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An integrative approach for embodied energy: Towards an *LCA*-based data-driven design method

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ABSTRACT

The built environment is one of the major contributors of greenhouse gas (GHG) emissions. To tackle climate change, global targets have been set for this sector. Although life-cycle assessment (LCA) methods are typically used to evaluate a building project's embodied energy in its final stages of development, this evaluation would be especially valuable at early design stages, when the opportunity to modify the design is greatest. In this paper, an extensive review of methods to improve the usability of LCA at the early design stage is presented. Three major issues regarding the application of LCA arose from this analysis at this stage: its time consumption, the lack of design details, and the non-reproducibility of results. Moreover, LCA makes it possible to assess environmental performance, but does not provide design alternatives, which are crucial to introduce environmental targets into an iterative design process. To that end, existing techniques that can address the major LCA issues were identified, together with their respective limits. These include some promising tools that provide and explore design alternatives and their respective environmental performances. Among these tools are exploration methods, which have not been applied to LCA insofar as it is not possible to do so in a reasonable computational time. To bridge this gap, the paper outlines the structure of an LCA-based data-driven design method, which uses a combination of LCA, parametric analysis, data visualization, sensitivity analysis, and target cascading techniques.

1. Introduction

In November 2015, 174 countries signed an agreement to plan a drastic reduction in greenhouse gas (*GHG*) emissions at the UN Conference on Climate Change in Paris. The built environment, a major *GHG* emission contributor, with 33% of the world's emissions [1,2], is a natural target in terms of mitigation potential. Life-cycle assessment (*LCA*) is likely to become more and more used by building design stakeholders as a tool to improve operating performance and to minimize the embodied energy and impact of buildings. There also seems to be a surge in the scientific community's work on this subject, as reflected by the 280 papers published on the topic of building LCA in 2016 alone [3], that is to say about three times more than in 2011. Only a few of these articles focus on the early design stage, despite this being the period when *LCA* results may have the highest impact on the design. However, an increasing interest over the past decade can be observed, as illustrated by Fig. 1.

Due to its complexity and time consumption, the implementation of *LCA* at early design stages has so far remained a challenge [4]. That is why this research aims to define the structure of an *LCA*-based method for the easy integration of *GHG* emissions targets into the design process.

First, this paper proposes a review of existing methods and points out their limits for the integration of environmental performance targets at the early design stage. Second, based on this review, a method combining different techniques is proposed and described in the last section.

Abbreviations: AEC, architecture, engineering, and construction; GHG, greenhouse gas; IP, induced problem; LCA, life-cycle assessment; NZEB, net zero energy balance; PCP, parallel coordinate plot

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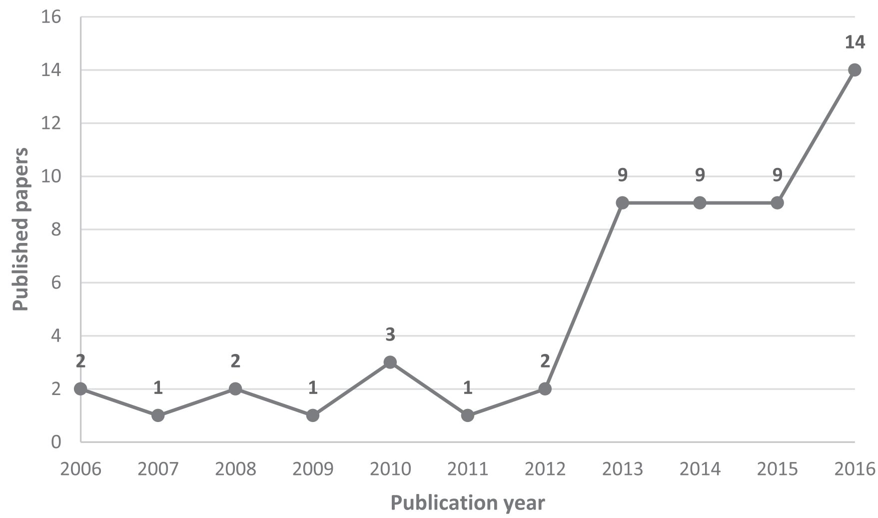

Fig. 1. Articles published in the last decade related to Building LCA at the early stage. Information obtained from Scopus for the keywords "LCA + early + building".

2. A review of existing methods and their respective limits

The following section is a review of methods that can provide knowledge about a project's energy and environmental performance at early design stages. The review does not claim to be exhaustive, but it is necessary in order to understand the pertinence of the techniques that will be combined and proposed as a new method later in this article. Each reviewed method has some limits and induced problems (*IP*), which are identified and indexed as *IP1*, *IP2*, etc. and are illustrated in Fig. 7. These represent the issues that our proposed methodology, detailed in Section 3, aims to overcome.

2.1. Life cycle assessment

LCA is fundamental for sustainability and improvement in building and construction [5]. Based on ISO-14040 [6], it consists of four successive phases: defining the goals and scope, creating the life-cycle inventory, assessing the impact, and, finally, interpreting the results. *LCA* is used to assess the environmental impact during the lifetime of a building, covering five major life-cycle stages according to the European Committee for Standardization: production, construction, use, exploitation, and end of life [7]. Within the architecture, engineering, and construction (*AEC*) fields, this is a complex process as each building is unique, with a long lifespan and multiple functions. As a consequence, performing *LCA* is time consuming (*IP1*), especially at the early building design stage [8].

Recent improvements in interoperability between computer-aided design software and building performance simulation tools facilitate the establishment of life-cycle inventories thanks to a common file exchange format. With building information modeling, it is now possible to assess life-cycle performance by coupling 3D modeling software with an *LCA* tool at the early design stage [9,10]. Indeed, it is at the beginning of the design process that designers have the widest range of options to influence their project. However, whereas a robust *LCA* needs a high resolution of detail to be applied to a building project, the early design stage implies a low resolution of detail [11,12]. Hence, there is a co-existence of highly incompatible needs at the early stages (*IP2*). As shown in previous work [13,14], every method used in the early design stage has to address the problem of system resolution. Two different possibilities have been identified to solve this problem. The first involves an oversimplification of the building based on macro-component descriptions, which can easily provide a rough assessment of the project [15]. The second option is to have a high definition of the building's usage and characteristics, which will obviously lead designers to use multiple hypotheses regarding parameters that are not yet defined in the early design phase. In both cases, the robustness of the results is low. Simplified techniques can provide results that deviate by up to 70% when compared with a detailed *LCA* [16].

