D5.1 PRE-MANUFACTURING WORKFLOW

WP 5 RESOURCE EFFICIENT (PRE) MANUFACTURING AND CONSTRUCTION WORKFLOWS

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[1] *ARV is a Norwegian word meaning "heritage" or "legacy". It reflects the emphasis on circularity, a key aspect in reaching the project's main goal of boosting the building retrofitting rate in Europe.*

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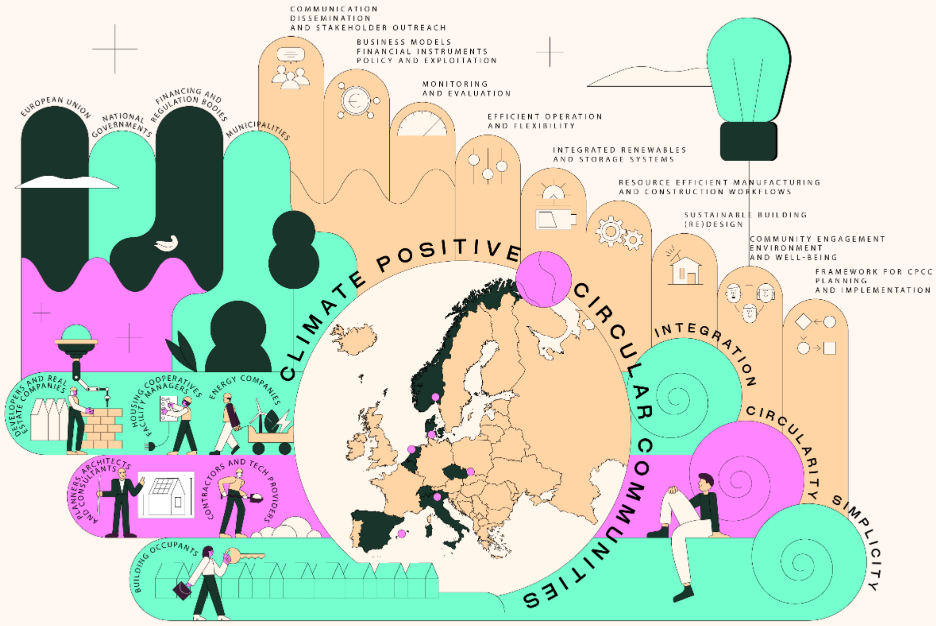
ABOUT THE ARV PROJECT

The vision of the ARV project is to contribute to speedy and wide scale implementation of Climate Positive Circular Communities (CPCC) where people can thrive and prosper for generations to come. The overall aim is to demonstrate and validate attractive, resilient, and affordable solutions for CPCC that will significantly speed up the deep energy retrofitting and the deployment of energy and climate measures in the construction and energy industries. To achieve this, the ARV project will employ a novel concept relying on a combination of 3 conceptual pillars, 6 demonstration projects, and 9 thematic focus areas.

The 3 conceptual pillars are integration, circularity, and simplicity. **Integration** in ARV means the coupling of people, buildings, and energy systems, through multi-stakeholder co-creation and use of innovative digital tools. **Circularity** in ARV means a systematic way of addressing circular economy through integrated use of Life Cycle Assessment, digital logbooks, and material banks. **Simplicity** in ARV means to make the solutions easy to understand and use for all stakeholders, from manufacturers to end-users.

The 6 demonstration projects are urban regeneration projects in 6 locations around Europe. They have been carefully selected to represent the different European climates and contexts, and due to their high ambitions in environmental, social, and economic sustainability. Retrofitting of social housing and public buildings are specifically focused. Together, they will demonstrate more than 50 innovations in more than 150,000 m^2 of buildings.

The 9 thematic focus areas are 1) Effective planning and implementation of CPCCs, 2) Enhancing citizen engagement, environment, and well-being, 3) Sustainable building re(design) 4) Resource efficient manufacturing and construction workflows, 5) Smart integration of renewables and storage systems, 6) Effective management of energy and flexibility, 7) Continuous monitoring and evaluation, 8) New business models and financial mechanisms, policy instruments and exploitation, and 9) Effective communication, dissemination, and stakeholder outreach.



The ARV project is an Innovation Action that has received funding under the Green Deal Call LC-GD-4-1-2020 - Building and renovating in an energy and resource efficient way. The project started in January 2022 and has a project period of 4 years, until December 2025. The project is coordinated by the Norwegian University of Science and Technology and involves 35 partners from 8 different European Countries.

1. TABLE OF CONTENTS

2. INTRODUCTION

To move towards a construction industry that is capable of renovating at speed necessary for meeting the Paris Agreement on climate change (United Nations Framework Convention on Climate Change, 2015) an important field of Industry 4.0, also known as 'smart manufacturing' is emerging in the construction industry. According to the principles of Industry 4.0 higher productivity in the construction industry is achieved by focussing on real-time decision making, digitalisation and agility (Barbosa et al., 2017). This philosophy means a deep digitalized (data driven) approach beyond the project-based industry. It should enable companies to create adaptable solutions to different circumstances and produce this in an advanced (robotised) industrial way. A change from a project-dependent industry towards a project-independent industry is needed to create solutions that connect better to customer needs.

In deliverable 5.1 Pre-manufacturing workflow, a variety of digital processes have been developed considering Industry 4.0 digitalisation steps. These include tools to map potential projects, digitalise knowledge acquisition on projects, and co-design prefabricated retrofitting products in a data-driven manner. To realise these goals, it is necessary to deepen insights on the existing building stock as well as design for modular data-driven fabrication of product systems. These insights are gathered and processed in the digital tools before, during and after the pre-manufacturing workflow.

2.3. VARIATION OF THE EXISTING BUILDING STOCK

To ensure a scalable project-independent workflow knowledge must be acquired of the variation in design background of the entire building stock that needs to be retrofitted. Multi-residential buildings that were post-war built until 1992 have deep similarities in construction method as opposed to single family houses which are more diverse. In the Netherlands as well as other parts of Europe these apartment buildings are ubiquitous (Barkmeijer, 2017). From 1992 onwards new building regulations were introduced which resulted in buildings with a better energetic performance and more tailored constructions, generally making industrial deep retrofitting solutions through insulating less necessary. Walraven (2021) identified that the building systems from the research of Barkmeijer were not able to be identified because of alterations throughout the lifespan of the building. A lot of buildings were for example retrofitted with an insulation cladding and window frames that hide the characteristics. We therefore aim to identify apartment buildings with similar construction systems that originate from the same design history, working towards a comprehensive typology.

A base for this typology lies in the EU-TABULA (Typology Approach for Building Stock Energy Assessment) approach, which is reflected in the study ''Voorbeeldwoningen 2022" (*example buildings 2022*) (see Voorbeeldwoningen 2022,), which identify 51 residential typologies in the Netherlands based on terraced, semi-detached, detached, and multi-residential buildings for several building age cohorts. In the Voorbeeldwoningen analysis typical building features as well as energetic performances have been indicated based on empirical data from qualitative inquiries among 4506 residential buildings (Lijzenga et al., 2019).

For multi-residential buildings there is a limited typology of cohorts: maisonette, galleries, porch apartments and diverse apartment housing. Also here, the cohorts are divided in between relevant transition years in Dutch building legislation.

Table 1. Dwellings per house type and construction period. Source: BouwhulpGroep, 2013

House type \ Constructio	-	<1945	1946-1964	1965-1974	1975-1991	1992-2011	1037000
Detached house		216.000	225.000	119.000	221.000	256.000	**1.037.000**
Semi-detached house		140.000	145.000	142.000	224.000	249.000	**900.000**
Terraced house		523.000	478.000	606.000	879.000	507.000	**2.993.000**
Maisonette house		113.000	113.000	22.000	94.000	57.000	399.000
Gallery apartment		5.000	64.000	174.000	109.000	162.000	514.000
Portico apartment		256.000	267.000	112.000	142.000	101.000	878.000
other flats		49.000	50.000	125.000	125.000	196.000	**545.000**
TOTAL		**1.302.000**	**1.342.000**	**1.300.000**	**1.794.000**	**1.528.000**	**7.266.000**
Apartment buildings		**423.000**	**494.000**	**433.000**	**470.000**	**516.000**	**2.336.000**

In Table 1 (deep red) the Bouwhulpgroep also identified the Gallery, Portico and Other flats between 1946 and 1992 as highly similar. Therefore, we focus on the post-war era and specifically the appartement buildings.

However, multi-residential buildings consist of at least 50 different construction systems for all multi-residential buildings with the 11 most prevalent systems originating from 1960-1970. The morphological variety among these construction systems is so distinct that a more refined categorisation can give more insight on technological potential for renovation product systems. By identifying these building systems more specified and realistic retrofitting pathways become clear by clustering similar systems on sufficient level of detail.

Currently GeoAI based tools have not been employed to automatically detect these systems. GIS analysis of public data assisted by novel data from computer vision models may enable the recognition of specified façade elements and roof features. The building envelope provides information about the texture, revealing the materialisation, the window-to-wall ratio, and the constructive delineations. The cadastre informs about the year of construction, as well as the amount of residences and properties. The façade and roof layout together with the region, construction year and number of floors can lead to a building system that dictates the basic design parameters for parametric building models of post-war multi-residential buildings.

2.1. PRODUCT SYSTEMS

Two product systems are highlighted as case studies, for which the digital tools for the pre-manufacturing workflow are designed and demonstrated.

The Alpha module is part of the Inside Out product system in which several modules are designed to work in conjunction with each other to improve buildings' energy performance.
The façade panels by Rc Panels showcases the connection between data-driven co-design and pre-fabrication.

In both product systems the pre-manufacturing workflow supports cost prediction (*quotation acceleration*) and File2Factory.

2.1.1. THE ALPHA MODULE AS A PART OF THE INSIDE OUT PROJECT SYSTEM IN UTRECHT

The Utrecht demo project uses six modules named after the first six items within the NATO alphabet (Figure 1). The Alpha Solar Module is one of the two main case studies of this deliverable. The Alpha is a specialised structure designed to be placed on the roof of a building. It allows more solar panels to be installed on the roof than on a flat roof alone. This, in turn, allows for more electricity from solar energy through the roof.

The Bravo solar module is constructed from steel and features fully prefabricated solar panel frames. The Charlie facade installation module includes a radiator, decentralised ventilation system and a solar panel and can be easily installed in the frame in one day. The Delta facade module is a revolutionary solution combining facade and installation technology. Integrating installation technology enables a house to be fitted with a new facade that can insulate, heat, ventilate, and generate energy all in just one day. In addition, the Echo Balcony Module is a unique modular solution designed to maximise the use of solar energy in high-rise buildings. It allows for the retrofitting of the balcony and provides an opportunity to generate power from the balcony railing through integrated solar panels. Furthermore, the Foxtrot Data module is the central processing unit of the energy system. It serves as the brain of the system and makes buildings more intelligent.

Figure 1. Modules within the Utrecht Demo Project.

2.1.2. RC PANELS

Rc Panels is a factory for prefabricated panels to realise energy-neutral houses. They are specialised in industrialisation and digitisation, running a “File2Factory” process. By investing heavily in knowledge development, combined with a different view of the construction process, Rc Panels has developed a technological lead supported by patents. ICT technology developed and applied includes the “File2Factory” approach. Rc Panels factory works with a patented glue lamination process as well as patented robotics for stone slip finishing. The IPR developed and under development in other programs is applied by Rc Panels in the ARV project for cost effective production for the Utrecht demo.

Figure 2. Left: Prefabricated facade panel design by Rc Panels showcasing its five layers: polyester, OSB, EPS in various thicknesses, polyester, and a finishing stone slip layer. Right: retrofitting of Hoge Kampen flats with a prefabricated building envelope. Source: Rc Panels

2.2. FRAMEWORK FOR PRE-RECOGNITION TO PRE-MANUFACTURING AND FILE2FACTORY WORKFLOW

In D5.1 we explore how novel digital tools may aid in the transition towards energy-positive retrofitting products for post-war residential buildings. Conditions essential to this transition process in the technical domain include (i) the development of integral retrofitting products that are in line with the market, (ii) developing profitable business cases for both housing associations and construction parties, (iii) creating companies that develop products independently in industrial manners and (iv) providing products that are tailored in collaboration with residents (Stutvoet, 2018).

Specifically, the mentioned transition is supported by preparatory digital processes that aid product system development of business plans (ii) and streamlining the determination of quotations and co-design (iv) ('Pre-manufacturing'). Whereas pre-manufacturing comprises resource-intensive project-dependent information workflows, scalability is realised when a substantial amount of information is collected in a project-independent manner for the entire building stock from open data and remote data capture (i) ('Pre-recognition'). The rich library of information aggregated during Pre-manufacturing can ultimately lead to digital instructions for prefabricated products (iii) ('File2Factory').

In summary, the conditions for the transition towards energy-positive retrofitting of residential buildings can be achieved in three distinct chronological technical workflows: 'pre-recognition', 'pre-manufacturing' and 'File2Factory' (
Figure 3). The following paragraphs will shortly introduce the specific digital processes that were developed for these three workflows.

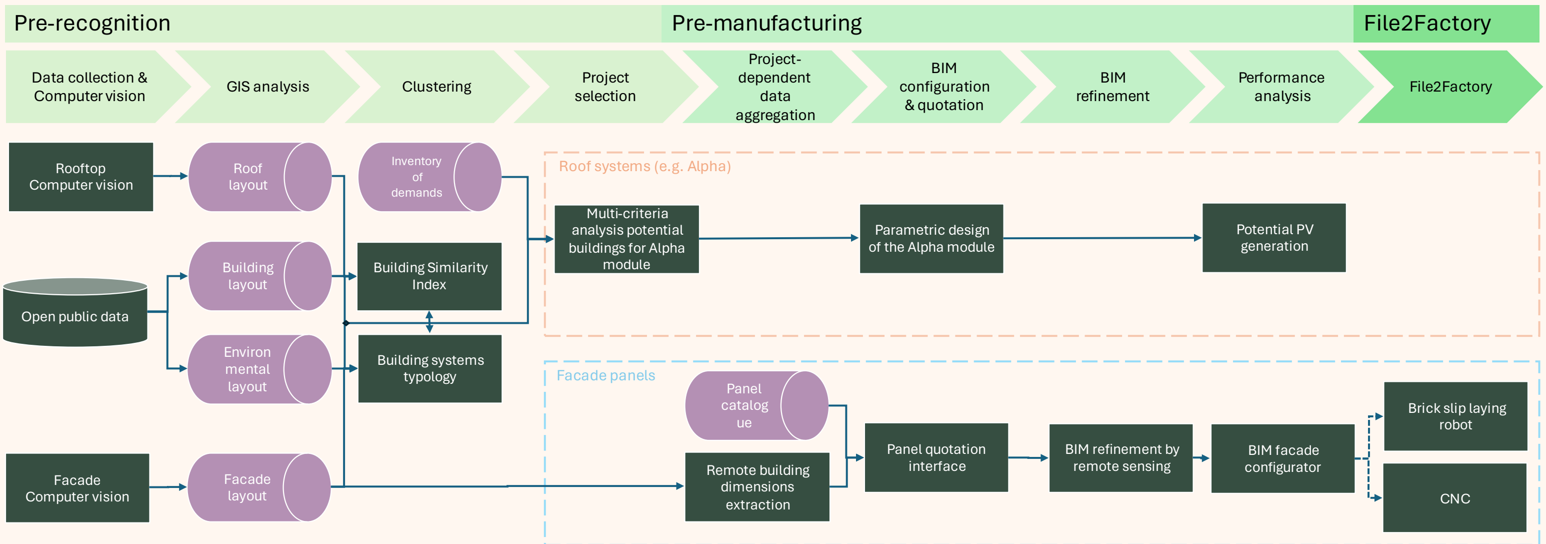


Figure 3. Overview of digital workflow from pre-recognition to pre-manufacturing to File2Factory. Green boxes indicate digital processes that have been developed during the ARV research period. Pink tubes indicate datasets aggregated in the research period. Large green arrows indicate research domains that consecutively connect to form the digital workflow. Thin arrows indicate the intended flow of data between modules. The orange box contains all innovations related to implementation of the Alpha module by Inside Out. The blue box contains all digital processes related to accelerated design and quotation of prefabricated panels by RC-Panels.

2.3. PRE-RECOGNITION

The pre-recognition workflow entails a project-independent exploration, where a large amount of open data is utilised to make smart prioritisation which buildings to retrofit with which product systems. In summary, the pre-recognition workflow is aimed at building selection. Pre-recognition fosters the conditions of developing profitable business cases (ii) and creates more insight on the 'landscape' of possible building clusters for which to create compatible product systems and business plans (iii).

Figure 4. Facade view of INTERVAM flat at Henriettedreef, retrofitted by the Inside Out project as the first energy-positive high-rise apartment building in Europe

The four sequential research domains defined in the pre-recognition workflow are Computer vision (4.1), GIS analysis (4.3), Clustering (4.2; 4.4) and Project selection (4.5).

With computer vision HU aims to create new building information from imagery that is not yet available for the Dutch building stock in open datasets. By Geographical Information System (GIS) analysis open public data is aggregated to describe building design background (building layout), environmental conditions relevant to technical potential for product systems (environmental layout) and computer vision data into a dataset on post-war complexes.

In Clustering, an inventory of demands is collected from product developer Inside Out on building conditions that influence technical potential for implementing a product system like the Alpha module. An example of such a condition is a permitted building height of over 2 meters. Additionally, it is aimed to cluster buildings based on design background from both an architectural and a data science perspective. From an architectural perspective the evolution of multi-residential buildings and building systems is studied, with a focus on structural changes over time in visible features of the building envelope. These features are to be found by computer vision and GIS analysis, such as the window-to-wall ratio and number of floor levels. As such, it is explored whether buildings can be clustered on common design background linked to construction features relevant to retrofitting product systems.

For example, Inside Out designed their Delta façade module to easily replace the former detachable façade panels of the INTERVAM building system (Figure 4).

Since clustering buildings on design background heavily relies on qualitative data and computer vision, as a counterpart a more quantitative mathematical cluster method was developed named the 'Building similarity index'. In this method, information acquired in GIS analysis is used to cluster buildings in an unsupervised multi-variable feature space.

In Project Selection a multi-criteria analysis is performed on the acquired GIS dataset to identify buildings with potential for retrofitting with the Alpha module of Inside Out. The goal of this final part of the pre-recognition workflow is to identify projects with high technical potential for applying the Alpha module. The subsequent goal of the pre-recognition workflow is to forward a base dataset for subsequent projects' Building Information Models (BIM) that aid in predicting quotations before any on-the-ground inspections have taken place, saving a significant amount of man-hours.

2.4. PRE-MANUFACTURING

As opposed to the Pre-recognition workflow, the subsequent Pre-manufacturing workflow moves from open data to more resource-intensive project-dependent data acquisition. The workflow narrows to project-specific development for product systems to accelerate the prediction of cost and other performance indicators, as well as steer on design tailored to customer and project environment.

Two application tracks are investigated for the Pre-manufacturing workflow: automated design and quotation of the Alpha module by Inside Out (5.2) and all innovations related to automated client-steered design and quotation of prefabricated panels by RC-Panels (5.3).

The Pre-manufacturing workflow builds on data from the pre-recognition workflow as well as project-specific aggregated data, e.g. digitally extracted building dimensions from street-view imagery and a library of possible façade materials to be used.

Building design, construction and materialisation are configured in BIM configuration. It is at this stage that the cost of the proposed retrofitting can be predicted with a significant level of detail for quotation. For retrofitting with the Alpha module this means that a parametric design BIM is created in Dynamo, fed by data acquired in the Pre-recognition workflow. The Alpha BIM model is used to determine the amount and orientation of solar panels to calculate potential solar energy generation.

For retrofitting with prefabricated panels, the extracted building dimensions and library of materials are used to create an interface for the client to make design choices that form the basis of a gross quotation for the retrofitting project. Subsequently, a higher level of detail for designing the panels is explored with BIM refinement by point cloud scanning and photogrammetry. The enriched BIM model can be used to evaluate more detailed design choices with the architect.

2.5. FILE2FACTORY

When a final choice for materialisation and dimensions of the prefabricated product (in this study façade panels) has been determined in collaboration with the client and architect, it is time to export the specifications to the production facility; this process we call 'File2Factory'. To convert a BIM model to factory instructions, Buro de Haan developed add-ins for BIM software Revit to instruct a CNC Machine and a brick slip laying robot.

3. METHODS AND TOOLS FOR LARGE-SCALE RETROFITTING AND CLIMATE ENERGY COMMUNITIES IN CPCC

Within the ARV project digital tools are developed for the realisation of climate positive circular communities (CPCC) on different scales. Next to the product system focussed efforts of WP5.2, WP2 addressed two main actions for CPCC in urban context. By one hand, how to accelerate the energy retrofitting of the existing building stock by large scale actions. By the other, how to promote and create Citizen Energy Communities.

The following section will recap the efforts of WP2 and discuss its relation to WP5.2 in realising CPCC with digital tools.

Citizen Energy Communities (CECs) are expected to be crucial in the energy transition. Although Directive (EU) 2019/944 has enabled the creation of CECs, there is a lack of integrated tools that can be used in the planning, selection, design, implementation, and evaluation of new citizen and Renewable Energy Communities (RECs), particularly in urban contexts. In the framework of WP2, several methods and tools are integrated and developed to address those needs. As part of the activities linked to the demos in the ARV project, the methodologies will be tested in some countries: Czechia, Denmark and Spain. Two deliverables describe the holistic approach and workflows proposed in WP2.

- D2.2 Description of methods and tools for Large-Scale Retrofitting in CPCC
- D2.3 Description of methods and tools for CEC in CPCC

The report D2.2s one of the main outcomes under Task 2.3 (T2.3) Use and testing tools for Large Scale Retrofitting actions in CPCC. The aim of the task is to improve and adapt District Energy Simulation tools to effectively plan, design and analyse large scale retrofitting actions of the built environment and assess the impact at district level. The various tools integrate different modelling strategies of the building stock and new constructions in a district, based on the use of building archetypes through different approaches such as white box detailed models; grey-box models, data driven models, etc. and availability of data at urban scale, e.g., GIS-based data. The methods and algorithms to calculate relevant KPIs based on the results of the ARV assessment framework are integrated to provide techno-socio-economic outputs. The main objective of the use of these tools is to take informed decisions, and to showcase their usefulness to accelerate the retrofitting of building stock in cities. In the report two large scale retrofitting demo cases (in Palma and Sønderborg) have been presented to facilitate the replicability in other environments at EU scale.

The aim of D2.3 report is to describe the integration of existing methods and tools in order to assess local RES generation in an urban environment by using the available free space in public and/or private buildings and public spaces and linking it to the individual and aggregated energy consumption of participants in CECs. ARV is testing decision-making tools that integrate available city-level information, models of local RES production, and estimates energy consumption of potential CEC participants. The methods and tools should be able to calculate Photovoltaic (PV) and Building-Integrated Photovoltaics (BIPV) generation and community energy demand and be adaptable to the local regulatory context as well as to different governance aspects and financing models. These methods and tools are under test and validation in the demo projects of Karviná and Palma de Mallorca to assess the energy and economic aspects of different business models (Work Package - WP9) and of energy flexibility strategies (WP7) leading to optimised economic and environmental systems and civic engagement of participants in the CEC.

In general, the methodologies proposed in WP2 can be classified as part of pre-manufacturing workflows. The double aim of the workflows is to facilitate viable technical designs or pre-design solutions as well to calculate their economic impact, both the investment needs and the total life global costs. Methods and tools are addressed to owners, designers and decision makers that need assessment tools based on simulation to take informed decisions among different options and/or be engaged on accelerating projects for neighbourhood regeneration. By the contrary, the aim of the tools is not to generate detailed engineering neither detailed construction documents which will be needed to create once basic design options have been agreed.

3.3. ADDING TO THE DIGITAL TOOLBOX: PRE-MANUFACTURING WORKFLOW FOR PRODUCT SYSTEMS

Where WP2 discusses pre-manufacturing workflows to inform different stakeholders in CEC context, WP5.2 explores the possibility to translate open data of buildings to engineering specifications that are specific enough to accelerate the quotation process and realise File2Factory for product systems. The application of these product systems is evaluated per complex.

D5.1 zooms in on predicting the technical potential of retrofit solutions for complexes from open data, addressing knowledge gaps in data through computer vision. For example, predicting Energy KPIs may be more refined by considering the obstructions that previously undetected roof superstructures may pose in implementing proposed optimal PV layouts (Krapf, Kemmerzell, Uddin, et al., 2021). In terms of Global Cost, D5.1 contributes to streamlined market analysis by pre-recognition of suitable buildings for energy retrofitting, therewith decreasing time and cost expenditure for prospecting.

Instead of conventional retrofitting approaches such as single solar panels, D5.1 explores the potential for modular prefabricated integral energy installations. For example, product systems are considered where elevated rooftop structures like the Alpha module enlarge the amount of available space for solar panels compared to conventional practice.

Nevertheless, geometric 3D modelling, irradiance & shading analysis for solar potential, as well as simulation of electrical mechanics and business modelling are covered in more detail in WP2. It was stated that for the adopted workflow it is essential to accurately estimate the available rooftop area, considering the shadows from the surrounding building and exclude the unsuitable installation area. As such, from the Rooftop Recognition model of D5.1 (4.1.1) a new level of detail can be added to 3D geometries by including rooftop superstructures such as building services technology (e.g. HVAC, chimneys), formerly placed PV panels, and safety infrastructure.

4. PRE-RECOGNITION WORKFLOW

4.1. COMPUTER VISION

As a base for pre-recognition, it was explored how to increase the amount of data available for the entire Dutch stock of complexes using public aerial imagery and BAG building footprints. In this chapter we present a Rooftop Recognition model, as well as a Rooftop material model and a Façade Recognition model.

