International Conference on Business and Economics - Hellenic Open University

Vol 4, No 1 (2024)

Proceedings of the ICBE-HOU 2024

A user interactive decision-making approach for the improvement of energy efficiency in buildings: A realistic case study

Christina Diakaki

A user interactive decision-making approach for the improvement of energy efficiency in buildings: A realistic case study

Christina Diakaki*

Abstract

Improving energy efficiency in buildings is a major priority and challenge worldwide, as the available measures vary in nature, and the resulting decision problem becomes complex, due to the numerous decision variables involved, which reflect the alternative measures available, and the multiple, usually competitive objectives, in terms of cost, energy consumption, environmental concerns, etc., of the respective decision-maker, who is usually the user, occupant, and/or owner of the building. Another challenge arises from the need to satisfy the preferences of the involved decision-maker, which can be hardly prescribed, and should be elicited in a rather indirect way. To address the above challenges, a mixed-integer nonlinear mathematical programming model has been integrated with the UTASTAR value elicitation method, under an interactive decision-making framework. To examine the feasibility and efficiency of the integrated decision-making approach, an existing building is examined under realistic operating conditions. The study confirms the feasibility and efficiency of the approach, demonstrates its functionality, exploits its qualities, and highlights its strengths, weaknesses and limitations.

JEL Classifications: C61, C63, C69, Q49.

Keywords: Buildings' energy efficiency improvement, Multi-objective optimization, Multi-criteria decision aid, Value system, Preference elicitation

* Corresponding author. School of Social Sciences, Hellenic Open University, Patra, Greece. Email: cdiakaki@eap.gr

1 Introduction

Improving energy efficiency in buildings is a major priority and challenge worldwide, as the available measures vary in nature, and the involved decision analyst, who is usually an architect, engineer, or building expert, faces a complex decision problem (Diakaki et al., 2008). The complexity arises from the numerous decision variables involved, which reflect the alternative measures available (Wulfinghoff, 1999), and the multiple, usually competitive objectives, in terms of cost, energy consumption, environmental concerns, etc., of the respective decision-maker, who is usually the user, occupant, and/or owner of the building.

Such decision-making problems are addressed through some form of modelling, which may be undertaken in various, more, or less complex, ways (Kolokotsa et al., 2009). It is, however, important, to adopt modelling approaches that aggregate the objectives in a way that leads to specific problem solutions rather than a set of non-dominated solutions (i.e. a Pareto set), which are then presented to the decision-maker, to choose the one that is the most satisfactory based on his/her own preferences and value system (Diakaki and Grigoroudis, 2021). To achieve this, the modeling approach should be capable of incorporating the decision-maker's preferences regarding the decision objectives being considered—a challenging task in itself—while simultaneously addressing the difficulty of eliciting these preferences.

The above challenges have been addressed (Diakaki and Grigoroudis, 2021) by integrating a mixed-integer nonlinear mathematical programming model with the UTASTAR value elicitation method (Siskos and Yannacopoulos, 1985) under an interactive decision-making framework. To ensure validity of the mathematical model, the initially proposed approach is extended herein, and simulation is employed to check the model's performance. The proposed extended framework facilitates the decision-making process, so that decisions are made, which conform to the value system of the decision-maker, without this system having to be prescribed in advance.

To examine the feasibility and efficiency of the extended decision-making framework, under realistic operating conditions, an existing building is examined herein for retrofit purposes (Kolokotsa et al., 2012).The study of this building confirms the feasibility and efficiency of the approach, demonstrates its functionality, exploits its qualities, and highlights its strengths, weaknesses and limitations. The remaining paper is structured in four sections. Section 2 presents the examined problem and the challenge, Section 3 outlines the adopted decision-making approach, Section 4 describes the case study, and Section 5 summarizes some concluding thoughts.

