EARLY DESIGN STAGE MULTI-OBJECTIVE OPTIMIZATION FOR THERMAL REFURBISHMENT OF BUILDINGS: A CASE IN ISTANBUL

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Abstract

To improve the energy efficiency of the large existing building stock, there is a need for decision-support to determine optimal solutions considering different objectives. In the study, it is aimed to find appropriate optimization methods through their hyperparameter optimization that will support designers at the early design stage of a building refurbishment project for environmental and economic sustainability. For this, NSGA-II, NSGA-III, C-TAEA, RVEA were investigated with a case study on residential buildings. The first three methods were observed to give limited renewal proposals, while RVEA provided diversified renovation scenarios with its models' features open to preference related to this.

Introduction

In energy efficient buildings, it is important to achieve simultaneously high performance in all aspects, even when dealing with conflicting goals. Studies for comfortable and energy efficient buildings address various objective functions such as energy consumption, thermal comfort and economic benefit indicators as single, multi or many objective/s. In addition, the differences in building functions (e.g., housing, office), decision variables (e.g., building form parameters, envelope) or constraints (e.g., budgets, thermal comfort conditions) in the optimization studies have resulted in datasets with a wide variety of features (Motlagh et al., 2021). Optimization methods suitable for problems with such different characteristics have also varied.

In comparative evaluation studies conducted to find the appropriate optimization method for the problem at hand, different methods have yielded superior performance results. To find the optimal design solutions for a passive building with a green roof for instance, six optimization algorithms [Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D), Non-dominated Sorting Genetic Algorithm (NSGA)-II, NSGA-III, Multi-objective Particle Swarm algorithm (MOPSO), multi-objective dragonfly algorithm (MODA), Multi-objective ant lion optimization algorithm (MOALO)], were compared and MOALO algorithm was reported to lead to the best pareto front (Lin et al., 2021). In another study on minimizing the building energy consumption, CO_2 emission, and indoor thermal discomfort degree, an Adaptive Evolutionary Algorithm based on Non-Euclidean Geometry for the Many-Objective Optimization (AGE-MOEA), compared to the other four popular multi-objective optimization methods [NSGA-II, NSGA-III, MOEA/D, Constrained multi-objective optimization (C-TAEA)], was found to identify a set of pareto optimal solutions with a maximum optimization rate of 13.43% (Shen and Pan, 2023). A study to optimize the life cycle performance of the building on the other hand, compared NSGA-II, NSGA-III, and C-TAEA; and C-TAEA was the best bringing a reduction for the life cycle carbon emissions by 34.7%, for the life cycle costs by 13.9%, and for the indoor discomfort hours by 26.6% (Chen et al., 2023). In a study to be a reference for retrofit planners, the comparison of NSGA-II, MOPSO, MOEA/D, and NSGA-III showed that NSGA-III derives a comprehensive set of trade-off alternatives from possible retrofit scenarios (Son and Kim, 2018).

This study, therefore, aimed to find appropriate multi-objective optimization methods to support decision-making at the early design stage for thermal refurbishment through the building envelope to improve the energy efficiency of existing buildings considering both economic and environmental sustainability dimensions, which are sometimes conflicting. For this purpose, the optimization results of different methods were evaluated comparatively taking existing residential buildings in Istanbul as a case. In the paper, the information related to the application is given in the 'Methodology' section, and the detailed results are given in the 'Result and Discussion' section.

Methodology

The study consisted of three main steps: (1) case study and the multi-objective optimization problem definition, (2) optimization method selection, and (3) optimization study and evaluation of results (Figure 1). The studies carried out in these steps are explained in the following subsections.

Step 1: Case study and the multi-objective optimization problem definition

For the case study, the data given in Cetiner and Edis' (2011) study was decided to be used. That study was carried out to develop an environmental and economic sustainability assessment method regarding the improvements at the scale of building elements to reduce the use phase heating energy consumption of existing residential buildings in Istanbul (Cetiner and Edis, 2014). Environmental and economic sustainability scores were calculated based on the gain rate calculated by comparing the results of refurbished buildings with that of the base existing building condition obtained by EnergyPlus and SimaPro tools. Production, construction, and use periods were considered as building life cycle stages. For these phases, the environmental impact was calculated based on emissions and solid/liquid waste; the economic impact was calculated considering the cost based on the required water, material, energy (heating, cooling, transportation, and application), labor, and equipment. Design variables and objective functions, and their value ranges are given in Table 1. The distribution of the whole data by building age and by the element that would be thermally refurbished concerning their economic and environmental sustainability scores are given in Figure 2.

