Applied Energy 88 (2011) 1386–1394

Contents lists available at ScienceDirect

Applied Energy

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

Development of a multicriteria tool for optimizing the renovation of buildings

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ARTICLE INFO

Article history:
Received 5 May 2010
Received in revised form 7 September 2010
Accepted 4 October 2010
Available online 13 November 2010

Keywords:
Multicriteria optimization
Genetic algorithm
TRNSYS
Renovation
Energy performance
Decision-making tool

ABSTRACT

The renovation of a building involves not just the fulfilment of functional requirements, but also considerations such as energy consumption, investment costs, environmental impact and wellbeing. As things stand, new design methods and tools are needed, and the aim of the research presented in this article was to develop a multicriteria tool, MultiOpt, for the optimization of renovation operations, with an emphasis on building envelopes, heating and cooling loads and control strategies. MultiOpt is based on existing assessment software and methods: it uses a genetic algorithm (NSGA-II) coupled to TRNSYS, and economic and environmental databases. This article illustrates its utilization in the renovation of a school in the southern French city of Nice which was representative of France's building stock. The study started with the monocriterion optimization of energy consumption, cost, thermal comfort, and life-cycle environmental impact. It then moved onto multicriteria optimizations. The monocriterion analyses focussed on the building's characteristics and performance; the multicriteria analyses were concerned with the interactions between the different objectives, and with identifying their convergences and divergences. The results demonstrated that MultiOpt can be used to compare different combinations of options and constraints, thus constituting a basis for operational decision-making.

1. Introduction

The constraints inherent in renovating a building may also provide incentives to look at ways of saving energy and limiting the life-cycle environmental impact of building materials by "going green".

Software exists for assessing buildings in terms of energy consumption (TRNSYS, Energy Plus, DOE2.1E), natural and artificial lighting systems [1] and acoustics [2]. There are also software and databases that can be used to assess the life-cycle environmental impact of building materials [3,4]. It will be noted that all these tools are function-specific.

It is easy to classify buildings on the basis of, say, cost alone, but less so if one wants to look simultaneously at two or more parameters, such as cost and energy consumption [5], or energy consumption and visual comfort [6]. In this case one needs multicriteria methods that can be applied to particular types of equipment [7,8] or buildings [9]. Studies have been done on monocriterion and multicriteria methods coupled with simplified, and more detailed, assessment tools.

This article traces the development of MultiOpt, a tool for the multicriteria optimization of building renovation operations, based on existing optimization methods and assessment software. To begin with, currently-used methods are discussed. The appropriate features of a multicriteria optimization system are then presented, along with the development of MultiOpt. Finally, there is a case study that illustrates its implementation.

2. Existing studies on the optimization of buildings

2.1. The optimization of design elements

The abundant literature on the optimization of buildings may be classified according to the characteristics optimized. HVAC systems, for example, have been extensively studied. Wright et al. [10] investigated the design of a single-zone "all outside air" HVAC system. Chow et al. [7] carried out a detailed optimization of an absorption chiller system, and Kumar et al. [11] assessed and optimized the heating and cooling potential of an earth-to-air heat exchange system.

Research has also been done on optimizing specific characteristics of buildings, e.g. form [9,12], or particular structural elements such as multilayered walls [13] or double facades with integrated photovoltaic panels or electrically-operated blinds [14].

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doi:10.1016/j.apenergy.2010.10.002

A certain amount of work has been done on optimizing combinations of characteristics of building envelopes such as wall or window type, orientation, or type of HVAC system [14–22]. Here the difficulties stem, in particular, from the nature of the parameters under consideration. But the process is made more complex by the interactions that occur between the different parameters. For example, the orientation of a building will determine the incidence of natural light, which in turn will influence the choice of window type. And Caldas [21] points out that the optimization problem becomes more complicated still if it is the geometry of the building in its entirety that is the object of the exercise.

2.2. Optimization methods

Goldberg [23] suggested that the optimization methods could be divided up into three groups: enumerative methods, calculus-based methods and random methods. And we would concur.

2.2.1. Enumerative methods

The principle of enumerative methods is simple. Within a finite search space, or a discretized infinite search space, an algorithm sequentially assesses the objective function at every point in the space. But methods of this type lack real-world applicability. Though they are an improvement on basic trial-and-error heuristics, search spaces in the field of building design are generally too large for enumerative methods to be a practical proposition.

2.2.2. Calculus-based methods

These methods are sometimes termed "systematic" [17] or "exact" [24]. They are based on the rigorous mathematical expression of objectives, or their gradients.

Such methods have been widely used in the field of building design. To optimize the thickness of insulation layers, for example, Bolattürk [5] used the following method: a mathematical expression of the life-cycle cost is produced, the derivative is calculated, and the optimum value is the one for which the derivative is zero.

This "simplex" method and its variants, such as the Hooke-Jeeves method, were used by Peippo et al. [25] to optimize the design of solar low-energy buildings, on the basis of capital and energy costs. Bouchlaghem and Letherman [16] focused on the building envelope, and used analytical and graphical methods to optimize its thermal performance.

The main drawback of these methods is that the possibility of convergence depends on the regularity of the objective functions, which, as a result, must have an explicit expression, or permit derivatives.

2.2.3. Random (or stochastic) methods

With methods of this type, no hypothesis about the regularity of objective functions is necessary. This makes them easier to couple to building assessment tools.

