



HAL
open science

Integration of phasing on multi-objective optimization of building stock energy retrofit

Yannis Merlet, Simon Rouchier, Arnaud JAY, Nicolas Cellier, Monika Woloszyn

► To cite this version:

Yannis Merlet, Simon Rouchier, Arnaud JAY, Nicolas Cellier, Monika Woloszyn. Integration of phasing on multi-objective optimization of building stock energy retrofit. *Energy and Buildings*, 2022, 257, pp.111776. 10.1016/j.enbuild.2021.111776 . hal-03285996

HAL Id: hal-03285996

<https://hal.science/hal-03285996v1>

Submitted on 13 Jul 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 Integration of phasing on multi-objective optimization of building
2 stock energy retrofit

3 Yannis MERLET¹, Simon ROUCHIER¹, Arnaud JAY², Nicolas CELLIER¹, and Monika
4 WOLOSZYN¹

5 ¹Univ. Savoie Mont Blanc, CNRS, LOCIE, 73000 Chambéry, France

6 ²Univ Grenoble Alpes, CEA, LITEN, DTS, INES, F-38000 Grenoble, France

7 June 4, 2021

8 **Abstract**

9 This article presents the integration of phasing (ie. temporal distribution of retrofit actions over time) into
10 multi-objective optimization of retrofit. The aim of this method is to get closer to real world practice in
11 the construction sites. The case study is carried out on a small building stock with the NSGA-II genetic
12 algorithm. The search space of the optimization are vertical and horizontal walls and windows of each
13 building; objective functions are heating demand, price of the proposed retrofit and an overheating indicator
14 based on adaptive comfort. Overheating and heating demand are evaluated using EnergyPlus simulations.
15 Phasing is implemented directly into the optimization formalisation with a separated chromosome describing
16 temporality. As a result, different retrofit strategies were obtained by integrating phasing than with a standard
17 optimisation with no temporal planning of operations. The main difference lies into the which building is
18 selected to be retrofitted first, and in the improved performance of each retrofit material proposed : it led
19 to an increase of performance of 10% in the overheating while thermal performance decreased for 2% in the
20 retrofit strategies possible in reality when including the phasing. These results highlight the importance of
21 formulating the optimization problem as close as possible to the real world constraints in construction in
22 order to have accurate retrofit strategies.

23 Highlights

- 24 • Optimal retrofit plans for building stocks are generated using genetic algorithm
- 25 • The phasing of retrofit actions is integrated in the optimisation search space
- 26 • Results show that proposed optimal strategies are different when phasing is integrated

27 Keywords

28 Multi-objective optimization; building stocks; retrofit; phasing; planning

29 1 Introduction

30 According to the International Energy Agency [1], buildings are responsible for 30% of the worldwide primary
31 energy use. The energy efficiency of buildings is a key to meet the ambitious target of 1.5°C of climate change.
32 The Intergovernmental Panel on Climate Change suggests a decrease of building energy demand of 8 to 14%
33 by 2030 [2] in order to meet with proposed scenarios.

34 In addition, the building stock is renewed in France at a 1% yearly rate [3] and existing buildings are often
35 considered architectural heritage [4]: the highest potential for energy savings therefore lies in retrofitting the
36 existing building stock. Generally, property managers base their retrofitting decisions on expert knowledge,
37 then attempt to balance and optimize these decisions with constraints such as the global cost, including
38 public financial assistance, energy efficiency, or comfort of the tenants. Although the solutions proposed by
39 experts are generally suitable, they are not necessarily the most efficient.

40 A step further could be to automatize the balancing of the constraints with simple methods like weighted
41 sum or weighted product. The proposed solution would then be part of the optimal solutions, but would be
42 unique [5]. This limits the power of the decision maker: such methods could thus suffer of a low acceptability
43 because of the lack of control on the process [6]. The weighted sum method suffers from another drawback,
44 which is the difficulty to rank objectives among themselves. This difficulty has also been showed in different
45 approaches at building stock level using multi-criteria decision aid methods like REDIS [7]. Consequently,
46 multi-objective optimization (MOO) is a promising approach to efficiently propose a set of optimal solutions
47 so the experts may focus on selecting one solution among several optimal candidates. Among MOO methods,

48 genetic algorithms has been extensively used to optimize building retrofit, as stated in the review of Costa-
49 Carrapiço [8].

50 Multi-objective optimization has also been used to set up energy policies at larger scales. Tools have been
51 developed to allow the evaluation of energy efficiency measures at city scale such as Stockholm [9]: buildings
52 are first broken down into clusters and three energy conservation measures are evaluated regarding CO₂
53 emission, heat demand and economic criteria. A similar approach has been carried out at the region level
54 in Italy [10] and assesses energy efficiency measures based on a cost-benefit approach on environmental and
55 economic criteria. Such methods help decision makers generate efficient energy policies but do not enable
56 planning if and when the measures will be implemented.

57 In order to be useful to decision makers, MOO should be as close as possible to the real-life construction
58 management workflow. A key point of any building stock management is the phasing plan of the construction
59 work. The phasing of a construction work is how each action is broken down and arranged on a timeline
60 with respect to construction constraints, site requirements, or time constraints. This timeline can last from
61 less than a month on simple construction sites to a few years when dealing with a whole neighbourhood or
62 a building stock managed by the same owner.

63 Phasing has been extensively studied in civil engineering at the construction site level [11] in order to
64 optimize the scheduling of the construction. The prioritization of retrofit between multiple buildings has
65 been studied by [12] with the seismic risk as an objective function. This objective function is calculated with
66 subjective weights given to each variable of the problem (economy, safety, regulations) in order to come up
67 with a mono-objective optimization problem. This is an efficient method if the decision maker is able to
68 affect a weight to each objective, but it can only be applied if all objectives may be ranked. Another way to
69 deal with the phasing plan of construction is the use of a risk-based approach to carry out decisions about
70 the retrofit. Taillandier [13] qualitatively evaluates whether an action should be undertaken or not and aims
71 to rank actions. However, each action must be proposed by an expert: the method loses efficiency as the size
72 of the building stock increases. Moreover, the choice of action is subjective as the expert is influenced by his
73 experience. Finally, Rivallain [14] proposed a method to sequence each retrofit action for optimization. This
74 method was applied to two small fictional buildings and was limited to one retrofit action per year.

75 The purpose of this paper is to propose a formulation of temporal arrangement of retrofit strategies
76 in the multi-objective optimization of a building stock, and then observe whether including this temporal
77 dimension has any impact on the strategies proposed by optimization. This approach aims to get closer to
78 the real world practice and to enable the planning of efficient retrofit projects for building stocks thanks to

79 multi-objective optimization. In our terminology, the term of "stock" refers to a set of buildings managed
80 by a unique property owner, with shared portfolio for refurbishment funds (e.g. social housing). The paper
81 first describes the general framework for the optimization, then details the specifics of the implementation
82 of temporal phasing in the optimization. Finally, outputs of the optimization are compared in order to put
83 forward the effect of the integration of temporal distribution of construction on optimal retrofit strategies.

84 2 Optimization methodology

85 In order to allow optimizing different and often contradictory objectives, we use multi-objective optimization.
86 The formulation of the problem plays a significant role in the success of the process and in the interpretability
87 of the results. Thus the problem should be carefully formulated with regards to which parameters to optimize,
88 the decision space including the possible values of parameters, and the objective functions of the model.

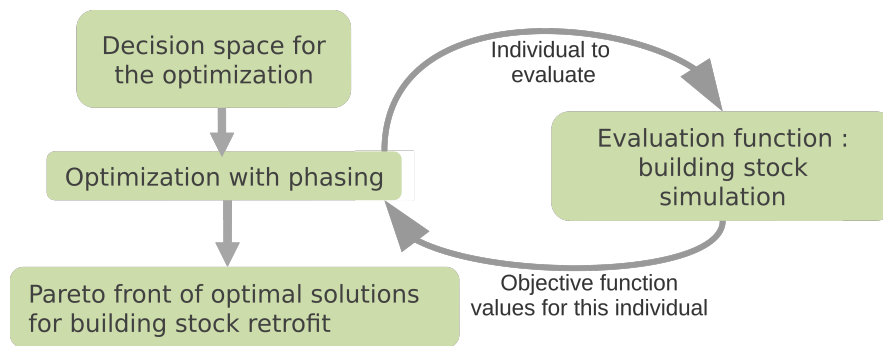


Figure 1: General optimization workflow

89 Figure 1 illustrates the global optimization process: in our case the aim is to generate optimal retrofit
90 strategies for a building stock, which will form a set of candidates for decision (Pareto front). The global
91 optimization process can be broken down into 3 main parts:

- 92 • the optimization algorithm which should consistently find optimal solutions;
- 93 • the decision space which is an input of the optimization algorithm;
- 94 • the objective functions in which the building stock performance are evaluated.