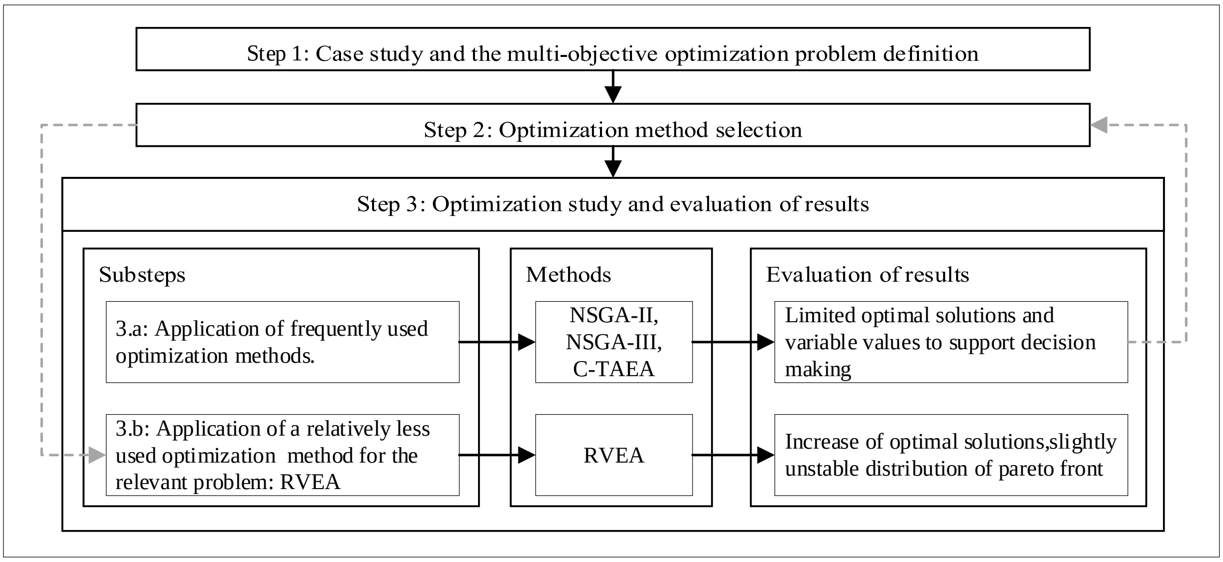
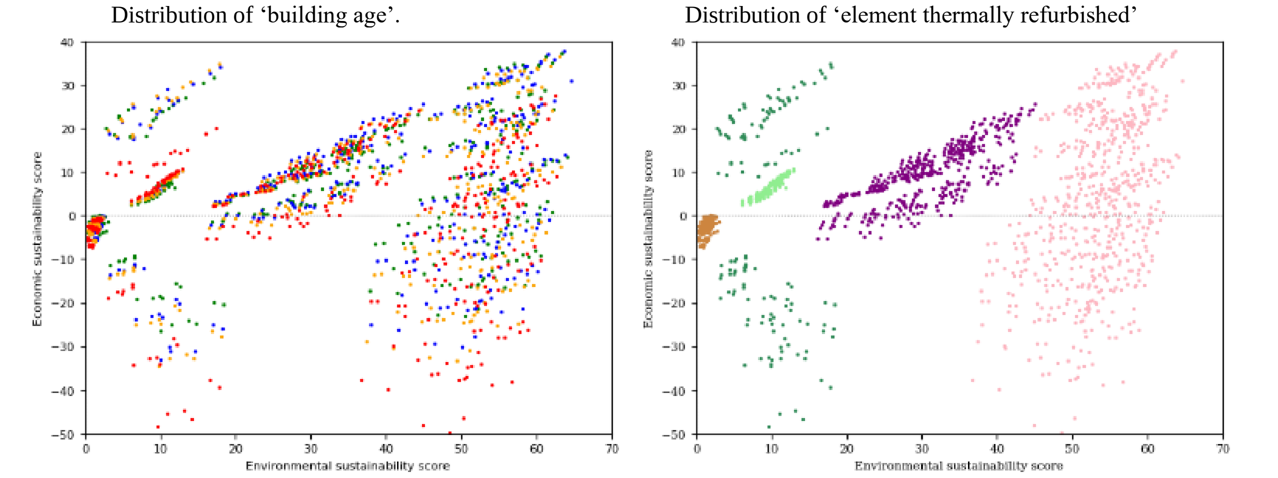