4.1.1. ROOFTOP RECOGNITION MODEL

The location and identity of rooftop contours and roof superstructures provides a wealth of information about the technological and economical potential for renovation product systems. For instance, predicting the roof area free of obstructions or knowing the presence of already placed PV panels. For more practical purposes of see 4.3.5.

Method

A computer vision network was set up deploying YOLOv8 instance segmentation on publicly available Dutch aerial imagery (8 cm resolution) of 2022 via the PDOK web platform (Jocher et al., 2023).
The Rooftop Recognition model consists of three separate consecutive Yolov8 models that ultimately feed their predictions to a geodataframe builder, generating a GIS dataset to explore the roof layout of complexes (Figure 5).

Input images were downloaded from the PDOK WFS API using bounding boxes from complexes' aggregated building footprints of the Key Register Addresses and Buildings (BAG) in the Province of Utrecht with a 2-meter buffer (4.3.5).

The publicly available PDOK images are not true-ortho, therefore there is a discrepancy between the BAG building footprint and the building on the input image, hence resulting in a slight skew in the resulting predictions of roofs and roof superstructures compared to true position on the Rijksdriehoek coordinate system.

760 images were labelled with polygons in Roboflow (Dwyer et al., 2024) distinguishing 12 rooftop (superstructure) classes (Table 2). Classes were initially defined according to find features of interest for product system developers (Table 4), but definitions were adjusted to maximise visual distinction of each class. For instance, a window with a curtain and a latch are too hard to distinguish in colour and geometry in current image resolution; therefore, these objects had to be merged to the same class.

Pipeline

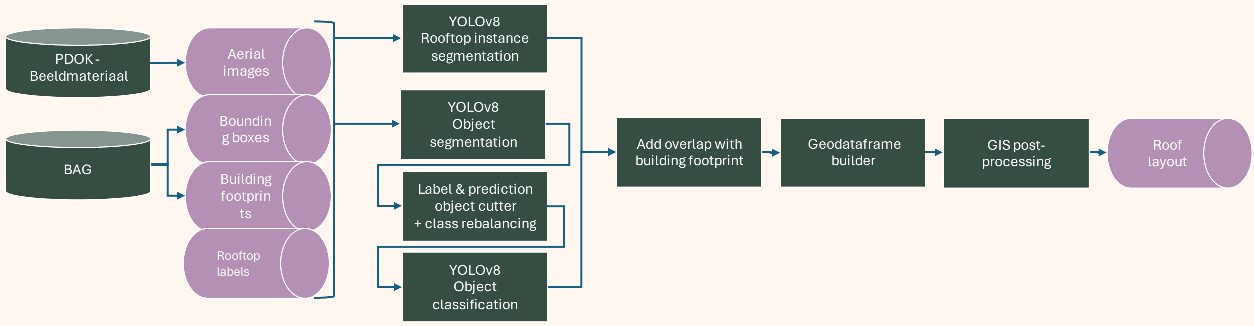


Figure 5. Overview of Rooftop Recognition model

For the Rooftop instance segmentation module: roofs were labelled into flat and slanted surfaces of the main load bearing structure. Their distinction is visibly assisted by materialisation. Roof terraces and sub-constructions such as dormers, boiler rooms and elevator shafts take up a large part of the roof outline as well and are therefore also included in the same roof segmentation step.

Controlling bias in object segmentation and classification

After labelling roof superstructures (*objects*) it was evident that roof ducts represented more than 50% of all object instances in the dataset compared other object classes. To prevent strong bias in object classification, roof ducts were divided into label classes 'small', 'medium' and 'large'. The definition of these classes is not strictly defined by size, but manually distinguished by level of material intensity and grouping of ducts (Table 2). It is still evident that roof ducts are not easily distinguished into separate groups given their continuous variation in size and materialisation, leaving opportunities for model optimisation.

The amount and types of objects also differ strongly per roof, introducing bias in object classification per image. Therefore, object labels within training images are cut out into an exploded training dataset of separate ground-truth objects independent of the roof they reside on. Objects are cut out from the image with a buffer of 15px (1.2m), where part of the surrounding roof is preserved but darkened to leave context for classification. In a rebalancing step, omitting labels of the largest classes and augmentation (flipping and rotating) allowed to train on an equal number of instances per class. The Object segmentation module first detects roof objects on images and cuts them out to be then classified in the Object classification module, using the cut-out label objects as the mirroring training dataset.

Table 2. Classes applied for the rooftop recognition model, divided over the rooftop and roof object detection submodels.

No	Class	Submodel	Explanation
1	Flat roof	Roof	Separate elevated surfaces that belong to the load bearing structure and are visually flat
2	Slanted roof	Roof	Separate elevated surfaces that belong to the load-bearing structure and are visually slanted
3	Elevated outdoor space	Roof	Any elevated construction of which the roof surface is accessible to residents. Mostly roof terraces
4	Subconstruction	Roof	Any elevated construction of which the roof surface is not accessible to residents and does not belong to the load-bearing structure of the roof. E.g. dormers, elevator shafts, boiler houses.
5	Infrastructure	Object	Safety infrastructure: mostly fencing either for protection or window cleaner services. Staircases are also included.
6	HVAC	Object	HVAC, building service technology, broadcasting equipment. Box-like devices often connected to cables.
7	Cables	Object	Protected wire channels, ventilation tunnels that connect other objects
8	Roof duct small	Object	singular loose black or white roof ducts with absence of support construction or extra housing around or on top of the vent . Often only visible as a point or a thin line-like shadow on aerial imagery. Indicator for sewer gas ducts.
9	Roof duct medium	Object	Singular loose/non-aggregated roof ducts of varying colours with extra housing around or on top of the vent and/or a support construction like masonry or metal. Often more volumous and visible as a circular or square object on aerial imagery. Do not house multiple ducts in one object. Indicator for flue gas duct.
10	Roof duct large	Object	Roof duct (large): aggregated roof ducts of varying colours with extra housing around or on top of the vent an a support construction like masonry or metal. Often more voluminous and visible as rectangular or an accumulation of round or square objects on aerial imagery. House multiple ducts in one object. Indicator for flue gas duct.
11	Thermic or PV panel	Object	Singular modules or rows of similarly oriented thermic or PV panels of all colours

12	Window (or latch)	Object	Horizontal or diagonally placed windows/skylights or latches, loose, or aggregated.

Training & prediction

Only qualitative assessment was used to determine the best settings. Both Rooftop and Object segmentation modules' parameters were qualitatively assessed and ultimately trained as a pre-trained YOLOv8 instance segmentation model with batch size 9, image size 972px planned for 300 epochs. Cutting objects into separate labels and rebalancing resulted in 4720 labels for training and 2066 for testing (30%).

Object classification module was trained with batch size 177, image size 240 planned for 300 epochs.

Table 3. Dataset description for training of Rooftop Recognition model

Datasets	Subset	Number of images
Complexes	Total	752
	Training	603 (80%)
	Validation	75 (10%)
	Test	74 (10%)

Results

Rooftop detection & classification

The following results are preliminary and cannot be used as a benchmark.

The instance segmentation of roofs stopped at 109 epochs and achieved a mean Average Precision of 54% (at an IOU threshold of 50%). However, omitting elevated outdoor space, the mean Average Precision for the test dataset amounts to 68% (Figure 6). This means that on average currently 68% of unoccupied roof space is accurately segmented and classified.

The normalized confusion matrix of the roof classification (Figure 7) shows that under the given circumstances 64% of flat roofs, 70% of slanted roofs and 71% of sub constructions are correctly classified with most false negatives being background. Elevated outdoor space is barely recognised, where 72% of observations are false negatives as background.

The lacking recognition of elevated outdoor space knows several causes including underrepresentation by 25% compared to the dominant roof classes, as well as the definition of the class allowing for noisy and highly variable labels, containing elements (such as furniture and plants) that occur on ground floor gardens in abundance as well.

The result suggests that RGB based computer vision becomes less accurate for determining roof shape and area when roofs get a function that is comparable to the ground floor.

It is proposed that rooftop segmentation can be further improved by hyperparameter tuning, a larger dataset of labels, and possibly training different models for pre-defined roof types such as complex versus simple rectangles.

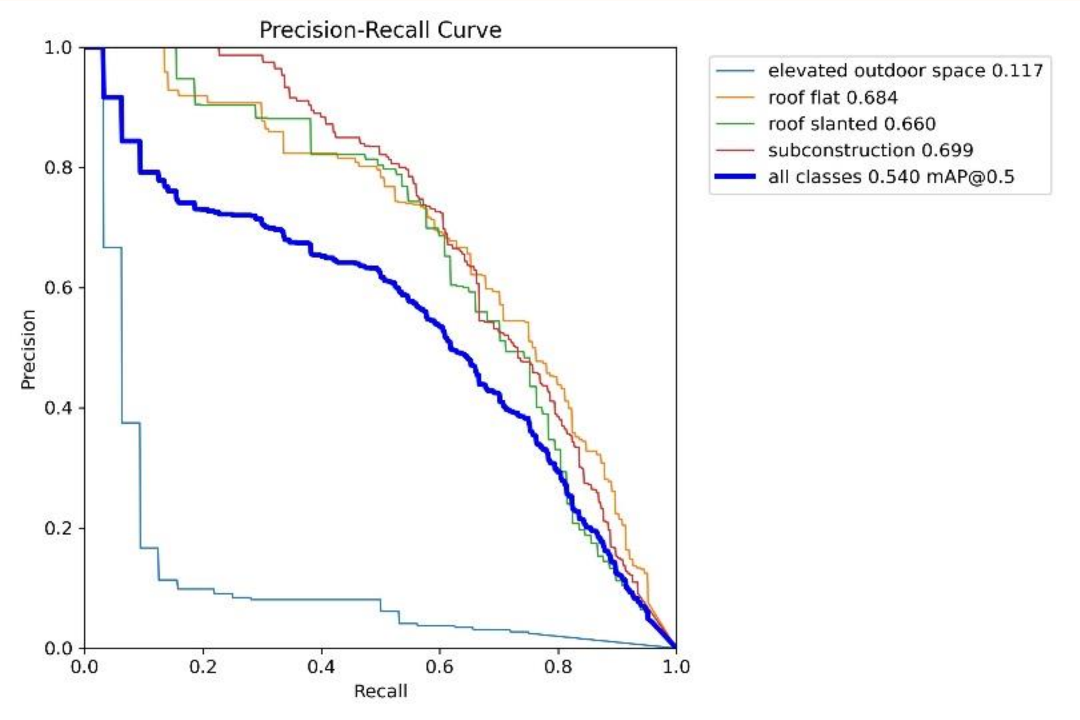


Figure 6. Precision-Recall Curve of YOLOv8 rooftop instance segmentation. Precision describes the proportion of true positive predictions out of all predicted objects, recall describes the proportion of true positive predictions out of all ground-truth objects. Mean average precision (mAP) at 50% intersection over union (IOU) is portrayed by area under curves of each class.

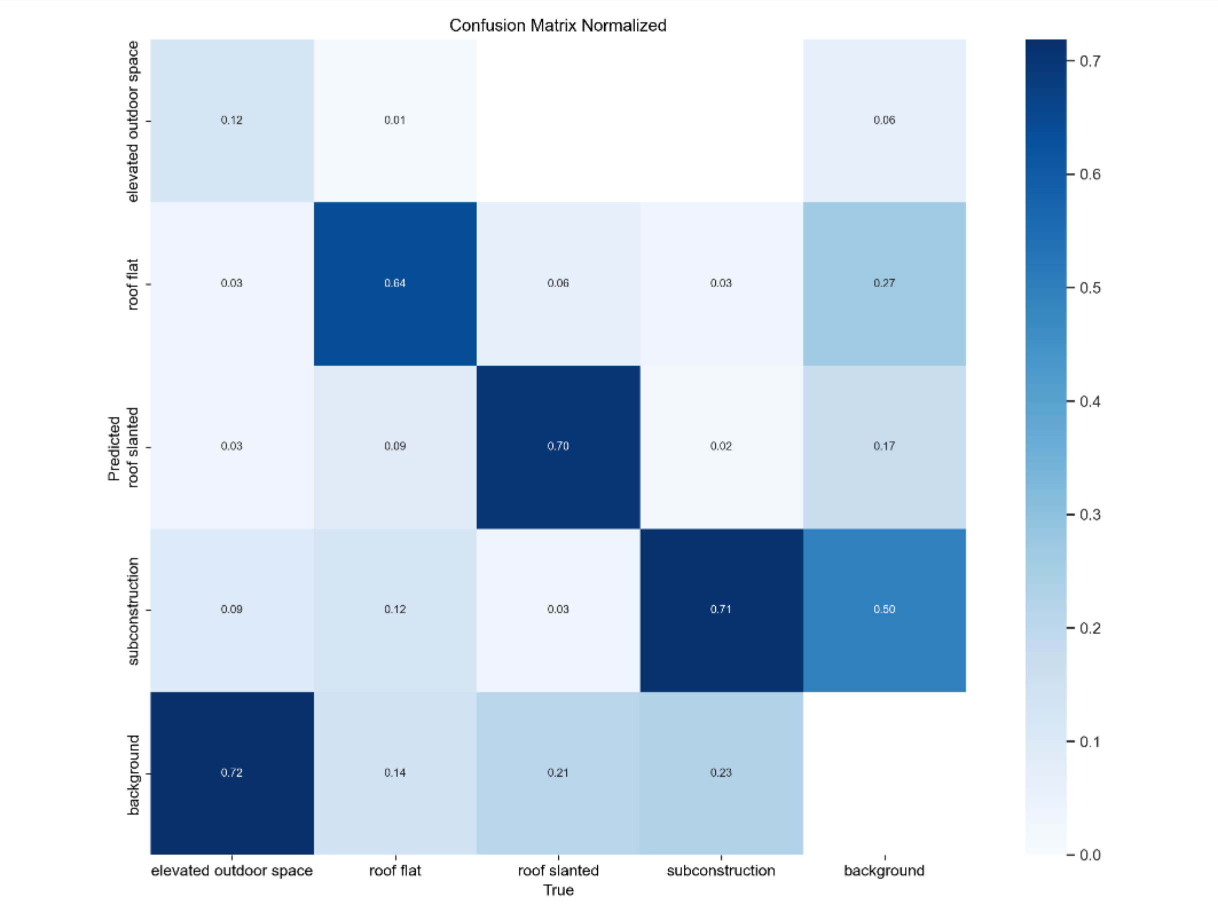


Figure 7. Normalized confusion matrix of YOLOv8 Rooftop instance segmentation. Diagonal positions indicate true positive rates for classes. Vertical orientation indicates percentage of positive/false predictions for certain class ground-truth.

Object segmentation, cut and classification

Object segmentation showed a mean Average Precision of 60% (at an IOU threshold of 50%). After cutting and rebalancing, the classification shows that for small and large roof ducts as well as windows and thermic/PV panels the true positive rate is above 86% (Figure 8). Classification performs best for small (96%) and large roof ducts (94%). HVAC is detected with a true positive rate of 63%, but since the class is of a more variable nature it is also mistaken for windows (12%) or large roof ducts (15%). Medium roof ducts have a true positive rate of 56% and are more often mistaken for largest roof ducts (20%) as opposed to small roof ducts (7%), false positives in more functionally distant classes are HVAC (9%) and windows (6%). Infrastructure is the class with least performance (14%), more often being falsely predicted as cables (57%) or thermic/PV panels (29%).

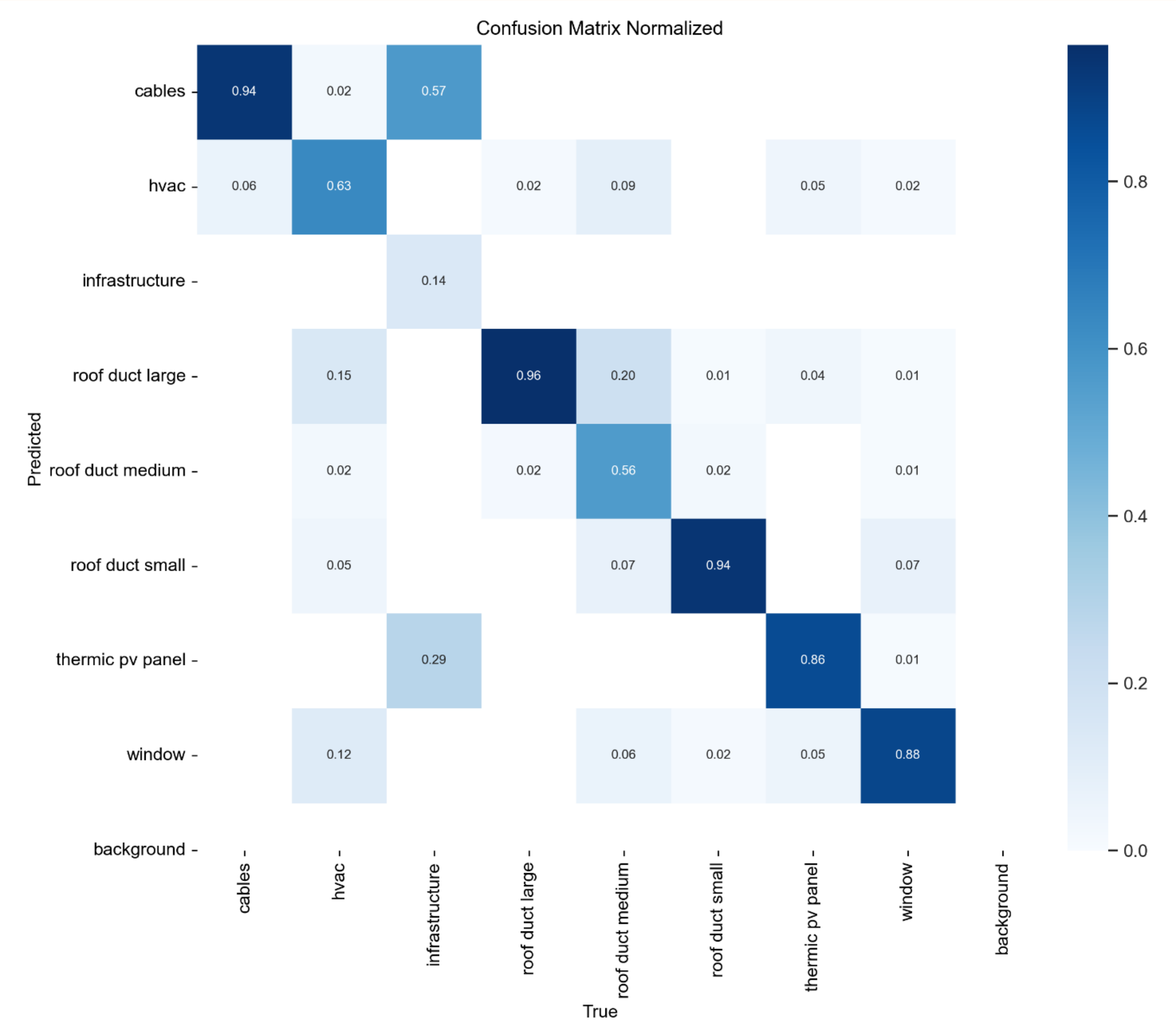


Figure 8. Normalized confusion matrix of YOLOv8 Rooftop superstructure classification. Note that background is not considered since the input images are cut-outs of the Rooftop superstructure segmentation.

Figure 9. Overview of Rooftop Recognition output.
Roof segments and superstructures of all complexes between 1945-1992 in the Netherlands have been mapped by YOLOv8 on aerial imagery. Notable classes include dormers (upper-left subconstructions), Thermic/PV panels (upper-right), and the distinction between flat, slanted and 'extra' roof segments (subconstructions) (bottom-left)

Geodataframe builder

Using the Python Geopandas package (den Bossche et al., 2024; Python Software Foundation, n.d.) results of Rooftop & Object modules were processed and exported to polygons in two Esri shapefiles, to be post-processed and interpreted in QGIS.

In the geodataframe builder complex footprints were used to calculate an overlap metric providing a ground-truth check whether a prediction is indeed focussed on the roof area. The overlap metric is added as an attribute for each prediction that is exported as a polygon to the geodataframe builder.
The detection confidence of each roof and object segmentation is added as an attribute as well as a descending array with the confidence for each possible class that could have been assigned to the object (Figure 10). As a result, rooftops along with relevant superstructures of all complexes between 1945-1992 in the Netherlands have been mapped (Figure 9).

Post-processing

Predicted polygons were loaded in QGIS. The peak of F1-Confidence curves for Rooftop and Object segmentation were used as a confidence threshold to filter out faulty segmentations, in this case detection confidence threshold was 0.486 for roofs and 0.255 for objects.
Polygons were filtered on an overlap with complex footprints of 40%.
Rectangularity was calculated for each object as in 4.3 to filter out objects with 100% rectangularity as these are faulty segmentations. Finally, geometries were validated and if necessary corrected in QGIS using the *Fix geometries* tool.

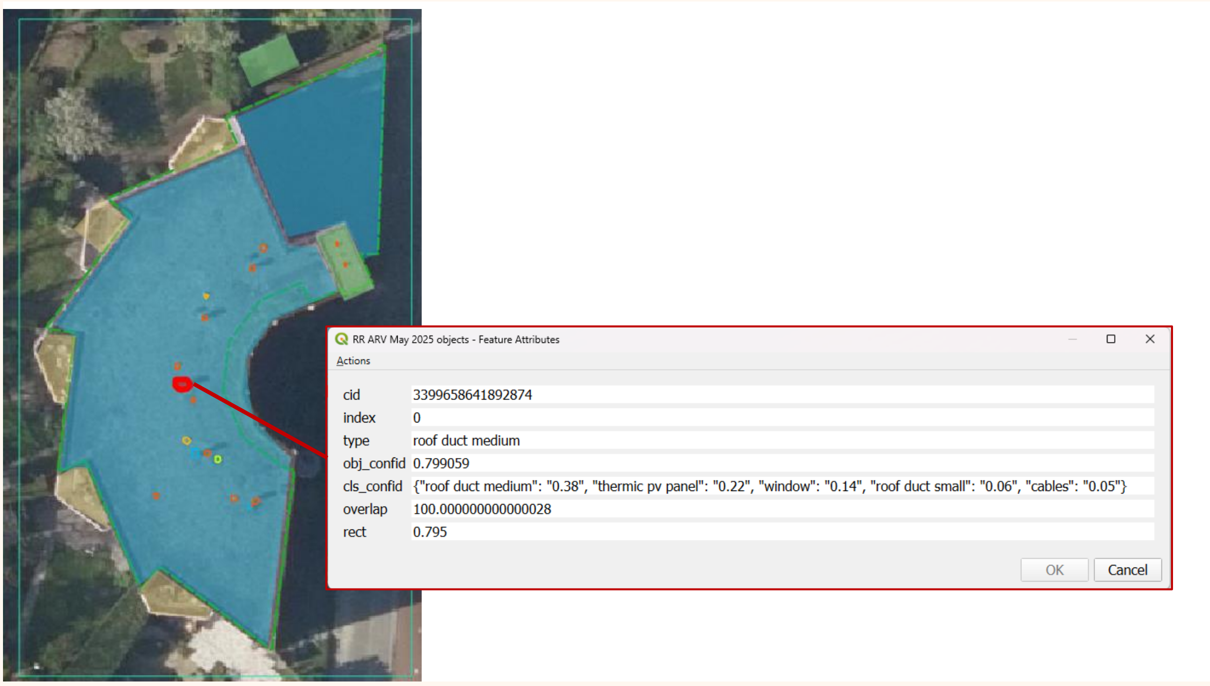


Figure 10. The object feature in the geodataframe of each detected superstructure of the Rooftop recognition model contains a segmentation, classification confidence per class and rectangularity index for post-processing

Figure 11. Boiler and elevator houses detected by post-processing of Rooftop recognition model on 60s high-rise in Delft

Validation

The Rooftop Recognition model was validated at the demo site on complex Alexander de Grotelaan 1-129 by comparing predictions of rooftop and superstructure segmentation on aerial imagery with actual drone images (Figure 12). It was found that 8cm/pixel resolution was functionally not limiting in locating rooftop ducts. Surprisingly, it tends to make a distinction between ducts that have separate outlets but are physically connected.

Figure 12. Source aerial imagery of Alexander de Grotelaan 1-129 with Rooftop Recognition predictions overlay of roof ducts versus stitched georeferenced picture by DJI mini pro 4 drone. Green is BAG building footprint, Red is rooftop segmentation, Yellow is object segmentation.

Scalability and the combination of RGB and LiDAR

The built Convolutional Neural Network (CNN) pipeline can potentially be trained on any other aerial imagery and label dataset, meaning that true-ortho photos could be used as well as imagery from other regions. Fully open-source OpenStreetMap has been used by (Pueblas et al., 2023) but poses the challenge of varying in resolution per region, meaning that the pipeline must be made more resilient to standardise image sizes with minimal quality loss. Because object class distinction is dependent on image resolution, it is likely that the class definition will have to be more generalised, and labels need to be omitted for image sources of lower resolution.

Even though the resulting GIS dataset of the Rooftop Recognition model makes use of information of the LiDAR derived 3D attributes of the 3DBAG, the implemented rooftop recognition model has been trained to detect roof surface types (flat, slanted, terrace) on aerial imagery without consulting LiDAR data. Additionally, it was trained on ortho-images, but not on more exclusive true-ortho imagery. As such, the rooftop recognition model has been designed to achieve useful results in regions where data availability is more reliant on public aerial imagery and less likely to facilitate LiDAR or true-ortho imagery.

Additional value: supporting PV technical potential estimation with computer vision

The efforts made on computer vision of aerial imagery aims to contribute to a more refined technical PV potential estimation, as well as contribute to an extensive rooftop information dataset that may answer questions of technical, economic, or social relevance. Current most common practice is to estimate PVGIS solar potential from 3D city models (LoD2) or roof plane slope estimation by aerial imagery. PV potential is calculated over four domains: physical, geographical, technical and economical (Krapf, Kemmerzell, Khawaja, et al., 2021).

