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Abstract

Reduction of energy consumption in the building sector has been identified as a major instrument to tackle global climate change and improve sustainability. In this paper, we propose a methodology to address a retrofit planning problem at a community level, with a building resolution. The resulting tool helps local decision-makers identify pertinent actions to improve the environmental behavior of their territories. Two building retrofit levers are considered, namely envelope insulation and heating systems replacement. Retrofit planning is treated here as a single-objective optimization problem aimed at reducing the total costs of retrofit actions by minimizing their net present value. A multidimensional multiple-choice knapsack problem formulation is proposed through the adoption of adequate decision variables. It suitably balances the complexity induced by the large number of potential retrofit action combinations and the number of variables in the problem and permits a linear formulation. An optimization of virtual building stocks is performed to highlight the developed model's capacity to tackle large problems (5,000 buildings) in a few minutes. Finally, three analyses finally are led on a real case-study territory, featuring both appropriate retrofit solutions and building stock information. Long-term evaluation of retrofit strategies over the short-term results in an additional 10% reduction of energy consumption and greenhouse gases emissions and encourages thermal insulation. When targeting a 40% reduction in energy demand, retrofit costs ranging from 20 to 800€/m^2 are observed. Finally, the developed method was used to draw a CO^2 abatement cost curve at territory level. A 70% reduction of emissions can be achieved with costs under 50 €/tCO_2e.

Keywords: Energy savings, Retrofit, Linear Integer Programming, Cost optimization, Knapsack Problem, Territory scale

1. Introduction

Final energy consumption mainly originates from three sectors: industry, transport and building. In 2016, the building sector accounted for about 29.7% of energy consumption worldwide, divided into residential (21.6%) and commercial and public service (8.1%) usages [1]. In the European Union, the building sector represents nearly 40% of energy consumption [2]. In recent decades, many efforts have been made to control and reduce building energy consumption, mainly driven by heating and cooling demand and supply, which involves defining global strategic orientations and objectives at national and international levels.

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Achieving such targets requires commitment from local decision-makers to the energy transition process, as the definition of concrete measures is highly dependent on local context [3]. For instance, in France, action plans have to be drawn up at various geographical scales by the corresponding authorities to define their own territory's strategy to achieve a cleaner future [4].

Consequently, designing retrofit measures is a major concern for local decision-makers who want to improve the energy efficiency of the building stock they manage, as part of the wider problem of energy planning in the context of energy transition. Energy planning in cities and territories is a complex procedure that can seem overwhelming to decision-makers [5] due to multiple stakeholders, problems and solutions, complexity and uncertainty, and sometimes unstable contexts, all of which call for adequate methods and decision-support tools at territory scale [6, 7].

In view of this growing need for decision-aid tools at territory-scale, several studies address the assessment of building retrofit potential at national, regional and urban scales [8–10]. As a complement, this work focuses on identifying the most efficient retrofits to be activated with a view to meeting macro strategic targets. In doing so, the designed methodology aims at giving decision-makers practical advice i.e. at building level, on undertaking building-envelope and energy-system retrofits on their building stock.

Bottom-up approaches model heating needs from the underlying physics phenomena, which makes them particularly well-suited to modeling integrated energy supply-demand technologies and explains their common use in urban building energy models (UBEM) [11]. Dynamic models, such as the EnergyPlus building performance simulation software [12], consider detailed and complex behavior equations appropriate for modeling the energy demand of buildings. These models are also widely employed in retrofit optimization approaches using simulation-based algorithms [13]. Three major and similar works [14–16] integrate physics-based energy demand simulations into a multi-objective optimization of building-envelope retrofits, considering four objective axes. Due to the complexity of the integrated model, the study cases featured in these three papers consider a single building. Jie et al. [17] optimize the retrofit of a building by considering the heating and cooling demands as cubic functions of continuous decision variables that describe the insulation thickness of the exterior walls and roof. A case study quantifies the impact of the insulation thickness on objective functions depending on, e.g., heat generation technology, considering a single apartment block in China.

The above research promotes the observation that the complex energy demand models considered, i.e. dynamic simulation tools or non-linear models, result in a highly complex problem for a single-building retrofit optimization. The complexity and temporal resolution of the underlying models induces prohibitively high data and time requirements when the problem is scaled up [18]. Moreover, the impacts of the urban environment on the behavior of buildings must be considered [19].

As a consequence, modeling the building energy demand at urban scale requires reducing the problem's dimension, and all the more so for retrofit design problems, which involve numerous decision variables [20].

One option to reduce the dimension of a problem is scenario-based optimization. This approach reduces the decision space by defining, simulating and evaluating scenarios, for instance through Multi-Criteria Decision Analysis (MCDA). This approach has been employed for energy-planning resolution using complex, integrated, physics-based simulation tools [21, 22]. Such methods explore a limited number of action plans as they require manual intervention by decision-makers. Since the entire decision space cannot be covered, the diversity of buildings and potential retrofit combinations are overlooked. Consequently, it is highly probable that the chosen solution will be far from *optimal*.

Another option is to reduce the complexity of the models to make them compatible with urban usage in terms of data and time requirements. He et al. [23] uses a simplified model to optimize building-envelope retrofits of 27 non-governmental organization (NGO) buildings, considering economic and environmental objectives. The usage of steady-state energy demand models is also identified in two multi-objective optimization approaches presented by Asadi et al. [24] and Fan and Xia [25]. They both seek to optimize building-envelope retrofits at building level, based on the fast resolution permitted by binary variables and the usage of a simplified model. Nonetheless, the case studies involved only apply to single buildings, and the consideration of building-envelope retrofits alone oversimplifies the retrofit problem and can lead to suboptimal solutions.

When considering both energy systems and building-envelope retrofits, two kinds of optimization can be adopted, i.e. one-stage optimizations, also called holistic, and multi-stage optimizations. The latter are adopted when complex energy models are involved and numerous combinations of energy-related retrofits are considered [26], which explains their wide use in simulation-based optimization. In contrast, holistic approaches can be used when simpler models are involved or when few retrofits are considered.

