Dynamic LCA methodology to support post-occupancy decision-making for carbon budget compliance

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Abstract

In response to the climate crisis and ever diminishing global carbon budget targets, managing carbon emissions, particularly during the post-occupancy phase in the building sector, is pivotal. This study presents a novel approach

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Abbreviations*: BAU, Business-As-Usual; CB, Carbon Budget; CMM, Carbon Mitigation Measures; DM, Decision-Making; DP, Dynamic Parameters; DLCA, Dynamic LCA; EE, Embodied Emissions; EOL, End-Of-Life; EI, Environmental Impact; GA, Genetic Algorithm; LCA, Life Cycle Assessment; MOO, Multi-Objective Optimization; OE, Operational Emissions, PC, Parallel Coordinates; SA, Sensitivity Analysis; SM, Surrogate Model*

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that uses a parametric Life Cycle Assessment (LCA) workflow that integrates the temporal dimension to align post-occupancy decision-making with carbon budgets. Applying this method to a French residential case study, this work explores optimization, sensitivity analysis, and different visualization techniques in hopes to inform building actors not only of which carbon mitigation measures to implement, but also when to execute them. The temporal aspect of decision-making proved to be extremely useful as a renovation plan for the remaining building life cycle is proposed. Interestingly however, similar optimization solutions emerged from static and dynamic LCAs despite very distinct Global Warming Potential values, suggesting a possible overlook of dynamic parameters. Findings also illuminate the complexity of conveying multifaceted decision-making information, emphasizing the importance of tailoring solutions. Nonetheless, the specificity of results necessitates further research across varied building typologies. This study is another step towards sustainable building management, underlining the urgency of adhering to carbon budgets.

1 Introduction

Buildings' contribution to greenhouse gas (GHG) emissions was 37% in 2021 [1], underlining the critical role this sector plays in global decarbonization efforts, notably, adhering to the Global Carbon Budget of 400 GtCO2-eq necessary to maintain global warming within 1.5°C [2]. French legislative targets aim at a reduction of 49% in building emissions by 2030 [3]. However, one of the challenges resides in the fact that 80% of the building infrastructure projected for occupancy in 2050 already exist [4]. Hence, the incumbent building stock significantly impacts carbon emission targets, rendering renovations an unavoidable and recurring undertaking [5].

Life Cycle Assessment (LCA) emerges as an invaluable tool in the efforts towards adhering to these carbon targets in the building sector. It facilitates the comprehensive evaluation of environmental impacts (EI) of products and services throughout their lifecycle, as set out in ISO 14040 [6] and ISO 14044 [7] standards. However, the distinctiveness of buildings – specifically their long lifespan and the complexity stemming from the multitude of components – necessitates the introduction of supplementary standards. These include the building-specific LCA standards such as EN 15878 [8] and EN 15804 [9].

In the context of decarbonizing the building sector then, it is pivotal to employ LCAs during the post-occupancy stage, specially renovations. The subsequent assessment of EI is then utilized to assist in decision-making (DM). This process empowers building owners to not just manage carbon emission trajectories, but also to anticipate and react to potential deviations. By doing so, they can continually steer their course towards ensuring carbon budget compliance. Nevertheless, it is important to note that typical LCA approaches often involve replacing components with identical ones at the end of the aging component's reference lifespan. This strategy, however, overlooks the inevitable evolution of the building and its environment, a factor that could significantly impact the carbon trajectory.

In this work then, we propose a methodology for decision-making at post-occupancy stages that includes this temporal dimension. Specifically, we introduce a parametric dynamic LCA (DLCA) methodology. By applying optimization and sensitivity analysis (SA), we aim to identify and evaluate parameters related to carbon mitigation measures (CMMs) towards the goal is to find sets of solutions that comply with carbon budgets (CBs).

To start with this task, a literature review on DLCA and post-occupancy decision-making is made over the next chapter. Subsequently, a methodology is developed, and results are presented from a case-study application. Finally, we will discuss and conclude on the method chosen and the limitations of the work proposed.

2 Literature Review

2.1 Dynamic LCA

While the integration of building renovations and LCA holds significant steppingstones for the decarbonization of the building sector, it is not without methodological challenges. Some of these difficulties stem from the uncertainties surrounding energy consumption and electricity mix decarbonization [5], for instance. Addressing temporal uncertainties necessitates an evolution from traditional static LCA models to more nuanced DLCAs. DLCAs employ time-varying parameters in the assessment of EI, providing a more realistic representation of a building's performance over time [10].

To illustrate, Collinge et al. incorporated the evolution of national electricity mix, energy consumption, and water use into their DLCA [11] [12]. Similarly, Roux et al. factored in global warming scenarios [13], while Negishi [14] and Su et al. [15] proposed novel DLCA methodologies that incorporated a range of dynamic variables, including the radiative forcing of different GHGs. By adding these layers of complexity, DLCAs can generate more accurate EI assessments, ultimately supporting well-informed and timely decision-making [16].

2.2 Decision-making for building environmental performance

Indeed, the unpredictable nature of long-term building performance parameters presents the risk of environmental performances straying from what might be necessary to meet GHG emission targets. To address this, the DM process in building design is increasingly leveraging LCAs, particularly during the early stages. This early integration of LCA into the design process fosters a higher degree of project flexibility [17], [18]. Yet, pre-construction LCAs carry their own uncertainties. Hypotheses and standards in these assessments can deviate from reality, much like the gap between simulated and actual energy consumption – a discrepancy that arises not only from modelling error but also from unexpected occupant behaviour [19]–[22].

2.2.1 Sensitivity analysis

Coupled with LCA, SA assists in the DM process by identifying which parameters have the largest impact in the results [23] and thus, are able to focus on the decisions that matter most. In buildings, SA has seen a plethora of applications, such as finding which daylight strategies have major impact in EE [24], finding the design decisions that matter the most in energy needs, EE and construction costs [25] and for identifying the biggest sources of uncertainty in building LCA [26]. Depending on the method applied however, a great number of samples is necessary, indeed in a variance-based method, such as Sobol SA, a sample size a thousand times larger than the number of parameters is recommended [27].

2.2.2 Optimization

As for optimization techniques, calculating life cycle EI is a daunting task, as building energy simulations are time-consuming and resource intensive [28]. Optimizations can be classified into three categories: type of parameters (discrete or continuous), the number of objectives (single- or multi-objective) and by the type of algorithm (i.e. Genetic algorithm (GA) and Differential evolution) [29]. In the case of building retrofit, which typically deals with the window types, heating fuels and other categorical parameters, the parameters often are discrete. For multi-objective optimizations (MOOs), the objectives have divergent tendencies [28] and in life cycle GWP and the embodied and operational impact often does present this independent behaviour [30], [31].

In building simulations, gradient-free methods have been largely preferred. They are advantageous because gradient-based methods depend on initial predictions, regularity of the objective function, and are often exposed to local minima [32]. One such gradient-free method is GA, which has widely been applied to topics such as energy cost versus thermal comfort [33] or life cycle embodied and operational energy [34]. This algorithm starts with a population of potential solutions, which are then evolved iteratively. In each iteration, the "fittest" solutions are selected and recombined into another population to be used in the next iteration. With a large enough population then, the local minimum problem is avoided.

2.3 Decision-making with DLCA

The field of building DLCA has observed most of its evolution in the past 5 to 10 years. The integration of dynamic parameters (DP) into LCA processes has demonstrated substantial impact. For instance, in one case study, the dynamic Global Warming Potential (GWP) was found to fluctuate between 87% and 108% of its static value, contingent on the DLCA scenario and the time horizon of emissions [30]. This comparison between static and dynamic values is further echoed in studies like [11], [35], [36] and [37].

Nevertheless, to our knowledge, only Van de Moortel et al. [38] have investigated how DLCA influences the decision-making process during building renovation. Their work involved multiple scenarios, including variations in energy mix, degradation of airtightness, and occupant behaviour. Notably, their findings suggest that under certain conditions, a gas boiler could be more preferable than a heat pump. But these choices cannot be made in isolation, as they also stressed the importance of considering the building's remaining service life post-renovation. This consideration stems from the need for the 'investment' in embodied GHG emissions (EE) to be offset by the reduction in operational emissions (OE) over time [38].

2.4 Research gap

Despite the contributions found in the literature, a research gap persists. It is clear from the reviewed literature that the temporal aspect of building LCAs significantly influences outcomes over the multi-decade life cycle of a building. However, the precise impact of this temporal factor and its potential integration into the DM processes remain ambiguous. More specifically, the integration of these dynamic, time-dependent parameters into DM methodologies, especially with a goal of ensuring carbon budget compliance, remains vague.

Addressing this research gap, the methodology detailed in the next chapter proposes an innovative approach that integrates time as a crucial parameter in both the LCA and DM. This novel methodology will involve the parametric calculation of annual operational and embodied emissions over a building's life cycle of 50 years, starting by defining dynamic parameters and renovation/replacement options for the building. The ultimate goal is to inform and facilitate decision-making processes that are committed to carbon budget compliance, addressing the identified deficiencies in current research.