Another obstacle that has been identified is the non-reproducibility of *LCA* results [17] (*IP3*). This is due to the method itself, which allows practitioners to define their own system boundaries (Fig. 2) and functional units, and to choose among different *LCA* databases. Indeed, two different practitioners who perform an *LCA* on the same building will obtain two different results [18]. In addition, results will not be applicable from one case study to another if they are not considered within the same boundaries [19].

In conclusion, the non-reproducibility of *LCA* results dramatically limits the use that *AEC* actors may make of results from other case studies. Furthermore, the early building design stage and its low-resolution detail remain an obstacle to performing *LCA* with trustworthy results. Increasing the number of simulations in order to bridge this detail resolution gap might lead to a better understanding of the consequences of having design variables that have not been chosen yet. That is the purpose behind the parametric assessment developed in the

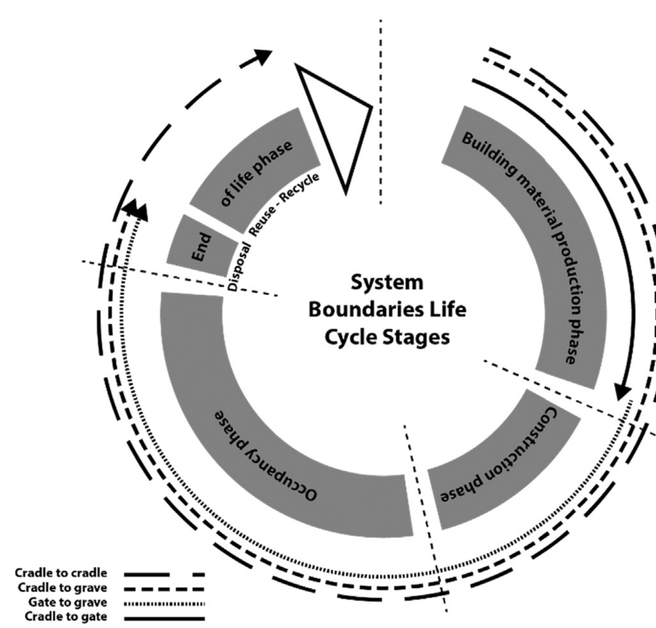

Fig. 2. System boundaries and life-cycle stages of a building, according to different approaches. Inspired by [18].

next section.

2.2. Parametric assessment

The literature review of current early design simulation tools highlights the fact that most of them guide designers through an optimization process, assessment after assessment [20,21]. They tend to suggest one optimized solution according to the environmental performance criteria, although this solution might not be seen as optimal by designers, who also consider other design requirements. Considering the multi-criteria complexity of the building design process, it appears essential to suggest a pool of solutions rather than one optimized one. Also, architectural design is an iterative process between problems and solutions [22,23]. Therefore, many types of references (e.g. case studies or design alternatives) are commonly used as metaphors to transform the design brief into solutions. Whereas designers commonly use aesthetical references, this is far from being the case for technical aspects at the building level. Most technical references that are used are related to a technical construction detail and not to the building as a complex system.

One solution that could feed this multi-criteria and iterative design process would be to develop a wide range of design alternatives. The greater the number of design alternatives, the easier it is for designers to address every constraint [24]. However, as was previously indicated, to apply *LCA* to buildings is time consuming (*IP1*) because of the need to describe dozens or even hundreds of building elements [17]. This reduces the scope for developing an iterative process, which is crucial for project quality. In 2007, a survey demonstrated that it takes more than a month for designers to complete an iteration, with no more than three of these design cycles at the conceptual design phase [25].

The ability to provide fast feedback on the project assessment is without any doubt one of the most important features of a decision-making tool [26,27]. In the literature review, mathematical methods are developed to assess the results of a project quickly, avoiding building performance simulation and using techniques such as multivariate regression [28].

Another way to generate more design alternatives is to use parametric assessment methods. Multiplying the alternatives and their assessment allows for improvements to be made to the design's energy performance. A comparison between a manual optimization process and an automated approach using cloud computing carried out by Naboni et al. demonstrates that, within the same period (71 h), an architect with a standard dual core PC was able to test 64 design options manually [29]. In the meantime, the parametric approach using cloud computing was able to provide 221,184 options, and the best solution under this approach was 33% less energy-consuming than the best one from the conventional approach. The fundamental benefits of the parametric approach are that it can increase energy savings, but most of all it allows more time for evaluating the results, rather than modeling and assessing alternatives [25]. This is made possible thanks to the emerging cloud computing services, which now allow us to perform large and customized parametric studies [30].

Hollberg et al. developed a parametric model that easily compares building variants and their relative operational and embodied impacts [31]. The first model using EnergyPlus [32] had a calculation time of between 20 s and 3 min, which has been considered as too long by users. A second model [33] was able to perform the assessment in only 10 s using a simple energy simulation based on the German standard DIN V 18599-2. However, in the discussion, the authors underline that a tool such as EnergyPlus may still be necessary for complex buildings (noting the multifunctionality of the building and the high performance parameters).

In conclusion, parametric assessment allows for fast calculations in order to find an optimized solution, but does not fully exploit the generated database, which consists of thousands of design alternatives. The exploration of these alternatives in order to acquire knowledge about the project seems to offer an efficient way to integrate environmental targets at the early design stage, although this remains a challenge (*IP4*). The following sections will focus on methods that evaluate the database as a source of knowledge for early decisions.

2.3. Sensitivity analysis

The main purpose of a sensitivity analysis is to rank design parameters according to their influence on the result [34]. Therefore, it is possible to simplify a simulation model by removing parameters that did not affect the result. Sensitivity analysis is already used for decision-making support, but should be more integrated in building performance simulation tools [35].

