GENETIC MULTI CRITERIA OPTIMIZATION
FOR EXISTING BUILDINGS HOLISTIC RETROFIT

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Abstract

Building design is multi criteria. In view of the increasing environmental burdens related to the development of our modern societies, buildings environmental impacts have to be considered, at early design stage. Energy consumptions linked to existing buildings use are responsible for significant environmental impacts. Moreover, the existing stock replacement rate is inferior to 1% annually, in most of developed countries. Consequently, stock retrofit represents a major lever to reach commitments on climate change and non renewable energy consumptions mitigation. Yet, the identification of optimal sustainable retrofit programs, including actions planning, is still a difficult task for professionals.

The present paper is a contribution to decision support through optimal energy retrofit programs identification. A multi criteria genetic algorithm (NSGA-II) is used to optimize retrofit programs, on both their content and planning. The retrofit measures address building envelopes and equipments replacement. For each of these, various options are considered.

The objective functions considered target environmental impacts, financial indicators and occupants' well-being. Solutions performances are evaluated through life cycle assessment and life cycle cost models, using dynamic thermal simulation for heating load and thermal comfort evaluation.

These methods contribute to decision support through the identification of Pareto non dominated retrofit programs, on a multi criteria basis, over life cycle.

1. INTRODUCTION

Buildings expected performances have significantly evolved and increased over time. Today, buildings have to fulfil numerous objectives involving both regulations compliance and client expectations: structural and fire safety; durability; thermal, visual and acoustic comfort; interior air quality; energy consumptions mitigation, etc. In the context of increasing environmental burdens related to the development of our modern societies, environmental impacts have to be taken in account, at early design stage. Indeed, the preservation of energy and the improvement of indoor environmental quality have been set as clear orientations by the European energy policy [1][2].

Under our latitudes, existing buildings energy consumptions – related to the use phase: heating, cooling, ventilation, domestic hot water production (DHW), and lighting – are responsible for significant environmental burdens. Moreover, the replacement rate of existing buildings is inferior to 1% per year, in most developed countries. Consequently, existing stock retrofit represents a major lever to reach national and international commitments on climate change and non renewable energy consumption mitigation [3].

However, the identification of optimal sustainable retrofit programs, including actions planning over a time period, is still a difficult task for professional sector. Most operational approaches are based on iterative building simulations guided by experience [5][6].

This paper is a contribution to decision support for energy retrofit programs identification through genetic multi criteria optimization.

2. MULTI CRITERIA OPTIMIZATION FOR BUILDING RETROFIT DECISION SUPPORT

2.1 Decision space definition: alternative retrofit programs

The search space is defined as a set of building energy retrofit programs, characterized by both their content and planning. The content refers to the combination of energy retrofit measures implemented, addressing holistically building envelopes (thermal insulation on façades, bottom floor and roof; windows replacement; windows to wall ratios), and the replacement of equipments for ventilation, heating and DHW production. For each of these retrofit measures, various alternatives are studied. They are considered to be discrete variables because of industrial constraints related to production. The planning refers to the permutation of these measures, defining the time sequence for implementation. From a mathematical standpoint, the solutions are permutations of discrete variables. The problem is combinatorial.

2.2 Decision criteria

The solutions – building energy retrofit programs – are evaluated on a multi criteria and life cycle basis. The objective functions considered target environmental impacts (i.e. primary energy consumption, climate change potential, abiotic resources depletion, etc.), financial indicators (i.e. investment cost, global cost), and occupants' well-being (thermal comfort indicator), over life cycle. Some objectives are obviously conflicting (investment cost and primary energy mitigation), trade-offs have to be identified.

Figure 1 represents the life cycle assessment (LCA) and life cycle cost (LCC) models implemented to assess solutions performances. Over the life cycle steps, materials and energy consumptions and emissions are related to environmental and economic impacts through LCA and LCC databases. The use phase is modelled by a consumption of energy related to heating, cooling, ventilation and DHW production. Heating loads and thermal comfort are evaluated through building dynamic thermal simulation. The present LCA model does not account for materials transportation (from factory to construction site), construction operations on site and maintenance over life cycle.