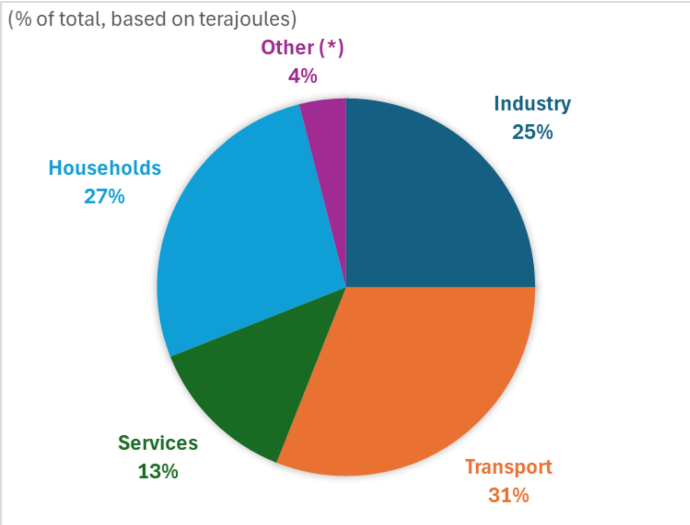
2 The problem and the challenge

The building sector is among the greater energy consumer sectors worldwide, as Figure 1 clearly demonstrates.

From an energy point of view, buildings are complex systems considering the building envelope and its insulation, the space heating and cooling systems, the water heating systems, the lightning appliances and other equipment. In contrast, however, to other systems, most buildings have a long lifespan, which means that most of the energy savings potential[1] lies in the retrofitting and purchasing of new technologies for the existing building stock, as well as in the efficient design and establishment of improved standards for the new buildings. Energy savings can be generally achieved by using (Li et al., 2022):

- building shell improvement measures;
- modern / improved heating, cooling and hot water systems;
- new materials, technologies and renewable energy sources;
- smart automation systems; etc.

Figure 1: Final energy consumption by sector, EU, 2022
(adopted by Eurostat;https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview#Final_energy_consumption)



(*) International aviation and maritime bunkers are excluded from category "Final energy consumption for transport"

To decide on the best combination of measures to adopt, a decision problem is typically developed, to allow for the best possible choice of alternatives. This means that the desired outcome of the decision process should include those measures that will prove to be more efficient and reliable in the long run, compensating, typically competitive, energy, environmental, economic, etc., objectives, and at the same time satisfying the decision-maker, who in this case is the user, occupant, and/or owner of the building.

The total possible solutions to the decision problem outlined above are practically unlimited (Wulfinghoff, 1999) and the typical approach involves:

- collection of data and creation of a reference building;
- definition of alternative actions;
- evaluation of actions using simulation techniques; and
- subjective final choice or choice supported using multi-criteria decision analysis techniques.

The strong points of this approach are summarized in two points. The approach

[1]https://www.iea.org/energy-system/buildings [last accessed 26.11.2024]

provides in a quantified manner the effects of the examined alternatives, and fully utilizes the experience and knowledge of the building expert, that is the person who implements the approach. At the same time, however, the approach suffers from two main drawbacks. Through this approach, only a small finite number of alternatives may be considered. As the number of alternatives increases, the required computing load increases too, and may become even impossible to perform the computations. On the other hand, as the number of alternatives to consider decreases to compensate for the previous problem, the likelihood of finding not just the best, but even a good solution diminishes. Moreover, the experience and knowledge of the building expert determines both the solutions to be considered and the final choice, which might not always be the most effective method.

Due to the weak elements of the typical approach, other efforts have been studied and proposed, which suggest modelling the problem as a multi-objective optimization one and, depending on the resulting/pursued problem formulation solve it, if possible, with some mathematical programming technique, or try a genetic algorithm or any other heuristic approach capable to handle it (Diakaki et al., 2008, 2010; Diakaki and Grigoroudis,2013). The aim is to reach a single decision that satisfies the decision-maker, rather than a Pareto optimal set, which would then require further treatment to lead to a single suggestion to the decision-maker, a fact that gives rise to another problem. The decision-maker's preferences are unknown and hard to assess.

To address the above problems, an interactive mathematical programming approach has been adopted (Diakaki and Grigoroudis, 2021). This approach assists the development of a multi-objective decision model that incorporates decision-maker's preferences, elicited via the assessment of his/her utility function with the assistance of the UTASTAR method (Siskos and Yannacopoulos, 1985).The approach facilitates the decision-making process, so that decisions are made that conform to the value system of the decision-maker, without this system having to be prescribed in advance. To ensure the validity of the employed mathematical programming model, the initially developed decision-making framework is enhanced by integrating simulation specifically for model validation.