In practice, roof superstructures like windows, existing solar panels or – in case of multi-residential buildings – complex safety or heating infrastructure may significantly limit the options for PV panel placement by shadow-casting or increased costs for roof plan adaptation.

Predicted PV technical potential according to the conventional PVGIS approach may be reduced by >30% when considering that panels are chosen to be placed around predicted rooftop superstructures (Krapf, Bogenrieder, et al., 2022).

Increasing level of detail for 3D building models

This study can contribute to an increased level of detail (LoD) for 3D building models, namely from the existing Dutch 3DBAG with maximum LoD2.2 to LoD3.0, where not only dormers and boiler rooms (> 2x2m^2) but also smaller rooftop superstructures like individual flue gas outlets (>0.2m) are fully chartered (Figure 13). Note that for a higher LoD2.x or LoD3.x more data collection must take place on façade level using street view imagery (4.1.3). In the future we envision research steps to LoD4.0, where we can predict interior building design assisted by the configuration of rooftop and façade elements, as well as open data sources such as building system and construction year.

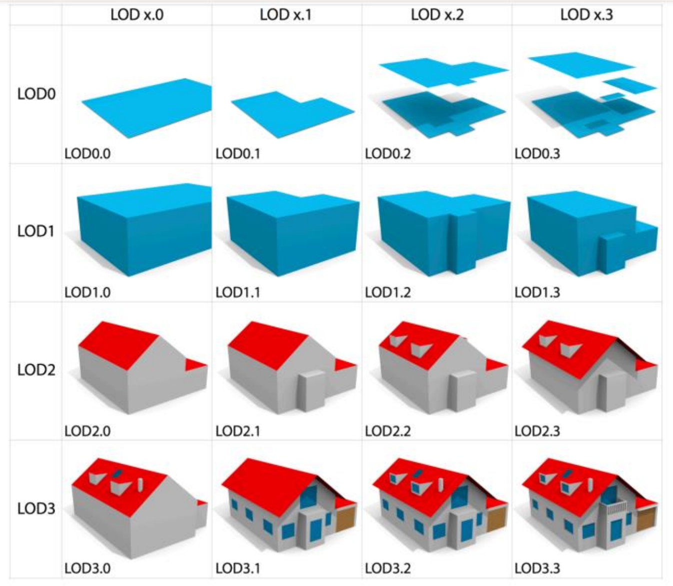


Figure 13. Levels of detail (LOD) as explained by Biljecki et al., (2016). From LOD2 to LOD3 roof superstructures are specified down from dormers to the smallest elements like flue outlets.

4.1.2. ROOFTOP MATERIAL RECOGNITION

Inspired by the CASMATELLE project, a roof material computer vision model was trained to classify roof materials based on multispectral imagery (Wyard et al., 2023). The Dutch government offers Pleiades NEO multiple spectral imagery as the current state-of-the-art public satellite dataset for the Netherlands via Satellietdataportaal.nl. These satellites provide six bands in 30cm pan-sharpened resolution.

A U-net computer vision model was trained and tested on imagery of the Province of Utrecht on a cloudless day (3rd of May 2023). Training data were labelled in Roboflow considering the following classes:

- Black tiles
- Brown tiles
- Glass
- Gravel
- Membranes
- Metal
- Orange tiles
- Solar panel
- Vegetation

Results

As a proof of concept, the rooftop material recognition model demonstrates the ability to effectively differentiate buildings from their background. However, the delineation between specific material classes remains imprecise (Figure 14). Despite this, by identifying the class with the largest surface area, the model can successfully classify the predominant rooftop material suggesting more accurate results with a larger training dataset and hyperparameter tuning.

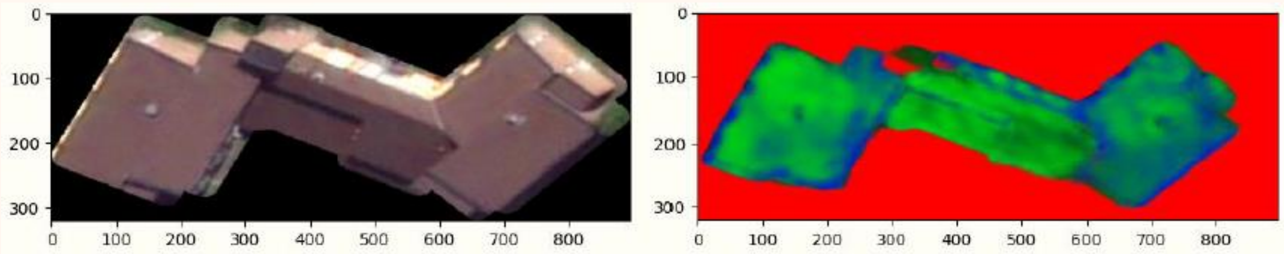


Figure 14. Left: U-net input sample, Pleiades-NEO image of complex. Right: U-net material segmentation output

4.1.3. FACADE RECOGNITION

Facade layout recognition

A first exploratory effort was made to utilize computer vision for façade images. For the investigation into image recognition, a Proof Of Concept application was developed in .Net. An existing Machine Learning model for object classification was utilized by this application. The self-training of a model to achieve even better results was not included. Data from the images was extracted using an existing ML model from TensorFlow HUB.

Figure 15: .NET application POC from Buro de Haan.

The identified Facade vantage points, in combination with the possible Cyclomedia recording locations, were used to find the most suitable photo location as described in 4.3.5. Training images were classified into 'House', 'Window' and 'Door'. As a result, a proof-of-concept of the Facade recognition model was developed by Buro de Haan that divided facades into open and closed parts (Figure 15).

Facade layout recognition (production level)

To recognise buildings BdH has ventured into the development of a novel algorithm capable of recognizing point clouds. This innovative approach enables to precisely determine the geometry of buildings, including their tilt and potential subsidence, as well as misalignments in façade openings.

However, the reliability of this technique has posed challenges, as inaccuracies could lead to significant material and man hours wastage in the event of a deviation that becomes visible on the construction site. To mitigate this, we explored the integration of image recognition technology as an alternative method for determining dimensions. By employing dual independent methodologies for building analysis the likelihood of deviations is significantly reduced through cross-verification.

Despite the advancements, the need still exists to elevate the accuracy of the currently employed image recognition method to a deviation margin of merely 2mm.

To achieve this accuracy stationary point cloud scanners are no suitable candidate due to height limits, therefore future research is focussed on a drone carrying a dual-camera system with a fixed position and a centrally located point cloud laser.

As an alternative measure to increase precision, the manual measurement of diagonal corner points of openings was considered using a total station. However, this method presents limitations in terms of height, which is a significant constraint given the focus on high-rise buildings.
In response to these challenges, research has pivoted towards drone technology equipped to carry a dual-camera system with a fixed position relative to each other and a centrally located point cloud laser.

4.2. BUILDING TYPOLOGY

Digitalisation in the construction industry is mainly focused on BIM; a project based industry. To move towards a construction industry that has a project-independent product approach with solutions that can be configured to the customer needs, it is necessary to start with a deep understanding of the buildings that potentially benefit from retrofit solutions. To create deep and relevant insight in these buildings we start with the identification of building typologies and their characteristics.

As an example of a general means of starting the clustering and identifying the characteristics, TABULA has started out with distinguishing the access types of complexes. The corridor appartement building can be identified as a very thick building (+18 meters wide) and on both sides are balconies. The gallery appartement buildings can be identified by observing front doors along a corridor that is at the one side of the building (on the other side are balconies). A portico flat has multiple main entrances because from the main stairs the appartements are directly accessed. Additionally, the lack of galleries is a strong indicator for a portico flat (Figure 16). Distinguish the entry type is relevant because the façade layout will differ strongly, influencing design requirements for retrofitting significantly.

Gallery appartement building | Portico appartement building | Corridor apartment building

Figure 16. Examples, access to appartements (Google maps and Rijksdienst voor Ondernemend Nederland, 2022)

4.2.1. BUILDING SYSTEMS ANALYSES

Through a literature review and related data analysis technical characteristics are extracted (Barkmeijer, 2017; BouwhulpGroep, 2013; van Elk & Priemus, 1971; Walraven, 2021)
It is part of the necessity of the identification of the characteristics of the building stock to identify the need for standardisation and flexibility. The goal is through these characteristics to identify the amount of standardisation and need for flexibility to retrofit as many apartment buildings as possible with an industrial approach.

Existing high-rise building systems from the period 1945-1975 were mapped (Figure 18). In total, there are 89 building systems, many of which were developed for low-rise buildings. There are 11 dominant appartement building systems and have an 88% market share, about 211,000 houses, in high-rise system construction. More than half of this number is in the provinces North Holland and South Holland. This is where scale-up opportunities are greatest.

After systematic research based on 11 post war building systems, these eleven building systems were built using different construction methods and therefore show a number of differences. All properties have been incorporated into system documents for each building system. The data about characteristics of the building systems was validated by fieldwork, among other methods (Figure 17). In the fieldwork, 125 buildings were deeply analysed and used as a validation of the assumptions.

The differences in execution within the building systems has meant that grouping based on details/connections do not work because the building parts are leading for the retrofitting. Due to the four implementation variants, each building system requires four retrofitting principles, namely: insulate inside, insulate outside, demolish outer wall, and demolish entire façade. The implementation variant determines the retrofitting principle.

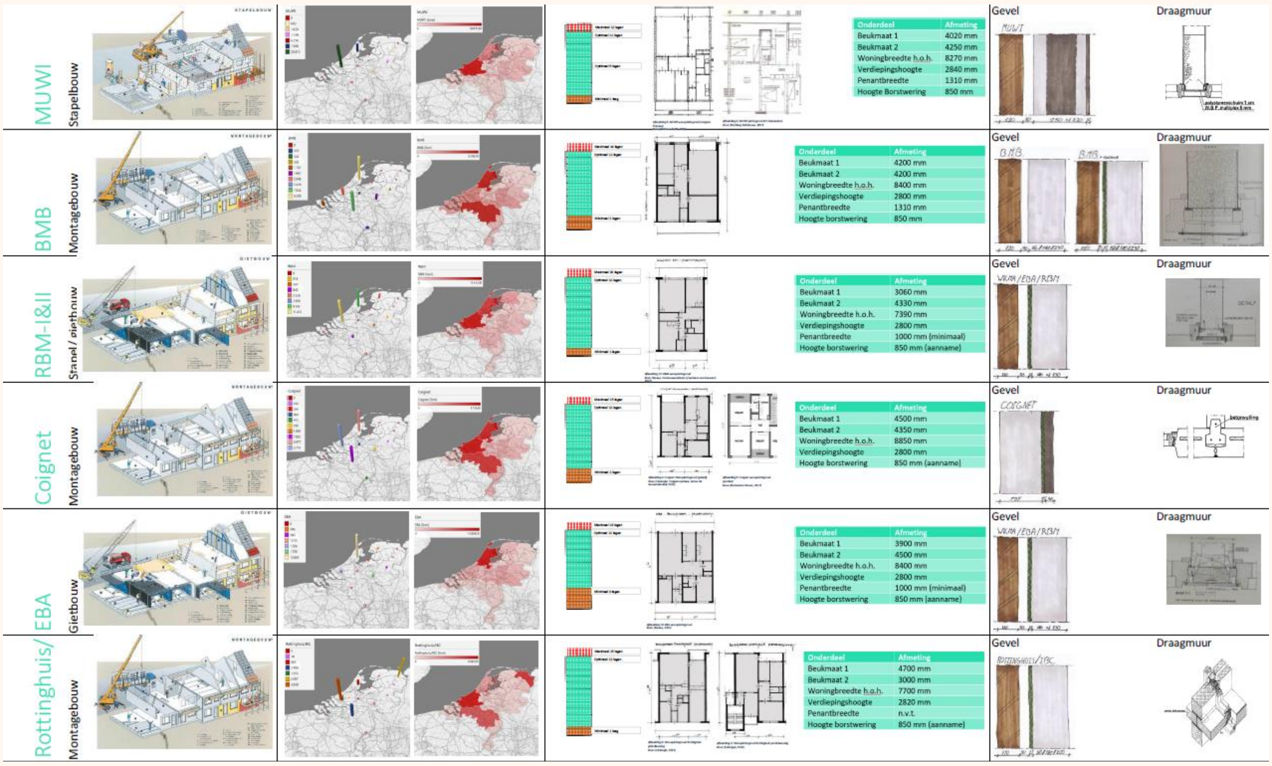


***Figure** 17. Examples of building systems of high rise apartments .. Source: Barkmeijer (2017) available in supplementary material S1.*

4.2.2. LOCATING BUILDING TYPOLOGIES

Systemic building typologies have been mapped by Cultural Heritage Agency of the Netherlands (Ministerie van Onderwijs, 2018), Walraven (2021) and Barkmeijer (2017).

The Cultural Heritage Agency has selected 30 areas deemed of national importance to represent the characteristics of the Dutch reconstruction period after the second World War. Within these areas, a total of 509 buildings with an assigned systemic building typology have been localised. Walraven (2021) has created a dataset that covers an additional 520, including partially overlapping selections with the Cultural Heritage Agency in the neighborhoods Ommoord Rotterdam, De Heuvel en Prinsenhof Leidschendam Voorburg and Mariahoeve, The Hague. Joining and filtering these datasets has resulted in a set of 638 located post-war pre-1992 systemic building typologies that are still in use multi-residential buildings.

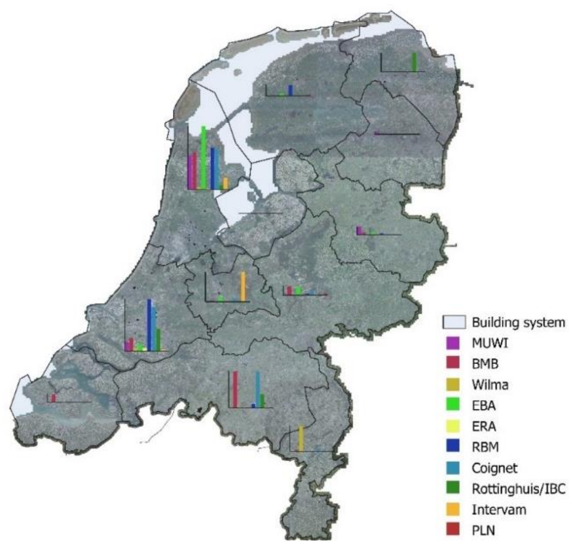


Figure 18. Estimation of building systems per province. Source: Barkmeijer (2017)

4.3. GIS DATA COLLECTION

4.3.1. SETUP

GIS analysis allows aggregating large amounts of data per complex on national level as well as obtaining the necessary imagery to direct towards computer vision models. The main open-source interface used for data display and user-friendly data analysis was QGIS (QGIS Project, 2022).

To support high-speed processing, large copies of open data were imported into a custom database infrastructure; a SURF Research Cloud hosting a PostgreSQL server with PostGIS extension (PostGIS steering committee, 2018).

Used sources of open data on the built environment of the Netherlands are described in 4.3.3, To regularly update local copies of national open data, an Apache Airflow environment was set up with Docker on SURF Research Cloud (The Apache Software Foundation, 2024)

4.3.2. METHOD

Data aggregation and spatial analysis of complexes was conducted in 4.3 was performed with QGIS and PostgreSQL queries where large queries were run in batch processing using Python with the package SQLAlchemy 1.4 (Bayer, 2012).

The usage of QGIS together with PostGIS and Python allows for a fully open source workflow. Nevertheless, part of data collection and analysis was also conducted in private ETL (*Extract transform load*) tool Feature Manipulation Engine by Safe Software as it allowed for powerful batch processing of imported open data from Web Map / Feature Services (WMS/WFS).

4.3.3. SOURCE DATA

BAG (Basis registratie Adressen en Gebouwen)[2]

An INSPIRE standardized database containing official data on all addresses and buildings in the country, including their construction year, usage function, and building footprints. The dataset is continuously updated by municipalities and crowd-sourced mutation requests. The data from BAG are frequently used in GIS applications to provide a reliable foundation for spatial decision-making processes, urban planning, and emergency response planning.

3DBAG

An initiative of the 3D Geoinformation Research Group of Delft University of Technology and spin-off 3DGI. The 3DBAG is an open dataset of the Dutch building stock as 3D building models, generated by the BAG and AHN.

[2]

Decentralised data updates

The BAG is a dataset that is continuously updated and mutated by decentralised governments. As a result, rule-based aggregations of building footprints such as in selecting complexes, may change or become faulty. For instance, residential objects may be registered within corner premises of a complex, which results into two (in reality faulty) complexes. The involved municipality may address this faulty placement of residential units or adjust the boundaries of the premise footprints, meaning that in a next update the amount and shape of identified complexes in the complexes dataset may change accordingly. To leave features of interest of all complexes relevant, it is recommended to constantly update input data like the BAG and streamline the data analysis workflow to update accordingly using infrastructure such as Apache airflow.

Beeldmateriaal via PDOK

Aerial imagery is captured on a national scale by Beeldmateriaal and provided through the open Dutch PDOK geoplatform. Imagery is captured yearly in 8cm resolution.

AHN4

The fourth edition of the Actual Height Model of the Netherlands. This dataset provides highly detailed laser altimetry data (LiDAR) which captures the topography of the Netherlands at 12 points/m2, standardised to 50cm resolution. In GIS applications, AHN4 data supports elevation and terrain analysis.

4.3.4. SCOPE: RESIDENTIAL COMPLEXES

Multi-residential buildings are often registered over multiple adjacent premises in BAG. However, these premises often share the same owner, and same load-bearing structure, meaning that for total energy retrofitting they would be approached as one block. Thus, from a functional perspective these premises can be summarised as one 'complex'. Therefore, on top of the premise and residential object hierarchy in BAG, newly defined 'complexes' were aggregated according to the following rules:

- Aggregated premise footprints are within 2.5m from each other (considering possible bridges), clustered by DBSCAN algorithm
- In case of a singular premise, more than 3 residential objects should be of a residential nature
- In case of multiple premises, more than 1.2 residential objects per premise should be of a residential nature
- Singular residential addresses cannot exceed the premise footprint area >10m^2, since this would suggest the entire premise is a single residential unit
- The oldest registered construction year among premises is taken as the complex construction year

Because the scope of this study is systemic post-war multi-residential buildings, the stock of complexes studied is limited from cohorts 1945-1992 (Figure 19).

Complexes are generated by SQL query on BAG premises and residential objects in batch using Python 3.9. As a result, 47196 complexes were defined as the scope of this study.

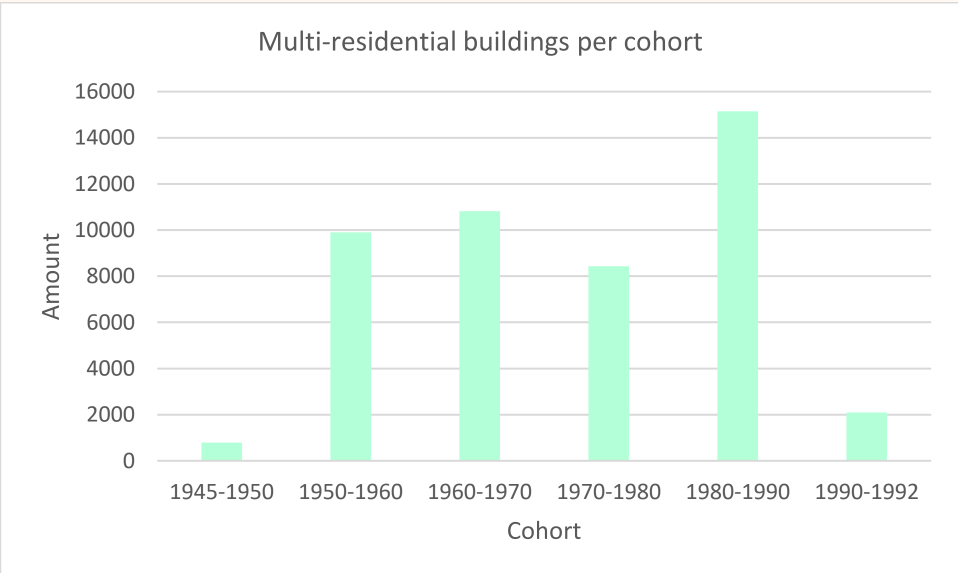


Figure 19. Residential complexes distributed over cohorts in the Netherlands based on the scope of the GIS analysis of D5.1.

Unique identifiers
BAG premises are registered by unique feature and geometry id's as well as a registration id 'identificatie'. The id's are used as primary keys for quick data engineering but also inform about the relation with other objects such as addresses. Complexes must also get an unique identifier that is both concise as well as relatable to other objects.

Initially when generating complexes unique complex id 'cid' was attributed by order of creation. However, this has been deprecated and replaced by a shortened SHA256 encryption of premise id's. By using a hash algorithm, each time complexes are recalculated the id remains the same when being generated from the same premises as before. This means hashes as unique identifiers remain constant along dataset updates, but change when underlying premises change registration id, are newly created or are assigned to be demolished. Additionally, the chance of an id collision is outside realistic proportions, but hashes are kept in a separate PostGIS table as a safeguard.

4.3.5. FEATURES OF INTEREST
The Pre-recognition workflow was put in practice for exploring potential projects for the Alpha based on multiple criteria, as well as forward building information from GIS to BIM for parametric design. A national dataset was created of all complexes between 1945-1992 with the aim to include all features of Table 4. Features of interest were determined by interviews with Inside Out where requests and argumentation were given why certain criteria influence project selection or design of the Alpha module.

Table 4. Features of interest as individual dataset attributes for the Pre-recognition workflow. Each feature is obtained with a certain success (status) in the study period. 'Present' features are integrated in the GIS dataset of 4.5, 'partly' means that features are not directly present but indicators are given, or NULL values exist. Absent means that research was constrained on this part. Reason for obtaining this feature is the result of interviews with product system developers Inside Out and Buro de Haan. Features are grouped by focus area in data collection. Data sources are further explained in 4.3.3.

Feature of interest	Status	Why?	Group	Data source
Building footprints	present	Basic location and geometric layout of the building from cadastre for visualisation and GIS analysis	Building layout	BAG
Complex	present	To aggregate physically connected premises that share the same rooftop and owner association	Building layout	BAG
Construction year	present	Base information, can be used to discern building systems	Building layout	BAG
Energy label	present	Indicates perceived urgency for energy positive retrofitting	Building layout	ep-online
Building height & no. floor levels	present	Minimum height for placement of Alpha, distinction of building systems. Above 7 levels exceed the conventional roof heights where PV panels are placed making the Alpha module a preferable option for energy generation. Base information for parametric design of Alpha module, indicator for wind load, used to calculate permitted building height	Building layout	Street view imagery, 3DBAG, AHN4
Building 2D shape	present	There is a preference for rectangular complexes	Building layout	BAG
Building length and width	present	For parametric design of the Alpha to fit the building footprint	Building layout	BAG
Unique ID complex	present	Fast indexing of dataset, consistent data management	Building layout	-
Adress	present	Localising and communicating projects	Building layout	BAG
Municipality	present	Localising and communicating projects, summarising statistics	Building layout	Administrative units
Link to google maps	present	Access Google street view for manual building inspection	Building layout	-
Ground level elevation	present	To determine building height	Building layout	3DBAG

Secondary function	present	To stress the need for extra research in policy plans on building	Building layout	BAG
no. registered residential addresses	present	Number of apartments, determines how many stakeholders are involved in decision making	Building layout	BAG
Permitted building height	present	Critical risk in the feasibility of placing the Alpha module	Building layout	Ruimtelijkeplannen.nl, 3DBAG
Vertical special	partly	To distinguish complex buildings with an exceptionally large lower area that decrease accessibility for regular hoisting methods	Building layout	BAG
Owner type	partly	Different user groups indicate a different timeline for negotiations	Building layout	Housing corporations, cadastre, government
External elevator	partly	Shadow casting, inhibiting placement of new rooftop superstructures	Building layout	Aerial imagery
Building system typology	partly	To find characteristics of similar buildings with a shared design history and blueprint, allowing similar technical proposals	Building layout	Wederopbouw, Bouwhulpgroep, diverse
Building similarity index	partly	To find similar buildings for combined retrofitting based on geometric, visual and background data	Building layout	BAG, diverse
Load bearing capacity	absent	To determine maximum weight of proposed steel constructions for Alpha, and determine whether heat-storage is possible on the roof	Building layout	n.a.
Heating infrastructure	absent	If connected to heating net there is no business case for all-electric retrofitting	Building layout	n.a.
no. residents	absent	Indicator for energy consumption in the complex	Building layout	BAG, CBS open data
Available blueprint	absent	Lack of available blueprints brings along extra costs and makes it impossible to pro-actively promote a product system. In the future, building system typologies may fill necessary knowledge gaps for quotation	Building layout	Archieven.nl

Wind speed zone	present	To adapt the parametric design to wind load	Environmental layout	NEN-EN 1991-1-4
Heritage conservation area	absent	Subjective assessment, some categories may pose higher risk of rejection	Environmental layout	Municipality portals
Aerial image extract	present	To deploy computer vision	Rooftop CV	BAG
Roof type	present	Flat roofs with no elevation differences are preferred to avoid shadow casting and select complex with maximum available roof area	Rooftop CV	3DBAG
Dormer	present	In case of lower multi-residential buildings: Prohibits placement of PV panels or building service technology	Rooftop CV	Aerial imagery
presence PV(T)-panels	present	Indication whether sustainability efforts have already been instigated	Rooftop CV	Aerial imagery, ep-online
HVAC	present	May cast possible shadows on PV panels. If higher than 2 meter it can obstruct Alpha	Rooftop CV	Aerial imagery
Safety infrastructure	present	Fences guide walking paths and may thus indicate accessibility, but fence work also forms obstructions for new superstructures	Rooftop CV	Aerial imagery
Hatch	present	Roof accessibility for installation and maintenance, cost indicator for transport of components on roof	Rooftop CV	Aerial imagery
Boiler room	present	Indicator for central heating by gas, may prohibit placement of building service technology and PV, may possibly cast shadows	Rooftop CV	Aerial imagery
Flue gas duct	present	If absent indicates that collective heat network is present, which decreases chances for implementing an all-electric retrofitting	Rooftop CV	Aerial imagery
Sewer gas duct	present	Indication of location sanitary spaces in building	Rooftop CV	Aerial imagery

Rooftop footprints and objects	present	Available space for PV and installation placement, objects of interest	Rooftop CV	Aerial imagery
Free roof space	present	To determine more accurately the amount of PV panels that can be placed, to know the maximum dimensions of rooftop modules	Rooftop CV	Aerial imagery
Roof window	present	Prohibits placement of PV panels or building service technology	Rooftop CV	Aerial imagery
Staircase	partly	Determines accessibility of roof for maintenance, also influences design that needs to be adapted to its position	Rooftop CV	Aerial imagery
Broadcasting infrastructure	partly	Broadcasting companies may slow down rooftop interventions	Rooftop CV	Aerial imagery
Lightning rod	absent	Indicator for extra cost when absent, will need to be acquired with retrofitting budget	Rooftop CV	Aerial imagery
Structural bay dimensions	absent	Construction happens on top of existing walls, therefore the Alpha module is parametrised to bay dimensions	Rooftop CV	Aerial imagery, street view imagery
3D rooftop superstructures	absent	Height data on superstructures can aid shadow casting and indicate minimal height for Alpha module	Rooftop CV	Aerial imagery, BAG3D
Green roof	absent	Indicates whether insulation has already been retrofitd. Increased interest for sustainability can be assumed	Rooftop CV	Aerial imagery
Roofing material	investigated	Gravel may reveal over-dimensioning of load bearing structure, allowing for heavy structures to be placed. Green roofs are often preferred to be left untouched	Rooftop CV	Aerial imagery
Façade vantage point	present	For determining vantage points for computer vision	Facade CV	BAG

Facade orientation	present	To model Alpha and calculate PV potential	Facade CV	BAG
Entry typology	partly	As defined in TABULA: gallery, portico, maisonette, other ..	Facade CV	Province, EP-online
Ground floor function	absent	To determine mixed usage and more complex building process	Facade CV	BAG, Chamber of Commerce
Window-to-wall ratio	absent	Facade dimensioning for configurator	Facade CV	Street view imagery, Voorbeeldwoningen 2022
Facade materialisation	absent	Facade materialisation for configuration on current state	Facade CV	Street view imagery

BUILDING FOOTPRINTS

Building footprints are based on BAG.

