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Integrating Environmental Considerations in Structural Engineering: Challenges, Opportunities and Solutions

Sandie Kate FENTON[*abc], Klaas DE RYCKE[*b], Lars DE LAET[c]

[*] Bollinger + Grohmann S.A.R.L
15 rue Eugène Varlin, 75010 Paris
Sandie.Kate.Fenton@vub.be

[a] EUR Humanities, Creation, Heritage (PSGS HCH), "Investissement d'Avenir ANR-17-EURE-0021"
[b] Ecole Nationale Supérieure d'Architecture de Versailles
[c] Vrije Universiteit Brussel

Abstract

The building sector is aiming for carbon neutrality and the field of structural engineering is witnessing a surge in regulatory requirements. In order to meet environmental policies and with their strong impact on building carbon footprints, structural designers have to update their methods. It is therefore of great interest to familiarize them with Life Cycle Assessment (LCA) principles and integrate efficient LCA tools to their workflow, and avoid having to refer exclusively to external environmental practices. This industry-driven research delves into the challenges faced by structural engineers and explores key changes and steps that can be implemented to reduce the environmental impacts of projects without adding to the workload. A first challenge lies in the diverse array of working habits and tools used by engineers within the same office, and the need to propose solutions tailored to all of them. Additionally, the dynamic nature of projects, evolving at each design stage, means LCAs are usually deferred to final stages to avoid time inefficiencies, meaning building designs are fixed and no changes can be made. Solutions implemented and presented range from the development of user-friendly LCA plug-ins directly integrated to in-house tools, to the creation of early design tools for real-time approximation of embodied GHG emissions, making for rapid verification of computed results, as well as facilitating decision-making and impact assessment. For this purpose, the research presents a Machine Learning methodology that could systematically gather in-house data and leverage knowledge from these databases, to enable a broader understanding of project footprints and help bridge the data gap in the building industry. By examining both challenges and opportunities experienced in their every day work, this study aims to assist structural engineering practices in meeting current environmental objectives.

Keywords: Structural Engineering, Life Cycle Analysis, Workflow, Tool Development, Machine Learning

Acronyms: **BG** Bollinger + Grohmann; **CF** Carbon Footprint; **EE** Embodied GHG Emissions; **GHG** Greenhouse Gas; **LCA** Life Cycle Analysis; **ML** Machine Learning; **SHAP** SHapley Additive exPlanations

1. Introduction

Embodied emissions (EE), and in particular the production stage of structural components, represent a rising proportion of building whole-life emissions. Structural engineers have a key role to play in reducing building carbon footprints (CF), and taking the right decisions from early stages onwards has become part of both their mission and responsibility. On the one hand, they are confronted to public measures and regulatory frameworks with increasing limits on EEs. On the other hand, they are exposed to private initiatives, with the development of assessment tools and in-house strategies sensitizing to environmental concerns. In order to be impactful, research has highlighted the need for tools to be straightforward to use, well integrated in the workflow and exempted of increasing any user workload [1]. Moreover, the tools should allow users to understand the impacts of their design choices on building emissions and indicate recommended changes [2]. In this paper we discuss the specific challenges and opportunities observed within the structural engineering consultancy Bollinger + Grohmann (BG) and solutions developed to answer them.

2. Environmental strategies

Bollinger + Grohmann (BG) has initiated multiple actions and environmental strategies to reduce the impact of its projects on climate change. First, it has set up a Life Cycle Analysis (LCA) core team, responsible for deploying mitigation strategies for the company. The team assembles one representative per office responsible for sharing information internally, via intranet, workshops, lunchtalks and surveys. Second, it has established a list of practical in-house measures towards lean design, low carbon and zero waste as well as checks to help employees in their decision-making. Third, LCA calculations have become mandatory within the company for all new projects and with an increasing level of detail as the planning process evolves. The goal is to familiarize all employees with the LCA process and to make them aware of their impact on projects. Fourth, tools have been developed in-house and integrated to the existing workflow, allowing to track and optimize building structural EEs. The BG LCA Spreadsheet has been developed as a quick and pragmatic excel tool for easy calculation of the LCA of structures. It is aimed at practising structural engineers within BG, doesn't require any expert knowledge on LCA and allows to compare 4 design alternatives. Calculations are provided on a summary sheet and can be used directly to communicate with clients and architects. Moreover, BG LCA plug-ins integrating all the spreadsheet functionalities have been developed for RFEM, Rhino and Grasshopper and allow to retrieve the LCA for any open 3D model. Assessments are linked to a colour map, allowing to visualize emission hotspots on the models and to track the impacts of material and geometry changes. Fifth, all BG LCA tools have been linked to an in-house database keeping track of results. The database is expected to act as a feedback loop by learning from projects, experiences and trends. It lists geometrical and material information as well as project descriptions, including project number, name, location, phase, date, author, sector, type, storeys, basement, foundations, groundfloor, superstructure, typical span, liveload, environmental certification scheme and seismicity. Finally, importance has been given to promoting communication about sustainability and structural EEs externally. by explaining concepts, comparing alternatives and discussing options with clients, as well as in the industry, by taking part in assemblies, conferences, research projects and journal publications.