3 The interactive decision-making approach

The general idea of the proposed approach starts with the formulation of the decision problem as a multi-objective decision problem of the following form (Diakaki et al., 2010):

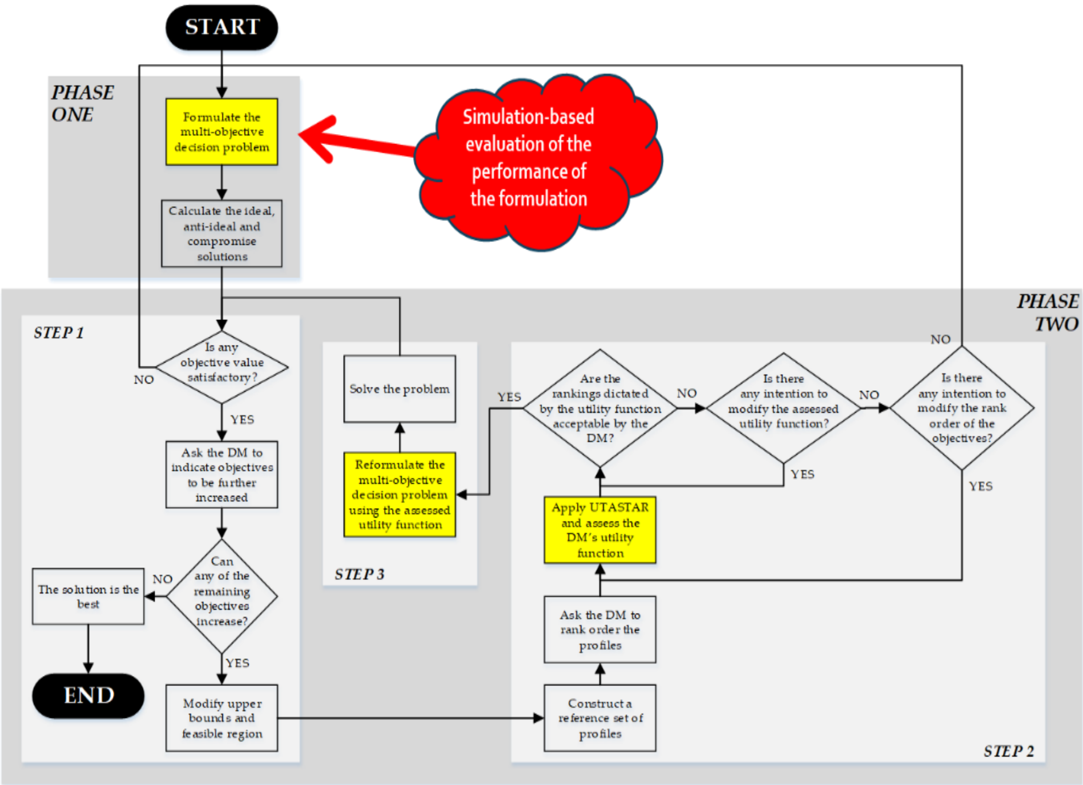
$$\min[g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_n(\mathbf{x})] \text{ subject to } \mathbf{x}\in X$$

where

- $\mathbf{x}=(x_1, x_2, \ldots, x_m)$ is the vector of m binary or continuous decision variables reflecting alternative choices (e.g., doors' and windows' types, structures of multi-layer components such as walls, ceilings, and floors, materials to be used for their construction, and systems that can be used for heating, cooling and hot water supply);
- $X\subseteq R^m$ is the feasible region or decision space of the problem under study, which is implicitly dictated by a set of constraints concerning the decision variables and their intermediary relations; and
- $g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_n(\mathbf{x})$ are the values of n considered objectives.

This problem is then solved under the integrated and interactive framework graphically depicted in Figure 2.

