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Financial and energy performance analysis of efficiency measures in residential buildings. A probabilistic approach

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A B S T R A C T

The present paper presents a methodology to effectively address the evaluation of building energy retrofitting projects in a highly uncertain context. Buildings are modelled in terms of archetypes which are characterized by specific features, e.g., U-values, heating plant typology, surface to volume ratio, etc. By using the Monte Carlo approach, the proposed method can address the influence of more than thirty important parameters on the final result in terms of energy savings, Net Present Value and other indices aimed to quantify the level of risk associated to complex energy efficiency interventions, e.g., energy saving at risk. The methodology is tested on a case study related to a building built in the '60s and located in Rome, Italy. However, the method is applicable irrespectively of the location, climatic conditions, and typology of the building. Results highlight that a retrofitting intervention consisting in wall insulation has a risk to be unprofitable equal to 47%. This can be ascribed to the mild climatic conditions of the location.

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1. Introduction

Buildings are one of the most relevant sectors to implement energy efficiency measures, in fact at EU level they represent about 40% of final energy consumption and the share of the residential segment accounts for about 25% [1]. Similar figures are also reported for the US market [2].

Due to this opportunity, as illustrated by Annunziata et al. [3], different countries promoted regulations to support the transition towards the so-called "nearly zero energy buildings".

The aim of the proposed regulatory frameworks is to support and drive the deployment of renovations to reduce energy consumption and mitigate the environmental impact of the buildings sector.

In particular, the highest saving potential is to be found in existing buildings which can be retrofitted to improve their energy performance. To this aim, it is necessary to implement accurate evaluations suggesting the most appropriate and advisable measures, from both the energy and the financial points of view.

During the last years, many authors tried to address these problems and many studies can be found in the literature. For example, Ascione et al. [4] developed an analysis to optimize building envelope design by minimizing energy consumption, investment costs and occupants' discomfort. Similarly, Bianco et al. [5] determined the energy demand of residential buildings located in different climatic areas. They analysed the impact on energy demand of different parameters, namely wall insulation, orientation, windows surface, and thermal capacity. Likewise, Krarti et al. [6] evaluated different energy efficiency options for various building typologies in Saudi Arabia. Detailed estimations on achievable savings are proposed even in the presence of highly subsidized energy prices. They found that the implementation of cheap measures in the residential sector can guarantee appreciable energy savings. A similar study was conducted by Spandagos and Ng [7] for large Asian cities. In particular, they evaluated the impact of heating and cooling energy consumption by introducing a simplified method of estimation.

Furthermore, Jermyn and Richman [8] presented a process for implementing deep renovation strategies in cold climates. In particular, they developed a case study for residential buildings in the city of Toronto by taking into account three different building archetypes. They found that the interventions to prioritize are related to the insulation of the building envelope and to the substitution of the boiler.

A country-based analysis was developed by Bianco et al. [9], who estimated the possible savings resulting from the

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implementation of energy efficiency measures in the Italian hotel sector by analysing different scenarios. The savings in externalities were also considered.

The relevance and scientific importance of energy analysis for buildings is also confirmed by the different review papers developed on this topic during the last years.

A review summarizing the latest approaches in the estimation of energy consumption in buildings has been recently developed by Bourdeau et al. [10]. They tried to summarize the available literature related to the methodologies for the estimation of energy consumption in buildings and the corresponding evaluation of energy efficiency measures. Similarly, Soares et al. [11] analysed the literature devoted to the study of energetic and environmental performance of buildings. Furthermore, Fumo [12] proposes a review of the different tools used for energy simulations and estimations in buildings, whereas Zhao and Magoules [13] review many techniques, encompassing from simple engineering methods to artificial intelligence approach, for predicting energy consumption in buildings. Finally, Tian [14] offers a summary of the methodologies to be employed in the sensitivity analysis of building energy simulations.

The above analyses offer a complete picture of the state of art related to the quantitative estimation of energy consumption in buildings. From the reviewed literature, it can be observed that the problem of energy efficiency in buildings attracted the attention of researchers from many countries demonstrating that the issue is considered of global importance.

The main weakness revealed by the analysed literature is the prevalent utilization of deterministic approaches, whereas many of the parameters utilized in the calculations are characterized by a level of uncertainty. For example, external weather conditions are characterized by a high level of uncertainty, as well as the transmittance of the envelope of existing buildings is known only with a certain degree of approximation. Similarly, in case of technic-economic analysis, financial variables are affected by substantial level of uncertainties, as is the case of expected energy prices, which are a fundamental parameter for evaluating the convenience of energy efficiency interventions. Addressing this gap is a challenge to consider in future research. To this aim, it is necessary to switch to a fully probabilistic method, in order to have more realistic estimations. However, the literature illustrating probabilistic methods is much less developed compared to that available for deterministic approaches.

One example is provided by Heo et al. [2], who proposed a methodology to account for uncertainty in the usual models utilized for energy consumption estimations in buildings. In particular, the study accounts for uncertainties deriving from the implementation of the interventions and uses them to estimate the risk of under-performance associated with the retrofitting interventions. Furthermore, Tagliabue et al. [15] illustrate a probabilistic methodology to consider the users' behaviour, which affects the real energy consumption in a building but, often, this is not taken into account in engineering calculations. They statistically describe user dependent parameters, such as air changes, in order to obtain probabilistic distributions of thermal load profiles. Instead, Touzani et al. [16] focused on the evaluation of the uncertainty associated with the estimation of energy savings. The aim was to evaluate the modelling error with respect to the savings actually achieved. They found that the methodologies currently employed tend to underestimate the uncertainty.

The impact of building components in the energy design of buildings in tropical locations is analysed in Ref. [17]. Energy Plus is used in the simulation and the Taguchi method is considered for statistical analysis of uncontrollable factors. Authors conclude that an appropriate selection of these factors determines a good enhancement of energy efficiency.

Bordbari et al. [18] compared two statistical methods, namely two points-estimate method and Monte Carlo, to model uncertainties in energy consumption analysis of buildings. They implement both the methods in EnergyPlus. They demonstrate a relevant save of time with the two points method at the expenses of a bit of accuracy.

A review of recent literature concentrated on the impact of uncertainty on the energy performance estimation of efficiency interventions can be found in Ref. [19].

Other studies focus on the statistical analysis of large sets of buildings to obtain straightforward equations, i.e., by linear regressions estimation [20] or mixed engineering-statistics methods [21], for evaluation of energy consumption. Statistical approaches are also considered for energy design optimization [22], for the post-processing of the results of energy models [23] or for comparing results from calculations and measurements [24].

Other authors focus on the impact that uncertainty may have on the evaluation of energy efficiency investments in buildings. For example, Copiello et al. [25] focused on the uncertainty linked to the evolution of energy costs. In particular, they proposed to integrate a life cycle cost analysis with a Monte Carlo approach, in order to take into account the variability of the energy cost. Similarly, Togashi [26] analysed the risk connected with an energy-saving investment by calculating the probability distribution of the energy reduction and evaluating the results using financial methods. He employed the Monte Carlo method in order to develop a complete risk analysis.

Another field of investigation is linked to the estimation of the uncertainty related to Energy Performance Contracts (EPCs). Lee et al. [27] proposed a probabilistic approach to the estimation of the performance risk in common lighting retrofitting projects. They consider the variability of some fundamental parameters, such as daylight availability, occupancy, lamp conditions, etc. They conclude that the impact of the variability of these parameters can be substantial. Likewise, Deng et al. [28] suggested a framework tailored on the needs of Energy Service Companies (ESCOs) for the evaluation of potential energy saving profits. In particular, they suggest modelling energy performance and energy price as stochastic processes.

More general analytical frameworks which include both the technical and financial aspects of the probabilistic estimation of energy efficiency interventions in buildings, as well as some considerations linked to the development of a risk analysis can be found in Refs. [29,30]. In particular, Sadeghi and Shavvalpour [29] discuss the possible approaches for the calculation of the Value at Risk (VaR), whereas Jackson [30] extends the VaR approach from the financial to the energy performance by introducing the concept of *Energy Budgets at Risk* (EBaR).

Finally, Bozorgi [31] established a conceptual framework for the implementation of an integrated energy retrofit assessment tools to include value, risk, and uncertainty.

The reviewed literature highlights the lack of an integrated quantitative methodology which considers both financial and technical aspects of energy efficiency interventions aimed at residential buildings retrofitting by including probabilistic calculations and risk assessment methodologies. This represents a relevant research gap since the evaluation of energy efficiency measures comprises both the technical analysis of the retrofitting interventions and the corresponding financial evaluations. These two aspects are characterized by many parameters subjected to uncertainty; therefore, a probabilistic analysis is necessary to perform accurate evaluations and to quantify the investment risk.

