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A new methodology for investigating the cost-optimality of energy retrofitting a building category

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ABSTRACT

According to the Energy Performance of Buildings Directive (EPBD) Recast, building energy retrofitting should aim “to achieving cost-optimal levels”. However, the detection of cost-optimal levels for an entire building stock is a complex task. This paper tackles such issue by introducing a novel methodology, aimed at supporting robust cost-optimal energy retrofit solutions for building categories. Since the members of one building category provide highly different energy performance, they cannot be correctly represented by only one reference design as stipulated by the EPBD Recast. Therefore, a representative building sample (RBS) is here used to consider potential variations in all parameters affecting energy performance. Simulation-based uncertainty analysis is employed to identify the optimal RBS size, followed by simulation-based sensitivity analysis to identify proper retrofit actions. Then post-processing is performed to investigate the cost-effectiveness of all possible retrofit packages including energy-efficient HVAC systems, renewables, and energy saving measures. The methodology is denoted as SLABE, ‘Simulation-based Large-scale uncertainty/sensitivity Analysis of Building Energy performance’. It employs EnergyPlus and MATLAB®. For demonstration, SLABE is applied to office buildings built in South Italy during 1920–1970. The results show that the cost-optimal retrofit package includes the installation of condensing gas boiler, water-cooled chiller and full-roof photovoltaic system.

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1. Introduction

In recent years, the interest of the scientific community toward building energy performance is more and more increasing because the building sector accounts for around 40% of energy demand in the European Union (EU) and 32% in the world [1]. This leads to international calls for achieving net/nearly zero-energy buildings in order to reduce the energy consumption of the future building stock. However, it is well known that the building turnover rate is quite low, especially in the industrialized countries, which are responsible of a wide part of world consumption.

Therefore, building energy retrofitting is a key-strategy to achieve tangible results in the reduction of world energy demand and thus polluting emissions. For instance, Nemry et al. [2] showed that, concerning the residential category at EU level, the potential reduction of the environmental impact of new buildings can be neglected compared to that of existing ones. Similar conclusions are valid for other categories, such as office buildings [3,4].

The scientific community supports the necessity of acting on the existing building stock as shown by Ma et al. [5], who proposed an admirable review of worthy studies in the field of building energy retrofitting. Such studies are subdivided into two groups: those focused on residential buildings and those focused on office buildings. This distinction is made because the best energy retrofit packages for heterogeneous building types and uses generally differ. The attention is directed to these two categories because they cover the vast majority of the building stock of any country.

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Nomenclature

$a, b, \dots, g, h$	labels of the EEMs ^d
a	absorption coefficient for solar radiation
c	specific heat [J/kg K]
d	density [kg/m ³]
e	number of parameters describing the EEMs ^d
k	thermal conductivity [W/m K]
n	number of characteristic parameters describing the existing building stock
p_i	i th parameter
r	ratio between the number of sampled cases and the number of characteristic parameters
$r_{\min}$	minimum value of r for achieving a reliable RBS
t	thickness [m]
ACC	efficient air-cooled chiller
BPS	building performance simulation
CB	condensing boiler
COP	coefficient of performance of heat pumps [W_{th}/W_{el}]
DH	percentage of discomfort hours [%]
DHW	district hot water
EB	efficient boiler
ED	thermal energy demand [kWh/m ² a]
EEM ^d	energy efficiency measure for the reduction of thermal energy demand
EER	energy efficiency ratio of chillers [W_{th}/W_{el}]
GC	global cost [€ per building]
HP	heat pump
HVAC	heating, ventilating and air conditioning
LHS	latin hypercube sampling
N	number of cases included in the RBS (RBS size)
$N_{\min}$	minimum value of N for achieving reliable results
PEC	primary energy consumption [kWh/a per building]
PI	performance indicator
PV	photovoltaic
R	thermal resistance [m ² K/W]
RB	reference boiler
RBS	representative building sample
RefB	reference building
RC	reference chiller
RES	renewable energy source
S_1	sample set representing the existing building stock (RBS)
S_2	sample set representing the renovated building stock
S_3	sample set representing the packages of the most important EEMs ^d
SA	sensitivity analysis
SLABE	simulation-based large-scale uncertainty/sensitivity analysis of building energy performance
SRRC	standardized rank regression coefficient
U	thermal transmittance [W/m ² K]
U_w	thermal transmittance of the windows (glass + frame) [W/m ² K]
UA	uncertainty analysis
WCC	water-cooled chiller
μ	mean value
σ	standard deviation

Subscripts

c	referred to the cooling season
h	referred to the heating season

Concerning residential buildings, their energy performance is highly affected by the characteristics of the building envelope, mainly because of the low ventilation needs. Thus, the thermal insulation of the building shell [6–8] can induce high energy and economic savings. Furthermore, if this measure is combined with the use of more efficient building HVAC systems and with the exploitation of renewable energy sources (RESs), especially photovoltaic panels, the energy retrofit of existing buildings to nearly zero-energy ones is possible [9]. However, this outcome is valid only for heating-dominated climates (e.g., North Europe), whereas in presence of cooling-dominated climates (e.g., Mediterranean area) a deeper analysis is necessary in order to take into account the issue of summer overheating. In this regard, two macro-strategies can be identified for reducing the cooling need and avoiding the overheating effect in warm climates: (a) the reduction of the solar gain by means the use of solar shadings [10,11] and/or reflective coatings [12]; (b) the adoption of techniques for discharging the building envelope, thereby operating a passive cooling of indoor spaces [13–15].

Concerning office buildings, they are characterized, compared to dwellings, by a higher demand for lighting and various electric uses, as well as by a much larger ventilation need and endogenous heat gain that increases the energy demand for space cooling. Therefore, also in heating-dominated climates, the main components of annual primary energy consumption, i.e., space heating, space cooling, lighting and electric uses, are more balanced [16] compared to residential buildings, whose consumption is highly affected by space heating. This determines major issues in the design of retrofit strategies, which simultaneously should take into account environmental, sociocultural and economic criteria [3]. In this vein, Hestnes and Kofoed [17] investigated ten existing office buildings by exploring the impact of different retrofit strategies, including measures addressed to building envelope, HVAC system and lighting. The outcomes confirmed the complexity of energy retrofitting the considered building category, since the optimal strategy significantly depends on the specific building characteristics. Definitely, the energy retrofit of office buildings should be designed ‘ad hoc’ by taking into account all levers affecting energy performance [18,19]. In this regard, different interactive decision support tools have been conceived [20,21] in order to detect optimal energy retrofit packages for office buildings, based on the trade-off among different performance indicators, such as energy consumption, investment and operating costs, environmental impact.

As shown by the mentioned studies, the design of building energy retrofit is a challenging task that requires a holistic and integrated team approach [22] because conflicting objectives generally subsist. The two main objectives are the minimization of energy consumption and the maximization of economic benefits. Since they are generally conflicting, multi-objective optimization is recommended [23–35]. In order to harmonize such objectives, the Energy Performance of Buildings Directive 2010/31/EU (EPBD Recast) [36] focuses on the concept of ‘cost-optimality’. More in detail, this directive has introduced a new comparative methodology framework in order to assess building energy performance “with a view to achieving cost-optimal levels”. The energy retrofit actions should be effective by minimizing the global cost over the lifecycle of the building. Since the cost-optimal analysis cannot be performed to each building, for reason of complexity, reference buildings (RefBs) have to be defined to represent the national building stock. They should cover all the building categories, where a category is meant as a stock of buildings that share climatic conditions (location), functionality and construction type. Thus, the cost-optimal analysis should be applied to these RefBs in order to detect cost-optimal packages of energy measures [37,38]. Then,

the results achieved for a RefB should be extended to the other buildings of the represented category [39]. However:

- (a) Does this procedure ensure reliable results for all the buildings of the category (category's members)?
- (b) Otherwise, how to investigate, in a more rigorous way, the cost-optimality of energy retrofitting a building category?

The energy analysis of a building stock, rather than of single buildings, is essential when the purpose is to estimate the baseline energy consumption of existing buildings as well as the global potential energy saving, or to give general indications about the cost-effectiveness of energy measures. The scientific literature presents different methods for investigating and modeling a building stock in order to assess energy performance, as shown by the exhaustive reviews provided by Swan and Ugursal [40] and Kavgić et al. [41]. These methods can be subdivided into two groups according to the adopted approach: top-down and bottom-up. The top-down approach operates at an aggregated level by handling cumulative historic data of energy consumption and/or polluting emissions. The bottom-up approach operates at a disaggregated level by extrapolating the energy consumption of a representative sample of buildings to regional/national level.

Most studies adopting the top-down approach exploited statistical data collections just to provide a picture of the existing stock [42–45], and/or explore the potential savings induced by few energy measures in a simplified manner without considering the complex building dynamic behavior [46,47]. For instance, Balaras et al. [42] investigated 193 residential buildings, located in five European countries, by performing energy audits for assessing the influence of thermal insulation level, age, HVAC system type and geographical location on heating energy consumption and resulting environmental impact. In the same vein, Dascalaki et al. [43] proposed an original methodology aimed at collecting and analyzing relevant national data on the building stock in order to monitor energy performance and extract information concerning the impact of possible energy measures. Sardanou [44] and Theodoridou et al. [45] presented methodological approaches aimed to give detailed information on the Greek residential building stock, thereby detecting the energy saving potential via the statistical analysis of survey data. Also Balaras et al. [46] focused on the Greek residential stock by providing a detailed picture of the stock's current energy consumption through the collection and aggregation of statistical data. Furthermore, they elaborated a simplified methodology to quantify the impact and effectiveness of different energy conservation measures, by assigning to each measure an established potential energy saving. Analogously, Fracastoro et al. [47] developed an analytical procedure for estimating the primary energy consumption of a large-scale building stock, starting from statistical data. The procedure can be adopted to define the performance scale for building energy certification, as well as to evaluate the energy saving potential of large-scale retrofit measures addressed to the building envelope.

