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A Decision Making Technique to Optimize a Buildings' Stock Energy Efficiency

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***Abstract*—This paper focuses on applying multicriteria decision making tools to determine an optimal energy retrofit plan for a portfolio of buildings. We present a two-step decision making technique employing a multiobjective optimization algorithm followed by a multiattribute ranking procedure. The method aims at deciding, in an integrated way, the optimal energy retrofit plan for a whole stock of buildings, optimizing efficiency, sustainability, and comfort, while effectively allocating the available financial resources to the buildings. The proposed methodology is applied to a real stock of public buildings in Bari, Italy. The obtained results demonstrate that the approach effectively supports the city governance in making decisions for the optimal management of the buildings' energy efficiency.**

***Index Terms*—Building management, energy efficiency, multiattribute analysis, multicriteria decision making, multiobjective optimization (MOO), optimization algorithms.**

I. Introduction

THE current energy shortage around the world is the main reason why energy efficiency is an important subject of interest today [31]. The most viable option to counteract this problem is reducing the current energy consumption [44]. While reducing the energy used in the industrial sector has traditionally attracted the attention of researchers [39], recent studies are focusing on methods and models for improving buildings' energy efficiency. In fact, the energy consumption of buildings accounts for around 30% of all energy consumed in advanced countries, while also exceeding the energy consumption of the industrial and transportation sectors in the EU and U.S. [51]. Therefore, enhancing energy efficiency in the building sector is essential for the reduction of global energy use and promotion of environmental sustainability. This emerging need has led international organizations and governments to invest significant resources in the building renovation process and to establish restrictive governmental policies [50]. However, in the building sector most of the energy consumption is due to existing buildings [5], [53]. Therefore, a real reduction of emissions in the building sector can only be achieved by acting on the existing building stocks. Accordingly, an effective alternative to increase building efficiency is developing building automation, control, and management systems [7]. Consequently, the development of specific application tools able to assist decision makers to reach a final decision among a set of alternative actions to improve energy efficiency in existing buildings is required.

To the best of the authors' knowledge, the related literature clearly lacks efforts to propose decision tools aimed at determining the optimal energy retrofit strategies for a whole portfolio of buildings under multiple conflicting objectives. To fill this gap, this paper presents a two-step decision support tool for determining the optimal energy retrofit plan to optimize the energy efficiency of a stock of buildings. The proposed approach is based on a two-step multicriteria optimization model designed to take into account different and conflicting decision criteria in the renovation plan and the limited available financial resources for the given portfolio of buildings. The presented methodology is applied to an existing stock of public buildings located in the municipality of Bari, Italy. The obtained results demonstrate that the approach supports the city governance in making optimal decisions for improving the buildings energy efficiency.

The remainder of this paper is organized as follows. Section II provides a literature overview on multicriteria decision techniques in buildings' energy retrofit planning, positioning the paper contribution with respect to the related literature, and showing its advancement. Section III presents the decision model and the optimization algorithms. Hence, Section IV presents the case study and results. Finally, Section V provides the concluding remarks and future research lines.

II. Literature Review and Paper Positioning

A. Related Works on Single-Building Energy Retrofit

Several research studies have been carried out to develop and investigate different energy efficiency opportunities in order to improve the energy performance of single buildings. As technologies for energy efficiency improvement in buildings are well known [6], nowadays the main issue is to identify which energy retrofit technology (or measure) could be used

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for a particular project and select the most effective and reliable ones in the long term. The traditionally used approach is economical, privileging actions that, given the same initial investment, generate the highest energy savings [18]. This approach, however, is somewhat limited, since it does not consider other important aspects. In fact, when choosing among a variety of measures, the decision maker (DM) (the building expert) has to deal with environmental, energy related, financial, legal, and social factors, in order to find the best possible compromise that satisfies the final occupant needs and requirements [2]. As a result, a critical aspect in the choice of building renovation or retrofit actions is the evaluation of alternative measures based on a set of criteria, such as, e.g., energy consumption, environmental performance, investment cost, operational cost, indoor environment quality, security, social factors, etc. [42]. These criteria are generally conflicting in nature, or they at least interrelate in a nonlinear way. As a result, it is impossible to find a solution to the problem that is optimal against all criteria, and a feasible tradeoff solution that satisfies the requirements of the building's final user/occupant/owner has to be sought for.

The common practice usually employs methods like simulation [14], [37] for what-if analyses and, more generally, techniques that allow investigating only a limited number of alternative options. In other words, in the context of multicriteria approaches, multiattribute decision making (MADM) techniques are typically adopted. MADM is concerned with choosing the best alternative in a given set of viable options—without addressing the computation of alternative solutions to be ranked. In the context of MADM approaches for single building refurbishment for improved energy efficiency, Roulet *et al.* [54] presented a multicriteria methodology based on the so-called principal component analysis to provide the DM with a rating of retrofit plans of the considered building according to an extended list of criteria. In addition, Caccavelli and Gugerli [8] developed an MADM model to help professionals solve problems associated with the retrofitting of office buildings taking into account the degradation of building elements, energy efficiency, and internal environment comfort. A similar approach is proposed in [41], where a multivariant design for the refurbishment of a building is used to rank the alternative solutions. However, in the building energy retrofit context, the DM is faced with a potentially infinite number of alternative measures, to be evaluated according to a set of multiple conflicting criteria.

Due to the complexity of the recalled decision-making problems, especially in case of multiple objectives, techniques based on multiobjective optimization (MOO) are suitable candidates to solve these problems [44]. As a result, multiobjective decision making (MODM) approaches, which refer to a continuous decision space where alternatives are not predetermined, are clearly more suitable than MADM techniques for solving energy retrofit problems. In the context of MODM approaches, Diakaki *et al.* [20], [21] develop a multiobjective decision model that examines a potentially infinite number of alternative measures, and simultaneously minimizes three criteria: 1) the energy consumption of the building; 2) the initial investment cost; and 3) the annual carbon dioxide emission. Similarly, Asadi *et al.* [2] proposed and solved via Tchebycheff programming an MOO model to assist stakeholders in the definition of intervention measures aimed at minimizing the energy use in the building in a cost effective manner. Moreover, Juan *et al.* [36] developed a decision support system to assess existing office building conditions and recommend an optimal set of sustainable renovation actions, considering a tradeoff between renovation costs, improved building quality, and environmental impact. Further, Malatji *et al.* [44] formulated a multiple objective optimization model that maximizes energy savings and minimizes the payback period for a given initial investment. In addition, Rysanek and Choudhary [55] considered a two-criterion decision making technique taking into account on the one hand energy and environmental concerns and on the other hand financial aspects, including uncertainty on costs in the model. Finally, Alanne [1] uses a multicriteria knapsack model to determine the most feasible renovation actions in the design of a refurbishment project.