Table 1 highlights that most of the contributions applies the probabilistic approach on the technical or on the financial analysis, if included. Studies which consider the joint impact of the uncertainty on technical and financial aspects are missing. Thus, the current literature is highly fragmented.

The purpose of the present research work is to overcome the detected fragmentation and to propose an integrated methodology for the assessment of energy efficiency in buildings including technical and financial parameters. In addition, the developed approach is also suitable for analysing clusters of buildings/dwellings.

The present contribution includes a detailed building energy model to calculate the impact of energy efficiency measures. Then, the energy saving is the driver to estimate the generated cash flows and the corresponding investment valuation. The novelty of the paper resides in the joint considerations of uncertainties on technical and financial parameters to develop an overall probabilistic analysis of the energy efficiency measures. The proposed methodology is general and can be applied irrespectively of the considered country, climatic conditions, and typology of the buildings. Furthermore, it can be extended to cases other than buildings, e.g., industrial processes. Another original contribution is represented by the introduction of new indicators, i.e., “at risk” values, which are introduced to provide a quantitative measure of the technical and financial risk of the interventions. Uncertainty in the weather conditions is considered too by accounting for the volatility of the Heating Degree Days (HDD) and solar radiation.

If compared to the existing literature, the perspective reported in the present work is different from the evaluation of the impact of a specific intervention on one or more existing dwellings. Most of the reviewed literature has a focus on the single building or dwelling and considerations related to bundles of energy efficiency measures on different typologies of buildings located in different locations are missing.

Conversely, the present analysis is aimed at the case of an investor, typically a utility, an energy supplier or a financial institution, which needs to decide in advance what types of energy renovation, and on which type of building, would be profitable. Therefore, the characteristics of the buildings are known only in a probabilistic sense and the only applicable approach is a probabilistic analysis. This problem can also be seen from the perspective of a policy maker which wants to establish a support program for energy efficiency. It is necessary to plan in advance which are the most efficient and profitable measures to support, but the key parameters are only known in a probabilistic venue.

The present paper differs from other research by introducing additional uncertainties and hence aligning the calculation model more with the real-world viewpoint of third parties.

To exemplify the potential of the presented approach, the methodology is applied to evaluate the feasibility of thermal wall insulation of a typical Italian building. The presence of tax incentives and loans is also considered.

To the best of authors' knowledge, this paper represents the first contribution to approach this topic with a high level of detail on a probabilistic base.

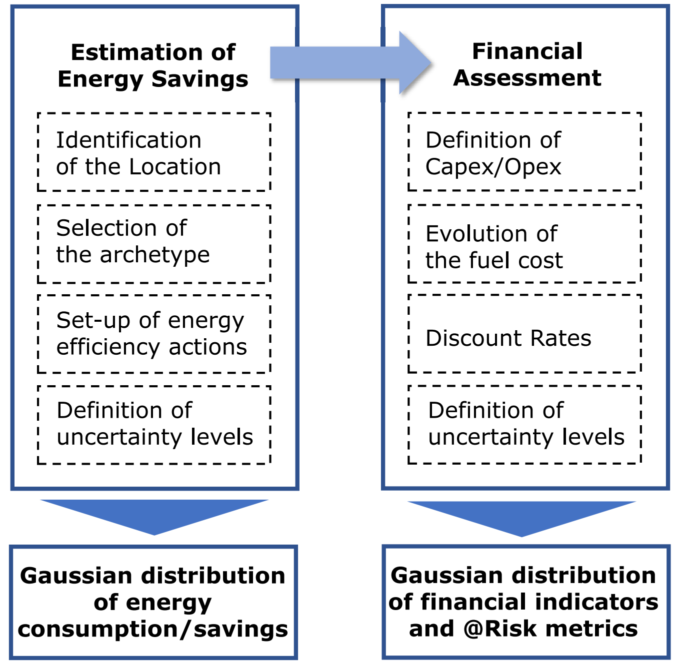

Fig. 1. Representation of the workflow for the execution of the analysis.

2. Methodology

2.1. Energy analysis

The design of energy efficiency measures generally intends to decrease the energy consumption of a dwelling. This requires a preliminary estimation and comparison between the energy performance of the dwelling before and after the application of the planned renovation measures.

The proposed methodology is not targeted at the energy evaluation of a given existing building. It aims to analyse various types of buildings in an aggregate and statistical manner, thus the considered analytical approach will be less detailed than the one used, for instance, in the energy performance certificate (EPC). Fig. 1 reports a schematic of the workflow for the energy saving and financial estimations.

In the considered framework, the actual planimetry of the considered dwellings is unknown as well as details about their envelope insulation, window frames and heating equipment. The thermal profile can be assigned only by typology, referring to coarse geometric and thermal features of buildings. In particular, the definition of the buildings to analyse is given in terms of archetypes as suggested in Ref. [32]. The relevant thermal dispersions are identified by separating the following contributions, schematized in Fig. 2:

Table 1
Summary of selected reviewed contributions on the application of a probabilistic approach to the study of energy efficiency in buildings.

Paper	Approach
Hoe et al. [2]	Uncertainties due to retrofitting interventions and valuation of the under-performance risk
Tagliabue et al. [15]	Probabilistic methodology to take into account users' behavior on energy consumption
Copiello et al. [25]	Uncertainty linked to the evolution of energy cost in the assessment of energy efficiency investments
Togashi [26]	Stochastic valuation of energy efficiency investment in buildings by assuming a probability distribution in energy saving
Lee et al. [27]	Estimation of performance risk in EPC focused on lighting
Jackson [30]	Utilization of VaR approach for the estimation of investments in energy efficiency measures

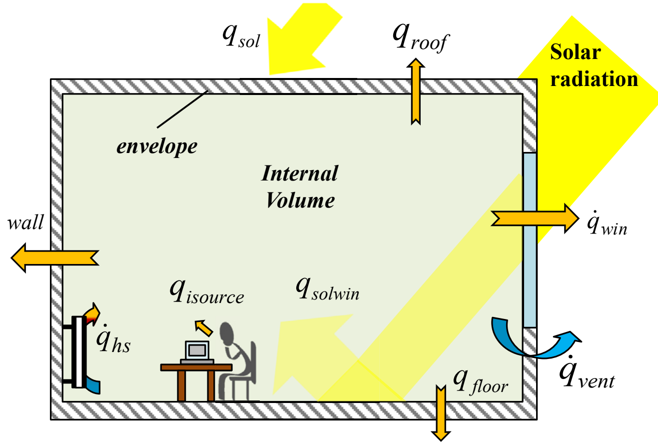

Fig. 2. Schematic view of the built envelope and associated heat transfers.

- q_{env}: heat transfer through the envelope, namely the sum of q_{wall}, q_{roof}, q_{floor} and q_{win}
- q_{wall}: heat transfer through the external walls
- q_{roof}: heat transfer through the roof
- q_{floor}: heat transfer through the floor
- q_{win}: heat transfer across windows (conduction/convection)

plus other terms which must be taken in to account to complete the energy balance of the building.

- $q_{isource}$: internal heat source due to persons and equipment
- q_{vent}: heat transfer due to ventilation (air exchange)
- q_{solwin}: direct solar radiation entering the windows
- q_{hs}: heat transfer due to the heating system

All the above energy contributions must be roughly compensated by an equal energy quantity, E_h, provided by the heating system in order to maintain a constant comfortable temperature of the internal environment.

The basic energy equation for a generic opaque envelope element, e.g., a wall, is:

$$E_{wall} = U_{wall} \cdot S_{wall} \cdot HDD \cdot C_{u1} \tag{1}$$

where U [$Wm^{-2}K^{-1}$] is the thermal transmittance of the element, S [m^2] its surface and HDD [K day] represents the heating degree days relative to a given time interval (N_{days}), usually the heating period, dependent on the climatic zone of the considered city according to the local law. C_{u1} is set equal to 3600 × 24 [s/day] if [J] is the desired unit for E_{wall}.

Eq. (1) must be slightly modified in case of direct solar radiation hitting the external surface. Indeed, the term U, as usually provided for structural elements like wall, roof and others, also comprises the thermal resistance of the internal and external boundary layers, R_i and R_e, that is:

$$R_{wall} = R_i + R_{w\ int} + R_e \text{ or } U_{wall} = \frac{1}{1/h_i + 1/U_{wint} + 1/h_e} \tag{2}$$

The reference heat transfer scheme is depicted in the following Fig. 3 that shows the wall, some key temperature points, and the thermal resistances, according to the electro-thermal analogy.

