Evaluation of daylighting strategies based on their embodied carbon emissions: a first methodological framework and case study

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Abstract

The impact of daylighting strategies on a building's carbon emissions have so far been assessed mostly based on the building's use phase and their resulting operational benefits, overlooking embodied carbon emissions of material production, construction, maintenance and end of life. This paper proposes a new methodological framework that combines different techniques including sensitivity analysis, target cascading and a method called Design Space Exploration. The framework was tested on a case study, namely the winning entry of Solar decathlon 2012, to evaluate daylighting strategies based on both daylight availability and embodied carbon emissions. . This study allowed to show through a formal process that while choices made on window head height, glazing type, interior surface reflectance and window-to-wall ratio (WWR) basically define daylight access potential, they only have a minor impact on embodied carbon emissions.

Key Innovations

- First multi-criteria platform to explore a design space with a focus on illuminance and embodied carbon;
- Uncover relationships between Daylight Factor (DF) targets and induced embodied Global Warming Potential (GWP) of influential building components;
- Ability to rank design parameters based on their influence on daylight access and embodied carbon emissions through sensitivity analysis;
- Weighing of embodied carbon impact per façade element (wall, frame and glazing) thanks to target cascading techniques.

Practical Implications

The methodology proposed in this article aims to offer useful guidance to practitioners by helping them identify which design parameters may impact daylighting performance or GWP or – most interestingly – both of them.

Introduction

The overwhelming impact of buildings on the environment has been stressed repeatedly. With rising global climate change concerns, several international agreements (e.g. UN Conference on Climate Change in Paris, 2015) are aiming to impose a significant decrease in every sector's carbon budget (including for buildings), which altogether should not exceed 420 Gt CO_2 until 2050 based on the recent IPCC report (IPCC, 2018).

The built environment plays a critical role in carbon emissions (39%) and total energy use (36%), and has a high potential for long-term and cost-effective carbon emission reductions (Pérez-Lombard et al., 2008). Given that the global population is likely to increase by 9.7 billion by 2050 (United Nations, 2019), along with a raise in the time spent indoors (85-90%) and always higher requirements in terms of building comfort, energy use will probably continue to increase in coming years (Lucon et al., 2014). Reaching carbon neutrality to limit impact on global warming (IPCC, 2018) will thus require a drastic mitigation of the buildings' overall carbon content, for which solely increasing energy efficiency, while necessary, will not be sufficient.

Amongst the numerous ways in which the overall environmental impact can be assessed, the LCA has become a method of reference on an international level. To effectively offer the means to limit a (future) building's lifecycle carbon emissions, this type of analysis must make its way into the design process and do so both in terms of embodied and of operative energy (i.e. in terms of total carbon footprint).

The consideration of daylight performance is integral to meet low-carbon and climate-resilient objectives in building design (Konis & Selkowitz, 2017) as its impact pertains both to operative and embodied carbon emissions of buildings. However, based on existing literature, the embodied carbon emissions of daylighting strategies, heavily influenced by choices of material and construction techniques, has not yet received a lot of attention. To address this gap, this paper presents a proof-of-concept for ranking daylighting strategies based on their embodied carbon emissions. This study provides a multi-criteria platform to assess daylight performance (for now based on the simple and static Daylight Factor metric (Reinhart et al., 2006)) alongside embodied carbon emissions (based on GWP) of different design options. The proposed method aims to provide insights about the extent to which, achieving daylight performance targets may affect the amount of embodied GWP and vice-versa.

Recent approaches

The impact of daylighting strategies on a building's carbon emissions have been assessed mostly based on the

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building's use phase and their resulting operational benefits so far (Mardaljevic et al., 2009; Yu & Su, 2015; Shen et al., 2014), thereby overlooking embodied carbon emissions of material production, construction, maintenance and end of life. Among the variety of existing methods to assess a buildings' carbon emissions, LCA stands out as being the most widely accepted and developed in the building design context and is likely to shift the focus of daylighting from operational carbon impacts to life cycle carbon impacts. LCA can effectively reduce the environmental impacts of future buildings if applied at early stages of design (Hegger et al., 2012).

