

Moreover, Figure 6 presents the relationship between property energy performance, as measured by EP_H, and the average thermal transmittances of walls, roofs, and windows in classes with worse energy labels. It is evident that although the lines representing clusters gather with some consistency on the vertical axis for energy performances, they frequently cross on the other axes. This means that the DB records with the highest average envelope transmittance do not always have the worst energy performance and vice versa. Therefore, the clustering technique significantly helped in the objective analysis of the DB.

a)



b)



c)

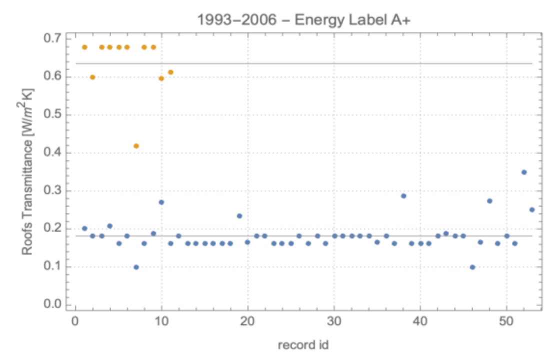


Figure 4: Clustering of the dataset based on the envelope components (Roof) Thermal transmittance: clusters of average Roof transmittance of the properties built between 1993-2006 and labeled a) G; b) F; c) A^{+}. The gray line is the average transmittance of the cluster

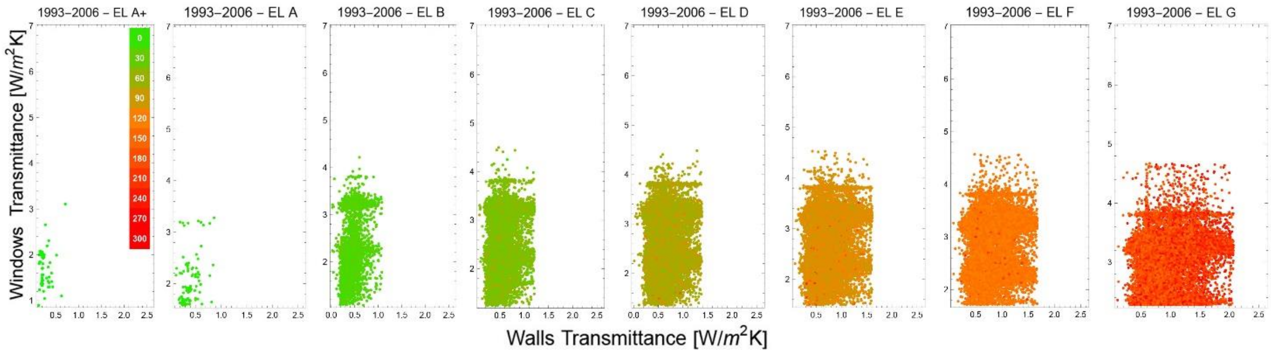


Figure 5: The correlation between windows and walls transmittance of building clusters constructed between 1993-2006

Following the clustering process, an integer number was assigned to each one of the clusters relating to the three envelope components: C_U_{wall} for walls' clusters, C_U_{window} for windows' clusters and C_U_{roof} for roofs' clusters as the identifier of the cluster:

$$I=\{C\_U_{wall}, C\_U_{window}, C\_U_{roof}\};$$

Where: I is the identifier associated with each record

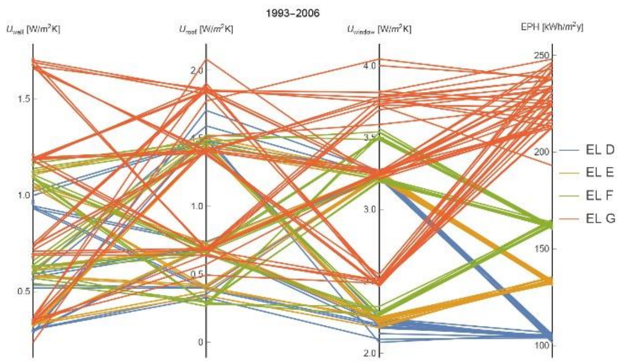


Figure 6: Relationships among the average thermal transmittance of walls (Uwall), roofs (Uroof) and windows (Uwindow) and the average EP_H of the clusters belonging to YoC "1993-2006"

"I" value was used to associate with the TABULA Database to find the building technologies with the closest U values. "National Scientific report on the TABULA activities in Italy" is a scientific report published by Politecnico di Torino University to assess the energy consumption of national building stocks and predict the impact of energy efficiency measures to select effective retrofit strategies for existing buildings. This report is based on the Building Typology concept and groups building elements based on their construction period and building element thermal transmittance (U value). Therefore, the typical building materials and construction technology are indicated for each construction period and U value.