3. Challenges and opportunities in structural engineering

3.1. Tools

Research facilitating the assessment of EEs in the building industry focuses primarily on developing calculation tools such as tables and spreadsheets, or plug-ins for 3D-models, with different levels of precision and focus [3]. Tables involve manually inserting volumes and materials retrieved from building plans, models or tender documents for the calculations [4, 5, 6, 7, 8]. They are increasingly difficult to use as the complexity of projects increases and their manual inputs are prone to error. Finally, since they aren't integrated to pre-existing structural tools, they constitute an extra step in the workflow and increase the workload. Plug-ins compute the EEs at different stages based on volumes and materials automatically retrieved from 3D-models [9, 10]. Once building geometries and materials are defined, LCAs are updated at every design change. Their colour maps facilitate the comparison of design alternatives and the visualization of results and design impacts. However, they require having access to a 3D model and mastering tools and design parameters.

In general, calculation tools allow thorough and precise calculations, but require making an inventory of all building components, or defining material attributes in the models, a time-intensive task which can last multiple days, increases the workload and generates costs [1, 11]. To avoid having to repeat this task, and given the dynamic nature and regular changes in projects, LCA is often deferred to final stages and rarely used to inform the design. Moreover, they are usually run by external consultants [12]. While this brings benefits, such as impartiality and expertise, drawbacks include low integration with project goals, limited customization, and delayed feedback as well as a reduced sense of accountability for sustainability outcomes, as stakeholders feel less responsible when not directly involved in the assessment.

3.2. Data

Databases compiling information on real-world buildings and carbon emissions originate from public and private entities [13, 14, 15, 16, 17, 18, 19]. They are essential to improve our understanding of current emissions, targeted emissions and to make recommendations from their analysis. Despite their growing number, databases remain rare, and data on EEs is largely lacking. Algorithms and design tools trained on real-world building data can serve a wide range of applications. Unfortunately, in the case of EEs, applying complex algorithms and Machine Learning (ML) to existing databases is hindered by the rarity and lack of consistency of their data, resulting from three main factors. First, the cross-sectoral and international nature of EEs, which makes it hard to define assessment boundaries. Second, the sensitivity of the EE values to the calculation hypothesis, which means values retrieved for an identical building vary greatly depending on the building parts and life cycle stages included [20, 21, 22]. Third, the non-uniformity of features assembled in the database, which makes it hard to compare and combine them [2, 23].

3.3. Opportunity

Building typology and contextual information, available in design briefs at early stages, provide information which can be leveraged using ML models, to estimate building EEs. Given the high sensitivity of LCA values to calculation hypothesis, and given the fact that building regulations and Environmental Product Declaration values are constantly updated, there is an interest in developing a robust model that can be trained on different databases and units, optimized for different evaluation metrics and tailored to meet different thresholds. The ”soft feature approach” was developed within BG to investigate this opportunity [24]. It is a ML method which can be trained on databases of existing buildings to predict the EEs of new projects from a small input set of features easily accessible at early design stages. The method can adapt to different databases and provides robust results as a result of integrated feature selection, diverse regression models and blending techniques [25].

4. Data-driven methodology

In this section, the potential of the ”soft feature approach” for predicting the EEs of real-world buildings is tested on existing BG projects.