One of the main differences between the sensitivity analysis methods lies in the computational cost of their assessment models [36]. In any case, it is necessary to automate the creation of the assessment model and the collection of the simulation results. The Morris method [37] is a screening-based technique that is particularly suitable when a large number of input variables are involved in the analysis. However, the results are only expressed in a qualitative way, and the method does not allow for quantifying the effects of different parameters on outputs [36]. The Morris method was used in [38] to analyze the sensitivity of *GHG* emissions in designing parameters within the smart living building case study in Fribourg, Switzerland. The method provides two sensitivity indexes: μ assesses the sensitivity of the results regarding one input, and σ evaluates the interaction between one parameter and the others.

If quantitative results are needed, the Sobol method can be used. This is a global sensitivity analysis and a variance-based approach, which uses the Monte Carlo strategy [39]. It provides more reliable quantitative results. Furthermore, the second-order sensitivity index makes it possible to understand interactions between parameters. Another advantage of this method is its low-discrepancy sampling, which covers the input combination possibilities more evenly than a simple random sampling. However, compared with the Morris method, Sobol increases the computational time by a factor of around 100 [40].

The Sobol method was used in [41] to identify the most influential parameters affecting the final energy consumption in office buildings. Although this case study involved 68 parameters, it showed that just eight were responsible for 80% of the variance (Fig. 3).

The Morris method and the Sobol method are both useful sensitivity analysis techniques that facilitate a ranking of the design parameters' sensitivity. However, although sensitivity analysis supported the design process, it did not allow for quantifying the environmental impact of design parameters as specifications for designers. This is the purpose of target cascading, which is further developed in the next section.

2.4. Target cascading

In mechanical engineering, the issue of a system's complexity has already been addressed by the target cascading approach. This may be defined as a process which splits top-level design requirements into subsystems and component targets in order to design these subsystems and components at the same time, without considering the complexity of the whole system [42]. It guides designers towards optimal targets at the component level, allows them to make assessments within a smaller scope than the entire building, and attributes responsibilities to each design team member (e.g. the *GHG* emissions targets of the structure assigned to the civil engineer).

In the context of the built environment, target cascading has been used to break down the top-level building objectives of energy performance and comfort on a spatial basis into two sub-objectives for office and workshop areas [43]. Only a limited amount of research has been conducted regarding *LCA* targets. The 2000-Watt society concept defines targets per capita [44]. SIA defines sub-targets for buildings and mobility [45], and Kellenberger et al. assign targets for every building

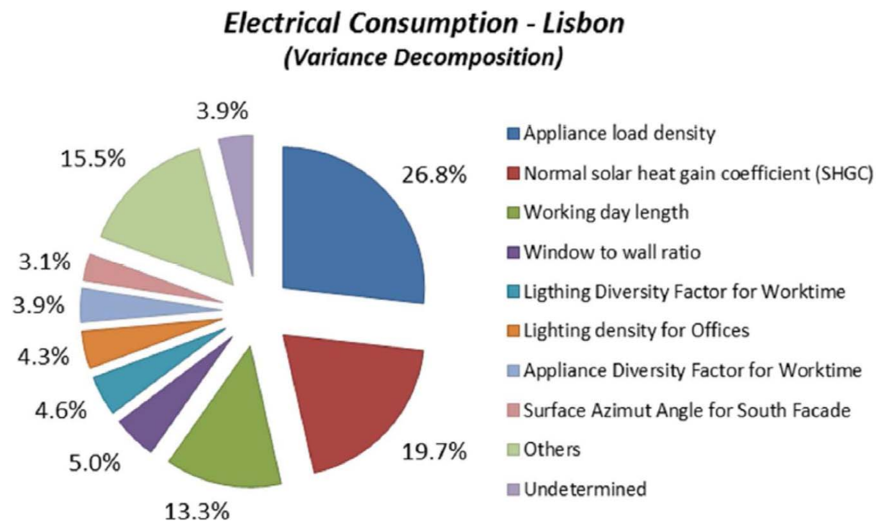

Fig. 3. Variance decomposition for annual electrical consumption with the Sobol method. Image courtesy: Roberto Ruiz [41].

function [46], in order to discriminate between dwellings, offices, schools, hotels, etc.

One major drawback of this approach might be the reduced level of freedom in the design process. Indeed, if performance targets are set at the building component level, it is no longer possible to balance the lack of performance of one component by the high efficiency of another. This may be observed in most current energy labels and certifications where a global energy target is requested, while this is supplemented by other sub-targets by way of design guidance. As an example, the Minergie P label, which is widely used in Switzerland, applies the target cascading principle by setting up the overall target of a net zero energy balance (*NZEB*) building. Two of the sub-targets are to decrease heating demand to a level 10% lower than that specified in Swiss building regulations and to keep the level of embodied non-renewable primary energy below 50 $kWh_{EPnren}/(m^2a)$ [47]. As a consequence, a designer cannot exceed the heating demand threshold by producing more renewable energy on site even if the overall *NZEB* target is respected. This obviously decreases design freedom, preventing a project from being adapted to local specificities.

The literature review highlights that target cascading is a powerful approach to simplifying the design process by decreasing the number of iterations between the design team members, although special attention must be paid to the decrease in design freedom (*IP5*).

2.5. Coupled techniques

As computers, and now cloud computing, dramatically reduce time consumption, it is more important to increase the software's usability rather than to simplify the calculation process [11]. To that end, techniques can start to be associated, as proposed under the exploration methods. These aim to couple parametric simulation with an interactive visualization technique. Miyamoto et al. reduced the building energy model to seven parameters (e.g. thermal transmittance or U value) for assessing heating energy demand with a parametric approach [48]. Each parameter was quantified with three levels of performance (e.g. 0.2; 0.5; 0.8 W/m^2 K for the U value). In this example, exploring all design solutions means performing $3^7 = 2187$ energy simulations, which are calculated with a fast and simplified estimation method called the “Dynamic Equivalent Degree Day”. Excel software is used to generate all possible combinations and to simulate the heating energy demand. Once all the simulations are performed, a parallel coordinate plot (*PCP*) [49] is used as a visualization tool to explore the design possibilities and their heating demand consequences. Miyamoto's paper demonstrates that the combination of parametric simulations with data visualization techniques is powerful, allowing architects to translate numerical language into visual representations. In addition, it is very useful for a quick understanding of each parameter's impact on the results and the interaction between them at early design stages.

