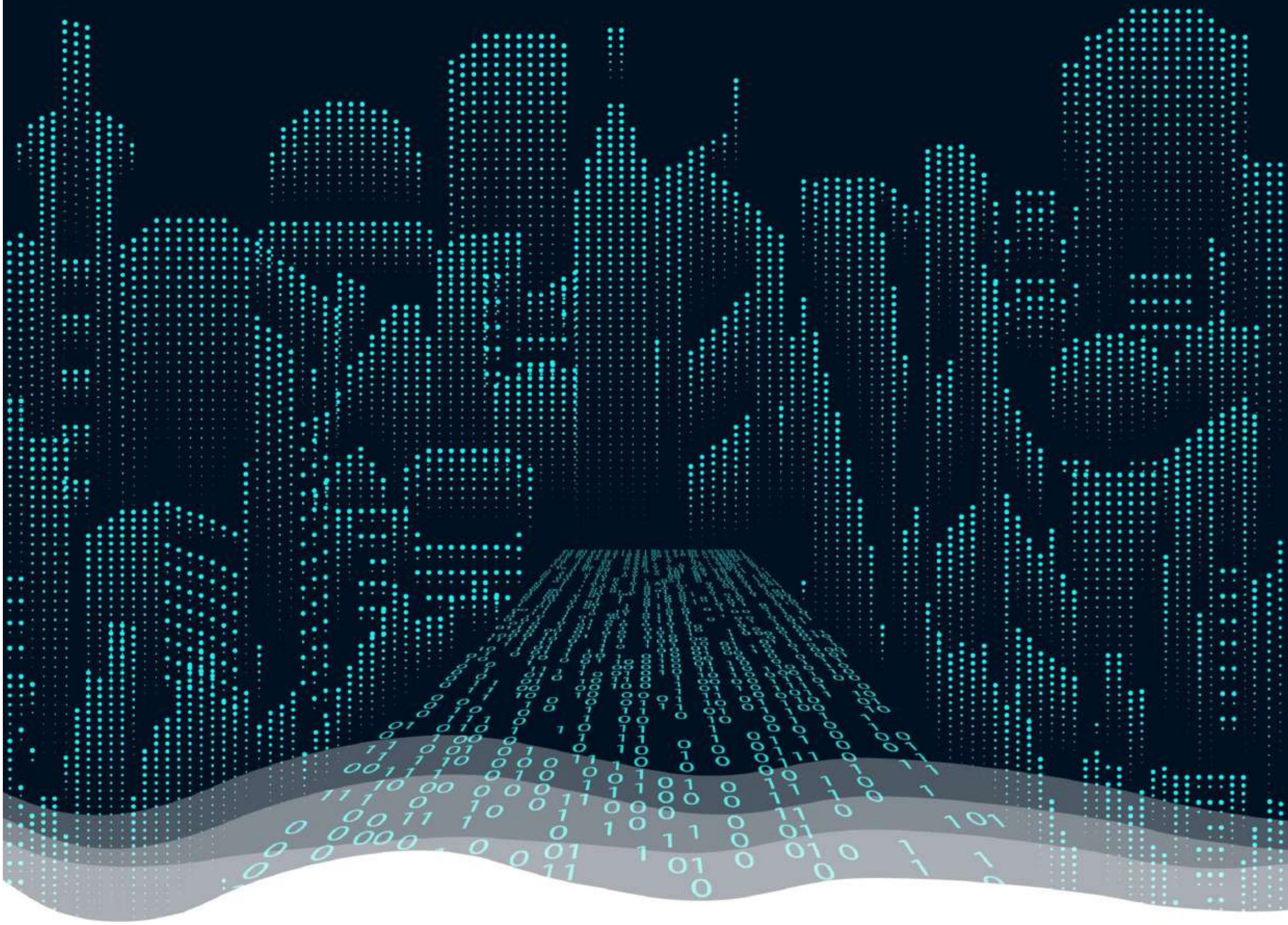
# Proceedings of the 2nd 4TU/14 UAS Research Day on Digitalization of the Built Environment

# PROCEEDINGS OF THE 2nd RESEARCH DAY ON DIGITALIZATION OF THE BUILT ENVIRONMENT



**27-MARCH-2023**
**EINDHOVEN**
**THE NETHERLANDS**

**EDITED BY:**
**EKATERINA PETROVA**
**PIETER PAUWELS**

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4TU.Built Environment

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# 2nd 4TU/14UAS Research Day on Digitalization of the Built Environment

## Proceedings of the 2nd 4TU/14 UAS Research Day on Digitalization of the Built Environment

March 27, 2023

Eindhoven, the Netherlands

Edited by

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## Preface

The 2nd 4TU/14UAS Research Day on Digitalization of the Built Environment was held in Eindhoven on the 27th of March 2023. The event was hosted by the Information Systems in the Built Environment (ISBE) Research Group at Eindhoven University of Technology. The Research Day gathered 75 attendees from the four Dutch Technical Universities (4TU) and 14 Universities of Applied Sciences (14UAS), as well as participants from their extended network. The attendees presented results, exchanged ideas, and shared experiences related to research and education within the area of digitalization of the built environment. The proceedings contain the extended scientific abstracts that were accepted for presentation at the event.

The Research Day on Digitalization of the Built Environment is one of the core activities of the Digitalization research initiative, which is part of the 4TU. Built Environment Center. The 4TU.Built Environment Center is a collaboration between the following five departments of the four Dutch TUs:

- Built Environment, Eindhoven University of Technology
- Architecture and the Built Environment, Delft University of Technology
- Civil Engineering and Geosciences, Delft University of Technology
- Engineering Technology, University of Twente
- Environmental Sciences Group, Wageningen University & Research

Furthermore, the Digitalization group is completed by partners from the 14 Dutch UAS, including:

- Hague University of Applied Sciences
- Hanze University of Applied Sciences
- Inholland University of Applied Sciences
- Saxion University of Applied Sciences

The present Research Day is the second annual event of the 4TU. Digitalization initiative.

The Proceedings of the 2nd 4TU/14UAS Research Day on Digitalization of the Built Environment present an overview of the program, as well as the names of the individuals and organisations who contributed to the technical program and organization of the event. Each submitted extended abstract was peer reviewed by at least two reviewers drawn from the scientific committee consisting of 4TU/14UAS researchers. As a result of the peer review process, 14 extended abstracts were accepted for presentation at the Research Day and included in the proceedings. The contributions were presented during two sessions and cover topics focusing on:

- Data modelling, management and visualization
- Building Information Management and City Information Management
- Analyses and simulations for the planning and design of buildings, urban spaces and infrastructure
- Digital Twins and Artificial Intelligence in the built environment
- Combining model-driven (BIM) and data-driven (ML, AI) design methods

- Smart buildings and infrastructure
- Industrialization & smart manufacturing systems
- Robots and 'cobots' on the building site
- VR/AR/MR/xR for design and life cycle management in the built environment

The proceedings are available as Open Access publication at no cost from the TU/e library.

In addition, a separate Demo Session gave participants the opportunity to demonstrate software and tools developed as part of research and education projects that aim to respond to challenges pertaining to the topics mentioned above.

Finally, the Research Day was concluded with a panel discussion on the future digital built environment from both research and education perspectives. The participants also had a chance to explore an urban Digital Twin via a VR-based driving simulator.

Besides the technical content in the presentation sessions, the demo session and the panel discussion, the Research Day also gave the opportunity for community building and networking in an informal setting.

We would like to thank the 4TU/14UAS community and scientific committee for their contributions and support during the peer review and development of the program; 4TU.Built Environment Center and Maaike Riemersma for the invaluable support that made this event possible; Maikel Brinkhoff for his invaluable support with the digital presence of the Research Day and the 4TU Digitalization initiative, as well as Karin van Nisselrooij-Steenbergen and Leanne Sanders for the invaluable help with the event organization.

Special thanks to Atasi Bhattacharjee, Christian Struck, Faridaddin Vahdatikhaki, Giorgio Agugiaro, Hans Voordijk, Léon Olde Scholtenhuis, Maikel Brinkhoff, Olivia Guerra-Santin, Perica Savanović, Ramon Vlaar, Rizal Sebastian and Roel Loonen for their extended support and contribution during the development and execution of the technical program of the event, before and during the day.

To all 2nd 4TU/14UAS Research Day on Digitalization of the Built Environment attendees: we are grateful that you took the time to contribute and share this day with us. We sincerely appreciate your participation in the event. We hope that the event renewed previous friendships and collaborations, conceived new ones, and provided opportunities to learn from each other. We hope that you leave enriched with new ideas and motivation, and we look forward to experiencing the fruits of the day's interactions and inspirations in upcoming events!

Dr. Ekaterina Petrova & Dr. Pieter Pauwels,

Organising Committee

**Organising Committee**

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## Table of Contents

# Smart Digital Infrastructure

## Developing a Lifecycle Digital Twin for asphalt pavements; A semantic modelling approach

*Inga Maria Giorgadze, University of Twente, i.m.giorgadze@utwente.nl*

***Abstract –*** *The current way of representing the asphalt failure modes impedes the creation of a lifecycle digital twin for roads, with the hindering factor being the lack of semantic representation of these failures. Missing such a structured approach for data representation hampers the linking of the lifecycle information and hence the insight into the failures propagation mechanism that would enable accurate predictions as dictated by the application of Digital Twins. The following is a work in progress addressing the development of a methodology for the semantic modelling of asphalt failure modes.*

Maintaining a good condition of the pavement infrastructure is a complex task for the different road authorities, especially in The Netherlands considering the density of the country's network. A proactive and predictive maintenance approach requires insight into the degradation mechanism of the pavement. To this end, the road condition data should be collected, stored, and analyzed across the entire lifecycle of the asset and associated with other relevant data (e.g., design, construction and use).

Linking the data from different lifecycle phases has been addressed using lifecycle digital twins in other sectors such as manufacturing, aerospace, energy, automotive, marine, petroleum, agricultural, healthcare and mining (Enders et al., 2019). The creation of a lifecycle digital twin requires a harmonious and coherent data structure and representation which is currently missing in the way road condition data is stored and represented. More specifically, the asphalt distresses are currently stored and represented solely geometrically, lacking a semantic representation which would enable a detailed analysis of the causes of different types of failures. This restricts the usability of the condition data regarding the traceability of the failures, the application of logic rules and the continuity of information throughout the lifecycle. Thereby, semantic enrichment processes are expected to address data representation limitations, elevate the machine's comprehension capacity of the virtual models and create communication channels between humans and computers. This research is a work in progress that aims to address the above-mentioned limitation by proposing a methodology for the semantic representation of asphalt distresses.

Regarding the state of the art of asphalt failure representation several forms of data such as point clouds, digital images, thermal images and sensor data from laser scanners, cameras, thermal imaging devices, sensors and other devices have been used to obtain geometric forms of pavement distresses (Jiang et al., 2021). Some initial approaches for semantic enrichment of these raw forms of data include manual annotation with images (Ji et al., 2020), the use of bounding boxes projected on images (Majidifard, 2020), the use of images for the calculation of the depth of potholes and further generation of the respective 3D meshes (Moazzam et al., 2013). Three-dimensional reconstructed mesh models have widely been adopted for the detection, representation and assessment of cracks, potholes, swelling, rutting and subsidence (Kalfarisi et al., 2020; Qiao et al., 2016). Finally, GIS software has also been suggested to plot delineated segments and geo-reference annotated pictures (Abdelaty et al., 2018; Silyanov et al., 2020). Overall, these cases indicate a variety of visualization techniques for the asset's condition during the O&M phase. However, these efforts are still conducted in isolation from other lifecycle phases.

Up to this moment, this research has implemented a few iterations between exploring different modelling possibilities and solution-designing activities for building a scalable visualization platform that can support the incorporation of lifecycle information. Single failures have been modelled as independent families in Autodesk Revit via the use of a Dynamo script. Unfortunately, the existing IFC schemas do not support the exportation of semantic properties of these entities, as they are not standardized classes. Therefore, in the current design iteration, the failures are visualized as polygons in GIS shapefiles via the use of Python scripts. The GIS environment is selected for its scalability potential. In other words, it is easy to navigate through both single failures but also aggregated failures for street segments of different sizes. Apart from the scalability of the condition overview, GIS allow the incorporation and visualization of temporal information as well, which sheds light on the behaviour and propagation mechanism of the failures. Overall, the final product is envisaged as a multilayer visualization structure that offers an integrated environment where the users will be able to navigate through different scales of data representation, from road segments to single failure entities, while enhancing 4D simulations to represent the damage evolution. Altogether, the proposed methodology is expected to offer a framework for a consistent representation of failure data by properly linking them through the road's lifecycle, as well as by incorporating the time component in the representation of the failures. On the basis of such a structured virtual model, it will be possible to implement a Lifecycle Digital Twin for pavements.

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# Excavation Damage Prediction by Machine Learning Approach

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***Abstract –*** *Excavation damages to underground cables and pipelines have serious economic and societal consequences. Data-driven analysis and prediction methods for such damages have not fully been explored and exploited but are promising since excavation and damage data are collected fairly systematically. As first step towards this goal, this study aims to develop a machine learning approach that accurately predicts utility strikes. To this end, we compared the accuracy, explainability and efficiency of three gradient boosting models, including XGBoost, LightGBM and CatBoost. These classifiers achieve Area Under the ROC curve (AUC) scores around 0.83. The result demonstrates the usefulness of gradient boosting approaches as a means to predict damages and shows how data collection and preprocessing can be improved increase reliability of predictions in the future.*

The Netherlands' construction industry has reported more than 40,000 excavation damages to underground cables and pipelines ("Feiten en cijfers over schade door graafwerkzaamheden 2021 - Publicatie - Agentschap Telecom," 2022). Construction organizations use expert opinion to interpret annually reported data about damages and excavation operations. Based on this, they develop policy to lower the number of damages. Recently, historical data has also been used for prediction of excavation damages. These predictions, however, included only a limited number of prediction factors (features) and utility network types. This study, therefore, develops a means to predict probabilities of utility damages by using machine learning approaches, which include historical excavation project features and more relevant features (e.g., land use type and soil type).

To identify the required data needed to train machine learning algorithms, we explored the literature on excavation damages. The literature indicates that there are a wide range of factors that cause damages to buried assets, and that these ultimately lead to different impacts and costs (Metje, Crossland, & Ahmad, 2015). Similarly, a Dutch study by SOMA College and University of Twente on improving safety risk awareness training shows that causes of incidents can be different, and for example relate to behavioral and communication aspects, training, technology, or information (olde Scholtenhuis, 2018). Examples features from the literature that can be included in prediction models are: attributes of excavation work and excavation companies, land use type, soil type and cable/pipeline density.