95 The objective function receives an individual to evaluate, which details the retrofit strategies components.
96 This is part of the optimization algorithm which is chosen in section 2.3.

97 Each of these components is detailed hereafter.

98 2.1 Objective functions

99 Building managers are optimizing retrofit plans on various objectives covering energy, environment, comfort
100 of the tenants, costs... As a starting point, we choose to optimize retrofit strategies based on 3 objective
101 functions selected in different fields based on the importance of the criteria for building managers in social
102 housing. Thus the following objective functions are selected:

- 103 • **Heating demand** : weighted average of the heating needs in kWh/m² of all of the buildings for all of
104 the years of the retrofit plan
- 105 • **Overheating** : sum of the °C.hours above the 90% operative temperature comfort zone [15] over all
106 years of the retrofit plan
- 107 • **Cost** : sum of the costs (in €) of all retrofit actions (global construction budget)

108 Concerning the overheating objective, it should be noted that in France, air conditioning is generally not
109 provided in residential buildings. Summer comfort is an increasing concern as heatwaves occurrences become
110 more frequent.

111 The definition of the time span is important, as it may impact the choice of retrofit actions. Here the
112 time span of 20 years has been chosen, matching the average lifetime of retrofit actions. Indeed, datasheets
113 for insulation materials show a lifetime of 15-25 years when properly implemented. Windows' lifetime lies
114 between 20 and 25 years according to manufacturers.

115 2.2 Decision space

116 The decision space is composed of the possibles values for all parameters to be varied through the optimization
117 process. In our case, the decision space was designed using the expert knowledge of engineering offices that
118 completed multiple energy retrofits as project manager and as on-site management.

119 Each of the retrofitting actions is broken down into elementary tasks that deal with one component of
120 one building (e.g. *Change insulation: 12cm of rockwool on ceiling of building 1*).

121 An example of decision space is available in the section 3.

122 2.3 Optimization algorithm

123 The characteristics of our problem guide the choice of the optimization algorithm:

- 124 • The decision space is discrete. For instance, insulation materials are available in a limited number of
125 thicknesses, and thus of R-values.
- 126 • It is preferable to keep multiple separate objectives, rather than a single weighted sum of indicators for
127 the decision makers to be able to apply preferences later on.

128 Thus, genetic programming is a suitable approach to deal with this problem. As shown by Evins [16], other
129 optimization methods do not meet our needs on either of the two points listed above while limiting the
130 number of evaluations needed. Within genetic programming, the NSGA2 ([17]) algorithm has been widely
131 used and its robustness has been validated by multiple studies in building physics [16, 18]. Finally, it is
132 applicable to large decision spaces, such as large combinatorial problems that can occur when dealing with
133 building stocks.

134 Genetic algorithms mimic evolution by reproducing a population of individuals, and adapting them to their
135 environment. In the end of the evolutionary process, only optimal individuals to their environment remain
136 : they were optimized according their objective of survival in this environment. An individual features its
137 chromosome, which is a representation of the set of parameters, and its fitness, which is the performance of
138 the individual on each objective function. In each chromosome, one gene represents one parameter of the
139 model to optimize. In order to explore the decision space of possible values for the parameters, chromosomes
140 may vary through mutation or crossover.

141 We chose to use an efficient implementation of NSGA2 available in the DEAP Python library [19]. This
142 implementation stands out with its improvement of the calculation of the crowding distance, as detailed in
143 Fortin and Parizeau [20].

144 2.4 Integration of temporality in optimization

145 The main goal of our work is to integrate temporality in the multi-objective optimization algorithm with
146 different levels of complexity while being able to compare the outputs of the optimization. We chose to
147 implement 2 types of temporality in the optimization: **sequencing** and **phasing**. They will be compared
148 with a **base** scenario, excluding temporality issues.

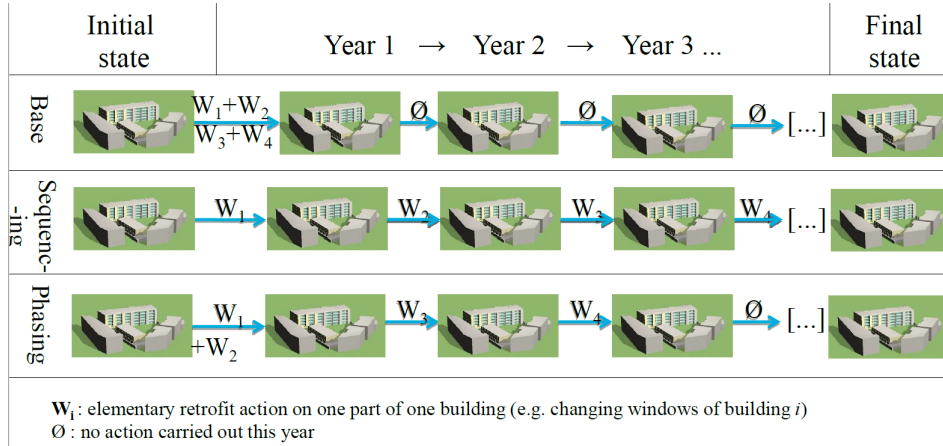


Figure 2: Workflow for base and sequenced optimization

149 In the **base** scenario, all operations are carried at the beginning of the first year. This is the reference
 150 scenario, which will be used to compare the outcome of the other scenario. No constraints were imposed on
 151 the budget either on base or sequenced optimization.

152 2.4.1 Implementations of sequencing

153 Sequencing is the first step in adding temporality in the retrofitting actions. In this approach, presented in
 154 Figure 2, one retrofit action is carried out every year on one building (e.g. *On year 2, insulation is replaced*
 155 *with 10cm of rockwool on Ceiling of building 2*).

156 The implementation of sequencing into the optimization algorithm is proposed by adding an extra chro-
 157 mosome that describes the temporality of actions. Consequently, each individual has now two chromosomes,
 158 as shown in Figure 3.

159 As previously stated, only one retrofit action is carried out at each stage (here, each stage equals one
 160 year). Consequently, in the case of sequencing, the chromosome that describes the temporality, visible on
 161 Figure 3, cannot include duplicate values, which means that specific mutation and crossover operators should
 162 be used. [21] proposed a crossover operator that respects the discrepancy and does not slow down nor reduces
 163 diversity [22].

Type of Ext. Walls of building1	12	2	Phase for Ext. Walls of building1
Type of Ceiling of building1	1	1	Phase for Ceiling of building1
Type of Top floor of building1	17	8	Phase for Top floor of building1
Type of Windows of building1	6	10	Phase for Windows of building1
Type of Ext. Walls of building2	8	6	Phase for Ext. Walls of building2
Type of Ceiling of building2	0	0	Phase for Ceiling of building2
Type of Top floor of building2	11	7	Phase for Top floor of building2
Type of Windows of building2	1	3	Phase for Windows of building2
Type of Ext. Walls of building3	19	5	Phase for Ext. Walls of building3
Type of Ceiling of building3	0	0	Phase for Ceiling of building3
Type of Top floor of building3	26	4	Phase for Top floor of building3
Type of Windows of building3	3	9	Phase for Windows of building3

Type of operation **Temporality of those operations**

Figure 3: Chromosomes setup for the optimization

164 2.4.2 Implementation of phasing

165 Phasing is meant here as a generalisation of sequencing. The main difference is that multiple retrofit actions
 166 may be carried out the same year. Here, the available yearly budget sets the limit to the yearly number of
 167 possible retrofit actions. Technically, it has been done by adding a phasing chromosome to the sequencing
 168 chromosome, as shown in Figure 4.