Concerning the bottom-up approach, Caldera et al. [48] elaborated a statistical model for assessing heating energy demand of residential buildings in the district of Turin (North Italy), based on a sample of 50 buildings. In the same vein, Al-Ghandoor et al. [49] developed a multivariate regression model, which adopts time series analysis in order to predict future energy demand and evaluate the potential energy saving induced by retrofit actions in the residential building stock of Jordan. When statistical data collections are insufficient or not available, models based on energy simulations can be used to estimate the energy performance of a building stock [50–53]. For instance, Mata et al. [50] developed a model in MATLAB® [54] environment – denoted as Energy, Carbon and Cost Assessment for Building Stocks (ECCABS) – based on

one-zone hourly heat balances in order to calculate the energy demand for buildings representative of a building stock, thereby extending the results to the entire stock through the adoption of weighting factors. Afterwards, ECCABS was used by Nik and Kalagasidis [51] for predicting the impact of climate change on the future energy consumption of the residential building stock in Stockholm by means of the investigation on a sample of 153 statistically selected buildings. For building shell energy labeling, Melo et al. [52] applied artificial neural networks (ANNs) to model the building stock of the city of Florianópolis (Brazil), based on the results provided by EnergyPlus [55] on a sample of 3200 heterogeneous buildings. In this regard, it should be noted that the reliability of the methods adopting the bottom-up approach highly depends on the size of the selected buildings' sample, which has to represent the entire building stock. As highlighted by Liang and Shen [53], the minimum sample size is affected by the number of parameters influencing stock energy performance as well as by the stock size; therefore it must be established carefully and 'ad hoc', based on the peculiarities of the investigated stock.

This paper aims to answer the aforementioned questions (a) and (b) by means of a novel methodology that supports a robust cost-optimal analysis of energy retrofit solutions for a building category. The methodology is denoted as SLABE, 'Simulation-based Large-scale uncertainty/sensitivity Analysis of Building Energy performance'. In order to consider all the category's peculiarities, SLABE investigates a Representative Building Sample (RBS) instead of only one Reference Building, thereby adopting an original bottom-up approach, based on detailed energy simulations, in stock modeling. Simulation-based uncertainty analysis (UA) is carried out to identify the optimal RBS size, followed by simulation-based sensitivity analysis (SA) to identify proper retrofit actions. Then post-processing is performed in order to reach two main targets:

- detecting the package of actions that represents the cost-optimal solution for most category's members;
- evaluating the effectiveness of current policy of state financial incentives directed to these actions.

In the following lines, the methodology is first described (Section 2) and then applied to a specific category: office buildings built in South Italy in the period 1920–1970 (Sections 3 and 4).

2. Methodology

2.1. Aim and originality

The methodology provides a robust cost-optimal analysis of energy retrofitting a building category. The cost-optimality is estimated in line with EPBD Recast [36], but the proposed approach introduces an original aspect regarding the simultaneous investigation of different buildings belonging to the same category. The main originality consists of performing the cost-optimal analysis by representing a building category by a representative building sample (RBS), instead of only one reference building (RefB) as stipulated by the EPBD Recast. The new approach replaces the concept of RefB by the concept of RBS, thereby performing an original bottom-up stock modeling, based on detailed energy simulations. The methodology presents a multi-stage framework, which allows to assess the influence of energy retrofit actions on primary energy consumption (PEC) and global cost (GC) related to RBS; this should be large enough to represent the considered category reliably. Simulation-based uncertainty analysis (UA) is employed to identify the optimal RBS size. Then, simulation-based sensitivity analysis (SA) allows to identify proper retrofit actions and post-processing

is performed to detect the retrofit packages most affecting PEC and GC savings. The final outcome is the energy retrofit package that provides the cost-optimality for most category's members. Furthermore, the effectiveness of state financial incentives directed to energy retrofit actions is evaluated. It is emphasized that UA and SA are generally carried out for a single building [56–58], in order to assess how the variations of some uncertain parameters affect energy performance. On the contrary, this study performs UA and SA on a large-scale, since the uncertainties in the parameters are introduced intentionally in order to generate a sample space that covers most category's members. However, they can be still denoted as uncertainties because they express the uncertainty of the energy behavior of each single building within the category. In other words, this study refers to a category-based uncertainty (large-scale) and not to building-based uncertainty (small-scale). The developed methodology is therefore denoted as 'Simulation-based Large-scale uncertainty/sensitivity Analysis of Building Energy performance' (SLABE).

2.2. Possible applications

SLABE can become a powerful tool for different stakeholders. On one hand, it allows to identify the package of energy retrofit actions that implies the cost-optimality for most buildings of the investigated category. Therefore, it can give global indications to building owners/occupants concerning the best retrofit strategy from a financial perspective. On the other hand, SLABE allows to evaluate the effectiveness of the state policy of financial incentives directed to energy retrofit actions. Therefore, it deals with a macroeconomic perspective, too.

Definitely, SLABE tackles both financial (looking at the investment itself) and macroeconomic (looking at the costs and benefits of energy efficiency investments for the society as a whole) perspectives, as recommended in the Guidelines of the EPBD Recast, i.e., Delegated Regulation (EU) No. 244/2012 [59]. Thus, the implementation of this methodology to different building categories can produce significant benefits in terms of reduction of energy consumption, and so polluting emissions, of the building sector as wells in terms of global cost savings concerning the buildings' owners/occupants. Eventually, SLABE arises from academic curiosity but its application can produce substantial practical results, as shown by the outcomes achieved for the investigated real case study.

2.3. Tools

SLABE is based on the coupling between EnergyPlus [55] and MATLAB® [54]. EnergyPlus is chosen as BPS (building performance simulation) tool because: it is a whole building energy simulation program that allows a detailed evaluation of each term of PEC; it works with text-based format inputs (.idf) and outputs (.csv), which facilitate the interaction with mathematical tools. MATLAB® is chosen for UA, SA and post-processing because: it has a very strong capability of running statistical routines for data analysis and interpretation; it can automatically launch EnergyPlus as well as manipulate EnergyPlus inputs and outputs.

The UA is performed by means of Monte Carlo analysis (MCA), which is widely applied to BPS [56–58,60]. As aforementioned, the UA is carried out on a large scale in order to investigate the distributions of some performance indicators (PIs) within RBS. Thus, the ranges of uncertainty of the parameters are wider than when the UA is applied to a single building [56–58].

As regards the SA, a global approach is used through the assessment of the standardized rank regression coefficients (SRRCs). In building energy analysis, the global approach is more reliable than the local one [23,61] and regression methods are the most used [61].

Moreover, BPS tools generally generate nonlinear, multi-modal, discontinuous outputs [23,62–64]. Thus, the SRRCs are selected as sensitivity indices, since they are fine for non-linear (but monotonic) functions between inputs and outputs. This choice is largely shared in the BPS community [65,66]. In particular, the SRRC provides a measure of how influential a parameter is on an output, based on the effect of moving such parameter away from its expected value while retaining all other parameters constant. It can vary from -1 to 1 ; a positive value indicates that the parameter and the output change with the same sign, while the opposite occurs for a negative value.

2.4. Multi-stage framework

SLABE consists of two main stages, which are subdivided in two and three steps respectively, as shown in Fig. 1 and summarized below. These steps are described in detail in the following subsections.

- Step 1 (stage I): the existing building stock is investigated in order to identify the optimal RBS size (by UA) and the parameters most affecting energy demand for micro-climatic control and thermal comfort (by SA).
- Step 2 (stage I): some energy efficiency measures for the reduction of energy demand (EEMs^d) are proposed; their impact on energy demand and thermal comfort is explored (by UA) and the most influential measures are detected (by SA).
- Step 3 (stage II): the implementation of new efficient HVAC systems is investigated, by assessing the effect on PEC and GC; this step allows to estimate the effectiveness of state incentives for HVAC systems and to identify the cost-optimal HVAC configuration.
- Step 4 (stage II): the implementation of renewable energy source (RES) systems is investigated, by assessing the effect on PEC and GC; this step allows to estimate the effectiveness of state incentives for RES systems and to identify the cost-optimal combination of HVAC system and RESs.
- Step 5 (stage II): the implementation of the most influential EEMs^d, identified in step 2, is investigated, by assessing the effect on PEC and GC; this step allows to estimate the effectiveness of state incentives for EEMs^d and to identify the cost-optimal package of energy retrofit actions, including HVAC system, RESs and EEMs^d.

2.5. Stage I. Investigation of energy demand (ED) and discomfort hours (DH)

In this stage (see Fig. 1), energy demand and thermal comfort are investigated, by means of UA and SA. In particular four PIs are considered:

- annual energy demand for heating, ED_h [kWh/m² a];
- annual energy demand for cooling, ED_c [kWh/m² a];
- percentage of discomfort hours on occupied hours, during the heating season, DH_h [%];
- percentage of discomfort hours on occupied hours, during the cooling season, DH_c [%].

The energy demand is the annual request of thermal energy for micro-climatic control per unit of conditioned area. As regards the assessment of thermal comfort, the weighted under- or over-heating/cooling hours criterion [57], based on Fanger theory [67], is used. Discomfort hours represent the occupied hours during which the average predicted mean vote (PMV) in the thermal zones of the building does not fall in the range -0.85 to 0.85 , resulting in a predicted percentage of dissatisfied (PPD) greater than 20%. The

Fig. 1. Framework of SLABE. The symbol e+ indicates the data provided by EnergyPlus and handled by MATLAB®, required for the evaluation of PEC (and so GC).

acceptability range of PMV has been chosen on the basis of the minimum level of thermal comfort required in a building by ASHRAE [68]. Nevertheless, stricter criteria can be used, if required.

As shown in the next sections, the four PIs are first investigated for the existing building stock (step 1) and then for the renovated stock (step 2), namely in presence of EEMs^d. In the second step, also the annual values of energy demand (ED) and discomfort hours (DH) are considered in order to explore the overall effects of the EEMs^d.