In response to the limitations of early-stage LCA, such as low level of details and time-consumption, parametric approaches to LCA have started to emerge (Hollberg et al., 2016; Jusselme et al., 2018). Once combined with Building Performance Simulation (BPS), new opportunities are offered to designers to explore the design space – i.e. the hypothetical combinations of the design parameters – and deliver fast feedback on them (Lin & Gerber, 2014). Thanks to the Design Space Exploration (DSE) approach, LCA has thus evolved gradually from post-design evaluation to pre-design assessment methods.

In the traditional LCA, designers would resort to variations of a baseline model or to varying "One [parameter] At a Time" or OAT (Østergård et al., 2017). The DSE, however, can enable designers to investigate a design space through suitable sampling that combines pre-defined design parameters, without trial-and-error at a reasonable computation time (Haymaker et al., 2018).

While the usefulness of DSE methods for both daylight performance and life cycle analyses is not necessarily questioned (Østergård et al., 2017; Samuelson et al., 2016), challenges have to be highlighted. First, DSE itself does not reveal the impact of each variable (design parameter) on the model output. In other words, it is not clear how much each design parameter impacts the model outputs and what are the most and least impactful design parameters. Second, DSE-based LCA calculates overall life cycle impacts of design options, which means that the impact of an individual component of the building (or group of components) cannot be easily inferred. For instance, while choosing smaller windows might seem to decrease the life cycle impact of a building due to lower amounts of glazing material and reduced heat exchanges, this decision may ultimately increase overall carbon emissions of the building because of reduced reliance on solar gains, increased wall area and/or higher electric lighting needs to maintain adequate illumination. A combination of methods involving DSE – but not limited to it – thus seems required to cope with the aforementioned challenges.

Methodology

This section presents a DSE-based method developed specifically to evaluate daylighting strategies based on their embodied carbon emissions, before discussing the usefulness of adding complementary techniques to it, namely Sensitivity Analysis (SA) and Target Cascading (TC).

Design space exploration

Design Space Exploration (DSE) pertains the investigation and evaluation of design alternatives for a given project, and is typically done alongside system development and/or early prototyping before implementation (Kang et al., 2010). As such, DSE is a parametric method and a data visualization technique that generates a set of design alternatives together with their corresponding performance to provide a knowledge database, whose exploration supports the design process.

Based on the number of parameters and associated performance levels to be considered, the design space may contain thousands of alternatives. For instance, Miyamoto and co-workers used DSE to assess the heating demand of their design space with seven parameters that each had three levels of performance (e.g. window U value=0.2, 0.5, 0.8 W/m^{2}K), which meant that the design space contained 3^7=2187 alternatives and the same number of energy simulations (Miyamoto et al., 2015). Given that the number of parameters in a building LCA is high – as every building component has a GWP impact – it is important to highlight the most influential parameters to the designers. To this end, a Sensitivity Analysis complementary to the DSE should be performed.

Sensitivity analysis

A Sensitivity Analysis (SA) is applied to rank design parameters based on their influence on defined outcomes (Heiselberg et al., 2009). SA is able to uncover the influence of each input parameter on the model output and identify parameters with the highest and lowest influence on a pre-determined performance metric (Saltelli et al., 2008). There are different methods for SA amongst which the most popular include linear regression (Chatterjee & Hadi, 2009), the Morris method (Morris, 1991) and Sobol's indices (Sobol, 2001). Each of them has advantages and disadvantages but two important decision factors in choosing which is the proper method are the readability of the SA outputs and computational effort (Tian, 2013).

When a high number of design parameters are involved in such an analysis, the screening-based Morris method seems to be a reasonable choice. Its strength lies in estimating how sensitive results are to a single input while providing information on interaction effects between design parameters as well (Saltelli et al., 2008). This technique thus offers a high reliability, but expresses interaction effects in a qualitative way, which cannot reveal relative impacts (i.e. how much more impactful input parameter 1 is compared to input parameter 2).