4.1. Steps

First, the algorithms are trained on a database compiling features of existing buildings and calculated EEs. At the time of writing, the BG database lists too few projects to train the underlying algorithms of the methodology. The algorithms are therefore trained on another database with similar content (boundaries, stages, units), the Price & Myers database [26]. Second, three building structures are selected from the BG database to serve as test samples. Their structural EEs have been calculated by structural engineers using the BG LCA spreadsheet. The spreadsheet also attributes a Structural Carbon Rating Scheme (SCORS) to the projects, consisting in a letter [A - G] per step of 50 $kgCO2e/m^2$, and including A1–A5 emissions of the primary structures (superstructure and substructure). SCORS allow to rank projects and provide sufficient EE information for early design stages [4]. Third, the EEs of the 3 samples are predicted using only their descriptive features listed in Table 1 as input for the pre-trained algorithms. When features are missing, mean values and modes are used. Fourth, the predicted values and predicted SCORS rating are compared to groundtruth values. Fifth, SHapley Additive exPlanations (SHAP) methods are used in combination with the trained algorithms to explain feature impacts on predicted values [27].

4.2. Results

Predictions and explanation plots are presented in this section to evaluate the potential of the methodology in comparison with standard LCA tools. Observations and values serve as indicators and should not be taken as absolute values.

Table 1: Input features, predicted EEs and SCORS ratings for 3 Sample Structures in the BG database.

Features	Structure A	Structure B	Structure C
Floor Area [m²]	13187	3330	120
Storeys [-]	3	2	5
Year [-]	2023	2023	2023
Value [m£]	11	11	11
Stage	5	5	5
Sector	Educational	Educational	Residential Single
Type	New Brownfield	New Greenfield	New Brownfield
Foundation	Raft	Piled Ground Beams	Raft
Basement	None	None	Full Footprint
Ground Floor	Ground Bearing RC	Ground Bearing RC	Other
Cladding	Other	Other	Other
Superstructure	Timber Frame Glulam-CLT	Other	Timber Frame Glulam-CLT
Fire Rating	60	60	60
Passive	No	No	No
Embodied Emissions	value $\sim$ SCORS		
Prediction $[kgCO_2e/m^2]$	240.46 $\sim C$	294.68 $\sim D$	444.72 $\sim G$
Groundtruth $[kgCO_2e/m^2]$	195.53 $\sim B$	223.94 $\sim C$	396.62 $\sim F$

As indicated in Table 1, for all 3 structures, predicted EEs are far under groundtruth. However, the order of structure EEs, from less emissive to most emissive, corresponds to groundtruth order, and the predicted SCORS ratings systematically fall 1 category short of groundtruth ratings. The negative bias could be explained by the differing properties such as location, company or building regulations between projects in the Price & Myers database, and projects in the BG database.

