Sustainable Energy Technologies and Assessments 82 (2025) 104506

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

journal homepage: www.elsevier.com/locate/seta

Investigation of multi-objective decision making approaches for the optimization in building envelope thermal design

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ARTICLE INFO

Keywords:
Building Envelope Thermal Design
Building Energy Efficiency
Decision Making
Single and Multi-Objective Optimization
Mathematical Programming
Pareto

ABSTRACT

Improving the energy efficiency of building envelope components and technologies is of utmost importance, as it aligns with the crucial goals of providing carbon neutrality worldwide. This study presents a decision-making methodology for selecting thermal insulation materials and their thickness, as well as window frame materials, under the optimization of multiple criteria (economic, energy and environmental), giving a life cycle perspective too. Different Mathematical Programming models were formulated, examining the optimal solutions compared with the optimal Pareto solutions. The proposed method was implemented to a residential building considering different climate conditions of the Greek territory. Results of single-objective optimization show that a well-thermally protected building increases the economic, energy and environmental costs; for the case of climate zone A, an increase of 4.6, 2.8 and 8.3 times, compared to the optimal values of each criterion, is reported, while for the other climate zones the respective increase is lower. This highlights the importance of balancing the criteria, under a weighting sensitivity analysis. In the multi-objective optimization problem, compromise programming and Chebyshev goal programming are beneficial, reaching a percentage of 90 % for fitting the Pareto optimal results, in comparison to the global criterion and goal programming methods with a fitting of 13.5 %.

Introduction

The escalating energy consumption worldwide, driven by economic progress, population growth, and technological advancements, is contributing to the rise in global warming. In 2021 the residential and the service sectors in the European Union (EU) reached to consume 262 and 130 Mtoe of final energy respectively. A significant percentage of 40 % of this energy consumption came from the building sector, while this sector seems also to hold a substantial position in the global environmental landscape, accounting for 325-million-ton CO_2 eq. emissions in the EU, with a share of 12.5 %, compared to the other sectors [1,2].

The above statistics highlight the importance of the energy problem and climate change, providing the need of formulating innovative strategies to enhance energy efficiency and decarbonization, as well as to optimize the way of managing energy demand/consumption in the building sector. This can be achieved through restricting the existing certificates, that assess the energy performance of buildings, as presented in the recent recast of the Energy Performance of Buildings Directive (EPBD) [3], that focuses on implementing long-term renovations to convert the existing building stock into Nearly Zero Energy Buildings (NZEBs), for balancing energy consumption and production. Enhancing the thermal resistance of buildings and adopting passive retrofitting strategies, including the utilization of renewable energy sources (RES) (Directive 2010/31/EU) are essential measures for the EPBD goals [4]. For these reasons, the EU Member States need to develop comprehensive plans for building renovation by setting short- and long-term milestones. For instance, many European countries with Mediterranean climates, such as Greece, incorporate regulations, in line with the EPBD, that restrict both heating and cooling energy demands, especially by setting limitations in thermal transmittance for different building components, based on climate conditions. In such regulations, it is considered that improving the thermal resistance of building envelopes plays a vital role for enhancing their energy efficiency, as depicted in [5], proofing that their design contributes to 20 %–50 % of their heating and cooling demands. In addition, the proper implementation of thermal insulation can lead to significant reductions in both economic and environmental costs, as well as energy savings of about 40–45 % [6,7]. Moreover, considerable efforts have been devoted

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https://doi.org/10.1016/j.seta.2025.104506
Received 18 December 2024; Received in revised form 25 July 2025; Accepted 4 August 2025
Available online 11 August 2025

to research/develop/improve technologies for low-energy and sustainable buildings, in order to meet the objectives of high thermal efficiency described in the regulations. Such efforts include the integration of RES into buildings [8], the utilization of high-performance devices [9], the formulation of innovative building design methods [10], like multi-energy systems and Energy Hubs [11,12], the use of models based on data for improving the energy efficiency of buildings during their operation [13], the assurance of indoor thermal comfort through energy-efficient solutions [14] etc.

However, it is noted that the energy consumed during building construction is not specified in detail and often surpasses the initially designed levels. This difference is known as the energy performance gap, identifying additional energy consumption or a deviation from energy efficiency standards during the building's operation [15]. Also, the unlimited increase of insulation thickness until the complete elimination of heat losses/gains in space heating/cooling, or the installation of over-sized energy systems should be avoided. This is due to practical and economic issues, as well as due to the costs of embodied energy consumption and the associated carbon emissions emerged during different life cycle stages of the materials production, such as raw material extraction, production processes, installation, and disposal [16,17]. Dealing with such issues, the optimization concept seems to be crucial for not only combining alternative design scenarios, but also for considering multiple goals for enhancing sustainability and efficiency of buildings.

In the literature, most research studies adopt single-objective optimization (SOO) approaches upon building design, focusing on the reduction of economic and energy costs, the mitigation of environmental emissions, as well as enhancing the energy efficiency and thermal comfort [18]. Various optimization methods have been suggested, employing both mathematical and simulation-based approaches, focusing on the optimal selection of insulation materials. Mathematical approaches typically rely on deriving classical heat transfer equations to identify optimal solutions, while simulation-based techniques, such as genetic algorithms (GA) and particle swarm optimization, are integrated into energy simulation tools like Energy Plus [19,20,21]. Similarly, various SOO approaches address life cycle costing (LCC) and life cycle assessment (LCA) perspectives, addressing economic and environmental concerns in the building sector [22,23].

However, real-world building design involves dealing with conflicting optimization criteria, setting MOO problems for investigating different scenarios of alternative building envelope materials and considering factors like different insulation types, roofing materials, finishing materials, types of windows, their size and glazing etc. [24]. Some studies explore the effects of building shape, size and solar orientation of each facade on energy consumption too, showing that proper parameter adjustments during the design stage can lead to significant improvements [25]. One of the first attempts of formulating mathematical models considering multiple criteria was developed by [26], where multiple optimal solutions were investigated for improving the thermal operation of a building, concerning both cost and surface area during the design phase. Also, [27] utilized a simulation-based MOO approach, in order to reduce building energy consumption in a cost-effective way, by utilizing energy simulation and optimization tools, such as TRNSYS, GenOpt and MATLAB. A wide range of multiple alternative options was considered, such as decision making for external wall and roof insulation materials, the type of windows and the installation of solar thermal collectors, with a focus on compromising the conflicting optimal solutions. [28] investigated multiple criteria for building optimization, including the minimization of the annual primary energy consumption, the amount of CO_2 emissions and the initial investment costs. MOO methods were formulated, according to the principles of MP, in order to provide balanced optimal solutions towards the conflicting criteria by applying weighting factors [29]. Similarly, a systematic tool for building retrofitting optimization was developed by [30] considering the selection of insulation materials, window types and solar panels, while different environmental criteria were implemented too. [31] proposed the development of a simulation-based MOO model, called RETROSIM, for assessing different alternative retrofitting choices of a building, such as the optimum material selection for external walls and roof insulation, different window types as well as the installation of solar thermal collectors and HVAC systems to meet heating and cooling demands. The main objectives consider primary energy consumption, costs and thermal comfort. [32] examined the advantages of implementing external wall insulation for buildings through a dynamic simulation and a MOO optimization methodology by utilizing GA and considering economic, energy and environmental criteria. [33] proposed a multi-criteria approach for designing green building envelopes by combining EnergyPlus with GA and artificial neural networks for minimizing material costs, CO_2 emissions and energy consumption under a life cycle perspective.