Our model, Fig. 4, considers the external direct solar contribution only since the part transmitted across the windows is directly added to the energy balance equation. In this case the equivalent circuit is the following and the true power value to balance is given

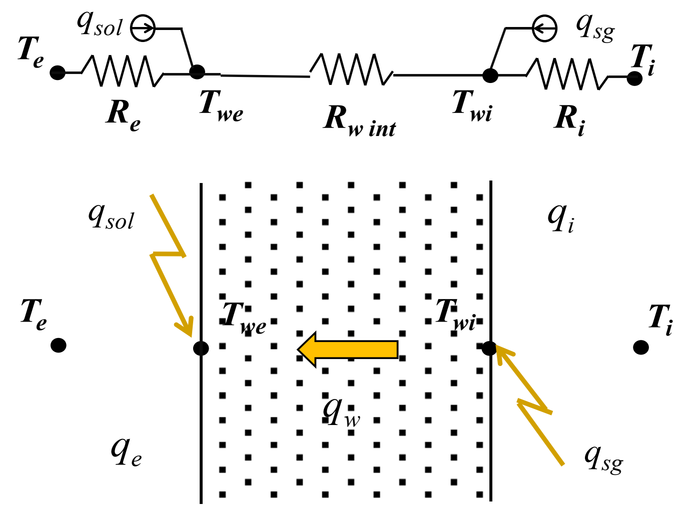

Fig. 3. Electro-thermal analogy for a wall. The current generators are associated to the solar radiation components.

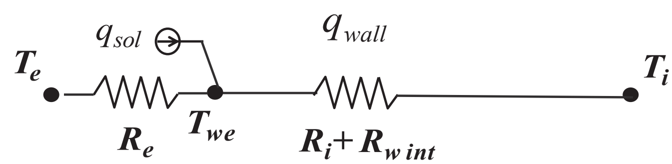

Fig. 4. Implemented simplified wall model.

by:

$$q_{wall} = U_{wall} \cdot S_{wall} \cdot (T_i - T_e) - U_{wall}/h_e \cdot q_{sol} \tag{3}$$

or, in terms of energy

$$E_{wall} = U_{wall} \cdot S_{wall} \cdot HDD \cdot C_{u1} - U_{wall}/h_e \cdot E_{sol} \tag{4}$$

with h_e set as usual to 23 [W/m^2K] and

$$E_{sol} = C_{shad} \alpha \cdot S_{wall} \cdot RAD \tag{5}$$

where RAD [Jm^{-2}] is the solar energy normal to a vertical plane, integrated over the considered period. α is the absorption coefficient of the considered external boundary (e.g. plaster), while C_{shad} accounts for both the shading and the fraction of a building surface hit, on average, by solar radiation. Since the building is an abstraction, its orientation and shading context are unknown and C_{shad} is set to a constant usually smaller than 0.5.

Direct solar radiation across the windows is accounted by the following:

$$E_{solwin} = C_{shad} \cdot SF \cdot S_{win} \cdot RAD \tag{6}$$

where SF, the Sun Factor, accounts for the attenuation of the radiation beams due to the considered glasses.

Detailed modelling of thermal bridges is not considered in the present work. Their impact is accounted by adding an equivalent heat exchange area to be estimated for each considered archetype.

Ventilation heat transfers are described as a function of the number of volume changes to which the internal ambient must adhere according to the energy and comfort regulations. However, this rule does not hold for aged buildings where the energy lost due to ventilation is somewhat a random variable depending on occupants use and on the amount of air leaks through the dwelling, which in turn depends on the quality of the frames and on external weather (wind) conditions. We put this quantity proportional to the net volume, following the formula:

$$E_{vent} = C_{vent} \cdot V_{net} \cdot \rho_{air} c_{p\ \ air} HDD \tag{7}$$

with.

$C_{vent} = 0.33$ [h^{-1}], from the standard.

Internal sources account for heat produced by persons and heat sourced by household equipment [33].

$$E_{isource} = \begin{cases} \left(5.294 \cdot S_{floor} - 0.01557 \cdot S_{floor}^2\right) \cdot N_{days} \text{if } S_{floor} < 170 \left[m^2\right] \\ 450 \cdot N_{days} \text{ otherwise} \end{cases} \tag{8}$$

Once all the heat dispersion terms are identified, the heating energy required to maintain constant, on average, the internal temperature of a dwelling is obtained by Eq. (9):

$$E_h = \max(\ 0,\ \ E_{env} + E_{vent} - E_{isource} - E_{solwin}) \tag{9}$$

since the right-hand side of Eq. (9) can assume negative values in case of well insulated envelope. Please note that the present model assumes a perfect temperature control of the heating system, able to exploit any possible free energy source available.

The needed thermal energy for Domestic Hot Water (DHW) production is computed by:

$$E_{DHW} = \left(0.04 \cdot S_{floor}\right) \cdot c_{p\ \ H2O} (45 - 15) M_{DHW} 365 \tag{10}$$

where four persons for 100 square meter and a typical hot water load of 30 kg/d/person of DHW are assumed.

The values of 15 °C and 45 °C represent the temperature of the available tap water and that of the desired DHW [34].

From the values of the needed thermal energy, the required fuel or electric energy amounts can be derived once the heating equipment of the dwelling along with the efficiency of each device are given.

2.1.1. Energy analysis validation

Since all the energy and financial analyses, both deterministic and stochastic, are based on the energy balance of the considered dwellings, the estimation of the needed integration to compensate for the heat losses must be validated against some reference methods. As said, the implemented energy analysis leaves aside the actual planimetry of the building and the details about its shape and orientation, so that the comparison must be made against a reference based on a similar approach.

The IEE Project TABULA [32,35] conforms to this requirement. Tabula (Typology Approach for Building Stock Energy Assessment), cofounded by the Intelligent Energy Europe Programme of the European Union, developed residential building typologies for some European Countries. The approach consists of a classification scheme grouping buildings according to their size, age and other features. A web tool has been developed too, providing online calculation of energy related features of buildings and their energy needs.

The present methodology for the calculation of energy losses was compared to the one proposed by TABULA with reference to a set of buildings of various size and structure. The city of Rome, Italy, has been selected as location, since it represents an “average” case for Italy in terms of climatic conditions.

The investigated buildings are multi-storey construction of two or three floors with different plant area, inter floor height, dispersing surface area to volume ratio and wall transmittance. A sample of the results is reported in the following table.

Table 2 shows an acceptable agreement between TABULA calculation and results performed with the present methodology. The error is typically below 10% but, in a few cases, increases up to 20%.

It is difficult to identify the cause of this discrepancy, but it is probably due to the use of different formulas in the evaluation of the internal heat source contribution and the heat transfer due to ventilation.

Focusing on this last aspect, in the case reported in the second-last row, for example, the heat loss due to ventilation calculated using Eq. (7) are 16 kWh/m^2, and, in the lack of specific information, is supposed independent on the age of the building. This fact alone can bring to sensible discrepancies between the methods, differences that can be avoided if more refined information about the dwelling is available. The choice not to take this factor into account derives from the decision to exactly follow the available rules which do not consider an explicit dependence of the ventilation losses on the age of the building.

2.2. Financial analysis

To assess the financial viability of the foreseen energy efficiency measures, different indicators can be calculated, namely Net Present Value (NPV), Internal Rate of Return (IRR) and Discounted PayBack Period (DPBP).

The calculations of the considered indexes are based (i) on the estimation of the amount of capital needed to implement the energy efficiency measures, assuming that such investment is made for its entirety at inception (time 0), and (ii) on the estimation of the future cash flows resulting from the investment, namely the savings in the energy bills deriving from the implemented energy efficiency interventions.

Thus, the NPV can be estimated in the following way [36]:

$$\text{NPV} = -INV + \text{DCF} \tag{11}$$

where *INV* is the initial investment and DCF is the sum of the discounted cash flows occurring during the operating life of the energy efficiency interventions, calculated according to Eq. (12):

$$\text{DCF} = \sum_{i=1}^{n} \frac{CF_i}{(1+r)^i} \tag{12}$$

where n is the operating life, i is the time index (usually one year) and r is the discount rate. The NPV provides an absolute measure of profitability (a monetary amount), the scale of which is often the result of the size of the initial amount invested (*i.e.,* huge investments can lead to huge profits).

The IRR is calculated starting from the same definition of the NPV and it consists in the calculation of the value of “r” which makes the NPV equal to 0:

$$\sum_{t=1}^{n} \frac{CF_i}{(1+r)^i} = INV \tag{13}$$

The IRR represents a relative measure of profitability (it shows the percentage return per unit of invested capital), and as such it allows to compare different investments independently from their size. The decision rule is to accept all the investments that have an

Table 2
Comparison of building performances in terms of Heat Losses (kWh/m^2) as evaluated by the present methodology against the results obtained by using the TABULA project dedicated tool.