2.5.1. Step 1. Analysis of the existing building stock

In the first step, the existing building stock is defined by detecting n characteristic parameters relevant to energy demand and thermal comfort. The sampling of such parameters generates the RBS that should represent the building category. A range of variability and a probability distribution (e.g., uniform or normal) are assigned to each parameter in order to sample across the whole category. A reference building (RefB) related to the investigated category can be exploited to set the mean values of such distributions, as shown in Section 3. The characteristic parameters are classified in three groups, respectively related to geometry (form and orientation), envelope (thermo-physical characteristics of materials) and other parameters that cannot be placed in the first two groups (e.g., set point temperatures, internal loads, people density). SLABE is limited to rectangular buildings. This choice facilitates the parameterization process [60], and it is proper for most building categories because of the high percentage of rectangular shapes.

In order to build a reliable RBS, a statistical analysis is necessary for detecting the ranges and distributions of all characteristic

parameters (the same analysis is required when the goal is to generate a robust RefB of the category). Such analysis allows to define the sampling space to be spanned. It is noted that the parameters' selection requires expertise and a thorough knowledge of the problem. Furthermore, this selection should be carried out by considering the trade-off between the reliability of RBS and the computational burden, since more parameters imply more EnergyPlus simulations in order to obtain good results. Thus, parameters that have an insignificant influence on energy performance should not be chosen. For instance, in this study (see Section 3.2) the thermal characteristics of some layers of the building envelope (e.g., internal plasters, screeds, tiles) are not contemplated because they do not significantly affect building energy behavior. The characteristic parameters should be independent in order to enable 'free sampling' and to not compromise the reliability of the sensitivity analysis [69]. Therefore, the category's members should be characterized by the same construction type in order to avoid relations between parameters (e.g., certain materials being more common for certain building sizes). In other words, the building category should not be too extended. That is why in this study (see Section 3) we consider office buildings built in a specified time horizon; thus, they present the same construction type (i.e., reinforced concrete as structural frame) and the size varies within a limited range (e.g., the number of floors varies from one to five). Consequently, characteristic parameters can be considered independent.

The three groups of parameters and their correlated ranges define the sample space to investigate. Latin hypercube sampling (LHS) is applied to these parameters within a Monte Carlo framework, in order to generate N cases, which correspond to N building

Table 1Framework of the sample set S_2 (renovated building stock).

SAMPLE SET		PARAMETERS DESCRIBING THE EXISTING BUILDING STOCK					PARAMETERS DESCRIBING THE ENERGY EFFICIENCY MEASURES (EEMs ^b)				
S_2		p_1	p_2	...	p_{n-1}	p_n	p_{n+1}	p_{n+2}	...	p_{n+e-1}	p_{n+e}
CASES	1	set S_1					LHS				
	2										
	...										
	$N-1$										
	N										

model instances and, thus, to N EnergyPlus simulations. These cases constitute the sample set S_1 , which corresponds to RBS. It represents the existing building stock. LHS is used because it ensures uniformity and coverage in the sample space, thanks to its efficient stratification properties [69,70]. It is widely-used in the scientific literature concerning BPS [56,57,65,71,72]. Therefore, once established the sample space adequately as previously described, LHS ensures to sample across any category. It is noted that the value of N must be chosen carefully in order to thoroughly represent the building stock [53]. The N building model instances are run in EnergyPlus, by means of the coupling with MATLAB®, obtaining N sets of values of the four PIs. Of course, the proposed sampling methodology cannot represent all the category's members (there are always buildings with singularities), but it covers the majority of them. Definitely, the generation of RBSs requires a statistical analysis similar to that necessary for the definition of RefBs, but allows to take into account many more category peculiarities, thereby ensuring highly more accurate and reliable outcomes concerning the assessment of the building category's energy performance.

Once built the RBS (i.e., the sample S_1), the UA is carried out in order to explore the dispersion (distribution) of PIs and to identify the optimal RBS size, denoted with $N_{\min}$. This consists of the minimum number of cases (building instances) to be investigated for ensuring the stability in mean value and standard deviation of all PIs (see Section 4.1.1). Thus, $N_{\min}$ is the minimum RBS size that provides reliable results, valid for most category's members. The value achieved for $N_{\min}$ is used in step 5 and can be exploited also in other studies related to the same or similar categories (for instance, for setting the initial value of N).

Finally, the SA (assessment of the SRRCs) is performed to evaluate which parameters have the most/least influence on the PIs. The values assumed by the SRRCs can guide the choice of the EEMs^d that will be investigated in the next step, since they highlight the most critical parts of the building system from an energy point of view.

2.5.2. Step 2. Analysis of the renovated building stock

In the second step, the renovated building stock is explored. In more detail, some EEMs^d are introduced, based on outcomes of step 1, category's peculiarities and best-practice. Each EEM^d is parameterized through a Boolean parameter, which assumes the value of 0 if the relative measure is absent, 1 if present. These new parameters vary according a uniform distribution, so that the probability that one EEM^d occurs is equal to the 50%. Furthermore, the implementation of the EEMs^d generally requires the introduction of other parameters (e.g., the thermo-physical characteristics of thermal insulation), for a total of new e parameters.

Therefore, the renovated building stock is defined by $(n+e)$ parameters – n for the existing buildings and e for the EEMs^d – whose sampling leads to the second sample set S_2 consisting of N cases alike S_1 . In particular, a correspondence between S_1 and S_2 is established, as shown in Table 1. Each case of S_2 provides the same values of the first n parameters assumed by the homologous case of S_1 , while the remaining e parameters are sampled by LHS.

In light of this, S_2 gathers the same building instances of S_1 , but in presence of one or more EEMs^d. This expedient allows the direct comparison between the two sets (case by case), by detecting the effects of some EEMs^d on each building instance.

The N building model instances, gathered in S_2 , are run in EnergyPlus in order to evaluate the new sets of values assumed by the four PIs. At this point, the UA allows the estimation of the effects induced by the EEMs^d on energy demand and thermal comfort in the heating and cooling seasons. In addition, the values of the SRRCs are assessed for the Boolean parameters representing the EEMs^d, in correspondence of ED_h, ED_c, DH_h, DH_c, ED, DH. Thus, the SA allows to detect the most influential EEMs^d on the seasonal and annual values of energy demand and discomfort hours.

2.6. Stage II. Investigation of primary energy consumption (PEC) and global cost (GC)

In this stage (see Fig. 1), the potential savings in PEC and GC induced by well-selected energy retrofit actions are investigated. The actions are selected on the basis of category's peculiarities, best-practice, outcomes of step 2 (only for step 5). Since RBS reliably represents the building stock, the outcomes are valid for the whole category.

The PEC is an appropriate metric according to EPBD Recast [36]. It represents the sum of the different components of the building energy use, which are converted by means of primary energy factors. Heating, cooling, ventilation, pumps and fans, domestic hot water (DHW), lighting, electrical equipment are considered. If RES systems are present, produced and used energy must be subtracted to the previous terms, in a consistent way. SLABE calculates the PEC through the post-process performed in MATLAB®, after EnergyPlus simulations. This expedient allows the reduction of the computational time [29]. EnergyPlus provides the hourly values of the energy demand for heating, cooling, DHW and electricity (which gathers the remaining components of building energy use). These values are handled in MATLAB®. First, heating, cooling and DHW demands are turned into hourly demand of electricity or fuel (depending on the type of HVAC system) through the hourly performance curves of the HVAC system. Then, the overall values of electricity and fuel demand are converted in primary energy, by means of primary energy factors. The PEC is so calculated. In presence of RESs, EnergyPlus also yields the hourly values of produced energy. If produced energy is consumed according to an hourly balance, it represents a subtractive term in PEC evaluation.

The GC over the lifecycle of the buildings is calculated in MATLAB®, according to the Guidelines of EPBD Recast [59]. The real interest rate and the energy price escalation rate are set equal to 3% and 2%, respectively. The annual energy demand is assumed constant during the calculation period.

The exploration of the achievable savings in PEC and GC is carried out in three steps, in order to consider the effects produced by three distinct groups of retrofit actions: replacement of the primary heating/cooling system (step 3), installation of RES systems (step 4), implementation of EEMs^d (step 5).

Fig. 2. Main peculiarities of boxplots.

2.6.1. Step 3. Replacement of the primary heating/cooling system

In this step, the replacement of the primary heating/cooling (HVAC) system is considered as the only possible retrofit action, in order to detect the impact of new efficient HVAC systems on PEC and GC. In fact, this generally represents the most influential action on energy and economic savings [29].

The PEC-GC analysis is performed. Specifically, the values of PEC and GC are calculated for each case of S_1 (existing building stock) in correspondence of the reference HVAC system and of different new efficient options. The potential savings are then evaluated. Hence, the best configurations of the HVAC system are identified, as regards energy and cost perspectives, respectively. In the first case, the best solution is the one that ensures the highest PEC saving in the building stock. In the second case, it is the one that leads to the highest number of category's members (sampled cases) with positive GC savings; this represents the cost-optimal configuration. The best compromise between these two perspectives is investigated via the concurrent representation of PEC and GC savings:

- mean values are considered for PEC savings, because they are proportional to the energy saving in the whole stock;
- the boxplot is chosen for the representation of GC savings, because it allows to estimate, qualitatively, the percentage of members characterized by cost savings. The main peculiarities of boxplots are resumed in Fig. 2. About them, outliers are not depicted in this study (see following figures) because they represent a very restricted, insignificant part of the building stock.

The described analysis is carried out in absence and in presence of state incentives in order to examine the effect of the current policy of financial grants addressed to energy retrofit actions. The cost-optimal solution refers to the presence of current incentives.

Therefore, this step allows to:

- evaluate the effectiveness of current incentives directed to HVAC systems;
- detect the cost-optimal HVAC system, when the replacement of such system is the unique retrofit action.