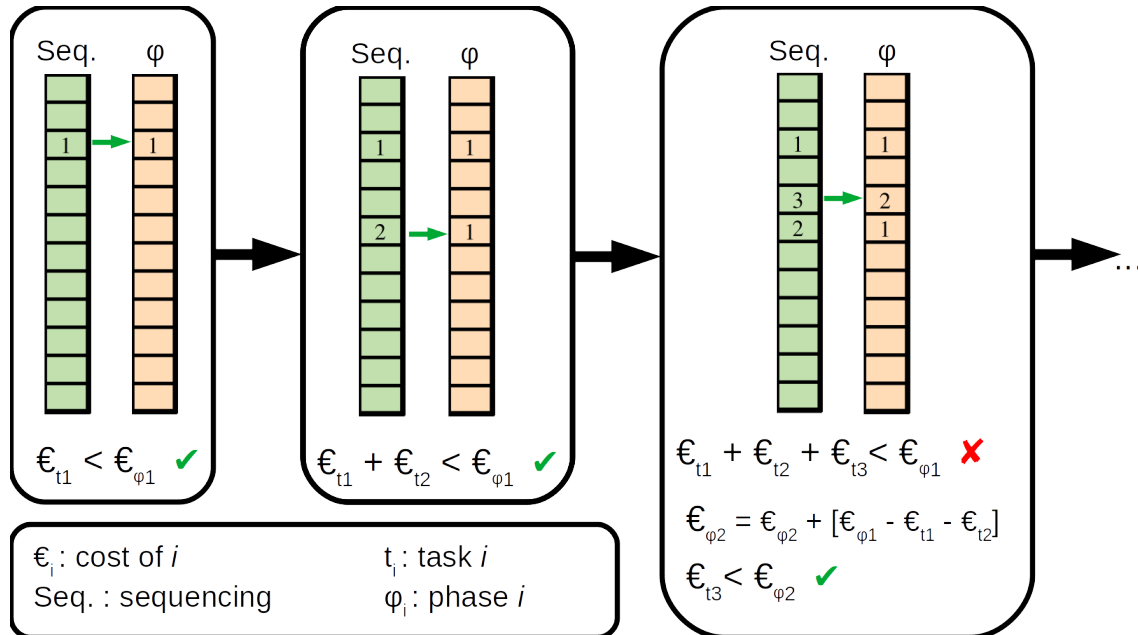


Figure 4: Creation of phasing chromosome

169 For each individual of the optimization, the cost of each retrofit task is evaluated. Next, each retrofit task
170 is affected to a phase with respect to their order and the available budget by phase.

171 Retrofit actions exceeding the budget are not applied on the building stock, and not evaluated. If an
172 individual has a lot of non-applied actions due to budget limits, the convergence speed of the optimization
173 may be affected.

174 2.5 Summary of the optimization scenarios

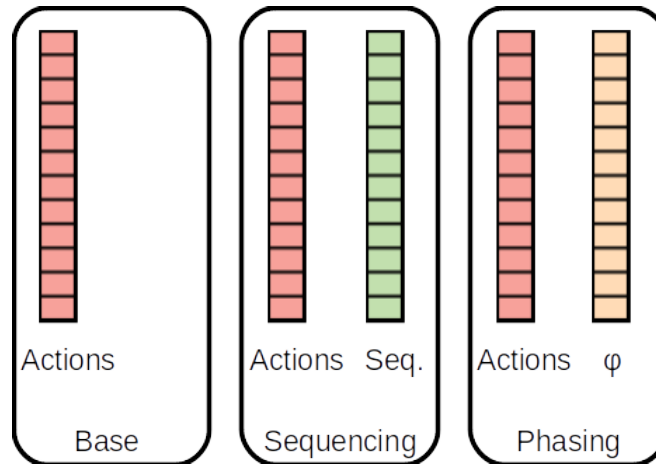


Figure 5: Summary of optimization scenarios

175 In summary, 3 optimization scenarios, listed on Figure 5, will be compared. The base scenario does
176 not include a temporal chromosome and only optimizes the retrofit actions carried out on the building
177 stock. The sequenced optimization uses the chromosome for the retrofit actions as well as the sequencing
178 chromosome. Finally, phased optimization uses the retrofit actions chromosome and the phasing chromosome
179 which elaboration is detailed in Figure 4.

180

181 3 Case Study

182 3.1 Building stock

183 Proposed optimization scenarios are applied here on a social housing stock located close to Paris, France.
184 The investigated building stock is composed of 3 apartment blocks, chosen as representative of the whole

185 building stock. The specifications of these buildings have been provided by the property manager.

Table 1: Initial characteristics of the buildings.

	Building 1	Building 2	Building 3
Total floor area	3020 m ²	850 m ²	6667 m ²
Shape	Low-rise	High-rise	Low-rise
Energy label	D (151-230kWh/m ² /year)	E (231-330kWh/m ² /year)	D
Number of floors	5	9	5
Year of construction	<1979	<1979	<1979
Window to wall ratio	27%	24%	14%
R-Value walls (m ² .K/W)	1.25	1.25	3.1
U window (W/m ² .K)	2.4	2.4	2.6

186 Buildings were modeled in EnergyPlus using Design Builder for the geometry. Their characteristics are
 187 listed in Tab. 1. They are initially poorly or not insulated, and have never been renovated before. Building
 188 models are detailed in the following section.

189 3.2 EnergyPlus modeling and settings

190 The choice of EnergyPlus algorithm and parameters reflects the needs of the optimization and the need to
 191 describe accurately the buildings: having comparable values for the overheating and heating needs criteria.
 192 Consequently the shadowing calculation is kept to the minimum, and no reflections for the radiation were
 193 computed. Moreover, convection algorithm were kept to simple indoor and outdoor heat transfer coefficients.
 194 According to the EnergyPlus documentation, these settings have a low impact (less than 1.5% difference) on
 195 all output criteria. Used timestep is 30min.

196 3.2.1 Schedules

197 Occupation and heating schedules are selected to allow a practical comparison between retrofit strategies.
 198 Standard schedules from the French Thermal Regulation are selected ([23]). An example is shown by Tab.
 199 2.

Table 2: Temperature heating setpoint from [23]

	Mon-Fri (except Wed)	Wednesday	Weekend
00:00-09:00	19°C	19°C	19°C
09:00-14:00	16°C	16°C	19°C
14:00-18:00	16°C	19°C	19°C
18:00-00:00	19°C	19°C	19°C

200 Old apartment blocks like those buildings are often naturally ventilated, and although the absence of
201 mechanical ventilation is easy to model, past studies showed that in this case the occupant behavior had
202 a great impact on the ventilation rate ([24, 25]). Indeed, natural ventilation through the window openings
203 has a major influence on the overheating indicator calculated at each evaluation of the model. The model
204 for windows opening proposed by [25] accounts for indoor and outdoor temperatures, but adds a large
205 computational cost to each evaluation. We have therefore chosen a simple assumption. As all buildings are
206 located in a quiet area, the model includes the following natural ventilation rule: If $T_{indoor} > 26^{\circ}C$ and
207 $T_{indoor} > T_{outdoor}$ then tenants are opening windows in order to facilitate natural ventilation.

208 Air tightness has been modeled with a constant air flow equal to 0.7 vol/h. This is an observed measure-
209 ment in old collective housing buildings [26].

210 3.2.2 Zoning

211 Zoning of the building is kept to the minimum of zones in order to speed up calculation while having an
212 acceptable accuracy on simulation results. On such simple building shapes, it has been shown that a limited
213 amount of zones is enough to have accurate results for the heating demand [27]. Consequently we chose to
214 split each building in 7 zones:

- 215 • 2 zones for the ground floor: one south, one north
- 216 • 2 zones for the top floor: one south, one north
- 217 • 2 zones for other floors: one north, one south
- 218 • 1 zone for not heated spaces such as stairs and circulations.

219 An illustration of this zoning is given Figure 6

220 3.2.3 Weather

221 The weather file selected in a typical reference year (TRY) of Trappes (France). This TRY files has been
222 generated with Meteonorm software with data from the GEBA (Global Energy Balance Archive), from the
223 World Meteorological Organization (WMO/OMM) Climato-logical Normals 1961-1990. It is the weather file
224 used as reference is the French Thermal Regulation [23]. The weather data are used for all of the 20 years of
225 evaluation.



Figure 6: Building 1 with its zoning: each color represent a thermal zone. Grey is for unheated spaces such as stairs and circulation

226 3.3 Response of the model

First, annual heating needs and the overheating criteria were computed. They are shown in Table 3. Buildings

Table 3: Simulated characteristics of the buildings before retrofit

	Building 1	Building 2	Building 3
Heating needs	146 kWh/m ²	228 kWh/m ²	191 kWh/m ²
Overheating	297 °C.h/m ²	180 °C.h/m ²	306 °C.h/m ²

227

228 are in accordance with their energy label provided by the property manager(cf. Table 1). Building 2 overheats
 229 slightly less than the two other buildings. This is due to the difference of building shape: since Building 2 is
 230 a high-rise building, it has a lower surface south oriented and a lower roof surface, thus less surface directly
 231 exposed to high solar radiations.

