LCA Calculation of Retrofitting Scenarios using Geometric Model Reconstruction and Semantic Enrichment of Point Clouds and Images

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ABSTRACT

To achieve global climate goals, a greater focus needs to be on the energy-efficient conversion of the existing building stock in industrialized countries. To prioritize the retrofitting scenarios of large stocks of existing buildings, holistic life cycle assessments (LCA) help to consider the environmental impacts in the decision-making. To enable the effortless creation of large building stock information, we propose a methodology to automatically create semantically rich 3D models for calculating the LCA of retrofitting variants. Robustness is achieved by providing flexibility towards input data, e.g., geometric reconstruction based on different point clouds, such as laser scans, drone-based photogrammetry, or derived from Google Maps. Similarly, various image sources are used for the semantic enrichment of windows, such as from hand-held devices or Google Street View. Using a case study, we compare the performance of the geometric reconstruction, test window detection, and calculate first LCA results.

INTRODUCTION

The current situation in the construction industry is characterized by the scarcity of building materials and energy sources, as well as increasing requirements related to climate targets. This creates strong incentives to increase the construction volume of existing building renovations. Since it is difficult to make reliable statements about the renovation potential of existing buildings, especially in the early planning stages, it’s currently not economical to make a comprehensive assessment for prioritizing specific projects in large building stocks. This increasing demand represents great potential for automated digital workflows in the construction industry. Therefore, we propose a method that enables building engineers in early project phases to efficiently capture the building stock using point clouds, transfer it into digital, semantically rich models, and then automatically calculate retrofitting scenarios using Life Cycle Assessments (LCA) for decision-making. In this way, various professional groups, e.g., building owners and valuers or project acquisition managers, are supported in creating retrofitting scenarios for existing buildings in semi-automated steps. While most of the current approaches are based on manual modeling of existing buildings, e.g., using Building Information Modelling (BIM), our approach is using more automated processing steps. There are two levels of input data types, which require different efforts in acquisition. On the one hand, point clouds based on airborne or mobile laser scans (ALS/ MLS) or photogrammetry of Unmanned Aircraft Vehicle (UAV) have high accuracy, if available, but take some time for acquisition. On the other hand, Google Maps and Street View are less accurate but often available in dense urban areas. We want to investigate the performances of these different input data and compare the LCA results to determine if they are sufficiently accurate.

BACKGROUND AND RELATED WORKS

Geometric Reconstruction. In this paper, we show current concepts of geometric reconstruction of buildings for 3D surface models, focusing on building envelopes based on different point clouds. Nan and Wonka published a framework for Polygonal Surface Reconstruction from Point Clouds called PolyFit (Nan and Wonka 2017). It consists of generating a set of face candidates, selecting a subset of these by optimization based on y binary linear programming formulation, and finally reconstructing a watertight surface model. Chen et al. recently proposed a new approach for the geometric reconstruction of watertight building models based on point clouds, which has better performance results than the PolyFit approach (Chen et al. 2022). Bruno and Roncella investigated the accuracy and reliability of 3D models obtained from Google Street View panoramas (Bruno and Roncella 2019). In the domain of Geoinformatics, other approaches in the field of automated generation of LOD3 building models already combine semantic segmentation and geometric reconstruction. Hoegner and Gleixner automatically extracted facades and windows from MLS point clouds (Hoegner and Gleixner 2022). Pantoja-Rosero et al. use the PolyFit approach and a trained deep learning model of a segmented façade and openings for LOD3 city models (Pantoja-Rosero et al. 2022).

Semantic segmentation of façade Windows. Liu et al. introduce a novel translational symmetry-based approach to façade parsing in order to geometrically reconstruct buildings (Liu et al. 2022), further refining their previous DeepFacade approach (Liu et al. 2017). Also, Ma et al. improve the pixel-wise classification of DeepFacade by proposing an end-to-end deep network for façade parsing using occlusion reasoning (Ma et al. 2022). Also, Zhang et al. improved the accuracy of their deep learning approach for detecting building façade elements compared to DeepFacade by considering prior knowledge (Zhang et al. 2022). Dai et al. use street-view building façade image datasets of residential buildings as input for training their building façade semantic segmentation model (Dai et al. 2021). Nordmark and Ayenew propose an approach to window detection in façade imagery using Mask R-CNN (Nordmark and Ayenew 2021). Although they only focus on windows, their approach using instance segmentation produces a bounding box and segmentation mask for each window instance. More recently, Sun et al. also proposed an improved Mask R-CNN network using spatial attention and relation modules for windows instance segmentation, called “DeepWindows” (Sun et al. 2022).