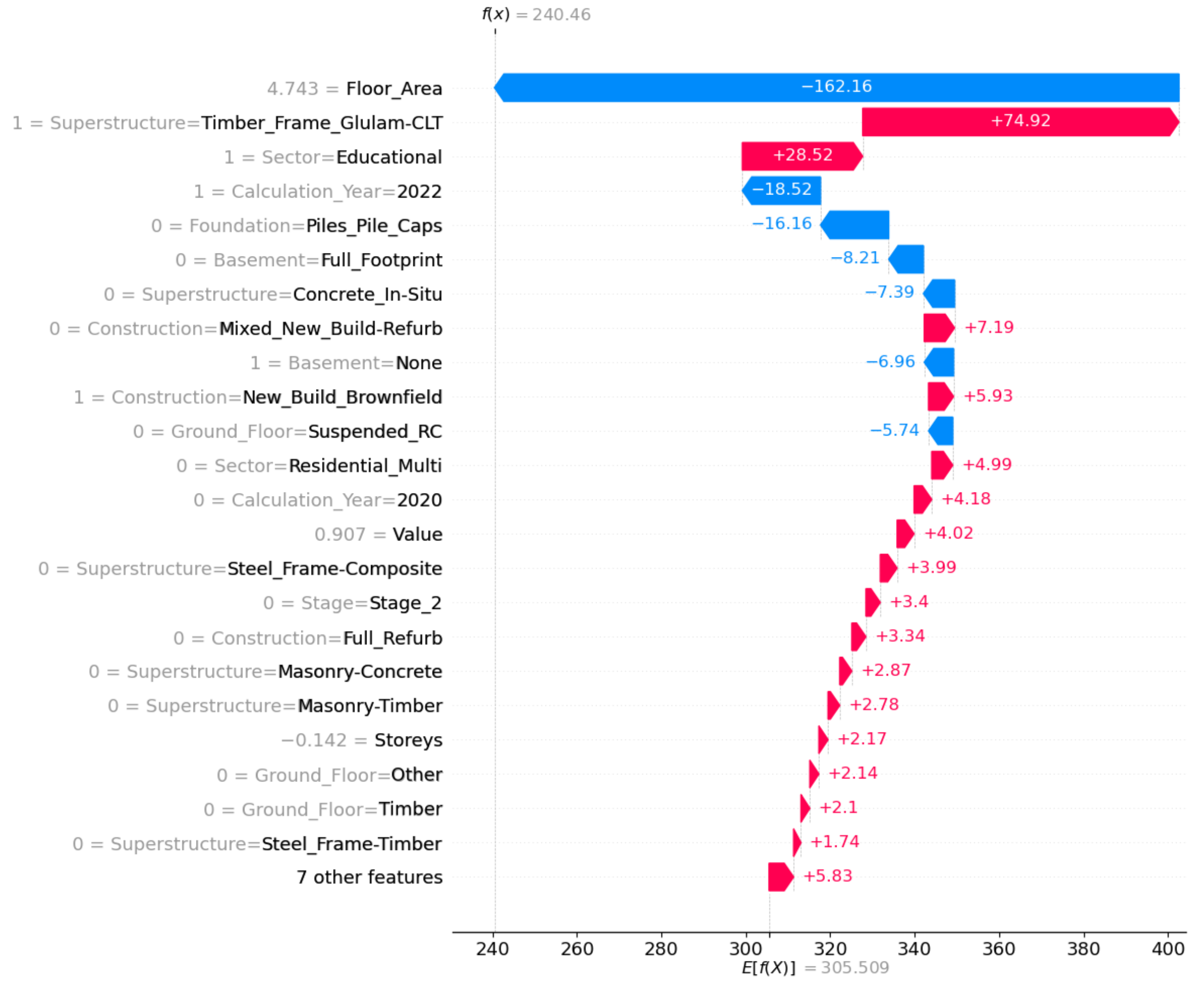

Figure 1: The value predicted for Structure A (f(x) = 240.5 $kgCO2e/m^2$) is lower than the average dataset value (E[f(x)] = 305.6 $kgCO2e/m^2$), The 13187 m^2 "Floor Area" generates the strongest structural EEs decrease (-162.16 $kgCO2e/m^2$), indicating high floor areas tend to reduce structural EEs. The "Glulam-CLT Timber frame" generates the strongest EEs increase (+74.92 $kgCO2e/m^2$). In the training database such superstructures have very low absolute EEs ($kgCO2e$) and very high EE rates ($kgCO2e/m^2$), indicating they might be preferred for smaller-scale projects.