3 Methodology

3.1 Carbon trajectory mitigation measures

In order to correct GHG emission pathways of existing buildings, the following actions were studied included in the simulations. These will be referred to as carbon mitigation measures (CMMs). Additionally, for each of the listed measures, the moment when to apply these changes were defined as a parameter. For replacements, the following elements were considered, which were in line with other building optimization works, such as [39] and [33]:

- Addition of insulation material (material and thickness)
- Addition of Photovoltaic (PV) panels (surface of installation)
- Replacement of the heating system (heating fuel)
- Replacement of the windows (framing material and number of glazing layers)
- Replacement of the ventilation system (heat-recovery system)

It is vital to distinguish between 'addition' and 'replacement'. 'Addition' implies that none of the existing components will be removed to install the new material. Thus, new insulation complements the existing one. This decision aligns with the study's scope—limited to a reference life cycle of the building of 50 years—and hence the insulation installed during construction is still within its lifespan throughout. 'Replacement,' on the other hand, necessitates the removal of an existing component to make room for the new one, as seen in the case of heating systems.

All optimization parameters in this study are integer values, primarily derived from the Environmental Product Declarations (EPDs) available on the French database, INIES [40]. Table 1 lists the heating system types incorporated into this optimization workflow, along with their respective efficiencies, inclusive of heat distribution and emission losses. Table 2 showcases the various combinations of glazing types and frames with their respective conductance and Solar Gain Heat Coefficient (SGHC). Finally, Table 3 associates different insulation thicknesses with each material. Instead of optimizing a real ($\mathbb{R}$) value representing insulation thickness, we opted to create categorical values representing combinations of insulation materials and thicknesses existing in the EPD database.

Table 1 - Heating system types included in the parametric simulations. BAU represents the current heating system in the building, "Joules effect" radiators.

Heating System	Efficiency	Static embodied GWP per unit of heating power [kgCO2/kW]
Natural Gas	*0.90*	*1112.84*
Joule effect radiators	*1.00*	*506.93*
Wood pellet	*0.93*	*1260.21*
LG Air-water HP	*3.72*	*1802.11*
LG Air-air HP	*3.15*	*1529.39*

Table 2 - Number of glazing layers and frame type of glazed surfaces included in the parametric simulations. BAU represents the current glazed surface type in the building.

Glazing Type + Frame	*U-value*	*SGHC*	*Static embodied GWP per window surface [kgCO2/m²]*

Double - Alu+PVC	1.2	0.8	127.85
Triple - Alu+PVC	1	0.5	170.24
Double - Wood	1.4	0.7	50.49
Triple - Wood	1.2	0.5	65.67
Double - Wood+Alu	1.1	0.7	195.2
Triple - Wood+Alu	0.8	0.5	367.84

Table 3 - Insulation materials and their respective studied thicknesses, as each material has different standard thicknesses. BAU represents the current insulation in the building, which is polyurethane panels of 10 cm.

Insulation Material's GWP	***Polyurethane***	***Cotton Wool***	***Glass Wool***	***Wood Fibre***	***Compressed rice straw***	***Wood Straw***
Thinnest	*BAU*	*6 cm/ -0.30 kgCO_2-eq/m^2*	*14 cm/ 3.2 kgCO_2-eq/m^2*	*4 cm/ -0.13 kgCO_2-eq/m^2*	*10 cm/ 0.22 kgCO_2-eq/m^2*	*10 cm/ -11.0 kgCO_2-eq/m^2*
Thin	*10 cm/ 13.7 kgCO_2-eq/m^2*	*8 cm/ -0.39 kgCO_2-eq/m^2*	*16 cm/ 3.8 kgCO_2-eq/m^2*	*8 cm/ -0.48 kgCO_2-eq/m^2*	*20 cm/ 0.44 kgCO_2-eq/m^2*	*20 cm/ -17.4 kgCO_2-eq/m^2*
Thick	*12 cm/ 17.2 kgCO_2-eq/m^2*	*10 cm/ -0.45 kgCO_2-eq/m^2*	*20 cm 5.2 kgCO_2-eq/m^2*	*10 cm/ -0.84 kgCO_2-eq/m^2*	*30 cm/ 0.66 kgCO_2-eq/m^2*	*30 cm/ -23.85 kgCO_2-eq/m^2*
Thickest	*14 cm/ 20.2 kgCO_2-eq/m^2*	*16 cm/ -0.78 kgCO_2-eq/m^2*	*22 cm/ 6.4 kgCO_2-eq/m^2*	*20 cm/ -2.6 kgCO_2-eq/m^2*	*40 cm/ 0.88 kgCO_2-eq/m^2*	*40 cm/ -30.3 kgCO_2-eq/m^2*

The PV panel installation boundaries range from no renewable energy production to the maximum roof surface available for PV installation in the case study, identified as 32 m² and with 3.2 m² steps. The ventilation system is a binary choice, either a humidity-controlled simple-flow mechanical ventilation or a double-flow mechanical ventilation with a heat recovery system. Lastly, the addition of a thermostat in every room with an electric heater is considered. This assumes users can configure the setpoint temperature inside the house to be 4°C lower when unoccupied, for 7 hours of the day. Without this equipment, the building is always conditioned to the setpoint of 19°C.

3.2 Renovation and replacement years

The time of application for each of the identified measures is considered as part of the parametrization process, with different strategies applied for renovations and replacements.

Renovation measures, namely the addition of PV panels or insulation, can be implemented anytime from the current year (i.e., as early as possible) until the year preceding the building's demolition. This interval can be expressed as:

$$Renovation\ Year = [y_{Current}, y_{Building\ EOL}[\qquad , y \in \mathbb{Z}$$

Conversely, the timing for replacements, such as windows or heating systems, is restricted to the period from the current year until the expected end-of-life (EOL) for the existing component. This ensures that the methodology respects the reference life cycle of the component. This interval can be expressed as:

$$Replacement\ Year = [y_{Current}, y_{Component\ EOL}] \quad , y \in \mathbb{Z}$$

In practical terms, consider a building constructed in 2013. Assuming the current year is 2023 and the windows have a 30-year life cycle, the interval for potential window replacement would be from 2023 to the expected window replacement year of 2043. In this same scenario, however, the potential addition of PV panels could be studied anytime from 2023 until 2062. This distinction in approach accommodates the unique factors and impacts of both renovations and replacements in the optimization process.

3.3 Dynamic parameters

Bringing temporal parameters into the decision-making process necessitates the employment of a DLCA workflow, which not only provides more detail, but also elucidates the significance of timing with respect to the optimal decision-making process.

Some DLCA frameworks have been proposed, with the most comprehensive identified in [15], which recognized ten categories of dynamic parameters. These include degradation of components, technological evolution, waste recycling dynamics, and dynamic characterisation. However, implementing a full DLCA framework is a complex undertaking and beyond the scope of this study. In response to this constraint, this study employs a simpler approach based on the French RE2020 norm [41].

Under the RE2020 norm, a decreasing weighting factor is assigned to all GHGs emitted by a building in a given year. The factor linearly decreases from 1 in the building's inaugural year to 0.58 in its 50th year of operation. The equation below outlines the total GWP of a component, where GWP_{total} represents the component's lifecycle emissions, GWP_y its emissions in a given year "y", and F_y the weighting factor for that year.

$$GWP_{total} = \sum_{y=0}^{50} GWP_y \times F_y$$

The components' emissions in the initial year are associated with its A1-5 modules and are not affected by the dynamic parameter, as defined by the EN 15804 [9]. As the building's life cycle progresses, the GHG emissions will have a diminishing impact on its life cycle carbon footprint, encompassing both OE and EE. The subsequent equation illustrates the calculation of the weighting factor, where "y" is the year under consideration.

$$F_y = 1 - \left(\frac{1 - 0.58}{50} \times y\right)$$

In considering this weighting factor, the question of when a renovation should occur becomes more complex as there is an embodied emission incentive to delay renovations. Contrary to a static approach, which incentivizes energy-saving renovations to occur as early as possible, this approach encourages a more judicious temporal strategy.

This policy-related dynamic parameter was established to incentivize the use of bio-based materials [41], which generally exhibit lower A1-5 emissions and greater C1-4 emissions compared to traditional components. This is evidenced in Table 4, which compares a laminated wood beam to a steel beam of the same functional unit. The static emissions of the laminated wood beam are -1.5 kgCO2-eq, but when considering the dynamic calculations, they become -14.6 kgCO2-eq. Conversely, the steel beam's emissions increase from 71 kgCO2-eq in the static LCA to 78.8 kgCO2-eq in the DLCA.

Table 4 - DLCA calculation demonstration comparing a steel and a wood beam with identical functional units for building life cycle of 50 years. Adapted from [42].