The above literature analysis mentioned the need to incorporate decision-making methodologies considering multiple optimization criteria into the thermal building design, in order to investigate a wide range of alternative scenarios in line with the new legislation for mitigating the energy and environmental problems. The current optimization problem deals with decisions which are related to the optimum insulation thickness and materials, as well as the choice of window frame materials, considering different climatic conditions; a residential building (240 m^2) in Greece has been selected as a case study. While the examined criteria include the maximization of the building thermal resistance, as well as the minimization of economic, energy and environmental footprint, under a life cycle perspective (embodied energy and emissions), considering only the design phase of implementing thermal intervention strategies in the building envelope. This concept seems to be crucial for MOO decision-making in building thermal design, proposing a methodological framework that can be incorporated into relevant building certifications, in order to achieve energy saving and pollution reduction targets, considering economic constraints too. This has been achieved by providing multiple thermal design solutions under a comprehensive approach that examines different MP models. Even if several MOO methodologies can be found in literature (MP, GA, Pareto etc.), there is a research gap of comparing different optimization models, which is the main innovation of this study, highlighting their advantages and drawbacks. To do so, the proposed investigation aims to provide different MP models considering MOO, providing optimal solutions that compromise the examined criteria. The Pareto set considered as the brute-force analysis of comparing the MP approaches. General Algebraic Modelling System (GAMS) was used for modelling and solving the MP problems, while a script in PYTHON was developed in order to calculate all the combinations of the proposed retrofitting alternatives and present the Pareto set. More specifically, in this paper four different MP methods were examined (global criterion, compromise programming, goal programming and Chebyshev goal programming). In global criterion (GC), the criteria of the baseline optimization problem were integrated into one objective function, leading to optimal solutions as close as possible to those achieved in SOO. The basic idea of the compromise programming (CP) method is to indicate an ideal solution that is a reference point for the decision-making problem, focusing on finding compromised as close as possible to this point. For investigating the set of solutions nearest to the optimal point, the concept of distance is introduced, which is a measure showing the deviation of the optimal solution from the ideal one. The main scope of the goal programming (GP) method is to find optimal solutions by setting distinct goals for each optimization objective. Such goals represent the optimal values arising from SOO. The objective functions of this method were designed to minimise the deviations from such goals. The focus of reducing the gap between the set goals and the actual performance, leads to solutions as close as possible with the desired outcomes. Last but not least, the Chebyshev goal programming (ChGP) method is based on the GP one and their key difference is that the ChGP can achieve a better weighting/balancing between the goals, finding intermediate solutions more easily.

This is achieved by introducing further constraints in the form of inequalities.

Methodology

Optimization framework

The proposed decision-making methodology focuses on improving thermal energy efficiency of building envelopes by evaluating various design investments, considering the optimal insulation thickness and material selection, as well as the proper window frame material. The goal of this study is to develop a MP model in GAMS for defining the optimal decisions for each optimization criterion (thermal resistance, economic, energy, environmental) under SOO. Also, several MOO models were developed, in order to provide balanced optimal solutions between the criteria examined. The results of four MOO methods were compared with the Pareto set. Fig. 1 presents the general concept of the proposed methodology in a flow chart.

Building case study

The optimization methodology proposed in this study was implemented in a case study building with a total surface of 240 m^2. The building envelope structure is composed of the following five primary components, each of them having a specific material composition.

- Masonry: construction of the external walls consisting of brick.
- Structural Frame Elements: construction consisting of concrete (beams, columns, shear walls).
- Flat Roof.
- Floor: open-to-air floor (pilotis).
- Windows: argon filled; triple glazed.

Fig. 2 presents a 3D illustration of the outer building envelope examined, indicating the basic dimensions and the facades orientation. While Table 1 presents the construction of each building envelope component, identifying the thickness and the thermal conductivity of each structure.

Optimization parameters

Decision-making for selecting building envelope materials is considered as a laborious and complex process, due to the existence of an extensive variety of such materials in the market, as well as due to considering the improvement of alternative objectives. In this context, this study examined the optimal thermal insulation and window frame materials, considering economic, energy and environmental criteria, under the limitations of thermal resistance for each climate zone provided by the Greek EPBD [34]. The proposed insulation materials are representative for the building sector and include Expanded (EPS) and Extruded Polystyrene (XPS), Polyurethane (PU), Rock Wool (RW) and Glass Wool (GW). While Aluminium, PVC and Timber define the alternative materials for framing the windows. The economic cost encompasses both the capital purchase and installation expenses associated with all the above, while for the environmental and energy footprint, the analysis includes CO_2 equivalent emissions and Non-Renewable Primary Energy (NRPE) consumption, according to LCA principles. NRPE represents the total energy derived from fossil fuels used in the construction of a system or material. Such data were collected from literature, considering the stages from row material extraction until the installation of final products. An important aspect for defining the energy and environmental footprint is the functional unit (FU) of the analysis. Considering the insulation materials, the FU represents the material amount needed to achieve thermal resistance of 1 m^2K/W over 1 m^2 surface area. As for the windows LCA, the FU is specified as a standard

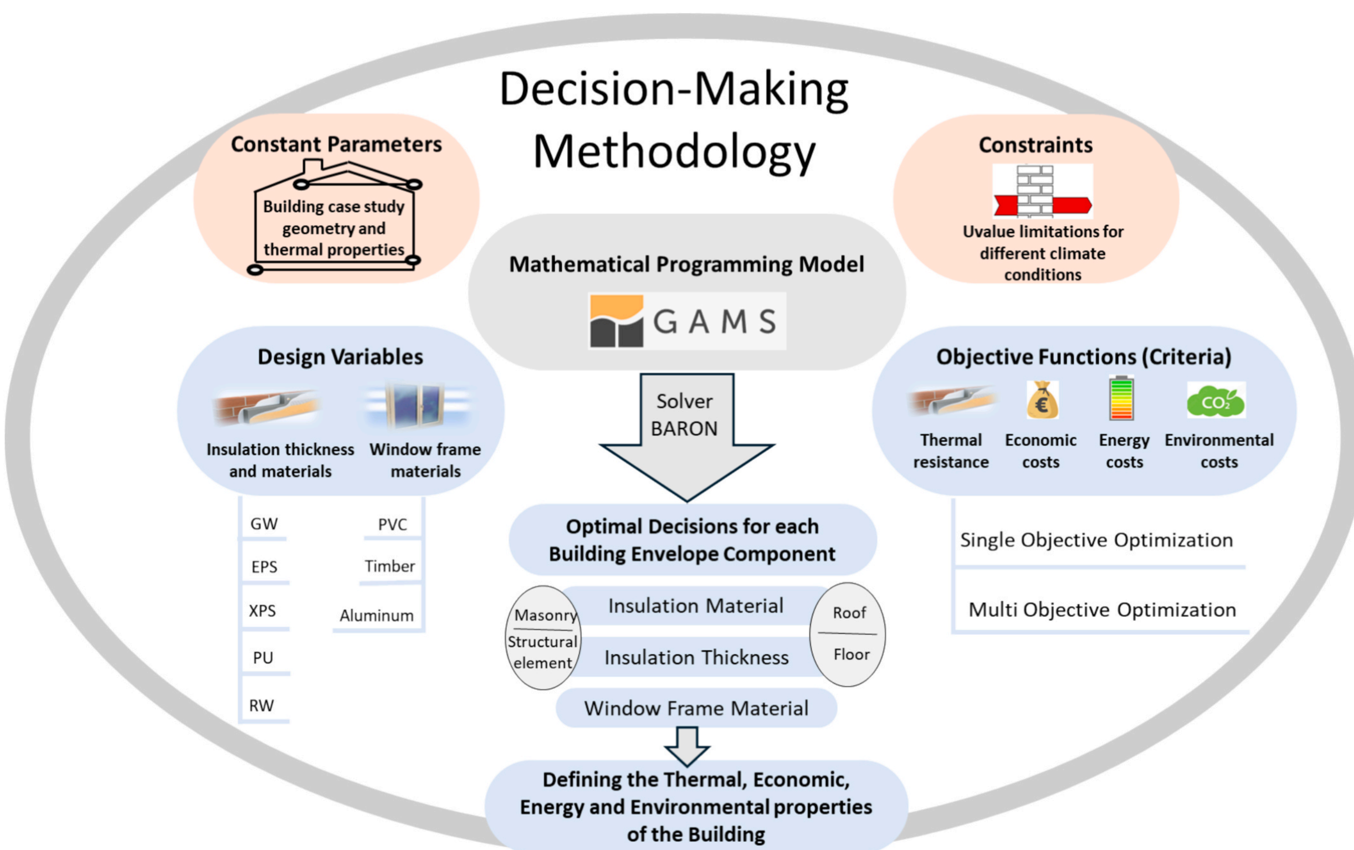

Fig. 1. The framework of the decision-making process.

