Integration of materials in life cycle assessment (LCA) of buildings: tool for future renovation scenarios

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ABSTRACT

TODO
> Residential buildings have a significant impact on the global emissions.
> There are many studies evaluating operational and embodied impacts of buildings separately.
> But not many models integrate them, especially while considering the impacts of the materials on both embodied and in-use impacts.
> Thus we develop a interface where this material data can be integrated with models estimating in-use demands, giving a final LCA of buildings.
> We further add scenarios to estimate the maintenance phase of the building as well for a case study data.
> Our results show clearly that our model helps estimate the in-use emissions better (more accurate).
> Scenarios in this case, for new buildings, show that energy source change is effective but insulation addition is not always as effective to save building's impacts.
> Model can be used to test for other types of buildings, where the results on the same scenarios may vary.

1. Introduction

Nearly one third of the total global final energy consumption can be attributed to the buildings and building construction sectors (IEA, 2022). Together these two sectors are responsible for a large share of globally emitted greenhouse gases (GHG). The potential for emissions reduction presents a great opportunity for both newly engineered as well as already existing building stock (Jennings, Hirst, Gambhir et al., 2011).

GHG emissions are released throughout all lifecycle stages of buildings starting from construction, and ending with final demolition. Researchers distinguish between *operational emissions* from energy demand for space heating/cooling, lighting, ventilation and the use of appliances, and *embodied emissions* arising from extraction and processing of raw materials, manufacturing and transportation of building components, buildings construction, maintenance and renovation (Ramesh, Prakash and Shukla, 2010). Past studies estimated a rather small magnitude of embodied emissions compared to operational emissions accumulated over the complete life span of buildings, with the respective shares being 10-30% and 70-90% (Ramesh et al., 2010; Adalberth, 1997; Utama and Gheewala, 2009). However, nowadays, due to better insulation, enhanced building designs, and higher environmental performance of energy sources, the operational emissions have been decreasing, while the shares of embodied greenhouse gas (GHG) emissions increased (Chastas, Theodosiou, Kontoleon and Bikas, 2018). For these reasons, there is a shift from studies with a sole focus on operational energy demand and towards more comprehensive assessments that include both operational and embodied impacts (Ibn-Mohammed, Greenough, Taylor, Ozawa-Meida and Acquaye, 2013).

Assessment of energy demand, GHG of residential buildings, and potential mitigation pathways is possible by means of building stock models (Nägeli, Camarasa, Jakob, Catenazzi and Ostermeyer, 2018). They are commonly categorized into top-down and bottom-up approaches (Swan and Ugursal, 2009; Kavgic, Mavrogianni, Mumovic, Summerfield, Stevanovic and Djurovic-Petrovic, 2010; Keirstead, Jennings and Sivakumar, 2012; Reinhart and Davila, 2016; Sun, Haghighat and Fung, 2020). The former analyze aggregate energy consumption of the entire residential sector, and use historical data to understand future trends as a function of broader technological and econometric

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factors, such as income, fuel prices, technological advancements, and others. However, top-down models do not allow detailed analysis of buildings' environmental performance. In contrast, the bottom-up methods investigate characteristics of individual buildings and quantify their energy consumption and environmental impact depending on building properties. This allows for explicit modeling of e.g. renovation scenarios.

Buffat, Froemelt, Heeren, Raubal and Hellweg (2017) introduced a bottom-up model to estimate building space heating demands based on large-scale geographic information systems (GIS), and with high temporal resolution. By employing light detection and ranging (LiDAR) data in combination with digital elevation models and building footprint data, the authors were able to derive building geometries and accurate building volumes. At the same time, digital elevation models in combination with 30-minute temporal resolution of spatial climate data, allowed to evaluate solar gains through windows and shading effects while accounting for the surrounding topology. This study showed that in computing the spatially-explicit heating demand, the most sensitive parameters are room temperature and thermal transmittance (U-values) of materials in building components such as floors and walls. Despite recognizing the importance of the U-values, they have been artificially sampled for each building from a generic probability distribution constructed according to the building type and construction period. This approach leads to low accuracy of the U-values.

A more comprehensive analysis to estimate the U-values requires primary data on the material composition of the building components. It can be obtained from building owners, planners and architects. These datasets can be helpful in better estimations of not just the U-values, but also the embodied emissions of buildings. One of the ways to include them lies in providing an interface to the building stock models, where model users can input additional building data to overwrite the default values. As the total emissions of a building are affected by multitude of parameters, the possible user inputs should not be restricted to material data, and should incorporate other building properties including its volume, geometry, ventilation flow rates, and others. Such interfaces exist as propriety software platforms that have limited flexibility with respect to user inputs and possible parameter modifications (for instance, most of them do not allow inputs on windows and their properties). The other type of models with user interfaces are called Building Information Models (BIM) (Azhar, 2011; Anand and Amor, 2017). They allow better range of inputs than the proprietary tools, and in some cases also integrate Life Cycle Assessment (LCA) to estimate building emissions (Soust-Verdaguer, Llatas and García-Martínez, 2017). However, none of the existing BIM models compare in complexity to the building stock models. Thus, there is a clear need of a tool that combines flexible user inputs with elaborate building stock models.

The aim of this study is to provide a model that pays equal attention to more accurate estimation of both embodied and operational emissions of residential buildings. To this end, (1) we conduct life cycle assessment to estimate building impacts from operational emissions, given more precise space heating demand estimates, and compute embodied emissions from the material data; (2) for better operational emissions estimates, we improve the GIS-based bottom-up energy demand model from (Buffat et al., 2017) by replacing the generic probabilistic U-values with building specific material composition data; (3) we develop our model as a stepwise tool to allow for integration of additional building data and sequential user inputs; (4) we apply our model to a case study of 12 Swiss residential buildings containing detailed building data that, among other information, includes material compositions (John, 2012); (5) for this case study, we introduce and evaluate impacts of two renovation scenarios and their potential environmental benefits; and finally (6) we validate U-values, space heating demands and embodied GHG emissions with reported data from the case study.

The paper is laid out as follows to achieve the above aims: first, we provide the datasets used in the study (Section 2), followed by discussion of our model, which estimates the total operational and embodied emissions of the building (Section 3). Then, we introduce a case study (Section 4) to validate and showcase our results (Section 5). Finally we conclude the paper with further discussions and outlook (Section 6 - Section 7).