Component	*LCA stage*	*Emissions ($kgCO_2$-eq)*	*Weighting factor*	*Dynamic Emissions ($kgCO_2$-eq)*
Laminated wood beam Functional unit: 1 ml of (360 x 170) mm beam Life cycle: 50 years	A1-3	-34.1	F_0=1	-34.1
	A4-5	1.5	F_0=1	1.5
	B1-7	0	-	0
	C1-4	38.9	F_{50}=0.58	22.5
	D	-7.8	F_{50}=0.58	-4.5
	Total A-D	-1.5	-	-14.6
Steel beam Functional unit: 1 ml of (360 x 170) mm beam Life cycle: 100 years	A1-3	80.5	F_0=1	80.5
	A4-5	9.1	F_0=1	9.1
	B1-7	0	-	0
	C1-4	2.5	F_{50}=0.58	1.4
	D	-21.1	F_{50}=0.58	-12.2
	Total A-D	71	-	78.8

In addition, the RE2020 norm uses DLCA to establish carbon budgets for new residences built in France since 2022. These budgets are defined per square meter of liveable area, with limits set for embodied and operational GHG emissions in equivalent carbon-dioxide. These limits are calculated based on location, climate, size, parking space, and other factors. In line with national emissions targets, several budgetary targets have been set for buildings built in various periods: prior to 2023, 2023 to 2025, 2025 to 2028, and post-2031. These budgets provide the reference for this study and are illustrated in Figure 3.

3.4 Parametric DLCA methodology for post-occupancy decision-making

Having established the CMMs and DLCA methodology, we can now define the complete workflow, as summarized in Figure 1. In addition to the previously mentioned inputs, the workflow also requires LCA to establish a business-as-usual (BAU) scenario - a situation in which no CMMs are implemented throughout the building's life cycle. This scenario informs in DM about the carbon trajectory of the building and whether it performs adequately. The final input is the EPD database, which contributed to the creation of Table 1 and Table 3 and all associated GWP values.

In the calculations module of Figure 1, the initial step involves the development of a surrogate model (SM) for OE assessment. The inclusion of a SM is beneficial for the life cycle emissions calculations, since operational impacts are simulated yearly over the 50-year building life cycle. Indeed, the EnergyPlus simulations that would typically take around 16 seconds each (depending on building size and simulation setup), were reduced to approximately 2.3 milliseconds.

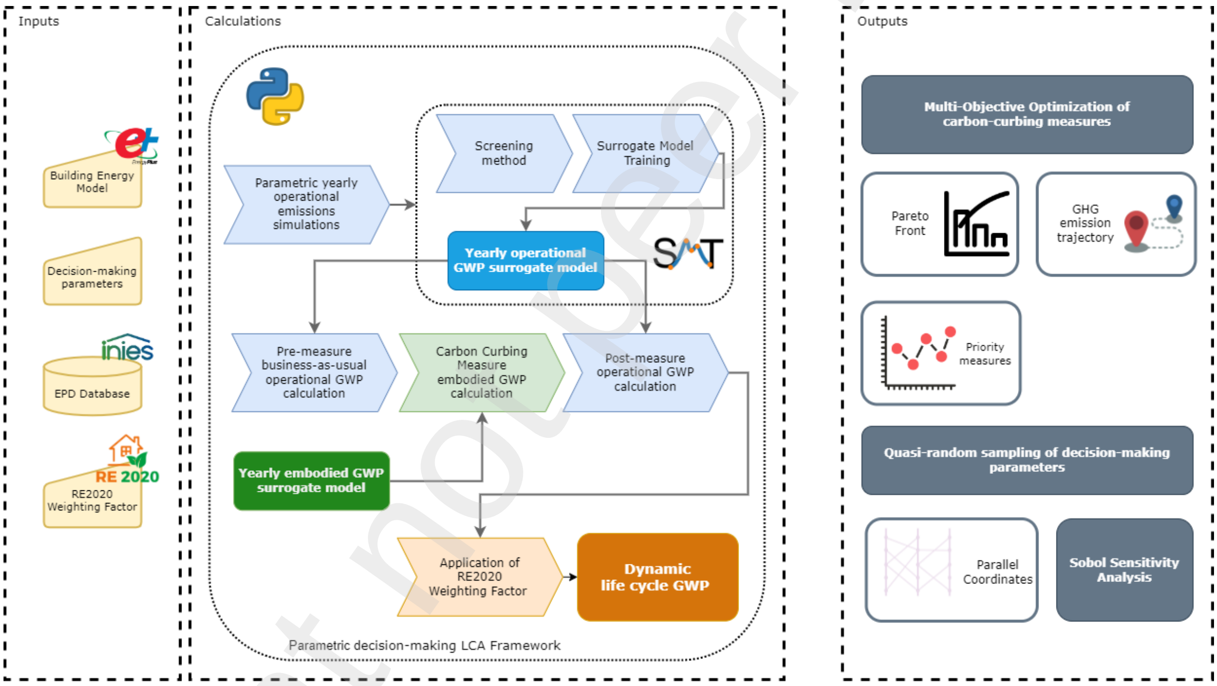

Figure 1 - Full optimization methodology in terms of its inputs, calculations and outputs.

Training this surrogate model required the execution of 1000 one-year energy simulations using EnergyPlus [43], in conjunction with a couple of Python libraries: EPPY [44] for energy model manipulation and simulation management and SMT [45] for the SM's screening method and training. EPPY enabled 40 simulations to run in parallel, while SMT's advantage lay in its ability to incorporate mixed-integer parameters into the training of the SM. The energy simulations, conducted on a server with an Intel Xeon CPU with 40 cores and 80 threads running at 2.2 GHz and 256 GB of RAM, took a total of 55 minutes and 20 seconds.

Sampling was performed using the Latin Hypercube, a quasi-random method common in building applications of SMs [46]. The model training adopted the Kriging interpolation model, given its extensive strategies for dealing with mixed-integer problems [47].

Once the surrogate model is trained, the lifecycle OE can be evaluated in a fraction of a second, and we can proceed to calculate EE. These are primarily dependent on the building components and their quantities, established via a quantity take-off process. Each component is associated with an EPD found in the INIES database, sometimes corresponding to the actual component used, or otherwise replaced by a default component when an exact match wasn't available. This process was executed using an LCA tool named Vizcab [48], which allows all components and their respective quantities, life cycles, and EIs to be exported into an Excel file. This file's data is then processed by a Python script that calculates the building's life cycle embodied emissions. Overall, the complete workflow for operational and embodied life cycle emissions takes about 0.8 second.

With the parametric DLCA calculation modules set up, the thousands of evaluations required for the optimization and the quasi-random sampling were made. In the optimization, the genetic algorithm implemented was configured with a population size of 100 and programmed to explore 100 generations. Each optimization took 1h06min. Meanwhile, 13 thousand samples acquired with the Saltelli sampling were evaluated for the Sobol sensitivity to be executed, which took 3h13min.

The final stage of the workflow is the output, which also is a challenge. The results of these evaluations need to convey an appropriate amount of information for DM not only for which measures to take, but also when to apply them. In the application part of this work then, we'll explore some visualization techniques in the hopes to convey the information detailed below:

- The user should be able to compare a set of solutions to a given target that is set for carbon emission targets or other constraints.
- They also need to be able to compare it to the refence scenario.
- The ability to visualize renovations made through time is particularly important in a dynamic method, specially to track progress.
- The exploration of solution space should also be encouraged and available for the user to find the most adapted solution.
- How important interactivity is for a proper amount of information to be conveyed needs to be analysed as well.
- How the different parameters interact amongst each other is also important.
- The identification of DM parameters that should be prioritized can, of course, be an extremely useful information.

With the methodology establish, we shall now characterize the case-study through which its feasibility was investigated.

3.5 Case-study

The ability to compute annual emissions allows us to observe GHG emissions dynamically, where emission sources become clearer along time. This dynamic visualization is represented by a business-as-usual (BAU) scenario in Figure 2. On the left y-axis, depicted in blue, we can observe that the production and construction stage of the lifecycle (stages A1-5) is responsible for the emission of 50 tCO2-eq. Towards the end of the building's life cycle (stages C1-4), the emissions tally to around 23 tCO2-eq. During the use-stage (stages B1-7), an additional 47 tCO2-eq of GHGs are emitted, contributing significantly to the building's overall emissions.

The right y-axis, shown in red, offers a different perspective: it represents the cumulative sum, or trajectory, of the building's carbon emissions over time. As the building ages, the cumulative emissions present a clear indication of the total environmental impact.

The systematic replacements that cause spikes in emissions are also clearly visible in Figure 2. Different coloured arrows represent different types of components being replaced. Specifically:

1. **HVAC (blue)**: Both the heating and ventilation systems have a service life of 17 years and so they are replaced after 17 and then 34 years of operation.
2. **Glazing (orange)**: The double-glazing windows have a service life of 30 years; thus they are changed only once.
3. **Electrical components (green)**: Plenty of components linked to the electrical installation have a service life of 25 year, requiring a replacement during the building lifetime.
4. **Sanitary elements (yellow)**: A lot of components in the bathroom and kitchen of the residence have a 20-year service life. This means two replacements are made.

