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Building energy retrofit index for policy making and decision support at regional and national scales

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HIGHLIGHTS

- Machine learning is used for pre-processing, fine-tuning and post-processing data.
- A new indicator is introduced to support building energy retrofit policies.
- The presented indicator is evaluated by a case study of 4767 buildings.
- Current energy indicators can misrepresent the building energy retrofit potential.

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ABSTRACT

The vast data collected since the enforcement of building energy labelling in Italy has provided valuable information that is useful for planning the future of building energy efficiency. However, the indicators provided through energy certificates are not suitable to support decisions, which target building energy retrofit in a regional scale. Considering the bias of the energy performance index toward a building's shape, decisions based on this index will favor buildings with a specific geometric characteristics. This study tends to overcome this issue by introducing a new indicator, tailored to rank buildings based on retrofitable characteristics. The proposed framework is validated by a case study, in which a large dataset of office buildings are assigned with the new index. Results indicate that the proposed indicator succeeds to extract a single index, which is representative of all building characteristics subject to energy retrofit. A new labeling procedure is also compared with the conventional classification of buildings. It is observed that the proposed labels properly partitions the dataset, according to buildings' potential to undergo energy retrofit.

1. Introduction

As part of the climate change counterfeiting objectives of the European Union, the Energy Performance for Buildings Directive (EPBD recast) mandates EU Member States to promote building energy efficiency [1]. Even though building energy efficiency was already enforced in some EU Member States [2]; the implementation of the EPBD resulted in national and regional legislations that persuade public and private bodies to undergo building energy audit, often by means of an Energy Performance Certificate (EPC) [3]. The outcomes of implementing EPCs has been widely investigated from various perspectives: reliability and credibility of the certificates [4,5], Socio-economic impacts [6], energy retrofit scenarios [7,8], renting and trading properties [9–11], social participation [12,13], and the impacts of EPCs on other policies that promote building energy efficiency [14].

It has been argued that alongside other functionalities, EPCs should also serve decision makers and energy planners at regional and national scales [15]. As a result, studies have approached EPC outcomes from an energy planning perspective [16–20], and underlined the necessity of better energy efficiency policies for the building sector [21,22]. Meanwhile, it has been reasoned that relying on the wrong indicators may lead to misconceptions on the actual status of the building stock [23] and result in suboptimal policies [24]. The literature outlines this issue by indicating that: the geometry of the building may have a too strong effect on the estimated energy need [25], the relation between the building geometry and the estimated energy consumption is nonlinear [26], and energy efficient renovation may render unrealistic as some pivotal information could be missing from the indicators [27]. For instance, a statistical analysis on the covariation between building properties and the energy use intensity has revealed that the thermal characteristics of walls can have a strong influence on the energy use intensity, while the correlation between window characteristics and the

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Nomenclature

Abbreviations

EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificate
CENED	Certificazione Energetica degli Edifici
KL	Kullback-Leibler divergence
MAPE	Mean Absolute Percentage of Error
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
MSEsparse	Mean Squared Error of sparsity
PCA	Principal Component Analysis
R^2	Squared correlation coefficient
S/V	Surface to Volume ratio
SoD	Sum of Distances
SSE	Sum Squared Error
tMLP	truncated Multi-Layer Perceptron

Variables

Eff_G	global efficiency of system [–]
EP_i	energy performance index [kW h/m^2 y]
ERi	energy retrofit index [–]
U_b	average U-value of basement [W/m^2 K]
U_e	average U-value of walls [W/m^2 K]
U_r	average U-value of roof [W/m^2 K]
U_w	average U-value of windows [W/m^2 K]

energy use intensity may be difficult to comprehend [28].