CONSTRUCTION YEAR

Construction year is registered for each premise but aggregated to complex level as the oldest known construction year.

ENERGY PERFORMANCE INDICATOR

Energy performance indicators were interpreted as the energy label certificates that are mandatory to be assessed for Dutch buildings since 2008 when a premise is built, sold or rented. Energy labels are determined according to standardised methodology NTA8800 (Stichting Koninklijk Nederlands Normalisatie Instituut, 2022) and registered in public database EP-Online. EP-Online hosts an API to consult energy labels registered per BAG residential object. Energy performance indicators were determined as the minimum, median and maximum energy label registered for residential objects within a complex.

BUILDING 2D SHAPE

Buildings that deviate from a rectangular shape quickly increase the complexity of both data analysis in the pre-recognition phase as well as BIM in the pre-manufacturing phase.

Basic building shapes have therefore been characterised from 2D building footprints to quickly query on a level of complexity for retrofitting projects (Table 2). Shape classes were calculated and classified in Python according to the order of rotations and number of vertices in the medial axis. For example, an L-shaped outline has 2 edges that are roughly +- 90 degrees from each other.

Although this approach introduces a general classification for complexity of the building project, it is observed that complexes of the non-rectangle shapes may exist out of multiple rectangles that are suitable for retrofitting products meant for rectangular roof structures (Figure 20). A next step would be to discern these rectangles using a MER algorithm.

Table 2. Basic shape descriptors for building footprints

Shape	
Rectangle	
Box	
Kink	
L-shape	
U-shape	
Special	

GROUND LEVEL ELEVATION

Ground level elevation was taken from premises in 3DBAG as a mean of attribute h_maaiveld per complex.

BUILDING DIMENSIONS

A general roof height was estimated from the 3DBAG LOD 1.2, where the minimum measured height at the premise (assumed as absolute ground level at building edge) was subtracted from the 70th percentile height.

Length, width and main axis orientation from North to the long side of the oriented bounding box (OBB) were calculated as first proxies of building dimensions and azimuth. In practice, building footprints have a large amount of negative space within the OBB because of e.g. porches and elevator shafts, with only 'perfect' rectangles practically matching the dimensions of the OBB. By determining the rectangularity and equivalent rectangular index (ERI, Basaraner & Cetinkaya, 2017) 'perfect' rectangles were identified to indicate that OBB dimensions match true building dimensions and can be used as direct input for parametric modelling of rectangular roof designs.

Figure 20. L-shaped complexes consisting of multiple rectangular apartment buildings.

For determining the available rectangular roof space on more complex footprints, a maximum enclosed rectangle (MER) must be calculated. In the current study such an algorithm has proven costly in terms of processing power. Alternatively building footprints or 3D CityGML models of buildings are immediately transferred to BIM environments, meaning that parametric models of the pre-manufacturing workflow must be adapted to fit roof intervention geometries such as the Alpha at project-level. However, the purpose of the pre-recognition workflow is to predict the fit of retrofitting systems at a project-independent level, stressing the recommendation to calculate features such as the MER with less costly algorithms in the future.

NUMBER OF FLOOR LEVELS

By default, the number of floor levels is assumed to be the building height divided over an average floor level height of 3 meters. However, in reality this estimate may regularly deviate by 1 to 2 levels due to the high variability of floor height between ground- and upper levels as well as per high-rise typology. Since the 3DBAG update of 28 February 2024 the results of the floor level prediction model of Roy (2022) are included, but these are limited up to 5 floor levels due to reduced accuracy of the prediction model for higher buildings. As Roy showed, machine learning based on empirical data and 3D geometries improved floor level prediction, but there is still room for improvement in model performance. A complementary approach would be to infer floor level height from façade computer vision predictions and building system classification.

ADDRESS

Addresses were found by HTTP request to the PDOK Geolocation server API (*API Locatieserver · PDOK/Locatieserver Wiki*, n.d.) in FME. IDs of residential objects within complexes were sent and street name and house numbers for objects were retrieved. Address was aggregated as the street name together with the minimal and maximal house number of residential objects as a range within the complex.

MUNICIPALITY

Municipality was added by analysing which complexes fell within which administrative boundaries.

LINK TO GOOGLE MAPS

Google maps URLs were added as an attribute to complexes using parsed address and municipality as attributes to create the following link:

$$\text{https://www.google.com/maps/search/?api} = 1\&\text{query} \\ = [\text{Street name}] + \min([\text{House } number]) + [Municipality]$$

SECONDARY FUNCTION

Multifunctional complexes can facilitate offices, commerce, healthcare and other secondary functions than housing. On the socio-economical side, this means that other parties are involved for retrofitting than housing corporations or private apartment owners. On the technical side, the presence of secondary functions indicate less conventional building layouts, with the most prevalent case being a ground floor that has higher walls than all upper floors to facilitate special ground floor functions like shops.

All BAG residential units within a complex that did not have a residential function were summarised in an array per complex.

GROUND FLOOR FUNCTION

Ground floor function entails the main function the ground level floor serves, e.g. commercial, office or residential. In the current state of research ground floor function is not explicitly available for a complex other than secondary function. This knowledge gap showcases new research questions for façade computer vision development.

NUMBER OF APPARTMENTS

Number of apartments is determined as the count of BAG residential objects within a complex with residential function.

PERMITTED CONSTRUCTION HEIGHT

The Dutch urban development plan is a binding juridic instrument that covers land use type and dimensions (allowed heights, volumes, premises) of buildings and infrastructure.

Urban development plan systems vary significantly across Europe in terms of juridic power and negotiation style (Berisha et al., 2021). The Netherlands is characterised as a *market-led neo-performative* system, meaning land use allocation is preferred to be postponed until negotiation with specific landowners and project-developers. In contrast, Southern European countries such as Italy and Spain are characterised as *conformative* systems which highlight public control by traditional binding general plans subdivided in variants which can be subsequently modified.

Since 2010 Dutch urban development plans must be centrally digitised according to the law Ruimtelijke Ordening. The permitted construction height has been derived from the WMS of dataset Ruimtelijke Plannen, which indicates permitted construction height, gutter height or floor levels, updated monthly (PDOK, 2024). Permitted gutter height is assumed to reflect the maximum 70^{th} percentile height of LOD1.2, meaning the maximum building height in this case is defined as the max 70^{th} percentile height of LOD1.2. In case of permitted number of floor levels, a standard floor level height of 3m is assumed, making permitted construction height the permitted number of floor levels * 3.
Remaining available permitted construction height is calculated as follows:

$$\begin{aligned} Available\ permitted\ construction\ height\ = \ & Permitted\ construction\ height \\ & - Maximum\ building\ height \end{aligned}$$

VERTICAL SPECIAL

Some complexes exist of high rise combined with a large understory, for instance when a stretched out low-rise shopping mall exists at the ground floor. For this purpose, 3DBAG LOD1.2 and LOD2.2 were merged per premise using PostgreSQL. LOD1.2 50^{th} percentile height as general roof height together with LOD2.2 70^{th} percentile height of roof planes. If more than 30% of roof plane areas exist under the general roof height, the premise is labelled as 'vertical special'. Complexes are labelled as 'vertical special' if it is comprised of one or more vertical special premises, however this threshold can be adjusted by introducing additional rules whether the area and position of each premise truly introduces complications.

OWNER TYPE

Different owners and user groups of a complex lead to different impacts on the duration and terms of negotiations for an energy retrofitting. On the address level different types of owners are identified by the cadastre such as residing owners, small and large investors, but for complexes two aggregate types are investigated: housing corporation or community of owners.

This information resides with the semi-public national cadastre, housing corporations and government bodies, but cannot readily be distributed to private parties.

Ownership data can therefore be used for independent research such as energy performance analysis, but is not available for multi-criteria analyses that lead to commercial application to speed up the quotation process (personal communication, Noëlle Peters Sengers, 2023; Peter Hoogeweg, 2023).

AVAILABLE BLUEPRINTS

As there is not a centralized national archive for drawings of the building permits. It is mainly organised in decentralised, non-standardised archives at cities. It would be very interesting to get access to these archives because for example to identify the level of update the building has had and the deep knowledge of the construction methods. Future research is needed.

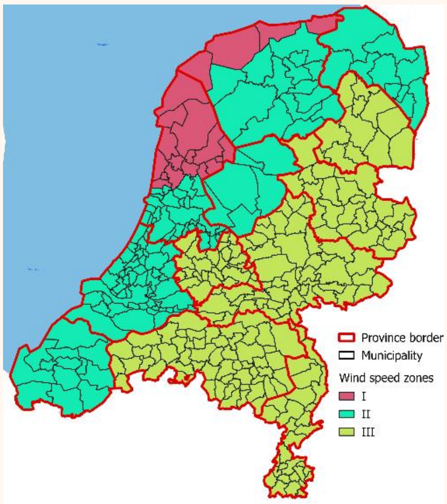


Figure 21. Wind speed zones in Dutch building policy. GIS map adapted from textual description by Bouwend Nederland of NEN-EN 1991-1-4

WIND SPEED ZONE

The wind speed zone and the building height indicate the amount of wind load the steel construction of the Alpha module will experience. The dimensions of wind boxes and number of anchor points in the steel construction of the Alpha module will have to be adapted to the wind load to prevent uplifting or damage of building and module.

NEN-EN 1991-1-1, a European standard, provides guidelines for relevant construction actions in response to wind load, delineating three wind speed zones in the Netherlands. These zones are used as a guideline for wind load calculations. Wind speed zones follow municipality borders and have been assigned to each complex (Figure 21).

HERITAGE CONSERVATION AREA

The block-level implementation of retrofitting product systems influences the aesthetics of a neighbourhood. Therefore, it is important to have a clear understanding of the vision that the aesthetic committee of a municipality has for each neighbourhood that a complex of interest resides in. The aesthetic committee is the only juridic advisory instrument over the displayed architecture in a neighbourhood including use of material, colouring and superstructures such as dormers. Aesthetic committees are common among European countries, varying significantly in their level of formality, project engagement, and forcefulness in intervention (Carmona et al., 2023).

In the Netherlands aesthetic committees are organised as independent advisory bodies at municipality-level (Federatie Ruimtelijke Kwaliteit, 2016). Unfortunately, this level of organisation also results in a decentralised and non-standardised storage of aesthetic visions per neighbourhood.

It was therefore not possible to conduct a national pre-recognition analysis on the potential setbacks by aesthetic visions to implement retrofitting product systems like the Alpha module.

In the sales funnel, it is recommended that aesthetic visions are consulted after a neighbourhood of interest has been identified by pre-recognition.

On a holistic level, it is of interest to integrate aesthetic visions in an environmental DNA, as the same logic may be applied as with building typologies: all municipalities are different, but municipalities with similar soft powers may facilitate similar retrofitting practices that are adapted to these powers (Carmona et al., 2023).

AERIAL IMAGE EXTRACTS

To analyse rooftops with computer vision, aerial image extracts were generated from Beeldmateriaal. Extracts were requested by PDOK WMS API as non-oriented bounding boxes of 2 m buffered complexes (Figure 9). Aerial images of all complexes in the Netherlands were taken for calendar year 2022. A subset of 4066 complexes in the province of Utrecht was taken of which a random 760 images were labelled in Roboflow as training data for the Rooftop Recognition model.

ROOF TYPE

Roof type is about the general slope of the roof, divided in 'horizontal', 'multiple horizontal', 'slanted/special'. 3DBAG already defines roof type as an attribute. However, for the scope of this study roof types had to be redefined from individual premise to complex level. Additionally, it was found that due to small segmentation errors of roof planes in the 3DBAG, horizontal roofs are regularly mistaken for 'slanted' or 'multiple horizontal' roof types.

Roof types were therefore redefined in this study by calculating roof slopes from 3DBAG LOD2.2 roof planes using SQL. Roof planes that make up <3% of the total roof area are discarded as not relevant for the general roof type. It is assumed that in practice a roof is deemed flat when the load bearing structure and materialisation are not adjusted to a slanted design; a roof plane <10° is thus considered flat. Complexes with only flat roof planes are considered 'horizontal', except when a standard deviation of >2m in 70th percentile height occurs between roof planes it is classified as 'multiple horizontal'. Complexes with slanted roof planes are 'slanted/special'.

FREE VS OCCUPIED ROOF SPACE

Using the outcomes of the Rooftop Recognition model, the percentage of free/occupied rooftop space can be calculated. Predicted rooftop polygons are merged using QGIS *dissolve* function. Subsequently, the predicted superstructures are subtracted with *difference* to calculate the area of free space. Note that PV panels can be counted either as obstruction or flexible in positioning, thus optionally being exclude from the subtraction. To generalise the finding, the free space over complete rooftop space is calculated. This percentage of free rooftop space is an estimation as segmentations are based on non-orthorectified imagery and contain a significant level of uncertainty (4.1.1).

PRESENCE OF PV

The Rooftop Recognition model is trained to segment solar panels in rows of similarly oriented PV panels instead of singular panels. In practice, arbitrary boundaries exist between segmented solar panel rows. This means that an exact count of individual panels is not possible at this stage of development. However, a percentage of solar panels can be given, as well as a Boolean value indicating whether any solar panels are present at a complex. With higher precision instance segmentation in the future solar energy potential may be calculated from this feature.

BOILER ROOMS

Boiler rooms on top of complexes can be approached by further processing of the Rooftop Recognition model. For this analysis it is assumed that boiler rooms are always large sub constructions on roofs on which visible service technology and/or ducts reside. Polygons with class Sub-construction which contained polygons of HVAC and ducts were classified as possible boiler houses. For each complex a count was given how many possible boiler houses could exist on the roof. However, the resulting selection still also contains elevator shafts, meaning that this is still mostly an indicator for large superstructures with integrated building service technologies (Figure 11).

OTHER ROOFTOP SUPERSTRUCTURES

Albeit requested, lightning rods, staircases and broadcasting infrastructure could not be clearly labelled in the current aerial image resolution. Green roofs were little available in the training dataset and need to be added in the future when labelling capacity increases. Research opportunities exist to further investigate these objects of interest.

STRUCTURAL BAY DIMENSIONS

Instance segmentation of rooftop superstructures allows the analysis of their distribution and relative distances. In turn, it is assumed these relative distances may give an indication of structural bay dimensions (Figure 22).

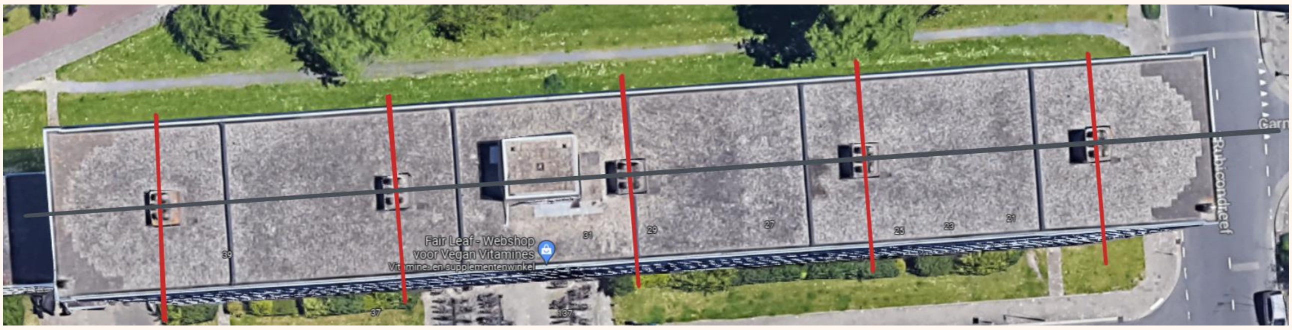


Figure 22. Proposed analysis to predict structural bay dimensions from rooftop superstructures by comparing relative distances between ducts on main axis.

3D ROOFTOP SUPERSTRUCTURES

For further integration of the geoAI-located superstructures into standardised GIS processes, it is fruitful to translate the predicted polygons into 3D geometries of the OGC cityGML standard (Open Geospatial Consortium, n.d.) in the near future. This process can be achieved by the 3DcityDB toolkit. 3D superstructures may aid in modelling shadowcasting on small scale for calculating technical PV potential.

ROOFING MATERIAL

See 4.1.2.

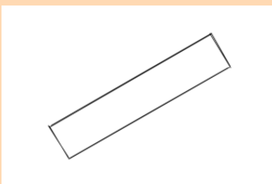
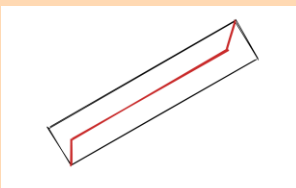
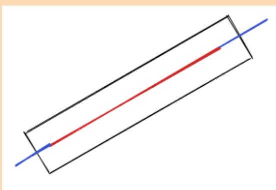
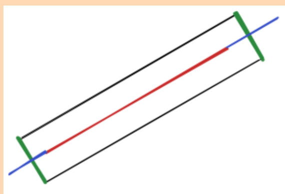
FAÇADE VANTAGE POINTS


Figure 23: an example image of an end wall, or 'kopgevel in Dutch

In preparation for 6.6.2, GIS analysis creates a dataset that contains end walls (Figure 23). In high rise multi-residential buildings, these façade parts are often relatively easy to retrofit, making a good case for this proof of concept. The side façade images can be exported to facade computer vision models trained to detect open and close parts of a façade, ultimately needed to calculate the window-to-wall ratio (WWR). Two features must be acquired by GIS analysis to get images of the relevant façade segments:

1. A 2D plane in 3D space that represents the façade segment.
2. A suitable panorama recording location for each façade segment.

The first challenge was extracting the relevant façade segments. This was done by calculating the straight skeleton from the simplified footprints of the complexes using PostGIS ST_SimplifyPreserveTopology and the medial axis was derived with ST_ApproximateMedialAxis. The centre line of the straight skeleton was then extended at both ends, resulting in a line that intersected with the relevant end walls. This roughly looks like this:

			
Original outline of the building	Calculated straight skeleton (red line)	Center line extracted and extended (blue lines)	Intersection with original outline shows end facades (green lines)

This method not only works for rectangular polygons, but also for L-, T-, U-, and C-shaped buildings (Table 2). Other shapes can sometimes have unexpected outcomes.
Now that a rough dataset of relevant facades was available, suitable recordings needed to be found.

Cyclomedia has provided an API key with free credits for this research project, providing a nationwide dataset with yearly imaging on most public roads in the Netherlands. Although this part of the methodology thus does not rely on public data, the proposed workflow for finding façade images can be applied in a broader context. The only requirement is that images have (accurate) GPS coordinates. Using the extracted façade segments, the 'acceptable recording region' (ARR) was calculated. This algorithm takes a plane in 3D and calculates a 2D polygon that depicts the area in which a panoramic image is deemed suitable for this façade segment. This means that when looking from a panoramic image, the distance and angle to the facade can't be too large. This prevents distortions which could interfere with the computer vision model.

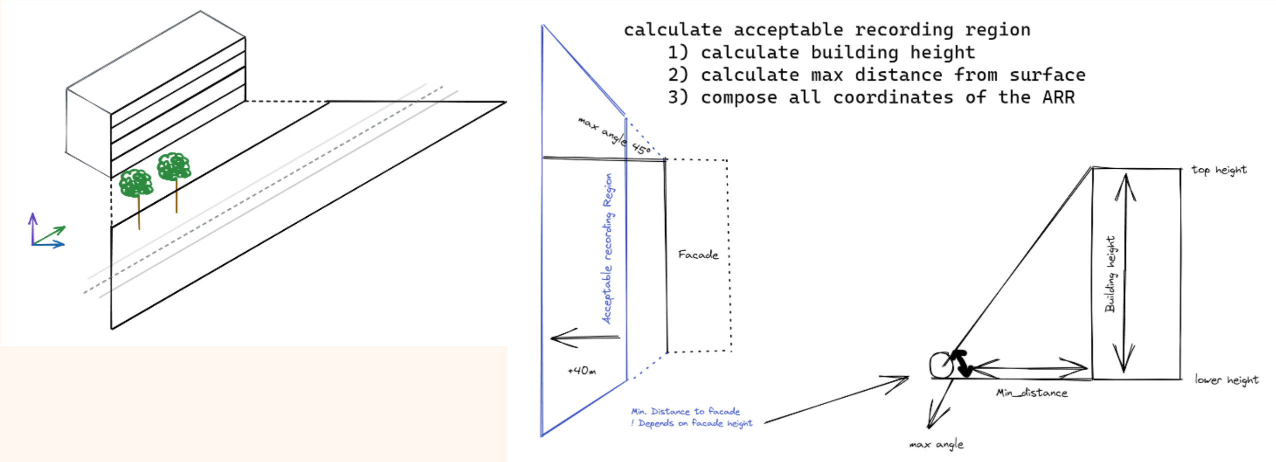


Figure 24: 3D view of the ARR (left) and calculation parameters of ARR (right)

This 2D polygon is then used to send a request to Cyclomedia's ATLAS WFS Recording Service API. Recordings that intersect with the ARR are requested. The optimal recording is then selected by calculating the angle between the recordings that were returned by the API and the façade. The one with the smallest angle (so most perpendicular) is then selected as the optimal recording, if the line between the recording and the façade doesn't intersect with other buildings. A real example of this process can be found Table 5. These images were collected for a large set of end walls, which could then be used as a dataset for a facade computer vision model (4.1.3).

Table 5. GIS workflow to retrieve facade imagery of end walls for computer vision.

	Building outlines from the BAG
	Buildings are filtered and aggregated into 'complexen'
	Straight skeleton is calculated for each complex. Middle line is extracted and extended. Composition of middle line angles depicts shape, which is rectangular (rechthoek) because it is a straight line in this case. The end points are then extended.
	The acceptable recording region (ARR, in pink) is then calculated for each façade segment which intersects with the extended center line. Cyclomedia's ATLAS WFS recording service API is then used to collect relevant panorama recordings. The most optimal recording is algorithmically calculated.
	Selected recording is then selected and requested via the ATLAS PanoramaRendering Service API.

FAÇADE ORIENTATION

By determining the angle of the main axis of the complex footprint in respect to North a basic parameter is derived for BIM modelling. This can be achieved by QGIS function *Minimum oriented bounding rectangle*, which passes parameter 'main angle'.

ENTRY TYPOLOGY

Entry typology per premise is derived from EP-online and is sometimes registered by governmental bodies such as Provinces. Possible entry typologies include 'portiek', 'gallerij' and 'corridor', of which the latter is often characterised as 'other'.

WINDOW-TO-WALL RATIO

See 4.1.3.

FAÇADE MATERIALISATION

Façade materialisation is a promising attribute to cluster buildings on similar design background and gives rich information about the current state of the building. Nevertheless, current efforts have not yet resulted in a façade materialisation recognition model.

4.4. BUILDING SIMILARITY INDEX

To enable an economy of scale in renovation product systems, one method is to cluster buildings that are compatible for a particular design solution or – reversely - to create a design that is particularly suitable for a certain cluster of buildings. Building systems provide an information-dense norm to cluster buildings, but in practice many buildings do not belong or are not known to belong to a building system.