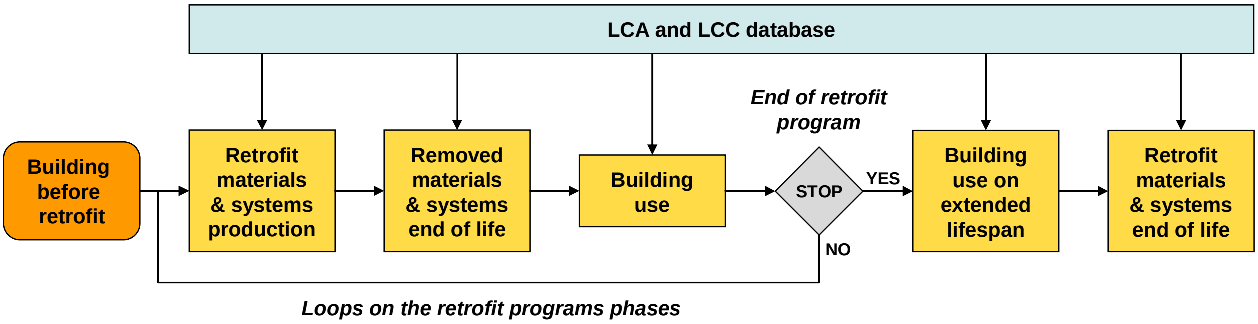

Figure 1 : LCA and LCC models, over retrofitted building extended life cycle.

2.3 Multi criteria approaches for energy retrofit decision support

The present decision problem is multi criteria, the decision space is finite. All the solutions are identified by their content and planning, yet their performances are not known a priori. In this case, various methodologies can support multi criteria decision making. There are roughly two types of decision making methodologies: preference based approaches and generative approaches [7].

Preference based methods include classical transformations from a multi criteria to a mono criterion optimization problem: weighting, goal programming, E-constraints, etc. These procedures generally require some knowledge of the solutions, to set weights, constraints or goals. They lead to the identification of a single solution. Moreover, weighting and E-constraints are sensible to problem convexity properties. If the problem is non convex, some solutions may not be accessible to decision [7].

Generative approaches aim at providing the decision makers with a set of good trade-off solutions, describing the various compromises that can be considered. Theses ones are often represented by Pareto frontiers. The Pareto frontier is the set of non dominated solutions among the considered alternatives. By definition, a given solution is said to be non dominated if there is no other solution, from the set of considered alternatives, being no worse in all objectives and strictly better in at least one objective[7]. Figure 2 represents the Pareto frontier and the dominated solutions for a two objectives minimization problem.

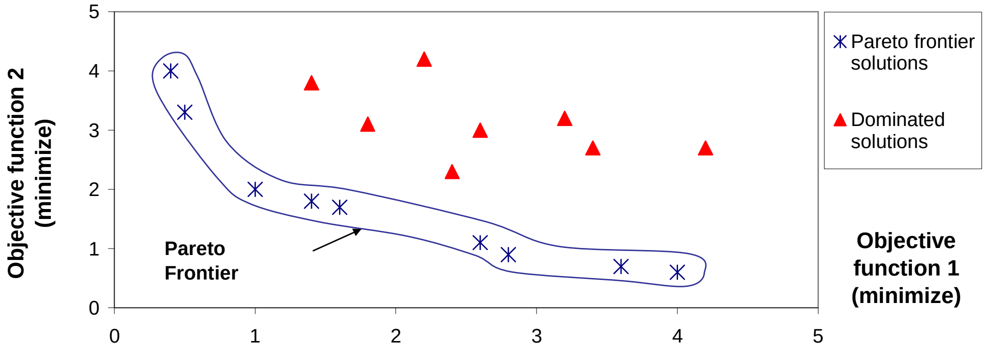

Figure 2 : Example of dominated solutions and Pareto frontier

The present contribution addresses decision support based on generative approaches. The search for the Pareto frontier can be supported by multi criteria optimization. The considered problem is combinatorial, the variables are discrete, and the objective functions are implicit (involving dynamic thermal simulations). Thus, the optimization methods classification set by Colette et al.[8], suggests to use metaheuristics. These stochastic approximate methods are adapted to the search for optimal solutions on rather large search spaces. Facing a given problem, the practical relevance of a metaheuristic in comparison to the others is still an open question [9]. We decided to implement a genetic algorithm considering previous successful applications on building design problems [4].

3. MULTI CRITERIA GENETIC OPTIMIZATION FOR BUILDING SEQUENTIAL ENERGY RETROFIT

Genetic algorithms (GA) are stochastic optimisation methods inspired from the Evolution theory mechanisms. Solutions are represented by chromosomes, which are sets of genes. The alleles coded on genes account for the values taken by specific describing parameter, for a given solution. Regarding building energy retrofit, the solutions are energy retrofit programs. They are represented by two chromosomes: one coding the content, the other for the planning. Each gene of the content chromosome represents a specific retrofit measure. The allele is the alternative considered for the given retrofit measure. Each gene of the planning chromosome stands for the position of a given retrofit measure in the time sequence.