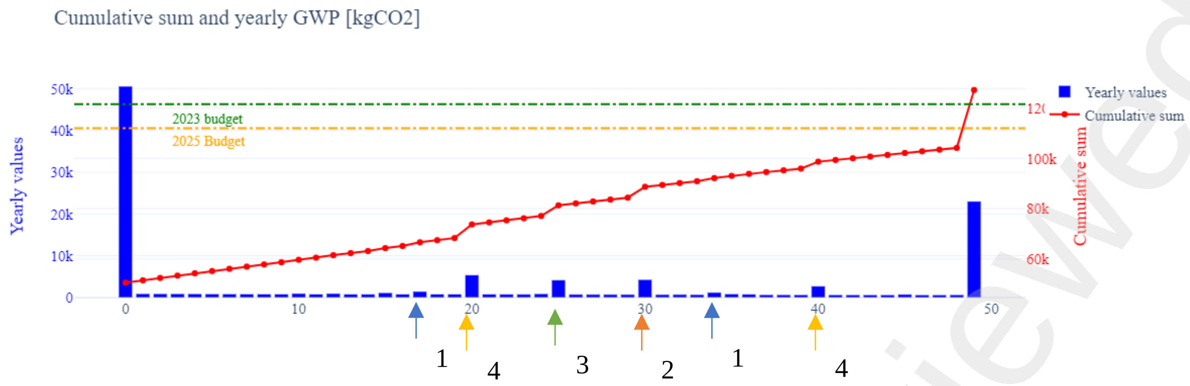

Figure 2 - Yearly instantaneous (in blue) and cumulated (in red) GHG emissions throughout the 50-year lifespan of the building in kgCO$_2$-eq. Mind that the left-axis is in a different scale and does not start at zero.

The case study used in this work focuses on a two-story single-family house near Paris. This concrete slab and cinder block façade construction, with 146 m² of living space and 366 m3 of internal volume, is detailed more extensively in Table 5. It was selected to represent a typical French residence since 55% of French dwellings are single-family homes [49]. These details represent the BAU scenario and with the case-study established, the results will be shown in the following chapter.

Table 5 - Case study main characteristics in a business-as-usual scenario

Characteristics	***Value***
Year of construction	*2017*
Horizontal structure	*Cast concrete*
Façade's structure	*Cinder block*
Insulation material	*Polyurethane*
Opaque surface conductance	*0.25 W/(m².K)*
Glazing type	*Double-glazing*
Glazing frame	*PVC + Aluminium*
Glazed surface conductance	*1.2 W/(m².K)*
Ventilation system	*Simple-flow*
Heating system	*Electrical radiators*
Domestic hot water production	*Heat Pump water heater*
BAU embodied emissions	*562 kgCO^2-eq/m²*
BAU operational emissions	*225 kgCO^2-eq/m²*

4 Results

In this results section, two ways to explore the CMMs and its solution space will be investigated, first with the optimization and then with the quasi-random Saltelli sampling. These methodologies offer complementary ways to find the most adapted solution to a case, depending on the building and its constraints. This chapter is organized into 3 sub-chapters: In the first one, we'll apply the method supposing that the building has been operating for 5 years in a BAU scenario; in the second subchapter, we'll investigate the difference in results that applying the method 20 years after would generate; and lastly, we shall compare the static and dynamic approached to LCA.

4.1 Case study after 5 years of use

4.1.1 Optimization

Each proposed optimization solution is constructed from a mix of measures to be implemented for better environmental performance. The most intuitive visualisation technique in a MOO is a scatter plot featuring the Pareto front of the two objectives. The embodied and operational GWP are displayed on the x- and y-axis, respectively. In this plot, in Figure 3, the life cycle GHG emissions budgets, defined by the RE2020, are included. The BAU scenario, which signifies a case where no measures occur, is also represented in this plot.

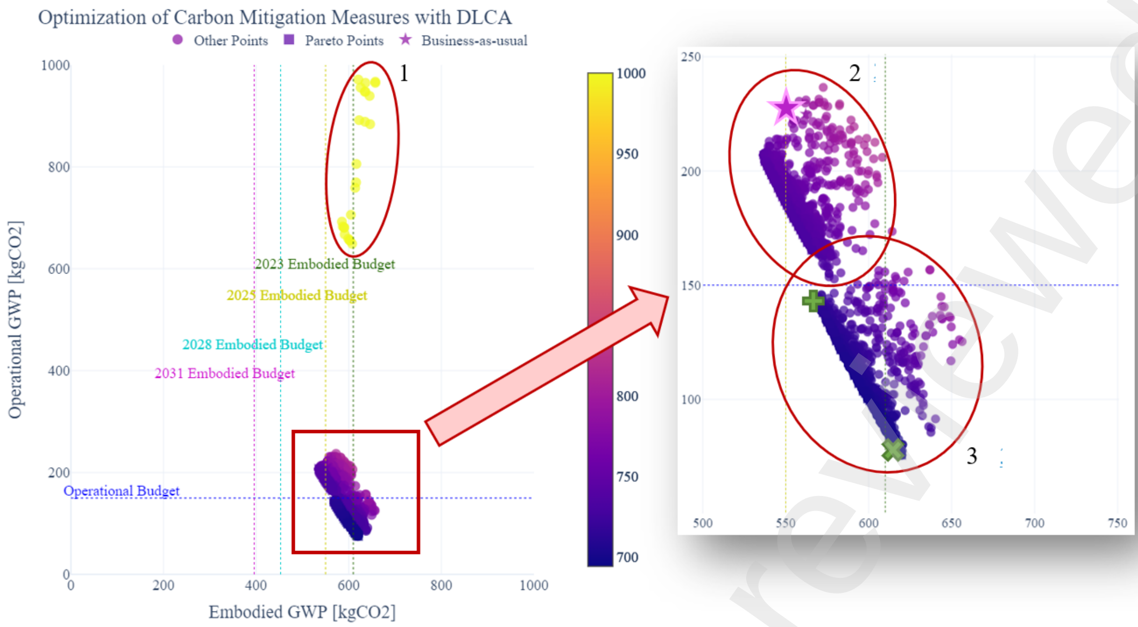

Figure 3 – In this scatter plot, the Pareto Front of the MOO is presented. The dotted lines in the plot represent the carbon budgets defined by the RE2020 norm. The colour scale on the right is the overall GWP, meaning the sum of operational and embodied GWP. On the plot to the right is the same plot at a different scale to better show the pareto front. The green "x" in this plot represents the best solution in terms of overall GWP (Solution 1), whereas the "+" represents the CMMs that most closely satisfy the embodied budget of 550 kgCO2-eq/m² (Solution 2). The BAU scenario, represented by the star, shows a deviation of the building's emissions from its operational targets of 150 kgCO2-eq /m².

From an initial analysis of the scatter plot, three main clusters of solutions can be identified: (1) presents the solutions with a gas boiler replacement; (2) consists of keeping the Joules Effect heating system as is; (3) proposes a drastic enhanced OE by suggesting the installation of heat pumps at the detriment of EE. The variations within the clusters relate to ventilation, photovoltaic system size, timing of the renovations and insulation.

Given that only five years have passed since construction in this first scenario, there's significant "room" for improvement to align the carbon trajectory with the carbon budgets. Indeed, several solutions can amend the OE trajectory to adhere to the operational budget while still complying with the 2023 embodied budget limit of 610 kgCO2-eq/m² (to the left of the green line in Figure 3). However, no solutions were identified that align with the 2025 budget for embodied emissions of 550 kgCO2-eq/m² (to the left of the yellow line in Figure 3).

This work emphasizes the inclusion of time parameters in the decision-making process. In this first scenario, the building has been in operation for 5 years. With the use of MOO, we aim to study the CMMs that can be implemented presently or in the future to reduce this GWP trajectory. The results seen in show a plethora of solutions, where each point includes an extensive list of measures to be undertaken, or a renovation plan. This figure illustrates well the potential reductions in both lifecycle EE and OE, however the temporal aspect of DLCA is completely lost. The user needs to hover over the points in order to explore the proposed solutions.

From Figure 3, two interesting solutions were highlighted, first the most effective solution in terms of overall GWP (the sum of OE and EE) comprises the following measures, resulting in embodied and operational GWP of 617 and 89 kgCO2-eq/m², respectively (hereafter referred to as "Solution 1"):

- Replacement of the glazed surfaces to wood-framed double-glazed windows when the exiting windows reach the end of their service lives at year 30.
- Replacement of heating system to an air-air heat pump at year 6, despite the electric heaters still having 11 extra years in their lifespans. Interestingly, changing the heating system as early as possible (at year 5) increases overall GWP by 0.5 kgCO2-eq/m².
- Addition of bio-sourced insulation as soon as possible, at year 5.
- Installation of 32 m² of PV panels in 2 years' time, at year 7.

These measures drastically cut operational GWP at the detriment of EE. Indeed, it exceeds the 610 kgCO2-eq/m² 2023 budget. However, to adhere as closely as possible to the 2025 embodied budget in yellow, the following measures can be executed, which will be referred to as Solution 2:

- Replacement of the glazed surfaces to wood-framing double-glazed windows at year 30.
- Replacement of heating system to an air-air heat pump (HP) at the end of the current heating system's life cycle at year 17.
- Addition of bio-sourced insulation at year 5.