H (m)	S_d/V (m^{-1})	Area (m^2)	n.Floors	U_{wall} (W/m^{2}K)	U_{roof} (W/m^{2}K)	U_{floor} (W/m^2 K)	U_{wind} (W/m^{2}K)	TABULA Heat losses	Present study	Unsigned Difference %
3,90	0,82	115	2	1,61	1,8	2	5,7	357	335,7	6,0
3,90	0,82	115	2	0,25	0,23	0,23	1,7	55,7	50,7	9,0
3,64	0,72	199	2	0,76	0,98	1,14	2,8	136	141,4	4,0
3,64	0,72	199	2	0,25	0,23	0,23	1,7	44,4	42,9	3,4
3,15	0,54	1121	3	0,58	0,69	0,815	2,2	70,3	81,0	15,2
3,20	0,51	961	3	1,59	1,65	1,3	4,9	170	166,5	2,1
3,03	0,43	3271	6	0,59	0,69	0,77	3,4	62,9	74,8	18,9
3,29	0,46	2869	8	1,10	1,65	1,43	4,9	134	127	5,2

IRR higher than the required rate of return (discount rate). Furthermore, by comparing the value of the IRR with the discount rate, a rough estimation of the risk of having an unprofitable investment can be obtained. If the values of IRR and *r* are close, the risk is higher; on the contrary, if the difference is large, the risk is lower. However, as opposite to the NPV, IRR does not provide any information about the absolute level of profitability.

The DPBP can be defined as the time required to recover the initial investment. The equation has the same form as Eq. (13), but the unknown variable is the number of years "n". The solution is obtained via a numerical method rather than by means of a closed formula. The DPBP does not consider any cash flow beyond the payback period. For this reason, instead of a measure of profitability, it is a measure of liquidity of the project. It is then usually used as a proxy of the liquidity risk associated with an investment, based on the intuitive principle that the shorter is the period to recover the investment, the quicker it is converted into cash (*i.e.,* the quicker it is possible to exit from the position, without costs).

2.3. Probabilistic approach

Since both the energy and the economic analyses are based on uncertain values, meaningful results require the knowledge of their quality, i.e., of their associated confidence bounds.

Uncertainty on the evaluation of energy efficiency investments in buildings is not only due to unknown future variables like the evolution of energy costs or unpredictable future weather conditions: all the geometric and thermal properties of the considered ensemble of buildings are known only as average, approximated values. The same holds for the considered heating equipment in terms of efficiencies and heating power.

Various techniques can be implemented in a random or stochastic context. If the shape of the probability distribution is known, and the system is linear or weakly nonlinear, standard covariance propagation techniques, i.e., the Lyapunov equation, can be profitably utilized. More sophisticated approaches are required if those hypotheses do not hold as, for instance, the unscented transform [37]. However, if step functions are discretized, then multimodal distributions could emerge. In these cases, the application of the brute force Monte Carlo approach is advisable.

To give an example, though very rough, of the surfacing of a multimodal distribution, reference will be made to the function that links the required power of a condensing boiler to the set of powers of boilers available for sale. Usually, only a finite number of heating powers is found for sale, typically 24 kW, 28 kW, 35 kW and so on. In this case, the continuous probability distribution associated with the required power due to the uncertainty affecting, for instance, the heat dispersions, will collapse in a comb distribution as per Fig. 5.

Then, the price being linked to the power; a bimodal random price distribution could emerge that is shaped around discrete values.

In similar contexts, the Monte Carlo method, though heavy in terms of processor time and memory usage, represents an effective way to analyse uncertainty propagation in nonlinear discrete state models.

In a Monte Carlo analysis, for each new simulation, input values for geometry, thermophysical properties, climatic conditions, and design parameters, are randomly sampled from their assumed probability density functions. A random sampling is utilized, and variables are considered completely independent and uncorrelated even if correlation coefficients can be easily implemented.

The physics of the problem is not very demanding in term of computational resources thus the use of more sophisticated sampling techniques [38] can be avoided.

Table 3 presents the variables considered to be uncertain in the proposed methodology; namely, more than 30 random variables are considered.

Application of the Monte Carlo method is straightforward. A single energy and/or economic analysis is repeated thousands of times using randomly extracted values of the pertinent variables.

Expected values and confidence bounds are then calculated for the desired indices by using sample mean and variance, that is with reference to the generic variable X:

$$\widehat{X} = \frac{1}{N_{mc}} \sum_i X_i \tag{14}$$

$$\widehat{\sigma}_X^2 = \frac{1}{N_{mc} - 1} \sum_i \left(X_i - \widehat{X} \right)^2 \tag{15}$$

where N_{mc} is the number of Monte Carlo simulations.

As per Table 2, the extraction process is not the same for all the variables; referring for instance to the evaluation of the NPV and considering a single analysis, those marked with a "t" must be extracted every year since they are not constant, e.g., the yearly heating degree days. Other variables, marked with a "d", like the windows transmittance or the burner efficiency, must be extracted twice if the considered renovation involves replacing the windows or the burner: a random extraction for the old building configuration and one for the renovated one. The remaining unmarked variables are extracted only once for each simulation: the floor surface area, for example, does not change with time and is the same in the given and restructured configuration.

Each quantity is supposed to be Gaussian distributed with given mean and variance, but other distributions can be selected, e.g., triangular, or rectangular, if needed.

The opportunity of changing the variance allows to test the sensitivity of a particular index to the uncertainty of the single parameter, thus providing information about which parameter requires a greater attention when optimizing some economic or

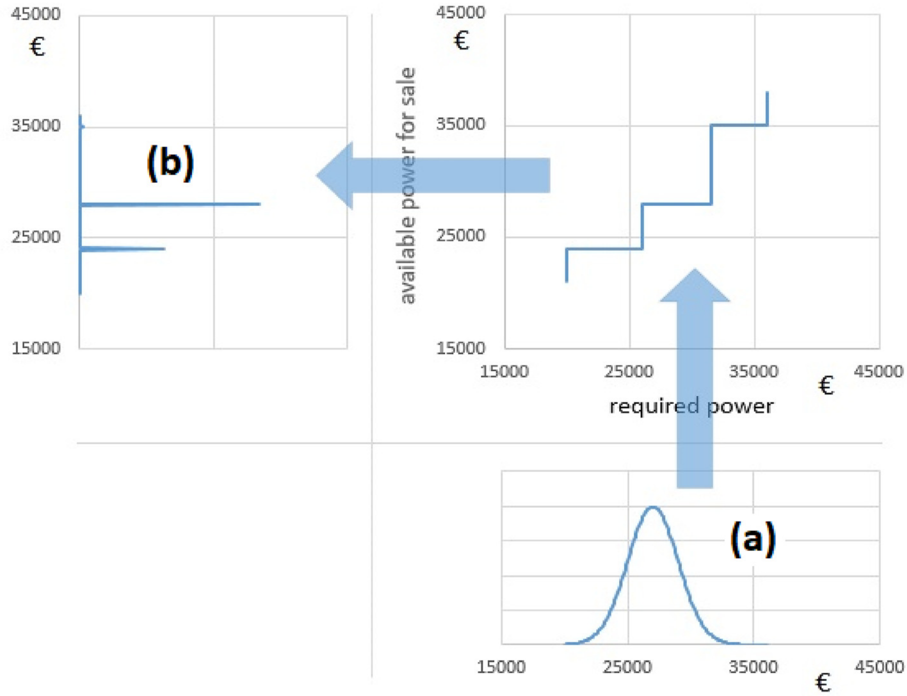

Fig. 5. From the continuous distribution of required power (a) to the comb distribution (b) since only a finite number of heating powers is found for boilers on the market.

Table 3
List of uncertain variables: "t" refers to variables whose value randomly changes over time; "d" means a double extraction is needed: one for the old dwelling configuration and one for the renovated.

Geometric		Thermophysical		Heating equipment		External environment		Economic	
Floor area		Wall transmittance		Burner efficiency	d	HDD	t	Fixed costs	
Dispersing area to volume ratio		Roof transmittance		Heat Pump COP	d	Radiation	t	Electric energy cost	t
Floor to floor height		Floor transmittance		Distribution efficiency	d	Heating days	t	Fuel energy cost	t
Windows to floor area ratio	d	Windows transmittance	d	Regulation efficiency	d	Ext. convection coefficient	t	Discount rate	t
		Plaster absorption coeff.	d	Emitter efficiency	d	Air change rate	t		
		Sun factor	d	Solar fraction	d	Shadow coefficient			
		Insul. thickness (wall)	d	Burner efficiency (DHW)	d				
		Insul. conductivity (wall)	d	Heat Pump COP (DHW)	d				
		Insul. thickness (roof)	d	Electric boiler efficiency (DHW)	d				
		Insul. conductivity (roof)	d	Heat Pump COP (DHW)	d				
		Insul. thickness (floor)	d	Hot water load	d				
		Insul. conductivity (floor)	d	Solar fraction (DHW)	d				
				Primary to electric energy conversion factor	t				

energy related index.