Such methods have often been developed by analogy with others. For example, simulated annealing methods are based on thermodynamics, and they can be compared to annealing processes whereby a molten metal is slowly cooled to form crystals. The internal energy represents an objective, and the genetic algorithm defines a minimal energy state. Nielsen [17] developed a method based on simulated annealing to optimize building design on the basis of a life-cycle analysis.

Genetic algorithms (GA) use stochastic methods, and are based on the mechanisms of natural selection and genetics [23]. The basic form of the GA, the "simple genetic algorithm", is widely used in the field of building optimization. Huang and Lam [26], for example, used a simple genetic algorithm to optimize controller parameters for HVAC systems, and Wright et al. [10] used one to determine the optimal dimensioning of a HVAC system. GAs can also be used to solve more complex problems. Wang et al. [19,27] used an adapted and improved GA to optimize "green" building design, and Caldas [21] applied the method to problems of architectural optimization.

In sum, the classification of optimization methods depends on the elements to be optimized, and on the search method. Multicriteria analytical approaches also differ, as we shall now see.

2.3. Existing approaches to multicriteria analysis

The renovation of a building involves factors such as energy consumption, cost and thermal comfort. Where the problem arises is in dealing simultaneously with these potentially conflicting objectives.

Znouda et al. [28] studied the optimization of building design in a Mediterranean context, beginning with the minimization of energy consumption, then looking at costs. As expected, the results diverged, and no single optimum was found. They then tried another approach [20] whose aim was to find a solution for which the sum of its distances from the two previous solutions would be minimized. The result was a compromise, but all of the objectives were not examined simultaneously.

In the application of aggregative methods to multicriteria problems, constraints and penalty functions can serve as arbiters. Charron and Athienitis [14], in their optimization of a solar zero-energy home, took cost as their main objective. Energy consumption was predetermined, and the objective was defined as the sum of the cost function and a penalty function linked to thermal discomfort. A similar approach was taken in a study using the optimization toll OPTISOL [29] with two objectives, namely energy consumption and costs, each of which could be taken either as an objective function or a fixed target in a penalty function. This type of method allows several objectives to be treated simultaneously, but with different types of status.

Multiobjective problems are susceptible to the "Pareto approach", which, for optimization purposes, assigns the same weight to each objective [30], treats them all individually, and arrives at compromises between them by identifying those solutions that are non-dominated, or "Pareto optimal". A solution is non-dominated when no alternative solution exists that will promote a particular objective without simultaneously hampering the attainment of another.

Fig. 1 gives an example of a Pareto curve for an optimization problem with two objectives.

The optimization of three objectives results in a "Pareto surface". For more than three objectives, a Pareto optimization can still be carried out, but direct visualization is not possible.

Pareto optimization was introduced in the 1980s by Radford, Gero and D'Cruz [31–34], and it is now widely used in building design optimization [10,14,35]. It was used, for example, by Wang et al. [19] to optimize "green" buildings according to life-cycle exergetic assessment and costs, and by Verbeeck and Hens [36] to minimize the global warming potential of low-energy dwellings, with a particular focus on energy consumption and construction costs. Caldas developed a tool [21] that dealt with the same type

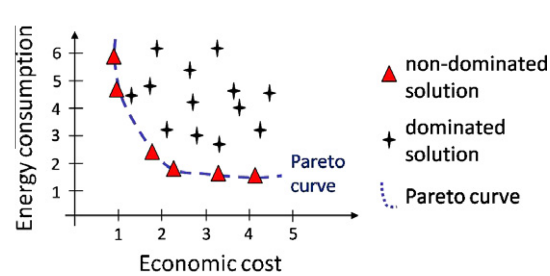

Fig. 1. Example of a Pareto curve.

of questions: energy, economics and sustainability issues such as greenhouse gas emissions. And this tool could equally be used to minimize the energy consumption of HVAC and lighting systems. Sambou has used a Pareto optimization approach [13] to optimize the thermal capacity and resistance of multilayered and alveolar walls. And there are also applications in ventilation control [37,38].

The fact that this method produces pluralities of optimized solutions is one of its big advantages, particularly in view of the fact that where buildings are concerned, the solution to a problem is rarely clear and simple. And for Wang et al. [19] and Pernodet et al. [29], it also provides a better understanding of how each of a set of objectives affects the overall picture.

3. Development of a multicriteria tool for optimizing the renovation of buildings

The aim of the present study was to build on previous work related to building assessment and design optimization in order to develop a new tool, MultiOpt, for the multicriteria optimization of renovation operations, with regard to building envelopes, HVAC systems and control strategies. Four criteria were considered: energy consumption, cost, life-cycle environmental impact and thermal comfort. MultiOpt is based on an existing optimization method, NSGA-II, a non-dominated sorting genetic algorithm (NSGA).

3.1. An optimization tool based on NSGA-II

NSGA-II was developed by Professor Kalyanmoy Deb's team at Kanpur Genetic Algorithms Laboratory [39,40]. It is one of the most efficient genetic algorithms for multiobjective optimization, and is often used for multicriteria optimization in different domains, including construction [41–44].

Like any other genetic algorithm, NSGA-II is based on the evolution of a population of "individuals", each of which is a solution to an optimization problem. In our work, an individual represents the result of a renovation operation carried out on a building. To use a genetic analogy, each individual is represented by a chromosome whose genes correspond to a number of the individual's characteristics, as in Fig. 2.