Asl and co-workers used parametric simulation and a visual programming interface to tackle a multi-objective optimization process [50]. Coupled with a cloud-based energy analysis tool, trade-offs between daylighting and energy were highlighted thanks to an optimization algorithm and an interactive *PCP*.

Cianfrone et al. implemented a parametric analysis, performing more than 100,000 simulations with EnergyPlus software to design low-energy high-rise residential buildings [51]. They explored solutions that were outside the fundamental thermal principles for reducing loads, but that instead related to architect and client requirements (e.g. maximum glazing surface). This research illustrates that performance is not the only driver that leads the design, and that tools should also be able to propose alternatives that are not optimum, but still achieve the client's objectives. The graphical display proposed through a *PCP* filters parameter combinations well according to a targeted performance, and it highlights the diversity of the possible parameter combinations according to a specified performance threshold.

Ritter and co-workers proposed a “Design Space Exploration Assistance Method” (DSEAM) [52]. Their research highlighted the necessity of proposing an alternative to optimization algorithms, which do not help designers to find solutions that fit with their own requirements. As in [48], parametric simulations and *PCPs* are used to explore the design possibilities and their related performances. Here, however, response surface methodology [53] is used to generate a meta-model with the supporting points. An energy analysis is performed using EnergyPlus software. The meta-model is then explored using two techniques. First, response surfaces are displayed with 3D charts in order to visualize two parameters and their related impact on energy consumption. Second, the meta-model is explored using a PCP (Fig. 4).

The comparison of these two different ways of visualizing the meta-model clearly indicates that the *PCP* is what allows us to understand all the dimensions at the same time. In addition, this multidimensional *PCP* visualization is useful not only for the parameter input but for the result output, which may be obtained with different analysis tools if necessary.

The literature survey reveals substantial examples of exploration methods [25,29,48,52]. However, in order to decrease calculation complexity, the number of parameters involved in these studies is limited (*IP6*), and operative energy is the only impact considered. Exploration methods applied to *LCA*, with a higher number of parameters describing the building life-cycle, were not found. Another limit of the exploration method lies in the method itself. Its usability depends on

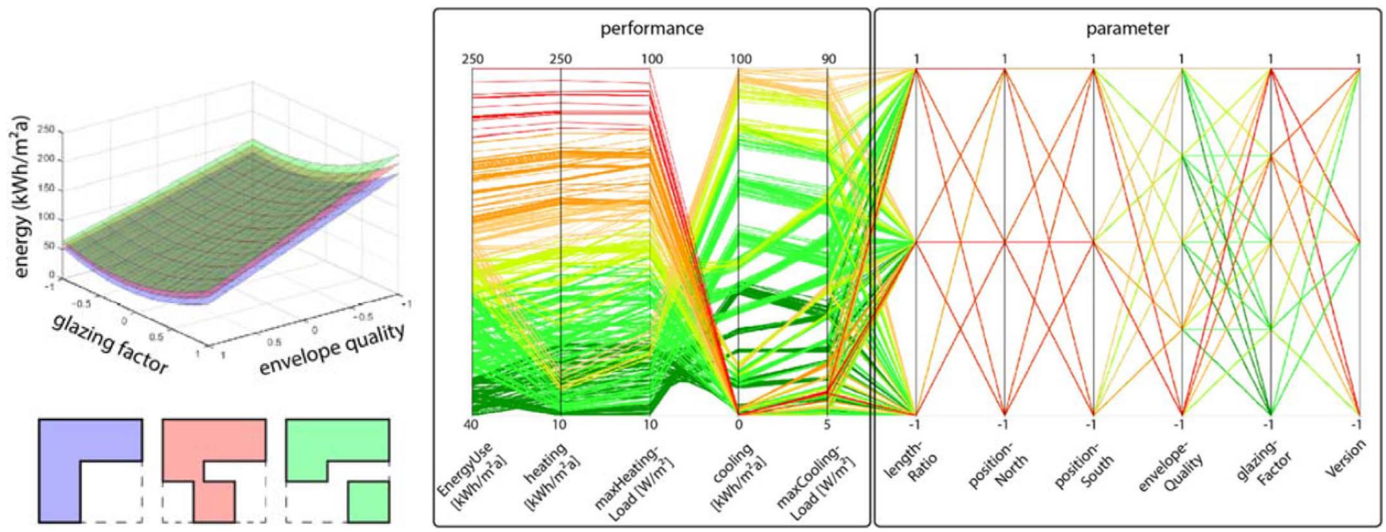

Fig. 4. Visualization of the meta-model with the response surfaces (left) and results of the different office building variants that form the supporting points for the meta-model in parallel coordinate plot (right) Image courtesy: Fabian Ritter [52].

the way in which the building is broken up into design parameters. Indeed, designers cannot explore solutions outside the frame of these defined parameters (*IP7*).

However, the coupling of techniques seems to offer a promising approach, as was illustrated by a previous study [54]. A trend was outlined where a simulation framework was proposed, based on a review of academic and commercial software, in order to support decision making in early design. This workflow integrates statistical analysis, parametric performance simulations and visualization "with the ambition to facilitate proactive, intelligent, and experience based building simulations". The main goal is to develop a knowledge database that assists the design process. Thousands of simulations are run to cover a design space based on a building model. A statistical analysis of these simulations generates knowledge about the design space possibilities. This knowledge, as extracted from statistical analysis and simulation results, is explored in detail through visualization.

2.6. Synthesis

Methods for learning about energy and environmental assessment at early design stages have been reviewed. *LCA* is widely used for obtaining a comprehensive assessment of a building's environmental impacts. However, this methodology is time consuming (*IP1*). In addition, *LCA* is hardly usable at an early design stage, because of the mismatch between the project resolution detail and *LCA* detail requirements (*IP2*). Finally, *LCA* results are specific to a case study, but also to the scope of study, which differs from one project to another. This makes the results non-reproducible (*IP3*).