Scan-to-BIM approaches for sustainability assessments of existing buildings. Honic et al. developed a methodology that generates Material-Passports for existing buildings based on laser scans and modeling as-built BIM models for further assessment (Honic et al. 2020). Nevertheless, the modeling process was conducted semi-automatically to integrate material information. Benz et al. introduced a framework for assessing energy performances of existing buildings based on an Unmanned Aircraft System (UAS) (Benz et al. 2021). Besides their photogrammetric 3D reconstruction, they included thermographic images to detect the U-Values and performed energy simulations using TRNSYS translating the surface model to IDF. A similar approach was introduced by Valero et al. using an integrated Scan-to-BIM approach for energy performance evaluation but also focusing on retrofitting existing buildings (Valero et al. 2021). They also combined processed point cloud information with object detection methods of images for semantic enrichment of MEP objects in the IFC model.

PROPOSED METHODOLOGY

In this Section, we propose a methodology for creating semantically rich 3D models for LCA-calculation of retrofitting scenarios for building envelopes. In previous research, we demonstrated a step-wise approach using laser scan point clouds with some further manual input (Selimovic et al. 2022). This paper aims for a more robust and holistic approach using point clouds and images based on different, broadly available data sources, which are suitable for calculating sufficient accuracy of LCA results. After describing the overall framework, we focus on the steps of geometric reconstruction and semantic enrichment in the following.

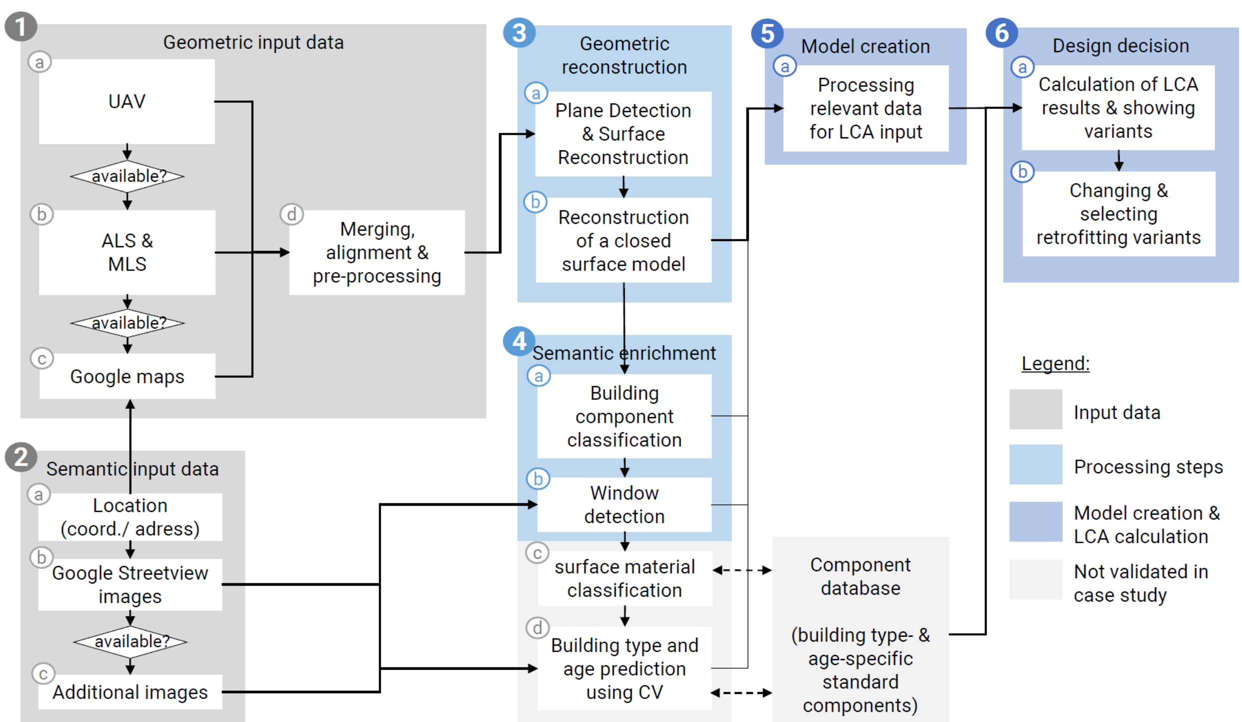

Figure 1. Workflow of design decision support for retrofitting variants in early design stages using point cloud-based geometric reconstruction and semantic enrichment.

