Decision aiding & multi criteria optimization for existing buildings holistic retrofit

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ABSTRACT: In most developed countries, existing building stock energy retrofit represents a major lever to reach commitments on climate change and non renewable energy consumption mitigation. Yet, the identification of optimal sustainable retrofit programs, including actions planning over a time period, is still a difficult task for professionals. The present paper is a contribution to decision aiding through optimal energy retrofit programs identification. A multi criteria genetic algorithm (NSGA-II) is used to optimize solutions – retrofit programs – on both their content and planning. The retrofit measures address building envelopes and the replacement of equipments. The potential solutions are evaluated on a multi criteria and life cycle basis. The objective functions considered target environmental impacts, financial indicators and occupants' well-being. These methods and tools contribute to decision aiding; identifying Pareto non dominated holistic retrofit programs, at a building scale, on a multi criteria basis, over life cycle.

1 INTRODUCTION

Building design is multi criteria. Buildings expected performances have significantly increased over time. Today, buildings have to fulfill 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 view of increasing environmental burdens related to the development of our modern societies, environmental impacts have to be taken in account, at early design stage. Energy preservation and indoor environmental quality have been set as clear orientations by the European energy policy (EC, 2003).

Under our latitudes, existing buildings use and related energy consumptions – 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. Thus, existing stock retrofit represents a major lever to reach national and international commitments on climate change and non renewable energy consumption mitigation (IEA, 2008).

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 (Alanne, 2004).

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

The identification of an approach for multi criteria decision support hardly depends on the nature of both the decision space (set of solutions) and the decision criteria.

2.1 *Decision space definition*

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 obvious 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, air acidification potential, etc.), financial indicators (i.e. investment cost, global cost), and occupants' well-being (summer thermal comfort indicator), over life cycle. Some objectives are obviously conflicting (investment cost and primary energy mitigation), trade-offs have to be identified.

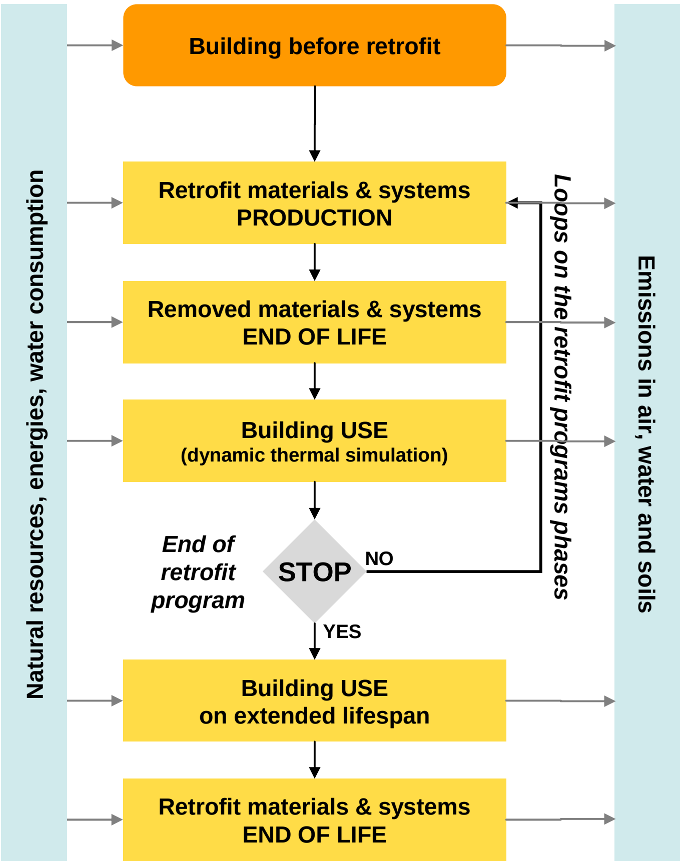

Figure 1. Life Cycle Assessment & Life Cycle Cost models, over the retrofitted building extended life cycle.