2. Data

In the following, we provide a description of various datasets used in this research. The overview of the datasets is listed in Table 1.

2.1. Building properties

In this work we employ a dataset that contains information about high-level building properties. The main source of this data for Switzerland is the Federal Register of Buildings and Dwellings (FRBD) that collects basic data about

Table 1
An overview of the datasets used in the model

Category	Dataset source	Parameters
Building properties	Federal Register of Buildings and Dwellings (FSO, 2022)	Building identifier number Canton and municipality (address) Number of accommodation units Type and year of construction Year of renovation Energy reference area Heating and hot water sources
	- Swiss cartographic SwissTLM dataset (Fan, Zipf, Fu and Neis, 2014) - OpenStreetMap (Schmassmann and Bovier, 2010)	Geocoordinates Footprint area Building volume
Dimensions of building components	Digital elevation models (swisstopo, 2022)	Statistical estimations of : - External and inner wall areas - Number of floors - Roof area - Windows location and orientation
Materials of building components	Material intensities based on: - (Heeren and Fishman, 2019) - (Heeren and Hellweg, 2019) - (Gauch et al., 2016)	Materials used in: - façade - walls and windows - roofs and ceilings - floors
	Material compositions from: - literature sources - architects and planners - building owners	
Material properties	Literature sources (see comprehensive list in the SI excel)	Thermal conductivities of: - walls and windows - roofs and ceilings - floors
Ventilation data	Ventilation rates (Murray and Burmaster, 1995)	- Air flow rates
Site data	Climate (MeteoSwiss, 2022)	Daily mean temperature
	Solar radiation (Müller et al., 2015)	Global irradiance Direct normal irradiance Cloud albedo
	Digital elevation models (swisstopo, 2022)	Geocoordinates Shading effects
Environmental data	Life cycle inventories from ecoinvent (Wernet et al., 2016)	Energy inputs in product systems Emissions to and from the natural environment
	Life cycle impact assessment (Stocker, 2014; Myhre et al., 2014)	Global warming potential values for greenhouse gases
	KBOB platform (Koordinationskonferenz der Bau- und Liegenschaftsorgane der öffentlichen Bauherren) (KBOB, 2022)	Impacts per kilograms of various construction materials

individual buildings (FSO, 2022). The Register has been established in 2000 on the basis of a buildings and dwellings survey, and is maintained by the Swiss Federal Statistical Office (FSO). Nowadays it contains a wide variety of building types with an extensive coverage of residential buildings. The specific building parameters provided by the FRBD are listed in Table 1, and include physical parameters, information on building's construction and renovation, as well as energy and hot water sources. In addition to the FRBD, Buffat et al. (2017) computed better estimates for building footprint areas that include sets of polygons describing geocoordinates, shapes and dimensions of each building in Switzerland based on the Swiss cartographic SwissTLM dataset (Fan et al., 2014) and OpenStreetMap (Schmassmann and Bovier, 2010).

2.2. Dimensions of building components

The Swiss Federal Office of Topography (swisstopo) is a crucial source of geoinformation data in Switzerland. It is responsible for the collection, management and provision of official geodata and the provision of spatial services (swisstopo, 2022). Swisstopo has a long history of developing high-resolution digital elevation models of Swiss landscape such as (1) digital surface models (DSMs) that incorporate all items above ground, and (2) digital terrain models (DTMs) outlining the bare ground natural terrain, excluding natural and built surface objects. Following previous research in combination with the building properties dataset described above, these models were used to derive various properties of building components i.e. their dimensions and configurations. These include statistical estimations of walls and their areas, number of floors, orientation and location of windows, and other attributes of various building components (Buffat et al., 2017; Buffat, Heeren, Froemelt and Raubal, 2019).

2.3. Materials of building components

The materials and their amount (thickness and weight) used in building components constitute life cycle inventories that are needed to estimate buildings embodied emissions. At the same time, component areas and material data allows for the computation of the heat losses from walls, roofs, ceilings, floors and other components of a building during its operational phase (see Section 3.2). This information can be provided as material composition or material intensity data.

Material composition can be defined for various building components as the different materials constituting the layers of these components, and their thickness in the component's cross-section. The composition includes but is not limited to construction, cover, finish, and insulation materials. For instance, floor composition might include combination of insulated wood panel, bitumen membrane, cement cast plaster floor and concrete floor slab. Material composition data can be collected from architects, planners and building owners, remote sensing for outer layers, as well as from literature sources. In case it is not available, we use the default material intensities of buildings instead, as described below.

Material intensity is the total mass of a construction material present in an entire building divided by the building's volume (or sometimes its floor area). Due to the changes in material technology and policies on sustainable construction, materials used in the construction of buildings evolve significantly over time. Thus, in this work, we develop a material intensity dataset for typical buildings categorised based on their construction periods (spanning at least 15 years). The dataset includes mass-to-area ratios of minerals, metals, timber, brick, concrete, and combustible materials for 5 types of typical Swiss buildings based on their construction period (<1945, 1946-1960, 1961-1980, 1981-2000, >2000). This dataset was derived using (1) multi-family building footprint area and building volume estimations (based on construction year) from a building model developed by an architecture firm based in Zurich, (2) ratio (weight and volume wise) of each material in the building from Gauch et al. (2016); Heeren and Hellweg (2019); Guerra and Kast (2015) and the building model estimations provided by the architecture firm, and (3) validation of the derived material intensities with generic values provided for all Swiss buildings by Heeren and Fishman (2019).

2.4. Material properties

Each construction material has different physical properties that determine its contribution towards the overall emissions of a building. In our model, one such important property is thermal conductivity - the rate at which the heat is conducted through material (Bird, 2002). It is measured in watts per meter-kelvin $[W/mK]$, ranging from 0.01 W/mK for gases and all the way up to 1000 W/mK for metals, where lower values point to better insulators. Based on various literature sources, we have collected thermal conductivity of 165 materials, including timber, concrete, insulation, and other materials of varying densities (see SI excel). Subsequently, thermal conductivities allow us to compute thermal transmittance, or U-value, that is the heat transfer coefficient describing how well a building component conducts heat (see Section 3.2).