These measures result in EE and OE of 571 and 149 kgCO2-eq/m² respectively, thus adhering to the operational budget while 21 kgCO2-eq/m² away from the 2025 budget. Figure 4 provides a better visualization of these measures through time. It highlights the introduction of insulation resulting in negative emissions at year 5 and a significant reduction in OE following the heat pump installation at year 17. This visualization provides better understanding of the timing of the CCM, however does not describe the solution space proposed in the Pareto front and fails to indicate the improvements relative to the BAU case.

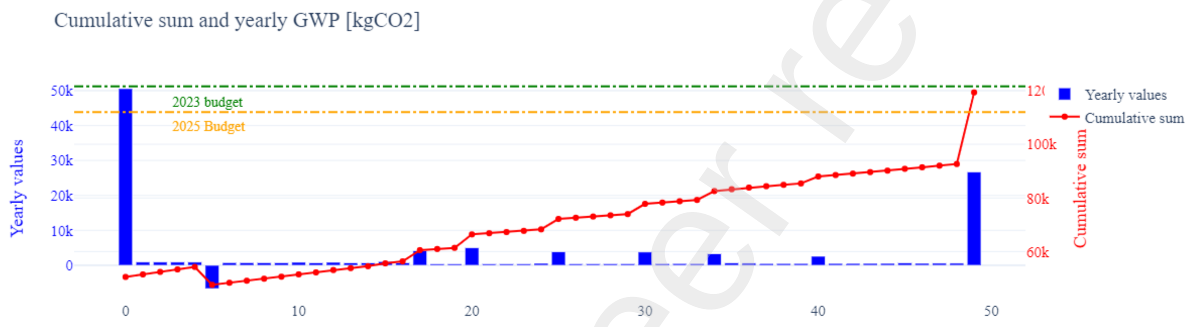

Figure 4 - Yearly and cumulated GWP after applying renovation measures in blue and in red, respectively. This GHG trajectory. Reminder that there are two y-axis and that the one on the right does not start at zero.

To amend this, we examined the optimizer's frequency of parameters proposed in the Pareto front. From this plot shown in Figure 5Figure 5, it is clear that four of the twelve parameters are consistently selected:

- Mechanical ventilation: heat recovery is never added.
- Insulation material: the addition of bio-based insulation as carbon storage is always selected at year 5. Moreover, the largest thickness of insulation is also very frequent.
- Glazing: 2-layered fenestrations is always preferred, although the frame material sometimes diverge. The wood-framed windows are slightly less energy performant, but has a lower EE associated. The recommended year of replacement remains unchanged from BAU, at year 30.

Meanwhile, approximately 65% of the heating system solutions involve the replacement of electric radiators with heat pumps. However, the timing for this replacement seems to be somewhat ambiguous, largely depending on the priority given to operational and embodied emissions. Early replacement of Joules Effect heating with heat pumps minimizes OE but incurs a significant EE cost, because of the high weighting factor at year 5. Conversely, waiting for the existing system to reach its EOL at year 17 reduces the embodied GWP.

The recommendations for a PV system are often high and when PV is factored into the building renovations, the solutions consistently suggest its installation as soon as possible. However, some solutions appear to suggest the decision-maker to wait 4 to 6 more years. Regarding the thermostat, around 90% of solutions regard it as a worthwhile decision.

What this graphical representation allows decision-makers to understand then, is the identification of the systems that can be left in BAU operation Indeed, thanks to this analysis of the pareto front, the choice of ventilation is a complete "no brainer", since under no circumstances is double-flow ventilation interesting. It does not need replacement before its current life cycle ends and the installation of a system with heat recovery is not warranted.

At the same time though, the decision-maker should not simply take the most represented solution for each parameter and apply it to the case-study, as this plot fails to represent how they interact with each other. This interaction can be explored in the scatter plot of Figure 1, but it would still be a rather complicated experience. A more appropriate solution then, shall be explored in the following chapter.

Figure 5 - Parameter count for the solutions in the Pareto Front.

To conclude with this sub-chapter, the optimization gives the decision-makers a set of optimal solutions in the form of a pareto front. This is useful in DM, but a glaring limitation of the proposed methodology is the sole inclusion of GWP, excluding key factors such as cost, intervention time and even other EIs. The solution to rectify this problem then, is to include instead, the idea of enabling the user to explore the solution space.

4.1.2 Quasi-random evaluation

As we delve deeper into the interplay between these parameters, we turn into Parallel Coordinates (PC) plot, depicted in Figure 6. This visualization enables users to observe and explore how different parameters interact with each other. But to derive meaningful insights from such a PC plot, a representative sample from the design space is required. The optimization process, guided by a GA, will instead acquire a lot more detail close to the pareto front.

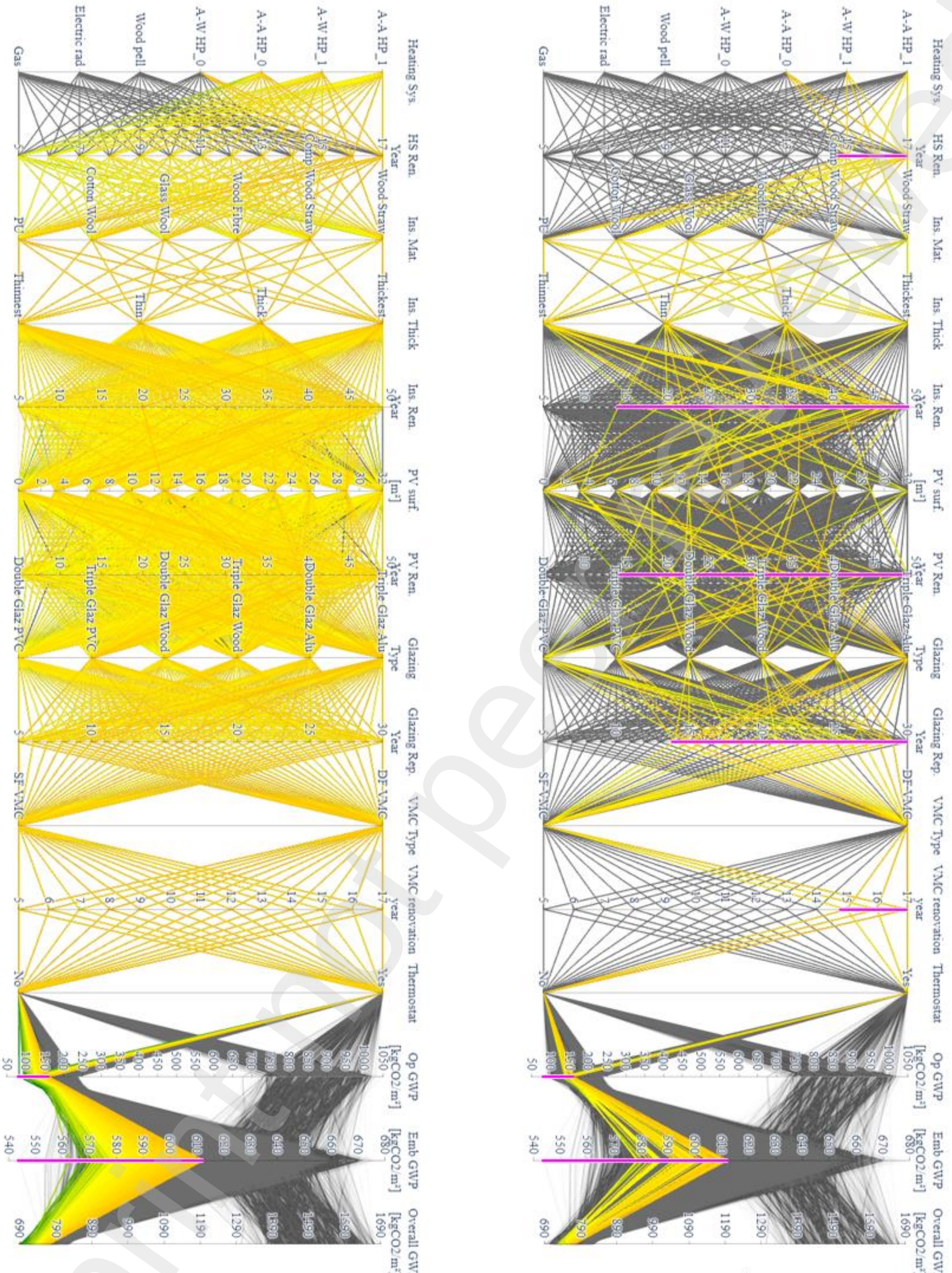

Figure 6a

Figure 6b

Figure 6 – Illustration of Parallel coordinates plot of the 13k simulations acquired from a quasi-random sample of the DM parameters. With interactive filters a decision-maker can explore viable the solutions. On the left, the only filters applied are on the operational and embodied GWP, arcing back to the carbon budgets of 2022. On the right, additional filters are applied to renovation and replacement years.

Then, to generate a representative sample, a quasi-random screening method known as Saltelli sampling was employed, which also allowed a sensitivity analysis of the input parameters on the overall GWP to be executed.