To investigate whether new building systems can be identified from GIS analysis, parallel to the architectural analysis performed in 4.20, a clustering algorithm was developed in collaboration with the Hogeschool Arnhem Nijmegen (HAN) based on Principal Component Analysis (PCA). Comparing buildings in a concise manner requires to summarise diverse information into a 1-dimensional numerical value: 'the building similarity index'. As a validation dataset describing building similarity, 638 complexes were assigned building typologies taken from Walraven (2021) and Cultural Heritage Agency (Ministerie van Onderwijs, 2018).

The building similarity index is an Euclidean distance in an n-dimensional feature space, realising an cluster algorithm that can be fed with a virtually unlimited amount of building information to identify most alike buildings, possibly even identifying clusters that highly correlate with building systems. At this moment the analysis incorporates 2D building footprint shape descriptors (morphological metrics) together with building layout information like number of apartments, construction year and height.

The application of this clustering approach is that when a building with high potential for application of product systems (such as the Alpha) has been identified, an array of most similar buildings can be consulted (Figure 27). The most similar building list reveals nearby as well as distant buildings that have a high likelihood of a similar building design history, revealing technical potential at a larger scale than a single project. As such, it can be chosen to expand the business case towards a cluster of similar buildings, bolstering industrial capacity.

Introducing the Turning function

Previous methods have compared building footprints by investigating the power of morphological metrics such as rectangularity and convexity to rank these buildings on similarity (Basaraner & Cetinkaya, 2017). This set of metrics is expanded by incorporating methods to directly compute the distance between two footprints using turning functions (Equation 1). To construct a turning function from a polygon, the polygon first is rescaled such that the perimeter of the footprint is of unit length. The turning function is constructed by walking along the edges of the polygon and keeping track of the angle relative to some reference vector, usually the direction from the starting point. For a two-dimensional polygon, this results in a piecewise constant function, as shown in Figure 25b. Let $\phi(s)$ denote the value of the turning function at point $s \in [0, 1]$ along the perimeter. For computational convenience, the turning function is defined to be periodic, with $\phi(s + 1) = \phi(s)$. The d_l distance between two turning functions is then given by:

Equation 1

$$d_l\big(\phi_1(s), \phi_2(s)\big) = \left(\min_{c\in[0,1]} \frac{1}{\pi}\int_0^1 |\phi_1(s) - \phi_2(s+c)|^l ds\right)^{\frac{1}{l}}$$

where the factor $1/\pi$ was added for normalization. This satisfies all requirements for a proper distance measure.

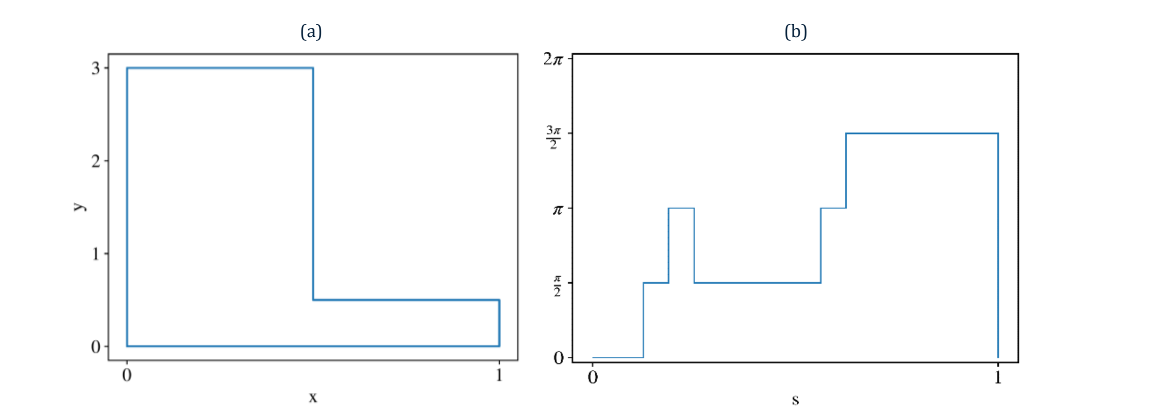


Figure 25. An example of a building footprint (a) with the corresponding turning function (b).

Building similarity index: calculating Euclidean distance in feature space

While this method allows for direct comparison between two footprints, it is not tractable to compute the pairwise distances between all building complexes, as this scales quadratically in the number of buildings with O(5 × 10^4) complexes in the Netherlands. Instead, a feature space is constructed by computing the distance from each complex to a small number of reference polygons, which scales linearly in the number of complexes. Initially, reference polygons are constructed from parameterized shapes and a feature space is constructed from a sample of complexes.

The PCA reveals which polygons best represent the variability in the data. A new feature space is constructed by throwing out the reference polygons that are least representative for the data and adding new reference polygons. This loop is repeated 30 times, resulting in a set of reference polygons that accurately represents the variability in the data. This feature space can be extended by adding any other relevant building properties, resulting in an extended feature space that is called the 'building similarity index'. At this moment construction year, building height and number of apartments are included.

The similarity between two buildings can easily be estimated by computing their distance in the extended feature space. Thus, if a candidate for retrofitting is identified, similar buildings can be found simply by finding the closest points in the n-dimensional feature space. Note that a scaling factor is introduced to weigh the relative importance of different properties. Where n reference polygons are used to represent building footprint, other normalized properties such as construction year are scaled by a factor of $\sqrt{n}$.

For each complex of the validation dataset a top 10 was calculated of nearest neighbours in the feature space, representing the most similar buildings based on the given data.

Note that while no location is given in the feature space, based on given data top 10 similar buildings are still found geographically near each other. This hints that the feature space can distinguish location-specific building design backgrounds (shape, age, number of apartments, height) without information on building location.

Correlation similar building clusters with building system typology

The buildings can be clustered based on their distance in the n-dimensional feature space. Unsupervised K-means identified groups of similar buildings, and the results are correlated to qualitative distinctions of buildings, namely the known building system typology for each building. 638 complexes, with assigned building typologies taken from Walraven (2021) and Cultural Heritage Agency (Ministerie van Onderwijs, 2018), were distributed among 13 clusters using the building feature space. The clustering is seeded by taking the mean points of each system typology as initial centroids for the K-means algorithm. Currently variance is still high within clusters given the morphological metrics and background information (Figure 26). Given current efforts, the 2D morphology, construction year, height and number of apartments still ask for additional building information to distinguish building systems by GIS analysis. To obtain a clustering similar to the building typology in particular, it is necessary to enrich the feature space by adding the same building characteristics that are used to distinguish the building typologies from an architectural viewpoint.

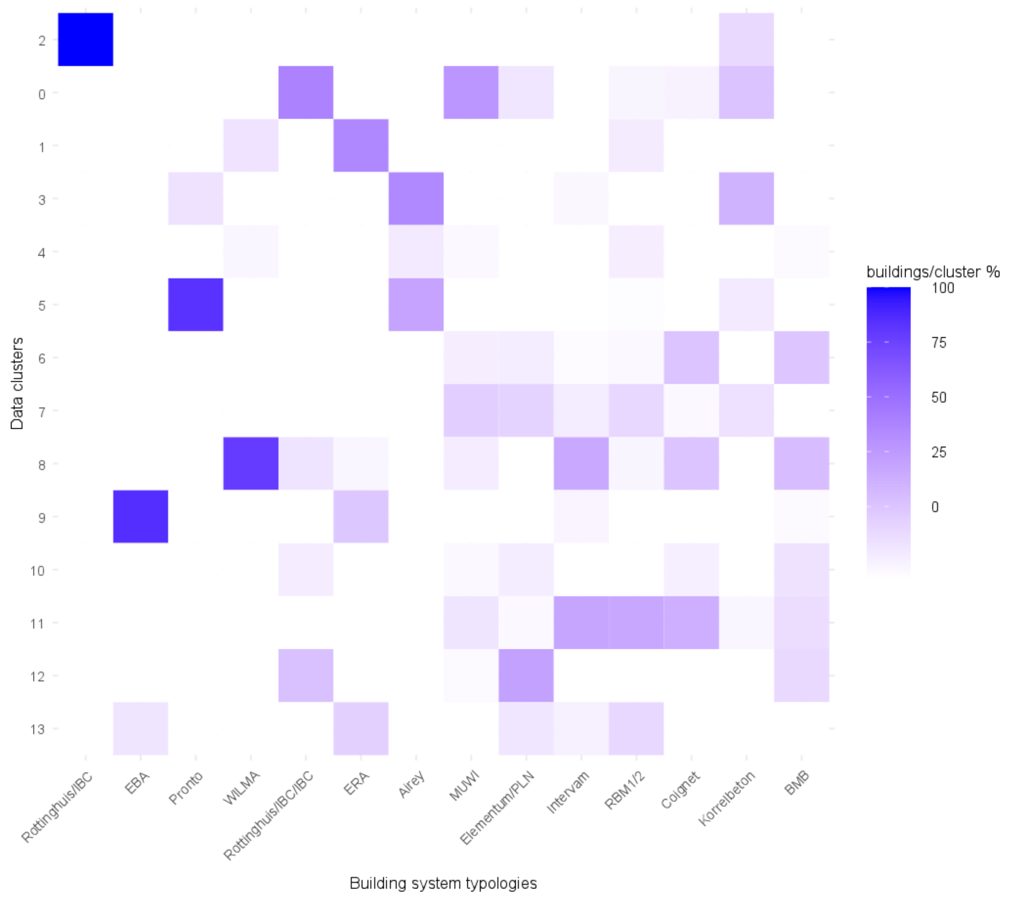


Figure 26. Confusion matrix of complexes divided over 13 unsupervised building clusters based on building information feature space, set out against their original building system typologies.

Figure 27. Top 10 most similar complexes in descending order (green to white) compared to complex 1 in Mariahoeve, The Hague. Similarity is defined as Euclidean distance in a feature space considering morphology, construction year, height and number of apartments. Number 10 is drastically distant in Zeeland.

Discussion

It is evident that more building information should be collected to be able to make a distinction between building system. Types of additional information could be materialisation or entrance type. This finding also resonates with the descriptions of building systems, which often boil down to construction methods and materialisation.

The metrics that have been included as input for the PCA are solely based on 2D building footprints of the BAG. However, large efforts have been made to identify 3D building metrics from 3D CityGML models (Labetski et al., 2023). 3D building models are increasingly used across the globe, depending on the availability of LiDAR data. 3D building metrics contribute as a useful supplement for 2D building metrics in addressing increased architectural complexity, but do not replace the functionality of 2D footprint analysis for shape recognition. In future studies 3D object information will be added to this methodology, however the current method is operational for regions with only 2D building footprints.

As discussed in 4.2, building systems have been identified manually for certain regions of the Netherlands in different time periods by a limited number of experts.

As such, the chance on bias in identification of building system is present since only 638 building systems have been assigned out of >47.000 complexes.

Similar clustering efforts based on building morphology have been performed as a proof-of-concept prior to this study, but it is in this study that building morphology clustering is tested on application-specific needs; namely finding complexes with a shared design history (Labetski et al., 2023). Morphological buildings metrics have been tested on suitability for shape recognition before, where Basaraner & Cetinkaya (2017) highlighted the high performance of Equivalent Rectangular index, Roughness index Convexity and Rectangularity.

Apart from the scope of D5.1 to develop business cases for industry 4.0, morphology analysis such as performed in the numerical building similarity index can serve large range of studies like the relation between building similarity clusters and urban climatology or socio-economic aspects (Biljecki & Chow, 2022).

4.5. MARKET: MULTI-CRITERIA ANALYSIS FOR POTENTIAL ALPHA LOCATIONS

Introduction
To prepare for the pre-manufacturing workflow, an output of the pre-recognition workflow is a project-independent multi-criteria analysis on the potential for implementation of a product system. New clustering tools (4.4) and architectural insights (4.2) may aid in identifying high-potential clusters in the future. In the case of D5.1, the gathered GIS dataset (4.3) has used to identify high-potential locations for the Alpha module, as well as provide the necessary input data for a Dynamo script to optimise the construction of the Alpha (5.2.2).

Method
A basic scope was defined following the basic technical requirements for placement and parametric modelling of the Alpha module, the following filters were applied on the features assimilated in4.3.5 :

- Building floor levels >= 7
- 2D building footprint = Rectangle
- Length-width ratio > 1.2
- Roof type = Horizontal OR multiple horizontal
- Permitted construction height >= 2 m

Results
1324 complexes were selected following the filters for a basic scope for the Alpha module. In total this selection mounts up to 1961 registered premises with a sum of 97198 residences.

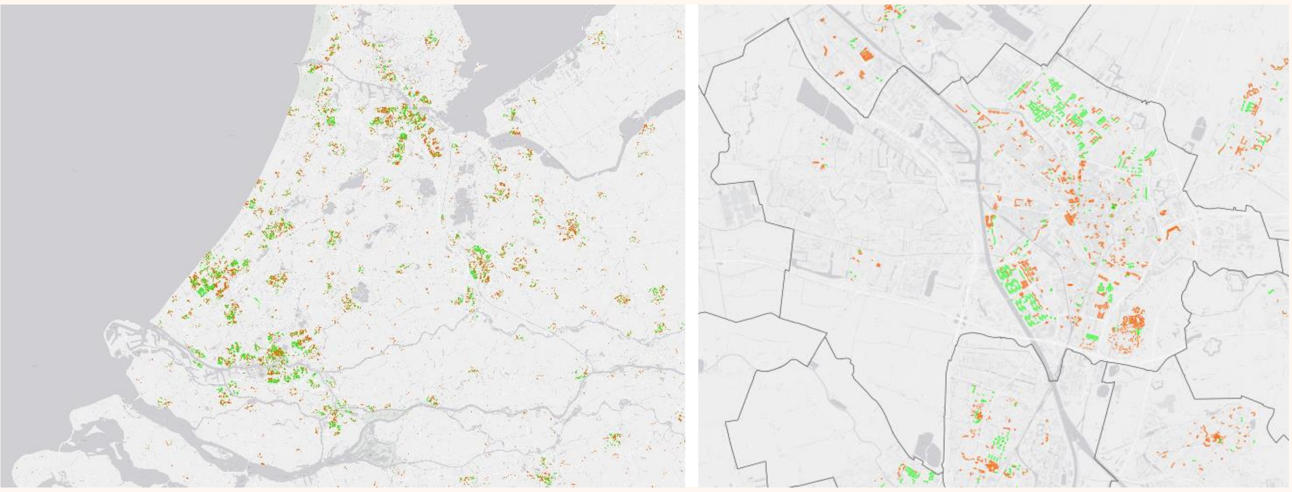


Figure 28. Selection of complexes that meet basic technical requirements for implementation of the Alpha module. Green: suitable complexes, orange: other identified complexes. Left: Overview of possible Alpha locations in the polycentric urban Randstad region (NL). Right: Overview of possible Alpha locations in Utrecht municipality

4.5.1. COMMUNICATION OF THE PRE-RECOGNITION WORKFLOW THROUGH GIS WEB ENVIRONMENT: TAILORMAP

To support the exploration of high-potential complexes for retrofitting, a connection with open-source map publishing platform Tailormap was achieved. GIS datasets are converted to WMS on QGIS server, which is hosted on SURF research cloud. The WMS URL is then uploaded together with a duplicate

PostGIS connection URL to a custom Tailormap web environment (Figure 29) also hosted on SURF research cloud. Product developers, policymakers and academia can quickly explore the collected GIS data and explore future projects with high potential for implementing the Alpha module, or other product systems in the future.

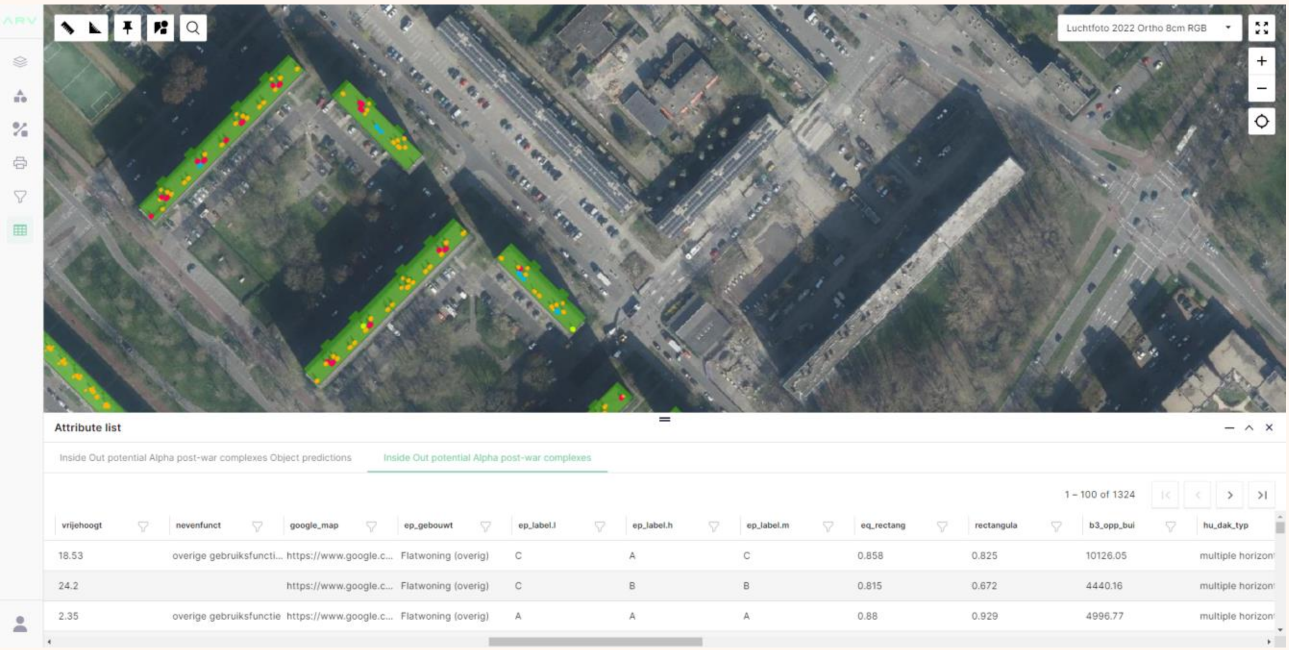


Figure 29. The Tailormap viewer for Inside Out with 1324 high-potential complexes (green) for implementing the Alpha. Hosted in a test web domain. Complexes can be filtered further based on attributes in the lower table, including permitted building height, secondary functions, energy performance label, shape and roof angle. Roof superstructures identified by computer vision have been added as a second layer.

5. PRE-MANUFACTURING

5.1. PRE-MANUFACTURING / BIM CONFIGURATION

5.2. ALPHA

5.2.1. THE ALPHA SOLAR MODULE

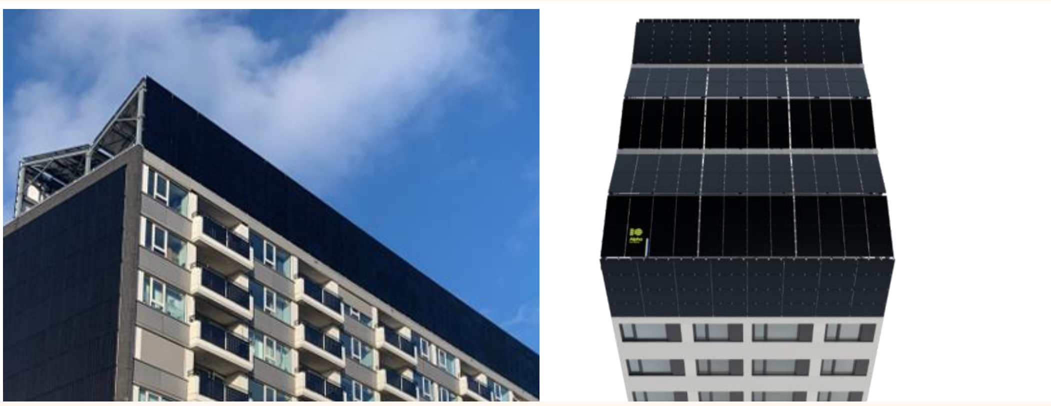


Figure 30. Alpha module 2021 (left) and 2024 (right). Source: Inside Out

In the realm of solar energy utilization, high-rise buildings pose unique challenges due to limited rooftop space. Traditional methods often struggle to harness sufficient solar power in such environments. To address this issue, Inside Out has developed the Alpha Solar module, a groundbreaking solution tailored specifically for high-rise structures (Figure 30).

Key Features
The Alpha Solar module is distinguished by its innovative design and functionality, offering several key features:

1. Prefabricated steel frame: The module comprises a Prefabricated steel frame equipped with plug-and-play compartments for solar panels. This streamlined design enables rapid assembly, with installation typically completed within weeks.

2. Modular Flexibility: One of the Alpha's standout features is its modular construction, allowing seamless adaptation to various building types. Whether deployed on residential complexes or commercial towers, the Alpha Solar module offers unparalleled versatility.

3. Overcoming Obstacles: Existing rooftop infrastructure, such as boiler rooms or chimneys, often limits available space for solar panel installation. The Alpha module circumvents this challenge by ingeniously integrating over existing components, eliminating barriers to optimal solar panel placement.

4. Stormproof Design: Engineered to withstand adverse weather conditions, the Alpha module boasts robust construction that ensures resilience against high winds. Through rigorous testing and proven performance in reference projects, the Alpha has demonstrated its stormproof capabilities.

5. Scalable Integration: Beyond solar power generation, the Alpha Solar module can be seamlessly integrated with electrical or thermal battery systems. This scalability enables efficient

management of peak loads and alleviates grid congestion, enhancing overall energy sustainability.

Specifications
- Prefabricated steel construction with integrated PV systems
- Connection options include central utilities, individual residences, or energy collectives
- Scaffold-free assembly for enhanced efficiency
- Rapid construction with minimal disruption
- Waterproof column bases with cold bridge interruption for durability
- Micro-inverters per panel or string inverters for efficient energy conversion
- Built-in provisions for cable routing
- Optional monitoring system and maintenance contract
- Provision for group panel replacement or modification
- Eligible for 0% VAT on purchase

5.2.2. PARAMETRIC DESIGN OF THE ALPHA MODULE

Dynamo is deployed as a visual programming plug-in for Revit, enabling parametric BIM design. Users leverage its capabilities to create custom scripts or workflows that automate specific tasks or processes within Revit.

The tool operates based on a node-based interface, where users can drag and drop elements to create logical sequences of actions. These actions are defined by nodes, which represent different operations or functions within Revit.

In the context of the Alpha module, Dynamo for Revit enables the automatic and flexible generation of the module based on a set of pre-defined parameters and rules. Users can define parameters such as the type of PV panels, dimensions of the building, or specific design constraints.

By creating a custom Dynamo script tailored to the requirements of the Alpha module, users can streamline the design and implementation process (Jacobs, T., 2024, *unpublished*). This automation significantly enhances efficiency and accuracy, reducing the time and effort required for manual modelling and design iterations.

This tool empowers designers and engineers to create complex parametric designs efficiently within the Revit environment, ultimately leading to enhanced productivity and innovation in architectural and engineering projects.

Method
Parametric design in the context of the Alpha module involves the dynamic manipulation of its geometry and components to optimize solar energy capture while accommodating the structural and aesthetic constraints of existing buildings. This approach not only facilitates a highly customized solution for each application but also significantly reduces the design and planning time, making the process more efficient and cost-effective. The Alpha module's parametric design process begins with the collection and analysis of relevant data, including building length, width and height, orientation, structural limitations, and local environmental conditions such as wind speed zone. This data is crucial for defining the initial set of parameters that guide the design process. Acquisition of nationally available GIS open data sources and AI visual recognition techniques are employed to gather and process this information, ensuring a fully scalable model.

In Dynamo for Revit, the parametric model of the Alpha module is constructed using nodes that represent various design and engineering elements, such as structural supports, PV panel arrays, and connection details. Each node is interconnected to form a network that processes input parameters to generate the module's geometry. This visual programming environment allows for the rapid exploration of design alternatives and the assessment of their performance, facilitating decision-making and iteration.

Results

The parametric design process for the Alpha module begins with the collection and analysis of relevant data, including building dimensions (length, width, and height), orientation, structural limitations, and local environmental conditions such as wind speed zones. This data is essential for defining the initial set of parameters that guide the design process. Nationally available GIS open data sources and AI visual recognition techniques are utilized to gather and process this information, ensuring a scalable model.

In Dynamo for Revit, the parametric model of the Alpha module is constructed using interconnected nodes that represent various design and engineering elements, such as structural supports, PV panel arrays, and connection details (Figure 31 & Figure 32). This visual programming environment allows for rapid exploration of design alternatives and the assessment of their performance, facilitating decision-making and iteration.