Figure 1 represents the main steps of 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 are required and generate emissions in the environment. The life cycle models developed are limited to the elements differentiating the alternative energy retrofit programs. Energy and natural resources consumption and generated emissions are then related to environmental and economic impacts through LCA and LCC databases. The use phase is modeled by the consumption of energy needed for 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.

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 (DEB, 2002).

Preference based methods include classical transformations from a multi criteria to a mono criterion optimization problem: weighting, goal programming, ε-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, per simulation run. 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 makers (DEB, 2002).

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 (DEB, 2002). Figure 2 represents the Pareto frontier and the dominated solutions for a two objectives minimization problem.

The present contribution addresses decision support based on a generative approach. 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., 2002), suggests to use metaheuristics. These stochastic approximate optimization methods are well 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 (Dréo et al., 2003). We decided to implement a genetic algorithm considering previous successful applications on building design problems (Pernodet Chanterelle, 2010).

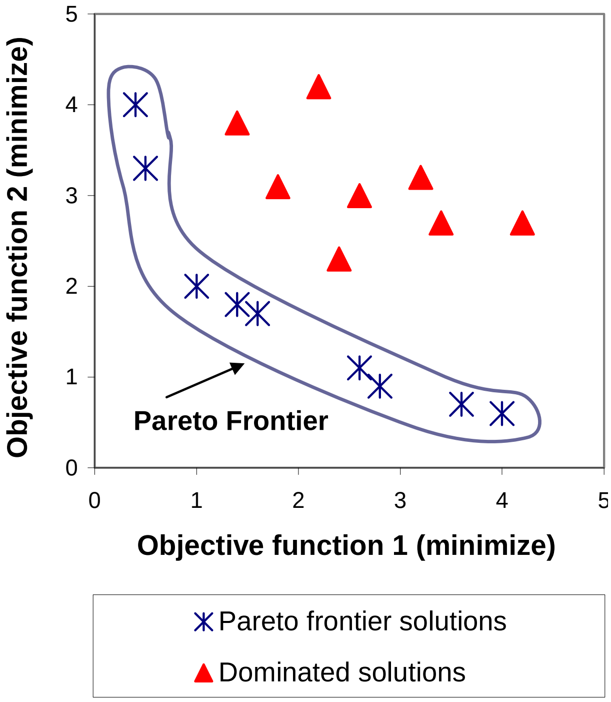

Figure 2 : Example of dominated solutions and Pareto frontier

3 MULTI CRITERIA GENETIC OPTIMIZATION FOR BUILDING SEQUENTIAL ENERGY RETROFIT

Genetic algorithms (GA) are stochastic optimization 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 parameters, for a given solution. Regarding building energy retrofit, the solutions are energy retrofit programs. Each solution is 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 (Deb et al., 2000) (Zitzler et al., 2000).

NSGA-II 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" (Deb, 2002). 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.

Because of the specific solution representation implemented for energy retrofit programs, on two chromosomes, crossover operators are differentiated for content and planning chromosomes. A simple two-point crossover operation is used for the content chromosome whereas a two-point order crossover operator (Murata et al., 1995) is implemented for the planning chromosome, so as to preserve some information from the parents' time sequences.

4 BUILDING RETROFIT CASE STUDY

The multi criteria genetic algorithm (NSGA-II) presented has been implemented to study sequential energy retrofit programs, on different existing buildings. 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 describes the building envelope and the systems used for heating, ventilation and domestic hot water production (DHW), at present state. Before energy retrofit actions implementation, the building envelope is not thermally insulated.

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

Systems & equipments	State before retrofit
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

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

Systems & equipments	State before retrofit
External walls	Mineral wool exterior insulation (100, 120, 150, 180, 200, 250, or 300)
Bottom floor	Polystyrene exterior insulation (100, 120, 150, 180, 200, or 250)
Terrace roof	Polyurethane exterior insulation (100, 150, 200, 250, 300, 350, or 400)
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%

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 define the three zones considered.