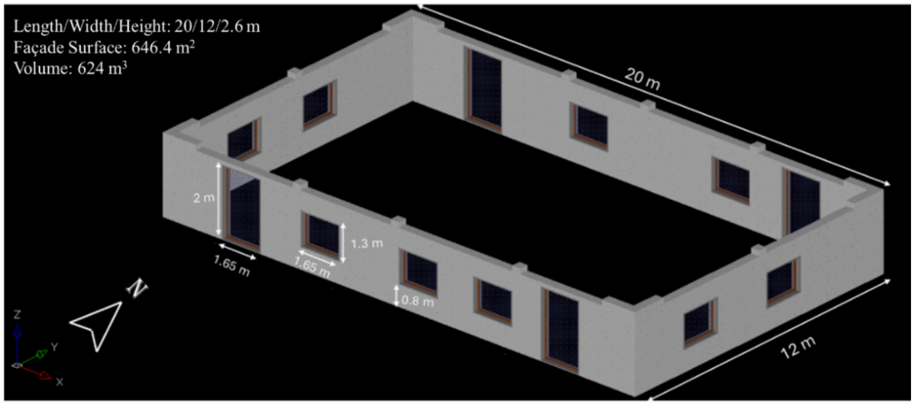

Fig. 2. 3D illustration of the building envelope.

Table 1
Construction of each building envelope component.

Components	Materials	Thermal conductivity (W/mK)	Thickness (m)
Structural Element (A_{be} = 48.9 m^2)	Inner plaster roughcast	0.87	0.02
	Reinforced concrete	2.03	0.35
	Outer plaster roughcast	0.87	0.02
Masonry (A_{br} = 78.9 m^2)	Inner plaster roughcast	0.87	0.02
	Brick	0.52	0.09
	Brick	0.52	0.12
	Outer plaster roughcast	0.87	0.02
Floor (A_{fl} = 240 m^2)	Tile	1.05	0.01
	Cement	0.72	0.004
	Fine aggregates concrete	0.64	0.04
	Polyethylene film	1.76	0.001
	Reinforced concrete	2.03	0.35
	Outer plaster roughcast	0.87	0.025
Roof (A_{rf} = 240 m^2)	Tile	1.05	0.038
	Cement mortar	1.4	0.02
	Polyethylene film	1.76	0.001
	Waterproofing material	0.17	0.004
	Fine aggregates concrete	0.64	0.08
	Polyethylene film	1.76	0.001
	Vapor barrier	1.76	0.01
	Reinforced concrete	2.03	0.2
	Outer plaster roughcast	0.87	0.025

triple-glazed window (1.65 x 1.3 m^2), featuring a 4 mm thick glass pane, 16 mm of argon-filled gas spacing, and a percentage of 25 % for the framing. The Life Cycle Inventory defined by the Environmental Product Declaration, while the CML 2001 and Cumulative Energy Demand methods were used in [35] and [36] for estimating the environmental impacts. The thermal, economic, energy, and environmental characteristics of the materials evaluated are presented in Table 2.

Table 2
Basic data of the examined insulation and frame materials.

Materials	Thermal *W/mK **W/m^2K	Economic *€/m^3 **€/m^2	Energy MJ/FU	Environmental kg CO_2/FU
Glass Wool	0.033*	149*	25.8	1.49
Expanded Polystyrene	0.034*	223.5*	67.0	2.00
Extruded Polystyrene	0.035*	464*	112.0	4.95
Polyurethane	0.023*	765*	80.0	3.60
Rock Wool	0.033*	287*	18.0	3.02
PVC	1.225**	205.4**	4443.5	205
Timber	1.35**	393.4**	1769.2	108
Aluminium	1.85**	525.6**	9322.1	502

Optimization model

Creating decision-making methodologies for improving thermal envelope design, considering both SOO and MOO, requires the formulation of representative mathematical models. This study formulates MP models by defining the following key aspects.

- Design variables: define the key factors influencing the decision-making optimization process and providing optimal solutions.
- Constraints: identify limitations or requirements of the optimization problem, resulting into feasible optimal solutions.
- Objective functions (optimization criteria): determine the goals of the optimization problem, including the design variables.
- Mathematical techniques: involves the selection of the appropriate mathematical method and solver for defining the optimal solutions.

For this study, the above MP concept was structured in GAMS, which is a computational tool specialized in the formulation of such optimization problems, incorporating several solvers for providing optimal solutions. In more detail, the process begins with setting constant values, which are represented as parameters, vectors and tables in GAMS, associated with relative indexes. These values could be automatically integrated into the primary equations of the objective functions and the constraints, along with the design variables. The final step involves specifying the type of optimization model and selecting the appropriate solver, in order for the optimal solutions to be defined by setting values to the design variables. For example, the optimal decisions were provided by identifying the insulation thickness and materials through calculations made in the objective functions. The proposed MP problem is mixed-integer nonlinear, and the BARON solver was used for investigating the optimal solutions [37].

Design variables and constraints

The proposed optimization methodology deals with the decision-making towards the optimal selection of thermal insulation materials and their appropriate thickness for each examined component of the building envelope, as well as the best fitted frame material choice for the triple glazed windows. In this context, relevant design variables should be set in the MP problem, in order for the aforementioned choices to be defined in the optimization process.

- $x_{wn,i}$: Binary variables for choosing window frame material (i: Aluminum, PVC, Timber).
- $x_{ins,k,j}$: Binary variables for selecting thermal insulation material (j: RW, GW, EPS, XPS, PU) for each building envelope component (k: Masonry (br), Structural frame elements (be), Roof (rf), Floor(fl)).
- x_k: Integer variables for choosing the thickness per ds = 1 cm of the thermal insulation material for each building envelope component (k).

The above binary design variables should be constrained, in order to select only one frame material for all the windows and one thermal insulation material, for each building envelope component.

There are also constraints defining thermal resistance bounds, considering each component of the building envelope, as well as the climate zone. The upper bounds should come with thermal transmittance values (U-values) proposed by the Greek EPBD, ranging upon the climate zones from 0.35-0.6 W/m^2K for the building envelope components and from 2.6-3.2 W/m^2K for windows. While, for the lower bounds, it is assumed that the U-values should be higher than 0.15 W/m^2 K.

Single objective optimization

The optimization criteria were structured as objective functions shown in Eqs. (1) and (2). These formulas include the constant values of the building envelope characteristics defined in 2.2 and the design variables described in section 2.4.1, which are connected to the values shown in Table 2. Eqs. (1) and (2) calculate the thermal, economic, energy and environmental properties of the building case study, in order to provide the optimal decisions considering the options of insulation thickness and materials.

The first objective is to minimize the coefficient of thermal transmittance (ΣUA), along with U_m, which is a critical index for identifying thermal resistance of building envelopes (objective function of Eq.1). This is considered as the only criterion for evaluating the thermal performance of a building envelope during the design stage in the Greek version of the EPBD [34].

$$\min \Sigma UA = A_{wn} \bullet b_{wn} \bullet \sum_i \left(U_{wn,i} \bullet x_{wn,i}\right) + \sum_k \left(A_k \bullet b_k \bullet \frac{1}{R_{in} + \sum_{nk}\left(\frac{d_{nk}}{\lambda_{nk}}\right) + \frac{x_k \bullet d_s}{\sum_j \left(\lambda_{ins,j} \bullet x_{ins,k,j}\right)} + R_{out}} \right) \tag{1}$$

where,

- R_{in}, R_{out} (m^2 K/W): thermal resistance caused by indoor and outdoor air convection.
- nk: represents the layers of the building envelope structure for each k component (Table 1).
- A_{wn}, A_k (m^2): the overall area of the windows and the components of the building envelope (Table 1).
- b_{wn}, b_k: a reducing rate, which is considered as 1 for surfaces in contact with ambient air.