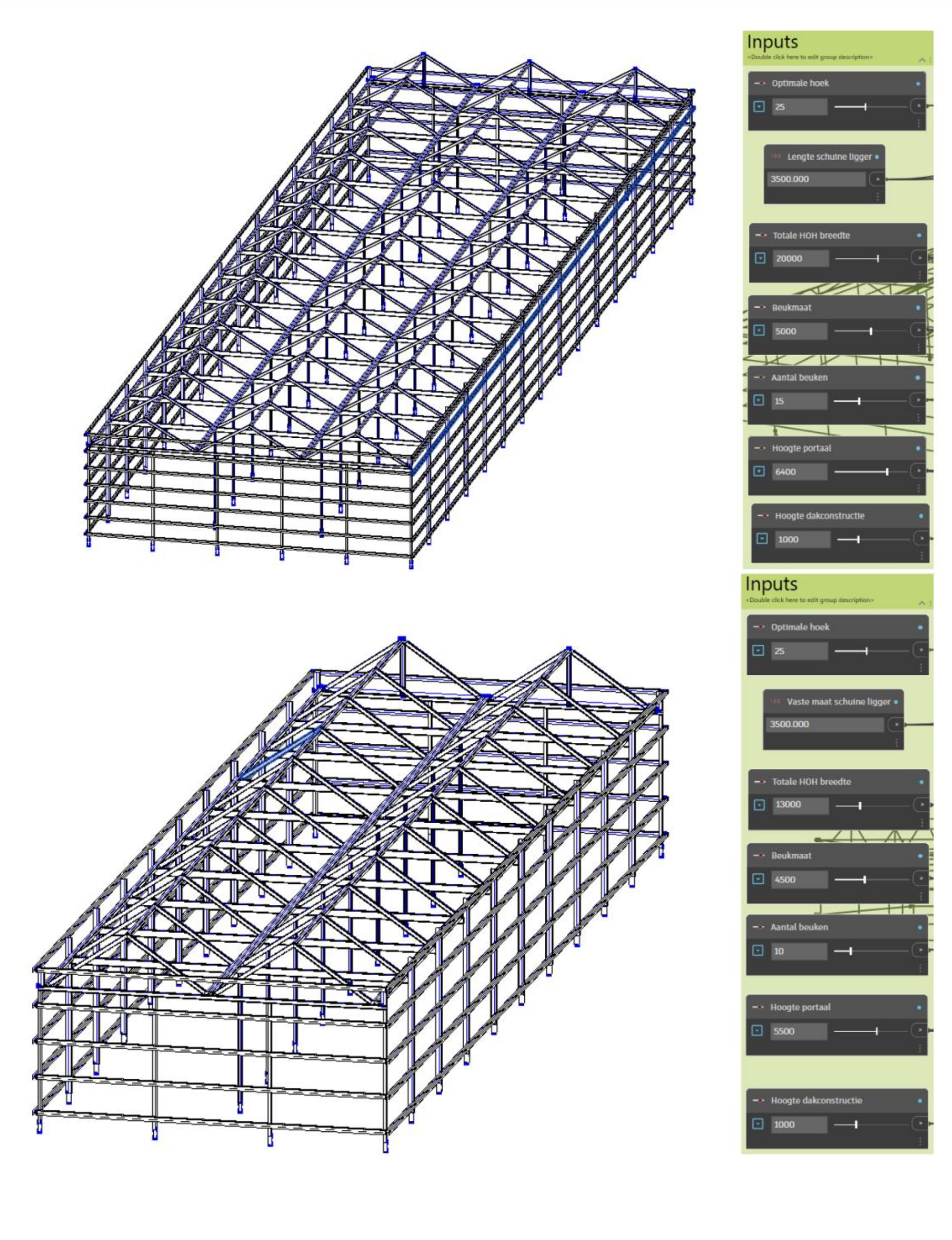


Figure 31. Alpha parametric design model in Dynamo with building dimensions as input parameters.

Figure 32. Parametric design of the Alpha module for Middelmonde 2-192, Nieuwegein, the Netherlands.

Discussion

In principle, the parameters can be adjusted to explore various design scenarios, such as different PV panel layouts or structural configurations, to identify the optimal solution for each specific project. At this development stage, the model uses length and width of the building and assumes a rectangular design on a rectangular surface.

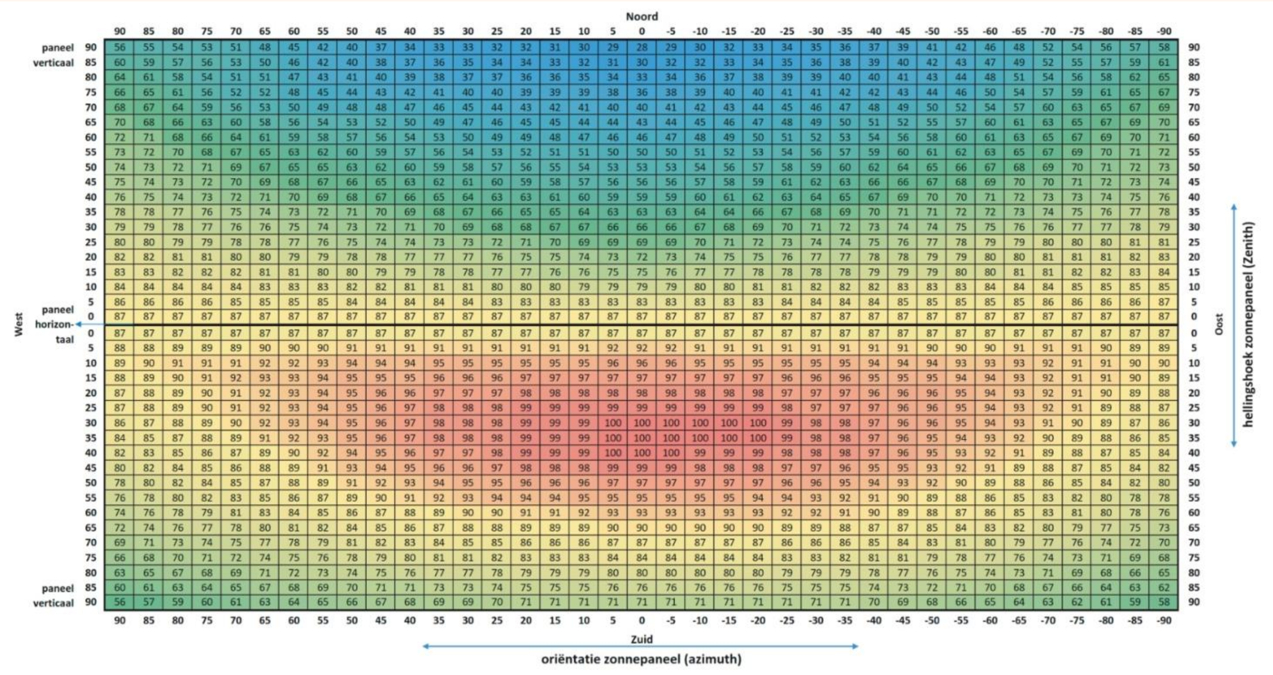
In conclusion, the parametric design of the Alpha module represents a forward-thinking approach to the integration of renewable energy technologies in urban buildings. The flexibility and efficiency of this process hold significant potential for future applications.

5.2.3. AUTOMATED SOLAR POTENTIAL CALCULATION

The results of the parametric model result in a listing of the number of PV panels on each façade part enabling further calculation of potential PV generation. KNMI's hourly solar radiation model was used as a reference tool to calculate the energy production of PV panels with precision. This detailed data is essential as it encompasses the intensity of sunlight reaching the ground at various times throughout the year, which includes both direct sunlight and diffused light resulting from clouds and other atmospheric conditions.

The process of calculating solar energy in the model involves several steps. First, hourly solar radiation data specific to the location is obtained from KNMI. This information is then used to calculate hourly energy production using a formula that factors in solar radiation (W/m^2), the panel's surface area (m^2), its efficiency, and orientation reduction factors (Table 6). The formula used is:

$$Energy\ (Wh) = Solar\ Radiation\ (W/m^2) * Panel\ Area\ (m^2) * PV\ Panel\ Efficiency * Orientation\ and\ Reduction\ Factors$$



	90	85	80	75	70	65	60	55	50	45	40	35	30	25	20	15	10	5	0	-5	-10	-15	-20	-25	-30	-35	-40	-45	-50	-55	-60	-65	-70	-75	-80	-85	-90
paneel verticaal 90	56	55	54	53	51	48	45	42	40	37	34	33	33	32	32	31	30	29	28	29	30	32	33	34	35	36	37	39	41	42	46	48	52	54	56	57	58
85	60	59	57	56	53	50	46	42	40	38	37	36	35	34	34	33	32	31	30	32	32	33	34	35	36	38	39	40	42	43	47	49	52	55	57	59	61
80	64	61	58	54	51	51	47	43	41	40	39	38	37	37	36	36	35	34	33	34	36	37	38	39	39	40	40	41	43	44	48	51	54	56	58	62	65
75	66	65	61	56	52	52	48	45	44	43	42	41	40	40	39	39	39	38	36	38	39	40	40	41	41	42	42	43	44	46	50	54	57	59	61	65	67
70	68	67	64	59	56	53	50	49	48	48	47	46	45	44	43	42	41	40	40	41	42	43	44	45	46	47	48	49	50	52	54	57	60	63	65	67	69
65	70	68	66	63	60	58	56	54	53	52	50	49	47	46	45	45	44	44	43	44	45	46	47	48	49	50	51	52	55	57	60	61	63	65	67	69	70
60	72	71	68	66	64	61	59	58	57	56	54	53	50	49	49	48	47	46	46	47	48	49	50	51	52	53	54	56	58	60	61	63	65	67	69	70	71
55	73	72	70	68	67	65	63	62	60	59	57	56	54	53	52	51	51	50	50	50	51	52	53	54	56	57	59	60	61	62	63	65	67	69	70	71	72
50	74	73	72	71	69	67	65	65	63	62	60	59	58	57	56	55	54	53	53	53	54	56	57	58	59	60	62	64	65	66	67	68	69	70	71	72	73
45	75	74	73	72	70	69	68	67	66	65	63	62	61	60	59	58	57	56	56	56	57	58	59	61	62	63	66	66	67	68	69	70	70	71	72	73	74
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20	82	82	81	81	80	80	79	79	78	78	77	77	77	76	75	75	74	73	72	73	74	75	75	76	77	77	78	78	79	79	80	80	81	81	81	82	83
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0	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87
paneel horizontaal 0	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87
5	88	88	89	89	89	90	90	90	91	91	91	91	91	91	91	91	91	92	92	92	91	91	91	91	91	91	91	91	90	90	90	91	91	91	90	89	89
10	89	90	91	91	91	92	92	93	94	94	94	95	95	95	95	95	95	96	96	96	95	95	95	95	95	95	94	94	94	93	93	93	92	91	91	90	90
15	88	89	90	91	92	93	93	94	95	95	95	96	96	96	97	97	97	97	97	97	97	97	97	96	96	96	95	95	95	94	94	93	92	91	91	90	89
20	87	88	89	90	91	92	93	94	95	96	96	97	97	97	98	98	98	98	98	98	98	98	98	97	97	97	96	96	96	95	94	93	92	91	90	89	88
25	87	88	89	90	91	92	93	94	95	96	97	98	98	98	99	99	99	99	99	99	99	99	99	98	97	97	97	96	96	95	94	93	92	91	89	88	87
30	86	87	88	89	90	92	93	94	95	96	97	98	98	98	99	99	99	100	100	100	100	100	100	99	98	98	97	96	96	95	94	93	91	90	89	87	86
35	84	85	87	88	89	91	92	93	95	96	97	98	98	98	99	99	99	100	100	100	100	100	100	99	98	98	97	96	95	94	93	92	90	89	88	86	85
40	82	83	85	86	87	89	90	92	94	95	96	97	97	98	99	99	99	100	100	100	99	99	99	98	98	98	97	96	95	93	92	91	89	88	87	85	84
45	80	82	84	85	86	88	89	91	93	94	95	96	96	97	98	98	98	99	99	99	98	98	98	97	97	96	95	95	93	92	91	89	88	87	85	84	82
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85	60	61	63	64	65	67	68	69	70	71	71	73	73	74	75	75	75	76	76	76	76	76	76	75	75	75	74	73	72	71	70	68	67	66	64	63	62
paneel verticaal 90	56	57	59	60	61	63	64	65	66	67	68	69	69	70	71	71	71	71	71	71	71	71	71	71	71	71	70	69	68	66	65	64	63	62	61	59	58

Figure 33. A visual guide to the optimal orientation and tilt angles for PV panels. Source: ISSO, Kennisinstituut voor de installatiesector (Rotterdam), 2016

By applying this formula, the model determines the energy produced each hour, which is then aggregated to provide an annual energy output in kWh. This method ensures an accurate estimation of the PV system's performance, considering local weather conditions and the specific installation setup. Accompanying this model is a visual guide (Figure 33) which displays the efficiency of PV panels based on their orientation and tilt angle. The chart illustrates how different positions relative to the sun—ranging from vertical to horizontal inclinations and various azimuth angles—affect the panel's ability to capture solar energy. To optimise the Alpha module's panel configurations for maximum PV energy yield, this table guides towards the ideal orientation and slope of each PV panel.

Table 6. Calculation module translates PV amount and orientation by parametric Alpha model to potential positive solar energy generation (kWh/year) over different timeframes. Input data is highlighted in green. Source: adapted from Brouwers (2024), Inside Out

PV construction Herwijnenplantsoen 1-223	Azimuth	Slope	n panels	Wp of Viasolis PV-panel	Reduction orientation	Placed power after reduction	Placed power 14% loss (0.86 kwh per wp)	Annual generation	Annual generation 10th year	Annual generation 10th year incl possible PV replacement	Yearly generation after 20 years
Facade	+/- 22.5 degrees	degrees	[pieces]	[Wp]	% WP	[kWp]	[kWp]	[kWh/year]	[kWh/year]	[kWh/year]	[kWh/year]
Left end wall Alpha	NNO	90	44	400	45	792	681	681,120	647,064	647,064	613,008
Right end wall Alpha	ZZW	90	44	400	71	1,250	1,075	1,074,656	1,020,923	1,020,923	967,190
Front wall Alpha	NWW	90	76	400	50	1,520	1,307	1,307,200	1,241,840	1,241,840	1,176,480
Behind wall Alpha	ZOO	90	76	400	61	1,854	1,595	1,594,784	1,515,045	1,515,045	1,435,306
Roof	NWW	35	168	400	81	5,443	4,681	4,681,152	4,447,094	4,447,094	4,213,037
Roof 2	ZOO	35	168	400	89	5,981	5,144	5,143,488	4,886,314	4,886,314	4,629,139
Total			**576**			**16,840**	**14,482**	**14,482,400**	**13,758,280**	**13,758,280**	**13,034,160**

5.2.4. QUOTATION ACCELERATION AND FILE2FACTORY OF THE ALPHA MODULE

The detailed digital model of the Alpha in Dynamo results in critical data for construction and budget considerations, including the geometric dimensioning of steel beams, assembly details, list of construction materials and estimated number of PV panels. This data is translated to input for automatic quotation calculation as well as for instructions File2Factory. By using a parametric model, alterations in input data, such as roof geometry or intended material intensity directly translate to changes in budget estimates. Early in the project cycles stakeholders are provided with a clear and reliable financial overview. Subsequently, the parametric model provides a platform for collaboration between building designers, product manufacturers and construction teams.

5.3. QUOTATION ACCELERATION OF FAÇADE PANELS

Within the current retrofitting process a significant amount of time is spent on generating quotations upon request. This issue can be addressed by the "Quotation Accelerator" (*Offerteversneller*) application developed by Buro de Haan (BdH), which has access to extensive public data related to buildings. This will enable providers of retrofitting products to submit quotes without physically visiting the location. The public data includes GIS information and imagery such as Google Street View.

If public data can address the technical feasibility and necessary information on the existing building to predict the quotation for applying a retrofitting product system, there is also the possibility of building owners being proactively engaged. Automated data-driven quotation allows for a concrete proposal to persuade building owners to proceed with retrofitting in this manner.

In addition to supporting the personnel creating quotations, it is also desired to make it easier for the client to configure the assignment. In the current process, a lot of time is lost in back-and-forth communication between the client and the project designer (being or including a BIM modeler). This often involves visual choices such as stone strip pattern or window frame colour. It is desired to avoid this communication flow and give the client direct (limited) influence over the choices.

Speeding up the quotation process is part of the optimization. By storing building information in a structured manner in a quotation database, the process can be further automated after approval of the quotation. This is a 'zero engineering approach'. The structured information can be used to set up a BIM model that serves as a kickstart for the modeler. In an ideal situation, the modeler only has a supervisory function, but this requires extremely precise input.

A final optimization is the output from the BIM model. Traditionally, this often involves redrawing from another drawing, which is desired to be avoided by being able to generate files directly from the BIM model that can be read by the machines.

To realize this vision, research into the technical feasibility of various necessary components has been conducted.

5.3.1. REMOTE BUILDING DIMENSIONS EXTRACTION

Street-view building dimensions extraction

As part of an Industry 4.0 workflow for accelerated quotation, BdH embedded Google Street View Imagery in a user interface to manually select an area with buildings which are of interest to be retrofitted (Figure 34). A street view image and background information can then be displayed for the selected addresses (Figure 35). By drawing a (yellow) reference line, it is then possible to extract dimensions from the image. Based on the outer dimensions of a building and the drawn reference in the image, the length per pixel is calculated. Based on the pixel-length ratio the dimensions of the windows and doors are calculated (Figure 36).

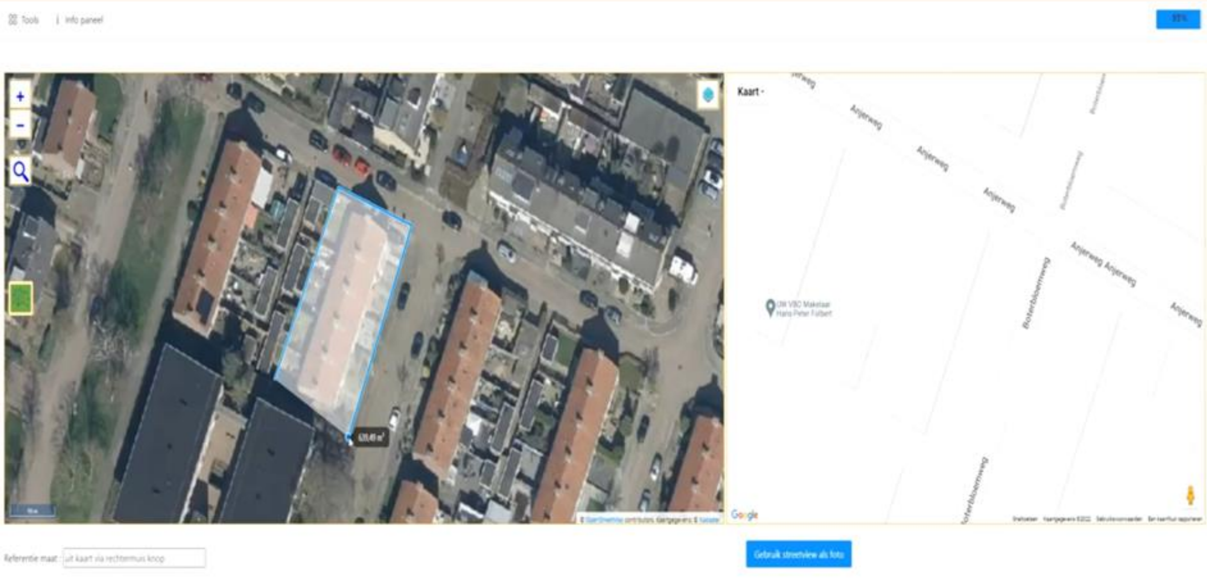

Figure 34. Interface to select the buildings for the pre-manufacturing workflow. Source: Buro de Haan & Rc Panels

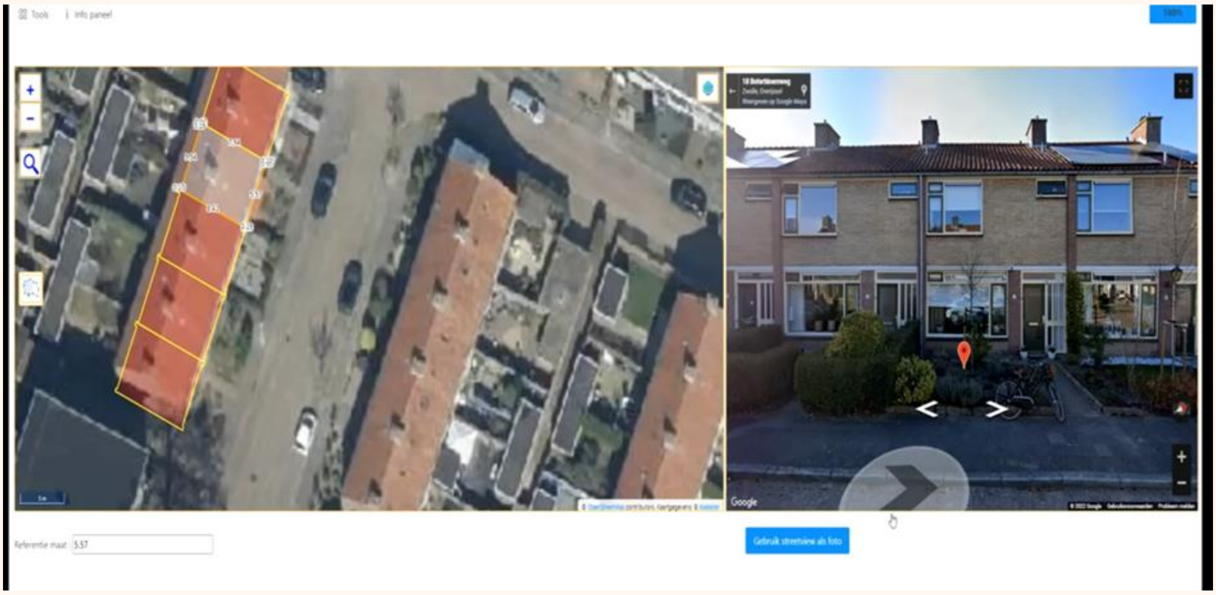

Figure 35. On the left, information about the different buildings in the selection, including outer dimensions. On the right, Google Street view image of the selected area. Source: Buro de Haan & Rc Panels

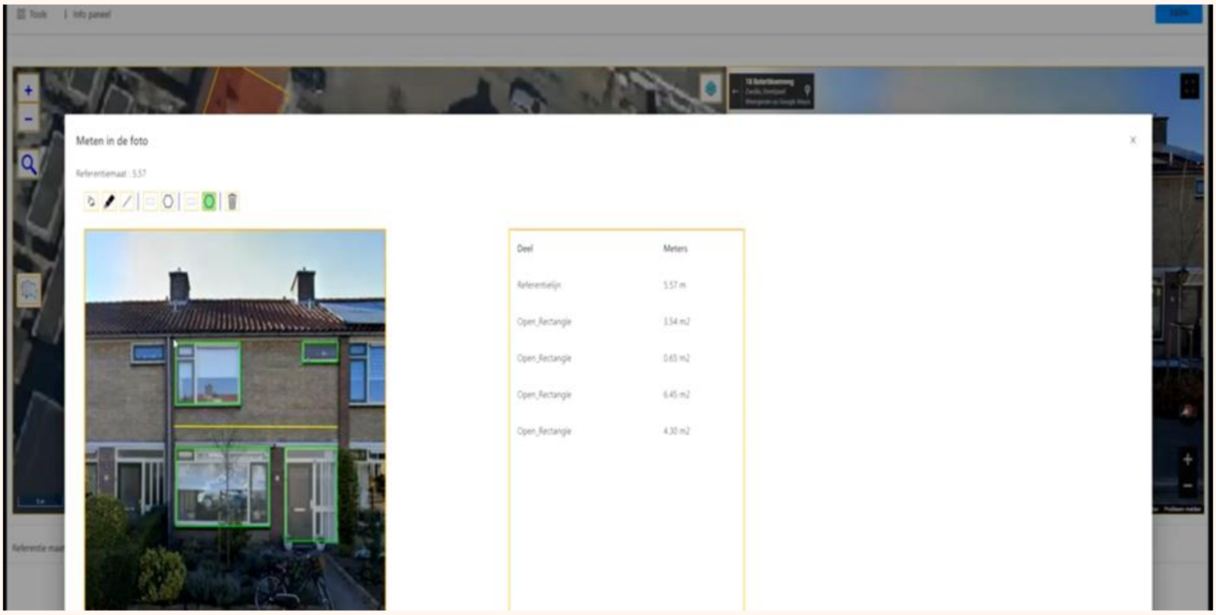

Figure 36. A drawn reference line and openings in the facade.

Floor plan building dimensions extraction

For many projects, floor plans are also provided as a basis for a quote. For this reason, the application has been expanded to include the ability to upload and measure PDF files (Figure 37).

Figure 37. An uploaded PDF file of a floorplan is used to extract building dimensions. Source: Buro de Haan & Rc Panels

5.3.2. PANEL QUOTATION INTERFACE

As a manufacturer of facade elements, for Rc Panels the most important information being the dimensions and openings in a panel. The focus was on expanding the quote accelerator so that quotes can be created, panels can be defined, and placed on a facade. At the start of a quote, Rc Panels defines the types of panels. For each type of panel, the dimensions and the locations of the doors and/or windows are known. Instances of those types are then placed on a view (Figure 38, Figure 39).

This way, it's not just individual frames, but also structured data that can be used later in the process. Subsequently, the entire set of configured facade elements can be translated to a list of dimensions and materials in CSV format for cost estimation and File2Factory (Figure 40).