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.

Among retrofit options, window types and window-to-wall increase ratios 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 the 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, because of 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 27,3E9 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 CO2 eq.]
- Abiotic resources depletion [kg Sb eq.]
- Air acidification [kg SO2 eq.]
- Investment cost [k€]
- Global cost on life cycle (involving investments and energy consumptions over use) [k€]
- Thermal comfort indicator [hours]

4.4 *GA simulations parameters*

The multi criteria genetic optimization has been conducted with the following parameters:

- Size of the population: 100
- Size for reproduction: 100
- Crossover probability : 80%
- Mutation probability: from 1% to 10% (linear increase over 100 generations)
- Number of generations: 100

4.5 *Results and interpretation*

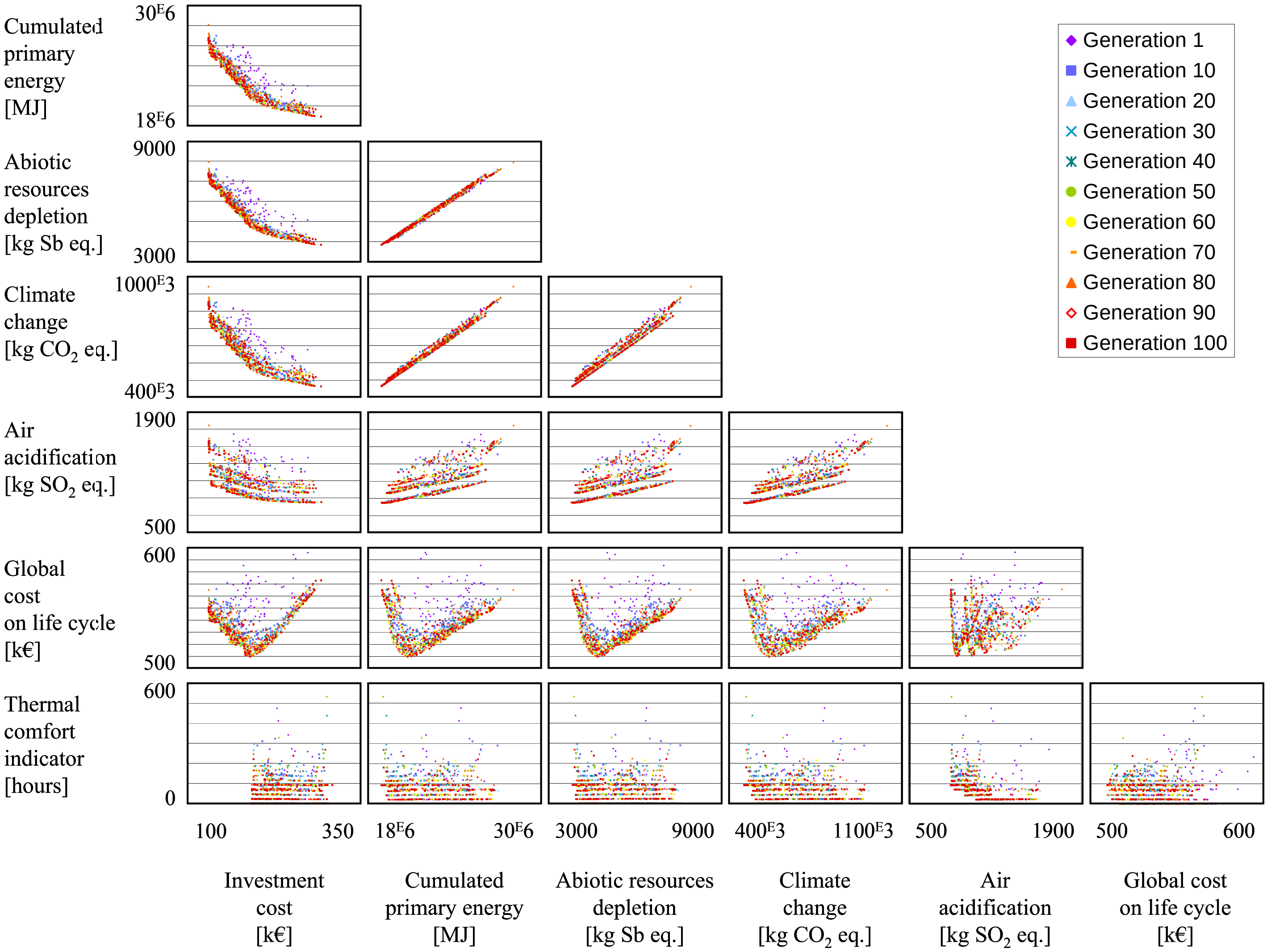

Figure 3. Pareto frontiers for different generations, projected onto the 21 2-dimension planes defined by the objective functions

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.

The solutions obtained after 100 generations have been represented on the 21 different 2-dimension graphs defined by the 7 objectives considered (Figure 3). On each these, the sets of Pareto non-dominated solutions identified for the generations 1, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 is projected onto the plane defined by the two axis.

From the analysis of Figure 3, various remarks can be set out:

- All related graphs highlight a necessary trade-off between investment and environmental impacts. Roughly, the more a retrofit program mitigates the environmental impacts, the more expensive it is, on the search space defined.
- Some of the non-dominated solutions are clearly dominated in terms of compromise in between global cost on life cycle (investment + use over 50 years) and the other indicators. Considering the given 50 year extended life cycle, the most expensive or the less energy efficient retrofit programs are not the best solutions.

- Some correlations are clearly observed in between the following environmental indicators: climate change potential, cumulated primary energy consumption, abiotic resources depletion, and to a lesser extend with air acidification potential. Some explanation is given further.

- All the energy retrofit programs identified as Pareto non-dominated solutions, guaranty high summer thermal comfort. The number of hours with interior zone temperature superior to 28°C, is inferior to 600 hours over the 50 years of the extended life cycle, for all solutions. This remark is valid with respect to average Paris climate conditions, and in the case of adapted occupant behavior (use of solar protections in summer, overnight purge).

The three retrofit programs named “A, B and C”, systematically identified on the following figures, aim at illustrating some of the previous remarks.