2.6.2. Step 4. Installation of RES systems

In this step, the potential savings in PEC and GC induced by the exploitation of RESs are investigated for S_1 . First, the PEC-GC analysis is performed in presence of the reference HVAC system, in order to assess how the mere implementation of a RES system influence PEC and GC. The best configurations of the RES (e.g., area of PV panels), as for PEC and GC savings, are detected in absence and in presence of current state incentives, in order to:

- evaluate the effectiveness of incentives directed to the considered RES system;
- determine the cost-optimal configuration of the RES system.

If more RESs are examined, the same procedure is repeated for each of them.

Then, well-selected combinations of HVAC system and RESs are investigated by assessing PEC and GC savings in presence of current incentives. These combinations are identified on the basis of the previous results achieved in correspondence of the mere implementation respectively of new HVAC systems (step 3) and RESs (first part of step 4);

Eventually, this step allows to:

- detect the cost-optimal combination between the replacement of the HVAC system and the installation of RES systems, when merely these retrofit actions are implemented.

2.6.3. Step 5. Implementation of EEMs^d

In this step, the effects of EEMs^d on PEC and GC are explored. In this regard, the SA performed in stage I (step 2) identifies the EEMs^d that have a significant influence on the annual value of energy demand (ED). This step considers only these EEMs^d because the remaining ones are generally not effective from both analyzed perspectives (PEC and GC). This conclusion is not rigorous, since some EEMs^d slightly affecting ED might have a higher influence on PEC and (mainly) GC assessment for some buildings. Nevertheless, a screening of the EEMs^d investigated in this step is fundamental in order to ensure a reasonable computational burden because all the possible combinations of EEMs^d are explored. The adopted criterion for screening, albeit not rigorous concerning the cost-optimal analysis, allows to achieve reliable global indications for the whole building category. Thus, the new sample set S_3 is generated through exhaustive sampling, in order to represent all the n_p possible packages (combinations) of the selected EEMs^d. S_3 has a framework similar to S_2 . It collects $n_p \cdot N_{\min}$ cases, which are composed of n_p groups of $N_{\min}$ cases. As aforementioned, $N_{\min}$ denotes the minimal RBS size that provides reliable results. Its value, detected in step 1, is here exploited. $N_{\min}$ cases are sufficient to represent the existing building stock, and consequently are also sufficient to represent the building stock in presence of the same retrofit package. Each of the n_p groups of S_3 gathers the same buildings represented by the first $N_{\min}$ cases of S_1 , in presence of one of the n_p possible EEMs^d packages, so that all packages are covered.

Hence, the potential savings in PEC and GC induced by the EEMs^d are investigated, by referring to S_3 . The analysis follows the logical order used in step 4.

First, the reference HVAC system is considered. The best packages of EEMs^d, as for PEC and GC savings, are detected in absence and in presence of state current incentives, in order to:

- evaluate the effectiveness of incentives directed to the considered EEMs^d;
- identify the cost-optimal package of EEMs^d, when only these energy retrofit actions are applied.

Then, PEC and GC savings are evaluated in correspondence of well-selected combinations of HVAC system, RESs and EEMs^d, in order to find the cost-optimal package of retrofit actions. Likewise step 4, the examined combinations are chosen on the basis of previous results. Eventually, this step allows to:

- detect the cost-optimal package of energy retrofit actions, including replacement of the HVAC system, installation of RES systems and implementation of EEMs^d; if different packages ensure similar values of GC savings, the thermal comfort can be used as discriminating criterion, on the basis of the results achieved in stage I (step 2).

3. Case study

For demonstration and testing purposes, SLABE is applied to a category with a large amount of statistical data available in current literature, namely office buildings built in South Italy in the period 1920–1970.

A research study performed by ENEA [73] (Italian national agency for new technologies, energy and sustainable economic development) provides a deep statistical analysis of structural characteristics and plant conditions of the Italian office building stock, which is composed of around 65,000 units. This study defines two RefBs respectively for office buildings built in the period 1920–1970 and from 1971 until now. Buildings built in the period 1920–1970 are explored in this study, because they are characterized by worse energy performance. Thus, the energy retrofit of these buildings can induce huge energy savings. Moreover, they represent a significant percentage (32.4%) of the national office building stock.

South Italy is chosen as geographical location for two main reasons. First, the scientific literature concerning the study of office buildings in South Italy is quite meager. Secondly, a high percentage (around 60%) of such building dates back before 1970 [73]. Thus, investigated buildings cover a wide segment of office buildings in South Italy and ensure high energy saving potentials, as aforementioned.

Finally, the explored building category is composed of around 8800 units. This is the number of office buildings built in South Italy (excluding islands) in the period 1920–1970. Islands are not considered because they are characterized by singular weather conditions.

The weather file of the city of Naples is used in EnergyPlus simulations. Naples is the second district in South Italy concerning the number of office buildings and thus the use of such weather file allows to cover rigorously a good percentage (around 8% [73]) of the buildings belonging to the considered category. It should be noted that the first district is Lecce, but Naples is preferred because of its climatic conditions, which are closer to average conditions in South Italy. Therefore, the results obtained for Naples can be extended to many other cities of South Italy with an acceptable approximation and, consequently, the adoption of the weather file

of Naples yields energy outcomes that are valid for a considerable part of the investigated category.

Definitely, the energy retrofit of the chosen category can have a significant impact on the reduction of energy consumption, and thus polluting emissions, at national level. Indeed, the category represents around 13% [73] of the whole Italian office building stock. Nevertheless, although the case study is very interesting, our main purpose is to propose SLABE as a new methodology that can be applied to any building category in order to ensure a more rigorous and robust cost-optimal analysis of energy retrofitting the existing building stock, compared to the RefB approach.

3.1. Reference building

The considered RefB, relative to office buildings built in South Italy in the period 1920–1970, has a rectangular shape, thus perfectly fits to SLABE. The structural frame is in reinforced concrete; the vertical walls are made of two layers of bricks separated by an air gap; a structure in mixed brick-reinforced concrete characterizes floor and roof. Table 2 shows the stratigraphy of these elements. The composition of internal walls and ceilings are not indicated by ENEA; thus, they are supposed to be made of 0.15 m thick concrete. The windows have single glasses and wooden frames ($U_w = 5.0 \text{ W/m}^2 \text{ K}$). Their height is equal to 1.5 m. There is no solar shading. All the other characteristics related to geometry, envelope and operation are reported in Table 3 (column denoted with RefB).

The definition of the HVAC system is not explicit, since only statistical data are reported by ENEA. Thus, this study is based on the following assumptions. Fan coils and hot water radiators are alternately considered as heating terminals, since the presence of one or the other can significantly affect energy performance and thermal comfort. Cooling terminals consist of fan coils, which allow to investigate different options of the primary cooling system. The primary heating system is a natural gas boiler, with nominal efficiency equal to 0.85, indicated with reference boiler (RB). The primary cooling system is an air-cooled chiller, with nominal EER (energy efficiency ratio) equal to 2.4, indicated with reference chiller (RC). There are not RES systems.

3.2. Existing building stock

As aforementioned, SLABE is limited to rectangular constructions. Thus, the buildings belonging to the investigated category are supposed to have a rectangular shape (Fig. 3a), constituted by equal height stories. Each floor is subdivided into five thermal zones in order to contemplate the different sun exposures, as shown in Fig. 3b.

The study of ENEA and the authors' expertise have allowed to detect the characteristic parameters affecting the energy behavior of the category's members, based on the recommendations reported in Section 2.5.1. In particular, the existing building stock is defined by the 46 parameters reported in Table 3: 9 for geometry, 30 for envelope and 7 other parameters. They are assumed as the most influencing energy performance and thermal comfort of the stock. Thus, other possible parameters (e.g., thermo-physical characteristics of plasters, screeds, tiles) are not contemplated, since they are considered insignificant. The thickness of the concrete of internal walls and ceilings (parameter p_{13}) is included in order to represent the internal thermal inertia. The study of ENEA does not provide exactly the ranges and distributions of the aforementioned characteristic parameters within the explored category, but reports the most popular configurations concerning building geometry, envelope – and thus size, construction type, materials – and HVAC system. Such analysis has led to the development of the described RefB, which presents average thermal-energy characteristics across

Table 2Reference building: stratigraphy of floor, external walls and roof. The values of solar absorptance (α) are indicated only for the external layers.

	t [m]	k [W/mK]	d [kg/m ³]	c [J/kg K]	R [m ² K/W]	α
Floor						
Cobblestone	0.18	0.70	1500	880	–	–
Floor block	0.18	0.66	1800	840	–	–
Clay	0.06	0.12	450	1200	–	–
Screed	0.03	0.90	1800	840	–	–
Tiles	0.02	1.00	2300	–	–	–
External walls						
External brick	0.12	0.72	1800	840	–	0.5
Air gap	0.20	–	1.03	1010	0.156	–
Internal brick	0.08	0.90	2000	840	–	–
Plaster	0.02	1.4	2000	820	–	–
Floor						
Cement	0.03	1.40	1000	–	–	0.5
Screed	0.03	1.40	400	1000	–	–
Expanded clay	0.05	0.27	900	1000	–	–
Roof block	0.22	0.66	1800	840	–	–
Plaster	0.02	0.70	800	1000	–	–

Table 3Characterization of the parameters describing the building stock: value assumed in the RefB; type of distribution in the stock; mean value (μ) and standard deviation (σ) for normal distributions; range of variability.