Figure 1: Research framework

Table 1: Design variables and objective functions, and their value ranges

	Variables- level 1	Variables- level 2	Ranges
Building	Building age	-	15, 20, 25, 30
	Plan type- floor area	Rectangular plan	ca. 230 sqm, and ca. 420 sqm
		Square / close to square plan	ca. 210 sqm, and ca. 400 sqm
	Orientation	Rectangular plan	Long sides facing East and West, Long sides facing North and South
		Square / close to square plan	Main orientations only
Envelope	Window-to-wall ratio	-	10%, 20%, 30%
	Window frame materials/ glass and glazing type	-	Wooden/ clear single glass, PVC/ clear double glass
	Element thermally refurbished - Insulation material and window frame (if specified) used	Floor over unheated spaces (uninsulated in base cases)	EPS, Stone wool, XPS
		Roof (uninsulated in base cases)	Glass wool
		Exterior wall and projected floor (uninsulated in base cases)	EPS, Stone wool, XPS
		Window frame (wood frame with clear single glazing in base cases)	Wood frame/double glazing, PVC frame/double glazing
		All of the abovementioned elements	
		Group 1 (wood frame with clear single glazing in the base cases)	EPS and wood frame/double glazing, EPS and PVC frame/double glazing, Stone wool and wood frame/double glazing, Stone wool and PVC frame/double glazing, XPS and wood frame/double glazing, XPS and PVC frame/double glazing
		Group 2 (PVC frame with clear double glazing in the base cases)	EPS and PVC frame/double glazing, Stone wool and PVC frame/double glazing, XPS and PVC frame/double glazing
Objective functions	Environmental sustainability score		(0, 65)
	Economic sustainability score		(-50, 38)
	Total sustainability score		(-39, 102)



Colors used for 'building age'

15 years old — 20 years old — 25 years old — 30 years old

Colors used for 'element thermally refurbished'

Floor above unheated spaces roof — Roof — Exterior wall and projected floor — Window frame and glazing — All elements mentioned on the left side

Figure 2: Distribution of the data by building age and element thermally refurbished

The multi-objective optimization study aimed to maximize environmental and economic sustainability scores for the two-objective functions; and, to maximize the total sustainability score (sum of environmental and economic sustainability scores) added to them for the three-objective functions. For the purpose of supporting the designer at the early design stage, building variables (building age, plan type, and orientation) were used as controlled variables in the study. This setup brought a total of 24 data sets with a population size of 75 for each.

Step 2: Optimization method selection

First, the methods that were observed to be frequently used in the literature were selected for the application. After the application of methods, the results were observed to be insufficient in terms of decision support performance. For this reason, another research study was conducted to select another optimization method suitable for this problem.

NSGA-II and NSGA-III are among the most frequently used methods in the studies (Pan et al., 2023; Hashempour et al., 2020; Shi et al., 2016). NSGA-II is a method that was designed based on a genetic algorithm, and a modified mating and survival selection calculation is applied, additionally (Deb et al., 2002; Blank and Deb, 2020). NSGA-III, developed from NSGA-II, specializes in many-objective optimization (Deb and Jain, 2014; Jain and Deb, 2014). C-TAEA, one of the state-of-the-art methods, is also increasingly used in studies and shows competitive performance in comparative evaluations of algorithms (Chen et al., 2023; Zhan and Huang, 2024; Picard and Schiffmann ,2021; Tian et al., 2021; Tian et al., 2022; Chen et al., 2024). It utilizes convergence-oriented archiving (CA) and diversity-oriented archiving (DA). Driving the population to the feasible area and approaching the Pareto front is primarily the responsibility of CA as the main force. To explore the area of CA development, DA is used as a supplement. The evolutionary state of CA and DA was used to select mating parents during reproduction (Li et al., 2019). For the optimization study, these three methods were selected considering their frequently usage.