Figure 2: The integrated and interactive decision framework



More specifically, the whole decision process is undertaken in two major phases:

- Phase 1: In the first phase, a multi-objective mathematical programming model is formulated as proposed in Diakaki et al. (2010). The performance of this model is examined via simulation means as described in Diakaki et al. (2013), and if it is acceptable, it is used to determine, for each considered objective, an ideal and an anti-ideal solution, as well as a compromise solution for the whole problem at hand.
- Phase 2: The ideal, anti-ideal and compromise solutions are presented to the decision-maker, to examine the level of his/her satisfaction with respect to the different objectives considered, and to determine the range of possible improvements, if any. This phase is iterative and is iterated as many times as necessary to reach a solution that will satisfy the decision-maker. When first entering, the decision-maker is shown the basic information generated by Phase 1, i.e. the ideal, anti-ideal and compromise solutions, and is asked to express his/her satisfaction with respect to the compromise solution. If the decision-maker is not satisfied by any of the objectives achieved in the compromise solution, the multi-objective decision problem has no satisfactory solution, and the problem should be reviewed and revised, and then restart the whole procedure from Phase 1. If the decision-maker is fully satisfied with the compromise solution, then the decision-making process comes to an end, while

if the decision-maker is satisfied in some objectives but not all, based on the information generated through Phase 1, and the objectives suggested by the decision-maker for improvement, a reference set of possible objective values (profiles) is developed, and the decision-maker is asked to rank order them. Based on this ranking, the utility function of the decision-maker is assessed with the assistance of the UTASTAR method, and it is then used to reformulate the decision problem and solve the resulting problem. The new solution is shown to the decision-maker and Phase 2 is repeated if the decision-maker asks for further improvements.

The details of the iterative process may be found in Diakaki and Grigoroudis (2021), while a realistic application is presented in the following section, based on an existing building, which is considered for retrofit purposes.

4 Case study

The building considered herein is a 50 m^2 building located in Iraklion, Crete, Greece, used and operated as a typical office. Table 1 summarizes the characteristics of this building, as determined in the frame of a previous study (Kolokotsa et al., 2012).

Table 1: Summary of the characteristics of the considered building

Generics	
Operation hours (excluding national holidays)	Monday & Wednesday 08:00-14:30 Tuesday, Thursday & Friday 08:00-14:30 &17:00-21:00
Orientation	North-South
Building envelope characteristics	
Walls	3-layer outer walls (insulation, brick, & plasterboard) with thermal conductivities of insulation, brick and plasterboard layers equal to 0.04, 0.89, and 0.14 W/mK, respectively
Roof	2-layer ceiling (concrete & insulation) with thermal conductivities of concrete, and insulation layers equal to 2.1, and 0.04 W/mK, respectively
Windows	Double glazing windows with thermal transmittance U=1.4 W/m^{2}K and effective total solar energy transmittance g=58.9%
Floor	Single layer floor (concrete) with thermal conductivity equal to 2.1 W/mK
Building services	
Single system for both cooling & heating	A/C Inverter of 3.4 kW (electricity)

Based on an indoor environmental conditions' analysis (Kolokotsa et al., 2012), the energy requirements of the building have been identified to be mostly due to increased cooling load during the summer season, attributed mainly to the climatic conditions in Crete, Greece. For the same reason, energy consumption for heating is only a small portion of the total energy demand.

Given the above, to reduce the energy load of the building, the following alternatives have been considered as being the most appropriate (Diakaki et al., 2013):

- increase of roof insulation;
- replacement of doors and windows with others that will prevent the high levels

of solar radiation;

- replacement of the heating/cooling system with a more efficient one.

Table 2: Alternative window/door types

Type		U value (W/m^{2}K)	Effective total solar energy transmittance (%)	Cost (Euros/m^2)
1	Insulating Xenon	0.40	0.408	85
2	Insulating Krypton	0.70	0.407	90
3	Low SHGC Argon, gold	1.26	0.212	100

Table 3: Alternative electrical heating/cooling systems

Type		Coefficient of Performance	Cost (Euros)
1	A/C Inverter of 3.8 kW	2.10	700
2	A/C Inverter of 5.3 kW	2.30	900
3	A/C Inverter of 7.0 kW	2.50	1300

Tables 2 and 3 summarize the characteristics and costs of the alternative solutions considered. An additional cost of 150 Euros/m^3 is also considered for the ceiling's insulation material, which due to space limitations may not exceed 0.10m totally. The values in Tables 2 and 3 were identified in a previous study of the building (Diakaki et al., 2013).

For the considered building, a detailed TRNSYS simulation model was developed (Kolokotsa et al., 2012), which allows for the evaluation of alternative retrofit solutions. The simulation model was validated against real data, thus ensuring an acceptable level of representation of reality.