Parameters			RefB	Distribution	μ	σ	Range
Geometry	p_1	Orientation (North Axis)	0°	Uniform	–	–	0; ± 30 ; ± 60 ; 90
	p_2	Area of each floor [m ²]	216	Uniform	–	–	100–500
	p_3	Form ratio	1.5	Uniform	–	–	1–5
	p_4	Floor height [m]	3.4	Uniform	–	–	2.7–4.2
	p_5	Window to wall ratio: S	29%	Uniform	–	–	10–40
	p_6	Window to wall ratio: E	33%	Uniform	–	–	10–40
	p_7	Window to wall ratio: N	17%	Uniform	–	–	10–40
	p_8	Window to wall ratio: W	33%	Uniform	–	–	10–40
	p_9	Number of floors	2	Uniform	–	–	1; 2; 3; 4; 5
Envelope	p_{10}	Air gap R [m ² K/W]	0.156	Normal	RefB	0.01	0.116 $\div$ 0.196
	p_{11}	Roof α	0.5	Normal	RefB	0.2	0.1–0.9
	p_{12}	External walls α	0.5	Normal	RefB	0.2	0.1–0.9
	p_{13}	Thickness of concrete [m]	0.15	Normal	RefB	0.05	0.05–0.25
	p_{14}	Type of glass	Single	Uniform	–	–	Single/Double
	p_{15}	Type of frame	Wood	Uniform	–	–	Wood/Aluminum
	p_{16}	Clay t [m]	0.06	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{17}	Clay k [W/m K]	0.12	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{18}	Clay d [kg/m ³]	450	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{19}	Clay c [J/kg K]	1200	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{20}	Expanded clay t [m]	0.05	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{21}	Expanded clay k [W/m K]	0.27	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{22}	Expanded clay d [kg/m ³]	900	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{23}	Expanded clay c [J/kg K]	1000	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{24}	External brick t [m]	0.12	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{25}	External brick k [W/m K]	0.72	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{26}	External brick d [kg/m ³]	1800	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{27}	External brick c [J/kg K]	840	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{28}	Floor block t [m]	0.18	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{29}	Floor block k [W/m K]	0.66	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{30}	Floor block d [kg/m ³]	1800	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{31}	Floor block c [J/kg K]	840	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{32}	Internal brick t [m]	0.08	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{33}	Internal brick k [W/m K]	0.9	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{34}	Internal brick d [kg/m ³]	2000	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{35}	Internal brick c [J/kg K]	840	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{36}	Roof block t [m]	0.22	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{37}	Roof block k [W/m K]	0.66	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{38}	Roof block d [kg/m ³]	1800	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
	p_{39}	Roof block c [J/kg K]	840	Normal	RefB	0.2μ	$(\mu - 3\sigma) - (\mu + 3\sigma)$
Other	p_{40}	People density [people/m ²]	0.12	Normal	RefB	0.2μ	$(\mu - 2\sigma) - (\mu + 2\sigma)$
	p_{41}	Light load [W/m ²]	15	Normal	RefB	0.2μ	$(\mu - 2\sigma) - (\mu + 2\sigma)$
	p_{42}	Equipment load [W/m ²]	15	Normal	RefB	0.2μ	$(\mu - 2\sigma) - (\mu + 2\sigma)$
	p_{43}	Infiltration rate [h ⁻¹]	0.5	Normal	RefB	0.2μ	$(\mu - 2\sigma) - (\mu + 2\sigma)$
	p_{44}	Heating set point T [°C]	20	Normal	RefB	1	19–22
	p_{45}	Cooling set point T [°C]	26	Normal	RefB	1	24–27
	p_{46}	Heating terminals	Fc ^a /Rad ^b	Uniform	–	–	Fc/Rad

^a Fan coils.^b Hot water radiators.

Fig. 3. An example of the investigated rectangular geometries: (a) axonometric view; (b) plan view with specification of orientation and thermal zones.

the category. This RefB is exploited for defining the sample space to be explored.

More in detail, the mean values of characteristic parameters' distributions are set equal to the values assumed in the RefB, while the ranges and distribution types (see Table 3) are based on the statistical survey of ENEA and on the authors' experience. Also previous studies on UA applied to single buildings [56–58] have been taken into account, but ranges and distributions are different for a building stock. The uniform distribution is chosen when the probability that the parameter assumes a certain value is supposed constant for all the values of the range (e.g., geometry parameters). Diversely, when the parameter has a higher probability to take the value assumed in the RefB (e.g., most envelope parameters), a normal distribution centered on the value in the RefB is used. As shown in Table 3, the normal distributions present a confidence interval either equal to 95% (e.g., for other parameters) or higher than 99% (e.g., for envelope parameters) depending on the parameters' variability within the category. The ranges of variability are such to cover a huge segment of the stock.

3.3. Proposed energy retrofit actions

The proposed energy retrofit is based on three groups of actions: energy efficiency measures for the reduction of energy demand (EEMs^d), replacement of the HVAC system, RES systems. These measures are detailed below. Also the relative investment costs, needed for the evaluation of GC are indicated. They have been obtained through quotations from suppliers.

Eight EEMs^d, detailed in Table 4, are investigated. They are denoted with the letters from *a* to *h*. These EEMs^d introduce 18 new parameters. In particular, the presence or absence of the eight EEMs^d is encoded by the first eight Boolean parameters. Other nine parameters represent the thermo-physical characteristics of the thermal insulants. The values of *k*, *d* and *c* of the three insulants (EEMs^d *a*, *b*, *c*) vary according normal distributions and cover a great part of most used thermal insulants in building application. The insulation thicknesses are automatically deduced, in such a way to ensure the U values prescribed by Italian law to obtain state incentives, in case of refurbishment [74]. The last new parameter is related to the solar shading (EEM^d *g*). Shading is active if beam plus diffuse solar radiation incident on the window exceeds the solar set point, which varies according to an uniform distribution in the range 300–600 W/m², chosen to represent a broad segment of occupants' behavior.

Therefore, the renovated building stock is defined by 64 parameters.

Regarding the replacement of the HVAC system, the investigated options are described in Table 5, which also recalls the characteristics of the reference systems. The hourly performance curves of these systems – provided by suppliers – have been implemented in MATLAB®.

Finally as for RESs, photovoltaic (PV) panels are considered, since solar energy is one of the most advantageous RESs in Europe [75], and particularly in Italy because of favorable climatic conditions. PV panels are preferred to solar thermal because they are more cost-effective [29], in particular for office buildings. In fact, the demand of electricity is predominant, so that PV panels ensure high energy saving potentials. On the other hand, the demand of DHW is very low; thus, the best application of solar thermal is limited. In this study, PV panels are characterized by 34° tilt angle and 0° azimuth angle (orientation to south), in order to achieve the maximum annual production of electricity, as verified by means of PV-GIS Software [76]. They have conversion efficiency equal to 14% and investment cost (including inverter and installation) equal to 5 €/W.

4. Results and discussion

The results are organized in sections and subsections – which follow the steps described in the Methodology (Section 2) – in order to provide a clear and systematic study of the building stock.

4.1. Stage I. Investigation of energy demand (ED) and discomfort hours (DH)

Energy demand and thermal comfort (more precisely, the percentage of discomfort hours) are investigated for both heating and cooling seasons, by means of UA and SA, in two steps:

- step 1 refers to the existing building stock (step 1);
- step 2 refers to the renovated building stock.

4.1.1. Step 1. Analysis of the existing building stock

The existing building stock is defined by 46 characteristic parameters, whose sampling determines the generation of the set *S*₁, which corresponds to the category's RBS. As aforementioned, the investigated building category is composed of around 8800 buildings. Therefore, it is clear that the RBS size should be lower than 8800. In this regard, an important factor relevant to the sample generation is the ratio *r* between the number of sampled cases (*N*) and the number of characteristic parameters (*n*). Most studies on UA and SA applied to buildings [56–58] used *r* values in the

Table 4Energy efficiency measures for the reduction of energy demand (EEMs^d) and associated parameters.

EEM ^d	DESCRIPTION	INVESTMENT COST	BOOLEAN PARAMETERS ⁽¹⁾	ADDITIONAL PARAMETERS		
				DESCRIPTION	DISTRIBUTION	
a) Insulation of the vertical walls	the thickness (t_v) ensures $U=0.34 \text{ W/m}^2 \text{ K}$	$500 - 3000 \times t_v$ $\text{€}/\text{m}^3$ ⁽²⁾	p ₄₇	0		
				1	p ₅₅ k [W/mK]	normal ⁽³⁾ with $\mu=0.04$
					p ₅₆ d [kg/m ³]	normal with $\mu=15$
b) Insulation of the roof	the thickness (t_r) ensures $U=0.32 \text{ W/m}^2 \text{ K}$	$500 - 3000 \times t_r$ $\text{€}/\text{m}^3$ ⁽²⁾	p ₄₈	0		
				1	p ₅₈ k [W/mK]	normal with $\mu=0.04$
					p ₅₉ d [kg/m ³]	normal with $\mu=15$
c) Insulation of the floor	the thickness (t_f) ensures $U=0.40 \text{ W/m}^2 \text{ K}$	$500 - 3000 \times t_f$ $\text{€}/\text{m}^3$ ⁽²⁾	p ₄₉	0		
				1	p ₆₁ k [W/mK]	normal with $\mu=0.04$
					p ₆₂ d [kg/m ³]	normal with $\mu=15$
d) Low-a plastering of the vertical walls	the absorption coefficient to solar radiation (a) is 0.05	20 €/m ²	p ₅₀	0		
				1		
e) Low-a plastering of the roof	the absorption coefficient for solar radiation (a) is 0.05	20 €/m ²	p ₅₁	0		
				1		
f) Replacement of the windows	double-glazed low-e windows with PVC frame ($U_w=1.8 \text{ W/m}^2 \text{ K}$)	250 €/m ²	p ₅₂	0		
				1		
g) External shading	diffusive blinds, solar and visible transmittances equal to 0.5	50 €/m ²	p ₅₃	0		
				1		
h) Free cooling by means of mechanical ventilation	in the cooling season (nights), ACH = 2 h ⁻¹	10 €/m ²	p ₅₄	0		
				1	p ₆₄ shading set point [W/m ²]	uniform within the range 300÷600

⁽¹⁾Each Boolean parameter assumes the value of 0 if the relative EEM^d is absent, 1 if present.⁽²⁾The symbol (–) stands for minus.⁽³⁾All the normal distributions are characterized by $\sigma=0.1 \mu$ and range $\equiv (\mu - 2\sigma) - (\mu + 2\sigma)$.

range $r=2-5$. In this study, a higher r value is used for the following reasons:

- a building category is considered and thus the parameters' ranges of variability are higher;
- the authors want to investigate which is the minimum RBS size ($N_{\min}$) that ensures reliable, representative results for the whole category; the r value in correspondence of $N_{\min}$ is denoted as $r_{\min}$.