Overview of the General Workflow. The general idea is to use different data sources to process point clouds, as shown in Figure 1 (1.a-1.d). Ideally, the point clouds are getting pre-processed by UAV images (1.a). If these are not available, it can be checked if airborne laser scans (ALS) in combination with mobile laser scans (MLS) are available (1.b). If none of these input data is available, Google Maps meshes are used to create a point cloud (1.c), for which the location or address is needed as an input (2.a).

After the pre-processing and, if necessary, merging and alignment of different point clouds (1.d), including adjusting the density of points and deleting unnecessary points, the point cloud is used for geometric reconstruction (3). First (3.a), different planes are detected, and surfaces are reconstructed. A closed surface model is reconstructed in the next step (3.b).

This output is used to generally classify the surface according to its location and orientation to different building envelope classes (4.a), e.g., vertical surfaces are exterior walls. The invisible ground floor slab is assumed to be a “floor to unheated cellar,” as the basements are considered to be not heated in older buildings.

In the next step, the vertical façade surfaces are specified in more detail to detect the window areas for semantic enrichment (4.b) based on different image input, either from Google Streetview (2.b) or additional images, e.g., from smartphones (2.c). Additionally, the surface material shall be classified according to 2D images (4.c), as proved by (Raghu et al. 2022). In the following step, the building type and age shall be predicted by using computer vision methods based on the location coordinates and the related Google Street View images (4.d). According to the “Typology Approach for Building Stock Energy Assessment “(TABULA) and its database (Loga et al. 2012), the missing element layers can be assumed by this information, e.g., surface material, building age and type, thermal class, or environmental impacts.

In the next step, all geometric models need to be merged and aligned (5.a), and all additional information shall be processed to a useful input format for LCA calculation (5.b). For this purpose, a suitable LCA data schema is used, which needs minimum geometric and semantic data to be still able to conduct LCA calculations also for existing buildings (6.a). In the LCA software, different variants shall be analyzed for retrofitting potentials (6.b).

Geometric Reconstruction. All different input sources, such as meshed surfaces from Google Maps, ALS and MLS, and Photogrammetry, are processed into point clouds. To reconstruct a “watertight” geometric building model, the building’s envelope surfaces, such as walls or roofs, are detected in the point cloud. In the first step, individual planes are identified based on the points and their normals using RANSAC (Schnabel et al. 2007), which results in several face candidates. In the next step, these face candidates are joined into a combined surface model using the optimization solver of PolyFit (Nan and Wonka 2017). Finally, the watertight building model is exported as an OBJ file for further semantic enrichment.

Semantic Enrichment. In this paper, we put the focus of semantic enrichment on window segmentation to identify the window-to-wall ratio. We enrich building element and material layers manually by assigning components to thermal layers based on the TABULA database (Loga et al. 2012). As we want to identify the window-to-wall ratio for every facade, several images need to be processed and evaluated. As input, we either use manually taken images or images queried from Google Street View (Google 2023). These differ from the image quality by the focal length of the used camera, so the results might differ in the evaluation. As we need information on the number of windows and the surface, we use instance segmentation. Sun et al. trained a Mask RNN called “DeepWindows,” using Detectron2 (Sun et al. 2022), which we used for identifying the windows. Nevertheless, the assignment of windows to the reconstructed 3D surface is here done manually, however, as a temporary solution only. Finally, all semantic information and the assigned geometric model are exported into a gbXML file (Green Building XML 2023).

CASE STUDY & RESULTS

Case study. As a first case study, a university building of the Technical University of Munich, located in Munich, Germany, is selected to indicate feasibility. The building is of solid construction with an internal skeleton and reinforced concrete ribbed ceiling. The space usage mainly includes researchers' offices, meeting rooms, lecture rooms, computer and server rooms, postal offices, and sanitary facilities. The building was initially built in 1926 and rebuilt after heavy war damages in 1946.