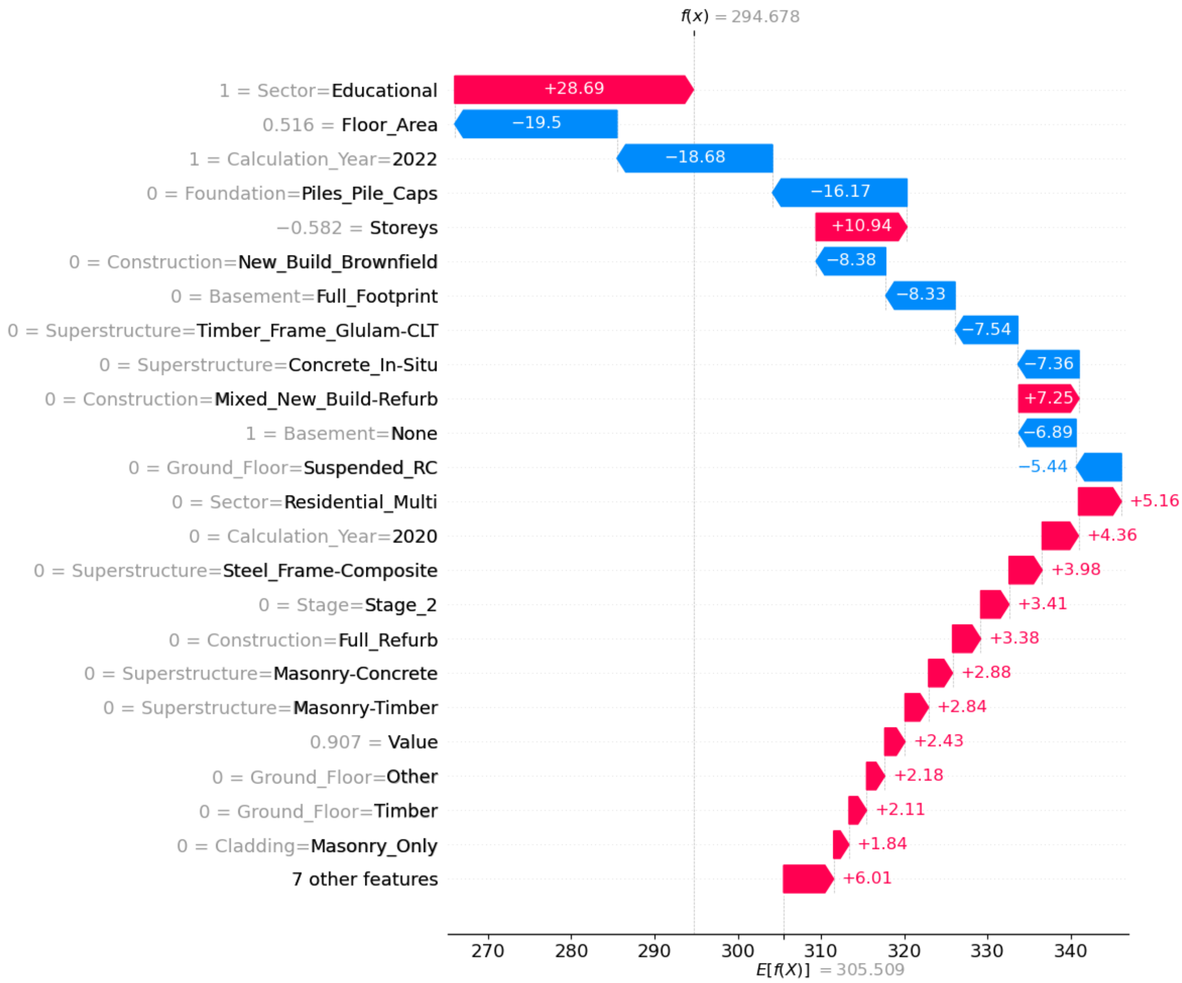

Figure 2: The value predicted for Structure B (f(x) = 294.7 $kgCO2e/m^2$) is lower than the average dataset value (E[f(x)] = 305.6 $kgCO2e/m^2$), Again, the 3330 m^2 "Floor Area" generates the strongest EEs decrease (-19.5 $kgCO2e/m^2$). The "Educational" Sector generates the strongest EEs increase (+28.69 $kgCO2e/m^2$), indicating this activity might induce higher structural EEs than other sectors in the training database.