2.5. Ventilation data

Each building's ventilation significantly affects the ventilation related heat losses of the building, and thus affect the final space heating demand of the building. There are two types of broad ventilation systems Santamouris and Wouters (2006): (1) natural ventilation, where the inner and outer pressure differences in the building drive the ventilation flow of the building, and (2) mechanical ventilation (mostly centralised for all apartments in the building) which use fans, and other mechanical systems to provide air flow in the building. In our model, the default ventilation rates are set up for natural ventilation using the probabilistic distributions provided (based on yearly quarters) by Murray and Burmaster (1995).

2.6. Site data

In addition to the building and material datasets described above, the location of buildings significantly affects their environmental performance. For instance, **climate** conditions, such as local air temperature and solar radiation, influence heat flows between building components and its surroundings. To compute time-series of heat losses, Buffat et al. (2017) used the temperature data collected by the Swiss Federal Office of Meteorology and Climatology MeteoSwiss for the years 1994-2013 that contains daily mean temperature values on the 1.6 km in longitude and 2.3 km in latitude resolution (MeteoSwiss, 2022). To account for the effects of solar radiation, the authors employed the spatially and temporally explicit surface **solar radiation** dataset Heliosat (SARAH) provided by the Satellite Application Facility on Climate Monitoring (Müller et al., 2015). It contains solar radiation data for the entire Switzerland given on a 30 minute basis, and on a 3.8 km in longitude and 5.6 km in latitude grid. Combining these datasets with the **digital elevation models** that can account for the shading effects of neighboring structures, provides a more complete picture about the contribution of site conditions to building performance.

2.7. Environmental data

In order to compute operational and embodied emissions of buildings, life cycle assessment environmental data is needed. In this work we used ecoinvent - a well-established **life cycle inventory** (LCI) database that contains (1) datasets on energy and material inputs in a wide variety of product systems present in global supply chains, as well as (2) natural resources taken from the natural environment and emissions released to the water, air and soil (Wernet et al., 2016). We focus on the climate change **life cycle impact assessment** method, with the global warming potential values of greenhouse gases estimated in the Technical Report by the Intergovernmental Panel on Climate Change (IPCC) (Stocker, 2014; Myhre et al., 2014). For the materials, we employ data available on the **KBOB platform** (Koordinationskonferenz der Bau- und Liegenschaftsorgane der öffentlichen Bauherren) (KBOB, 2022). KBOB datasets were originally based on ecoinvent. They contain impact assessment results for various construction materials, while taking into account services, transport and energy systems representative specifically for the building sector in Switzerland. For example, climate change impacts are given in kilograms of CO_2 equivalents per kilograms of materials.

3. Model

The above described data was taken from various models and literature sources. However, in order to obtain more accurate estimates of emissions for a particular building, it is preferable to replace general values with the building's specific measurements that can be provided by architects and building planners. Thus, in our model we make a provision for such model "users" to complement the existing building properties, components and material compositions with additional data. To that end, we developed a stepwise model that takes user inputs, and yields more accurate estimates of the building cumulative emissions, as shown in Figure 1. The steps were laid out in the order of sequential user inputs, and with the objective of calculating the total emissions of a building. The final step 5 collects data on (1) operational emissions due to the space heating demand computed in step 4, and (2) embodied emissions which need the material components and properties data gathered (from a user) in the steps 1-3. This model can also be used in a tiered hierarchy based on the extent of information provided by the user. Case in point, if the user provides no information, the model allocates default values to building data, while if the user has any information (e.g. the material composition) the model replaces the default values (e.g. the material intensities) with the user provided information.

The described model was developed in Python[1] to complement the model of Buffat et al. (2017), and is available as a Github repository[2]. At each step of the model, default building characteristics are combined with available user

[1] `https://www.python.org/`
[2] `https://github.com/rhythimashinde/building-model`