The Sobol method, on the other hand, can overcome the aforementioned shortcomings as it is a variance-based approach and thus provides quantitative Sensitivity Indices (SI), which measure the fractional contribution of an input parameter on the output variance (Sobol, 2001). The higher SI of an input parameter, the more influential the parameter is. The results of the Sobol method thus

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tend to be more readable compared to the Morris method (Yang, 2011), though at the expense of computational time, which increases significantly compared to Morris (Saltelli et al., 2008). A recent study comparing Sobol, regression-based and Morris demonstrated that Sobol is still the most appropriate technique for coupling DSE and LCA calculations due both to its ability to manage large datasets and to its accuracy (Duprez et al., 2019).

Target cascading

Target cascading (TC) can be defined as a process which splits top-level design targets into sub-targets in order to design the subsystems without considering the complexity of the whole system (Kim et al., 2003). When applied to the context of the built environment, overall building performance targets are broken down into sub-targets at the building component level (Jusselme et al., 2018): for building life cycle carbon emissions, this means defining carbon emissions sub-targets at the components' level (Hoxha et al., 2016; Jusselme et al., 2020). TC is complementary to SA because the choice regarding a given design parameter, say a slab type, could have a low influence on GWP (if all slab options have similar impacts anyway), while being responsible for a large share of the building carbon emissions (Jusselme et al., 2020). When it comes to the building envelope, which is the focus of the present study, as no carbon budget has yet been defined at the façade level, we will evaluate the relative weight of the building components against the façade's carbon content, by using Equation 1.

$$RW = \frac{\sum_{i=1}^{n} I_{Ci}}{\sum_{i=1}^{n} I_{Fi}} \quad (1)$$

where

RW refers to the relative weight of each façade component's carbon emissions (%)

I_{Ci} represents the embodied carbon emissions associated to façade Component i (kg CO_2-eq)

I_{Fi} represents the embodied carbon emissions associated to the whole façade (kg CO_2-eq)

I is the index of the considered design alternative

N is the number of design alternatives.

In this study, the embodied carbon emissions of each façade's components (I_{Ci}), i.e. glazing, frame and wall (which includes the wall structure, insulation and the external coating) during the building life span for each alternative is calculated by using Equation 2. The embodied carbon emissions associated to the whole façade (I_{Fi}) are also considered as the sum of embodied carbon emissions of the glazing, frame and wall in each design alternative. For instance, by dividing the sum of all frames' I_{Ci} by the sum of I_{Fi} of all design alternatives, the relative weight of frame's carbon emissions can be calculated. These weights (y) are specific to the pre-defined parameters that are involved into the DSE process (e.g. glazing type) and the context in which the project is located (e.g. climate conditions). By calculating the relative weight of each component's carbon emissions, designers are able to independently produce and evaluate different façade design options at the component level, while maintaining an overall façade carbon budget.

Embodied impact calculation

The life-cycle impact of a building is the sum of operational impact (OI) resulting from operational phase and embodied impacts (EI) resulting from material production, construction, replacement and end of life. In this study, we consider only the operational impacts to simplify this first prototype. According to Jusselme et.al (2018), the embodied impact I_E of a building can be calculated by decomposing it into n components (such as the frame, glazing, or walls). Each component i is then expressed as a mass (kg), a surface (m²) or a quantity (unity) M_i and multiplied by its specific environmental impact conversion factor CF_i thanks to a lifecycle inventory database. Finally, the ratio between the building's lifetime LB and the component's lifetime LM_i is calculated and multiplied to obtain the component's environmental impact over the whole lifetime of the building (Jusselme et al., 2018). I_E is thus calculated based on Equation 2:

$$I_E = \sum_{i=1}^{n} (M_i \,.\, CF_i) . \frac{LB}{LM_i} \quad (2)$$

By combining DSE, SA, TC, a methodological framework is proposed to make design decisions according to daylight and GWP objectives. To test its applicability, it is applied to a simple case study, a small-scale residential project developed for a solar housing competition. The methodology can be structured in three steps:

1. Phase I: Definition of design parameters and performance targets
2. Phase II: Implementation of the computational workflow
3. Phase III: Daylight factor and embodied carbon emissions calculation