Therefore, to reach a better energy label, which is the purpose of the retrofit process, we can easily match the given cluster's current U values of wall, roof, and window with the U values of elements provided in TABULA to identify the current and desired materials and building techniques. It can be logically concluded that the properties in the same construction period with better energy labels have been retrofitted. Therefore, to achieve a better energy label, we can compare the materials and building technologies of the current and target clusters to identify the building retrofit strategy.

Figure 7 presents the matching process constructed between 1946-1960 with Els of "G" and "A^{+}". For each building cluster in a given construction period and EL the I value is presented, based on which is possible to identify the building materials in TABULA. For this purpose, the building materials with the closes U values are selected and presented in Figure 7. Therefore, to reach from a specific cluster to a better one, the building materials of these two should be compared and necessary retrofit strategy should be determined accordingly.

For systematic registration, an Excel spreadsheet was used. Table 1 presents some of the clusters of buildings constructed between 1946-1960 with "G" and "A+" ELs and their associated building materials. In order to propose the most optimum retrofit scenario, a comparison between the current and desired materials detected based on the TABULA DB should be made, which is itself based on evidence and building topologies in Lombardy region.

Discussion

The research framework is applicable to the Lombardy region's residential properties, as it creates a working link between its two main databases. In addition, the TABULA can provide a precise and comprehensive inventory of building technologies and materials. As a result, based on the desired Energy Label, which is itself defined based on available resources and technical obligations, most optimum retrofit strategies can be recommended for any given record in the database. The scope of this research is to describe the proposed framework and its implementation steps; nevertheless, future steps are needed to put it into practice.

While it is obvious that improving the energy performance of all the target buildings would be ideal in order to meet recent EU decarbonization targets for the built environment, it is equally clear that this cannot be done without taking into account the retrofit costs. Furthermore, there are properties in the DB where it would be unwise to invest money because the after-retrofit savings would be too little, resulting in a low