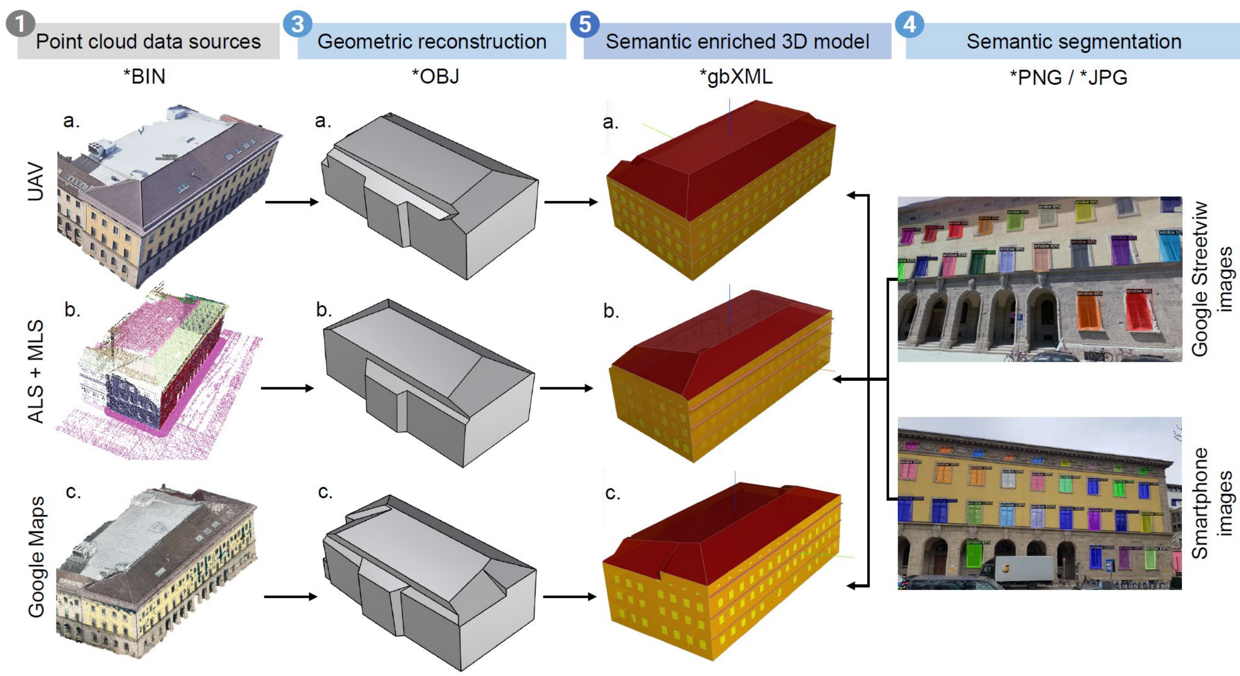

Figure 2. Case study results of different workflow steps: Different point cloud data sources, such as UAV/ Photogrammetry, ALS & MLS, Google Maps (1.a-1.c, left), geometric reconstruction (3.a-3.c, middle left), semantic segmentation of Google Stree view (4.a, right) & smartphone images (4.b, right), and semantically enriched 3D model (5.a-5.c, mid right).

Comparison of different geometric input sources. In this Section, we discuss the results of the geometric reconstruction of the three input sources and compare the surface areas of roofs, ground floor, and exterior walls with CityGML models (LOD2) and a manually created BIM model using Industry Foundation Class (IFC) based on technical drawings. Figure 2 also shows the geometric reconstructed surface models, and Table 1 compares the total surface area for the different data sources. The results show that the CityGML model provides a simplified geometry.

Table 1. Overview of the surfaces of the geometric model reconstruction in [sqm].

	a. GM	b. ALS-MLS	c. UAV.	d. CityGML	e. IFC
Ground slab surface	2.048,46	2.015,78	2.046,84	2.110,48	2.113,89
Roof Surface	2.254,35	2.099,32	2.264,75	2.280,97	2.316,33
Exterior Wall surface	3.490,62	3.991,59	3.442,44	4.409,56	4.031,95

Results of instance segmentation and model enrichment of windows. As shown in Figure 2, instance segmentation of windows using the DeepWindows network by (Sun et al. 2022) provide sufficient results for both types of input data, Google Street View images as well as Smartphone images. For the further enrichment of the geometric model, we are manually assigning the detected windows in the images to the related façade surfaces. The final energy model encoded as gbXML is shown in Figure 2 (5.a-5.c), which was further enriched by manually adjusting thermal and material properties in the LCA software CAALA (CAALA 2023).