Studies have previously demonstrated the positive effects of optimal building energy retrofit on energy savings at municipal scales [29]. However, building energy retrofit planning at regional scales may face challenges due to the misconception of EPCs as the indicators often present the performance of the building by means of energy use intensity [30]. Consequently, energy performance indicators may be biased toward geometric characteristics of buildings [31,32], and fail to render the actual potential of a building to undergo an energy retrofit. This issue is particularly important in the energy retrofit planning process, during which decision makers have to prioritize a number of buildings that merit financial assistance while handling subsets of multidimensional data [33]. The challenge of a ranking system dedicated to retrofit potential is worth deepening since grants, tax deductions, loans and similar financial promotions have proved to be effective strategies for encouraging the public toward energy efficiency [34–36]. Therefore, it is necessary to support energy planning with a reliable indicator that does not merely present the energy consumption of the building, but also maps the characteristics of one building compared to others. Moreover, a new classification of buildings' features is inevitable since the conventional energy labels (classes of energy) do not necessarily reflect the thermal characteristics of a building's envelope. To counter the bias of energy use intensity towards a unit's geometry, studies have proposed the application of energy benchmarking [37]. Sun and Price introduced a classification strategy by resorting to prototype building characteristics as the basis of retrofit analysis [38]. This approach succeeds to rank buildings based on their retrofitbale characteristics and overcomes the bias towards geometry. However, a predefined database of reference buildings (similar to that of the USEDOE [39]) is an essential part of the framework, and may not be available for all EPC databases.

Clustering is a suitable alternative to the traditional frequency-based classification of buildings as it can return more robust subsets [40,41]. Building energy rating has been tackled by opting for various clustering techniques, namely, decision tree [42], fuzzy [43], k-means [44], as well as Gaussian, hierarchical and self-organizing maps [45]. While much progress has been achieved in obtaining better partitions between the subset clusters, there has been no attempts to tailor Machine-Learning-based ranking techniques with building energy retrofit in mind. Since an EPC has a high correlation with a unit's floor area [46], it cannot explain whether a low energy performance is related to poor envelope characteristics, or due to high surface to volume (S/V) ratio. Such level of information is critical for decision making in a regional scale: according to the EU policies aimed at buildings' energy consumption, the priority in energy efficiency is to initially prevent buildings from excessive energy use, and then promote the application of renewable energies [47]. Therefore, a building with suitable envelope characteristics and a high S/V ratio should have higher priority to receive financial aid for installing renewable systems, compared to a competitor who has worse envelope characteristics but stands higher in the energy efficiency rankings due to a lower S/V ratio. This issue is significantly important since there are other parameters similar to S/V which affect a building's energy consumption, but cannot be subject to retrofit. This paper tends to overcome the described challenge by introducing a novel framework for ranking buildings. This ranking system is based on a new indicator that is specifically designed to target retrofitable building characteristics. Therefore, decision makers can easily distinguish buildings which have higher merit to undergo an energy retrofit. The proposed indicators can assist administrations in aiming policies at specific subsets of buildings. This is essential for assessing hypothetical funding policies, as well as creating trajectories of possible updates in the EPC database [48]. The original scientific contributions of this study include:

– Contrasting the ineffectiveness of the "Energy Performance index" for ranking buildings according to retrofitable properties.
– Presenting a robust and replicable Machine-Learning-based pipeline for extracting weighted nonlinear features from building characteristics.
– Introducing the "Energy Retrofit index"; a new measure specifically tailored to support the allocation of financial aids for boosting building energy retrofit at regional scales.

The rest of the paper is structured in the following manner: Section 2 provides an overview on the machine learning techniques applied in the study i.e. Multi-Layer Perceptrons, nonlinear Principal Component Analysis and k-means clustering. Section 3 applies the framework to a dataset of building energy certificates extracted from the Lombardy region in Italy, and compares the results of the proposed method with available indexes and conventional clustering techniques. Section 4 concludes the paper by summarizing the advantages of the proposed method when compared to its predecessors, as well as applications and possible expansions for future studies.

2. Methodology

The proposed framework resorts to three tools, which are adopted from the field of machine learning i.e. neural networks, autoencoders and k-means clustering. Based on the type of learning, the exploited tools can be divided into two main categories of supervised (neural networks) and unsupervised learning (autoencoders, k-means). The supervised learning of the framework tends to find covariations between some input data and the targets. Unsupervised learning on the other hand, seek structures and covariations in the input data itself. To ensure that the study provides a clear description of the framework, initially, each tool is briefly described.