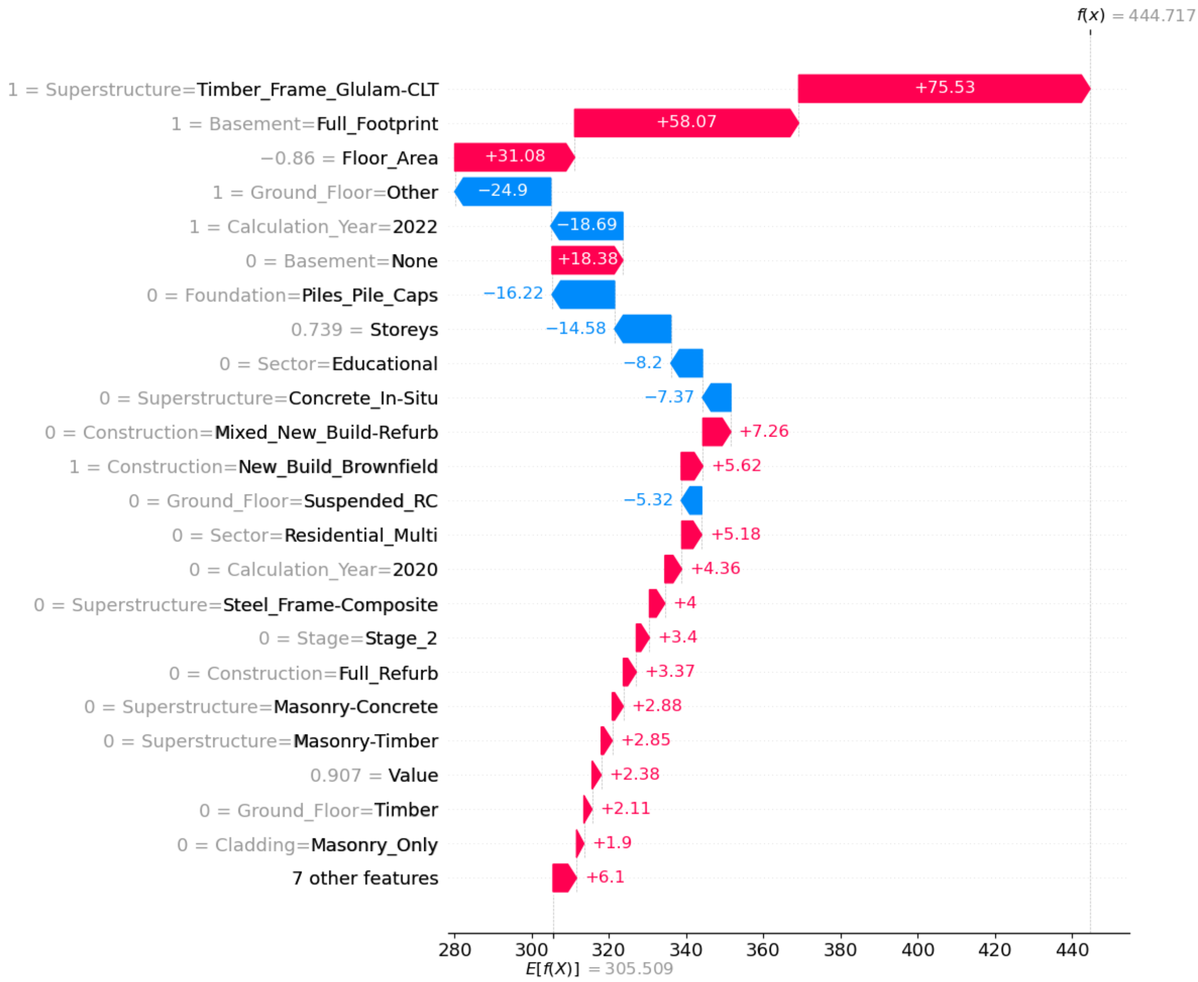

Figure 3: The value predicted for Structure C (f(x) = 444.7 $kgCO2e/m^2$) is higher than the average dataset value (E[f(x)] = 305.6 $kgCO2e/m^2$), The "Other" ground floor generates the strongest EEs decrease (-24.9 $kgCO2e/m^2$). The "Glulam-CLT Timber frame" generates the strongest EEs increase (+75.53 $kgCO2e/m^2$), followed by the "Full footprint" basement and 120 m^2 "Floor Area".

Feature impacts on predicted values are explained on Figures 1, 2 and 3. The waterfall plots display the SHAP explanations per feature for the 3 studied structures. SHAP explanations indicate the magnitude of the impact of features on the predicted value, and are ranked in descending order of importance [28]. Binary values to the left of the features indicate the presence (1) or absence (0) of these features in the building. Their positive (red) or negative (blue) contribution moves the target value from the average dataset value (E[f(x)]) or "expected model output", to the predicted value (f(x)). As commented in their captions, feature impacts on the plots are coherent with common knowledge and database content.

Despite inaccurate predictions, results from this case study prove the potential of the methodology. Predictions and explanations are obtained instantaneously, using only soft features as input. Furthermore, satisfying results are obtained despite having had to train and test the algorithms with data from two different databases. Predictions retrieved from algorithms trained and tested on the BG database, once it contains enough projects, should be more accurate.

4.3. Tool implementation

The envisioned implementation of this methodology, illustrated in Figure 4 is a two-step tool that can first learn from an input database, and further predict emissions for new projects. Applications in the first step include providing a global analysis, feature comparison and explanation of overall impacts. Applications in the second step include real-time approximation of EEs based on user-defined features, allowing early and hands-on access to LCA, as well as comparison, explanation and recommendation of design changes. Trained on private data, the tool has direct applications for design and decision-making. Trained on a national database, it can help inform policy models and mitigation strategies. In both cases, the tool performance is entirely dependent on the quantity and quality of the learning data, which is still largely lacking. The setup aims for rapidity and simplicity and limits exposure to mistakes. This should motivate users to assess their buildings at every stage, and compare multiple designs. Rather than calculating a precise value, it returns values within a tolerance range. It does not aim to replace precise standard EE calculations which should always be made at later design stages.