Following their application and the assessment of their results, Reference Vector Guided Evolutionary Algorithm (RVEA) was then selected to be assessed as an alternative method. In RVEA method application, a scalarization approach known as angle penalized distance (APD) is proposed to measure the distance of the solutions to the ideal point and the closeness of the solutions to the reference vectors; this could be used as a diversity measure or a degree of satisfaction to the preferences (Cheng et al., 2019). An adaptation strategy is to adjust the distribution of reference vectors dynamically according to the scales of objective functions.

Step 3: Optimization study and evaluation of results

In the optimization applications with the selected methods, the pymoo framework was used (Blank and Deb, 2020). As aforementioned, due to the need for a new method search and application in relation to the limited number of refurbishment scenarios obtained with the initially selected methods, this step consisted of two sub-steps, which are detailed below. In each of these sub-steps, hyperparameter optimization and evaluation of the obtained optimal solutions in terms of decision support were carried out.

3.a: Application of frequently used optimization methods

In the study, NSGA-II method was used for two-objective functions. NSGA-III and C-TAEA methods were used both for two and three-objective functions.

The hyperparameter values that control the optimization process were selected based on the performance evaluations made in other studies. The hyperparameters evaluated in this study and their values and explanations are as follows:

- Das-Dennis and Riesz s-Energy options were selected for hyperparameter optimization for the reference directions (ref_dirs), which need to be defined for models with three-objective functions. These reference directions consist of a set of predefined reference points to guide the evolutionary search, and help to produce diverse and well-distributed solutions on the Pareto front. While Das-Dennis requires the use of more structured point sets and dimensions, Riesz s-Energy was developed to solve this problem (Ma et al., 2021).
- Termination Criterion (n_gen) is the parameter that determines when to terminate an algorithm run. For the hyperparameter optimization study, 250, 500, 1000, and 1500 values were studied (Rohit et al., 2021; Blank and Deb, 2020).
- Crossover operators were used to generate the offspring for all optimization models in the study (Katoch et al., 2021). For this purpose, Simulated Binary Crossover (SBX) was applied. SBX is a real-parameter recombination operator, and the spread of offspring solutions is determined by the operator's parameter in relation to their parent solutions (Deb et al., 2007). For all optimization studies related to this operator, the probability of SBX is set as 0.5 for two objectives, and as 1 for three objectives (Deb et al., 2007; Blank and Deb, 2020). For the hyperparameter optimization study, mutation probability (mut) values of 0.1, 0.2, and 0.3 were studied by keeping eta value constant at 30.
- Random sampling was used for unbiased representation of populations (Blank and Deb, 2020).

For all optimization studies, hyperparameters were optimized for the dataset that had 15-year-old buildings with rectangular plans of ca. 230 sqm, where long sides were facing east and west. Hyperparameter search space and settings selected accordingly are given in Table 2. For the first group of methods, mostly, values that will take less calculation time have been chosen because different parameter configurations did not produce any change in the results. NSGA-III produced mostly the same solutions as other methods, but for certain datasets, they were less than others. Therefore, hyperparameter setting determination criteria for this method were decided to be as giving the optimal solutions being the same as the optimal solutions obtained in all other methods.

Following the hyperparameter optimization, optimization studies were done for all data sets with the selected hyperparameter values. These optimization studies done with the selected methods led to limited optimal solutions and limited design scheme proposals to support decision-making (Figure 4), and these are given in detail and discussed in the 'Results and Discussion' section.