Fig. 6 qualitatively shows the typical NPV output, as a function of time and with a time horizon of 20 years, that can be expected from a Monte Carlo analysis while in the next paragraph an application to an actual case will be provided.

Beyond the NPV, the probabilistic approach allows estimating the confidence of the results and to identify possible risk areas, also as a function of time. In the example of Fig. 6, time horizons smaller than ten years yield negative NPV values with a probability of 97.5%. After 20 years there is still a 10% risk of loss.

All the reported confidence bounds are sampled results. No assumption has been made on the shape of the probability distribution involved.

Based on the aforementioned probabilistic analysis, it is possible to define some metrics which are able to quantitatively measure the performance risk, both energetic and financial, of an energy efficiency project.

If X is a metric of interest with its associated probability density, e.g., energy saving (ES), NPV, IRR, etc., it is possible to determine its expected value E(X), as well as the value $VaR_{5\%}$ (X) with an associated probability of 5% of worst outcome. This value is usually called Value at Risk (VaR).

$$\Delta X_{@RISK} = E(X) - VaR_{5\%}(X) \tag{16}$$

which represents the loss of value of X with a probability of 5% with respect to its expected value.

X can be substituted with all the energy and financial indexes of interest to develop a complete risk analysis for the project under investigation.

VaR is complemented with another quantity, namely, the Conditional Value at Risk (CVaR) that, together with VaR, quantifies the amount of "tail risk" an investment has. Fig. 7 graphically depicts the difference between the two variables. The Value at Risk divide the PDF in two regions, the grey one identifying the 5% of worst, undesired results. The conditional expectation of these results is CVaR, that is the mean value of the grey region.

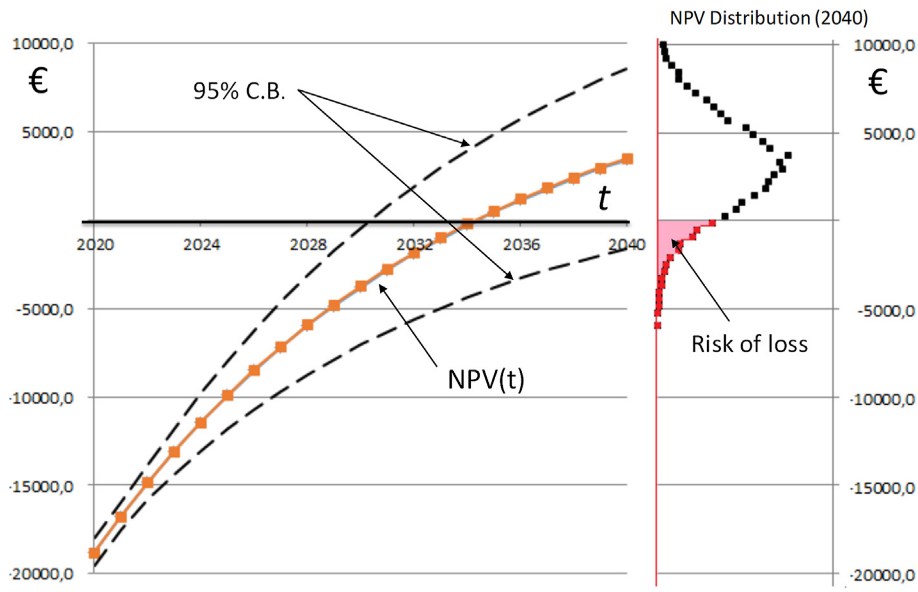

Fig. 6. NPV results as a function of time. Example case. Monte Carlo method. 10,000 runs. Dashed lines represent the sampled confidence bounds (95%) while the graph on the right shows the expected frequency distribution of the NPV20 (20 years). The red zone comprises cases with negative NPV that is investments at a loss. In the depicted case the risk of loss at 20 years' operation is about 10%. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

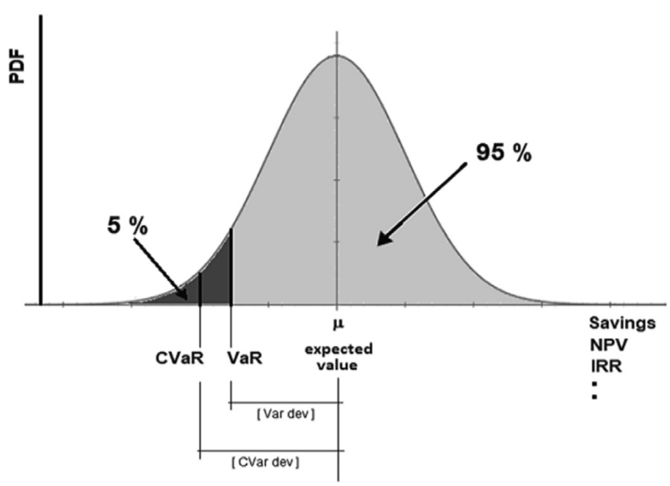

Fig. 7. Safe and Risk zones of an arbitrary metric. The Value at Risk (VaR) represents the zone border while the conditional Value at Risk (CVaR) is the mean of the Risk region, that is the expected value of the tail risk, beyond the VaR cutoff point.

3. A multi-storey application

The presented methodology is applied to the energy and financial evaluation of a large energy efficiency refurbishment, namely wall thermal insulation, considered in the renovation of a hypothetical residential six-storey building located in the city of Rome, Italy. All the calculations are developed in Visual Basic for Applications and embedded in a MS-Excel calculation tool which is used as interface for launching the simulations and for I/O purposes.

The location has been selected since energy renovation interventions for heating in a warm climate are difficult to design. In fact, due to the low energy savings achievable, they often lead to long pay back times and to negative or very small NPV values. In these cases, an accurate investigation about the influence of various source or uncertainty is very useful and the application of the Monte Carlo technique is advisable.

Apart from the usual indicators concerning the energy savings and the investment feasibility, the interest is focused on the influence of variations of some intrinsic quantities which are rarely known with great accuracy.

For clarity, given the high number of variables illustrated in Table 3, we restrict the investigation to the following:

- the ratio between dispersing surface and rough heated volume, S_d/V,
- the wall thermal transmittance, U_w,
- the heating degree days, HDD,
- the energy price, E_{price}.

This case study is not aimed to simply evaluate the joint influence of a bunch of parameters. The idea is to focus on the very different effects that the uncertainty of each of the selected variables can have on the decision process with particular reference to the NPV estimation, as will be evident in Fig. 9 up to 13.

So, different interesting aspects of the intervention are covered, that is the dependence on geometry, thermophysical properties, climatic conditions, and energy cost. We also note that the uncertain knowledge about the internal ambient temperature, also dependent on personal preferences and control strategies, can be accounted for by including it in the HDD uncertainty.

It is important to underline that in the investment analysis the values attributed to the variances of each individual parameter are fundamental. Without the quantitative knowledge of the uncertainty of the parameters, it is not possible to assess the risk associated with the investment. Nonetheless, also in this case, the methodology can be used for a preliminary investigation of the sensitivity of the various performance indices with respect to the considered parameters.

Given the type of analysis, the consumption related to DHW was not considered for conciseness.

3.1. Case study

The considered construction belongs to the social housing of the sixties as shown in Fig. 8. The image is only exemplificative since the building is hypothetical. The following tables, namely Tables 4–6, summarize the main characteristics of the location, the building, and the heating system.

Energy losses through the envelope, also accounting for ventilation and internal sources, lead to a yearly thermal energy need of about 202 MWh, that is 84.1 kWh/m^2 (DHW was not considered).

In front of this request, a fuel energy consumption of about 316 MWh per year emerges, with an associated annual fuel bill of k€ 22.3 for a fuel energy price of 0.15 €/kWh.

The Monte Carlo analysis provides the results shown in Table 7, obtained in terms of confidence bounds where the 95% bounds of the uncertain variables S_v, U_w, HDD and E_{price} are assumed, quite arbitrarily, as 20%, 20%, 20%, and 1% of their respective value. The low uncertainty on the energy price reflects the good knowledge of current values. When future estimates are utilized, as for NPV calculations, a linear increasing value of uncertainty will be assumed.

The percentage effect is the same since losses, consumption and bill are simply scaled values.

Effect of Energy price at year 0 is null since it is assumed a linearly increasing uncertainty with perfectly known prices at year 0. In any case, any value of C.B. assumed at year 0 will reflect, with the same figure, on the energy bill only.

3.2. Planned intervention

The considered refurbishment, wall thermal insulation, strongly decreases the heat losses of a building, but it is very invasive, and it is usually accomplished only if a structural intervention on the façade is already planned. Only the added cost of the insulation and that of the associated installation are here considered.

Wall insulation is also an expensive renewal, and it is usually advisable in cold climate. For the considered building, the rough overall cost of wall insulation only (no roof and floor insulation), 10 cm of rockwool at 1 €/m^2/cm plus installation (€40/m^2), for the considered surface of 2800 m^2, is k€ 140.