Machine learning is an artificial intelligence technique allowing computer systems to make predictions using past experiences (Baştanlar & Özuysal, 2014). Excavation damage prediction can benefit from machine learning by training models on historical data of excavation projects and damages to predict the likelihood of damage for future projects. Gradient boosting models are mostly used because of their advantage in training large dataset efficiently with high prediction accuracy and the ability to provide feature importance. They are also applied by previous excavation damage prediction projects from Agentschap Telecom and Alliander. A testing though PyCaret validates the good performance of Gradient Boosting models in this problem. EXtreme Gradient Boosting (XGBoost) is picked for its good performance in Kaggle competitions and result from previous studies. Light Gradient Boosting Machine (LightGBM) and Categorical Boosting (CatBoost) are selected for their advantages in dealing with categorical values.Previous prediction work used historical damage and excavation data of 2014 to compare logistic regression, decision tree and random forest models. The work shows that the latter performs best (Meijer, 2017). Similarly, utility owners of Enexis, Alliander and Stedin used their own network data, and applied the models LightGBM and XGBoostThese models were pragmatically chosen but show that tree and gradient boosting models can be successfully applied for prediction purposes.

To fulfill the goal of this study, we apply the workflow in Figure 1 modified from the data mining cycle (Jackson, 2002). We firstly collected and cleaned data. Excavation dataset and damage dataset of 2021 from Kadaster, landuse data of 2017 from CBS, soiltype data of 2014 from Basisregistratie Ondergrond (BRO), and tree density data from Rijksinstituut voor Volksgezondheid en Milieu (Rijk) are used. The dataset after cleaning and encoding has 769,398 observations and 126 variables. Then we conducted a literature review and Pycaret testing (Python) to select a prediction model. For each model, we pre-processed data, trained the model, selected features, conducted hyperparameter tuning, and trained the optimized model. Finally an evaluation was conducted on the accuracy, efficiency and explainability of the classifiers. Evaluation metrics of Area under the Receiver Operating Characteristic Curve (AUC score), Area under the Precision-Recall Curve (PR score) and balanced accuracy are calculated.

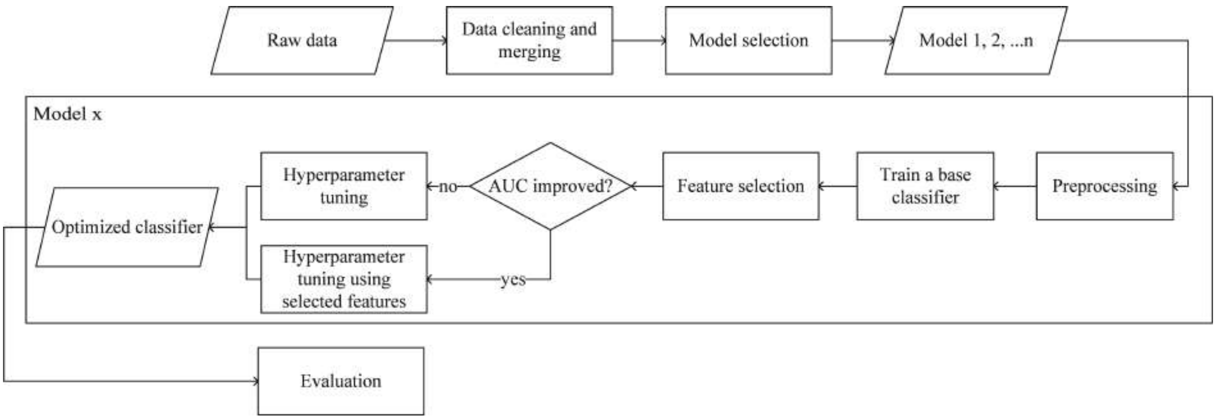


Figure 1: Applied machine learning workflow

The overall result in Table 1 shows an acceptable AUC score and balanced accuracy more than 0.80 and 0.70, but a low PR score around 0.19. CatBoost has higher AUC, PR and balanced accuracy scores than XGBoost and LightGBM, but it requires significantly more training time. Further, all models are explainable as they can indicate the usefulness of features in building decision trees.

After training and feature selection, we found that the following features help explain damages: excavation polygon geometry (i.e., perimeter, number of vertices, surface area), company name and client company name, lead time between utility map data request and excavation day, weekdays (of requesting and excavating), and land use type of build-up. There are differences among the three models in interpretation. LightGBM, for example, interprets that client company and excavation company features are significantly more important than rest of the features.

Table 1: Evaluation of classifiers in excavation damage prediction

| Model | XGBoost | LightGBM | CatBoost |
|---|---|---|---|
| Features used | 63 | 63 | 125 |
| Training time (s) | 28 | 10 | 480 |
| Predicting time (s) | 2 | 2 | 4 |
| **AUC score** | **0.829** | **0.827** | **0.833** |
| PR score | 0.186 | 0.185 | 0.193 |
| Balanced accuracy | 0.749 | 0.743 | 0.749 |
| Precision | 0.090 | 0.100 | 0.110 |
| Recall | 0.660 | 0.610 | 0.620 |
| F1-score | 0.160 | 0.180 | 0.180 |

We found that gradient boosting models can efficiently predict excavation damages while dealing with imbalanced data, missing value and categorical features. XGBoost, LightGBM and CatBoost models are explainable and show similar prediction accuracy: their poor PR curve and PR score shows the limitation of classifiers in predicting positive cases. Due to the limitation in data matching and encoding of company names, future improvement can be done on the data collection and preprocessing.

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# Coupling road construction process quality indicators with product quality indicators

*Qinshuo Shen, University of Twente, q.shen@utwente.nl*

***Abstract –*** *The correlation between the road construction process quality and product quality is treated implicitly and intuitively in the current quality assurance. To address this issue, this research proposed a data-driven approach to perform machine learning regressions and develop predictive models for multiple pavement product quality indicators, including density degree, pavement residual lifespan, and pavement roughness, achieving R2 of 0.1954, 0.8297, and 0.8284 respectively. Model interpretations were also performed, demonstrating the considerable importance of construction process quality indicators in contributing to the predictive performance of the developed models.*

The steadily growing demand for road infrastructure and lengthy guarantee periods has created strong momentum in the asphalt construction sector, obliging contractors to adjust their strategies from a quality-driven perspective. This would require an explicit understanding regarding the correlations between the road construction process quality and pavement product quality.

However, the asphalt construction sector is notorious for its high reliance on craftmanship and experience-based decision-making, rendering the quality assurance practice a challenging task. To cope with this issue, the methodology of Process Quality improvement (PQi) has been proposed to closely monitor the asphalt construction operations, with the aim of improving the performance of the asphalt layer during the operation phase by identifying the root causes of variability in the asphalt construction process (Miller, 2010). Specifically, the PQi framework quantitatively measures and analyzes the variability during the asphalt construction process, thus providing the assessment of the construction process quality and feedback to the contractors (Bijleveld et al., 2015; Makarov et al., 2019, 2021). However, although the operational strategies and other key construction process parameters have been explicitly monitored and assessed, the extent of the impact of construction process quality on pavement product quality is still unknown, primarily owing to the system's non-linearities.

In the past few years, great attempts have been made to develop empirical models to explore the possibility of predicting the corresponding pavement product quality using data-driven techniques (Gong et al., 2018; Li, Yin, et al., 2022; Li, Zhang, et al., 2022; Mazari & Rodriguez, 2016). However, these previous studies have neglected the importance of the construction process quality in affecting pavement product quality. In order to provide a more comprehensive profile of the causal correlation between process and product quality in road construction, it is essential to take the quality of the construction process into consideration.

On these premises, this research aims to explicitly investigate the correlations between the asphalt construction process quality and the product quality, using data-driven techniques to incorporate the historical PQi data with data regarding the product quality of asphalt pavement. The latter will be with a specific focus on the density degree, residual lifespan, and pavement roughness represented by the international roughness index (IRI).

Firstly, the input-output structure of the datasets required for the machine learning (ML) model development was identified, including input variables such as the quality indicator of the on-site operational strategies, weather conditions, mixture type, and auxiliary parameters in the operational phase of the pavement (such as traffic intensity and climate condition). More specifically, the quality indicator of the on-site operational strategies will be represented by the Effective Compaction Rate (ECR), indicating to which extent the compaction meets the requirements considering the compaction temperature windows and target number of roller passes. The outputs of the identified data structure include density degree, residual lifespan, and IRI, covering the short- and long-term perspectives of the pavement product quality.

A Genetic-Algorithm-based ML model development framework was designed. Given the research context, the regression problem will be applied to the ML model development. Specifically, Random Forest (RF) was selected as the ML algorithm due to its promising performance, capability of overcoming overfitting issues, and interpretability. In addition, because of the time-variant nature of the output regarding long-term pavement performance indicators, the time-series regression will also be applied, where Gated Recurrent Unit (GRU) was utilized to tackle the complexities of non-linear regression concerned with time-series data.

For validation, case studies were conducted. The regression of density degree will be based on the data provided by the Dutch contractor Heijmans, collected from a series of construction projects around the Schiphol Airport. For the regression of residual lifespan and IRI, two Dutch highway sections (A58 and A4) with a total length of 4.1 km, were selected. Based on the collected data, the regression model for the density degree using RF failed to satisfy the corresponding requirements regarding the model performance.

For the regression of residual lifespan and IRI, both the RF and GRU were used to develop corresponding models. For residual lifespan, the developed RF model outperformed the GRU model, with an $R^2$ of 0. 8297, while the regression of IRI shows contradictory results, where the developed GRU model significantly outperformed ($R^2$ is 0.8284). After interpreting the permutation importance, both cases show that the construction process quality indicator represented by ECR achieved the third highest importance, revealing the rather high correlation between process quality and product quality in asphalt construction. Figure 1 and 2 illustrate the permutation importance of each input feature from the models obtained for the regression of residual lifespan and IRI respectively.

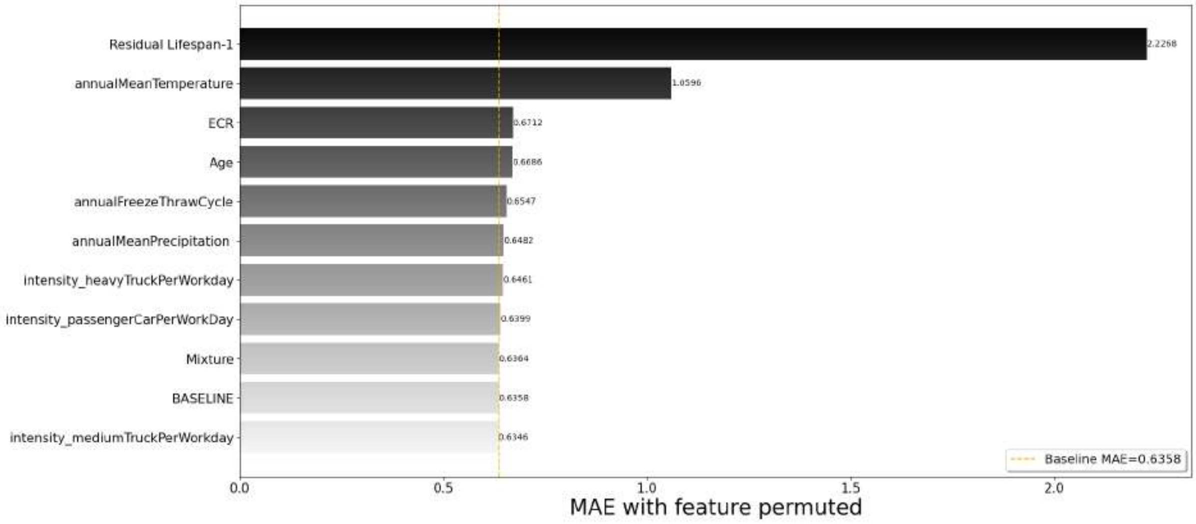


Figure 2: The permutation feature importance of the RF model for the regression of residual lifespan

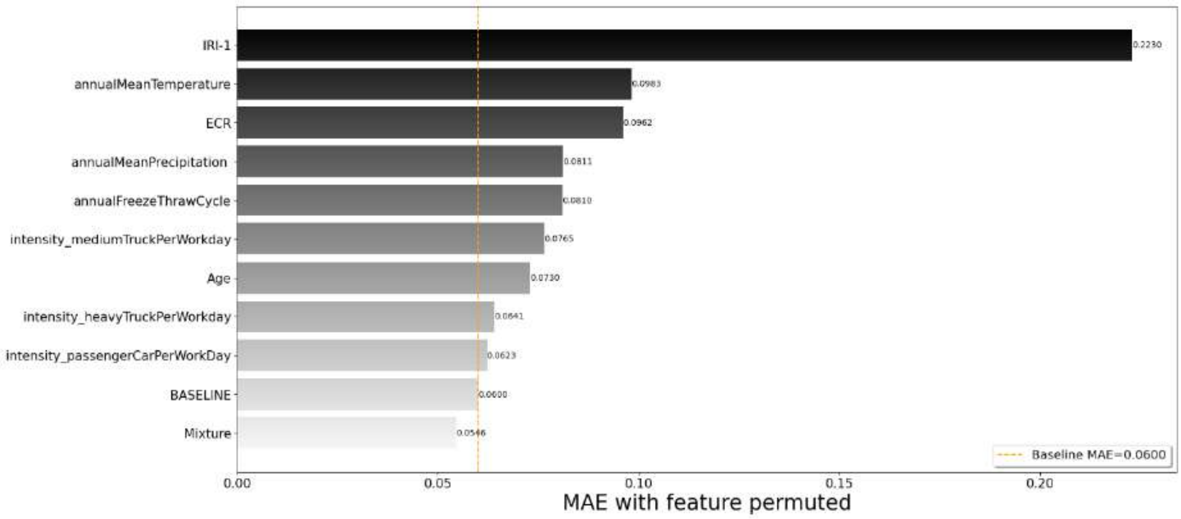


Figure 3: The permutation feature importance of the GRU model for the regression of IRI

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# Demystifying the Urban Heat Island Phenomenon: Through High Resolution Temporal and Spatial Urban Data and Machine Learning

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***Abstract –*** *The risk of heat-related illnesses has risen due to the effects of climate change and urbanization. The Urban Heat Island (UHI) effect has worsened the impact of global warming in the cities, making it crucial to effectively mitigate the phenomenon. However, existing simulation methods are complicated and difficult for users to navigate, leading to a lack of understanding about UHI at the street level. This highlights the need for simpler and more accessible simulation techniques to improve our understanding of the UHI and aid in its mitigation. This research aims to develop a user-friendly UHI simulation tool based on data-driven methods to generate insights into the dynamic nature of the UHI driving mechanism. The research objectives include developing a user-friendly urban data collection pipeline, investigating the spatiotemporal patterns of CUHI/SUHI and their interplay with a wide range of street-level urban planning and socioeconomic parameters, and investigating how CUHI/SUHI is influenced by various street level urban planning parameters when considering different groups of streets. The findings suggest that investigating both CUHI and SUHI concurrently and the socio-economic and morphological features of the built environment at street level is critical to understanding and addressing UHI.*

The impact of climate change on the built environment is a mounting concern as heat waves become more frequent and severe (Wamsler et al., 2013; Bednar-Friedl et al., 2022) heightening the risk of heat-related illnesses (Piracha & Chaudhary, 2022; Shahmohamadi et al., 2011; Mohammad et al., 2022). The Urban Heat Island (UHI) phenomenon, which occurs in urban areas where natural landscapes are replaced with man-made surfaces that trap and retain heat (Oke, 1982), exacerbates the effects of global warming. Efficient mitigation of UHI requires an understanding of how urban design decisions affect both types of UHI - canopy (CUHI) and surface (SUHI). However, current simulation techniques are complex and not user-friendly (Mirzaei, 2015; Li et al., 2019), often take an isolated view of the phenomenon, and focus on building blocks rather than street level analysis, leaving a gap in the understanding of the phenomenon at the street level. To address this, data-driven methods have become increasingly popular in solving complex multi-dimensional problems, providing more user-friendly tools to analyze the phenomenon (Nallaperuma et al., 2019; Eggimann et al., 2017; Sun et al., 2020; Adilkhanova et al., 2022). However, these methods require comprehensive datasets that capture the relevant elements of the built environment at the same spatiotemporal resolution.