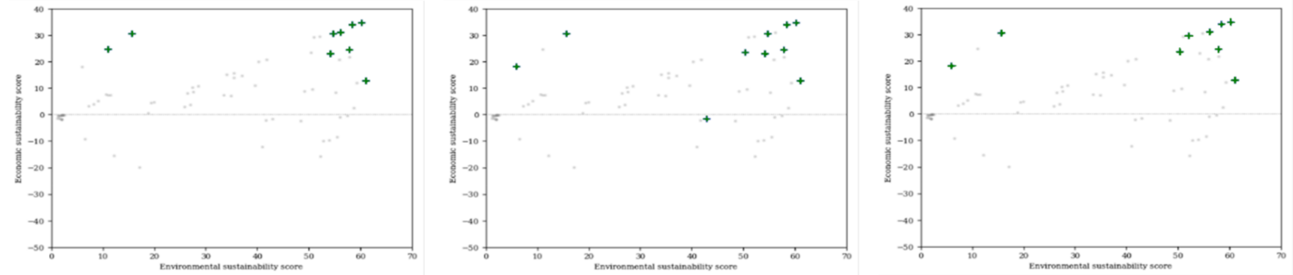
Table 2: Hyperparameter search space and parameter values selected from it for optimization models (Note: values shown in bold provided better results, others made no difference in solutions with different settings)

Objective numbers and optimization methods		Hyperparameter search space, and the parameter values chosen for the related methods.		
		Generation	Mutation	Reference direction
		250, 500, 1000, 1500	0.1, 0.2,0.3	Das-Dennis, Riesz s-Energy (energy)
2 objectives	NSGA-II	250	0.1	-
	NSGA-III	250	0.1	energy
	C-TAEA	250	0.1	energy
3 objectives	NSGA-III	250	**0.1**	**energy**
	C-TAEA	250	0.1	energy
	RVEA	**500**	**0.2**	**energy**

3.b: Application of a relatively less used optimization method: RVEA

Because of the limited optimal solution obtained in the previous step, RVEA, in which the Pareto front result can be determined depending on the user preference, was chosen to be used.

The hyperparameter search space and parameters were chosen the same as in the application of previous methods. Compared to the results of all previous optimizations in this study, changes in the hyperparameter settings were observed to have a significant impact on the Pareto front distribution for RVEA. In response to this, hypervolume (mean and standard deviation) and Pareto front were used as criteria for the hyperparameter value selection in the RVEA application. The Pareto front was evaluated by expecting to have a distribution that is concentrated as close to the ideal point as possible depending on the objective functions without any outlier in the distribution. Regarding this, hyperparameter value settings and corresponding hv values (mean and standard deviation) obtained by RVEA are given in Table 3 and three Pareto front graphs obtained by specific hyperparameter settings are given in Figure 3. Considering pareto front, n_gen is more effective during hyperparameter optimization, since it operates for the optimization of the distance of the solutions to the ideal point and the closeness of the solution for APD in RVEA. Additionally, compared to the other methods in Step 3.a, an increase in optimal solutions was also observed. Yet, the Pareto front distribution was slightly unstable.



Hyperparameter settings:
n_gen: 500, mut:0.2, ref_dirs: energy

Hyperparameter settings:
n_gen: 1000, mut: 0.3, ref_dirs: energy

Hyperparameter settings
n_gen:1500, mut:0.1, ref_dirs: das-dennis

Figure 3: Pareto front obtained by RVEA with specified hyperparameter settings for the dataset that had 15-year-old buildings with rectangular plans of ca. 230 sqm, where long sides were facing east and west only

Table 3: Hyperparameter value settings and corresponding hv values (mean and standard deviation) obtained by RVEA

n_gen	mut	ref_dirs	hv(mean)	hv(std)
250	0.1	das-dennis	3.349152	0.0
		energy	3.349152	0.0
	0.2	das-dennis	3.349152	0.0
		energy	3.354702	8,90E-10
	0.3	das-dennis	3.349152	0.0
		energy	3.349152	0.0
500	0.1	das-dennis	3.349152	8,89E-10
		energy	3.356645	8,89E-10
	0.2	das-dennis	3.349152	8,89E-10
		energy	3.34602	0.0
	0.3	das-dennis	3.349152	8,89E-10
		energy	3.34915	8,89E-10
1000	0.1	das-dennis	3.349152	8,89E-10
		energy	3.34602	8,89E-10
	0.2	das-dennis	3.349152	8,89E-10
		energy	3.349152	8,89E-10
	0.3	das-dennis	3.349152	8,89E-10
		energy	3.356645	8,89E+05
1500	0.1	das-dennis	3.349152	0.0
		energy	3.356645	0.0
	0.2	das-dennis	3.349152	0.0
		energy	3.356645	0.0
	0.3	das-dennis	3.349152	0.0
		energy	3.356645	0.0

Results and discussion

The optimization methods applied within the scope of the study gave different results in terms of the diversity and stability of optimal solutions.