The interactivity aspect of the PC plot is a key feature. For instance, by choosing a maximum GWP – operational, embodied, or overall – the decision-maker can identify immediate necessary actions to achieve that goal. In Figure 6a, the RE2020 carbon budgets have been applied and clearly, some form of heating system replacement will most definitely be required into a more performant heat pump system.

In Figure 6b however, we suppose that the building owners are unwilling to realize any sort of renovation before year 15 and thus, the decision-makers can explore CMMs alternatives that suit these limitations. If an additional constraint is to limit the overall GWP to 750 kgCO2-eq/m², this is only achievable if the building's heating needs are enhanced by installing at least 6 cm of cotton wool insulation by year 8, in 3 years' time. This can be an undesirable and costly renovation, but by showing a bit more flexibility and agreeing to replace the heating system by year 10, a number of alternatives emerge, including the option to avoid all renovations to opaque surfaces.

Clearly then, from Figure 6, heating system seems to be the most basic decision to be made. In order to further investigate this and by utilizing the same samples as in the creation of the PC, a Sobol sensitivity analysis was performed which should inform decision-makers about which decisions matter the most. The results in Figure 7 confirm that the choice of heating fuel is the most critical decision in this case-study. The dramatically high value of this parameter's Sobol indices can be attributed to the consideration of a wide range of heating fuels. From a heat-pump connected to low-carbon electricity to a fossil fuel-dependent boiler, the carbon intensity ranges from 225 gCO2-eq/kWh to 79 gCO2-eq/kWh. This difference becomes even more pronounced when considering the 3- to 4-fold efficiency improvements of a heat-pump system.

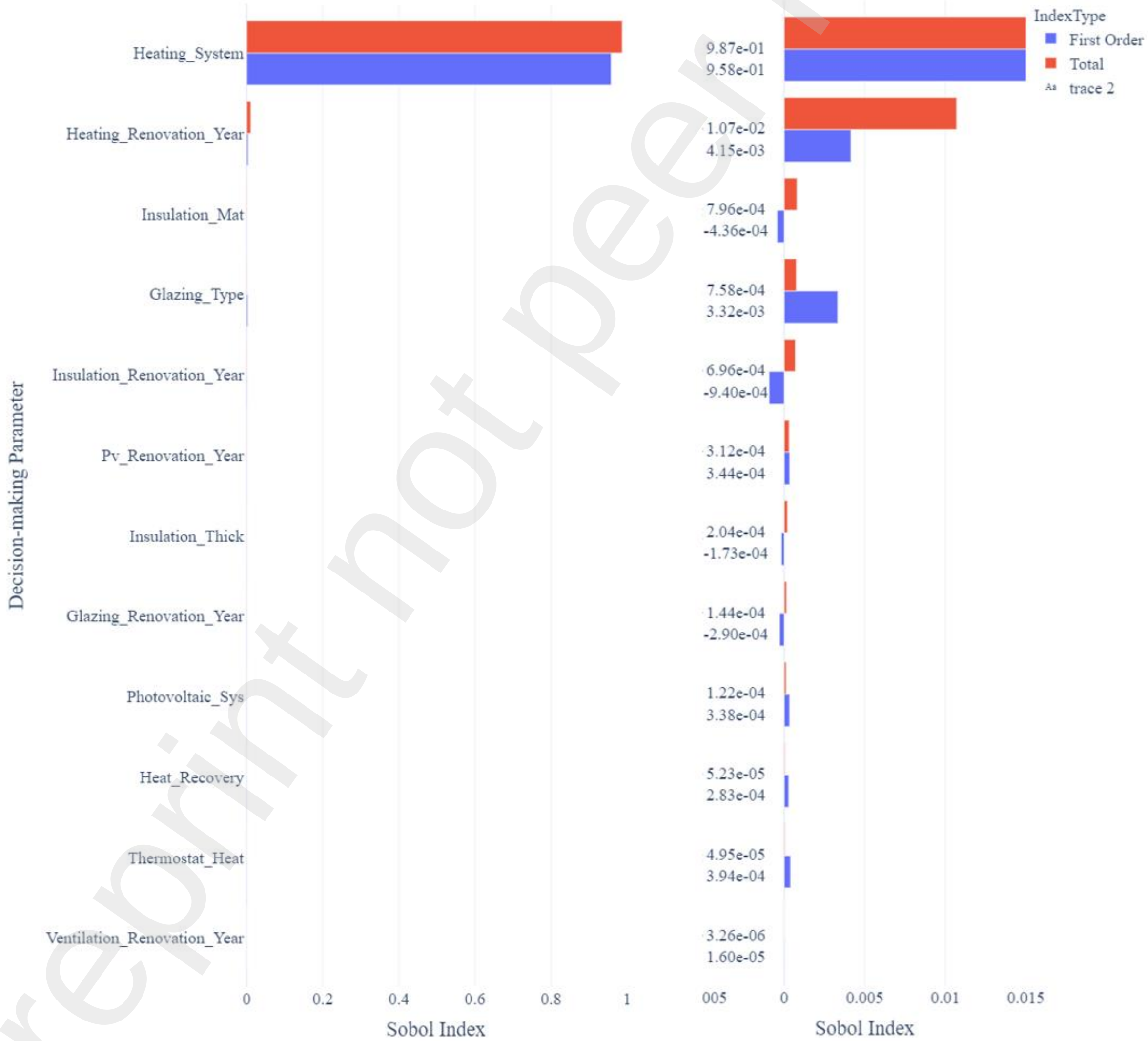

Figure 7a *Figure 7b*

Figure 7 - Sobol indices of the DM parameters after 5 years of building operation. Notice that the x-axis has been truncated in Figure 10b to show the detail of the parameters, since the total index for "Heating_System" is around 0.98, an order of magnitude greater than the second most relevant parameter.

All of the information and visualization techniques demonstrated until now in this chapter convey complementary information to the user. Table 6 analyses how they fair against the requirements listed in the preceding chapter and clearly, no technique score all marks.

Requirements	Pareto	Trajectory plot	Solution frequency	Parallel Coordinates	Sobol Indices
Visible constraints	✓	✓		✓	
Reference scenario	✓	✓			
Temporal view		✓			
Exploration	✓		✓	✓	
Interactivity needed	✓			✓	
Parameter interactions				✓	✓
Priority identification			✓		✓

Table 6 - Comparison between the visualization techniques displayed in the results chapter.

4.2 Case study after 25 years of use

In order to further study the relevancy of the temporal dimension, we have also done the MOO considering that the building operated for 25 years in BAU state (instead of 5). When analysing the Pareto front, the solution with the lowest OE is still greater than the operational budget, meaning the building at year 25 is beyond a point of no return for this objective to be attained. Effectively, even the most energy-efficient solutions are not sufficient. Much like during conception and design then, when early DM gives more flexibility to practitioners, the same applies to post-occupancy DM, where early actions have a bigger impact on building EI.

4.3 Static and Dynamic LCA

Having established the effect of the weighting factor in the DM process, the differences between static and dynamic LCA should be further investigated. To do so, the MOO was run without the weighting factor with the building operating in BAU scenario for 5 years. In static LCA the, the GHGs emitted at year 5 and year 50 have the same impact towards lifecycle carbon footprint.

The most important difference from its dynamic counterpart in is the fact that no static solution come close to following the 2023 embodied carbon budget, although the operational budget is still attainable. This clearly demonstrates how carbon budgets need to be sized with the LCA methodology in mind. It is worth highlighting as well that EE were the most heavily affected by the transition from static to dynamic. This is explained by the peak in emissions at year 50 in the form of EOL EI and thus, is multiplied by 0.58. Indeed, with the DLCA approach, EOL emissions represent around 20% of life cycle GWP, while with the static approach, this percentage jumps to 26%.

However, when analysing the MOO results, it was found that best overall static GWP solution is almost identical to the set of CMM given by the dynamic LCA optimization in Solution 1. The only difference was the replacement of the heating system at year 5 instead of year 6, while all other CMMs were the same as the ones found with the DLCA, including the use of bio-based materials.

5 Discussions and limitations

This chapter presents a comprehensive analysis of results presented in the preceding chapter. The objective is to offer actionable insights for both short-term and long-term planning, ensuring that buildings meet their carbon emission targets throughout their life cycle. We draw upon a case study to further evaluate the results, adding a discursive layer to our analysis.

5.1 How information is conveyed to the decision-makers

One of the key elements that emerged from this analysis is the complex task of conveying information suitable for effective decision-making. Various potential solutions were proposed, with their suitability largely depending on the particular circumstances of each case. Utilizing a classic Pareto front, depicted in Figure 3, is a common strategy in a multi-objective optimization. However, in the given context, interpreting the information it presents becomes challenging due to the multi-dimensional nature of the decisions it represents. The frequency count of Pareto solutions in Figure 5 provides a more comprehensive overview of the solutions given by the optimizer, albeit without the granular details of action plans and parameter interactions. These visualizations rely on the outcomes of the optimization algorithm.