The other objective of the optimization problem is to minimize the costs of the economic (C_{ins}, C_{wn}), energy ($NRPE_{ins}$, $NRPE_{wn}$) and environmental (Env_{ins}, Env_{wn}) parameters, which are illustrated as S in the objective function of Eq. (2).

$$\min \mathrm{Cost/Env/NRPE} = A_{wn} \bullet \sum_i \left(S_{wn,i} \bullet x_{wn,i}\right) + \sum_k \left(A_k \bullet x_k \bullet d_s \bullet \sum_j \left(S_{ins,j} \bullet x_{ins,k,j}\right) \right) \tag{2}$$

Multi-Objective optimization

The complex and multi-dimensional nature of building envelope design requires the formulation of MOO models, for evaluating various criteria. The criteria examined include the minimization of thermal transmittance, economic, energy and environmental costs, as illustrated in the previous section (2.4.2) incorporating the same objective functions in MOO formulas. Four MOO methods of MP were examined in this study, to address pairs of all the beforementioned criteria. To ensure comparability of each optimization criterion, it is important to normalize the objective functions on a common scale, assessing their impact on the optimization problem, as described in Eq. (3) and (4). Two distinct approaches of normalizing the objective functions were examined (Norm 01, Norm mm), considering the objective functions described in Eq. (1) and (2), as well as the optimal results of SOO. Also, weighting factors were assigned to the MOO methods in order to indicate the relative importance of each criterion. For these weights, a sensitivity analysis was conducted, considering that the summing of the weighting values of the examined criteria should be at 100 % so as to evaluate their effect on the optimal decision outcomes. Two distribution steps were implemented for the analysis (1 % and 0.1 %) to check the effectiveness of each method. So, the optimization process for the MOO models includes the minimization of a normalized objective function that considers weighting factors for each optimization criterion. The implementation of different values in the weighting factors (sensitivity analysis) defines a complex optimization process that can lead to a wide range of optimal solutions, which is the ultimate objective for balancing the conflicting criteria.

The flow chart presented in Fig. 3 summarizes the basic aspects and steps of implementing the MOO methods examined.

The form of the normalized objective functions used in GC and CP methods are presented in Eq. (3), respectively.

$$f^{cr}_{Norm} = \begin{cases} w_{cr} \bullet \dfrac{z_{cr} - z_{cr,min}}{z_{cr}}, \mathit{Norm01} \\ w_{cr} \bullet \dfrac{z_{cr} - z_{cr,min}}{z_{cr,max} - z_{cr,min}}, \mathit{Normmm} \end{cases} \tag{3}$$

where,

- z_{cr}: The objective functions of SOO (ΣUA, Cost, Env, NRPE).
- $z_{cr,min}$, $z_{cr,max}$: The optimum values (minimum and maximum) derived from SOO for each criterion (ΣUA, Cost, Env, NRPE).
- w_{cr}: Weights of each criterion (cr).

In GC the criteria of the SOO problem were integrated into one objective function that minimizes the summing of the f^{cr}_{Norm} terms shown in Eq. (3) for each normalization type and for the examined criteria each time. This process leads to optimal solutions as close as possible to those achieved in SOO. While, in CP, the objective is the minimization of a variable that is bigger than the value of f^{cr}_{Norm} for each criterion. This is achieved by setting inadequate constraints which are linked to the variable set under minimization. The basic idea of CP is to indicate an ideal solution that is a reference point (optimal point) for decision-making, trying to find a solution as close as possible to this point.

Similarly, the form of the normalized functions used in Goal Programming (GP) and Chebyshev Goal Programming (ChGP) is presented in Eq. (4), while the form of constraints is shown in Eq. (5).

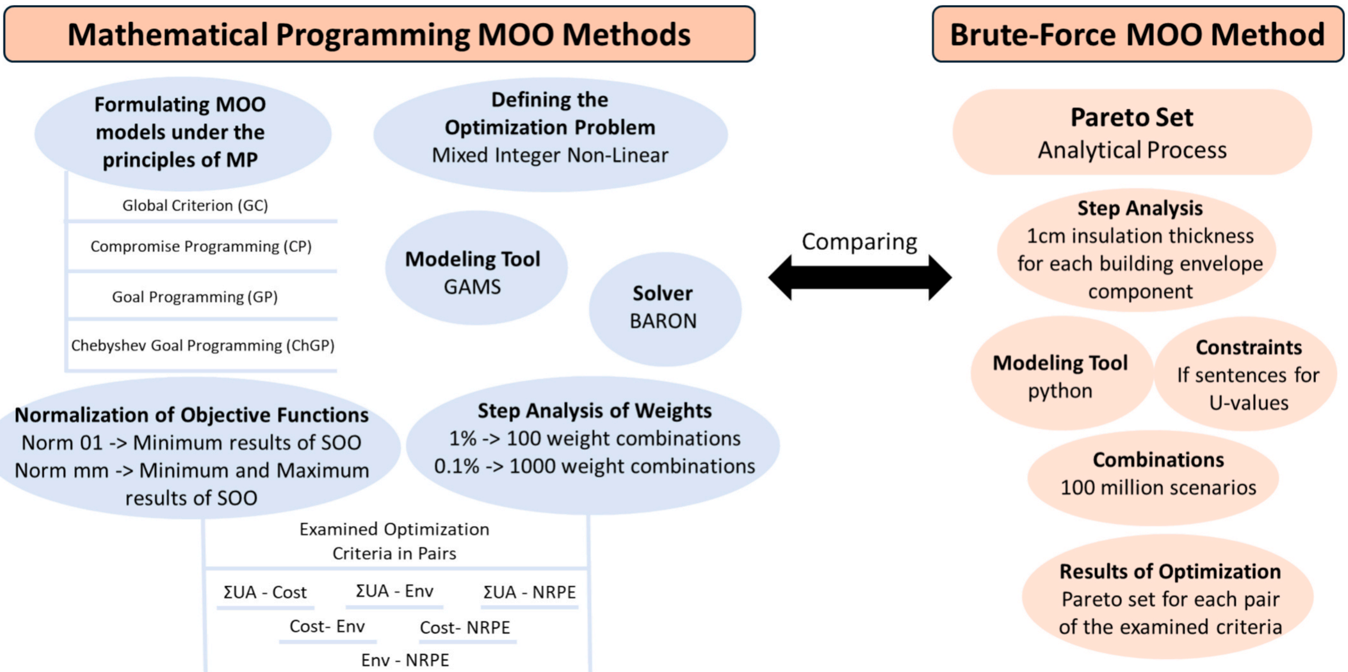

Fig. 3. Description of the MOO process.

$$h^{cr}_{Norm} = \begin{cases} w_{cr} \bullet \dfrac{n^-_{cr} + p^+_{cr}}{z_{cr}}, Norm01 \\ w_{cr} \bullet \dfrac{n^-_{cr} + p^+_{cr}}{z_{cr,max} - z_{cr,min}}, Normmm \end{cases} \quad (4)$$

$$z_{cr} + n^-_{cr} - p^+_{cr} = z_{cr,min} \quad (5)$$

where,

- n^-_{cr}, n^-_{cr}, p^+_{cr}, p^+_{cr}: Negative and positive deviation variables from the optimal goals of each criterion (cr).