The first group of methods that is commonly used in literature, together with the dataset with a limited Pareto front solution caused by the data distribution depending on the objective functions in this study, gave very precise results that did not show any difference with different hyperparameter values in the optimization of the methods. The Pareto front obtained by this first group of methods resulted in two optimal solutions for each of the 24 datasets one of which is shown in Figure 4, and these results provided only three design options as presented in Figure 5.

These design options were all for the building envelopes with a 10% window-to-wall ratio (WWR) and wooden window frame, except for an option with a 20% WWR, and only the renewal by thermally refurbishing 'all elements' came up for all. When evaluated through the graph, it can be concluded that these methods give accurate results regarding the optimum renewal solution. However, those results provided no other alternative solutions for refurbishment projects for instance with a limited budget where an option for renewing a single building element would therefore be more preferable. This situation was considered to be an issue that would limit the designer's decisions considerably.

To obtain more alternative design options, the use of RVEA, where user preferences are effective, has been tried. The optimum results obtained with that method not only include the Pareto front but also include feasible options further inside of the periphery (Figure 4). Results were obtained above the average of the economic sustainability score, and the environmental sustainability score ranged from a minimum of 3 to a maximum of 64.

Regarding the decision-support for the designer at the early design stage, optimal solutions obtained by RVEA provided diversified thermal refurbishment options. Design schemes corresponding to these optimal solutions given in Figures 5 and 6 show that:

- Renewal through all elements was the most proposed design by RVEA, same with the first group of methods because this option was the only one where the corresponding results for the values regarding the economic sustainability scores are the highest (Figure 2). Yet, depending on the budget, options for thermally refurbishing an individual element (i.e., 'roof', 'window', or 'exterior wall and projected floor') came up too.
- Options for 10% WWR and wooden frames were recommended more frequently. However, when the WWR of the building with a wooden window frame increased to 20% or 30% and refurbishment of all elements was preferred, replacing wood with a PVC frame was the only recommendation.
- More options were proposed for rectangular planned buildings than square alternatives.