The implementation procedure for NSGA-II was presented by Deb, Huang, Hammage and Sanaye [39,40,45–47], as follows. The first generation of the population is randomly selected. It is then sorted into fronts by Pareto optimization. Individuals that are not dominated by any other are assigned to front number 1. Individuals dominated only by individuals in front number 1 are assigned to front number 2, etc. Each individual in each front is assigned a rank value based on the front to which it belongs.

Each individual is also assigned a "crowding distance", which is a measure of how close an individual is to its neighbours. A large average crowding distance indicates a high degree of diversity.

Parents are selected for the first generation of individuals using binary tournament selection based on rank and crowding distance. *N* individuals are selected on the basis of low rank number, with crowding distance being a secondary selection criterion. After undergoing crossover and mutation, the parents and their offspring are sorted once more on the basis of non-domination, and *N* individuals are selected, as before, to form the next generation, on the basis of previous rank and crowding distance.

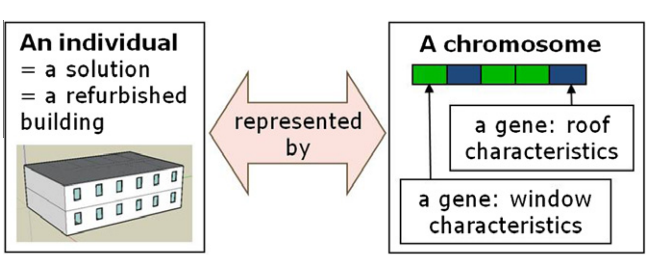

Fig. 2. A solution to an optimization problem, as represented by a chromosome.

3.2. Definition of parameters

With genetic algorithms, as already mentioned, solutions to optimization problems are represented by chromosomes. And the parameters of the optimization procedure are the genes that make up these chromosomes. In MultiOpt, these parameters are related to building renovation operations. Renovation operations of varying scope are proposed.

3.2.1. Parameters related to control strategies

Some parameters are related to building control strategies. Cooling and shade control can improve a building's performance

Table 1
Reference components of building envelopes.

	Composition (thickness in mm)
External wall type	
EW1	Plaster (13) + polyurethane (50) + concrete (180)
EW2	Plaster (13) + glass wool (100) + concrete (180)
EW3	Plaster (10) + polystyrene (100) + concrete (180)
EW4	Plaster (13) + hemp wool (100) + concrete (180)
EW5	Plaster (13) + glass wool (160) + concrete (180)
EW6	Plaster (13) + mineral wool (100) + concrete (180)
EW7	Plaster (13) + mineral wool (55) + concrete (180)
EW8	Plaster (13) + insulation with feather (40) + concrete (180)
EW9	Plaster (13) + insulation with feather (110) + concrete (180)
Roof type	
R1	Mineral wool (false ceiling, 40) + air layer (200) + concrete (240) + expanded perlite board (50) + waterproofing membrane (5)
R2	Mineral wool (40) + air layer (200) + concrete (240) + mineral wool (80) + waterproofing membrane (5)
R3	Mineral wool (40) + air layer (200) + concrete (240) + polystyrene (100) + waterproofing membrane (5)
R4	concrete (240) + expanded perlite board (50) + waterproofing membrane (5)
R5	concrete (240) + mineral wool (80) + waterproofing membrane (5)
R6	concrete (240) + polyurethane (80) + waterproofing membrane (5)
R7	concrete (240) + polystyrene (100) + waterproofing membrane (5)
R8	concrete (240) + polystyrene (200) + waterproofing membrane (5)
Ground floor	
GF1	PVC floor covering (3) + concrete (50) + polystyrene (80) + concrete (130)
GF2	PVC floor covering (3) + concrete (50) + polyurethane (50) + concrete (130)
GF3	Carpet (10) + concrete (50) + polystyrene (80) + concrete (130)
GF4	Carpet (10) + concrete (50) + polyurethane (50) + concrete (130)
GF5	Floor tiles (10) + concrete (50) + polystyrene (80) + concrete (130)
GF6	Floor tiles (10) + concrete (50) + polyurethane (50) + concrete (130)
Intermediate floor	
IF1	PVC floor covering (3) + concrete (160) + air layer (200) + mineral wool (false ceiling, 40)
IF2	PVC floor covering (3) + concrete (160)
IF3	Carpet (10) + concrete (160) + air layer (200) + mineral wool (40)
IF4	Carpet (10) + concrete (160)
IF5	Floor tiles (10) + concrete (160) + air layer (200) + mineral wool (40)
IF6	Floor tiles (10) + concrete (160)
Internal partition wall	
PW1	Plaster (70)
PW2	Brick (50)
PW3	Concrete (100)
PW4	Plaster (13) + mineral wool (70) + Plaster (13)
Window	
W1	Single pane
W2	Double pane
W3	Triple pane
W4	Double pane, low-e
W5	Double pane, low-e, argon

at minimal cost. And HVAC systems may also be taken into account in a renovation operation.

Parameters related to control strategies and HVAC systems are considered to be continuous variables, in the sense that they may take any given value within their definition domain. For example, the threshold value for the opening of a blind varies between 50 and 500 W/m^2 (with a default setting that can be changed by the user).