In GP there is one objective function minimizing the summing of the h^{cr}_{Norm} terms shown in Eq. (4) for each normalization type and for the examined criteria each time. The aim of this method is to find optimal solutions by setting distinct goals for each optimization objective. Such goals represent the optimal values arising from SOO. The objective functions of this method are designed to minimize the deviations from such goals. The focus of reducing the gap between the set goals and the actual performance, leads to solutions as close as possible to the desired outcomes. While the objective function of ChGP is in line with the concept of CP by inserting inadequate constraints for the deviations. This leads to improving the goal weighting/balancing and finding intermediate solutions more easily.

Also, a brute-force approach for defining the Pareto set was applied, in order to provide a benchmark for evaluating the accuracy of the examined MOO methods. Pareto set can find optimal solutions under a balancing perspective of the optimization criteria. Scripts in Python were developed in order to calculate all possible combinations, considering five insulation materials, three window frame materials and insulation thickness with a step analysis of 1 cm in the thickness ranges set by the U-value constraints. This process resulted in roughly 100 million different combinations for climate zone A, used to calculate the values of the four optimization criteria examined and the Pareto set was defined for all the pairs of them.

Results

Results of SOO

In case of maximizing the thermal resistance of the building envelope, the limit of 0.15 W/m^2K was set leading to the same optimal solution for all the climate zones. This solution includes three insulation materials with different thicknesses (in cm) for the examined components ($21^{br:XPS}/21^{be:EPS}/14^{rf:PUR}/22^{fl:XPS}$). PUR is chosen for roof insulation, with low thickness, because of its low thermal conductivity, while XPS and EPS were chosen with higher thicknesses, leading to U-values nearest to 0.15 W/m^2K. Also, the low U-value of the PVC sets it as the optimal solution for windows framing.

Considering the economic, energy and environmental optimization criteria, the optimal decisions made for the insulation thickness were aligned with the restrictions of the U-values set for each climate zone. The optimization outcomes indicate a progressive increase in insulation thickness moving from warmer to colder regions (A:$4^{br}/5^{be}/5^{rf}/6^{fl}$, B:$5^{br}/6^{be}/6^{rf}/7^{fl}$, C:$6^{br}/7^{be}/7^{rf}/8^{fl}$, D:$7^{br}/7^{be}/8^{rf}/9^{fl}$). This is due to the stricter restrictions set by the Greek EPBD for regions with adverse climatic conditions. GW is selected as the economically and environmentally friendlier material, while RW is identified as having the minimum embodied energy. While, for the window frames, PVC was the economically optimal decision, and Timber was the optimal result for the energy and environmental criteria.

The pattern of the optimal results reflects the need for higher thermal resistance in colder climates in order to meet the energy efficiency standards, highlighting the trade-offs in material selection based on various sustainable metrics.

Further analysis of the optimization outcomes, a contradiction between the examined criteria was observed in Fig. 4, as the selection of materials with low U-values (ΣUA criterion) for improving the insulation properties of the building envelope leads to higher economic costs. This is in-line with the results in [28], where double glazed windows and high insulation thickness were selected. It is also depicted that the goal of high thermal protection of the building envelope leads to higher energy wastes and emissions to the environment. Results in Fig. 4 (a) show that an extremely thermally protected building envelope (high

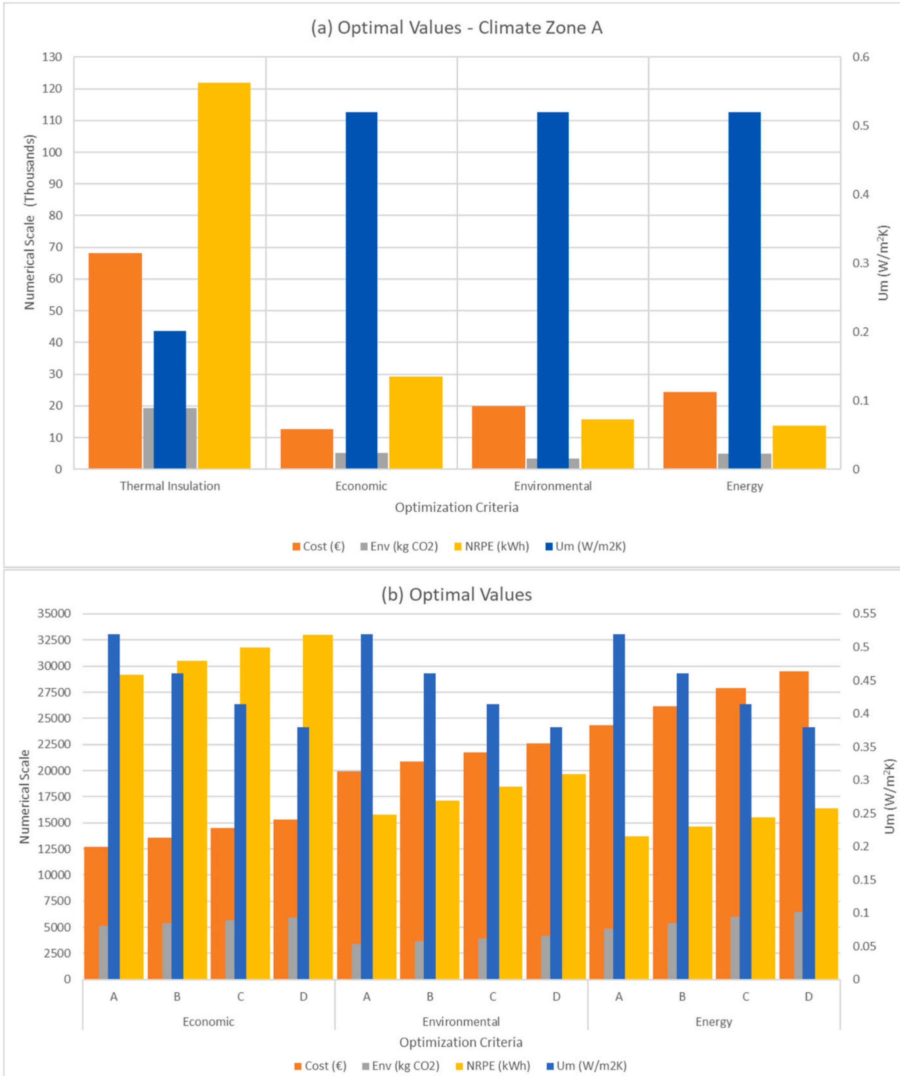

Fig. 4. Optimal values of Um, Cost, Env and NRPE considering (a) all the optimization criteria for climate zone A, and (b) the costing criteria for all climate zones.

insulation thickness) in climate zone A increases the economic, energy and environmental costs by 4.6, 2.8 and 8.3 times, compared to the optimal values when optimizing each criterion separately. In addition, when minimizing energy and environmental footprints, an increase in the economic parameters is observed, while the quality of insulation protection worsens to the levels provided by the Greek EPBD restrictions for each climate zone conditions. This pattern is aligned with the results presented in [30], where the minimization of the environmental impacts (especially climate change) of their case study force to spending more economic resources by utilizing environmentally friendlier materials and systems based on RES. Last but not least, results in Fig. 4 (b) show that the warmer climate zone (i.e., A), the lighter the insulation restrictions, which lead to lower economic, energy and environmental costs. It is also highlighted that the economic costs are higher when minimizing the energy and environmental criteria for all the climate conditions, while the energy costs seem to be higher when the economic criterion is considered. This is due to the change in the window frame material, while the insulation status stays constant for both the material and the thickness selection.

Results of MOO

Pareto results

The Pareto set provides balanced optimal solutions between the examined criteria for all the examined climate zones, providing feasible decisions. For example, when the economic budget is fixed into a specific range of values, final decisions could be made considering the other three criteria simultaneously. It is also highlighted that there is a high contradiction between ΣUA and all the other criteria (Fig. 5), which leads to a higher number of balanced results, rather than in the cases of Cost-Env-NRPE optimization (Fig. 6). The number of optimal solutions, when the ΣUA criterion is included, is smaller in climate zone D than in A, due to the higher U-value restrictions in the climate zones with worsened climatic conditions. While, for the other criteria combinations provide fewer solutions, due to their lack of contradiction. For example, in Cost-Env optimization, only two possible solutions were provided, for each climate zone, which are the same as the results of single criteria optimization.