To the authors' knowledge, the simultaneous optimization of building envelopes and heating systems has been insufficiently investigated at urban scale, with only two major papers considering this issue. On this subject, Wu et al. [27] consider representative buildings within a study territory on which a limited number of retrofit scenarios are simulated to generate heating energy demand profiles. An optimization of the heating systems for each of the retrofit scenarios is then carried out using an energy-hub approach, leading to an optimal action plan. The case study employed is a large neighborhood, which leads to conclusions on the pertinence of, for instance, certain fuels. In actual fact, the approach involves a two-stage optimization, combining a heuristic approach on each building-envelope retrofit followed by an optimization of the energy systems of the whole community. Jennings et al. [28] also work on large-scale retrofit optimization, but reduce the dimensions of the problems by dividing the territory into spatial nodes, with one representative building modeled per spatial node. The defined problem minimizes the discounted cash flow by adjusting the proportion of retrofitted building envelopes and the replacement of energy systems using an energy-hub approach at each node. Once again, optimization decisions are taken at an aggregated level due to the spatial node approach.

Consequently, both studies provide valuable insights into the energy situation of a local area to quantify its savings potential. Nevertheless, the energy-hub and representative building approaches cannot be used to define concrete recommendations for building owners or to lead targeted construction works on specific buildings, which are highly valuable for local decision-makers. In addition, the heuristic approach is used to avoid optimizing building envelopes and heating systems at the same time, due to their interactions in energy consumption.

Finally, note that most of the papers consider multi-objective optimization, as they adopt an omniscient position and consider opposing objectives [29]. This approach might not suit local decision-makers' considerations, which may for example consider economic objectives as a priority.

In view of the present state of the art and considering the strengths and weaknesses of the described literature, the objective of the present paper is to develop a modeling of the retrofit context at territory-scale: it must enable optimization of both energy-demand and energy-supply retrofits within a holistic approach. It is considered that an urban building model is available, containing credible and sufficient information on the building stock at building level. Urban building energy modeling is out of the scope of this paper, but can be discussed from external references.

The main contributions of this paper are thus fourfold:

- A global modeling environment, compatible with urban-scale evaluations, is set up to represent the energy retrofit context. Economic, environmental and technical indicators are modeled at building level as functions of both building-envelope and heating-system characteristics, taking into consideration their interactions.

- The modeling is integrated into a one-stage, single-objective optimization which reflects decision-makers' considerations. Decision variables are properly defined to build a linear problem, formulated as a variant of a knapsack problem, which can solve large-scale (i.e. neighborhood) retrofit design problems in a reasonable time (a few minutes) with a building-level resolution.

- Three analyses are carried out on a case-study territory, where the optimization algorithm is applied to a real building stock. The results are used to quantify the importance of the evaluation horizon for activated retrofits, determine the distribution of retrofit costs depending on macro-scale objectives, and draw up the abatement costs curve of the building's energy retrofit context.

The present work is divided into four sections. The first section presents the modeling of the retrofit context before introducing the optimization model structure based on the adequate decision variables in the second section. The third section quantifies the performances of the optimization model, while the fourth section presents the results of the optimization process from a case study.

2. Modeling of the retrofit context

The first prerequisite for adequately designing retrofit measures is to properly model the impact of these measures on both investment costs and the energy-related indicators of a building. For this study, two major action types are modeled: (1) demand-side interventions through the activation of building envelope retrofits (BE) and (2) supply-side interventions through the modification of buildings' heating systems (HS). The building envelope includes all elements of a building that induce heat loss to the outside through either conduction or radiation. We assume that the building envelope is divided into four different surfaces, namely roof, floors, walls and windows. The heating system of a building is composed of a heat generation system (HG) and a heat distribution and emission system (HDE). Note that the action of not modifying any elements of the building (i.e. leaving a surface in its initial state or keeping the heating system) is considered as a retrofit measure with null investment costs.

2.1. Decision variables

In many previous works on retrofit optimization, demand-side or supply-side interventions are implemented using binary decision variables [23–25]. As a matter of fact, this formulation faithfully transcribes whether or not the decision-maker is adopting a retrofit solution. The binary decision variables x and y thus represent the activation (1) or not (0) of the different retrofit technologies.

$$x_{b,s,r} \in \{0,1\}, \quad \forall b \in B, s \in S, r \in R_s \tag{1}$$
$$y_{b,h} \in \{0,1\}, \quad \forall b \in B, h \in H_b \tag{2}$$

where

- B - Set of modeled buildings
- S - Set of retrofittable surfaces
- R_s - Set of retrofit solutions available for surface s
- H_b - Set of heating systems available for building b

Only one BE retrofit solution can be installed per surface and only one HS replacement can be performed per building - two statements formulated as constraints by Eq. (3) and (4).

$$\sum_{r \in R_s} x_{b,s,r} = 1, \quad \forall b, s \tag{3}$$
$$\sum_{h \in H_b} y_{b,h} = 1, \quad \forall b \tag{4}$$

$X_b = \{x_{b,s,r}, s \in S, r \in R_s\}$ and $Y_b = \{y_{b,h}, h \in H_b\}$ denote the vectors of all BE retrofits and HS replacement decision variables related to building b.

This decision level allows us to represent the detailed losses and technical solutions of the distinct building elements and to consider potential incompatibilities between certain buildings and technical solutions. For example, exterior wall retrofits may be prohibited by local planning regulations, and some heating systems cannot be installed in buildings for technical reasons. The corresponding technical solutions are made unavailable by forcing relative decision variables to zero.

2.2. Modeling of investments

The investment cost in BE retrofit solution I^{BE} can be calculated for each building b depending on the associated BE retrofit decision variables X_b.

$$I_b^{BE}(X_b) = \sum_{s \in S} \sum_{r \in R_s} x_{b,s,r} C_r^{BE} A_{b,s} \tag{5}$$

where

- A - Area of a BE surface [m^2]
- C^{BE} - Cost of retrofitting the BE (furniture and labor) [€/m^2]
- I^{BE} - Investment cost in the building envelope [€]

Note that C^{BE} does not depend on b and is equal to zero if the surface is maintained in its initial state. The modeling of the investment cost of changing the heat generator I^{HG} and the emission and distribution system I^{HDE} in building b is presented in (6).

$$I_b^{HG}(X_b, Y_b) = \sum_{h \in H_b} y_{b,h} \left(IC_h^{HG} + FC_h^{HG} + VC_h^{HG} Q_b^{peak}(X_b) \right) \tag{6}$$

$$I_b^{HDE}(X_b, Y_b) = \sum_{h \in H_b} y_{b,h} \left(VC_{b,h}^{HDE} Q_b^{peak}(X_b) \right) \tag{7}$$

where

- FC - Fixed cost of HG (furniture) [€]
- I^{HG} - Investment cost in the heat generator [€]
- I^{HDE} - Investment cost in heat distribution and emission [€]
- IC - Installation cost of HG (labor) [€]
- Q^{peak} - Peak load used for HS sizing [W]
- VC - Variable cost of HG and HDE (furniture) [€/W]

The peak load Q^{peak} depends on the thermal behavior of the considered building and is thus impacted by retrofit measures X_b. Its modeling is presented below, by Eq. (17). Note that the cost of the HDE depends on the modeled building b since it is dependent on the previously installed HDE system. Indeed, if the new HG can be connected to the initial heating distribution and emission equipment, there is no need to install a new HDE system and the corresponding HDE costs are set to zero. Both fixed and variable costs are equal to zero if the heating system is not modified.