On the other hand, we employed the PC illustrated in Figure 6, a technique that thrives on interactivity and exploration by the user. Though it may require a larger sample size and considerable exploration efforts, it excels in showcasing a significant representation of combinatorial possibilities when the decision-maker has a set of pre-established constraints. This plot does not rely on optimization, thereby offering an alternative perspective on the DM landscape. Furthermore, the same sample of data was used for a Sobol SA, that provides useful information to the decision-makers on which parameters their efforts should be concentrated.

The visualization techniques were found to have complementary, but sometimes redundant features for DM, however the execution of a quasi-random evaluation and of an optimization is a costly effort. Thus, when choosing graphical representations, one should to choose a combination of techniques that can be done with a single set of evaluations. Two of the plots studied though, can and should be applied to both of them: trajectory plot, as it only shows one solution at a time and solution frequency, where no matter the technique, the user can easily understand the solution space.

Finally, when comparing the capabilities and information conveyed by the quasi-random sampling to the optimization, the choice depends on what the decision-makers need to understand their options. Indeed, the optimization is excellent in finding the solutions most adapted to the objective functions, namely OE and EE. However, in a more realistic scenario with constraints other than GWP, the more representative evaluation possible solutions offered by the Saltelli sample better allow the exploration of the CMM. Therefore, if additional constraints are put in place, such as to the wall thickness, they are able to explore possible solutions. Of the two then, despite taking almost 3 times as long to evaluate, we believe the random sample is more useful for the DM process.

For future works, it would be fruitful to validate these methods' effectiveness through feedback from practitioners. Furthermore, we also hope adding real-time simulations as an exploration method, where users can fine-tune their case-specific limitations.

5.2 The case-study and its results

The analysis revealed that all Pareto solutions proposed by the optimization algorithm unanimously included the addition of 40 cm of wood straw insulation. This choice is remarkable given the relatively high conductivity of the material compared to synthetic alternatives. This is in accordance with the findings in [30], where bio-based materials, despite their performance drawbacks, were found to significantly contribute to carbon sequestration. Despite the traditional trade-off paradigm in MOO then not being evidenced in this case, we retained this parameter to underscore the benefits of bio-based materials. A solution to this issue is to include more constraints, such as wall thickness or other objective functions such as life cycle cost

However, it is imperative to consider the specificities of the case study building and their potential influence on the results. For instance, the case study building, being relatively inefficient, presented a larger room for operational emissions improvement. Comparatively, only a modest reduction potential existed for embodied emissions. However, this scenario could significantly differ in a near-zero energy building, which may present substantial embodied emission savings through component replacement. Furthermore, the geographical factors, such as the low carbon intensity of electricity in France, can influence the results. Indeed, the low carbon intensity favours electrical heating systems and making the PV panel's EE take longer to compensate.

5.3 Time dimension in decision-making

On the DLCA workflow, it is important to highlight the interaction between the weighting factor and the temporal decision-making parameters, namely when the renovations and replacements are to take place. Take the Solution 1's operational emissions, for instance. They are extremely low at half of the OE budget of 150 $kgCO^2$-eq/m². This solution, ends up shortening the lifespan of the existing radiators by 12 years, which is a rather wasteful practice, however it does drastically reduce overall GWP as well. The introduction of the time dimension then, clearly adds another useful layer of flexibility to the DM process.

However, when comparing the MOO's pareto front with static and dynamic workflows, virtually no difference was found in the DM process. This happens despite the very large difference in raw GWP results between the two. Additionally, as mentioned in the literature review section of this paper, this DLCA methodology was conceptualized with the intent of incentivizing the use of bio-based materials. It was found in this work though, that in both LCA methods, bio-based materials are preferred.

Arguably then, there is no usefulness in including this layer of complexity to the DM process if no difference is found. However, the current study investigated a single application and thus, future work should explore the influence of different dynamic parameters on the optimization and sensitivity analysis results. Indeed, the weighting factor considered impact both OE and EE equally.

A recommendation stays true with every LCA method however, the earlier in the building's life cycle, the more flexibility and possibilities are presented to the decision-makers. Indeed, the effectiveness of any CMM depends on the remaining building life cycle, as found in [38].

6 Conclusions

This study embarked on a mission to illuminate the post-occupancy decision-making landscape for buildings, focusing on managing carbon emissions. Through detailed examination of a case study and critical evaluation of results, several compelling insights surfaced.

The methodology adopted in the paper centres on the computation of yearly operational and embodied emissions during a building's 50-year life cycle while considering a varying dynamic LCA method proposed by the most recent French norm. It starts with the definition of renovation and replacement choices for the building, including the addition of insulation material and PV panels, and the replacement of the heating system, windows, and ventilation system. Furthermore, the study addresses the timing for these carbon mitigation measures to be implemented.

Our exploration then, demonstrated the multidimensional nature of decision-making and the challenge in conveying information for effective actions. Notably, we investigated a combination of optimization algorithms and sensitivity analysis with the aid of visualization techniques. We recognized the necessity of employing these techniques in a complementary manner, broadening our understanding of the solution space. Future work though, could include a survey with practitioners on the subject matter.

Thanks to the application of the method to a French residential case-study, a couple of conclusions can be drawn on their results. However, they cannot be generalized, as it is particular to the context of the studied building. In fact, when comparing static and dynamic LCA in the optimization, similar solutions were found, despite the drastically different GWP raw values obtained. This might evidence a disinterest in including dynamic parameters in decision-making, but it is important to keep in mind the specificities of this French residential building. If additional conclusions should be made, a large sample of building typologies are required.

Additionally, the case study's specific characteristics also illustrated the importance of tailoring solutions to each building's circumstances. For instance, in the pareto front, two solutions were highlighted. One proposing the existing radiators in the house to be replaced by a heat pump despite being only 5 years into its 17-year life cycle, minimizing operational emissions. The other solution however, proposed the radiators to be utilized until its end-of-life before being replaced. The latter offers perhaps a better compromise between operational and embodied emissions, while avoiding a wasteful practice. In future work though, it is highly encouraged to include more carbon mitigation measures, such as the installation of solar thermal panels, geothermal heating and replacement of electrical devices for more efficient ones.

Indeed, while this study has provided insights, it also highlights the need for future work. It's a complex journey towards sustainable building management, but one that is critical in our carbon budget objectives.

CRediT authorship contribution statement

L. H. Neves Mosquini: Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing original draft. **B. Delinchant**: Conceptualization, Supervision, Validation. Writing – review & editing. **T. Jusselme:** Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Global Alliance For Buildings and Construction, '2022 Global Status Report for Buildings and Construction', *United Nations Environment Programme*, 2022.

[2] Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, and D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield, 'IPCC, 2018: Global Warming of 1.5°C.An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.' 2018.

[3] Ministère de la Transition Ecologique et Solidaire, 'Stratégie nationale bas-carbone : La transition écologique et solidaire vers la neutralité carbone (Synthèse)'. Mar. 2020.

[4] D. King, *Engineering a low carbon built environment: the discipline of building engineering physics*. London: Royal Academy of Engineering, 2010.

[5] A. Vilches, A. Garcia-Martinez, and B. Sanchez-Montañes, 'Life cycle assessment (LCA) of building refurbishment: A literature review', *Energy and Buildings*, vol. 135, pp. 286–301, Jan. 2017, doi: 10.1016/j.enbuild.2016.11.042.

[6] International Organization for Standardization, 'ISO 14040:2006 Management environnemental – Analyse du cycle de vie – Principes et cadre'. Jun. 19, 2006.

[7] International Organization for Standardization, 'ISO 14044:2006 Environmental Management—Life Cycle Assessment—Requirements and Guidelines'. ISO Geneva, 2006.

[8] European Comitee for Standardization, 'EN 15978:2011 Methodology For The Environmental Assessment of Buildings'. BRE Global, Jan. 01, 2018.

[9] European Comitee for Standardization, 'NF EN 15804:2012+A2:2019 Contribution des ouvrages de construction au développement durable — Déclarations environnementales sur les produits — Règles régissant les catégories de produits de construction'. Association Française de Normalisation, Oct. 2019.

[10] S. Su, H. Zhang, J. Zuo, X. Li, and J. Yuan, 'Assessment models and dynamic variables for dynamic life cycle assessment of buildings: a review', *Environ Sci Pollut Res*, vol. 28, no. 21, pp. 26199–26214, Jun. 2021, doi: 10.1007/s11356-021-13614-1.

[11] W. O. Collinge, A. E. Landis, A. K. Jones, L. A. Schaefer, and M. M. Bilec, 'Dynamic life cycle assessment: framework and application to an institutional building', *Int J Life Cycle Assess*, vol. 18, no. 3, pp. 538–552, Mar. 2013, doi: 10.1007/s11367-012-0528-2.

[12] W. O. Collinge, H. J. Rickenbacker, A. E. Landis, C. L. Thiel, and M. M. Bilec, 'Dynamic Life Cycle Assessments of a Conventional Green Building and a Net Zero Energy Building: Exploration of Static, Dynamic, Attributional, and Consequential Electricity Grid Models', *Environmental Science & Technology*, vol. 52, no. 19, pp. 11429–11438, Oct. 2018, doi: 10.1021/acs.est.7b06535.