The application of the multi-objective decision modelling approach considered herein to the decision problem at hand leads to a mathematical model of the form generally presented in Section 3, which aims at determining measures that minimize the following two objectives:

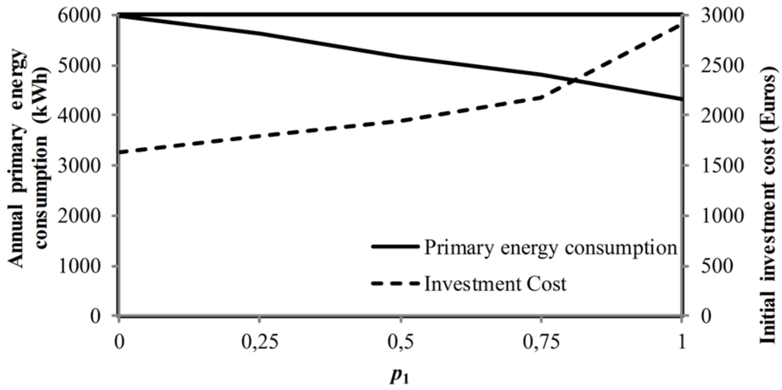
- the primary energy consumption $g_1(\mathbf{x})$; and
- the initial investment cost $g_2(\mathbf{x})$.

These objectives are competitive as the cost-efficient solutions are typically less environmentally friendly and vice versa. Therefore, searching for a solution that would be globally optimal is meaningless. Instead, a feasible solution that will comply as much as possible with the preferences and value system of the involved decision-maker is pursued, as described below.

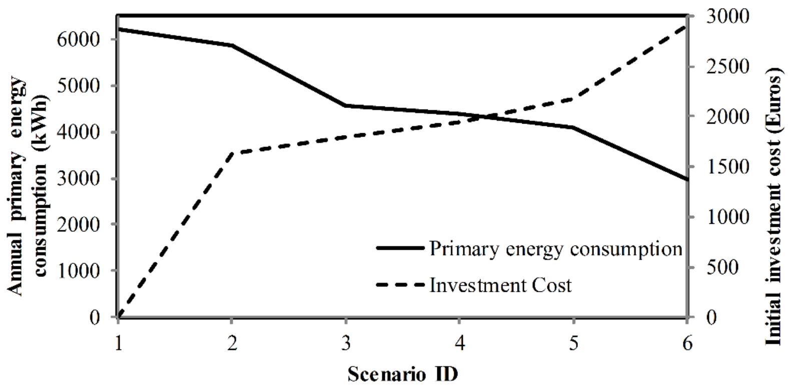
To start with, the developed multi-objective decision model is first applied, and then, several simulation investigations are performed to study and evaluate the quality of the retrofit alternatives proposed by this model. The results of the simulation investigations confirm, as depicted in Figure 3 that, despite its reduced precision compared to the corresponding simulation model of the building, the decision model allows for the realistic comparative evaluation of the considered alternatives. More specifically, as Figure 3 graphically displays, the values of the considered objectives show the same trend either calculated via the simulation model (see Figure 3a), or calculated via the decision model, (see Figure 3b).

The above behavior suggests that the decision model is successful in capturing the significant elements of the building operation, thus suggesting solutions that can satisfy the decision-maker. It is therefore suitable for use in the frame of the decision process presented in Section 3 and graphically displayed in Figure 2.

Figure 3: TRNSYS simulation validation of the performance of the decision model



(a) Decision model results ($p_1 \in [0,1]$ is a weight coefficient expressing the preference of the decision-maker towards the decrease of annual primary energy consumption; when $p_1=0$, the decision-maker cares only about cost decrease, while for $p_1=1$ he/she is indifferent about cost)



(b) Simulation model results (scenario 1 corresponds to the do-nothing case, while scenarios 2 to 6 explore the decisions suggested by the decision model, for the p_1 values 0, 0.25, 0.5, 0.75 and 1, respectively)

In Phase 1 of the proposed approach (see also Figure 2), the individual objectives of the examined decision problem are minimized and maximized individually, to establish the ideal and anti-ideal solutions to the problem. In addition, an initial compromise solution is identified. Table 4 summarizes the outcomes of Phase 1, while Table 5 summarizes the basic information that has been generated through this phase and will be used in the next one, to assess whether a satisfactory solution has already been identified or whether the process of finding a satisfactory solution should continue. It is important to note that the rate of closeness shown in Table 5 reflects the quality of the solution achieved for each objective considered; lower values correspond to better solutions.