In contrast, the design process is iterative and involves multiple criteria. Parametric analysis allows us to accelerate the generation of design alternatives that will feed the process, but so far they have been commonly used to optimize projects rather than provide design alternatives, as put forward in the exploration methods. Through that approach, the benefit of parametric assessment becomes the design alternative database that it generates—not the optimization process. However, exploration techniques still have to be developed to extract knowledge from this database (*IP4*). Another limitation of parametric assessment when it comes to *LCA* is the high number of design parameters needed to describe all the building components that substantially influence the performance (*IP6*). Very little prior research has combined parametric assessment and *LCA*, and results have been limited by the simplification of the description of the building model. A new trend consisting of coupling techniques is observed, in the form of exploration methods. However, the usability of such methods is limited by the way in which buildings are divided into parameters and by the way in which these parameters are qualified (*IP7*). For example, the possibility of reaching a target using aluminum-framed windows cannot be explored if aluminum or windows are not included as individual parameters within the database. Furthermore, exploration methods have never been applied to *LCA* so far. Finally, target cascading offers useful guidance for designers by fixing sub-targets and then decreasing the number of design iterations and time consumption. However, the decrease in design freedom appears to be a limitation (*IP5*).

3. A new *LCA*-based data-driven design method

The previous section has demonstrated that building design alternatives can help designers to integrate environmental performance into the design process. One way of providing such alternatives would be to compile a catalogue for designers using examples of low carbon buildings as references. However, there are only a very few low carbon references so far. This can be explained by the two following reasons:

- The fact that widespread awareness of climate change is still recent limits the amount of low carbon buildings that can be considered as references. For instance, only 350 net zero energy buildings have been referenced worldwide by the IEA in the Solar Heating and Cooling program [55].
- The expected constant reduction of the *GHG* emission thresholds during the next century [45], which makes the few available references quickly obsolete.

In addition, even if these references are multiplied in the future, they would still be of limited use because of the non-reproducibility of the *LCA* methodology results (*IP3*). That is why exploration methods are promising for the discovery of design alternatives through their related performance. Based on the literature review (Section 2), this section aims to define a methodology towards an *LCA*-based data-driven design for low-energy and low-carbon buildings.

3.1. Method fundamentals

The methodology objective is to use *LCA* results at the early design stage, as illustrated in Fig. 5.

To achieve this objective, a combination of the techniques reviewed in the previous section is proposed and illustrated by Fig. 7. In this

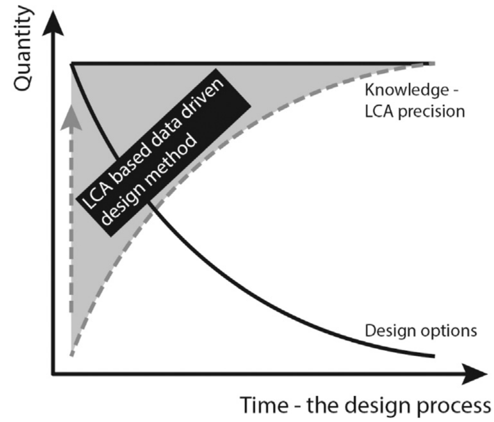

Fig. 5. LCA-based data-driven design method. The method proposes to increase the LCA precision (grey arrow on the left) which is very low at the early design stage and which usually follows the dashed grey curve. The method allows to explore the design space represented by the grey surface in this graph. Inspired by [11].

figure, all the techniques involved in the new method are coupled on the left. The appropriateness of their combination lies in their solutions to the induced problems identified on the right.

3.1.1. Parametric analysis as a design alternative provider

Parametric assessment generates thousands of simulations, which makes result interpretation very challenging (*IP4*). Data visualization techniques such as the *PCP* allow knowledge to be obtained about the data, and they address this issue. An exploration method can be defined as the association of parametric analysis and data visualization.

Using current techniques, it would not be possible to investigate all the solutions, as the number of design parameters used in *LCA* is too high to stay within a reasonable computational time (*IP6*). According to [29], 221,184 alternatives were computed in 71 h for 8 design parameters, qualified by up to 16 performance levels. However, the scope of this research was limited to operative energy consumption. In a previous co-authored work [56], a building was broken down into 17 significant design parameters. Without considering a higher computational cost per design alternative for an *LCA* (which is obviously optimistic, as embodied impacts have to be calculated in addition to operating impacts), representing an increase to 17 design parameters with 4 performance levels each, a parametric analysis covering the full design space requires 1.7×10^{10} simulations to be performed. This is of course incompatible with the design process timeline. Even if we consider Moore's law, doubling computing performance every two years, and considering the computational time from Naboni's research, it would take more than 17 years to develop a cloud-computing infrastructure that would enable this amount of simulation to be performed in 71 h. This is presumably why no exploration techniques based on *LCA* have been found in the literature review so far.

3.1.2. Sensitivity analysis as a sampling process and design support technique

There are two solutions for reducing the computational time to a reasonable length. First, some of the parameters that do not affect *GHG* emissions could be removed from the parametric simulation. Second, the simulation resolution could be reduced thanks to a sampling of the parameter combinations. According to the literature review, this would be possible with a sensitivity analysis that provides a sampling of the parameter combinations and a ranking of the parameter sensitivities. Sensitivity analysis proceeds by changing the parameters of a simulation model. It provides a wide range of parameter combinations, showing the effect on the results, and inspiring designers regarding the path they must choose to achieve their goals. In addition, it assesses the robustness of these combinations in relation to the future adaptability of the building, considering parameters that allow for the highest number of combinations to reach an environmental target.

The Sobol method seems to be suitable for that purpose, as this variance-based approach gives quantitative sensitivity results and provides a low-discrepancy sampling so as to screen the parameter combinations evenly. In their case study, Ruiz and co-workers [41] demonstrated that only 8 parameters out of 64 were responsible for 80% of the variance regarding the electricity consumption of buildings. Therefore, when reducing the computational cost by using parametric analysis, sensitivity analysis and data-visualization, an *LCA*-based data-driven design method starts to be developed by solving four induced problems: *IP1*, *IP2*, *IP4* and *IP6*. A first piece of co-authored research describes the high potential of a prototype based on this technique combination [56] and shows promising results.