Case study description

The case study chosen to evaluate the daylighting strategies and their corresponding carbon emissions was inspired from the Canopea project, which was the winning project in the Solar Decathlon Europe 2012 competition, held in Madrid. The project provides a single-family living area as well as a winter greenhouse, which have been distributed over 2 floors with a total area of 300 m^2. This actual project is meant to provide an average of 250 lux of daylight in the living room (the space selected for our study, see Figure 1) for 70% of the occupancy time between 9 a.m and 5 p.m. in Madrid (Team Rhône-Alpes, 2012).Glare is managed thanks to three shading strategies that form the second layer of the façade: external rolling blinds, sliding panels and vertical louvers.

Our aim here is to reveal the variation in daylight performance and in embodied carbon emissions for different design options of the façade portion highlighted in blue in Figure 1. For the purposes of this study, which pertain to testing a method rather than evaluating a project, we mainly borrowed dimensional characteristics and orientation from the actual Canopea project, and made several further simplifications: only the ground

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floor was considered (the greenhouse on the first floor was excluded) and as glare and thermal comfort fell beyond the scope of this study, the second layer of façade as well as the first-floor overhang were also excluded, which led toa façade consisting of triple glazed windows, a wood-framed wall structure and cellulose wadding as insulation.

We will consider alternatives with different façade components (wall, glazing and frame types), window dimensions (WWR) and interior surface reflectance to see what façade configurations could meet the daylight and carbon emissions targets.

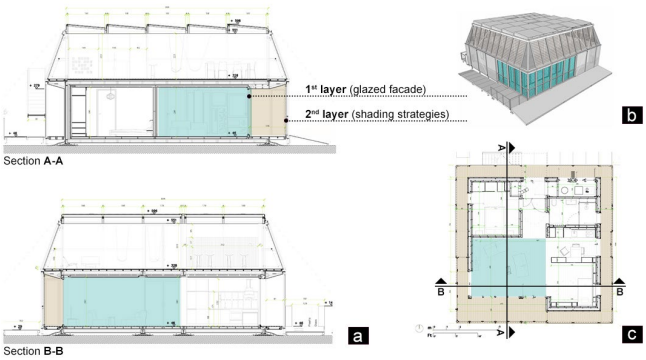

Figure 1. (a) section view of façade system around the living room, (b) the living room position in the 3D model in the southern façade, (c) the living room position in the ground floor plan

Phase I: Design parameters and performance targets

Daylight Factor or DF is a static metric commonly used for simplified daylighting evaluations and defined as the ratio of indoor and outdoor horizontal illuminance under overcast conditions. It is directly affected by building geometry as well as surface properties, i.e. specularity, reflectance and transmittance (Reinhart et al., 2006) and as it assumes an overcast sky, it is insensitive to orientation or latitude. DF is typically calculated for each sensor point on a grid covering the occupied area in a space, which is commonly placed at the assumed work plane (desk height). As GWP is expressed as a single number for any given design scenario, the distribution of DF values within the living room area had to be converted for comparison purposes into a meaningful single number as well. However, rather than taking the average DF over the considered area (which could hide poor performance due to extreme values with a good-looking average), a threshold-based approach was chosen instead, based on anextension of the spatial Daylight Autonomy (sDA) metric (LM-83-12, 2012) and here referred to as spatial Daylight Factor or sDF. While $sDA_{300/50\%}$ describes the percentage of space that receives at least 300 lux in at least 50% of the occupied hours over the year, we will define $sDF_{2\%}$ as the percentage of space (or work plane) that reaches a DF greater or equal to 2% when evaluating the daylight performance of a given design scenario. The threshold of 2% for DF was chosen based on the LEED v4 standard, that recommends, for a well-daylit space, that the DF should reach at least 2% for at least 50% of the space (US Green Building Council, 2019).