3.2.2. Parameters related to the building envelope

A renovation operation may encompass the envelope of a building whose characteristics, e.g. external wall type, are considered as discrete variables that can take only a limited number of reference values. This decision was influenced by the conclusions of studies by Sambou [13] and Pernodet et al. [29]. The point is that if wall characteristics are considered as combinations of continuous variables, they can be represented in the model as genes. But the fact that they evolve independently means that links between them are not preserved. In other words, the characteristics of optimized walls may not be mutually compatible. In order to avoid this difficulty, the characteristics of walls to be optimized are grouped in sets that correspond to reference walls [29].

Though it may be possible to assess the thermal transmittance of a wall in terms of efficiency and/or cost, it is difficult to assess the life-cycle environmental impact of insulation if the nature of the material is unspecified. Hence the need for reference walls using materials of known, certified performance.

MultiOpt includes six discrete parameters for building envelopes:

- external wall type;
- roof type;
- ground floor type;
- intermediate floor type;
- internal partition wall type; and
- window type.

Reference walls cover the range of available building materials, as shown in Table 1.

3.3. Objectives

For our case study (see below, Section 4) we used four optimization criteria: energy consumption, thermal comfort, cost and environmental impact.

The annual final energy consumption criterion covers heating, cooling, ventilation and lighting. It is calculated by TRNSYS and COMIS [48–50].

The thermal comfort criterion is based on the PPD (percentage of people dissatisfied) index [51]. It represents the number of hours during which the PPD is above 15%, as determined by the TRNSYS multizone “Type 56” component.

The economic criterion is the initial investment cost. A price database has been established for the reference walls presented in Table 1.

Equivalent CO_2 units are used in assessing environmental impact over the life cycle of the building materials. The reference data was procured from a database, INIES [52].

3.4. The structure of MultiOpt

To summarize, MultiOpt has three structural components: a graphical user interface (GUI), a genetic algorithm and a set of assessment methods. It is presented schematically in Fig. 3.

MultiOpt is used for the optimization of building renovation schemes. The procedure begins with a model that has certain characteristics: a given external form and internal configuration, and an occupation schedule corresponding to that of the actual building. The parameters to be optimized, for example the window type or the set point for shade control, are of course not defined.

The optimization problem is set out in the GUI, with parameters and combined variation domains that are determined by the model of the building. Objectives and genetic algorithm settings are also chosen in the GUI. With MultiOpt, one or more objectives can be pursued simultaneously. The description of the building and the choice of parameters, objectives and algorithm settings constitute the definition of the optimization problem. The genetic algorithm then carries out the process. The characteristics of the first generation of individuals are randomly selected, i.e. the values of the parameters are randomly chosen in the definition domains for those that are continuous, and among the reference walls for those that are discrete. Any given population consists of individuals representing buildings resulting from renovation operations carried out on the model, assessed according to the chosen objectives using tools and databases coordinated by TRNSYS. The assessment results provide the basis for selecting the parents of the next generation (see the description of NSGA-II in Section 3.1), and so on. The optimization process continues until the “Stop” command is triggered. In MultiOpt this occurs after a predetermined number of generations.

At the end of the optimization process, the GUI displays the results, i.e. descriptions of optimized scenarios for the renovation of

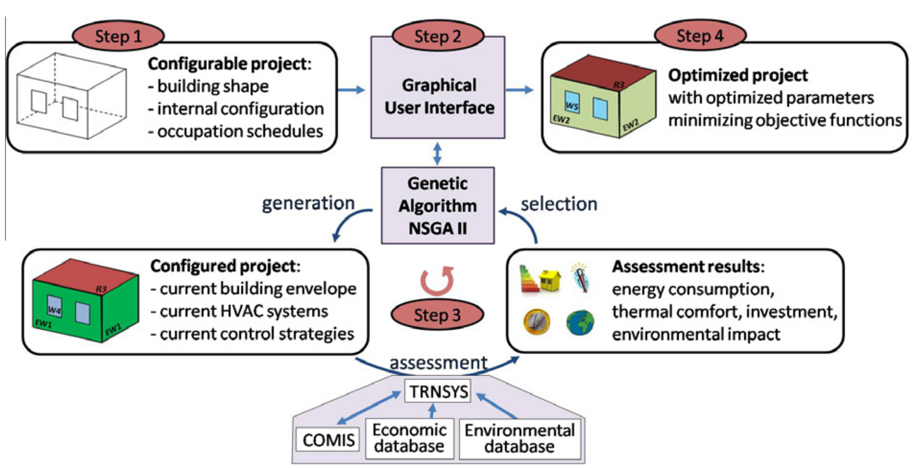

Fig. 3. Schematic structure of MultiOpt.

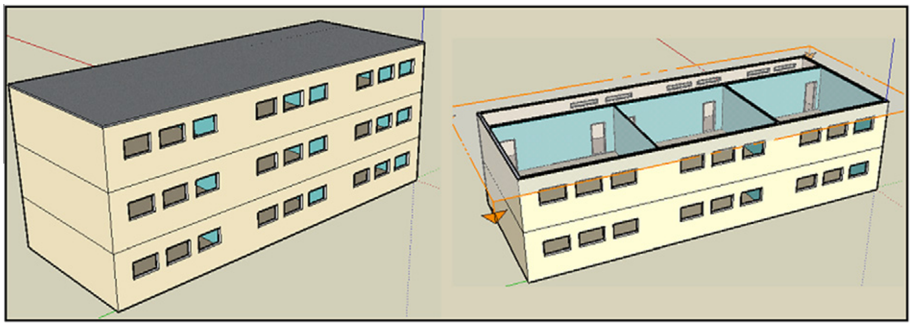

Fig. 4. Schematic views of the building used for the case study.

the building in question, and their degree of success in achieving the stated objectives.