3.1.3. Target cascading to increase the usability of the method

The proposition as previously described still has two unresolved induced impacts, previously identified as *IP3* and *IP7*. First, *LCA* results will still not be reproducible (*IP3*). Second, designers will not be able to pursue all their requirements (*IP7*), as the design alternative exploration will be limited by the way in which the buildings have been broken down and by how the parameters have been described.

Section 2 points out that an interesting way to tackle these problems seems to lie in the target cascading approach, which would break down the building into subsystems and building components. However, no research has so far tried to define targets for the components and systems of buildings. This has never been used as a decision-making method to guide designers towards enhancing environmental performance. Recently, and in the same research project, Jusselme et al. used the target cascading approach to break down the 2000-Watt society objectives into subsystems (i.e. building function) and component targets [57]. A Sankey diagram [58] was used to identify the *GHG* emission fluxes from the 2000-Watt society top-level targets (2 t CO_2-eq/p*y in 2050) to the component level targets (Fig. 6).

Following this work, Hoxha and co-workers introduced *GHG* emission targets at the building component level as a guideline for designers [59]. A project population was generated by means of a sensitivity analysis. Targets were attributed to each component and system of a case study. The means and the intervals and coefficients of variation

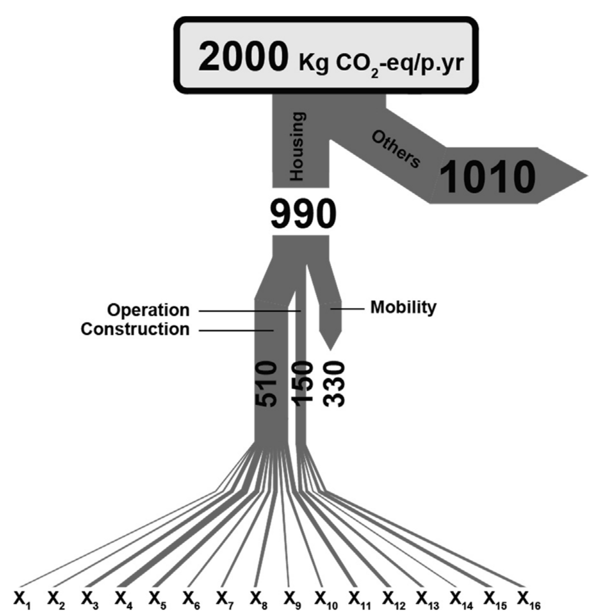

Fig. 6. Target cascading with a top down approach from the 2000-Watt society vision and its 2050 intermediate target of 2 t of CO2-eq per people and per year, toward sub-targets: operation, construction and induced mobility of housing. These sub-targets are finally decomposed into GHG emission objectives at the component and system level Xn [57].

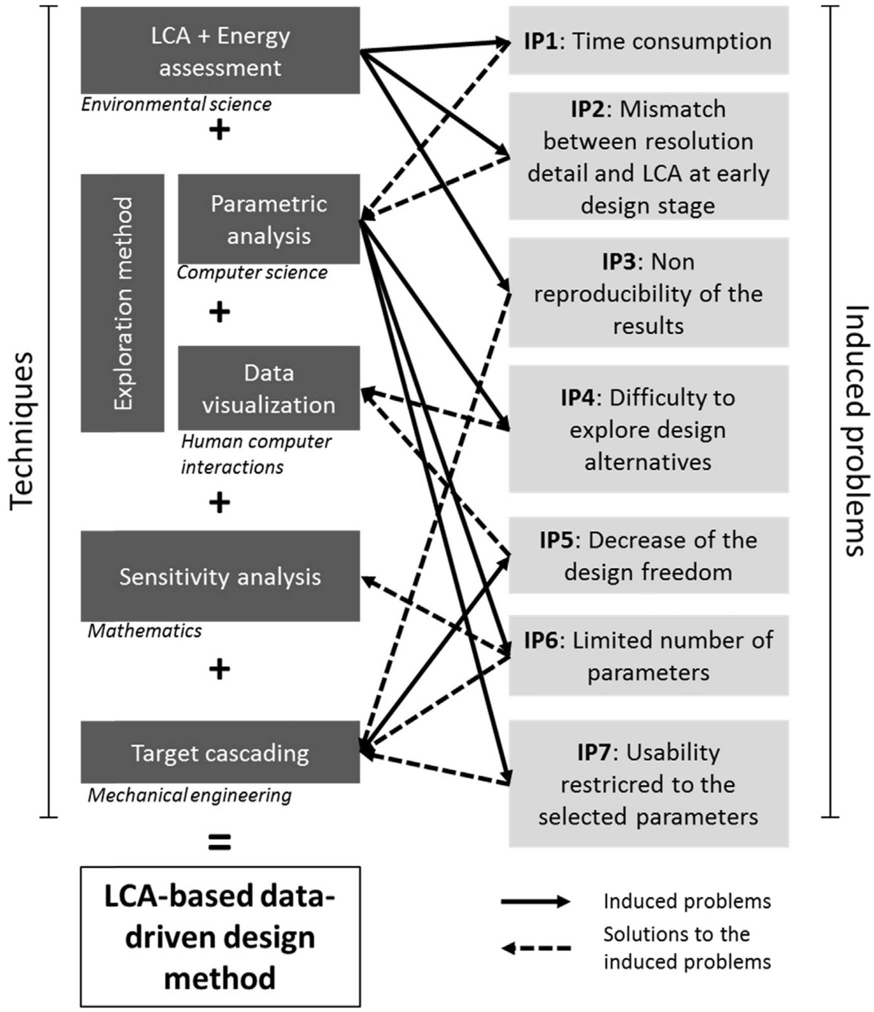

Fig. 7. Technique combination towards a LCA-based data-driven design method. Techniques on the left induce problems identified on the right, which can be tackled by other techniques. Text in italic font specifies the original scientific field of each technique.

were presented for each target. This information provides an understanding of the environmental weight of each component in the global system. Parametric analysis provides a project population as ground material for setting up targets at the component level, as proposed in a previous co-authored work [59]. Moreover, target cascading, combined with exploration method and sensitivity analysis, allows specific targets to be set for sub-populations that fit the designer's requirements. In this way, it is possible to integrate an innovative building component or system into an architectural strategy if the *GHG* emission levels of the innovation fit with the component or system target. In addition, target cascading can become dynamic, as it is possible to update targets according to the designer's strategies. In such conditions, there will not be a decrease in the design freedom as previously highlighted as *IP5*.

