Application of sensitivity analysis on building dynamic lifecycle assessment of GHG emissions: a French case study

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Abstract. This study presents a novel approach to simplify the dynamic life cycle assessment (DLCA) of buildings by identifying and prioritizing influential dynamic parameters (DPs) to improve building energy performance and reduce greenhouse gas emissions. Current life cycle assessment (LCA) methodologies lack temporal considerations, which can significantly impact a building's environmental footprint over its multi-decade life span. We conducted an extensive literature review on DPs in DLCA, informing the creation of a multi-scenario parametric framework. A case study was then selected to apply the developed DLCA methodology and perform a global Sensitivity Analysis to pinpoint the most influential DPs on global warming potential. The DLCA framework integrates data from the French database for environmental product declarations and utilizes EnergyPlus simulations for operational emissions assessment. The study identifies ten DPs, revealing the most impactful ones to be industry and waste sector's emissions reductions, building occupancy, and global warming. Additionally, we found minimal interactions between DPs, which facilitates the simplification of the DLCA process. This research enables building stakeholders to focus on a more selective set of parameters, enhancing the efficiency and accuracy of building life cycle assessments. Overall, our findings contribute to the continuous improvement of LCA methodologies and promote sustainable building practices.

1. Introduction

The urgency of addressing the climate crisis has intensified, and as buildings account for 37% of greenhouse gas (GHG) emissions [1], it is crucial to ensure the compliance of the building sector with carbon budgets through comprehensive lifecycle assessments (LCAs) [2]. Traditionally, building LCAs have employed a static approach, which disregards temporal variations throughout the building's multi-decade lifecycle, thus limiting the accuracy of the assessments [3]. A more holistic understanding of a building's environmental impact can be achieved through Building Dynamic LCA (DLCA), which accounts for temporal elements such as variations in the national electricity mix, component ageing, and the effects of climate change [4].

However, the modelling of these long-term dynamic parameters (DPs) has proven to be the most challenging step towards a comprehensive DLCA methodology due to the 50-year (or more) time-horizons in a building's lifecycle and the scarcity of related DLCA data [4]. Recent research on DLCA, has incorporated up to seven DPs [4], [5]. While these studies represent progress in the field, there is still a need to simplify DLCA methodology, making it more accessible and efficient for practitioners. The objective of this study then, is to propose a methodology for simplifying DLCA by reducing the number of DPs.

The remainder of this paper is structured as follows: Section 2 presents the methodology, which includes (1) the identification and description of DPs, (2) the development of the DLCA framework and (3) the selection of a case study for the application of the methodology and a sensitivity analysis (SA). Section 3 discusses the results of the DLCA, highlighting the most impactful DPs and their implications for building DLCA. Section 4 provides a discussion of the findings, offering recommendations for future research and potential applications of this DLCA methodology. And finally, Section 5 presents the conclusions of this study and outlines the contributions to the field of building energy performance and LCA.

2. Methodology

To achieve the aforementioned objective, we first conducted a literature review on DPs in DLCA, which informed the creation of a multi-scenario parametric framework. Then, a DLCA methodology is developed and subsequently, a case study was selected to conduct a global Sobol SA towards pinpointing the most influential DPs on GWP. This variance-based SA informs its user about the contribution of each input factor to the output variability, quantifying their individual and interaction effects [6].

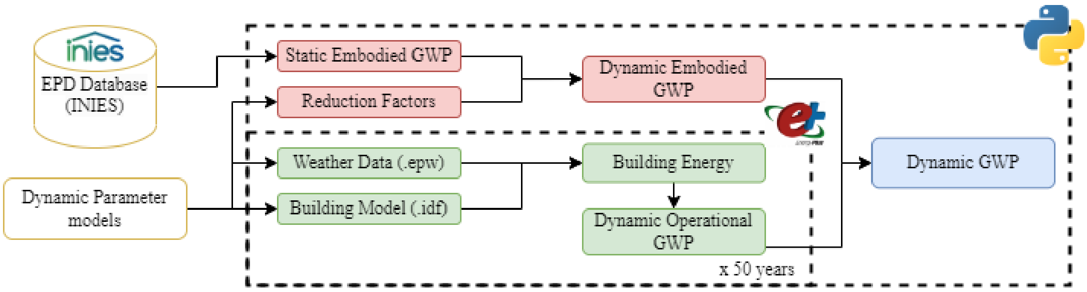

Figure 1. Simplified overview of the DLCA framework.