In the second phase, the basic information obtained through Phase 1 is shown to the decision-maker, and it is assumed that the decision-maker is not satisfied with the cost that results from the compromise solution. This means that, according to the considered decision framework, the utility function of the decision-maker should be developed, to assist the continuation of the decision-making process. To this end, the profiles displayed in Table 6 are developed, the decision-maker ranks the profiles (see last column in Table 6), UTASTAR is fed with all this information, and the utility functions displayed graphically in Figure 4 are generated.

Using the generated utility functions, the decision problem is reformulated so that the resulting decision problem aims at the maximization of the decision-maker's global utility. The solution to this problem is summarized in Table 7, and is assumed to satisfy the decision-maker, thus leading to the end of the decision-making process. Table 8 summarizes the final solution to the examined problem and compares it with the initial one.

Table 4: Summary of Phase 1 outcomes

Decisions and objectives	**Type of Solution**				
	Minimize		**Maximize**		**Compromise**
	$g_1(\mathbf{x})$	$g_2(\mathbf{x})$	$g_1(\mathbf{x})$	$g_2(\mathbf{x})$	
Window/Door type	3	1	2	3	3
Roof insulation thickness (m)	0.07	0	0	0.07	0.01
Heating/Cooling system	3	1	1	3	3
$g_1(\mathbf{x})$: Primary energy consumption (MJ/year)	15585.43	21508.98	21822.66	15585.43	16882.07
$g_2(\mathbf{x})$: Initial investment cost (€)	2916.62	1625.91	1680.38	2916.62	2463.36

Table 5: Basic information generated in Phase 1

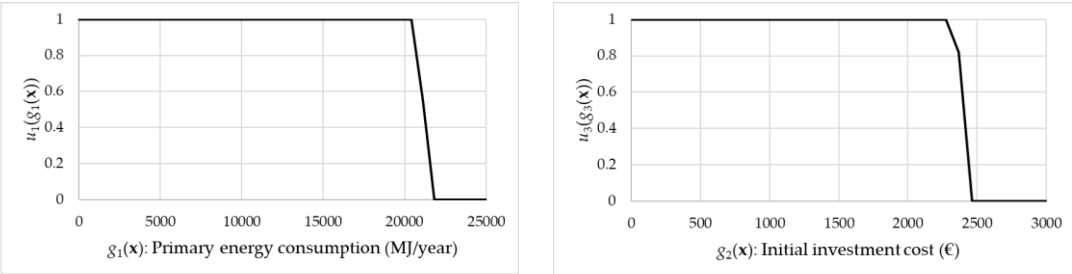
Information	**Primary Energy Consumption** (MJ/Year)	**Initial Investment Cost** (€)
Ideal solution per objective	15585.43	1625.91
Anti-ideal solution per objective	21822.66	2916.62
Initial compromise solution	16882.07	2463.36
Rate of closeness of initial compromise solution to the ideal solution	20.79%	64.88%

Table 6: Reference set of alternative profiles

Profile	**Primary Energy Consumption** (MJ/Year)	**Initial Investment Cost** (€)	**Decision-maker's ranking**
a_0	15585	2463	3
a_1	17145	2254	2
a_2	18704	2045	1
a_3	20263	1835	4
a_4	21823	1626	5

As the comparison of the final with the initial solution reveals (see Tables 7 and 8), the decision-maker was not satisfied by the initial solution due to the resulting cost, which was, by his/her assumed standards, far from its ideal value; it had a high rate of closeness to the ideal solution, compared to the other objective. The final solution decreased the rate of closeness, that is, it offered a less costly alternative. The cost decrease resulted in an increase of the energy consumption, but at an acceptable level for the assumed decision-maker.