B. Related Works on Building Stock Energy Retrofit

While all the studies recalled in the previous section develop tools to assist the DM in making a decision when investing in the energy efficiency retrofit of a given building, they cannot solve the problem for a building stock. To the best of the authors' knowledge, only minor efforts have been devoted in the related literature to propose decision tools aimed at determining the optimal retrofit strategies for a portfolio of buildings. Nevertheless, it is a well-recognized need, particularly for organizations and public administrations, to efficiently allocate the available budget among different buildings, establishing the optimal energy retrofit strategy of each building in accordance to an integrated and holistic view of the entire portfolio [37]. Indeed, in the presence of limited resources, the DM is periodically faced with the dilemma of which building to treat and at what level of upgrading (i.e., with what budget). Hence, in order to achieve a near-optimal allocation of the limited resources, objective and transparent decision support tools are required. In this context, empirical methods are traditionally used to allocate the available budget to a stock of buildings, using two main classes of approaches [52]. In the first class, the DM invests a major part of the budget in the few most valuable buildings and/or in those exhibiting urgent problems, while the remaining budget is uniformly distributed among the others. In the second class, the DM allocates an equal amount of the budget to each building on the basis of fairness. However, these approaches do neither allow making decisions with an in-depth analysis of the building stock characteristics nor considering other criteria than price. To overcome these drawbacks of traditional empirical approaches, few contributions have appeared in the related literature. For instance, an optimization model using genetic algorithms is presented in [52] to address the optimal budget allocation for a stock of historical buildings, using interventions prioritization and synergy. Moreover, a model for generating an optimal planning of building retrofit for a portfolio of buildings is proposed in [37]: several objective functions are considered but

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only in a single-objective way: cost, greenhouse gas emission, and energy. Note that in both the mentioned works related to the buildings portfolio case, the problem of retrofit strategy determination is not approached by a multicriteria analysis, so that solutions are optimal only from a single criterion perspective.

C. Paper Contribution

The discussed related literature clearly shows two gaps in the context of retrofit strategies for building stocks: on the one hand, there is an evident lack of techniques that look at the portfolio of existing buildings in an integrated way rather than on a building by building basis; moreover, there is a lack of strategies that allow a multicriteria intervention on a building stock scale to ensure the integrated achievement of competing objectives to the whole building portfolio. In order to fill the discussed gaps in the literature, this paper develops a decision support technique that identifies an optimal set of retrofit interventions in a building stock to improve the global stock performance (e.g., energy efficiency, environmental sustainability, building's user/occupant/owner satisfaction, etc.), within the given budget. In particular, the contribution of this paper with respect to the related literature is twofold. First, this paper defines and solves the problem of determining an integrated strategy for the optimal energy efficient refurbishment of a stock of buildings, maximizing the overall energy efficiency performance, and optimizing the financial resource allocation among buildings in the portfolio. With this regard, the proposed approach allows managing buildings by different priority weights, according to the DM needs. Second, the presented multicriteria technique aims at providing the DM with a set of optimal alternative solutions without requiring any *a priori* articulation of criteria preference information. As a result, differently from the related literature, the main objective of the decision model is determining a set of optimal retrofit actions for the entire buildings portfolio, allowing the DM to analyze the various solutions and rank them in accordance to his preferences.

III. Two-Step Decision Making Technique for the Optimal Retrofit of Buildings' Stock

The proposed decision making technique aims at helping DMs select the optimal actions to take in order to improve the performance of a building stock against a set of conflicting criteria within a given budget. Hence, the problem statement may be described as follows. Given a set of buildings $B = \{B_1, \ldots, B_k, \ldots, B_K\}$, a budget E, a set of conflicting criteria $\Gamma = \{\Gamma_1, \ldots, \Gamma_h, \ldots, \Gamma_H\}$ for measuring the stock energy efficiency and a set of possible retrofit actions $A = \{A_1, \ldots, A_j, \ldots, A_J\}$, determine the optimal building stock overall action plan, that is: 1) the budget E_k—such that $\sum_{k=1}^{K} E_k \leq E$—to assign to each kth building B_k; 2) the binary decision variables x_{jk}—equal to 1 (0) if the jth action is (is not) to be applied to the kth building; and 3) the action budget e_{jk}—such that $\sum_{j=1}^{J} e_{jk} = E_k$—to assign to each jth action for the kth building.

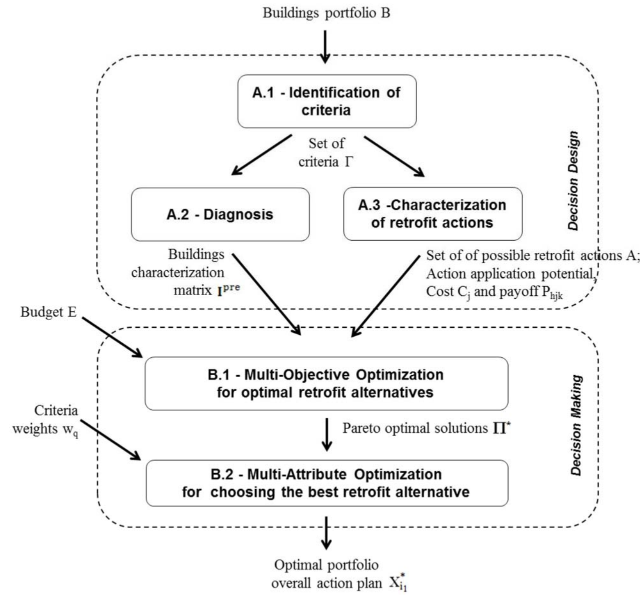

Fig. 1. Scheme of the proposed two-step decision making technique.

A scheme of the proposed two-step multicriteria decision technique is shown in Fig. 1. All activities involved in the decision process may be ideally divided into two macro-phases: a first part that comprises building status acquisition activities as well as identification of convenient retrofitting measures activities (the decision design dashed rectangle at the top of Fig. 1), and a second phase which includes the actual multicriteria analysis of the possible actions (the decision making dashed rectangle at the bottom of Fig. 1).

A. Decision Design Phase of the Technique

The first phase of the decision process in Fig. 1, called decision design, is performed by the DM in conjunction with building operators and stakeholders. This phase of the decision process aims at understanding and defining metrics and models that can be used to simulate the impact of potential modifications on buildings' performance. The decision design phase includes three steps: 1) identification of criteria; 2) diagnosis; and 3) characterization of retrofit actions.

1) Identification of Criteria: Primarily, since energy efficiency and environmental sustainability are the overall goals of the decision process, it is required to identify the specific criteria for characterizing and assessing buildings and retrofitting actions (i.e., the building characteristics or qualities that the DM is pursuing). In fact, in order to assess the compliance of a building to the regulation, to evaluate the efficiency of a building's retrofitting action, or to assess and classify the current state of buildings, it is important to define a set of characteristics based on a predefined number of criteria (namely, energy consumption, indoor environmental quality, etc.). Beyond monetary costs, the literature suggests a wide number of criteria to characterize the state of a building that can be grouped into the following macro-categories: energy, environment, internal environment quality, sustainability and others. Table I summarizes the main criteria which

TABLE I
BUILDING CHARACTERIZATION CRITERIA

Category	Criteria	Source
Energy	Annual normalized energy use for heating; Annual normalized energy use for cooling; Annual normalized energy use for other; Energy consumption for: heating, cooling and ventilation, heat for services and water, lighting, equipment, electromechanical installations, water use; Domestic Hot Water (DHW); Renewable energy; net consumption of water	[8, 15, 19, 38, 45, 54]
Environment	Annual normalized nuclear wastes emission; Annual normalized CO_2 emission	[15, 38, 54]
Internal Environment Quality	Predicted % of dissatisfaction; Outdoor airflow rate per person; Noise level; Lighting; Indoor air quality; Internal-external temperature; Indoor air temperature; Temperature and relative humidity; Carbon dioxide (CO_2); Carbon monoxide (CO); Particle matter mass; Nitrogen dioxide (NO_2); Acetaldeide; Formaldehyde; Ventilation rate; Sound level pressure; Thermal comfort; Heat island effect	[8, 9, 12, 13, 15, 16, 22, 38, 45, 46, 47, 48, 49, 54, 59]
Sustainability and others	Physical degradation; Maintainability; Compliance with regulations; Use of land and change in quality of land	[8, 15, 30, 61]

may be found in the related literature for the aforementioned categories. Hence, in this phase the DM selects in the building characterization criteria listed in Table I the set Γ of criteria to characterize the energy efficiency of the buildings stock.

