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Elaboration of the decision space for an optimization of building retrofit

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ABSTRACT

Multiobjective optimization is widely used in building physics but it has to face construction and regulation constraints to elaborate feasible solutions. This paper investigate how to integrate constraints in genetic optimization carried out with NSGA2 algorithm: it studies the implementation of constraints in the decision space and its impact on convergence speed and diversity in the optimization. The study was carried out on a 8 apartments building with three objective function to optimize: energy demand, comfort of the tenants and economic cost. As a result, convergence speed was improved and expert knowledge was included inside the decision space in a comprehensive way.

KEYWORDS

Multiobjective optimization, retrofit, building stocks, decision space

INTRODUCTION

In France, new buildings represent 1% of constructions each year. Decreasing the energy demand of the entire building stock will only be achieved if existing building are refurbished. On this topic social housing tenants have specific constraints and opportunities, and build their refurbishment strategies based on expert judgment. Experts try to balance constraints such as environmental impact, energy consumption, comfort of tenants to end up on a good solution and it is not possible to confirm that they are objectively the best solutions. Multi-objective optimization is an appropriate approach to efficiently suggest optimal solutions, so the expert could focus on picking a solution in the optimal ones. This work has been carried out in the scope of Reha-Parcs project which aim to apply multi-objective optimization on building stocks constituted of approximately 100 buildings owned by the same entity. Optimal solutions may then feed a decision-making tool for managers to pick the best one according to subjective needs like local policy, and funding.

Multi-objective optimization has been carried out on the design stage of new buildings to improve the shape and windows with respect to the energy demand and comfort (Tuhus-Dubrow and Krarti 2010; Diakaki, Grigoroudis, and Kolokotsa 2013) . Other work addresses the optimization of HVAC Systems in addition to the building envelope (Machairas, Tsangrassoulis, and Axarli 2014).

In multi-objective optimization, the formulation of the problem has a significant role in the success of the process, in order to get solutions that fit with construction and regulation constraints. The implementation of these constraints is mostly done at the optimization level by a penalty function (Coello Coello 2002). This approach limits the number of valid individuals in the population and consequently limits the diversity of the solutions. This seems to imply more generations to be computed in order to achieve the same diversity. This can be

time consuming depending on the computational cost of the evaluation function, especially on multiple buildings, as it limited previous works (Rivallain 2013)

A novel approach is to integrate constraints directly into the decision space, and this is the main focus in this paper. The aim of the study is to determine the impact of the integration of constraints in the decision space in term of convergence speed and diversity of the optimization.

METHODS

Optimization involve multiple parts: in this section will be detailed the evaluation function used to affect a fitness value to each retrofit strategy, the algorithm that has been chosen to carry out the optimization and the decision space of the optimization.

To evaluate the energy efficiency of a retrofit strategy, a test building has been modelled. This building is constituted of 4 floors and 8 apartments. Each apartment is 65m² large and is 2,3m high. In the model, each of those apartments is a thermal zone. The building is modelled in Modelica language using models issued from the *BuildSysPro* library, developed by EDF (Plessis et al. 2014). The model features an ideal heating generator and will be upgraded in future work with realistic systems. A TMY file is used to simulate the weather of the city of Nice (France). The objective function of the simulation are the energy needs of the building and summer comfort of the inhabitants that is presented in degrees.hours above an adaptive comfort temperature. The adaptive comfort model chosen is the revised standard 55 of ASHRAE (De Dear and Brager, 2002).

The last objective function is the economic cost of retrofit strategies. It is calculated with expert data provided in Reha-Parcs project: material price is a function of its thickness, then labour time cost is included and added to it.

First of all, the choice of an appropriate algorithm has been made with respect to the discrete nature of the problem: in order to keep only possible strategies. Indeed we had to comply with commercial solutions (eg. insulation is available for only selected thickness). In a discrete decision space, genetic programming suits better to the problem (Evins 2013). Moreover, genetic algorithm are widely used in building physics, especially NSGA2 (Deb et al. 2000) as it has proven to be both stable and efficient. In this paper, we used the implementation of NSGA2 provided in Python library DEAP (Fortin et al. 2012). The parameters used are the following:

Table 1: Settings of NSGA2 algorithm

Number of individuals	96
Number of generations	50
Probability of crossing	0,8
Probability of mutation	0,2

Those parameters were selected after a literature study (Rosenthal and Borschbach). They enable to have a good exploration of the decision space with mutation while the convergence speed towards Pareto front is not slowed down. The number of individuals has been selected to be 96 for a good diversity and to suit the 48 cores available for parallel computation.