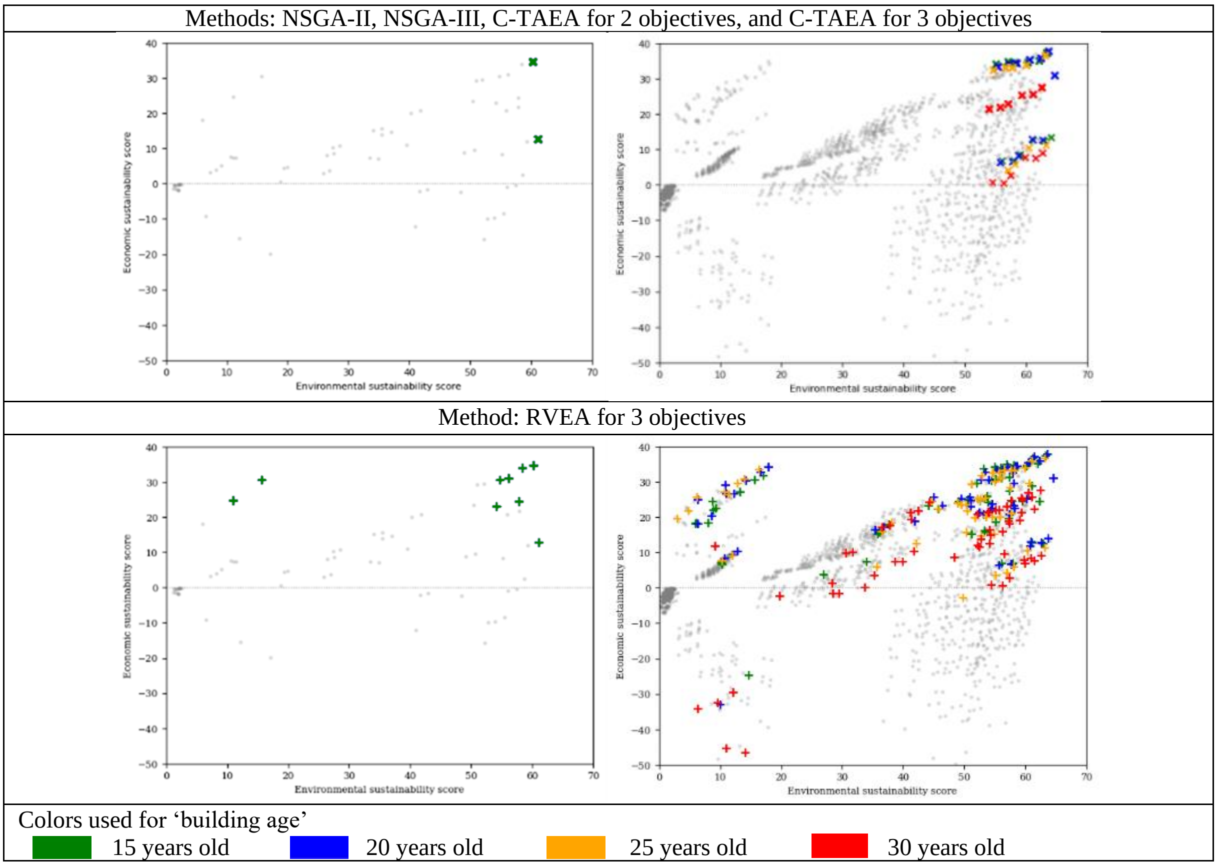


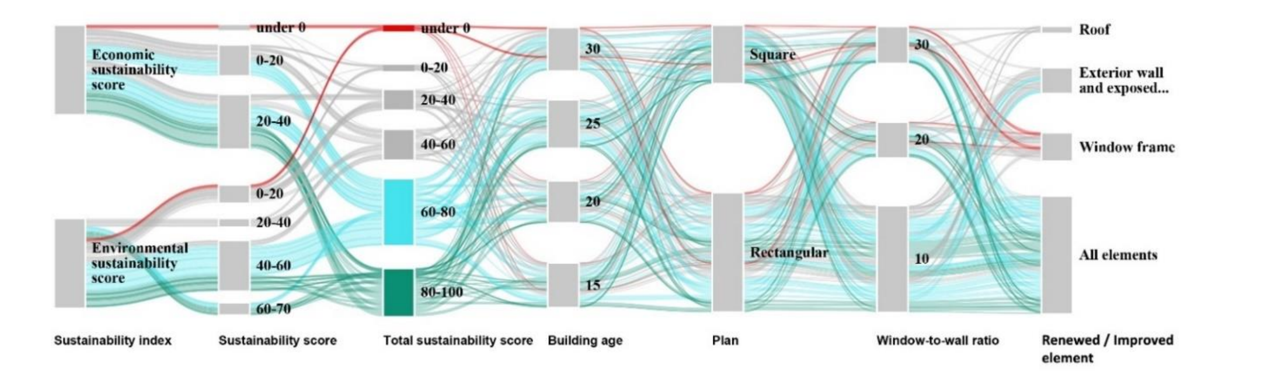
Figure 4: Optimal solutions for the dataset that had 15-year-old buildings with rectangular plans of ca. 230 sqm, where long sides were facing east and west only (left), and all optimum solutions obtained with all sets colored according to building age (right)