The final investment cost I is calculated as the sum of the costs of the BE retrofit solution and the HS replacement.

$$I_b(X_b, Y_b) = I_b^{BE}(X_b) + I_b^{HG}(X_b, Y_b) + I_b^{HDE}(X_b, Y_b) \tag{8}$$

2.3. Modeling of heating needs

Dynamic building performance simulation softwares are not appropriate for estimating heating needs at territory scale, and especially for integration into a retrofit optimization problem. Given the level of uncertainties at this scale, the underlying models often require over-complex input data and rely on complex modeling, inducing long computation times and difficult integration into optimization algorithms. One alternative solution is the use of steady-state models, such as ISO 13790, which are known to generally reliably predict heating loads [11]. This steady-state modeling approach neglects the thermal inertia of buildings, which can be justified by the temporal resolution (yearly) and scale (territory) of the evaluation.

Steady-state models are widely observed in the academic literature for energy demand modeling, at both individual-scale [18, 24, 25] and urban-scale [30–32]. They are also employed by authorities for establishing Energy Performance Certificates [33]. These simplified models can be enriched by morphological analysis to consider urban context through topology or shading [34].

Buildings are considered as a single thermal zone, the temperature target is set to 18°C and is presumed to be constant within buildings and from one building to another, so that we do not consider losses between two adjacent buildings. The annual heating needs Q_b of a building b are commonly estimated by considering three heat transfer sources, i.e. thermal loss through the BE surfaces Q^{surf}, thermal loss due to ventilation Q^{vent}, and solar gains through windows Q^{gain} . Eq. (9) accordingly describes the heating needs of a building.

The modification of the air ventilation rate by ventilation systems replacement is not considered in this work. Indeed, it depends not only on the actual ventilation systems, but also on inhabitants' behavior. Nonetheless, the heat losses induced by air renewal in the thermal zone must be included in the heat transfer equation through an air ventilation rate parameter (τ^{vent}). A heating period (HP) is considered, starting on 1$^{\text{st}}$ October and ending on 20$^{\text{th}}$ May. During this period, heat losses are accounted when the outdoor temperature T is lower than a starting temperature T_{st}, which is set at 15°C.

$$Q_b(X_b) = \left(Q_b^{surf}(X_b) + Q_b^{vent} - Q_b^{gain}(X_b)\right) \tag{9}$$

$$Q_b^{surf}(X_b) = DH \sum_{s\in S} \sum_{r\in R_s} x_{b,s,r} u_{b,s,r} A_{b,s} \tag{10}$$

$$Q_b^{vent} = DH \frac{c_{air}}{3.6} \tau_b^{vent} V_b \tag{11}$$

$$Q_b^{gain}(X_b) = \sum_{r\in R_w} IH_{b,w} x_{b,w,r} Sw_{b,w,r} A_{b,w} \tag{12}$$

$$DH = \sum_{\substack{t\in HP \\ T(t)<T_{st}}} (T_{in} - T(t))\Delta t \tag{13}$$

$$IH_{b,w} = \sum_{\substack{t\in HP \\ T(t)<T_{st}}} J_{b,w}(t)\Delta t \tag{14}$$

where

- c_{air} - Volumetric heat capacity of air [kJ/m^3/K]
- Δt - Time step [h]
- DH - Annual degree hours [Kh]
- Q - Heat loss [Wh]
- IH - Annual irradiance hours on windows [Wh/m^2]
- J - Solar irradiance on windows [W/m^2]
- Sw - Solar factor of the surface [-]
- T_{in} - Indoor design temperature [K]

- T_{st} - Heating starting temperature [K]
- T - Outdoor temperature [K]
- τ^{vent} - Air ventilation rate [h^{-1}]
- u - Heat transfer coefficient of an RS applied to a surface [W/m^2/K]
- V - Volume of the building [m^3]
- w - Subscript for windows [-]

To consider the urban context, surfaces are adjusted to consider adjacency between buildings, and a dynamic solar shading model, based on a ray-tracing algorithm, calculates the solar irradiance time-series at the center of each facade of every building (see model 4.2 from Garreau et al. [35]). The annual solar irradiance J on the windows (subscripted as w) is deduced from this detailed simulation, allowing us to consider urban-scale building interactions; it is estimated once and for all as it is not impacted by the considered retrofits.

If a surface is not modified, the thermal coefficient (u) and the solar factor (Sw) are set to the initial state of the surface (u^0,Sw^0), otherwise they are modified depending on the nature of the retrofit.

$$u_{b,s,r} = \begin{cases} u_r, & \text{if replacement (windows)} \\ \frac{u^0_{b,s} u_r}{u^0_{b,s} + u_r}, & \text{if addition (opaque surfaces)} \end{cases} \tag{15}$$

$$Sw_{b,s,r} = \begin{cases} Sw_r, & \text{if replacement (windows)} \\ 0, & \text{if addition (opaque surfaces)} \end{cases} \tag{16}$$

The annual peak load Q^{peak} is calculated similarly, considering the maximal heating needs, which occur at night when the exterior temperature is minimal (i.e. at maximal temperature difference ΔT_{max} and without solar gain).

$$Q^{peak}_b(X_b) = \left(\sum_{\substack{s \in S \\ r \in R_s}} x_{b,s,r} u_{b,s,r} A_{b,s} + \frac{c_{air}}{3.6} \tau^{vent}_b V_b \right) \Delta T_{max} \tag{17}$$

where

- ΔT_{max} - maximal temperature difference [K]

2.4. Cash flows over time

2.4.1. End-of-life replacement

Although immediate impacts are sought (e.g. energy consumption reduction), retrofit strategies are generally evaluated over a long period so as to consider not only investments, but also other costs and benefits induced by the energy consumption reduction.