In ΣUA-Cost optimization, a continuous distribution of optimal solutions within the cost range of 12,700€ to 26,000€ spreads out, while above the threshold of 26,000€, only some separated solutions emerged. This distinction arises from the uniformity of insulation materials across all building envelope components (GW), as well as there is a continuous distribution of insulation thicknesses. However, in the latter cost range, alternative combinations of both the insulation materials and their thicknesses were witnessed. For all the optimal results, PVC window frame material is the optimal choice. Considering ΣUA-Env and ΣUA-NRPE optimization, the above distribution ranges were different,

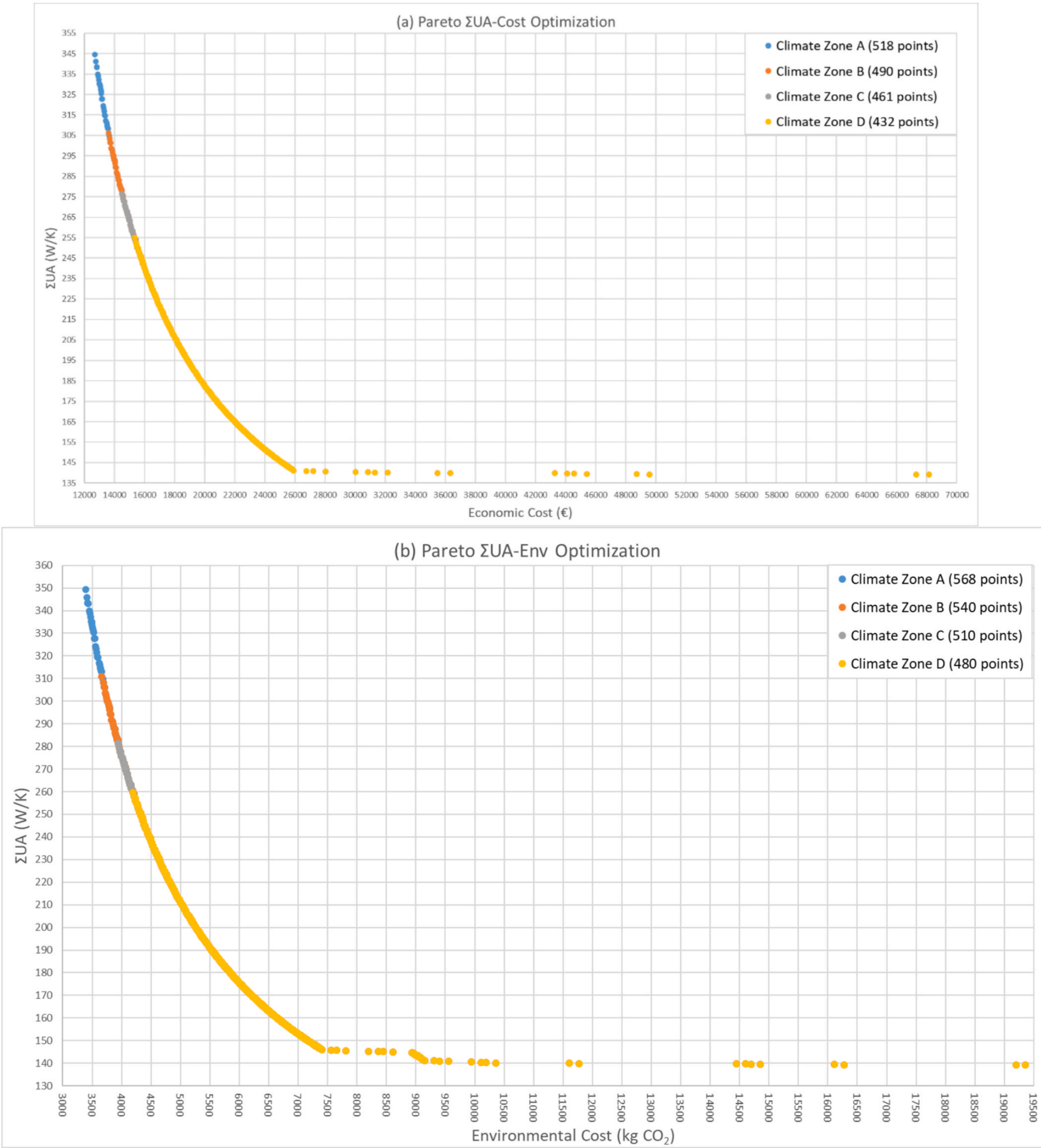

Fig. 5. The optimal Pareto values of (a) ΣUA-Cost, (b) ΣUA-Env and (c) ΣUA-NRPE optimization criteria, for all the climate zones.

because of the change of the window frame material too (PVC and Timber).

In Cost-Env, Cost-NRPE and Env-NRPE, the insulation thicknesses are the minimum ones, in order to meet the thermal insulation limits for each climate zone. However, the differentiation of optimal solutions is attributed to the combinations of different insulating materials, especially between GW and RW, which are the first two materials with the lowest values in economic, energy and environmental costs. In Cost-NRPE optimization, a significant change can be depicted, which is due to the simultaneous alteration of the window frame material and the insulating material. Such a change is not presented in Env-NRPE, as timber is the optimal choice.

MP results

This section presents the results of a weighting sensitivity analysis (distribution step analysis of 1 % and 0.1 %) in the MP models compared