Moreover, current methodologies to alleviate the UHI effects often assume that the UHI mechanism is identical across different urban contexts, which recent research has shown is not always the case (Cartier, 2019). A user-friendly UHI simulation tool is therefore necessary to capture and reflect the dynamism in developing mitigation strategies. This research aims to develop a userfriendly UHI simulation tool based on data-driven methods to generate insights into the dynamic nature of the UHI driving mechanism vis-à-vis decision making jurisdiction and different types of UHI. The research objectives include developing a user-friendly urban data collection pipeline, developing a user-friendly tool for assessing the impact of urban planning decisions on UHI at the street level, investigating the spatiotemporal patterns of

CUHI/SUHI and their interplay with a wide range of street level urban planning and socio-economic parameters, performing a comprehensive generalizability assessment of data-driven UHI models, and investigating how CUHI/SUHI is influenced by various street-level urban planning parameters when considering different groups of streets

To achieve these objectives, publicly available urban data were gathered to develop a data-driven methodology that mines explicit rules about the correlation between socio-economic and urban morphology features and UHI at the street level. A tailor-made mobile data collection unit, as shown in Figure 1, was built, and used to collect street level data in Apeldoorn, the Netherlands, to investigate the interplay between SUHI and CUHI. The generalizability of the models was assessed by conducting a comparative study across five different cities from three different countries. Finally, different configurations of urban streets were considered to build different types of streets to investigate whether a disaggregated modeling approach could provide a more accurate understanding of the phenomenon.

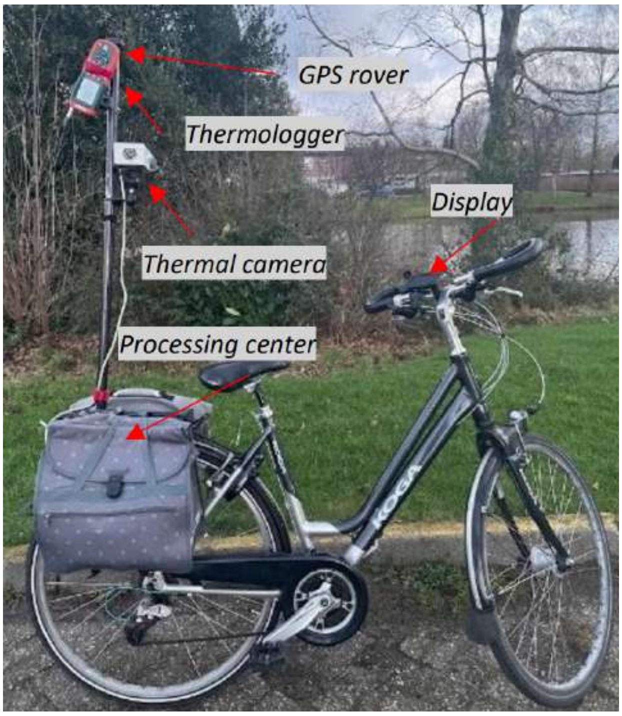


Figure 4: Bicycle-Based Mobile Urban Data-Gathering Station

The findings suggest that investigating both CUHI and SUHI concurrently and considering the time of day and the socio-economic and morphological features of urban streets is critical to understanding and addressing UHI. While data-driven UHI models may be accurate for the cities for which they are trained, their generalizability is limited, emphasizing the importance of tailor-made mitigation strategies. The context-specific nature of the phenomenon highlights the singularities of each city, and street-level typologies can provide a more accurate and context-specific understanding of the phenomenon. This research provides a solid foundation for future studies to build upon and offers practical tools to bring data-driven knowledge to the urban planning design table, paving the way for the design of more heat-resilient built environments.

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# Findings in the calculation of solar irradiance in urban areas using several GIS tools

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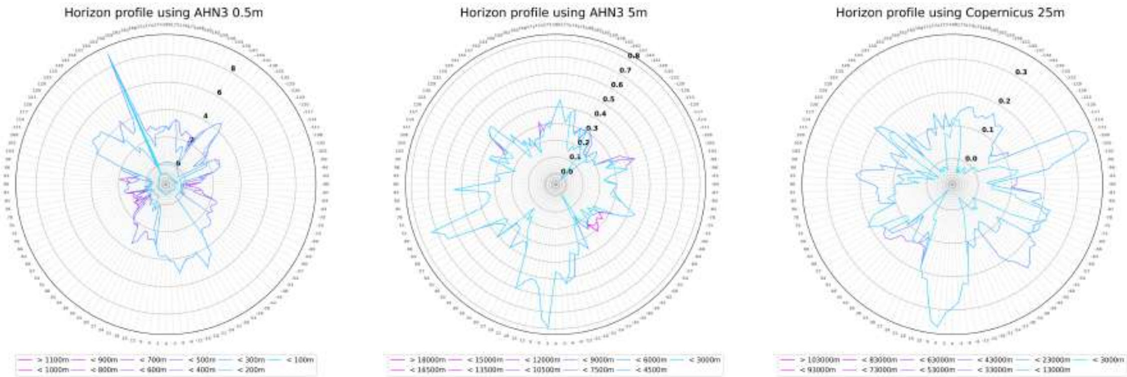
***Abstract –*** *Current GIS software offer tools to perform the solar irradiance calculations. However, these computations based their work on data assumptions or generalisations to speed up their processing time. In this work, a method is shown to perform the calculation using very high and very low spatial resolution open datasets. The results show that there too detailed raster data like 50cm horizontal spatial resolution DSM does not improve the calculations compared to lower resolution datasets.*

In 2018, at least 55% of the global population lives urban areas and by 2023 it will increase to 60% (United Nations, 2018). Wrong quantification of the current and expected energy demand of buildings, will lead to erroneous decisions and misguided planning for energy supply. Solar gains play a major role in any energy demand simulation. For that reason, it is important to have a precise calculation of the solar radiation for a given area of interest. This work shows a method to perform the solar radiation using raster open datasets in the Netherlands and three GIS software tools. Liang et al. (2020) proposes a method to extend the GRASS GIS r.sun model by feeding it with 3D data including 3DCity models and photogrammetric meshes, Gianelli (2021) performs a solar analysis on buildings of favelas in Sao Paulo using several software tools and different input format datasets (raster and 3D semantic City Models)

The proposed method includes the use of digital surface models (DSM) in a raster format at different spatial resolutions. Our purpose is to test the influence of the spatial resolution in the solar irradiation simulations. We use raster-based DSM with different spatial resolutions, the Netherlands current elevation database (Actueel Hoogtebestand Nederland – AHN) at 50cm and 5m (stuurgroep AHN, 2019) and the European Digital Elevation Model (EU-DEM) (European Environment Agency (EEA), 2016). The study is located at the weather station of Heino in The Netherlands. Since we are working with several data sources and different spatial resolutions, we analyse the horizon profile from the weather station at a systematic interval distance to identify changes in the Orography. Once the right distance is found, we evaluate the influence of large distance obstacles in the horizon. The resulting input DSM is used as an input for several Solar Irradiance GIS software tools, this is the case of ArcGIS (esri, 2023), GRASS (Hofierka et al., 2007), SAGA GIS (Conrad, 2010). Simulation results are compared against typical year data open data available by the open climate project (Lawrie & Crawley, 2019) which offers weather data for the whole planet.

First, we calculate the sky view for the very height resolution DSM. **Error! Reference source not found.** shows the resulting sky view of each of the input datasets, from left to right the spatial resolution decreases. Each of the plots contains the same colour palette going from cyan (closest) to magenta (furthest). For the point of interest, the highest obstacle is in less than 200m with an azimuth of 156º and an elevation angle of 9º (**Error! Reference source not found.**A). **Error! Reference source not found.**B and **Error! Reference source not found.**C give show the orography of the up to 18Km and 103Km for the AHN3 5m and Copernicus datasets respectively. For the latter two plots, we remove from the analyses the area covered by the very-high resolution DSM. This indicates that the weather station is not affected by far away obstacles.

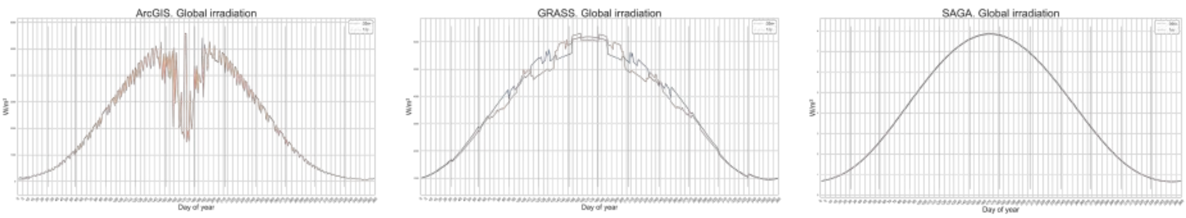



A B C

Figure 5. Horizon profile (Sky view) for the input datasets.

Since there is no change from 1.200m (**Error! Reference source not found.**A), we decided to use as input DSM for the solar irradiance calculations a square raster with a side size of 1200m. We decide to test the influence of the spatial resolution in the calculations, for that reason we resample the 50cm dataset to 1m, which is still a very-high resolution dataset.

**Error! Reference source not found.** shows the year profile for each of the simulation tools for a typical year in the selected spatial resolutions.




A B C

Figure 6. Daily global irradiation by software tool

The vertical thicker lines in **Error! Reference source not found.** indicate the starting day of the month. Despite of ArcGIS, which only request the DSM, we used as input dataset for the Linke turbidity factor the dataset published by Solar radiation Data (SoDa, 2010). Since this is a very low-resolution dataset of 1/12°, we extract the value at each pixel location of the input DSM so there is no difference in the input data resolution when the software tools perform their calculations.

**Error! Reference source not found.** shows the line plot for the global irradiance values of the weather station against the results obtained from the simulation tools.

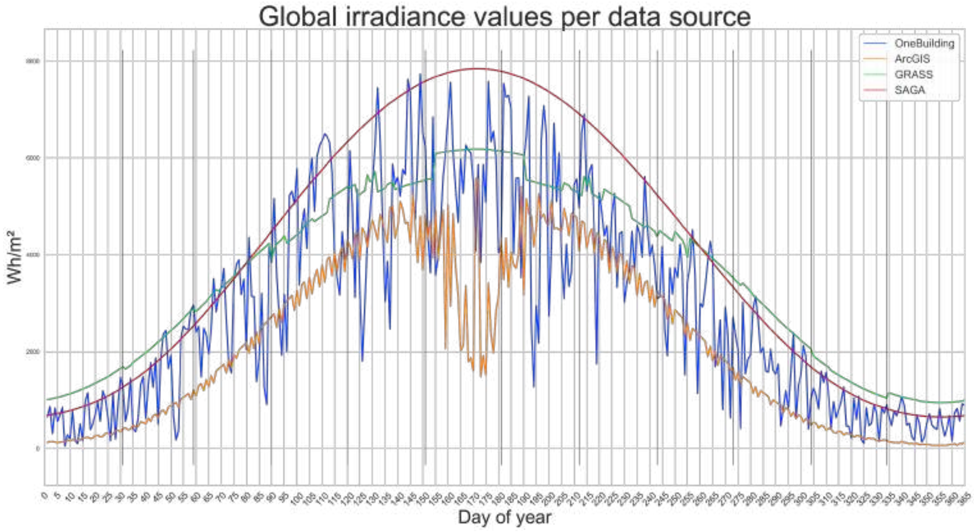



Figure 7. Daily global irradiance values for the weather station and simulation tools

The results obtained by the calculation using ArcGIS shows that there is practically no difference between the results obtained using 50cm or 1m spatial resolution DSMs, which is not the case of the other two simulation tools. ArcGIS values are the lowest one of the three while SAGA produces the highest values. It is possible to see as well that SAGA do not consider weather data for its calculations since the results are quite normalised, not showing the normal cloud behaviour in the sky.

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# Integrating Image Classification and Morphological Processing to Detect 3D Underground Utility Lines

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***Abstract** – Underground utilities need to be registered to support their detection and localization during maintenance and construction work. Current survey practice registers utility lines as geo-information data in 2D, often later enriched with semantic information. Recent technological advancements in 3D modeling of spaces can help advance this practice through the collection of 3D information (i.e., depth of cover, geometry) about deployed utilities on a site. This, however, often requires laborious manual processing. To automate part of the 3D detection and registration, this study aims to detect the location of utility lines from a 3D trench scan. We use a photogrammetric approach, followed by image classification, and morphological processing. Preliminary results from a visual inspection show that the proposed approach successfully distinguishes utility lines from their background.*

Pipeline infrastructures distribute commodities such as fresh water, electricity, and district city heating energy. Damages to these may lead to catastrophes, drastically reduce access to basic needs, and cause economic damage (Hamada 2014). Therefore, registration of utilities at a post-construction stage is essential to support future planning of underground space and to enable safe construction work in urban space (von der Tann et al., 2018). Particularly, linking overground and underground environment data has become a popular research topic recently, since it aids the proper localization of utility lines in a 3D spatial context (Stoter et al., 2013). This integration requires 3D underground models too.

The process of underground utility registration starts with surveying. Current surveying and mapping methods use Real Time Kinematic Global Navigation Satellite Systems (RTK GNSS) positioning methods to register the 2D location of characteristic topological elements of a network. This task is executed by professional land surveyors. They register network elements such as the start and end points of pipe sections, pipe bends, shutters, valves, and cable curvatures. After measurement, the location data for these elements are stored in a geospatial database system. In the Netherlands, this data is then shared via the Land Registry Office with utility owners and contractors who all together contribute to the design, construction, and supervision of excavation work (Scholtenhuis et al., 2017). The current survey process, however, is labor intensive and it results in a sparse dataset that lacks geometric and depth information.

3D reconstruction technology may help improve the current underground registration process through the semi-automatic generation of 3D data This technology has a key feature that it integrates geospatial 3D data such as 3D models, point clouds, and their derivatives (Deng et al., 2021, Nikoohemat et al., 2020). The technology uses photogrammetry to first acquire robust visual and structural information about utilities; and secondly, it uses supervised machine learning methods to recognize visual patterns in the data (Arena et al., 2022).