BE retrofits are considered as long-term investments, discounted once and for all at the beginning of the evaluation period and not replaced during buildings' remaining lifetime. By contrast, heat generators present shorter lifetimes, after which they are considered outdated and in need of replacement.

The original HG is considered as being halfway through its lifetime, after which, and if no HS replacement is activated, it will be replaced by a similar (same type and fuel) but more modern HG, inducing a natural improvement in efficiency. Similarly, modern HGs are also replaced when outdated, but efficiency and other HG characteristics are not modified. A replacement results in a new investment I^{EoL}, non-null if a lifetime is reached and null otherwise, calculated and discounted annually over the evaluation period P and considering a discount rate r [36].

$$I'_b(X_b, Y_b) = \sum_{t \in P} \left(\frac{1}{(1+t)^r} \sum_{h \in H_b} y_{b,h} I^{EoL}_{b,h}(t, X_b) \right) \tag{18}$$

where

- I' - Replacement costs of the heat generator [€]
- I^{EoL} - Investment at end of life [€]
- P - Evaluation period [y]
- r - Discount rate [-]

The residual value of the HG is calculated at the end of the evaluation period, considering a linear depreciation over its lifetime, and is discounted to the global cost.

2.4.2. Billing costs

Billing costs are directly impacted by the retrofit strategy of buildings. Annual billing costs B are derived from the annual energy demand, considering the efficiency and fuel cost of the heating system at each time step of the evaluation period.

$$B_b(X_b, Y_b) = Q_b(X_b) \sum_{t \in P} \left(\frac{1}{(1+t)^r} \sum_{h \in H_b} y_{b,h} \frac{C^e_{b,h}}{\eta_{b,h}}(t) \right) \tag{19}$$

where

- B - Billing costs for heating [€]
- C^e - Energy cost of the fuel used [€/Wh]
- η - Efficiency of the HS [-]

2.5. Modeling of global impact

Similarly to billing costs, energy consumption E and GHG emissions G can be calculated as follows.

$$E_b(X_b, Y_b) = Q_b(X_b) \sum_{h \in H_b} y_{b,h} \frac{1}{\eta_{b,h}} \tag{20}$$

$$G_b(X_b, Y_b) = Q_b(X_b) \sum_{h \in H_b} y_{b,h} \frac{EF_{b,h}}{\eta_{b,h}} \tag{21}$$

where

- E - Annual energy consumption [Wh]
- EF - Emission factor of the fuel [gCO_2e/Wh]
- G - Greenhouse gas emissions [gCO_2e]

3. Optimization model

To respond to local decision-makers' concerns, an optimization model is designed to provide retrofit advice. It considers an economy-based objective function because financial indicators such as investments, net present value and profitability are the most important criteria for local governments and building owners when considering retrofit problems. Nonetheless, decision-makers, and particularly local authorities, do have some obligations concerning e.g. global GHG emissions mitigation and energy consumption reduction, due to either national or regional commitments or their own strategic targets. These restrictions can be considered within the single-objective optimization problem as constraints to be respected.

3.1. Adaptation of decision variables

By adopting separate binary variables to model the installation of BE retrofit solutions and the HS replacement, the energy demand (20) and HS cost (6) formulations introduce non-linearities into the problem through the product of x and y variables. Although this formulation is the most natural and requires the minimal number of decision variables to represent the problem (see Table 1), optimization problems that include non-linearity in either the objective or the constraint functions are complex to solve, all the more so when working with binary variables [37]. The latter are considered as NP-hard problems [38–40]. Some linearization techniques exist to remove the non-linearity, as described by Buchheim and Klein [41], but they introduce a large number of new variables and constraints, making the problem hard to solve when working at territory-scale.

One option to absorb the non-linearity of the optimization problem is to expand all the combinations of BE and HS retrofit solutions, rather than considering independent variables. Although this formulation allows us to consider a linear 0-1 optimization model, it requires a large number of decision variables as described in Table 1.

Taking advantage of the structure of the functions identified above, it is possible to simplify the optimization problem by considering decision variables $Z_b = \{z_{b,s,r,h}, s \in S, r \in R_s, h \in H_b\}$, which couple BE retrofits with HS replacements. The number of variables is intermediary compared with both of the other formulations (see Table 1). New variables z are set to one if both the corresponding BE and the HS retrofits are activated and Z_b are *by construction* equal to the product of X_b and Y_b.

$$z_{b,s,r,h} = \begin{cases} 1, & \text{if } x_{b,s,r} = 1 \text{ and } y_{b,h} = 1 \\ 0, & \text{otherwise.} \end{cases} \tag{22}$$

The non-linearities are thus internalized within the decision variables z. Consequently, the decision variables initially defined can be expressed in terms of the new decision variables.

$$x_{b,s,r} y_{b,h} = z_{b,s,r,h} \tag{23}$$

$$x_{b,s,r} = \sum_{h \in H_b} z_{b,s,r,h} \tag{24}$$

$$y_{b,h} = \frac{1}{|S|} \sum_{s \in S} \sum_{r \in R_s} z_{b,s,r,h} \tag{25}$$

The use of the number of retrofittable surfaces $|S|$ permits a generic expression of y, which does not depend on the index s (Eq. (25)).