The building façade parameters, which include the window-to-wall ratio (WWR), the windows' vertical dimension and the window head height, as well as the interior finishing (expressed as surface reflectance of all indoor surfaces) all have a direct impact on DF values (Reinhart et al., 2006) – and thus on the resulting sDF – and will therefore be considered in the study. On the other hand, GWP depends on the type and quantity of material used i.e. most notably pertaining to wall, insulation, glazing and window frames. Note that solar control systems will not be accounted for in this study as only overcast conditions will be considered, under which shading is typically unnecessary; they are, however, the topic of a dedicated development in terms of carbon content (Rezaei et al., 2021).

Table 1. Façade design parameters and associated performance levels

Parameters	Performance levels	GWP (kg CO_2-eq/m^2)
WWR	0.25 - 0.30 - 0.35 - 0.40	-
Window vertical dimension (m)	1.30 - 1.40 - 1.50 - 1.60	-
Window head height (m)	1.70 - 2.00 - 2.30 - 2.60	-
Number of windows	1 - 2	-
Window frame type	Aluminium	724
	Wood	256
	Wood-Aluminium	434
	Plastic/PVC	570
Glazing type	Double (18 mm), visible light transmittance 0.8	95.8
	Double (24 mm), visible light transmittance 0.7	87.4
	Triple (36 mm), visible light transmittance 0.7	154.6
	Triple (40 mm), visible light transmittance 0.6	133.6
Wall type	Reinforced concrete	111.07
	Laminated Wood	64.8
	Wood Framed	63.55
	Fired clay block	97.27
Interior surfaces	White, surface reflectance 0.8	-
	Medium grey, surface reflectance 0.3	-

For this first proof-of-concept, 8 façade design parameters were selected and are provided in Table 1. Their associated "performance levels" based on their assumed properties, are provided in the second column and are based on the Swiss KBOB material database (KBOB, 2016) and the Swiss Federal Office of Energy database (Swiss Federal Office of Energy SFOE, 2002). As a wall's U-value should be lower than 0.2 W/m²K for individual

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residential houses according to the SIA 380 norm (SIA 380, 2016), rock wool insulation (λ=0.035 W/mK^{-1}) has been chosen for all types of walls in Table 1 and their thickness has been calculated accordingly. For walls, the reported GWP includes the wall structure, insulation and external coating. Regarding interior surface reflectance, GWP of interior surfaces have not been considered in this study as it is assumed that reflectance properties of surfaces do not change their GWP.

Phase II: Implementation of computational workflow

The 3D model of the living room was first built in Rhino 6 (McNeel & Associates, 2019b) and parametrized thanks to Grasshopper (McNeel & Associates, 2019a). The base model is a 6*4.5*3 m^3 (width, depth, height) room with windows on the southern wall.As the study involves all 8 parameters listed in Table 1, exploring the entire design space contains 4^7=16,384 simulations. If we assume that 4 seconds are needed to complete an sDF calculation, the total duration of the calculations will be more than 18 hours. The radiance parameters are presented in Table 2.

Table 2. Radiance parameters

Ambient accuracy	Ambient bounces	Ambient divisions	Ambient resolution
0.15	2	512	256
Ambient sampling	Direct threshold	Direct sampling	Limit reflection
128	0.05	0.2	6

According to Duprez and co-workers, the minimum number of design scenarios needed to have a reliable SA is 1000 per input parameter (Duprez et al., 2019). Accordingly, at least 8000 simulation runs will be required for our study. Based on SimLab software suggestions (European Commission-IPSC, 2008), we made 9216 design scenarios. To that end, each input parameter was defined in SimLab and their performance levels were considered as discrete numbers (i.e. 1, 2, 3, 4). Thanks to the Sobol sampling method (Yang, 2011), a first sample of 9216 design options was created and imported as an Excel file to Grasshopper by using the TT toolbox (The Core Studio, 2017) so as to vary the dimensions of the windows and easily assign materials to the glazing, frame, wall and interior surfaces. Using DIVA for Grasshopper (Solemma LLC, 2017) and some customized codes, the following outputs were calculated and stored in an Excel file for SA and TC: sDF, GWP of wall, frame, glazing and façade as well as wall, frame and glazing area (m^2) of each design alternative. Figure 2 gives an overview of the full workflow.