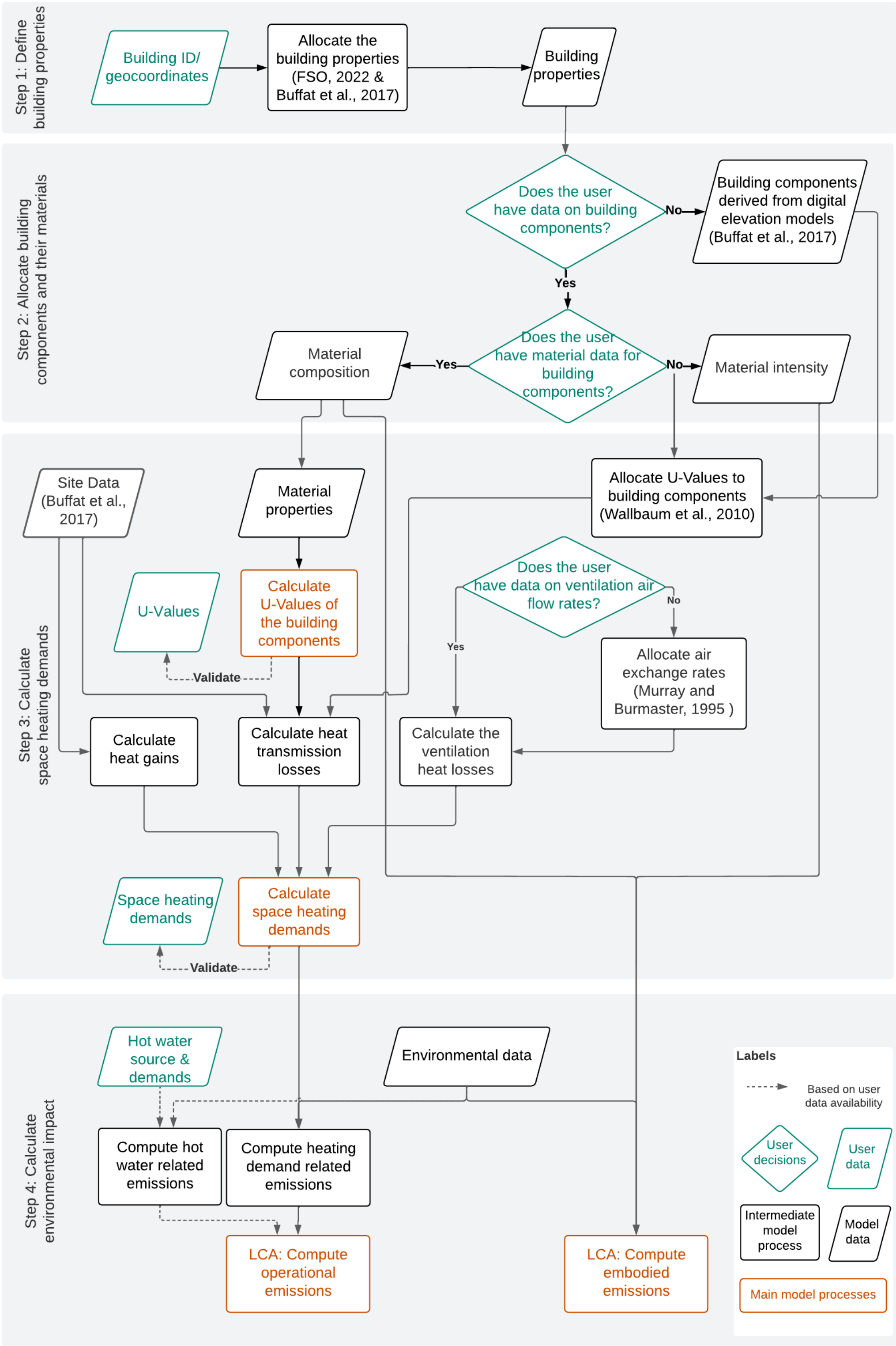

Figure 1: Methodological approach for material-data integration and validation

inputs and passed as a python dictionary[3] onto the next step. The implemented user prompts, examples of user provided inputs, and default model values are listed in the SI excel document. In the following, we first provide an overview of the stepwise model, then detail the model calculation processes in Sections 3.1-3.3, and finally in Section 4 we apply the model to a case study of 12 residential buildings in Switzerland (John, 2012).

Step 1: In the first step, the user inputs the unique building identifier or building geocoordinates (e.g. derived from address of the building, if provided), from which the stepwise model derives the **building properties** (FSO, 2022; Buffat et al., 2017). For Swiss buildings, the identifier is "Eidgenössische Gebäudeidentifikator (EGID)", or unique federal building identifier, allocated to each building in Switzerland. Based on the user input, the model locates the building and assigns it default building properties. In cases, when the model is not able to find the exact match due to missing information, it prompts the user with further questions on other building properties, and then employs the "least distance approach" that finds closest building in the database, where "closest" refers to similarity in terms of building properties. As we use this approach for our case study, it is further explained in Section 4.1.

Step 2: Next, the user is prompted to provide the information on different **building components**, such as areas of walls, roofs and number of floors. If no data is available, the building components are derived with the digital elevation models (Buffat et al., 2017). Otherwise, the user is asked to provide information on the components and their respective **material compositions**. In case the detailed material compositions are unknown, the model assigns the default **material intensity** values for the building based on its construction year. If, on the other hand, the user can provide the material composition data, then the stepwise model allocates materials and their thicknesses to the various building components.

Step 3: When the material composition data is available, each material is linked to its respective **material properties**. Knowing the thermal conductivities and thicknesses of materials in a building component, one can calculate the component's thermal transmittance, also called the U-Value (see Section 3.1). In case the users cannot provide the material compositions, the stepwise model selects default U-values for each building component based on its construction year (Wallbaum, Heeren, Jakob and Martius, 2010). Once the U-values are allocated to the building components, the model estimates the heat transmission losses, which contribute towards the building's space heating demand (Section 3.2). In this step, we also account for the heat gains and ventilation losses based on the air exchange rates, either provided by the user or taken from Murray and Burmaster (1995). Notably, we make provision for the model validation if the user provides the U-values of the building components, and the space heating demand of the building (preferably measured).

Step 4: Finally, the model estimates total building GHG emissions, based on **environmental data** (Section 3.3). Operational emissions are computed with (1) emission factors per unit of space heating demand and the space heating source (part of the building properties); (2) hot water demands and source in case this data is given by the user. Embodied GHG emissions are calculated based on the collected material information data (material compositions of building components).

3.1. Calculate U-values

In the steps 1-2, the user is prompted to provide the construction and insulation materials used in the walls, roofs, ceilings, windows and floors of a building. The purpose of gathering this information is to estimate how each of the building components loses heat given its exposure to the outer air or (un)heated spaces of the building like the basements and the shared walls, and thus contributes to the space heating demand (see Section 3.2). These heat transmission losses are denoted as Q_T and are primarily defined by the thermal transmittance, or U-Value, of the building components. For a component c, its U-Value U_c is calculated based on the properties of constituting materials:

$$U_c = \left(\sum_i \frac{t_i}{k_i} \right)^{-1}, \tag{1}$$

where t_i is the thickness (m) and k_i is thermal conductivity (W/mK) of a material i. Note that the considered U-values (W/m^2K) fall into 5 categories: (1-3) floors, roofs, and walls against outside air (external walls), and (4-5) floors and walls against unheated spaces (e.g. the shared walls). If there are multiple U-values in one of the categories listed above, e.g. several walls against outside air, then we select the average U-Value for that category. If no material composition data is available for a building component, the model allocates its U-Value based on the construction

[3] https://docs.python.org/3/tutorial/datastructures.html#dictionaries

period and renovation rate of the building as estimated by Wallbaum et al. (2010); Heeren, Jakob, Martius, Gross and Wallbaum (2013).

3.2. Calculate space heating demand

The goal of step 3 is to calculate the total space heating demand in order to later estimate the final operational emissions. In our model (as in Buffat et al. (2017)), the space heating demand is defined by SIA-380/1 (2009), which is a building heat model used in Switzerland to verify that buildings meet the heating insulation obligations. This SIA model estimates the heat demand of a building based on the EN ISO 13790 norm [4] while providing fairly accurate results across different building stocks. It defines the heat demand (MJ) of a building Q_H summed over different time periods t as follows:

$$Q_H = \sum_t \sum_c Q_{T,t,c} + Q_{V,t} - Q_{G,t}, \tag{2}$$

where Q_T are the heat transmission losses, Q_V are the ventilation losses, and Q_G are the heat gains. Note that in this model, using spatial climate datasets allows for a time resolution t of up to half an hour.