3.2. Joint optimization problem

All of the modeled indicators can be expressed as weighted sums of the decision variables Z_b. As a consequence, the joint optimization of building-envelope and heating-system retrofits at territory scale can

Formulation	Nature	Number of variables
Separate HS & BE	Non-linear	$\sum_b (\lvert H_b \rvert + \sum_s \lvert R_s \rvert)$
All combinations	Linear	$\sum_b (\lvert H_b \rvert \times \prod_s \lvert R_s \rvert)$
Coupled HS & BE	Linear	$\sum_b (\lvert H_b \rvert \times \sum_s \lvert R_s \rvert)$

Table 1: Nature and number of variables of each described formulation of the optimization problem

be formulated as a variation of the 0-1 knapsack problem (KP), which often arises in resource allocation problems, no matter which indicators are moved to objective or constraints.

$$
\begin{aligned}
&\underset{Z}{\text{minimize}} \quad \sum_{\substack{b\in B\\ s\in S}} \sum_{\substack{r\in R_s\\ h\in H_b}} z_{b,s,r,h} O_{b,s,r,h} \\
&\text{subject to} \\
&\sum_{\substack{b\in B\\ s\in S}} \sum_{\substack{r\in R_s\\ h\in H_b}} z_{b,s,r,h} f^i_{b,s,r,h} \leq F^i, && i \in K, \\
&\sum_{\substack{r\in R_s\\ h\in H_b}} z_{b,s,r,h} = 1, && b \in B, s \in S, \\
&\sum_{r\in R_s} z_{b,s_1,r,h} = \sum_{r\in R_s} z_{b,s_2,r,h}, && b \in B, s_1, s_2 \in S, h \in H_b, \\
&z_{b,s,r,h} \in \{0,1\}, && b \in B, s \in S, r \in R_s, h \in H_b
\end{aligned}
$$

$$\underset{Z}{\text{minimize}} \sum_{\substack{b\in B\\ s\in S}} \sum_{\substack{r\in R_s\\ h\in H_b}} z_{b,s,r,h} O_{b,s,r,h} \text{subject to} \sum_{\substack{b\in B\\ s\in S}} \sum_{\substack{r\in R_s\\ h\in H_b}} z_{b,s,r,h} f^i_{b,s,r,h} \leq F^i, \quad i \in K \sum_{\substack{r\in R_s\\ h\in H_b}} z_{b,s,r,h} = 1, \quad b \in B, s \in S \sum_{r\in R_s} z_{b,s_1,r,h}$$

where

- K - Set of indicators considered as constraints
- f^i - Respective participation of each variable in the constraint function
- F^i - Overall constraint target
- O - Respective participation of each variable in the objective function

Moreover, the second constraint corresponds to the adaptation of Eq. (3) and (4) when considering the new decision variables Z_b. The third constraint describes the necessity that all decision variables over one surface must correspond to the same activated HS. We call this constraint a *coupling constraint*, which ensures that for any surface s_1 of building b, if one decision variable is activated for a heating system h, it must also be activated for a decision variable corresponding to any other surface s_2 of the same building b.

According to the knapsack problem formalism, the retrofits to be activated on each building are items, the corresponding O are values, the contribution of each retrofit to indicators f^i are weights, and the corresponding targets F^i are provided as the capacity of the knapsack. Due to the coupled nature of the decision variables, the defined optimization problem will be referred to as a Multidimensional Multiple Coupled-choice Knapsack Problem (MMCKP).

In order to represent the local energy retrofit context, the total costs of an investment, also called the net present cost (NPC), are considered as an objective function. They are calculated as the sum of the one-time investments (I) made at the beginning of the evaluation period and the replacement and billing costs (I' and B respectively) induced over the evaluation period.

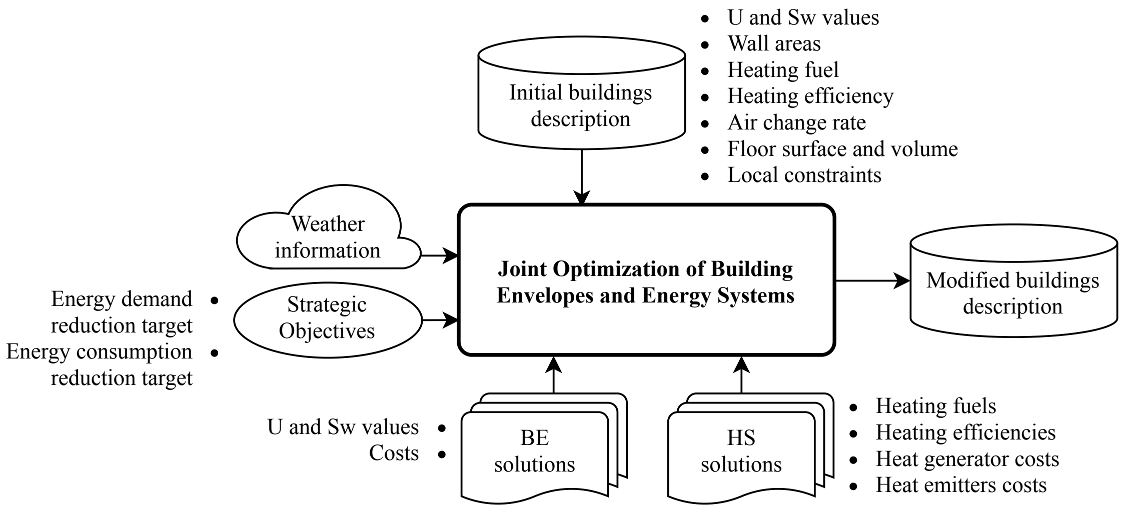

Figure 1: Schematic of the proposed method: Description of the different inputs needed to perform the developed joint optimization and obtain the final state of the territory

$$NPC = \sum_{b \in B} (I_b(Z_b) + B_b(Z_b) + I'_b(Z_b)) \tag{26}$$

where

- NPC - Net present cost [€]

3.3. Model input requirements

Fig. 1 illustrates the proposed method by presenting all of the information required to perform the optimization problem:

- A detailed description of the initial state of the territory. This must include for every building the thermal characteristics of the distinct surfaces and their respective areas, the heating fuels and efficiency of the initial heating system, the air change rate, the building floor surface, and the volume. Building-specific constraints can be provided to reduce the decision space locally.
- A set of building-envelope solutions available for building-envelope retrofits containing the U-values and Sw-values of each technology and the variable and fixed costs.
- A set of heating solutions, combining heat generator technology and emitters and describing the fuel and the efficiency of the solution, along with the variable, fixed and fuel costs.
- The weather information for the modeled territory which will be used to estimate the heating needs and the efficiency of heat pumps.

Finally, a definition of the strategic objectives of the territory in terms of reduction targets can be passed on to the constraints as described in Section 3. Other strategic objectives can be integrated by writing new constraint functions.

4. Experiments

4.1. Implementation details

The optimization problem was implemented on a 3.50 GHz desktop computer with 16 GB of RAM, using R and RStudio language and software [42, 43], and solved with the ILOG IBM CPLEX solver [44].