Results

The design alternatives were generated within 10.24 hours by using a core i7-8550U CPU@1.80 GHz processor. A selection of the tested façade configurations and their resulting daylight performance (sDF values calculated on the work plane) is provided in Figure 3.

Once design alternatives and their corresponding sDF and GWP are fully determined, i.e. the knowledge database is populated, design decisions can be supported by the following actions: a sensitivity analysis (SA) to identify the design variables with the highest influence on sDF and GWP; target cascading (TC) to specify the RW of each façade component's embodied impacts; exploring the design space (DSE) by filtering the knowledge database and identify the dominant characteristics of the top performers, e.g. their WWR, window type, etc.

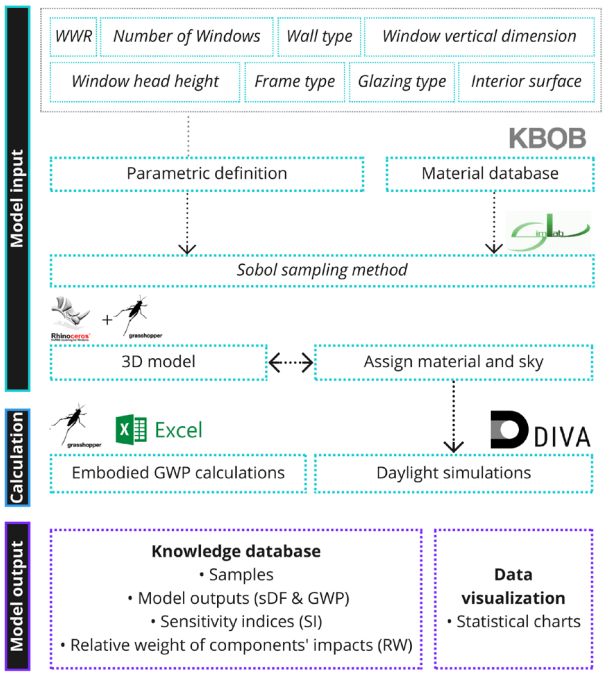

Figure 2. The method's workflow and description of the model input, calculations and model output

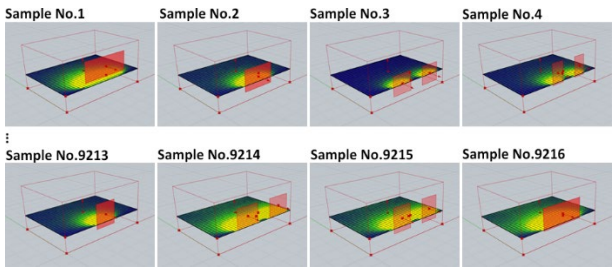

Figure 3. An example of 3D models and their associated DF maps over the work plane

Sensitivity indices: Identifying the most influential parameters

Figure 4 summarizes the results by showing each parameter's relative impact on either sDF or GWP based on their associated Sobol Sensitivity Indices (SI). The Sobol indices are defined as the fractional contribution of an input parameter on the output variance (Sobol, 2001) and allow to compare to what extent parameter 1 is more impactful on a model output compared to parameter 2. From this figure, it appears clearly that wall type has the highest impact among all design parameters on GWP and thus the highest SI, equal to 0.77. Changing the type of

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wall, which includes wall structure, insulation and external coating, indeed explains 77% of the variance of the GWP on its own. This dominance can be explained in particular because walls represent the largest quantity of material in the generated design alternatives, which are characterised by relatively lower WWR compared to the reference case. Furthermore, the GWP variation of the pre-defined walls is much higher than GWP variation of glazing and frame types (see Figure 6) and thus glazing and frame type have a lower SI. In summary, glazing type, frame type and WWR all influence GWP, in that order, with a clear dominance of wall type.

Regarding daylight performance, the window head height has by far the highest impact on sDF performance (SI=0.50). Glazing type with SI=0.33 is the second influential design parameter, followed by interior surface reflectance and WWR, in that order, with somewhat similar SI. Then, window vertical dimension and finally the least influential parameter in general in our study, the number of windows. Glazing type and WWR are thus the only parameters that impact both sDF and GWP.