GAs base the exploration of the search space on the evolution of a population of solutions, over generations. At each generation, the performances of population’s solutions are assessed. Then, best solutions are selected for reproduction. The offspring is generated by crossover and mutation operations from parents’ chromosomes. Finally, a selection procedure is applied to build the population of the next generation, from the current parents’ population and the generated offspring. The evolution of the random initial population over generations improves solutions quality and the description of accessible trade-offs.

Multi criteria genetic optimization includes a broad variety of algorithms. The Non Dominated sorted algorithms (NSGA-II) implemented in this work has demonstrated good performances over various test problems [10][11].

This algorithm implements a differentiated operator for selection. Solutions are first sorted into Pareto frontiers. Non dominated solutions are assigned to the Pareto frontier ranked 1. The remaining solutions are iteratively attributed to Pareto frontiers of increasing ranks. Then, solutions are assigned a “crowding distance”. This indicator represents the relative distance separating a given solution from its closest neighbours, on the Pareto frontier they belong to. Solutions are then selected according to: first, the rank; and second, the crowding distance they have been assigned. This approach targets both solutions quality and dispersion on the compromise surface they describe.

4. BUILDING RETROFIT CASE STUDY

The multi criteria genetic algorithm (NSGA II) presented has been implemented to study sequential energy retrofit programs. The construction considered for this case study is a multi family building, referred to as “barre Grimaud” in the following developments.

Barre Grimaud is a five-storey multi family building, located in Paris suburban area. The construction was completed in 1974, before the introduction of the first building energy regulation in France (1975). The 10 enclosed apartments represent a floor area of 792 m^2.

4.1 Barre Grimaud description

Table 1 details, at present state, the building envelope and the systems used for heating, ventilation and domestic hot water production (DHW).

Table 1 : Barre Grimaud, envelope and systems features before energy retrofit
(thicknesses given in mm; envelope composition detailed from exterior to interior)

External walls	Coating (20) + solid concrete blocks (150) + air (10) + plaster (50)
Bottom floor	Concrete slab (150) above cellars + mortar (50) + tiles (10)
Intermediate floors	Concrete slab (150) + mortar (50) + tiles (10)
Terrace roof	Gravels (30) + bitumen (4) + Concrete slab (150)
Windows	Single glazing with PVC frames
Ventilation	Non modulated mechanical ventilation
Heating system	Collective gas boiler, installed before 1988
DHW production	Individual gas boiler

Before the retrofit actions, the building envelope is not thermally insulated. The set point temperature is 19°C from early October to late April. During the summer, solar protections (louvers) are used to improve thermal comfort. Occupation scenarios are independent of the retrofit program assessed. A three zone thermal model has been associated to the building: ground floor, intermediate floors, and top floor.

4.2 Retrofit programs content and sequence

For each energy retrofit program, the content is defined as a combination of options chosen from the 8 retrofit measures classes presented on Table 2.

Table 2 : Energy retrofit options considered for Barre Grimaud (thicknesses given in mm)

External walls	Mineral wool exterior insulation (100, 150, 200 or 250)
Bottom floor	Polystyrene exterior insulation (100, 150, 200 or 250)
Terrace roof	Polyurethane exterior insulation (100, 150, 200, 250, 300)
Windows type	Low-e double glazing or triple glazing, with wood frames
Windows size	North increasing ratio options : 0.8, 1 or 1.5 West, South, East increasing ratio options : 0.8, 1, 1.25 or 1.5
Ventilation	Heat recovery or humidity controlled
Heating system	Low temperature condensing gas boiler
DHW production	Solar thermal fraction of DHW needs : 35%, 55% or 75%

Thermal insulation, window type and ratio can be differentiated according to the façades. For a given retrofit program, the design (nominal power) of the condensing gas boiler is adapted to the building heating demand, at the retrofit step considered for boiler replacement.

From the sequence standpoint, each of the retrofit measures classes is considered for a different step of the retrofit program, except windows resizing. Windows replacement and resizing get necessarily involved at the same retrofit step, considering economic constraints. The external walls and the windows of all façades are respectively retrofitted at the same step. The different steps are implemented one after the other and separated by one year.