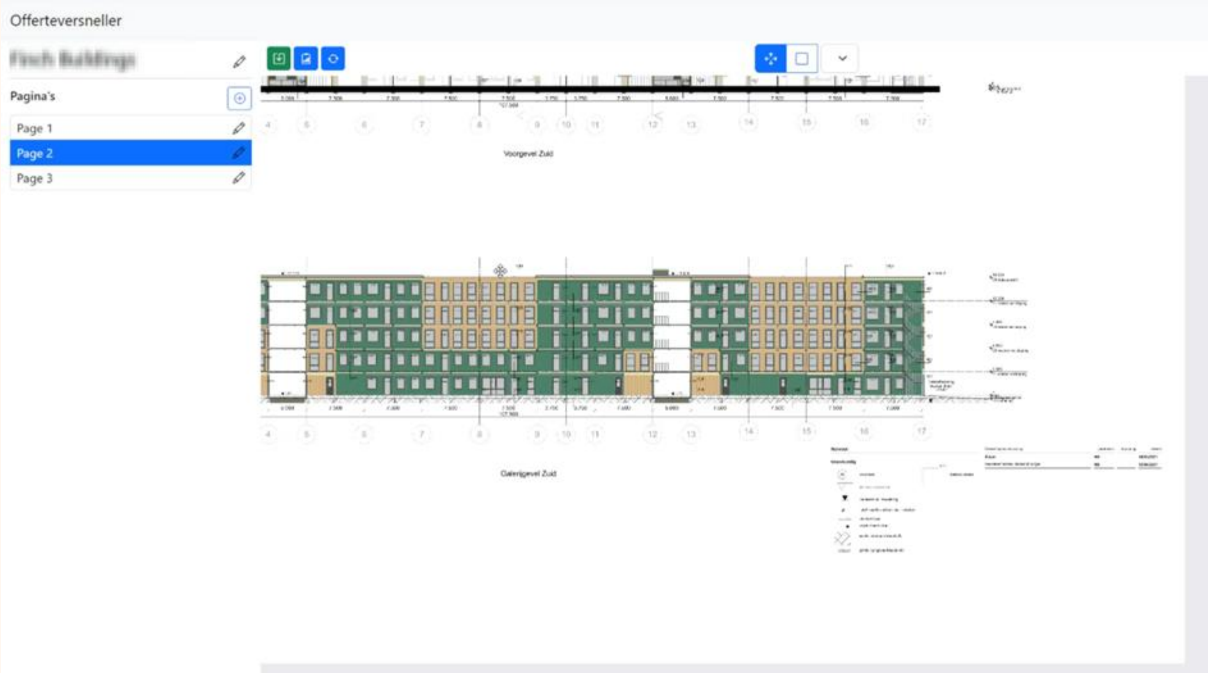

Figure 38. Multipage uploaded PDF with facades which is the input for the quote. Source: Buro de Haan & Rc Panels

Figure 39. Placed panels with facade on the background. Source: Buro de Haan & Rc Panels

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Gevel	Breedte	Hoogte	Aantal	Kozijn	Breedte	Hoogte	Type	Kozijn	Breedte	Hoogte	Type			
2	G01	3727	3050	3	Merk G	1073	2398	Raam	Merg I	1350	2416	Raam			
3	G02	3744	3000	3	Merk G	1073	2398	Raam							
4															
5															
6															

Figure 40. Export data of the placed panels in CSV format. Source: Buro de Haan & Rc Panels

5.3.3. FURTHER DEVELOPMENT

Functionality for manually indicating wall and opening dimensions was initially developed for both Google Maps and PDF as sources. Integration with image recognition technology is still desired for future development. In the quotation accelerator, the end user currently needs to manually draw frames to indicate windows and doors. With the help of image recognition, this ideally would happen automatically, but a more realistic approach would be for the software to make a proposal and for the end user to only make adjustments. BdH started by facilitating the manual process, as it seemed unfeasible for everything to be automatically recognized, and manual correction would be necessary in any case. By starting here, it was possible to deliver an application that could be tested and used.

Generating a BIM model based on the current information is not yet possible. Positioning of facade panels is done on a plane, but it is not known whether this is the front, side, or back of the building. One possible solution could be to retrieve the 2D shape of the building from BAG data and link images and/or PDF files to a specific facade.

5.3.4. PHOTOGRAMMETRY

To assess the possibilities of photogrammetry, a test was conducted in an open field using a drone to take photos at predetermined points over a set grid.

A large collection of overlapping imagery is converted by Pix4D or Reality Capture software to create a MESH model. Unlike a point cloud, a MESH model consists of planes and provides additional insight into the existing environment. The potential to perform this with a drone also presents opportunities for high-rise buildings. A MESH model can serve as a useful base layer in various software applications (Figure 41).

This method is particularly valuable for quickly gaining insight, such as for preparing a quote. However, it is too imprecise for generating production models. Nonetheless, it can be one of the sources used to create an accurate production model. Another consideration is obtaining permission to fly in built-up areas when capturing photos.

To demonstrate photogrammetry by drone on the Demo site, a flight was executed with a DJI Mini 4 Pro around the Bredero flats in Kanaleneiland Zuid. Images were constructed into a 3d mesh model using Reality Capture and further exported to 3D tiles in visualisation platform Cesium ion (Figure 42).

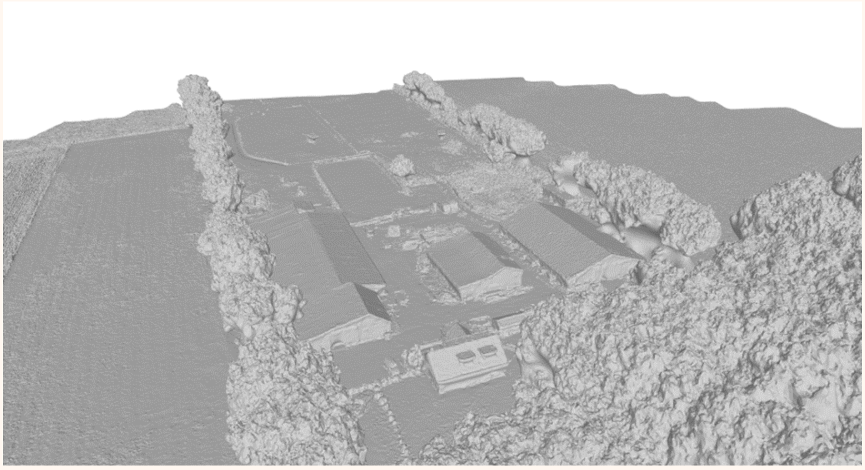

Figure 41. MESH model created by drone in rural environment. Source: Buro de Haan & Rc Panels

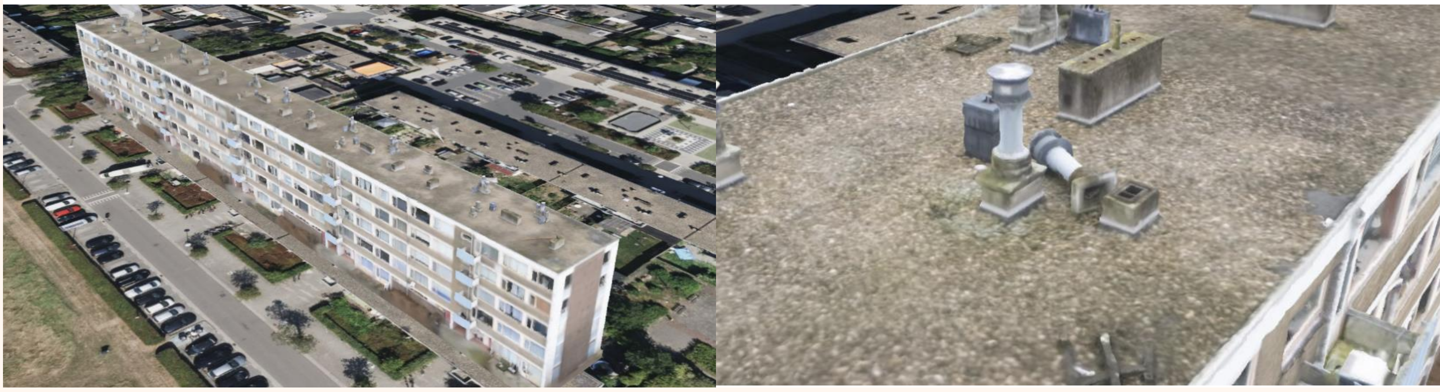

Figure 42. Photogrammetry of Alexander de Grotelaan 1-129, Utrecht, the Netherlands. Drone: DJI mini pro 4. Software: Reality Capture

5.3.5. BIM REFINEMENT BY POINT CLOUD RECOGNITION

One way to reduce engineering costs during retrofitting is by decreasing the time needed to convert the existing situation into a BIM model. While a rough estimate is sufficient for a quote, a higher level of accuracy is required for production modelling. Point cloud scanners, which can measure the existing situation with up to 2mm accuracy, are used for this purpose. The resulting point cloud can then be used as a base layer in BIM software such as Revit.

Traditionally, this base layer is traced by hand. This is not only a monotonous task but also a costly effort. To expedite this process, BdH have begun developing a system to recognize a point cloud and convert it into BIM facade objects. A point cloud is also known as a 'point cloud' because it is a file with detected points. Millions of laser beams are emitted from the scanner, and when something is 'hit,' its coordinates relative to the scanner's position are stored in the point cloud (Figure 43).

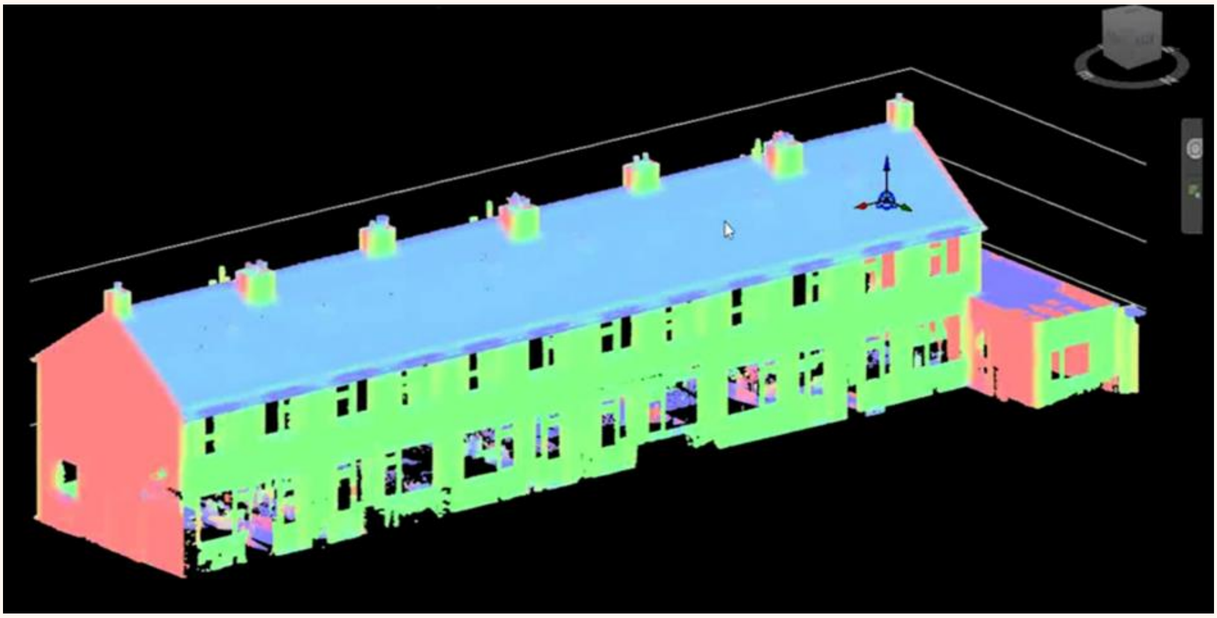

Figure 43. Example of pointcloud segmentation displayed in Revit. Colours indicate the type (front, roof, ...) of segmentation. Source: Buro de Haan & Rc Panels

The starting point for recognizing the existing environment is the identification of the existing walls. The best way to do this turned out to be 'counting' points along the X and/or Y axis (Figure 44). In the presence of a high point density in a particular area, it can be assumed that a wall is present in that location. The challenge is that every obstacle results in a 'hit' in the point cloud, including bushes, curtains, etc.

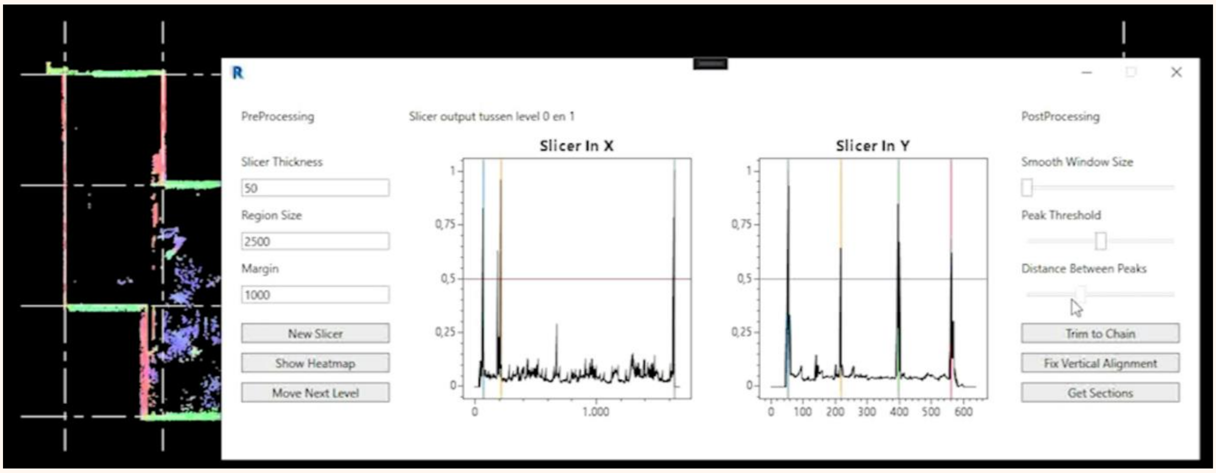

Figure 44. Revit AddIn, UI which shows the point density along the X and Y axis. A high point density mostly indicates a wall.

Figure 45. Revit AddIn, UI where the end user can view detected panels from the point cloud one by one

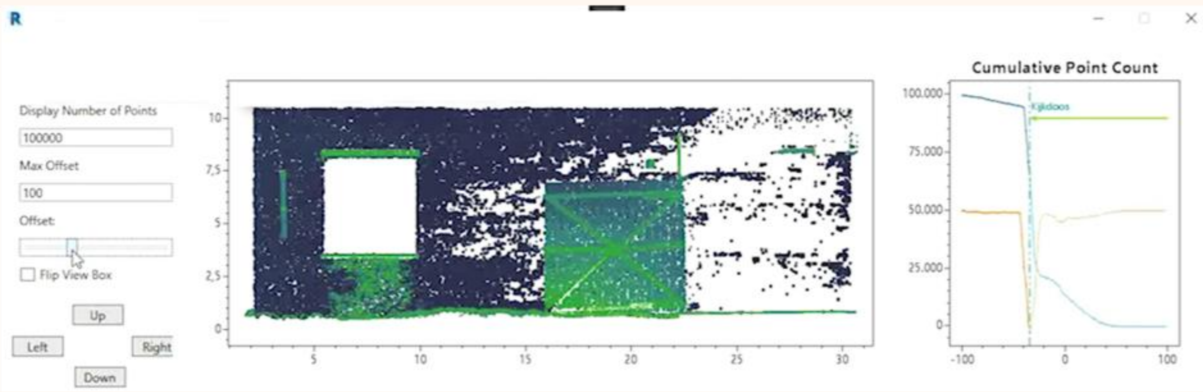

Figure 46. Revit AddIn, UI where the end user can view the point density of the point cloud in a specific bounding box

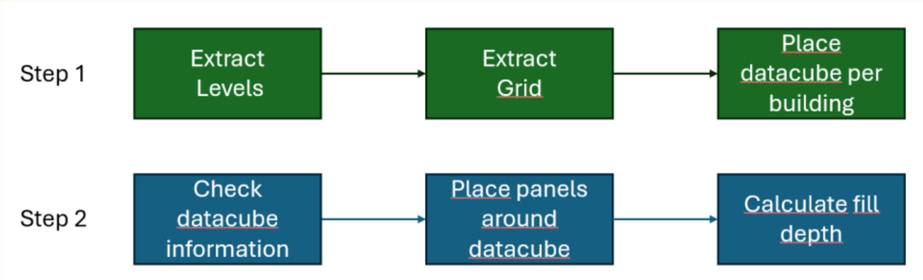

Figure 47. A step-by-step approach to refine a building façade in a BIM model assisted by point cloud recognition

A BIM model of a building façade based on point cloud recognition is performed in the following processes (Figure 47):

Extract Levels: Calculate based on point density number of floor levels from point cloud model (informed by GIS).

Extract Grid: Extract a 2D building footprint and convert to grid positions (Figure 45; Figure 46)

Place datacube per building: Place a parametrical geometry object containing aggregated building information from the GIS workflow such as address and construction year.

Check datacube information: If needed add or correct information of the datacube.

Place panels around cube: Place retrofitting panels (BIM objects) around the datacube. From the point cloud information geometric information is extracted, like dimensions, doors, and windows. From the datacube for example address information is extracted which is used for creating unique, traceable element numbers.

Calculate filling depth: Calculate the filling depth of the new panels compared to the existing situation using point cloud information. Correct for slight leaning of façade. The information is stored in parameters of the panel (BIM object) which can be used later in the process when the panels are mounted to the wall.

5.3.6. FACADE CONFIGURATOR – BIM INTEGRATION

Research was conducted on how to ensure that retrofitting solutions can be configured outside of BIM software such as Revit/Tekla. It is important that the user gets a clear picture of their choices and that these are driven parametrically so that this information can be used to create a BIM model.

A facade product was programmed in the proof of concept with a few simple parameters for dimensions and the possibility of adding openings. Further development could include the ability to choose slip patterns, for example.

This proof of concept is a web application that can be used in any modern browser (Figure 48).
The product visualization is done using Three.js and CSG technology.

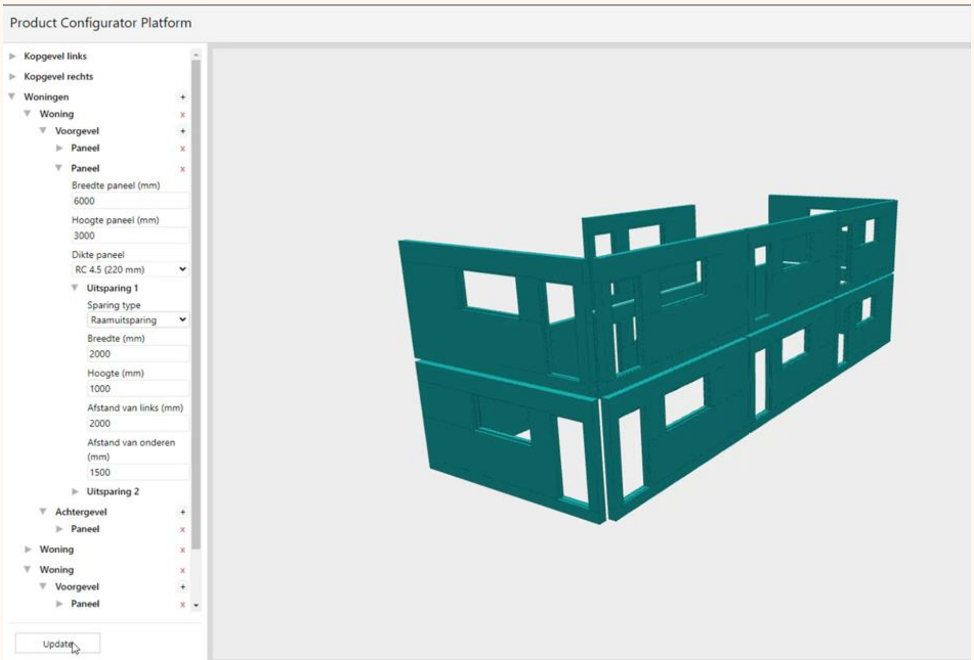

Figure 48. Visualization of the BIM model in the Product Configurator Platform. Source: Buro de Haan

5.3.7. FUTURE OF BIM FED BY PRE-RECOGNITION

Further exploring point cloud segmentation certainly offers perspective, but it should be supported by other data such as photogrammetry and/or image recognition. Ideally, a pre-recognised BIM system is informed by at least 3 sources of data for a building, with each system being executed separately, but combined for the end result.

From the point cloud, there are occasional false positives for a window frame if something reflective is mounted on the wall. By combining this with optical image recognition, which also indicates the likely locations of window frames, the quality improves. A proposed workflow entails that when 2 of the 3 sources indicate the presence of an opening in the facade, it is assumed that a façade opening should be modelled.

In the initial development of the functionality for both Google Maps and PDF sources (5.3.2), the capability to manually specify the dimensions of walls and openings was established. Further development that would have been desired involves the integration with image recognition technology. Currently, in the quotation accelerator, end users are required to manually draw frames around windows and doors; ideally, image recognition would automate this process, though a more realistic scenario involves the software suggesting outlines that the end user merely needs to tweak. The decision to begin with manual processes was made consciously, recognizing that perfect automatic recognition was unlikely and manual adjustments would invariably be necessary. This approach allowed for the delivery of an application that could be tested in operation.

The generation of a Building Information Modelling (BIM) model based on current information is not yet feasible. Although the positioning of false facades is performed on a plane, it is not specified whether this pertains to the front, side, or rear of the building. A potential solution could involve retrieving the 2D shape of the building from BAG and associating images or PDF files with specific facades.

6. FILE2FACTORY

A time-consuming step in the engineering process is transferring data from one software package to another. Consider a BIM model that's detailed but lacks export options to the file format required by machines (such as CNC or glue robots) in the factory. A common practice is exporting 2D drawings from a BIM model, which are then redrawn by a machine operator in the corresponding machine software. This process is both time-consuming and error-prone. The solution for this problem is a File2Factory (F2F) methodology, where machine files are generated directly from the source BIM model. Consortium partner Rc Panels has advanced machinery, and BIM engineering for Rc Panels' projects is carried out by Buro De Haan. In this context, we've developed two F2F projects.

6.1. BTL ADDIN FOR CNC MACHINE

Rc Panels' CNC machine utilizes a BTL file import module, a format supported by many woodworking machines. Revit doesn't natively support this, so BdH developed a custom AddIn for Revit (Figure 51). In the initial approach, a BTL file was generated based on the geometry of a panel. The advantage is that changes in shape don't affect the export. However, complex CNC instructions require assumptions based on geometry. Not all panel cutouts are done the same way; choices depend on their purpose/finish. A saw is preferred for speed, but for visible finishes, milling may be necessary. With only geometry as input, there's insufficient guidance for these choices.

In the second approach, Revit families were developed containing BTL instruction parameters (Figure 49) . The Revit AddIn can read and convert these to BTL data (Figure 50). These BTL instruction families are part of the visually represented BIM objects, with relevant parameters linked (Figure 51). If a panel's dimensions change, so do the BTL instructions (Figure 52). BdH developed a mapping for common operations in the study context, enabling File2Factory with CNC machinery (Figure 53). Some BTL instructions, like 'Birds Mouth,' aren't currently needed and thus aren't implemented. This approach empowers modelers to influence machine operations, without requiring IT support for changes.