When combined with methods such as image segmentation, machine learning can be used to extract meaning from images. Feed-forward neural networks (FFNN) can classify images (Touvron et al., 2022). They are applicable to images that have geometries and textures which are similar across various project sites. Excavation trenches have these properties. Utilities, in contrast, have shapes, textures, and colors that deviate from the visual properties of the trench. Given these properties, we have developed and tested a method that combines segmentation and FFNN-based to automatically detect the location of utilities from 3D scans of a constructed utility trench.

The method we developed comprises five main steps, some of which are concurrently executed. First, we create a georeferenced 3D model of the constructed utility line in a trench. This uses GNSS-aided close-range photogrammetry. We attach a GNSS receiver to a smartphone. We used this to take geo-tagged photos of a utility trench that was recently dug (but not backfilled) on a construction site. We use conventional processing structure from motion (SfM) software to translate photos into 3D point clouds, 3D textured meshes, Digital Elevation Models (DEM); and, orthomosaic data. Figure 1 shows elements of the hardware setup of the measurement systems.

Figure 1. The hardware setup of the measurement system. The system includes a GNSS receiver (Leica FLX100+), a smartphone or tablet, and the Zeno Connect app.

Second, we process the DEM data by segmenting the greyscale image of the DEM with a 2D seed region growing method. The method separates the image based on their pixel's values and it results in an image with distinctive 'objects' that share greyscale values within the same range. Third, we introduce these objects to the supervised learning method. We input the structural (DEM), textural (orthophoto), and spectral descriptors in the model, and conduct a classification by training a multi-layered feed-forward neural network to classify image objects into predefined classes.

Fourth, and in parallel, we try to detect regions that have meaningful elevation differences with the surface of the trench as a sign of the existence of man-made objects such as utility lines. This can be done by subtracting terrain models from surface models, as also happens when extracting buildings from digital surface models. In these processes, Digital Surface Models (DSM) and Digital Terrain Models (DTM) are subtracted (Arefi et al., 2005). Similarly, we subtract the results of the morphological opening applied to the trench's DEM from the original DEM, resulting in the probable location of the utility lines.

Fifth, the results of both methods are integrated by multiplication of the results of classification and morphological processing to detect the utility line robustly and reliably. These steps can visually show whether the results of the supervised classification are in line with the objects detected during the morphological processing. Figure 2 illustrates the procedure and the results of integrating the two solutions.

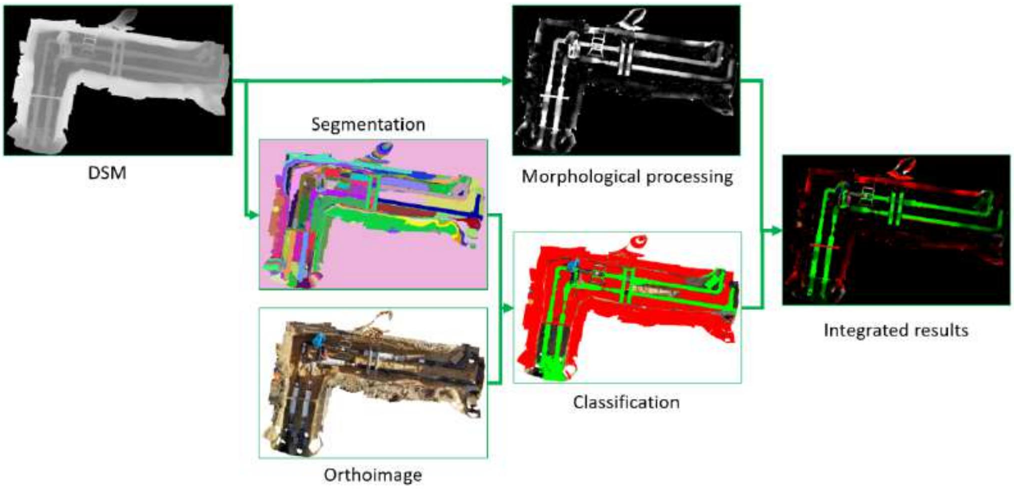


Figure 2. The procedure of the proposed method to detect utility items combining the classification and morphological processing.

The results visually show that the method is able to detect and extract constructed utilities. The method could correctly achieve a true positive rate of 94 percent (94 percent of all the detected utility lines were correctly detected, and 6 percent were not).

This study combined image segmentation and FFNN to extract features from 3D point clouds. Current literature on utility detection and classification methods has explored the use of SfM and machine learning to extract features to a limited extent. This study hence contributes to a niche of photogrammetry applications in construction, allowing the development of more comprehensive 3D underground models. A future task is to further expand the data collection and train the methods to identify utilities from different onsite trenches, utility types, and field conditions (light). After this step, acquiring 3D models and automatic detection and registration of underground utilities seems feasible.

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## Formula Inholland

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***Abstract –*** *Urban, building and infrastructural designs usually need to be fitted in existing built environment. In order to test functional aspects of design proposals, digital twins are increasingly being used or asked for. Students at Inholland UAS were challenged to design a virtual 'race circuit' representation of an existing location in Alkmaar. This practice driven design research concerned the following questions: (1) what is needed in order to make a digital twin of an existing urban context wherein new infrastructural design proposals can be fitted, and (2) how to develop it further into a digital 'driving simulations' environment for dynamic testing?*

Digital twins for testing and analysis of functional aspects of design proposals are increasingly required and used in practice. The analysis of lighting schemes or sighting lines are some of the (technical) examples, but even aspects of human behavior related to design are inquired. The new developments regarding digital twins, regardless how exciting they are to the involved professionals, are however often literally invisible and non-tangible to various stakeholders – from decision makers to end-users. The here presented practice driven research directly involving students, had the aim to create and capture an efficient approach to developing digital twins that can be used in 'virtual driving simulations' in order to experience new infrastructural proposals in existing urban environments.

Looking at current development in the engineering sector, there seems to be a visible trend towards digitalization, virtualization and simulations. Based on the works of different engineering firms (Ingenieursbureau Geonius, 2018) (Infranea, n.d.), this practice based and practice driven research focusses on the methods used to develop these environments and their use cases.

The first digital twin design iteration was done by a group of 4th year built environment (three) and civil engineering (one) BSc students. They have looked at which (open) data sources are suitable for digitalization of the project context. Additionally, they have defined which steps are required to come to a digital representation of an existing Alkmaar urban location and workflows to transfer data between different applications. Different methods were analysed and tested (Figure 1) that can be used to get the desired results.

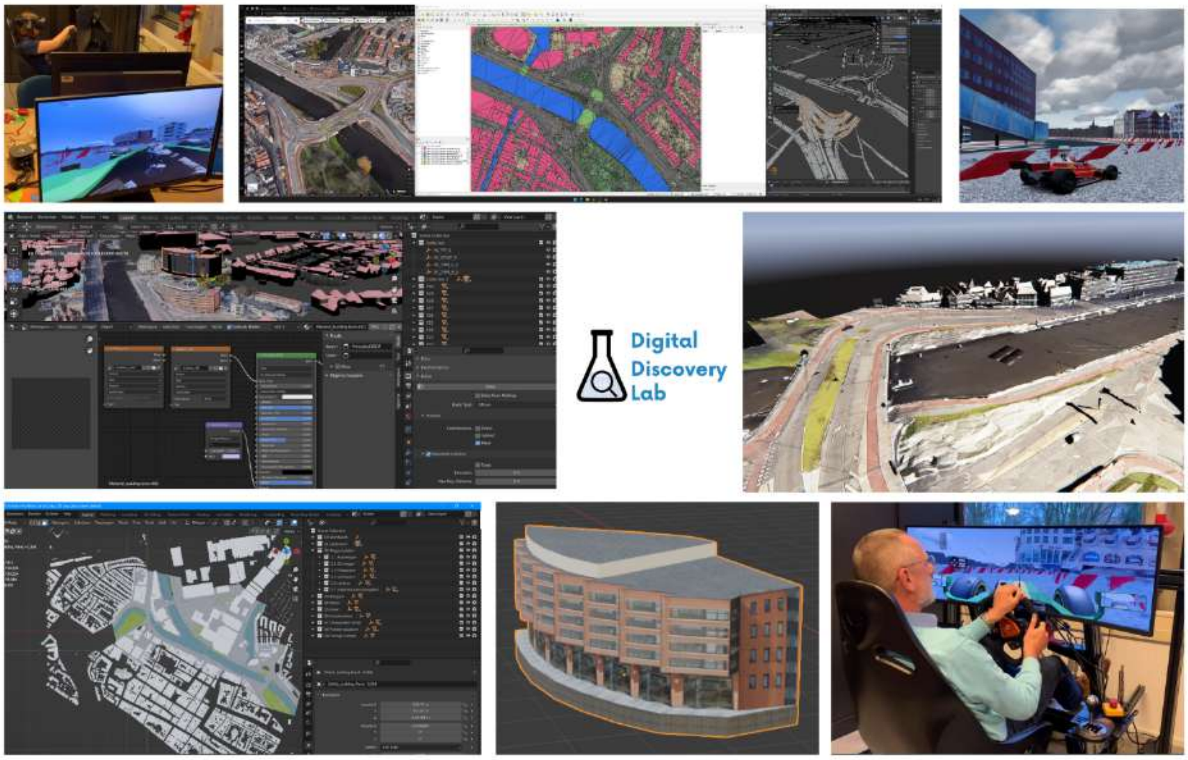


Figure 1: Overview of methods and results. Seen from top to bottom. The first row: testing simulation in virtual reality; comparison data between Google Earth, GIS, and Blender; screenshot of simulation of distinct buildings of Alkmaar. Second row: combining datasets in blender and texturization; geometry of dataset imported in SDK of Assetto Corsa. Third row: analyzing ground surface geometry; high LOD building asset made in Blender; validation of build minimum viable product.

Based on an agile workflow, the first goal was to create a minimum viable product. A driving simulation with minimum functionality. Next, data and functionality were incrementally added in every sprint. Different existing data sources have been analysed to check their relevance to the end goal of this research such as: BGT, AHN, 3D BAG, 3D Basisvoorziening, 3dfier(*) and Google Earth. The scope of the relevant aspects was mainly graphical and geometrical such as LOD, tessellation, polycount and texturization.  In the first design iteration is subsequently looked at possibilities to integrate the new designed geometries for both building and roads/infrastructure. For both situations, data had to be transformed to be functionally implemented in the SDK. Coordinate system transformations, scale, geometry polybudget, texture-mappings and file formats are examples.

The first results show foremost a *practical work approach* which enables the use of built environment open data and (own) design proposals in order to create digital twin 'driving simulation' for dynamic testing. Furthermore, the result is used for implementation in the curricula of Inholland UAS and an addition of the DD-lab knowledgebase, which is publicly available.

Further research and development will be aimed at expanding the use of different 'data-capturing' methods e.g., photogrammetry, point clouds and nerfs. Also, the integration of 'meta-data' and functional systems in the digital twin simulation environment.

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# Data-Driven Buildings and Urban Transformation

# The use of artificial intelligence to determine neighborhood typologies for the Netherlands

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***Abstract** – The classification of urban typologies for The Netherlands projected on a map to facilitate local and regional authorities in selecting climate adaptation measures. A first map from 2017 based on a handmade decision tree had limits in recognizing spatial variations. The map was renewed using artificial intelligence, learning from a validated set and local geodata, making a prediction for the Netherlands. The method classifies built-up areas in sixteen neighborhood typologies on postal code and neighborhood level with the possibility to upgrade datasets in the future. The map is available on the national website for Climate Adaptation Services (www.klimaateffectatlas.nl/).*

The impact of climate change poses challenges for the built environment and require a range of climate adaptation measures. Categorizing the built environment into neighborhood types gives local and regional authorities first insights into which measures are most appropriate given the spatial context. Through categorization, certain spatial characteristics immediately become clear (e.g., construction period, architectural style, degree of urbanization, type and size of homes, type and amount of greenery and water, the layout of the public space and road profile). Adaptation measures can be linked to these urban features, which we have categorized into a set of sixteen neighborhood typologies. The map with neighborhood typologies is useful in practice and in research, at multiple scales and for a variety of themes such as climate adaptation, energy transition or biodiversity in the urban environment. In 2017, Amsterdam University of Applied Sciences has published practical solutions for climate-proof design is in the example book on climate-proof design of residential streets.

In this research, neighborhood typologies were used as a basis to suggest which interventions would be most suitable given the spatial challenges and opportunities per neighborhood type (Kluck et al., 2017). The research illustrates cost-benefit analysis and a variety of water-resilient best practices for eight different neighborhood typologies that can be applied throughout the whole country. The Coolkit (Kluck et al., 2020) provides advice for each neighborhood typology about the optimal layout of the outdoor space – including the target percentage of greenery, the form and location of heat mitigating measure(s) – to enhance the street or neighborhood to make it more heat resilient. Large scale renovation projects like the Dutch project Integral Energy transition in Existing Buildings-IEBB (TUDelft, 2020) can use the neighborhood typologies to evaluate different energy transition options for specific building types, street organizations and neighborhood structures. The neighborhood typologies are based on research by Kleerekoper (2016). The neighborhood typologies are a refined classification with adjustments to the Dutch built environment of the Local Climate Zones by Stewart and Oke (2012). The prior map based on a handmade decision tree has been introduced in Stadswerk (Kleerekoper et al., 2018) and RO magazine (Kleerekoper et al., 2017) and was available online via the national website of Climate Adaptation Services.

The map of 2017 was based on a handmade decision tree and had limits in recognizing spatial variations. To improve this, a study has been conducted where supervised machine learning, a field within artificial intelligence, helped determine neighborhood typologies for the Netherlands. The neighborhood typologies were determined based on public available geographical data such as year of construction, building height, housing density, percentage of greenery and function of the buildings. Machine learning can automatically determine the most distinguishing patterns based on labeled examples leading to better predictive performance of the classification model. As input for the machine learning model, a dataset containing a large set of variables describing the built environment was processed using GIS and expert validation; an interpretation of the typology at a postal code 6 (PC6) level (such as 1234AB). At this level, built-up areas are often homogeneous and a clear distinction can be made between neighborhood typologies.

The validation set was assessed against manual classifications of neighborhood typologies. This was done for five test municipalities on PC6 level based on expert estimates. This validation set has been an important input in determining the neighborhood typologies. A random forest classifier has been trained to recognize distinctive patterns from the validation set that consisted of datapoints per PC6 level with all urban features and the neighborhood typology. A Random Forest classifier is a supervised learning ensemble method which operates by constructing a multitude of decision trees and it was chosen because it is particularly good at including interaction effects (finding combinations of different variables that are typical for a certain category) and non-linear effects (sudden changes such as the disappearance of an architectural style within 5 years). The supervision of improvements or impairments when adding and adjusting data is possible by looking at the accuracy of the whole model. This is not sufficient to determine whether the model performs good enough for each typology. If the model scores high on the common typologies, it can still score low on the less common typologies. Therefore, we looked at the precision, recall and f1-score of each individual typology.