Heat transmission losses Q_T occur in different building components c including windows, walls, floors and roofs. For each component they are measured based on the component area A_c (m^2), its U-Value U_c, the temperature difference $\Delta_{T,c}$ (K) between warmer and colder areas, and reduction factor b_c due to reduced thermal losses from surfaces whose thermal conductivities are unknown, such as shared walls and soil:

$$Q_{T,t,c} = A_c \cdot U_c \cdot \Delta_{T,t,c} \cdot b_c \tag{3}$$

Ventilation losses Q_V depend on the air exchange rates a ($1/h$) affected by the presence of inhabitants and their behavioral changes (such as keeping windows open), where the rates are derived from a probability distribution following the approach of Murray and Burmaster (1995). Additional to the air exchange rates, the losses are modelled by taking into account the volume V (m^3) of the building, which is either given by the user or the digital elevation models (Buffat et al., 2017), and the specific heat storage capacity of air s ($MJ/m^3/K^1$):

$$Q_{V,t} = a_t \cdot V \cdot \Delta_{T,t} \cdot s \tag{4}$$

In addition to including these various contributors, our stepwise model prompts the user to provide the air flow rates, f (m^3/h) to estimate the air exchange rate a and replace the probabilistic values in the model whenever possible:

$$a_t = \frac{f_t}{V} \tag{5}$$

Heat gains Q_G of a building include solar heat gains Q_S (MJ/m^2), cumulative heat gains from electric devices Q_E (MJ/m^2) and cumulative heat gains from the inhabitants Q_P (MJ/m^2), weighted by the degree of utilisation η_g of the cumulative heat gains:

$$Q_{G,t} = (Q_{S,t} + Q_{E,t} + Q_{P,t}) \cdot \eta_g \tag{6}$$

Here, the solar heat gains are derived from the site data that considers the solar radiation at different times of the day, sizes and orientations of windows in a building, energy conductivity of each window, and the shadowing effect of the neighboring building as estimated in the digital elevation models. The electricity heat gains are based on typical electricity heat gains per year and the energy reference area of the building (SIA-380/1, 2009). The heat gain from inhabitants is modelled from the occupancy and heat produced per inhabitant (Buffat et al., 2017). The stepwise model allows the users to additionally update the occupancy, the energy reference area of the building and the windows size and orientations to refine the estimations of the total heat gains.

[4] `https://www.iso.org/standard/41974.html`

3.3. Life cycle assessment

The goal of this study with respect to LCA was to compute operational and embodied emissions of buildings. We consider the construction, maintenance and operation phases of the buildings, but exclude demolition and recycling processes. The functional unit was chosen as one square meter area of dwelling per one year lifetime (1 m^2a), and the lifetime of all the buildings was assumed to be 80 years (Ianchenko, Simonen and Barnes, 2020). LCAs were performed with Brightway - an open source Python library for advanced LCA calculations (Mutel, 2017).

To estimate the **operational emissions**, LCIA (Life Cycle Impact Assessment) was conducted for the computed space heating demand for each building, where the specified heating source was matched against the processes in ecoinvent LCI (Life Cycle Inventory) database version 3.8, cutoff system model (Wernet et al., 2016). The foreground system for the **embodied emissions** was constructed based on the material composition dataset (Section 2.3) linked to the KBOB platform (Section 2.7).

Environmental performance for the climate change impact category is assessed via the 100-year time horizon GWP values of numerous greenhouse gases based on the IPCC report (Stocker, 2014). This LCIA method was implemented for ecoinvent environmental flows by Bourgault (2020). Final LCIA scores are expressed in kilograms of CO_2 equivalent (kg CO_2-eq) per square meter area and one year. Naturally, this analysis can be easily extended to other impact categories and LCI databases.

4. Case study

To demonstrate how the user inputs can be incorporated into the developed stepwise model, we use a case study data that was collected from Swiss architects and planners (John, 2012). This dataset represents 12 relatively modern residential buildings constructed post 2000, and serves as a good case study to test the stepwise model performance due to the differences in the selected buildings. The major advantage of this dataset is the availability of detailed information on every building's properties, components and material compositions. Among other things, this data includes annual space heating demands of the buildings and thermal transmittance values of the building components that are needed for the validation of the model results (see Figure 1). Additionally, the dataset contains information on the ventilation air exchange rates and the hot water demands for some buildings, which leads to higher quality estimates of operational emissions compared to the results of Buffat et al. (2017). The basic characteristics of these buildings are laid out in Table 2, and the details are provided in the SI excel document.

4.1. Compile building properties

To include the case study data as the user inputs, the first step is to allocate building properties to each of the case study building given its ID or geocoordinates (Figure 1). As a general rule, we expect this data to be available to the users of the developed tool. However, the given case study does not contain information that uniquely identifies the buildings, since it is part of the open access doctoral thesis, where the anonymity of the buildings needed to be maintained (John, 2012). Thus, in this paper we use a two step approach to find the building properties:

Step 1 Prompt the user to provide three of the building properties: the year of construction, its municipality and number of floors. These building properties were chosen because they are typically accessible to the user, and are least likely to be measured wrong or be affected by the renovations over the building's lifetime.

Step 2 If the model fails to find a unique match and identifies a set of buildings instead, we employ the "least distance approach", where the model looks for a closest match of a building in terms of the provided building properties.

The 12 matched building and their properties are given in the SI excel file.

4.2. Scenario assessment

Since renovations significantly affect the environmental impact of buildings (Hasik, Escott, Bates, Carlisle, Faircloth and Bilec, 2019; Itard and Klunder, 2007), we perform scenario assessment to estimate emissions related to renovations. In the following, we introduce two sets of scenarios, which focus on estimating the potential emissions savings. Note that in this paper the purpose of the scenario assessment is to showcase that the stepwise model allows the users (building owners, policymakers, architects) to introduce various renovation scenarios to compare building emissions based on different renovation options for better informed environmental decision-making (see (Fishman,

Table 2
Basic information on 12 Swiss buildings used in this model as case study (John, 2012)