4. Implementation of the optimization method: a case study

In this study, MultiOpt was used to optimize the renovation of a building. The criteria were energy consumption, cost, the life-cycle environmental impact of the building materials and thermal comfort.

4.1. The building in question

The building was a school whose floor plan was typical of current French building stock. Fig. 4 shows schematic views of the building in question.

This is a three-storey building with a total floor area of 640 m^2. On each storey, a corridor gives access to three west-facing classrooms. The building is in Nice, in southern France. The climate is Mediterranean.

The building is occupied from Monday to Friday, 8:00 to 18:00, nominally by 20 people/classroom. There is artificial lighting, controlled by luminosity sensors and switches, at 10 W/m^2 in the rooms and 5 W/m^2 in the corridors. The building is heated by electricity at 100 W/m^2. The set point temperature is 20 °C during the day and 16 °C during the night and at weekends. There is natural ventilation, and no active cooling system. The airtightness of the building is 0.53 ach at 4 Pa. The west facade has automatically-controlled shading equipment.

4.2. Optimization settings

All the eight optimization parameters treated in this article were handled by MultiOpt. Six of them concerned the building's envelope: external wall type (EW), roof type (R), ground floor type (GF), intermediate floor type (IF), partition wall type (PW) and window type (W). The other two involved shade control, namely the threshold value for the illumination of the facade (S) and the dead band associated with the on–off controller (ΔS).

The parameters relating to the envelope of the building were discrete, and their possible values are given in Table 1. Those relating to shade control were continuous. S varied between 50 and 500 W/m^2, and ΔS between 0 and 500 W/m^2.

The setting of the genetic algorithm was the same for all the optimizations. The studied population consisted of 40 individuals, and the optimization process was terminated after 70 iterations.

The protocol carried out by TRNSYS and COMIS to assess energy consumption consisted essentially of annual simulations, with time steps of one hour. The process took 60 h of computing time.

Three sets of optimizations were carried out. The first set focussed on monocriterion optimization, the aim being to minimize the values of four criteria: environmental impact, cost, energy consumption and thermal discomfort. The second set involved the multicriteria optimization of pairs of criteria, with the aim of understanding the interactions between objectives, and how each could affect the building's characteristics and performance. The third set involved the multicriteria optimization of groups of three criteria. The general aim was to find out how the results varied between the first two sets of optimizations and the last one, and to produce the visualization of the results that would be best suited to their analysis.

4.3. First set of optimizations (monocriterion)

The objective of these optimizations was to minimize the values of four criteria: environmental impact, cost, energy consumption and thermal discomfort. Given that there was only one overall objective, i.e. minimization, a single optimized solution was obtained in each case.

4.3.1. Monocriterion minimization of life-cycle environmental impact

Here, the aim was to minimize CO_2 over the life cycle of the building materials. Shade control was taken to have no significant effect.

The results are given in Fig. 5 and Table 2.

In the optimized building, the quantity of building materials used was a minimum: the thickness of the insulation layers was low, there was no false ceiling, and the windows were single-glazed. In other words, the lower the amount of building materials used, the lower the amount of CO_2 discharged.

For this operation, the results were checked against the environmental database. They matched the results obtained by MultiOpt.

4.3.2. Monocriterion minimization of costs

The results of this procedure are given in Fig. 5 and Table 2.

As in the previous case, the optimized building had low insulation levels: the windows were single-glazed, there was no false ceiling, and the insulation on the walls was thin. In other words, the minimization of costs also meant a minimization of the quantity of building materials used. And, as in the previous case, the optimal floor covering was PVC. A comparison with the price database gave similar results to those obtained by MultiOpt.

4.3.3. Monocriterion minimization of energy consumption

This consisted of minimizing the consumption of energy for heating and lighting purposes. The results are given in Fig. 5 and Table 2.

The optimization results were very different from those of the previous two procedures, in that the insulation level was high,

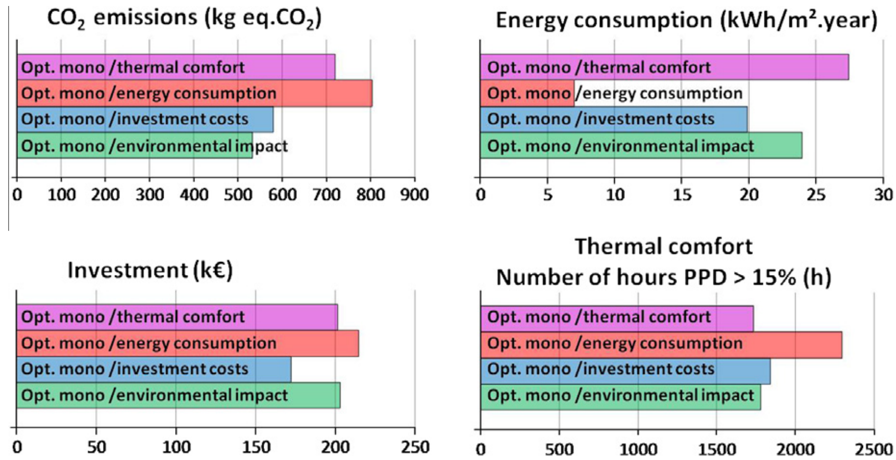

Fig. 5. Results of the monocriterion trials.