From a design process perspective, these kinds of results could help focus on parameters having the highest SI when confronting different performance criteria (here daylighting vs. carbon emissions), thereby reducing the complexity induced by considering multiple design parameters.

Target cascading: weighing the embodied impacts of each component over the entire façade

According to the TC technique, it is possible to split the carbon emissions between building elements. Using Equation 1, the average GWP of frame, glazing and walls among 9216 samples were calculated and presented in Table 2, and their relative weight (RW) over the whole southern façade is presented in Figure 5. Walls show the highest impact, with an average value of 1238.3 kg CO_2-eq during 60 years of their life-time in Switzerland. As illustrated in Figure 5, the average weight of the frame's GWP among all samples is almost equal to that of the glazing GWP, while the area of frame in each window is maximum 20% of the window area. Also, one can observe that window (glazed area and frame) are responsible for almost 40% of the façade GWP while the wall delivers the rest. RW gives a useful insight to designers regarding the share of GWP between façade components. Indeed, to properly allocate the carbon budget to the façade, an LCA for entire building would have to be performed.

Table 2. Average GWP shared between frame, glazing and wall (over 60 years)

	Frame	Glazing	Wall
Average GWP (kg CO_2-eq)	274.29	338.27	1238.29

Exploring the knowledge database

Exploring the database thanks to statistical charts makes it possible to extract further knowledge. We particularly intended to answer how much GWP may vary by increasing sDF. Considering that walls have a large impact on the total GWP (SI=0.77), one may expect that by reducing the wall area (or increasing WWR), the sDF will increase while the GWP decreases. However, an analysis of the knowledge database does not show any significant relationship between sDF and GWP (R^2=0.006). Still, the average GWP and average sDF both increase by 11% and 16% when WWR is increased from 25% to 40%, as illustrated in Figure 8. This is because windows are carbon-intensive components and their carbon impact compensates the reduced GWP of walls when increasing WWR. As shown in Figure 7, each square meter of frame, glazing and window (glazing and frame) releases much more CO_2 compared to walls. Note that in this study, the frame-to-window ratio is considered 12% and 20% of window area for metal and non-metal frames respectively, based on (Jusselme et al., 2015).

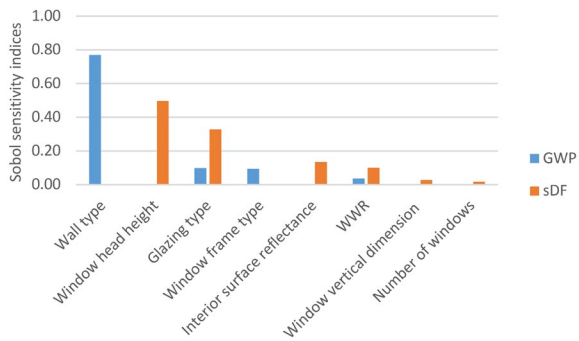

Figure 4. Total order Sobol SI for 8 design parameters

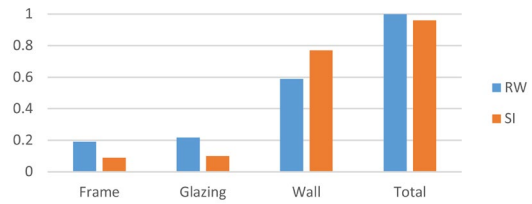

Figure 5. Comparison between the relative weight (RW) of embodied impacts and Sobol SI

According to Figure 9, 27% of the design alternatives have an sDF above 50% (datapoints within the green frame) i.e. meet the 2% DF threshold for more than half of the considered area. Almost 75% of the designs alternatives in that same green are also associated with higher window head height (either 2.6 m or 2.3 m i.e. the two highest positions), whereas window head heights equal to 1.7 m never reached a $sDF_{2\%}$ of 50%. It is of course not surprising that higher window head heights are associated with higher sDF values, nor that this parameter does not affect GWP. On the other hand, choosing a double glazing (which has a lower embodied GWP compared to triple glazing) allows designers to have WWR up to 40%. This is achieved while keeping the average GWP for this subpopulation below the average of the whole dataset, which is 1941 kg CO_2-eq (the black dash line in Figure 9).