[13] C. Roux, P. Schalbart, E. Assoumou, and B. Peuportier, 'Integrating climate change and energy mix scenarios in LCA of buildings and districts', *Applied Energy*, vol. 184, pp. 619–629, Dec. 2016, doi: 10.1016/j.apenergy.2016.10.043.

[14] K. Negishi, 'Development of a methodology of Dynamic LCA applied to the buildings', Ph.D. dissertation, Other, INSA de Toulouse, 2019.

[15] S. Su, C. Zhu, X. Li, and Q. Wang, 'Dynamic global warming impact assessment integrating temporal variables: Application to a residential building in China', *Environmental Impact Assessment Review*, vol. 88, p. 106568, May 2021, doi: 10.1016/j.eiar.2021.106568.

[16] S. Su, X. Li, and Y. Zhu, 'Dynamic assessment elements and their prospective solutions in dynamic life cycle assessment of buildings', *Building and Environment*, vol. 158, pp. 248–259, Jul. 2019, doi: 10.1016/j.buildenv.2019.05.008.

[17] A. Hollberg, 'A parametric method for building design optimization based on Life Cycle Assessment', Ph.D. dissertation, Fakultät Architektur und Urbanistik, Universität Weimar, 2016.

[18] T. B. P. Jusselme, 'Data-driven method for low-carbon building design at early stages', Ph.D. dissertation, Faculté de l'environnement naturel, architectural et construit, Ecole Polytechnique de Fédérale de Lausanne, 2020.

[19] G. Branco, B. Lachal, P. Gallinelli, and W. Weber, 'Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data', *Energy and Buildings*, vol. 36, no. 6, pp. 543–555, Jun. 2004, doi: 10.1016/j.enbuild.2004.01.028.

[20] S. Beemsterboer, H. Baumann, and H. Wallbaum, 'Bridging the gap between assessment and action: recommendations for the effective use of LCA in the building process', *IOP Conference Series: Earth and Environmental Science*, vol. 588, p. 022007, Nov. 2020, doi: 10.1088/1755-1315/588/2/022007.

[21] S. Cozza, J. Chambers, and M. K. Patel, 'Measuring the thermal energy performance gap of labelled residential buildings in Switzerland', *Energy Policy*, vol. 137, p. 111085, Feb. 2020, doi: 10.1016/j.enpol.2019.111085.

[22] A. C. Menezes, A. Cripps, D. Bouchlaghem, and R. Buswell, 'Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap', *Applied Energy*, vol. 97, pp. 355–364, Sep. 2012, doi: 10.1016/j.apenergy.2011.11.075.
[23] I. M. Sobol, 'Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates', *Mathematics and Computers in Simulation*, vol. 55, no. 1–3, pp. 271–280, Feb. 2001, doi: 10.1016/S0378-4754(00)00270-6.
[24] N. Rezaei Oghazi, T. Jusselme, and M. Andersen, 'Evaluation of daylighting strategies based on their embodied carbon emissions: a first methodological framework and case study', presented at the 2021 Building Simulation Conference, Sep. 2021. doi: 10.26868/25222708.2021.30691.
[25] H. L. Gauch, C. F. Dunant, W. Hawkins, and A. Cabrera Serrenho, 'What really matters in multi-storey building design? A simultaneous sensitivity study of embodied carbon, construction cost, and operational energy', *Applied Energy*, vol. 333, p. 120585, Mar. 2023, doi: 10.1016/j.apenergy.2022.120585.
[26] M.-L. Pannier, 'Étude de la quantification des incertitudes en analyse de cycle de vie des bâtiments', Ph.D. dissertation, Eco-conception, Université Paris sciences et lettres, 2017.
[27] S. Duprez, M. Fouquet, Q. Herreros, and T. Jusselme, 'Improving life cycle-based exploration methods by coupling sensitivity analysis and metamodels', *Sustainable Cities and Society*, vol. 44, pp. 70–84, Jan. 2019, doi: 10.1016/j.scs.2018.09.032.
[28] E. Asadi, M. G. da Silva, C. H. Antunes, L. Dias, and L. Glicksman, 'Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application', *Energy and Buildings*, vol. 81, pp. 444–456, Oct. 2014, doi: 10.1016/j.enbuild.2014.06.009.
[29] J. L. Cohon, *Multiobjective Programming and Planning*. Courier Corporation, 2004.
[30] L. H. Neves Mosquini, V. Tappy, and T. Jusselme, 'A carbon-focus parametric study on building insulation materials and thicknesses for different heating systems: A Swiss case study', *IOP Conf. Ser.: Earth Environ. Sci.*, vol. 1078, no. 1, p. 012102, Sep. 2022, doi: 10.1088/1755-1315/1078/1/012102.
[31] M. Röck, 'Embodied GHG emissions of buildings – The hidden challenge for effective climate change mitigation', *Applied Energy*, p. 12, 2020.
[32] S. A. Sharif and A. Hammad, 'Simulation-Based Multi-Objective Optimization of institutional building renovation considering energy consumption, Life-Cycle Cost and Life-Cycle Assessment', *Journal of Building Engineering*, vol. 21, pp. 429–445, Jan. 2019, doi: 10.1016/j.jobe.2018.11.006.
[33] J. A. Wright, H. A. Loosemore, and R. Farmani, 'Optimization of building thermal design and control by multi-criterion genetic algorithm', *Energy and Buildings*, vol. 34, no. 9, pp. 959–972, Oct. 2002, doi: 10.1016/S0378-7788(02)00071-3.
[34] S. Abbasi and E. Noorzai, 'The BIM-Based multi-optimization approach in order to determine the trade-off between embodied and operation energy focused on renewable energy use', *Journal of Cleaner Production*, vol. 281, p. 125359, Jan. 2021, doi: 10.1016/j.jclepro.2020.125359.
[35] W. O. Collinge *et al.*, 'Measuring whole-building performance with dynamic LCA: a case study of a green university building', presented at the International Symposium on Life Cycle Assessment and Construction, Nantes, France, Jul. 2012.
[36] K. Negishi, A. Lebert, D. Almeida, J. Chevalier, and L. Tiruta-Barna, 'Evaluating climate change pathways through a building's lifecycle based on Dynamic Life Cycle Assessment', *Building and Environment*, vol. 164, p. 106377, Oct. 2019, doi: 10.1016/j.buildenv.2019.106377.
[37] A. Levasseur, P. Lesage, M. Margni, L. Deschênes, and R. Samson, 'Considering Time in LCA: Dynamic LCA and Its Application to Global Warming Impact Assessments', *Environmental Science & Technology*, vol. 44, no. 8, pp. 3169–3174, Apr. 2010, doi: 10.1021/es9030003.
[38] E. Van de moortel, K. Allacker, F. De Troyer, E. Schoofs, and L. Stijnen, 'Dynamic Versus Static Life Cycle Assessment of Energy Renovation for Residential Buildings', *Sustainability*, vol. 14, no. 11, p. 6838, Jun. 2022, doi: 10.3390/su14116838.
[39] E. Asadi, M. G. da Silva, C. H. Antunes, and L. Dias, 'Multi-objective optimization for building retrofit strategies: A model and an application', *Energy and Buildings*, vol. 44, pp. 81–87, Jan. 2012, doi: 10.1016/j.enbuild.2011.10.016.
[40] INIES, 'About the INIES database – INIES'. https://www.inies.fr/about-the-inies-database/ (accessed Jun. 24, 2021).
[41] Ministère de la Transition Ecologique et Solidaire, 'Réglementation environnementale RE2020', *Ministères Écologie Énergie Territoires*, Feb. 17, 2023. https://www.ecologie.gouv.fr/reglementation-environnementale-re2020 (accessed Apr. 24, 2023).
[42] M. Villey, 'L'ACV Dynamique dans la RE2020', *Cerema*.
[43] U.S. Department of Energy, 'EnergyPlus'. https://energyplus.net/ (accessed Apr. 21, 2023).
[44] P. Santosh, 'Eppy', 2020. https://eppy.readthedocs.io/en/latest/readme.html (accessed Apr. 19, 2023).
[45] P. Saves *et al.*, 'SMT 2.0: A Surrogate Modeling Toolbox with a focus on Hierarchical and Mixed Variables Gaussian Processes'. arXiv, May 23, 2023. doi: 10.48550/arXiv.2305.13998.

[46] P. Westermann and R. Evins, 'Surrogate modelling for sustainable building design – A review', *Energy and Buildings*, vol. 198, pp. 170–186, Sep. 2019, doi: 10.1016/j.enbuild.2019.05.057.
[47] P. Saves, Y. Diouane, N. Bartoli, T. Lefebvre, and J. Morlier, 'A new mixed-categorical correlation kernel for Gaussian process', no. 2023, 2023.
[48] Vizcab, 'Solutions pour la transition environnementale du bâtiment', *Vizcab*. https://vizcab.io/ (accessed Apr. 21, 2023).
[49] '37,2 millions de logements en France au 1er janvier 2021 - Insee Focus - 254'. https://www.insee.fr/fr/statistiques/5761272#tableau-figure3 (accessed Apr. 27, 2023).