3.1.4. Combining five techniques as a method

The combination of *LCA*, parametric analysis, data visualization, sensitivity analysis, and target cascading represents a powerful solution for developing an *LCA*-based data-driven design method (Fig. 7).

In order to transform this dataflow into insights and patterns that will be helpful for designers, specific data-visualization techniques have to be used. *PCPs* seem to be very useful when it comes to visualizing multidimensional data. The sensitivity analysis should enable users to remove the dimensions that do not affect *GHG* emissions in order to increase the usability of the method. Regarding target cascading, a Sankey diagram could be used for the *GHG* emissions fluxes, from a building's top-level targets to the component level. Linking and brushing interaction techniques [60] could combine a *PCP* and a Sankey diagram so as to visualize design alternatives as suitable low carbon architectural strategies and, at the same time, the resulting objectives that will be set under the target cascading method at the component level.

3.2. Description of the LCA-based data-driven design method

This section aims to describe the *LCA*-based data-driven design method as it should be implemented in a computer program. Fig. 8 represents the method in five major steps, which must be completed consecutively, and which can be performed with various pieces of software and tools that are not described in this paper. The five steps represent an iteration with the design process, which can be reproduced throughout this process as long as undefined variables exist in the design space. Each iteration will enable the designer to make choices within the design space that are covered by the selected parameters and that will help him/her to better understand which variables have to be carefully considered, and also which design parameters make it possible to reach a specific environmental target.

Step 1 - Project definition: the project is described and located in a specific context. A weather file corresponding to the project location is selected. The architectural project is described by choosing an archetypal geometry, or by importing a 3D model. Finally, the building function is required in order to define the building's

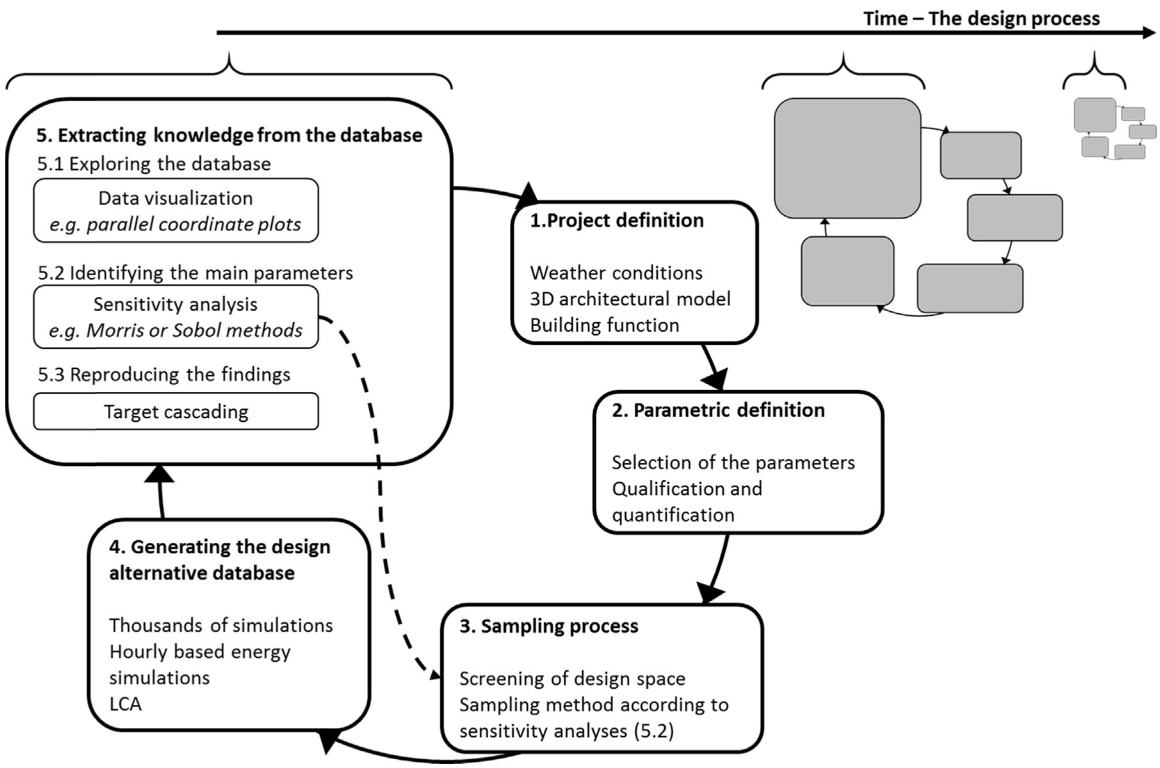

Fig. 8. Description of the LCA-based data-driven design method. The five steps of the method can be replicated all over the design process timeline.

occupation scenario. The simulation software will further use all this information for the main hypotheses. It will ensure that the design alternative database is unique and specific to one architectural project.

Step 2 – Parametric definition: the scope of the design space that the method will cover is described. Designers select the design parameters for their interest or for their influence on the results, according to the literature or according to a previous application of the method. Each parameter is qualified or quantified using different values within boundaries that must be chosen in line with the designer's practice:

- Example 1: design parameter: Thermal resistance of the walls; from 0.1 W/m^2 K to 0.2 W/m^2 K in five steps of 0.02 W/m^2 K,
- Example 2: design parameter: Insulation material: wood wool, rock wool and polystyrene.

Step 3 – Sampling process: design alternatives are described by combining all the design parameter values. The number of design alternatives that will be generated by the sampling process to cover the design space will depend on the number of design parameters and their values. Current exploration methods focus on the building occupancy phase and limit the number of parameters to five or six in order to keep the computational time reasonable. However, in our case, the methodology has to be used at an early design stage for better efficiency where the design space is the widest. In addition, the whole life-cycle of the building will be analyzed, increasing the number of parameters influencing the results. In this method, the sampling process of a sensitivity analysis will be used in order to generate a database with a limited number of design alternatives, without covering the full combinations of possibilities.