Based on the previous hypothesis, more than 4.75E11 different retrofit programs can be generated. Genetic algorithms, as NSGA-II, are adapted to large search space exploration.

4.3 Objective functions

7 objective functions have been considered to assess retrofit programs performances over the building extended life span (assumed to be 50 years): cumulated primary energy consumption [MJ]; climate change potential [kg CO_2 eq.]; abiotic resources depletion [kg Sb eq.]; air acidification [kg SO_2 eq.]; investment cost [k€]; global cost on life cycle (involving investments and energy consumptions over use) [k€]; thermal comfort indicator [hours].

4.4 Results and interpretation

The optimal retrofit programs are identified through the application of the NGSA-II procedure to a random initial population of solutions. The results are presented as Pareto frontiers describing the admissible compromises for decision makers. Three retrofit programs named “A, B and C” are systematically identified on the following figures. The solutions obtained can be represented on 21 different 2 dimension graphs.

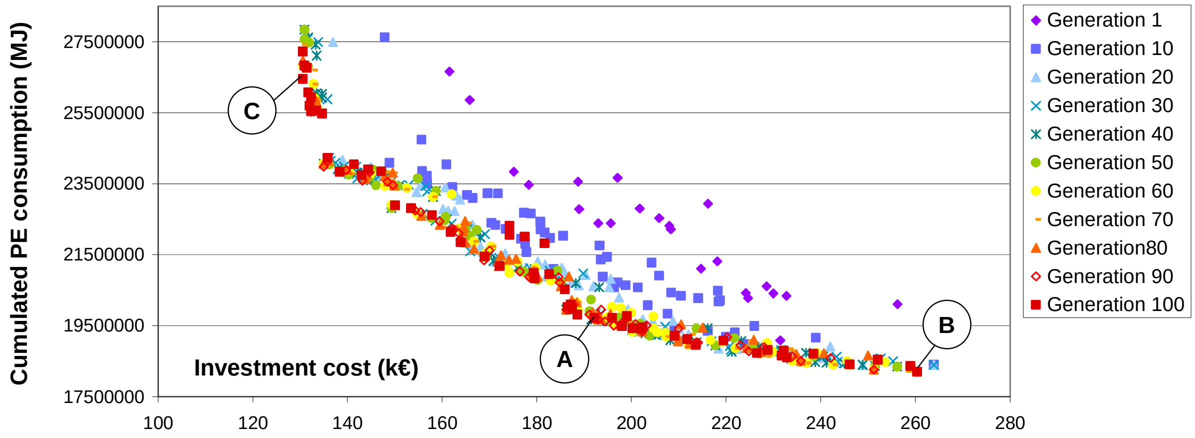

Figure 3 : Pareto frontiers on investment cost
and cumulated primary energy (PE) consumption, over generations

Figure 3 highlights the necessary trade-off between investment cost and primary energy consumption over building extended life cycle. The most efficient solutions in terms of primary energy consumption mitigation are also the most expensive ones (ex: solution B). These involve envelope thermal transmittance minimization, associated with equipments efficiency and integration of renewable energy use. In terms of content and planning, solution B involves sequentially: boiler replacement, solar DHW production (75%), exterior wall thermal insulation (R = 6,25 m^2.K/W), roof insulation (R = 8,3 m^2.K/W), ventilation (heat recovery), bottom floor insulation (R = 5 m^2.K/W), and windows replacement (triple glazing).

On the same Pareto frontier, solution A offers a significant reduction of investment cost for a relatively limited decrease in energy efficiency. This solution uses the same planning but involves a different content on the following aspects: external walls thermal resistance: R =

2,5 m^2.K/W; roof thermal resistance: R = 3,3 m^2.K/W; bottom floor thermal resistance: R = 2,5 m^2.K/W; double gazing windows.

The most energy efficient solutions are not the most cost effective ones over fifty years, as underlined on Figure 4. For example, solution A is the identified energy retrofit program minimizing the global cost on the extended life cycle.