Table 2
Results of monocriterion optimizations of the building's envelope.

	EW	R	GF	IF	PW	W	S (W/m^2)	ΔS (W/m^2)
Opt. mono environmental impact	8	6	1	2	3	1	500	500
Opt. mono investment costs	3	4	1	2	3	1	500	500
Opt. mono energy consumption	5	3	3	4	3	5	495	320
Opt. mono thermal comfort	8	4	5	4	2	1	50	47

with thick layers of insulating material, a false ceiling for the top storey, energy-efficient windows and carpeting.

The shade control values were high. In other words, shade control did not come into play, because the incident solar radiation was never strong enough. So the optimized building was to all intents and purposes a building without shade control.

4.3.4. Monocriterion optimization of thermal comfort

Here, the aim was to minimize the duration of thermal discomfort. The building was in a region with a Mediterranean climate, but there was no cooling system, either active or passive. PPD was used to measure discomfort in terms of both heat and cold. The results are given in Fig. 5 and Table 2.

In the optimized building, the insulation level was relatively low, with no false ceiling, and single-glazed windows. Shade control was used to avoid overheating.

The results produced by this first set of optimizations are given in Fig. 5. Those for energy consumption diverged significantly from the others. Those for CO_2 and cost were comparable.

In sum, the results produced by the monocriterion trials brought out some of the interactions between the different objectives. The second set of optimizations produced further information about these interactions.

4.4. Second set of optimizations (multicriteria)

In each of these multicriteria optimizations, two criteria were chosen from among the following: environmental impact, cost, energy consumption and thermal comfort. This gave rise to a number of optimized solutions, which were integrated into a Pareto front.

4.4.1. Multicriteria optimization of CO_2 emissions and costs

Here, the aim was to simultaneously minimize CO_2 (over the life cycle of the building materials) and the cost of the renovation operation. The results are given in Fig. 6.

The optimization process generated four solutions, which formed a Pareto front. One of them corresponded to the monocriterion optimum minimizing the costs. The monocriterion results for CO_2 and cost were quite similar. There were the same reference walls for the ground floor and the middle floor, the same partition walls and windows. As regards these envelope components, the solutions for the multicriteria optimizations were the same as for the monocriteria optimizations. And in the multicriteria trials, as in the monocriterion trials, there was a minimization of the quantities of materials used for the other envelope components, namely the external walls and the roof.

The similarities between the monocriterion results meant that there was little variation among the multicriteria results.

4.4.2. Multicriteria optimization of energy consumption and costs

The monocriterion trials would suggest that, in contrast to the previous case, these objectives were mutually opposed. The results are given in Fig. 7.

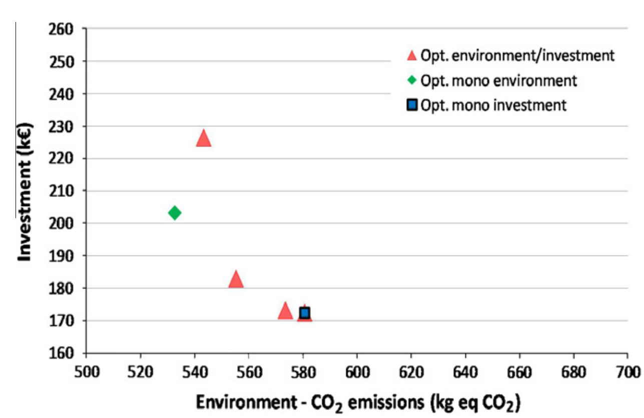

Fig. 6. Results of the multicriteria optimization of environmental impact and cost.

The results fall between the monocriterion optima. There is a larger number of solutions than in the previous case, and some of them are characterised by low energy consumption.

With regard to the characteristics of the envelope, the solutions are all similar to one or other of the monocriterion solutions, except as regards the roof, for which the solutions are intermediate, with high levels of relatively cheap insulation materials.

4.4.3. Multicriteria optimization of energy consumption and thermal comfort

The results of these trials are given in Fig. 8.

The numerous solutions all fall between the two monocriterion optima, though none is identical to either.

There are various shade control values, and the minimization of thermal discomfort does involve shade control.

As regards the characteristics of the envelope, a large number of solutions were obtained. This may be due to the fact that the monocriterion optimizations for these two parameters gave very different results.

4.4.4. Comparisons between multicriteria optimizations involving two objectives

The three sets of optimizations presented above resulted in the following observations. Firstly, the number of solutions generated seems to depend on the chosen objectives, and on their degree of convergence. And the number of solutions for objectives with similar characteristics (e.g. environmental impact and cost) is lower than for those with dissimilar characteristics (e.g. energy consumption and thermal comfort).

Regarding the characteristics of the building, the diversity of the multicriteria solutions was inversely proportional to the degree of similarity of the monocriterion results.

4.5. Third set of optimizations: multicriteria, with three criteria

The three criteria dealt with in this set of optimizations were energy consumption, cost and thermal comfort. They were treated simultaneously, and the optimized solutions formed a Pareto surface in three dimensions.