232 Then, in order to verify the usability of the model, we plotted the following data over a typical winter
 233 and a typical summer week:

- 234 • Air temperature of a south oriented zone
- 235 • Air temperature of a north oriented zone
- 236 • Outdoor air temperature
- 237 • Direct horizontal solar radiation

238 As shown in Figure 7a, the south zone reaches more than 35° C. This is due to the fact that during the
239 day, the occupants are scheduled to be out of their apartment, therefore they can not open the window to
240 ventilate. Moreover, the building has no insulation and a fair amount of windows without solar shadings
241 (27%) which ensures a quick rise of temperature on days with high solar radiation. It can be noted that as
242 soon as occupants come back home, the temperature drops dramatically because of the windows' opening,
243 modelled as stated in section 3.2.1.

244 In winter (Figure 7b), the model reaches the setpoint temperature flawlessly as the heater is modelled as
245 an ideal heating system. It is striking to realize that the building has low inertia therefore drops quickly to
246 the low temperature setpoints each day. It can also be noted that the building is sensitive to solar gain even
247 in winter, thanks to its large windows area.

248 The same analysis can be made with the other buildings which share the same typology as this one.

249 3.4 Parameters of the model to optimize

250 The present case study focuses on the retrofit of the building envelope. For each of the three buildings,
251 we optimized vertical walls, ceilings and floors as well as windows. Each of these variables to optimize is
252 a parameter of the model. There are three buildings with 4 parameters to optimize on each one, hence 12
253 parameters which are listed as parts of the chromosome *Type of operation* in Figure 3.

254 3.5 Decision space

255 The decision space is the set of possible parameter values of the model to be optimized. The parameters can
256 be broken down into two types:

- 257 • Window properties: genes 4, 8, 12 of the pictured chromosome as shown in Figure 3.
- 258 • Wall properties (vertical walls, floors and ceilings): all other genes.

259 For the windows parameters, the decision space is defined by the possible U-values, solar factor and visible
260 transmittance that may be applied to all windows of a building. Possible values, taken from a manufacturer
261 catalogue, are:

Table 4: Description of the decision space for windows

U_w values (W/m ² .K)	0.8	1	1.2	1.4	2.0
Solar factor	0.76	0.73	0.67	0.64	0.61
Visible Transmittance	0.81	0.83	0.86	0.88	0.9

For walls, the decision space covers different insulation materials. Each material may replace the current insulation of the wall, which is external on all of the three buildings. Possible materials are:

Table 5: Description of the decision space for walls

Materials	Thicknesses (cm)
Glasswool ($\lambda = 0.04$ W/m ² .K)	2, 4, 6, 8, 10, 12, 14, 16, 18, 20
Rockwool ($\lambda = 0.042$ W/m ² .K)	2, 4, 6, 8, 10, 12, 14, 16, 18, 20
Polystyrene ($\lambda = 0.032$ W/m ² .K)	2, 4, 6, 8, 10, 12, 14, 16, 18, 20
Polyurethane ($\lambda = 0.03$ W/m ² .K)	2, 4, 6, 8, 10, 12, 14, 16, 18, 20

Each of these materials has its own thermal properties and its price is computed according to expert knowledge provided by engineering companies. The price can be split in two parts: the cost of the material itself, that depends on the thickness and the type of the material, and the price of the construction that depends only on the material.

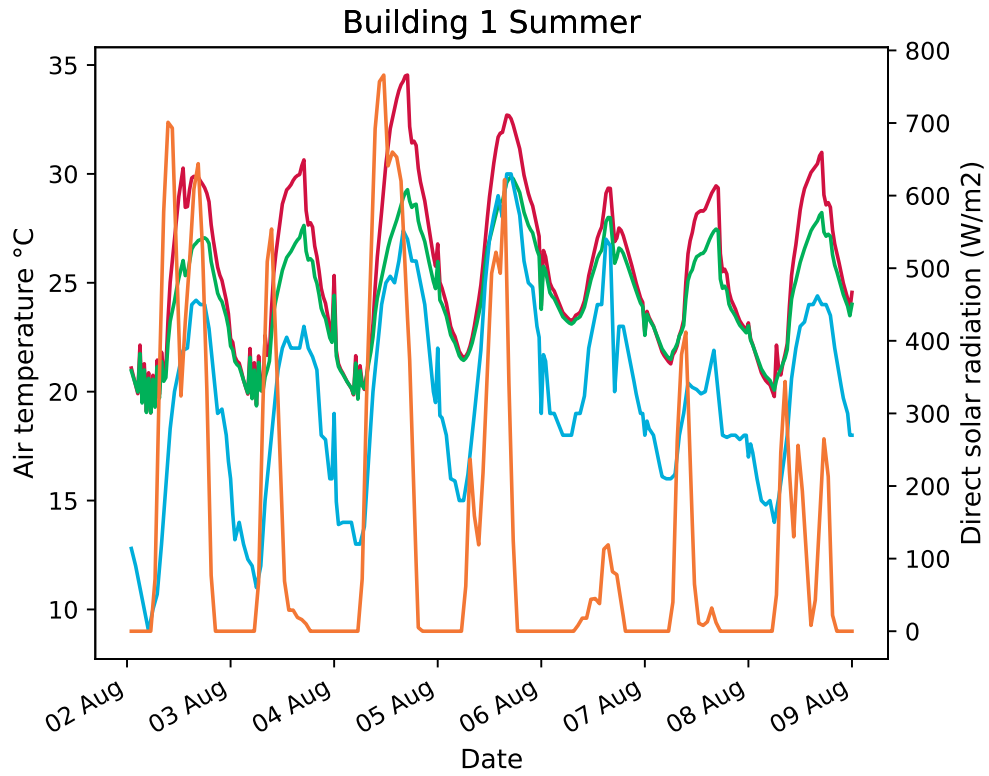
3.6 Hyperparameters of the algorithm

The NSGA2 algorithm has 3 main hyperparameters to be set: the number of individuals, number of generations and crossover probability. [28] and [16] state that convergence was reached in genetic algorithm optimization on 12 parameters with 30 individuals and 10 generations with a crossover probability in the range [0.8;1]. After checking the convergence and the repeatability of the optimisation for multiple hyperparameters, the following parameters are chosen:

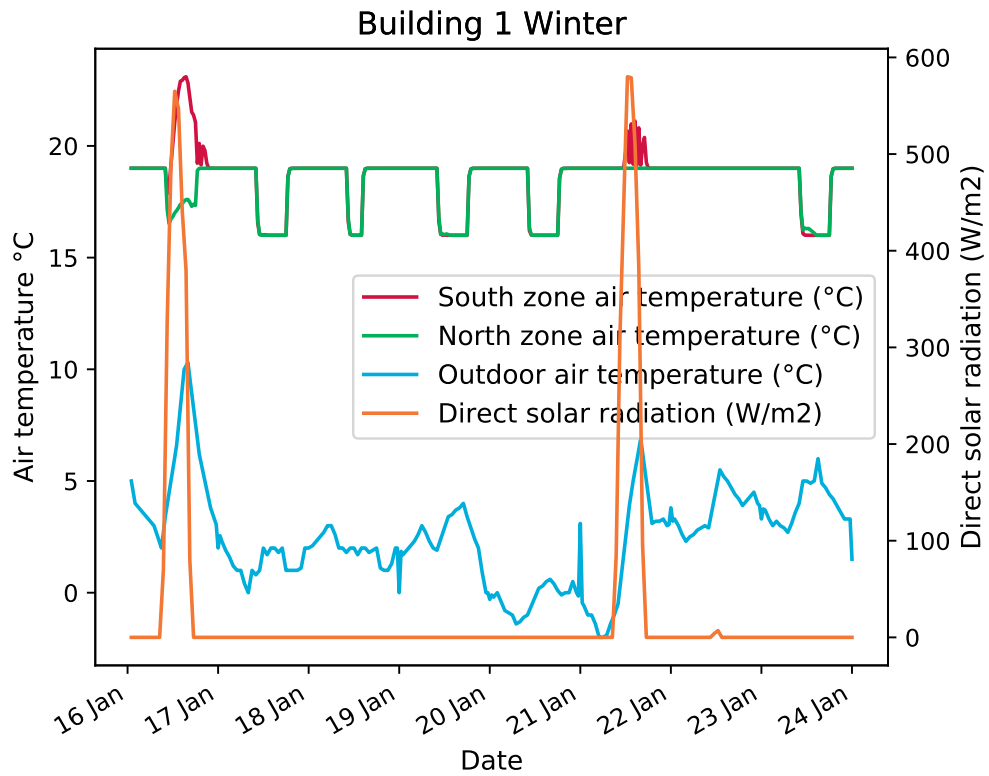
Table 6: Hyperparameters of NSGA2 for our case study

Number of individuals	96
Number of generations	100
Crossover probability	0.8
Mutation probability	0.2

The validity of these parameters is checked after the optimization through hypervolume monitoring and qualitative evaluation of convergence.