The identification and modelling of dynamic parameters (DPs) is a crucial first step towards the development of a robust dynamic lifecycle assessment (DLCA) methodology and they are characterized by a timestep of variability and a model of time-varying parameters of the system [5]. In this study, the included DPs were classified into three perimeters: External system, Building Technology and User Level [5]. In order to incorporate them into our DLCA methodology, we first conducted a literature review to identify the common DPs for each level. The result from this review is summarized in Figure 2, where the model is described, however a more qualitative description will be made below.

- Presence hours. This parameter is based on the French demography statistics institution, which provided with data on how employed, young and retired French citizens spend their days [7]. From this data, we were able to estimate the number of hours they spend per day inside their households. In conclusion, retired women were found to spend the longest amount of time at home (around 20 hours), while working men spend the least (13 hours).
- Electricity mix's Carbon Intensity. This parameter is based on 2050 forecasts by the French transmission system operator: RTE [13]. They were then converted into an average carbon intensity (CI), which is then used for the calculation of a yearly reduction factor.
- Occupant density. The number of occupants in a residence is certain to change in a household as children are born or leave their parents houses. This model, for simplicity's sake, was kept constant.
- Industrial and waste sector's emissions reduction. Both of these values are based on the carbon budget allocated for each sector through the National Low-Carbon Strategy (SNBC, in French) [15]. In order to achieve carbon neutrality, emissions in the industrial and waste sectors have to reduce by 81% and 66% by 2050 in relation to 2015 levels, respectively.

The approach to the modelling of DPs was focused on finding the extreme case-scenarios and does not intend to create a detailed model of the long-term evolutions of each parameter, due to the difficulty linked to modelling these parameters. In fact, the sensitivity analysis will serve as indicator to which parameters require the most attention and should be refined for a more accurate model.

Once the DPs were defined, the next step was to elaborate a DLCA framework capable of integrating these variables into the LCA. First, the static LCA methodology on which this work is based on is described by the ISO 14040/14044 and French RE2020 norms. As demonstrated in Figure 1, component data was sourced from the French environmental product declarations (EPDs) database, INIES, and exported using the LCA tool, Vizcab [8]. Energy simulations were performed using automated EnergyPlus [9] simulations, facilitated by Python for data manipulation, treatment, and energy model modifications. This enabled hourly operational emission simulations over the 50-year building lifecycle (reference lifetime imposed by the RE2020). Key libraries utilized in this workflow include EPPY [10] for EnergyPlus integration and SALib for Sobol sensitivity analysis [11]. Thanks to this framework over 10k simulations were run over the span of a couple of days for the calculation of the Sobol indices.

Finally, this short paragraph encompasses a presentation of the case studies used for the SA. This two-storey single-family house near Paris is built with concrete slabs and cinder blocks. Additionally, it is equipped with 3 kWp of PV panels and a heat-pump heating and domestic hot water system. This building with 146 m² of living space and 366 m^3 of internal volume is insulated and equipped with double-glazing, resulting in an overall U-value of 0.26 W/m².K.

Table 1. Dynamic parameters with their time-steps, descriptions and intervals used in the Sobol SA

Perimeter	DLCA parameter	Time-Step	Model Description	Value Interval	Data Source
External	Global warming	Year	Linear increase of temperature from current to 2100 weather. The parameter is modelled based on global warming temperature by 2100 in relation to pre-industrial revolution.	1°C to 4°C	[2] [12]
External	Electricity mix's Carbon Intensity	Year	Yearly linear reduction factor of electricity carbon intensity. After 2050, the CI remains constant until the end of the building's LC.	-2.07% to -0.5%	[13] [12]
External	Electricity mix's Carbon Intensity	Hour	Hourly electricity mix's production data between 2010 and 2020	-	[14]
External	Industrial sector's emissions reduction.	Year	Linear yearly reduction factor between 2020 and 2050 to GHG emissions linked to component fabrication. After 2050, the emissions remain constant.	-2.3% to 0%	[15]
External	Waste sector's emissions reduction.	Year	Linear yearly reduction factor between 2020 and 2050 to GHG emissions linked to component end-of-life. After 2050, the emissions remain constant.	-1.8% to 0%	[15]
Building technology	Improvement to Heat-pump technology	Year	Exponential yearly improvement to a heat-pump's nominal coefficient of performance (COP).	0.15% to 1%	[5] [16]
Building technology	Insulation ageing	Year	Linear increase of the thermal conductivity of closed-cell foam insulation materials.	0.1425% to 0.76%	[17] [18]
Building technology	Heat-pump ageing	Year	Exponential yearly decrease to the COP.	1% to 3%	[5] [18]
Building technology	Photovoltaic system ageing	Year	Linear yearly decrease in PV system efficiency.	0.17% to 1%	[19]
User level	Occupant density	Static	Number of occupants is based on the case study's size.	2 to 8	-
User level	Presence hours	Static	This represents the number of hours in a day which someone will be inside the building.	13h to 20h	[7]