Fig. 8. A typical low-cost Italian multi-storey (1965).

The effects of the intervention are visible in Table 8 while Table 9 shows the possible savings and associated confidence bounds caused by the uncertainty of four selected variables S_v, U_w, HDD and investment cost, C_{FIX}.

Only S_v uncertainty (i.e., the uncertainty on the dispersing surface) will affect intervention cost. The influence of the bare wall thermal transmittances, U_w, is greatly decreased by the presence of the insulation, while the HDD effect slightly augments since it is a percentage quantity, and the heat losses are smaller in the planned configuration. In fact, if we compare the value of the confidence bound due to HDD uncertainty, before and after the intervention we find:

$$\text{C.B. } 95\%_{before} = 54.4 \text{ MWH C.B. } 95\%_{after} = 26.4 \text{ MWH}$$

Following the "at risk" measure introduced in paragraph 2.3, Table 9 also reports the *Conditional Value at Risk,* for both energy savings and bill savings, as signed distance from the expected value as per Fig. 7.

By considering a time horizon of 20 years from the renovation action, with annual time periods, some useful financial indices can be calculated to evaluate the feasibility of the proposed intervention. In what follows, the indices NPV, IRR and Discounted PayBack time (DPB) are given along with their 95% confidence bounds emerging from the Monte Carlo simulation. The NPV is graphically reported year by year, starting from the date of the intervention, to give a better view of the investment. Tax incentives and loans examples are considered to complete the case study.

The 20 yrs. NPV is weakly positive, €1324, but this figure is surely low compared to the investment cost of €140 k required. Indeed, the DPB is 19.7 years, and the IRR is equal to 8.12% assuming a discount rate of 8% and an annual increase of the fuel cost of 2%.

Differently from Ref. [25], which focuses on probabilistic analysis of the financial performance of the interventions, the present approach reports a comprehensive framework for the analysis. In fact, as highlighted in Tables 8 and 9, the probabilistic estimation of energy savings and financial performances are connected and jointly developed according to the methodology reported in the previous sections of the paper. This is relevant since energy savings are one of the main drivers for the determination of the financial performance. This concept is also stressed by Jackson [30], but his work is more qualitative and descriptive, rather than quantitative as in the present case.

The methodology illustrated in the present work is more comparable to Togashi [26], where a deep focus is given to the stochastic behaviour of weather conditions, buildings occupants, and energy cost. On the other hand, Togashi [26] analyses a specific building with well known features. In fact, he does not consider any uncertainty on the building elements (e.g., dimensions, U-values, etc.). The present work is conceived in a different way. The base assumption is that the building (or group of buildings) is known only in average without any specific information. Thus, also all the building parameters are subjected to certain degree of uncertainty. As shown in Tables 8 and 9, the present methodology allows to estimate the impact of the uncertainty of selected parameters on the main figures of merit of the retrofitting project (e.g., energy savings, NPV, IRR, etc.). A more in-depth analysis of the uncertainty of building parameters on the financial indicators is illustrated in the next section.

3.3. NPV confidence bounds

The questionability of the intervention is better explained by means of the results reported in Figs. 9–13, showing the NPV and its confidence bounds (95% confidence) as a function of time when

Table 4
Main building properties (6 storey building).

Number of Floors	Country	City	Building Type	Year	Surface in plan [m^2]	Floor Area [m^2]	Total Floor Area [m^2]	Storey height [m]	S disp/V [m^{-1}]	Wall thermal transmittance [W/(m2K)	Roof thermal transmittance [W/(m2K)	Floor thermal transmittance [W/(m2K)
6	Italy	Rome	multi-storey	1961 −1975	400	2400	2400	3	0.5	1.76	1.85	1.3

Table 5
Climatic conditions for the considered location.

Rome T_{avg} = 11.5 °C T_{min} = 3 °C				Average Daily Solar Radiation [MJ/m^2] South Vertical Wall											
HDD	Heating days	Heating on/off	Heating hours per day	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
1415	166	01/11–15/04 (121 days)	12	10.6	11.9	12.6	11.6	10.6	9.9	10.8	12.4	14.2	15.1	11.8	9.3

Table 6
Summary of the main features of the heating system.

Heating System	Type	Efficiency
heating means	Type B open chamber	0.76
Regulation		0.95
Emitters	Radiators	0.94
Distribution		0.94
Windows	Single Glazed	U = 5.7 [W/m^2K]
Envelope Insulation	No	

Table 7
Annual energy need, consumption, and Monte Carlo 95% confidence bounds, C.B., (10,000 runs) calculated on the current configuration.

		Perturbed Variables			
		S_v	U_w	HDD	All
Energy losses	201.7 MWh	18%	13.0%	26%	34%
Energy consumption	316 MWh	18%	13.0%	26%	34%
Energy bill	22.3 k€	18%	13.0%	26%	34%

Table 8
Annual energy need, consumption and Monte Carlo 95% C.B. (10,000 runs). Planned configuration (wall insulation).

		Perturbed Variables				All
		S_d/V	U_w	HDD	C_{FIX}	
Energy losses	89.25 MWh	6%	0.6%	29.5%	–	30.5%
Energy consumption	140 MWh	6%	0.6%	29.5%	–	30.5%
Bill	9.9 k€	6%	0.6%	29.5%	–	30.5%
Intervention cost (C_{FIX})	140 k€	25.5%	–	–	20%	32.6%

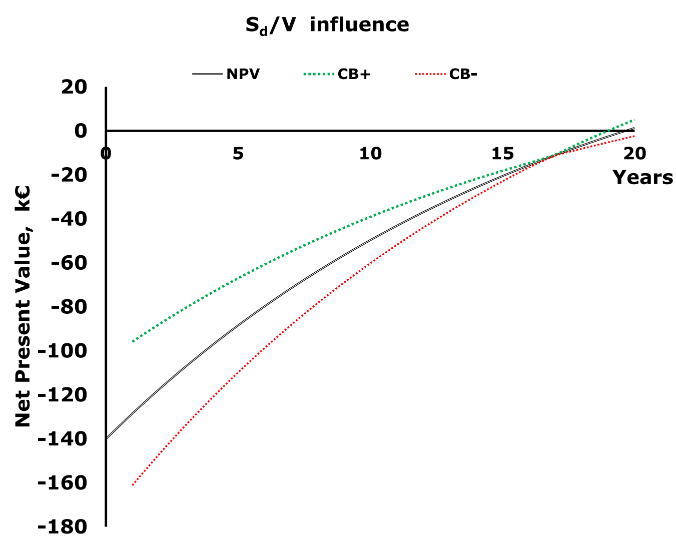

Fig. 9. Effect on the NPV of uncertainty in the dispersing surface to volume ratio. The main effect is an increased saving with greater wall surface, corresponding to greater investment. This fact generates the observed convergent NPV bounds.

uncertainty is accounted for some important variables.

It can be noted that the behaviour of the confidence region is very different for the considered variables. If unknown variations are considered in the ratio between dispersing surface and heated volume, a typical decrease of the bounds is noted. This counterintuitive effect is due to the link between investment and savings and to the specific constraint here assumed. Since the floor area and the inter-floor height are fixed, a variation of S_d/V value corresponds to a variation of wall surface. With larger surface the heating losses are greater and wall insulation requires larger investment, but it is more effective, thus producing higher bill savings and therefore higher cash flows. Conversely for a smaller surface. So, the lower bound, for instance, is characterized by a steeper slope. The resulting effect is therefore the reduction of the confidence in the first period of about 17 years and a subsequent increase.

In this case, the uncertainty in the knowledge of the S_d/V ratio has little influence on the final NPV bound which are small in any case, Fig. 9.

Table 9
Annual savings: CVaR and Monte Carlo 95% C.B. (10,000 runs).

		Perturbed Variables			
		S_d/V	U_w	HDD	All
Energy savings	176 MWh CVAR→	−51 MWh	−42 MWh	−43 MWh	−70 MWh
	95%C.B.→	28.3%	22.7%	23.2%	42.7%
Bill savings	12.4 k€ CVAR→	−3.6 k€	−2.9 k€	−3.0 k€	−4.9 k€
	95%C.B.→	28.3%	22.7%	23.2%	42.7%

Fig. 10 shows that U_w has a completely different influence, in comparison to S_d/V. Here, a variation of the current, before intervention, thermal transmittance of the wall gives rise to diverging confidence bounds. This represents a common case where variation on U_w, even if mitigated by the planned insulation, causes variation in thermal losses that are constant in time. These losses translate in bill variations, which accumulate in time giving an explanation of the observed behaviour. In this example large, 20%, confidence bounds have been assumed to the aim of presenting meaningful graphics.