2) Diagnosis: The building diagnosis aims at evaluating the general state of buildings in the stock with respect to the criteria selected in Section III-A1, e.g., deterioration, functional obsolescence, energy consumption, indoor environment quality, etc. Hence, the diagnosis consists in evaluating the current state of each building in terms of the set of criteria defined by the DM in the previous step. Let I_{hk}^{pre} be the resulting value of the criterion Γ_h on the kth building B_k, where the symbol "pre" in apex indicates the indicator value is relative to the ex-ante building status (i.e., preceding the implementation of the retrofit actions).

Conducting the analysis on all buildings of the stock, the result is the so-called stock multicriteria characterization matrix of dimensions $H \times K$, i.e., a matrix whose generic element is a number evaluating the performance of the kth building with respect to the hth criterion

$$\mathbf{I}^{\text{pre}} = \left[I_{hk}^{\text{pre}}\right] \wedge h = 1, \ldots, H, k = 1, \ldots, K. \tag{1}$$

Fig. 2 depicts a possible result of the diagnosis for a building in the stock: each black dot represents the value before retrofit for the specific criteria, while the gray regular polygon collects the building target values for all criteria.

3) Characterization of Retrofit Actions: This task is aimed at defining retrofitting actions that can potentially be executed to improve the global performance of the buildings, with their corresponding impact on building performance and

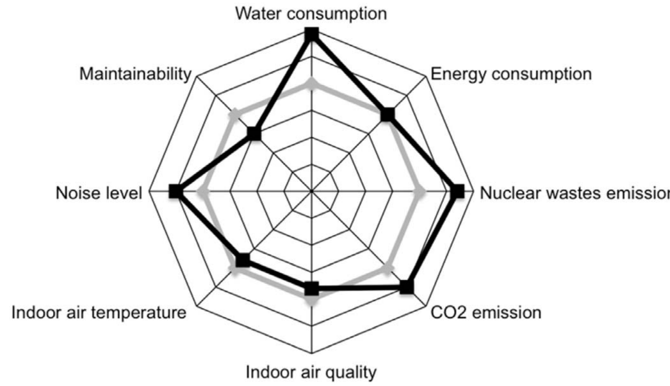

Fig. 2. Example of diagnosis results for a building of the stock.

costs. This step requires an applicability and feasibility study that is conducted on a building-by-building basis. In fact, each building in the stock may exhibit unique architectural, technical, and/or structural characteristics, and customized retrofit options must be individually investigated. The retrofit measures may include: retrofitting of the building fabric, either construction or mechanical systems (e.g., wall insulation and HVAC systems, respectively); building heating or cooling equipment (e.g., boiler replacement, thermostatic radiator valves installation, etc.); replacement of home/building appliances (e.g., installation of water tap aerators) and lighting fixtures (e.g., electric lighting replacement). Lists of retrofit measures examples are provided by various researchers (see [43], [60]). We remark that operational changes (e.g., modifications of operating hours, behavioral changes such as running appliances when electricity prices are lower, set-point optimization, etc.) are hereby disregarded because these changes may be optimally determined on a single building scale, i.e., they do not require a holistic approach for the whole building stock.

The outcome of the evaluation of renovation and energy efficiency measures is the list A of J identified actions to be possibly implemented in the buildings. Note that each retrofit action may concern either a simple retrofit measure (such as window replacement or heating equipment replacement) or a combination of measures regarding the same building element (such as more than one measure on the building envelope, more than one measure acting on the HVAC equipment or lighting equipment). In this model we assume that each of the action selected by the energy manager (simple or combined) may be implemented to each building. Each determined action is successively characterized from three perspectives: 1) the application potential; 2) the cost; and 3) its payoff.

The application potential of an action is defined as the estimation of a metric related to the action implementation. For instance, in case of a thermal insulation work on external walls, the application potential consists in the walls' surface extension, measured in square meters.

The cost of each action (simple or combined) is calculated by adding individual retrofit measure costs. The cost of each individual measure is simply modeled in accordance to a linear pricing model, as the product between the unitary cost of the simple measure, that is expressed as unit of

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surface [€/m^2], unit of energy [€/kWh], and so on, and the related application potential. The cost for implementing the jth action (simple or combined) on the kth building is denoted as C_{jk}. Let P_{hjk} be the payoff, namely the benefit (or detriment) that the application of the specific action j (simple or combined) is expected to produce on the beneficiary building. Since an action could impact on different criteria, the estimate of a payoff for each indicator is provided. For the kth building, the jth action produces the payoff P_{hjk} for the hth criterion.

The general procedure for estimating the payoff P_{hjk} from a retrofit project is based on the calculation of the difference between the pre-retrofit value of the hth indicator predicted from a model and the post-retrofit value of the indicator, that is

$$P_{hjk} = I_{hk}^{\text{pre}} - I_{hk}^{\text{post-}j\text{ action}} \tag{2}$$

where

I_{hk}^{pre} is the value of the hth indicator derived from a pre-retrofit simulation of the kth building;

$I_{hk}^{\text{post-}j\text{ action}}$ is the value of the hth indicator after implementing the retrofit action j predicted by simulation.

Note that, while the payoff of a given action P_{hjk} is dependent on the building to which it is applied, in the action cost model the unitary cost of each individual measure is modeled as an invariant with respect to buildings. In fact, although buildings in the portfolio generally differ from each other, the estimated action cost can be approximated to be invariant in the stock, e.g., because buildings are located in the same zone. Of course, this assumption may be suitably removed and the model may be changed accordingly, by simply defining a different unitary cost for each building.

B. Decision Making Phase of the Technique

The second phase of the decision process in Fig. 1, called decision making, is a responsibility of the DM, i.e., the building stock owner, facility manager, or investor. The decision making phase is constituted by two steps. The first step (Section III-B1) consists in the definition of an MOO problem. The solution of such a problem provides a set of Pareto-optimal retrofit strategies, also called nondominated solutions, defining the so-called Pareto frontier. The second step (Section III-B2) refers to the selection of the best retrofit alternative among the Pareto-optimal solutions.

1) Multiobjective Optimization Model: An MOO problem is defined to determine the Pareto frontier collecting all possible optimal retrofit strategies. The decision model relies on several decision variables reflecting the choices on actions. To this aim, for each action $j = 1, \ldots, J$ and each building $k = 1, \ldots, K$ the binary decision variables x_{jk} have to be determined. Hence, matrix $\mathbf{X}$ of the $J \times K$ decision variables of the optimization model is constructed as follows:

$$\mathbf{X} = \left[x_{jk}\right] \wedge j = 1, \ldots, J, k = 1, \ldots, K. \tag{3}$$

As previously remarked, we assume that each building may be subject to a number of retrofit actions among all the identified actions set A.

The H criteria objective functions of the problem are determined using the improvements of the identified performance indicators obtained with the retrofit implementation. Note that, for the sake of simplicity, all the indicators are assumed to have a range whose upper level stands for poor performance, while its lower level indicates excellent performance. Hence, the MOO problem is concerned with the minimization of all the indicators. Of course, if this hypothesis is not verified for a given indicator, a maximization has to be operated with respect to that indicator and the problem may be straightforwardly changed accordingly.