The Random Forest classifier is a robust method able to generate predictions over a wide range of data. This approach is an example of the application of existing tools from the field of AI to the climate adaptation domain. The method has been extended from the standard implementation to account for spatial autocorrelation in the data by grouping the data into spatial clusters for the training process. After finding the optimal configuration, the trained model was used to generate predictions for the Netherlands on PC6 level.

In the next step the PC6 areas were aggregated into neighborhoods based on the most common typology per neighborhood. A two-step interpretation was needed because many neighborhoods are not homogeneous in practice, but consist of different typologies (due to infill development and urban renewal). By aggregating data at neighborhood level, the maps for the whole of the Netherlands remain clear. In assigning a typology on neighbourhood level, a decision tree was formed based on a prioritization logic with assigned thresholds (e.g., when the surface of the neighbourhood was less than 70% green, the living area that covers more than 10% of the surface area was chosen).

The model calculated a probability for each neighborhood typology for each PC6 area (these add up to 100%). The model classified the postcode area as the neighborhood type corresponding to the highest probability. The prediction, compared with the expert classifications, has an accuracy of 81%. For those areas which had a maximum probability lower than 30%, the neighborhood type was assigned the value 'Undetermined'. On the remaining data points, the model scores an accuracy of 84.9%.

The output of the model shows that the variable 'construction year' and 'height' are the most influential in distinguishing the neighborhood typologies. It was observed that some neighborhood typologies score higher than others. For example, high-rise buildings score high, since high-rise buildings have a very distinctive aspect, namely a building height higher than thirty meters. Villa scores quite low because villa areas can have different manifestations, which makes it difficult for the model to predict this neighborhood type. This is reflected in the confusion matrix (see figure 1), a table that visualizes the performance of the machine learning. In this matrix, the predictions (on the horizontal axis) and expert classifications (on the vertical axis) are compared. When the predicted label matches the true label, the model has a correct prediction (the values on the diagonal in the matrix).

The confusion matrix also gives insights into which categories are often mistaken for which other ones. By looking at the matrix row by row, it can be observed that for most pc6 areas most of the data points match the predicted label and therefore can be classified with high reliability. For those combinations where urban features of different typologies are more similar, the predictions of the pc6 areas are more spread across different typologies (for example, 'bloemkoolwijken' are often misclassified as 'naoorlogse woonwijken' which were built in the same period).

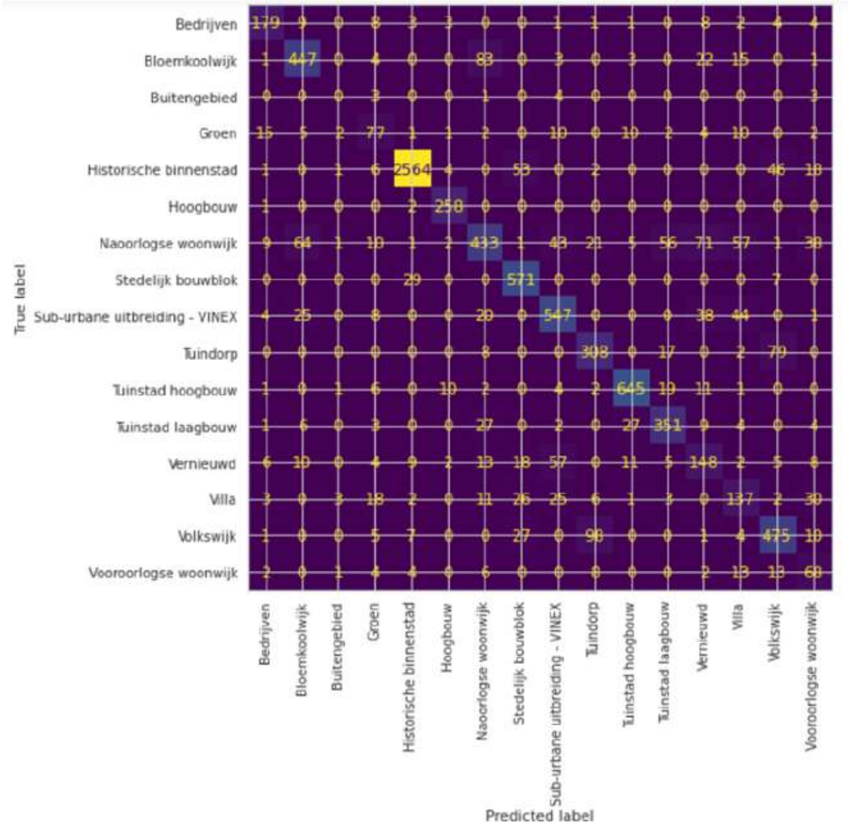


Figure 1: Confusion Matrix model for neighbourhood typologies

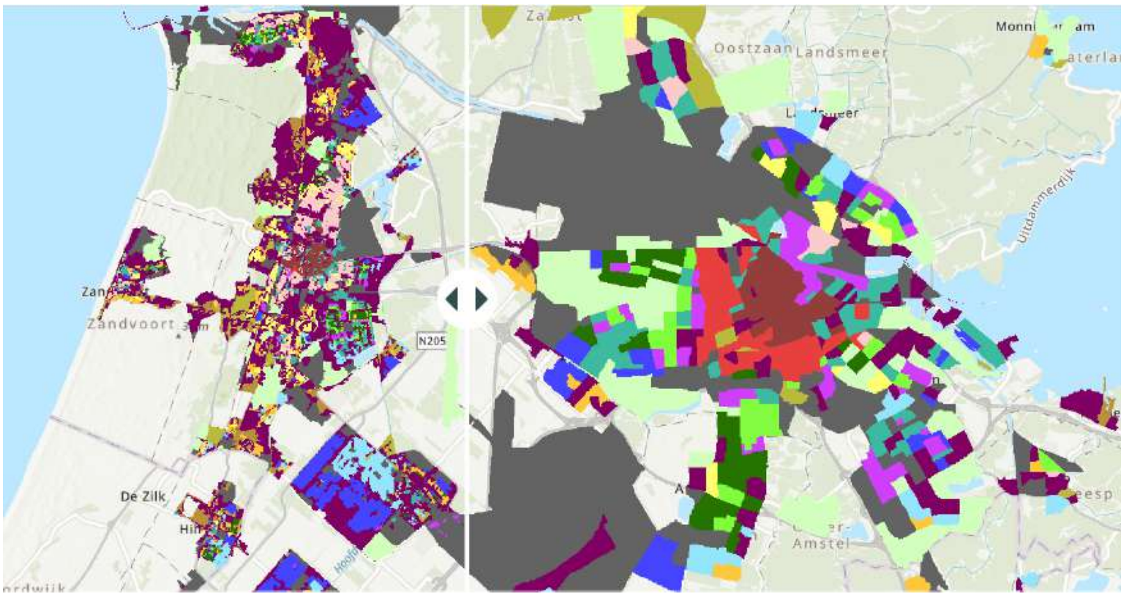


Figure 8. Example of the map of the Neighbourhood Typology. On the left the city of Haarlem is divided per neighbourhood typologies on PC6 level, on the right, the city of Amsterdam is presented by neighbourhood typology on district level.

The model provides a good prediction for the neighborhood typologies. The end product is a map of the built environment divided by neighborhood typologies on a PC6 and neighborhood level. The map is publicly available at the website of climate adaptation services, so that municipalities and consultancies throughout the Netherlands can use this as a base to start off with for climate adaptation measures.

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# Generating metadata schema for data-driven smart buildings

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***Abstract** – The integration of data from a variety of systems is critical for developing smart building applications. Design, construction, maintenance, energy management, and automation data are among few. For this integration, having a comprehensive metadata schema is crucial. Semantic web technologies and domain ontologies have been proposed as a means of modeling and linking domains and their relationships. This study proposes a semi-automatic metadata schema generator that combines an ontology database and a text search engine to generate a metadata schema. The proposed method is tested for a real-world building, and the resulting metadata schema is used to link timeseries data to the sensors and equipment in the building automation system.*

Semantic web and domain ontologies enable modeling and linking relationships between different domains. However, the process of generating a metadata schema for a specific building using ontologies cannot be generalized and need case by case approach. Previous attempts include point matching using occupant's inputs (Fürst et al., 2016), regular expressions to detect common patterns in metadata descriptors (Bhattacharya et al., 2015), utilize time-series values from Building Automation System (BAS) points to learn the mapping (Gao & Bergés, 2018), linguistic matching (Schumann et al., 2014), and using a combination of tags and time-series data (Balaji et al., 2015). However, not all buildings have accessible timeseries data storages, cannot use occupants as an input, or a combination of above. This study proposes a semi-automatic metadata schema generation process based on the metadata extracted from the BAS. The proposed method uses an ontology database and a text search engine to generate the scheme. This method is tested on a campus building and a metadata schema was generated successfully. Finally, timeseries data of the BAS is visualized using a web application using the generated scheme.

Table 1 presents a list of BAS object identifiers. The "Name" column contains a naming convention consisting of four elements, representing the building number (33), system number (201), control code (CV), and point type (V). Although the "Description" column partly describes the point's full details, it fails to convey that point in #1 pertains to AHU 201. As such, we chose to deconstruct the naming convention in the "Name" column to extract all metadata related to the point by using three additional mapping tables that detail the system number, control code, and point type. These three tables were initially in Dutch and were subsequently translated to English using the googletrans API. An example of this decomposition is illustrated in the "Description (EN)" column of Figure 2.

Table 1: Metadata extraction from BMS

| # | Item Reference | Object ID | Object Type | Name | Description (NL) | Description (EN) |
|---|---|---|---|---|---|---|
| 1 | XXX.FEC005.CLG-O | CLG-O | AO Mapper | (33) 201.CV-02V-- | Regelafsluiter koeler | Cooler control valve |
| 2 | XXX.FEC006.CLG-O | CLG-O | AO Mapper | (33) 202.CV-02V-- | Regelafsluiter koeler | Cooler control valve |
| 3 | XXX.SHWP1-FAULT | SHWP1-FAULT | BI Mapper | (33) 001.TP-01A-- | Transportpomp 1 storing | Transport pump 1 malfunction |

Each of the three mapping sets was matched with its corresponding Brick counterpart individually, using a text search engine[1]. The search engine was populated with Brick class names and their definitions extracted from the Brick ontology[2], which contain the necessary keywords to locate a match with the point names in the three mapping sets, as depicted in Figure 2. However, some object identifiers were not entirely recognized by the text search engine, expert human input was necessary. We then identified a logical pattern among the three identifiers in the subsequent phase. Using Brick relationships, we connected these three identifiers, as shown in Figure 2.

Out of the total of 2338 BAS object identifiers in the building, only 948 points had linked time series records. Of those 948 points, only 763 conformed to the logical naming structure and could be successfully incorporated into an RDF-based metadata schema using Brick classes and relationships. This scheme is used to link the BAS points and their time series data in the real time data stream and historical data storage. In conclusion, the metadata schema generation method was successful, and the resulting schema can be used to support data driven applications. Further expansion is possible to integrate with BIM and use real time monitoring applications. Figure 3 shows the Grafana[3] web application showing the historical data of the sensors connected to BAS. Using the graph generated greatly improves the efficiency of querying the historical data.

[1] https://docs.meilisearch.com/
[2] https://brickschema.org/ontology
[3] https://grafana.com/