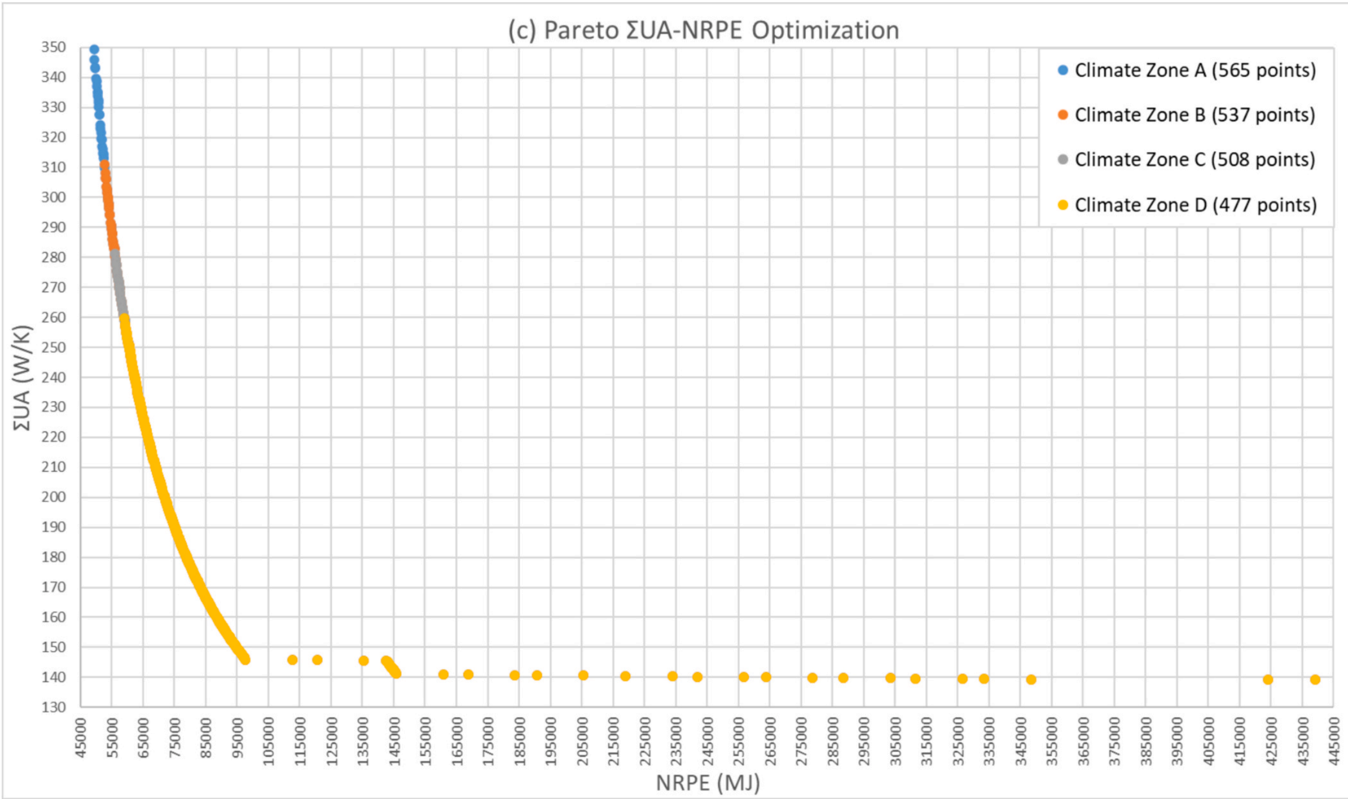

Fig. 5. (*continued*).

to the Pareto results. Fig. 7 presents the percentage of matching the optimal Pareto values from the MP models for high (ΣUA-Cost) and low (Env-NRPE) contradictive criteria. In particular, the Pareto set was more accurately represented by the finer step analysis across all the MP optimization scenarios, as a higher number of weight combinations were investigating leading to an increased number of optimal solutions. However, when the criteria are less contradictive with each other, the step of 1 % is adequate for meeting the Pareto set.

As far as the best fitted method is conserved, the CP and ChGP seem to be the most appropriate models (especially with normalization mm), capturing a significant number of values in the Pareto set, as shon in Fig. 7 (a). In more detail, the ChGP method can capture 467 optimal solutions out of 518 points belonging in the Pareto set (90.2 %) when ΣUA-Cost optimization criteria were considered and with a step analysis of the weights at 0.1 %. While the GC and GP methods for the same optimization problem can capture only 70 out of 518 optimal points. When the step analysis has been increased to 1 %, the best MOO method is again the ChGP (Norm mm), but the fitted optimal solutions were decreased to 97 out of 518. Similar conclusions can derive when ΣUA-Env and ΣUA-NRPE optimization criteria were examined, with ChGP being the best method as it can reach 503 out of 568 solutions in ΣUA-Env and 495 out of 565 solutions in ΣUA-NRPE. This is due to the high contradiction expressed between such criteria.

In addition, in Cost-Env, Cost-NRPE and Env-NRPE optimization, where the Pareto set is smaller, CP and ChGP can identify the entire Pareto set. More specifically, the results presented in Fig. 7 (b) show that both CP and ChGP can capture all the 16 optimal results belonging in the Pareto set, even if the step analysis of the weights is set at 1 %. This is due to the flexibility given by the inequality constraints in such models. While GC and GP seem to be less accurate for capturing the optimal Pareto results, especially the models with Norm 01, that can only fit the Pareto set at 12.5 %, i.e., 2 out of 16 optimal solutions.

Comparing the MOO models examined, it is important to mention their basic advantages and drawbacks.

- The computational time of formulating and solving each MP model was at the same range of time for a specific time-step analysis, but always lower compared to Pareto analysis.
- The lower time-step analysis of the MP models, the higher computational time spent, due to the increased number of goals set for each criterion, examining more alternative solution scenarios.
- Increasing the number of the optimization parameters (design variables or objectives functions) is simpler when formulating a MP problem, rather than generating all the combinations for defining new Pareto sets.
- The concept of creating MP problems seems to be more difficult than generating a brute-force methodology including specific steps, which can be easily formulated step-by-step.

The suitability and accuracy of MP models is not clear from an initial stage.

Conclusion

This paper presents a decision-making methodology, focusing on improving building envelope design through optimization. The analysis was conducted to a residential building, incorporating an analysis for different climatic conditions in Greece. The optimization technique includes the formulation of different MP models considering four basic criteria; economic, energy, environmental (based on LCA) and thermal insulation, noting that the latter one is in line with the design criteria imposed by the Greek version of the EPBD. The objective of the optimization is to make optimal decisions related to the insulation material and thickness choices, as well as the optimal frame material of a triple glazed window. The analysis incorporates mathematical models for both SOO and MOO, focusing on implementing and comparing different MOO methods too. In this way, the different envelope design solutions for insulation thickness and materials can be evaluated under an economic, energy and environmental perspective. This is essential in practice, as

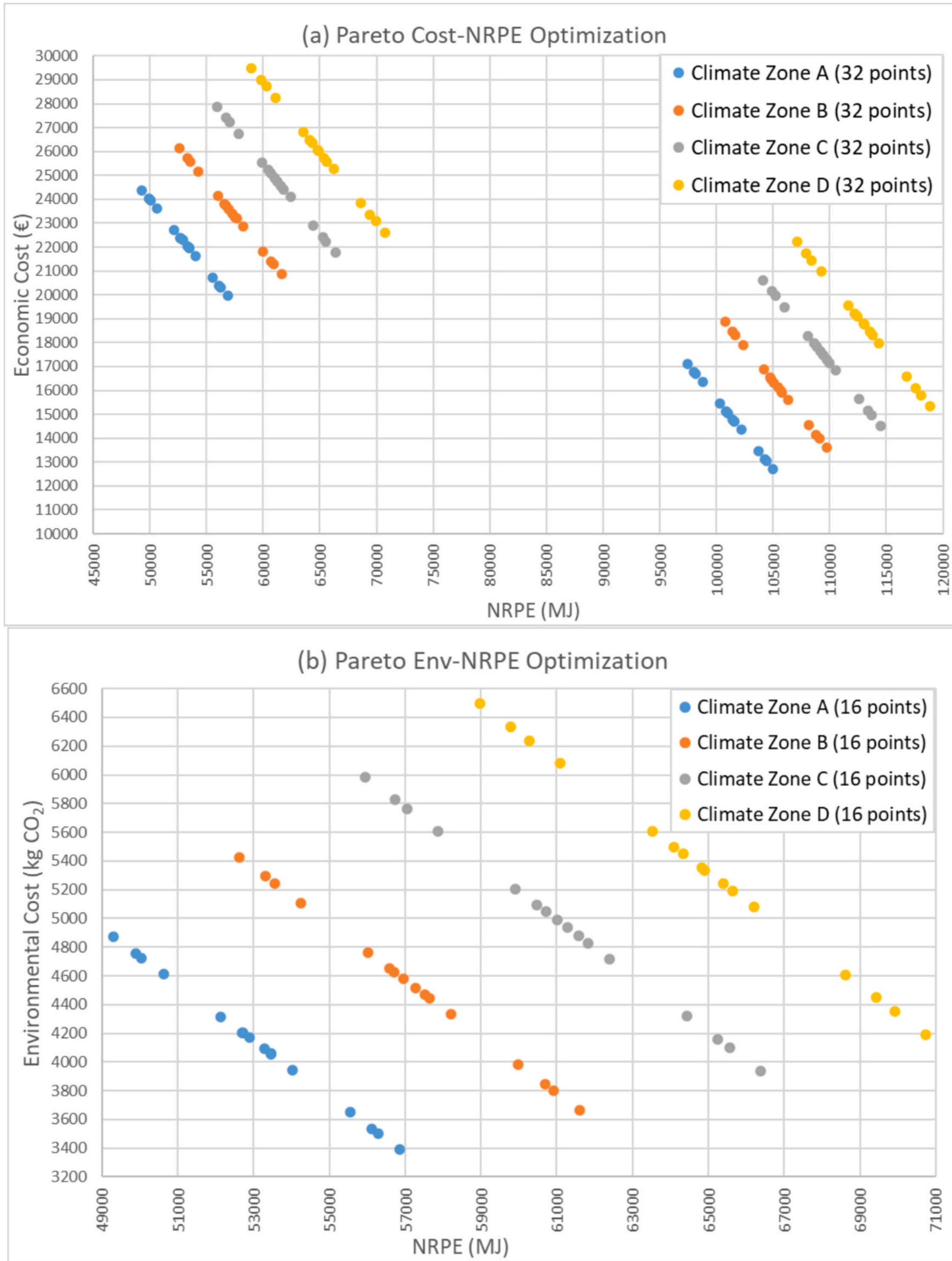

Fig. 6. The optimal Pareto values of (a) Cost-NRPE and (b) Env-NRPE optimization criteria, for all the climate zones.