4.2. Performance of the optimization model

To evaluate the performances of the developed method, a virtual territory is modeled by defining all of the inputs presented in Fig. 1. A virtual building stock description is generated using squared footprints with realistic surfaces, thermal coefficients and heating systems information. Similarly, virtual BE solutions are generated using realistic economic and technical properties, while HS solutions are sampled from a set of real technologies - details on some technology characteristics and calculations are presented in 5.1.3 for the upcoming study case. Weather information is imported at an arbitrary location from IWEC [45] and no strategic objectives are implemented.

As the developed optimization problem is meant to be performed on territories composed of hundreds of buildings, Fig. 2 represents the evolution of the evaluation time when increasing the number of modeled buildings. A fast evaluation time enhances deeper analyses of, for instance, the impact of strategic targets or objective functions on the proposed action plans.

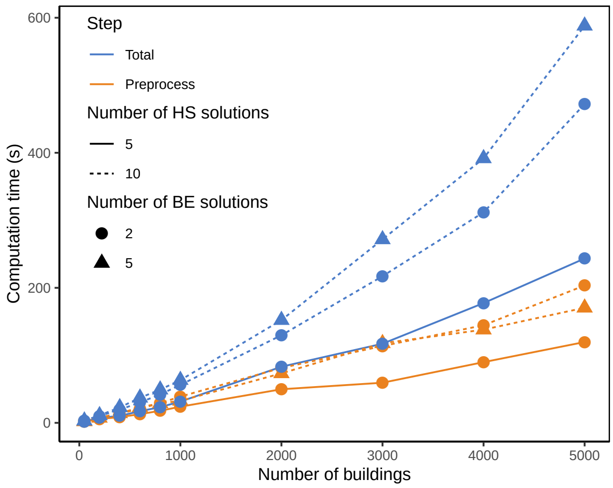

Figure 2: Computational performances of the developed method: Evolution of the computational effort with the number of buildings, HS and BE solutions considered in the evaluation.

The total evaluation time is observed to increase exponentially with the number of buildings, while the preprocess time needed to evaluate the impact of retrofit technologies on each building evolves linearly. The number of BE and HS solutions considered also impacts the computation performances of the algorithm, as they increase the number of decision variables and the preprocess requirements. The number of BE retrofits considered has a limited impact on the computational time due to the simplicity of the calculation, while increasing the number of HS solutions strongly impacts the preprocess and solving burden. The complete evaluation of large territories composed of 5,000 buildings lasts less than 10 minutes. For even larger territories, it might be necessary to group the buildings into representative archetypes or use decomposition methods to speed up the optimization process.

5. Case study: optimizations on a real territory

5.1. Parameters

5.1.1. Weather data

The weather for the French city of Lyon is provided by IWEC weather data [45], including outside temperature (T) and irradiation (J). These weather files are built from the combination of several years of weather data to represent realistic weather conditions.

5.1.2. Definition of BE retrofit solutions

Four surfaces can be retrofitted, namely windows and three opaque surfaces: roof, floors and walls. For each surface, different types of retrofit can be operated. The availability of each retrofit is defined building by building, as local constraints can apply (town planning, typology of buildings etc.). Finally, two levels of retrofit - standard and deep - are defined to represent the possibility of reaching highly efficient buildings if needed. Corresponding technical and economic characteristics are estimated and presented in Table 2.

				Characteristics		Costs
Surface	**Type**	**Retrofit level**	**Technology**	**U-value** (W.m^{-2}.K^{-1})	**Sw-value** (%)	**Variable** (€/m^2)
Wall	Interior	Standard	Glass wool 15cm	0.30	-	65
		Deep	Glass wool 25cm	0.20	-	100
	Exterior	Standard	Glass wool 10cm	0.40	-	120
		Deep	Glass wool 20cm	0.20	-	210
Roof	Rolls	Standard	Glass wool 15cm	0.27	-	15
		Deep	Glass wool 30cm	0.14	-	25
	Boards	Standard	Glass wool 15cm	0.27	-	80
		Deep	Glass wool 30cm	0.14	-	115
	Terrace	Standard	XPS 15cm	0.21	-	80
		Deep	XPS 30cm	0.13	-	95
Floor	Boards	Standard	EPS 10cm	0.33	-	45
		Deep	EPS 15cm	0.23	-	50
Window		Standard	Double glazing	1.8	0.7	300
		Deep	Triple glazing	0.8	0.6	500

Table 2: Economic and technical parameters of the distinct solutions for building-envelope retrofits

5.1.3. Definition of HS retrofit solutions

Recent surveys provide valuable feedback on retrofit solutions activated by private stakeholders in France [46, 47]. Seven common heat generator technologies have been identified, whose technical and economic characteristics are presented in Table 3. Some of the HGs provide a share of the building's total heating needs, such as air-to-air heat pumps and stoves. The remaining heat is presumed to be supplied by decentralized electric panels, which impacts the global efficiencies, fuel costs and emission factors. For the specific case of heat pumps, an efficiency-like seasonal coefficient of performance ($SCOP$) is estimated for the simulated location, depending on the heated water temperature and the outdoor temperature.

The technical and economic hypotheses on heat emitters are listed in Table 4. When compatible, existing heat emitters can be maintained, thus lowering the new HS cost due to an HDE variable cost pulled down to zero. Moreover, we consider that the installation of a heating system requiring an HDE is impossible if no hydraulic loop was initially present, due to the induced cost and works. The initial presence of a decentralized HS forces air-to-air heat pumps and radiant panels to be the only authorized systems.

Finally, the available heating systems per building are obtained through combinations of heat generators and emitters, according to their respective fluid and operating temperatures and considering fuel availability in the building.

			Characteristics			Costs		
Type	**Fuel**	**Technology**	**Emitters**	η (%)	**Share** (%)	**Variable** (€/kW)	**Fixed** (€/u)	**Instal.** (€/u)
Boiler	gas	condensing	LT-HT	0.91	1.0	19	2000	1000
	oil	condensing	LT-HT	0.89	1.0	19	3500	1500
Stove	biomass	pellets	-	0.80	0.5	25	1000	1000
Heat pump	electricity	air-to-air	-	4.57	0.5	415	0	800
		air-to-water	LT	4.08	1.0	415	3000	4000
		air-to-water	HT	3.30	1.0	415	3000	4000
Decentralized	electricity	radiant panels	-	1.00	1.0	290	0	0

Table 3: Economic and technical parameters of the distinct heat generator technologies available

	Efficiency (%)		**Cost**
Emitter	Indiv.	Coll.	(€/kW)
HT	0.94	0.87	510
LT	0.97	0.91	1155

Table 4: Technical and economic hypotheses of emitters

Network and practical restrictions on the available HS retrofits are defined for each building. Biomass is only eligible for individual houses as the storage of pellets or logs requires space and is thus not an option in apartment blocks. Oil-fired boilers can only be installed if the former HG used oil, while gas solutions can be chosen if the building is connected to a gas distribution network. Lastly, electric systems are compatible with every building *a priori*.