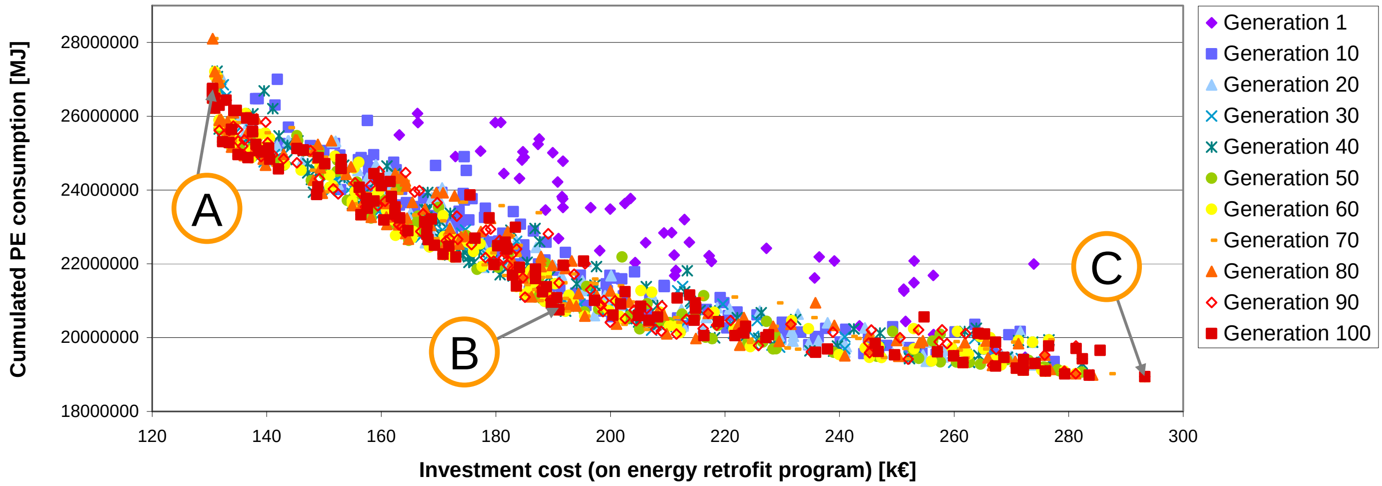

Figure 4. Pareto frontiers on investment cost and cumulated primary energy (PE) consumption, over generations

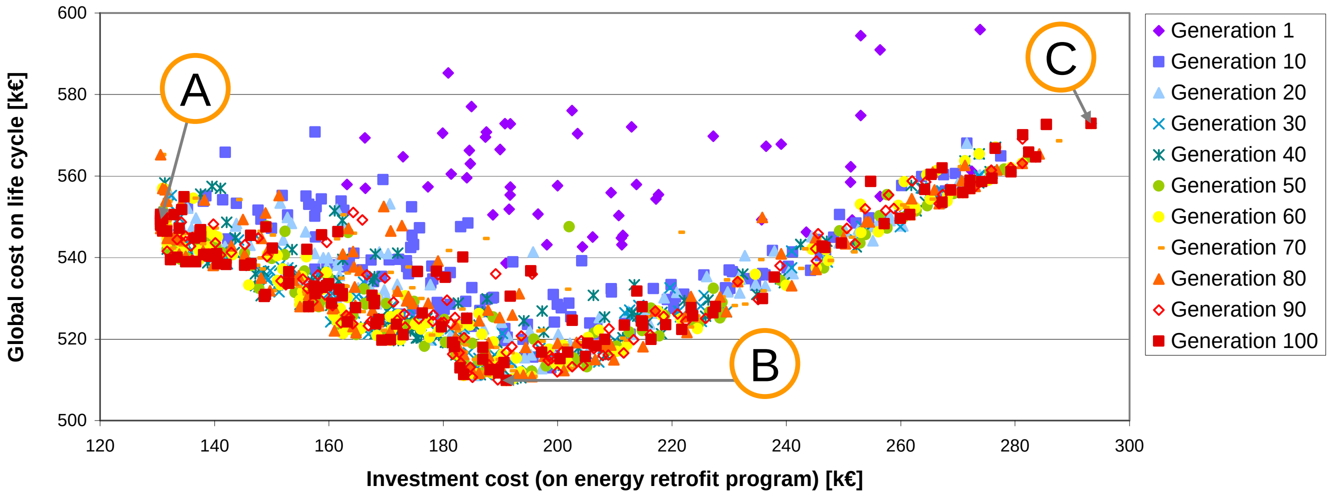

Figure 5. Pareto frontiers on investment cost and global cost on life cycle, over generations