(a) Summer week for Building 1



(b) Winter week for Building 1

Figure 7: Building 1

276 **4 Results**

277 First of all, the global behavior of the optimization will be verified. Then we will compare the optimal
 278 strategies given by the optimization with base, sequencing or phasing.

279 **4.1 Pareto front at the end of the optimization : overview**

280 On Figure 8, the Pareto fronts of the optimal retrofit strategies are compared. The first one concerns the base
 281 optimization, which includes no temporality effect. The second one is the sequenced optimization, where one
 282 retrofit task is proposed per year. The third one is the phased optimization which enables multiple tasks to
 283 be carried on the same year.

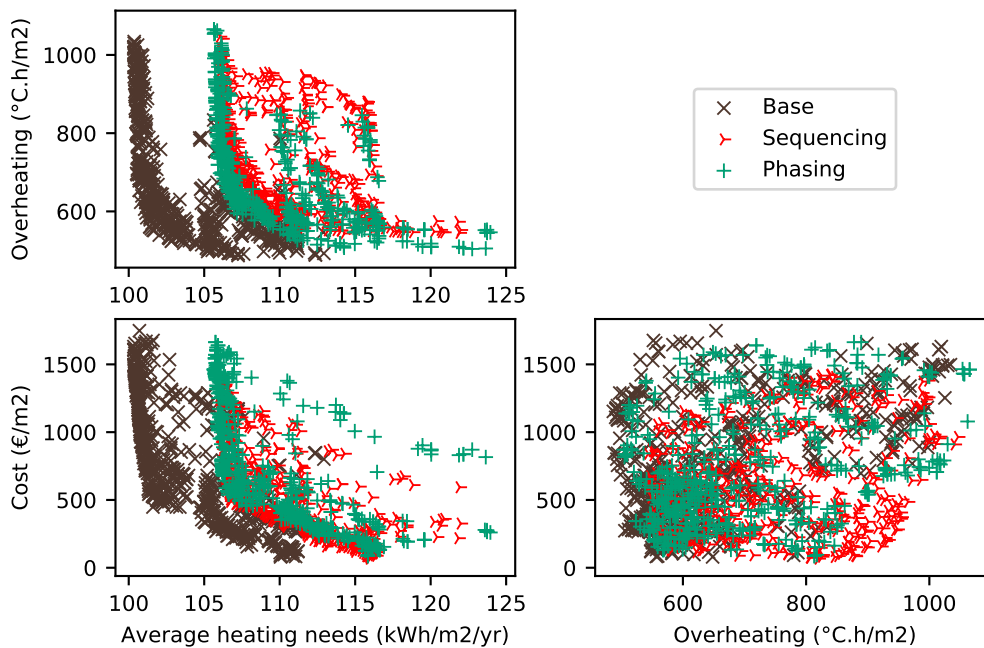


Figure 8: Pareto front comparison of based, sequenced and phased optimization

284 In each subplot of Figure 8, we can see individuals that are "dominated" if we take only two objectives
 285 into account. It can be noticed on Figure 9: as the individuals perform less on the *cost* and *heating needs*
 286 objective, they perform better on the *overheating objective*. This behavior is expected in a multi-objective
 287 optimization and enables the verification of the implementation of the algorithm for our problem.

288 The three Pareto fronts are different and this difference can be explained by the formulation of the

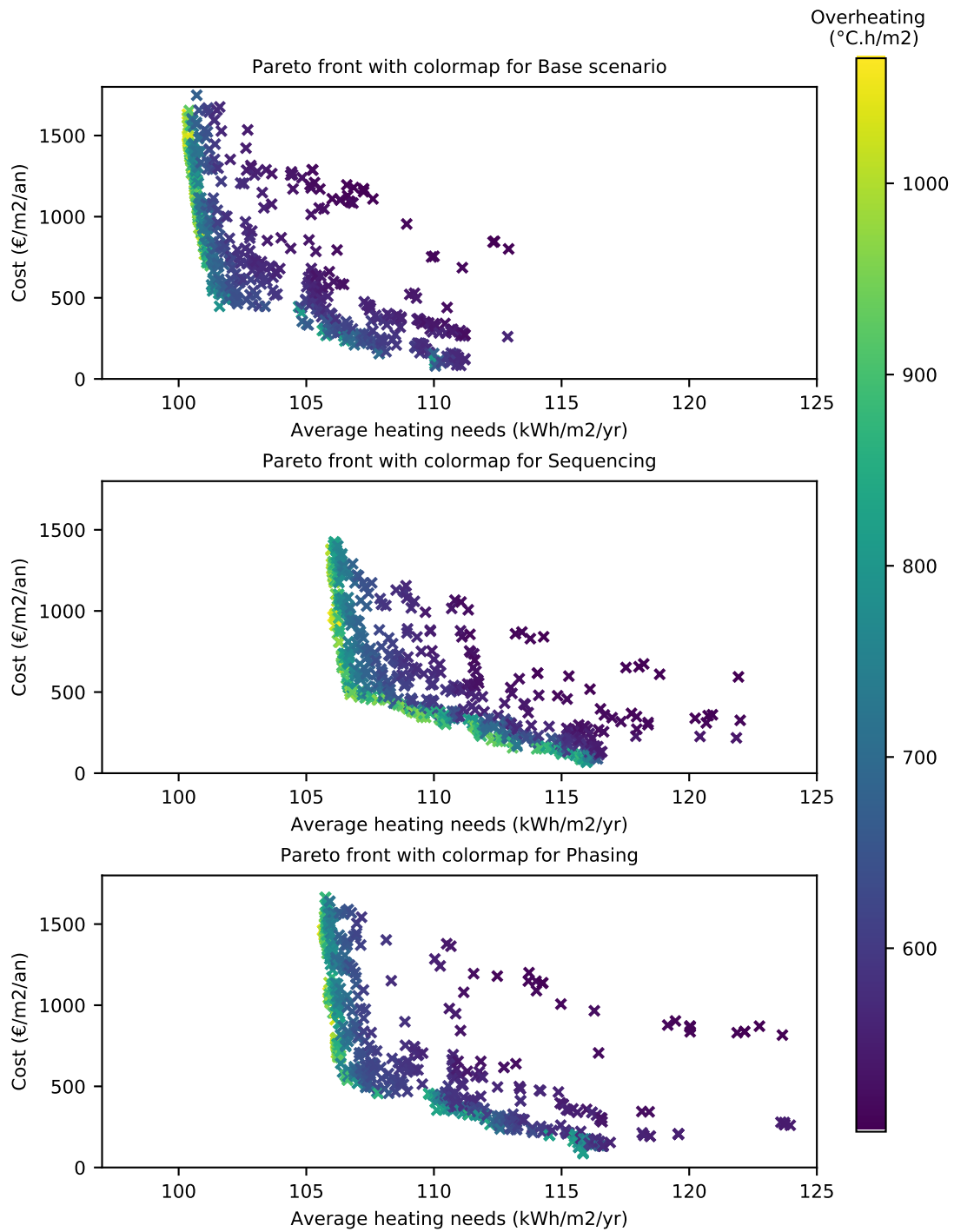


Figure 9: Comparison of optimal retrofit strategies

289 problem. Indeed, in Figure 8, the best performances seem to be achieved by the *base* optimization, then
290 the *phasing* optimization and finally the *sequenced* optimization. This is due to the fact that in the *base*
291 scenario, all of the retrofit actions are done at the very beginning, from the first year. In the *sequenced*
292 optimization, the retrofit actions are spread over 12 years and in the *phasing* optimization over 4 years. As
293 the evaluation has been carried out on 20 years, this implies that the amount of years where the building
294 has a poor performance is the longest for the *sequenced* optimization, which explains its lower performance
295 compared to the two other scenarios.