Window-to-wall ratio	Window frame materials/ glass and glazing type	Element thermally refurbished - Insulation material and window frame (if specified) used																Optimization methods
		Floor over unheated spaces			Roof	Exterior wall and projected floor			Window frame		All elements							
		EPS	Stone wool	XPS	Glass wool	EPS	Stone wool	XPS	Wood frame	PVC frame	EPS and Wood frame	EPS and PVC frame	Stone wool and wood frame	Stone wool and PVC frame	XPS and wood frame	XPS and PVC frame		
10	Wood/ clear single glass														🟩🟦🟧🟥 ▯■ (n=22**)	🟩🟦🟧🟥 ▯■ (n=24-all)		Group 1*
							🟥 ▯ (n=2)	🟦🟥 ▯■ (n=4)		🟩🟦🟧 ▯■ (n=4)	🟦🟧🟥 ▯■ (n=4)	🟩🟦🟧🟥 ▯■ (n=24-all)		🟩🟦🟧🟥 ▯■ (n=8)	🟩🟦🟧🟥 ▯■ (n=20)	🟩🟦🟧🟥 ▯■ (n=24-all)		RVEA
	PVC/ clear double glass				🟩🟧 ▯■ (n=3)		🟧🟥 ▯■ (n=7)	🟩🟦🟧🟥 ▯■ (n=14)				🟩🟦🟧🟥 ▯■ (n=10)		🟧 ▯ (n=1)		🟩🟦🟧🟥 ▯■ (n=14)		RVEA
20	Wood/ clear single glass															🟦 ■ (n=1)		Group 1*
									🟥 ▯■ (n=3)	🟩🟦🟧🟥 ▯■ (n=10)		🟩🟦🟧🟥 ▯■ (n=11)		🟩🟦🟧 ▯■ (n=4)		🟩🟦🟧 ▯■ (n=12)		RVEA
	PVC/ clear double glass				🟩 ▯ (n=1)		🟩 ▯ (n=1)											RVEA
30	Wood/ clear single glass								🟩🟦🟥 ▯■ (n=4)	🟩🟦🟧 ▯■ (n=14)		🟩🟦🟧 ▯■ (n=11)		🟩🟦🟥 ▯■ (n=5)		🟩🟦🟧 ▯■ (n=5)		RVEA
	PVC/ clear double glass				🟦🟧 ▯ (n=4)													RVEA

Colors used for 'building age'
🟩 15 years old 🟦 20 years old 🟧 25 years old 🟥 30 years old
Symbols used for 'plan type'
▯ Rectangular plan ■ Square / close to square plan

(n=…): the number of data sets for which the corresponding configuration is recommended
*: Group 1 methods include those used for 2 objectives (i.e., NSGA-II, NSGA-III, C-TAEA), and 3 objectives (i.e., C-TAEA).
**: the related design schemes are optimum options for 18 datasets with NSGA-III for 3 objectives.

Figure 5: Variable values corresponding to optimal solution



Colors by ‘Total sustainability score’

Score between ‘80-100’ | Score between 60-80
Score between ‘0-60’ | Score under 0

Figure 6: Optimum design scheme with RVEA (colored depending on the value of ‘Total sustainability score’)

- For 30-year-old buildings, designs for 20% and 30% WWRs have been less commonly recommended even with RVEA.
- In addition to XPS, which was the only insulation material recommended by the first group of methods, EPS has become a frequently recommended option with the use of RVEA in the cases of replacement of all elements for all building ages and in all plan types. However, it was not recommended in the case of the replacement of any single element.
- There were some solutions which RVEA gave as the optimal solution to maximize objective functions, but they correspond to low economic values (values specified as under 0 in Figure 6), and therefore they can be considered incorrect. These were the options in which the window frames of 30-year-old buildings with 20% and 30% WWR were renewed in by wooden window frames. These options were clustered in a corner opposite to the ideal point completely.
- Regarding the refurbishment option of renewing the floor above the unheated spaces on the other hand, which are clustered far from the ideal point similarly, no suggestions came up.

Conclusion

The objective of this study was to find appropriate multi-objective optimization method(s) to support decision-making during early design for building thermal refurbishment through the building envelope. In this manner, four evolutionary algorithm methods were compared for a case in Istanbul, Turkey concerning residential buildings.

As a result of the studies conducted on the dataset used, NSGA-II, NSGA-III, C-TAEA methods brought limited solutions that were highly close to the Pareto front; and, setting the hyperparameters differently didn't change or expand these limited solutions in almost all individual optimization cases. The reason for this is due to the characteristics of the dataset studied: the distribution of the data in a way that the Pareto front does not spread widely and the fact that the dataset is in a discrete distribution. As a solution to these undesirable situations from the decision support perspective, RVEA, which allows user preferences to bring alternative design schemes, was evaluated. As a result, RVEA provided more solutions in number and variety of designs with reasonable stability regarding the study related to hyperparameter optimization.

Further research is planned on the application of optimization methods to other problems to evaluate the effect of problem characteristics on optimization performance.

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