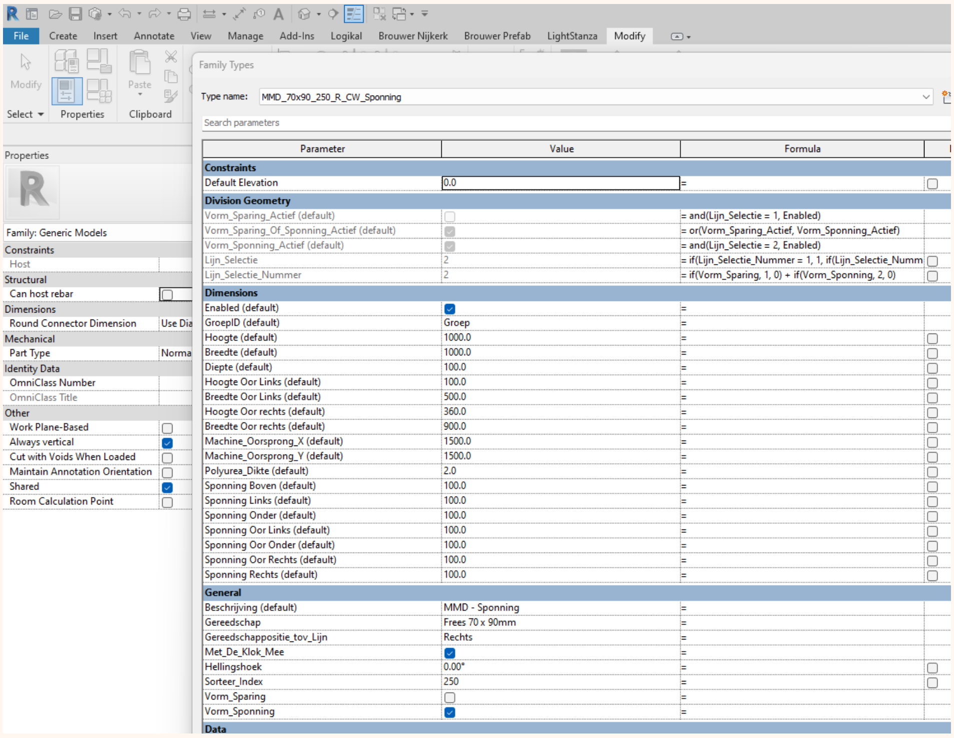

Figure 49. Revit family editor which shows parameters used by BTL data generation

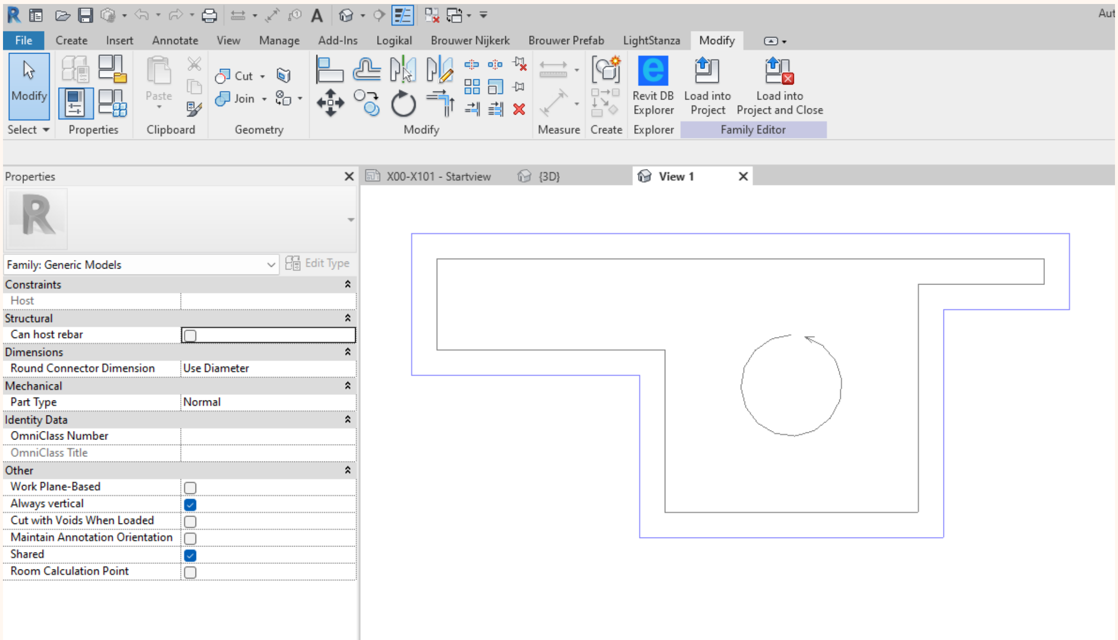

Figure 50. The BTL family gives a preview of the CNC actions

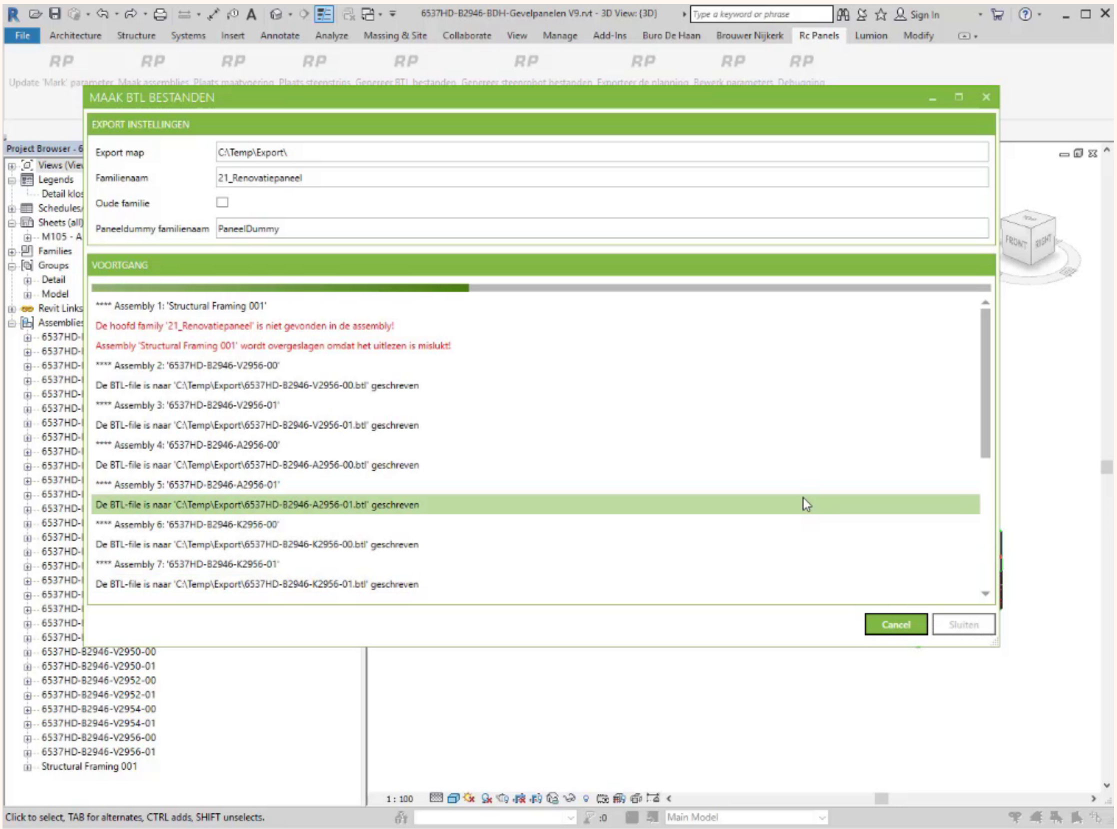

Figure 51. The Revit BTL AddIn which generates BTL files

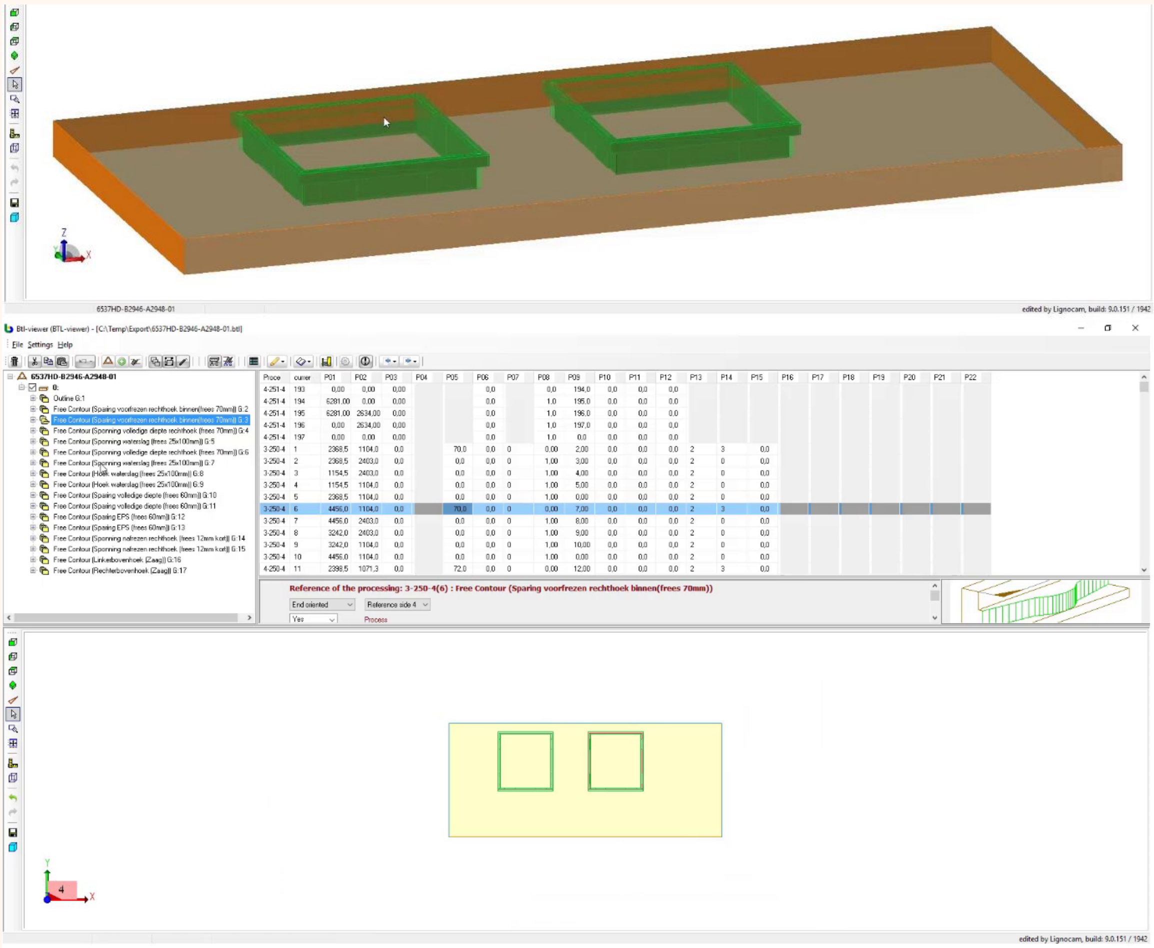

Figure 52. The generated BTL file in the BTL Viewer specified in consecutive order (upper left panel)

Figure 53. The CNC Cutting machine which creates the Rc Panels façade element.

6.2. STONE SLIP LAYING ROBOT

For Rc Panels' stone slip laying robot, another F2F solution was developed (Figure 56). This custom-made machine doesn't have a standard coupling format. The XML format has been determined that is compatible with the factory. BdH also developed a Revit AddIn that generates an image and an XML file based on placed stones in the BIM model (Figure 54; Figure 55). The machine lacks intelligence: each stone in the export file receives an X/Y position and rotation. This gives BIM modelers and architects freedom in stone patterns without modifying the machine. The AddIn also generates an image of the panel with the stones to assist the operator at the machine, ensuring correct panel placement.

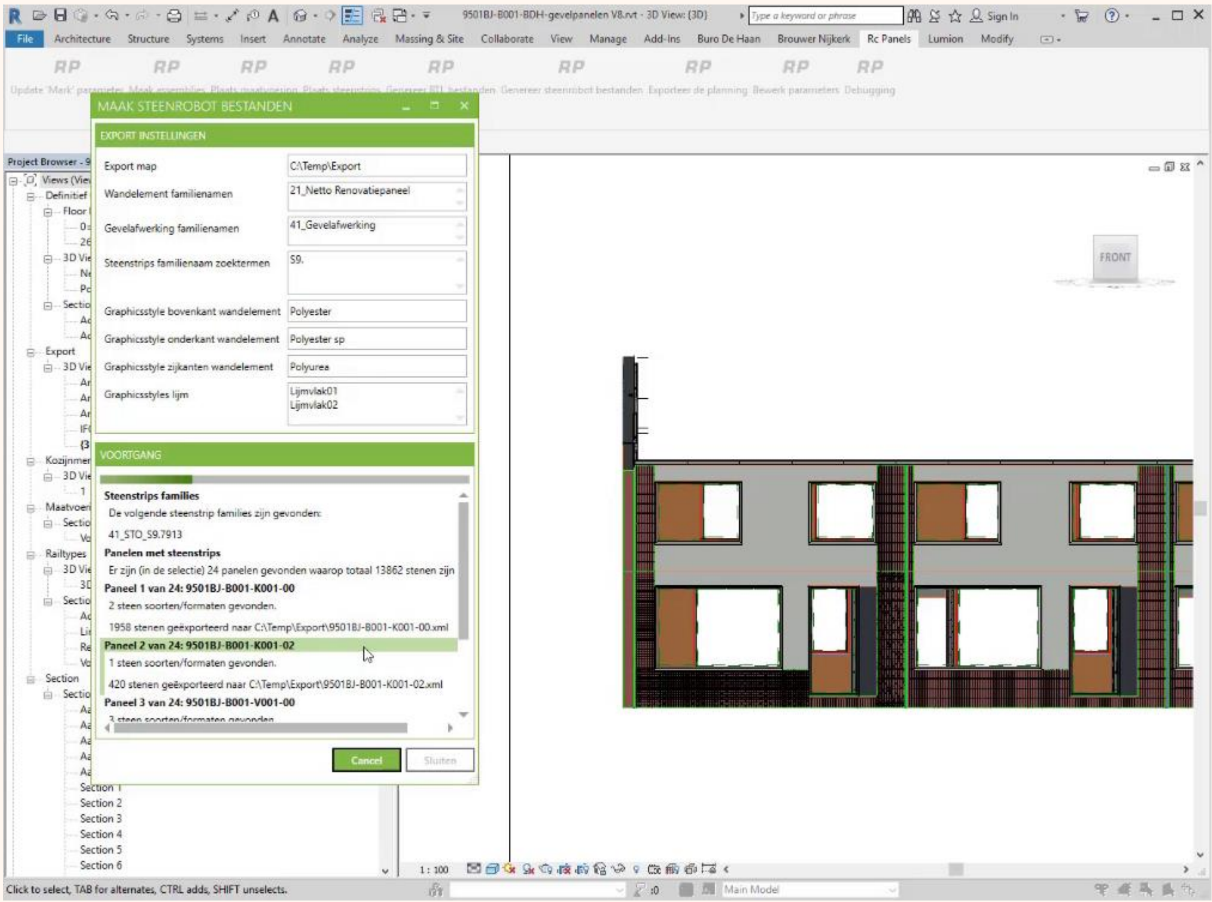

Figure 54. The Revit XML AddIn for exporting to stone slip laying robot.

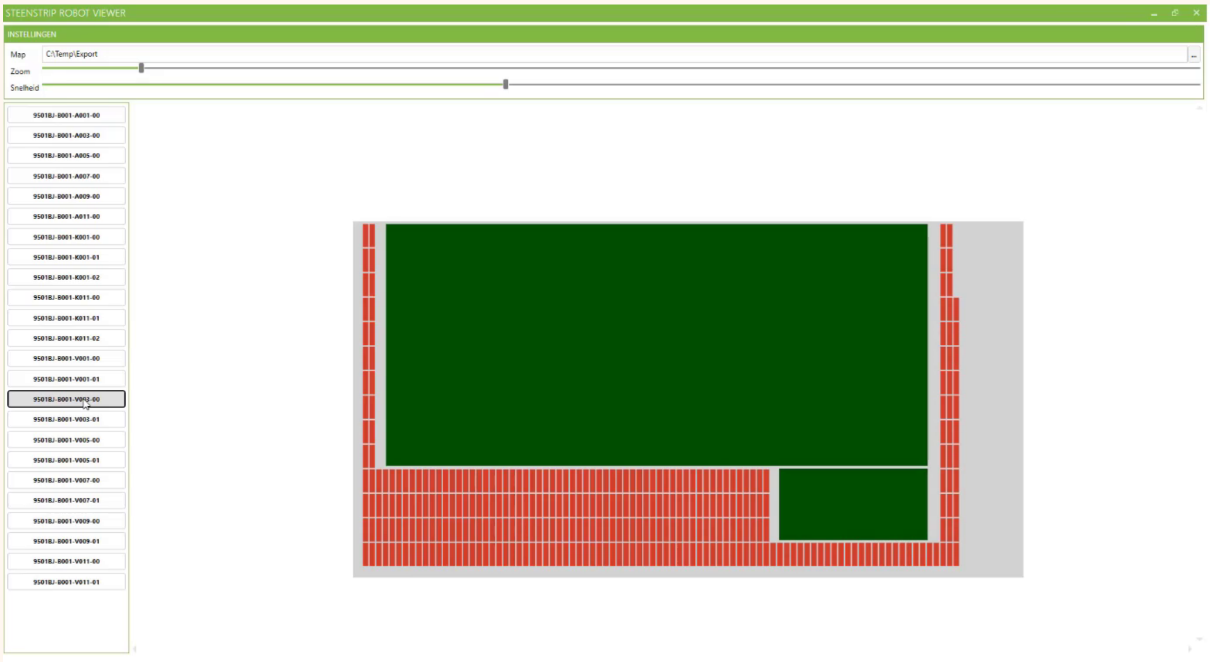

Figure 55. Test application which reads generated stone slip robot files and visualizes the layout.

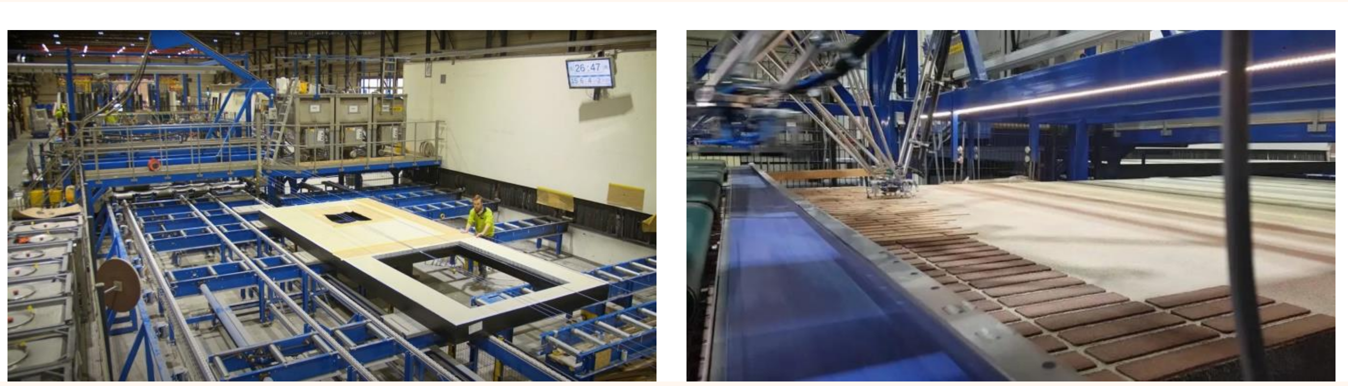
Figure 56. Left: Overview of the stone slip laying robot at Rc Panels, featuring a prefabricated façade to receive stone slips. Right: Close-up of the stone slip laying robot at Rc Panels.

7. DISCUSSION & CONCLUSION

Digitalisation is key to move towards a radically more productive construction industry. The current study highlights the different domains in which digitalisation may accelerate the selection, design, evaluation and fabrication of product systems for building retrofitting. It is stressed that to create an economy of scale, product systems must be designed with a more thorough consideration of the variety of the building stock. This variation can be made more apparent by the proposed digital tools, but is still a major topic of future study.

A workflow is presented that aims to accelerate large-scale PEB retrofitting by developing a range of subsequent digital tools that are part of the pre-recognition, pre-manufacturing and File2Factory workflow. The following section summarises the efforts to develop these tools, reflects on their capabilities and potential for future developments. Despite the potential of the presented methods, they are largely limited to a technocratic approach, meaning that socio-economic studies are considered an essential counterpart.

Rooftop and façade computer vision to extend data availability

The developed rooftop and façade recognition models extend the amount of information on existing buildings that can be derived from public data, for example the recent presence of PV-panels or the window-to-wall ratio of the façade. The main contribution of this study is a method that produces a national rooftop superstructure dataset focussed on multi-residential buildings.

Previous studies have employed CNN on aerial imagery or point cloud segmentation for rooftop recognition in Western Europe, focussing on specific elements such as PV and/or roof superstructures in general (Apra, 2022; Apra et al., 2021; Krapf, Kemmerzell, Khawaja, et al., 2021; Krapf, Willenborg, et al., 2022; Wu & Biljecki, 2021). These studies show pathways to estimate solar potential from our findings that have not been fully exploited yet in this study. However, these studies focus either on classifying rooftop superstructures within smaller rural regions, or on the national building stock with a more generic approach to rooftop superstructures. Based on current knowledge, this study pioneers in demonstrating instance segmentation of rooftop superstructures on post-war multi-residential buildings in both rural and dense urban regions; allowing for detection and classification of more complex residential building rooftop superstructures on a national scale.

The acquired rooftop dataset informs e.g. which buildings have PV-panels, what the free available roof space is for installations, and allows the expansion of current building information datasets by including smaller rooftop superstructures with specific classes. It must be further explored whether the distribution and types of superstructures can elicit properties such as bay width, heating infrastructure and high obstructions for placing product systems. These properties can then be further utilized in project selection and parametric design.

Current models are trained and predict on Dutch aerial imagery and private street view imagery, however the model architecture and choices for classes are scalable to different countries depending on the resolution of available imagery.

The POCs in this study to derive façade dimensions based on street view imagery and point clouds are still in an early phase of development and have only been deployed on a small set of test buildings. However, similar studies on CNN for façade recognition have shown its potential to derive window-to-wall ratio, positioning and dimensions of window frames to feed the façade panel configuration of the pre-manufacturing workflow (Ayenew, 2021; Szcześniak et al., 2022).

From building system typologies to building DNA

It can be concluded that we don't necessarily need information about building systems. We need the specific building construction methods of how buildings were constructed to make the identification of a building DNA. But because building systems are well documented it is a useful starting point to identify the characteristics. A decomposition of apartment buildings is therefore needed to create a comprehensive approach towards characteristics and create a building DNA.

Unsupervised clustering with the Building similarity index

A novel unsupervised clustering method was developed to determine similarity of buildings based on an unlimited variety of building properties. Based on current efforts the 2D building footprint together with chosen building properties do not bring forth clusters that correspond with known building system typologies. However, it is notable that on a national level, buildings in the same neighbourhood are often assigned high similarity, despite the clustering method not having received information on location.

When a building of high potential for retrofitting is identified, the Building Similarity Index may be a promising method to quickly identify buildings with a similar compatibility for the proposed product system. More research is necessary to test the effect of more building properties, as well as to validate the applicability of the Building Similarity Index to contribute to large scale retrofitting.

GIS data collection of relevant building properties for project selection and pre-manufacturing workflow

A dataset of >40.000 complexes was created based mainly on BAG, PDOK aerial imagery and 3DBAG derived from AHN4.0 (BAG, PDOK, AHN4.0 are all accessible via the EU INSPIRE Geoportal), covering 31 building properties that were of interest for the discussed product systems. From Table 4 it is clear that not all relevant building properties were successfully obtained within the study period.

In summary, some features were not obtained on national scale due to manual collection (e.g. entry type, heritage conservation area), confidentiality (e.g. housing corporation portfolio) or lack of scalable research methods (e.g. bay width). Despite the current lack of these features, it must be highlighted that this information is of interest to be obtained in future research.

Identifying high potential project locations for the Alpha module

The obtained dataset allowed to filter 1324 out of 47200 identified post-war complexes with high potential for the placement of the Alpha module based on a few criteria defined by expert opinion.

Within this selection however, it was clear that former retrofitting activities are not always registered and must be detected by future data analysis methods such as façade computer vision of materialisation. The open-source web environment allowed for a fast communication of potential projects for the Alpha module to be placed, with a connection to the PostGIS infrastructure through a QGIS server. The use of open-source applications for both offline and online GIS environment in the presented Pre-recognition workflow may stimulate a fast uptake by fellow researchers in Industry 4.0.

The data obtained in the pre-recognition workflow on technical potential and permitted building height facilitates the early start of the permitting process for product systems. By enabling the generation of preliminary quotes with minimal engineering efforts, the workflow speeds up the decision-making process for renovation projects. This allows for an earlier provision of a price estimate and helps clients in financial considerations without intensive engineering, thus requiring fewer man hours. This streamlined approach not only reduces overall construction time but also improves project efficiency and execution. Ultimately, the pre-recognition workflow at itself could increase market uptake for renovation product systems.

Data-driven design of the Alpha solar module

The parametric design of the Alpha module is a demonstration of connecting data of the pre-recognition workflow (e.g. building dimensions) to the pre-manufacturing workflow, with results that are close to instructions for File2Factory. The parametric model enables rapid configuration of parameters that may influence cost and sustainability by adjustable PV panel types and intended material intensity. The current model still assumes rectangular surfaces and no significantly high obstructions. Integration of more complex building footprints from GIS and as well as the positioning of high rooftop superstructures. The model still requires tabular data as input, with potential for a seamless connection to a GIS environment. The results of the parametric model enable solar potential calculation, but additional information on building energy demand and grid stability is necessary for further automatic energy configuration.

The data obtained in the pre-recognition workflow on technical potential a permitted building height facilitates the early start of the permitting process for product systems. By enabling the generation of preliminary quotes with minimal engineering efforts, the workflow speeds up the decision-making process for renovation projects. This allows for an earlier provision of a price estimate and helps clients in financial considerations without intensive engineering, thus requiring fewer man hours. This streamlined approach not only reduces overall construction time but also improves project efficiency and execution. Ultimately, the pre-recognition workflow at itself could increase market uptake for renovation product systems.

Accelerating quotations and File2Factory of pre-fab façade panels

An interface was created to accelerate the quotation process for façade panels. The interface allows a building owner to access tools for digitally measuring façade dimensions, choosing façade panel types and planning their placement all in one place, exporting a list of the required quantity and dimensions per façade type. Further development will integrate the proposed façade computer vision, photogrammetry and point cloud recognition to extract the required dimensions of façade panels. Besides dimensions of the façade panel, the catalogue of available panel designs in terms of material and colour can be extended in synchrony with the File2Factory options for Rc Panels.

These choices should also be reflected in a BIM model which will be generated based on project created in the quotation accelerator.

Conclusion

The current study has demonstrated several digital tools that aid in accelerated quotation for two product systems based largely on public data. It must be noted that the data requirements for the Alpha module are quite distinct from RC Panels, having also resulted in a set of different interfaces and tools.
In summary, digital tools for the Alpha module comprise selecting a project based on open data and forwarding building dimensions to a parametric design model, which results in a potential PV energy calculation. On the contrary, for RC Panels projects of interest are manually selected, building dimensions are extracted from façade recognition tools, and plugged into configuration interfaces. These configuration interfaces aid in the design of product instructions ready for File2Factory. In the future, it is of interest to cross-pollinate these efforts, e.g. using the façade recognition model to derive bay widths, and the parametric design approach for faster configuration of RC Panels.

Current efforts have brought about a range of tools that are however not yet connected into a single sequence of pre-recognition, pre-manufacturing workflow, File2Factory and bid a promising avenue for further research.

In conclusion, the digital tools developed in D5.1 create novel opportunities for accelerating market uptake of product systems that can realise Positive Energy Buildings. The pre-recognition workflow finds its roots mainly in INSPIRE harmonised public datasets, which leaves opportunities for adapting to public datasets of other European countries. It is believed that the framework of the pre-recognition, pre-manufacturing and File2Factory workflow functions as a canvas to scale up other renovation product systems in the future.

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10. APPENDIX A – GLOSSARY OF TERMS

Table A.1 Terms and abbreviations used in the report.

Term/Abbreviation	Description	References
CPCC	Climate Positive Circular Communities.	See ARV Deliverable D2.1 for a detailed definition of CPCC
GIS	Geographic Information System	
BIM	Building Information Model	
Residential unit	Point data coupled to address and function (residential/commercial/office/..) of area in building	BAG: Verblijfsobject
Premise	Building or part of building holding residential units	BAG: Pand
Complex	A unit of connected multi-residential premises delineated by BAG	4.3.4
KPI	Key performance indicator	
CNN	Convolutional neural network	Teuwen & Moriakov, 2020
CEC	Citizen Energy Communities	See ARV Deliverable D2.3 for a detailed definition of CPCC

11. PARTNER LOGOS

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