Figure 4: Normalized marginal utility functions



(a) for primary energy consumption

(b) for initial investment cost

Table 7: Summary of basic information generated by both phases

Information	**Primary Energy Consumption** (MJ/Year)	**Initial Investment Cost** (€)
Ideal solution per objective	15585.43	1625.91
Initial compromise solution	16882.07	2463.36
Rate of closeness of initial compromise solution to the ideal solution	20.79%	64.88%
New compromise solution	18942.50	1989.62
Rate of closeness of new compromise solution to the ideal solution	53.82%	43.43%

Table 8: Initial and final compromise solution

Decisions and objectives	**Compromise solution** Initial	Final
Window/Door type	3	3
Roof insulation thickness (m)	0.01	0.03
Heating/Cooling system	3	1
$g_1(\mathbf{x})$: Primary energy consumption (MJ/year)	16882.07	18942.50
$g_2(\mathbf{x})$: Initial investment cost (€)	2463.36	1989.62

5 Conclusions

This paper has discussed an interactive mathematical programming approach designed to improve energy efficiency in buildings. This method addresses a challenging problem characterized by multiple competing objectives and numerous decision variables. The complexity is heightened by the need for the decision-maker to express preferences regarding these objectives.

The approach offers a structured framework that simultaneously evaluates all possible combinations of alternative actions, accounting also for logical, physical, and technical constraints, and enabling the integration of the preferences and values of the decision-maker without requiring prior explicit definition. Thus, it provides a systematic foundation for developing a decision support system (DSS) to assist decision-makers in selecting the most suitable measures from a vast array of options.

While primarily focused on energy efficiency, the approach presented and discussed herein is adaptable to other domains with adjustments for domain-specific objectives and preferences (see e.g., Zopounidis et al., 1998). It also demonstrates that multiple methods can work together synergistically to identify feasible and satisfactory solutions to various decision problems, aligning with the involved decision-makers' preferences. Achieving such outcomes requires decision analysts to leverage all available tools that are appropriate and tailored to the specific challenges they encounter.

References

Diakaki, C., & Grigoroudis, E. (2013). Applying genetic algorithms to optimise energy efficiency in buildings. In Doumpos, M., & Grigoroudis, E. (eds), Multicriteria Decision Aid and Artificial Intelligence: Links, Theory and Applications, John Wiley & Sons, Ltd, 309-333.https://doi.org/10.1002/9781118522516.ch13

Diakaki, C., & Grigoroudis, E. (2021). Improving Energy Efficiency in Buildings Using an Interactive Mathematical Programming Approach. Sustainability, 13(8), 4436. https://doi.org/10.3390/su13084436

Diakaki, C., Grigoroudis, E., & Kolokotsa, D. (2008). Towards a multi-objective optimization approach for improving energy efficiency in buildings. Energy and Buildings, 40, 1747-1754. https://doi.org/10.1016/j.enbuild.2008.03.002

Diakaki, C., Grigoroudis, E., & Kolokotsa, D. (2013). Performance study of a multi-objective mathematical programming modelling approach for energy decision-making in buildings. Energy, 59, 534-542. https://doi.org/10.1016/j.energy.2013.07.034

Diakaki, C., Grigoroudis, E., Kabelis, N., Kolokotsa, D., Kalaitzakis, K., & Stavrakakis. G, (2010). A multi-objective decision model for the improvement of energy efficiency in buildings. Energy, 35, 5483-5496. https://doi.org/10.1016/j.energy.2010.05.012

Kolokotsa, D., Diakaki, C., Grigoroudis, E., Stavrakakis, G., & Kalaitzakis K. (2009). Decision support methodologies on the energy efficiency and energy management in buildings. Advances in Building Energy Research, 3, 121-146. https://doi.org/10.3763/aber.2009.0305

Kolokotsa, D., Diakaki, C., Papantoniou, S., & Vlissidis, A. (2012). Numerical and experimental analysis of cool roofs application on a laboratory building in Iraklion, Crete, Greece. Energy and Buildings 55, 85-93. https://doi.org/10.1016/j.enbuild.2011.09.011

Li, C.Z., Zhang, L., Liang, X., Xiao, B., Tam, V.W.Y., Lai, X., & Chen, Z. (2022). Advances in the research of building energy saving. Energy and Buildings, 254, 111556. https://doi.org/10.1016/j.enbuild.2021.111556

Siskos, Y., & Yannacopoulos, D. (1985). UTASTAR: An ordinal regression method for building additive value functions. Investigação Operacional, 5(1), 39-53.

Wulfinghoff, D.R. (1999). Energy Efficiency Manual. Energy Institute Press.

Zopounidis, C., Despotis, D.K., & Kamaratou, I. (1998). Portfolio selection using the ADELAIS multiobjective linear programming System. Computational Economics, 11, 189-204. https://doi.org/10.1023/A:1008660309379