Step 4 – Generating the design alternative database: all the design alternatives consisting of parameter combinations (Step 3) applied to the building geometry (Step 1) are assessed with an energy simulation tool and a life-cycle assessment tool. This step generates the ground data from which all the knowledge will be extracted. Tools should be chosen according to the metrics that the designer wants to assess, but also according to their time consumption.

Step 5 – Extracting knowledge from the database: various techniques are used to extract knowledge from the database.

5.1: First, data visualization allows us to explore a set of design alternatives and their related performance, using *PCP* techniques, for instance (cf. Section 2). However, as not all the combinations of possibilities are covered, two other techniques are added.

5.2: The sensitivity analysis used as a sampling process in step 3 provides the sensitivity of all the design parameters. This allows for a reduction in the number of parameters while exploring the database so as to focus on only the most sensitive ones. The entire method could also be used in a two-step process by following the dashed arrow in Fig. 8. In this way, a sensitivity analysis is only conducted by using a low time-consumption technique such as the Morris method (cf. Section 2). Based on the results, Step 2 is redefined according to the most sensitive parameters (removing the others from the parametric analysis), and steps 3 and 4 generate a design alternative database with a higher design space resolution on more sensitive parameters and within the same computational time. In this way, the sensitivity analysis contributes to tackling the *IP6* issue induced by the high number of parameters required to perform an *LCA*. The sensitivity analysis can be performed on the full database, but only on the design alternatives within this database that comply with the constraints chosen by the designer while exploring the database. For example, the *GHG* sensitivity of the insulation quantity of a subpopulation of design alternatives that use a wood boiler for the heating system will be far lower than that of the subpopulation that uses a gas boiler. By linking exploration techniques and sensitivity analysis, the designer is encouraged to explore the most sensitive parameters according to his previous choices, not according to the full database.

5:3: At this stage, the method still has to deal with three issues identified in Section 3: *IP3* and *IP7*, i.e. the non-reproducibility of the results, and the usability being limited to the selected parameters. This is where the target cascading approach comes into play.

Linking target cascading and exploration of the database automatically processes targets at the component level, giving the designers independent and specific objectives. It also consequently addresses *IP5*, namely the design freedom decrease, as the target becomes specific to a project or design situation. For example, it is possible to have an energy or carbon emission amount as an objective for the building's windows according to a specific architectural strategy (e.g. concrete structure and fully glazed façade). Thus, even if an innovative new window is not included in the database as a design parameter, it is still possible for designers to know whether this new window is efficient enough for them to use it within the framework of the architectural strategy that they are exploring. In addition, these targets can be further used as guidelines in other projects to start the design process, thus allowing for reproducible results.

3.3. Synthesis of the method and limitations

Life-cycle analysis is the main technique used to assess the environmental performance of buildings. However, this technique induces mainly three problems, namely the time consumption of the method, the mismatch between the resolution detail of the project and the *LCA* building description level at the early design stage, and the non-reproducibility of the *LCA* results.

Exploration methods already exist and combine parametric assessment with data-visualization in order to provide design alternatives within the iterative process. However, they are currently limited to the operative energy impacts of the building. Adapting exploration methods to *LCA* means increasing the complexity of the simulation model by adding all the other life-cycle stages, e.g. materials and components as embodied impacts. If this is done, the number of variables will increase and will prevent designers from investigating the full range of possible parameter combinations for the design space. An initial solution would have been to oversimplify the *LCA* simulation model in order to decrease the variable number, but this approach was not chosen, as it leads to less robust results and a weaker impact of the results on the design. There is a second solution that has better potential: exploring the *LCA*'s complexity, rather than simplifying it. Retaining the complexity of the *LCA* simulation model allows the design parameters that contribute the most to performance to be identified more precisely. It also makes it possible to explore correlations between them more effectively. The computational cost induced by this complexity can be lowered by a sensitivity analysis, using a sampling approach that limits the combinations to a reasonable computational time and allowing the diversity of the design alternatives to be narrowed down to the most sensitive parameters. Another approach that haven't been discussed in these article and that might be explored to tackle the computational cost issue is the usage of metamodels trained on the sensitivity analysis dataset. These metamodels might represent a way to fast generate new alternatives in order to explore a specific design space with a higher resolution.

Target cascading has been identified as a powerful technique to open up this method to innovative components and systems, which would not have been integrated in the parametric simulation initially. In this way, specific targets can be fixed at the component or system level, resolving at the same time the issue of exploring the alternatives in a non-exhaustive way. However, as the application of target cascading to buildings is a recent research field, which brings part of the added value of the proposed method, further research should be developed on this technique, e.g. the issue of interaction between components.

The parallel coordinates plot has been defined as an interesting data-visualization technique to explore multidimensional data. However, a specific literature review of the Human-Computer Interaction field would be helpful to compare the different available visualization techniques and choose the one with the best potential, according to the context of use (i.e. the design process), and according to the building performance simulation dataset specificities.

4. Conclusions

The aim of this article is to outline a method to consider environmental targets at the early design stage based on *LCA*. A literature review allows for a better understanding of the design process and the identification of the most promising technologies, as well as the relative induced problems that occur to the designers. It was pointed out that the design process is iterative and needs references to feed these iterations. However, considering the environmental impacts and low carbon buildings in particular, there is a lack of built references that can be considered as design alternatives. Thus, the first objective of the method is to produce design alternatives and to evaluate their related performance in order to support the decision-making process. To achieve this, it is proposed to combine five techniques in a single workflow as an *LCA*-based data-driven design method. These five techniques are *LCA*, parametric analysis, data visualization, sensitivity analysis, and target cascading.

The usability and feasibility of this new method will be investigated in further research, using case studies and usability assessment. A prototype of the method will be set up to verify its ability to impact the design process and to simplify the use of LCA at early design stages.

The final purpose of this new methodology is to set out a path towards a new generation of building assessment tools, where a proactive exploration of data by the designer is as important as the performance assessment in order to fully understand the complexity of the problems faced. This offers a powerful way to disseminate *LCA* among designers.

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Image courtesy of Dr. Fabian Ritter and Dr. Roberto Ruiz.

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