Therefore, 500 (N) cases (building model instances) are generated via LHS in order to build the sample S_1 (RBS), resulting in a r value equal to 10.9. For each of these 500 cases, an EnergyPlus simulation (automatically launched by MATLAB[®]) is performed, thereby achieving the four PIs explored in this stage, namely the values of energy demand and percentage of discomfort hours in the heating (ED_h and DH_h) and cooling season (ED_c and DH_c), respectively. Such outcomes are investigated in order to verify whether

Table 5

Investigated options for the HVAC system.

Description			Investment cost [€]
Heating system			
RB	Reference boiler	Existing natural gas boiler, nominal LCV ^a efficiency equal to 0.85	–
EB	Efficient boiler	New natural gas boiler, nominal LCV efficiency equal to 0.95	45 × kW _p + 1500
CB	Condensing boiler	Condensing natural gas boiler, nominal LCV efficiency ($T_w^b=35/55^\circ\text{C}$) equal to 1.06	80 × kW _p + 1900
HP	Heat pump	Air–water heat pump, nominal COP ($T_w=40/45^\circ\text{C}$; $T_e^c=7^\circ\text{C}$) equal to 3.7	150 × kW _p + 5000
Cooling system			
RC	Reference chiller	Existing air-cooled chiller, nominal EER ($T_w=12/7^\circ\text{C}$; $T_e=35^\circ\text{C}$) equal to 2.4	–
ACC	Efficient air-cooled chiller	New air-cooled chiller, nominal EER ($T_w=12/7^\circ\text{C}$; $T_e=35^\circ\text{C}$) equal to 3.5	150 × kW _p + 5000
WCC	Water-cooled chiller	Water-cooled chiller with cooling tower, nominal EER ($T_w=12/7^\circ\text{C}$; $T_c^d=28^\circ\text{C}$) equal to 5.0	250 × kW _p + 8000

^a Lower calorific value.^b Water inlet/outlet temperatures.^c External temperature.^d Water inlet temperature to condenser.

Fig. 4. Mean values (a) and standard deviations (b) of the PIs, in function of the number of sampled cases, for the existing building stock (S_1).

the adopted value of N is sufficient, and eventually which is the value of N_{min} . More in detail, the trends of mean values and standard deviations related to the four PIs in function of the number of sampled cases are analyzed, as depicted in Fig. 4. This shows that the stabilization of the PIs starts to occur after 100 sampled cases demonstrating that a r value just higher than 2 is sufficient for the representation of the considered building category. Therefore, N_{min} is approximately equal to 100 resulting in a value of r_{min} around 2.2. However, this step considers all 500 cases, since the simulations have been already performed: thus, higher accuracy and reliability are ensured. Nevertheless, in future applications of SLABE to other building categories (or in similar studies) the detected value of r_{min} can be exploited in order to set the RBS size.

The values assumed by the four PIs in correspondence of the 500 simulations are depicted in the histograms of Fig. 5, where the dots represent the values obtained for the RefB. In particular, the distinction between the presence of hot water radiators (rectangular dot) and fan coils (circular dot) is made as regards the heating season (Fig. 5a and c). Furthermore, the normal distributions that approximate the four sets of PI values are reported.

The values of the PIs for the RefB are very close to the mean values of the distributions, showing that the RefB is able to gather the average characteristics of the building category. However, a strong dispersion of results occurs in each case, so that the RefB can represent only a very limited part of the stock, although the HVAC system is not even considered yet. In fact, an error higher than 100% can be committed, by using the RefB to evaluate energy demand and thermal comfort for other buildings belonging to the category. Furthermore, Fig. 5c confirms that the type of hydronic terminals mainly affects DH_h , since a discontinuity in the distribution of such PI occurs, due to the alternation between radiators and fan coils.

The performed UA is followed by the SA, in order to detect the most relevant parameters. The values of the SRRC are calculated for the three groups of parameters in relation to the four PIs. These sensitivity indices are shown in Figs. 6–8 respectively for geometry, envelope and other parameters: figures a refer to the energy demand, figures b refer to the discomfort hours.

First, it should be noted that the SRRCs achieved for all groups are consistent with thermo-physical considerations, as argued below for some parameters.

Geometry parameters exercise the strongest influence on PIs; among them, the highest values of the SRRCs (Fig. 6) occur in correspondence of *number of floors* (N_F) and *area of each floor* (A_F). This happens because these two parameters greatly affect the ratio S/V between the external surface and the conditioned volume as well as the entity of solar gain. In particular, S/V decreases when N_F increases, considering the other parameters constant. This represents a clear benefit during the heating season, confirmed by the negative values of the SRRCs related to ED_h and DH_h . This phenomenon, on the contrary, is adverse in the cooling season

Fig. 5. Distributions of the values assumed by the PIs in the existing building stock (S_1): (a) ED_h ; (b) ED_c ; (c) DH_h ; (d) DH_c .

Fig. 6. Standard rank regression coefficients (SRRCs) for the geometry parameters in relation to: (a) energy demand (ED_h and ED_c); (b) discomfort hours (DH_h and DH_c).

(SRRCs > 0 for ED_c and DH_c), since it reduces the rate at which the high internal gain is dissipated. As regards A_F , when it increases, two main effects occur: both the ratio S/V and the incidence of solar gain decrease with conflicting consequences on the PIs. The first effect prevails in the heating season, the second one during the cooling season; this explains the negative values assumed by all the SRRCs in correspondence of this parameter.

Envelope parameters have the lowest influence on PIs; in fact only the *roof solar absorptance*, the *walls solar absorptance*, the *thickness* and *conductivity of internal brick*, *external brick*, *roof block* and *clay*, as well as the *type of glass*, are significant (Fig. 7), while the other parameters can be neglected in further analyses ($|SRRC| < 0.05$ for all PIs). However, the mentioned envelope parameters – albeit not negligible – provide quite lower values of the SRRCs, compared

Fig. 8. Standard rank regression coefficients (SRRCs) for the other parameters in relation to: (a) energy demand (ED_h and ED_c); (b) discomfort hours (DH_h and DH_c).

to the other two groups of parameters. This outcome is mainly due to the high ventilation rate required in office buildings, which covers a wide part of energy demand, so that building energy performance is slightly affected by the envelope. The *specific heat* of materials and the *thermal internal inertia* provide the lowest SRRCs, because of the characteristics of examined buildings, notably the lightweight structure and the high *window to wall ratio*.

At last, most parameters belonging to the third group (Fig. 8) present not negligible values of the SRRCs. As expected, among these, the *set point temperatures* have the greatest influence on energy demand and thermal comfort. The positive value of the SRRC based on ED_h for *people density* could appear strange: actually, it occurs because the required ventilation rate increases when this parameter increases.

Fig. 7. Standard rank regression coefficients (SRRCs) for the envelope parameters in relation to: (a) energy demand (ED_h and ED_c); (b) discomfort hours (DH_h and DH_c).

Fig. 9. Mean values (a) and standard deviations (b) of the Pls, in function of the number of sampled cases, for the renovated building stock (S_2).

4.1.2. Step 2: Analysis of the renovated building stock

The following EEMs^d are investigated, as described in Section 3:

- insulation of the external vertical walls;
- insulation of the roof;
- insulation of the floor;
- low-a plastering of the external vertical walls;
- low-a plastering of the roof;
- installation of double-glazed low-e windows with PVC frame;
- implementation of external shading of the windows;
- achievement of night free cooling, by means of mechanical ventilation.

The renovated building stock is characterized by 64 parameters. Specifically, in addition to the 46 ones describing the existing buildings, there are eight Boolean parameters (one for each EEM^d), nine parameters related to the characteristics of thermal insulants and one parameter related to the shading set point. The sampling (LHS) of these 64 parameters generates the sample S_2 , consisting of 500 cases alike S_1 . In particular, S_2 represents the same building instances of S_1 , but in presence of one or more of the eight EEMs^d.

Hence, other 500 EnergyPlus simulations are performed in order to assess the values of the four Pls investigated in this stage – i.e., ED_h , ED_c , DH_h and DH_c – for the cases collected in S_2 . The same analysis of step 1 is conducted to verify if the number of 500 cases is sufficient to achieve good results. The trends of mean values and standard deviations related to the four Pls in function of the number of sampled cases are investigated, as depicted in Fig. 9. This shows that also for the renovated building stock, 500 cases are sufficient to generate a reliable representative sample, since the stabilization of the Pls occur.

Definitely, the investigation of sample S_2 , composed of 500 cases, allows to quantify the global impact of the EEMs^d, thereby detecting the most influential ones on building energy performance. This worthy outcome derives from a careful selection of the EEMs^d, based on authors' expertise, best-practice and local constructive standards. If too many EEMs^d with wide ranges of variability are considered, there is the risk that N cases are not sufficient for representing the renovated building stock. In such cases,

a higher size for both S_1 and S_2 , which must have the same size for allowing the comparison, would be necessary.

The histograms of Fig. 10 show the comparison between the values assumed by the four Pls respectively in the existing building stock (S_1) and in the renovated stock (S_2).

As expected, the EEMs^d induce a desired reduction of the mean values of all Pls. However, the improvement related to ED_c (see Fig. 10b) is very slight compared to the other Pls. The reason is that some EEMs^d – mainly those related to thermal insulation (a, b, c) – have a negative effect on the cooling demand because of the magnitude of internal gain. Thus, most EEMs^d produce insignificant benefits on the annual values of energy demand, by virtue of the high relevance assumed by the cooling season for the considered case study.