296 Additional discussions will be proposed in section 4.2.2.

297 4.2 Global behavior of the optimization and convergence

298 First of all, convergence of the optimization has to be checked, and the hypervolume and its evolution is
299 a meaningful criteria to do so [29]. Figure 10 shows the evolution of the hypervolumes along generations
300 for base, sequenced and phased optimization. Hypervolume progression shows a convergence of phased and
301 sequenced optimisation towards the Pareto front that is obtained with based optimisation. However, the
302 gap of hypervolume values at generation 83 for phased optimization could question the convergence of the
303 optimization, but small variability of hypervolumes between the 3 fronts at generation 100 increase the
304 confidence in the convergence of this optimization. The gap at generation 83 is due to the progression of the
305 Pareto front on the overheating objective for solutions that cost between 1100 and 1250€/m², the evolution
306 on other criterias is not significant.

307 4.2.1 Interpretation of the results

308 The content of the retrofit strategies shows an overall difference between strategies from the base optimization
309 and phased strategies. The main differences lie in the retrofit of the windows and in the thickness of the
310 proposed insulation.

311 First of all observations, the higher the cost of the retrofit strategies, the more windows are treated:
312 cheapest strategies do not retrofit any windows, strategies a bit more costly retrofit windows on one building,
313 etc... This can be shown on Tables 7 and 8. Theses tables split the Pareto front in 8 clusters depending on
314 how which building gets its windows retrofitted. In the first three columns of this table is detailed whether
315 the windows get retrofitted for every building: if the building's windows are treated, the value in this column
316 is "1". In the following columns, the mean values and the standard deviation for each objective function are

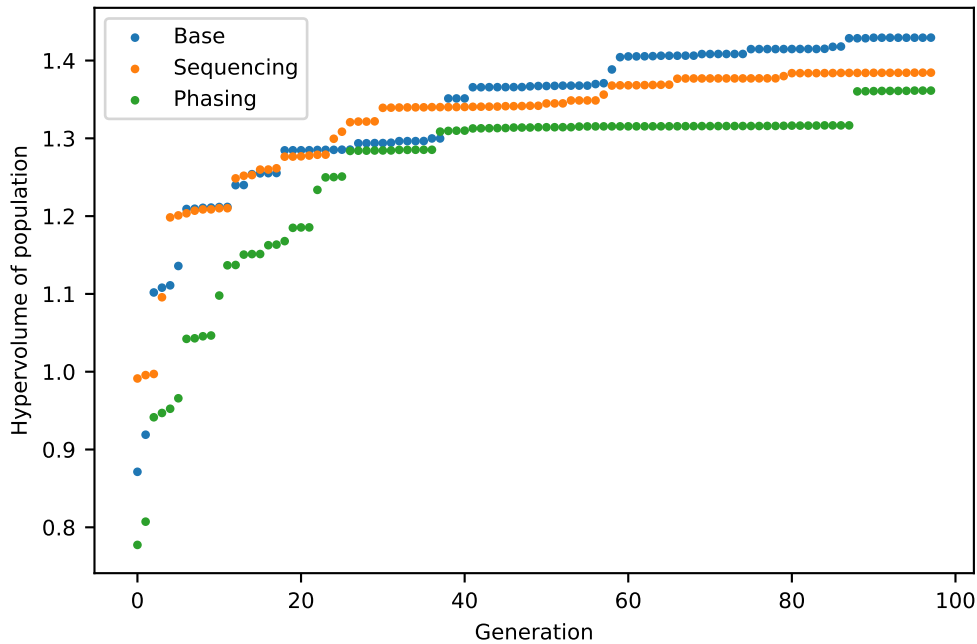


Figure 10: Hypervolume of Pareto front along generations

317 detailed for each cluster.

318 Figures 11 and 12 are using the same coding of Tables 7 and 8 to describe the retrofit of windows, which
 319 is detailed in the previous paragraph.

320 We can see a difference between in which building is treated when not all buildings are retrofitted. In
 321 the phased optimization, windows from Building 3 are treated first, then Building 1. In base optimization,
 322 windows from Building 1 are retrofitted first, then windows from Building 3. For bot of the optimization,
 323 windows from Building 2 are retrofitted in last.

324 On Figures 11 and 12, few differences are visible about the distribution of the solutions. However, in the
 325 phased optimisation, the transition between the solutions that are retrofitting the windows of Building 3 and
 326 the solutions retrofitting the windows of Building 1 and Building 3 is more clear and occurs at a lower cost
 327 than in the base optimization. This is confirmed by the datas from Tables 7 and 8. As the only differences
 328 between both of the optimizations are the integration of the temporality and the integration of a maximal
 329 cost of retrofit, and the fact that the concerned solutions are costing 600 to 700€/m², this observation can
 330 be accounted on the integration of temporality.

Table 7: Mean and standard deviation of solutions function of retrofitted windows: base optimization

Windows			Heating needs (kWh/m2.yr)		Overheating ($^{\circ}\text{C.h/m}^2\text{.yr}$)		Cost €/m2.yr	
Building 1	Building 2	Building 3	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
0	0	0	108.6	1.9	603	45	219	69
0	0	1	102.7	1.6	650	70	600	170
0	1	0	N/A	N/A	N/A	N/A	N/A	N/A
0	1	1	101	0.1	743	66	1206	113
1	0	0	109	1.3	537	19	361	57
1	0	1	102	1.7	711	192	882	208
1	1	0	111	1.8	495	2.7	828	94
1	1	1	102	1.9	748	196	1400	166

N/A: no retrofit strategies for this case
 1: windows retrofitted on this building
 0: windows not retrofitted on this building

331 For both optimizations, it is sensible to retrofit windows Building 1 and Building 3 first as their window-
 332 to-wall ratio is higher than Building 2 (0,27 for Building 1 and 0,23 for Building 3, only 0,16 for Building
 333 2)

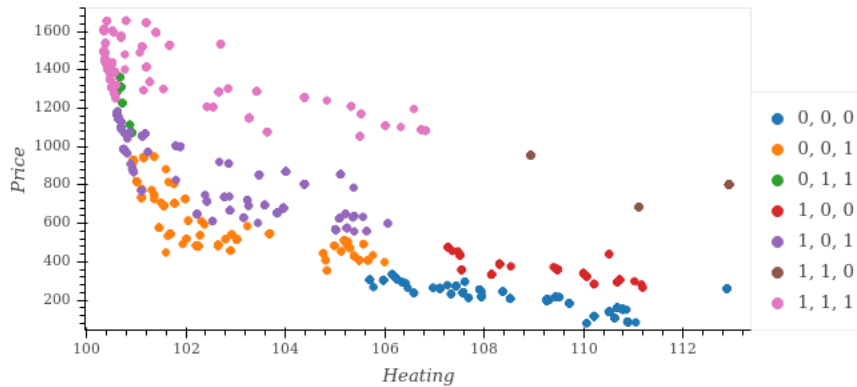


Figure 11: Individual from Pareto front function of retrofitted windows: base optimization

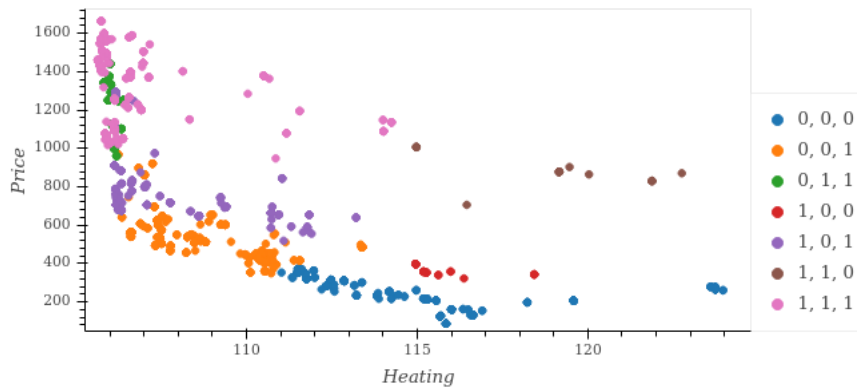


Figure 12: Individual from Pareto front function of retrofitted windows: phased optimization

Table 8: Mean and standard deviation of solutions function of retrofitted windows: phased optimization

Windows			Heating needs		Overheating		Cost	
Building 1	Building 2	Building 3	Moyenne	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
0	0	0	115	3.4	656	85	249	71
0	0	1	109	1.9	663	86	531	119
0	1	0	N/A	N/A	N/A	N/A	N/A	N/A
0	1	1	106	0.2	794	56	1257	124
1	0	0	116	1.2	547	12	365	24
1	0	1	107	1.8	778	170	774	164
1	1	0	119	2.6	514	4.2	886	79
1	1	1	107	1.8	775	149	1315	194
N/A: no retrofit strategies for this case 1: windows retrofitted on this building 0: windows not retrofitted on this building								

334 With the same data-exploration methods, we focused the analysis on insulation thickness. Even if thermal
 335 conductivities of insulations are different, it is a fair approximation of the global behavior of the optimization.
 336 We noticed that insulation proposed on phased optimization tend to be thicker than proposed insulation on
 337 base optimization. This is due to the fact that retrofit actions are limited by the budget in the case of
 338 phased optimization, thus the algorithm proposes solutions where less walls are retrofitted, but with a higher
 339 insulation.