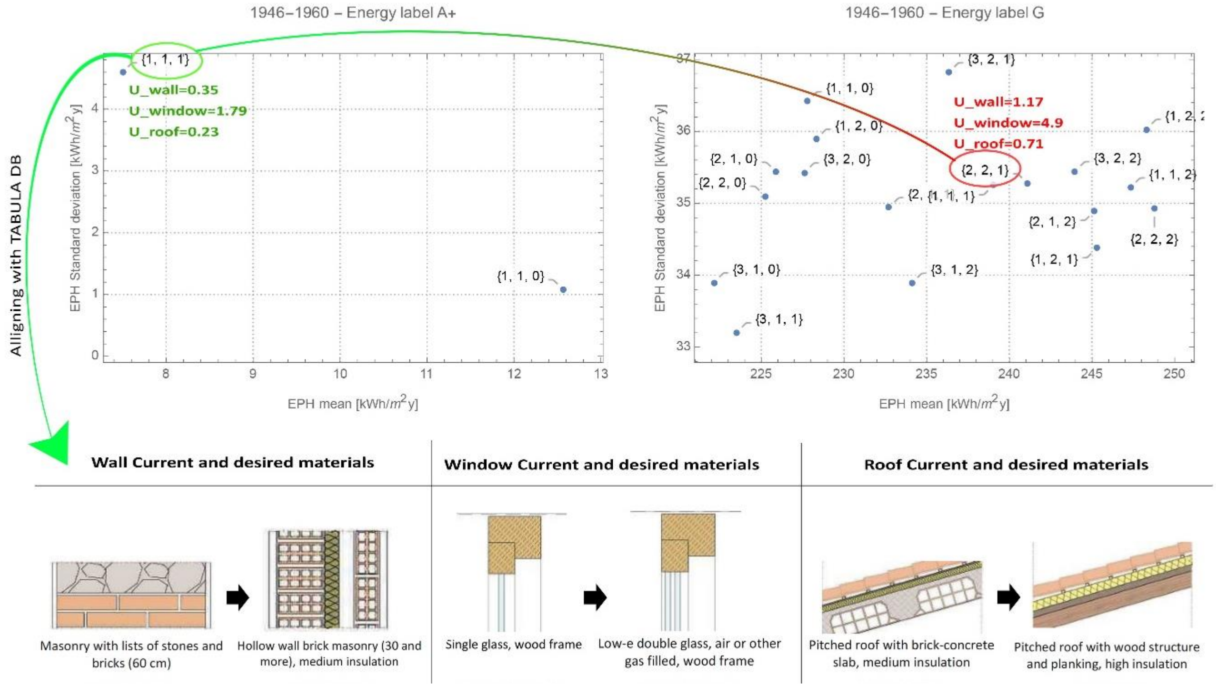


Figure 7: Clusters matching process with TABULA database to identify current and desired building materials and technologies for a given building cluster retrofit to reach a better energy label. For each YoC and EL there are building clusters identified each with different U_{wall}, U_{wondow}, and U_{roof} values. Considering that clusters with the same YoC and better EL are already retrofitted, the comparison between the clusters with worse Els with them can delineate the proper walls', windows' and roofs' retrofit strategies

decrease in CO_2 emissions. Therefore, as a future direction, this research will continue to define a criterion for deciding which properties to invest in and retrofit under a limited budget scenario, based on the Return on Investment.

In conclusion:

- AI application can be highly beneficial for building retrofit decision-making based on national databases.
- Clustering of properties based on energy metrics like thermal transmittance provide a more precise assessment of the current energy performance of residential properties.
- As a matter of fact, energy retrofit is carried out in order to improve the Energy Label. Hence, knowing the average cluster U values for a certain construction period can be helpful in determining retrofit strategies. The TABULA is used to identify the building technology and materials that are related with each U value of building elements.
- This study presents a data-driven and practical methodology for predicting energy retrofit strategies for residential properties in the Lombardy region.

Table 1: Building materials of some clusters in "G", "A" ELs and YoC 1946-1960

EL	Wall	Window	Roof
G	Cluster 1	Cluster 1	Cluster 1
	U_wall [W/Km^2] 1.27	U_window [W/Km^2] 3.26	U_roof [W/Km^2] 1.49
	Material: Hollow brick masonry (40) / Hollow wall brick masonry with solid and hollow bricks (40 cm)	Material: Double glass, air filled, metal frame with thermal break	Material: Pitched roof with wood structure and planking
G	Cluster 3	Cluster 3	Cluster 3
	U_wall [W/Km^2] 0.66	U_window [W/Km^2] 4.95	U_roof [W/Km^2] 2.52
	Material: Concrete masonry (also prefabricated, 18-20 cm), medium insulation	Material: Single glass, wood frame	Material: Pitched roof with brick-concrete slab
A	Cluster 2	Cluster 1	Cluster 1
	U_wall [W/Km^2] 0.70	U_window [W/Km^2] 1.43	U_roof [W/Km2] 0.27
	Material: Concrete masonry (also prefabricated, 18-20 cm), medium insulation	Material: Low-e double glass, air or other gas filled, wood frame	Material: Pitched roof with wood structure and planking, high insulation / Pitched roof with brick-concrete slab, high insulation /Flat roof with reinforced brick-concrete slab, high insulation

Conclusion

This research proposes an AI-based decision support system for building energy retrofit due to the great demand for lowering energy consumption in European residential building stock. AI algorithms can deal with complex and abundant data, learn from previous cases, and predict accurately and automatically for future projects. Being evidence-based and referring to previously conducted cases, the proposed model does not go through conventional retrofit models' time-consuming and complex process and is not associated with the intrinsic and technical complications of the retrofitting process. In this context, it uses clustering techniques to distinguish clusters of residential properties constructed in same period and with similar energy characteristics like the U value of building components. These clusters offer the possibility to make a comparison between properties with original and meliorated energy performance, logically inferring properties of the same age with the difference of being retrofitted or not. For a given construction year and U values of the building component, the TABULA database indicates the common building materials and techniques. Therefore, the current and desired building technology of a given property will be apparent, based on which the retrofit strategy can be determined. This research contributes to increasing the energy performance on an urban level by providing a precise, reliable and quick assessment tool, which solves the problems of traditional retrofit decision support tools. Benefiting from a huge database of nearly 1 million building records in the Lombardy Region, it can be easily implemented for energy retrofit decision-making of future cases. The offered retrofit strategies by the model serve as the basis for future cost-benefit analysis and multi-criteria decision making by the policymakers. It is worth mentioning that the validation of the proposed model will take place in the future steps of the ongoing research project, which is not in the scope of this publication.

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