5. Conclusion

In order to meet environmental policies and with their strong impact on building embodied emissions EE, structural designers have to update their methods. In this paper, we presented steps initiated by Bollinger+Grohmann for this purpose, including an internal LCA management and strategy, tables and plug-ins for EE calculation and a database to track building EEs and establish future budgets and benchmarks. Based on the challenges observed on existing tools and data and on the opportunities presented by Machine Learning for leveraging knowledge from real-world data, the "soft feature approach" was then introduced. It is a ML method which can be trained on databases of existing buildings to predict the EEs of new projects from a small input set of features accessible at early design stages. The potential of the methodology was confirmed when using it to predict and explain the EEs of three building structures from BG. Tool implementations include in-depth analysis of existing building databases, and tailored analysis of EEs and feature impacts on new projects. Ultimately the research aims to strengthen our capacity to generate novel designs in the field of architectural engineering via the valorization of data available, and motivate collaboration between governmental agencies, public and private entities for gathering and analyzing data efficiently.

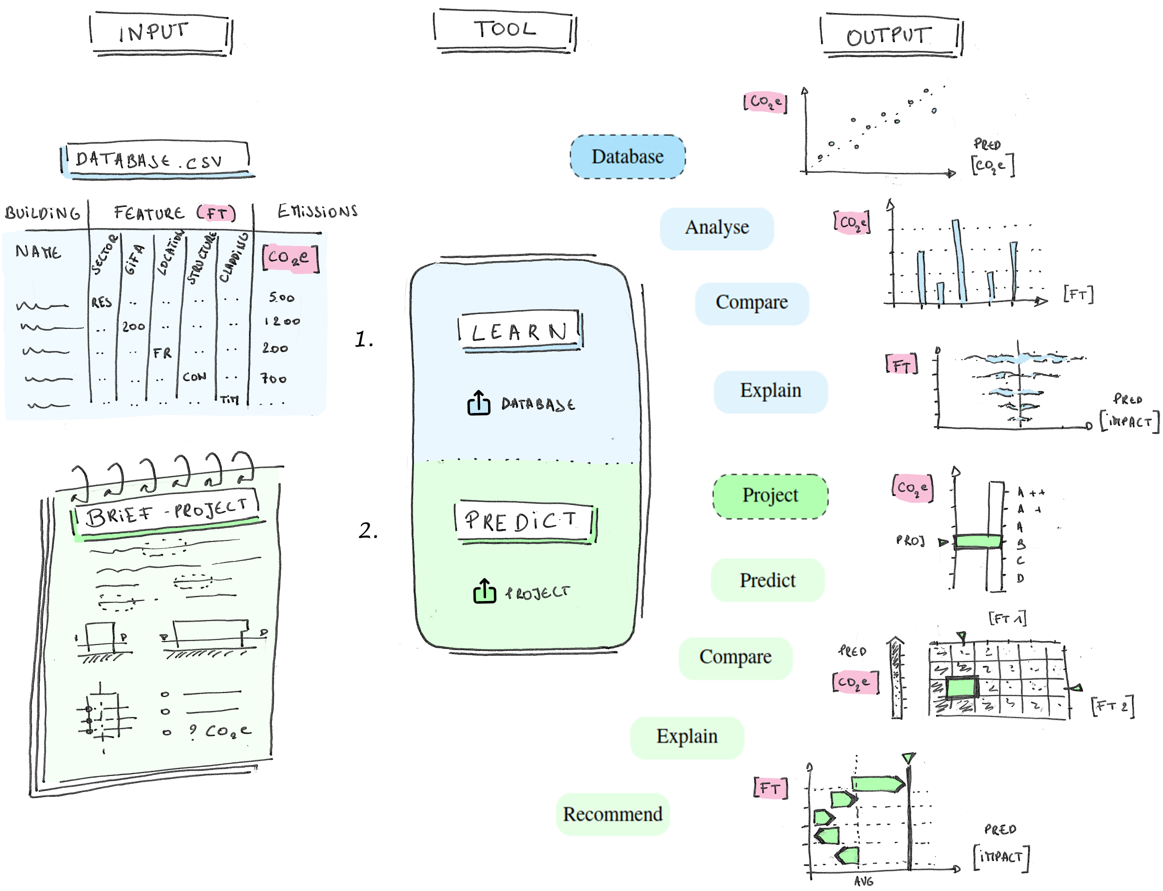

Figure 4: Tool implementation - (1) Learn from a building database to calibrate methodology and understand feature impacts on emissions. (2) Predict emissions for new projects with methodology and explain individual feature impacts.

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