In this paper, the main focus is on the decision space. In our case, the decision space is constituted of a series of retrofit possibilities. Those retrofit possibilities are considered for the

envelope: outer walls, top floor ceiling, bottom floor and windows. The comparison is made between a decision space that includes every retrofit possibility broken down into elementary tasks and a decision space composed of aggregated task for walls and windows operations. Both of them are described below.

Standard decision Space

The outer vertical walls, ceiling and floor have the same structure, which is 20cm of reinforced concrete. Vertical walls, ceiling and floor are independent from each other in the optimization. The insulation proposed features one of the following component:

Table 2: Insulation possibilities for outer walls in the optimization

Insulation material	Commercially available thickness (in cm)
Polyurethane	2, 4, 6, 8, 10, 12, 14, 16, 18, 20
Glasswool	6, 8, 10, 12, 14, 16, 18, 20
Polystyrene	6, 8, 10, 12, 14, 16

Another parameter of the optimization is the windows: the U coefficient for each type of window is the value that changes. Commercially available windows used in refurbishment in France where again provided by expert data within Reha-Parcs project, and are as follow:

Table 3: windows possibilities in the optimization

Windows U values	0.8, 1, 1.2, 1.4, 2
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As a result, this decision space provides 109760 possibilities of retrofit that could be applied on the building.

Constrained decision Space

The second decision space differs from the first one as windows and outer vertical walls are combined: in this problem, one gene of each individual corresponds to a facade solution which includes one type of window and one type of insulation of the vertical walls.

In order to fit construction constraints, some solutions are not possible: these solutions involve high performance wall with low performance windows or high performance windows with low performance walls. In this problem, 22 combination are forbidden. Should an individual propose on a forbidden solution, it will be mutated until it is an allowed combination. In this way, optimization avoids a costly evaluation function but can slow the convergence of the optimization. Constraints slightly reduce the decision space to 92512 possibilities offered to elaborate retrofit strategies.

RESULTS

In order to benchmark convergence speed of the optimization, we chose the Hypervolume criteria (Zitzler et al. 2002). Hypervolume is computed with a reference point chosen outside the objective space of both optimizations: depending on the shape of pareto front, the reference point can be selected from Nadir point to 150% of the values of Nadir point (Ishibuchi et al. 2017). Here, according to Ishibuchi and the shape of our Pareto fronts, the reference point should be between 120% and 150% of Nadir point's values. Whatever the value for the reference point results remain identical, hence figures for a reference point at 130% of Nadir point will be presented. Same reference point has been selected for both of hypervolumes computation.

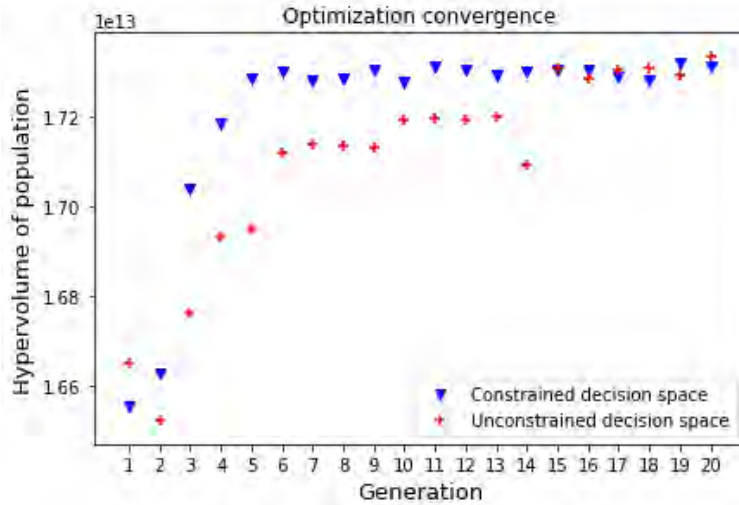


Figure 1: Convergence performance of each decision space

This figure shows a quickest convergence of the optimization when carried out with the constrained decision space. With this decision space, the best Pareto front is reached from generation 6 while with the first and unconstrained decision space, best solutions are found at generation 15. Moreover, the figure shows that with the unconstrained decision space, optimization does not reach global optimum before generation 15, while constrained decision space does reach it as soon as generation 5.

Pursuing the optimization until 50th generation shows that hypervolume does not vary significantly after generation 15, that is why only the first 20 generations are showed in Figure 1. It decreases for some generations due to mutations of individuals and get back to prior levels after two generations of selection.