These observations are confirmed by the values of the SRRCs evaluated for the 8 Boolean parameters representing the described EEMs^d, in correspondence of ED_h , ED_c (Fig. 11a), DH_h , DH_c (Fig. 11b) and ED , DH (Fig. 11c). The EEMs^d a, b, c induce unfavorable effects in the cooling season, since they provide positive SRRCs for ED_c and DH_c ; the opposite occurs for the EEMs^d e, f, g, h, which yield negative SRRCs in correspondence of these two Pls. These conflicting effects are balanced as for ED_c , while the benefits prevail as for DH_c . That's why the EEMs^d lead to a significant improvement of DH_c (Fig. 10d) and not of ED_c (Fig. 10b). On the other hand, the advantages induced by thermal insulation of external walls and roof (EEMs^d a, b) during the heating season are predominant for both energy demand and thermal comfort. This is demonstrated by the high absolute values of the SRRCs (which are negative), related to ED_h and DH_h , in correspondence of these EEMs^d. That is why the EEMs^d lead to a significant improvement of both ED_h (Fig. 10a) and DH_h (Fig. 10c).

Overall, the EEMs^d most affecting the four seasonal Pls are the insulation of walls and roof, but they have conflicting effects in the heating and cooling seasons; in fact, only new low-e windows ensure a positive result in both seasons, since they simultaneously induce an increase of thermal resistance and of reflectance to solar radiation.

Therefore, as predicted, Fig. 11c shows that the proposed EEMs^d do not have a strong influence on the annual values of thermal comfort and, mainly, energy demand. This occurs for two aforementioned reasons, here recalled: first, in most cases, there are opposite seasonal repercussions and, secondly, a significant percentage of energy demand for office buildings is affected by ventilation, independently of the characteristics of the envelope.

Only the four EEMs^d e, f, g, h – namely low-a roof plastering, low-e double glazed windows, solar shading and free cooling – have a not negligible advantageous effect on annual energy demand. On the other hand, among these, only f and g induce an improvement – albeit slight – of the annual value of discomfort hours, while e and h are irrelevant. In fact, the annual assessment of thermal comfort is mainly affected by the thermal insulation of the envelope (see Fig. 11c), since this measure has a positive effect on the mean radiant temperature of the walls, not only in the heating season but also during the intermediate seasons.

4.2. Stage II. Investigation of primary energy consumption (PEC) and global cost (GC)

The achievable savings in PEC and GC compared to the current configuration of the building stock are investigated. The exploration follows three steps:

- step 3 contemplates the mere replacement of the primary heating/cooling system;
- step 4 introduces the installation of RES systems, in particular photovoltaic (PV) panels;

Fig. 10. Distributions of the values assumed by the PIs in the existing building stock (S_1) and in the renovated stock (S_2): (a) ED_h ; (b) ED_c ; (c) DH_h ; (d) DH_c .

- step 5 introduces the implementation of EEMs^d, in order to find the cost-optimal package of energy retrofit actions.

For PEC evaluation the primary energy factor is set equal to 1 for natural gas and to 2.18 for electricity, according to Italian standards. Different metrics can be adopted, such as *energy per building* [MWh/a] and *energy per area* [kWh/m² a]. The second one is more used in building applications and recommended by the EPBD Recast, but the first one is more appropriate to this study because it allows a rapid estimation of the potential PEC saving in the whole building stock. Furthermore, as verified by the authors, the trends are similar, so that the observations made for *energy per building* are generally also valid for *energy per area*. Thus, the first metric is used hereinafter.

For GC evaluation, a calculation period of 20 years is used, as prescribed by the Guidelines [59] of the EPBD recast for non-residential buildings. The prices of electricity and natural

gas, considered constant, are set equal to 0.25 €/kWh_{el} and 0.90 €/Nm³, respectively [77].

Table 6 reports mean value and standard deviation of PEC and GC for the buildings belonging to S_1 (existing building stock).

4.2.1. Step 3. Replacement of the primary heating/cooling system

The analysis of savings in PEC and GC is initially carried out considering the mere replacement of the primary heating/cooling (HVAC) system. Therefore, the sample S_1 is considered in this step. As aforementioned, the RefB is characterized by a natural gas boiler (reference boiler: RB) and an air-cooled chiller (reference chiller: RC), while the proposed options for the replacement of the system (see Table 5) are listed below:

- efficient boiler (EB), condensing boiler (CB), heat pump (HP) for heating generation;
- efficient air-cooled chiller (ACC), water cooled-chiller (WCC) for cooling generation.

Fig. 11. Standard rank regression coefficients (SRRCs) for the proposed EEMs^d in relation to: (a) energy demand (ED_h and ED_c); (b) discomfort hours (DH_h and DH_c); (c) annual values (ED and DH).

Table 6Mean value and standard deviation of PEC and GC for the sample S_1 (existing building stock).

	Primary energy consumption [MWh/a per building]		Global cost [k€ per building]	
	Mean value	Standard deviation	Mean value	Standard deviation
Set S_1 Existing stock (500 cases)	73.5	45.6	157	98.5

Thus, twelve configurations of the HVAC system are investigated, including RB and RC.

Fig. 12 depicts the potential savings in PEC and GC in correspondence of these configurations, in absence of state incentives, respectively in presence of fan coils (Fig. 12a) and hot water radiators (Fig. 12b). In this step, the results are examined separately for these two subsets – characterized by 250 cases each – since the type of terminal highly affects the performance of the heating generation system. The observations on the cooling system are obviously the same for the two subsets, since only a type of cooling terminal is considered, namely fan coils.

Fig. 12 shows that both PEC and GC are highly influenced by the type of cooling system, since the cooling demand is predominant for office buildings in Naples. Thus, the best cooling system from both perspectives is the most efficient one, which is WCC. On the contrary, the congruency between the two analyzed perspectives is not always ensured as for the heating system, as argued below for the two subsets.

As expected, the presence of fan coils leads to higher values of PEC savings, mainly in correspondence of CB and HP. This occurs because of the lower temperature of inlet hot water for fan coils compared to radiators. On the contrary, GC savings are maximized

Fig. 12. Savings in PEC (mean values) and GC in case of the mere replacement of the HVAC system with no incentives, respectively in presence of fan coils (a) and hot water radiators (b).

Fig. 13. Savings in PEC (mean values) and GC in case of the mere replacement of the HVAC system with current incentives, respectively in presence of fan coils (a) and hot water radiators (b).

by RB and EB. Indeed, cost savings are ensured for about 75% of buildings using one of these two boilers together with the WCC, so that the probability that one of these two configurations will be implemented is very high. In this way, the larger potential energy savings guaranteed by CB and HP will be wasted. On the other hand, the radiators induce lower values of energy savings and ergo cost savings. The higher temperature of inlet hot water causes a deterioration of system efficiency mainly for CB and HP. This leads to a greater congruence between the energy and cost perspectives, in presence of radiators. Indeed, the EB represents an optimal compromise, since it is very close to both the best solutions respectively related to PEC (CB) and GC savings (RB).

At this point, the same analysis is carried out by considering current state incentives. The current incentives provided by Italian Government modify significantly the values of GC savings in presence of CB and HP (Fig. 13), which benefit from a capital grant, accorded in ten years, covering the 65% of the investment cost [78]. Instead, there are no incentives for cooling systems, so that the WCC remains the best solution from both perspectives. Thus, the attention is hereinafter focused on the heating system. Obviously

the values of PEC savings do not change compared to the case of absence of incentives.

The cost-optimal HVAC system is composed of WCC and CB, both in presence of fan coils (Fig. 13a) and radiators (Fig. 13b), while the highest PEC savings occur in correspondence of WCC–HP for fan coils and WCC–CB for radiators. Thus, current incentives are fine in the case of radiators since the two solutions match, but they are not effective in the case of fan coils, because they do not support enough the heat pumps, which can induce huge energy savings.

4.2.2. Step 4. Installation of RES systems (PV panels)

Once the best configurations of the HVAC system are identified, the implementation of PV panels is investigated. At first, the savings in PEC and GC are assessed in presence of RB and RC, in function of the percentage of PV power (area of PV panels) compared to the maximum installable power (maximum area) on the buildings' roofs. The whole sample S_1 is considered in this step. The mentioned savings are represented in Fig. 14, in the cases of:

Fig. 14. Savings in PEC (mean values) and GC in function of the percentage of PV power compared to the maximum installable power, in presence of RB and RC, respectively with no incentives (a) and current incentives (b).

- absence of incentives (Fig. 14a);
- presence of current state incentives, which cover (in ten years) the 50% [78] of the investment cost for PV panels (Fig. 14b).

The implementation of PV maximum power induces huge energy savings but it is very likely that, in absence of incentives, most buildings will install only a limited part (20–30%) of the available power, in order to achieve higher cost savings. Instead, current incentives support the installation of the maximum PV power, by ensuring GC savings for the whole building stock. Indeed the maximum power (100%) represents the cost-optimal configuration of PV panels. Therefore, current incentives are effective.

As regards the explored building category, the greatest part of electricity produced by PV panels is absorbed by lights and electrical equipment, since these provide a significant energy demand in office buildings. Thus, the replacement of the HVAC system and the implementation of PV panels can be considered as independent from an energy point of view. In other words, the installation of PV panels induces comparable PEC and GC savings for all the twelve HVAC configurations. Therefore, the cost-optimal combination of PV and HVAC system is provided by the installation of the maximum PV power and of the cost-optimal HVAC option, identified in the case of mere replacement of the HVAC system, namely WCC and CB in both cases of fan coils and radiators. These observations are confirmed by Fig. 15, which depicts the savings in PEC and GC provided by the adoption of WCC and CB, in function of the percentage of installed PV power, in presence of current incentives.

4.2.3. Step 5. Implementation of EEMs^d

As shown by SA in Section 4.1.2, only four EEMs^d have a positive impact on annual energy demand (Fig. 11c), so that they can reduce PEC and GC. Thus, only these EEMs^d are here considered. In particular, they consist of:

- (e) low-a plastering of the roof;
- (f) installation of double-glazed low-e windows with PVC frame;
- (g) implementation of external shading of the windows;
- (h) achievement of night free cooling, by means of mechanical ventilation.