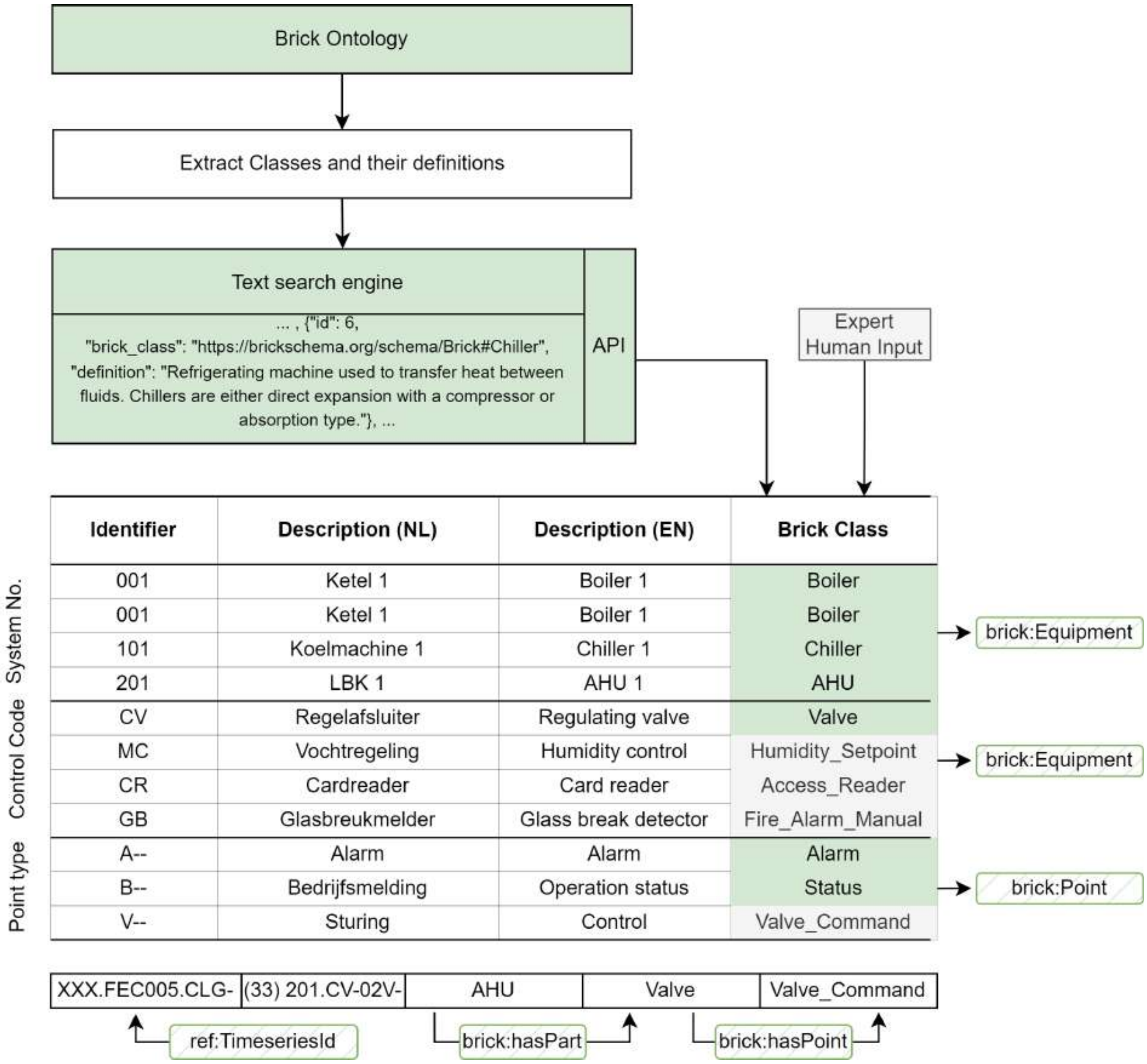


Figure 2 Workflow of mapping to Brick Ontology

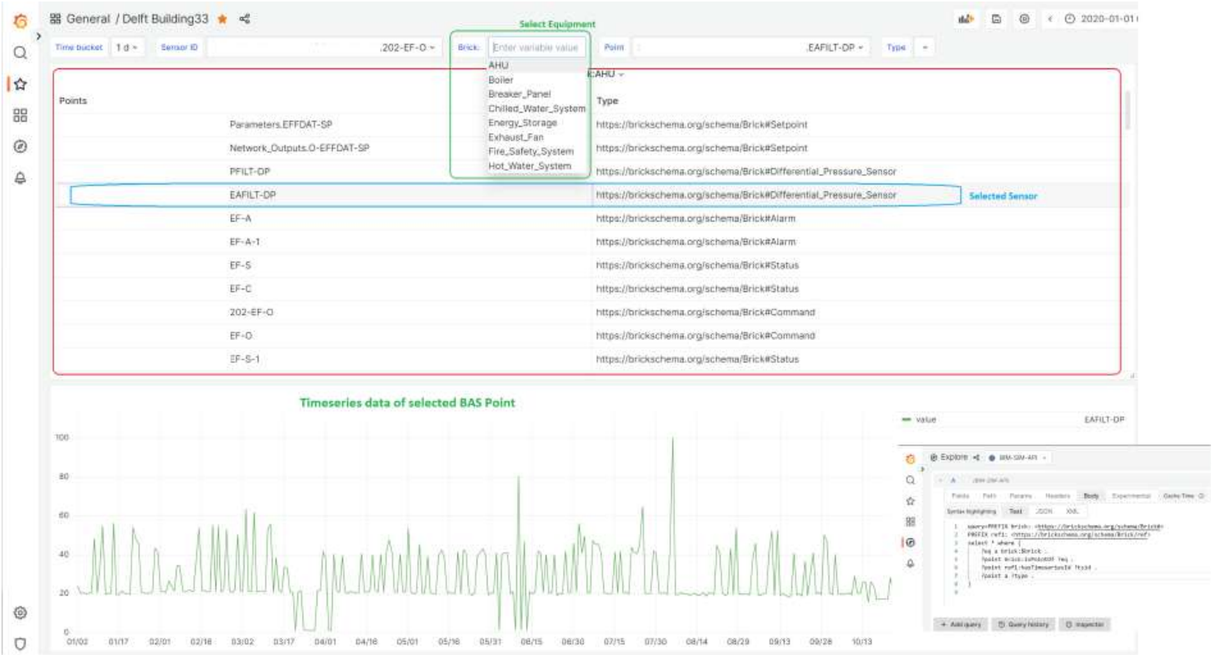


Figure 3 Visualizing time series data using Grafana web application using the metadata schema.

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# Multi-class semantic segmentation of digital surface models for solar energy applications

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***Abstract –*** *Deep learning-based segmentation of urban digital surface models (DSMs) endures challenges from limited features, class imbalance, and sparse data, which limits the application of DSMs in urban solar energy assessment. In this study we propose a dynamic graph CNN (DGCNN) based segmentation model and address abovementioned problems by adding artificial features, using adaptive-weighted loss function, and introducing a modified spatial transformation module. Our model achieved outstanding performance in predicting the test dataset with an average accuracy of 0.95 and F1 scores of 0.94 after 300 epochs of training. The presented approach inspired several potential applications for solar energy simulation.*

DSMs are pre-processed point clouds that provide detailed elevation information of the urban landscape (Martha et al., 2010), which enable various applications in solar resource assessment (Teves et al., 2016; Bognár et al., 2021; Zheng et al., 2018; Tian et al., 2022). The value of DSMs for such applications can be enhanced with the use of (semantic) segmentation (Cao et al., 2019; Zhang et al., 2019), as it enables the identification of urban objects and their interrelationships. While traditional analytical segmentation methods including similarity clustering (Ying et al., 2015), object-based (Zhang et al., 2014), and rule-based methods (Martínez et al., 2016) are effective for smooth and simple landscapes (Diab et al., 2022; Rizaldy et al., 2018), they struggle to handle the complexity of modern urban environments (i.e., shading obstructions are densely distributed) (Zhang et al., 2019).

Recent research in urban landscape segmentation has focused on deep learning models, which offer advantages over traditional approaches in detecting small or non-intuitive features (Diab et al., 2022; Zhang et al., 2019). Among popular models, DGCNN stands out as particularly suitable for point cloud segmentation due to its computational efficiency and ability to capture local and global features (Wang et al., 2019; Xing et al., 2021). While DGCNN has shown promising results in various segmentation tasks (Diab et al., 2022; Gamal et al., 2021; Widyaningrum et al., 2021), its application to DSMs has been limited due to three main problems:

- Limited features: DSM point clouds have limited features, preserving only (x, y, z) coordinates, which may be inadequate for accurate predictions.
- Class imbalance: Certain objects like building facades are underrepresented in DSMs, results in bias towards majority classes and lead to poor performance for minority classes (Sun et al., 2021).
- Sparse data: Sparse data is common in DSMs of building facades (Yan et al., 2017), where few points in the region make it challenging for the model to learn robust features.

This study proposes solutions to aforementioned challenges in accurately segmenting DSMs using DGCNN for urban solar assessment. We aim to segment DSMs into four classes:

vegetation, ground, façade, and roof. To address the limited features impacts, we augmented the DSM in the training/testing dataset with six artificial features (color features: R, G, B and normalized coordinates: nx, ny, nz) resulting in a 9-feature space. To overcome the class imbalance issue, we used a customized focal loss function with adaptive-weighting. Table 1 displays the prediction scores obtained after 50 epochs, where the adaptive-weighted case yields higher average accuracy and F1 scores than the non-weighted case, indicating the overall performance of the network is enhanced.

Table 1: Prediction scores before and after enabling auto-weighting with 50 epochs.

| Adaptive-weighting | Avg accuracy | Avg F1 | Vegetations F1 | Ground F1 | Façade F1 | Roof F1 |
|---|---|---|---|---|---|---|
| Disabled | 0.79 | 0.81 | 0.98 | 0.95 | 0.36 | 0.97 |
| Enabled | 0.89 | 0.84 | 0.98 | 0.95 | 0.47 | 0.96 |

To mitigate the impact of sparse data, we introduced a modified spatial transform module to the shallow network layer. The module (Figure 1), includes three 2D convolutional layers, three fully-connected layers, and a skip connection, and is designed to exhibit spatial transformations on the input point cloud to enhance the model's geometric invariance. It functions by first generating a transformation affine matrix, which is then multiplied with the input point cloud coordinates. This process aligns the point cloud in a canonical space, making the network more robust to different geometric transformations.

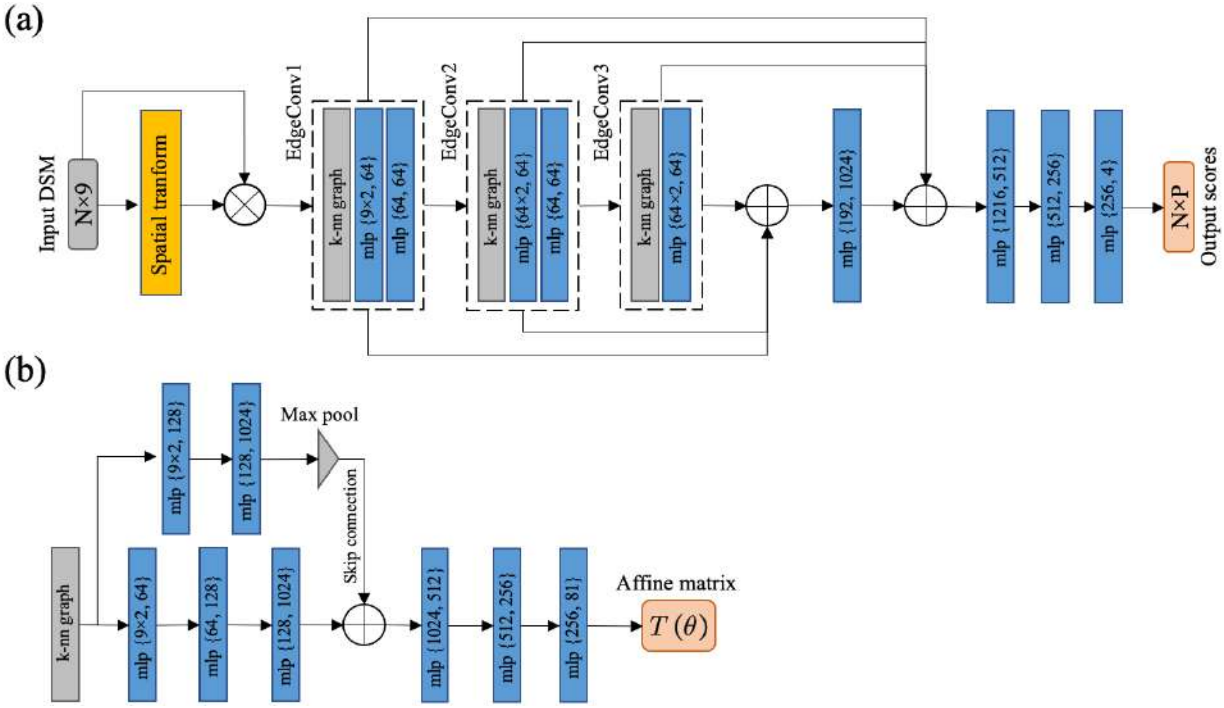


Figure 1: Diagram of the modified DGCNN architecture, with (a) segmentation network and (b) spatial transformation module.

As the number of training epochs and loss backpropagation increases, the module becomes more proficient in performing spatial transformations, resulting in improved performance (Table 2). Compared to results without spatial transformations, we observed significant increases in both averaged scores and per-class F1 scores. In particular, the F1 score for the façade class increased by 53%, indicating that the inclusion of spatial transformation is effective in mitigating sparse data impacts and increasing the model robustness.

Table 2: Prediction scores with and without spatial transform with 50 epochs.

| Spatial transform | Avg accuracy | Avg F1 | Vegetations F1 | Ground F1 | Façade F1 | Roof F1 |
|---|---|---|---|---|---|---|
| Disabled | 0.89 | 0.84 | 0.98 | 0.95 | 0.47 | 0.96 |
| Enabled | 0.94 | 0.89 | 0.96 | 0.94 | 0.72 | 0.95 |

After 300 training epochs, the prediction results and scores on the test dataset are displayed in Figure 2 and Table 3, respectively. The results demonstrate that the well-trained model exhibits a remarkably high level of accuracy and F1 scores, effectively fulfilling our segmentation requirements.

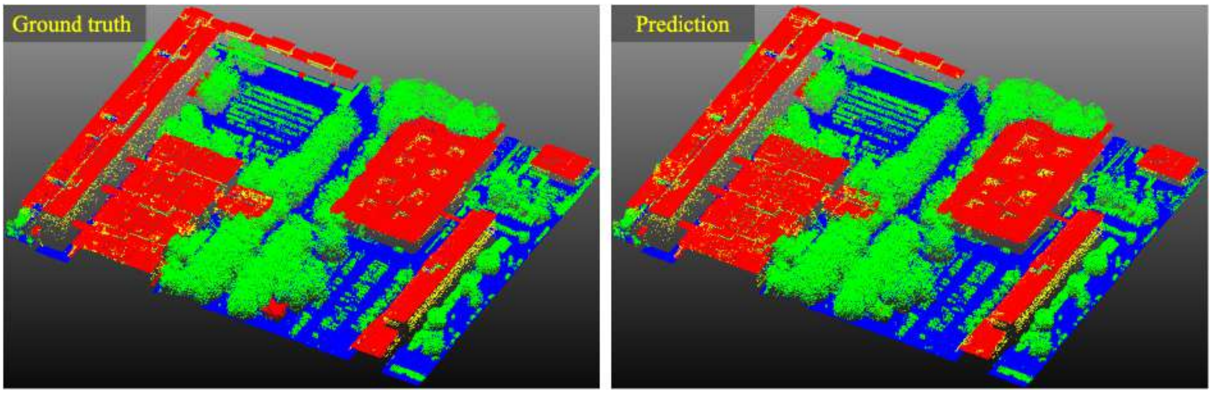


Figure 2: Ground truth and prediction of the testing DSM tile.

Table 3: Final prediction scores of segmentation model.

| Epoch | Avg accuracy | Avg F1 | Vegetations F1 | Ground F1 | Façade F1 | Roof F1 |
|---|---|---|---|---|---|---|
| 300 | 0.95 | 0.94 | 0.97 | 0.96 | 0.85 | 0.97 |

The segmented DSMs enable improvements in urban solar energy applications. Figure 3 demonstrates the predicted monthly solar irradiation [kWh/m$^2$] of the scene that uses DSM as solely simulation input. Based on the embedded semantic information, the solar potential at individual building components can be evaluated separately in follow-up studies. It is expected that the results can effectively guide building-integrated PV (BIPV) deployment strategies.

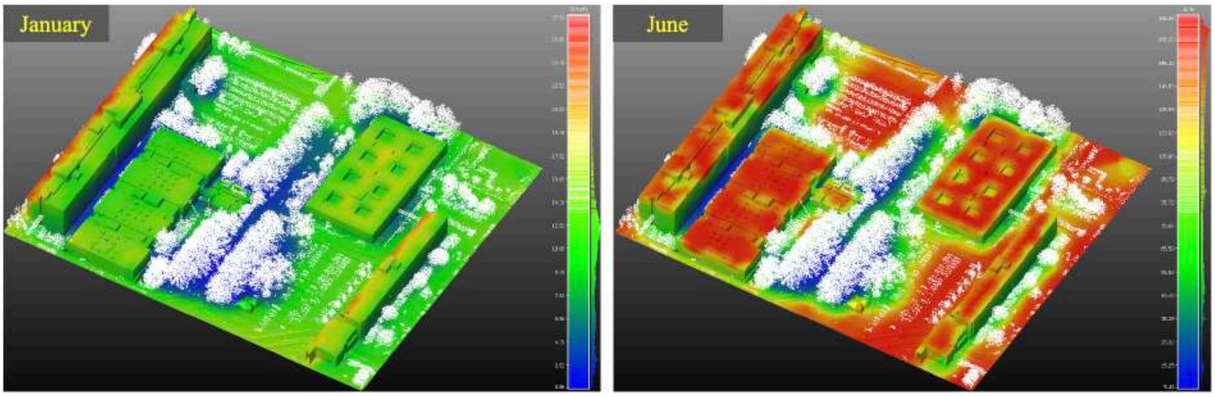


Figure 3: Simulated cumulative solar irradiation on the buildings and ground in January and June 2021, where the white points represent the segmented trees and other solar obstructions.