3. Results

In this third section of the paper, we will present the results obtained from the DLCA framework and subsequent SA. In Figure 2, the first and total Sobol indices for the 10 parameters are illustrated, with the magnitude of the index indicating the influence of a given parameter on the variance of the output, in this case, overall GWP. Several key takeaways can be gleaned:

- The notably higher Sobol index for waste sector emissions reduction can be attributed to the fact that most end-of-life (EOL) emissions occur at the very end of the building's lifecycle, allowing the sector ample time to decarbonize.
- The close values of the DLCA parameters' first-order and total indices suggest minimal interactions between them. This, together with the squiggles to the right of the plot also suggest a mostly linear behaviour.
- Despite operational GWP accounting for only 20% of static lifecycle GHG emissions, user-level DPs still exerted a significant influence on the dynamic GHG results.

In Figure 3, we compared the overall GWP of three levels of dynamisms: no dynamics or static; a hybrid approach, where only the five main DPs identified in Figure 2 and finally with all ten parameters. Since the results of DLCA are scenario-dependant, there will be maximum and minimum values. These values were simple to find, thanks to the aforementioned linearity. From this comparison we notice that the extra parameters added parameters less than 1 tCO_2-eq to the range of possible values.

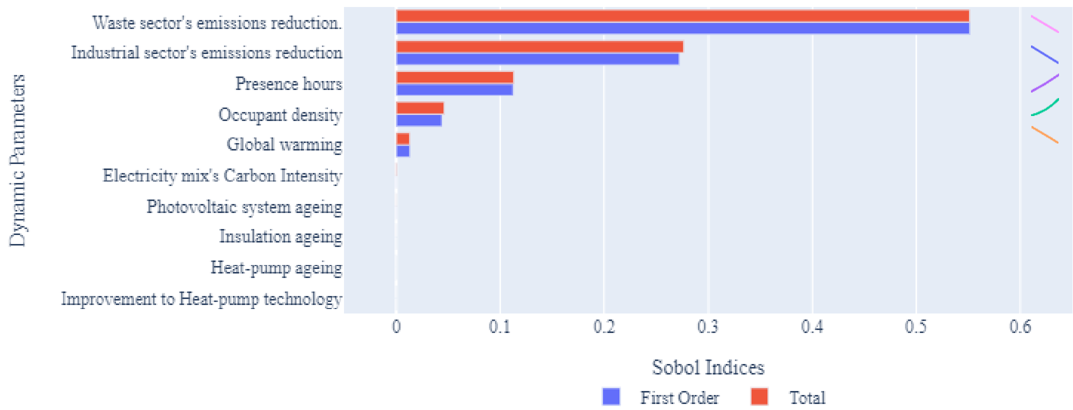

Figure 2. Results from the Sobol SA for the case study. The graphic shows the first-order and total Sobol indices. The squiggles to the right of the bar plot represents the tendency of the output for the respective parameters.

4. Discussions

In this discussion, we will delve into the key insights derived from the presented results. First and foremost, the evolution of waste and industrial sectors' emissions is highly relevant to the building's DLCA. This is despite the fact that these parameters exclusively impact the embodied emissions of the building and thus, their significance would be even more pronounced in a more energy-efficient building. In conclusion, this result is also proportional to the drastic improvements proposed by the SNBC [15] in these two sectors. In a future study, where accuracy becomes the priority, an obvious improvement to this model is to evaluate these improvements in more detail by considering evolutions to specific industries, instead of full sectors (ie. concrete industry instead of entire industry sector).