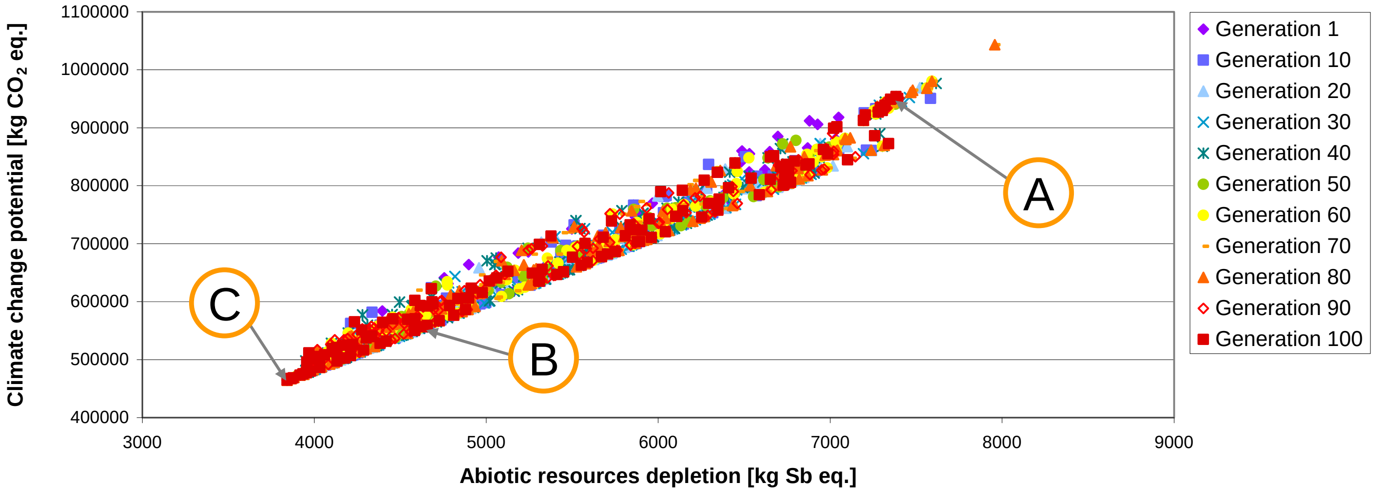

Figure 6. Pareto frontiers on abiotic resources depletion and climate change potential, over generations

Figure 4 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 C). These involve envelope thermal transmittance minimization, associated with equipments efficiency and integration of renewable energy use. In terms of content and planning, solution C involves sequentially: boiler replacement, exterior wall thermal insulation (R = 7,5 m^2.K/W), roof insulation (R = 8,3 m^2.K/W), ventilation (heat recovery), bottom floor insulation (R = 3,75 m^2.K/W), solar DHW production (75%), and windows replacement (triple glazing).

On the same Pareto frontier, solution B 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 = 3 m^2.K/W; roof thermal resistance: R = 3,3 m2.K/W; bottom floor thermal resistance: R = 2,5 m2.K/W; double gazing windows.

The most energy efficient solutions are not the most cost effective ones over fifty years, as underlined on Figure 5. For example, solution B is the identified energy retrofit program minimizing the global cost on the extended life cycle.

The retrofit programs minimizing investment cost, as solution A, imply a retrofit program content very similar to solution B. On the content, the only differences concern the ventilation system (humidity controlled) and the solar factor of the DHW production (35%).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 (Figure 6).

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.