The application of retrofit actions to the kth building provides the hth indicator related to the kth building with a decrease equal to the estimated payoff, that is

$$I_{hk} = I_{hk}^{\text{pre}} - \sum_{j=1}^{J} x_{jk} \cdot P_{hjk}, \quad \forall h = 1, \ldots, H, \forall k = 1, \ldots, K. \tag{4}$$

Considering all the improvements to each building, the hth indicator value for the stock may be formulated as the weighted average of indicators for all buildings

$$I_h = \frac{1}{K} \cdot \sum_{k=1}^{K} g_k \cdot \left(I_{hk}^{\text{pre}} - \sum_{j=1}^{J} x_{jk} \cdot P_{hjk} \right), \quad \forall h = 1, \ldots, H \tag{5}$$

where g_k is a priority coefficient in the [0, 1] range associated by the DM with the kth building. These given K building priority coefficients $(g_1, \ldots, g_k, \ldots, g_K)$ are normalized so that the summation of all such coefficients is unitary. Obviously, in case all the buildings have the same priority, these coefficients are all equal to $1/K$.

Since the minimization of the hth indicator in (5) is equivalent to the maximization of the overall estimated payoff for the hth indicator, the MOO problem may be defined as determining the $J \times K$ decision variables in $\mathbf{X}$ that maximize the overall estimated payoffs for the H criteria

$$\max_{\mathbf{X}} f_h(\mathbf{X}) = \sum_{k=1}^{K} g_k \cdot \sum_{j=1}^{J} x_{jk} \cdot P_{hjk}, \quad \forall h = 1, \ldots, H. \tag{6}$$

Of course, the main constraint in the choice of the decision variables lies in the financial resources' limitation. Hence, the following inequality has to be verified:

$$\sum_{j=1}^{J} \sum_{k=1}^{K} x_{jk} \cdot C_{jk} \leq E. \tag{7}$$

In addition, the following constraints for actions' mutual exclusion are introduced, indicating actions that cannot be simultaneously implemented for technical reasons:

$$\sum_{j \in M_p} x_{jk} \leq 1, \quad \forall k = 1, \ldots, K, \forall p = 1, \ldots, P \tag{8}$$

where M_p is the set of indices of the pth given group (also called building element) with $p = 1, \ldots, P$ collecting mutually exclusive actions.

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Solving the decision problem (6)–(8) allows determining the actions to apply (i.e., the nonzero x_{jk} variables), the budget associated to each jth action for the kth building

$$e_{jk} = x_{jk} \cdot C_{jk} \tag{9}$$

and the budget associated to each kth building

$$E_k = \sum_{j=1}^{J} e_{jk}. \tag{10}$$

The decision problem (6)–(8) is a vector maximization problem with binary variables, known as multiobjective knapsack problem (MOKP). This may be solved by means of several techniques. We choose a simple augmented ε-constraint (SAUGMECON) method [64], a variant of the ε-constraint method that can be properly used to produce the complete Pareto set of multiobjective integer programing problems. With SAUGMECON, (6)–(8) is initially rewritten as the following single-objective problem:

$$\begin{aligned} \max_{\mathbf{X}} \quad & f_H(\mathbf{X}) + \delta \cdot \sum_{h=1}^{H-1} \frac{f_h(\mathbf{X})}{\rho_h} \\ \text{s.t.} \quad & f_h(\mathbf{X}) \geq \varepsilon_h, \quad \forall h = 1, \ldots, H-1 \\ & \text{and constraints (7) and (8)} \end{aligned} \tag{11}$$

where ε_h ($\forall h = 1, \ldots, H-1$) is the satisfaction level which stipulates the minimum requirement on the hth constrained objective; ρ_h ($\forall h = 1, \ldots, H-1$) is the range of the hth objective; δ is an adequately small number usually between 10^{-6} and 10^{-3} [64]. The first step in applying the SAUGMECON method is to determine the range of objective functions which are used as constraints (ρ_h with $h = 1, \ldots, H-1$). To do so, we calculate the optimal (utopia) and pessimistic nadir values of objective functions over the feasible space. The optimal values may be obtained optimizing single objectives individually. Since the pessimistic values are not easily attainable, they are usually estimated by inversely optimizing single objectives individually. Subsequently, as a second phase, problem (11) is repeatedly solved by parametrically varying the value of satisfaction levels $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{h-1}$. These constrained objectives have to start with the less restrictive values (pessimistic) and gradually move to the more restricted values (utopia) with unitary step. In accordance with the SAUGMECON method, several innovative acceleration mechanisms may be used to avoid redundant iterations and thus speed up the process of searching for all the nondominated solutions [64]. Note that, since in MOKP problems it is well known that the size of the Pareto set is finite, it can be demonstrated that SAUGMECON is suitable for generating the exact Pareto set for problems such as (6)–(8) [64]. The only required condition is that the objective function coefficients in (6) are integer (note that this condition could be easily relaxed by transforming the problem to have integer objective function coefficients by multiplying with the appropriate power of 10).

Designating $\mathbf{X}_i{}^*$ as one of the determined Pareto-optimal solutions, the Pareto solutions set is defined as follows:

$$\mathbf{\Pi}^* = \left\{\mathbf{X}_i^*\right\}, i = 1, \ldots, N_{\Pi^*} \tag{12}$$

where N_{Π^*} is the cardinality of the set of Pareto-optimal solutions $\mathbf{\Pi}^*$.

2) Multiattribute Optimization: After the MOO problem (6)–(8) is solved, the DM has to select the best retrofit alternative among the determined Pareto-optimal solutions. In order to choose among the determined solutions, different approaches may be followed. Traditional methods base the choice on expert knowledge or preference. However, selecting one of the alternatives may be a complex task if the dimension of the solutions set is very large. Alternatively, a second level optimization can be performed using an MADM technique to provide a ranking of the obtained retrofit strategies [29], [33], [63]. MADM deals with a finite "selection" or "choice" problem, that is, the problem of choosing an option from a set of alternatives, which are characterized in terms of their attributes. MADM is a qualitative approach due to the existence of the criteria subjectivity. It requires information on the preferences among the instances of an attribute, and the preferences across the existing attributes [23], [56]. The DM may express or define a ranking of the attributes in terms of importance/weights. The aim of the MADM is to obtain the optimum alternative that has the highest degree of satisfaction for all of the relevant attributes [62].

The so-called technique for order preference by similarity to ideal solution (TOPSIS) [32], known as one of the most classical MADM methods and widely accepted for identifying solutions from a finite set of alternatives, is used in this paper to solve the MADM problem. TOPSIS is based on the idea that the chosen alternative should have the shortest distance from the positive-ideal solution and on the other side the farthest distance from the negative ideal solution (NIS).