The results are given in 3D in Fig. 9, and in 2D projections in Figs. 10–12.

In the 3D visualization (Fig. 9), which gives the results for all three objectives, the Pareto surface synthesizes the different solutions. The optimization operation has produced no single, definitive result. The Pareto front obtained by the optimization of energy consumption and thermal comfort was what determined the general form of the Pareto surface, which suggests that the link between these two objectives was stronger than either of their links to the other objective, namely cost.

Fig. 10 presents the results for energy consumption and cost. It is a 2D projection. The third criterion, thermal comfort, is not included. (The three monocriterion optima are given as "mono energy", "mono investment" and "mono thermal comfort".) The

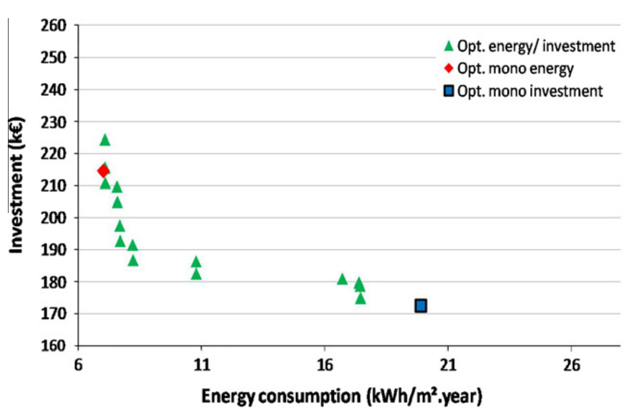

Fig. 7. Results of the multicriteria optimization of energy consumption and costs.

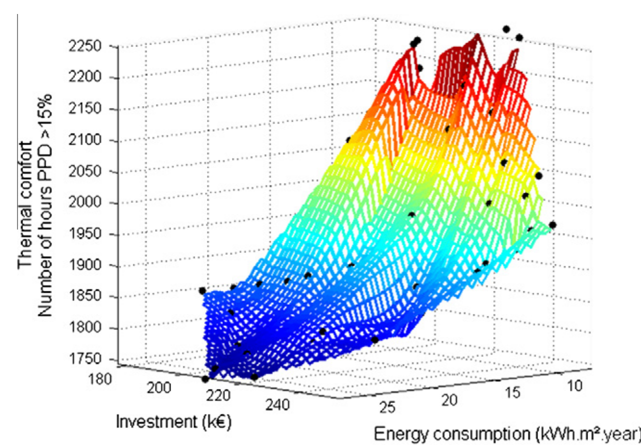

Fig. 9. Results of multicriteria optimization – 3D visualization.

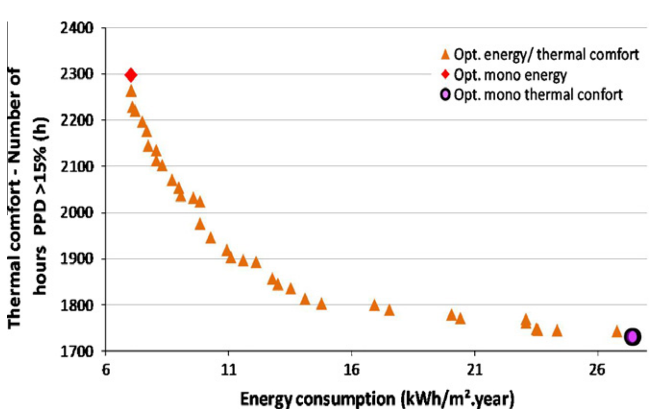

Fig. 8. Results of the multicriteria optimization of energy consumption and thermal comfort.

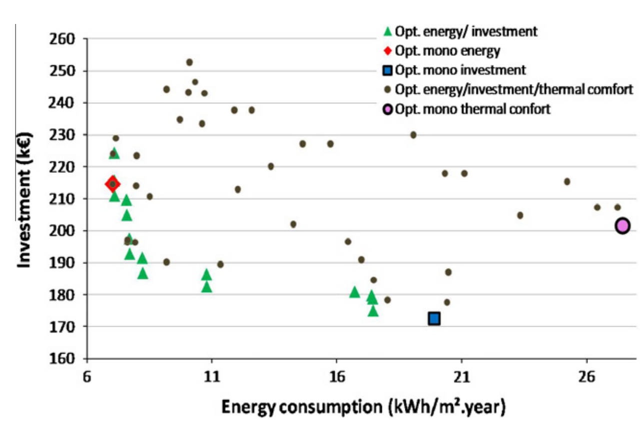

Fig. 10. Results of multicriteria optimization of energy consumption and cost – 2D projection.

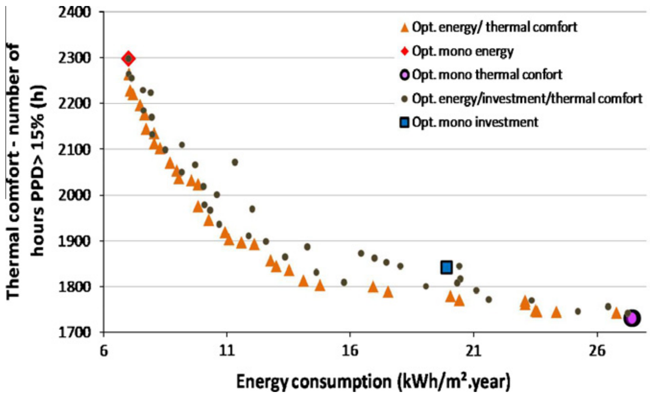

Fig. 11. Results of multicriteria optimization of energy consumption and thermal comfort – 2D projection.