Variation of the climatic conditions and internal base temperature (nominal set point at 20 °C), Fig. 11, has not a great influence on the investment analysis. Differently from case of the thermal transmittance, where random values are extracted one for all in correspondence of year 0 (U_w does not randomly changes with time). During the Monte Carlo simulation different values of HDD are extracted every year. Statistically, these values, assumed uncorrelated, are symmetrically disposed with respect to the mean so that their global effects in time result weakened (counterbalanced).

Clearer is the interpretation of the confidence region resulting from the uncertainty affecting the investment cost. In this case there are not consequences on the physics of the building or on the bill, so a constant confidence interval is expected. Fig. 12 reports the case of an investment cost characterized by an uncertainty of 20%.

The effect on the NPV due to energy price uncertainty is given in Fig. 13. The price behaviour in time is described by an auto correlated process which produces values characterized by a naturally increasing uncertainty starting from 0% at year 0, to increase up to 20% after 20 years since the intervention. This hypothesis is justified to simply describe a knowledge of the market that decreases for long time extrapolation.

The analysis is completed by Table 10, reporting value at risk relative to Energy and Financial indices associated to the presented scenarios of uncertainty.

As expected, wall insulation interventions in warm climate raises some doubts and all the evaluated indices suggest not to proceed in this direction. The picture definitively changes if tax incentives are disposable. For instance, energy saving interventions are supposed to be promoted with a 65% refund of the investment, sliced in ten annual repayments discounted from taxes.

Fig. 14(a) shows the changes in NPV and its confidence bounds emerging in case of uncertainty in the wall thermal transmittance (see Fig. 10) when the above incentive figure is applied. In this case an NPV value of 62,400 € is obtained with 0% of loss probability. Worthy economic results can also be obtained by applying for a loan. Fig. 14(b) presents the NPV obtained in case of a loan covering the 85% of the initial investment costs, at a fixed rate of 2% and a refund time of 8 years.

The NPV computed over 20 years is smaller than the previous

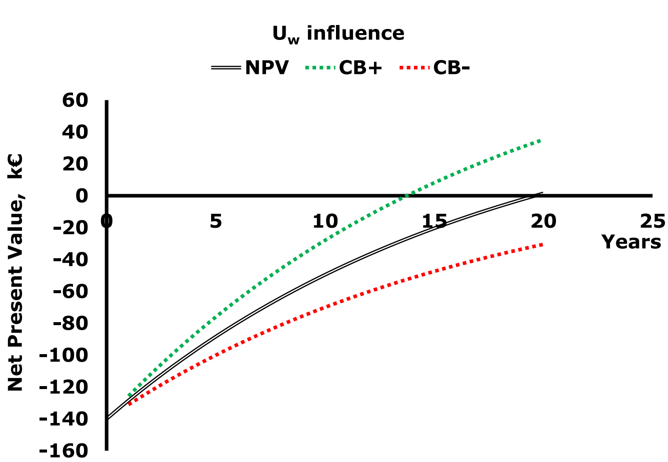

Fig. 10. Uncertainty in the wall thermal transmittance. Effect on the NPV and payback time.

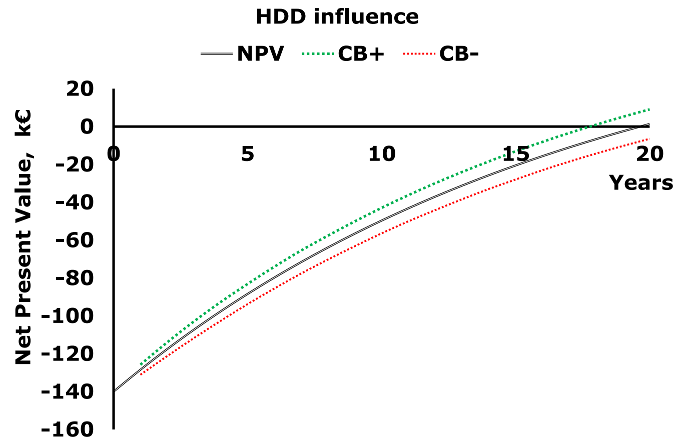

Fig. 11. Uncertainty in the heating degree days (also accounting for T_{base} variations). The slowly varying bounds are due to the very nature of the stochastic process.

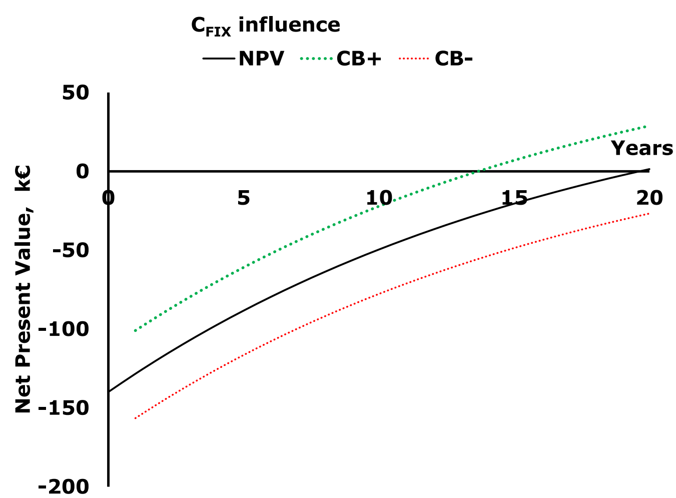

Fig. 12. Uncertainty on investment costs. The effect on NPV confidence is constant over time.

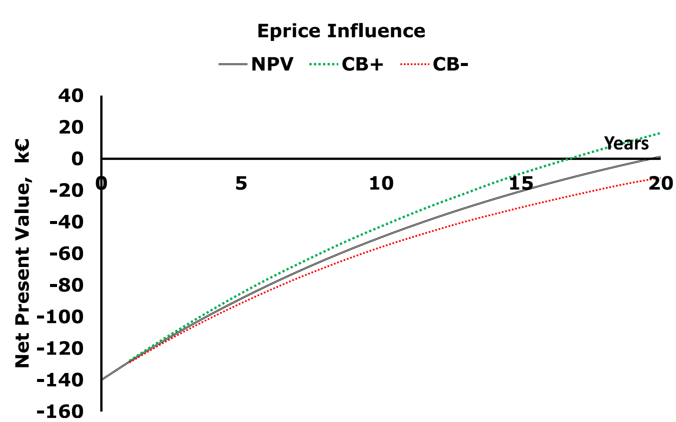

Fig. 13. Uncertainty on Energy price; correlated forecasting. 95% confidence bound at year 20 is 20% of the price value.

Table 10
Various financial indices and associated CVaR, VAR and 95% confidence bounds, C.B., at the horizon time of 20 years. CVaR, VAR are reported as signed distance from the expected value.

		Perturbed Variables					
		S_d/V	U_w	HDD	C_{FIX}	E_{price}	All
NPV, €	+1324 CVAR→	−3900	−34000	−8200	−29500	−14500	−33500
	VAR→	−3100	−27500	−6500	−24000	−12000	−26500
	95%C.B.→	±3730	±32,500	±7750	±28,000	±14,500	±34,500
IRR, %	8.12 CVAR→	−0.4	−3.2	−0.7	−2.4	−1.3	−4.2
	VAR→	−0.3	−2.5	−0.6	−2.0	−1.1	−3.4
	95%C.B.→	±0.32	±2.9	±0.7	±2.6	±1.3	±3.0
DPBP, yrs.	19.7 CVAR→	−1.2	+11	+2.2	+7.5	+4.3	+15
	VAR→	−0.9	+8	+1.7	+6.0	+3.3	+11
	95%C.B.→	±0.95	±8	±2	±6.5	±3.5	±8.5
Loss Risk		24%	47%	36.5%	46%	44%	47%
Exp. Loss, €		−1120	−13000	−2700	−11000	−5300	−13100

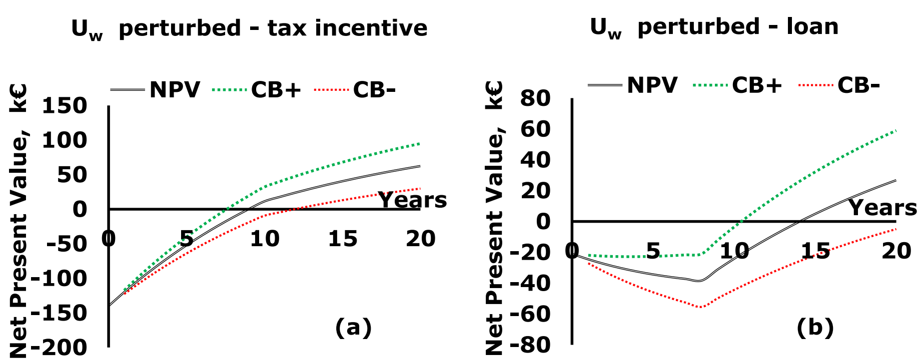

Fig. 14. NPV in case of wall insulation with uncertain thermal transmittance: (a) case of tax incentives with ten years refund time of 65% of investment costs; (b) case of loan on 85% of the fixed initial expenditures with 2% rate and 8 years' refund.

but acceptable, about 27,000 €, with the relatively low risk of loss of 5% (expected conditional loss = 6800€).