The TOPSIS method requires in input an $N_{\Pi^*} \times Q$ decision matrix D_M, where Q is the number of criteria used in the solution ranking. Note that the ranking may be performed on the basis of all or part of the H performance indicators considered in the first part of optimization model (Section III-B1) or by way of different criteria from the ones considered to solve the MOO problem. In particular, the DM may regard all the solutions of (6)–(8) as equally satisfactory and consider a novel set of Q criteria to perform the ranking. As an alternative, the DM may analyze the determined solutions considering additional Z criteria with respect to those considered in the previous steps (i.e., in this case $Q = H + Z$). Hence, the generic element d_{iq} of the decision matrix D_M, with $i = 1, \ldots, N_{\Pi^*}$ and $q = 1, \ldots, Q$, represents the qth performance value of the ith MOO solution $\mathbf{X}_i^*$ of problem (6)–(8) with respect to the Q criteria selected for classifying the N_{Π^*} alternatives. The method also requires cardinal attribute importance weights of the alternatives with respect to the criteria. Hence, a weight w_q, with $q = 1, \ldots, Q$, is associated by the DM to each of the ranking criteria in order to model the importance degree of the qth criterion in the ranking of the different retrofit configurations. The ranking criteria weights are chosen so that the summation of all such weights is unitary. TOPSIS consists of the following steps [32].

Step 1 (Constructing the Normalized Decision Matrix): Determine each element δ_{iq} of the $N_{\Pi^*} \times Q$ normalized decision matrix $\boldsymbol{\Delta}$ as follows:

$$\delta_{iq} = \frac{d_{iq}}{\sqrt{\sum_{i=1}^{N_{\Pi^*}} d_{iq}^2}}, i = 1, \ldots, N_{\Pi^*}, q = 1, \ldots, Q. \quad (13)$$

Step 2 (Constructing the Weighted Normalized Decision Matrix): Determine the $N_{\Pi^*} \times Q$ weighted normalized decision matrix Ω, whose element is computed as follows:

$$\omega_{iq} = \delta_{iq} \cdot w_q, \quad i = 1, \ldots, N_{\Pi^*}, q = 1, \ldots, Q. \quad (14)$$

Step 3 (Determining the Ideal and Negative Ideal Solutions): Determine the IS as the ideal solution with performance indicators given by the row vector $\Omega_{\max} = [\omega_{\max 1}, \ldots, \omega_{\max q}, \omega_{\max Q}]$, where $\omega_{\max q} = \max(\omega_{1q}, \ldots, \omega_{iq}, \ldots \omega_{N*q})$ with $q = 1, \ldots, Q$. Moreover, determine the NIS as the ideal solution associated to performance indicators of the row vector $\Omega_{\min} = [\omega_{\min 1}, \ldots, \omega_{\min q}, \ldots, \omega_{\min Q}]$, where $\omega_{\min q} = \min(\omega_{1q}, \ldots, \omega_{iq}, \ldots, \omega_{N_{\Pi^*} q})$ with $q = 1, \ldots, Q$.

Step 4 (Calculating the Separation Distances): Calculate the separation distance $S_{\max i}$ from the IS of each alternative $\mathbf{X}_i^*$ with $i = 1, \ldots, N_{\Pi} *$ as follows:

$$S_{\max i} = \sqrt{\sum_{q=1}^{Q} \left(\omega_{iq} - \omega_{\max q}\right)^2}. \quad (15)$$

Moreover, determine the separation distance $S_{\min i}$ of $\mathbf{X}_i^*$ with $i = 1, \ldots, N_{\Pi^*}$ from the NIS as follows:

$$S_{\min i} = \sqrt{\sum_{q=1}^{Q} \left(\omega_{iq} - \omega_{\min q}\right)^2}. \quad (16)$$

Step 5 (Calculating the Relative Closeness of Alternatives to the Ideal Solution): Determine the closeness Cl_i to the NIS of each alternative $\mathbf{X}_i^*$ with $i = 1, \ldots, N_{\Pi^*}$ as follows:

$$\mathrm{Cl}_i = \frac{S_{\min i}}{S_{\max i} + S_{\min i}}. \quad (17)$$

Step 6 (Ranking Alternatives): The ranked set of alternatives is represented by the ordered set $\tilde{\boldsymbol{\Pi}}$ defined as

$$\tilde{\boldsymbol{\Pi}} = \left\{ \mathbf{X}_{i_1}^*, \ldots, \mathbf{X}_{i_{N_{\Pi^*}}}^* \right\} \quad (18)$$

where all the elements of the set $\boldsymbol{\Pi}^*$ are arranged according to the decreasing order of the closeness value Cl_i associated to the ith solution for $i = 1, \ldots, N_{\Pi^*}$. Hence, $\mathbf{X}_{i_1}^*$ is the best retrofit alternative and $\mathbf{X}_{i_{N_{\Pi^*}}}^*$ is the worst one.

IV. Case Study

A. Problem Description

We apply the developed model to the case of the municipality of Bari, the capital city of Apulia region, southern Italy. Bari is currently engaged in a series of smart city initiatives promoted by the EU and mainly dedicated to the reduction of CO_2 emissions and increase of the quality of life [10], [11]. The Bari Smart city program has as a main goal implementing a creative, dynamic, and energy-efficient city, through a series of initiatives. These include energy efficiency projects, urban planning, improvements for heating and lighting infrastructure and networks, intelligent buildings, introducing renewable energy sources, and education campaigns. In particular, a specific initiative within the Bari smart city program focuses on the design, development, and testing of a new tool supporting the public administration (PA) for the energy efficient management of buildings occupied and governed by the PA.

Within this context, a real stock of $K = 5$ public buildings (five school buildings identified as B_1, B_2, B_3, B_4, and B_5) located in Bari has been examined to study the effectiveness of the decision model for building energy efficiency optimization presented in the previous section.

TABLE II
Results of Buildings Diagnosis

		Indicators		
		I_{1k}^{pre} [KWh/year]	I_{2k}^{pre} [m^3/year]	I_{3k}^{pre} [m^3/year]
Buildings	B_1	25290	50652	1950
	B_2	39500	84275	2700
	B_3	41026	36080	2250
	B_4	43851	86732	2500
	B_5	44582	33713	2400

TABLE III
Description of Individual Retrofit Measures

Retrofit measure	Description
external walls thermal insulation	thermal insulation in the extrados of outside walls by means of the application of insulating material
roof thermal insulation	solutions that not only increase the thermal resistance to the heat passage, but reduce the negative effects, in summer, of the solar radiation through techniques as ventilation, reflection and damping of the thermal wave with a layer of material (e.g. green roof technology)
windows replacement	replacement of the old windows with new, high energy-performance windows
boiler replacement	replacement of existing electric boilers for DHW (domestic hot water) with more energy efficient solutions
thermostatic radiator valves installation	replacement of the manual regulation valve installed at each terminal (e.g., radiator) with a thermostatic valve
water tap aerators installation	tap aerators and tap regulators to reduce the flow of water from taps
electric water heater replacement	replacement of an existing water heater for DHW with a heat pump
electric lighting replacement	replacement of existing lumps with new efficient lumps with lower electricity consumption

B. Decision Design

Problem (6)–(8) is first specified considering three criteria aimed simultaneously at energy and resource savings. More precisely, after a joint analysis and walk-through surveys conducted with technical experts, the following $H = 3$ performance indicators to minimize are considered.

1) Electrical energy consumption due to lighting and water heating (I_1).
2) Methane consumption due to heating (I_2).
3) Water consumption (I_3).

TABLE IV
RETROFIT MEASURE APPLICATION POTENTIALS AND UNITARY COSTS

		Application potential in each building						Unitary Cost
		B_1	B_2	B_3	B_4	B_5	unit	
Retrofit measures	external walls thermal insulation	2986	3322	2975	2344	1592	m^2	55.27 [€/m^2]
	roof thermal insulation	1541	1979	1005	2453	1684	m^2	51.60 [€/m^2]
	windows replacement	507	251	393	292	107	m^2	348.63 [€/m^2]
	boiler replacement	2	1	1	1	4	pc.	9,750.00 [€/pc.]
	thermostatic radiator valves installation	110	70	70	60	60	pc.	45.74 [€/pc.]
	water tap aerators installation	50	50	40	40	30	pc.	25.72 [€/pc.]
	electric water heater replacement	3	4	4	4	3	pc.	70.00 [€/pc.]
	electric lighting replacement	390	396	360	365	349	pc.	65.22 [€/pc.]