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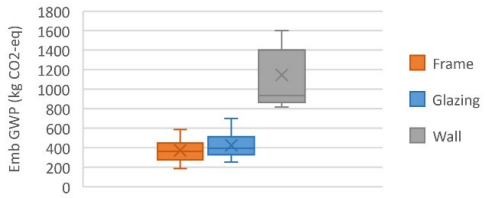

Figure 6. GWP variation of frame, glazing and wall for 9216 design alternatives

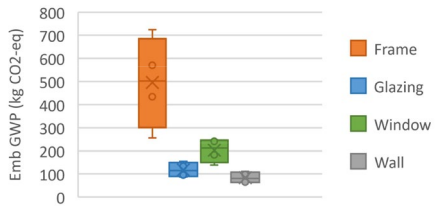

Figure 7. GWP variation for 1 m2 of frame, glazing, window and wall

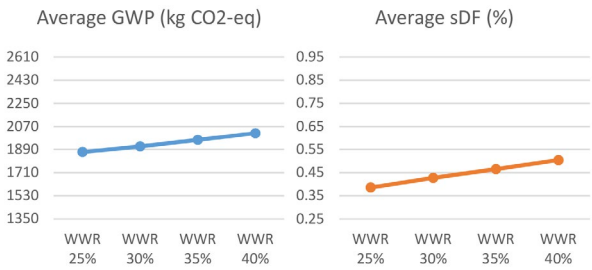

Figure 8. Average GWP and sDF for all design alternatives associated to given WWR

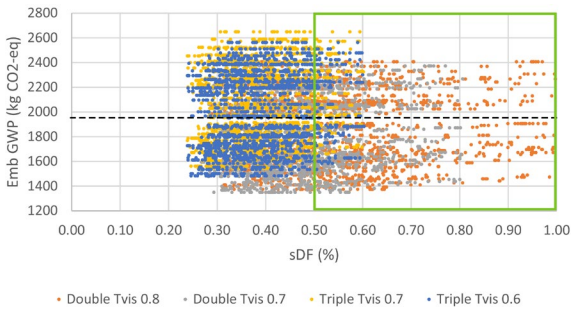

Figure 9. Daylight and carbon performance dispersion of the 9216 design alternatives, filtered by glazing type

Conclusion

This article proposes a method to evaluate daylighting strategies based on their embodied carbon emissions at early stages of design. A literature review allowed to highlight a current disregard of embodied carbon emissions of material production, construction, maintenance and end of life in daylight performance analyses. LCA offers a great potential in shifting the focus of daylighting from merely operational benefits to the total life cycle carbon emissions. While previous studies demonstrated that DSE has a great potential to implement LCA at early stages of design, there are challenges to apply DSE for LCA of daylighting strategies. To cope with the identified challenges, two complementary techniques, i.e. SA and TC were introduced and their feasibility was assessed in this paper, based on a case study. DSE-based LCA and static daylight performance assessment were implemented successfully in the proposed computational workflow, which generated a knowledge database at a reasonable computation cost. Our findings suggest that the southern façade of the considered example project could have a WWR up to 40% (instead of fully glazed façade), use double glazing (instead of triple glazing) and keep its window head height as it was designed to ensure $sDF_{2\%}$ above 50% and remove the second layer of the façade to decrease the embodied GWP. While exploring the knowledge database gives valuable design guidance, there are limitations that should be considered in future work. The operational phase must of course be considered if one wants to look at trade-offs between advanced technology with high embodied carbon and energy savings for instance. Dynamic rather than static energy and daylight simulations should also be favoured, so as to properly take solar control systems into account. Although currently requiring high computational time and based on a limited life cycle inventory database, the proposed method will hopefully bring new insights regarding the need to look at overall carbon impacts – both operational and embodied – for simple as well as complex buildings in the future.

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