	Canton	Construction year	Accommo-dation units	Built surface area [m^2]	Heating source	Energy standard
mfh01	Zurich	2012	111	2350	Electric heat pump water brine (343 kW)	MINERGIE
mfh02	Schwyz	2011	2	190	District heating	MINERGIE-ECO
mfh03	Bern	2011	3	163	Electric heat pump water brine	MINERGIE-P
mfh04	Zurich	2010	4	240	Electric heat pump water brine (16.7 kW)	SIA 380
mfh05	Zurich	2007	132	2218	Electric heat pump water brine (92 kW)	MINERGIE-P-ECO
mfh06	Bern	2006	3	777	Wood pellet heating (67.2 kW)	MINERGIE-P-ECO
mfh07	Zurich	2011	89	1810	Modulating condensating boiler (kW 200)	MINERGIE
mfh08	Lucerne	2011	6	375	Electric heat pump water brine (24.9 kW)	MINERGIE-P-ECO
mfh09	St Gallen	2008	4	135	Electric heat pump, air water (4.2 kW)	MINERGIE-P-ECO
mfh10	Zurich	2012	10	411	Near/ district heating from cogeneration	MINERGIE
mfh11	Bern	2012	22	665	Electric heat pump water brine (40.8 kW)	MINERGIE-P-ECO
mfh12	Lucerne	2008	10	168	Electric heat pump water brine (28.1 kW)	*not available*

Table 3
Maximum U-values for insulation scenarios.

renovation scenario	Max. U-values, W/m^2K			
	Walls	Windows	Roofs	Floors
Standard (Minergie)	0.15	1.00	-	-
Efficiency (Minergie-P)	0.10	0.60	0.15	0.15

Heeren, Pauliuk, Berrill, Tu, Wolfram and Hertwich, 2021; Heeren and Hellweg, 2019; Mastrucci, Marvuglia, Benetto and Leopold, 2020) for possible renovation scenarios).

Adding insulation: A common practice in reducing the heating demand of a building is to reduce its thermal losses via additional insulation layers or replacement of the existing insulation with better insulation materials. In this work, we follow the study of Ostermeyer, Nägeli, Heeren and Wallbaum (2018) that considers standard and efficiency renovation scenarios based on building types. The former scenario leads to the resulting U-Value of the refurbished building components between the legal minimum (SIA 280) and the MINERGIE standard[5], and the latter aims at transitioning towards a passive-house, such as MINERGIE-P (see Table 3).

Changing heating source: In addition to the insulation changes, which affect both the operational and embodied emissions, the change in heating sources can be quite influential to reduce the operational emissions of buildings. For the given case study, the primary heating and hot water sources with their respective climate change impacts are given in Table 4. The only case where changing a heating source could make a difference is the natural gas heating, because it has a comparatively high impact per unit of energy used. Asthe availability of district heating substantially depends on the location of a building, based on the second least environmental impact, in this scenario we introduce a change of natural gas to the brine water heat pump.

[5] https://www.minergie.ch/de/zertifizieren/minergie/

Table 4
Climate change impacts of various heating sources.

Heating source	Impact per unit of energy kg CO_2-eq / MJ
Electric heat pump (brine water)	0.033
District heating	0.00019
Wood pellet	0.013
Natural gas	0.065

5. Results and Validation

In this section, the results on the operational and embodied GHG emissions for the case study of 12 modern Swiss buildings are discussed. First, the estimated U-values of the building components are discussed (Section 5.1), which help estimate the final space heating demands of the buildings (Section 5.2). Then, the space heating demand, and the material composition of the buildings, are combined further with the life cycle inventory databases to estimate the LCA of the buildings (Section 5.3). Finally, to estimate the renovation impacts for this case study, the updated LCA results are discussed (Section 5.4).

5.1. U-values

As U-values of a component contributes towards the amount of heat lost through the component of a building, it is an important parameter to be calculated for estimation of operational emissions for a building. In our case study, building planners and architects have *reported* these U-values for some of the components for the 12 buildings. Additionally, based on the material composition of these components, we have *calculated* the U-values for these components. In the Figure 2, we present how the U-values for two of the components (the roofs and floor) compare from calculated to reported ones for the buildings in this case study.

The calculated and reported values are not significantly different (student's t-test, $p>0.05$), and thus for this case study we can assume that the calculated U-values are close enough to the reported U-values for all the components. In the SI excel, we present our calculated U-values, compared to the reported U-values by John (2012) and the probabilistic U-values which are allocated for these buildings by the Buffat et al. (2017) model.

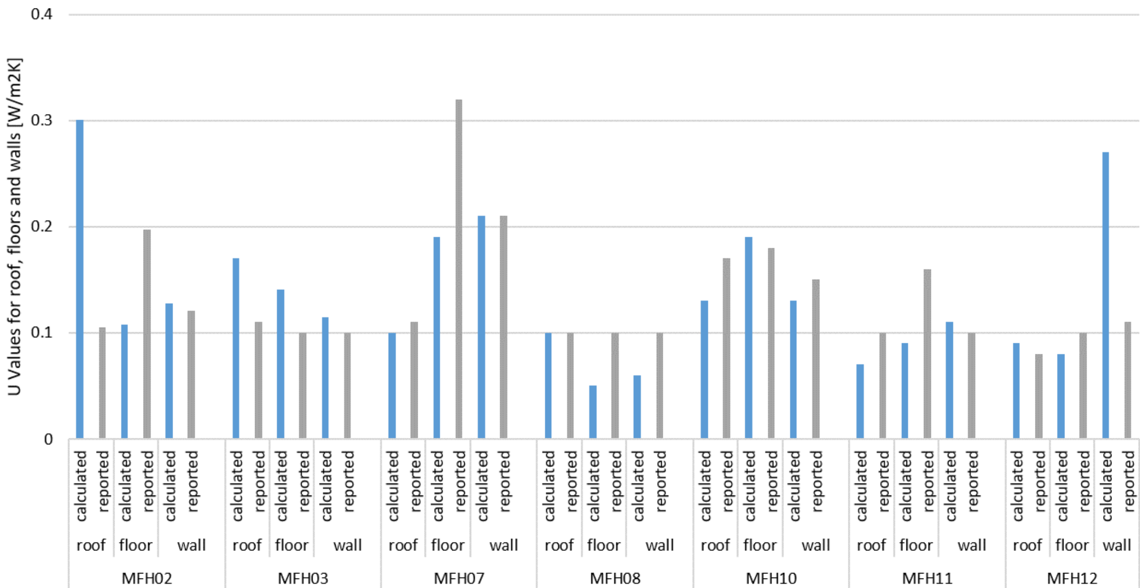

Figure 2: Results of U-values for floor and roofs: calculated (in our model) vs reported by John (2012). Note that the reported U-values are missing for roof for mfh01,mfh05 and floor for mfh01,mfh04,mfh05,mfh06

5.2. Space heating demand

The space heating demands as measured by the equation 2 is estimated as the cumulative effect of the heat losses and heat gains of the building, based on the above U-values for the building components, building properties and its site data. We have *calculated* the space heating demand in the model by using the reported U-values in the model, but whenever the reported U-values are not available, we have used the calculated U-values. The case study by John (2012) also contains the information on space heating demands, *reported* by architects and building planners. Figure 3 shows the calculated and reported heat demand values, alongside the *default* space heat demand values obtained by Buffat et al. (2017).