LCA results. In Figure 3, the results of the life cycle assessment are shown for three different input data sources and the existing and retrofitted buildings. As the building is located in Germany, the German LCA database ÖKOBAUDAT (BBSR 2021) and the German standard for LCA were used with a life span of 50 years, LCA modules A1-A3, B4, B6, and C3-C4. For the retrofitting scenario, the external walls and roofs are insulated with wood fiber, the ground floor is insulated using XPS, and the windows are exchanged with triple-glazed windows and wooden frames. As the results of the total GWP in Figure 3 show, the input data sources for calculating the LCA of the existing building have similar results and differ only a little (1,3% between UAV and ALS-MLS, and 5,1% between UAV and GM). For the retrofitting scenario, the GWP result has even the same value over the whole life cycle, 37 [kg CO_2-eq./ sqm*a]. This shows that the proposed methodology is robust for different input data, such as Google Maps meshes (GM), point clouds based on mobile and airborne laser scans (ALS-MLS) or based on photogrammetric images of unmanned aerial vehicles (UAV), and the LCA results hardly differ.

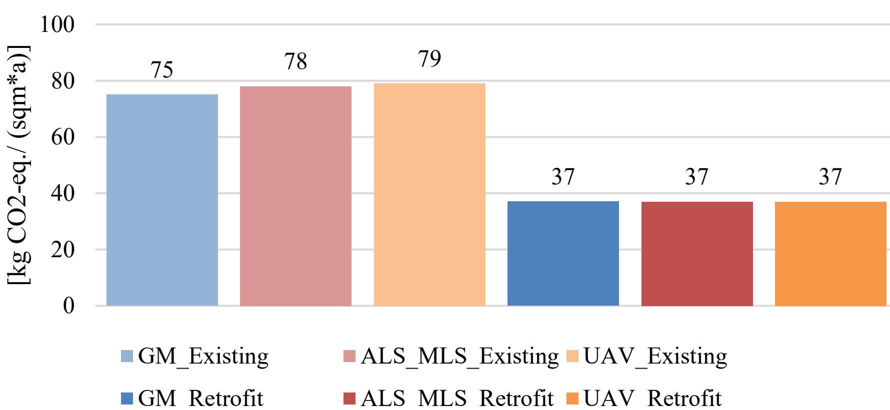

Figure 3. Total GWP results over the whole life cycle of existing and retrofitted scenarios and different input sources (Google Maps, ALS & MLS, UAV)

CONCLUSION

In this paper, we propose a holistic framework for calculating embodied and operational emissions of retrofitting scenarios of existing buildings based on a variety of input data. To achieve a robust and scalable workflow, different input data for the point cloud sources, such as those with high accuracy based on UAV photogrammetry and laser scans or lower accuracy based on Google Maps meshes, proved to be feasible for geometric reconstruction. For semantic model enrichment, different image sources are used, such as images based on Google Streetview and smartphones. We test the approach of geometric reconstruction using PolyFit based on a real-world case study of a university building. For semantic enrichment, only the façade segmentation is considered at

this stage. The implementation and application of the case study prove that the suggested workflow leads to comparable LCA results with only minor deviations. To verify the robustness of and validate the proposed methodology, we will test it on a more extensive set of buildings, but the results of the shown case study indicate feasibility.
In our future research work, an automated assignment of windows to the reconstructed 3D surface step is planned. For the step of model fusion of 3D point clouds and 2D images, an initial approach based on indoor geometries (Pan et al. 2022) shall be further extended for outdoor geometries. Furthermore, we want to extend the validation of the proposed approach considering automated semantic segmentation of façade surface materials and identification of building class to enrich element layers using TABULA. Additionally, for the building age detection part, the data sets of the project "ENOB:NWGdata," which consist of 100.000 buildings and classification information, such as age, retrofitting state, etc. (Busch and Spars 2022). In the final step, the extracted semantic information shall be automatically merged into the geometric model.

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