The economic and environmental characteristics of fuel costs presented in Table 5 are based on the French energy mix and market [48]. No evolution of the fuel costs over time is considered in this paper.

	Cost (€/kWh)	**Emission** (gCO_2e/kWh)
gas	0.0729	241
electricity	0.1707	190
oil	0.0931	323
biomass	0.0044	39

Table 5: Fuel economic and environmental hypotheses

5.1.4. Initial building description

The modeled territory is a suburban neighborhood featuring mixed housing blocks located in the Rhone district in France. It is composed of 525 buildings accommodating about 2,000 inhabitants in about 800 apartments and 300 individual houses.

Firstly, detailed geographic and structural information must be provided about the building stock of a case-study territory (as presented in Fig. 1) before estimating the irradiation through the shading estimation pre-process, and finally undertaking the retrofit optimization process. The floor areas and volumes of the buildings are directly extracted from geographic information systems (GIS) published by the French national geographic institute IGN [49]. To avoid an over-estimation of the heating losses, an adjacency detection process is employed to evaluate the exterior wall surface, i.e. the total wall surface in contact with the outside and responsible for heat loss. The thermal characteristics of the building walls, the air change rate and the heating system characteristics of each building are attributed through a sampling. The sample data for building characteristics are taken from the PHEBUS survey, carried out by the French statistical institute INSEE [50], and the sampling is carried out on analog groups depending on the age, location and altitude of the buildings. Details on this inference process are provided in [51].

This information reveals a mean building age of almost 80 years (built in 1940) and an initial annual consumption of 31.17 GWh, estimated with the modeling presented in Section 2.

5.2. Results and analyses

The novelty of this work mostly resides in the formulation of the optimization problem to enable analyses at territory scale. Thus, a detailed parametric analysis is left for further research. Nonetheless, three studies are presented below, enhancing the potential of the developed methodology for retrofit strategy analysis and local decision-aiding.

5.2.1. Impact of the horizon of evaluation

When considering net present costs as the objective function to be minimized, the choice of the horizon of evaluation highly influences the results. In parallel, this horizon is crucial for decision-makers and influences their decisions. This choice depends on the point-of-view adopted: a 10-year horizon models the goal of a short-term payback, e.g. a building-owner's position, while 50 years considers all of the costs and benefits occurring during the lifetime of the most durable elements, i.e. building envelope materials.

Consequently, Table 6 displays the results of the optimization considering an evaluation horizon ranging from 10 to 50 years. For this analysis, no strategic targets are defined at territory scale, and the discount rate is set at 5%. For this case-study territory, a reduction of about 25% in energy consumption can be reached by activating profitable retrofits over a 10-year period. This reduction rises to 35.3% when considering the longest lifetime of retrofit elements as a horizon, namely BE retrofits (50 years). The GHG emissions reduction seems mainly driven by energy consumption reduction, which emphasizes the adage that the cleanest energy is energy that remains unused. In consequence, it can be considered that 10% of "free" GHG emissions mitigation might be lost due to the goal of a short-term payback.

		Horizon (y.)				
		10	20	30	40	50
Energy demand	(GWh)	21.75	21.66	21.26	21.26	20.67
Reduction	*(%)*	*4.80*	*5.20*	*6.95*	*6.97*	*9.52*
Energy consumption	(GWh)	23.41	22.55	21.21	21.20	20.17
Reduction	*(%)*	*24.91*	*27.69*	*31.98*	*32.00*	*35.32*
GHG emissions	($ktCO_2e$)	5.21	4.98	4.64	4.64	4.39
Reduction	*(%)*	*27.64*	*30.85*	*35.45*	*35.46*	*38.94*
Net Present Cost	(M€)	17.14	27.20	33.22	36.93	39.13

Table 6: Results of unconstrained optimization of NPC: evolution of energetic, environmental and economic details

While HS retrofits are profitable at short term - about 3/4 of investments consist in HS replacements when considering a 10-year horizon - the share of activated retrofits tends to remain balanced as the evaluation horizon grows (see Fig. 3). Over 30 years, HS investments barely increase: as replacement costs occur cyclically, HS profitability does not evolve over time, unless replacement costs are notably lower than investments due e.g. to initial emitter replacements. BE investments, although high, become profitable in the long term as they do not need replacement or maintenance.

5.2.2. Thermal retrofit costs

The detailed resolution of the method also enables analyses of the diversity of retrofit actions. In particular, Fig. 4 represents the distribution of BE investments normalized by the floor area of buildings and its evolution when considering a demand reduction target at territory scale. Unconstrained optimization leads to a 10% reduction in energy demand, where most buildings are not impacted by BE retrofits. As the energy demand reduction increases, more and more buildings are retrofitted and the distribution is flattened. When targeting a 40% energy demand reduction, all buildings participate in the energy demand reduction: the investment costs range from 18 to 795 €/m^2 and a mean cost of 195€/m^2 is observed.