TABLE V
LIST OF THE ACTIONS CONSIDERED IN THE CASE STUDY

Code	Description	Building element
A_1	external walls thermal insulation	Envelope
A_2	roof thermal insulation	
A_3	windows replacement	
A_4	external walls thermal insulation + roof thermal insulation	
A_5	external walls thermal insulation + windows replacement	
A_6	roof thermal insulation + windows replacement	
A_7	external walls thermal insulation + roof thermal insulation + windows replacement	
A_8	boiler replacement	HVAC
A_9	thermostatic radiator valves installation	
A_{10}	boiler replacement + thermostatic radiator valves installation	
A_{11}	water tap aerators installation	Water equipment
A_{12}	electric water heater replacement	
A_{13}	water tap aerators installation + electric water heater replacement	
A_{14}	electric lighting replacement	Lighting equipment

Second, the current status of each building in the portfolio is estimated through various surveys and on-site measures. Table II reports the outcomes of the diagnosis phase performed for each building of the stock and accordingly reporting the current value of each indicator. Third, considering the existing operating conditions of buildings, a feasibility study on potential retrofitting intervention addressing both technical and architectural constraints is carried out. In this case study, the DM considers actions acting on the building envelope, and on the replacement of HVAC, water, and lighting equipment. Individual retrofit measures are described in Table III [17]. Table IV shows for each building the metric estimation related to each simple action implementation as well as the unitary cost of each action whose estimation is based on the list of prices for building works in the Bari city area [40]. Table V collects the findings of a feasibility study on the retrofitting (individual or combined) actions that are applicable to the portfolio for $P = 4$ building elements (groups). Further, Table VI contains the matrix of payoffs with respect to the selected criteria for each building.

The impact of each retrofit action on the discussed indicators is estimated—with the help of a building technical expert—through the application of energy performance assessment methods defined by regulations [24], [26], [27], [35], [57], [58] and the use of a series of data that have to be surveyed or measured in advance on site on a building by building basis. In particular, the input data used to perform the action characterization phase for each building of the stock in terms of payoff can be grouped into the following three categories.

1) Data related to context that is independent from specific building such as: climatic data (outside average temperature, degree days, etc.), occupants' data (human metabolism, dressed person average temperature, individual daily water requirement etc.).
2) Data related to building type (school, office, residential, etc.) that depends on the building intended use.
3) Data related to specific building such as: geographical location (e.g., orientation), geometry (e.g., exterior walls surface, windows surface, roof surface, etc.), structure (e.g., building materials, internal thermal capacity, etc.), and plants (e.g., heating, number of sinks, lighting). Note that this category includes building characteristics that are not impacted by retrofit actions (e.g., number of occupants, etc.) and building characteristics that are impacted (e.g., envelopes transmittance, external walls solar irradiance, etc.).

Last, Table VII reports other MOO parameters, namely the available budget and the building priority coefficients (note that the buildings are all assigned the same importance).

C. Decision Making

The MOO problem described in Section III-B1 is stated and implemented in the MATLAB environment with the Global Optimization Toolbox. In particular, the single objective optimization problem (11) used in the SAUGMECON resolution method has been solved with the MATLAB built-in binary integer programming solver based on a branch-and-bound approach. Note that, in accordance with the scenario described in the previous section, the single objective problem presents 70 binary variables and 16 inequality constraints.

Fig. 3(a) illustrates the profile of objective functions in the Pareto frontier, which includes 11 points, and demonstrates

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TABLE VI
BUILDINGS PAYOFFS

Buildings		B_1			B_2			B_3			B_4			B_5		
Payoffs		P_{1j1} [kWh/yr.]	P_{2j1} [m^3/yr.]	P_{3j1} [m^3/yr.]	P_{1j2} [kWh/yr.]	P_{2j2} [m^3/yr.]	P_{3j2} [m^3/yr.]	P_{1j3} [kWh/yr.]	P_{2j3} [m^3/yr.]	P_{3j3} [m^3/yr.]	P_{1j4} [kWh/yr.]	P_{2j4} [m^3/yr.]	P_{3j4} [m^3/yr.]	P_{1j5} [kWh/yr.]	P_{2j5} [m^3/yr.]	P_{3j5} [m^3/yr.]
Actions	A_1	-	1463	-	-	8404	-	-	2142	-	-	7783	-	-	2022	-
	A_2	-	1989	-	-	3364	-	-	1799	-	-	5201	-	-	1010	-
	A_3	-	1490	-	-	5055	-	-	1081	-	-	2603	-	-	1347	-
	A_4	-	4052	-	-	11799	-	-	3247	-	-	11275	-	-	2023	-
	A_5	-	2026	-	-	10956	-	-	2886	-	-	10408	-	-	3034	-
	A_6	-	4052	-	-	6742	-	-	2526	-	-	6071	-	-	3034	-
	A_7	-	4559	-	-	16012	-	-	4690	-	-	13010	-	-	3034	-
	A_8	-	7454	-	-	17698	-	-	3607	-	-	13876	-	-	6740	-
	A_9	-	1491	-	-	2528	-	-	901	-	-	1300	-	-	842	-
	A_{10}	-	8104	-	-	21069	-	-	5051	-	-	15612	-	-	7754	-
	A_{11}	113	-	390	178	-	594	213	-	453	211	-	475	200	-	456
	A_{12}	757	-	-	1184	-	-	2135	-	-	1643	-	-	1067	-	-
	A_{13}	794	-	390	1302	-	594	2277	-	453	1708	-	475	1335	-	456
	A_{14}	506	-	-	790	-	-	1228	-	-	1312	-	-	1335	-	-

TABLE VII
OTHER MOO PROBLEM PARAMETERS

Symbol	Quantity	Value
$[g_1, g_2, g_3, g_4, g_5]$	building priority coefficients	[0.2 0.2 0.2 0.2 0.2]
E	budget [€]	800,000.00

TABLE VIII
MOO UTOPIA POINTS

		Objective functions		
		f_1^O [KWh/year]	f_2^O [m^3/year]	f_3^O [m^3/year]
Types of solution	max f_1	**12587**	23802	1978
	max f_2	213	**87156**	453
	max f_3	10610	57752	**2368**

that the decision criteria are conflicting. In fact, in the majority of Pareto solutions, the maximization of an objective function typically corresponds to a low level assumed by the other ones. Even though some solutions (e.g., solution 2) seem to dominate others, the reader can note that all the computed solutions are actually nondominated examining in Table X the numerical values that indicators take in each Pareto solution. Moreover, Table VIII reports the utopia points for which each criterion is optimized, independently from the others. Also this table concisely demonstrates the competitiveness of the decision criteria and the effectiveness of the proposed approach in providing the DM with a set of alternative solutions that present an optimal tradeoff between the various competing criteria.

Fig. 3(b) shows the allocation of planned costs between buildings in each of Pareto-optimal solutions, while Fig. 3(c) illustrates the distribution of planned retrofit actions between buildings in each of the Pareto-optimal solutions. Given the prominent difference in the assignment of the amount of candidate retrofit actions (and associated budget) between buildings in one planned retrofit scenario with respect to others, this demonstrates the importance, and consequently the need, of an optimal allocation of budget between buildings in the stocks.