4. Conclusions

The investment in real estate projects involving building refurbishment by means of energy insulation retrofitting is a difficult decision, especially when long lasting operating time are needed. Indeed, a lot of uncertainties, both on actual values of the parameters and on time changing variables, make the decision quite uncertain. In the present paper the Monte Carlo simulation approach is proposed as a straightforward tool to make reliable forecasting of energy and financial parameters involved in building retrofitting projects, including random errors in most of the major physical, financial, and time-dependent parameters. The outcomes of this approach can quantify, for each given refurbishment project, the confidence bounds of the expected benefits as a function of approximations expected on more than 30 problem data, quantifying also the "value at risk" results. The analysis implemented using the proposed methodology shows that covariance propagation can be essential to evaluate the feasibility of an energy renovation project in uncertain environment, especially when climate or other conditions made the choice a *border line* decision.

The primacy of the current probabilistic approach over deterministic analysis is evident since without knowledge of the uncertainty the risk associated to every decision will remain unknown.

To highlight this aspect, the methodology was applied to a specific case: the wall insulation of a building sited in a relatively warm location, namely Rome (Italy). Only the careful application of statistical techniques leads to informed decisions, also providing correct information about the involved financial risk, and the right incentive and loan conditions to pursue a secure investment.

Author contribution

Vincenzo Bianco: Conceptualization, Methodology, Writing- Reviewing and Editing; Federico Scarpa: Conceptualization, Methodology, Writing- Reviewing and Editing; Luca A. Tagliafico: Writing- Reviewing and Editing.

Declaration of competing interest

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

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References

[1] BPIE. Buildings performance institute Europe. Europe's buildings under the microscope. 2011.

[2] Heo Y, Choudhary R, Augenbroe GA. Calibration of building energy models for retrofit analysis under uncertainty. Energy Build 2012;47:550–60.
[3] Annunziata E, Frey M, Rizzi F. Towards nearly zero-energy buildings: the state-of-art of national regulations in Europe. Energy 2013;57:125–33.
[4] Ascione F, Bianco N, Mauro GM, Napolitano DF. Building envelope design: multi-objective optimization to minimize energy consumption, global cost and thermal discomfort. Application to different Italian climatic zones. Energy 2019;174:359–74.
[5] Bianco V, De Rosa M, Scarpa F, Tagliafico LA. Analysis of energy demand in residential buildings for different climates by means of dynamic simulation. Int J Ambient Energy 2016;37(2):108–20.
[6] Krarti M, Dubey K, Howarth N. Evaluation of building energy efficiency investment options for the Kingdom of Saudi Arabia. Energy 2017;134: 595–610.
[7] Spandagos C, Ng TL. Equivalent full-load hours for assessing climate change impact on building cooling and heating energy consumption in large Asian cities. Appl Energy 2017;189:352–68.
[8] Jermyn D, Richman R. A process for developing deep energy retrofit strategies for single-family housing typologies: three Toronto case studies. Energy Build 2016;116:522–34.
[9] Bianco V, Righi D, Scarpa F, Tagliafico LA. Modeling energy consumption and efficiency measures in the Italian hotel sector. Energy Build 2017;149:329–38.
[10] Bourdeau M, Zhai XQ, Nefzaoui E, Guo X, Chatellier P. Modeling and forecasting building energy consumption: a review of data-driven techniques. Sustainable Cities and Society 2019;48:101533.
[11] Soares N, Bastos J, Pereira LD, Soares A, Amaral AR, Asadi E, Rodrigues E, Lamas FB, Monteiro H, Lopes MAR, Gaspar AR. A review on current advances in the energy and environmental performance of buildings towards a more sustainable built environment. Renew Sustain Energy Rev 2017;77:845–60.
[12] Fumo N. A review on the basics of building energy estimation. Renew Sustain Energy Rev 2014;31:53–60.
[13] Zhao H, Magoules F. A review on the prediction of building energy consumption. Renew Sustain Energy Rev 2012;16(6):3586–92.
[14] Tian W. A review of sensitivity analysis methods in building energy analysis. Renew Sustain Energy Rev 2013;20:411–9.
[15] Tagliabue LC, Manfrena M, Ciribini ALC, De Angelis E. Probabilistic behavioural modeling in building performance simulation—the Brescia eLUX lab. Energy Build 2016;128:119–31.
[16] Touzani S, Granderson J, Jump D, Rebello D. Evaluation of methods to assess the uncertainty in estimated energy savings. Energy Build 2019;193:216–25.
[17] Sadeghifam AN, Meynagh MM, Tabatabaee S, Mahdiyar A, Memaride A, Ismail S. Assessment of the building components in the energy efficient design of tropical residential buildings: an application of BIM and statistical Taguchi method. Energy 2019;188:116080.
[18] Bordbari MJ, Reza Seifi A, Rastegar M. Probabilistic energy consumption analysis in buildings using point estimate method. Energy 2018;142(1): 716–22.
[19] Tiana W, Heo Y, de Wilde P, Lia Z, Yan D, Park CS, Feng X, Augenbroe G. A review of uncertainty analysis in building energy assessment. Renew Sustain Energy Rev 2018;93:285–301.
[20] Kneifel J, Webb D. Predicting energy performance of a net-zero energy building: a statistical approach. Appl Energy 2016;178:468–83.
[21] Lu X, Lu T, Kibert CJ, Viljanen M. Modeling and forecasting energy consumption for heterogeneous buildings using a physical–statistical approach. Appl Energy 2015;144:261–75.
[22] Xu J, Kim JO, Hong H, Koo J. A systematic approach for energy efficient building design factors optimization. Energy Build 2015;89:87–96.
[23] Valovcin S, Hering AS, Polly B, Heaney M. A statistical approach for post-processing residential building energy simulation output. Energy Build 2014;85:165–79.
[24] Horner M, Lichtmeß M. Energy performance of buildings: a statistical approach to marry calculated demand and measured consumption. Energy Efficiency 2019;12:139–55.
[25] Copiello S, Gabrielli L, Bonifaci P. Evaluation of energy retrofit in buildings under conditions of uncertainty: the prominence of the discount rate. Energy 2017;137:104–17.
[26] Togashi E. Risk analysis of energy efficiency investments in buildings using the Monte Carlo method. Journal of Building Performance Simulation 2019;12(4):504–22.
[27] Lee P, Lam PTI, Lee WL. Performance risks of lighting retrofit in Energy Performance Contracting projects. Energy for Sustainable Development 2018;45: 219–29.
[28] Deng Q, Jiang X, Zhang L, Cui Q. Making optimal investment decisions for energy service companies under uncertainty: a case study. Energy 2015;88: 234–43.
[29] Sadeghi M, Shavvalpour S. Energy risk management and value at risk modeling. Energy Pol 2006;34:3367–73.
[30] Jackson J. Promoting energy efficiency investments with risk management decision tools. Energy Pol 2010;38:3865–73.
[31] Bozorgi A. Integrating value and uncertainty in the energy retrofit analysis in real estate investment—next generation of energy efficiency assessment tools. Energy Efficiency 2015;8:1015–34.
[32] Loga T, Stein B, Diefenbach N. TABULA building typologies in 20 European countries—making energy-related features of residential building stocks comparable. Energy Build 2016;132:4–12.
[33] UNI-TS 11300. Italian Technical Code for Internal Heat Source Estimation. http://store.uni.com/catalogo/index.php/uni-ts-11300-2-2019.html (accessed 28.09.2020).
[34] Besagni G, Borgarello M, Premoli Vilà L, Najafi B, Rinaldi F. Moirae – bottom-up MOdel to compute the energy consumption of the Italian REsidential sector: model design, validation and evaluation of electrification pathways. Energy 2020;2011:118674.
[35] Corrado V, Ballarini I. Refurbishment trends of the residential building stock: analysis of a regional pilot case in Italy. Energy Build 2016;132:91–106.
[36] Bianco V, De Rosa M, Scarpa F, Tagliafico LA. Implementation of a cogeneration plant for a food processing facility. A case study. Appl Therm Eng 2016;102: 500–12.
[37] Julier SJ. The scaled unscented transformation. In: Proceedings of the 2002 American control conference (IEEE cat. No.CH37301, vol. 6. USA: Anchorage, AK; 2002. p. 4555–9.
[38] Janssen H. Monte-Carlo based uncertainty analysis: sampling efficiency and sampling convergence. Reliab Eng Syst Saf 2013;109:123–32.