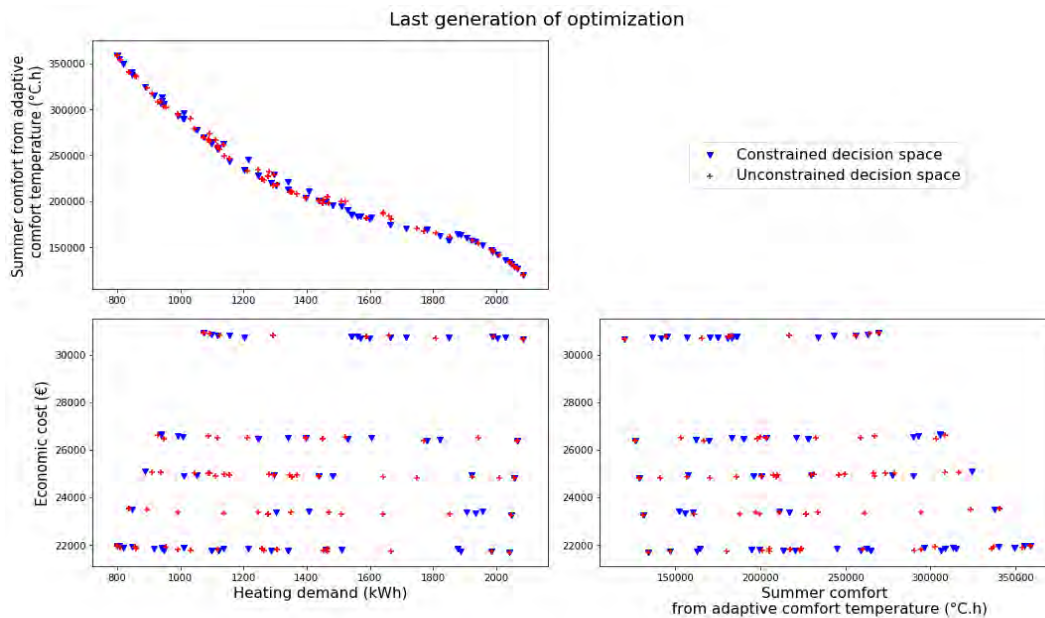


Figure 2: Pairwise plotting of last generation of optimization

Diversity of individuals is ensured with NSGA2's selection process. The diversity of proposed solutions can be checked by plotting Pareto fronts: Figure 2 shows Pareto fronts for all of the 3 objectives. A wide spread of the solution can be noticed and can sometimes be counter-intuitive regarding the performance of some of them. However, NSGA2 tends to keep only strictly non dominated solutions since it is an elitist algorithm.

DISCUSSIONS

Results support the integration of constraints in the decision space on a test case rather small with a decision space composed of around 100 000 possible combinations. It shows that optimization could be stopped 7 generations earlier with the same results if constraints are implemented in decision space, saving in our case 672 thermal simulations, which are the more costly part of the optimization calculation-wise.

This approach avoid implementing constraints by penalty function or by "death penalty" (Coello Coello 2002), but still enable to incorporate expert knowledge in the optimization problem. Moreover, it shows that adding expert knowledge in the algorithm can speed up the elaboration of retrofit strategies on this multi-family dwellings. Those results are promising since regulation and new construction solutions brought to market are generating more and more constraints, and we can implement them in a comprehensive way. Indeed it will help bringing multi-objective optimization to engineering by keeping the link between optimization constraints and practical solutions. In addition as a minor side effect, implementing constraints in the decision space saves time in post-processing to pick possible solutions and preventively clears out unrealistic solutions.

As optimization problem are quite specific, further studies will have to determine whether the impact is the same with more complex problems. First of all, the combinatorial will get bigger with the implementation of new possible retrofit tasks in the decision space. Secondly, the aim is to turn building model into a small building stock model of around 15 buildings with different shape and construction type. Finally, the application of such constraints should be verified with more than 3 objectives as NSGA2 algorithm is less efficient with more objectives (Campos Ciro et al. 2016).

CONCLUSIONS

This paper presents a method to integrate constraints in a problem of multi-objective optimization of building retrofit. A case test was studied in order to compare the performances of this approach: as a result, 25% less evaluation were needed during the optimization process in order to converge to Pareto front of optimal solutions. Some solutions proposed by the algorithm can be counter intuitive because of its performance on one objective but are still non-dominated on other objective, which illustrates that diversity is kept in the set of possible solutions.

Multi-objective optimization is a growing field when it comes to retrofitting buildings, and will get more important to develop strategies for energy conservation for buildings and building stocks. That is why we handled constraints here with a simple description that keeps the link between the decision space and the actual construction work. This method would be appropriate for an integration in an engineering tool featuring interactive decision-aid for the elaboration of optimal retrofit strategies developed by (Delhomme et al. 2017). This tool will enable designers to parse through optimal solutions for energy retrofit and to save time on

defining building stock-wide retrofit strategies and spend more time on non objective criteria such as the acceptability by users and urban integration of retrofit strategies.

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