340 For both of the optimization, we can notice that optimal retrofit solutions tend to insulate the largest parts
 341 of the buildings more. For example, optimal strategies for the high-rise building features a good insulation
 342 ($R > 3$ K/W) on vertical walls whereas the thermal resistance of ceilings and floors can be as low as $R = 1, 7$
 343 K/W in some optimal strategies. Similarly, optimal strategies for Building 1 tend to prioritize the insulation
 344 of roofs and ceilings over walls. This is due to the fact that this building is low-rise and features a greater
 345 amount of windows on vertical walls (27% of vertical surface).

346 Finally, we can conclude that the content of the optimal retrofit strategies does change with the integration
 347 of temporality. The same conclusion can be drawn for sequenced and phased optimization, and that increase
 348 the confidence we have in the result of the optimizations even with the convergence difference shown in
 349 section 4.2. Moreover, the fact that the differences between optimal strategies proposed for base and phased
 350 optimization can be explained is increasing our confidence into the results.

351 **4.2.2 Utility of the integration of phasing**

352 Originally, the motivation for the integration of phasing is to get closer to real world practice. The integration
 353 of phasing was done in the optimization and gave sensible results, in accordance with the base optimization
 354 and with real world figures. The question is now whether the integration of phasing proposes different
 355 solutions than the base optimization. In order to compare strategies proposed in the base and phased
 356 optimization, we plotted the performance of the building on its final state, i.e. on the last year of the 20
 357 years period considered for the evaluation of the performance. This plot is available on Figure 13.

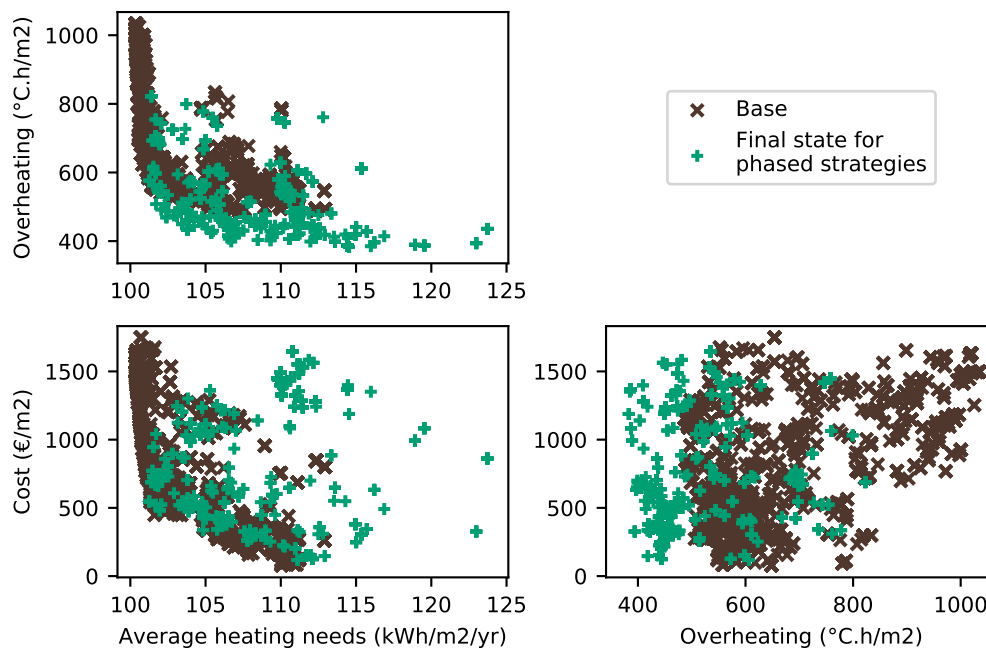


Figure 13: Comparison of final state of optimal retrofit

358 First of all, Figure 13 show that final states of phased optimal strategies have not the same performance
 359 than optimal strategies generated in base optimization. Indeed, retrofit strategies on Pareto front for phased
 360 optimization have in average a better performance on overheating objective and have in average a worse
 361 performance on the cost and heating needs. Moreover, as stated in Section 4.2.1, strategies differ between
 362 base and phased optimization mainly concerning the choice of windows to be retrofitted. This implies that
 363 the implementation of phasing in the optimization results in different optimal strategies than those proposed
 364 by the base version of the optimization.

365 4.3 Benefits and limitations

366 In the literature, sequenced optimization of energy retrofit started to be taken into account [14] but was
367 limited to one retrofit action per year. The real world practice in construction is to break down a major
368 retrofit operation in small phases containing multiple retrofit actions per year: the method aims to replicate
369 this practice.

370 The proposed method enables the elaboration of optimized retrofit strategies for a small building stock
371 and includes a temporal dimension in each strategy, in order to describe how the retrofit action should
372 be planned. Results show a small improvement between the performance of the proposed strategies when
373 compared to an optimization without phasing. The main result is that proposed strategies differ when the
374 optimization is carried out with phasing.

375 The major implication of this finding is that optimal strategies depend on how the problem is formulated
376 compared to the reality of retrofit actions: the closer the optimization process to the constraints of the
377 property manager, the more relevant the results will be .

378 Limitations of the work relates to two main areas. First of all, the cost criteria could be improved by
379 accounting inflation, or by optimizing the life-cycle cost of the building, as proposed by Milic et al. [30].
380 This would bring a new economy metric to the decision maker, although the construction cost would remain
381 a strong constraint for the realization of the retrofit work.

382 Secondly, the optimization algorithm, NSGA-II, is suitable for our problem with 12 parameters and 3
383 objective functions [31, 32]. Some limitations have however been found on the quality of the Pareto front
384 generated which can be improved by NSGA-III [33], especially on constrained optimization.

385 5 Conclusion

386 A method is proposed for the elaboration of optimal retrofit strategies of building stocks, including the
387 planning of retrofit actions over time. We applied this method on a small building stock of three buildings
388 as a test case.

389 The major finding is that integrating the temporal aspect of operations into the optimization leads to
390 different optimal strategies. The major difference between phased and non-phased strategies is illustrated
391 with the order of windows retrofit along the buildings of the stock. This difference is illustrated on Figure 9,

392 as we can see that objective function values are improved on the cost but can not be as good on the heating
393 needs and overheating objective, as explained in Section 4.1. This highlights the importance of formulating
394 the optimization problem as close as possible to the constraints of decision makers, in order to generate
395 realistic and useful optimal strategies.

396 Once the method proposed in this paper is applied, resulting strategies can then be limited to a few
397 strategies through multicriteria decision aid with the decision maker, in order to account for non-measurable
398 objectives such as politics, feeling of the tenants... This guarantees that the decision maker is part of the
399 process while ensuring that the final decision is optimal.

400 Considering the importance of the formulation of the problem on the relevance of optimal strategies,
401 further studies can be carried out to evaluate the sensitivity of the problem to different parameters such
402 as climate change or occupant behavior. The variability of the weather can also be investigated as more
403 frequent heatwaves may influence the overheating objective. Lastly, an additional objective function can be
404 optimized as well, such as an environmental objective (CO₂ emitted by the building along its life cycle and
405 environmental cost of the retrofit).

406 Acknowledgments

407 The authors would like to acknowledge French National Research Agency (ANR) for its funding within
408 ANR-15-CE22-0011 Reha-Parcs project.