To measure how well our model calculates the space heating demand, Q_H, as compared to the reported space heating demand, Q_H^o, we measure the relative error, r, as shown in equation 7. We also measure the default relative error of the model, r_d similarly by replacing the calculated space heating demand in the following equation with the default space heating demand, Q_H^d. The relative error, r measures how well the model performs, while the difference in the relative errors (r - r_d) allow us to further understand how much the model estimations improved as compared to estimations by Buffat et al. (2017). Table 5.2 shows these relative errors for the buildings in the case study.

$$r = \frac{(Q_H - Q_H^o)}{Q_H^o} \tag{7}$$

As seen in the table 5.2, our model heavily improves the estimations of space heating demands compared to the estimations from Buffat et al. (2017). The buildings with highest improvement in relative error (mfh 03, 06 and 08) are also those where the U-values changed most due to the new quantification of U-values and introduction of material composition. Also note that these are the buildings with some of the highest estimated heating demand. This shows significance of our model to correct the "default" U-values for these building typologies as set by Buffat et al. (2017), improving the estimations of buildings' energy demands.

Some buildings still have a high relative error. It is important to note in these cases that these reported values can be used for validation of our calculated space heating demand results, but as they are usually measured in duration of just one year, they are not representative of space heat demands of buildings for longer periods. Additionally, the high relative error can be attributed to the occupant behavior which is not included in the model e.g. the actual inside temperatures maintained by the occupants of the building.

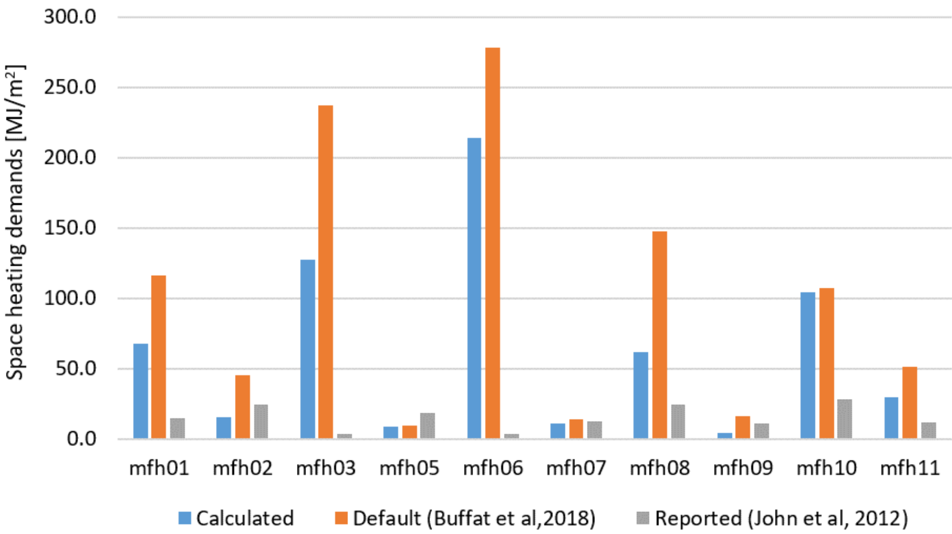

Figure 3: Heat demand estimation by our updated approach using accurate material, components, ventilation and site specifications for each building (left bar column), 'default' approach by Buffat et al. (2017)(middle bar column), and reported values by John (2012) (right bar column)

Table 5
Performance of the model in estimation of space heat demand arranged in an descending order of difference in relative error of the default values calculated by Buffat et al. (2017), r_d and the relative error of calculated values by our model, r. The relative errors are estimated based on the original reported values by John (2012).

Building	Decrease in relative error (r_d - r)	Relative error (r)
mfh03	33.22	37.58
mfh06	19.43	63.81
mfh08	3.55	1.58
mfh01	3.37	3.72
mfh11	1.81	1.47
mfh02	0.54	0.35
mfh10	0.11	2.75
mfh07	0.06	0.09
mfh12	0.00	1.00
mfh05	-0.01	0.51
mfh09	-0.15	0.61
Average	**5.63**	**10.32**

5.3. LCA results

The operational emissions for the buildings are estimated based on the reported space heating demand and the reported hot water demand, but whenever there are no reported values, we use only the calculated space heating demands. For the embodied emissions, we directly use the reported material composition or the default material intensities of the buildings, with preference given to the former (if available). The database of the material, energy sources and their impacts for the 12 Swiss buildings used in this case study is presented in the SI excel. In this case study, the operational and embodied emissions contribute to the LCA of these buildings. The Figure 4 shows the Greenhouse Gas (GHG) emissions calculated annually per metresquare of the 12 buildings.

The results show that the LCA of the buildings is rather high for the mfh02 and mfh06. One of the reasons explaining this could be the ratio of the building surface area per sq.m being the highest for these two buildings (96 m^2/ accommodation unit and 259 m^2/unit, respectively). The results also show that there is a higher ratio of embodied emissions in each building, and this is justified for these modern 12 buildings which meet MINERGIE or low-energy consumption standards.

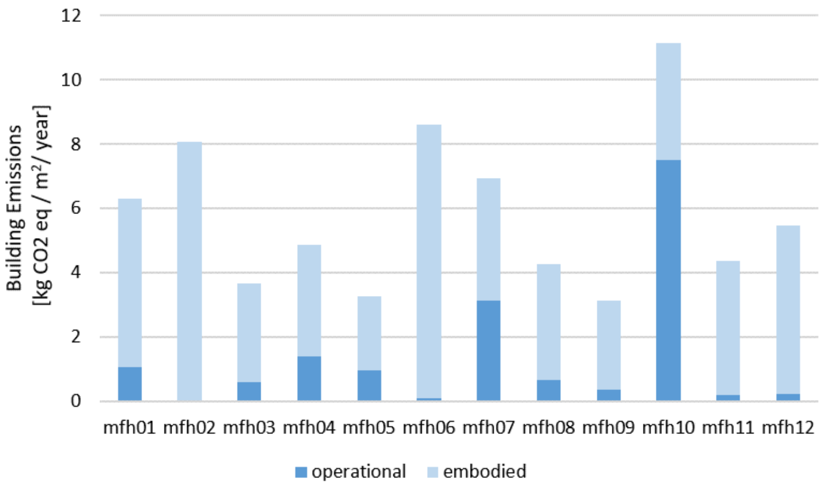

Figure 4: LCA (Greenhouse gas emissions) for all the buildings, split by the embodied and operational emissions. The lifetime assumed for all buildings was 80 years.