At this point, a new sample set S_3 is needed to consider the implementation of the 15 packages deriving from the combination of the EEMs^d e, f, g and h. Involved parameters are here 51, including 46 for buildings' description, 4 (Boolean parameters) for EEMs^d and 1 for shading set point. The exhaustive sampling of these 51 parameters generates the sample S_3 of 1500 cases, which are composed of 15 groups of 100 cases. Each group corresponds to a package of EEMs^d and collects a number of cases equal to $N_{\min}$ that is equal to 100 (see Section 4.1.1).

Hence, the potential savings in PEC and GC refer to S_3 . At first, these savings are assessed for all the considered packages of EEMs^d in presence of RB and RC, respectively:

- in absence of incentives (Fig. 16a);
- in presence of current incentives (Fig. 16b); among the considered EEMs^d, only the installation of low-e windows (EEM^d f) is

Fig. 15. Savings in PEC (mean values) and GC, in function of the percentage of PV power compared to the maximum installable power, provided by the cost-optimal HVAC system (CB + WCC) with current incentives.

supported by a capital grant that covers the 65% (in ten years) [78] of the investment cost.

The mere implementation of EEMs^d packages induce lower PEC savings compared to the other retrofit actions, because of the discussed characteristics of the building category. The EEM^d most affecting PEC is the installation of low-e windows, followed by the

solar shading, the roof low-a plastering and the implementation of free cooling. This confirms the results of the sensitivity analysis: the EEMs^d with higher absolute values of the SRRC related to annual energy demand (see Fig. 11c) have a higher influence on PEC. This outcome is not obvious, since thermal energy demand causes only a part of PEC. In fact, the replacement of the windows and the solar shading have very close values of the considered SRRC but the first

Fig. 16. Savings in PEC (mean values) and GC provided by the packages of EEMs^d in presence of RB and RC, respectively with no incentives (a) and current incentives (b).

Fig. 17. Savings in PEC (mean values) and GC for the cost-optimal combination of HVAC system (CB + WCC) and PV panels (100%), with current incentives, for the investigated packages of EEMs^d.

EEM is much more influential on PEC; this occurs because solar shading induces an increase of energy consumption for lighting, which represents another part of PEC.

Although the installation of low-e windows is the EEM^d that induces the highest energy savings, it is not cost-effective in absence of incentives. Instead, current incentives ensure GC savings for about the 50% of buildings that implement only this energy measure. However, the resulting PEC saving in the stock is much slighter than that produced by new efficient HVAC systems and RESs. Thus, it does not justify the huge state disbursement required by such financial grants. For this reason, current incentives addressed to new insulating windows are considered not effective, in relation to the investigated building category.

The GC savings provided by the packages of EEMs^d decrease with increasing the number of measures. Most packages are not cost-effective for the majority of explored sampled cases. In particular, in presence of incentives, only low-e windows, low-a roof and their combination ensure cost savings for more than half of the cases. The cost-optimal package includes only the low-a plastering of the roof that induces GC savings for the 75% of the stock.

Since the EEMs^d have a slight influence on PEC compared to the previous retrofit actions, their implementation does not alter the cost-optimal combination of HVAC system and PV panels, which includes CB, WCC and maximum PV power. Thus, the potential savings in PEC and GC provided by the packages of EEMs^d are calculated in correspondence of such combination, applied to the building instances gathered in S_3 . The outcomes, related to the existence of current incentives, are depicted in Fig. 17.

As anticipated, the mean increase of PEC saving per building (maximum value of 8.9 MWh/a) is slight compared to the mean saving induced by the replacement of the HVAC system and the implementation of PV panels (63.3 MWh/a). This shows that the EEMs^d do not lead to substantial energy benefits, once improved the heating/cooling/electricity generation system.

Furthermore, none of the EEMs^d introduces evident GC savings, so that the best choice for the buildings' owners is to not implement them. Thus, the cost-optimal package of energy retrofit actions for most category's members is represented by the mere installation of the cost-optimal combination of HVAC system and PV panels, namely CB, WCC and maximum PV power. This retrofit package implies a PEC saving equal to 63.3 MWh/a per building, resulting in a global potential saving across the category (if the package is implemented to all category's members) around 550 GWh/a.

In conclusion, once improved the heating/cooling/electricity generation system, the implementation of EEMs^d is not convenient from both energy and cost perspectives. These considerations are valid for office buildings in Naples and in other localities of South Italy with similar climatic conditions, where the energy demand for cooling is predominant.

5. Conclusions

A multi-stage methodology has been developed in order to investigate the implementation of energy actions for the retrofitting of buildings belonging to the same category. The effects of these actions on primary energy consumption (PEC) and global cost (GC) are explored in order to achieve two main objectives:

- to detect the package of actions that produces the cost-optimality for most buildings of the category;
- to evaluate the effectiveness of current policy of state incentives directed to such actions.

The methodology is based on uncertainty (UA) and sensitivity (SA) analyses, carried out via the coupling between EnergyPlus and MATLAB[®]. Thus, it is denoted as "Simulation-based Large-scale uncertainty/sensitivity Analysis of Building Energy performance" (SLABE). The main originality of this novel methodology is performing cost-optimal analysis by representing a building category by a Representative Building Sample (RBS), instead of only one Reference Building as stipulated by the EPBD Recast. Therefore, an original bottom-up approach, based on detailed energy simulations, is adopted in stock modeling. SLABE consists of two main stages, which are subdivided in two and three steps, respectively.

- Step 1 (stage 1) the existing building stock is investigated in order to identify the optimal size of RBS (by UA) and the parameters (related to geometry, envelope and other) most affecting thermal energy demand for micro-climatic control and thermal comfort (by SA).
- Step 2 (stage I): some energy efficiency measures for the reduction of thermal energy demand (EEMs^d) are proposed based on outcomes of step 1, category's peculiarities and best-practice; their impact on energy demand and thermal comfort is explored (by UA) and the most influential measures are detected (by SA).

- Step 3 (stage II): the implementation of new efficient HVAC systems is investigated by assessing the impact on PEC and GC; this step allows to estimate the effectiveness of state incentives for HVAC systems and to identify the cost-optimal HVAC configuration.
- Step 4 (stage II): the implementation of RESs is investigated by assessing the impact on PEC and GC; this step allows to estimate the effectiveness of state incentives for RESs and to identify the cost-optimal combination of HVAC system and RESs.
- Step 5 (stage II): the implementation of the most influential EEMs^d, identified in step 2, is investigated, by assessing the impact on PEC and GC; this step allows to estimate the effectiveness of state incentives for EEMs^d and to identify the cost-optimal package of energy retrofit actions, including HVAC system, RESs and EEMs^d.

As a case study, SLABE is applied to a specific category: office buildings built in South Italy in the period 1920–1970. The results imply the following conclusions for the examined stock.

- The minimum RBS size that ensures a reliable sample is approximately equal to 100 cases, resulting in a ratio between the number of sampled cases and the number of characteristic parameters around 2.2.
- A strong dispersion of the values assumed by energy demand and thermal comfort occurs; thus, the reference building cannot provide reliable results for all the buildings of the category (an error higher than 100% can be committed), although the investigated category is quite restricted.
- The energy performance is mainly affected by geometry parameters (in particular *number of floors* and *area of each floor*) and other parameters (in particular *set point temperatures*), while most of the envelope parameters are negligible. This occurs because of the magnitude of the ventilation load.
- The most influential EEMs^d on annual energy demand are: the low- α plastering of the roof, the installation of double-glazed low-e windows, the implementation of external shading of the windows, the achievement of night free cooling by means of mechanical ventilation. On the contrary, they are almost irrelevant to the annual value of discomfort hours, which is mainly reduced by the thermal insulation of the envelope. However, this latter EEM^d even produces a slight increase of energy demand, by virtue of the high relevance assumed by the cooling season.
- The incentives provided by current state policy are effective for condensing gas boilers and photovoltaic (PV) panels. Instead, they are inefficient for heat pumps and thermal insulated windows: in the first case, they do not support enough the implementation of heat pumps, while, in the second case, the restricted induced energy saving does not justify the huge state disbursement.
- The cost-optimal package of energy retrofit actions for most buildings of the stock does not include EEMs^d, but it is represented by the mere installation of the cost-optimal combination of HVAC system and PV panels, namely condensing boiler, water-cooled chiller and maximum installable PV power.
- The cost-optimal retrofit package implies a PEC saving equal to 63.3 MWh/a per building, resulting in a global potential saving across the category (if the package is implemented to all category's members) around 550 GWh/a.

6. Future developments

Future studies will concern the application of SLABE to other building categories in order to detect the influence of climatic conditions (location), functionality and construction type on

the cost-optimal package of retrofit actions. Furthermore, the investigation of the best strategy of incentives to address to such actions will be deepened in order to identify the optimal state policies that produce the maximum ratio between potential energy saving and state disbursement.

A worthy development of this study could consist in the comparison between SLABE versus a simulation-based multi-objective (Pareto) optimization approach, as the one adopted by some of these authors in [25,27–29,32,34,35]. However, such optimization methodology is quite time-consuming and thus it cannot be applied to all category's members. Thus, it could be implemented only to the RefB by finding out the retrofit packages that minimize energy consumption and global cost (points on the Pareto front), thereby comparing this packages versus those provided by SLABE.

Finally, a possible interesting enhancement of the methodology concerns the development of surrogate models [51,57,59,79–81] (e.g., artificial neural networks) valid for a whole building category. These would enable a fast (computationally cheap) prevision of the energy behavior of each category's member, in function of the most significant parameters and energy actions detected by means of SLABE. Then, the surrogate models could be integrated in multi-objective optimization algorithms, as done in [79–81], in order to provide the actual cost-optimal retrofit package for each single building of the category. This combination between SLABE, surrogate models and optimization algorithms would allow to overcome the main limit of SLABE, which consists in the impossibility of obtaining detailed indications on the cost-optimal energy retrofit strategy for each single building, since global recommendations about the investigated category are provided.

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