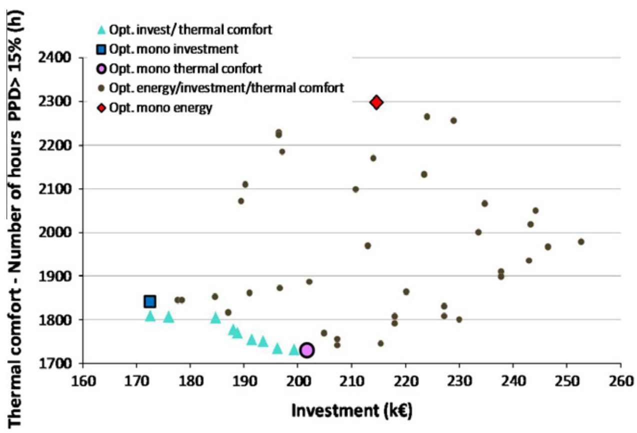

Fig. 12. Results of multicriteria optimization of cost and thermal comfort – 2D projection.

inclusion of thermal comfort in the analysis would have resulted in an increase in both energy consumption and cost.

Fig. 11 presents the results for energy consumption and thermal comfort. It is a 2D projection. The third criterion, cost, is not included. To do so would have produced similar results.

Fig. 12 presents the results for cost and thermal comfort. It is a 2D projection. The third criterion, energy consumption, is not included. To do so would have resulted in a higher level of both thermal discomfort and cost.

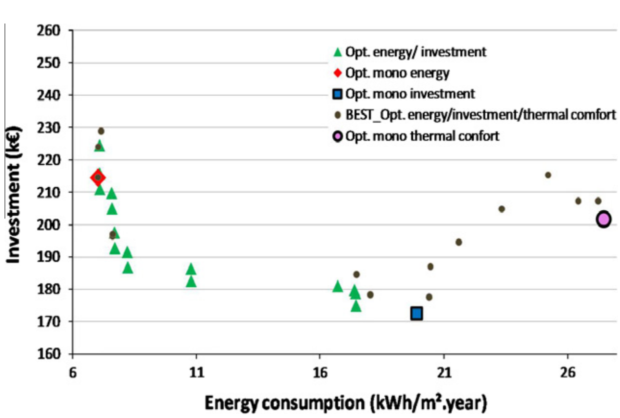

Fig. 13. Selection of the "best" results of multicriteria optimization.

Regarding the characteristics of the envelope, the simultaneous optimization of three objectives gave a high diversity of reference walls. Some solutions had one or two characteristics approximating to the monocriterion optima, but the characteristics themselves were generally different.

The solutions obtained by the simultaneous optimization of three objectives were numerous and diverse. Their performance in term of energy consumption, cost and thermal comfort was also diverse, as were the characteristics of their envelopes. The large number of solutions might be considered either as an advantage or a disadvantage: on the one hand, there is a large variety of interesting proposals; on the other hand, it may be difficult to choose between them.

In order to make such choices easier, only the "best" solutions for each objective were retained. The result of this operation for cost and energy consumption is given as an example in Fig. 13.

It is difficult to achieve a satisfactory outcome for two or more objectives treated simultaneously. If one of them is favoured, the results for the others will be inferior. The results will also be closer to monocriterion optima in terms of characteristics and performance. Regarding the envelope, diversity will decline. In this particular case, for example, all the results for the external walls corresponded well to the monocriterion optima.

In the selected group of "best" solutions, the interactions between objectives were further highlighted, and this is something that could facilitate decision-making in terms of overall performance.

5. Conclusion

The aim of the study presented in this article was to develop a tool, MultiOpt, that would optimize the renovation of buildings across a range of objectives, with contributions from databases and assessment software. The decision to use NSGA-II seems to have been justified, in view of the fact that where optima were available from a database, they were found to be consistent with those produced by MultiOpt. Furthermore, genetic algorithms can handle both discrete and continuous parameters, along with a wide diversity of characteristics, as regards, for example, the envelopes of buildings or systems control.

The nature of a building's envelope can be expressed as discrete properties of reference walls. This facilitates the characterisation of properties such as energy consumption, cost and life-cycle environmental impact, while also avoiding solutions that are incompatible with available building materials.

Regarding the case study in which MultiOpt was used to optimize the renovation of a building, the operation concerned only its envelope, and was based on four optimization criteria: energy consumption, thermal comfort, cost and life-cycle environmental impact. Assessment software and databases were used to check the solutions generated by MultiOpt. The simulation time for the multicriteria optimization was substantial, but not excessive. The preliminary optimization of single criteria provided an understanding of their impact on the building's overall performance, and comparisons of the different results revealed the convergences and divergences that existed between objectives. But MultiOpt can also be used to optimize a number of objectives simultaneously, and to produce alternative solutions for such combinations. It can assess their overall performance, while at the same time quantifying the impact of their individual components. In our view, this means that MultiOpt has the potential to serve as an aid to decision-making in the context of renovation operations.

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