The obtained Pareto-optimal solutions are subsequently ranked implementing in MATLAB the multiattribute optimization described in Section III-B2. To show the flexibility of the proposed technique, we consider two alternatives, with the DM using two different sets of ranking criteria according to the following cases.

Case 1: The ranking is based on $Q = 3$ criteria that are exactly coincident with the criteria adopted in the MOO, i.e., electrical energy consumption (I_1), methane consumption (I_2), and water consumption (I_3).

Case 2: A novel set of $Q = 4$ criteria is considered by adding a further indicator, namely the occupants' internal thermal comfort I_4, to the previously defined indicators I_1, I_2, and I_3. The metric used to assess thermal comfort is the so-called predicted mean vote (PMV), based on Fanger's model [28]. PMV is representative of what a large population would think of a thermal environment, and is used to assess thermal comfort in standards such as ISO 7730 [34] and ASHRAE 55 [4]. It ranges from -3 (too cold) to $+3$ (too warm), and a PMV value of zero is expected to provide the lowest percentage of dissatisfied people among a population [3]. The internal comfort related to the stock of buildings is assessed as the PMV of that virtual building having internal thermal conditions equal to the mean of the thermal conditions of retrofitted buildings in the stock.

In both cases, the DM assigns the same importance to the ranking criteria. The corresponding equal values of weights assigned to the ranking criteria are reported in Table IX.

Obviously, in case 2 the characterization data that are in input to the optimization problem have to be completed adding

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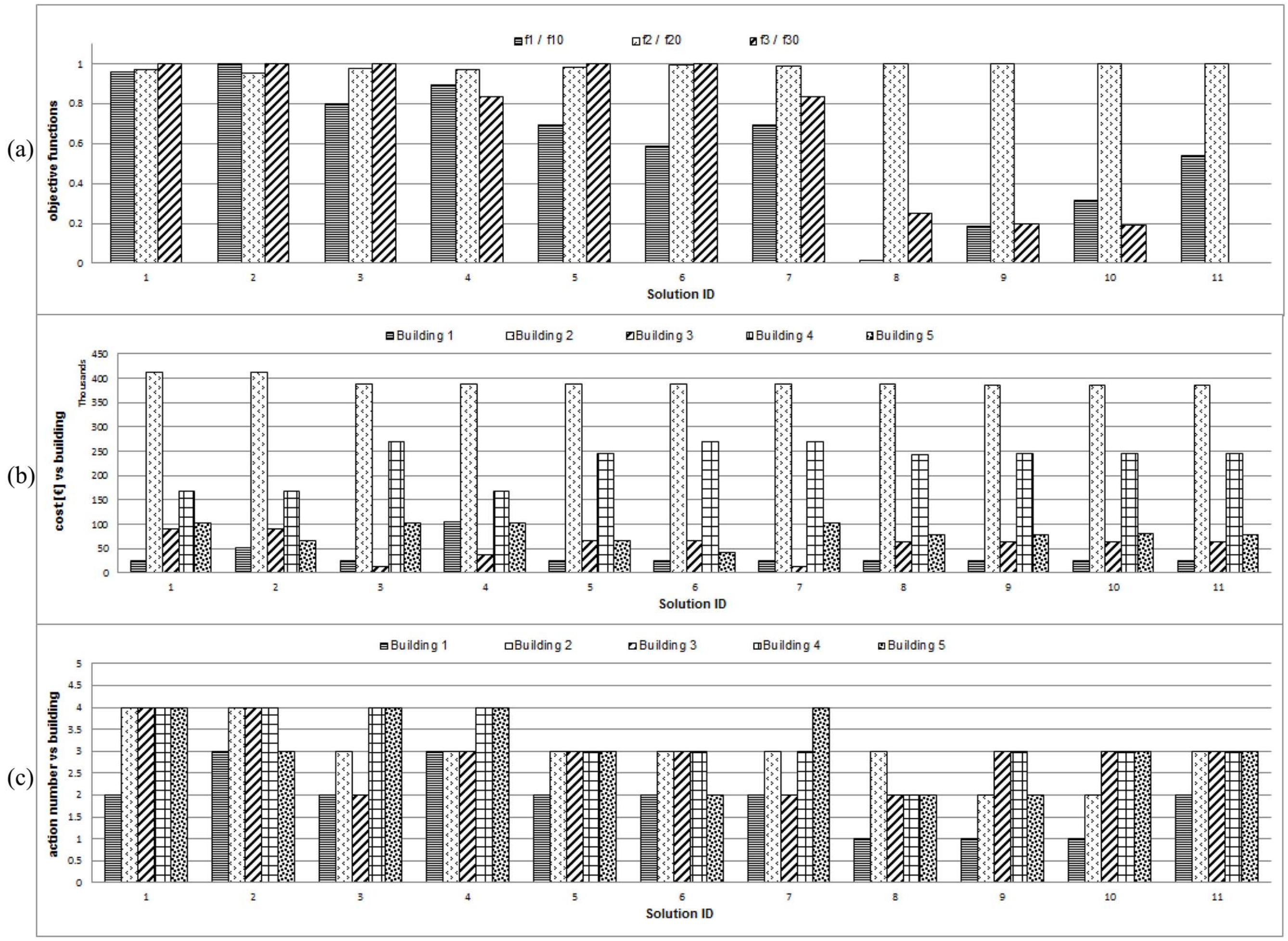

Fig. 3. Characteristics of Pareto-optimal solutions. (a) Objective function values normalized with respect to utopia points. (b) Allocation of planned costs between buildings. (c) Distribution of planned retrofit actions between buildings.

TABLE IX
RANKING CRITERIA WEIGHTS

Case	Symbol	Value
(1)	$[w_1, w_2, w_3]$	[1/3 1/3 1/3]
(2)	$[w_1, w_2, w_3, w_4]$	[0.25 0.25 0.25 0.25]

TABLE X
PARETO OPTIMAL SOLUTIONS DECISION MATRIX

Pareto optimal solution ID	Indicators I_1 [KWh/year]	I_2 [m^3/year]	I_3 [m^3/year]	I_4 [-]
1	36434	41384	1886	0.2
2	36332	41654	1886	0
3	36837	41219	1886	0
4	36599	41346	1964	0.1
5	37100	41129	1886	0.1
6	37367	40955	1886	0
7	37107	41046	1964	0.1
8	38814	40859	2241	0.1
9	38381	40859	2265	0
10	38054	40859	2269	0.1
11	37493	40859	2360	0.2

the evaluation of achieved occupants' internal thermal comfort for each retrofit scenario based on assessment methods defined by regulations [25]. Table X reports the value of the selected indicators for each optimal solution summarizing all the raw data available to the DM at the start of the analysis: the decision matrix exhibits 11×3 elements in case 1 (i.e., the first three columns of Table X) and 11×4 elements in case 2 (i.e., the whole Table X). Details on the intermediate results of the method are here neglected for the sake of brevity. Indeed, Table XI reports the final ranking of the 11 retrofit alternatives in both cases, showing that in the two cases alternatives are not ranked according to a similar order, i.e., adding the maximization of occupants' comfort as a further criterion impacts the ranking of optimal solutions. Hence, the retrofit alternatives (except solution 1) that are previously top-ranked are not quite as satisfactory also from the occupants' comfort perspective, as long as the weight of such this indicator is comparable to the weights of the other indicators. Obviously, as the weight assigned to the comfort indicator decreases, the final ranking approaches the ordering achieved in case 1. Tests that