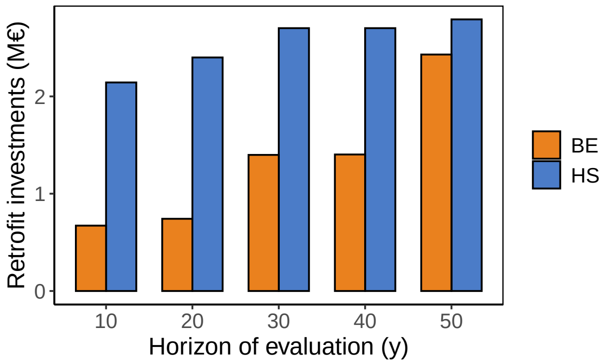

Figure 3: Evolution of investment costs with the evaluation horizon

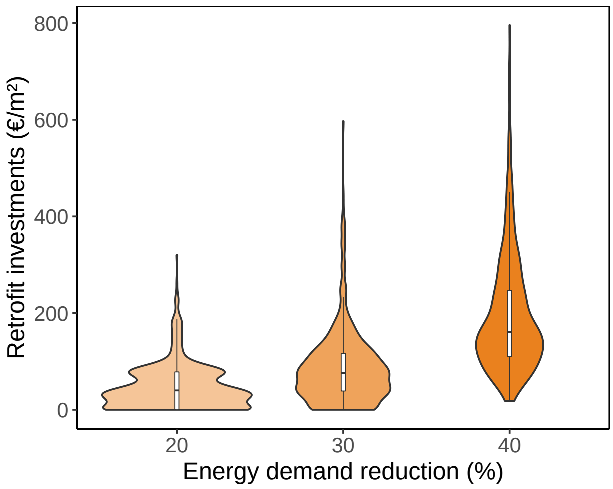

Figure 4: Evolution of building-envelope surfacic costs with energy demand reduction

5.2.3. Abatement costs

The last analysis aims at estimating the GHG abatement costs. For this purpose, the costs and GHG emissions of a base-case scenario (i.e. featuring no retrofits) and scenarios targeting incremental GHG emissions reductions are discounted over a 50-year horizon and compared. Fig. 5 represents the GHG abatement cost curve of the case-study territory. As observed in Table 6, about 35% of GHG emissions can be mitigated at negative costs, meaning that investments are profitable within a 50-year horizon. Very profitable investments are dominated by HS replacements, followed by the more economic thermal retrofits. To reach higher mitigation levels than that induced by profitable retrofits, heating-system replacements are mostly required, resulting in 70% mitigation at limited costs. Indeed, reasonable abatement costs are observed of less than 50€/tCO_2e. Deep retrofits of building envelopes are the only way to attain greater mitigation, involving much higher costs.

5.3. Decision-aiding potential

The modeling of the retrofit context presented in this paper makes it possible to work with a building resolution at territory scale. This modeling improves decision-aiding by providing retrofit information at building level. In view of decision-aiding at territory scale, this granularity allows decision-makers to target a specific area or building where high energy reduction can be achieved while remaining profitable at long term. For instance, Figure 6 displays the optimization results of problem (27), which seeks to maximize

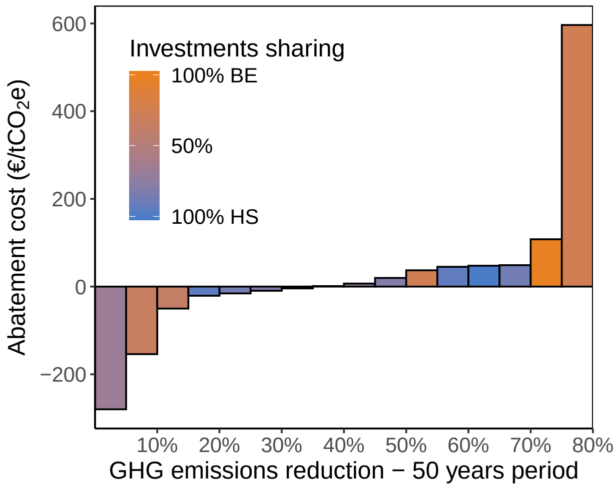

Figure 5: GHG abatement cost curve: The color indicates whether the marginal investments are made in BE or HS retrofits.

energy reductions while ensuring that the undertaken actions are profitable at building-scale. Such analyses are valuable for local decision-makers who can focus their efforts towards the most cost-efficient buildings.

$$\begin{aligned} \max_{Z} \quad & \sum_{b} E_b(Z_b) \\ \text{s.t.} \quad & NPC_b(Z_b) \leq NPC_b^0, \quad b \in B \end{aligned} \tag{27}$$

Figure 6: Visualization of maximum profitable savings on a map to enhance decision-aiding. Map background from OSM [52].

Moreover, this kind of modeling can be used to define building-scale constraints, thus restricting the decision space locally. It allows decision-makers to consider for instance the availability of gas from a network and town planning restrictions.

6. Conclusions and perspectives

This work presented an energy retrofit context modeling at territory scale which can be used to select both building-envelope and heating-system retrofit measures at building level, considering their economic and technical implications. The modeling structure formalizes the retrofit problem as a zero-one optimization, constructed as a variation of the knapsack problem, defined as a multidimensional multiple coupled-choices knapsack problem (MMCKP). The performances of the designed optimization problem were evaluated through virtual realistic building stocks considering variable numbers of buildings and retrofit actions. This study highlights the fast performance of the algorithm on large territories, even when including numerous BE solutions per surface and various HS solutions per building. This problem can thus be solved in high-dimensional contexts, namely large neighborhoods, while in the existing literature optimizations are limited to few buildings.

In a next step, real retrofit solutions were defined and implemented to optimize the retrofit actions on a case-study territory; three studies then highlighted the potential of the tool for decision-aiding and analysis of retrofit potential. A first study presented the optimization results when considering total costs over various evaluation horizons. The horizon proved to severely impact on the activated retrofits, and considering short-term payback over the long term was shown to reduce both energy consumption and GHG emissions mitigation by about 10%. A second study quantified the distribution of BE retrofit costs over buildings. To reach ambitious energy demand reduction targets all buildings need to be involved, but even the most impacted buildings present reasonable costs of under 800€/m^2. Finally, a third study led to the production of an abatement curve of the case-study territory in the energy retrofit context. A very high GHG emissions mitigation level can be achieved at limited cost - less than 50€/tCO_2e - while the remaining emissions need deep, and thus expensive, BE retrofits.

Nonetheless, the present paper has room for improvement. For instance, a more sophisticated energy demand model could be considered as long as it remains compatible with the proposed formalism (i.e. linear along decision variables). This energy demand model should be validated using observation data or simulations from a validated dynamic energy demand model. Many studies could be carried out on the basis of this framework, such as: a sensitivity analysis of the results depending on the technical solutions (costs and characteristics), the urbanization context, the initial stock characteristics etc. The consideration of the life-cycle carbon footprint of the technical solutions could also offer a new angle of discrimination between actions. Finally, this work does not consider network issues such as reinforcement costs due to peak loads appearing on the electric grid with the massive installation of heat pumps for example. Such analyses represent an interesting perspective for research.

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