409 References

- 410 [1] International Energy Agency, “Statistics — World - Total Primary Energy Supply (TPES) by source
411 (chart),” 2012.
- 412 [2] M. Babiker, P. Bertoldi, M. Buckeridge, A. Cartwright, M. Araos Maldives, S. Bakker, A. Bazaz,
413 E. Belfer, T. Benton, H. de Coninck, A. Revi, M. Babiker, P. Bertoldi, M. Buckeridge, A. Cartwright,
414 W. Dong, J. Ford, S. Fuss, J. Hourcade, D. Ley, R. Mechler, P. Newman, A. Revokatova, S. Schultz,
415 L. Steg, T. Sugiyama, V. Masson-Delmotte, P. Zhai, H. O. Pörtner, D. Roberts, J. Skea, P. Shukla,
416 A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. R Matthews, Y. Chen, X. Zhou,

- 417 M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield, "Chapter 4 - Strengthening and
418 Implementing the Global Response," p. 132, 2018.
- 419 [3] Programme Rage, *Analyse détaillée du parc résidentiel existant*. 2017.
- 420 [4] N. Kohler and U. Hassler, "The building stock as a research object," *Build. Res. Inf.*, vol. 30, no. 4,
421 pp. 226–236, 2002.
- 422 [5] D. Gossard, B. Lartigue, and F. Thellier, "Multi-objective optimization of a building envelope for thermal
423 performance using genetic algorithms and artificial neural network," *Energy Build.*, vol. 67, pp. 253–260,
424 2013.
- 425 [6] K. Mela, T. Tiainen, and M. Heinisuo, "Comparative study of multiple criteria decision making methods
426 for building design," *Adv. Eng. Informatics*, vol. 26, pp. 716–726, oct 2012.
- 427 [7] A. N. Gade, T. S. Larsen, S. B. Nissen, and R. L. Jensen, "REDIS: A value-based decision support tool
428 for renovation of building portfolios," *Build. Environ.*, vol. 142, no. June, pp. 107–118, 2018.
- 429 [8] I. Costa-Carrapiço, R. Raslan, and J. N. González, "A systematic review of genetic algorithm-based
430 multi-objective optimisation for building retrofitting strategies towards energy efficiency," *Energy Build.*,
431 vol. 210, 2020.
- 432 [9] O. Pasichnyi, F. Levihn, H. Shahrokni, J. Wallin, and O. Kordas, "Data-driven strategic planning of
433 building energy retrofitting: The case of Stockholm," *J. Clean. Prod.*, 2019.
- 434 [10] G. Guariso and M. Sangiorgio, "Multi-objective planning of building stock renovation," *Energy Policy*,
435 vol. 130, no. March, pp. 101–110, 2019.
- 436 [11] J. Zhou, P. E. Love, X. Wang, K. L. Teo, and Z. Irani, "A review of methods and algorithms for
437 optimizing construction scheduling," *J. Oper. Res. Soc.*, vol. 64, no. 8, pp. 1091–1105, 2013.
- 438 [12] D. N. Grant, J. J. Bommer, R. Pinho, G. M. Calvi, A. Goretti, and F. Meroni, "A prioritization scheme
439 for seismic intervention in school buildings in Italy," *Earthq. Spectra*, vol. 23, pp. 291–314, may 2007.
- 440 [13] F. Taillandier, G. Sauce, and R. Bonetto, "Elaboration of a long-term maintenance plan for building
441 stock based on arbitration using a risk approach," *Eur. J. Environ. Civ. Eng.*, vol. 13, pp. 383–397, apr
442 2009.
- 443 [14] M. Rivallain, *Étude de l'aide à la décision par optimisation multicritère des programmes de réhabilitation
444 énergétique séquentielle des bâtiments existants*. PhD thesis, jan 2013.

- 445 [15] ASHRAE, “ANSI/ASHRAE 55-2004: Thermal Environmental Conditions for Human Occupancy,” tech.
446 rep., 2004.
- 447 [16] R. Evins, “A review of computational optimisation methods applied to sustainable building design,”
448 *Renew. Sustain. Energy Rev.*, vol. 22, pp. 230–245, jun 2013.
- 449 [17] G. Valkanas, A. N. Papadopoulos, and D. Gunopulos, “Skyline ranking ?? la IR,” in *CEUR Workshop*
450 *Proc.* (M. Schoenauer, K. Deb, G. Rudolph, X. Yao, E. Lutton, J. J. Merelo, and H.-P. Schwefel, eds.),
451 vol. 1133 of *Lecture Notes in Computer Science*, pp. 182–187, Springer Berlin Heidelberg, sep 2014.
- 452 [18] V. Machairas, A. Tsangrassoulis, and K. Axarli, “Algorithms for optimization of building design: A
453 review,” *Renew. Sustain. Energy Rev.*, vol. 31, pp. 101–112, mar 2014.
- 454 [19] F.-A. Fortin, F.-M. De Rainville, M.-A. Gardner, M. Parizeau, and C. Gagné, “DEAP : Evolutionary
455 Algorithms Made Easy,” *J. Mach. Learn. Res.*, vol. 13, pp. 2171–2175, 2012.
- 456 [20] F.-A. Fortin and M. Parizeau, “Revisiting the NSGA-II crowding-distance computation,” *Proceeding*
457 *fifteenth Annu. Conf. Genet. Evol. Comput. Conf. - GECCO '13*, p. 623, 2013.
- 458 [21] V. A. Cicirello and S. F. Smith, “Modeling GA Performance for Control Parameter Optimization 2
459 Largest Common Subgraph Genetic,” 1995.
- 460 [22] F.-M. D. D. Rainville, C. Gagné, O. Teytaud, D. Laurendeau, F.-M. D. D. Rainville, C. Gagné, O. Tey-
461 taud, and D. L. E. Op, “Evolutionary Optimization of Low-Discrepancy Sequences,” *ACM Trans. Model.*
462 *Comput. Simul.*, vol. 22, pp. 1–25, mar 2012.
- 463 [23] CSTB, “Arrêté du 30 avril 2013 portant approbation de la méthode de calcul Th-BCE 2012 prévue aux
464 articles 4, 5 et 6 de l’arrêté du 26 octobre 2010 relatif aux caractéristiques thermiques et aux exigences
465 de performance énergétique des bâtiments nouveaux et des,” *J. Off.*, vol. n0106: 77, 2012.
- 466 [24] R. Andersen, V. Fabi, J. Toftum, S. P. Corgnati, and B. W. Olesen, “Window opening behaviour
467 modelled from measurements in Danish dwellings,” *Build. Environ.*, vol. 69, pp. 101–113, 2013.
- 468 [25] F. Haldi and D. Robinson, “Interactions with window openings by office occupants,” *Build. Environ.*,
469 vol. 44, no. 12, pp. 2378–2395, 2009.
- 470 [26] A. Litvak, K. Guillot, M. Kilberger, and D. Boze, “Airtightness of French dwellings Results from field
471 measurement studies,” *Proc. 21st AIVC Annu. Conf. “Innovations Vent. Technol. 26-29 Sept. 2000*,
472 no. September 2000, pp. 1–12, 2000.

- 473 [27] M. Heidarinejad, N. Mattise, M. Dahlhausen, K. Sharma, K. Benne, D. Macumber, L. Brackney, and
474 J. Srebric, “Demonstration of reduced-order urban scale building energy models,” *Energy Build.*, vol. 156,
475 pp. 17–28, 2017.
- 476 [28] J. Wright and A. Alajmi, “The robustness of genetic algorithms in solving unconstrained building op-
477 timization problems,” in *IBPSA 2005 - Int. Build. Perform. Simul. Assoc. 2005*, no. November, (Mon-
478 treal), pp. 1361–1368, 2005.
- 479 [29] E. Zitzler, L. Thiele, and M. Laumanns, “Performance Assessment of Multiobjective Optimizers: An
480 Analysis and Review. IEEE Transactions on Evolutionary Computation,” *IEEE Trans. Evol. Comput.*,
481 vol. 7, no. 2, pp. 117–132, 2002.
- 482 [30] V. Milić, K. Ekelöw, M. Andersson, and B. Moshfegh, “Evaluation of energy renovation strategies for
483 12 historic building types using LCC optimization,” *Energy Build.*, vol. 197, pp. 156–170, aug 2019.
- 484 [31] D. Tuhus-Dubrow and M. Krarti, “Genetic-algorithm based approach to optimize building envelope
485 design for residential buildings,” *Build. Environ.*, vol. 45, pp. 1574–1581, jul 2010.
- 486 [32] M. Hamdy, A. T. Nguyen, and J. L. Hensen, “A performance comparison of multi-objective optimization
487 algorithms for solving nearly-zero-energy-building design problems,” *Energy Build.*, vol. 121, pp. 57–71,
488 jun 2016.
- 489 [33] G. Campos-Ciro, F. Dugardin, F. Yalaoui, and R. Kelly, “A NSGA-II and NSGA-III comparison for solv-
490 ing an open shop scheduling problem with resource constraints,” *IFAC-PapersOnLine*, vol. 49, pp. 1272–
491 1277, jan 2016.