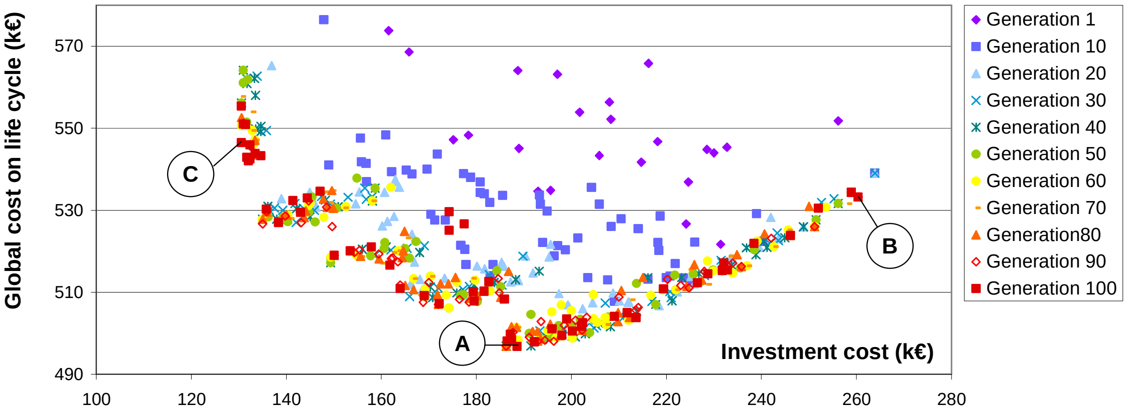

Figure 4 : Pareto frontiers on investment cost and global cost on life cycle, over generations

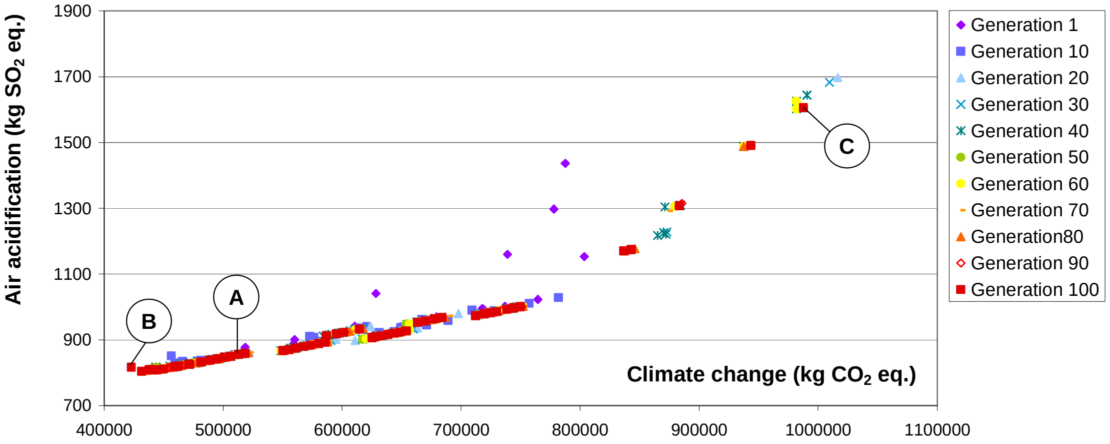

Figure 5 : Pareto frontiers on climate change and air acidification, over generations

Figure 5 tends to demonstrate a correlation between climate change potential and air acidification, specifically for efficient solutions. On this case study, the results also underline strong correlations in between cumulated primary energy consumptions, climate change, abiotic resources depletion and air acidification. These correlations allow here to reduce the complexity of multi criteria decision making. They are related to the reduction of energy consumptions during the use phase. In this case study, gas is used as the heating energy before and after retrofit operations. The observed correlations have to be questioned in the case of a change in the type of energy for the heating system.

The retrofit programs minimizing investment cost, as solution C, imply the retrofit of the building with program content similar to solution A. Yet, the replacement of the heating system is then considered ultimately. The resulting significant heating energy consumptions, over the first steps of the retrofit program, affect the results on most environmental indicators.

Solutions A, B and C are all local optima, on one or more criteria. They are different in content, planning and performances, and represent different trade-off priorities.

5. CONCLUSIONS

Multi criteria genetic optimization can support decision making for existing buildings energy retrofit through the identification of Pareto non-dominated retrofit programs, on a multi criteria basis, over life cycle, providing a set of accessible trade-offs.

The case study analysed reveals that the most cost effective ones, over extended life cycle, are not necessarily the most energy efficient solutions. Some correlations, observed in this case, in-between considered environmental criteria help simplify decision making.

These few remarks have to be challenged on different case studies, testing parameters sensitivity, involving other LCA indicators. The life cycle models for solutions assessment will be completed on transport, construction and maintenance aspects. Decision support will be extended to the case of existing building stocks.

ACKNOWLEDGEMENT

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