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TABLE XI
PARETO OPTIMAL SOLUTIONS RANKING

	Case			
	(1) Q=3 ranking criteria		(2) Q=4 ranking criteria	
Ranking	**Solution ID**	**score**	**Solution ID**	**score**
1st	1	0.948	1	0.993
2nd	3	0.936	11	0.888
3rd	2	0.925	5	0.508
4th	5	0.916	4	0.506
5th	6	0.894	7	0.505
6th	4	0.833	8	0.496
7th	7	0.820	10	0.495
8th	8	0.248	2	0.115
9th	10	0.215	3	0.114
10th	9	0.211	6	0.113
11st	11	0.148	9	0.027

TABLE XII
OPTIMAL ENERGY RETROFIT PLAN

Actions	B_1	B_2	B_3	B_4	B_5
A_1	0	0	0	1	0
A_2	0	0	1	0	0
A_3	0	0	0	0	1
A_4	0	0	0	0	0
A_5	0	0	0	0	0
A_6	0	0	0	0	0
A_7	0	1	0	0	0
A_8	0	0	0	0	0
A_9	0	0	0	0	0
A_{10}	1	1	1	1	1
A_{11}	0	0	0	0	0
A_{12}	0	0	0	0	0
A_{13}	1	1	1	1	1
A_{14}	0	1	1	1	1

prove this evident remark are omitted for the sake of brevity. Finally, Table XII reports the detailed retrofit action plan for the best solution by the four criteria (solution 1).

Last, as a general finding about the overall two-step decision making tool, we remark that in all cases the total run time to determine the Pareto-optimal solutions set and rank them is lower than 1 s, on a PC equipped with a 2.4-GHz Intel Core 2 Duo CPU and 4 GB RAM.

D. Discussion of the Results

Applying the proposed method to the case study shows that it exhibits several distinctive features in the context of decision tools for energy efficient refurbishment of a portfolio of buildings. First, the method provides a decision support tool to the building stock owner, facility manager, or investor in the planning phase of the optimal retrofit integrated strategy. On the one hand, thanks to the MOO problem solution, the tool

TABLE XIII
BUILDING INDICATORS IN OPTIMAL RETROFIT BY SINGLE BUILDING PLANNING

Budget	Building	I_{1k} [KWh/year]	I_{2k} [m^3/year]	I_{3k} [m^3/year]	I_{4k} [-]
$E/5$	B_1	23990	40559	1560	0.4
$E/5$	B_2	37408	58151	2106	-0.5
$E/5$	B_3	37521	29230	1797	0.3
$E/5$	B_4	42143	63337	2025	0
$E/5$	B_5	41912	23937	1944	0.2

TABLE XIV
PORTFOLIO GLOBAL PLANNING VERSUS SINGLE BUILDING PLANNING

	I_1 [KWh/year]	I_2 [m^3/year]	I_3 [m^3/year]	I_4 [-]
Single Building Planning	36595	43043	1886	0.1
Portfolio Global Planning	36434	41384	1886	0.2

is able to automatically evaluate a large amount of potential renovation actions combinations, in the presence of conflicting criteria and budget constraints. On the other hand, thanks to the integration of the TOPSIS technique into the approach, the tool enables the DM to select from the large set of alternatives only few (or just one) optimal solutions. Globally, these two complementary characteristics constitute the most important strength of the tool, that allow improving traditional approaches based only on empirical generation of a few alternative retrofit scenarios which are then screened by the DM for the final choice. Second, the proposed method is effective in simultaneously obtaining the optimization of the identified objectives and the optimal partition of the budget among the buildings. To demonstrate this, a further analysis of the case study is conducted. As a reference scenario, for each building of the stock the best retrofit strategy is computed by solving the MOO and the multiattribute optimization problems. We assume that the portfolio contains just one building at a time and use in constraint (7) an equally distributed budget between all the buildings. In other words, a budget equal to E/5 is allocated to each of the five buildings. Table XIII reports the values of indicators (I_{1k}, I_{2k}, I_{3k}, I_{4k}) attained by the best retrofit strategy for each building ($k = 1, 2, 3, 4, 5$). Subsequently, the value of each indicator related to the stock is computed as the weighted average of indicators related to buildings in the stock. For the first indicators I_1, I_2, and I_3 we use (5) setting the building priorities indicated in Table VII, while for the indicator I_4 we consider the PMV of the ideal building having internal thermal conditions equal to the mean of the thermal conditions of retrofitted buildings in the stock. Results are reported in the first row of Table XIV. Instead, the second row of Table XIV reports the results obtained via the holistic planning of the retrofit action in the entire stock. The results'

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comparison demonstrates that the performance achieved for each indicator with the holistic planning of the retrofit action in the stock (second row in Table XIV) is better than that achieved by individually determining the building retrofit plans (first row in Table XIV). Obviously, a similar study may be conducted for any other *a priori* budget distribution among the buildings and for any other choice of the criteria preferences. Third and finally, we remark that the proposed decision making technique is flexible and customizable. Different criteria could be used for generating Pareto-optimal solutions and ranking alternatives in accordance to the DM preferences. A reduced set of criteria could be used to generate several retrofit alternatives. At the same time, the final choice could be evaluated in accordance with an extended set of criteria related to further aspects the DM is interested in. Finally, the relative importance of selected ranking criteria could also be changed depending on the DM's preferences by simply changing weights.

V. Conclusion

This paper addresses the energy efficient renovation of a portfolio of buildings. A two-step decision making technique is presented, including a decision design phase and a decision making phase. The underlying MOO problem allows making decisions in an integrated way on a stock of buildings, considering preferences, conflicting criteria, as well as financial and feasibility constraints. The model takes also into account ranking criteria weights and/or building priority coefficients. The final step, defining and solving a multiattribute optimization problem, provides the DM with an effective tool for screening optimal solutions. It is important to note that, although the decision making technique addresses the optimal energy retrofit for a portfolio of existing buildings, its use is not restricted to this specific context. Indeed, the model can also be used in problems where retrofit interventions are sought for with conflicting goals (e.g., reducing energy consumption, maintaining required comfort and quality of life, protecting the environment, and minimizing costs), e.g., in the case of public street lighting.

The main limitations of the presented approach are related to the assessment of the impact of each action on the selected criteria as well as the definition of criteria weights. The definition of a criterion, in fact, implies a non-negligible decision design phase mainly oriented to estimating the impact of each action on that criterion. This constitutes the most sensitive issue in the proposed decision process, together with the nontrivial hypothesis of perfect knowledge on model parameters (no inaccuracy is considered). Furthermore, the method requires the definition of criteria weights, which means the user has to be able to provide his global cardinal scale of values. Sometimes this does not completely make sense: either an ordinal importance ranking or a list of paired comparisons among criteria is preferable.

Future research will be devoted to overcoming the identified limitations: first, extensions of the technique considering variable action costs with respect to buildings and nonlinear payoffs formulation will be investigated; second, fuzzy inference systems will be considered to determine the weights characterizing the ranking criteria in an automated way depending on retrofit alternatives characteristics; third, future work will also address modeling uncertainties that affect the estimation of optimization model parameters. A further research could also be devoted to aiding the DM in selecting the raking criteria weights and building priority coefficients. Finally, the integration of simulation in the decision technique may also be considered, to perform what-if analyses of the determined retrofit actions implementation.

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