In conclusion, our study showed that DGCNN is effective for segmenting urban DSMs and demonstrated the importance of addressing inherent issues such as limited features, class imbalance, and sparse data. Our proposed techniques, including artificial features, an adaptive-weighted loss function, and a spatial transformer, mitigated these issues and achieved high prediction accuracy and F1 scores. This improved performance in DSM segmentation has broad implications for applications in solar energy assessment. For instance, it can enable effective BIPV systems deployment by assessing solar energy yield from individual building components, and support decision-making in sustainable building and city design by estimating shading impacts from various obstructions.

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# Unraveling the costs of improving indoor comfort using semantic digital twins

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***Abstract –*** *Improving indoor comfort should be a priority of real estate owners, however, the current energy crisis causes an extra financial burden. Information related to indoor comfort and energy is currently scattered across silos, complicating decision-making. This paper presents a method to integrate these types of information and show them in a 3D viewer using state-of-the- art semantic web technologies. Our tool, LBDviz, enables end-users to monitor comfort-related complaints and energy consumption on building and device levels, while also enabling them to control individual devices. The data integration enables better decision-making and is a stepping stone to fully automating indoor comfort systems.*

As poor indoor comfort can lead to lower knowledge worker performance (Geng, Ji, Lin, & Zhu, 2017; Lee et al., 2012) and increase sick leave, symptoms of sick building syndrome, and negative health conditions (Fisk, Black and Brunner, 2011; Patino and Siegel, 2018), improving the indoor climate should be a priority for real estate managers. While both employers and employees endorse the importance of healthy environments, improving the physical workspace is not often considered (Kropman, Appel-Meulenbroek, Bergefurt, & LeBlanc, 2022).

The recent energy crisis in The Netherlands caused an extra financial burden on real estate finances, causing many property managers to downgrade their indoor comfort systems. The Dutch government initiated a campaign to stimulate people to save energy, for example by setting the thermostat to a maximum of 19 °C, making less use of climate installations, and reducing the use of lights. The campaign is expected to reduce indoor comfort on the short term, and it is highly unlikely that a one-size-fits-all advice does justice to the versatile building stock.

This research, therefore, presents a method to integrate energy-related data with indoor comfort-related data and show this in real-time in a 3D viewer, so that the energy consumption can be considered in comfort-related decision-making.

Semantic web technologies have proven to be a successful method to integrate cross-domain data into semantic digital twins (Donkers, De Vries and Yang, 2022). A dashboard that could cope with occupant feedback and gives personalized feedback based on the available linked data was recently developed (Donkers, Van Midden, & Yang, 2022). This dashboard, however, did not take energy consumption into account. Other work already linked building information with energy performance (Hu et al., 2021).

This paper applies semantic web technologies to integrate data from heterogeneous sources into a knowledge graph (Figure 1). Building information was acquired from an IFC file and transformed using the IFC-to-LBD converter (Bonduel, Oraskari, Pauwels, Vergauwen, & Klein, 2018).

Feedback from the occupant was acquired using a custom-built smartwatch application, through which the occupant could give feedback on indoor comfort variables. The process of converting this feedback to linked data is described in earlier work (Donkers, De Vries and Yang, 2022). Metadata related to illuminance sensors (Eltek LS50) and the lighting system were created manually. Multiple ontologies were reused to build this graph. BOT (Rasmussen, Lefrançois, Schneider, & Pauwels, 2020) describes the topological components of the building, BOP (Donkers, Yang, de Vries, & Baken, 2022) describes static and dynamic properties of those components, and OFO (Donkers, De Vries and Yang, 2022) describes the occupant's feedback.

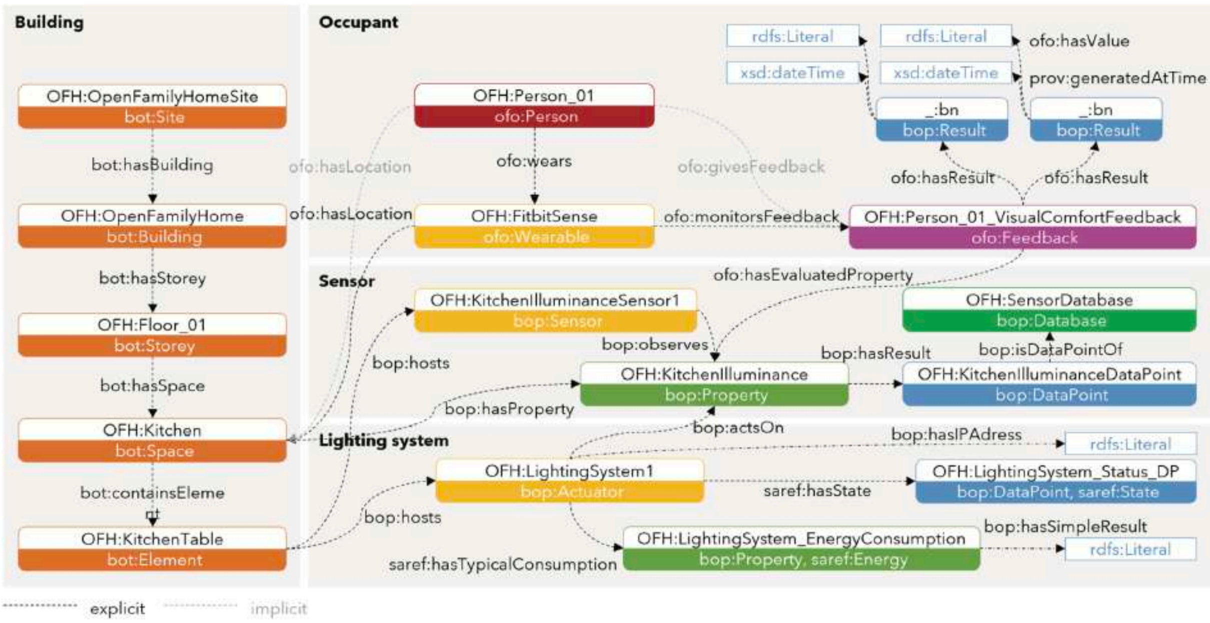


Figure 9: Integration of building information, occupants, sensors, and actuators

The linked data is visualized in a front-end application called LBDviz (Figure 2). The application is built upon IFC.js[1] – which is a JavaScript library to display IFC models in the browser – and Comunica[2] – which is a meta-query engine that enables executing SPARQL queries over decentralized knowledge graphs. The query bar shows how to query occupant feedback on illuminance in a specific area of the building. The result bar shows feedback given using the smartwatch application. An energy widget was created to visualize the current and total energy of a single power socket (measuring the energy consumption of the lighting system in Figure 1), a P1 meter (measuring the energy consumption of the entire building), and a water meter.

[1] https://ifcjs.io/
[2] https://comunica.dev/about/


Figure 10: Visualizing feedback on illuminance and the energy consumption of a lighting system

Two main functionalities were tested in this paper: monitoring the energy consumption and controlling the lighting system (Figure 3). To monitor the energy consumption, the viewer queries the IP address of the lighting system and the P1 meter. It then sends an HTTP GET request to an API using this IP address, which returns the current and total energy consumption. This is plotted in the energy widget, next to a status indicator showing whether a device has an active status.Secondly, the user could control the lighting system by clicking on it in the IFC file. The viewer would query the IP address of this system using its GUID. The user could then click a button to trigger an HTTP PUT request to the API, that changes the status of the lighting source. After changing this status, the energy widget is updated.

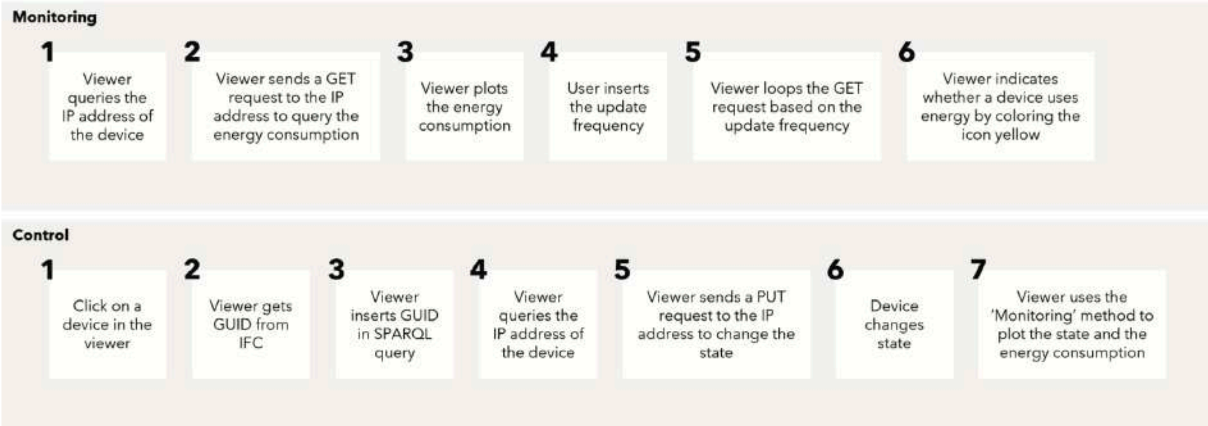


Figure 11: Decision-making steps for monitoring and controlling a device

Improving indoor comfort is vital in real estate decision-making, and developments in the internet of things stimulate new opportunities in this field. However, the current energy crisis causes gas and electricity prices to rise and reduces homeowners' possibilities to keep the indoor environment comfortable. This research aimed to integrate indoor comfort-related information with energy- related information and visualize this data in a 3D viewer so that the costs of specific improvements in indoor comfort become visible. In the future, further statistical analyses could automate the process of controlling devices by finding an optimal pay-off between costs, sustainability, and comfort.

## Acknowledgments

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# Track & Trace: closing the energy performance gap through real-time performance tracking of buildings

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Facing the need to reduce (fossil) energy use and $CO_2$ emissions from the built environment, new buildings and renovation concepts have been designed to reach ever better energy performances over the last decades. At the same time, however, several studies (e.g. Majcen et al., 2013) have shown that the realized energy performance of buildings can deviate significantly from the designed value, with buildings often performing worse than intended (see Figure 1). This is referred to as the performance gap phenomenon, which may result from invalid simplifications in models, differences between theoretical and actual material properties, workmanship issues, incorrect modelling or malfunctioning of building services, and the incorrect modelling of user behaviour (De Wilde, 2014; Senave et al., 2019; Zou et al., 2018).

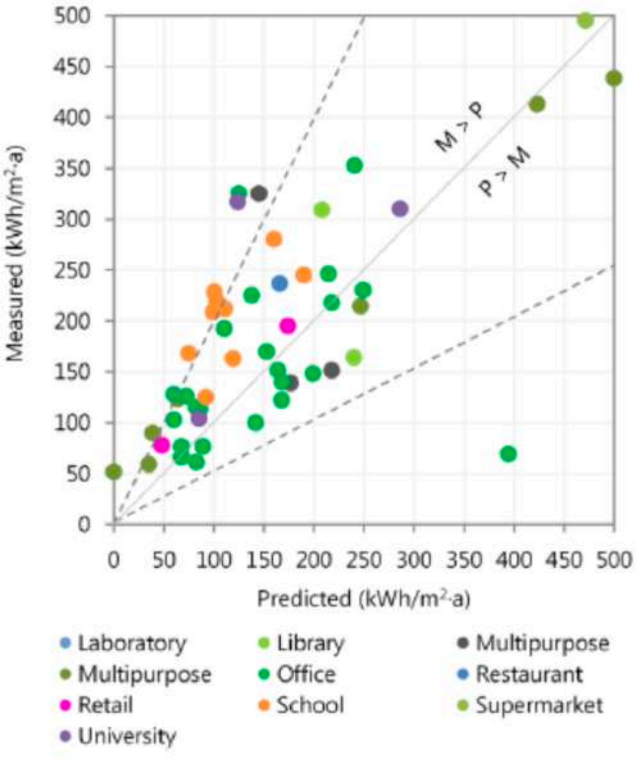


Figure 12: Measured vs predicted energy performance (van Dronkelaar et al., 2016)

The energetic underperformance of buildings leads to higher energy bills for the building owner or occupants, unnecessary $CO_2$ emissions and high repair costs for contractors and HVAC installers. Monitoring of the actual energy performance of the building can provide early insights in the performance of the thermal shell, HVAC installations and the impact of user behaviour, which can be used to offer suggestions for improving the energy performance of the building.

Current research efforts entail (i) the composition of sensor sets which can be used to measure relevant parameters with sufficient accuracy and suitable temporal resolution, (ii) the development of grey-box models which are used to dynamically assess the (impact on) energy performance of the different components (thermal shell, HVAC installations and user behaviour), (iii) development of a dashboard which provides the building occupant or facility manager with feedback, and (iv) verification and validation of the sensor sets, models and dashboard.

In this contribution, the four elements of the project as discussed above are illustrated using Saxion's Smart TinyLab as a case object, focusing on (a) the efficiency of the heat pump and (b) the performance of the thermal shell. The relevant metrics to be monitored are discussed, as well as different possible sensor types to do so. Different grey-box models of increasing complexity are developed and tested on their ability to reliably and dynamically assess the performance of the thermal shell (expressed as the Heat Transfer Coefficient, HTC), Figure 2.

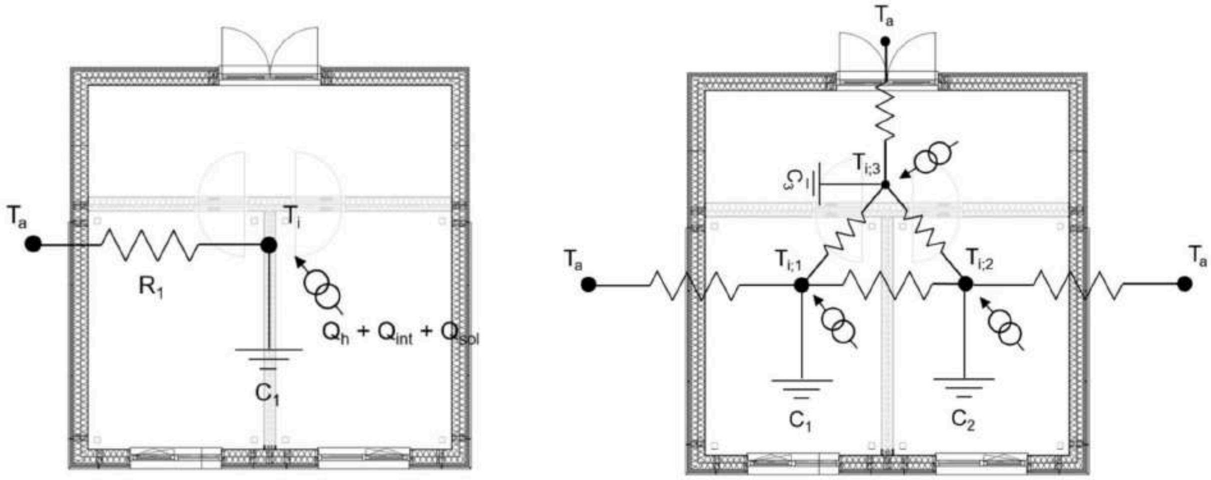


Figure 13: First (left) and third (right) order grey-box model

The thus assessed performances of the heat pump and the thermal shell are compared with the benchmark design values to visualize any performance gaps.