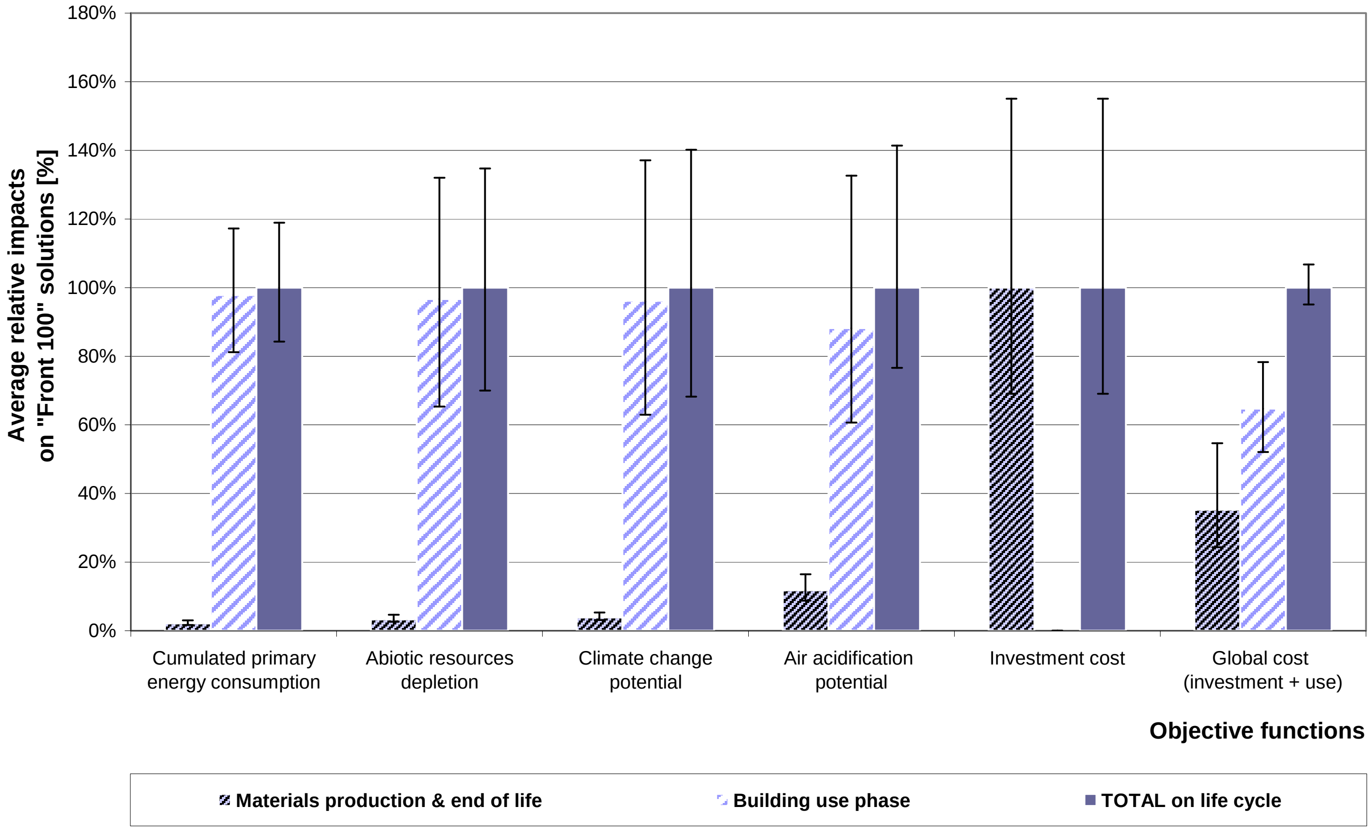

Figure 7. Relative average share and intervals of variation (on the non-dominated solutions of the 100th generation) of the life cycle steps on the whole life cycle.

Figure 7 represents, on the different objective functions, the average share and the intervals of variation (on the non-dominated solutions of the 100th generation) of two sets of life cycle steps: “materials and systems production and end of life”, and “building use phase”. The results justify the correlations noticed in between: climate change potential, abiotic resources depletion, and cumulated primary energy consumption. For these three environmental indicators, the share of “materials and systems production and end-of-life” impacts is much inferior to the share of the impacts related to the use phase (energy consumption), even with respect to the intervals of variations. The impacts on these 3 indicators are close to linear functions of the retrofitted building energy performance, explaining the strong correlations observed.

From a decision making prospective, these correlations allow here to reduce the complexity of multi criteria decision making. However, 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.

5 CONCLUSION

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

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

However, these few remarks have to be challenged on other case studies, testing parameters sensitivity (extended lifespan, search space definition, energy cost evolutions over time), involving complementary 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.

6 ACKNOWLEDGEMENTS

This study results from a collaboration between Navier and CEP institutes organized in the framework of Chair ParisTech-VINCI “Ecodesign of buildings and infrastructure”.

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