The importance of the user-level DPs are also expected, since behaviour has been found to be the largest source of uncertainty in building energy modelling [20]. The modelling of "Presence Hours" could be further improved by including a stochastic model of building usages by occupant's characteristics.

Nonetheless, the evolution of the electricity mix plays a small impact on the overall GWP, which can be explained by the fact that the French electricity mix, which is already low-carbon compared to other European countries. Meanwhile, regarding component aging, the impact of insulation, heat-pump and PV degradations on the results were found to be negligible for this case study and one of the reasons for that could be attributed to the relatively short lifecycle of the construction.

As for the squiggles in Figure 1, they provide insights into the relationships between DPs and GWP. At least four of the five main DPs exhibit a close-to-linear relationship with GWP, suggesting ways to streamline the DLCA process, such as regressive models or longer time-steps and interpolations. Additionally, with the identification of impactful parameters, it is recommended that future research start with a review of DPs that cannot be extrapolated to different contexts.

Finally, from Figure 2 it is possible to evaluate the information loss due to the reduction down to 5 parameters. Indeed, here we find that the 5 most influential parameters are responsible for over 96% of the calculated range of possible value of overall GWP. Thus, a reduction by 50% in the number of parameters, implicated a loss of around 4% of information, which is in accordance with the Sobol results.

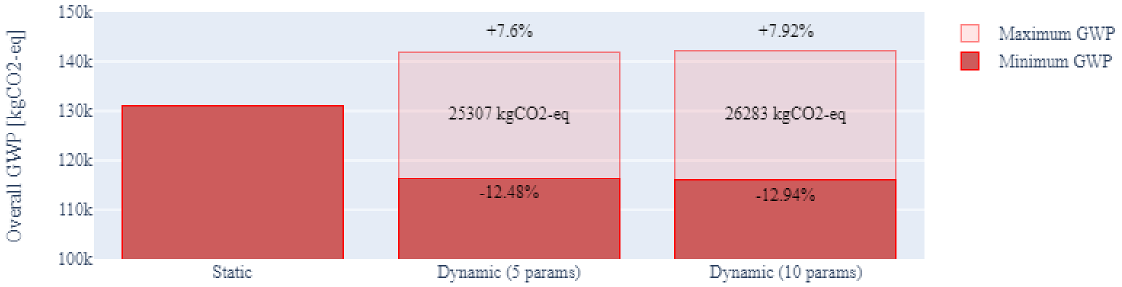

Figure 3. Comparison between Static and Dynamic LCA calculations of lifecycle GWP with all 10 parameters and with 5 of the most influent. The percentages represent the difference in relation to the static GWP and the value inside the bar-plots represent the different in minima and maxima.

5. Conclusion

This study presents a potential approach to simplifying the workflow for building dynamic LCA by modelling 10 parameters and applying them to a French building's assessment of GHG emissions and a Sobol sensitivity analysis. This research successfully identified the most influential dynamic parameters of a case-study, enabling stakeholders to focus on crucial factors and disregard less relevant ones, thus enhancing the assessment's efficiency and accuracy. Indeed, it addresses the issue of complexity in DLCA by proposing a targeted approach that reduces the number of DPs, paving the way for broader adoption and application in the building sector, ultimately contributing to more effective strategies for mitigating the environmental impacts of buildings.

Upon applying this methodology to a case study, we determined that the most significant parameters include reductions in carbon emissions from the industrial and waste sectors, the building's occupancy duration, and global warming. Notably, our findings indicate minimal interactivity between these parameters, further emphasizing their individual importance in the assessment process. However, it is important to establish that these results cannot be extrapolated to other cases, nor should the takeaway of this work to ignore or give less importance to certain parameters. In order to do so, a diverse group of case-studies should be explored with the proposed methodology, which goes beyond of the scope of this work.

Credit-author statement

L.H. Neves Mosquini: Conceptualization, Methodology, Software, Visualization, Writing original draft. **B. Delinchant**: Conceptualization, Supervision, Validation. Writing – review & editing. **T. Jusselme**: Conceptualization, Supervision, Validation, Writing – review & editing.

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Keywords: dynamic LCA, building LCA, energy simulation, global warming potential

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