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# On-site Robotic Construction with Material Uncertainties

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***Abstract*** *– The engineering and construction industry aims to increase its efficiency and output using concepts and technologies of Industry 4.0. The applicability of one such technology, on-site robotics, is researched in this work. A construction site is dynamic and therefore introduces many uncertainties. One example of uncertainty is (the use of) construction materials, specifically geometric deviations. This study aims to design and construct a structure (e.g., arch or column) with irregular and varying geometries to mimic said geometric deviations. This problem is NP-Hard, meaning it cannot be solved in polynomial time by regular algorithms. To that end, Deep-Q Learning is used as a sequential decision-making algorithm to approach the best solution.*

Industry 4.0 technologies like data analytics, artificial intelligence, Building Information Modelling (BIM), digital twins, and robotics and automation increase efficiency (Turner et al., 2020), with on-site robotics bridging the digital process and analogue execution. Wagner et al. (2020) demonstrate that a digital process is fully utilized when execution is digitalized as well, making on-site robotics an imperative component. However, the presence of uncertainties presents a challenge to the successful implementation of on-site robotics. This study focuses on material uncertainties resulting from geometric deviations, similar to Lundeen et al. (2019). One can argue that, depending on the degree of deviations, constructing with material uncertainties can be considered constructing with a priori unknown materials. Dry stacking provides a use case to explore this (Liu et al., 2021; Sander & Larson, 2015). Furthermore, dry stacking using in-situ materials can be a sustainable option, using virgin materials over processed ones.

Research on dry-stacking can be approached from either a robotic or construction perspective. Robotic stacking often involves training a reinforcement learning (RL) agent using a target structure or demonstration (Funk et al., 2022; Chen et al., 2021). Early studies use masonry heuristics as input for an optimization function with piling 3D rocks (Furrer et al., 2017) or as a hierarchical filter to stack 2D rocks (Thangavelu et al., 2018). In contrast, more recent research has focused on RL methods that train an agent without relying on target structures or shapes, such as those proposed by Menezes et al. (2021) and Belousov et al. (2022). Generally, more complex designs with more straightforward geometries or more elementary structures with complex materials (e.g., rocks) are verified. In this context, this work seeks to design and construct an arch using moderately complex geometries (i.e., cubes, rectangular cuboids, and triangular prisms) with a dry-stacking approach.

Dry-stacking with varying geometries is a sequential-decision-making problem in a vast design space. Reinforcement learning has emerged as a successful approach to designing dry-stacked structures (Li et al., 2021; Menezes et al., 2021). Figure 1 visualizes the process of how dry-stacked structures can be designed and robotically constructed. At the core of the process is the design generator, which uses an open-source and benchmarked Deep-Q Learning algorithm, provided by Stable Baselines3 (Raffin et al., 2021). The generator's objective is to determine the most stable configuration of the structure, using a target shape or arch, consisting of numerous target points that dictate where the building materials should be placed. The structure is designed inside the environment of the physics engine PyBullet. In doing so, physical phenomena such as stability, friction, and self-weight are taken into account. Additionally, PyBullet is widely used as a training environment for reinforcement learning (Coumans, 2013). The environment's inputs are the construction materials and a set of requirements. These requirements are functional (structure height, width, span), set by the user, and structural (stability, friction, and self-weight). From the simulation, the necessary information for the action space, state space, and rewards can be obtained to train the RL agent. Stable Baselines follow the structure of a gym environment. To create a custom environment, the observation space needs to be defined. The observation space is defined as a 3D matrix containing the material location, orientation, and velocity. Velocity above a certain threshold indicates instability or faulty placement (dropping material) and results in a punishment and reset. The action space is a 9D matrix and allows the agent to place and orient the building material along the target points. The matrix consists of six rotations, material and target point selection, and material placement. Three reward functions incentivize the agent to design stable structures, rewarded at each step:

- Material contact area reward: $R_{area} = weight * A^2_{contact}$
- Deposit-height reward: $R_{deposit} = weight * \left(1 - \frac{CoM_{z,coord}}{height\ work\ domain}\right)$
- Optional, material usage: $R_{material} = weight * \left(1 - \frac{\#\ material\ used}{available\ material}\right)$

Physical construction is crucial to validate designs, given that a physics engine is an approximation of reality. For this purpose, an ABB Robot will be employed. In this study, the construction environment is relatively simple, eliminating the need to train motion planning or use extensive planning algorithms. A Python script is used to generate a RAPID code script based on the coordinates and rotation obtained from the simulation to control the ABB robot. The RAPID code's structue is predetermined to work with this specific construction case (e.g., home-point, hover-object1, object1, activate end-effector, home-point, hover-target1, target1, de-activate end-effector, home-point, etc.). Figure 2 visualizes the path-planning and construction process. The pick-and-place procedure is verified in ABB's simulation software RobotStudio. Further physical testing is required to tune the process and adjust movement speed. After this is done, the construction experiments can be performed. The experiments to verify the designs follow the logic of curriculum learning. Initially, simple geometries and target shapes will be used, to finally build up to using a set of different geometries that will create an arch.

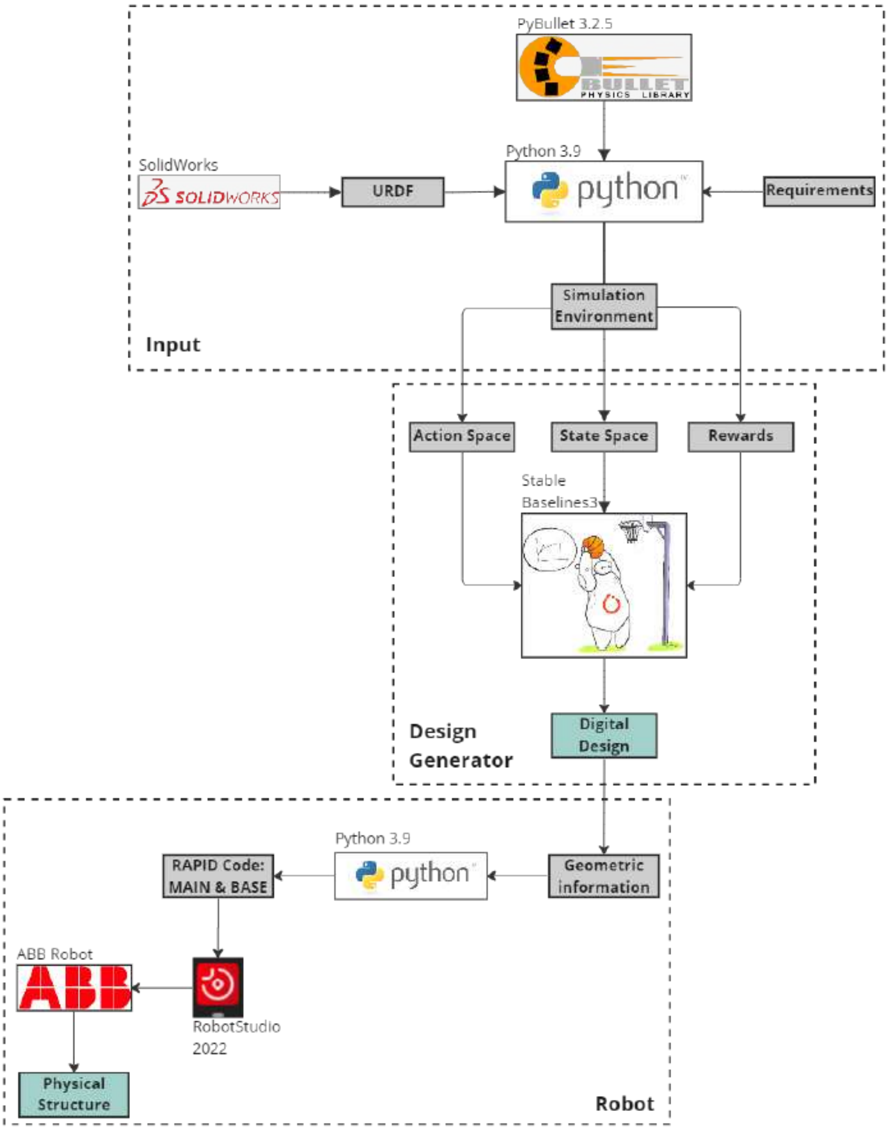


Figure 1: Design and construction process for dry-stacked structures

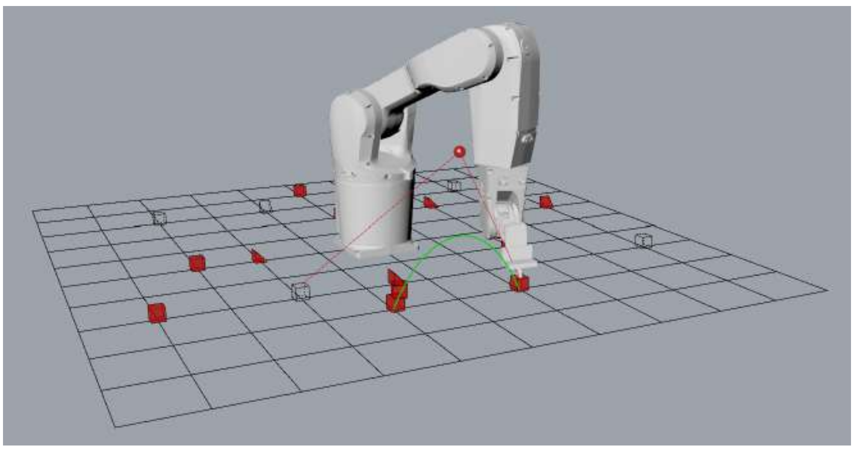

Figure 2: Path-planning for robotic construction

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# Exploratory study for deployment of digital twins for circular energy, heat and building materials in new development of Greenport Horti Campus Westland

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***Abstract –*** *This paper describes a plan for applied research that will commence later in 2023. The municipality of Westland, in collaboration with the landowners and other stakeholders, is working towards a new area development of Greenport Horti Campus. Circular Economy (CE) is the fundamental ambition for this project with the focus on digital backbone for circular energy, heat and building materials. However, the realization of CE with the practical application of digitalization –especially digital twin technologies– is yet underexplored. This study will investigate the feasibility and strategy for setting up and deploying digital twins for the circular campus development project through a collaboration with project stakeholders.*

For the development of the Greenport Horti Campus Westland, HortusLab as the client has the ambition for a harmonized district around the World Horti Center where world-class research, education and innovation of horticulture engineering take place. The Greenport Horti Campus Westland, covering an area of 3 hectares, is aiming to expand as an urban area where innovations can flourish attracting high-quality business opportunities, teaching and research facilities. Under this overarching vision, Hortuslab's goal is to develop a smart, sustainable and inclusive campus where living, working, innovation and recreation take place side by side. The plan is to build buildings and urban infrastructures for living and working in horticulture in support of the existing housing vision 2020-2030 of Westland (Peijs,K., Boon,H. Hofman, G. & Raamsdonk, L., 2022).

Circular Economy (CE) is the fundamental approach for this new area development-the buildings are circular built and the energy, heat and materials at the campus are reused or repurposed. With CE in mind, Hortuslab's grand vision is to become an example of global character as well as the heart of a local community: 'from a greenhouse town to a blue zone with a green heart'.

Greenport Horti Campus Westland World Hort Center

Figure 1: Layout of Greenport Horti Campus Westland

In the Westland region, circular solutions for energy and water are widely used. However, the realization plan for CE in energy, heat and building materials has only been developed to a limited extent (Gemeente Westland, 2022). In addition, the local stakeholders still need more precise knowledge on digitalization, especially the digital twin technologies, that incorporate expert knowledge for analyzing and predicting the performance of a physical object (Sebastian, Bohms, & Luiten, 2021). Hence, the practical application of digitization in the design, realization, and long-term management and maintenance for circular campus development still needs to be explored.

Therefore, the underlying research question of this project is: how can the client, design and construction actors develop a cost-effective strategy to deploy digital twins in supporting the World Horti Campus ambition for CE in energy, heat and building materials?

From the CE perspective, digital building logbook (DBL), material passport, building information modeling (BIM) are believed to have the potential capability to estimate recoverable materials or track existing materials for reuse in various design alternatives. Measurement data from sensors and simulations to monitor, analyze and predict energy and material consumptions and building performance are also emerging. However, very few studies have investigated the practical solutions for interoperable digital twins that comprehend circular energy systems and material use to predict and optimize the performance of a campus area throughout its life-cycle stages. Most studies are still theoretical and conceptual (Yu, Yazan, Junjan, & Lacob, 2022). In order to understand the real-life constraints, a number of scholars ( (Awan, Sroufe, & Shahbaz, 2021), (Munaro & Tavares, 2021), (Ranta, Aarikka-Stenroos, & Vaisanen, 2021)) also called for empirical research with practical case studies where circular strategies are implemented and measured by deploying digital technologies.

Hence, the main objective of this study is to investigate the feasibility of developing a digital twin that can incorporate a Building Information Model (BIM), IoT sensor networks and Material Passport for circular electricity, heat and building materials at Greenport Horti Campus Westland.

In particular, this study focuses on the feasibility of three aspects:

1. Digital twin platforms for smart multi-commodity grids which enable flexible generation, storage and distribution of electricity and heat.
2. Use of digital twin for material passport and circular construction materials in local areas.
3. Long-term strategy for circular electricity, heat and material in whole campus management supported by digital twins.

Given the characteristics of digital twins for circular use of electricity, heat and building materials, empirical and qualitative research approaches will be applied through an iterative stepwise method:

1. Consolidation of the CE objectives in Key Performance Indicators (KPIs), including the intended roles of digital twin. This will be done through desk research and interviews with project stakeholders.
2. Drawing up basic functional requirements for the digital twins and the needed competencies of the stakeholders. This will be discussed in expert workshops.

3. Feasibility study of digital twin by means of a field lab. In this field lab, the partners from education, research and practice will work collaboratively while knowledge circulation will take place through the lens of the principal stakeholders.

The main result of this project will be presented in a report with analysis and conclusions aiming 1) the feasibility of using the digital twin for CE purposes and 2) an outline plan for the follow-up approach.

The study will be carried out by a project consortium consisting of The Hague University of Applied Science (THUAS), HortusLab, an architectural design and engineering firm, a real estate developer and the Municipality of Westland. Active participation of higher professional education at HBO and MBO level has been enabled in this project where students take real design challenges on the circularity within the new area development. The HortusLab campus development has already been used as case study in the European Project Semester curriculum of Sustainable Urban Engineering led by THUAS. Through this study, the consortium will take the next step with which education, research and practice can work together.

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