Table 6
Changes in building parameters introduced as per the scenario 1 on insulation

	Old U Value for walls	New U Value for walls	material	New material intensity
mfh07	0.116 W/m^2K	0.05 W/m^2K	rockwool insulation	0.089 kg/m^2a
mfh10	0.16 W/m^2K	0.033 W/m^2K	cellulose fiber	0.468 kg/m^2a

Table 7
Changes in total emissions due to the scenarios

	base	scenario 1: insulation	scenario 2: heating
mfh07	3.84 $kgCO_2eq$	3.96 $kgCO_2eq$	3.81 $kgCO_2eq$
mfh10	3.72 $kgCO_2eq$	3.8 $kgCO_2eq$	3.63 $kgCO_2eq$

5.4. Scenarios

Additional to the operational and embodied emissions, which contribute to the LCA of the buildings, we have introduced scenarios to estimate the effects of the maintenance and renovation of the building. These renovation scenarios and their associated emissions help building planners decide whether the renovation is desirable in terms of saving the emissions caused by the building. For this case study, we have introduced two scenarios on insulation and heating system change, for only two buildings mfh07 and mfh10. These two buildings have a natural gas as a heating system, and thus it provides an opportunity to save operational emissions. We keep the same buildings for further improvements in insulation to study the effects of different scenarios on the same buildings.

Scenario 1- Insulation: For this scenario of adding a layer of insulation, a new insulation material is added in the building walls which is not already present to effectively change the thermal conductivity of the walls and reduce the U-values. This affects the LCA of the building in two ways: the additional material increases the embodied impact of the building, while the additional insulation reduces the energy impact (usage) for heating the building. The exact changes for the walls' insulation based on the introduction of new material, U-Value and material intensity are listed in the Table 6. As shown in Table 7, for both the rockwool insulation in the mfh07 and cellulose fiber in mfh10, the insulation is not very effective way for reducing the impacts. It should be noted the energy benefit of adding insulation is only about 5%, comparable to the second scenario of heating system change.

Scenario 2- Heating source change: For change in the heating source, we chose to convert the natural gas systems in the two buildings to brine water heat pumps, as they have low impact. Table 7 shows that the change in energy sources help in always reducing the impacts of the building. It should be noted that these are MINERGIE buildings with a very low impact already, and thus the change in the heating source or insulation doesn't necessarily show an improvement, but for other buildings, the case might be different based on their initial construct.

6. Discussion and Outlook

Takeaways and highlights:
> Considering the results, for the case of the 12 buildings (new energy-efficient buildings, only around 10 years old), operational emissions rather low, so relatively the embodied emissions clearly show to have a significant impact.
> Note that the scenarios showcased here are performed for illustrating the capabilities of the tool developed here. All buildings in Table 2 are relatively new and well insulated, and in reality, they would probably not be the candidates for energy-related renovations.
> The method improved the energy estimations for all of the buildings (still greatly deviating for the MINERGIE-P buildings, which have very low operational emissions)
>Note that although the relative error reduces with the new model, the high error for some of the buildings (compared to the measured values) exist due to...
> The method proposed here presents an improved way of calculating the LCA for the buildings, with the possibility for integrating data provided by users. The stepwise approach allows for large scale modeling while allowing for detailed assessment if data is not available.
> We can also integrate data from other research in different regions, e.g. an extension of our study can allow integration of approaches like Kleemann, Lederer, Aschenbrenner, Rechberger and Fellner (2016), which used construction data in combination with on-site investigations to characterize material composition of buildings in Austria; as well as Gontia, Nägeli, Rosado, Kalmykova and Österbring (2018), who created a material intensity database for residential buildings in Sweden that is based on architectural data and densities of construction materials. > Thus this is a truly bottom-up model while in comparison with other bottom up models (A detail analysis of bottom up model here Trigaux, Allacker and Debacker (2021))
> Results
> scenarios

Limitations and improvements:
> Uncertainties in thermal conductivity for similar materials, but still good results in figure 4
> Electricity consumption and hot water source not included in LCA - but can be
> Currently only monthly scale of temporal data is used in the model right now, and this can be modified for different scenarios like solar
> User behavior is not included
> Operational GHG emissions need to include estimating negative c-storage from material, and this can be done via this model as an improvement.
> For ventilation, improve the model on mechanical ventilations - consider the age of the building.

7. Conclusion

> Buildings are high emitters, in their construction, maintenance and renovation phase.
Though these phases are well estimated across various studies, they are not always well connected to each other e.g. the materials impacting the embodies emissions, also affect the final operational emissions
> Our model creates a interface and a data pipeline to integrate the data from users or studies to better estimate the LCA of buildings.
> It also allows estimating LCA better for buildings with missing data.
> Our study shows significant improvement in the energy estimations compared to a high resolution energy space heating demand model (Buffat's)
> It also shows that not all renovations affect the buildings for lower environmental impact when both the energy and material emissions are considered together
> There is a possibility to improve this model further with better data sources from electricity and heating water sources, and user behavior.

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Authors contribution

All authors contributed to the presented study in conceiving and designing the analysis, and have reviewed and given approval to the final version of the manuscript. S.H. proposed the idea for this study and provided feedback throughout the project. R.S. conducted literature review, set up the models, performed the analytic calculations, the numerical simulations and drafted the paper. A.K. helped in writing and reviewing, and also contributing towards the LCA calculations in the model. All authors contributed to the writing of the manuscript. S.H. supervised the project.

Associated Content

Supporting_Information.xlsx
Sheet 1-2: Material intensities and material properties data, Sheet 3: Different user prompts in the model, Sheet 4-9: Case study data, Sheet 10: Final U-values and the energy demands, Sheet 11: ecoinvent and KBOB material and energy impact factors
Complete Code available on `https://github.com/rhythimashinde/building-model`

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