the decision-maker (stakeholder or engineer) can evaluate the optimal decisions provided as optimal results of this study, leading to insulation interventions, considering the available economic budget, the restrictions of U-values for different climate conditions, as well as the energy and environmental costs of such interventions. In this context, the steps that should be conducted by the decision maker for adapting real-world applications into the methodology of this study start with the definition of the geometry and thermal properties of the building envelope that is going to be examined. The next step is to set the input data, considering the alternative options of insulation or window frame materials, as well as their costs (optimization criteria). Choosing the appropriate optimization model, the results could provide optimal decisions considering the criteria examined. The results provided in the current study can be utilized by engineers for optimal decisions for thermal insulation considering different climate condition in Greece, following the restrictions provided by the regulations.

The optimization results show that the four examined criteria seem to be in conflict, as depicted in both the SOO and MOO approaches,

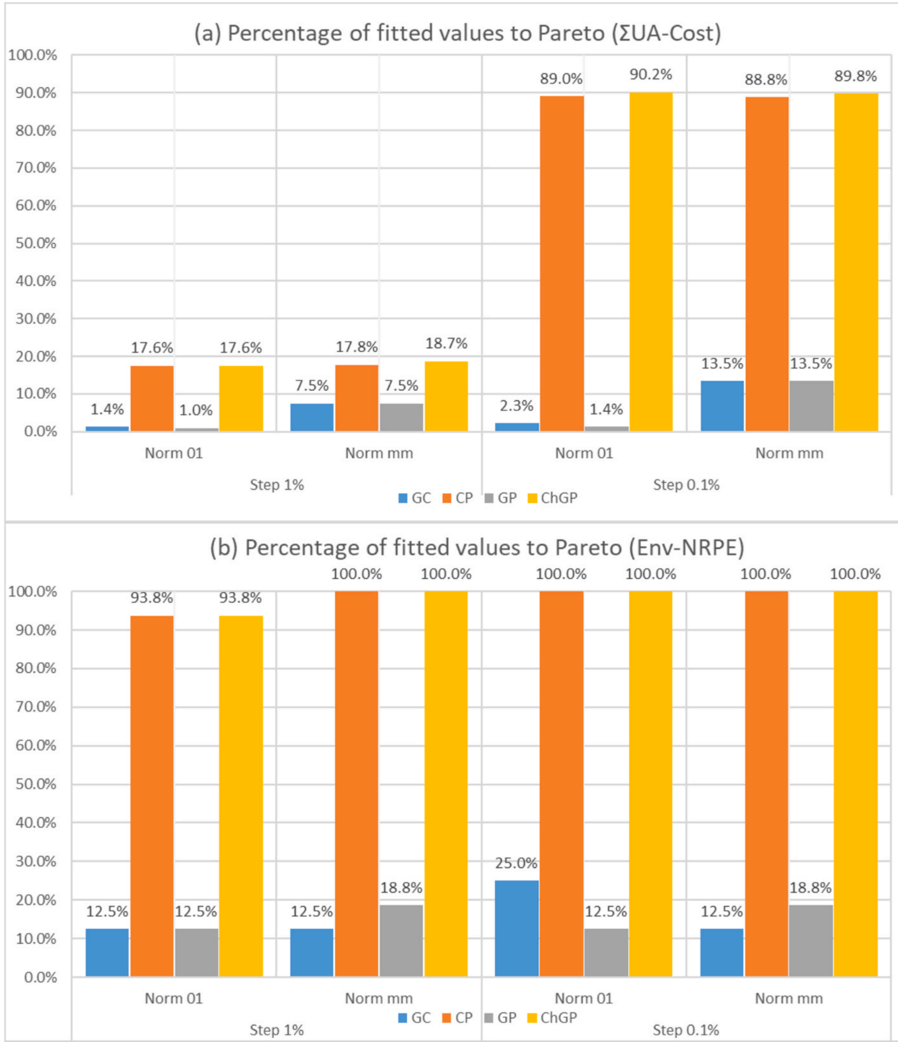

Fig. 7. Percentage of fitted values to the Pareto set for optimizing (a) ΣUA-Cost and (b) Env-NRPE criteria.

especially when the criterion of thermal insulation is included. While a milder degree of conflict among the other criteria is depicted, even though results show that economic costs increase when using environmentally friendlier materials. These highlight the trade-offs among the objectives and emphasize the need to strike a balance between the competing criteria through MOO. To address this issue, the Pareto set was generated, presenting the optimal values for all the criteria combinations, while different MP approaches were examined too, in order to decrease the computational time compared to a brute-force analysis.

Considering the contradiction between the optimization criteria, the following should be highlighted:

- High contradiction for all the climate conditions is depicted when considering the following criteria ΣUA-Cost, ΣUA-Env and ΣUA-NRPE. This is due to the ΣUA criterion that leads to high insulation thickness.
- Medium contradiction is depicted when considering Cost-Env and Cost-NRPE criteria, where the optimal selection of PVC window frame material leads to lower economic but higher energy costs.
- Low contradiction is depicted when considering Env-NRPE, because of similar optimal choices.

As for the comparison between the MOO methods, different MP models were formulated, and by implementing a sensitivity analysis of different weighting combinations, the optimum results were compared to the ones provided by the Pareto set. Results showed that:

- The lower step analysis of the weights considered, the higher number of optimal solutions resulted in the Pareto set.
- The higher contradiction between the optimization criteria shows that the methods of GC and GP are not appropriate for finding the Pareto set.
- The CP and especially the ChGP methods can capture the Pareto set in an effective manner, even in higher or lower contradiction between the criteria.

Considering the above analysis, the contradiction between the optimization criteria depicted in SOO highlights the need of balancing them in MOO approaches. So, the formulation and utilization of efficient MP models can streamline the decision-making process, mitigating the need for time-consuming brute-force MOO methods, in order to provide an effective method for evaluating different intervention scenarios during building envelope design. The more efficient model proposed from this analysis (ChGP) can be utilized by decision makers, in order to adapt the input parameters for their case building. The use of such a model reduces computational time for such optimization problems, leading to accurate decisions in low time.

Looking forward, future research could extend the current methodology to the building operation by calculating energy demands, offering insights into energy system managing and highlighting the importance of reducing the payback period for energy-efficient design projects. More specifically, the optimal decisions obtained from this study could be used to estimate heat gains and losses, considering heating loads from sun, occupants, lighting, airtightness, thermal conductivity, thermal capacity etc. Moreover, the proposed methodology can incorporate more optimization criteria, such as indoor air quality parameters or parameters that impact the shading of the building. This would pave the way for developing a more comprehensive approach affecting building energy efficiency.

CRediT authorship contribution statement

V Kilis: Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **N Ploskas:** Writing – review & editing, Software, Methodology, Formal analysis, Data curation. **G Panaras:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Vasileios Kilis reports financial support was provided by Hellenic Foundation for Research and Innovation. Vasileios Kilis reports a relationship with Hellenic Foundation for Research and Innovation that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

H.F.R.I. Hellenic Foundation for Research & Innovation The research was supported by the Hellenic Foundation for Research and Innovation (HFRI) under the 4th Call for HFRI PhD Fellowships title.

Data availability

Data will be made available on request.

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